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THEORETICAL NOTE

Unpacking, Repacking, and Anchoring: Advances in Support Theory

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Support theory represents probability judgment in terms of the support, or strength of evidence, of the focal relative to the alternative hypothesis. It assumes that the judged probability of an event generally increases when its description is unpacked into disjoint components (implicit subadditivity). This article presents a significant extension of the theory in which the judged probability of an explicit disjunction is less than or equal to the sum of the judged probabilities of its disjoint components (explicit subadditivity). Several studies of probability and frequency judgment demonstrate both implicit and explicit subadditivity. The former is attributed to enhanced availability, whereas the latter is attributed to repacking and anchoring.

The study of intuitive probability judgment has shown that people often do not follow the extensional logic of probability theory (see, e.g., Kahneman, Slovic, & Tversky, 1982). In particular, alternative descriptions of the same event can give rise to different probability judgments, and a specific event (e.g., that 1,000 people will die in an earthquake) may appear more likely than a more inclusive event (e.g., that 1,000 people will die in a natural disaster). To accommodate such findings, Tversky and Koehler (1994) have developed a nonextensional theory of belief in which subjective probability is not attached to events, as in other models, but to descriptions of events, called *hypotheses.* According to this account, called *support theory,* each hypothesis A has a support value, $s(A)$, corresponding to the strength of the evidence for this hypothesis. The judged probability, $P(A, B)$, that hypothesis A rather than B holds, assuming that one and only one of them obtains, is given by

$$P(A, B) = \frac{s(A)}{s(A) + s(B)}.$$

Thus, judged probability is interpreted in terms of the support of the focal hypothesis A relative to the alternative hypothesis B. The key assumption of support theory is that unpacking a description of an event (e.g., a plane crash, C) into disjoint components (e.g., an accidental plane crash, C_a, caused by human error or mechanical failure, or a nonaccidental plane crash, C_n, caused by terrorism or sabotage) generally increases its support. Thus, the support of the explicit disjunction $C_a \vee C_n$ is equal to or greater than the support of the implicit disjunction C that does not mention any cause. That is, $s(C) \leq s(C_a \vee C_n)$. The rationale for this assumption is twofold. First, unpacking an implicit hypothesis may remind people of possibilities they might have overlooked. Second, the explicit mention of a possibility tends to increase its salience and hence its perceived support.

Support theory provides a unified framework for the analysis and the interpretation of a wide range of findings. It predicts that the judged probability of an event increases by unpacking the focal hypothesis and decreases by unpacking the alternative hypothesis. For instance, the judged probability that a given person will die a natural rather than an unnatural death increases by listing various causes of natural death (e.g., heart attack, stroke, cancer) and decreases by listing various causes of unnatural death (e.g., car accident, homicide, fire). Furthermore, support theory implies that the judged probability of a hypothesis plus the judged probability of its complement, evaluated by different groups of participants, adds up to one. For finer partitions, however, the sum of the judged probabilities of a set of mutually exclusive and exhaustive hypotheses generally is greater than one. These predictions have been confirmed in numerous studies; earlier experiments are reviewed by Tversky and Koehler (1994), some later experiments are discussed by Fox and Tversky (in press).

This article presents a significant generalization of support theory that allows subadditivity for explicit disjunctions. To illustrate this extension, consider the possibilities that the winner of the next presidential election in the United States will be a Democrat (*Dem*), a Republican (*Rep*), or an Independent (*Ind*). The original version of support theory assumes that support is additive for explicit disjunctions, with the result that

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$s(Rep \vee Ind) = s(Rep) + s(Ind)$, and consequently, judged probability (P) is also additive for explicit disjunctions as in the standard theory of probability. As is shown next, however, several observations suggest that support is subadditive for explicit disjunctions such that $s(Rep \vee Ind) \leq s(Rep) + s(Ind)$, and hence

$$P(Rep \vee Ind, Dem) \leq P(Rep, Dem \vee Ind) + P(Ind, Rep \vee Dem).$$

That is, the judged probability that the winner of the upcoming election will be a Republican or an Independent rather than a Democrat is less than or equal to the judged probability that the winner will be a Republican rather than a Democrat or an Independent plus the judged probability that the winner will be an Independent rather than a Republican or a Democrat. More generally, we assume that if A and B are mutually exclusive hypotheses, and (A_1, A_2) is recognized as a partition of A, then $s(A) \leq s(A_1 \vee A_2) \leq s(A_1) + s(A_2)$. This assumption regarding the support function s imposes the following constraints on the observed measure P. In particular, the left inequality implies a testable condition, called *implicit subadditivity,*

$$\begin{aligned} P(A, B) &= \frac{s(A)}{s(A) + s(B)} \\ &\leq \frac{s(A_1 \vee A_2)}{s(A_1 \vee A_2) + s(B)} \quad \text{because } s(A) \leq s(A_1 \vee A_2) \\ &= P(A_1 \vee A_2, B). \end{aligned}$$

And the right inequality implies a second testable condition, called *explicit subadditivity,*

$$\begin{aligned} P(A_1 \vee A_2, B) &= \frac{s(A_1 \vee A_2)}{s(A_1 \vee A_2) + s(B)} \\ &\leq \frac{s(A_1) + s(A_2)}{s(A_1) + s(A_2) + s(B)} \\ &\qquad \text{because } s(A_1 \vee A_2) \leq s(A_1) + s(A_2) \\ &\leq \frac{s(A_1)}{s(A_1) + s(B \vee A_2)} + \frac{s(A_2)}{s(A_2) + s(B \vee A_1)} \\ &\qquad \text{by the same logic} \\ &= P(A_1, B \vee A_2) + P(A_2, B \vee A_1). \end{aligned}$$

Note that probability theory requires additivity throughout, whereas the theory of belief functions (Shafer, 1976) assumes superadditivity. Thus, support theory and Shafer's theory depart from the probability calculus in opposite directions. The contrast between the two theories is discussed in the last section.

