Salience Theory: Calibration and Heterogeneity in Probability Distortion[☆]

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Abstract

Bordalo, Gennaioli, and Shleifer (2012b) propose *salience theory* as an alternative to existing descriptive decision theories. However, the authors do not provide a formal calibration of the central *local thinking parameter*, which measures by how much individuals distort the probabilities of less salient lottery outcomes. Based on an experiment with multiple price lists, we jointly estimate the parameters of salience theory and alternative decision theories as well as the fraction of decisions described by each theory. We obtain three main results: first, 30% to 45% of the subjects in our sample behave in line with salience theory, and the local thinking parameter equals about 0.7 to 0.8, which is roughly consistent with the assumption of Bordalo, Gennaioli, and Shleifer (2012b). Second, our estimates of the local thinking parameter remain virtually unchanged when non-linear utility is assumed instead of linear utility. Third, our results reveal substantial heterogeneity: the local thinking parameter is significantly smaller when a lottery's downside is more salient than when its upside is most salient.

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1. Introduction

Empirical and experimental studies have documented numerous departures from the workhorse model of expected utility theory (EUT). Most notably, the consistency of decisions under risk across domains has proven fruitful for such illustrations—why do people gamble (thereby exhibiting risk-seeking behavior), but insure themselves against tiny risks (thereby being risk-averse) at the same time? As an alternative to existing decision theories, Bordalo, Gennaioli, and Shleifer (2012b) (BGS) introduce *salience theory*, which is based on the context-dependent relationship between lottery payoffs in different states of nature. In the eyes of a decision maker that acts according to salience theory (*local thinkers*, LTs), some of these states are more salient than others and catch her attention more easily. This leads her to relatively overweight the probability of the more salient states. Thus, if the upside of a lottery is most salient, LTs will be risk-seeking. However, when the downside of a lottery becomes most salient, the LT will be risk-averse.

The *local thinking parameter* δ (LT parameter) lies at the core of salience theory. It provides a measure of how strongly LTs distort the probabilities of risky outcomes. BGS assume a value of $\delta \sim 0.7$ since this value is able to account for several empirically observed anomalies. As conceded by BGS, this assumption is not a formal calibration, and they do not provide an estimate of the proportion of individuals whose behavior is consistent with salience theory. Adding to that, it is not clear whether the distortion of probabilities is independent of either a lottery's upside or downside being salient.

The central goal of this study is to experimentally estimate the LT parameter δ of individuals that can be classified as LTs and the fraction of subjects whose behavior can be characterized by salience theory. Our

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experiment is based on multiple price lists (MPLs) in the spirit of Holt and Laury (2002) (HL). Each subject is provided with two MPLs of 12 rows each. In each row, subjects have to choose between a risky lottery and a safe payoff. In one list, the risky lottery's upside is most salient; in the other list, its downside is most salient. This setup allows us to separate LTs from subjects that are consistently risk-averse or risk-seeking and to estimate δ for the subsample of LTs. In addition, it enables us to investigate potential differences between lotteries with salient downsides and lotteries with salient upsides.

Besides the possibility to estimate the LT parameter depending on a salient downside or a salient upside, a further key advantage of our experimental design is that it allows us to estimate specifications of alternative decision theories such as expected utility theory (EUT) or rank-dependent utility (RDU). In our experiment, the parameters of such alternative theories can be estimated in finite mixture models along with salience theory using maximum likelihood estimation and we are thus able to estimate the fraction of decisions characterized by each theory. It is important to note that it is not a purpose of this study to conduct a horse race of alternative decision theories. Instead, we are interested in reconciling salience theory and alternative decision theories (see Harrison and Rutström (2009) for a related discussion regarding EUT and prospect theory).

We obtain three main results: first, between 30% and 45% of the decisions in our sample are consistent with salience theory, and the LT parameter equals about 0.7 to 0.8, which is broadly in line with the assumption of BGS. Second, our estimates of the LT parameter are not significantly changed when non-linear utility is assumed instead of linear utility, the standard assumption of BGS. Third, our results reveal a substantial degree of heterogeneity: the LT parameter is significantly smaller when a lottery's downside is most salient than when its upside is most salient. Thus, while the first two results reveal that the basic assumptions of BGS with respect to the LT parameter δ (on average) and the curvature of the utility function are roughly supported, our findings question the assumption of a stable LT parameter for all salience configurations.

The remainder of this paper proceeds as follows. In Section 2, we review the related literature. Section 3 discusses the foundations of salience theory. The experimental design is described in Section 4. Section 5 presents our descriptive results. The results of our structural estimations are described in Section 6. Section 7 discusses the key implications of our results and concludes.

2. Related Literature

The general concept of salience to explain observed behavioral patterns is used by a wide array of studies. Barber and Odean (2008) find that investors are net buyers of "attention-grabbing" stocks, i.e., stocks that are displayed most prominently in the news, experience high abnormal trading volume, or have extreme one-day returns. Birz (2017) reports that investors in the stock market are affected by the salience of newspaper articles more than by their informational content. Frydman and Wang (2017) show that a shock that increases the salience of a stock's purchase price without changing the investor's information set increases the disposition effect. Lacetera, Pope, and Sydnor (2012) and Busse, Lacetera, Pope, Silva-Risso, and Sydnor (2013) investigate the salience of the leftmost digit of a used car's mileage in pricing and buying decisions in the used car market. They find that car buyers mostly consider the (salient) first digits of the car's mileage, but pay less attention to the following numbers. Chetty, Looney, and Kroft (2009) find that consumers underreact to taxes that are not salient. Englmaier, Roider, and Sunde (2017) show that the salience of incentives has positive effects on workforce productivity. McLeish and Oxoby (2011) show that the salience of social identity impacts behavior in social interactions. Jonas, Sullivan, and Greenberg (2013) document that norms which are salient in a decision situation determine whether mortality salience fosters generosity or greed in charitable behavior. Fochmann, Hemmerich, and Kiesewetter (2016) argue that tax salience might influence the willingness to take risks in individual investment decisions. Bollinger, Leslie, and Sorensen (2011) find that both salience and learning reduce average calories per transaction in Starbucks stores with mandatory calorie posting. Gilbert and Graff Zivin (2014) report that households reduce electricity consumption when consumption information is more salient (e.g., following the receipt of an electricity bill or a spending reminder). Sugden (2011) shows that the spontaneous emergence of conventions depends on shared conceptions of salience. Even though these numerous examples are formally unrelated to the salience theory of BGS, they show that the concept of salience plays an important role in various key domains of economic decision-making.

Using salience theory, BGS explain several departures from EUT such as the Allais paradox and preference reversals. Bordalo, Gennaioli, and Shleifer (2013a) apply salience theory to anomalies in asset pricing such as the overpricing of growth stocks, the equity premium, or countercyclical valuation of stocks. Even for decisions under certainty, salience theory can account for the overproportional consideration of certain product attributes (Bordalo, Gennaioli, and Shleifer, 2012a, 2013b). In Bordalo, Gennaioli, and Shleifer (2016), companies compete for customer attention by emphasizing salient product attributes. Bordalo, Gennaioli, and Shleifer (2015) develop a model of judicial decision-making which is based on the judge's overweighting of salient information. Bordalo, Gennaioli, and Shleifer (2017) argue that attention and choice are driven by surprises relative to a norm; in this context, surprises are modeled using salience theory.

As conceded by BGS, they are not the first to develop a decision theory based on context-dependent choice. Rubinstein (1988) proposes a model in which decision makers use similarity relations on the probability and prize spaces when choosing among alternative lotteries; his experimental results are difficult to reconcile with expected utility theory. These ideas are further developed in Leland (1994) and Leland (1998).[2] Leland and Schneider (2016b) develop a comparative model of decision-making under risk, uncertainty, and time. In their model, large differences in payoffs and probabilities or dates of receipt are perceived as salient and receive a higher weight in the evaluation process. The model predicts that individuals systematically violate the assumptions of rational choice theory and show behavior that is consistent with the Allais paradox, the common ratio effect, or the Ellsberg paradox when the choice options are represented in a minimal frame. However, individuals will behave more consistently with the classical axioms when the same choices are presented in a transparent frame. Leland and Schneider (2016a) derive axioms for the general class of salience functions. Leland and Schneider (2017) present a model of salience weighted utility over presentations (SWUP) that predicts systematic violations of expected utility and discounted utility—based on the same mathematical structure and psychological intuition. In SWUP, individuals assign weights to utility differences that depend on their importance and their salience or similarity. Schneider, Leland, and Wilcox (2018) examine a salience-based choice model and find that the type of presentation format that reduces violations of expected utility theory in the spirit of Allais also reduces violations of subjective expected utility theory in the spirit of Ellsberg; their experimental results are consistent with this intuition. In sum, it is important to note that salience theory as suggested by BGS uses one specific salience function (which we will discuss in greater detail in the next section), which is only one of various possible similarity relations.[3]

BGS state that both rank-dependent expected utility (RDU) as suggested by Quiggin (1982) and cumulative prospect theory (CPT) as proposed by Tversky and Kahneman (1992) are based on weighting functions in which probability weighting is determined by the rank order of a lottery's payoffs. BGS argue that their theory differs from RDU and CPT in two ways: first, in BGS, not only the rank of payoffs but also their magnitude affects salience and probability weights such that unlikely events are overweighted when they are associated with salient payoffs and underweighted otherwise. This is why a lottery's upside may still be underweighted if the corresponding payoff is not sufficiently high. BGS suggest that this characteristic is central to shifts in risk attitudes. Second, in the BGS model, decision weights depend on the respective choice context, i.e., on the presentation of the alternatives available to the decision maker.

