Journal of Economic Literature 2020, 58(2), 299–347
https://doi.org/10.1257/jel.20191074

Measuring Time Preferences†

Jonathan Cohen, Keith Marzilli Ericson, David Laibson, and John Myles White*

We review research that measures time preferences—i.e., preferences over intertemporal trade-offs. We distinguish between studies using financial flows, which we call "money earlier or later" (MEL) decisions, and studies that use time-dated consumption/effort. Under different structural models, we show how to translate what MEL experiments directly measure (required rates of return for financial flows) into a discount function over utils. We summarize empirical regularities found in MEL studies and the predictive power of those studies. We explain why MEL choices are driven in part by some factors that are distinct from underlying time preferences. (*JEL* C61, D15)

1. *Introduction*

In the early 1980s, almost all economists embraced a single model of intertemporal choice: the classical discounted utility model (Samuelson 1937), which features time-separable utility flows and exponential discounting. In this parsimonious framework, utils delayed τ periods from the present are given weight δ^{τ}, where δ is the discount factor.

During the 1980s, researchers began conducting experiments that were designed to test the classical discounted utility model. Since it is hard to give subjects "utils," experimenters gave them what was considered to be the next best thing: money. For example, subjects would choose between X dollars at an early date or Y dollars at a later date. We call these experiments, which offer participants time-dated monetary payments, <u>m</u>oney <u>e</u>arlier or <u>l</u>ater (MEL) experiments. Under the assumption that promised time-dated payments and time-dated utils are interchangeable—an assumption that we will critically examine—MEL experiments generate numerous empirical regularities that contradict the standard discounted utility model. These anomalies, which are discussed below (section 5), include the magnitude effect, diminishing impatience, sub-additive discounting, and many others.

As this apparently anomalous experimental evidence accumulated, researchers began to propose theoretical fixes. Several theories were proposed that could account for some of the anomalous data emerging

* Cohen: Princeton University. Ericson: Boston University Questrom School of Business and NBER. Laibson: NBER and Harvard University. White: Princeton University. We thank Steven Durlauf and five anonymous referees at the *Journal of Economic Literature* for thoughtful comments. We thank Layne Kirshon, Omeed Maghzian, Lea Nagel, and Kartik Vira for outstanding research assistance. We acknowledge financial support from the National Institutes of Health (NIA R01AG021650 and P01AG005842) and the Pershing Square Fund for Research in the Foundations of Human Behavior.

† Go to https://doi.org/10.1257/jel.20191074 to visit the article page and view author disclosure statement(s).

from MEL studies. These included hyperbolic discounting (Strotz 1955; Ainslie 1975, 1992, 2001, 2012; Loewenstein and Prelec 1992), present-biased preferences (Laibson 1997; O'Donoghue and Rabin 1999a, b), temptation-based preferences (Gul and Pesendorfer 2001), dual-self preferences (Metcalfe and Mischel 1999; Thaler and Shefrin 1981; Fudenberg and Levine 2006; Loewenstein and O'Donoghue 2004), and psychometric distortions such as log time perceptions (Read 2001 originates this idea which is expanded upon by Zauberman et al. 2009).

The literature has continued to evolve, growing more complicated as the number of theories has mushroomed. Some observers have argued that no existing framework can explain the rich set of anomalies that have emerged from the MEL experimental paradigm (Frederick, Loewenstein, and O'Donoghue 2002).

In recent years, a new set of challenges has arisen. Researchers have begun to question the MEL methodology itself. This experimental paradigm can be motivated by assuming that a monetary payment at date t generates a dollar-equivalent incremental consumption event at time t (and the corresponding utility flow at time t). This assumption is inconsistent both with the empirical evidence and with standard economic theory. Only perfectly liquidity-constrained consumers or perfectly myopic consumers would instantly consume every payment they receive, with zero intertemporal smoothing.

Alternatively, the MEL paradigm can be motivated by assuming that income (or financial flows) *is* the appropriate fundamental argument of the utility function. This assumption is made occasionally in the economics literature, and is a coherent alternative to the reigning consumption-based model of utility. Nevertheless, an *income*-based utility function is not usually used in the economics literature. Indeed, the consumption literature starts by assuming that consumption is the argument of the utility function and that consumption is therefore being smoothed over the life cycle (i.e., consumption is not equal to income) because the utility function is concave (e.g., see Friedman 1957, Modigliani and Brumberg 1954, and Hall 1978).

Because the myopic consumption model (consumption = income) is empirically contradicted and because most economists believe that *consumption* is the proper argument of the utility function, the MEL methodology itself has become a target of criticism. In light of these criticisms, it has become less clear what the MEL methodology is measuring.

The literature is now divided on many dimensions, including both the theoretical foundations of intertemporal preferences and the empirical methods that we should use to measure intertemporal preferences. On the theory side, there is a division between models that assume dynamic inconsistency (often adopted by behavioral economists) and models that assume dynamically consistent preferences.[1] On the empirical side, there is a division between recent work critical of the MEL framework (Chabris et al. 2008; Epper, Fehr-Duda, and Bruhin 2011; Augenblick, Niederle, and Sprenger 2015; Ericson et al. 2015), and research that uses the assumption that choices in MEL experiments are equivalent to choices over time-dated utility flows (for instance, much of the literature reviewed in Frederick, Loewenstein, and O'Donoghue 2002; Andersen et al. 2008; Benhabib, Bisin, and Schotter 2010; and Halevy 2014, 2015). Because of its methodological simplicity, the MEL framework remains the most

[1] Preferences are dynamically consistent if and only if all the state-contingent preferences held at time t agree with the state-contingent preferences held at time $t + \tau$ for all values of t and τ.

widely used paradigm for estimating time preferences.

In this review, we take the reader through this developing literature, pointing out the explicit and implicit assumptions that researchers have made along the way and the problems with those assumptions. We offer tips on how researchers should navigate the shoals of the time preferences literature: what are the pros and cons of the different theories and the different empirical methods that are now available?

The bad news is that the literature is in discord, without a shared theoretical framework or a broadly accepted empirical methodology. The good news is that conceptual discord is invigorating the intertemporal choice literature and opening the way for new ideas that we hope will resolve the multiple conceptual and methodological contradictions that have emerged.

Despite this discord, most of the empirical literature relies on a common method: MEL. In figure 1, we demonstrate this by providing a snapshot of the empirical side of the discounting literature. Figure 1 summarizes the characteristics of empirical studies identified using Google Scholar to search for papers reporting measurements of time preferences (see our appendix for details, including keywords used and a complete list of the papers identified). While the results of such a search are crude—we undoubtedly missed some relevant papers—they provide a rough-and-ready guide to the overall state of the literature. MEL is a common methodology, with column 2 showing that more than 60 percent of papers use it. Most papers examine behavior in the lab, but a substantial minority examines behavior in the field (column 3). Columns 4 and 5 describe the type of individuals being studied. While students still form an important study population, a majority of papers examine the behavior of the general population (column 4); about two-thirds of the papers study respondents in the United States or Europe. Although the literature currently relies on MEL, there is substantial disagreement about the interpretation of MEL data as well as other data from intertemporal choice studies. Much of our review struggles to interpret and reconcile these competing interpretations.

The paper is organized as follows. Section 2 introduces the theoretical frameworks that economists have used to study time preferences. We focus on the discounted utility model, which is the paradigm most commonly employed when modeling time preferences. We also discuss other modeling frameworks, including multiple-self models, temptation models, and models of heuristic-based decision making.

Section 3 introduces the conceptually simplest and most direct way to measure time preferences. It focuses on empirical studies in which individuals choose among mutually exclusive *consumption* events that are available at various points in time (e.g., eating a spoonful of ice cream now or two spoonfuls of ice cream at a specific later date), holding fixed all other consumption. We then generalize these ideas and describe a wider class of empirical strategies that measure time preferences using real consumption events. This *contrasts* with studies that analyze preferences over financial flows by manipulating the dates on which cash payments are received by an experimental subject.

Section 4 then considers experiments in which *financial* events, rather than consumption events, are the objects of choice. The vast majority of such studies, and of intertemporal choice more generally, have used the MEL framework (see the eighth column in figure 1: "Rewards"). We describe the strong assumptions that are needed to use MEL studies to measure time preferences.

Section 5 summarizes the regularities—often inconsistent with classical theory—observed in MEL studies. We explain why many of these regularities are not predicted

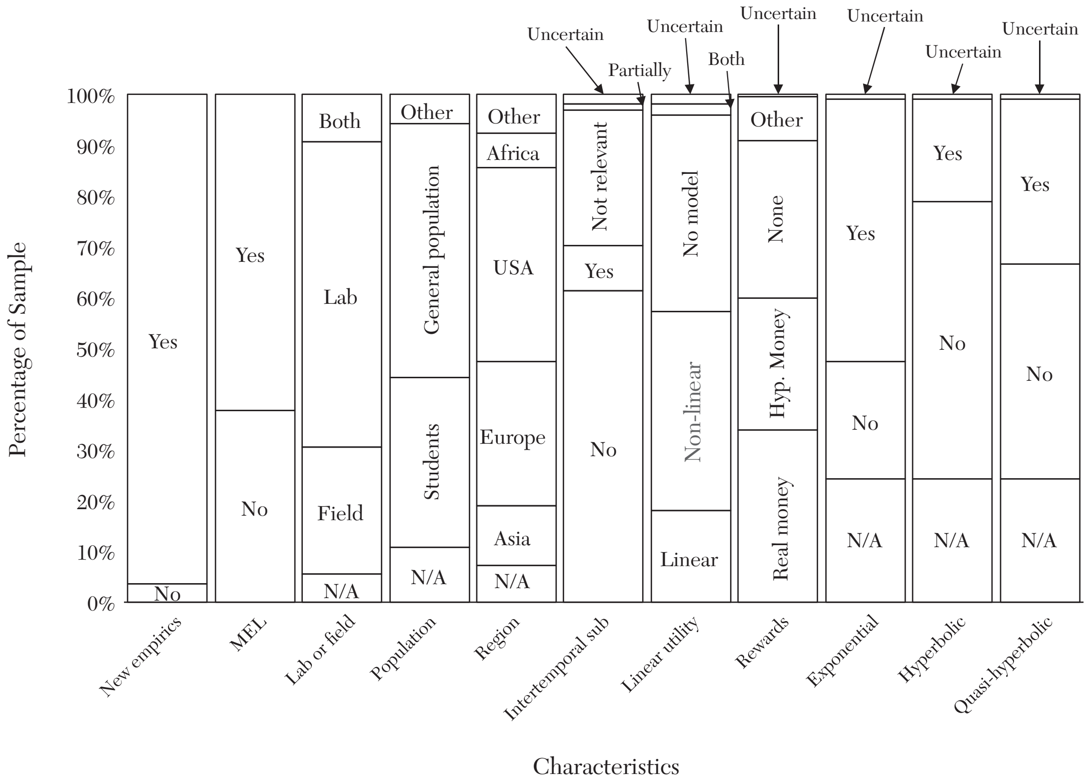

Figure 1. Distribution of Characteristics for Recent Empirical Discounting Papers

Notes: Result of the following Google Scholar Search conducted August 2014: (discount OR discounting) AND utility AND "intertemporal choice" AND "time preferences" AND "standard errors." After eliminating duplicates and reprints, 222 publications remain. Year of publication min = 1980, max = 2014, mean = 2009.8. Papers may appear more than once in the "Lab or Field," "Linear Utility," and "Rewards" columns if they fit more than one category (e.g., a paper with a lab and a field component). The "Intertemporal Substitution" column classifies whether a paper allowed for the possibility that individuals might substitute consumption across time when estimating its discounting model ("Yes") or assumed individuals consumed money or other rewards when they were received ("No"). The "Linear Utility" column classifies whether the paper's model allows for non-linear utility functions in its model. The "Exponential," "Hyperbolic," and "Quasi-Hyperbolic" indicate whether any of those discount functions were estimated in the paper.

by the discounted utility model and examine potential explanations for the anomalies.

Section 6 compares findings from MEL studies inside and outside of the laboratory. We review the predictive power of time preference measurements from such studies for other economic behavior that involves intertemporal trade-offs. This predictive power is usually weak in terms of effect sizes (though the results are often statistically significant): in almost all cases, measures of time preference (and self-regulation) explain less than 5 percent of the cross-sectional variation in economic behaviors that require intertemporal trade-offs. This predictive power is likely to improve as we obtain better methods for inferring time preferences. However, we argue that it is not likely to improve a great deal, because complex intertemporal choices are affected by many factors, not just domain general time preferences.

Section 7 discusses the broad lessons that can be drawn from the existing literature. We argue that the structure of time preferences is still poorly understood and that the most commonly used methodologies for measuring time preferences are not well-suited to the study of time preferences (if consumption is the argument of the utility function). We provide a summary of the alternative methods that are likely to be the most fruitful.

2. *What Are Time Preferences?*

2.1 *The General Form of the Discounted Utility Model*

In this section, we review the theoretical framework commonly used by economists to model time preferences. This model is used for both positive applications (describing and predicting behavior) and normative applications (prescribing optimal individual behavior and/or optimal public policy).

We begin with discrete-time notation. Let t index the time of the current period and τ index relative time (i.e., an event τ periods after date t). Let $x_{t+\tau}$ represent total consumption (a consumption vector) at time $t+\tau$. Assume that a stationary discount function $D(\tau)$ devalues future utility flows based on their distance, τ, from the present. This discount function $D(\tau)$ is *stationary* in the sense that it does not depend on the current period t and only varies with the discounting horizon, τ. Without loss of generality, $D(0)$ is normalized to 1. The value of $D(\tau)$ is referred to as the discount *function* at horizon τ.

It is also common to assume a stationary flow utility function (a.k.a. felicity function) $u(x_t)$ that depends on current consumption x_t. The flow utility function is stationary in the sense that it does not depend directly on time, t, and only depends on consumption. This is sometimes generalized to allow the utility function $u(\cdot)$ to also depend on other state variables Ω_t (e.g., habits as in Abel 1990 or health status), implying $u(x_t, \Omega_t)$. In some implementations, especially papers that estimate discount functions, the argument of the utility function is monetary payment (or income) received by the individual on that date, rather than consumption. We return to this alternative approach below.

The utility flow in period $t+\tau$, viewed from the perspective of period t, has discounted value $D(\tau)u(x_{t+\tau}, \Omega_{t+\tau})$. To simplify notation, we drop the state vector, $\Omega_{t+\tau}$, going forward. Total forward-looking utility (from the perspective of time t) is then the sum of the per period discounted utility flows:[2]

$$\sum_{\tau=0}^{\infty} D(\tau)u(x_{t+\tau}). \tag{1}$$

We call the following set of three assumptions (A1–A3) the discounted utility model:

A1. Stationary[3] discount function $D(\tau)$.

A2. Stationary flow utility function $u(x_{t+\tau})$.

A3. Total utility from the perspective of date t is a sum of discounted flow utilities: $\sum_{\tau=0}^{\infty} D(\tau)u(x_{t+\tau})$.

Time preferences are also often expressed in terms of a discount *rate*, which is the rate at which the value of the discount function

[2] Some researchers have contemplated utility functions that look both forward and backward (e.g., Caplin and Leahy 2004).

[3] Stationary functions depend only on relative time (and other state and flow variables), not on absolute time. Age-dependent discounting (e.g., as in Robson and Samuelson 2009) would be an example of a discount function that violates assumption A1.

declines (at a particular horizon τ). In discrete time, the discount rate at horizon τ is usually defined as

$$\text{Discount rate at horizon } \tau$$
$$= \rho(\tau) \equiv -\ln[D(\tau+1)/D(\tau)]$$
$$\approx -[D(\tau+1) - D(\tau)]/D(\tau).$$

This final approximation is a first-order Taylor expansion of $-\ln[D(\tau+1)/D(\tau)]$ around $D(\tau+1)/D(\tau) = 1$.

The (one-period) discount *factor* with respect to horizons $\tau + 1$ and τ is defined as

$$\text{Discount factor at horizon } \tau \equiv \frac{D(\tau+1)}{D(\tau)}.$$

The n-period discount factor with respect to horizons $\tau + n$ and τ is $D(\tau+n)/D(\tau)$. Thus, the (one-period) discount factor is the level of devaluation of 1 util when its consumption is moved from horizon τ to horizon $\tau + 1$. The discount rate and the discount factor are related by the equation:

$$\text{(2)} \quad \text{Discount rate} = \rho(\tau)$$
$$= -\ln(\text{Discount factor})$$
$$\approx 1 - (\text{Discount factor})$$
$$= 1 - \frac{D(\tau+1)}{D(\tau)}.$$

These concepts also have continuous-time generalizations. When the discount function is differentiable, the instantaneous discount rate is defined:

$$\text{(3)} \quad \text{Instantaneous discount rate at horizon } \tau$$
$$\equiv \rho(\tau) = -\frac{\frac{dD(\tau)}{d\tau}}{D(\tau)}.$$

Likewise, we can define an instantaneous discount factor:

$$\text{(4)} \quad \text{Instantaneous discount}$$
$$\text{factor at horizon } \tau \equiv \exp\big(-\rho(\tau)\big).$$

Depending on the application, time discounting may be motivated by many different mechanisms, including mortality (i.e., the chance that the agent won't be alive to experience utils in the future), myopia (i.e., an inability to accurately forecast the future[4]), and *pure time preferences* (i.e., even excluding mortality effects, economic agents might not value utils in the future as much as they value utils today).[5]

Note that a discount rate is different, in theory, from an interest rate, though they may be linked in general equilibrium. Time preferences are (usually) defined by utility tradeoffs. Interest rates are defined as the return on savings or the cost of borrowing. We will discuss the wedge between time preferences and interest rates below. In principle, time preferences are also distinct from risk preferences, however, some authors have argued that delay in reward receipt is inherently (or at least, usually) linked to risk (e.g., Sozou 1998; Dasgupta and Maskin 2005; Halevy 2008; Epper, Fehr-Duda, and Bruhin 2011; Saito 2011; and Andreoni and Sprenger 2012b), creating a confound for the standard

[4] See Von Böhm-Bawerk (1890), Pigou (1920), Loewenstein (1992), and Gabaix and Laibson (2017).

[5] Ethicists disagree whether pure time preferences (which exclude mortality risk) can be normatively justified. There is a related debate over the normatively correct discount rate to use for intergenerational discounting (see Sen 1957, Schelling 1995, Gollier 2013, and discussions in the literature on climate change in Stern 2007 and Goulder and Williams 2012). The evolution of time discounting has also been studied: for instance, Robson and Samuelson (2009) argue that evolution selects for time discounting rates that are linked to the mortality rate and population growth rate, and can produce present bias in the presence of aggregate mortality shocks.

model, which assumes a conceptual distinction between the two phenomena.

Finally, it is important to emphasize that our benchmark model makes no restriction regarding heterogeneity across economic agents; see Coller, Harrison, and Rutström (2012) for a conceptual framework and evidence of such heterogeneity.

2.2 *Samuelson's Classical Discounted Utility Model*

The classical discounted utility model (Samuelson 1937; axiomatized by Koopmans 1960) uses the three assumptions discussed above (A1–A3) and employs the additional restriction that the discount function is *exponential*:

$$(5) \quad \text{Discount function} = D(\tau) = \delta^{\tau}.$$

This gives the following:

$$(6) \quad \text{Discount factor} = \frac{D(\tau+1)}{D(\tau)} = \delta,$$

$$(7) \quad \text{Discount rate} = -\ln(\delta) \approx 1-\delta.$$

The classical discounted utility model implies that choices are time-consistent, that is, individuals will make the same utility trade-off between two periods (s versus $s+\tau$) regardless of when (on or before date s) they make the allocation (Strotz 1955). To see why, consider an agent making a decision at time $t \leq s$ over a trade-off of utils at times s versus $s+\tau$. From the perspective of time t, the relative value of a util at $s+\tau$ versus time s is given by the ratio

$$(8) \quad \frac{D(s+\tau-t)}{D(s-t)} = \frac{\delta^{s+\tau-t}}{\delta^{s-t}} = \delta^{\tau}.$$

Note that the final expression does not depend on either t (the decision time, which is also the current period) or s (the date of the earliest utils). Accordingly, the discount factor from s to $s+\tau$ is δ^{τ}, which depends only on the time gap between the two rewards (τ) and not absolute time (either t or s). The exponential discount function implies that a person's discount factor between two dates depends only on the length of the delay interval.

The converse is also true: if (i) choices are always *time consistent*, and (ii) behavior is generated by a (stationary) discounted utility model that satisfies A1–A3 above, then the discount function must be exponential. Time consistency is defined as the property that the relative value of utility in periods $s+\tau$ and s must always be the same regardless of when, on or before date s, the preferences are evaluated. Combining this consistency property with stationarity of time preferences implies that the discount function from the perspective of time t for utils experienced at time $t+\tau$ must be δ^{τ}.

Accordingly, the exponential discounted utility model is the only (stationary) time-consistent discounted utility model; recall that we are working in a class of stationary models.[6] Time consistency has many desirable properties. It simplifies welfare analysis and dynamic programming (i.e., solving dynamic optimization problems, like a life cycle consumption problem). However, it has been criticized for being empirically unrealistic, an issue to which we will return.

2.3 *Economic Models of Self-Control*[7]

Samuelson's discounted utility model has many useful properties—first and foremost, it is tractable and parsimonious—but it is not designed to explain empirical patterns that fall under the general category of self-control problems. Specifically, the agents in Samuelson's model do exactly

[6] With non-stationary models (dropping Assumption A1), an individual can have time-consistent preferences without having an exponential discount function.

