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**e-companion**

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# Electronic Companion—"An Empirical Test of Gain-Loss Separability in Prospect Theory" by George Wu and Alex B. Markle, *Management Science*, DOI 10.1287/mnsc.1080.0846.

# Introduction

This paper supplements the main paper. In Section EC.1, we develop in greater detail the error model presented in Section 3.3 of that paper. In Section EC.2, we derive implications of these error models on various measures of double matching violations. In Section EC.3, we examine these four measures empirically. Section EC.4 details the likelihood-ratio test used to analyze the Study 1 data. Section EC.5 presents robustness analyses of our fits of the probability weighting function.

We then present some supplementary material for Study 2 of the main paper. Section EC.6 details the stochastic choice procedure used to test gain-loss separability for Study 2, and Section EC.7 presents robustness analyses of the probability weighting function estimation for Study 2. Section EC.8 concludes.

For completeness and to improve readability, this companion paper repeats some of the text from the main paper.

## EC.1. Error Models

The goal of this error analysis is to examine whether the empirical pattern of double matching violations in Study 1 could be explained by random error. Recall Problems 1 through 3 (also Study 1, Test 7) from the Introduction of the main paper:

Problem 1 ($n = 81$):

$$H = \begin{pmatrix} \text{.50 chance at \$4200} \\ \text{.50 chance at \$-3000} \end{pmatrix} \text{ vs. } L = \begin{pmatrix} \text{.75 chance at \$3000} \\ \text{.25 chance at \$-4500} \end{pmatrix}$$

[52%] [48%]

Problem 2 ($n = 81$):

$$H^+ = \begin{pmatrix} \text{.50 chance at \$4200} \\ \text{.50 chance at \$0} \end{pmatrix} \text{ vs. } L^+ = \begin{pmatrix} \text{.75 chance at \$3000} \\ \text{.25 chance at \$0} \end{pmatrix}$$

[15%] [85%]

Problem 3 ($n = 81$):

$$H^- = \begin{pmatrix} \text{.50 chance at \$0} \\ \text{.50 chance at \$-3000} \end{pmatrix} \text{ vs. } L^- = \begin{pmatrix} \text{.75 chance at \$0} \\ \text{.25 chance at \$-4500} \end{pmatrix}$$

[37%] [63%]

We suggested that the modal pattern of choices, $H$, $L^+$, and $L^-$, was consistent with a process in which decision makers were less sensitive to probability differences for mixed gambles than for either gain or loss gambles. In Study 1, our primary empirical investigation of double matching, we found that $\%H > \frac{\%H^+ + \%H^-}{2}$ for 29 of our 34 Study 1 tests, all of which had the same basic structure as Problems 1 through 3.

Could this pattern of data, however, be an artifact of random error? To investigate this possibility, we compare a random error model with several models in which the error is "systematic." We show that the random error model cannot account for the full set of data presented in the main paper. On the other hand, a model that employs systematic or asymmetric error and is consistent with the intuition suggested by our introductory example captures the basic qualitative patterns found in our data.

We outline the basic assumptions underlying the proposed error models. We consider assumptions about preference types, satisfaction of the double matching axiom, and error rates.

### EC.1.1. Preference Types

We assume that there are four types, $\theta_{H^+H^-}$, $\theta_{H^+L^-}$, $\theta_{L^+H^-}$, and $\theta_{L^+L^-}$. Each type has "underlying preferences," though their "revealed preferences" reflect some error (see Section EC.1.3 below). Type $\theta_{H^+H^-}$ prefers $H^+$ over $L^+$ and $H^-$ over $L^-$, type $\theta_{H^+L^-}$ prefers $H^+$ over $L^+$ and $L^-$ over $H^-$, type $\theta_{L^+H^-}$ prefers $L^+$ over $H^+$ and $H^-$ over $L^-$, and type $\theta_{L^+L^-}$ prefers $L^+$ over $H^+$ and $L^-$ over $H^-$. The probabilities of the four types are given by $p_{H^+H^-}$, $p_{H^+L^-}$, $p_{L^+H^-}$, and $p_{L^+L^-}$, or $p_{HH}$, $p_{HL}$, $p_{LH}$, and $p_{LL}$ for short. Table EC.1 summarizes the assumptions about types.

**Table EC.1 Probabilities of combinations of preferences for the types described in Section EC.1.1.**

| | $H^- \succ L^-$ | $L^- \succ H^-$ |
|---|---|---|
| $H^+ \succ L^+$ | $p_{H^+H^-}$ | $p_{H^+L^-}$ |
| $L^+ \succ H^+$ | $p_{L^+H^-}$ | $p_{L^+L^-}$ |

### EC.1.2. Double Matching

We assume that "underlying preferences" satisfy double matching. Type $\theta_{H^+H^-}$ prefers $H^+$ over $L^+$ and $H^-$ over $L^-$, and thus $H$ over $L$, whereas type $\theta_{L^+L^-}$ prefers $L^+$ over $H^+$ and $L^-$ over $H^-$, and hence $L$ over $H$. We consider the other two types, $\theta_{H^+L^-}$ and $\theta_{L^+H^-}$, "indeterminate" and assume that they choose according to their gain or loss preferences with equal probability (see below).

### EC.1.3. Error Rates

We also assume that decision makers choose with error. Let $\epsilon_S$ be the error rate for single-domain gambles, such that $\epsilon_S = P(L^+ \succ H^+|\theta_{H^+H^-}) = P(L^+ \succ H^+|\theta_{H^+L^-}) = P(L^- \succ H^-|\theta_{H^+H^-}) = P(H^+ \succ L^+|\theta_{L^+L^-}) = P(H^- \succ L^-|\theta_{L^+L^-})$, etc. The remaining conditional probabilities are defined analogously.

We consider several error models for the choice between mixed gambles $H$ and $L$. Let $\epsilon_L = P(L \succ H|\theta_{H^+H^-})$ and $\epsilon_H = P(H \succ L|\theta_{L^+L^-})$. We assume that the two indeterminate types, $\theta_{H^+L^-}$ and $\theta_{L^+H^-}$, choose like type $\theta_{H^+H^-}$ or type $\theta_{L^+L^-}$ with equal probability. Therefore, $P(H \succ L|\theta_{H^+L^-}) = P(H \succ L|\theta_{L^+H^-}) = (1/2)P(H \succ L|\theta_{H^+H^-}) + (1/2)P(H \succ L|\theta_{L^+L^-}) = (1/2)(1-\epsilon_L) + (1/2)(\epsilon_H)$.

The four models below make different restrictions on the relationship among the four error rates, $\epsilon_S$, $\epsilon_L$, $\epsilon_H$:

"Null" model: $\epsilon_S = \epsilon_L = \epsilon_H$.
"Mixed" error model: $\epsilon_S \le \epsilon_L = \epsilon_H$.
"Asymmetric" error model: $\epsilon_S = \epsilon_L \le \epsilon_H$.
"General" error model: $\epsilon_S$, $\epsilon_L$, $\epsilon_H$.

The null error model assumes that the same error rate applies to all gambles, whereas the mixed error model permits a different error rate for mixed gambles than single-domain gambles. The asymmetric model allows a different error rate for type $\theta_{L^+L^-}$ than type $\theta_{H^+H^-}$. The empirical pattern observed in Study 1 of the main paper, $\%H > \max(\%H^+, \%H^-)$, as well as the hypothesized process, suggests that $\epsilon_H > \epsilon_L = \epsilon_S$ for the asymmetric model. The general model allows all three error rates to differ.

Note also that the indeterminate types, $\theta_{H^+L^-}$ and $\theta_{L^+H^-}$, reflect the error structures posited in each of these models. Thus, $P(H \succ L|\theta_{H^+L^-}) = \frac{1}{2}P(H \succ L|\theta_{H^+H^-}) + \frac{1}{2}P(H \succ L|\theta_{L^+L^-}) = \frac{1}{2}(1 - \epsilon_S) + \frac{1}{2}(\epsilon_H) = \frac{1}{2}(1 - \epsilon_S + \epsilon_H)$.

## EC.2. Implications of error models

We develop four implications of the null, mixed, and asymmetric error models. We assume the type structure depicted in Table EC.1. We also assume that all error rates are between 0 and $\frac{1}{2}$: $0 < \epsilon_S < \frac{1}{2}$, $0 < \epsilon_H < \frac{1}{2}$, and $0 \le \epsilon_L < \frac{1}{2}$.

We consider implications of each error model on: (i) choice percentages for single-domain gambles and mixed gambles; (ii) double matching violation rates; (iii) the relationship between error rates, $P(H|L^+L^-)$ and $P(L|H^+H^-)$; and (iv) the likelihood of choosing $H$ for the "indeterminate" patterns, $H^+L^-$ and $L^+H^-$. The derivations below are summarized in Table EC.2. Note that the

**Table EC.2 Qualitative implications of the null, mixed, and asymmetric error models. These implications are depicted graphically in Figures EC.1 through EC.3.**

| | Null error model | Mixed error model | Asymmetric error model |
|---|---|---|---|
| Restriction on error rates | $\epsilon_S = \epsilon_L = \epsilon_H$ | $\epsilon_H = \epsilon_L > \epsilon_S$ | $\epsilon_H > \epsilon_S = \epsilon_L$ |
| Choice percentages | $P(H)$ vs. $\frac{P(H^+)+P(H^-)}{2}$<br>• $=$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $=$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $=$, if $p_{H^+H^-} > p_{L^+L^-}$ | $P(H)$ vs. $\frac{P(H^+)+P(H^-)}{2}$<br>• $>$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $=$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $<$, if $p_{H^+H^-} > p_{L^+L^-}$ | $P(H)$ vs. $\frac{P(H^+)+P(H^-)}{2}$<br>• $>$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $>$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $>$, if $p_{H^+H^-} > p_{L^+L^-}$ |
| Double matching violation rates | $P(HL^+L^-)$ vs. $P(LH^+H^-)$<br>• $>$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $=$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $<$, if $p_{H^+H^-} > p_{L^+L^-}$ | $P(HL^+L^-)$ vs. $P(LH^+H^-)$<br>• $>$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $=$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $<$, if $p_{H^+H^-} > p_{L^+L^-}$ | $P(HL^+L^-)$ vs. $P(LH^+H^-)$<br>• $>$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $>$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $>$ then $<$, if $p_{H^+H^-} > p_{L^+L^-}$ |
| Error rates $P(H\|L^+L^-)$ and $P(L\|H^+H^-)$ | $P(H\|L^+L^-)$ vs. $P(L\|H^+H^-)$<br>• $<$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $=$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $>$, if $p_{H^+H^-} > p_{L^+L^-}$ | $P(H\|L^+L^-)$ vs. $P(L\|H^+H^-)$<br>• $<$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $=$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $>$, if $p_{H^+H^-} > p_{L^+L^-}$ | $P(H\|L^+L^-)$ vs. $P(L\|H^+H^-)$<br>• $<$ then $>$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $>$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $>$, if $p_{H^+H^-} > p_{L^+L^-}$ |
| Likelihood of choosing $H$ for "indeterminate" patterns | $P(H\|H^+L^-)$ and $P(H\|L^+H^-)$ vs. .5<br>• $<$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $=$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $>$, if $p_{H^+H^-} > p_{L^+L^-}$ | $P(H\|H^+L^-)$ and $P(H\|L^+H^-)$ vs. .5<br>• $<$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $=$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $>$, if $p_{H^+H^-} > p_{L^+L^-}$ | $P(H\|H^+L^-)$ and $P(H\|L^+H^-)$ vs. .5<br>• $<$ then $>$, if $p_{H^+H^-} < p_{L^+L^-}$<br>• $>$, if $p_{H^+H^-} = p_{L^+L^-}$<br>• $>$, if $p_{H^+H^-} > p_{L^+L^-}$ |

null and the mixed error models have identical qualitative implications for all measures except for choice percentages. Most critically, both models require a symmetry around $p_{HH} = p_{LL}$, whereas the asymmetric model does not.

### EC.2.1. Implications of null error model

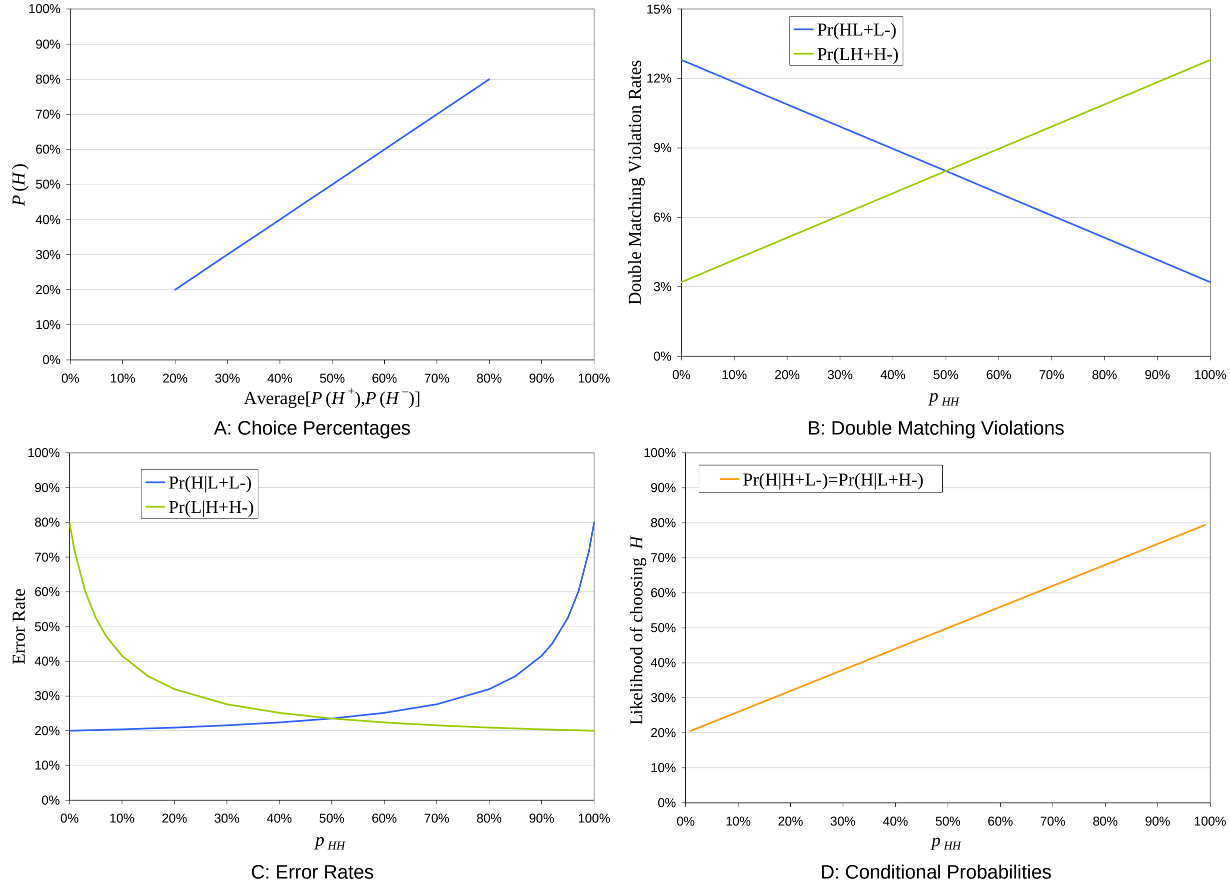
We derive the implications of the null error model on the four quantities described above. We denote $0 < \epsilon = \epsilon_S = \epsilon_L = \epsilon_H < .5$, the probability of an error, i.e., $\epsilon = P(H^+ \succ L^+|\theta_{L^+L^-}) = P(H^- \succ L^-|\theta_{L^+L^-}) = P(H \succ L|\theta_{L^+L^-})$, and $1-\epsilon = P(L^+ \succ H^+|\theta_{L^+L^-}) = P(L^- \succ H^-|\theta_{L^+L^-}) = P(L \succ H|\theta_{L^+L^-})$, etc.