In contrast to RDU and CPT, the so-called SP/A model by Lopes (1984)[4] is a dual-criteria model; its key feature is that it allows for two ways in which the same individual evaluates a lottery. The SP component refers to the weighting of the *security* and the *potential* of a lottery (similar to RDU). The A component is related to the *aspirations* of the individual; it shows the extent to which a lottery satisfies the aspiration level of an individual. In this way, it defines a threshold for each lottery: if a lottery exceeds the threshold, an individual is more likely to choose it. To the extent that the threshold function reflects some sort of psychometric salience, the SP/A model can be viewed as an alternative theory of decision-making based on salience.

Subsequent to the publication of the first studies on salience theory by BGS, several theoretical and empirical analyses have been provided. Based on US stock market data, Cosemans and Frehen (2017) find that investors prefer stocks with salient upsides, which tend to be overvalued and yield low subsequent returns, while stocks with salient downsides tend to be undervalued and earn high future returns. Based on three experiments in which subjects choose between alternative lotteries, Frydman and Mormann (2018) also find supporting evidence in favor of salience theory. In Booth and Nolen (2012), subjects make hypothetical decisions between two lottery pairs.[5] 37% of their subjects choose combinations which imply risk-averse behavior in one lottery pair and risk-seeking in the other, which is consistent with the predictions of salience theory. Dertwinkel-Kalt and Köster (2017) argue that salience theory is better able to explain newsvendor-

[2] See also the summary in Leland (2010).
[3] See the related discussion in Rubinstein (1988).
[4] See also the summary in Andersen, Harrison, Lau, and Rutström (2014).
[5] The same lottery pairs are used by BGS to illustrate salience theory.

Figure 1: Lottery Setup

Lottery $L_1 = (y_1, p; y_2, 1-p)$ pays an amount y_1 with probability p and an amount y_2 with the counter-probability of $1-p$. The safe payoff is $L_2 = (y_3, 1)$. The payoffs always have the ranking $y_1 > y_3 > y_2$.

like behavior than models based on loss aversion. As a critical voice, Kontek (2016) identifies two potential problems of salience theory: first, the lottery certainty equivalent might not be defined for some ranges of probabilities. Second, monotonicity might be violated in some cases.

The LT parameter δ, which determines by how much the probability of less salient states is distorted according to salience theory, is not measured in any of these studies. Instead, it is based on explicit or implicit assumptions.

From a methodological point of view, our study is related to experiments designed to elicit parameters of models of decision-making under risk.[6] Early examples include studies such as Binswanger (1980), who finds evidence for slight risk aversion on average, and Hey and Orme (1994), who estimate parameters for several generalizations of EUT.[7] One of the most widely used methods for eliciting risk preferences is to provide experimental subjects with MPLs as suggested by HL. Subjects are provided with a list of ten rows that each consist of two lotteries $L_A = (2, p; 1.6, 1-p)$ and $L_B = (3.85, p; 0.1, 1-p)$. While these payoffs are held constant, p increases from 0.1 to 1 by steps of 0.1 in each row. Since in the first rows, $E(L_B) < E(L_A)$, only very risk-seeking subjects choose L_B, while risk-averse subjects choose L_A. Starting in the fifth row, however, $E(L_B) > E(L_A)$. This induces risk-neutral subjects to switch to L_B immediately and risk-averse subjects to switch to L_B at some later point, when L_B offers an adequate risk premium compared to L_A. Subjects with monotonous preferences will not switch back to L_A after choosing L_B. Under this assumption, it is possible to use the row in which a subject switches to estimate her personal risk coefficient.

Since the contribution of HL, the MPL method has been used extensively and for various purposes. Andersen, Harrison, Lau, and Rutström (2006) examine three different concepts of MPLs for the elicitation of risk attitudes. Although they find that the extent of risk aversion is sensitive to the specific format used, the qualitative result of moderate risk aversion holds. Harrison, List, and Towe (2007) compare the elicitation of risk attitudes using artificial monetary prizes with naturally occuring non-monetary outcomes. Andersen, Harrison, Lau, and Rutström (2008) use structural estimation methods to simultaneously estimate risk and time preferences. Based on an MPL-related method, Dohmen, Falk, Huffman, and Sunde (2010) examine the willingness of subjects with higher cognitive capability to take risks. Using a representative sample of the Danish population, von Gaudecker, van Soest, and Wengström (2011) use MPLs to estimate risk preferences. Other studies concentrate on parameters of non-EUT models. Wu and Gonzalez (1996) and Gonzalez and Wu (1999) estimate the curvature of the probability weighting function (PWF) in prospect theory. Bleichrodt, Cillo, and Diecidue (2010) develop a related method to measure regret theory (Loomes and Sugden, 1982). In this paper, we apply the MPL method to salience theory.

3. Theory

Consider a lottery $L_1 = (y_1, p; y_2, 1-p)$ that pays an amount y_1 with probability p and an amount y_2 with probability $1-p$. Assume that the alternative choice option is the safe payoff $L_2 = (y_3, 1)$. The payoffs always have the ranking $y_1 > y_3 > y_2$. L_1 and L_2 are depicted in Figure 1.

[6] Some of these studies also estimate individual discount factors for intertemporal consumption. In this paper, we only focus on risk parameters.

[7] See the overview in Harrison and Rutström (2008) for further related studies.

In this setting, there are two different states of nature. With probability p, the risky lottery pays y_1, while the safe payoff is y_3. We denote this state by $s_1 \equiv (y_1, y_3)$. In the same way, we define state $s_2 \equiv (y_2, y_3)$. The state space is defined as $S \equiv \{s_1, s_2\} = \{(y_1, y_3), (y_2, y_3)\}$.

Consider the choice between the risky lottery L_1 and the safe payoff $y_3 = E(L_1)$. A risk-averse decision maker prefers the safe payoff while a risk-seeking decision maker chooses L_1. In order to choose L_1, a risk-averse decision maker demands a risk premium, i.e., an expected payoff from the lottery that is sufficiently larger than the safe payoff.

One of the core principles of EUT is to assume a decision maker with a stable utility function $v(\cdot)$. When faced with a risky choice, the agent maximizes her expected utility, i.e., her probability-weighted utility in different states of nature.[8] She assigns expected utility V_{EUT} to a lottery L_m:

$$V_{EUT}(L_m) = \sum_i p_i v(x_i^m), \tag{1}$$

where x_i^m is lottery L_m's payoff in state i. The decision maker prefers L_1 to L_2 iff

$$\sum_i p_i \left[v(x_i^1) - v(x_i^2)\right] > 0, \tag{2}$$

i.e., $V_{EUT}(L_1) > V_{EUT}(L_2)$. The risk attitudes of individuals are determined by the curvature of their utility functions. Suppose that $v(\cdot)$ is differentiable at least twice. An individual is risk-averse if and only if she has concave utility with $v' > 0$ and $v'' < 0$. The same applies to convex utility for risk-seeking individuals ($v' > 0$ and $v'' > 0$). An individual with concave (convex) utility makes risk-averse (risk-seeking) choices in any setting. Importantly, decision makers are *consistently* risk-averse or risk-seeking.

Salience theory as suggested by BGS assumes that, depending on the context, some payoffs attract the decision maker's attention more easily than others and the probability of the more salient states is relatively overweighted. Risk aversion (risk seeking) results from overweighting the probability of salient negative (positive) outcomes. By this means, salience theory is able to account for switches in risk attitudes between different settings.[9]

Salience theory assumes two steps. In the first step, the LT constructs a ranking of the possible states of nature according to their salience. In the second step, the LT distorts the probability of the most (least) salient states upwards (downwards). The states $s_i \in S$ for $L_1 = (y_1, p; y_2, 1-p)$ and $L_2 = (y_3, 1)$ are ranked according to their salience—the most salient state is ranked first ($k^i = 1$), the second-most salient state is ranked second ($k^j_{i \neq j} = 2$), and so on.[10] This is done via a salience function $\sigma(x_i^1, x_i^2)$ for which BGS propose the following functional form:

$$\sigma(x_i^1, x_i^2) = \frac{\mid x_i^1 - x_i^2 \mid}{\mid x_i^1 \mid + \mid x_i^2 \mid + \theta}, \tag{3}$$

where $\theta > 0$. The most important attributes of Equation (3) are *ordering* (states with larger absolute payoff differences are more salient than those with smaller differences) and *diminishing sensitivity* (a state with a constant payoff difference becomes less salient the further it lies from zero).[11] An LT then distorts the probability of less salient states using the LT parameter $\delta \in (0, 1]$. The distorted probability of state i is

$$p_i^{LT} = p_i \frac{\delta^{k^i}}{\sum_j \delta^{k^j} p_j}, \tag{4}$$

where δ^{k^i} is the LT parameter δ to the power of state i's salience ranking k^i. p_i is the objective probability

[8] This basic principle is usually attributed to von Neumann and Morgenstern (1944).