[7] This subsection is based in part on the section on intertemporal choice in Camerer et al. (2016).

what they plan/intend to do. More formally, their state-contingent plans are always perfectly aligned with their subsequent state-contingent actions. For example, they stick to exercise schedules and savings plans. Naturally, they sometimes spend more than they had expected to spend, but these episodes are tied to normatively legitimate shocks (e.g., an unanticipated medical bill) and not a violation of their state-contingent spending plans. Indeed, their state-contingent plans include allowances for adverse shocks. Accordingly, agents in Samuelson's model do *not* experience (state-contingent) preference reversals. They will not keep planning to start writing their term paper and keep failing to follow through. Relatedly, they will not be willing to restrict their choice sets to limit their own scope for future action. However, there is a growing literature that finds that people do make choices that are characterized by systematic preference reversals (e.g., Read and Van Leeuwen 1998; Read, Loewenstein, and Kalyanaraman 1999; and Augenblick, Niederle, and Sprenger 2015) and that people are sometimes willing to use commitment devices that have the sole purpose of limiting their choices (e.g., Ashraf, Karlan, and Yin 2006 and Kaur, Kremer, and Mullainathan 2010; for a review, see Bryan, Karlan, and Nelson 2010). This contemporary literature was anticipated by Hume (1896 [1738], p. 536), who wrote:

> In reflecting on any action, which I am to perform a twelve-month hence, I always resolve to prefer the greater good, whether at that time it will be more contiguous or remote; nor does any difference in that particular make a difference in my present intentions and resolutions. My distance from the final determination makes all those minute differences vanish, nor am I affected by any thing, but the general and more discernible qualities of good and evil. But on my nearer approach, those circumstances, which I at first over-looked, begin to appear, and have an influence on my conduct and affections. A new inclination to the present good springs up, and makes it difficult for me to adhere inflexibly to my first purpose and resolution. This natural infirmity I may very much regret, and I may endeavour, by all possible means, to free my self from it. I may have recourse to study and reflection within myself; to the advice of friends; to frequent meditation, and repeated resolution: And having experienced how ineffectual all these are, I may embrace with pleasure any other expedient, by which I may impose a restraint upon myself, and guard against this weakness.

In an effort to develop models that can explain such phenomena, three types of deviations from the classical discounted utility model have been proposed: (i) multiple-self models in which the multiple selves have overlapping periods of control or influence; (ii) multiple-self models with nonoverlapping periods of control (i.e., a sequence of selves, each of which has its own period of control over the actions of the agent); and (iii) models that have a single ("unitary") self, which has dynamically consistent preferences over choice sets. All of these classes of models have been developed to explain the same types of empirical phenomena (e.g., preference reversals and choice-set-constraining commitments) so the models make similar qualitative predictions. Indeed, in some limit cases they make identical quantitative predictions (e.g., Krusell, Kuruşçu, and Smith 2010). Hence, these models are difficult to distinguish empirically (if one is constrained to use data on behaviors, as opposed to data on attitudes, beliefs, forecasts, and hedonics).[8]

[8] For example, agents could be asked if their current preferences for future actions (in the absence of commitment) match the preferences that they will hold in the future.

2.3.1 *Models in Which Multiple Selves Have Overlapping Periods of Control*

One class of models assumes that multiple selves with conflicting preferences *coexist simultaneously* within the agent—in other words these selves exist in parallel with one another. Such conflicts could be generated by neural systems with goals/valuations that are imperfectly aligned.

Models of a divided self can be traced back at least as early as Plato, who described a person as a charioteer pulled by two horses with conflicting personalities:

> one of the horses is noble and of noble breed, but the other quite the opposite in breed and character. Therefore in our case the driving is necessarily difficult and troublesome (Plato, *Phaedrus 246b*).

Adam Smith (1761, 1776) explained human behavior with a similar description of two conflicting motivational systems: "interests" and "passions." With examples like this in mind, Ashraf, Camerer, and Loewenstein (2005) describe Smith as the first behavioral economist.

In the twentieth century, multiple-self models were first embraced by psychologists. Starting in the 1980s, the economic literature has also proposed theories of two conflicting/interacting systems, where one system is relatively patient and forward looking (e.g., a "planner") and one system is relatively myopic (Thaler and Shefrin 1981; Shefrin and Thaler 1988; Loewenstein 1996; Bernheim and Rangel 2004; Fudenberg and Levine 2006, 2011; Brocas and Carrillo 2008a, b, 2012; Loewenstein and O'Donoghue 2004). In a related variation on these themes, Jackson and Yariv (2014, 2015) examine collective decision making, which can be interpreted as multiple simultaneous selves. They show that if there is heterogeneity in time preference, any Pareto-efficient, nondictatorial way of aggregating utility functions will be characterized by present bias.

2.3.2 *Models in Which Multiple Selves Have Nonoverlapping Periods of Control*

Researchers have also argued that self-control problems are a reflection of dynamically inconsistent preferences generated by a series of (nonoverlapping) selves that arise sequentially and don't agree about optimal behavior. Strotz (1955) was the first to propose such a model, though his ideas were partially anticipated by Ramsey (1928) and Samuelson (1937).

Strotz's model falls within the general class of discounted utility models (assumptions A1–A3 above), but his model does not adopt exponential discounting, and thereby deviates from Samuelson's approach. In Strotz's framework, a nonexponential discount function induces preferences to be dynamically inconsistent: i.e., self t and self $t+n$ don't agree about the preference ranking of consumption paths that are identical before date $t+n$ and at least partially different thereafter (see a formal example below). Figure 2 plots the exponential discount function, along with two common alternatives: continuous-time hyperbolic discounting (i.e., $D(\tau) = \left(1+\alpha\tau\right)^{-\gamma/\alpha}$, which is taken from Loewenstein and Prelec 1992) and discrete-time quasi-hyperbolic discounting (see Phelps and Pollak 1968; Akerlof 1991; and Laibson 1997).

With a hyperbolic discount function, the discount *rate* (i.e., the rate of decline of the discount function at a particular horizon) falls as the horizon increases. The quasi-hyperbolic model reflects this property, and, because of its simplicity, enables equilibrium analysis to take a tractable recursive structure.[9] The quasi-hyperbolic discount function is given by $D(\tau) = 1$ at

[9] For example, see Harris and Laibson (2001, 2013) for analyses that exploit this recursiveness.

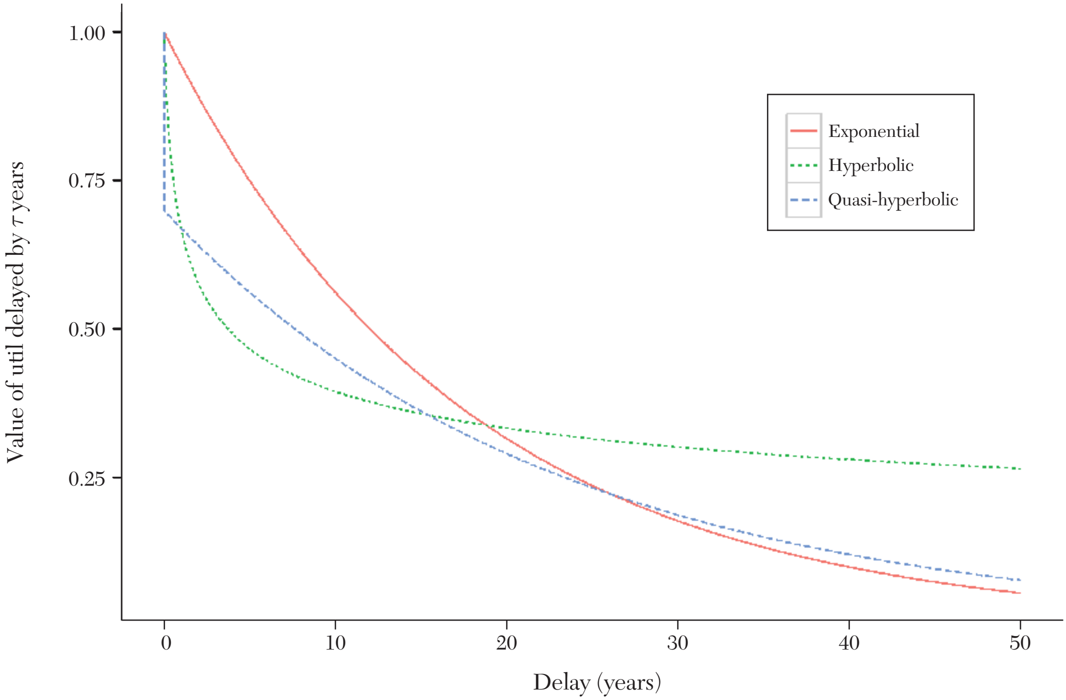

Figure 2. The Shape of Different Discount Functions

Notes: Plots of the exponential δ^{τ} with $\delta = 0.944$, hyperbolic $(1+\alpha\tau)^{-\gamma/\alpha}$ with $\alpha = 4, \ \gamma = 1,$ and quasi-hyperbolic $\beta^{\mathbf{1}_{(\tau>0)}}\delta^{\tau}$ with $\beta = 0.7, \delta = 0.957$.

$\tau = 0$ and $D(\tau) = \beta\delta^{\tau}$ for all $\tau > 0$, where $0 < \beta < 1$ and $0 < \delta \leq 1$. Current rewards are normalized to have unit weight, and future rewards have weight $\beta\delta^{\tau}$. From the perspective of self 0, dates 1 and 2 have respective weights $\beta\delta$ and $\beta\delta^2$ so one util at date 2 is worth δ times as much as one util at date 1. But from the perspective of self 1, one util at date 2 is worth only $\beta\delta$ times the value of one util at date 1. Hence, self 0 and self 1 don't agree on the relative value of rewards at dates 1 and 2 (i.e., $\beta\delta < \delta$). Self 0 wishes to act more patiently than self 1 with regard to trade-offs between periods 1 and 2. This implies that the economic agent has dynamically inconsistent preferences: self 0 and self 1 hold inconsistent preferences (and this generalizes in the sense that all future selves have preferences that are inconsistent with the preferences of the current self). Commitment may be valued by this agent if three conditions hold: (i) she partially understands her dynamic inconsistency (i.e., she is not fully naïve about her time preferences—see Strotz 1955 and O'Donoghue and Rabin 1999a); (ii) commitment technologies are sufficiently low cost (i.e., inexpensive to construct or obtain); and (iii) there is sufficiently little non-contractible uncertainty in the environment (see Laibson 2015 for a joint analysis of these three conditions).

2.3.3 *Unitary-Self Models*

In the last fifteen years, a third approach has emerged. This new class of models explains (apparent) preference reversals and commitment (i.e., voluntary choice set restrictions) without assuming the existence of multiple selves. This new class of models features dynamically consistent preferences expressed by a single self. Accordingly, we refer to this class as unitary-self models (emphasizing a distinction with the *multipl*e-self models summarized in sections 2.3.1 and 2.3.2).

These unitary-self models assume that agents have preferences over choice sets. In *traditional* economic models, the bigger the choice set the (weakly) better off the individual. However, in these new models, agents suffer from temptation effects which imply a potential *cost* to having a larger choice set (e.g., Gul and Pesendorfer 2001; Dekel, Lipman, and Rustichini 2009). With temptation effects, agents may be made worse off if their choice set is enlarged, even if they don't pick any of the new options that have been added to the choice set. Intuitively, resisting a tempting option (e.g., a second helping of cake at a birthday party) may be aversive, making an agent worse off from exposure to an option even if the option isn't chosen. Accordingly, an agent may prefer to ex ante eliminate items from her choice set, regardless of whether or not she would have chosen to consume that particular item if it were available. These temptation effects are related to cue effects in which environmental cues (e.g., Pavlov's (1927) bells or the sight of drug paraphernalia) stimulate appetites that may create aversive cravings (e.g., Laibson 2001; and Bernheim and Rangel 2004).

2.4 *Other Classes of Models That Deviate from the Classical Discounted Utility Model*

There are many models that fall outside the boundaries of the discounted utility model. While the discounted utility model, which features a domain-general discount function, has the benefit of being applicable to any intertemporal choice environment in principle, this generality may be empirically invalid. Alternative, domain-*specific,* models of intertemporal choice have also been proposed. For example, some authors have developed models with domain-specific discount functions (i.e., discounting health differently than discounting the consumption of material goods; e.g., Chapman 1996).[10]

Relaxing the assumption that utility is the sum of discounted flow utilities—assumption A3 above—allows risk aversion to be separated from the intertemporal elasticity of substitution (see Epstein and Zin 1989; Bommier 2006, 2007, 2013; Bommier and Rochet 2006; Cheung 2015; Abdellaoui et al. 2018; and Andersen et al. 2018). For instance, Andersen et al. (2018) consider utility that can be written $U = E\left[\varphi\left[\sum_{\tau=0}^{T} D(\tau)u(x_{t+\tau})\right]\right]$ for some function φ. When φ is the identity function, this is simply the discounted utility model, but this functional form allows for the concavity of intertemporal utility. DeJarnette

[10] Another literature examines systematic features of intertemporal choice that can operate on top of discounted utility or other models of time preference. For instance, Koszegi and Szeidel (2013) develop a model of focusing and apply it to intertemporal choice. In their model, individuals maximize focus-weighted utility and focus more on attributes in which their options differ more. Their model predicts no present bias when choices are equally concentrated (e.g., 10 utils or 20 utils tomorrow), but does predict present bias for "lifestyle choices," in which costs are incurred at a single point in time but benefits come as a stream of payoffs (e.g., going to the gym is costly, but produces a flow of health benefits on many future dates). Focusing could operate alongside traditional discounting.

et al. (2018) show that this model is what results from the combination of the axioms of expected utility with those of discounted utility, and call this model generalized expected discounted utility.[11]

Benhabib, Bisin, and Schotter (2010) propose a "fixed cost of delay model," in which the later option in a pairwise comparison incurs a "fixed cost" that does not depend on the length of the delay between the earlier and later options. In a similar class of models, Kable and Glimcher (2010) examine choices between two rewards, and argue for a modification of hyperbolic discounting that starts the hyperbola at the arrival time of the earlier reward (which might be at a horizon $\tau > 0$). They find that this fits their choice data better than an exponential discount function or a standard hyperbolic discount function (which starts at horizon 0).

Other models deviate more drastically from the classical discounted utility model. For example, heuristic-based models are designed to reflect the specific cognitive algorithms that individuals use and the biases that result from those cognitive processes. Such models have been widely applied in the psychology literature (Tversky and Kahneman 1974, Gigerenzer and Todd 1999). To date, heuristic-based models in the domain of intertemporal choice have primarily been descriptive and difficult to generalize. They would not typically be used for welfare or policy evaluation. In other words, these heuristic models are primarily positive and not normative in scope.

Early examples of heuristic-based models applied to intertemporal choice include Read, Frederick, and Scholten (2011, 2013). They propose a model ("DRIFT") that explains choice between pairs of monetary rewards based on four factors:

(i) The absolute difference between the larger and smaller amounts of reward.
(ii) The absolute delay between the arrival times of the later and earlier rewards.
(iii) The implicit discount rate between the later/larger and earlier/smaller rewards.
(iv) The descriptive frame of the experiment: consumption or investment.

In a closely related line of work, Ericson et al. (2015) propose an intertemporal choice heuristics (ITCH) model, which is also based on four simple factors. The ITCH model employs the first two factors listed above, but changes the final two factors so that they are the percentage difference between the reward amounts and the percentage difference in reward delays. Using a cross-validation framework (which implicitly penalizes overfitting because the tests are all out-of-sample), Ericson et al. (2015) find that both of these heuristic-based models fit a broad dataset of MEL choices better than any of the commonly studied discounted utility models. However, these findings have been challenged by Wulff and Van den Bos (2018), who show that population-level models of the type used by Ericson et al. (2015) distort inference and give a misleading advantage to heuristic models. Wulff and Van den Bos (2018) recommend fitting parameters at the level of the individual experimental participant, but this is problematic when sample sizes are small (at the level of the individual).

3. *Measuring Time Preferences Using Real Consumption Events*

In the discounted utility model, an individual's time preferences are summarized by the discount function, $D(\tau)$. In principle, to empirically identify the shape of the discount function, a researcher would like to ask experimental participants to choose between (separable) increments of utility

[11] Cheung (2015) and Andersen et al. (2018) present experimental evidence for concavity of intertemporal utility based on intertemporal correlation aversion.

available at different dates in time. For example, holding all else fixed, would you prefer one util now or two utils in a week? However, experimenters cannot directly deliver utils—rather, they deliver rewards that experimental participants value: direct consumption experiences—e.g., food, goods, effort—or money (which can be used to purchase consumption experiences). The differences between time-dated utils and the rewards provided in experiments raise two measurement challenges.

First, the economic analysis must translate the rewards into marginal time-dated utils. Utility is usually not linear in units of reward, like ounces of ice cream or dollars spent on a meal (the mapping is usually assumed to be concave). In addition, a specific reward, like potato chips, may be a complement or a substitute for other real rewards (respectively, soft drinks and Doritos).

Second, the economic analysis must determine how receipt of the experimental rewards changes the overall time path of utils. For instance, subjects need *not* consume money when they receive it. Moreover, as discussed by Augenblick, Niederle, and Sprenger (2015), even if the experimenter directly controls consumption of a reward (food or effort), the subject might engage in offsetting behavior outside the lab (e.g., skipping an afternoon snack after receiving ice cream during an afternoon experiment, or taking a break after the conclusion of a grueling experimental task).

To illustrate the second issue, consider the following example. Let time be divided into periods of one full *day*. Let the individual have a concave instantaneous utility function $u(c_t)$ applied to total (real) consumption c_t in each period. Within each period, let consumption be *perfectly substitutable*, so the utility of consuming q units of a good during a period is the same no matter when those q units are consumed over the course of the day. Although the experimenter controls an individual's consumption during part of the day (e.g., eating food or experiencing entertainment during an experiment), the subject chooses consumption for the rest of the period. In an optimizing model in which the subject is not constrained, the subject chooses total consumption to satisfy the Euler equation: $u'(c_t) = \delta(1+r)u'(c_{t+1})$, where δ is the one-period discount factor and r is the real interest rate. In such a model, the delivery of a small reward during an experiment is almost[12] perfectly offset by a reduction in consumption outside the experiment during the same modeling period (i.e., during the same calendar day).

These methodological problems do not arise if the period length (within which substitution can occur) is shorter than the duration of the experimental session, or if substitution does not occur for some other reason. For example, mental accounting, like narrow bracketing, could cause the subject to treat the experimental rewards as separable from all of the other consumption in their life. Likewise, a myopic consumption heuristic—consume experimental windfalls when they are received, not when they are initially promised, and do not adjust background consumption—would also eliminate the problem of intertemporal substitution.

Research has attempted to address these issues in measuring intertemporal preferences with several different methodological approaches. In this section, we review the leading examples of the efforts to resolve the difficulties surrounding the use of real rewards.

[12] An income effect (deriving from unexpectedly high or low income received during the experiment) might cause a small change in the annuity value of total lifetime resources, thus increasing overall consumption during the modeling period by a tiny amount.

3.1 *Experimental Studies Using Time-Yoked Consumption (Instead of Financial Flows)*

The seminal study using time-dated consumption of real rewards is Walter Mischel's "marshmallow" experiment (Mischel and Ebbesen 1970; Mischel, Shoda, and Rodriguez 1989). Children from the Stanford University Bing Nursery School ranging from 3 to 5 years of age were seated alone in a room and told that if they waited until the experimenter returned they would obtain a preferred food reward. The children were able to receive a *less* preferred food reward at any point during the experiment (e.g., by ringing a bell), which would cause them to lose the opportunity to wait for the more preferred reward. Accordingly, the children were making intertemporal choices at every moment during the experiment between an immediate reward and a delayed reward: e.g., one marshmallow now versus two marshmallows if they could wait until the experimenter returned. The children were not told how long they would need to wait until the experimenter returned. In fact, the experimenters returned 15 minutes after the start of the task. In the marshmallow task it is probably safe to assume that the food rewards are consumed in real time. They are not saved for later that day and they plausibly do not crowd out other consumption—at least, it is reasonable to assume that the 3-to-5-year-old subjects do not anticipate such crowd out, which may result from parental decisions later during the day of the experiment.

Despite these advantages, it is difficult to use the marshmallow study to estimate the parameters in the discounted utility model (even if one *knew* the curvature of the utility function for marshmallows). First, it is not clear what each child initially believed about the time it would take the experimenter to return. A child's unmeasured belief about the distribution of return times is essential to an application of the discounted utility model, but such beliefs were not measured in the experiment. Second, it is likely that the children's beliefs about return time changed as the experiment unfolded. As McGuire and Kable (2013) note, the decision to wait a few minutes and then opt out of the experiment may imply that the children are updating their posteriors toward expectations of a longer remaining waiting time. In short, Mischel's study measures behavior that is related to (i) time preference, (ii) the capacity to stick to a previously made decision, (iii) beliefs about the future actions of the experimenter, and numerous other factors. Despite these methodological confounds, Mischel's task predicts (correlation 0.19) scores on personality scales that are designed to measure self-regulatory capacity (Benjamin et al. 2019).

In addition to Mischel's study, there have been several other studies of decision making that focus on the consumption of goods for which the time of consumption is at least partially controlled by the experimenter. Because of difficulties involved in estimating the exact form of a person's flow utility function, the majority of these studies have not estimated the discount function, but have instead focused on qualitative properties of intertemporal choice behavior. In particular, these studies have used real consumption flows to demonstrate that intertemporal choices often exhibit dynamic inconsistency.

For example, Read and Van Leeuwen (1998) implemented a design in which participants chose a single snack from a set of eight snacks, some of which were healthy (e.g., fruit) and some of which were unhealthy (e.g., candy bar). Participants *chose* while they were either hungry (i.e., before lunch) or sated (i.e., after lunch). Subjects *ate* the chosen snack while they were either hungry (i.e., before lunch) or sated (i.e., after lunch).[13] Subjects *chose* twice: one week before the eating event and, *again*, at the time of the eating event—in other words, they were given a chance to change their mind, though they didn't know they would have this chance when they made their first choice. Varying satiation allowed Read and Van Leeuwen to determine the extent to which current emotional states affect preferences (e.g., projection bias[14]), whereas varying the time horizon of the choice allowed Read and Van Leeuwen to assess whether preferences are dynamically inconsistent. Demonstrating dynamic inconsistency in the absence of a cardinal measure of utility is a common strategy in the literature: it is possible to establish qualitative properties of the discount function without estimating its exact parametric form. Collapsing across individuals and conditions, Read and Van Leeuwen found that unhealthy snacks were chosen 51 percent of the time when offered for consumption one week in the future (this number averages across their conditions). The same unhealthy snacks were chosen 83 percent of the time when offered for immediate consumption. This was one of the first studies to use real consumption events to investigate dynamic inconsistency.