Before addressing the cognitive processes that give rise to explicit subadditivity, we discuss three issues regarding the interpretation of support theory. First, we wish to emphasize that the predictions of the theory, notably binary complementarity, that is, $P(A, B) + P(B, A) = 1$, concern hypotheses not events. This distinction is particularly important in tasks where the alternative to the focal hypothesis is not explicitly stated. Consider, for example, the outcome of a race between an incumbent and a challenger, and let *In* denote the hypothesis that the incumbent will win the race and *Ch* denote the hypothesis that the challenger will win the race. Support theory implies that the judged probability of *In* plus the judged probability of not-*In* (i.e., the incumbent will not win the race) equals one, but the theory is not committed to the prediction that the judged probability of *In* plus the judged probability of *Ch* will equal one. In this simple example it is immediately obvious that *Ch* is the same as not-*In*, hence additivity is likely to hold, assuming it is clear that there are no other candidates and that ties are excluded. However, when the hypotheses under discussion are more complicated and the setting is less familiar, additivity need not hold (see Gonzales & Bonini, 1995; Macchi, Osherson, & Legrenzi, 1995).

Second, the unpacking inequality $s(A) \leq s(A_1 \vee A_2)$ is assumed to hold only when the judge knows, or believes, that $A_1 \vee A_2$ has the same extension as A. Thus, the theory predicts that the judged probability that a patient has meningitis (M), for example, is less than or equal to the judged probability that the patient has either viral meningitis or nonviral meningitis because their disjunction is clearly coextensional with M. However, the theory does not require that the judged probability of meningitis will be less than or equal to the judged probability of either viral meningitis (M_v) or bacterial meningitis (M_b), unless the judge happens to know that $M_v \vee M_b$ is coextensional with M. Note that a judge presented with the explicit disjunction $M_v \vee M_b$ may recognize that it has the same extension as the implicit disjunction M even though, presented with M alone, the judge may not be able to unpack it into M_v and M_b. Thus, the theory permits recognition without recall.

Third, the present theory expresses an observed probability judgment, $P(A, B)$, in terms of the underlying support, $s(A)$ and $s(B)$, of the individual hypotheses. Although it is possible, in some cases, to predict judged probability from independent assessments of support (see Tversky & Koehler, 1994), the present theory treats support as a psychological construct derived from probability judgment. A formal statement of the theory is presented in the Appendix. It provides necessary and sufficient conditions for the representation of probability judgments in terms of subadditive support; it also provides a simple method for constructing an essentially unique support function from observed judgments of probability.

Let us turn now from the interpretation of support theory to the main topic of this article, namely the psychological processes that can produce explicit subadditivity. More specifically, we investigate two such mechanisms, repacking and anchoring, that are discussed in turn.

As noted in the original version of the theory, a judge presented with an explicit disjunction may, nevertheless, think about it as an implicit disjunction, and vice versa. Consider, for example, the probability that a particular student majors in industrial, mechanical, or electrical engineering. A judge presented with such an explicit disjunction may repack the various disciplines and evaluate the implicit disjunction *engineering.* Because unpacking increases support, repacking reduces support giving rise to explicit subadditivity. Furthermore, we expect more explicit subadditivity for disjunctions of similar components than for disjunctions of dissimilar components because similar components are more easily repacked.

A second source of explicit subadditivity is the use of anchoring and adjustment. Instead of assessing independently the support of each component of an explicit disjunction and then adding the separate assessments, the judge may assess one of the components (perhaps the larger or the more familiar) and then adjust this value upward to accommodate the other components. Because such adjustments are generally insufficient (Poulton, 1994; Slovic & Lichtenstein, 1968; Tversky & Kahneman, 1974), the use of this heuristic is likely to produce explicit subadditivity. An individual who is asked to assess the combined population of the United States and Canada, for example, may anchor on the U.S. population and then adjust it upward, without making an explicit assessment of the population of Canada. If frequency, probability, or support are evaluated in this manner, we expect subadditivity for explicit disjunctions, even if their components are not repacked.

The effects of repacking and anchoring are explored in the following studies. Studies 1 and 2 test both implicit and explicit subadditivity in intuitive judgments of probability. Studies 3 and 4 investigate explicit subadditivity in judgments of frequency.

Study 1: Implicit and Explicit Subadditivity

This study employs two problems that have the same formal structure. Let A_1, A_2, and B denote three mutually exclusive and exhaustive hypotheses, and let A be an implicit disjunction of A_1 and A_2. In each problem, different groups of participants evaluated the implicit disjunction $P(A, B)$, the explicit disjunction $P(A_1 \vee A_2, B)$, the component, $P(A_1, A_2 \vee B)$, and the component $P(A_2, A_1 \vee B)$.

A total of 178 Stanford students participated in the study to fulfill course requirements. They were divided into four groups of roughly equal size. Every group evaluated both problems, each in a different condition. The two problems were embedded in a packet that included several other questionnaires, unrelated to the present study. Participants received the packet in class, completed it in their free time, and returned it anonymously 1 week later.

The first problem concerns the outcome of the next presidential election in the United States. Participants in the implicit group evaluated "the probability that the winner of the next presidential election will not be a Democrat." Participants in the explicit group evaluated the probability that "the winner of the next presidential election will be a Republican or an Independent rather than a Democrat." Participants in the two remaining groups evaluated either "the probability that the winner of the next presidential election will be a Republican rather than a Democrat or an Independent" or "the probability that the winner of the next presidential election will be an Independent rather than a Democrat or a Republican."