[9] For some parameter constellations, this behavior can also be explained by other theories of decision-making under risk, such as (cumulative) prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) or regret theory/disappointment aversion (Loomes and Sugden, 1982; Bell, 1982; Gul, 1991).

[10] We refer to a *salient upside (downside)* when the state including the lottery's upside (downside) is the most salient state.

[11] In some contexts, these attributes are only defined for payoffs $x_i \neq 0$. This is mainly relevant for comparisons of lotteries that each have a payoff of 0, which is not the case for the lotteries used here. States with a payoff of 0 are used frequently by BGS in their explanation of anomalies. Furthermore, the parameter $\theta > 0$ in Equation (3) is useful for the ranking of states including zero payoffs. BGS assume the value of θ to be around 0.1; all of our calculations of salience ranks hold for any $\theta \in (-4, 32)$.

of state i. An LT uses these distorted probabilities to assign the value $V_{LT}(L_m)$ to each lottery m:

$$V_{LT}(L_m) = \sum_i p_i^{LT} v(x_i^m), \tag{5}$$

where $v(\cdot)$ is assumed to be linear.[12] An LT chooses L_1 over L_2 iff

$$\sum_i \delta^{k^i} p_i \left[v(x_i^1) - v(x_i^2)\right] > 0, \tag{6}$$

i.e., $V_{LT}(L_1) > V_{LT}(L_2)$. Note that Equation (6) and Equation (2) only differ with respect to the LT parameter δ. Risk attitudes now arise endogenously due to context-specific probability distortion. Depending on whether the downside or upside of a lottery is salient, an LT will switch between risk aversion and risk seeking, which cannot be explained using EUT.

For the lotteries $L_1 = (y_1, p; y_2, 1-p)$ and $L_2 = (y_3, 1)$, any $p \in [0, 1]$, and $y_1 > y_3 > y_2$, we classify decision makers as

- *consistent risk averters* (CRA) if they always make risk-averse choices,
- *consistent risk seekers* (CRS) if they always make risk-seeking choices, and
- *local thinkers* (LT) if they make risk-averse (risk-seeking) choices for settings with a salient downside (upside).

In the following section, we describe our experimental setting. In that context, we describe our approach to (descriptively) identify the types of decision makers in our data.

4. Experimental Setup

Our experiment serves four purposes. The first is to identify the LTs in our sample. For the group of identified LTs, the second purpose is to elicit the intervals in which their values of δ are located. Third, we want to test whether there is a unique value of δ that is valid both for lotteries with salient downsides and for lotteries with salient upsides. By using two MPLs where the downside and upside of the lottery are most salient, respectively, we are able to capture potential heterogeneity of the LT parameter with respect to the specific context. Since different value functions and PWFs for prospect theory have been developed for the domains of gains and losses, respectively, we aim at eliciting the LT parameter in different salience variations. Fourth, we are interested in the share of decisions that can be characterized by salience theory and the share of decisions that can be best described by alternative decision theories, which is examined by structural maximum likelihood estimations.

4.1. Experimental Design

We use choices between $L_1 = (y_1, p; y_2, 1-p)$ and $L_2 = (y_3, 1)$ with $y_1 > y_3 > y_2$ to construct two versions of MPLs. In the first version (V1), the state in which L_1 pays its downside y_2 is most salient (*salient downside*), while in the second version (V2), the state in which L_1 pays its upside y_1 is most salient (*salient upside*).

To ensure that the salience ranking of states remains unchanged within each MPL, we let the payoffs of L_1 and L_2 differ between, but not within the MPL versions. Thus, the implied intervals of δ are determined by p only. The probabilities are chosen such that we can observe equally long intervals of δ in steps of 0.1 in every row.

For V1 (salient downside), we use the payoff combination $y_1 = 20$, $y_2 = 0$, and $y_3 = 8$, such that, using Equation (3), $\sigma(y_1, y_3) < \sigma(y_2, y_3)$. For V2 (salient upside), we change the low payoff of L_1 to $y_2 = 4$, which results in the salience ranking $\sigma(y_1, y_3) > \sigma(y_2, y_3)$.[13] The probabilities p are chosen such that they provide

[12] BGS assume linear utility but emphasize that their model allows for any utility function. In our parametric estimations, we will estimate specifications with both linear utility and non-linear utility.

[13] Moreover, the choice of $y_2 = 4$ is useful as y_1 and y_3 are multiples of y_2, which is likely to make calculations easier for subjects.

Table 1: Parameter Values for Salience Configurations

This table shows the parameter values for both MPL versions of the experiment. For both V1 and V2, $y_1 = 20$ and $y_3 = 8$. $E(L_1)$ is the expected value of lottery L_1. Δ is the risk premium $\Delta = E(L_1) - y_3$. *Risk* is the implied risk attitude for a switch in the respective row—risk-averse (RA) or risk-seeking (RS). In V1 (V2), subjects are expected to switch from L_1 to L_2 (L_2 to L_1).

Row	Range of δ	V1 (Salient downside, $y_2 = 0$)				V2 (Salient upside, $y_2 = 4$)			
		p	$E(L_1)$	Δ	Risk	p	$E(L_1)$	Δ	Risk
1	$0 < \delta < 0.1$	87%	17.40	9.40	RA	3%	4.48	−3.52	RS
2	$0.1 < \delta < 0.2$	77%	15.40	7.40	RA	6%	4.96	−3.04	RS
3	$0.2 < \delta < 0.3$	69%	13.80	5.80	RA	9%	5.44	−2.56	RS
4	$0.3 < \delta < 0.4$	63%	12.60	4.60	RA	12%	5.92	−2.08	RS
5	$0.4 < \delta < 0.5$	57%	11.40	3.40	RA	14%	6.24	−1.76	RS
6	$0.5 < \delta < 0.6$	53%	10.60	2.60	RA	17%	6.72	−1.28	RS
7	$0.6 < \delta < 0.7$	49%	9.80	1.80	RA	19%	7.04	−0.96	RS
8	$0.7 < \delta < 0.8$	45%	9.00	1.00	RA	21%	7.36	−0.64	RS
9	$0.8 < \delta < 0.9$	43%	8.60	0.60	RA	23%	7.68	−0.32	RS
10	$0.9 < \delta < 1.0$	40%	8.00	0	RA	25%	8.00	0	RS
11	$1.0 < \delta < 1.1$	38%	7.60	−0.40	RS	27%	8.32	0.32	RA
12	$1.1 < \delta < 1.2$	36%	7.20	−0.80	RS	29%	8.64	0.64	RA

the δ intervals depicted in Table 1. As the risk premium $\Delta = E(L_1) - y_3$ is high in the first rows of V1, we expect subjects to choose L_1 in the beginning and switch to L_2 at some point. A switch in row 10 or lower implies risk aversion, while a switch in row 11 or 12 implies risk-seeking behavior. In V2, we expect subjects to choose L_2 first and switch to L_1 in a later row. The implied risk attitudes mirror the setup of V1: a switch in row 10 or less implies risk-seeking behavior, while a switch in row 11 or 12 implies risk aversion.[14] For every row in Table 1, the second column from the left displays the implied intervals of δ—for example, if a subject switches to L_2 in row 8 of V1, this implies an interval of $0.7 < \delta < 0.8$.

Since by definition, $\delta \in (0, 1]$, switches in rows 11 and 12 (probabilities below 40% in V1 and above 25% in V2) are out of the decision space covered by salience theory. Thus, they are included as a robustness measure, making it easier for subjects to stick to consistent risk attitudes. In other words, in V1, only probabilities above or equal to 40% are covered by the model since an explanation of a decision switch for lower probabilities in our experiment requires that $\delta > 1$. Similarly, in V2, only probabilities below or equal to 25% are covered; as before, a decision switch for higher probabilities would require that $\delta > 1$.

An important goal is to keep the experimental design as simple as possible. The payoffs are integers and easily divisible by each other. From V1 to V2, only one of the three payoffs (y_2) is varied in order to transfer salience from the lottery's downside to its upside. By these means, subjects are familiar with the layout of the choice options when switching from one MPL to the other.[15] Moreover, the display of the lotteries includes pie charts illustrating the probabilities for an easier understanding of the trade-offs at hand (von Gaudecker, van Soest, and Wengström, 2011).

The instructions (translated from German) can be found in Appendix A.1. Screenshots of the MPLs are available in Appendix A.2.4.