We depict the results of our derivations graphically in Figure EC.1. To simplify the graphical presentation and clarify the implications, we assume that $p_{HL} = p_{LH} = 0$.

**EC.2.1.1. Choice percentages** First, we consider the implication of the null error model for choice percentages. Let $P(H)$, $P(H^+)$, and $P(H^-)$ be the expected choice percentages for mixed gamble $H$, gain gamble $H^+$, and loss gamble $H^-$, respectively. Then, $P(H^+) = (p_{HH} + p_{HL})(1-\epsilon) + (p_{LH} + p_{LL})(\epsilon)$, $P(H^-) = (p_{HH} + p_{LH})(1-\epsilon) + (p_{HL} + p_{LL})(\epsilon)$, and $P(H) = (p_{HH})(1-\epsilon) + \frac{1}{2}(p_{HL} + p_{LH}) + (p_{LL})(\epsilon)$. It is easy to see that $P(H) = \frac{P(H^+)+P(H^-)}{2}$.

Figure EC.1A plots the choice percentage, $P(H)$ as a function of the average of $P(H^+)$ and $P(H^-)$. Note that the minimum and maximum choice percentages are limited by the error rate, $\epsilon$. For example, if $p_{HH} = 1$, then $P(H^+) = P(H^-) = P(H) = 1-\epsilon$.

**Figure EC.1 Implications of null error model on choice percentages, double matching violation rates, error rates, and conditional probabilities.**




*Note.* To simplify the presentation, we assume that $p_{HL} = p_{LH} = 0$ and $\epsilon_S = \epsilon_H = \epsilon_L = .2$. Panel A illustrates expected choice percentages, $P(H)$, as a function of the average of $P(H^+)$ and $P(H^-)$. The null error model requires that $P(H)$ be identical to $\frac{P(H^+)+P(H^-)}{2}$. Panel B depicts double matching violation rates, $P(HL^+L^-)$ and $P(LH^+H^-)$, as a function of $p_{HH}$, the probability of type $\theta_{H^+H^-}$. The null error model requires that double matching violations $HL^+L^-$ exceed double matching violations $LH^+H^-$ if $p_{HH} < p_{LL}$, but that the reverse holds for $p_{HH} > p_{LL}$. Panel C shows error rates, $P(H|L^+L^-)$ and $P(L|H^+H^-)$, as a function of the frequency of $p_{HH}$. The null error model requires that error rate $P(L|H^+H^-)$ exceed $P(H|L^+L^-)$ for $p_{HH} < p_{LL}$, with the reverse holding for $p_{HH} > p_{LL}$. Panel D illustrates conditional probabilities, $P(H|H^+L^-)$ and $P(H|L^+H^-)$ as a function of $p_{HH}$. The null error model requires that the likelihood of choosing $H$ given one of the indeterminate patterns, $H^+L^-$ and $L^+H^-$, be less than $\frac{1}{2}$ if $p_{HH} < p_{LL}$ and greater than $\frac{1}{2}$ if $p_{HH} > p_{LL}$.

**EC.2.1.2. Double Matching Violation Rates** We show how the frequency of the two types of violations depends on the frequency of the various types. Recall that the two types of double matching violations $HL^+L^-$ and $LH^+H^-$ with frequencies denoted $P(HL^+L^-)$ and $P(LH^+H^-)$. Since,

$$\begin{aligned} P(HL^+L^-) &= P(HL^+L^-|\theta_{H^+H^-})P(\theta_{H^+H^-}) + P(HL^+L^-|\theta_{H^+L^-})P(\theta_{H^+L^-}) + \\ &\quad P(HL^+L^-|\theta_{L^+H^-})P(\theta_{L^+H^-}) + P(HL^+L^-|\theta_{L^+L^-})P(\theta_{L^+L^-}) \\ &= p_{HH}(1-\epsilon)(\epsilon^2) + \frac{1}{2}p_{HL}(\epsilon)(1-\epsilon) + \frac{1}{2}p_{LH}(\epsilon)(1-\epsilon) + p_{LL}(1-\epsilon)^2(\epsilon), \end{aligned}$$

and

$$P(LH^+H^-) = p_{HH}(1-\epsilon)^2(\epsilon) + \frac{1}{2}p_{HL}(\epsilon)(1-\epsilon) + \frac{1}{2}p_{LH}(\epsilon)(1-\epsilon) + p_{LL}(1-\epsilon)(\epsilon^2),$$

$P(HL^+L^-) > P(LH^+H^-)$ if $(p_{LL} - p_{HH})(1-\epsilon)(\epsilon)(1-2\epsilon) > 0$. Thus, if $\epsilon < .5$, $P(HL^+L^-) > P(LH^+H^-)$ if $p_{HH} < p_{LL}$; otherwise, $P(LH^+H^-) > P(HL^+L^-)$ if $p_{HH} > p_{LL}$.

Figure EC.1B plots the rates of double matching violations of the two types as a function of $p_{HH}$.

**EC.2.1.3. Error rates: $P(H|L^+L^-)$ and $P(L|H^+H^-)$** We next consider the implication for the null error model for the comparison of the error rates, $P(H|L^+L^-)$ and $P(L|H^+H^-)$. To show that these error rates depend on the probability of the different types, note that

$$P(H|L^+L^-) = P(H|\theta_{H^+H^-})P(\theta_{H^+H^-}|L^+L^-) + P(H|\theta_{H^+L^-})P(\theta_{H^+L^-}|L^+L^-) + P(H|\theta_{L^+H^-})P(\theta_{L^+H^-}|L^+L^-) + P(H|\theta_{L^+L^-})P(\theta_{H^+H^-}|L^+L^-).$$

Since $P(L^+L^-) = p_{HH}(\epsilon^2) + p_{HL}(\epsilon)(1-\epsilon) + p_{LH}(1-\epsilon)(\epsilon) + p_{LL}(1-\epsilon)^2$, $P(\theta_{H^+H^-}|L^+L^-) = \frac{p_{HH}(\epsilon^2)}{P(L^+L^-)}$, $P(\theta_{H^+L^-}|L^+L^-) = \frac{p_{HL}(\epsilon)(1-\epsilon)}{P(L^+L^-)}$, $P(\theta_{L^+H^-}|L^+L^-) = \frac{p_{LH}(1-\epsilon)(\epsilon)}{P(L^+L^-)}$, and $P(\theta_{L^+L^-}|L^+L^-) = \frac{p_{LL}(1-\epsilon)^2}{P(L^+L^-)}$, therefore,

$$P(H|L^+L^-) = \frac{p_{HH}(1-\epsilon)(\epsilon^2) + \frac{1}{2}p_{HL}(\epsilon)(1-\epsilon) + \frac{1}{2}p_{LH}(1-\epsilon)(\epsilon) + p_{LL}(\epsilon)(1-\epsilon)^2}{p_{HH}(\epsilon^2) + p_{HL}(\epsilon)(1-\epsilon) + p_{LH}(1-\epsilon)(\epsilon) + p_{LL}(1-\epsilon)^2}.$$

Similarly,

$$P(L|H^+H^-) = \frac{p_{HH}(\epsilon)(1-\epsilon)^2 + \frac{1}{2}p_{HL}(\epsilon)(1-\epsilon) + \frac{1}{2}p_{LH}(1-\epsilon)(\epsilon) + p_{LL}(1-\epsilon)(\epsilon^2)}{p_{HH}(1-\epsilon)^2 + p_{HL}(\epsilon)(1-\epsilon) + p_{LH}(1-\epsilon)(\epsilon) + p_{LL}(\epsilon^2)}.$$

It is easy to see that $P(H|L^+L^-) = P(L|H^+H^-)$ if $p_{HH} = p_{LL}$. To show that $P(H|L^+L^-) > P(L|H^+H^-)$ if $p_{HH} > p_{LL}$ and that $P(L|H^+H^-) > P(H|L^+L^-)$ if $p_{HH} < p_{LL}$, we simplify $P(H|L^+L^-) > P(L|H^+H^-)$ to get:

$$(p_{HH} - p_{LL})(1-2\epsilon)\left[(p_{HH} + p_{LL})(1-\epsilon)(\epsilon) + (p_{HL} + p_{LH})\left(\tfrac{1}{2} - (1-\epsilon)(\epsilon)\right)\right] > 0, \qquad \text{(EC.1)}$$

which holds if $p_{HH} > p_{LL}$ and $\epsilon < .5$. Reversing the sign of Eq. (1) gives $P(L|H^+H^-) > P(H|L^+L^-)$ if $p_{HH} < p_{LL}$.

Figure EC.1C plots $P(H|L^+L^-)$ and $P(L|H^+H^-)$ as a function of $p_{HH}$, assuming $\epsilon = .2$.

**EC.2.1.4. Likelihood of choosing $H$ for "indeterminate" patterns** Finally, we consider the likelihood of choosing $H$ given the "indeterminate" patterns, $H^+L^-$ and $L^+H^-$. Note that

$$P(H|H^+L^-) = P(H|\theta_{H^+H^-})P(\theta_{H^+H^-}|H^+L^-) + P(H|\theta_{H^+L^-})P(\theta_{H^+L^-}|H^+L^-) + P(H|\theta_{L^+H^-})P(\theta_{L^+H^-}|H^+L^-) + P(H|\theta_{L^+L^-})P(\theta_{H^+H^-}|H^+L^-).$$

Then, $P(H^+L^-) = p_{HH}(1-\epsilon)(\epsilon) + p_{HL}(1-\epsilon)^2 + p_{LH}(\epsilon^2) + p_{LL}(1-\epsilon)(\epsilon)$, and, therefore,

$$P(H|H^+L^-) = \frac{p_{HH}(1-\epsilon)^2(\epsilon) + \frac{1}{2}p_{HL}(1-\epsilon)^2 + \frac{1}{2}p_{LH}(\epsilon^2) + p_{LL}(\epsilon^2)(1-\epsilon)}{p_{HH}(1-\epsilon)(\epsilon) + p_{HL}(1-\epsilon)^2 + p_{LH}(\epsilon^2) + p_{LL}(1-\epsilon)(\epsilon)}.$$

Thus, $P(H|H^+L^-) > \frac{1}{2}$ if $(p_{HH} - p_{LL})(1-\epsilon)(\epsilon)(1-2\epsilon) > 0$, which holds if $\epsilon < .5$ and $p_{HH} > p_{LL}$. Reversing the sign, we get $P(H|H^+L^-) < \frac{1}{2}$ if $p_{HH} < p_{LL}$, provided that $\epsilon < .5$. A similar manipulation shows that $P(H|L^+H^-) > \frac{1}{2}$ if $\epsilon < .5$ and $p_{HH} > p_{LL}$, whereas $P(H|L^+H^-) < \frac{1}{2}$ if $\epsilon < .5$ and $p_{HH} < p_{LL}$.

Figure EC.1D plots $P(H|H^+L^-)$ and $P(H|L^+H^-)$ as a function of $p_{HH}$, assuming $\epsilon = .2$.

### EC.2.2. Implications of mixed error model

We next consider the implications of the mixed error model for the measures analyzed in the previous subsection. Again, we examine how these measures vary as a function of the probability of the four types in Table EC.1. Recall that the mixed error model allows a different error rate to govern single-domain gambles and mixed gambles. We denote $\epsilon_M = \epsilon_H = \epsilon_L < .5$ the error rate for mixed gambles. Our introductory example is consistent with $\epsilon_S < \epsilon_M$.

**EC.2.2.1. Choice percentages** We begin by considering the implication of the mixed error model for choice percentages, $P(H)$, $P(H^+)$, and $P(H^-)$. Since, $P(H^+) = (p_{HH} + p_{HL})(1 - \epsilon_S) + (p_{LH} + p_{LL})(\epsilon_S)$, $P(H^-) = (p_{HH} + p_{LH})(1 - \epsilon_S) + (p_{HL} + p_{LL})(\epsilon_S)$, and $P(H) = (p_{HH})(1 - \epsilon_M) + \frac{1}{2}(p_{HL} + p_{LH}) + (p_{LL})(\epsilon_M)$, $P(H) > \frac{P(H^+)+P(H^-)}{2} = (p_{HH})(1 - \epsilon_S) + \frac{1}{2}(p_{HL} + p_{LH}) + (p_{LL})(\epsilon_S)$ if $\epsilon_M > \epsilon_S$ and $p_{HH} < p_{LL}$, whereas $P(H) < \frac{P(H^+)+P(H^-)}{2}$ if $\epsilon_M > \epsilon_S$ and $p_{HH} > p_{LL}$. Figure EC.2A plots the choice percentage, $P(H)$ as a function of the average of $P(H^+)$ and $P(H^-)$, assuming $\epsilon_S = .2$ and $\epsilon_M = .3$.

Figure EC.2A illustrates that $P(H)$ is regressive as a function of the average of $P(H^+)$ and $P(H^-)$.

**EC.2.2.2. Double Matching Violation Rates** To show that the frequency of double matching violations of the two types depends on the frequency of the various types, we compare

$$P(HL^+L^-) = p_{HH}(1 - \epsilon_M)(\epsilon_S^2) + \tfrac{1}{2}p_{HL}(\epsilon)(1 - \epsilon_S) + \tfrac{1}{2}p_{LH}(\epsilon_S)(1 - \epsilon_S) + p_{LL}(\epsilon_M)(1 - \epsilon_S)^2$$

with

$$P(LH^+H^-) = p_{HH}(\epsilon_M)(1 - \epsilon_S)^2 + \tfrac{1}{2}p_{HL}(\epsilon_S)(1 - \epsilon_S) + \tfrac{1}{2}p_{LH}(\epsilon_S)(1 - \epsilon_S) + p_{LL}(1 - \epsilon_M)(\epsilon_S^2).$$

Simplifying $P(HL^+L^-) > P(LH^+H^-)$, we get $(p_{HH} - p_{LL})\left(\epsilon_S^2(1 - 2\epsilon_M) - \epsilon_M(1 - 2\epsilon_S)\right) > 0$. Note that if $\epsilon_S < \epsilon_M$, then $\epsilon_S^2(1 - 2\epsilon_M) - \epsilon_M(1 - 2\epsilon_S) < 0$, since $\epsilon_S^2 < \epsilon_M$. Thus, $P(LH^+H^-) > P(HL^+L^-)$ if $p_{HH} < p_{LL}$ and $P(HL^+L^-) > P(LH^+H^-)$ if $p_{HH} > p_{LL}$.

Figure EC.2B plots the rates of double matching violations of the two types as a function of $p_{HH}$, assuming $\epsilon_S = .2$ and $\epsilon_M = .3$.