The second problem concerns the outcome of a criminal trial. All participants read the following scenario:

> Susan L. has accused her boss, Frank G., of unwelcome sexual advances and the promise of promotion in exchange for sexual favors. Frank G. denies any wrongdoing. The case has been brought before a jury consisting of seven men and five women. There were no eyewitnesses, but Susan's boyfriend has testified that she told him about the incidents in question. The jury is now deliberating.

Participants in the implicit group evaluated "the probability that this trial will not result in a guilty verdict." Participants in the explicit group evaluated "the probability of either a not guilty verdict or a hung jury rather than a guilty verdict." Participants in the two remaining groups evaluated either "the probability of a not guilty verdict rather than a guilty verdict or a hung jury" or "the probability of a hung jury rather than a not guilty verdict or a guilty verdict."

Table 1 presents median probability judgments for each of the two problems. Although support theory does not require strict inequalities for implicit and explicit subadditivity, the statistical tests reported in this article test the strict version of these inequalities against the null hypothesis of equality. In particular, we used the Mann–Whitney statistic to test the hypothesis that the judged probability of the implicit disjunction, $P(A, B)$, is strictly smaller than the judged probability of the explicit disjunction, $P(A_1 \vee A_2, B)$. This analysis provides some evidence for implicit subadditivity in Problem 2 ($p < .05$, one-sided) but not in Problem 1. We used the same statistic to test the hypothesis that the judged probability of the explicit disjunction, $P(A_1 \vee A_2, B)$, is strictly smaller than the sum of the judged probabilities of the single components, $P(A_1, A_2 \vee B) + P(A_2, A_1 \vee B)$. Because the latter were assessed by different groups of participants, we generated 100 "synthetic" distributions of such sums by pairing at random participants from the two groups. The median of the Mann–Whitney statistics across these distributions was significant in both Problem 1 (median $p < .05$) and Problem 2 (median $p < .0001$). Thus, strict explicit subadditivity was confirmed for both problems, and strict implicit subadditivity was observed in the trial problem but not in the election problem. The latter observation is not too surprising because here the implicit disjunction, non-Democrat, is naturally unpacked into the explicit disjunction, Republican or Independent.

Study 2: Causal Versus Temporal Unpacking

If implicit and explicit subadditivity are generated by different mechanisms, as suggested above, their relative contributions should vary depending on the nature of the partition. Some partitions are expected to induce primarily implicit subadditivity, whereas others are expected to produce primarily explicit subadditivity. The following study explores these effects and estimates their relative contributions.

Table 1
Median Probability Judgments Used to Test Implicit and Explicit Subadditivity in Study 1

Probability judgments	Problem 1: presidential election	Problem 2: criminal trial
$\alpha = P(A, B)$	60	50
$\beta = P(A_1 \vee A_2, B)$	60	60
$\gamma = P(A_1, A_2 \vee B)$	59	58
$\delta = P(A_2, A_1 \vee B)$	5	40

Note. In Problem 1, A_1 = Republican, A_2 = Independent, A = not Democrat, and B = Democrat. In Problem 2, A_1 = not guilty, A_2 = hung jury, A = result other than guilty, and B = guilty.

Participants in the study were 165 Stanford students attending an introductory economics class. They answered, in a classroom setting, a few questions concerning the probability of various causes of death. Participants were informed that

> Each year in the United States, approximately 2 million people (or 1% of the population) die from a variety of causes. In this questionnaire you will be asked to estimate the probability that a randomly selected death is due to one cause rather than another. Obviously, you are not expected to know the exact figures, but everyone has some idea about the prevalence of various causes of death. To give you a feel for the numbers involved, note that 1.5% of deaths each year are attributable to suicide.

This study consists of two cases. In Case 1 the focal hypothesis, homicide (H) is unpacked according to the causal agent: homicide by an acquaintance (H_a) and homicide by a stranger (H_s). In Case 2 the same focal hypothesis, H is unpacked according to the time of occurrence: daytime homicide (H_d) and nighttime homicide (H_n). The alternative hypothesis in all judgments is accidental death (X).

In this study, unlike the previous one, the focal and the alternative hypotheses are not exhaustive; the cause of death may be other than homicide or accident. Thus, participants here are asked to evaluate the conditional probability of the focal against the alternative hypothesis, assuming that one and only one of them holds. It is essential, of course, that participants understand and respect this assumption. Because the alternative hypothesis (X) in this design is held constant, probability theory requires additivity of odds, not of conditional probability. In particular, it implies $R(H_a \vee H_s, X) = R(H_a, X) + R(H_s, X)$, where $R(A, B)$ denotes the probability ratio $P(A, B)/P(B, A)$, provided $P(B, A) \neq 0$.

We conjectured that the causal partition is more likely to bring to mind additional possibilities than the temporal partition. Homicide by an acquaintance suggests domestic violence or a partners' quarrel, whereas homicide by a stranger suggests armed robbery or drive-by shooting. In contrast, daytime homicide and nighttime homicide are less likely to bring to mind disparate acts and hence are more readily repacked as an implicit disjunction. Consequently, we expect more implicit subadditivity in Case 1, due to enhanced availability, and more explicit subadditivity in Case 2, due to repacking of the explicit disjunction.