Read, Loewenstein, and Kalyanaraman (1999) implemented a related design in which the real consumption good was viewing movies. Subjects chose what to watch from a set of movies that was evenly split between low-brow and high-brow films. Participants selected a movie to watch the day of the experiment. In addition, participants selected (that day) a movie to watch in a future week. On average, participants picked low-brow movies to watch that day and high-brow movies to watch in the future. (In this study there was no opportunity for participants to later change their mind.[15])

McClure et al. (2007) employed time-dated juice rewards[16] in a neuroimaging experiment in which participants were asked to choose one of two time-yoked juice squirts (subjects were thirsty because they were denied fluid for three hours before the experiment and then fed salty snacks at the start of the experiment). All of the squirts of juice were delivered during a single one-hour experiment. Like Read and Van Leeuwen, McClure et al. found strong evidence for dynamic inconsistency. Roughly 40 percent of participants chose the early option when it was available immediately (e.g., now versus 5 minutes), whereas 30 percent chose the early option when it was delayed 10 minutes (e.g., 10 minutes versus 15 minutes) and 20 percent chose the early option when it was delayed 20 minutes (e.g., 20 minutes versus 25 minutes).

Many papers study both monetary rewards and primary rewards (e.g., food). For example, Reuben, Sapienza, and Zingales (2010) compared discounting for a primary reward (chocolate) with discounting for a monetary reward. They found that individuals' elicited discount rates correlated across these two choice domains ($R^2 = 0.12$). However, the actual discount rates were much higher for the primary reward than the monetary reward.

13 Actually, the experimenters did not directly observe when the snack was eaten. Here we assume that the snack was eaten when it was received, which is probably not true in all cases.

14 See Loewenstein, O'Donoghue, and Rabin (2003).

15 Accordingly, this study is only evidence for dynamic inconsistency under the maintained assumption of preference stationarity.

16 Food rewards have also been used to compare time preferences across species in the psychology literature. Tobin and Logue (1994) studied food choices at short delays with human and nonhuman populations. They showed that the required rate of return increased as the subject population switched from pigeons, to rats, to human children, to human adults. However, this position is challenged by research that argues that high rates of impatience in non-human species are observed in food-deprived animals, invalidating comparisons to relatively sated human subjects (e.g., Rosati et al. 2007).

Using a time-yoked work/effort task, Augenblick, Niederle, and Sprenger (2015) found evidence of dynamic inconsistency. Experimental participants made work plans for *future* weeks. When the time to work arrived, some participants were given the opportunity to change their self-selected work plans. Participants tended to use this flexibility to shift work further into the future, rather than shifting work from the future towards the present. In contrast, they found much weaker (but still statistically significant) evidence of dynamic inconsistency with respect to participant decisions that involved time-dated *financial* flows.[17] Relatedly, Carvalho, Meier, and Wang (2016) found that present bias in MEL choices differed significantly before and after payday for a low-income population, while present bias in real effort choices was not significantly different. Bisin and Hyndman (2014) also studied real-effort procrastination tasks and found evidence of present bias.[18] These results provide some support for the prediction that choices over time-yoked consumption/effort identify the discount function, whereas choices over (intertemporally substitutable) financial rewards do not reveal the discount function (e.g., if consumers smooth consumption).

Many other studies have measured higher discount rates for consumption rewards relative to monetary rewards. Odum, Baumann, and Rimington (2006) found that food is discounted more steeply than money using hypothetical choices. Odum and Rainaud (2003) examined hypothetical discounting for money, alcohol, and food. They found that individuals are more patient for money than for alcohol or food, but that alcohol and food are discounted similarly. Similarly, Estle et al. (2007) compared the discounting of money to primary, directly consumable rewards (candy, soda, and beer). They reported that monetary rewards are discounted less than directly consumable rewards; their subjects discounted the consumable rewards—candy, soda and beer—at similar rates. Likewise, Tsukayama and Duckworth (2010) found that primary rewards are discounted more than money. Ubfal (2016) examined discount rates for six different goods for rural Ugandan households and also found that estimated discount rates vary by type of good; generally, monetary rewards are discounted less than sugar, beef, or plantains.

The assumed degree of curvature in the utility function influences the imputed discount rate. For instance, consider Lawyer et al. (2010), who studied delay discounting tasks with respect to hypothetical money and (minutes of) hypothetical sexual activity. They found that sexual activity is discounted more than money. They assumed that utility is linear in money and linear in minutes of sexual activity. If the *actual* utility function is concave, their estimated discount rates will be biased upward. Moreover, it seems likely that the utility function for sexual activity is more concave than the utility function for money (since money is highly fungible). Like Lawyer et al., most of the studies that we have reviewed assume linear utility for primary and monetary rewards. By contrast, Augenblick, Niederle, and Sprenger (2015) estimated separate curvature parameters for money and real-effort tasks. Ubfal (2016) measured the curvature of the utility function using risky choices and imposed a common risk aversion (utility curvature) parameter across goods.

Although the literature reviewed in this section is highly multifaceted and

[17] Gill and Prowse (2012) employ a similar effort-based task that could be adapted for use in studying intertemporal choice. Casari and Dragone (2015) also use a consumption based task (listening to unpleasant noise) to examine patterns of preference reversals.

[18] However, note that Ericson (2017) shows that assuming individuals have perfect memory leads to biased estimates of present bias parameters from task-completion rates.

conceptually diverse, a common thread emerges. When discount rates are measured with MEL tasks, the implied discount *rate* is lower than it is when the discount rate is measured with primary rewards like food. Researchers also commonly find that when discounting is measured with MEL tasks, the implied discount *function* is less hyperbolic than it is when discounting is measured with primary rewards.

Another literature has studied the appeal of commitment devices. For example, Ashraf, Karlan, and Yin (2006) found that one-quarter of their (rural Philippine) subjects were willing to put some of their savings in an illiquid account with the same interest rate as an alternative liquid account. Beshears et al. (2020) document a willingness to store money in an illiquid account, even when the illiquid account has a slightly lower interest rate than the liquid account (21 percent versus 22 percent). In their experiment, Beshears et al. (2020) found that illiquid savings accounts attracted more deposits the *higher* the penalty for early withdrawal, holding all else equal. However, these results may not generalize because the participants were using an experimental endowment/windfall of $100 when they made these illiquid deposits, as opposed to their own outside assets. Hence, this may be a house money effect (treating windfalls differently than money obtained through "normal" channels). Nonetheless, commitment has been documented in a wide range of settings: e.g., preference for costly single-unit packaging of tempting snacks (Wertenbroch 1998); self-imposed work deadlines with financial penalties (Ariely and Wertenbroch 2002, Bisin and Hyndman 2014); self-imposed financial penalties for smoking or drinking (Giné, Karlan, and Zinman 2010; Schilbach 2019); self-imposed financial penalties for underperformance in the workplace (Kaur, Kremer, and Mullainathan 2010); self-imposed restrictions on internet access (Houser et al. 2018); self-imposed restrictions on work scheduling (Augenblick, Niederle, and Sprenger 2015); and self-imposed financial penalties for failure to exercise (Royer, Stehr, and Sydnor 2015). Despite all of these examples of experimentally measured commitment demand, researchers have noted that very little pure commitment is demanded/provided in real markets (Laibson 2015). Website blockers—deployed to temporarily stop oneself from straying during work tasks—are one exception to this observation. Another example is the decision to delete a video game from one's game tablet/cellphone. One of the authors of the current paper has saved tens of thousands of hours with this last trick.

3.2 *Consumption Models Estimated with Observational Field Data*

Another literature studies consumption patterns over the life cycle and uses consumption, income, wealth, and borrowing data to estimate preference parameters and test theories of consumption smoothing (see Attanasio and Weber 2010 for a review).[19] Here, we selectively discuss some of those papers focused specifically on measuring time preference. The literature has used the Euler equation to estimate discount rates, but additional data (asset allocation or high frequency consumption data) is useful to distinguish between exponential and quasi-hyperbolic discounting.

The Euler equation[20] provides one way to estimate time preferences, although linearizing the Euler equation undermines its usefulness (Carroll 2001; see also Attanasio

[19] Because of the role of arbitrage, assets prices generally do not identify whether preferences are time-consistent or not (Kocherlakota 2001).

[20] The Euler equation is the first order optimization condition that equates marginal utility of consumption at date t to the discounted and return-scaled value of expected marginal utility of consumption at date $t+1$: $u'(c_t) = E_t \delta R_{t+1} u'(c_{t+1})$, where $R_{t+1} = (1 + r_{t+1})$.

and Low 2004 for a review of the literature estimating Euler equations). In early work, Lawrance (1991) uses the Euler equation to estimate the discount rate of an exponential discount function and then compares discount rates across demographic groups (e.g., high- versus low-income households). Though the estimates are sensitive to the specification, this analysis implies that the (annual) discount rate is about 12 percent for white, college-educated families in the top quintile of the income distribution and 19 percent for non-white families without a college education in the bottom quintile of the income distribution. However, her analysis does not control for differences in income growth rates across demographic groups; when consumption tracks income (due to rule-of-thumb behavior or liquidity constraints), consumption growth may have little to do with time preferences.

Gourinchas and Parker (2002) incorporate liquidity constraints and solve for a structural life cycle savings model with age-dependent family dynamics and age-dependent (stochastic) income. This is a demographically enriched version of the buffer stock model pioneered by Deaton (1991, 1992) and Carroll (1992). Gourinchas and Parker use an empirical aggregate life cycle consumption profile to pin down their estimates of the discount function (using the method of simulated moments). They assume that the discount function is exponential and estimate an annual discount rate of 5 percent.

Like Gourinchas and Parker, Angeletos et al. (2001) solve a buffer stock model (with a liquidity constraint). Angeletos et al. incorporate three kinds of assets: liquid assets, illiquid assets, and credit card debt. They use their model to study wealth accumulation, consumption–income comovement, and credit card borrowing. Angeletos et al. assume a quasi-hyperbolic $\beta - \delta$ discount function. Their model needs a low value of β to explain the empirical rate of credit card borrowing and the empirically estimated marginal propensity to consume out of predictable movements in income. However, their model needs a high value of δ to explain the empirical level of voluntary long-run wealth accumulation, such as defined contribution retirement wealth and home equity. In equilibrium, the surviving assets on households' balance sheets tend to be overwhelmingly illiquid; the liquid assets tend to be consumed quickly due to present bias.

Laibson et al. (2015) use the method of simulated moments to estimate a structural life cycle model with multiple types of assets—some liquid and some illiquid—following the modeling approach taken by Angeletos et al. (2001). Laibson et al. (2015) estimate that the long-run discount factor, δ, is 0.96 and the short-term discount factor, β, is 0.50. This line of research highlights the parameter identification that is achieved by modeling and measuring wealth formation and borrowing across assets/debts with different degrees of liquidity (rather than studying the household balance sheet by collapsing wealth to a single net value). Likewise, Laibson (1997), Angeletos et al. (2001), Barro (1999), and Gustman and Steinmeier (2012) show that it is difficult to econometrically identify different functional forms of the discount function using *only* data on consumption paths.

High-frequency consumption data (e.g., caloric consumption taken from daily food diaries) provides another way to distinguish between exponential and quasi-hyperbolic discounting. Some authors have argued that consumption covaries too much with high frequency income flows to be consistent with exponential discounting (and classical consumption smoothing motives). Shapiro (2005) shows that calories consumed decline by 10–15 percent over the monthly food-stamp cycle. He shows that quasi-hyperbolic discounting is needed to explain this pattern (or an implausibly high level of exponential discounting). Mastrobuoni and Weinberg (2009) follow a related strategy, but they study the intra-month caloric consumption of social security recipients. They find that only liquidity-constrained households have a β (in the quasi-hyperbolic formulation) that is well below 1, while individuals who are not liquidity constrained have a β that is indistinguishable from 1.

A large literature examines consumers' marginal propensity to consume out of foreseeable income flows, including social security payments (Stephens 2003, Mastrobuoni and Weinberg 2009) and tax rebates (e.g., Shapiro and Slemrod 2003; Parker et al. 2013; Broda and Parker 2014). Papers in this literature typically do not estimate a discount rate from consumers' choices, but the literature has found anomalously high marginal propensities to consume. For example, Broda and Parker (2014) estimate the marginal propensity to consume (MPC) using exogenous variation in the timing of Treasury Department tax rebates (approximately $1,000 per household) that were part of the 2008 fiscal stimulus package. They estimate a one-quarter MPC of 65 percent. Such high marginal propensities to consume are difficult to reconcile with the standard life cycle permanent income hypothesis, but are predicted by models in which individuals have self-control problems and face liquidity constraints.

3.3 *Other Models Estimated with Observational Field Data (Including Financial Flows)*

A diverse literature estimates the discount rate (or required rate of return for financial flows) implied by various decisions. For instance, Viscusi and Moore (1989) infer time preference from choice of job and occupational fatality risk. They find average annual discount rates of 11 percent, with educational levels negatively correlated with the estimated discount rates.

This approach can also be used to distinguish between models of discounting (e.g., DellaVigna and Malmendier 2004, 2006). DellaVigna and Paserman (2005) examine the job search behavior of the unemployed, and find evidence that impatience has a sizable effect on search effort and matching in the particular way predicted by the quasi-hyperbolic discounting model. They find that variation in short-run patience (β) drives search intensity, and variation in long-run patience (δ) is associated with the worker's required wage threshold, so that households with low values of β and high values of δ have the slowest exit rates from unemployment. Because patience is empirically associated with high rates of job finding, they conclude that variation in β is the key source of interpersonal variation. They perform a calibration exercise, and find that $\beta = 0.9$ for workers classified as "impatient" based on behaviors signaling impatience (e.g. smoking, not having a bank account). Ben Halima and Ben Halima (2009) estimate DellaVigna and Paserman's model with French data and find similar results. Paserman (2008) estimates a related structural model of job search and unemployment with a quasi-hyperbolic discount function; he estimates that β is approximately 0.5 for low-income workers and 0.9 for high-income workers.

Another literature examines preferences over financial flows using durable goods. The seminal paper in this durables literature is Hausman (1979), which examines how individuals trade off a higher purchase price for lower ongoing operating costs (air conditioners in this case). In his sample of 46 households, he finds required rates of return of about 20 percent per year for this financial flow. This high required rate of return has been used to support energy efficiency standards on the grounds that individuals are myopic when purchasing durable goods.

A more recent literature has examined fuel efficiency choice in automobile purchasing. Dreyfus and Viscusi (1995), following a line of previous work, estimate a hedonic price model that allows for exponential discounting of future benefits arising from fuel efficiency and safety. They estimate a required rate of return of 11–17 percent.[21] Busse, Knittel, and Zettelmeyer (2013) use a novel identification strategy to examine preferences over financial flows: they estimate the willingness to pay for more fuel efficient cars, and examine how this responds to shocks to gasoline prices. They find large changes in market shares of new cars in response to gas prices; in a structural model, their results imply that individuals' required rates of return roughly match the interest rates consumers pay (a range of nominal interest rates from 2–11 percent for new cars and 6–20 percent for used cars). Allcott and Wozny (2014) use a similar identification strategy and find a required rate of return of 15 percent to rationalize purchase behavior. However, as Allcott and Wozny argue, these product attribute trade-off studies do not capture time preference alone. The implied required rate of return can also measure such factors as beliefs, knowledge, and attention.

Other research has studied how individuals structure long-run income flows, and find surprisingly high required rates of return. Warner and Pleeter (2001) estimate required rates of return from military personnel choosing between a term annuity payment (i.e., ten years) and a lump-sum payment when leaving the military. The amounts were sizable—lump sums worth about \$25,000 to \$50,000. Based on the offers that the armed services made, break-even discount rates (before taxes) were between 17–20 percent, meaning that the annuity was more valuable unless you exponentially discounted cash flows at a rate that exceeded this 17 to 20 percent break-even rate. In a large sample (over 65,000 individuals), 90 percent of enlisted personnel and 50 percent of the officers took the lump-sum payment. However, there is a potential confound in the Warner and Pleeter study: the choice of the term annuity obligated the recipient to remain connected to the military in a type of reserve role. If separated soldiers perceived this reserve connection to be meaningful and negatively valued, this would bias Warner and Pleeter's calculations toward finding higher implied required rates of return. In a related study on the military retirement system, which is not confounded by this reserve issue, Simon, Warner, and Pleeter (2015) measure much lower discount rates.

Similarly, Coile et al. (2002) examine the decision to delay claiming Social Security benefits in exchange for higher payments in the future; they argue that standard models and levels of time preference predict much more delay than is observed.[22]

The literature estimating time preference from consumption decisions is promising, though it requires correctly modeling individual's beliefs and dealing with the implications of limited knowledge or attention. A key question for the literature using financial flows (as opposed to consumption) is to what extent required rates of return on financial flows are informative about time preference. Similar questions of interpretation arise in MEL experiments, as discussed in the next section.

[21] They refer to their estimate as a "rate of time preference," but they estimate a rate for financial flows, not consumption.

[22] A large literature examines Social Security claiming and annuitization; these decisions are affected by survival rates and framing, and time preference has not been a focus of this literature.

4. *Measuring Time Preferences Using MEL Experiments*

In this section, we describe the most common experimental design used to measure time preferences in the laboratory: the MEL task. MEL tasks have the methodological virtue of being easy to administer, especially because the procedure is easy to explain to subjects. The analysis of MEL data is also theoretically tractable if one makes the necessary identifying assumptions. In addition, MEL experiments study preferences over financial flows, which would seem to be a topic of natural interest to economists. However, using MEL tasks to infer an individual's discount function requires highly restrictive identifying assumptions, as we will explain below.

In a typical MEL task, individuals choose their preferred option from a set of two or more time-dated monetary payments. In the most common case, each choice set is a pair of options containing a smaller, earlier payment and a larger, later one. For example, an experimental participant might be asked to choose between receiving \$20 today or \$30 in seven days, followed by a series of other such pairs in which the pair of dollar amounts and the pair of times of delivery would vary. Note that the earlier of the two payments need not be "now," and may vary across binary choices. The decisions recorded across all choice sets are then used to identify points of indifference which, under some additional assumptions, pin down a particular discount function.

To describe such indifference points,[23] we want to be precise. We use the construct of a required rate of return (*RRR*). If and only if the decision maker is indifferent between $\{\$x_1, t_1\}$ and $\{\$x_2, t_2\}$, (where $t_2 > t_1$), we define the associated required rate of return between t_1 and t_2 to be

$$RRR \equiv \ln\frac{x_2}{x_1} \approx \frac{x_2 - x_1}{x_1}.$$

The approximation is obtained from a first-order Taylor expansion around $x_2/x_1 = 1$. The definition of *RRR* can be approximated by the percent change in the time-dated rewards. In the example given above, indifference between $\{\$20, \text{today}\}$ and $\{\$30, 1 \text{ week}\}$ implies an *RRR* of 40.5 percent for this indifference pair.

Note that the *RRR* is not necessarily a preference parameter. Rather, it is simply an observed (or estimated) indifference point in the experimental data. The relationship between *RRR*s and preference parameters is complex and will be discussed at the end of this section, as it depends on when monetary payments are consumed (if consumption is the argument of the utility function), as well as on the curvature of the utility function. Finally, it is important to note that we are *not* annualizing the *RRR* in this definition.

4.1 *Experimental MEL Mechanisms for Estimating RRRs*

A substantial amount of research has gone into the methodology of eliciting MEL choices.[24] We focus on the economics-related literature here, but also note key papers in other disciplines that have examined MEL behavior. The majority of published MEL studies

[23] For now, we will assume that the two options are presented simultaneously as alternatives and neither is presented as the default outcome.

[24] We are not certain of the origins of the MEL methodology. We believe that the first implementation in humans was an unpublished working paper by Maital and Maital (1977). However, the first published MEL paper—and the one that is the most influential in the intertemporal choice literature—is Thaler (1981). A related stream of work studied discounting in animal behavior (e.g., Chung and Herrnstein 1967; Ainslie 1975). The MEL design was used by several other economists after Thaler (e.g., Loewenstein and Thaler 1989; Prelec and Loewenstein 1991); it was popularized in the psychology literature by Kirby and Herrnstein (1995).

employ one of three designs: multiple price list (MPL), randomized binary choice, and matching. The first two designs are closely related to the illustrative description of a MEL task presented above: an experimental subject repeatedly selects one option from a choice set of time-dated monetary payments. These three designs vary only in the way in which choice sets are presented.

The first design presents many related choice sets at a single time, organized in a list. We refer to this as the *multiple price list* design (Andersen et al. 2008). In a typical MPL design, a subject chooses between $\$x$ at time t and an ordered series of amounts at a given delay $t' > t$. For example, a participant might first choose between ($10, 0 days) and ($11, 1 day), and then choose between ($10, 0 days) and ($12, 1 day), and then choose between ($10, 0 days) and ($13, 1 day), etc. In principle, subjects should have a single crossover point as the value of the delayed reward monotonically rises. At this crossing point, the subject switches from preferring the smaller sooner reward to the larger, later reward. Such crossover points are used to estimate the *RRR* between t and t'. By ordering questions so that either money or time values change monotonically, the MPL design estimates indifference points efficiently and reduces the frequency of inconsistent choices.

In an alternative design, each choice between $\{\$x_1, t_1\}$ and $\{\$x_2, t_2\}$ is presented in isolation and in a random order. We refer to this design as the *randomized binary choice* paradigm. Although this design makes it much more likely that subjects will make choices that violate transitivity, it has other benefits. First, it can make it easier to determine the focus of attention, since there is only one binary choice on the screen at a point in time (e.g., Johnson et al. 1989). In addition, the tradition of presenting choice sets in isolation is more amenable to psychological and neuroscientific experiments (e.g., using fMRI) in which the experimenter would like to assert that the psychological and/or neural processes of interest are triggered by the content of specific options being shown at a specific moment in the experiment.

The multiple price list and randomized binary choice variants of the MEL paradigm are usually incentivized by paying participants in accord with their expressed preferences, while constraining overall payouts in the experiment to affordable amounts. For example, it is common to randomly select and implement one choice from all of the binary choices that a participant makes in the course of the experiment (often termed the “random incentive system”).