**EC.2.2.3. Error rates: $P(H|L^+L^-)$ and $P(L|H^+H^-)$** The analysis of the error rates, $P(H|L^+L^-)$ and $P(L|H^+H^-)$, under the mixed model is nearly identical to the analysis under the null model. The only change is that a different error rate applies to mixed gambles. Thus,

$$P(H|L^+L^-) = \frac{p_{HH}(1 - \epsilon_M)(\epsilon_S^2) + \frac{1}{2}p_{HL}(\epsilon_S)(1 - \epsilon_S) + \frac{1}{2}p_{LH}(1 - \epsilon_S)(\epsilon_S) + p_{LL}(\epsilon_M)(1 - \epsilon_S)^2}{p_{HH}(\epsilon_S^2) + p_{HL}(\epsilon_S)(1 - \epsilon_S) + p_{LH}(1 - \epsilon_S)(\epsilon_S) + p_{LL}(1 - \epsilon_S)^2},$$

and

$$P(L|H^+H^-) = \frac{p_{HH}(\epsilon_M)(1 - \epsilon_S)^2 + \frac{1}{2}p_{HL}(\epsilon_S)(1 - \epsilon_S) + \frac{1}{2}p_{LH}(1 - \epsilon_S)(\epsilon_S) + p_{LL}(1 - \epsilon_M)(\epsilon_S^2)}{p_{HH}(1 - \epsilon_S)^2 + p_{HL}(\epsilon_S)(1 - \epsilon_S) + p_{LH}(1 - \epsilon_S)(\epsilon_S) + p_{LL}(\epsilon_S^2)}.$$

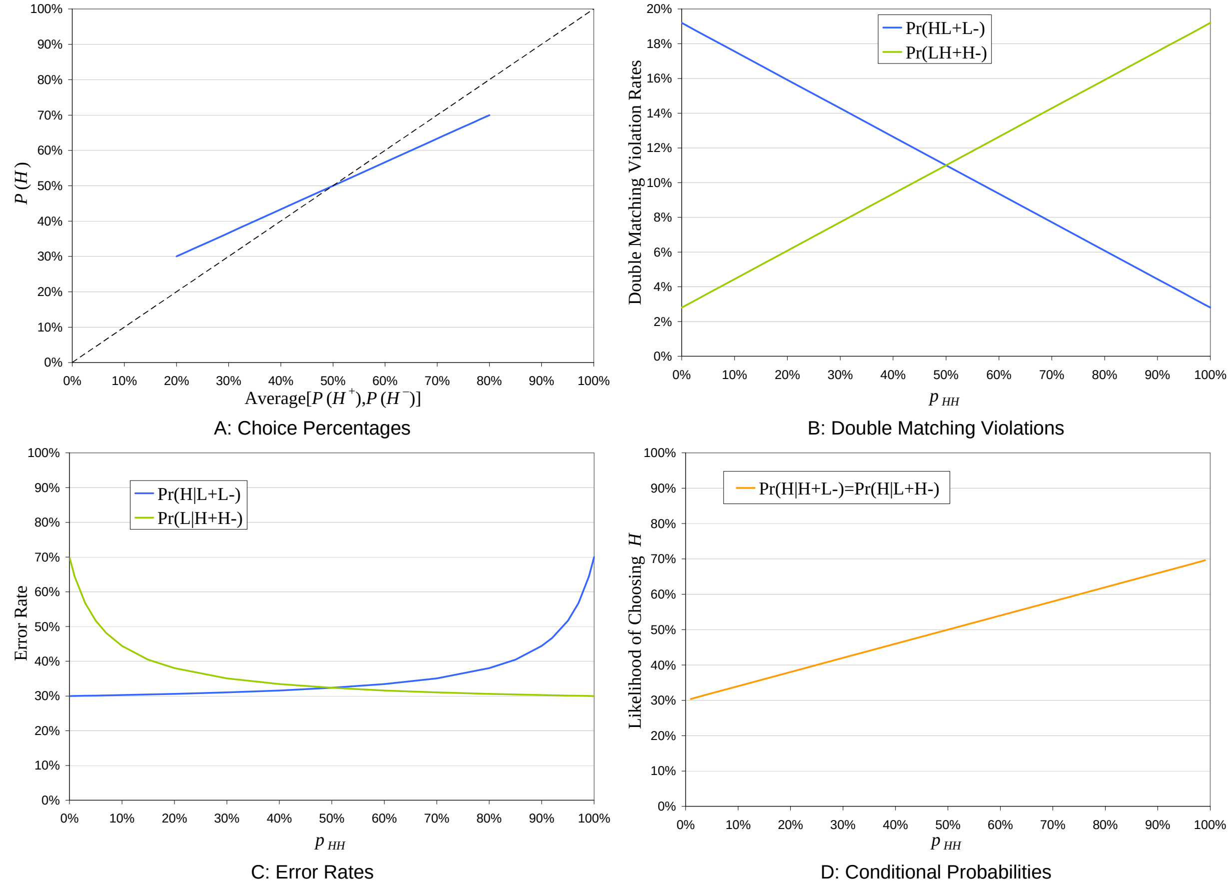
Simplifying $P(H|L^+L^-) > P(L|H^+H^-)$, we get

$$(p_{HH} - p_{LL})(\epsilon_S)(1 - \epsilon_S)\times$$
$$\left((p_{HH} + p_{LL})(1 - 2\epsilon_M)(1 - \epsilon_S)(\epsilon_S) + (p_{HL} + p_{LH})\left[\tfrac{1}{2}(1 - 2\epsilon_S) + (1 - \epsilon_M)(\epsilon_S^2) - \epsilon_M(1 - \epsilon_S)^2\right]\right) > 0,$$

where $\frac{1}{2}(1 - 2\epsilon_S) + (1 - \epsilon_M)(\epsilon_S^2) - \epsilon_M(1 - \epsilon_S)^2 \geq 0$ if $\epsilon_M < .5$ and $\epsilon_S < .5$. Thus, $P(H|L^+L^-) > P(L|H^+H^-)$ if $p_{HH} > p_{LL}$, with the reverse holding if $p_{HH} < p_{LL}$.

Figure EC.2C plots $P(H|L^+L^-)$ and $P(L|H^+H^-)$ as a function of $p_{HH}$, assuming $\epsilon_S = .2$ and $\epsilon_M = .3$.

**Figure EC.2 Implications of mixed error model on choice percentages, double matching violation rates, error rates, and conditional probabilities.**




*Note.* To simplify the presentation, we assume that $p_{HL} = p_{LH} = 0$ and $\epsilon_S = .2$ and $\epsilon_M = \epsilon_H = \epsilon_L = .3$. Panel A illustrates choice percentages, $P(H)$, as a function of the average of $P(H^+)$ and $P(H^-)$. The mixed error model requires that $P(H)$ exceed $\frac{P(H^+)+P(H^-)}{2}$ if $p_{HH} < p_{LL}$, but the reverse hold for $p_{HH} > p_{LL}$. Panel B depicts double matching violation rates, $P(HL^+L^-)$ and $P(LH^+H^-)$, as a function of $p_{HH}$, the probability of type $\theta_{H^+H^-}$. The mixed error model requires that double matching violations $HL^+L^-$ exceed double matching violations $LH^+H^-$ if $p_{HH} < p_{LL}$, but that the reverse holds for $p_{HH} > p_{LL}$. Panel C shows error rates, $P(H|L^+L^-)$ and $P(L|H^+H^-)$, as a function of the frequency of $p_{HH}$. The mixed error model requires that error rate $P(L|H^+H^-)$ exceed $P(H|L^+L^-)$ for $p_{HH} < p_{LL}$, with the reverse holding for $p_{HH} > p_{LL}$. Panel D illustrates conditional probabilities, $P(H|H^+L^-)$ and $P(H|L^+H^-)$ as a function of $p_{HH}$. The mixed error model requires that the likelihood of choosing $H$ given one of the indeterminate patterns, $H^+L^-$ and $L^+H^-$, be less than $\frac{1}{2}$ if $p_{HH} < p_{LL}$ and greater than $\frac{1}{2}$ if $p_{HH} > p_{LL}$.

**EC.2.2.4. Likelihood of choosing $H$ for "indeterminate" patterns** The logic of deriving restrictions on the likelihood of choosing $H$ given the "indeterminate" patterns, $H^+L^-$ and $L^+H^-$, is identical under the mixed error model as under the null error model. Since

$$P(H|H^+L^-) = \frac{p_{HH}(1-\epsilon_M)(1-\epsilon_S)(\epsilon_S) + \frac{1}{2}p_{HL}(1-\epsilon_S)^2 + \frac{1}{2}p_{LH}(\epsilon_S^2) + p_{LL}(\epsilon_M)(\epsilon_S)(1-\epsilon_S)}{p_{HH}(1-\epsilon_S)(\epsilon_S) + p_{HL}(1-\epsilon_S)^2 + p_{LH}(\epsilon_S^2) + p_{LL}(1-\epsilon_S)(\epsilon_S)},$$

$P(H|H^+L^-) >$ (resp. $<$) $\frac{1}{2}$ if $(p_{HH} - p_{LL})(1-\epsilon_S)(\epsilon_S)(1-2\epsilon_M) >$ (resp. $<$) $0$, which holds if $\epsilon_S < .5$, $\epsilon_M < .5$ and $p_{HH} >$ (resp. $<$) $p_{LL}$. A similar manipulation shows that $P(H|L^+H^-) >$ (resp. $<$) $\frac{1}{2}$ if $\epsilon_S < .5$ and $p_{HH} >$ (resp. $<$) $p_{LL}$.

Figure EC.2D plots $P(H|H^+L^-)$ and $P(H|L^+H^-)$ as a function of $p_{HH}$, assuming $\epsilon_S = .2$ and $\epsilon_M = .3$.

### EC.2.3. Implications of asymmetric model

We next show that the asymmetric error model has different implications on the measures considered than either the null error model or the mixed error model. The null and mixed error models all require a symmetry around $p_{HH} = p_{LL}$, whereas the asymmetric error model does not.

Recall that Problems 1 through 3 suggested a process in which decision makers were less sensitive to probability differences when choosing among mixed gambles than when choosing among single-domain gambles. This process applied to our gambles suggests that a greater tendency to choose $H$ over $L$, than $H^+$ over $L^+$ or $H^-$ over $L^-$. The asymmetric error model captures this choice pattern by requiring that the error rate for $\theta_{L^+L^-}$ types choosing $H$ be higher the other error rates: $\epsilon_H > \epsilon_S = \epsilon_L$. Throughout this section, we let $\epsilon_{\bar{H}} = \epsilon_S = \epsilon_L$.

**EC.2.3.1. Choice percentages** We begin by considering the implications of the asymmetric error model for the choice percentages, $P(H)$, $P(H^+)$, and $P(H^-)$: $P(H^+) = (p_{HH} + p_{HL})(1 - \epsilon_{\bar{H}}) + (p_{LH} + p_{LL})(\epsilon_{\bar{H}})$, $P(H^-) = (p_{HH} + p_{LH})(1 - \epsilon_{\bar{H}}) + (p_{HL} + p_{LL})(\epsilon_{\bar{H}})$, and $P(H) = (p_{HH})(1 - \epsilon_{\bar{H}}) + \frac{1}{2}(1 - (\epsilon_{\bar{H}} - \epsilon_H))(p_{HL} + p_{LH}) + (p_{LL})(\epsilon_H)$. Then, $P(H) > \frac{P(H^+)+P(H^-)}{2}$ if $(p_{HH})(1 - \epsilon_{\bar{H}}) + \frac{1}{2}(1 - (\epsilon_{\bar{H}} - \epsilon_H))(p_{HL} + p_{LH}) + (p_{LL})(\epsilon_H) > (p_{HH})(1 - \epsilon_{\bar{H}}) + \frac{1}{2}(p_{HL} + p_{LH}) + (p_{LL})(\epsilon_{\bar{H}})$, or $(\epsilon_H - \epsilon_{\bar{H}})\left[\frac{1}{2}(p_{HL} + p_{LH}) + p_{LL}\right] > 0$, which holds if $\epsilon_H > \epsilon_{\bar{H}}$.

Figure EC.3A plots $P(H)$ as a function of the average of $P(H^+)$ and $P(H^-)$, assuming $\epsilon_{\bar{H}} = .2$ and $\epsilon_H = .3$.

**EC.2.3.2. Double Matching Violation Rates** We next consider the implications of the asymmetric error model on the frequency of double matching violations. We compare the probabilities of the two types of double matching violations,

$$P(HL^+L^-) = p_{HH}(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}}^2) + \tfrac{1}{2}p_{HL}(1-(\epsilon_{\bar{H}} - \epsilon_H))(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}}) + \tfrac{1}{2}p_{LH}(1-(\epsilon_{\bar{H}} - \epsilon_H))(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}}) + p_{LL}(1-\epsilon_{\bar{H}})^2(\epsilon_H)$$

and

$$P(LH^+H^-) = p_{HH}(1-\epsilon_{\bar{H}})^2(\epsilon_{\bar{H}}) + \tfrac{1}{2}p_{HL}(1-(\epsilon_H - \epsilon_{\bar{H}}))(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}}) + \tfrac{1}{2}p_{LH}(1-(\epsilon_H - \epsilon_{\bar{H}}))(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}}) + p_{LL}(1-\epsilon_H)(\epsilon_{\bar{H}}^2).$$

Then, $P(HL^+L^-) > P(LH^+H^-)$ if

$$p_{HH}(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}})(2\epsilon_{\bar{H}} - 1) + \tfrac{1}{2}p_{HL}(2\epsilon_H - 2\epsilon_{\bar{H}})(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}}) + \tfrac{1}{2}p_{LH}(2\epsilon_H - 2\epsilon_{\bar{H}})(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}}) + p_{LL}\left[(1-\epsilon_{\bar{H}})^2(\epsilon_H) - (1-\epsilon_H)(\epsilon_{\bar{H}}^2)\right] > 0.$$

Letting $p_{HH} = p_{LL}$, we get

$$p_{HH}\left[(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}})(2\epsilon_{\bar{H}} - 1) + (1-\epsilon_{\bar{H}})^2(\epsilon_H) - (1-\epsilon_H)(\epsilon_{\bar{H}}^2)\right] + \tfrac{1}{2}(p_{HL} + p_{LH})(2\epsilon_H - 2\epsilon_{\bar{H}})(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}}) > 0,$$

or

$$p_{HH}\left[(\epsilon_H - \epsilon_{\bar{H}})(2\epsilon_{\bar{H}}^2 - 2\epsilon_{\bar{H}} + 1)\right] + \tfrac{1}{2}(p_{HL} + p_{LH})(2\epsilon_H - 2\epsilon_{\bar{H}})(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}}) > 0,$$