The study was designed as follows. In Case 1, the participants were randomly divided into three groups. One group (N = 55) evaluated the probability of the implicit disjunction that a randomly selected death is a homicide rather than an accidental death, $P(H, X)$. A second group (N = 54) evaluated the probability of the explicit disjunction that a randomly selected death is a homicide committed by an acquaintance or a homicide committed by a stranger rather than an accidental death, $P(H_a \vee H_s, X)$. A third group (N = 56) evaluated the probability of the two individual components, $P(H_a, X)$ and $P(H_s, X)$.

Case 2 was presented to the same participants a few weeks later. The design and the procedures were the same, except for the use of the temporal partition instead of the causal partition. As above, the participants were randomly divided into three groups. One group (N = 53) evaluated the implicit disjunction $P(H, X)$; a second group (N = 53) evaluated the explicit disjunction $P(H_a \vee H_n, X)$; and a third group (N = 56) evaluated the two individual components, $P(H_d, X)$ and $P(H_n, X)$. The median estimates for both cases are presented in the upper part of Table 2.

The lower part of Table 2 presents the supports and the weights derived from the median judgments, as will be shown later. Note that according to support theory, the odds $P(A, B)/[1 - P(A, B)]$ equal $s(A)/s(B)$. Letting $s(X) = 1$, the support of each focal hypothesis in this study equals the odds of this hypothesis against the alternative X. For example,

$$s(H) = \frac{s(H)}{s(X)} = \frac{P(H, X)}{1 - P(H, X)} = \frac{.20}{.80} = .25.$$

Table 2
Median Probability Judgments (P) and Estimated Supports (s) and Weights (w) for the Two Partitions in Study 2

	Homicide unpacked	
Hypothesis	Case 1 (causal agent): acquaintance vs. stranger	Case 2 (by time): day vs. night
Implicit	$P(H, X) = .20$	$P(H, X) = .20$
Explicit	$P(H_a \vee H_s, X) = .25$	$P(H_d \vee H_n, X) = .20$
	$P(H_a, X) = .15$	$P(H_d, X) = .10$
	$P(H_s, X) = .15$	$P(H_n, X) = .21$
Implicit	$s(H) = .25$	$s(H) = .25$
Explicit	$s(H_a \vee H_s) = .33$	$s(H_d \vee H_n) = .25$
	$s(H_a) + s(H_s) = .18 + .18 = .36$	$s(H_d) + s(H_n) = .11 + .29 = .40$
Implicit (I)	$w_{HI} = .25/.33 = .76$	$w_{HI} = .25/.25 = 1.00$
Explicit (E)	$w_{HE} = .33/.36 = .92$	$w_{HE} = .25/.40 = .63$
Global	$w_H = .25/.36 = .69$	$w_H = .25/.40 = .63$

Note. H denotes homicide, X denotes accidental death, and H_a, H_s, H_d, H_n denote, respectively, homicide by an acquaintance, by a stranger, during daytime, and during nighttime.

Other support values were obtained similarly.

Support theory offers simple measures of implicit and explicit subadditivity. Let $(A_1, \ldots, A_n)$ be a partition of the implicit hypothesis A. The ratio

$$w_A = \frac{s(A)}{s(A_1) + \ldots + s(A_n)}$$

provides a global measure of the degree of subadditivity induced by the above partition. Note that $w_A = 1$ if probability judgments are additive, and $w_A < 1$ if they exhibit either implicit or explicit subadditivity. Thus, lower w implies greater subadditivity. To assess the separate contributions of implicit and explicit subadditivity, define

$$w_{AI} = \frac{s(A)}{s(A_1 \vee \ldots \vee A_n)}$$

$$w_{AE} = \frac{s(A_1 \vee \ldots \vee A_n)}{s(A_1) + \ldots + s(A_n)}$$

so that $w_A = w_{AI}w_{AE}$. Hence, the global measure of subadditivity, w_A, is decomposed into its implicit (w_{AI}) and explicit (w_{AE}) components that can be estimated from the data.

Applying the preceding analysis to the data of Table 2 reveals more implicit subadditivity in Case 1 ($w_{HI} = .76$) than in Case 2 ($w_{HI} = 1.00$), and more explicit subadditivity in Case 2 ($w_{HI} = .62$) than in Case 1 ($w_{HE} = .92$). Strict implicit subadditivity was tested by comparing the supports of the implicit and explicit disjunctions in each case, that is, $s(H)$ versus $s(H_a \vee H_s)$ and $s(H)$ versus $s(H_d \vee H_n)$, using the Mann–Whitney statistic. Strict explicit subadditivity was tested by comparing the sum of the supports of the component hypotheses, within the data of a participant, to the support of the corresponding explicit disjunction, that is $s(H_a) + s(H_s)$ versus $s(H_a \vee H_s)$ and $s(H_d) + s(H_n)$ versus $s(H_d \vee H_n)$. The analysis yielded significant strict implicit subadditivity in Case 1 ($p < .01$) but not in Case 2, and significant strict explicit subadditivity in Case 2 ($p < .005$), but not in Case 1. These findings support our conjecture that the causal partition induces more implicit subadditivity, whereas the temporal partition induces more explicit subadditivity.

Study 3: Similar Versus Dissimilar Components

Although support theory has been conceived as a model of probability judgment, it can be readily applied to assessments of percentage or relative frequency (Tversky & Koehler, 1994). Moreover, judgments of absolute frequency can serve as support for certain hypotheses. For example, the probability that it will snow in Chicago next November may be based on an estimate of the frequency of snowy and nonsnowy Novembers in the last decade. It is instructive, therefore, to test whether assessed frequency satisfies implicit and explicit subadditivity. One might expect that judgments of absolute frequency are less vulnerable to these biases because the additivity of frequency is simpler and more intuitive than the additivity of probability.