A third variant of the MEL task is the *matching* paradigm (also called fill-in-the-blank). In this paradigm, participants are asked to give an open-ended response by reporting the amount (or time delay) that would make them indifferent between two options. For example, a participant might be asked to state the value of x for which she would be indifferent between ($10, 0 days) and ($$x$, 1 day). The virtue of the matching paradigm is that, in principle, every question identifies an indifference point. However, it is not simple to incentivize choice. The matching paradigm is often used in psychology experiments with hypothetical choices; psychologists have argued that, despite the lack of incentives, participants often give truthful answers (see, e.g., Chapman 1996). The matching method can be made incentive compatible by pairing it with the Becker, DeGroot, and Marschak (1964) method as done by, for instance, Benhabib, Bisin, and Schotter (2010).

The multiple price list and randomized binary choice paradigms ask the subject to choose among pre-specified alternatives, while the matching paradigm asks the subject to generate their own indifference points. It is known that tasks with prespecified alternatives and tasks with self-generated indifference points yield inconsistent results (e.g., Lichtenstein and Slovic's 1973 results on risky gambles). Read and Roelofsma (2003) find lower *RRR*s in the matching paradigm than in randomized binary choice. Hardisty et al. (2013) compare the matching paradigm with two methods that use prespecified alternatives, and argue that prespecified alternatives have greater potential for anchoring or experimenter demand effects, but that tasks with prespecified alternatives better predict behavior outside the lab. Hardisty et al. (2013) employ randomized binary choice and a dynamic "multiple-staircase method." The latter is not incentive compatible, and incentives were not used for most of the study.

In general, the elicitation format seems to matter for imputed *RRR* levels (as well as the shape of the inferred discount function). Freeman et al. (2016) elicit *RRR*s and compare results from the MPL paradigm to two implementations of the matching method: the Becker, DeGroot, and Marschak method and a second-price auction method. They find higher *RRR*s with multiple price lists as compared to the two matching methods, but find similar results in the two matching methods.

Recently, Andreoni and Sprenger (2012a, b) have introduced the *convex time budget* elicitation paradigm.[25] For fixed delivery dates, t_1 and t_2, the participant chooses between (\$$x$ at t_1, \$0 at t_2) and (\$0 at t_1, \$$y$ at t_2) or any convex combination of the two. By varying the implied interest rate, this paradigm can simultaneously elicit utility curvature and discounting (under the assumption that payments are completely consumed when received or the assumption that income— and not consumption— is the argument of the utility function). Using these data, they use nonlinear regression to estimate the discount rate.

Varying time rather than money, Olea and Strzalecki (2014) estimate a $\beta - \delta$ discount function using a MEL format that avoids the need to estimate the curvature of the utility function. They fix the earlier and later consumption levels, and vary the length of time between them. They use this tool for MEL (and find wide bounds for the fraction of agents with present bias). Their method can also be applied to primary rewards. In a similar spirit, Ericson and Noor (2015) show that the "multiple delay list" can test for the *shape* of the discount function without assumptions on the utility function.[26] Ericson and Noor's method can estimate the shape of the discount function but not the level of discounting, while Olea and Strzalecki can measure the level of discounting under the identifying assumption of the $\beta - \delta$ model.

Andreoni, Kuhn, and Sprenger (2015) use a double MPL, which is an MPL for MEL and another MPL for risky choices (see Andersen et al. 2008, who pioneered this method). They integrate this paradigm with the convex budget paradigm of Andreoni and Sprenger (2012a, b). Both methods infer curvature in the utility function even for small amounts of money, indicating that *RRR*s cannot be directly translated into discount rates (a point we will discuss at greater length below). The degree of curvature of the estimated discount rates differs substantially between the two methods. They find that the convex time budget method outperforms the double MPL out of sample (predicting *RRR* in a Becker, DeGroot, Marschak task and a fill-in-the-blank task). This might be related to the fact that the out-of-sample tasks are all matching tasks, as is the particular convex budget task implemented in their paper.

[25] See also the mixing matching tasks proposed by Cubitt and Read (2007).

[26] See also Takeuchi's (2011) "equivalent delay" method for testing for present bias without making any assumptions on the utility function.

4.2 *The Relationship between the RRR and Time Preference*

MEL paradigms produce data that can be used to generate *RRR*s. However, the researcher is often interested in the discount rate for consumption. Understanding the relationship between *RRR*s and discount rates requires a model of individual behavior. We discuss three theoretical frameworks that have been used in the literature (see, e.g., Cubitt and Read 2007).

4.2.1 Model 1: The Optimization Model

First, we consider the case of optimization. In this context, MEL choices are predicted to be only weakly related to the discount function.

In the optimization model, consumers smooth consumption across the life cycle, subject to financing constraints, such as liquidity constraints (e.g., Modigliani and Brumberg 1954; Hall 1978; Deaton 1991, 1992; Carroll 1992; Gourinchas and Parker 2002). The optimization model implies that the subject's financial flows at date t are only weakly linked to the subject's consumption at date t. If a household has ample liquid resources (or a line of credit), then an experimental windfall affects permanent income but has little impact on today's consumption. For example, in the standard life cycle model, a \$100 windfall at age 20 should increase annual consumption by about \$5.[27] Hence, it should affect daily consumption by about one penny.

Even if the agent is liquidity constrained, the marginal propensity to consume may be low. For instance, consider a rising college junior who receives a modest stipend now but will experience a big bump in income when she graduates. For her, the \$100 windfall is smoothed over the next two years, and should only raise daily consumption during that period by 15 cents per day. Hence, under the optimization model, even if the consumer is liquidity constrained, the time-date of the financial payment has only a weak relationship to the time-path of consumption. Of course, there will be rare cases in which it will be optimal to consume the entire windfall as soon as it is received, but those cases are exceptional and would apply to only a small fraction of experimental participants. Under the optimization model, even college students would be expected to consume far less than 1 percent of their windfall per day.

The optimization model predicts that market interest rates place a constraint on what individuals would choose in an experiment: if they could borrow and lend at the same market interest rate, their *RRR* in an experiment should equal that market interest rate and reveal little or nothing about their discount rates (i.e., their rate of time preference). Even imperfect capital markets (e.g., the borrowing interest rate exceeds that of the lending interest rate) don't allow the researcher to directly translate the *RRR* into a discount rate.

Coller and Williams (1999) treat this problem as one of censored data: in their model, a participant's choices only reveal her discount rate if her *RRR* is between her borrowing and lending interest rates. Thus, if an individual demands an *RRR* of 15 percent to take a later payment, we do not know whether that reveals her discount rate or her outside borrowing opportunities.

Cubitt and Read (2007) show that the problem is even more difficult than suggested by the censored data view. They show that, with the optimization model, an individual's *RRR* does not reveal her discount rate even if the *RRR* is between the interest

[27] For example, under ln utility, the consumption function is equal to the exponential discount rate times total wealth, generating an annualized MPC equal to the annualized exponential discount rate (which is often assumed to be 5 percent).

rates faced for borrowing and lending. For instance, consider an individual in a MEL task who would prefer consuming an additional \$20 at date $t+1$ over consuming an additional \$15 at date t. Nonetheless, she might still choose the "\$15 at date t" option in a MEL task because it allows her to spread some consumption across date t and $t+1$. As a result, under the optimizing model, even if an individual's *RRR* is between her borrowing and lending interest rates, it still does not reveal her discount rate.

4.2.2 Model 2: The Consume-on-Receipt Model (with Background Consumption)

In contrast to the optimization model (which features a high degree of consumption smoothing), it is common in the MEL literature to assume that monetary payments from an experiment produce immediate one-for-one marginal consumption (when the payments are received, and not when they are initially promised). In the language of the consumption literature, this amounts to assuming that the daily marginal propensity to consume out of cash flow is 1. This assumption is related to the flypaper effect in the public finance literature (see Hines and Thaler 1995 for a review), which refers to the idea that targeted government expenditure (e.g., federal education funding of local education) does not fully crowd out local expenditure in the targeted category because the local expenditure is sticky.

One can take the flypaper analogy to an extreme, and analyze MEL data by assuming that financial flows "stick exactly where they land," with zero crowd out. We call this the *consume-on-receipt* model.[28] Figure 1 shows that much of the literature uses this assumption either explicitly or implicitly: the "Intertemporal sub" column shows that nearly 90 percent of papers matching our search did not model substitution of consumption across time, but instead assumed individuals consume money when it is received (with no crowd out).

By pinning down the timing of marginal consumption resulting from monetary payments, the consume-on-receipt model makes analysis of MEL data more tractable. But the consume-on-receipt model leaves the mental accounting unresolved: is the payment viewed/framed in isolation, or is it viewed as supplemental to the other consumption that was going to occur on that day anyway?

This issue is sometimes addressed by assuming a fixed level of background consumption (e.g., Andersen et al. 2008). In this case, the participant trades off utility as

$$D(\tau_1)u(b+x_1)+D(\tau_2)u(b)$$

versus

$$D(\tau_1)u(b)+D(\tau_2)u(b+x_2),$$

where b is the background consumption and the binary trade-off is between $\{\$x_1,\tau_1\}$ and $\{\$x_2,\tau_2\}$.

However, background consumption can vary over time (e.g., due to liquidity constraints and/or time-varying income flows). For example, Noor (2009) notes that MEL choices can be difficult to interpret if there is varying marginal utility of money over time due to varying levels of base consumption. For instance, individuals may display (what appears to be) preference reversals in

[28] Andersen et al. (2008) argue that with a Fudenberg and Levine (2006) dual-self temptation model, income from experiments will not be integrated with background wealth. They assume that payments from risky choices are spent in one day. From individuals' choices, Andersen et al. estimate a parameter via maximum likelihood to capture the number of days over which income from discounting tasks is spent. In their model, the likelihood function is maximized when individuals consume the reward on the date they receive it.

choices over money even if they are classical exponential discounters.

In most of the literature, though, background consumption is not incorporated in the identifying assumptions. This leads to a restricted form of the consume-on-receipt model that is implicitly used in most analyses of MEL data. We describe this model next.

4.2.3 *Model 3: The Consume-On-Receipt Model without Background Consumption*

By setting background consumption, b, equal to zero we obtain a model in which subject payments x_1 received at delay τ_1 have value $D(\tau_1)u(x_1)$. Indifference between two time-dated payments, $\{\$x_1, \tau_1\}$ and $\{\$x_2, \tau_2\}$, implies:

$$D(\tau_1)u(x_1) + D(\tau_2)u(0)$$
$$= D(\tau_1)u(0) + D(\tau_2)u(x_2).$$

If $u(0)$ is well-defined, then this model can be estimated.[29]

It is common to make additional restrictions that further simplify the model. For example, if $u(0) = 0$, then the indifference points imply

$$D(\tau_1)u(x_1) = D(\tau_2)u(x_2).$$

For example, consider the (constant relative risk aversion) utility function with $0 < \gamma < 1$:

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma}.$$

This utility function is an additive shift of the standard form of constant relative risk aversion.[30] If we assume exponential discounting with annual discount factor δ (and time horizon variables τ_1 and τ_2 are measured in years), then this specification implies that at an indifference point

$$\delta^{\tau_1}\frac{x_1^{1-\gamma}}{1-\gamma} = \delta^{\tau_2}\frac{x_2^{1-\gamma}}{1-\gamma}.$$

Taking the natural log yields

$$-\tau_1\rho + (1-\gamma)\ln(x_1) = -\tau_2\rho + (1-\gamma)\ln(x_2),$$

where ρ is the annual discount rate: $-\ln(\delta)$. Collapsing terms yields

$$\rho = \frac{(1-\gamma)}{(\tau_2-\tau_1)}\ln\left(\frac{x_2}{x_1}\right) \tag{9}$$
$$= (1-\gamma) \times \frac{RRR}{(\tau_2-\tau_1)}.$$

This provides a simple expression relating the annual (exponential) discount rate (ρ), to the *RRR*, the coefficient of relative risk aversion (γ), and the span of the horizon, ($\tau_2 - \tau_1$).

Equation (9) implies that the discount rate is proportional to the *RRR*. Second, it implies that if one holds the *RRR* fixed, the discount rate is inversely proportional to the gap between the two reward dates (where time units are measured in years). Finally, the formula implies that risk aversion dampens the imputed level of discounting. (Note that $\gamma = 0$ is the case of risk neutrality.) The more risk averse the agent—i.e., the higher the value of γ—the lower the implied value of ρ (holding all else equal). This property emerges because larger, later rewards have lower marginal utility *both* because they are discounted *and* because they are moving further out along a concave utility function.

[29] For some commonly used utility functions, $u(0)$ is not well-defined. For example, with constant relative risk aversion, $u(0)$ is only defined when the coefficient of relative risk aversion is strictly less than one.

[30] The more common form incorporates an additive shift: $-1/(1-\gamma)$. This additive shift makes the function converge to $\ln(c)$ as γ goes to 1.

Hence, in this model discounting and risk aversion are substitutes.

This substitution effect is weakened when background consumption, b, is added back into the model (as in the previous section). Moreover, as b gets large (holding fixed the indifference pair, $\{\$x_1, \tau_1\}$ and $\{\$x_2, \tau_2\}$), the role of risk aversion vanishes altogether:

$$(10)\quad \lim_{b\to\infty} \rho = \frac{1}{(\tau_2 - \tau_1)} \ln\left(\frac{x_2}{x_1}\right) = \frac{RRR}{(\tau_2 - \tau_1)}.$$

The relative risk aversion parameter ceases to affect the estimate of ρ in the case of large b, because the utility function (with constant relative risk aversion) becomes locally linear when background consumption becomes large relative to the experimental rewards.

To summarize, in the consume-on-receipt model (holding fixed an indifference pair):

i. The higher the degree of risk aversion, γ, the lower the level of the imputed discount rate.
ii. The lower the level of background consumption, b, the lower the imputed discount rate.

Finally, the special property, $\rho = RRR/(\tau_2 - \tau_1)$ (i.e., the discount rate equals the time-horizon-normalized *RRR*), holds when the following conditions are simultaneously satisfied:

1. *Time-dated monetary payments are consumed at the time of receipt.* This is the distinction between the consume-on-receipt model and the optimization model.
2. *The utility function is locally linear.* This may arise either because (i) the utility function is globally linear (e.g., $\gamma = 0$ in the constant relative risk aversion utility function); or (ii) because background consumption, b, is large and the utility function has diminishing absolute risk aversion (e.g., constant relative risk aversion).

Condition 1 is problematic, a topic to which we return in the section on anomalies in the measurement of *RRR*s. Regarding condition 2.i, figure 1 shows that many papers do not make this restriction—instead, they allow for nonlinear utility when estimating their models. Accordingly, the inference $\rho = RRR/(\tau_2 - \tau_1)$ is not considered state of the art, though it was in the 1980s.

Evidence for Models.—Distinguishing among these different assumptions about consumption (described above) is important for interpreting MEL choices, but it is difficult to directly observe consumption and thereby evaluate these assumptions. Moreover, there is probably some heterogeneity in sophistication, leading some households to behave according to the consume-on-receipt model, others to behave according to the optimization model, and others to behave in yet other ways.

Curvature in the utility function is another key feature that affects interpretation of MEL data. There is strong evidence against linear utility. Despite expected utility theory implying that individuals should be risk neutral over lotteries with small prizes, a well-replicated literature estimates risk aversion for small gambles (see discussion in Rabin 2000). For example, Andersen et al. (2008) jointly estimate discount rates and risk aversion parameters from MEL choices and from choices between (static) risky gambles, and find that (local) utility curvature is an important mechanism. Andreoni and Sprenger (2012a) find that the level of background consumption assumed plays an important role in estimating the curvature of the utility function.

Turning to the issue of when payments are consumed, Krupka and Stephens (2013) show evidence that a household's MEL-elicited *RRR* is affected by factors (inflation, income shocks) that affect the marginal interest rate that the household faces. Krupka and Stephens examined panel data from 1972–74 with MEL choices from 1,194 individuals. They found that *RRR*s are sensitive to households' financial circumstances, with the *RRR* falling when households experience positive financial shocks. This is consistent with the predictions of optimization theory—if households face liquidity constraints, their measured *RRR* should fall as they move further away from the liquidity constraint (and the slope of their forward-looking consumption path endogenously falls). Krupka and Stephens thus provide evidence that MEL choices are affected by the real consumption path and real interest rate that households face. Moreover, during their study period, measured *RRR*s increased by 35 percentage points. They argue that this evidence is more consistent with MEL reflecting changing financial constraints and inflation rates than with MEL measuring changing rates of time preference.

Reuben, Sapienza, and Zingales (2015) do not observe consumption, but they do observe when experimental participants cashed their payment checks. They find that more than half of the participants who receive their check immediately (rather than waiting two weeks for a larger amount) subsequently take more than two weeks to cash it. Relatedly, the macroeconomics literature on consumption estimates the marginal propensity to consume from anticipated financial payments and generally finds that these payments are consumed over a time span of weeks, months, quarters, or even years and *not* consumed on (or before) the day of receipt (e.g., Broda and Parker 2014). The available evidence is hard to reconcile with the consume-on-receipt model.

In contrast to these results, Andersen et al. (2008) provide evidence in favor of the consume-on-receipt model: they find that the likelihood of their model is highest when time-dated payments are consumed when received (essentially, the consume-on-receipt model). However, they also estimate risk aversion from risky gambles under the maintained assumption that gamble proceeds are all consumed when received.

4.3 *The Role of Incentives in MEL Tasks*

There is a debate over the role of incentives in economics experiments generally. Using incentives is standard practice in the economics literature, under the rationale that it leads subjects to truthfully reveal their preferences.[31] A classic review by Camerer and Hogarth (1999) examines the effect of incentives in many types of experimental economics studies and finds that incentives do not reliably change average performance, but tend to decrease the variance of responses. Exceptions exist for judgment and clerical tasks, where payments do increase average performance. For individual preference tasks, Camerer and Hogarth find that incentives tend to lead to more risk aversion and less generosity.[32] They do not examine time preference experiments in particular.

Even when real incentives are used, most studies pay participants for just one of the many choices that they make, thereby reducing the strength of the incentives (see, e.g., Baltussen et al. 2012). Paying for all of a participant's experimental choices generates the

[31] For extended discussions of the role of incentives in experiments, see Read (2005) and Harrison (2014). A related debate is over the role of hypothetical choice in contingent valuation studies. For a range of viewpoints, see the symposium in the *Journal of Economic Perspectives:* Hausman (2012); Carson (2012); Kling, Phaneuf, and Zhao (2012).

[32] On risk aversion, see also Holt and Laury (2002, 2005) showing more risk averse behavior with incentives than in hypothetical choices. To the extent risk aversion tasks are used to measure utility curvature that is used to transform *RRR*s into discount rates, hypothetical choices will likely underestimate curvature and thus affect estimated discount rates. We do not know of evidence that *RRR*s are affected by incentives.

confound that early choices can affect the later choices through an income effect (e.g., see Thaler and Johnson 1990). However, paying for a single choice while making multiple choices is not necessarily incentive compatible if participants do not satisfy the independence axiom of expected utility (Holt 1986, Karni and Safra 1987). Nonetheless, experimental tests suggest that the random incentive system is unlikely to substantially contaminate behavior (Starmer and Sugden 1991; Cubitt, Starmer, and Sugden 1998; Hey and Lee 2005, though see Freeman, Halevy, and Kneeland forthcoming).[33]

Implementing incentives in MEL tasks can be challenging, as it is necessary to hold transaction costs constant and to assure a constant degree of payment reliability, both regardless of the payment date. For example, payments made "now" must be just as reliable as payments made in a month. Because of such logistical challenges, the desirability of using real payments in a MEL task, as opposed to hypothetical rewards, is open to debate.

Our reading of the MEL literature is that there is little evidence of systematic differences between *RRR* in incentivized and unincentivized experiments.[34] However, there is a need for more research here with larger, more representative samples. Madden et al. (2004) compared hypothetical choices with incentivized choices both within and between subjects and found no significant effect of incentives. Madden et al. (2003) estimate a hyperbolic discount rate for each subject based on their incentivized and hypothetical choices and find that the two are highly correlated ($r = 0.92$). In each paper, though point estimates were similar, power was limited ($N = 20$ to 40 per experiment) and confidence intervals wide. Johnson and Bickel (2002) provide similar results, but with an extremely small sample size: $N = 6$. Harrison, Lau, and Williams (2002) examine variation in the probability a subject would be paid for their choices based on variation in the group size (they paid one subject per group). Their results show a statistically insignificant effect of group size.

Coller and Williams (1999) compare MEL choices with incentivized and hypothetical monetary payments, randomizing between session. In their raw results, *RRR*s are higher when incentivized, but in regression results, *RRR*s are lower when incentivized. They conclude that this difference "is likely due to the fact that subjects were not adequately randomized into treatment cells, so that subject demographics are correlated with the treatment." By way of comparison, their regression-estimated effect of monetary incentives is similar in size to the estimated effects of providing information about the annual interest rates implied by choosing a given option.

In a much larger sample ($N = 449$), Ubfal (2016) examines discount rates for six different goods for rural Ugandan households, eliciting them with hypothetical choice or incentivized choice; he finds no significant effect of incentives. Bickel et al. (2009) compare delay discounting of money with real and hypothetical choice using neuroimaging. They replicate the behavioral results of no significant difference in discounting in the real versus hypothetical conditions. They also find that the brain regions related to considering real and hypothetical choices appear to be equivalent.

[33] For critiques on the ability of the Becker, DeGroot, and Marschak incentivization method to reveal preference, see Mazar, Koszegi, and Ariely (2014), who argue for context-dependent preferences, and Cason and Plott (2014), who show mistakes in participants' understanding of the method.

[34] In a cross-study comparison, Kirby (1997) found suggestive evidence that incentivized choice showed steeper discounting than hypothetical choice. However, incentives were confounded with the magnitude of the reward, with hypothetical choice studies using larger rewards. We now know that people are more patient for larger rewards (the magnitude effect, which we discuss below).

Finally, we note that the use of real incentive payments is not the same as the use of an incentive compatible mechanism. For example, titration methods that are commonly used in the psychology literature are not incentive compatible in the sense that sophisticated subjects could game the system by behaving impatiently early in the experiment to obtain outsize delayed rewards later in the experiment.