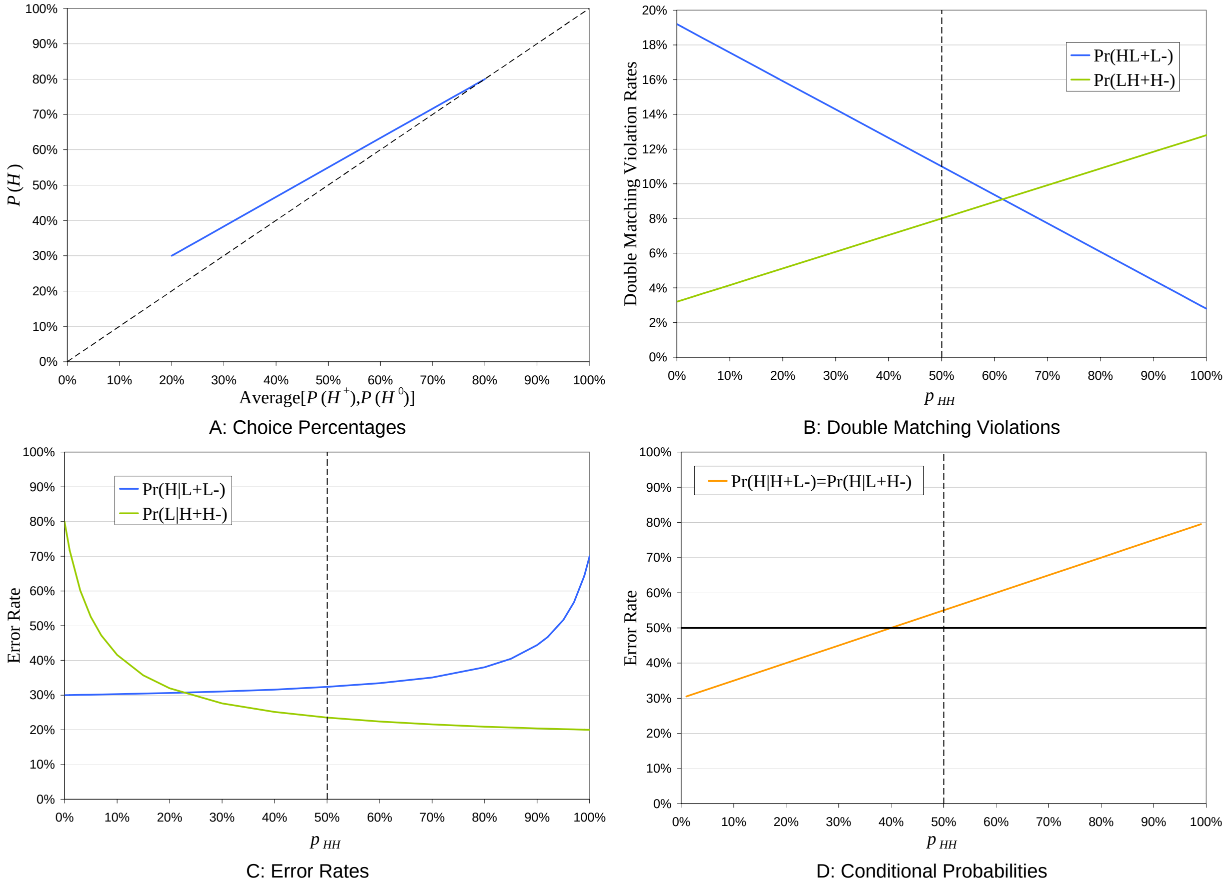
which holds if $\epsilon_H > \epsilon_{\bar{H}}$. To show that $P(HL^+L^-) > P(LH^+H^-)$ if $p_{HH} > p_{LL}$, we substitute $p_{LL} = 1 - p_{HH} - p_{HL} - p_{LH}$. It suffices to show that

$$\frac{dP(HL^+L^-)}{dp_{HH}} - \frac{P(LH^+H^-)}{dp_{HH}} = (\epsilon_H - \epsilon_{\bar{H}})\left[(1-\epsilon_{\bar{H}})^2 + \epsilon_{\bar{H}}^2\right] > 0,$$

which holds for $\epsilon_H > \epsilon_{\bar{H}}$.

Figure EC.3B plots the rates of double matching violations of the two types as a function of $p_{HH}$, assuming $\epsilon_{\bar{H}} = .2$ and $\epsilon_H = .3$.

**Figure EC.3 Implications of asymmetric error model on choice percentages, double matching violation rates, error rates, and conditional probabilities.**




*Note.* To simplify the presentation, we assume that $p_{HL} = p_{LH} = 0$ and $\epsilon_S = \epsilon_L = .2$ and $\epsilon_H = .3$. Panel A illustrates choice percentages, $P(H)$, as a function of the average of $P(H^+)$ and $P(H^-)$. The asymmetric error model requires $P(H)$ exceed $\frac{P(H^+)+P(H^-)}{2}$ for all $p_{HH}$. Panel B depicts double matching violation rates, $P(HL^+L^-)$ and $P(LH^+H^-)$, as a function of $p_{HH}$, the probability of type $\theta_{H^+H^-}$. The asymmetric error model implies an asymmetry in double matching violations. Double matching violation $HL^+L^-$ is more prevalent than double matching violations $LH^+H^-$ for $p_{HH} = p_{LL}$, with the reverse holding for some $p_{HH}$ larger than $p_{LL}$. Panel C shows error rates, $P(H|L^+L^-)$ and $P(L|H^+H^-)$, as a function of the frequency of $p_{HH}$. The asymmetric error model implies an asymmetry in error rates: error rate, $P(H|L^+L^-)$, exceeds error rate, $P(L|H^+H^-)$, for $p_{HH} = p_{LL}$, with the reverse holding for some $p_{HH}$ smaller than $p_{LL}$. Panel D illustrates conditional probabilities, $P(H|H^+L^-)$ and $P(H|L^+H^-)$ as a function of $p_{HH}$. The asymmetric error model implies an asymmetry in the likelihood of choosing $H$ given an indeterminate pattern: conditional probabilities $P(H|H^+L^-)$ and $P(H|L^+H^-)$ exceed $\frac{1}{2}$ for $p_{HH} = p_{LL}$, with the reverse holding for some $p_{HH}$ smaller than $p_{LL}$.

**EC.2.3.3. Error rates: $P(H|L^+L^-)$ and $P(L|H^+H^-)$** Note that $P(H|\theta_{H^+L^-}) = \frac{1}{2}P(H|\theta_{H^+H^-}) + \frac{1}{2}P(H|\theta_{L^+L^-}) = \frac{1}{2}(1-\epsilon_{\bar{H}}) + \frac{1}{2}(\epsilon_H) = \frac{1}{2}(1-(\epsilon_{\bar{H}}-\epsilon_H))$. Similarly, $P(L|\theta_{H^+L^-}) = \frac{1}{2}P(L|\theta_{H^+H^-}) + \frac{1}{2}P(L|\theta_{L^+L^-}) = \frac{1}{2}(\epsilon_{\bar{H}}) + \frac{1}{2}(1-\epsilon_H) = \frac{1}{2}(1-(\epsilon_H-\epsilon_{\bar{H}}))$. Therefore,

$$P(H|L^+L^-) = \frac{p_{HH}(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}}^2) + \frac{1}{2}\left(1-(\epsilon_{\bar{H}}-\epsilon_H)\right)(p_{HL}+p_{LH})(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}}) + p_{LL}(\epsilon_H)(1-\epsilon_{\bar{H}})^2}{p_{HH}(\epsilon_{\bar{H}}^2) + p_{HL}(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}}) + p_{LH}(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}}) + p_{LL}(1-\epsilon_{\bar{H}})^2},$$

and

$$P(L|H^+H^-) = \frac{p_{HH}(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}})^2 + \frac{1}{2}\left(1-(\epsilon_H-\epsilon_{\bar{H}})\right)(p_{HL}+p_{LH}) + p_{LL}(1-\epsilon_H)(\epsilon_{\bar{H}}^2)}{p_{HH}(1-\epsilon_{\bar{H}})^2 + p_{HL}(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}}) + p_{LH}(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}}) + p_{LL}(\epsilon_{\bar{H}}^2)}.$$

We show that $P(H|L^+L^-) > P(L|H^+H^-)$ if $p_{HH} = p_{LL}$. Letting $p_{HH} = p_{LL}$, we simplify $P(H|L^+L^-) > P(L|H^+H^-)$ to get:

$$\begin{aligned} & (p_{HH}{}^2)\left[(1-\epsilon_{\bar{H}})^2(\epsilon_{\bar{H}})^2(2\epsilon_H - 2\epsilon_{\bar{H}}) + (1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}})(\epsilon_{\bar{H}}^3 - (1-\epsilon_{\bar{H}})^3) + (\epsilon_H)(1-\epsilon_{\bar{H}})^4 - (1-\epsilon_H)(\epsilon_{\bar{H}}^4)\right] \\ + \quad & (p_{HL}+p_{LH})(p_{HH})(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}})\left[(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}})(2\epsilon_{\bar{H}}-1) + (\epsilon_H)(1-\epsilon_{\bar{H}})^2 - (1-\epsilon_H)(\epsilon_{\bar{H}}^2)\right] \\ + \quad & \left(\tfrac{1}{2}\right)(2\epsilon_H - 2\epsilon_{\bar{H}})\left[(p_{HL}+p_{LH})(p_{HH})\left((1-\epsilon_{\bar{H}})^3(\epsilon_{\bar{H}})^1 + (1-\epsilon_{\bar{H}})^1(\epsilon_{\bar{H}})^3\right) + (p_{HL}+p_{LH})^2(1-\epsilon_{\bar{H}})^2(\epsilon_{\bar{H}})^2\right] > 0, \end{aligned}$$

which after manipulation yields,

$$\begin{aligned} & (p_{HH}{}^2)(\epsilon_H - \epsilon_{\bar{H}})(2\epsilon_{\bar{H}}^2 - 2\epsilon_{\bar{H}} + 1)^2 \\ + \quad & (p_{HL}+p_{LH})(p_{HH})(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}})(\epsilon_H - \epsilon_{\bar{H}})(2\epsilon_{\bar{H}}^2 - 2\epsilon_{\bar{H}} + 1) \\ + \quad & \left(\tfrac{1}{2}\right)(2\epsilon_H - 2\epsilon_{\bar{H}})\left[(p_{HL}+p_{LH})(p_{HH})\left((1-\epsilon_{\bar{H}})^3(\epsilon_{\bar{H}})^1 + (1-\epsilon_{\bar{H}})^1(\epsilon_{\bar{H}})^3\right) + (p_{HL}+p_{LH})^2(1-\epsilon_{\bar{H}})^2(\epsilon_{\bar{H}})^2\right] > 0. \end{aligned}$$

which holds if $\epsilon_H > \epsilon_{\bar{H}}$ (since $2\epsilon_{\bar{H}}^2 - 2\epsilon_{\bar{H}} + 1 > 0$ if $\epsilon_{\bar{H}} < .5$).

Figure EC.3C plots $P(H|L^+L^-)$ and $P(L|H^+H^-)$ as a function of $p_{HH}$, assuming $\epsilon_{\bar{H}} = .2$ and $\epsilon_H = .3$.

**EC.2.3.4. Likelihood of choosing $H$ for "indeterminate" patterns** Finally, we derive restrictions on the likelihood of choosing $H$ given the "indeterminate" patterns, $H^+L^-$ and $L^+H^-$. Since $P(H|H^+L^-) =$

$$\frac{p_{HH}(1-\epsilon_{\bar{H}})^2(\epsilon_{\bar{H}}) + \frac{1}{2}p_{HL}(1-(\epsilon_{\bar{H}}-\epsilon_H))(1-\epsilon_{\bar{H}})^2 + \frac{1}{2}p_{LH}(1-(\epsilon_{\bar{H}}-\epsilon_H))(\epsilon_{\bar{H}}^2) + p_{LL}(\epsilon_H)(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}})}{p_{HH}(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}}) + p_{HL}(1-\epsilon_{\bar{H}})^2 + p_{LH}(\epsilon_{\bar{H}}^2) + p_{LL}(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}})},$$

$P(H|H^+L^-) > \frac{1}{2}$ if

$$p_{HH}(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}})(1-2\epsilon_{\bar{H}}) + p_{HL}(\epsilon_H - \epsilon_{\bar{H}})(1-\epsilon_{\bar{H}})^2 + p_{LH}(\epsilon_H - \epsilon_{\bar{H}})(\epsilon_{\bar{H}}^2) + p_{LL}(2\epsilon_H - 1)(\epsilon_{\bar{H}})(1-\epsilon_{\bar{H}}) > 0.$$

To show that $P(H|H^+L^-) > \frac{1}{2}$ if $p_{HH} = p_{LL}$, we substitute $p_{HH} = p_{LL}$ in the previous expression:

$$p_{HH}(1-\epsilon_{\bar{H}})(\epsilon_{\bar{H}})(2\epsilon_H - 2\epsilon_{\bar{H}}) + p_{HL}(\epsilon_H - \epsilon_{\bar{H}})(1-\epsilon_{\bar{H}})^2 + p_{LH}(\epsilon_H - \epsilon_{\bar{H}})(\epsilon_{\bar{H}}^2) > 0,$$

which holds if $\epsilon_H > \epsilon_{\bar{H}}$. A similar manipulation shows that $P(H|L^+H^-) > \frac{1}{2}$ if $p_{HH} = p_{LL}$.

Figure EC.3D plots $P(H|H^+L^-)$ and $P(H|L^+H^-)$ as a function of $p_{HH}$, assuming $\epsilon_{\bar{H}} = .2$ and $\epsilon_H = .3$.

## EC.3. Empirical Data and Implications of Error Models for Study 1

In this section, we analyze the empirical data from Study 1 of the main paper with respect to the four implications derived in the last section for each of the three error models. Most of the empirical implications from the previous section were functions of the relative frequency of types $\theta_{H^+H^-}$ and $\theta_{L^+L^-}$. Of course, the frequency of types is not observable. Therefore, we present the empirical data as a function of the average of $\%H^+$ and $\%H^-$, the percentage of participants choosing $H^+$ over $L^-$, and $H^-$ over $L^-$, respectively. To show that this analysis is equivalent in expectation, we need to show that $p_{HH} > p_{LL}$ if and only if $\frac{P(H^+)+P(H^-)}{2} > \frac{1}{2}$. Noting that $\frac{P(H^+)+P(H^-)}{2} = p_{HH}(1 - \epsilon_S) + \frac{1}{2}(p_{HL} + p_{LH}) + p_{LL}(\epsilon_S)$ for all 3 error models, we substitute $p_{HL} + p_{LH} = 1 - p_{HH} - p_{LL}$ to get $\frac{P(H^+)+P(H^-)}{2} = \frac{1}{2} + (p_{HH} - p_{LL})(\frac{1}{2} - \epsilon_S)$, which exceeds $\frac{1}{2}$ if and only if $p_{HH} > p_{LL}$.

The four measures of double matching violations are shown in Table EC.3. The first three measures are repeated from the main paper. The measures for the likelihood of choosing $H$ for indeterminate patterns is not found in the main text.