The study of frequency judgment also provides an opportunity for testing another potential source of explicit subadditivity, namely a regressive bias towards the midpoint of the scale (e.g., .5), reflecting either response bias or random error (see, e.g., Erev, Wallsten, & Budescu, 1994). This account implies explicit subadditivity when the two components are below the midpoint and explicit superadditivity when the two components are above the midpoint. Because the probability scale is bounded by one, the above prediction cannot be tested using judgments of probability or relative frequency, but it can be readily tested in judgments of absolute frequency.

The participants, 152 Stanford students, were asked to estimate the number of fellow undergraduates majoring in particular fields. They were recruited through ads placed in *The Stanford Daily* and were paid for their participation. Participants were run in groups of 8–12 members. In addition to the judgments of frequency, students participated in several unrelated two-person games. Participants were given the following instructions:

> Consider all Stanford students who have declared *one* major. We would like you to estimate the number of students majoring in particular fields. Obviously, you are not expected to know the exact figures. We are interested in your impressions regarding the popularity of different majors.
>
> For your information, 120 students major in History. Using this number as a standard of comparison, please give your best estimates of the following. The three most accurate respondents will receive a prize of $20.

Twenty-four majors, listed in Table 3, were divided into three sets of 8. From each set of 8 majors, we constructed four pairs of similar majors (e.g., mathematics and computer science), and four pairs of dissimilar majors (e.g., mathematics and Italian). Participants were randomly divided into three groups. The parti-

Table 3
Median Frequency Estimates and the Actual Number of Students in Each Major (Study 3)

Major	Median estimate	Actual number
Biology	250	265
Chemistry	100	51
Chemical engineering	70	56
Civil engineering	95	64
Communication	65	66
Comparative literature	40	6
Computer science	100	104
Electrical engineering	100	102
Earth systems	50	66
Economics	200	261
English	120	200
French	25	7
Geology	36	3
Industrial engineering	70	64
International relations	100	96
Italian	20	1
Mathematics	50	9
Mechanical engineering	100	97
Petroleum engineering	30	1
Philosophy	50	18
Political science	150	135
Public policy	80	72
Sociology	80	35
Symbolic systems	30	44

cipants in each group evaluated each of the 8 individual majors from one set (e.g., "The number of students majoring in mathematics"), the four similar pairs of majors from another set (e.g., "The total number of students majoring either in political science or international relations"), and the four dissimilar pairs from a third set (e.g., "The total number of students majoring either in chemistry or English"). Thus, each participant encountered each major exactly once.

Explicit subadditivity implies that the estimated number of students in a given pair of majors is less than or equal to the sum of the estimates of the individual majors. If this phenomenon is driven, at least in part, by participants' tendency to repack the individual components, then we should expect greater subadditivity for similar than for dissimilar pairs because it is easier and more natural to pack related majors (e.g., mathematics and computer science) than unrelated majors (e.g., mathematics and Italian). Finally, if participants estimate the total number of students who major in one of two fields by anchoring on the larger major and making an insufficient upward adjustment, then we expect the judgments to be more sensitive to the larger than to the smaller component of each pair.

Table 3 presents median estimates for each of the 24 majors, along with the official numbers. The correlation between the estimated and correct values is .93, and the average absolute deviation of prediction is 24, indicating that our respondents had a reasonably good idea of the relative popularity of the various majors at their university.

Tables 4 and 5 present, separately for similar and dissimilar pairs, the median frequency estimates for the pairs, denoted F_{AB}, the median sums of frequency estimates of the individual majors, computed within the data of each participant and denoted $F_A + F_B$, and the ratio of these values. The results provide strong evidence for subadditivity: The estimate of the pair is less than the sum of the individual estimates in 23 of 24 cases, and the mean value of $F_{AB}/(F_A + F_B)$ across all pairs is only .69. This effect cannot be explained by a regression towards a central value (e.g., 120, which was given as a standard of comparison) because subadditivity is very much in evidence for both large and small pairs of majors. Recall that a symmetric error model predicts subadditivity for pairs of small majors and superadditivity for pairs of large majors, contrary to the data in Tables 4 and 5.

In accord with repacking, the similar pairs tend to be more subadditive than the dissimilar pairs: The values of $F_{AB}/(F_A + F_B)$ are generally lower in Table 4 than in Table 5 ($p < .05$ by a one-sided Mann–Whitney test). However, the presence of strict explicit subadditivity in both cases suggests an anchoring and adjustment process.

To test this account we compared, separately for similar and dissimilar pairs, the median estimate of each pair, F_{AB}, with the higher of the two medians of estimates for individual majors forming the pair, denoted F_H. For similar pairs, the mean value of F_H was 108, whereas the mean value of F_{AB} was 113, (t = .22, *ns*). For dissimilar pairs, the mean value of F_H was 111, whereas the mean value of F_{AB} was 124 (t = .56, *ns*). Thus, the estimates for the pairs (overall mean = 119) are much closer to the higher of the two majors (overall mean = 109) than to the sum of the individual estimates (overall mean = 165). These data are consistent with the notion that participants estimated the pairs by focusing on the larger component.