4.2. Controls and Incentivization

Before the experiment is started, subjects are required to answer the *Cognitive Reflection Test* (Frederick (2005), CRT), which consists of three questions and is used as a measure of the cognitive effort a subject exerts in answering a question and avoiding an intuitive, but wrong answer.[16] Previous research shows that the achieved score is correlated with the willingness to take risks (Frederick, 2005; Dohmen, Falk, Huffman, and Sunde, 2010) and the susceptibility to behavioral biases (Oechssler, Roider, and Schmitz, 2009). At the end of the experiment, subjects are asked to answer some questions about the experiment and a short

[14] The special case of risk neutrality ($\delta = 1$) lies at the upper bound of row 10 and the lower bound of row 11 for each version. In case a subject never switches in the expected direction, we define $SP = 13$. Subjects that perform the expected switch in the first row are assumed to have $SP = 1$.

[15] To make this point especially obvious, the instructions explicitly point at the change of this parameter.

[16] All three questions of the CRT can be found in Appendix A.2.1.

Table 2: Summary Statistics

This table displays the summary statistics of the 176 experimental subjects. *SD* denotes the standard deviation. *Response time* describes how many seconds it took subjects to complete both MPLs (it does not include other parts of the experiment such as the CRT). *CRT score* is the score achieved in the CRT and ranges from 0 to 3. *Female* equals 1 for female subjects and 0 for male subjects. *Age* is subjects' age, measured in years. *Economics-related major* equals 1 for students with a major related to economics such as economics or business administration and 0 otherwise. *Undergraduate* equals 1 for undergraduate students.

Variable	Mean	Median	SD
Response time	220.03	192	102.24
CRT score	1.75	2	1.07
Female	0.47	0	0.50
Age	24.84	24	3.94
Economics-related major	0.45	0	0.50
Undergraduate	0.60	1	0.49

questionnaire concerning their demographic details (e.g., age, sex, major subject).[17] To control for potential order effects on our data (Harrison, Johnson, McInnes, and Rutström, 2005), V1 and V2 are presented to subjects in random order.

Subjects' decisions are incentivized by playing one randomly selected row of V1 or V2 for cash. For this purpose, after the experiment, each subject throws a die to determine the individual row to be played. If L_2 is chosen in that row, the subject receives the safe payoff y_3 of €8 plus a show-up fee of €5. If L_1 is chosen, the lottery is played, which is again decided by throwing a die. The subject then receives either the high payoff y_1 of €20 plus the show-up fee or the low payoff y_2 of €0 or €4 plus the show-up fee. This payoff scheme is consistent with related studies (Harrison and Rutström, 2008).

4.3. Type Identification

To distinguish between the types of decision makers defined in Section 3, we consider the implied risk attitudes of each individual's choices in the experiment expressed by their switching points (SP_1 for the row in which a subject switches in V1 and SP_2 for V2). The types defined above can be identified as follows:

- *CRA*—Both switching points imply risk aversion:
$$SP_1 \leq 10 \wedge SP_2 > 10.$$
- *CRS*—Both switching points imply risk seeking:
$$SP_1 > 10 \wedge SP_2 \leq 10.$$
- *LT*—The switching point in V1 (V2) implies risk aversion (risk seeking):
$$SP_1 \leq 10 \wedge SP_2 \leq 10.$$

Simply using descriptive methods, we are thus able to separate LTs from subjects with consistent risk attitudes (Section 5). Adding to that, we use maximum likelihood estimation to simultaneously estimate parameters of other behavioral models (Section 6).[18]

5. Descriptive Results

In this section, we use the classification introduced in Section 4.3 to identify LT subjects in our experiment and use this sub-sample of subjects to descriptively estimate the LT parameter δ (assuming linear utility as in BGS).

The experiment was conducted as a laboratory experiment with nine sessions and was implemented using PHP/MySQL.[19] Subjects were students recruited via the local experimental subjects pool. Because of the

[17] The exact wording can be found in Appendix A.2.2 and A.2.3.

[18] Appendix A.3 provides examples of LT and CRA choices in our data.

[19] The experiment was browser-based, but conducted in the laboratory using a full-screen mode. This approach had the usual benefits of the laboratory environment such as better control over distractions. Moreover, systematic differences in response times due to different connection capacities are unlikely since all subjects used the same internet connection.

Table 3: Distribution of Types of Decision Makers

This table shows the distribution of the types of decision makers among the 176 subjects. The rows and columns of the table display risk-averse (RA) and risk-seeking (RS) behavior in V1 and V2, respectively. The cells *CRA*, *CRS*, *LT*, and *Other* provide the absolute number and relative frequency of subjects that can be identified as members of the respective type. The *Total* rows and columns provide the absolute number and relative frequency of subjects with the respective choices in V1 or V2.

		V2 (Salient upside)		
		RA	RS	Total
V1 (Salient downside)	RA	**CRA** $N = 106$ 60%	**LT** $N = 60$ 34%	$N = 166$ 94%
	RS	Other $N = 2$ 1%	**CRS** $N = 8$ 5%	$N = 10$ 6%
	Total	$N = 108$ 61%	$N = 68$ 39%	$N = 176$ 100%

simple lottery setup, we refrained from using initial comprehension questions.[20] Throughout the experiment, subjects had the opportunity to ask questions.

Our sample consists of 176 subjects.[21] The average payoff per subject was €14. Summary statistics are shown in Table 2.

5.1. Identification of Local Thinkers

Table 3 summarizes the classification of the 176 subjects by the definitions of Section 4.3. 60 subjects (34%) can be categorized as LTs. The single largest group of subjects (106, 60%) fits the CRA category. The CRS group consists of 8 subjects (5%). Only 2 subjects (1%) are risk-seeking in V1 and switch to risk aversion in V2. This group is referred to as *other*, since their behavior cannot be explained by the theories of decision-making considered here. Five subjects switch back to their previous choice once. We keep these subjects in the sample and define their first switch as their switching point.[22] Partitioned by MPL version, 94% of subjects show risk-averse behavior in V1. This proportion decreases to 61% in V2, which is significantly different ($\chi^2 = 55.41$, $p = 0.000$).[23] In Appendix A.4, we examine if the LTs in our experiment have characteristics that set them apart from non-LT subjects.

5.2. Evaluation of the Local Thinking Parameter

In the next step, we derive estimates of the LT parameter δ for the 60 subjects classified as LTs. We find four subjects with $SP_2 = 1$. Since these observations might bias our estimations, we report our results with and without these outliers. Table 4 provides an overview of subjects' switching points. The average switching point of the LTs in our sample equals about 6 in V1 and 8 in V2; without outliers, it is slightly higher. Figure 2 shows kernel estimates of the switching point densities in V1 and V2.

We estimate the LT parameter δ using interval regressions. Table 5 shows the results with and without outliers. Since we observe two switching points per subject, we analyze 120 observations (112 without the outliers) in total. We first estimate the mean LT parameter over both salience configurations by estimating a constant-only model (Columns 1 and 4 of Table 5). The estimated constant is close to 0.7, which is consistent with the assumption made by BGS.

[20] We use the answers to our questions after the experiment to (anecdotally) examine subjects' grasp of the task. The answers provide support for our impression that no subject had difficulties in understanding the setup.

[21] 8 subjects ($\sim$ 4% of the total) were excluded due to obvious failure to complete the task (switches in the opposite direction, thus violating monotonicity, or a large number of multiple switches).

[22] In sum, we find ten multiple switchers in our data (five remaining in the sample and five that were excluded due to the high number of switches), which amounts to roughly 6% of all observations. Excluding all multiple switchers leaves our results unchanged. HL observe multiple switching by up to 13% of their subjects.

[23] Our results are in line with Booth and Nolen (2012), where around 37% of subjects can be classified as LTs. Subjects with consistent risk attitudes account for 48% of their sample, which, in our terminology, consist of 29% CRA and 19% CRS subjects. However, their sample also contains 15% of *other* subjects.

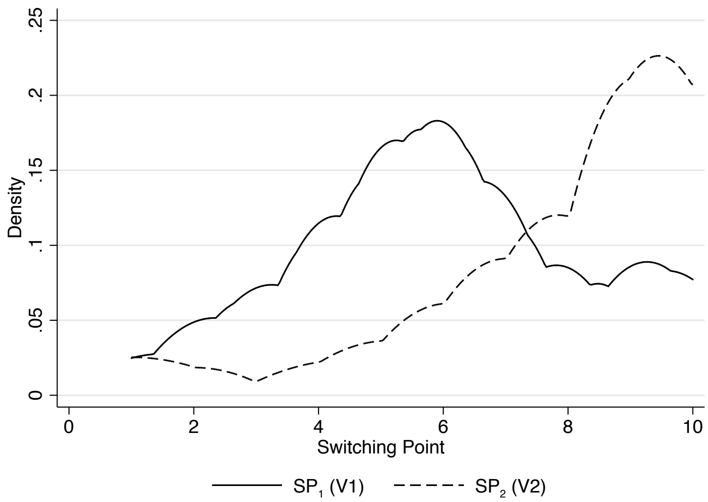
Table 4: Switching Points of Local Thinkers

This table displays the switching points of the 60 subjects classified as LTs. *SD* denotes the standard deviation.

MPL	With outliers ($N = 60$)			Without outliers ($N = 56$)		
	Mean	Median	SD	Mean	Median	SD
V1	6.05	6	2.38	6.27	6	2.28
V2	8.10	9	2.53	8.61	9	1.71

Figure 2: Switching Point Densities of Local Thinkers

This figure shows Epanechnikov kernel estimates of the switching point densities in V1 (solid) and V2 (dashed) for the 60 subjects classified as LTs.