**Table EC.3 Measures of double matching violations for 34 tests of double matching (Study 1)**

| | Choice Percentages | | | | Double Matching Violations | | Double Matching Error Rates | | Likelihood of Choosing $H$ for indeterminate patterns | |
|---|---|---|---|---|---|---|---|---|---|---|
| Test | $\%H$ | $\%H^+$ | $\%H^-$ | $\frac{\%H^+ + \%H^-}{2}$ | $\%HL^+L^-$ | $\%LH^+H^-$ | $P(H\|L^+L^-)$ | $P(L\|H^+H^-)$ | $P(H\|H^+L^-)$ | $P(H\|L^+H^-)$ |
| 1 | 22.2% | 9.9% | 17.3% | 13.6% | 12.3% | 1.2% | 16.4% | 50.0% | 50.0% | 33.3% |
| 2 | 21.0% | 17.3% | 14.8% | 16.1% | 6.2% | 2.5% | 8.6% | 66.7% | 54.5% | 55.6% |
| 3 | 28.3% | 11.9% | 20.3% | 16.1% | 11.9% | 0.0% | 16.7% | 0.0% | 40.0% | 60.0% |
| 4 | 33.3% | 18.1% | 22.2% | 20.2% | 16.7% | 2.8% | 25.5% | 50.0% | 33.3% | 58.3% |
| 5 | 43.1% | 20.8% | 25.0% | 22.9% | 25.0% | 6.9% | 37.5% | 55.6% | 83.3% | 44.4% |
| 6 | 51.4% | 26.4% | 25.0% | 25.7% | 23.6% | 4.2% | 41.5% | 50.0% | 61.5% | 75.0% |
| 7 | 51.9% | 14.8% | 37.0% | 25.9% | 28.4% | 2.5% | 50.0% | 28.6% | 20.0% | 56.5% |
| 8 | 48.3% | 16.7% | 46.7% | 31.7% | 21.7% | 6.7% | 43.3% | 50.0% | 0.0% | 60.0% |
| 9 | 58.3% | 16.7% | 55.0% | 35.9% | 18.3% | 3.3% | 45.8% | 28.6% | 33.3% | 69.2% |
| 10 | 51.3% | 47.5% | 27.5% | 37.5% | 17.5% | 6.3% | 41.2% | 35.7% | 62.5% | 37.5% |
| 11 | 54.2% | 33.3% | 44.4% | 38.9% | 15.3% | 6.9% | 45.8% | 62.5% | 56.3% | 66.7% |
| 12 | 59.3% | 42.0% | 35.8% | 38.9% | 16.0% | 2.5% | 43.3% | 16.7% | 77.3% | 47.1% |
| 13 | 51.7% | 38.3% | 41.7% | 40.0% | 11.7% | 5.0% | 30.4% | 27.3% | 66.7% | 57.1% |
| 14 | 57.6% | 33.9% | 47.5% | 40.7% | 15.3% | 3.4% | 56.3% | 40.0% | 73.3% | 47.8% |
| 15 | 51.3% | 51.3% | 32.5% | 41.9% | 10.0% | 5.0% | 29.6% | 28.6% | 59.3% | 58.3% |
| 16 | 65.0% | 42.5% | 42.5% | 42.5% | 15.0% | 1.3% | 46.2% | 7.1% | 80.0% | 55.0% |
| 17 | 58.8% | 47.5% | 41.3% | 44.4% | 16.3% | 8.8% | 44.8% | 35.0% | 61.1% | 76.9% |
| 18 | 71.7% | 51.7% | 41.7% | 46.7% | 16.7% | 1.7% | 62.5% | 8.3% | 63.2% | 76.9% |
| 19 | 57.5% | 55.0% | 43.8% | 49.4% | 11.3% | 5.0% | 42.9% | 20.0% | 58.3% | 46.7% |
| 20 | 40.0% | 46.7% | 53.3% | 50.0% | 5.0% | 6.7% | 27.3% | 36.4% | 41.2% | 33.3% |
| 21 | 71.3% | 58.8% | 47.5% | 53.2% | 11.3% | 1.3% | 45.0% | 4.0% | 77.3% | 53.8% |
| 22 | 63.3% | 58.3% | 48.3% | 53.3% | 10.0% | 8.3% | 54.5% | 33.3% | 50.0% | 85.7% |
| 23 | 70.0% | 58.8% | 50.0% | 54.4% | 17.5% | 5.0% | 63.6% | 13.8% | 55.6% | 63.6% |
| 24 | 78.8% | 53.8% | 55.0% | 54.4% | 18.8% | 3.8% | 75.0% | 11.1% | 68.8% | 76.5% |
| 25 | 57.5% | 63.8% | 51.3% | 57.6% | 10.0% | 11.3% | 38.1% | 27.3% | 61.1% | 37.5% |
| 26 | 71.3% | 61.3% | 58.8% | 60.1% | 8.8% | 3.8% | 50.0% | 10.0% | 68.4% | 58.8% |
| 27 | 72.5% | 57.5% | 63.8% | 60.7% | 7.5% | 7.5% | 37.5% | 18.2% | 69.2% | 88.9% |
| 28 | 75.0% | 58.8% | 62.5% | 60.7% | 10.0% | 5.0% | 42.1% | 11.1% | 90.9% | 71.4% |
| 29 | 72.5% | 60.0% | 68.8% | 64.4% | 6.3% | 6.3% | 55.6% | 15.6% | 62.5% | 69.6% |
| 30 | 65.0% | 66.3% | 62.5% | 64.4% | 3.8% | 7.5% | 33.3% | 18.8% | 66.7% | 50.0% |
| 31 | 80.0% | 62.5% | 68.8% | 65.7% | 8.8% | 3.8% | 53.8% | 7.9% | 75.0% | 76.5% |
| 32 | 77.5% | 63.8% | 67.5% | 65.7% | 8.8% | 5.0% | 46.7% | 10.0% | 81.8% | 71.4% |
| 33 | 70.0% | 73.8% | 61.3% | 67.6% | 2.5% | 10.0% | 25.0% | 22.2% | 69.6% | 76.9% |
| 34 | 77.5% | 71.3% | 70.0% | 70.7% | 10.0% | 5.0% | 61.5% | 8.7% | 54.5% | 60.0% |
| All | 58.7% | 45.3% | 45.9% | 45.6% | 13.0% | 4.9% | 38.2% | 19.3% | 63.4% | 61.2% |

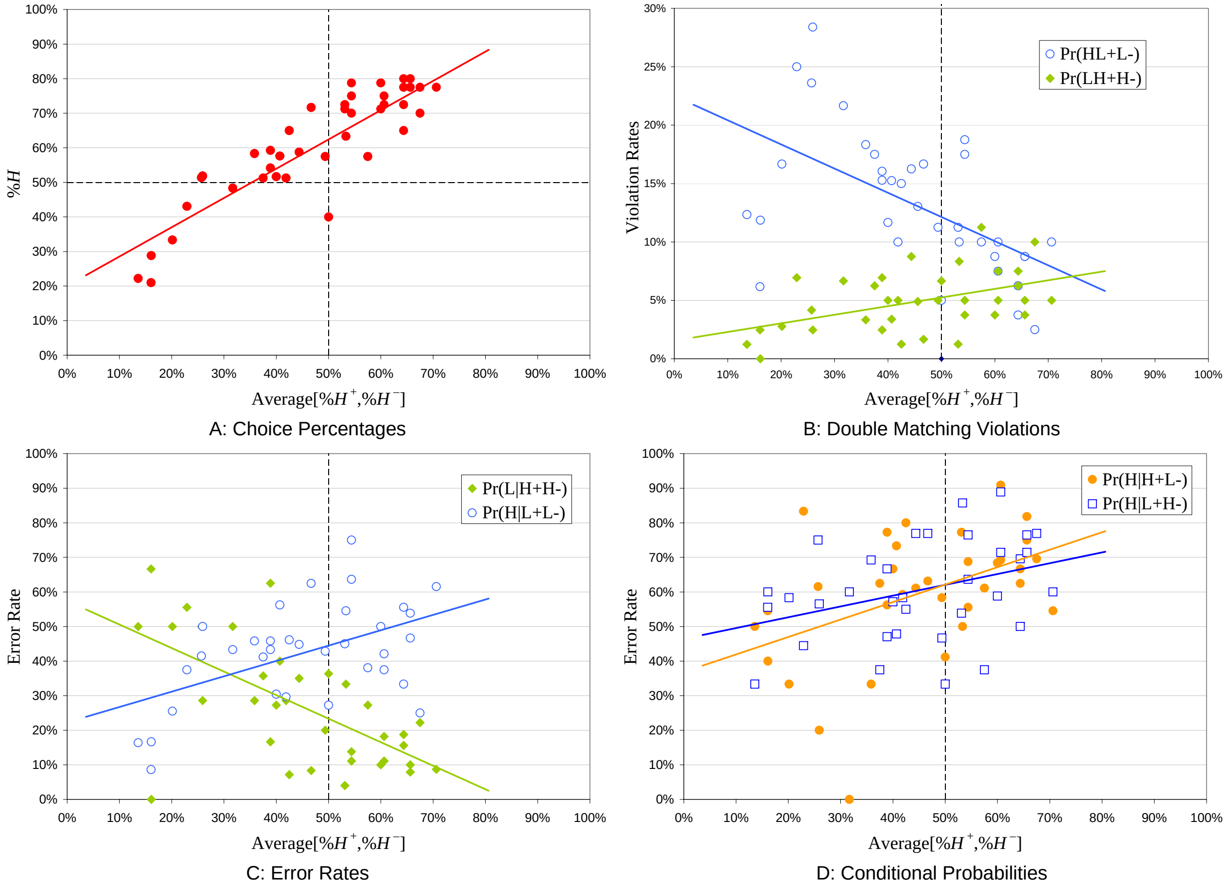
## EC.3.1. Choice percentages

Both the null and mixed error models require that $P(H)$ as a function of $\frac{p_{HH}+p_{LL}}{2}$ be symmetric around $p_{HH}=p_{LL}$, and hence symmetric around $\frac{\%H^+ + \%H^-}{2}$. Let $\%H$, $\%H^+$, and $\%H^-$ denote the percentage of participants choosing $H$ over $L$, $H^+$ over $L^+$ and $H^-$ over $L^-$, respectively. The discussion above indicates that symmetry around $p_{HH}=p_{LL}$ is identical to symmetry around $\frac{\%H^+ + \%H^-}{2}=\frac{1}{2}$. Figure EC.4A plots $\%H$ against $\frac{\%H^+ + \%H^-}{2}$. Figure EC.4A shows a clear asymmetry around $\frac{\%H^+ + \%H^-}{2}=\frac{1}{2}$. To test for this asymmetry statistically, we regress $\%H-.5$ against $\frac{\%H^+ + \%H^-}{2}-.5$, using each of the 34 double matching tests as an observation. The regression line is also shown in Figure EC.4A. The null and mixed error models predict that the intercept should be 0, whereas the asymmetric model predicts a positive intercept. We find a positive intercept ($\beta_0=.124$, $t(32)=8.95$), consistent with the asymmetric model.

## EC.3.2. Double Matching Violation Rates

The null and mixed error models imply that $P(HL^+L^-)=P(LH^+H^-)$ for $p_{HH}=p_{LL}$. In contrast, the asymmetric model implies that $P(HL^+L^-)>P(LH^+H^-)$ for $p_{HH}=p_{LL}$ if $\epsilon_H>\epsilon_S=$

**Figure EC.4 Empirical data on choice percentages, double matching violation rates, error rates, and conditional probabilities.**




*Note.* Panel A illustrates choice percentages, $\%H$, as a function of the average of $\%H^+$ and $\%H^-$. The empirical data show an asymmetry in that $\%H > \frac{\%H^+ + \%H^-}{2}$ for $\frac{\%H^+ + \%H^-}{2} = \frac{1}{2}$. Panel B depicts double matching violation rates, $\%HL^+L^-$ and $\%LH^+H^-$, as a function of the average of $\%H^+$ and $\%H^-$. The empirical data show an asymmetry in that $\%HL^+L^- > \%LH^+H^-$ for $\frac{\%H^+ + \%H^-}{2} = \frac{1}{2}$. Panel C shows error rates, $P(H|L^+L^-)$ and $P(L|H^+H^-)$, as a function of the average of $\%H^+$ and $\%H^-$. The empirical data show an asymmetry in that $P(H|L^+L^-) > P(L|H^+H^-)$ for $\frac{\%H^+ + \%H^-}{2} = \frac{1}{2}$. Panel D illustrates conditional probabilities, $P(H|H^+L^-)$ and $P(H|L^+H^-)$ as a function of the average of $\%H^+$ and $\%H^-$. The empirical data show an asymmetry in that $P(H|H^+L^-) > \frac{1}{2}$ and $P(H|L^+H^-) > \frac{1}{2}$ for $\frac{\%H^+ + \%H^-}{2} = \frac{1}{2}$.

$\epsilon_L$. Let $\%HL^+L^-$ and $\%LH^+H^-$ denote the percentage of double matching violations, $HL^+L^-$ and $LH^+H^-$, respectively. Figure EC.4B plots the double matching violation rates as a function of $\frac{\%H^+ + \%H^-}{2}$ and indicates an asymmetry in double matching violations consistent with the asymmetric model (regression lines are added to help visualize the asymmetry). We test for this asymmetry statistically by regressing the difference between the double matching violation rates, $\%HL^+L^- - \%LH^+H^-$, against $\frac{\%H^+ + \%H^-}{2} - .5$. Both the null and mixed error models predict that the intercept should be 0, whereas the asymmetric model predicts a positive intercept. The regression produces a positive intercept consistent with the asymmetric model ($\beta_0 = .069$, $t(32) = 6.78$).

### EC.3.3. Error rates: $P(H|L^+L^-)$ and $P(L|H^+H^-)$

Both the null and mixed error models require that $P(H|L^+L^-) = P(L|H^+H^-)$ if $p_{HH} = p_{LL}$, whereas the asymmetric model requires that $P(H|L^+L^-) > P(L|H^+H^-)$ if $p_{HH} = p_{LL}$. Figure EC.4C plots the two error rates as a function of $\frac{\%H^+ + \%H^-}{2}$. We see an asymmetry consistent with the asymmetric model. We regress the difference $P(H|L^+L^-) - P(L|H^+H^-)$ against $\frac{\%H^+ + \%H^-}{2}$. The null error model and the mixed model predict a zero intercept. In contrast, the asymmetric model predicts a positive intercept. We find a positive intercept, consistent with the asymmetric model ($\beta_0 = .211$, $t(32) = 5.78$).

### EC.3.4. Likelihood of choosing $H$ for "indeterminate" patterns

The null and error models again predict a symmetry around $p_{HH} = p_{LL}$: $P(H|H^+L^-) = P(H|L^+H^-) = .5$. On the other hand, the asymmetric model predicts that $P(H|H^+L^-) = P(H|L^+H^-) > .5$ for $p_{HH} = p_{LL}$. Figure EC.4D plots both error rates as a function of $\frac{\%H^+ + \%H^-}{2}$. The data reveal an asymmetry consistent with the asymmetric model. A regression of $P(H|H^+L^-) - .5$ and $P(H|L^+H^-) - .5$ against $\frac{\%H^+ + \%H^-}{2} - .5$ produces a positive intercept consistent with the asymmetric model ($P(H|H^+L^-)$: $\beta_0 = .121$, $t(32) = 3.98$; $P(H|L^+H^-)$: $\beta_0 = .120$, $t(32) = 4.85$).

## EC.4. Likelihood ratio test for Analysis of Study 1 Data

### EC.4.1. Procedure

To test the significance of each double matching violation, we employ a likelihood ratio test. We first describe the details of the procedure and then provide the results of the statistical test.

The full set of data $D$ to be fit is found in Table EC.4. Let $\mathbf{p}$ denote the vector of probabilities of the underlying types. Furthermore, let $L_0(D; \mathbf{p}, \epsilon)$ be the likelihood of the data under the null model for a given set of type parameters $\mathbf{p}$ and error rate, $\epsilon = \epsilon_S = \epsilon_H = \epsilon_L$, with $L_0^*(D) = \max_{\mathbf{p},\epsilon} L_0(D|\mathbf{p}, \epsilon)$ the maximum likelihood for the null model. We also perform a maximum likelihood procedure on the mixed error model and the asymmetric error model and compare whether the extra parameter used in these models improves the fit of the model using a likelihood ratio test. For example, let $L_A(D; \mathbf{p}, \epsilon_{\bar{H}}, \epsilon_H)$ be the likelihood of the data under the asymmetric model, with $L_A^*(D) = \max_{\mathbf{p},\epsilon_{\bar{H}},\epsilon_H} L_A(D|\mathbf{p}, \epsilon_{\bar{H}}, \epsilon_H)$ the maximum likelihood for the asymmetric model (where $0 \le \epsilon_{\bar{H}} \le \epsilon_H \le \frac{1}{2}$). Then the statistic $2\ln[L_A^*(D)/L_0^*(D)]$ is distributed approximately $\chi^2(1)$ (e.g., Mood and Graybill, 1963). The general error model has three error rate parameters, and thus a comparison of the general model and the null model uses $\chi^2(2)$.