4.4 *Neuroimaging of Intertemporal Choice Tasks*

Neuroimaging has been used in an effort to identify the neural mechanisms underlying intertemporal choice. There is an ongoing debate about what the neuroimaging findings imply about the psychological processes involved in intertemporal choice (see Carter, Meyer, and Huettel 2010; Kable 2014; and Camerer et al. 2016 for reviews). One finding is that brain regions associated with reward display a hyperbolic or quasi-hyperbolic decline in activation as the reward horizon is extended (McClure et al. 2004, Kable and Glimcher 2007, Albrecht et al. 2011).[35] A second finding is that the brain regions that are active when making intertemporal decisions about consumption (e.g., juice for thirsty subjects) are similar to those brain regions involved when making intertemporal decisions about monetary payments (McClure et al. 2007). A third finding is that self-regulation is associated with activity in the dorsal-lateral prefrontal cortex (McClure et al. 2004, 2007; Hare, Camerer, and Rangel 2009; Albrecht et al. 2011; Figner et al. 2010).

5. *Empirical Regularities in MEL Laboratory Studies*

In this section, we describe the empirical regularities that have emerged in MEL studies. Most of the research on intertemporal choice has treated the *RRR*s measured during MEL tasks as if they were measurements of discount rates. As discussed above, this is justified under the joint assumption of the consume-on-receipt model and (locally) linear utility. However, many of the results from the MEL literature are conceptually anomalous if measured *RRR*s actually *are* equivalent to discount rates. To avoid prejudging the meaning of these experimental findings and to enable us to compare results across studies that make different modeling assumptions, we defer discussing preference parameters until later and instead summarize the literature in terms of the direct object that is observed in MEL experiments, the *RRR*s.

We begin by enumerating the key empirical regularities of *RRR*s found in most MEL tasks. We then discuss the empirical basis and interpretation of these anomalies later in the section:

- *Decreasing impatience as the horizon increases*: the *RRR* per unit of time (i.e., $RRR/(\tau_2 - \tau_1)$) decreases as the length of time between the earlier and later option increases.
- *Weak effects of a front-end delay with MEL (in contrast to strong effects of front-end delay with primary rewards)*: Measured *RRR*s decrease weakly (or not at all) when a fixed delay is added

[35] McClure et al. (2004) conducted the first neuroimaging study of intertemporal choice. They used a MEL task in which subjects made a series of choices between time-dated Amazon gift certificates (which are a close proxy for money). The dopamine reward system displayed a rapid decline in activation as rewards were delayed. In contrast, delaying a reward led to only a weak decline in neural activation in areas associated with deliberation and other higher cortical functions (e.g., dorsal-lateral prefrontal cortex). McClure et al. (2007) report a similar pattern of neural activity in a paradigm using *food* rewards (i.e., water and fruit juice for thirsty subjects). These studies report different degrees of present bias in the *behavioral* data. The measured present bias is much stronger for the food rewards (McClure et al. 2007) than for the financial rewards (McClure et al. 2004, Albrecht et al. 2011).

to both the earlier and later options in a MEL task. The front-end delay effect is much stronger with primary goods that are yoked to a specific consumption date (like food rewards or effort).

- *Sub-additivity*: The total required rate of return for one long interval is less than the sum of the decomposed rates of return. Consider three rewards delivered at delays τ_1, τ_2, and τ_3. Assume that we have identified three indifference relationships: $\{\$x_1, \tau_1\} \sim \{\$x_2, \tau_2\}$, $\{\$x_2, \tau_2\} \sim \{\$x_3, \tau_3\}$, and $\{\$x_1, \tau_1\} \sim \{\$z_3, \tau_3\}$. Transitivity implies that $\{\$x_1, \tau_1\} \sim \{\$x_3, \tau_3\}$, so $x_3 = z_3$. Hence, under transitivity, the *RRR* between τ_1 and τ_3 should equal the sum of the *RRR* between τ_1 and τ_2 plus the *RRR* between τ_2 and τ_3:

$$RRR_{1,3} = \ln\left(\frac{z_3}{x_1}\right) = \ln\left(\frac{x_3}{x_1}\right)$$

$$= \ln\left(\frac{x_2}{x_1} \times \frac{x_3}{x_2}\right) = \ln\left(\frac{x_2}{x_1}\right) + \ln\left(\frac{x_3}{x_2}\right)$$

$$= RRR_{1,2} + RRR_{2,3}.$$

Sub-additivity contradicts transitivity, and instead implies that $x_3 > z_3$. This in turn implies that

$$RRR_{1,3} = \ln\left(\frac{z_3}{x_1}\right) < \ln\left(\frac{x_3}{x_1}\right)$$

$$= \ln\left(\frac{x_2}{x_1} \times \frac{x_3}{x_2}\right) = \ln\left(\frac{x_2}{x_1}\right) + \ln\left(\frac{x_3}{x_2}\right)$$

$$= RRR_{1,2} + RRR_{2,3}.$$

In other words, sub-additivity implies that $RRR_{1,3} < RRR_{1,2} + RRR_{2,3}$.

- *Magnitude effect*: *RRR*s decrease as the magnitudes of the rewards are proportionately scaled up.
- *Delay/Speed up asymmetry*: *RRR*s are higher when the later good is described as delayed relative to the earlier good; *RRR*s are lower when the earlier good is described as sped up relative to the later good.
- *Gain/Loss asymmetry*: *RRR*s are higher when rewards are gains than when the rewards are losses.

This bulleted list contains the regularities that have been most actively discussed in the literature, although it is not exhaustive. For example, Read et al. (2005) document a “date/delay” effect: i.e., MEL choices are more patient when choices are described using calendar dates for reward delivery than when choices are characterized in terms of time delay from the current moment. Magen, Dweck, and Gross (2008) find that when a MEL choice is framed as a sequence (e.g., an option might be “\$10 today and \$0 next week” rather than simply “\$10 today”), choices are more patient. Ebert and Prelec (2007) find that increasing participants’ attention to time lowers *RRR* for the near future and raises *RRR* for the far future. Ifcher and Zarghamee (2011) find that inducing positive affect significantly reduces required rate of return. Anderson and Stafford (2009) find that adding uncertainty raises *RRR*. Weber et al. (2007) study query theory, and show that thinking about reasons for choices in different orders affects choice. Other empirical regularities that are inconsistent with predictions of the models discussed above have been reported in the intertemporal choice literature, but are beyond the scope of this review.

Below, we describe each of the bulleted regularities in greater detail and consider how they conflict with properties predicted by the consume-on-receipt model.

5.1 Decreasing Impatience as the Horizon Increases

The consume-on-receipt model with background consumption, b, combined with exponential discounting, predicts that the RRR per unit of time will be given by:[36]

$$(11) \quad \frac{RRR}{\tau} = \frac{1}{\tau}\ln\left(\frac{x_\tau}{x_0}\right)$$

$$= \frac{1}{\tau}\left[\ln\left\{\left[\frac{(x_0+b)^{1-\gamma}+(\delta^\tau-1)b^{1-\gamma}}{\delta^\tau}\right]^{\frac{1}{1-\gamma}}-b\right\} - \ln(x_0)\right].$$

This equation is *increasing* in τ, which is the delay between the earlier reward and the later reward. (Intuitively, as the delay increases, the ratio x_τ/x_0 needs to increase for two reasons: to offset the increased delay and to offset diminishing returns in the utility function. The latter effect causes the horizon-normalized RRR to rise.) Hence, the consume-on-receipt model with exponential discounting predicts that the (horizon-normalized) RRR should *increase* as the time horizon increases, which is counterfactual.

In fact, empirically measured (horizon-normalized) RRRs strongly decrease as the time horizon increases. For example, Thaler (1981) studied intertemporal choices over many intervals, including 0–3 months, 0–1 year, and 0–3 years. Thaler reports that measured annualized RRRs decrease substantially as the length of the delay interval increases.

The finding that decision making becomes increasingly patient (per unit time) as the interval of delay grows longer (holding the interval's starting point fixed) has become a canonical result in the MEL literature. Many other experiments have reproduced this result (e.g., Benzion, Rapoport, and Yagil 1989, who also demonstrate the magnitude effect and the gain/loss asymmetry; Green, Myerson, and Mcfadden 1997; Kirby 1997). Moreover, Chapman and Elstein (1995) examine the effect that increasing the length of the time interval has on RRR for money, health, and holidays. They find decreasing impatience as the horizon increases in all three domains.

Decreasing impatience in measured discount rates is predicted by the hyperbolic discount function and its variants (e.g., the quasi-hyperbolic and generalized hyperbolic discount function) under the consume-on-receipt model. Decreasing impatience in MEL tasks has therefore often been interpreted (perhaps inappropriately, as we explain below) as evidence for hyperbolic discounting. Other nondiscounted utility models also predict decreasing impatience when increasing the length of the time interval, such as the fixed-cost-of-delay model in Benhabib, Bisin, and Schotter (2010), and the heuristic models proposed by Read, Frederick, and Scholten (2013) and Ericson et al. (2015).

5.2 Weak Effects of a Front-End Delay for MEL Tasks

The consume-on-receipt model with exponential discounting and constant background consumption predicts that the discount rate measured over any given time duration should be constant regardless of when that period begins (holding the period length fixed). In contrast, jointly assuming the consume-on-receipt model and some form of hyperbolic discounting implies a higher RRR if the earlier option includes the present than if all options (including the early option) are delayed.

[36] This equation is derived under the maintained assumption of reward indifference with constant relative risk aversion: $(x_0+b)^{1-\gamma}+\delta^\tau b^{1-\gamma} = b^{1-\gamma}+\delta^\tau(x_\tau+b)^{1-\gamma}$. Use this indifference equation to solve for x_τ.

Constant *RRR*s can be tested by measuring *RRR*s over a fixed length of delay time that is translated into the future by increasing the front-end delay before the earliest option is available. For example, *RRR* could be measured for the following two time intervals, both of which are one week long: reward now versus reward in 1 week and reward in 10 weeks versus reward in 11 weeks. Although the *RRR*s measured in MEL tasks do tend to decrease when a front-end delay is added, most studies find this decrease is somewhat weaker than predicted by popular non-exponential discount functions (maintaining the consume-on-receipt assumption). For example, for the quasi-hyperbolic model, the β identified from variation in the front-end delay is usually only slightly less than one, although the gap is often statistically significant (e.g., Coller and Williams 1999 and Augenblick, Niederle, and Sprenger 2015). McAlvanah (2010) finds an average annualized discount factor of 0.87 between the present and 6 years in the future, but an average discount factor of 0.94 between 12 years and 18 years in the future. Similarly, Slonim, Carlson, and Bettinger (2007) find that subjects are significantly less patient when there is no front-end delay in MEL choices, as do Green, Myerson, and Macaux (2005).

In contrast, Dohmen et al. (2012) examine the MEL choices of a representative sample of the German population. They find that the annualized *RRR*s are similar for trade-offs between 0 versus 6 months and for trade-offs between 6 versus 12 months, but that the (annualized) *RRR* is lower for 0 versus 12 month intervals.[37] Similarly, Kable and Glimcher (2010) find that the (time-length normalized) *RRR* declines as the delay period increases, but that the specific pattern of declining *RRR*s starts at the time of the earliest possible reward in the experimental choice set (regardless of whether that earliest option is "now").[38]

Andreoni and Sprenger (2012a) allow subjects to allocate rewards using convex budget sets and, using a concave utility version of the consume-on-receipt model, do not find evidence of present bias. They estimate little present bias for immediate payments delivered in the form of a check and relatively little concavity in the utility function. A number of papers interpret Andreoni and Sprenger (2012a, b) as measuring time preference over consumption in a discounted utility model,[39,40] though in

[37] Dohmen et al. (2012) also find that a substantial fraction of subjects choose in a pattern that is inconsistent with *any* type of discount function.

[38] Statistical results are not presented in Glimcher, Kable, and Louie (2007), but Kable and Glimcher (2010) estimate two hyperbolic discount rates for each subject: one from choices with an immediate option, and a modified one from a set of choices shifted forward 60 days, in which the soonest possible reward (60 days) is treated as "now." A scatter plot shows that they are similar, consistent with discounting in relative time.

[39] Cheung (2015) offers a substantially different interpretation of the results of Andreoni and Sprenger (2012a, b), arguing that behavior in the convex time budget task is driven by a diversification motive. By allocating money to two dates, a participant hedges her payment risk. In support of this argument, Cheung shows that making payments certain versus risky in an MPL elicitation (where diversification cannot play a role, since only one choice is paid) has no measurable effect on intertemporal choice. This is in contrast to Andreoni and Sprenger (2012b), which finds significant differences between convex time budget choices with and without risk. Moreover, when Andreoni and Sprenger (2012b) introduce risk into the convex time budget, the risks for the two dates are resolved independently. Cheung shows that when the lotteries determining payment in the convex time budget are perfectly correlated (i.e., one roll of the die determines both whether the earlier and the later date is paid), behavior is halfway between the case with certain payment and with risky, independent lotteries. Miao and Zhong (2015) provide similar evidence, also examining behavior in a negatively correlated lottery (either the sooner date will be paid or the later date, but not both).

[40] For instance, Epper and Fehr-Duda (2015) argue that rank-dependent probability weighting in which participants care about their whole portfolio's risk can explain the results (however, see Dean and Ortoleva 2015). Miao and Zhong (2015) argue that Epstein and Zin (1989) preferences can explain the results, though Andreoni and Sprenger (2015) reply and argue that because all risk was

a later comment Andreoni and Sprenger (2015) note the role of arbitrage in producing results that look like linear utility and non-present-biased *RRR*s.

Front-end delays have large effect sizes for primary rewards (e.g., juice, food, work) and relatively small effect sizes for MEL tasks (though usually these MEL effects are also statistically significant). For instance, McClure et al. (2007) examined choices over small amounts of juice (offered to thirsty subjects). They found substantial present bias in choices when the earliest juice reward is available immediately, but not when all options are shifted ten minutes in the future. Read, Loewenstein, and Kalyanaraman (1999) also found evidence of present bias in movie choices using a front-end-delay design (see also related results[41] in Milkman, Rogers, and Bazerman 2009), and Read and Van Leeuwen (1998) found evidence of present bias in food choices using a front-end-delay design.

The differential effect of front-end delays for primary versus monetary rewards is highlighted in Augenblick, Niederle, and Sprenger (2015), who examine the effect of a front-end delay on MEL choices and primary reward choices (a real effort task). They found small effects of front-end delay on MEL choices (they estimate $\beta = 0.97$, rejecting $\beta = 1$), but larger effects of front-end delay with real effort tasks ($\beta = 0.90$).

In short, the literature is inconclusive about the effects of front-end delays using MEL, but generally finds that they are weak in the financial domain. However, studies using primary rewards do display a strong effect of adding a front-end delay. (See also section 3, where we discuss intertemporal choice measured from primary rewards.)

5.3 Sub-Additivity

The weak effects of front-end delays on *RRR*s in MEL studies generate a tension with the robust tendency of longer time intervals to lower time-length-normalized *RRR*s. Under the assumption of the consume-on-receipt model, finding that front-end-delays do not change the *RRR* (or only weakly lower the *RRR*) implies that the discount function is exponential (or nearly exponential). At the same time, again under the assumption of the consume-on-receipt model, finding that increasing the length of a delay decreases the time-length-normalized *RRR* implies that the discount function must have a falling instantaneous discount rate (e.g., a hyperbolic form). Researchers consistently observe these contradictory empirical patterns.

Moreover, these empirical regularities contradict transitivity. Consider *RRR*s for three dates—1, 2, and 3—which need not be evenly spaced. Under transitivity the associated *RRR*s must have the following relationship (see the full argument above, where we first defined sub-additivity): $RRR_{1,3} = RRR_{1,2} + RRR_{2,3}$. However, experiments consistently find that $RRR_{1,3} < RRR_{1,2} + RRR_{2,3}$. In other words, longer time intervals have lower *RRR*s than would be expected from the observations of *RRR*s associated with shorter sub-intervals. This phenomenon is called sub-additivity (Read 2001).

Roughly, sub-additivity means that subdividing an interval leads to more overall discounting than if subjects are asked to evaluate options at the beginning and end of the interval as a whole. Averaging across the three experiments in Read (2001), the *RRR* was 40 percent higher if the interval was subdivided instead of being treated as a single interval. Similar results have

resolved at the end of the experiment, it may not be appropriate to apply these models here.

[41] They show that customers who use a DVD rental service are slower to return high-brow movies than low-brow movies.

been found in in Read and Roelofsma (2003) as well as Scholten and Read (2006).

While no discounted utility model predicts sub-additivity, some nondiscounted utility models discussed in section 2 produce sub-additive choices:

- Hyperbolic discounting, in which discounting is a function of the difference in delays (not the time horizon from the present period): e.g., $D(t_1, t_2) = 1/(1 + k \times (t_2 - t_1))$, where k is a constant. See Kable and Glimcher (2010).
- The fixed-cost-of-delay model of Benhabib, Bisin, and Schotter (2010).
- Heuristic models of Read, Frederick, and Scholten (2013) and Ericson et al. (2015).

While most of the evidence points to sub-additivity, others have found evidence of super-additivity in MEL tasks (Scholten and Read 2006).

5.4 Magnitude Effect

One of the most robust findings in the MEL literature is that *RRR*s over relatively small quantities of money are substantially higher than the *RRR*s over relatively large quantities of money. This is called the magnitude effect or absolute magnitude effect (Thaler 1981, Prelec and Loewenstein 1991, Loewenstein and Prelec 1992), and is widely replicated (e.g., Benzion, Rapoport, and Yagil 1989; Kirby 1997; Holcomb and Nelson 1992; Andersen et al. 2013; Halevy 2015; Ericson and Noor 2015). The magnitude effect is particularly puzzling because the consume-on-receipt model predicts the *opposite* effect. Equation (11) predicts that a rising level of x_0 should be associated with a rising *RRR*. Intuitively, larger monetary rewards cause the curvature of the utility function to become more relevant, thereby generating a higher *RRR* (for any given level of positive curvature in the utility function).

The magnitude effect is also observed when researchers take into account the curvature of the utility function and estimate discount rates (e.g., Chapman 1996, Meyer 2015). Ericson and Noor (2015) provide a method to directly test for magnitude-independent discounting without need to estimate the curvature of the utility function and show a magnitude effect. Andersen et al. (2013) also incorporate utility curvature and replicate a magnitude effect in estimated discount rates. They find a small magnitude effect relative to other researchers that emerges only after controlling for individual heterogeneity. Andersen et al. also provide a useful table reviewing the magnitude effect literature.

5.5 Speed-Up/Delay Asymmetry

Some MEL experiments present an early option as the default and a relatively delayed option as an alternative. This framing elicits much higher *RRR*s than the opposite frame: a future option as the default and a relatively earlier option as a sped-up alternative. Loewenstein and Prelec (1992) described this as the speed-up/delay asymmetry and it has been robustly replicated (e.g., Loewenstein 1988; Malkoc and Zauberman 2006; Appelt, Hardisty, and Weber 2011). These effects are hypothesized to arise from an intertemporal application of an endowment effect generated by a frame-induced reference point (Kahneman and Tversky 1979, Thaler 1980, see also Weber et al. 2007).

5.6 Gain/Loss Asymmetry

Thaler's (1981) intertemporal choice experiment found evidence that *RRR*s measured in intertemporal choices involving gains are substantially higher than *RRR*s measured in intertemporal choices involving losses. This finding has been replicated many times (e.g., Benzion, Rapoport, and Yagil

1989; Abdellaoui, Attema, and Bleichrodt 2010; Appelt, Hardisty, and Weber 2011; Tanaka, Camerer, and Nguyen 2010) and has come to be called the gain/loss asymmetry.[42] This effect has been attributed to anticipation effects: people obtain little psychological benefit from postponing losses because of negative anticipation (Loewenstein 1987).

6. *MEL Inside and Outside the Lab*

6.1 *MEL Outside the Lab and MEL with Non-Student Subjects*

Though MEL studies have often been run with students inside a laboratory, they have increasingly been run with nonstudent populations and/or outside the laboratory. We discuss such results here.[43] A key takeaway is that results from studies with students are similar to those with representative samples. Notably, Andersen et al. (2010) directly compare students to representative samples and find that average discounting is similar, though preference heterogeneity is more limited among university students.

One of the earliest papers to estimate discount functions for a representative sample is Harrison, Lau, and Williams (2002).[44] They examined a representative sample of 268 Danish residents who traveled to participate in a MEL experiment session with one participant per session paid for their choices. They adjust for potential censoring in choices (cf. Coller and Williams 1999). They assume a consume-on-receipt model and linear utility, and they conclude that the average annual discount rate is 28 percent, and examine variation by demographic characteristics.

Andersen et al. (2008) examine a similar Danish population and jointly estimate discount rates and risk aversion parameters from MEL choices and choices between risky gambles. They thus allow for curvature in the utility function. They assume risky gambles are all consumed when received, and find that the likelihood of their model is highest when time-dated payments are consumed when received (essentially, the consume-on-receipt model). They conclude that the average annual discount rate is approximately 10 percent. Andersen et al. (2014) examine another Danish sample using the consume-on-receipt model. They find that the average exponential discount rate is approximately 9 percent; they also find no evidence of quasi-hyperbolic discounting (i.e., present-biased preferences), and weak evidence for modest hyperbolic discounting.

In a very different sample, Meier and Sprenger (2010) examined a population of low- and middle-income individuals and found that the *RRR* is 16 percent (per month); they classify 36 percent of the sample as present biased and 9 percent as future biased.

MEL experiments have also been run in developing countries. Tanaka, Camerer, and Nguyen (2010) examined time preference in Vietnam using MEL experiments, and estimated a variety of discounting models (exponential, hyperbolic, etc.) under

[42] However, Ahlbrecht and Weber (1997) do not find a statistically significant gain/loss asymmetry in a median test, but do not report confidence intervals. Shelley (1994) and Tanaka, Camerer, and Nguyen (2010) find that a subset of individuals do not display gain/loss asymmetry (or even reverse the asymmetry, acting more impatient for losses).

[43] Although we continue, where possible, to describe findings in terms of the *RRR* (because this does not involve any identifying assumptions), we are forced in several instances to describe discount rates as some papers present only estimates of a discount rate filtered through a model, not the raw *RRR*.