Study 4: Anchoring and Adjustment

If instead of evaluating each major separately and then adding these individual estimates, participants evaluate pairs of majors by adjusting one of the estimates, then participants who had already evaluated one of the majors are likely to use this estimate as an anchor. In this case, the frequency estimate of a pair is higher when the participants had estimated beforehand the higher rather than the lower component of that pair. To test this prediction we selected 12 pairs of majors and identified each of their components as high or low according to the median estimates in Table 3. The participants (N = 81) were recruited and run as in the preceding study. They were divided randomly into three groups. All participants evaluated all 12 pairs. Prior to this task, however, each group evaluated a different set of 8

Table 4
Median Frequency Estimates for Each Similar Pair (F_{AB}), Median Sum of Estimated Components ($F_A + F_B$), and Their Ratio (Study 3)

Similar pair	Median estimate (F_{AB})	Median sum ($F_A + F_B$)	$\left(\frac{F_{AB}}{F_A + F_B}\right)$
Chemical engineering and petroleum engineering	50	110	.45
Geology and earth systems	50	110	.45
Mechanical engineering and civil engineering	100	200	.50
Biology and chemistry	200	360	.56
Philosophy and symbolic systems	50	90	.56
Political science and international relations	150	260	.58
English and comparative literature	105	160	.66
Economics and public policy	190	275	.69
Math and computer science	130	173	.75
Communication and sociology	115	150	.77
French and Italian	40	50	.80
Electrical engineering and industrial engineering	180	160	1.13
Median			.62

Table 5
Median Frequency Estimates for Each Dissimilar Pair (F_{AB}), Median Sum of Estimated Components ($F_A + F_B$), and Their Ratio (Study 3)

Dissimilar pair	Median estimate (F_{AB})	Median sum ($F_A + F_B$)	$\left(\frac{F_{AB}}{F_A + F_B}\right)$
Industrial engineering and political science	145	238	.61
Philosophy and earth systems	70	114	.61
Chemistry and English	150	230	.65
Chemical engineering and public policy	80	120	.67
Mechanical engineering and sociology	150	220	.68
Computer science and French	100	135	.74
Electrical engineering and international relations	150	195	.77
Geology and symbolic systems	50	65	.77
Communication and civil engineering	120	155	.77
Economics and petroleum engineering	200	250	.80
Biology and comparative literature	220	270	.81
Mathematics and Italian	58	70	.83
Median			.76

single majors. The single majors were selected so that for each pair of majors one group evaluated beforehand the high or more popular major, a second group evaluated the low or less popular major, and a third group did not evaluate either of the individual components prior to the evaluation of the pair. The order of presentation of both individual majors and pairs of majors was randomized.

If people focus on their prior estimate, we expect participants who first evaluated the high component of a pair to give higher estimates than participants who first evaluated the low component of that pair. And if, in the absence of a prior estimate, people tend to choose the larger of the two majors as an anchor because it is closer to the required estimate, we expect participants who made no prior estimate for a given pair to be closer to those who evaluated the high component than to those who evaluated the low component.

The results confirmed both predictions. The mean estimate for a pair of majors in the high condition was 251 students, whereas the mean estimate for a pair of majors in the low condition was 202 students ($t = 3.50$, $p < .001$). The mean estimate in the neutral condition was 237, significantly higher than the median estimate in the low condition ($t = 1.96$, $p = .05$) but not significantly lower than the mean estimate in the high condition ($t = .70$, *ns*).

Summary and Discussion

The present extension of support theory distinguishes between implicit subadditivity, induced by unpacking, and explicit subadditivity, resulting from the difference between the assessment of an explicit disjunction and separate assessments of its disjoint components. We have proposed that the former is caused by enhanced availability, whereas the latter is produced, in part at least, by repacking or anchoring. Consequently, different partitions are likely to give rise to different patterns of subadditivity. Study 1 established strict implicit and explicit subadditivity in judgments of unconditional probability. Study 2 showed that a causal partition produced more implicit subadditivity, whereas a temporal partition produced more explicit subadditivity, in judgments of conditional probability. Study 3 demonstrated greater explicit subadditivity for similar than for dissimilar components in judgments of frequency. Study 4 suggested that people follow an anchoring and adjustment heuristic that focuses on the larger, or the more familiar, component and increases the assessment of that component slightly to accommodate the larger extension.

The use of an anchoring and adjustment heuristic in this context is somewhat surprising because it seems easy to estimate the components separately and then add the estimates. Evidently, people are reluctant to add uncertain quantities. If they do not know the population of Spain and also do not know the population of Portugal, they are reluctant to estimate each of these numbers separately and add their guesses. Instead, they apparently form an overall impression of the combined population of the two states that is determined primarily by the larger of the two. Taken together, the present results imply that an adequate model of probability or frequency judgment should be able to accommodate both implicit and explicit subadditivity. The current version of support theory provides such a model.

We conclude with a discussion of the relation between support theory and Shafer's (1976) theory of belief functions. Although the theory of belief functions is based on logical rather than psychological considerations, it has been interpreted by several authors as a descriptive model of belief. In this theory, as in many other models, the belief in the disjunction of disjoint events is greater than or equal to the sum of the beliefs in each of the components. Thus, support theory and the theory of belief functions depart from the Bayesian model in opposite directions: Support theory predicts subadditivity, whereas the theory of belief functions assumes superadditivity. Using the notation of Table 1, probability theory requires $\alpha = \beta = \gamma + \delta$, Shafer's theory assumes $\alpha = \beta \geq \gamma + \delta$, and support theory implies $\alpha \leq \beta \leq \gamma + \delta$.

The experimental literature provides strong evidence that judged probability of both lay people and experts is subadditive rather than superadditive (see, e.g., Tversky & Koehler, 1994; Fox & Tversky, in press). For example, options traders who evaluated a set of four mutually exclusive and exhaustive hypotheses regarding the closing price of Microsoft stock did not hold any belief in reserve, as required by the theory of belief functions. On the contrary, the sum of the probabilities assigned to these hypotheses was substantially greater than 1,[1] and options traders were actually willing to bet on these values (Fox, Rogers, & Tversky, 1996). Although we do not wish to claim that superadditivity cannot arise in certain circumstances, the experimental evidence suggests that such instances represent the exception rather than the rule.