### EC.4.2. Results

We fit the choice patterns for each of the 34 double matching tests using the maximum likelihood procedure outlined in the previous section. We fit the mixed model under two different restrictions, $\epsilon_M \ge \epsilon_S$ and $\epsilon_M \le \epsilon_S$. Table EC.5 contains a comparison of all models relative to the null error model. The table also compares the general model with the asymmetric model and the mixed model.

The asymmetric model fits the choice patterns better than either the mixed model or the general model (adjusting for the extra degree of freedom), showing a significantly better fit than the null model in 71% of the tests (using the conventional $p < .05$ standard). In contrast, the mixed model provides a significantly better fit than the null model in only 41% of the tests when $\epsilon_S \le \epsilon_M$ and in 15% of the tests when $\epsilon_S \ge \epsilon_M$. In addition, the general model improves over the asymmetric model in only 1 of the 34 tests.

It is also instructive to look at the estimated error rates. Table EC.6 lists the estimated error rates for the null, asymmetric, mixed (with $\epsilon_S \le \epsilon_M$), and general models. The asymmetric model yields qualitatively consistent error rates: in 33 of the 34 tests, $\epsilon_H > \epsilon_{\bar{H}}$. In contrast, the error rates for the mixed error model often encounter the constraint: in 17 of the 34 tests, $\epsilon_M = \epsilon_S$. Moreover, this pattern appears systematic. For the double matching tests in which $\frac{\%H^+ + \%H^-}{2} < \frac{1}{2}$, 16 of 19 produce $\epsilon_M > \epsilon_S$, whereas $\epsilon_M = \epsilon_S$ in only 1 of the 14 tests in which $\frac{\%H^+ + \%H^-}{2} > \frac{1}{2}$. Finally, the

**Table EC.4 Choice percentages for the 8 possible choice patterns for 34 tests of double matching (Study 1)**

| | | Choice Patterns | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Test | $\frac{\%H^++\%H^-}{2}$ | $\%HH^+H^-$ | $\%HH^+L^-$ | $\%HL^+H^-$ | $\%HL^+L^-$ | $\%LH^+H^-$ | $\%LH^+L^-$ | $\%LL^+H^-$ | $\%LL^+L^-$ |
| 1 | 13.6% | 1.2% | 3.7% | 4.9% | 12.3% | 1.2% | 3.7% | 9.9% | 63.0% |
| 2 | 16.0% | 1.2% | 7.4% | 6.2% | 6.2% | 2.5% | 6.2% | 4.9% | 65.4% |
| 3 | 16.1% | 3.4% | 3.4% | 10.2% | 11.9% | 0.0% | 5.1% | 6.8% | 59.3% |
| 4 | 20.1% | 2.8% | 4.2% | 9.7% | 16.7% | 2.8% | 8.3% | 6.9% | 48.6% |
| 5 | 22.9% | 5.6% | 6.9% | 5.6% | 25.0% | 6.9% | 1.4% | 6.9% | 41.7% |
| 6 | 25.7% | 4.2% | 11.1% | 12.5% | 23.6% | 4.2% | 6.9% | 4.2% | 33.3% |
| 7 | 25.9% | 6.2% | 1.2% | 16.0% | 28.4% | 2.5% | 4.9% | 12.3% | 28.4% |
| 8 | 31.7% | 6.7% | 0.0% | 20.0% | 21.7% | 6.7% | 3.3% | 13.3% | 28.3% |
| 9 | 35.8% | 8.3% | 1.7% | 30.0% | 18.3% | 3.3% | 3.3% | 13.3% | 21.7% |
| 10 | 37.5% | 11.3% | 18.8% | 3.8% | 17.5% | 6.3% | 11.3% | 6.3% | 25.0% |
| 11 | 38.9% | 12.3% | 21.0% | 22.2% | 16.0% | 2.5% | 6.2% | 11.1% | 21.0% |
| 12 | 38.9% | 4.2% | 12.5% | 9.9% | 15.3% | 6.9% | 9.7% | 11.1% | 18.1% |
| 13 | 40.0% | 13.3% | 13.3% | 13.3% | 11.7% | 5.0% | 6.7% | 10.0% | 26.7% |
| 14 | 40.7% | 5.1% | 18.6% | 18.6% | 15.3% | 3.4% | 6.8% | 20.3% | 11.9% |
| 15 | 41.9% | 12.5% | 20.0% | 8.8% | 10.0% | 5.0% | 13.8% | 6.3% | 23.8% |
| 16 | 42.5% | 16.3% | 20.0% | 13.8% | 15.0% | 1.3% | 5.0% | 11.3% | 17.5% |
| 17 | 44.4% | 16.3% | 13.8% | 12.5% | 16.3% | 8.8% | 8.8% | 3.8% | 20.0% |
| 18 | 46.7% | 18.3% | 20.0% | 16.7% | 16.7% | 1.7% | 11.7% | 5.0% | 10.0% |
| 19 | 49.4% | 20.0% | 17.5% | 8.8% | 11.3% | 5.0% | 12.5% | 10.0% | 15.0% |
| 20 | 50.0% | 11.7% | 11.7% | 11.7% | 5.0% | 6.7% | 16.7% | 23.3% | 13.3% |
| 21 | 53.1% | 30.0% | 21.3% | 8.8% | 11.3% | 1.3% | 6.3% | 7.5% | 13.8% |
| 22 | 53.3% | 16.7% | 16.7% | 20.0% | 10.0% | 8.3% | 16.7% | 3.3% | 8.3% |
| 23 | 54.4% | 31.3% | 12.5% | 8.8% | 17.5% | 5.0% | 10.0% | 5.0% | 10.0% |
| 24 | 54.4% | 30.0% | 13.8% | 16.3% | 18.8% | 3.8% | 6.3% | 5.0% | 6.3% |
| 25 | 57.5% | 30.0% | 13.8% | 3.8% | 10.0% | 11.3% | 8.8% | 6.3% | 16.3% |
| 26 | 60.0% | 33.8% | 16.3% | 12.5% | 8.8% | 3.8% | 7.5% | 8.8% | 8.8% |
| 27 | 60.6% | 33.8% | 11.3% | 20.0% | 7.5% | 7.5% | 5.0% | 2.5% | 12.5% |
| 28 | 60.6% | 40.0% | 12.5% | 12.5% | 10.0% | 5.0% | 1.3% | 5.0% | 13.8% |
| 29 | 64.4% | 33.8% | 12.5% | 20.0% | 6.3% | 6.3% | 7.5% | 8.8% | 5.0% |
| 30 | 64.4% | 32.5% | 17.5% | 11.3% | 3.8% | 7.5% | 8.8% | 11.3% | 7.5% |
| 31 | 65.6% | 43.8% | 11.3% | 16.3% | 8.8% | 3.8% | 3.8% | 5.0% | 7.5% |
| 32 | 65.6% | 45.0% | 11.3% | 12.5% | 8.8% | 5.0% | 2.5% | 5.0% | 10.0% |
| 33 | 67.5% | 35.0% | 20.0% | 12.5% | 2.5% | 10.0% | 8.8% | 3.8% | 7.5% |
| 34 | 70.6% | 52.5% | 7.5% | 7.5% | 10.0% | 5.0% | 6.3% | 5.0% | 6.3% |

general model appears to be too flexible: in 22 of 34 tests, one of the three parameters encounters at least one of the constraints.

As a further test of whether each error model is "too flexible," we fit the choice patterns for the aggregate data (all 34 double matching tests) with a single set of error rates for each error model, while allowing the probability of individual types to differ for each test (see "All" row in Table EC.6). Thus, the null error model has 103 parameters (34 tests times 3 type parameters for each test + 1 error rate parameter), whereas the mixed and asymmetric models have 104 parameters, and the general model has 105 parameters. For the aggregate data, the mixed, asymmetric, and general model all improve on the null model. Interestingly, the general model is only marginally significantly better than the asymmetric model. Error rates for this test are also found in Table EC.6. We next use the estimates from this analysis to examine the four implications discussed in the previous section. We compare the null error model, the mixed model, and the asymmetric model. Consider, for example, the implications for choice percentages, $\%H$ and $\frac{\%H^++\%H^-}{2}$. Figure EC.5 plots the actual choice percentages, as well as a regression line to summarize the relationship (this

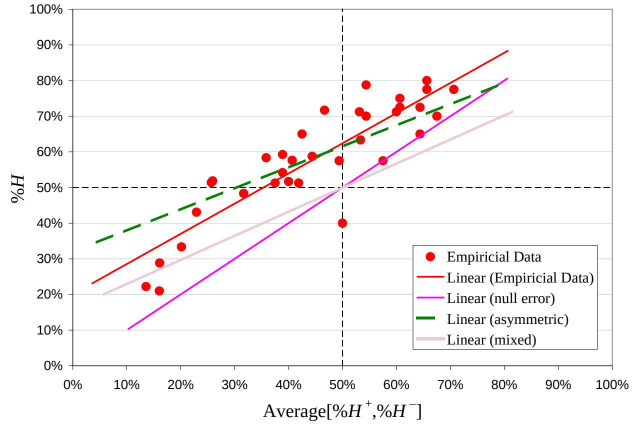
**Table EC.5 Error model comparisons using likelihood ratio analysis (Study 1).**

| Test | $\frac{\%H^{+}+\%H^{-}}{2}$ | null vs. Asymmetric ($\epsilon_H \geq \epsilon_L = \epsilon_S$) | null vs. mixed ($\epsilon_H = \epsilon_L \geq \epsilon_S$) | null vs. mixed ($\epsilon_S \geq \epsilon_L = \epsilon_H$) | null vs. general | Asymmetric vs. general |
|---|---|---|---|---|---|---|
| 1 | 13.6% | 0.048 | 0.040 | 1.000 | 0.087 | 0.326 |
| 2 | 16.0% | 0.359 | 0.383 | 1.000 | 0.528 | 0.513 |
| 3 | 16.1% | 0.012 | 0.018 | 1.000 | 0.043 | 0.858 |
| 4 | 20.1% | 0.024 | 0.024 | 1.000 | 0.075 | 0.796 |
| 5 | 22.9% | 0.001 | 0.000 | 1.000 | 0.000 | 0.016 |
| 6 | 25.7% | 0.000 | 0.000 | 1.000 | 0.000 | 0.453 |
| 7 | 25.9% | 0.000 | 0.000 | 1.000 | 0.000 | 0.388 |
| 8 | 31.7% | 0.010 | 0.001 | 1.000 | 0.006 | 0.061 |
| 9 | 35.8% | 0.001 | 0.010 | 1.000 | 0.005 | 0.948 |
| 10 | 37.5% | 0.017 | 0.026 | 1.000 | 0.051 | 0.646 |
| 11 | 38.9% | 0.001 | 0.036 | 1.000 | 0.073 | 0.959 |
| 12 | 38.9% | 0.022 | 0.049 | 1.000 | 0.002 | 0.623 |
| 13 | 40.0% | 0.092 | 0.136 | 1.000 | 0.219 | 0.667 |
| 14 | 40.7% | 0.021 | 0.029 | 1.000 | 0.049 | 0.400 |
| 15 | 41.9% | 0.003 | 0.005 | 0.012 | 0.294 | 0.979 |
| 16 | 42.5% | 0.000 | 0.060 | 1.000 | 0.000 | 0.961 |
| 17 | 44.4% | 0.019 | 0.094 | 1.000 | 0.051 | 0.513 |
| 18 | 46.7% | 0.000 | 1.000 | 0.002 | 0.002 | 0.728 |
| 19 | 49.4% | 0.147 | 1.000 | 0.286 | 0.335 | 0.777 |
| 20 | 50.0% | 1.000 | 1.000 | 0.610 | 0.324 | 0.722 |
| 21 | 53.1% | 0.000 | 1.000 | 0.003 | 0.001 | 0.870 |
| 22 | 53.3% | 0.195 | 1.000 | 0.133 | 0.286 | 0.360 |
| 23 | 54.4% | 0.002 | 1.000 | 0.039 | 0.008 | 0.877 |
| 24 | 54.4% | 0.000 | 0.000 | 1.000 | 0.000 | 0.158 |
| 25 | 57.5% | 0.396 | 0.144 | 1.000 | 0.232 | 0.138 |
| 26 | 60.0% | 0.027 | 1.000 | 0.043 | 0.085 | 0.791 |
| 27 | 60.6% | 0.086 | 1.000 | 0.061 | 0.150 | 0.356 |
| 28 | 60.6% | 0.010 | 1.000 | 0.064 | 0.025 | 0.385 |
| 29 | 64.4% | 0.138 | 1.000 | 0.168 | 0.323 | 0.836 |
| 30 | 64.4% | 0.888 | 1.000 | 1.000 | 0.903 | 0.665 |
| 31 | 65.6% | 0.004 | 1.000 | 0.110 | 0.015 | 0.873 |
| 32 | 65.6% | 0.017 | 1.000 | 0.068 | 0.052 | 0.609 |
| 33 | 67.5% | 0.888 | 1.000 | 0.624 | 0.767 | 0.475 |
| 34 | 70.6% | 0.009 | 1.000 | 0.439 | 0.014 | 0.206 |
| All | 45.00% | 0.000 | 0.000 | 1.000 | 0.000 | 0.083 |
| | | | | Summary | | |
| $p \leq .01$ | | 41% | 21% | 6% | 32% | 0% |
| $p \leq .05$ | | 71% | 41% | 15% | 47% | 3% |
| $p \leq .10$ | | 76% | 47% | 24% | 68% | 6% |

The last five columns shows $p$-values for comparisons of nested models. The summary at the bottom of the table indicates what percentage of the 34 tests are significant at various $p$ levels.

part of the figure is identical to Figure EC.4A). For each error model, we use the parameter estimates to calculate, $P(H)$ and $\frac{P(H^{+})+P(H^{-})}{2}$. We then regress the estimated values of $\frac{P(H^{+})+P(H^{-})}{2}$ on the estimated values of $P(H)$. Figure EC.5 also shows the regression lines for the null, mixed, and asymmetric models. The asymmetric model shows a close correspondence to the actual data, whereas the null error model and the mixed error model largely underpredict $\%H$. We conduct a runs test to test this underprediction formally. For each model, an underprediction is coded as

**Figure EC.5 Choice Percentages, Comparison of empirical data with error models (Study 1).**




"-1" and an overprediction is coded as "+1". We then tally the number of alternations (from "-1" to "+1" or from "+1" to "-1"). The runs test rejects the null and mixed error models, but not the asymmetric model ($p < .05$).

We perform a similar analysis on the double matching violations. Figure EC.6 depicts the empirical data compared with estimates from the null error model, the mixed error model, and the asymmetric model. The empirical data reveal a distinct asymmetry captured only by the asymmetric model: the violation rate $\%HL^+L^-$ exceeds the violation rate $\%LH^+H^-$ for double matching tests in which $\frac{\%H^+ + \%H^-}{2} > \frac{1}{2}$. A runs test rejects the mixed model for both types of double matching violations and the null error model for $HL^+L^-$ violations ($p < .05$). The asymmetric model is not rejected for either type of violation.