[44] Barsky et al. (1997) conduct a related study on a representative sample of 116 adults over the age of 50. They ask these adults to pick a long-run consumption path (holding net present value constant). They find that subjects tend to prefer a flat or rising slope of the real consumption path when the real interest rate is zero (implying a zero discount rate or a negative discount rate). The preference for rising consumption sequences has been reviewed by Loewenstein and Prelec (1993). See also Loewenstein and Sicherman (1991) and Bhatia et al. (2016).

the assumption of linear utility and the consume-on-receipt model; they found strong evidence of present bias. Bauer, Chytilová, and Morduch (2012) examined required rates of return for a sample drawn from rural India. Like Andersen et al. (2008), they used risky gambles to estimate the curvature of the utility function and assumed a consume-on-receipt consumption model; they found average 3-month discount rates of 22 percent and then 16 percent when an additional front-end delay is added. These results imply that about 35 percent of their sample is present biased. Wang, Rieger, and Hens (2016) provide evidence on hypothetical MEL choices for a sample of 53 countries.

6.2 *How Predictive Are MEL Studies?*

Whether or not MEL studies measure the precise quantitative form of the discount function, they still may provide a proxy for an individual's level of impatience. While one function of MEL studies is to measure the discount function, another is simply to predict behavior by classifying individuals as relatively patient or impatient. Hence, MEL studies could be assessed by how well they predict behaviors in other domains. Here, we examine whether MEL behavior predicts field behavior, the magnitude of such correlations, and alternative explanations for why MEL behavior predicts field behavior. In sum, the literature finds that the correlation between MEL behavior and any given field behavior is small in magnitude (and statistically significant in well-powered studies). Aggregated indices of behavior show stronger effect sizes.

Correlations between choices in MEL tasks and other behaviors (e.g., savings rates, educational attainment, medical adherence) have many mutually compatible interpretations. Behavior in MEL tasks can be a function not only of time preferences, but also of knowledge, framing, cognitive function, and beliefs. Similarly, other behaviors (e.g., outside the lab) are also a function of time preference in addition to tastes, knowledge, context, cognitive function, and beliefs. Accordingly, many mechanisms could give rise to the weak correlation between choices in MEL tasks and choices outside the lab. For instance, lower *RRR*s in MEL tasks can result from higher levels of trust in the experimenter or greater levels of financial sophistication (i.e., realizing that a 50 percent three-week return in a MEL task compares very favorably to rates of return in financial markets). Trust and financial sophistication likely affect behavior in many domains.

Dohmen et al. (2010) and Benjamin, Brown, and Shapiro (2013) found that behavior in MEL tasks is associated with performance on standardized cognitive tests. Burks et al. (2009) examined a sample of truckers and showed that cognitive ability (as measured by IQ tests) is positively correlated with both increased short-term and long-term patience in MEL tasks (correlation with normalized IQ is 0.14 for β and is 0.13 for δ, implying respective R^2 values of $0.14^2 = 0.020$ and $0.13^2 = 0.017$).

Chabris et al. (2008) examine how behavior in MEL tasks is correlated with a number of different field behaviors, including health behaviors (e.g., BMI, exercise, smoking[45]) and financial behaviors (saving, gambling, and paying late fees). In almost all cases the correlation is statistically indistinguishable from zero. Of the 20 different relationships that they studied, the median (unadjusted) R^2 is 0.005. However, almost all of the relationships go in the predicted direction and the *RRR* has at least as much predictive power as any other variable in their data set, including gender, age, and education. The correlation between the discount rate

[45] Harrison, Lau, and Ruström (2010) find that male smokers have significantly higher discount rates than male nonsmokers, but find no significant difference between female smokers and nonsmokers.

and field behavior rises when field behaviors are aggregated (after aggregation the R^2 is approximately 10 percent). Their work also highlights the difficulty in comparing R^2 across studies and populations. They find slightly higher R^2 for an in-lab study than for a web-interface study.

Daly, Delaney, and Harmon (2009) examined predictors of *RRR* in MEL tasks using rich data (time diaries, psychometric testing, and medical tests) on a sample of 204 students. They used factor analysis to reduce the dimensionality of their data, and identified a significant correlation between *RRR*s and a factor based on personality measures (consideration of the future, self-control, and elaboration of consequences). They also found an imprecisely measured correlation ($p < 0.10$) with a factor representing health (blood pressure and BMI). In a global sample with 80,000 individuals from 76 countries, Falk et al. (2015) show that *RRR* is predictive of savings behavior. Falk et al. (2016) then provide a brief survey instrument that is experimentally validated (based on the best predictors in choice experiments) for measuring *RRR* and various dimensions of preferences.

Burks et al. (2012) compared different measures of patience—β and δ—as elicited by MEL tasks, a personality survey, and a new task designed to capture the logic behind Mischel, Shoda, and Rodriguez's (1989) marshmallow delay-of-gratification tasks. In a sample of US truck drivers, all four tasks are significantly correlated with field behaviors as well as measures of numeracy. Bradford et al. (2017) use a representative sample of US residents and also show β and δ, elicited via survey questions, are related to a variety of consumer behaviors.

A variety of studies consider the correlation between MEL tasks and particular behaviors. Meier and Sprenger (2013) found that more impatient individuals are less likely to take up financial education programs. Meier and Sprenger (2012) found that MEL task behavior is correlated with individuals' credit scores. In both cases, it is unclear which way causality runs. Tanaka et al. (2010) examined risk and time preference in Vietnam and found that higher patience correlates with higher individual and village incomes. Reuben, Sapienza, and Zingales (2015) found that MEL-inferred discount rates predict procrastination on various tasks, including when participants cash their payment check.

Ashraf, Karlan, and Yin (2006) ran a field experiment examining preferences for a commitment savings product in the Philippines. They found marginally significant evidence (using hypothetical MEL questions) that individuals whose short-term and long-term discount rates differed more were more likely to use the commitment technology (12.5 percentage points higher); discount rates measured with rice and ice cream had a smaller effect.

Another literature has examined present bias in MEL studies, showing that *RRR*s derived from choices with an immediate option in the choice set have different correlations with field behavior than *RRR*s derived from choices among options that are all in the future. Meier and Sprenger (2010) examined credit card spending and present bias (measured by MEL) and found that present-biased individuals are more likely to hold credit card debt; the discount factor apart from present bias had no association with debt, a pattern also found by Harrison, Lau, and Williams (2002).

Relatedly, Cadena and Keys (2015) found that youth identified as "impatient or restless" by interviewers for the National Longitudinal Survey of Youth (NLSY) are more likely to drop out of high school and less likely to attend college. Moreover, impatient/restless youth are more likely to display behavior that seems dynamically inconsistent, such as dropping out despite a stated desire to finish, or completing only 3 out of 4 years for a degree. It is not clear how restlessness is related to time preference, as restlessness could also measure willingness to participate in the interview (social preferences) or an ability to pay attention (cognitive skill).

Finally, research has shown that the MEL choices of children are associated with contemporaneous or later life outcomes. Bettinger and Slonim (2007) measured about 200 children's MEL choices; they found that children have higher discount rates than adults (one-third of children aged 5–7 turn down a 150 percent return in two months), and found evidence of hyperbolic discounting (strong evidence of a front-end delay). Sutter et al. (2013) found that required rates of return in MEL tasks predict adolescents' health-related field behavior, saving decisions, and conduct at school. Similarly, Castillo et al. (2011) found that the MEL choices predict disciplinary problems at school. They also examined gender and ethnic differences in their sample of schools in Georgia, with boys and black children having higher *RRR*s than girls and white children.

In a very large Swedish study (12,000 observations), Golsteyn, Grönqvist, and Lindahl (2013) examined MEL choices at age 13 ($130 now or $1,300 in five years). They found that 13 percent prefer the earlier reward, and that this impatience predicts earnings, education, GPA, time spent on welfare, unemployment, and early death.

6.3 *Correlation with Personality Measures*

Another literature examines how MEL choices correlate with psychological personality measures. Daly, Delaney, and Harmon (2009) examined students' MEL choices and found that more patient MEL choices are positively associated with conscientiousness (correlation of 0.15) and a self-control scale (correlation of 0.18). Becker et al. (2012) found similar levels of correlation between personality measures and incentivized (as well as unincentivized) measures of economic preferences. In a representative sample of approximately 14,000 Germans (Socio-economic Panel), they found a positive correlation (0.11) between conscientiousness and patience in a MEL task. The strongest correlation is that individuals who make more patient MEL choices (lower *RRR*s) tend to score higher on the "agreeableness" personality trait (correlation of 0.31). The agreeableness correlation is replicated in two much smaller samples; however, the estimated correlation of conscientiousness with MEL drops substantially and becomes insignificant.

Wölbert and Riedl (2013) examined the correlation between *RRR* and various items of the Barratt Impulsiveness Scale. They found correlations with elements of the scale related to financial decision making (about 0.2), but not in other areas. They conclude: "intertemporal decisions over monetary rewards are not, or only very weakly, related to general impulsiveness and lack of self-control."

Dean and Ortoleva (2015) estimate 11 behavioral phenomena in a single sample of respondents (using monetary rewards that are mailed to respondents): short-term discount rates, small stakes risk aversion, present bias, loss aversion, the endowment effect, aversion to ambiguity and compound lotteries, the common ratio and common consequence effects, and sender/receiver behavior in trust games. They do not find evidence that probability weighting is related to present bias (as implied by cumulative prospect theory).

Finally, a line of research examines the fundamental question: how stable are MEL choices over time? At horizons of five weeks and one year, Kirby (2009) found that *RRR*s inferred from MEL choices displayed test–retest stability similar to other personality measures: correlations of 0.6 to 0.8 between

*RRR*s measured at different points in time. However, consistent with other research, Kirby found that measured *RRR*s increased between sessions (see also Simpson and Vuchinich 2000). Wölbert and Riedl (2013) found that *RRR*s are highly correlated within the same session (about 0.8) and across sessions (about 0.6). Meier and Sprenger (2015) examined a population of low- and middle-income individuals who made MEL choices a year apart. They found similar distributions at both points in time. The correlation between choice behavior (switching points in a multiple price list) was about 0.44, while the correlation of estimated discount parameters within individuals was 0.36 for β and 0.25 for δ. They characterize their stability of measured intertemporal choice as high by comparison to other traits studied in the personality literature.

7. *Conclusion*

The concept of time preferences modeled with a stationary discount function is simple and domain general, but it isn't clear whether this framework is the best approach to understanding and predicting intertemporal decisions in either the lab or the field. It is possible that other factors, such as mistrust, temptation, inattention, confusion, context, and beliefs explain why humans behave as if they devalue promised future payments in a wide range of settings (e.g., see Andreoni and Sprenger 2012b, Gabaix and Laibson 2017).

Even among the community of researchers who believe that the discount function framework is fruitful, there is no consensus about how we should measure the discount function. The role of money earlier or later (MEL) experiments is being actively debated. On one hand, MEL experiments are relatively easy to run and they generate a simple analytic output, the required rate of return (*RRR*). With this measurement in hand, it is easy to estimate time preferences if one makes key identifying assumptions (like the consume-on-receipt assumption with a fixed level of background consumption).

On the other hand, such identifying assumptions are controversial (Cubitt and Read 2007). Many consumers do not consume a financial flow on the day they receive it. Instead, consumers often anticipate the receipt of financial flows and consume partly in advance (e.g., credit card borrowing or payday loans). In addition, consumers often save some of their income and consume the claims some other day (e.g., saving to buy a durable good, rainy day savings, and retirement savings). Such complex intertemporal substitutions—both borrowing and saving—are predicted by all standard economic models of household behavior and occur in practice at almost every frequency. For example, a paycheck may be saved for a few days to fund a weekend splurge, or for a few weeks to fund a rent payment, or for a few decades to fund retirement. These intertemporal substitutions may need to be modeled when mapping preferences over time-dated financial flows into time preferences over utility flows.

There is a rapidly growing body of work that attempts to study consumption choices themselves (e.g., work tasks in real time or eating decisions in real time), rather than choices over the timing of monetary payments. These consumption-based analyses generate their own methodological tradeoffs. On one hand, consumption-based analyses are close to the economic theory on which economic models are based. Time preferences—i.e., the discount function—are theorized to discount utility flows, $u(c)$, and not financial flows. On the other hand, consumption-based analyses still require assumptions/inferences/controls regarding the curvature of the instantaneous utility function and the nature of intertemporal substitution (e.g., when a subject works an hour in an unpleasant experimental task, does that effort crowd out other unpleasant work that she would have done that day).

The future of the intertemporal choice literature is likely to be multifaceted.[46] Three complementary research programs are likely to coexist in the next decade. First, some researchers will try to use MEL measures to estimate discount functions. Second, some researchers will try to use consumption measures (e.g., high-frequency choices over consumption or effort) to estimate discount functions. These research programs are the continuation of the rich literature that this paper has reviewed.

However, there is also a third direction that deviates from most of the empirical work to date. Some research will study alternative mechanisms—like trust, temptation, imperfect forecasting, and confusion about future reward contingencies—that influence choices with intertemporal consequences. This third research program is a wildcard, because it is not clear whether this will be a minor addendum to the large literature on time preferences or whether these alternative mechanisms will turn out to play a major role in explaining why people tend to devalue promised, delayed rewards relative to instant gratification. A key goal of this literature should be to measure the practical empirical importance of these different theoretical mechanisms. Measuring these alternative mechanisms will require some new empirical methods—e.g., how do you measure confusion about the future (see Imas, Kuhn, and Mironova 2018 for a partial answer to this question).

Our research community will develop new empirical methods that help us analyze the myriad conceptual questions that jointly comprise the behavioral science of intertemporal choice. Unfortunately, there is no consensus on how we should proceed. We will need to be patient.

[46] See Ericson and Laibson (2019), who identify 16 open questions in the intertemporal choice literature.

References

Abdellaoui, Mohammed, Arthur E. Attema, and Han Bleichrodt. 2010. "Intertemporal Tradeoffs for Gains and Losses: An Experimental Measurement of Discounted Utility." *Economic Journal* 120 (545): 845–66.

Abdellaoui, Mohammed, Emmanuel Kemel, Amma Panin, and Ferdinand M. Vieider. 2018. "Take Your Time or Take Your Chance: Time Discounting as a Distorted Probability." Accessed April 28, 2020. http://ammapanin.com/assets/Abdellaoui_et_al_time_risk.pdf.

Abel, Andrew B. 1990. "Asset Prices under Habit Formation and Catching up with the Joneses." *American Economic Review* 80 (2): 38–42.

Ahlbrecht, Martin, and Martin Weber. 1997. "An Empirical Study on Intertemporal Decision Making under Risk." *Management Science* 43 (6): 813–26.

Ainslie, George. 1975. "Specious Reward: A Behavioral Theory of Impulsiveness and Impulse Control." *Psychological Bulletin* 82 (4): 463–96.

Ainslie, George. 1992. *Picoeconomics: The Strategic Interaction of Successive Motivational States within the Person*. New York: Cambridge University Press.

Ainslie, George. 2001. *Breakdown of Will*. Cambridge: Cambridge University Press.

Ainslie, George. 2012. "Pure Hyperbolic Discount Curves Predict 'Eyes Open' Self-control." *Theory and Decision* 73 (1): 3–34.

Akerlof, George A. 1991. "Procrastination and Obedience." *American Economic Review* 81 (2): 1–19.

Albrecht, Konstanze, Kirsten G. Volz, Matthias Sutter, David I. Laibson, and D. Yves von Cramon. 2011. "What Is for Me Is Not for You: Brain Correlates of Intertemporal Choice for Self and Other." *Social Cognitive and Affective Neuroscience* 6 (2): 218–25.

Allcott, Hunt, and Nathan Wozny. 2014. "Gasoline Prices, Fuel Economy, and the Energy Paradox." *Review of Economics and Statistics* 96 (5): 779–95.

Andersen, Steffen, Glenn W. Harrison, Morten I. Lau, and E. Elisabet Rutström. 2008. "Eliciting Risk and Time Preferences." *Econometrica* 76 (3): 583–618.

Andersen, Steffen, Glenn W. Harrison, Morten Igel Lau, and E. Elisabet Rutström. 2010. "Preference Heterogeneity in Experiments: Comparing the Field and Laboratory." *Journal of Economic Behavior and Organization* 73 (2): 209–24.

Andersen, Steffen, Glenn W. Harrison, Morten I. Lau, and E. Elisabet Rutström. 2013. "Discounting Behaviour and the Magnitude Effect: Evidence from a Field Experiment in Denmark." *Economica* 80 (320): 670–97.

Andersen, Steffen, Glenn W. Harrison, Morten I. Lau, and E. Elisabet Rutström. 2014. "Discounting Behavior: A Reconsideration." *European Economic*

Review 71: 15–33.

Andersen, Steffen, Glenn W. Harrison, Morten I. Lau, and E. Elisabet Rutström. 2018. "Multiattribute Utility Theory, Intertemporal Utility, and Correlation Aversion." *International Economic Review* 59 (2): 537–55.

Anderson, Lisa R., and Sarah L. Stafford. 2009. "Individual Decision-making Experiments with Risk and Intertemporal Choice." *Journal of Risk and Uncertainty* 38 (1): 51–72.

Andreoni, James, Michael A. Kuhn, and Charles Sprenger. 2015. "Measuring Time Preferences: A Comparison of Experimental Methods." *Journal of Economic Behavior and Organization* 116: 451–64.

Andreoni, James, and Charles Sprenger. 2012a. "Estimating Time Preferences from Convex Budgets." *American Economic Review* 102 (7): 3333–56.

Andreoni, James, and Charles Sprenger. 2012b. "Risk Preferences Are Not Time Preferences." *American Economic Review* 102 (7): 3357–76.

Andreoni, James, and Charles Sprenger. 2015. "Risk Preferences Are Not Time Preferences: Reply." *American Economic Review* 105 (7): 2287–93.

Angeletos, George-Marios, David Laibson, Andrea Repetto, Jeremy Tobacman, and Stephen Weinberg. 2001. "The Hyperbolic Consumption Model: Calibration, Simulation, and Empirical Evaluation." *Journal of Economic Perspectives* 15 (3): 47–68.

Appelt, Kirstin C., David J. Hardisty, and Elke U. Weber. 2011. "Asymmetric Discounting of Gains and Losses: A Query Theory Account." *Journal of Risk and Uncertainty* 43 (2): 107–26.

Ariely, Dan, and Klaus Wertenbroch. 2002. "Procrastination, Deadlines, and Performance: Self-Control by Precommitment." *Psychological Science* 13 (3): 219–24.

Ashraf, Nava, Colin F. Camerer, and George Loewenstein. 2005. "Adam Smith, Behavioral Economist." *Journal of Economic Perspectives* 19 (3): 131–45.

Ashraf, Nava, Dean Karlan, and Wesley Yin. 2006. "Tying Odysseus to the Mast: Evidence from a Commitment Savings Product in the Philippines." *Quarterly Journal of Economics* 121 (2): 635–72.

Attanasio, Orazio P., and Hamish Low. 2004. "Estimating Euler Equations." *Review of Economic Dynamics* 7 (2): 406–35.

Attanasio, Orazio P., and Guglielmo Weber. 2010. "Consumption and Saving: Models of Intertemporal Allocation and Their Implications for Public Policy." *Journal of Economic Literature* 48 (3): 693–751.

Augenblick, Ned, Muriel Niederle, and Charles Sprenger. 2015. "Working over Time: Dynamic Inconsistency in Real Effort Tasks." *Quarterly Journal of Economics* 130 (3): 1067–115.

Baltussen, Guido, G. Thierry Post, Martijn J. van den Assem, and Peter P. Wakker. 2012. "Random Incentive Systems in a Dynamic Choice Experiment." *Experimental Economics* 15 (3): 418–43.

Barro, Robert J. 1999. "Ramsey Meets Laibson in the Neoclassical Growth Model." *Quarterly Journal of Economics* 114 (4): 1125–52.

Barsky, Robert B., F. Thomas Juster, Miles S. Kimball, and Matthew D. Shapiro. 1997. "Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study." *Quarterly Journal of Economics* 112 (2): 537–79.

Bauer, Michal, Julie Chytilová, and Jonathan Morduch. 2012. "Behavioral Foundations of Microcredit: Experimental and Survey Evidence from Rural India." *American Economic Review* 102 (2): 1118–39.

Becker, Anke, Thomas Deckers, Thomas J. Dohmen, Armin Falk, and Fabian Kosse. 2012. "The Relationship between Economic Preferences and Psychological Personality Measures." Available on SSRN at 2039656.

Becker, Gordon M., Morris H. DeGroot, and Jacob Marschak. 1964. "Measuring Utility by a Single-Response Sequential Method." *Behavioral Science* 9 (3): 226–32.

Ben Halima, Bassem, and Mohamed Ali Ben Halima. 2009. "Time Preferences and Job Search: Evidence from France." *LABOUR* 23 (3): 535–58.

Benhabib, Jess, Alberto Bisin, and Andrew Schotter. 2010. "Present-Bias, Quasi-hyperbolic Discounting, and Fixed Costs." *Games and Economic Behavior* 69 (2): 205–23.

Benjamin, Daniel J., Sebastian A. Brown, and Jesse M. Shapiro. 2013. "Who Is 'Behavioral'? Cognitive Ability and Anomalous Preferences." *Journal of the European Economic Association* 11 (6): 1231–55.

Benjamin, Daniel, et al. 2019. "Predicing Mid-life Capital Formation with Pre-school Delay of Gratification and Life-Course Measures of Self-Regulation." *Journal of Economic Behavior & Organization*. https://doi.org/10.1016/j.jebo.2019.08.016.

Benzion, Uri, Amnon Rapoport, and Joseph Yagil. 1989. "Discount Rates Inferred from Decisions: An Experimental Study." *Management Science* 35 (3): 270–84.

Bernheim, B. Douglas, and Antonio Rangel. 2004. "Addiction and Cue-Triggered Decision Processes." *American Economic Review* 94 (5): 1558–90.

Beshears, John, James J. Choi, Christopher Harris, David Laibson, Brigitte C. Madrian, and Jung Sakong. 2020. "Which Early Withdrawal Penalty Attracts the Most Deposits to a Commitment Savings Account?" *Journal of Public Economics* 183: Article 104144.

Bettinger, Eric, and Robert Slonim. 2007. "Patience among Children." *Journal of Public Economics* 91 (1–2): 343–63.