After controlling for the switch of the salience configuration (Columns 2 and 5 of Table 5), we find that δ is higher in V2 than in V1 (significant at the 1% level). While the LT parameter in V2 is now estimated to be larger than 0.7, the estimate of the parameter in V1 is smaller than 0.7. The decrease in δ when the lottery's downside is salient equals more than 25% in relative terms. This asymmetry between a salient upside and a salient downside is consistent with the findings of Frydman and Mormann (2018), who—combining experimental data with eyetracking data—find that risk taking increases when the risky lottery's upside is visually salient and decreases when the downside is visually salient.

In Columns 3 and 6 of Table 5, we control for demographics, CRT scores, and response times. The constant in these columns can only be interpreted as the value when all other variables are set to zero (which, for example in the case of *age*, would not be possible). Thus, it does not represent a direct estimate of the value of the LT parameter anymore.

We find that our main result still holds—the LT parameter in V1 is significantly smaller than in V2. In the terms of BGS, our results indicate that when a lottery's upside is most salient, our subjects distort probabilities less than when the lottery's downside is most salient. This observation can be interpreted as a potential weakness of salience theory. In its original form suggested by BGS, salience theory relies on a single probability distortion parameter δ, which is assumed to be constant over different salience configurations. Our results suggest that δ is not constant, but can vary depending on whether a lottery's upside or downside is salient. Another degree of freedom might be necessary to accommodate this issue, which contradicts the theory's original aspiration to cut down on the number of degrees of freedom.[24]

[24]Several tests of robustness are presented in Appendix A.5.

Table 5: Estimation of LT Parameter

This table shows the coefficients of interval regressions. Dependent variable: LT parameter δ (elicited intervals); t-values in parentheses. Standard errors are clustered at the subject level. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. *V1 (salient downside)* equals 1 for the switch in V1 and 0 for the switch in V2. *Response time above median* equals 1 if a subject's time needed for both MPLs is above the median and 0 otherwise. *CRT score* is the score achieved by subjects in the CRT and ranges from 0 to 3. *Female* equals 1 for female subjects and 0 for male subjects. *Age* describes subjects' age, measured in years. *Economics-related major* equals 1 for students with a major related to economics such as economics or business administration and 0 otherwise. *V2 seen first*, a dummy for the order of the MPLs, equals 1 if the subject saw V2 first and 0 if the subject saw V1 first.

	With outliers ($N = 60$)			Without outliers ($N = 56$)		
	(1)	(2)	(3)	(4)	(5)	(6)
V1 (salient downside)		−0.205***	−0.205***		−0.234***	−0.234***
		(−5.23)	(−5.24)		(−6.04)	(−6.04)
Response time above median			0.073			0.094**
			(1.52)			(2.29)
CRT score			0.004			0.007
			(0.15)			(0.32)
Female			−0.106*			−0.059
			(−1.81)			(−1.19)
Age			−0.007			0.003
			(−0.82)			(0.47)
Economics−rel. major			−0.051			−0.018
			(−0.80)			(−0.35)
V2 seen first			0.017			0.030
			(0.25)			(0.67)
Constant	0.657***	0.760***	0.957***	0.694***	0.811***	0.659***
	(26.35)	(23.28)	(4.07)	(37.13)	(35.42)	(3.89)
Session dummies	No	No	Yes	No	No	Yes
# observations	120	120	120	112	112	112
Log-likelihood	−286.907	−277.130	−271.980	−252.871	−236.345	−229.971

6. Maximum Likelihood Estimation

In this section, we use maximum likelihood estimation to estimate parameter values for salience theory in mixture models with other decision theories. On the one hand, our experimental design allows us to descriptively estimate the LT parameter given the structural assumptions in Section 3. On the other hand, however, it is also possible to use structural maximum likelihood estimation to relax some of the assumptions used by BGS and to evaluate the role of other models in this context. In the following, similarly to Harrison and Rutström (2009), our goal is to reconcile salience theory and alternative decision theories. In order to do so, we estimate mixture models.[25] Moreover, choice behavior might not be entirely deterministic but also have a non-trivial stochastic component (Hey and Orme, 1994; Stott, 2006). In our experimental setup, LTs could switch too late by accident and be classified as CRA subjects, while CRA subjects could switch too early and be classified as LTs. These estimations allow us to overcome the possibility that we overrestrict salience theory by assuming that it only describes individuals who switch in their decision-making; in fact, some subjects could have not switched by error or have a non-linear utility function, which would imply entirely different behavior. These potential types of behavior can be accounted for in the following estimations.

6.1. Setup

Using structural maximum likelihood estimation, Harrison and Rutström (2009) estimate the best fit of EUT and prospect theory to their data. Subsequently, they estimate a mixture of both models together with the percentage of choices which can be best explained by the respective theory.[26] A further advantage of this method is that potential stochastic errors in comparing the expected values of lotteries can be incorporated into the analysis.

[25] The corresponding single-model estimations can be found in Appendix A.6.

[26] Other examples for studies estimating mixture models of choice under risk are Bruhin, Fehr-Duda, and Epper (2010) and Conte, Hey, and Moffatt (2011).

In the following, whenever we assume non-linear utility in our estimations, we use the popular CRRA specification as in HL or Harrison and Rutström (2008):

$$v(x) = \frac{x^{1-r}}{(1-r)}, \tag{7}$$

where r is the coefficient of relative risk aversion. For $r < 0$, the subject has convex utility, while for $r > 0$, her utility function is concave.

Our RDU specification is based on Quiggin (1982) and Harrison and Ng (2016). The utility function $v(x)$ over J outcomes used in this specification is the same as in Equation (7):

$$RDU_i = \sum_{j=1}^{J} w\left[p(x_j)\right] v(x_j) = \sum_{j=1}^{J} w_j v(x_j), \tag{8}$$

where $w_j = \omega(p_j + \ldots + p_J) - \omega(p_{j+1} + \ldots + p_J)$ for $j = 1, \ldots, J-1$ and $w_j = \omega(p_j)$ for $j = J$. The subscript j provides a ranking of outcomes (from worst to best). $\omega(p)$ is a PWF that subjectively distorts a lottery's probability. Here, we use the inverse-S shaped PWF proposed by Tversky and Kahneman (1992):[27]

$$\omega(p) = \frac{p^{\beta}}{\left(p^{\beta} + (1-p)^{\beta}\right)^{1/\beta}}. \tag{9}$$

We specify conditional log-likelihood functions of the form

$$\ln L(\Psi; y) = \sum_i \ln l_i^j = \sum_i \left[y_i \ln(\nabla V_j) + (1 - y_i) \ln(1 - \nabla V_j)\right], \tag{10}$$

where Ψ is a vector containing the model-specific parameters to be estimated and y is the vector containing all choice decisions. y_i is 1 if L_1 is chosen in decision task i and 0 if L_2 is chosen. The latent index ∇V_j, $j \in \{EUT, RDU, LT\}$ is linked to the values attributed to the different lotteries.[28] We use a Luce error term to capture errors in comparing the values of L_1 and L_2:[29]

$$\nabla V_j = \frac{V_j(L_1)^{1/\mu}}{V_j(L_1)^{1/\mu} + V_j(L_2)^{1/\mu}}, \tag{11}$$

where μ is the error parameter. For higher values of μ, choices become increasingly random, while for $\mu \to 0$, choices are purely determined by the values of L_1 and L_2. As in Harrison and Rutström (2009), we use the conditional log-likelihood functions of Equation (10) to estimate the probabilities π^{EUT}, π^{RDU}, and π^{LT} for each model. Note that δ is unconstrained in all estimations.

6.2. Results

The results of our estimations are shown in Table 6.[30] Throughout our estimations, the estimated error term μ (not reported) ranges between 0.075 and 0.1, which is comparable to related studies and indicates that the role of errors might not be too large for our data.[31]

Panel a) shows the estimates for a mixture model of EUT and RDU. More than 60% of choices are classified as RDU while about 40% of decisions are consistent with EUT; in this respect, the majority of subjects can be described by a "behavioral" decision theory. As for the respective parameters, $r^{EUT} = 0.146$, which implies slight risk aversion. The RDU decisions also imply a concave utility function ($r^{RDU} = 0.440$). The γ parameter of the PWF is estimated as 0.691, which is in line with the range reported by Gonzalez and Wu

[27] We use this weighting function for RDU in our main specification. Estimations using the power PWF proposed by Quiggin (1982) are reported in Appendix A.7. We refrain from using the weighting function described in Prelec (1998) because of numerical issues that cause our estimations to not converge.

[28] This index is often linked to the decision using the standard cumulative normal distribution function. However, since ∇V_j already has the form of a probability in our analysis, we can transform it using the natural logarithm (Harrison and Rutström, 2008).

[29] Alternatively using a Fechner error term, our results remain qualitatively unchanged.

[30] The outliers mentioned above are included here. Our results remain virtually unchanged when we exclude them.