We next consider the error rates, $P(H|L^+L^-)$ and $P(L|H^+H^-)$. Figure EC.7 depicts the empirical data relative to the estimates from the null, mixed, and asymmetric models. Again, the empirical data reveal an asymmetry: $P(H|L^+L^-) > P(L|H^+H^-)$ for $\frac{\%H^+ + \%H^-}{2} < \frac{1}{2}$, a pattern predicted only by the asymmetric model. A runs tests rejects the null error model for both error rates and the mixed error model for the $P(H|L^+L^-)$ error rate ($p < .05$). The asymmetric model is not rejected for either error rate.

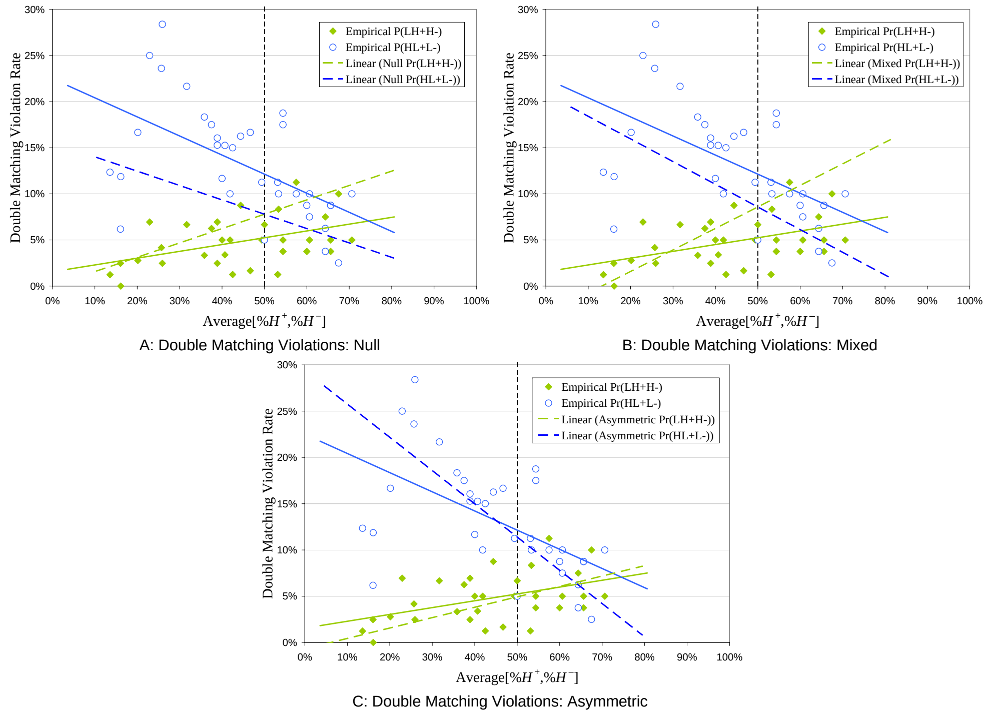
Finally, we turn to the probability of choosing $H$ for the indeterminate patterns, $H^+L^-$ and $L^+H^-$. Figure EC.8 contains the empirical data for these measures, as well as the estimates from the various error models. Again, the asymmetric model shows a close correspondence to the empirical data, whereas the null error model and the mixed error model largely underestimate the conditional probabilities. Once again, a runs test rejects both the null and mixed error models, but not the asymmetric model ($p < .05$).

## EC.5. Robustness Analysis for Weighting Function Estimation: Study 1

In Section 3.4 of the main paper, we formally tested the hypothesis that violations of double matching result from a diminished sensitivity to probability differences for mixed gambles relative to gain or loss gambles by fitting a probability weighting function to our double matching test data. This section presents robustness analyses.

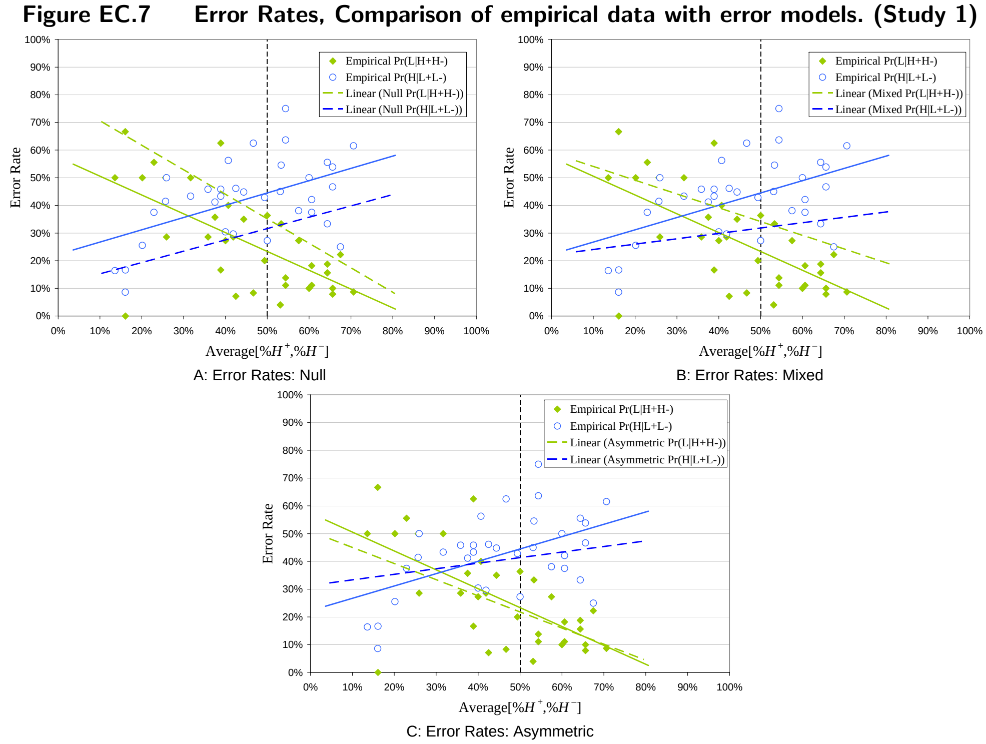
The estimation results support our hypothesis of greater curvature for mixed gambles. Our weighting function estimate for single-domain gambles, $\hat{\gamma}_S$, was .67, close to the parameter estimate of .71 from Wu and Gonzalez (1996). In contrast, the parameter value for mixed gambles was considerably lower, $\hat{\gamma}_M = .55$, a difference that was statistically significant ($t = 620.9, p < .0001$). (The best-fitting scaling parameter was found to be $\hat{\mu} = .18$.) We conducted a variety of sensitivity

**Figure EC.6 Double Matching Violations, Comparison of empirical data with error models (Study 1).**




*Note.* Panel A: null error model; Panel B: mixed error model; Panel C: asymmetric error model

**Figure EC.7 Error Rates, Comparison of empirical data with error models. (Study 1)**

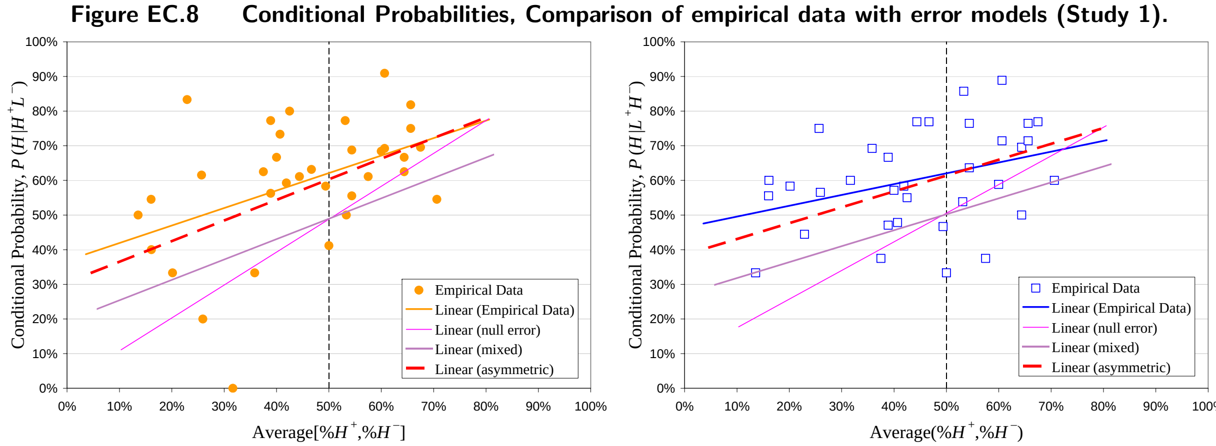



*Note.* Error rates shown are: $P(H|L^+L^-)$ and $P(L|H^+H^-)$. Panel A: null error model; Panel B: mixed error model; Panel C: asymmetric error model

**Table EC.6 Estimated error rates using likelihood ratio analysis for various error models (Study 1)**

| | | Null | | | Asymmetric | | | Mixed ($\epsilon_S \leq \epsilon_H = \epsilon_L$) | | | General | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Gamble | $\frac{\%H^{+}+\%H^{-}}{2}$ | $\epsilon_S$ | $\epsilon_L$ | $\epsilon_H$ | $\epsilon_S$ | $\epsilon_L$ | $\epsilon_H$ | $\epsilon_S$ | $\epsilon_L$ | $\epsilon_H$ | $\epsilon_S$ | $\epsilon_L$ | $\epsilon_H$ |
| 1 | 13.6% | 0.106 | 0.106 | 0.106 | 0.062 | 0.062 | 0.160 | 0.048 | 0.164 | 0.164 | 0.000 | 0.419 | 0.165 |
| 2 | 16.0% | 0.063 | 0.063 | 0.063 | 0.048 | 0.048 | 0.088 | 0.043 | 0.088 | 0.088 | 0.000 | 0.275 | 0.095 |
| 3 | 16.1% | 0.089 | 0.089 | 0.089 | 0.009 | 0.009 | 0.163 | 0.000 | 0.159 | 0.159 | 0.014 | 0.000 | 0.163 |
| 4 | 20.1% | 0.173 | 0.173 | 0.173 | 0.111 | 0.111 | 0.257 | 0.075 | 0.259 | 0.259 | 0.127 | 0.000 | 0.255 |
| 5 | 22.9% | 0.237 | 0.237 | 0.237 | 0.156 | 0.156 | 0.397 | 0.000 | 0.404 | 0.404 | 0.000 | 0.450 | 0.394 |
| 6 | 25.7% | 0.286 | 0.286 | 0.286 | 0.129 | 0.129 | 0.437 | 0.000 | 0.426 | 0.426 | 0.000 | 0.304 | 0.448 |
| 7 | 25.9% | 0.240 | 0.240 | 0.240 | 0.111 | 0.111 | 0.441 | 0.087 | 0.462 | 0.462 | 0.089 | 0.270 | 0.464 |
| 8 | 31.7% | 0.215 | 0.215 | 0.215 | 0.128 | 0.128 | 0.369 | 0.050 | 0.431 | 0.431 | 0.050 | 0.404 | 0.436 |
| 9 | 35.8% | 0.202 | 0.202 | 0.202 | 0.106 | 0.106 | 0.435 | 0.000 | 0.419 | 0.419 | 0.110 | 0.090 | 0.429 |
| 10 | 37.5% | 0.236 | 0.236 | 0.236 | 0.177 | 0.177 | 0.381 | 0.000 | 0.396 | 0.396 | 0.156 | 0.249 | 0.400 |
| 11 | 38.9% | 0.223 | 0.223 | 0.223 | 0.090 | 0.090 | 0.409 | 0.072 | 0.321 | 0.321 | 0.185 | 0.167 | 0.402 |
| 12 | 38.9% | 0.239 | 0.239 | 0.239 | 0.184 | 0.184 | 0.409 | 0.055 | 0.500 | 0.500 | 0.163 | 0.000 | 0.385 |
| 13 | 40.0% | 0.190 | 0.190 | 0.190 | 0.125 | 0.125 | 0.301 | 0.000 | 0.294 | 0.294 | 0.000 | 0.223 | 0.335 |
| 14 | 40.7% | 0.194 | 0.194 | 0.194 | 0.140 | 0.140 | 0.417 | 0.121 | 0.500 | 0.500 | 0.122 | 0.319 | 0.500 |
| 15 | 41.9% | 0.347 | 0.347 | 0.347 | 0.126 | 0.126 | 0.273 | 0.000 | 0.292 | 0.292 | 0.104 | 0.152 | 0.284 |
| 16 | 42.5% | 0.200 | 0.200 | 0.200 | 0.044 | 0.044 | 0.433 | 0.000 | 0.325 | 0.325 | 0.000 | 0.076 | 0.451 |
| 17 | 44.4% | 0.292 | 0.292 | 0.292 | 0.239 | 0.239 | 0.475 | 0.000 | 0.408 | 0.408 | 0.000 | 0.296 | 0.492 |
| 18 | 46.7% | 0.266 | 0.266 | 0.266 | 0.067 | 0.067 | 0.500 | 0.266 | 0.266 | 0.266 | 0.132 | 0.025 | 0.500 |
| 19 | 49.4% | 0.205 | 0.205 | 0.205 | 0.152 | 0.152 | 0.318 | 0.205 | 0.205 | 0.205 | 0.310 | 0.000 | 0.206 |
| 20 | 50.0% | 0.137 | 0.137 | 0.137 | 0.137 | 0.137 | 0.138 | 0.138 | 0.138 | 0.138 | 0.149 | 0.206 | 0.000 |
| 21 | 53.1% | 0.159 | 0.159 | 0.159 | 0.030 | 0.030 | 0.423 | 0.160 | 0.160 | 0.160 | 0.000 | 0.041 | 0.437 |
| 22 | 53.3% | 0.271 | 0.271 | 0.271 | 0.227 | 0.227 | 0.450 | 0.271 | 0.271 | 0.271 | 0.384 | 0.095 | 0.000 |
| 23 | 54.4% | 0.252 | 0.252 | 0.252 | 0.148 | 0.148 | 0.500 | 0.252 | 0.252 | 0.252 | 0.101 | 0.153 | 0.500 |
| 24 | 54.4% | 0.500 | 0.500 | 0.500 | 0.100 | 0.100 | 0.500 | 0.322 | 0.322 | 0.322 | 0.334 | 0.066 | 0.500 |
| 25 | 57.5% | 0.204 | 0.204 | 0.204 | 0.186 | 0.186 | 0.286 | 0.093 | 0.298 | 0.298 | 0.000 | 0.276 | 0.374 |
| 26 | 60.0% | 0.159 | 0.159 | 0.159 | 0.083 | 0.083 | 0.391 | 0.159 | 0.159 | 0.159 | 0.000 | 0.108 | 0.452 |
| 27 | 60.6% | 0.220 | 0.220 | 0.220 | 0.137 | 0.137 | 0.438 | 0.220 | 0.220 | 0.220 | 0.249 | 0.123 | 0.298 |
| 28 | 60.6% | 0.180 | 0.180 | 0.180 | 0.095 | 0.095 | 0.454 | 0.180 | 0.180 | 0.180 | 0.173 | 0.083 | 0.400 |
| 29 | 64.4% | 0.164 | 0.164 | 0.164 | 0.125 | 0.125 | 0.392 | 0.165 | 0.165 | 0.165 | 0.029 | 0.155 | 0.500 |
| 30 | 64.4% | 0.132 | 0.132 | 0.132 | 0.129 | 0.129 | 0.152 | 0.132 | 0.133 | 0.133 | 0.000 | 0.184 | 0.348 |
| 31 | 65.6% | 0.181 | 0.181 | 0.181 | 0.069 | 0.069 | 0.500 | 0.181 | 0.181 | 0.181 | 0.090 | 0.066 | 0.500 |
| 32 | 65.6% | 0.175 | 0.175 | 0.175 | 0.090 | 0.090 | 0.459 | 0.175 | 0.175 | 0.175 | 0.171 | 0.088 | 0.391 |
| 33 | 67.5% | 0.181 | 0.181 | 0.181 | 0.174 | 0.174 | 0.215 | 0.181 | 0.181 | 0.181 | 0.230 | 0.159 | 0.000 |
| 34 | 70.6% | 0.151 | 0.151 | 0.151 | 0.079 | 0.079 | 0.441 | 0.152 | 0.152 | 0.152 | 0.000 | 0.099 | 0.494 |
| All | 45.0% | 0.193 | 0.193 | 0.193 | 0.126 | 0.126 | 0.352 | 0.135 | 0.252 | 0.252 | 0.130 | 0.116 | 0.348 |

**Figure EC.8 Conditional Probabilities, Comparison of empirical data with error models (Study 1).**




*Note.* Panel A depicts $P(H|H^{+}L^{-})$, whereas Panel B illustrates $P(H|L^{+}H^{-})$.