What then is the psychological basis for the superadditivity assumption that underlies post-Bayesian models of degree of belief? The answer to this question goes back to Keynes's (1921) distinction between the balance of evidence in favor of a given proposition and the weight (or strength) of evidence for this proposition. Keynes has argued that the standard notion of probability can represent the balance of evidence but not the weight of evidence because a probability of one half, for example, may result either from strong evidence for and strong evidence against the proposition in question or from weak evidence for and weak evidence against that proposition. Following Keynes, we suggest that superadditivity often holds for judgments of evidence strength, that is, of the degree to which a designated body of evidence supports a particular hypothesis (see Briggs & Krantz, 1992), but it does not hold for probability judgments that reflect the global balance of evidence.

The contrast between these notions is most pronounced in situations where there is good evidence for some general hypothesis but there is no specific evidence for any of its components. Suppose, for example, that there is very strong evidence that a particular person was murdered, but there is no evidence regarding the identity of the killer. Let H, H_a, and H_s denote, respectively, homicide, homicide by an acquaintance, and homicide by a stranger. If people can make sensible assessments of the degree to which the evidence confirms each of these hypotheses (say on a scale from 0 to 1), we expect these assessments to be close to 1 for H, and close to 0 for H_a and for H_s, in accord with Shafer's (1976) model. On the other hand, the judged probabilities of H_a and H_s are expected to be substantially greater than 0, and their sum may even exceed the judged probability of H. Judgments of strength of evidence, we suggest, reflect the degree to which a specific body of evidence confirms a particular hypothesis, whereas judgments of probability express the relative support for the competing hypotheses based on the judge's general knowledge and prior belief. The two types of judgments, therefore, are expected to follow different rules. Indeed, Krantz (1991) has argued that Shafer's model is more suitable for judgments of evidence strength than for judgments of probability.

Because there is very little data on judgments of evidence strength, we can only speculate about the rules they follow. It appears that in the absence of specific evidence, as in the homicide example earlier, such judgments are likely to be superadditive. However, judgments of evidence strength are unlikely to be superadditive in general. To illustrate, consider a body of evidence, for example, a fragment of Linda's diary expressing moral objection to sexist language. Such evidence, we suggest, can provide stronger support for the hypothesis that Linda is a feminist bank teller than for the more inclusive hypothesis that Linda is a bank teller. This pattern, of course, is not only subadditive; it is actually nonmonotonic. Similarly, a postcard with an Alpine scene appears to provide stronger evidence for the hypothesis that it came from Switzerland than for the hypothesis that it came from Europe (see e.g., Bar-Hillel & Neter, 1993). In these cases the evidence matches the narrower hypothesis better than it matches the broader hypothesis, hence an assessment based on matching (or representativeness) can give rise to nonmonotonicity in judgment of evidence strength, as well as in judgment of probability (Tversky & Kahneman, 1983).

To summarize, the experimental evidence described here and elsewhere indicates that probability judgments, which are based on the balance of evidence, are generally subadditive. The preceding discussion, however, suggests that judgments of the strength of a designated body of evidence may exhibit a different pattern. Such judgments are likely to be superadditive when there is little evidence for each of the component hypotheses, and they are likely to be subadditive (or even nonmonotonic) when the evidence strongly favors one of the components. Whether or not these conjectures are valid, we suggest that the discussion of alternative representations of belief can be illuminated by the distinction between probability judgments based on the balance of evidence and judgments of the strength of a specific body of evidence.

[1] On the other hand, the prevalence of additivity for binary partitions, called binary complementarity, excludes the dual of the belief function, called the plausibility function. It follows readily that under binary complementarity all models of upper and lower probability reduce to the standard additive model.

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Appendix

Support Theory

This section presents a self-contained, formal statement of support theory and provides necessary and sufficient conditions for the present model in terms of judged probability. This analysis extends the treatment of Tversky and Koehler (1994, Theorem 1) by introducing explicit subadditivity and by restricting the assumption of implicit subadditivity.

Let T be a finite set including at least two elements, interpreted as states of the world. We assume that exactly one state obtains but it is generally not known to the judge. Subsets of T are called *events.* We distinguish between events and description of events, called *hypotheses.* We use H to denote the set of hypotheses that describe the events in T and prime (′) to denote the mapping that associates hypotheses with events. Thus, we assume that each hypothesis $A \in$ H corresponds to a unique event $A' \in$ T. Different hypotheses may describe the same event. For example, consider rolling a pair of dice. The hypotheses "the sum is 3" and "the product is 2" describe the same event: One die shows 1, and the other shows 2. We assume that H is finite and that it includes at least one hypothesis for each event. A is elementary if $A' \in$ T. A is null if $A' = \varnothing$. A and B are exclusive if $A' \cap B' = \varnothing$. If A and B are in H, and they are exclusive and nonnull, then their explicit disjunction, denoted $A \vee B$, is also in H. We assume that $\vee$ is associative and commutative and that $(A \vee B)' = A' \cup B'$.

Support theory distinguishes between explicit and implicit disjunctions. Formally, A is an implicit disjunction, or simply an implicit hypothesis, if it is neither elementary nor null, and it is not an explicit disjunction (i.e., there are no exclusive nonnull B, C in H such that $A = B \vee C$). For example, the explicit disjunction, "Homicide by an acquaintance or by a stranger," has the same extension as "Homicide," but the latter is an implicit hypothesis because it is not an explicit disjunction.