[31] Harrison and Rutström (2008) use the data of HL and estimate Luce error terms twice as large.

Table 6: Maximum Likelihood Estimation: Mixture Models (Inverse-S Shaped PWF)

This table contains maximum likelihood estimates using the linear form method. The inverse-S shaped PWF from Equation (9) is used in these estimations. Standard errors are clustered for $N = 176$ subjects. *SE* denotes standard errors. *Wald* is the p-value of a Wald test against the null hypothesis that the variables are equal to zero. *95% CI* is the 95% confidence interval around the respective estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively.

Parameter	Coefficient	SE	Wald	95% CI
Panel a): EUT and RDU				
r^{EUT}	0.146	0.029	0.000***	$[0.088, 0.203]$
r^{RDU}	0.440	0.069	0.000***	$[0.305, 0.576]$
γ	0.691	0.075	0.000***	$[0.543, 0.839]$
π^{EUT}	0.379	0.047	0.000***	$[0.287, 0.470]$
π^{RDU}	0.621	0.047	0.000***	$[0.530, 0.713]$
Panel b): EUT and LT ($v'' = 0$)				
r	0.572	0.021	0.000***	$[0.531, 0.614]$
δ	0.833	0.029	0.000***	$[0.776, 0.889]$
π^{EUT}	0.682	0.042	0.000***	$[0.599, 0.765]$
π^{LT}	0.318	0.042	0.000***	$[0.235, 0.401]$
Panel c): EUT and LT (v'' unconstrained)				
r^{EUT}	0.600	0.018	0.000***	$[0.564, 0.635]$
r^{LT}	0.076	0.031	0.015**	$[0.015, 0.137]$
δ	0.866	0.032	0.000***	$[0.803, 0.929]$
π^{EUT}	0.619	0.042	0.000***	$[0.537, 0.702]$
π^{LT}	0.381	0.042	0.000***	$[0.298, 0.463]$
Panel d): RDU and LT ($v'' = 0$)				
r	0.344	0.086	0.000***	$[0.176, 0.512]$
δ	0.801	0.035	0.000***	$[0.732, 0.870]$
γ	0.621	0.067	0.000***	$[0.489, 0.753]$
π^{RDU}	0.642	0.048	0.000***	$[0.547, 0.737]$
π^{LT}	0.358	0.048	0.000***	$[0.263, 0.453]$
Panel e): RDU and LT (v'' unconstrained)				
r^{RDU}	0.381	0.081	0.000***	$[0.221, 0.540]$
r^{LT}	0.082	0.032	0.010**	$[0.019, 0.145]$
γ	0.630	0.064	0.000***	$[0.504, 0.756]$
δ	0.843	0.033	0.000***	$[0.779, 0.906]$
π^{RDU}	0.583	0.047	0.000***	$[0.490, 0.676]$
π^{LT}	0.417	0.047	0.000***	$[0.324, 0.510]$
Panel f): EUT, RDU, and LT (v'' unconstrained)				
r^{EUT}	12.166	0.513	0.000***	$[11.160, 13.172]$
r^{RDU}	0.349	0.077	0.000***	$[0.198, 0.501]$
r^{LT}	0.133	0.041	0.001***	$[0.052, 0.214]$
γ	0.612	0.062	0.000***	$[0.491, 0.733]$
δ	0.850	0.035	0.000***	$[0.781, 0.918]$
π^{EUT}	0.063	0.021	0.003***	$[0.022, 0.104]$
π^{RDU}	0.529	0.063	0.000***	$[0.405, 0.652]$
π^{LT}	0.408	0.061	0.000***	$[0.289, 0.528]$

(1999), for example (0.56 to 0.71). This range of parameter values ($\gamma < 1$) implies the classic inverse-S shape, i.e., that small probabilities are overweighted and large probabilities are underweighted.

The mixture model of EUT and salience theory with a linear utility function in Panel b) essentially reproduces the findings of Table 3. However, the LT parameter of 0.833 is larger than in our estimations above. The estimated CRRA parameter r is within the range of related studies. Importantly, π^{LT} is close to the fraction of LTs identified in Section 5.1. Our previous estimate of 34% lies well within the estimated confidence interval; a Wald test of $H_0 : \pi^{LT} = 0.34$ cannot be rejected on conventional levels of significance

($p = 0.604$).

Panel c) reveals that about 62% of choices can be characterized by EUT and 38% can be characterized by salience theory in a mixture model of EUT and salience theory with an unconstrained utility function in the latter. Compared to Panel b), the number of LTs has increased, which might be due to the additional degree of freedom by not restricting $v(\cdot)$ to be linear. δ equals 0.866 in this specification and is thus virtually unchanged in comparison to Panel b). This suggests that the assumption of a non-linear utility function in salience theory does not substantially change the LT parameter. Consistent with these findings, r^{LT} is very small such that the respective utility function is almost linear.

In Panel d), we estimate a mixture model of RDU and salience theory, in which the latter is based on linear utility. The first observation is that 64% of choices are now classified as RDU choices and 36% of choices are consistent with salience theory. In this specification, δ equals 0.801 and is thus slightly smaller than in Panel b), but still in roughly the same range. The RDU parameters ($r = 0.344$ and $\gamma = 0.621$) are close to those reported in Panel a).

Panel e) extends the estimations of Panel d) to allow for non-linear utility in salience theory. We observe that 58% of choices are now characterized as RDU choices, while 42% are in line with salience theory. Similarly to the comparison of Panels b) and c), when comparing δ between Panels d) and e), we find that the unconstrained utility function in salience theory does not lead to substantially different estimates of the LT parameter since r^{LT} is very small (i.e., the utility function is almost linear) and that the fraction of LTs increases in the unconstrained case due to the additional degree of freedom used.

Finally, Panel f) reports the estimates of a single mixture model of EUT, RDU, and salience theory with unconstrained v''. This estimation is numerically demanding and takes a much longer time to converge than all previous estimations. We first observe that about 6% of choices are consistent with EUT, about 53% are in line with RDU, and 41% can be classified as choices of LTs. Second, we find that r^{EUT} is very large; we cannot fully rule out that this finding is a result of the numerical complexity. Besides, the other parameter values seem more or less comparable to our previous estimates. Importantly, the estimate of δ remains roughly unchanged. In sum, the role of EUT decisions is very small in comparison to both RDU and LT.

7. Discussion and Conclusion

In this article, we provide a calibration of salience theory as proposed by BGS. We analyze lottery choices of subjects in two different MPL versions. In one version, a lottery's downside is most salient, while in the other, its upside is most salient. This allows us to distinguish between LTs (i.e., subjects who act in accordance with salience theory) and subjects with consistent risk attitudes (i.e., subjects whose behavior can be described by EUT) and to descriptively estimate the LT parameter δ for the first group of subjects. Furthermore, using maximum likelihood estimation, we provide estimates of the fraction of decisions characterized by salience theory and alternative decision theories as well as of the LT parameter δ.

The first advantage of our experimental design is the possibility to conveniently derive the fraction of LT decisions and to estimate the LT parameter (and its heterogeneity) in a simple setting. The second advantage is the possibility to estimate the parameters and the relevance of alternative decision theories along with salience theory.

We obtain three results: first, about 30% to 45% of choices in our sample are consistent with salience theory. The LT parameter equals about 0.7 to 0.8. Second, our estimates of the LT parameter are not significantly changed when non-linear utility is assumed instead of linear utility. Third, our results reveal that the LT parameter δ is significantly smaller when a lottery's downside is most salient than when its upside is most salient.

Our results have three major implications: first, our mean estimate of the LT parameter δ is roughly consistent with the assumptions of BGS. Second, our structural estimations in Section 6 reveal that relaxing the assumption of linear utility in salience theory does not lead to substantially different estimates of the LT parameter δ since the estimated risk aversion parameter r^{LT} is close to zero. It thus seems that the BGS assumption of linear utility might be reasonable. However, the main observation from the structural estimations is that other decision theories such as EUT and RDU also do a good job in explaining subjects' behavior in our experiment. Third, however, as shown in Section 5, the estimate of the LT parameter δ significantly differs depending on whether a lottery's downside or upside is salient. Since salience theory (as proposed by BGS) does not intend the use of different values of δ depending on whether the downside or the upside of a lottery is salient, this heterogeneity in probability distortion expressed by heterogeneous estimates of δ questions the assumption of a stable value for δ. This is a critical point since the theory's appeal—inter alia—relies on the relatively small number of degrees of freedom.

In sum, the first two points show that the basic assumptions of BGS regarding the LT parameter δ (on average) and the curvature of the utility function are roughly supported by our experimental results. However, our findings question the assumption of a stable LT parameter for all salience configurations.

The directions for future work are manifold. From an empirical perspective, researchers might want to collect data from alternative experimental designs in order to provide more granular estimations of δ and its potential heterogeneity. From a theoretical perspective, it might be interesting to develop models of the mechanism behind the higher distortion of probabilities when the downsides of lotteries are most salient. At the same time, this marks a potential problem behind salience theory, since in effect, one additional degree of freedom is required to explain the behavior we observe in our experiment.