**Table EC.7 Probability weighting function parameter estimates (Tversky and Kahneman (1992) function) for single-domain gambles and mixed gambles (Study 1).**

| | Estimates for single-domain gambles ($\gamma_S$) | | | | | | |
|---|---|---|---|---|---|---|---|
| $\alpha\backslash\lambda$ | 1.00 | 1.25 | 1.50 | 1.75 | 2.00 | 2.25 | 2.50 |
| 0.4 | 0.571 | 0.572 | 0.572 | 0.572 | 0.572 | 0.572 | 0.572 |
| 0.5 | 0.684 | 0.681 | 0.678 | 0.676 | 0.675 | 0.673 | 0.672 |
| 0.6 | 0.796 | 0.788 | 0.782 | 0.778 | 0.775 | 0.772 | 0.770 |
| 0.7 | 0.910 | 0.896 | 0.886 | 0.879 | 0.874 | 0.870 | 0.867 |
| 0.8 | 1.031 | 1.008 | 0.992 | 0.982 | 0.974 | 0.968 | 0.964 |
| 0.9 | 1.162 | 1.126 | 1.103 | 1.087 | 1.076 | 1.068 | 1.062 |
| 1.0 | 1.313 | 1.257 | 1.221 | 1.198 | 1.182 | 1.170 | 1.162 |

| | Estimates for mixed gambles ($\gamma_M$) | | | | | | |
|---|---|---|---|---|---|---|---|
| $\alpha\backslash\lambda$ | 1.00 | 1.25 | 1.50 | 1.75 | 2.00 | 2.25 | 2.50 |
| 0.4 | 0.415 | 0.423 | 0.429 | 0.434 | 0.438 | 0.441 | 0.444 |
| 0.5 | 0.530 | 0.536 | 0.541 | 0.544 | 0.547 | 0.549 | 0.550 |
| 0.6 | 0.636 | 0.639 | 0.641 | 0.642 | 0.643 | 0.643 | 0.643 |
| 0.7 | 0.734 | 0.734 | 0.734 | 0.733 | 0.731 | 0.730 | 0.728 |
| 0.8 | 0.828 | 0.825 | 0.822 | 0.819 | 0.816 | 0.813 | 0.810 |
| 0.9 | 0.917 | 0.912 | 0.908 | 0.903 | 0.899 | 0.895 | 0.891 |
| 1.0 | 1.003 | 0.997 | 0.991 | 0.985 | 0.980 | 0.976 | 0.971 |

Table shows estimates for combinations of $\alpha$ and $\lambda$. In all cases, differences between $\gamma_S$ and $\gamma_M$ are significant ($t\text{s} > 100$).

analyses to test whether this finding was robust. We found that $\hat{\gamma}_M$ was significantly lower than $\hat{\gamma}_S$ for all combinations of values of $\alpha$ from .3 to 1.0 and $\lambda$ from 1 to 2.5 (see Table EC.5).

To further investigate the robustness of our analysis, we replaced the Tversky and Kahneman (1992) function with the weighting function proposed by Prelec (1998), $\pi(p) = \exp(-(-\ln p)^\beta)$. The Prelec weighting function is the identity function when $\beta = 1$, approaches a step function as $\beta \to 0$, and has a fixed point at $1/e \approx .368$ (i.e., $\pi(1/e) = 1/e$). We found qualitatively identical results ($\hat{\beta}_S = .61$, $\hat{\beta}_M = .47$, $t = 589.6$, $p < .0001$), with the Prelec function performing slightly worse in terms of log likelihood.

We also estimated a separate set of models in which we allowed $\gamma$ in the Tversky and Kahneman weighting function to differ for gain gambles, loss gambles, and mixed gambles. Specifically, we let $\gamma_{GS}$, $\gamma_{LS}$, $\gamma_{GM} = \gamma_{GS} - \delta$, and $\gamma_{LM} = \gamma_{LS} - \delta$, respectively, be the parameters for gain gambles, loss gambles, the gain portions of mixed gambles, and the loss portions of mixed gambles. Thus, $\delta$ captures the difference in curvature between mixed gambles and single-domain gambles. This specification yielded similar results to the analyses presented earlier. Contrary to most previous studies, the parameter for losses, $\hat{\gamma}_{LS} = .66$, was substantially lower than for gains, $\hat{\gamma}_{GS} = .76$ (however, see Baltussen et al., 2006), but most critically, the parameter capturing the difference between single-domain gambles and mixed gambles, $\hat{\delta} = .14$ was significantly positive ($t = 587.9$, $p < .0001$), indicating a more curved weighting function for mixed gambles than for single-domain gambles.

## EC.6. Stochastic Choice Analysis of Study 2

To test whether gain-loss separability is violated in Study 2, we develop two stochastic choice models. One model constrains preferences to follow gain-loss separability and one does not. We then test whether the unconstrained model provides a signficantly better fit to the choice data. We begin by making simplifying but standard assumption that the probability that prospect $S$ is chosen over prospect $T$ is captured by the logit model, $P(S \succ T) = \frac{1}{1+\exp(-\mu(U(S)-U(T)))}$.

We fit the choice data using maximum likelihood. Thus, the likelihood function is:

$$\begin{aligned}&\prod P(H^+ \succ A^+)^{(n)(\%(H^+ \succ A^+))} P(A^+ \succ H^+)^{(n)(\%(A^+ \succ H^+))} \times \\ &\prod P(L^+ \succ A^+)^{(n)(\%(L^+ \succ A^+))} P(A^+ \succ L^+)^{(n)(\%(A^+ \succ L^+))} \times \\ &\prod P([H^+, C^-] \succ B)^{(n)(\%([H^+, C^-] \succ B))} P(B \succ [H^+, C^-])^{(n)(\%(B \succ [H^+, C^-]))} \times \\ &\prod P([L^+, C^-] \succ B)^{(n)(\%([L^+, C^-] \succ B))} P(B \succ [L^+, C^-])^{(n)(\%(B \succ [L^+, C^-]))},\end{aligned}$$

where $n = 102$ and $\%(H^+ \succ A^+)$ is the percentage of participants who preferred $H^+$ to $A^+$, etc.

Unlike the analysis in Section EC.4, where we fit the choice data using prospect theory, we use a nonparametric procedure in which the utilities of the prospects are free parameters. Under this assumption, fitting the choice percentages in Table 2 of the main paper involves estimating 6 free parameters for each of the 8 tests: $U(H^+)$, $U(L^+)$, $U([H^+, C^-])$, $U([L^+, C^-])$, $U(A^+)$, and $U(B)$ (since $U(\cdot)$ can be rescaled multiplicatively, we are free to set $\mu = 1$). However, gain-loss separability imposes the restriction that $U([H^+, C^-]) = U(H^+) + U(C^-)$ and $U([L^+, C^-]) = U(L^+) + U(C^-)$, leaving 5 free parameters: $U(H^+)$, $U(L^+)$, $U(C^-)$, $U(A^+)$, and $U(B)$.

Thus, under both models,

$$P(H^+ \succ A^+) = \frac{1}{1 + \exp(-[U(H^+) - U(A^+)])}$$

and

$$P(L^+ \succ A^+) = \frac{1}{1 + \exp(-[U(L^+) - U(A^+)])}.$$

However,

$$P([H^+, C^-] \succ B) = \frac{1}{1 + \exp(-[U(H^+) + U(C^-) - U(B)])}$$

and

$$P([L^+, C^-] \succ B) = \frac{1}{1 + \exp(-[U(L^+) + U(C^-) - U(B)])},$$

if we assume gain-loss separability and

$$P([H^+, C^-] \succ B) = \frac{1}{1 + \exp(-[U([H^+, C^-]) - U(B)])}$$

and

$$P([L^+, C^-] \succ B) = \frac{1}{1 + \exp(-[U([L^+, C^-]) - U(B)])},$$

if gain-loss separability is not assumed.

To test whether gain-loss separability is violated, we examine whether the unconstrained 6 parameter model in which gain-loss separability does not necessarily hold provides a significantly better fit to the data than the 5 parameter model that imposes gain-loss separability. Let $L_0(D; U(H^+), U(L^+), U(C^-), U(A^+), U(B))$ be the likelihood of the data assuming gain-loss separability, with $L_0^*(D)$ being the maximum likelihood for this model. Similarly, let $L_U(D; U(H^+), U(L^+), U([H^+, C^-]), U(L^+, C^-]), U(A^+), U(B))$ be the likelihood of the data if gain-loss separability is relaxed, with $L_U^*(D)$ being the maximum likelihood for this model. Recall

**Table EC.8 Probability weighting function parameter estimates (Tversky and Kahneman (1992) function), single-domain gambles and mixed gambles (Study 2)**

| | Estimates for single-domain gambles ($\gamma_S$) | | | | | | |
|---|---|---|---|---|---|---|---|
| $\alpha\backslash\lambda$ | 1.00 | 1.25 | 1.50 | 1.75 | 2.00 | 2.25 | 2.50 |
| 0.4 | 0.876 | 0.812 | 0.745 | 0.736 | 0.695 | 0.586 | 0.428 |
| 0.5 | 0.894 | 0.830 | 0.767 | 0.754 | 0.677 | 0.415 | 0.415 |
| 0.6 | 0.912 | 0.812 | 0.803 | 0.740 | 0.654 | 0.437 | 0.437 |
| 0.7 | 0.925 | 0.812 | 0.767 | 0.722 | 0.469 | 0.476 | 0.383 |
| 0.8 | 0.383 | 0.383 | 0.383 | 0.383 | 0.383 | 0.383 | 0.383 |
| 0.9 | 0.383 | 0.383 | 0.383 | 0.383 | 0.383 | 0.383 | 0.281 |
| 1.0 | 0.383 | 0.383 | 0.383 | 0.281 | 0.281 | 0.281 | 0.270 |

| | Estimates for mixed gambles ($\gamma_M$) | | | | | | |
|---|---|---|---|---|---|---|---|
| $\alpha\backslash\lambda$ | 1.00 | 1.25 | 1.50 | 1.75 | 2.00 | 2.25 | 2.50 |
| 0.4 | 0.491 | 0.507 | 0.514 | 0.517 | 0.499 | 0.433 | 0.270 |
| 0.5 | 0.480 | 0.501 | 0.504 | 0.525 | 0.520 | 0.270 | 0.270 |
| 0.6 | 0.471 | 0.494 | 0.512 | 0.521 | 0.507 | 0.270 | 0.270 |
| 0.7 | 0.477 | 0.495 | 0.504 | 0.520 | 0.270 | 0.270 | 0.270 |
| 0.8 | 0.390 | 0.390 | 0.370 | 0.270 | 0.270 | 0.270 | 0.270 |
| 0.9 | 0.420 | 0.420 | 0.395 | 0.270 | 0.270 | 0.270 | 1.281 |
| 1.0 | 0.470 | 0.495 | 0.520 | 1.281 | 1.281 | 1.281 | 1.270 |

Table shows estimates for combinations of $\alpha$ and $\lambda$. For $\alpha \leq .7$, $\gamma_S$ is significantly larger than $\gamma_M$.

that the statistic $2\ln[L_U^*(D)/L_0^*(D)]$ is distributed approximately $\chi^2(1)$. The $p$-values for this test statistic for each of the 8 tests is shown in Table 2 of the main paper.

We also perform a test where we fit all 24 choices for the 8 tests. This test involves 20 free parameters for the model in which gain-loss separability is assumed (4 each for $U(H^+)$, $U(L^+)$, and $U(C^-)$, and 8 for $U(A^+)$). The unconstrained model has 24 free parameters (4 each for $U(H^+)$, $U(L^+)$, $U([H^+,C^-])$, and $U([L^+,C^-])$, and 8 for $U(A^+)$). Thus, the appropriate test statistic, $2\ln[L_U^*(D)/L_0^*(D)]$ is distributed approximately $\chi^2(4)$. The results of this test are shown in the last row of Table 2 of the main paper.

## EC.7. Weighting Function Estimation for Study 2

We repeated the same analysis from Section EC.5 for the data from Study 2. Each of the 102 participants in Study 2 made 24 choices, thus the likelihood is maximized over the 2448 choices in Table 2 of the main paper. All other aspects of the procedure were identical.

As with Study 1, our base analysis assumed that $\alpha = 0.5$ and $\lambda = 2$. The resulting parameter estimates were very close to the Study 1 estimates: $\hat{\gamma}_S = .68$ and $\hat{\gamma}_M = .52$, a difference that was statistically significant ($t = 8.28, p < .0001$). The best-fitting scaling parameter was $\hat{\mu} = .28$, somewhat higher than the estimate of Study 1. The estimates for the Prelec weighting function were also remarkably close to those found for the Study 1 data: $\hat{\beta}_S = .64$ and $\hat{\beta}_M = .44$ ($p < .0001$).

We also conducted sensitivity analyses on $\alpha$ and $\lambda$ to test whether these differences were robust. Table EC.8 shows that $\hat{\gamma}_S > \hat{\gamma}_M$ for most values of $\alpha$ and $\lambda$. However, unlike Study 1, $\hat{\gamma}_S < \hat{\gamma}_M$ when $\alpha \geq .9$. It is important to note, however, that the fits for $\alpha \geq .9$ were notably worse than the fits when $\alpha$ was low. In particular, $\hat{\alpha} = .54$ and $\hat{\lambda} = 1.68$ when we allowed $\alpha$ and $\lambda$ to be free parameters.

## EC.8. Summary

We have presented a number of error models, including models in which error is random and unsystematic and models in which error is systematic. We derived implications of these error models on choice percentages, violations of double matching, conditional probabilities, and error rates. The double matching data of Study 1 of the main paper are better explained by the asymmetric error model than either the null or mixed error models.

We also details of a procedure in which we estimated the probability weighting function for single-domain gambles and mixed gambles. We found that the probability weighting function for mixed gambles was considerably more curved than the weighting function single-domain gambles for the data for both Studies 1 and 2.

## References

*See references list in the main paper.*