Bhatia, Sudeep, Megan M. Grime, Rebecca Louise McDonald, Miguel Moreno, and Daniel Read. 2016. "Inconsistent Planning and the Allocation of Tasks Over Time." Paper presented at the Stirling PhD Conference in Behavioural Science, Stirling, UK, June 9.

Bickel, Warren K., Jeffery A. Pitcock, Richard Yi, and Edgardo J. C. Angtuaco. 2009. "Congruence of BOLD Response across Intertemporal Choice Conditions: Fictive and Real Money Gains and Losses." *Journal of Neuroscience* 29 (27): 8839–46.

Bisin, Alberto, and Kyle Hyndman. 2014. "Present-Bias, Procrastination and Deadlines in a Field Experiment." NBER Working Paper 19874.

Bommier, Antoine. 2006. "Uncertain Lifetime and Intertemporal Choice: Risk Aversion as a Rationale for Time Discounting." *International Economic Review* 47 (4): 1223–46.

Bommier, Antoine. 2007. "Risk Aversion, Intertemporal Elasticity of Substitution and Correlation Aversion." *Economics Bulletin* 4 (29): 1–8.

Bommier, Antoine. 2013. "Life-Cycle Preferences Revisited." *Journal of the European Economic Association* 11 (6): 1290–319.

Bommier, Antoine, and Jean-Charles Rochet. 2006. "Risk Aversion and Planning Horizons." *Journal of the European Economic Association* 4 (4): 708–34.

Bradford, David, Charles Courtemanche, Garth Heutel, Patrick McAlvanah, and Christopher Ruhm. 2017. "Time Preferences and Consumer Behavior." *Journal of Risk and Uncertainty* 55 (2–3): 119–45.

Brocas, Isabelle, and Juan D. Carrillo. 2008a. "Theories of the Mind." *American Economic Review* 98 (2): 175–80.

Brocas, Isabelle, and Juan D. Carrillo. 2008b. "The Brain as a Hierarchical Organization." *American Economic Review* 98 (4): 1312–46.

Brocas, Isabelle, and Juan D. Carrillo. 2012. "From Perception to Action: An Economic Model of Brain Processes." *Games and Economic Behavior* 75 (1): 81–103.

Broda, Christian, and Jonathan A. Parker. 2014. "The Economic Stimulus Payments of 2008 and the Aggregate Demand for Consumption." NBER Working Paper 20122.

Bryan, Gharad, Dean Karlan, and Scott Nelson. 2010. "Commitment Devices." *Annual Review of Economics* 2 (1): 671–98.

Burks, Stephen V., Jeffrey P. Carpenter, Lorenz Goette, and Aldo Rustichini. 2009. "Cognitive Skills Affect Economic Preferences, Strategic Behavior, and Job Attachment." *Proceedings of the National Academy of Sciences* 106 (19): 7745–50.

Burks, Stephen, Jeffrey Carpenter, Lorenz Götte, and Aldo Rustichini. 2012. "Which Measures of Time Preference Best Predict Outcomes: Evidence from a Large-Scale Field Experiment." *Journal of Economic Behavior and Organization* 84 (1): 308–20.

Busse, Meghan R., Christopher R. Knittel, and Florian Zettelmeyer. 2013. "Are Consumers Myopic? Evidence from New and Used Car Purchases." *American Economic Review* 103 (1): 220–56.

Cadena, Brian C., and Benjamin J. Keys. 2015. "Human Capital and the Lifetime Costs of Impatience." *American Economic Journal: Economic Policy* 7 (3): 126–53.

Camerer, Colin, Jonathan Cohen, Ernst Fehr, Paul Glimcher, and David Laibson. 2016. "Neuroeconomics." In *Handbook of Experimental Economics*, Vol. 2, edited by John H. Kagel and Alvin E. Roth, 153–216. Princeton: Princeton University Press.

Camerer, Colin F., and Robin M. Hogarth. 1999. "The Effects of Financial Incentives in Experiments: A Review and Capital-Labor-Production Framework." *Journal of Risk and Uncertainty* 19 (1–3): 7–42.

Caplin, Andrew, and John Leahy. 2004. "The Social Discount Rate." *Journal of Political Economy* 112 (6): 1257–68.

Carroll, Christopher D. 1992. "The Buffer-Stock Theory of Saving: Some Macroeconomic Evidence." *Brookings Papers on Economic Activity* 22 (2): 61–156.

Carroll, Christopher D. 2001. "Death to the Log-Linearized Consumption Euler Equation! (And Very Poor Health to the Second-Order Approximation)." *B. E. Journal of Macroeconomics* 1 (1): Article 7.

Carson, Richard T. 2012. "Contingent Valuation: A Practical Alternative When Prices Aren't Available." *Journal of Economic Perspectives* 26 (4): 27–42.

Carter, R. McKell, Justin R. Meyer, and Scott A. Huettel. 2010. "Functional Neuroimaging of Intertemporal Choice Models: A Review." *Journal of Neuroscience, Psychology, and Economics* 3 (1): 27–45.

Carvalho, Leandro S., Stephan Meier, and Stephanie W. Wang. 2016. "Poverty and Economic Decision-Making: Evidence from Changes in Financial Resources at Payday." *American Economic Review* 106 (2): 260–84.

Casari, Marco, and Davide Dragone. 2015. "Choice Reversal without Temptation: A Dynamic Experiment on Time Preferences." *Journal of Risk and Uncertainty* 50 (2): 119–40.

Cason, Timothy N., and Charles R. Plott. 2014. "Misconceptions and Game Form Recognition: Challenges to Theories of Revealed Preference and Framing." *Journal of Political Economy* 122 (6): 1235–70.

Castillo, Marco, Paul Ferraro, Jeffrey L. Jordan, and Ragan Petrie. 2011. "The Today and Tomorrow of Kids: Time Preferences and Educational Outcomes of Children." *Journal of Public Economics* 95 (11–12): 1377–85.

Chabris, Christopher F., David Laibson, Carrie L. Morris, Jonathon P. Schuldt, and Dmitry Taubinsky. 2008. "Individual Laboratory-Measured Discount Rates Predict Field Behavior." *Journal of Risk and Uncertainty* 37 (2-3): 237–69.

Chapman, Gretchen B. 1996. "Temporal Discounting and Utility for Health and Money." *Journal of Experimental Psychology: Learning, Memory, and Cognition* 22 (3): 771–91.

Chapman, G. B., and A. S. Elstein. 1995. "Valuing the Future: Temporal Discounting of Health and Money." *Medical Decision Making* 15 (4): 373–86.

Cheung, Stephen. 2015. "Comment on 'Risk Preferences Are Not Time Preferences': On the Elicitation of Time Preference under Conditions of Risk." *American Economic Review* 105 (7): 2242–60.

Chung, Shin-Ho, and R. J. Herrnstein. 1967. "Choice and Delay of Reinforcement." *Journal of the Experimental Analysis of Behavior* 10 (1): 67–74.

Coile, Courtney, Peter Diamond, Jonathan Gruber, and Alain Jousten. 2002. "Delays in Claiming Social

Security Benefits." *Journal of Public Economics* 84 (3): 357–85.

Coller, Maribeth, Glenn W. Harrison, and E. Elisabet Rutström. 2012. "Latent Process Heterogeneity in Discounting Behavior." *Oxford Economic Papers* 64 (2): 375–91.

Coller, Maribeth, and Melonie B. Williams. 1999. "Eliciting Individual Discount Rates." *Experimental Economics* 2 (2): 107–27.

Cubitt, Robin P., and Daniel Read. 2007. "Can Intertemporal Choice Experiments Elicit Time Preferences for Consumption?" *Experimental Economics* 10 (4): 369–89.

Cubitt, Robin P., Chris Starmer, and Robert Sugden. 1998. "On the Validity of the Random Lottery Incentive System." *Experimental Economics* 1 (2):115–31.

Daly, Michael, Colm P. Harmon, and Liam Delaney. 2009. "Psychological and Biological Foundations of Time Preference." *Journal of the European Economic Association* 7 (2–3): 659–69.

Dasgupta, Partha, and Eric Maskin. 2005. "Uncertainty and Hyperbolic Discounting." *American Economic Review* 95 (4): 1290–99.

Dean, Mark, and Pietro Ortoleva. 2015. "Is It All Connected? A Testing Ground for Unified Theories of Behavioral Economics Phenomena." Available on SSRN at 2643355.

Deaton, Angus. 1991. "Saving and Liquidity Constraints." *Econometrica* 59 (5): 1221–48.

Deaton, Angus. 1992. *Understanding Consumption*. Oxford: Oxford University Press.

DeJarnette, Patrick, David Dillenberger, Daniel Gottlieb, and Pietro Ortoleva. 2018. "Time Lotteries and Stochastic Impatience." Available on SSRN at 3252514.

Dekel, Eddie, Barton L. Lipman, and Aldo Rustichini. 2009. "Temptation-Driven Preferences." *Review of Economic Studies* 76 (3): 937–71.

DellaVigna, Stefano, and Ulrike Malmendier. 2004. "Contract Design and Self-Control: Theory and Evidence." *Quarterly Journal of Economics* 119 (2): 353–402.

DellaVigna, Stefano, and Ulrike Malmendier. 2006. "Paying Not to Go to the Gym." *American Economic Review* 96 (3): 694–719.

DellaVigna, Stefano, and M. Daniele Paserman. 2005. "Job Search and Impatience." *Journal of Labor Economics* 23 (3): 527–88.

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde. 2010. "Are Risk Aversion and Impatience Related to Cognitive Ability?" *American Economic Review* 100 (3): 1238–60.

Dohmen, Thomas J., Armin Falk, David Huffman, and Uwe Sunde. 2012. "Interpreting Time Horizon Effects in Intertemporal Choice." Institute of Labor Economics (IZA) Working Paper 6385.

Dreyfus, Mark K., and W. Kip Viscusi. 1995. "Rates of Time Preference and Consumer Valuations of Automobile Safety and Fuel Efficiency." *Journal of Law and Economics* 38 (1): 79–105.

Ebert, Jane E. J., and Drazen Prelec. 2007. "The Fragility of Time: Time-Insensitivity and Valuation of the Near and Far Future." *Management Science* 53 (9): 1423–38.

Epper, Thomas, and Helga Fehr-Duda 2015. "Comment on 'Risk Preferences Are Not Time Preferences': Balancing on a Budget Line." *American Economic Review* 105 (7): 2261–71.

Epper, Thomas, Helga Fehr-Duda, and Adrian Bruhin. 2011. "Viewing the Future through a Warped Lens: Why Uncertainty Generates Hyperbolic Discounting." *Journal of Risk and Uncertainty* 43 (3): 169–203.

Epstein, Larry G., and Stanley E. Zin. 1989. "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework." *Econometrica* 57 (4): 937–69.

Ericson, Keith Marzilli. 2017. "On the Interaction of Memory and Procrastination: Implications for Reminders, Deadlines, and Empirical Estimation." *Journal of the European Economic Association* 15 (3): 692–719.

Ericson, Keith Marzilli, and David Laibson. 2019. "Intertemporal Choice." In *Handbook of Behavioral Economics—Foundations and Applications*, Vol 2., edited by Douglas Bernheim, Stefano DellaVigna, and David Laibson. Amsterdam: North-Holland.

Ericson, Keith, and Jawwad Noor. 2015. "Delay Functions as the Foundation of Time Preference: Testing for Separable Discounted Utility." NBER Working Paper 21095.

Ericson, Keith M. Marzilli, John Myles White, David Laibson, and Jonathan D. Cohen. 2015. "Money Earlier or Later? Simple Heuristics Explain Intertemporal Choices Better Than Delay Discounting Does." *Psychological Science* 26 (6): 826–33.

Estle, Sara J., Leonard Green, Joel Myerson, and Daniel D. Holt. 2007. "Discounting of Monetary and Directly Consumable Rewards." *Psychological Science* 18 (1): 58–63.

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David B. Huffman, and Uwe Sunde. 2015. "The Nature and Predictive Power of Preferences: Global Evidence." IZA Discussion Paper 9504.

Falk, Armin, Anke Becker, Thomas Dohmen, David Huffman, and Uwe Sunde. 2016. "The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences." IZA Discussion Paper 9674.

Figner, Bernd, et al. 2010. "Lateral Prefrontal Cortex and Self-Control in Intertemporal Choice." *Nature Neuroscience* 13: 538–39.

Frederick, Shane, George Loewenstein, and Ted O'Donoghue. 2002. "Time Discounting and Time Preference: A Critical Review." *Journal of Economic Literature* 40 (2): 351–401.

Freeman, David J., Yoram Halevy, and Terri Kneeland. Forthcoming. "Eliciting Risk Preferences using Choice Lists." *Quantitative Economics*.

Freeman, David, Paola Manzini, Marco Mariotti, and Luigi Mittone. 2016. "Procedures for Eliciting Time Preferences." *Journal of Economic Behavior and Organization* 126 (A): 235–42.

Friedman, Milton. 1957. *A Theory of the Consumption Function*. Princeton: Princeton University Press.

Fudenberg, Drew, and David K. Levine. 2006. "A Dual-Self Model of Impulse Control." *American Economic Review* 96 (5): 1449–76.

Fudenberg, Drew, and David K. Levine. 2011. "Risk, Delay, and Convex Self-Control Costs." *American Economic Journal: Microeconomics* 3 (3): 34–68.

Gabaix, Xavier, and David Laibson. 2017. "Myopia and Discounting." NBER Working Paper 23254.

Gigerenzer, Gerd, and Peter M. Todd. 1999. "Fast and Frugal Heuristics: The Adaptive Toolbox." In *Simple Heuristics That Make Us Smart*, edited by Gerd Gigerenzer, Peter M. Todd, and ABC Research Group, 3–34. Oxford: Oxford University Press.

Gill, David, and Victoria Prowse. 2012. "A Structural Analysis of Disappointment Aversion in a Real Effort Competition." *American Economic Review* 102 (1): 469–503.

Giné, Xavier, Dean Karlan, and Jonathan Zinman. 2010. "Put Your Money Where Your Butt Is: A Commitment Contract for Smoking Cessation." *American Economic Journal: Applied Economics* 2 (4): 213–35.

Glimcher, Paul William, Joseph Kable, and Kenway Louie. 2007. "Neuroeconomic Studies of Impulsivity: Now or Just as Soon as Possible?" *American Economic Review* 97 (2): 142–47.

Gollier, Christian. 2013. "The Debate on Discounting: Reconciling Positivists and Ethicists." *Chicago Journal of International Law* 13 (2): 549-64.

Golsteyn, Bart H. H., Hans Grönqvist, and Lena Lindahl. 2013. "Time Preferences and Lifetime Outcomes." IZA Discussion Paper 7165.

Goulder, Lawrence H., and Roberton C. Williams, III. 2012. "The Choice of Discount Rate for Climate Change Policy Evaluation." *Climate Change Economics* 3 (4): Article 1250024.

Gourinchas, Pierre-Olivier, and Jonathan A. Parker. 2002. "Consumption over the Life Cycle." *Econometrica* 70 (1): 47–89.

Green, Leonard, Joel Myerson, and Eric W. Macaux. 2005. "Temporal Discounting When the Choice Is between Two Delayed Rewards." *Journal of Experimental Psychology: Learning, Memory, and Cognition* 31 (5): 1121–33.

Green, Leonard, Joel Myerson, and Edward Mcfadden. 1997. "Rate of Temporal Discounting Decreases with Amount of Reward." *Memory & Cognition* 25 (5): 715–23.

Gul, Faruk, and Wolfgang Pesendorfer. 2001. "Temptation and Self-Control." *Econometrica* 69 (6): 1403–35.

Gustman, Alan L., and Thomas L. Steinmeier. 2012. "Policy Effects in Hyperbolic vs. Exponential Models of Consumption and Retirement." *Journal of Public Economics* 96 (5–6): 465–73.

Halevy, Yoram. 2008. "Strotz Meets Allais: Diminishing Impatience and the Certainty Effect." *American Economic Review* 98 (3): 1145–62.

Halevy, Yoram. 2014. "Some Comments on the Use of Monetary and Primary Rewards in the Measurement of Time Preferences." Accessed April 28, 2020. https://pdfs.semanticscholar.org/8c22/4929bf11c276b991397bc20ccc459abd11f8.pdf.

Halevy, Yoram. 2015. "Time Consistency: Stationarity and Time Invariance." *Econometrica* 83 (1): 335–52.

Hall, Robert E. 1978. "Stochastic Implications of the Life Cycle–Permanent Income Hypothesis: Theory and Evidence." *Journal of Political Economy* 86 (6): 971–87.

Hardisty, David J., Katherine F. Thompson, David H. Krantz, and Elke U. Weber. 2013. "How to Measure Time Preferences: An Experimental Comparison of Three Methods." *Judgment and Decision Making* 8 (3): 236–49.

Hare, Todd A., Colin F. Camerer, and Antonio Rangel. 2009. "Self-Control in Decision-Making Involves Modulation of the vmPFC Valuation System." *Science* 324 (5927): 646–48.

Harris, Christopher, and David Laibson. 2001. "Dynamic Choices of Hyperbolic Consumers." *Econometrica* 69 (4): 935–57.

Harris, Christopher, and David Laibson. 2013. "Instantaneous Gratification." *Quarterly Journal of Economics* 128 (1): 205–48.

Harrison, Glenn W., Morten I. Lau, and E. Elisabet Rutström. 2010. "Individual Discount Rates and Smoking: Evidence from a Field Experiment in Denmark." *Journal of Health Economics* 29 (5): 708–17.

Harrison, Glenn W., Morten I. Lau, and Melonie B. Williams. 2002. "Estimating Individual Discount Rates in Denmark: A Field Experiment." *American Economic Review* 92 (5): 1606–17.

Harrison, Glenn W. 2014. "Real Choices and Hypothetical Choices." In *Handbook of Choice Modelling*, edited by Stephane Hess and Andrew Daly. Northampton: Edward Elgar.

Hausman, Jerry A. 1979. "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables." *Bell Journal of Economics* 10 (1): 33–54.

Hausman, Jerry. 2012. "Contingent Valuation: From Dubious to Hopeless." *Journal of Economic Perspectives* 26 (4): 43–56.

Hey, John D., and Jinkwon Lee. 2005. "Do Subjects Separate (or Are They Sophisticated)?" *Experimental Economics* 8 (3): 233–65.

Hines, James R., Jr., and Richard H. Thaler. 1995. "Anomalies: The Flypaper Effect." *Journal of Economic Perspectives* 9 (4): 217–26.

Holcomb, James H., and Paul S. Nelson. 1992. "Another Experimental Look at Individual Time Preference." *Rationality and Society* 4 (2): 199–220.

Holt, Charles A. 1986. "Preference Reversals and the Independence Axiom." *American Economic Review* 76 (3): 508–15.

Holt, Charles, A., and Susan K. Laury. 2002. "Risk Aversion and Incentive Effects." *American Economic Review* 92 (5): 1644–55.

Holt, Charles A., and Susan K. Laury. 2005. "Risk Aversion and Incentive Effects: New Data without Order Effects." *American Economic Review* 95 (3): 902–12.

Houser, Daniel, Daniel Schunk, Joachim Winter, and

Erte Xiao. 2018. "Temptation and Commitment in the Laboratory." *Games and Economic Behavior* 107: 329–44.

Hume, David. 1896. *A Treatise of Human Nature by David Hume, Reprinted from the Original Edition in Three Volumes and Edited, with an Analytical Index by L. A. Selby-Bigge, M.A.* Oxford: Clarendon Press. [1738].

Ifcher, John, and Homa Zarghamee. 2011. "Happiness and Time Preference: The Effect of Positive Affect in a Random-Assignment Experiment." *American Economic Review* 101 (7): 3109–29.

Imas, Alex, Michael A. Kuhn, and Vera Mironova. 2018. "Waiting to Choose." Accessed April 28, 2020. https://pages.uoregon.edu/mkuhn/pdfs/ikm.pdf.

Jackson, Matthew O., and Leeat Yariv. 2014. "Present Bias and Collective Dynamic Choice in the Lab." *American Economic Review* 104 (12): 4184–4204.

Jackson, Matthew O., and Leeat Yariv. 2015. "Collective Dynamic Choice: The Necessity of Time Inconsistency." *American Economic Journal: Microeconomics* 7 (4): 150–78.

Johnson, Eric J., John W. Payne, David A. Schkade, and James R. Bettman. 1989. *Monitoring Information Processing and Decisions: The Mouselab System*. Arlington: Office of Naval Research Perceptual Science Programs.

Johnson, Matthew W., and Warren K. Bickel. 2002. "Within-Subject Comparison of Real and Hypothetical Money Rewards in Delay Discounting." *Journal of the Experimental Analysis of Behavior* 77 (2): 129–46.

Kable, Joseph W. 2014. "Valuation, Intertemporal Choice, and Self-Control." In *Neuroeconomics: Decision Making and the Brain*, 2nd edition, edited by Paul W. Glimcher and Ernst Fehr. Amsterdam: North-Holland.

Kable, Joseph W., and Paul W. Glimcher. 2007. "The Neural Correlates of Subjective Value during Intertemporal Choice." *Nature Neuroscience* 10 (12): 1625–33.

Kable, Joseph W., and Paul W. Glimcher. 2010. "An 'as Soon as Possible' Effect in Human Intertemporal Decision Making: Behavioral Evidence and Neural Mechanisms." *Journal of Neurophysiology* 103 (5): 2513–31.

Kahneman, Daniel, and Amos Tversky. 1979. "Prospect Theory: An Analysis of Decision under Risk." *Econometrica* 47 (2): 263–92.

Karni, Edi, and Zvi Safra. 1987. "'Preference Reversal' and the Observability of Preferences by Experimental Methods." *Econometrica* 55 (3): 675–85.

Kaur, Supreet, Michael Kremer, and Sendhil Mullainathan. 2010. "Self-Control and the Development of Work Arrangements." *American Economic Review* 100 (2): 624–28.

Kirby, Kris N. 1997. "Bidding on the Future: Evidence against Normative Discounting of Delayed Rewards." *Journal of Experimental Psychology: General* 126 (1): 54–70.