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A. Appendix

A.1. Instructions

Welcome and thank you for participating in our experiment. Communication with other participants is prohibited during the experiment. The use of mobile phones and any other activities are also not allowed. A violation of these rules can lead to your expulsion from the experiment. Please always follow the experimenter's instructions. In case you have any questions, please raise your hand—an assistant will then approach you.

Regardless of your decisions in the experiment, you will receive a payment ("show-up fee") of *€5* for your appearance alone. In addition, you will receive another payment at the end of the experiment that depends on your decisions and, to some extent, on chance. The highest total payoff you can receive is *€25*. Some parts of the experiment do not have an influence on the amount of your payment, but are very interesting to us. Thus, please apply the same care when answering these parts that you would with the parts that are relevant for your payment.

The experiment will take around 60 minutes (including the payment procedure) and consists of three parts:

1. Starter questions
2. Main part
3. Closing questions

The parts of the experiment can be answered seamlessly without pausing in between. However, after completion of the experiment, we ask you to remain seated and wait for all other participants to finish up. There is no time limit for any part of the experiment.

Starter Questions

Please answer the questions on your screen. The correct answers do not require any prior knowledge. Your answers do not have an influence on the amount of your payment.

Main Part

Your decisions in this part of the experiment are relevant for your payment. On each of the following *two* screens, you will see a list comprised of 12 rows. Each row contains two options, A and B.

- *Option A* (left side) always consists of a risky payoff that can either be high or low. The probabilities for the high and low payoffs are given as percentages and pie charts in every row.
- *Option B* (right side) always consists of a safe payoff. The probability of this payoff is thus 100%.

The payoffs are constant for each list; only the probabilities of option A change in every row. *Caution: after you switch from the first to the second list, the low payoff of option A changes!*

Your task in this experiment is to choose one of the two options (A or B) in every row.

Note that your decisions cannot be changed after you click on "continue". Before you click on "continue", you should also check whether you really made a decision in every row. Do not use the "back" function of your browser and always pay attention to the instructions at the top of your screen.

Determination of your payment at the end of the experiment. At the end of the experiment, we ask you to come to the front of the experimental lab one after the other to determine your payment. Please remain seated until then.

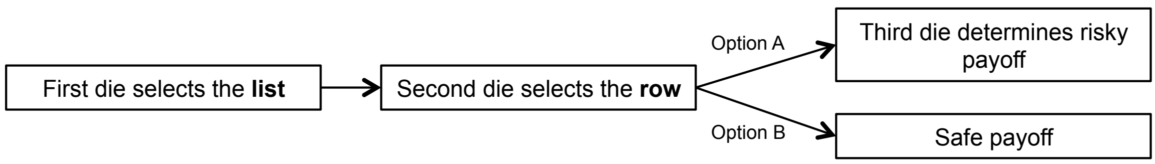
We will randomly select one row that will be paid out to you in cash. The dice that are used for the selection will be thrown by yourself.

1. The *first die* decides whether the first or second list you encountered will be relevant for your payment.
2. The *second die* selects the row on the determined list that will be used for your payment.
   a. If you chose option A in the respective row, a *third die throw* decides the outcome of the risky payoff (high or low).
   b. If you chose option B in the respective row, you receive the safe payoff.

Your total payment is comprised of this payoff and the show-up fee (*€5*).

Closing Questions

To finish the experiment, please answer some questions about this experiment in general and about yourself. Your answers do not have an influence on the amount of your payment. However, without truthful reporting of your personal data, no payment can be made.


First die selects the **list**
Second die selects the **row**
Option A
Option B
Third die determines risky payoff
Safe payoff

A.2. Experimental Procedures

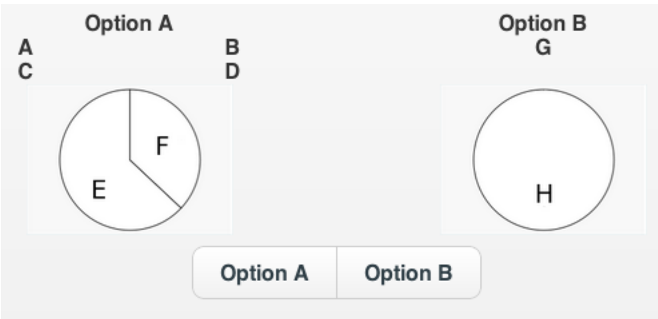
A.2.1. Cognitive Reflection Test

1. A bat and a ball cost €1.10 in total. The bat costs €1.00 more than the ball. How much does the ball cost? (In cents)
2. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? (In minutes)
3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? (In days)

A.2.2. Questions About the Experiment

1. Were some elements of the displayed options or their relationship to each other especially relevant to you? If yes, how were your decisions influenced by them? The following notation can help you to point at single elements in the image displayed below:

   A Amount of the high payoff
   B Amount of the low payoff
   C Probability of the high payoff
   D Probability of the low payoff
   E Graphical display of the probability of the high payoff
   F Graphical display of the probability of the low payoff
   G Amount of the safe payoff
   H Graphical display of the probability of the safe payoff



2. If all payoffs would have been ten times higher, would your behavior have changed? If yes, how?

A.2.3. Questionnaire

1. Name (for payment purposes only)
2. Sex
3. Age
4. Major subject
5. Aspired degree
6. Semester

A.2.4. Display of Multiple Price Lists

Figure A.1: Screenshot of Multiple Price Lists

This figure shows a screenshot of a multiple price list used in the experiment (rows 3 to 6 of 12). Displayed is the example of a switch in V1, implying $SP_1 = 5$.

A.3. Representative Choices for LT and CRA Subjects

Figure A.2: Representative Choices

These tables display the actual choices of three different subjects. A ticked box indicates the chosen lottery (L_1 or L_2) in the respective row. The subject in panel (a) is representative of an LT subject with $SP_1 = 5$ and $SP_2 = 8$, while the other two examples indicate CRA. For the subject in panel (b), $SP_1 = 7$ and $SP_2 = 11$. The subject in panel (c) never switches to L_1 in V2, such that $SP_1 = 5$ and $SP_2 = 13$.

Row	**V1**		**V2**	
	L_1	L_2	L_1	L_2
1	☒	☐	☐	☒
2	☒	☐	☐	☒
3	☒	☐	☐	☒
4	☒	☐	☐	☒
5	☐	☒	☐	☒
6	☐	☒	☐	☒
7	☐	☒	☐	☒
8	☐	☒	☒	☐
9	☐	☒	☒	☐
10	☐	☒	☒	☐
11	☐	☒	☒	☐
12	☐	☒	☒	☐

a) LT subject

Row	**V1**		**V2**	
	L_1	L_2	L_1	L_2
1	☒	☐	☐	☒
2	☒	☐	☐	☒
3	☒	☐	☐	☒
4	☒	☐	☐	☒
5	☒	☐	☐	☒
6	☒	☐	☐	☒
7	☐	☒	☐	☒
8	☐	☒	☐	☒
9	☐	☒	☐	☒
10	☐	☒	☐	☒
11	☐	☒	☒	☐
12	☐	☒	☒	☐

b) CRA subject, ex. 1

Row	**V1**		**V2**	
	L_1	L_2	L_1	L_2
1	☒	☐	☐	☒
2	☒	☐	☐	☒
3	☒	☐	☐	☒
4	☒	☐	☐	☒
5	☐	☒	☐	☒
6	☐	☒	☐	☒
7	☐	☒	☐	☒
8	☐	☒	☐	☒
9	☐	☒	☐	☒
10	☐	☒	☐	☒
11	☐	☒	☐	☒
12	☐	☒	☐	☒

c) CRA subject, ex. 2

A.4. Who Responds to Salience?

In this appendix, we examine if the LTs in our experiment have characteristics that set them apart from non-LT subjects. For this purpose, we perform probit regressions on the probability of being an LT and control for CRT scores, the time needed to complete the MPLs, and demographic variables. The results are presented in Table A.1.[32]

Table A.1: Who Responds to Salience?

This table shows the marginal effects of probit regressions among all 176 subjects. Dependent variable: local thinker (=1); z-values in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. *Response time above median* equals 1 if a subject's time needed for both MPLs is above the median and 0 otherwise. *CRT score* is the score achieved by subjects in the CRT and ranges from 0 to 3. *Female* equals 1 for female subjects and 0 for male subjects. *Age* describes subjects' age, measured in years. *Economics-related major* equals 1 for students with a major related to economics such as economics or business administration and 0 otherwise. *V2 seen first*, a dummy for the order of the MPLs, equals 1 if the subject saw V2 first and 0 if the subject saw V1 first.