An evaluation frame (A, B) consists of a pair of exclusive hypotheses: The first element, A, is the focal hypothesis that the judge evaluates, and the second element, B, is the alternative hypothesis. We interpret a person's probability judgment as a mapping P from an evaluation frame to the unit interval. To simplify matters, we assume that $P(A, B)$ equals zero if and only if A is null and equals one if and only if B is null. Thus, $P(A, B)$ is the judged probability that A rather than B holds, assuming that one and only one of them obtains. Obviously, A and B may each represent an explicit or an implicit disjunction. The extensional counterpart of $P(A, B)$ in probability theory is the conditional probability $P(A' | A' \cup B')$. Support theory is nonextensional because it assumes that probability judgment depends on the descriptions A and B, not on the events A' and B'.

As in the original version of the theory, we assume *binary complementarity:*

$$P(A, B) + P(B, A) = 1, \qquad \text{(Condition 1)}$$

which follows readily from the equation relating judged probability and support. To formulate the next two assumptions, we introduce the probability ratio $R(A, B) = P(A, B)/P(B, A)$, which is the odds for A against B, assuming B is nonnull. The use of odds is merely a notational device, not a change in the response scale. Our second assumption is the *product rule:*

$$R(A, B)R(B, D) = R(A, C)R(C, D)$$

$$\text{and} \quad R(A, B)R(B, D) = R(A, D), \qquad \text{(Condition 2)}$$

where each equation holds whenever the arguments of R in that equation are exclusive. Note that according to support theory, $R(A, B) = s(A)/s(B)$. Hence the product rule follows from this form by cancellation. This assumption is slightly stronger than the product rule used in the original version of the theory.[A1]

Our third assumption, called the *odds inequality,* replaces the unpacking condition of the original theory. Suppose A_1, A_2, and B are mutually exclusive, A is implicit, and $A_1 \vee A_2$ is recognized as a partition of A. That is, $(A_1 \vee A_2)' = A'$, and the judge recognizes that $A_1 \vee A_2$ has the same extension as A. Then

$$R(A, B) \leq R(A_1 \vee A_2, B)$$

$$\leq R(A_1, B) + R(A_2, B). \qquad \text{(Condition 3)}$$

Note that under the classical probability axioms both inequalities reduce to equalities. The recognition requirement, which restricts the assumption of implicit subadditivity, was not explicitly stated in the original version of the theory, although it was assumed in its applications.

The following theorem shows that Conditions 1, 2, and 3 are both necessary and sufficient for the extended version of support theory.

> Theorem: Suppose $P(A, B)$ is defined for all exclusive $A, B \in$ H and that it vanishes if and only if A is null. Conditions 1, 2, and 3 hold if and only if there exists a nonnegative ratio scale s on H such that for any pair of exclusive hypotheses A, B

$$P(A, B) = \frac{s(A)}{s(A) + s(B)}. \qquad \text{(Condition 4)}$$

[A1] The first part of Condition 2 is equivalent to the product rule used in the original theory; the second part of Condition 2 is implied by but does not imply the proportionality assumption of the original theory.

Furthermore, if A_1 and A_2 are exclusive, A is implicit, and $(A_1 \vee A_2)$ is recognized as a partition of A then

$$s(A) \leq s(A_1 \vee A_2) \leq s(A_1) + s(A_2). \quad \text{(Condition 5)}$$

Proof: Necessity is straightforward. To prove sufficiency we assume Conditions 1, 2, and 3 and construct the support function s. Let $E = \{A \in H | A' \in T\}$ be the set of elementary hypotheses. Select some $D \in E$ and set $s(D) = 1$. For any other elementary hypothesis $C \in E$ such that $C' \neq D'$, set $s(C) = R(C, D)$. Given any $A \in H$ such that $A' \neq T, \varnothing$, select some $C \in E$ such that $A' \cap C' = \varnothing$ and either $C = D$ or $C' \neq D'$. Set $s(A) = R(A, D)$ if $C = D$ and $s(A) = R(A, C)R(C, D)$ otherwise. It is easy to verify that the product rule (Condition 2), $R(A, B)R(B, D) = R(A, C)R(C, D)$ and $R(A, B)R(B, D) = R(A, D)$, ensures that $s(A)$ is independent of the choice of C. Apply the second equation when A and D are exclusive, and the first equation when they are not. To complete the construction of s, set $s(A) = 0$ when $A' = \varnothing$. When $A' = T$, set $s(A) = \min \Sigma s(B_n)$, where the minimum is taken over all explicit disjunctions $B = B_1 \vee \cdots \vee B_n$ such that $B' = T$.

To establish the representation for $P(A, B)$, suppose $A' \cap D' = \varnothing$. Thus, $s(A) = R(A, D)$. Furthermore, there exists $C \in E$ such that $s(B) = R(B, C)R(C, D)$. By the product rule, therefore, $s(B) = R(B, A)R(A, D)$, and $s(A)/s(B) = R(A, B)$. Applying binary complementarity (Condition 1), yields $P(A, B) = s(A)/[s(A) + s(B)]$ for all disjoint $A, B \in H$, where s is unique up to a choice of unit determined by the value of $s(D)$.

Finally, implicit subadditivity, $s(A) \leq s(A_1 \vee A_2)$, and explicit subadditivity, $s(A_1 \vee A_2) \leq s(A_1) + s(A_2)$, (see Condition 5), follow respectively from the left hand and the right hand of the odds inequality (Condition 3), $R(A, B) \leq R(A_1 \vee A_2, B) \leq R(A_1, B) + R(A_2, B)$, provided $A' \neq T$. Otherwise, these inequalities follow from the definition of $s(A)$ for $A' = T$.

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