Kirby, Kris N. 2009. "One-Year Temporal Stability of Delay-Discount Rates." *Psychonomic Bulletin and Review* 16 (3): 457–62.

Kirby, Kris N., and R. J. Herrnstein. 1995. "Preference Reversals Due to Myopic Discounting of Delayed Reward." *Psychological Science* 6 (2): 83–89.

Kling, Catherine L., Daniel J. Phaneuf, and Jinhua Zhao. 2012. "From Exxon to BP: Has Some Number Become Better Than No Number?" *Journal of Economic Perspectives* 26 (4): 3–26.

Kocherlakota, Narayana. 2001. "Looking for Evidence of Time-Inconsistent Preferences in Asset Market Data." *Federal Reserve Bank of Minneapolis Quarterly Review* 25 (3): 13–24.

Koopmans, Tjalling C. 1960. "Stationary Ordinal Utility and Impatience." *Econometrica* 28 (2): 287–309.

Kőszegi, Botond, and Adam Szeidl. 2013. "A Model of Focusing in Economic Choice." *Quarterly Journal of Economics* 128 (1): 53–104.

Krupka, Erin L., and Melvin Stephens, Jr. 2013. "The Stability of Measured Time Preferences." *Journal of Economic Behavior & Organization* 85: 11–19.

Krusell, Per, Burhanettin Kuruşçu, and Anthony A. Smith, Jr. 2010. "Temptation and Taxation." *Econometrica* 78 (6): 2063–84.

Laibson, David. 1997. "Golden Eggs and Hyperbolic Discounting." *Quarterly Journal of Economics* 112 (2): 443–78.

Laibson, David. 2001. "A Cue-Theory of Consumption." *Quarterly Journal of Economics* 116 (1): 81–119.

Laibson, David. 2015. "Why Don't Present-Biased Agents Make Commitments?" *American Economic Review* 105 (5): 267–72.

Laibson, David, Peter Maxted, Andrea Repetto, and Jeremy Tobacman. 2015. "Estimating Discount Functions with Consumption Choices over the Lifecycle." https://scholar.harvard.edu/files/maxted/files/estimating_discount_functions_10-15-15.pdf.

Lawrance, Emily C. 1991. "Poverty and the Rate of Time Preference: Evidence from Panel Data." *Journal of Political Economy* 99 (1): 54–77.

Lawyer, Steven R., Sonja A. Williams, Tereza Prihodova, Jason D. Rollins, and Anita C. Lester. 2010. "Probability and Delay Discounting of Hypothetical Sexual Outcomes." *Behavioural Processes* 84 (3): 687–92.

Lichtenstein, Sarah, and Paul Slovic. 1973. "Response-Induced Reversals of Preference in Gambling: An Extended Replication in Las Vegas." *Journal of Experimental Psychology* 101 (1): 16–20.

Loewenstein, George. 1987. "Anticipation and the Valuation of Delayed Consumption." *Economic Journal* 97 (387): 666–84.

Loewenstein, George F. 1988. "Frames of Mind in Intertemporal Choice." *Management Science* 34 (2): 200–214.

Loewenstein, George. 1992. "The Fall and Rise of Psychological Explanations in the Economics of Intertemporal Choice." In *Choice over Time*, edited by George Loewenstein and Jon Elster, 3–34. New York: Russell Sage Foundation.

Loewenstein, George. 1996. "Out of Control: Visceral Influences on Behavior." *Organizational Behavior and Human Decision Processes* 65 (3): 272–92.

Loewenstein, George, and Ted O'Donoghue. 2004. "Animal Spirits: Affective and Deliberative Processes in Economic Behavior." Available on SSRN at 539843.

Loewenstein, George, Ted O'Donoghue, and Matthew Rabin. 2003. "Projection Bias in Predicting Future Utility." *Quarterly Journal of Economics* 118 (4): 1209–48.

Loewenstein, George, and Drazen Prelec. 1992. "Anomalies in Intertemporal Choice: Evidence and Interpretation." *Quarterly Journal of Economics* 107 (2): 573–97.

Loewenstein, George F., and Dražen Prelec. 1993. "Preferences for Sequences of Outcomes." *Psychological Review* 100 (1): 91–108.

Loewenstein, George, and Nachum Sicherman. 1991. "Do Workers Prefer Increasing Wage Profiles?" *Journal of Labor Economics* 9 (1): 67–84.

Loewenstein, George, and Richard H. Thaler. 1989. "Anomalies: Intertemporal Choice." *Journal of Economic Perspectives* 3 (4): 181–93.

Madden, Gregory J., Andrea M. Begotka, Bethany R. Raiff, and Lana L. Kastern. 2003. "Delay Discounting of Real and Hypothetical Rewards." *Experimental and Clinical Psychopharmacology* 11 (2): 139–45.

Madden, Gregory J., et al. 2004. "Delay Discounting of Potentially Real and Hypothetical Rewards: II. Between- and Within-Subject Comparisons." *Experimental and Clinical Psychopharmacology* 12 (4): 251–61.

Magen, Eran, Carol S. Dweck, and James J. Gross. 2008. "The Hidden-Zero Effect: Representing a Single Choice as an Extended Sequence Reduces Impulsive Choice." *Psychological Science* 19 (7): 648–49.

Maital, S., and S. Maital. 1977. "Time Preference, Delay of Gratification and the Intergenerational Transmission of Economic Inequality: A Behavioral Theory of Income Distribution." In *Essays in Labor Market Analysis: In Memory of Yochanan Peter Comay*, edited by Orley C. Ashenfelter, Yochanan Peter Comay, and Wallace E. Oates, 179–200. New York: Wiley.

Malkoc, Selin A., and Gal Zauberman. 2006. "Deferring versus Expediting Consumption: The Effect of Outcome Concreteness on Sensitivity to Time Horizon." *Journal of Marketing Research* 43 (4): 618–27.

Mastrobuoni, Giovanni, and Matthew Weinberg. 2009. "Heterogeneity in Intra-monthly Consumption Patterns, Self-Control, and Savings at Retirement." *American Economic Journal: Economic Policy* 1 (2): 163–89.

Mazar, Nina, Botond Koszegi, and Dan Ariely. 2014. "True Context-Dependent Preferences? The Causes of Market-Dependent Valuations." *Journal of Behavioral Decision Making* 27 (3): 200–208.

McAlvanah, Patrick. 2010. "Subadditivity, Patience, and Utility: The Effects of Dividing Time Intervals." *Journal of Economic Behavior & Organization* 76 (2): 325–37.

McClure, Samuel M., Keith M. Ericson, David I. Laibson, George Loewenstein, and Jonathan D. Cohen. 2007. "Time Discounting for Primary Rewards." *Journal of Neuroscience* 27 (21): 5796–804.

McClure, Samuel M., David I. Laibson, George Loewenstein, and Jonathan D. Cohen. 2004. "Separate Neural Systems Value Immediate and Delayed Monetary Rewards." *Science* 306 (5695): 503–07.

McGuire, Joseph T., and Joseph W. Kable. 2013. "Rational Temporal Predictions Can Underlie Apparent Failures to Delay Gratification." *Psychological Review* 120 (2): 395–410.

Meier, Stephan, and Charles Sprenger. 2010. "Present-Biased Preferences and Credit Card Borrowing." *American Economic Journal: Applied Economics* 2 (1): 193–210.

Meier, Stephan, and Charles D. Sprenger. 2012. "Time Discounting Predicts Creditworthiness." *Psychological Science* 23 (1): 56–58.

Meier, Stephan, and Charles D. Sprenger. 2013. "Discounting Financial Literacy: Time Preferences and Participation in Financial Education Programs." *Journal of Economic Behavior & Organization* 95: 159–74.

Meier, Stephan, and Charles D. Sprenger. 2015. "Temporal Stability of Time Preferences." *Review of Economics and Statistics* 97 (2): 273–86.

Metcalfe, Janet, and Walter Mischel. 1999. "A Hot/Cold-System Analysis of Delay of Gratification: Dynamics of Willpower." *Psychological Review* 106 (1): 3–19.

Meyer, Andrew G. 2015. "The Impacts of Elicitation Mechanism and Reward Size on Estimated Rates of Time Preference." *Journal of Behavioral and Experimental Economics* 58: 132–48.

Miao, Bin, and Songfa Zhong. 2015. "Comment on 'Risk Preferences Are Not Time Preferences': Separating Risk and Time Preference." *American Economic Review* 105 (7): 2272–86.

Milkman, Katherine L., Todd Rogers, and Max H. Bazerman. 2009. "Highbrow Films Gather Dust: Time-Inconsistent Preferences and Online DVD Rentals." *Management Science* 55 (6): 1047–59.

Mischel, Walter, and Ebbe B. Ebbesen. 1970. "Attention in Delay of Gratification." *Journal of Personality and Social Psychology* 16 (2): 329–37.

Mischel, W., Y. Shoda, and M. I. Rodriguez. 1989. "Delay of Gratification in Children." *Science* 244 (4907): 933–38.

Modigliani, Franco, and R. H. Brumberg. 1954. "Utility Analysis and the Consumption Function: An Interpretation of Cross-Section Data." In *Post-Keynesian Economics*, edited by K. K. Kurihara. New Brunswick: Rutgers University Press.

Noor, Jawwad. 2009. "Hyperbolic Discounting and the Standard Model: Eliciting Discount Functions." *Journal of Economic Theory* 144 (5): 2077–83.

O'Donoghue, Ted, and Matthew Rabin. 1999a. "Doing It Now or Later." *American Economic Review* 89 (1):

103–24.
O'Donoghue, Ted, and Matthew Rabin. 1999b. "Incentives for Procrastinators." *Quarterly Journal of Economics* 114 (3): 769–816.
Odum, Amy L., Ana A. L. Baumann, and Delores D. Rimington. 2006. "Discounting of Delayed Hypothetical Money and Food: Effects of Amount." *Behavioural Processes* 73 (3): 278–84.
Odum, Amy L., and Carla P. Rainaud. 2003. "Discounting of Delayed Hypothetical Money, Alcohol, and Food." *Behavioural Processes* 64 (3): 305–13.
Olea, José Luis Montiel, and Tomasz Strzalecki. 2014. "Axiomatization and Measurement of Quasi-Hyperbolic Discounting." *Quarterly Journal of Economics* 129 (3): 1449–99.
Parker, Jonathan A., Nicholas S. Souleles, David S. Johnson, and Robert McClelland. 2013. "Consumer Spending and the Economic Stimulus Payments of 2008." *American Economic Review* 103 (6): 2530–53.
Paserman, M. Daniele. 2008. "Job Search and Hyperbolic Discounting: Structural Estimation and Policy Evaluation." *Economic Journal* 118 (531): 1418–52.
Pavlov, Ivan Petrovich. 1927. *Conditioned Reflexes: An Investigation of the Psychological Activity of the Cerebral Cortex*. Oxford: Oxford University Press.
Phelps, E. S., and R. A. Pollak. 1968. "On Second-Best National Saving and Game-Equilibrium Growth." *Review of Economic Studies* 35 (2): 185–99.
Pigou, Arthur C. 1920. *The Economics of Welfare*. London: Macmillan.
Plato, and Robert Gregg Bury. 1925. *Timaeus. Critias. Cleitophon. Menexenus. Epistles*. Vol. 9, *Plato in Twelve Volumes*. Cambridge: Harvard University Press.
Prelec, Drazen, and George Loewenstein. 1991. "Decision Making over Time and under Uncertainty: A Common Approach." *Management Science* 37 (7): 770–86.
Rabin, Matthew. 2000. "Risk Aversion and Expected-Utility Theory: A Calibration Theorem." *Econometrica* 68 (5): 1281–92.
Ramsey, Frank P. 1928. "A Mathematical Theory of Saving." *Economic Journal* 38 (152): 543–59.
Read, Daniel. 2001. "Is Time-Discounting Hyperbolic or Subadditive?" *Journal of Risk and Uncertainty* 23 (1): 5–32.
Read, Daniel. 2005 "Monetary Incentives, What Are They Good for?" *Journal of Economic Methodology* 12 (2): 265–76.
Read, Daniel, Shane Frederick, Burcu Orsel, and Juwaria Rahman. 2005. "Four Score and Seven Years from Now: The Date/Delay Effect in Temporal Discounting." *Management Science* 51 (9): 1326–35.
Read, Daniel, Shane Frederick, and Marc Scholten. 2011. "Outcome Framing in Intertemporal Choice: The DRIFT Model." Available on SSRN at 1933099.
Read, Daniel, Shane Frederick, and Marc Scholten. 2013. "DRIFT: An Analysis of Outcome Framing in Intertemporal Choice." *Journal of Experimental Psychology: Learning, Memory, and Cognition* 39 (2): 573–88.
Read, Daniel, George Loewenstein, and Shobana Kalyanaraman. 1999. "Mixing Virtue and Vice: Combining the Immediacy Effect and the Diversification Heuristic." *Journal of Behavioral Decision Making* 12 (4): 257–73.
Read, Daniel, and Peter H. M. P Roelofsma. 2003. "Subadditive versus Hyperbolic Discounting: A Comparison of Choice and Matching." *Organizational Behavior and Human Decision Processes* 91 (2): 140–53.
Read, Daniel, and Barbara van Leeuwen. 1998. "Predicting Hunger: The Effects of Appetite and Delay on Choice." *Organizational Behavior and Human Decision Processes* 76 (2): 189–205.
Reuben, Ernesto, Paola Sapienza, and Luigi Zingales. 2010. "Time Discounting for Primary and Monetary Rewards." *Economics Letters* 106 (2): 125–27.
Reuben, Ernesto, Paola Sapienza, and Luigi Zingales. 2015. "Procrastination and Impatience." *Journal of Behavioral and Experimental Economics* 58: 63–76.
Robson, Arthur J., and Larry Samuelson. 2009. "The Evolution of Time Preference with Aggregate Uncertainty." *American Economic Review* 99 (5): 1925–53.
Rosati, Alexandra G., Jeffrey R. Stevens, Brian Hare, and Marc D. Hauser. 2007. "The Evolutionary Origins of Human Patience: Temporal Preferences in Chimpanzees, Bonobos, and Human Adults." *Current Biology* 17 (19): 1663–68.
Royer, Heather, Mark Stehr, and Justin Sydnor. 2015. "Incentives, Commitments, and Habit Formation in Exercise: Evidence from a Field Experiment with Workers at a Fortune-500 Company." *American Economic Journal: Applied Economics* 7 (3): 51–84.
Saito, Kota. 2011. "Strotz Meets Allais: Diminishing Impatience and the Certainty Effect: Comment." *American Economic Review* 101 (5): 2271–75.
Samuelson, Paul. 1937. "A Note on Measurement of Utility." *Review of Economic Studies* 4 (2): 155–61.
Schelling, Thomas C. 1995. "Intergenerational Discounting." *Energy Policy* 23 (4–5): 395–401.
Schilbach, Frank. 2019. "Alcohol and Self-Control: A Field Experiment in India." *American Economic Review* 109 (4): 1290–322.
Scholten, Marc, and Daniel Read. 2006. "Discounting by Intervals: A Generalized Model of Intertemporal Choice." *Management Science* 52 (9): 1424–36.
Shapiro, Jesse M. 2005. "Is There a Daily Discount Rate? Evidence from the Food Stamp Nutrition Cycle." *Journal of Public Economics* 89 (2–3): 303–25.
Shapiro, Matthew D., and Joel Slemrod. 2003. "Did the 2001 Tax Rebate Stimulate Spending? Evidence from Taxpayer Surveys." *Tax Policy and the Economy* 17: 83–109.
Shefrin, Hersh M., and Richard H. Thaler. 1988. "The Behavioral Life-Cycle Hypothesis." *Economic Inquiry* 26 (4): 609–43.
Shelley, Marjorie K. 1994. "Gain/Loss Asymmetry in Risky Intertemporal Choice." *Organizational Behavior and Human Decision Processes* 59 (1): 124–59.
Simon, Curtis J., John T. Warner, and Saul Pleeter. 2015.

"Discounting, Cognition, and Financial Awareness: New Evidence from a Change in the Military Retirement System." *Economic Inquiry* 53 (1): 318–34.

Simpson, Cathy A., and Rudy E. Vuchinich. 2000. "Temporal Changes in the Value of Objects of Choice: Discounting, Behavior Patterns, and Health Behavior." In *Reframing Health Behavior Change with Behavioral Economics*, edited by Warren K. Bickel and Rudy E. Vuchinich, 195–217. Mahwah, NJ: Lawrence Erlbaum Associates, Publishers.

Slonim, Robert, James Carlson, and Eric Bettinger. 2007. "Possession and Discounting Behavior." *Economics Letters* 97 (3): 215–21.

Smith, Adam. 1761. *The Theory of Moral Sentiments*. 2nd ed. Strand and Edinburgh: A. Miller, A. Kincaid, and J. Bell.

Smith, Adam. 1776. *An Inquiry into the Nature and Causes of the Wealth of Nations*. London: W. Strahan and T. Cadell.

Sozou, P. D. 1998. "On Hyperbolic Discounting and Uncertain Hazard Rates." *Proceedings of the Royal Society of London. Series B, Biological Sciences* 265 (1409): 2015–20.

Starmer, Chris, and Robert Sugden. 1991. "Does the Random-Lottery Incentive System Elicit True Preferences? An Experimental Investigation." *American Economic Review* 81 (4): 971–78.

Stephens, Melvin. 2003. "'3rd of Tha Month': Do Social Security Recipients Smooth Consumption between Checks?" *American Economic Review* 93 (1): 406–22.

Stern, Nicholas. 2007. *The Economics of Climate Change: The Stern Review*. Cambridge: Cambridge University Press.

Strotz, R. H. 1955. "Myopia and Inconsistency in Dynamic Utility Maximization." *Review of Economic Studies* 23 (3): 165–80.

Sutter, Matthias, Martin G. Kocher, Daniela Glätzle-Rützler, and Stefan T. Trautmann. 2013. "Impatience and Uncertainty: Experimental Decisions Predict Adolescents' Field Behavior." *American Economic Review* 103 (1): 510–31.

Takeuchi, Kan. 2011. "Non-parametric Test of Time Consistency: Present Bias and Future Bias." *Games and Economic Behavior* 71 (2): 456–78.

Tanaka, Saori C., Katsunori Yamada, Hiroyasu Yoneda, and Fumio Ohtake. 2014. "Neural Mechanisms of Gain–Loss Asymmetry in Temporal Discounting." *Journal of Neuroscience* 34 (16): 5595–5602.

Tanaka, Tomomi, Colin F. Camerer, and Quang Nguyen. 2010. "Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam." *American Economic Review* 100 (1): 557–71.

Thaler, Richard. 1980. "Toward a Positive Theory of Consumer Choice." *Journal of Economic Behavior and Organization* 1 (1): 39–60.

Thaler, Richard. 1981. "Some Empirical Evidence on Dynamic Inconsistency." *Economics Letters* 8 (3): 201–07.

Thaler, Richard H., and Eric J. Johnson. 1990. "Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice." *Management Science* 36 (6): 643–60.

Thaler, Richard H., and H. M. Shefrin. 1981. "An Economic Theory of Self-Control." *Journal of Political Economy* 89 (2): 392–406.

Tobin, Henry, and A. W. Logue. 1994. "Self-Control across Species (Columba Livia, Homo Sapiens, and Rattus Norvegicus)." *Journal of Comparative Psychology* 108 (2): 126–33.

Tsukayama, Eli, and Angela Lee Duckworth. 2010. "Domain-Specific Temporal Discounting and Temptation." *Judgment and Decision Making* 5 (2): 72–82.

Tversky, Amos, and Daniel Kahneman. 1974. "Judgment under Uncertainty: Heuristics and Biases." *Science* 185 (4157): 1124–31.

Ubfal, Diego. 2016. "How General Are Time Preferences? Eliciting Good-Specific Discount Rates." *Journal of Development Economics* 118: 150–70.

Viscusi, W. Kip, and Michael J. Moore. 1989. "Rates of Time Preference and Valuations of the Duration of Life." *Journal of Public Economics* 38 (3): 297–317.

von Böhm-Bawerk, Eugen. 1890. *Capital and Interest: A Critical History of Economical Theory*. London and New York: Macmillan.

Wang, Mei, Marc Oliver Rieger, and Thorsten Hens. 2016. "How Time Preferences Differ: Evidence from 53 countries." *Journal of Economic Psychology* 52: 115–35.

Warner, John T., and Saul Pleeter. 2001. "The Personal Discount Rate: Evidence from Military Downsizing Programs." *American Economic Review* 91 (1): 33–53.

Weber, E. U., E. J. Johnson, K. F. Milch, H. Chang, J. Brodscholl, and D. G. Goldstein. 2007. "Asymmetric Discounting in Intertemporal Choice: A Query-Theory Account." *Psychological Science* 18 (6): 516–23.

Wertenbroch, Klaus. 1998. "Consumption Self-Control by Rationing Purchase Quantities of Virtue and Vice." *Marketing Science* 17 (4): 317–37.

Wölbert, Eva, and Arno Riedl. 2013. "Measuring Time and Risk Preferences: Reliability, Stability, Domain Specificity." CESifo Working Paper 4339.

Wulff, Dirk U., and Wouter van den Bos. 2018. "Modeling Choices in Delay Discounting." *Psychological Science* 29 (11): 1890–94.

Zauberman, Gal, B. Kyu Kim, Selin A. Malkoc, and James R. Bettman. 2009. "Discounting Time and Time Discounting: Subjective Time Perception and Intertemporal Preferences." *Journal of Marketing Research* 46 (4): 543–56.

This article has been cited by:

1. Felix Chopra, Armin Falk, Thomas Graeber. 2024. Intertemporal Altruism. *American Economic Journal: Microeconomics* **16**:1, 329-357. [Abstract] [View PDF article] [PDF with links]
2. Antony Millner, Geoffrey Heal. 2023. Choosing the Future: Markets, Ethics, and Rapprochement in Social Discounting. *Journal of Economic Literature* **61**:3, 1037-1087. [Abstract] [View PDF article] [PDF with links]
3. Alex Imas, Michael A. Kuhn, Vera Mironova. 2022. Waiting to Choose: The Role of Deliberation in Intertemporal Choice. *American Economic Journal: Microeconomics* **14**:3, 414-440. [Abstract] [View PDF article] [PDF with links]