	(1)	(2)	(3)
Response time above median (d)	0.364^{***}	0.354^{***}	0.354^{***}
	(5.51)	(5.29)	(4.82)
CRT Score		0.070^{**}	0.075^{**}
		(1.98)	(2.00)
Female (d)			0.012
			(0.14)
Age			-0.005
			(-0.47)
Economics-related major (d)			-0.010
			(-0.11)
V2 seen first (d)			-0.011
			(-0.14)
Session dummies	No	No	Yes
N	176	176	176
Pseudo R^2	0.12	0.14	0.19

We first find that subjects that take longer to finish the MPLs are significantly more likely to be LTs. A possible interpretation is that LTs take longer to finish the experiment because they are undecided and thus more likely to let their decision-making be influenced by salient attributes.[33] We also observe a significant positive correlation between CRT scores and the propensity to be an LT. This result is similar to Booth and Nolen (2012), who find that people with high cognitive capability are more likely to perform the switch predicted by salience theory. As for the other control variables, we do not find any significant correlations.[34]

[32] *Other* subjects are included in this regression. Removing them leaves the results unchanged.

[33] It is also possible that subjects who take longer also exert more cognitive effort. However, in that case, the time needed for the experiment and the CRT score should be positively related. While the sign of the correlation is positive, it is not significant.

[34] The dummy for undergraduate students was not included due to a high correlation with age. Including the dummy leaves our results unchanged.

A.5. Tests of Robustness

In this appendix, we discuss two potential challenges to our experimental design and our results.

A.5.1. Order Effects

Some studies find that the order in which MPLs are presented to subjects might influence their choices (Harrison, Johnson, McInnes, and Rutström, 2005). In order to avoid this pitfall, the MPLs were presented to our subjects in random order. The fraction of LT subjects is not significantly influenced by whether V1 or V2 was presented first (34.07% vs. 34.12%, $\chi^2 = 0.000$, $p = 0.994$). The same holds for SP_1 and SP_2. Student t-tests (Wilcoxon rank-sum tests) cannot reject the null hypothesis of equality of the means (medians) of SP_1 and SP_2 at common significance levels. Moreover, we include a dummy for the order of presentation of the MPLs in the regressions in Tables 5 and A.1 (*V2 seen first*); in both cases, there are no significant correlations. We conclude that the order of presentation is unlikely to have an influence on the elicited values.

A.5.2. Framing Towards the Middle

Another potential concern related to the MPL method is subjects' potential tendency to select a row in the middle of a list (Andersen, Harrison, Lau, and Rutström, 2006; Harrison, List, and Towe, 2007; Harrison and Rutström, 2008). Andersen, Harrison, Lau, and Rutström (2006) and Harrison, List, and Towe (2007) address this problem by offering three different MPLs where the conversion from risk-seeking choices to risk-averse choices occurs in the middle, above the middle, and below the middle of the respective MPL, respectively. Since each of the three MPLs has different implied risk parameters in the middle rows, there should be an effect on the estimated risk parameter if subjects have a tendency towards the middle of the list.

In our setting, this method is conceptually equivalent to testing whether subjects' switching points in V1 and V2 are close to each other and in the middle of the MPL. Table A.2 provides tests of the null hypothesis that switching points are equal in both MPL versions for the entire dataset and some subsamples. Using Wilcoxon rank-sum and Student t-tests, we reject the null hypothesis $H_0 : SP_1 = SP_2$ at high levels of significance for each subsample. Especially in V2, the mean switching point is relatively far from the middle of the list. Thus, we consider middle effects unlikely in this setting.[35]

Table A.2: Robustness: Framing Towards the Middle

SP_1 and SP_2 denote the mean switching point in V1 and V2, respectively. *Wilcoxon* and *Student t* are p-values of the Wilcoxon signed-ranks and Student t-test of the null hypothesis $H_0 : SP_1 = SP_2$ for each subsample. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. *Full* denotes the full sample, *LT only* and *CRA only* the respective subsamples. Since the removal of outliers would make the results even more pronounced, all outliers are included.

Sample	N	SP_1	SP_2	Wilcoxon	Student t
Full	176	5.30	10.64	0.000***	0.000***
LT only	60	6.05	8.10	0.000***	0.000***
CRA only	106	4.24	12.44	0.000***	0.000***

[35] Moreover, in their comparison of MPL formats, Andersen, Harrison, Lau, and Rutström (2006) do not find an influence of the framing of lottery lists on the elicited risk parameters in the original MPL method, which is the method used here.

A.6. Single-Model Estimations

This appendix presents single-model estimations for different decision-making theories. Note that in these estimations, we do not allow for stochastic errors as described in Equation (11).

Table A.3: Maximum Likelihood Estimation: Single-Model Estimations

This table contains maximum likelihood estimates using the linear form method. Standard errors are clustered for $N = 176$ subjects. *SE* denotes standard errors. *Wald* is the p-value of a Wald test against the null hypothesis that the variables are equal to zero. *95% CI* is the 95% confidence interval around the respective estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively.

Parameter	Coefficient	SE	Wald	95% CI
Panel a): EUT (CRRA)				
r	0.453	0.017	0.000***	[0.419, 0.487]
Panel b): RDU (CRRA)				
r	0.239	0.045	0.000***	[0.150, 0.328]
γ	0.627	0.035	0.000***	[0.558, 0.695]
Panel c): LT ($v'' = 0$)				
δ	0.636	0.012	0.000***	[0.614, 0.659]
Panel d): LT (v'' unconstrained)				
r	0.515	0.031	0.000***	[0.454, 0.576]
δ	1.181	0.086	0.000***	[1.013, 1.349]

A.7. Estimations Using Inverse-S Shaped Weighting Function

In this appendix, we repeat the estimations in Table 6 with the power PWF proposed by Quiggin (1982). To this end, the inverse-S shaped PWF of Equation (9) is replaced by

$$\omega(p) = p^{\gamma}. \tag{A.1}$$

The results are presented in Table A.4. Note that Panels b) and c) remain identical to those in Table 6 since they do not contain RDU estimations. Point estimates of the γ parameter of the PWF lie between 1.067 and 1.123, which implies slight "pessimism" (Harrison and Ng, 2016).

Table A.4: Maximum Likelihood Estimation: Mixture Models (Power PWF)

This table contains maximum likelihood estimates using the linear form method. The power PWF from Equation (A.1) is used in these estimations. Standard errors are clustered for $N = 176$ subjects. *SE* denotes standard errors. *Wald* is the p-value of a Wald test against the null hypothesis that the variables are equal to zero. *95% CI* is the 95% confidence interval around the respective estimate. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively.

Parameter	Coefficient	SE	Wald	95% CI
Panel a): EUT and RDU				
r^{EUT}	0.152	0.033	0.000***	$[0.086, 0.217]$
r^{RDU}	0.584	0.022	0.000***	$[0.541, 0.628]$
γ	1.067	0.057	0.000***	$[0.954, 1.180]$
π^{EUT}	0.389	0.054	0.000***	$[0.284, 0.494]$
π^{RDU}	0.611	0.054	0.000***	$[0.506, 0.716]$
Panel b): EUT and LT ($v'' = 0$)				
r	0.572	0.021	0.000***	$[0.531, 0.614]$
δ	0.833	0.029	0.000***	$[0.776, 0.889]$
π^{EUT}	0.682	0.042	0.000***	$[0.599, 0.765]$
π^{LT}	0.318	0.042	0.000***	$[0.235, 0.401]$
Panel c): EUT and LT (v'' unconstrained)				
r^{EUT}	0.600	0.018	0.000***	$[0.564, 0.635]$
r^{LT}	0.076	0.031	0.015**	$[0.015, 0.137]$
δ	0.866	0.032	0.000***	$[0.803, 0.929]$
π^{EUT}	0.619	0.042	0.000***	$[0.537, 0.702]$
π^{LT}	0.381	0.042	0.000***	$[0.298, 0.463]$
Panel d): RDU and LT ($v'' = 0$)				
r	0.546	0.038	0.000***	$[0.471, 0.620]$
δ	0.782	0.043	0.000***	$[0.697, 0.866]$
γ	1.121	0.082	0.000***	$[0.961, 1.281]$
π^{RDU}	0.620	0.048	0.000***	$[0.527, 0.713]$
π^{LT}	0.380	0.048	0.000***	$[0.287, 0.473]$
Panel e): RDU and LT (v'' unconstrained)				
r^{RDU}	0.576	0.040	0.000***	$[0.497, 0.655]$
r^{LT}	0.086	0.034	0.012**	$[0.018, 0.153]$
γ	1.123	0.113	0.000***	$[0.901, 1.345]$
δ	0.828	0.052	0.000***	$[0.726, 0.930]$
π^{RDU}	0.564	0.067	0.000***	$[0.433, 0.695]$
π^{LT}	0.436	0.067	0.000***	$[0.305, 0.567]$
Panel f): EUT, RDU, and LT (v'' unconstrained)				
r^{EUT}	9.730	0.364	0.000***	$[9.015, 10.444]$
r^{RDU}	0.589	0.023	0.000***	$[0.543, 0.634]$
r^{LT}	0.135	0.037	0.000***	$[0.062, 0.208]$
γ	1.095	0.051	0.000***	$[0.995, 1.196]$
δ	0.844	0.033	0.000***	$[0.781, 0.908]$
π^{EUT}	0.059	0.019	0.002***	$[0.022, 0.097]$
π^{RDU}	0.517	0.059	0.000***	$[0.402, 0.632]$
π^{LT}	0.423	0.056	0.000***	$[0.313, 0.533]$