The Prevalence Heuristic:

Mistaking What Has Been Chosen for What Will Be Chosen

Emily Reit & Clayton R. Critcher

University of California, Berkeley

Correspondence to: Emily Reit, Haas School of Business, 545 Student Services Bldg., #s300i, Berkeley, CA, 94720; email: emreit@berkeley.edu

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Abstract

In predicting what others are likely to choose (e.g., vanilla ice cream or tiramisu), people are led astray by a *prevalence heuristic*—overestimating how often common (but bland) items (e.g., vanilla ice cream) will be chosen over more unusual (but exciting) items (e.g., tiramisu). Given common items are often chosen merely because they are available, not because they are preferred (tiramisu is rarely offered as a dessert), prevalence is not particularly diagnostic of future choice. Studies 1-3 demonstrate the prevalence heuristic and uncover when and why it emerges. Perceived prevalence is spontaneously used as a guide when forecasting others' choices (suggesting people confuse what has been chosen with what people will choose), but not when forecasting what others would be pleased to receive. Upon conscious reflection, people realize the prevalence heuristic is unwise. A final, two-part marketplace simulation study found reliance on the prevalence heuristic prompts sellers to misprice goods.

KEYWORDS: choice, social judgment, heuristics, perspective taking, theory of mind

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People are often tasked with predicting others' choices. A dinner host must decide how many servings of vanilla ice cream vs. tiramisu to have on hand. A store owner must decide how many of the new dress shoes that come in black vs. blue to stock. A florist must decide how many bouquets of daisies vs. dragon snaps should be available in her pop-up flower shop every Sunday.

Knowing others' preferences is difficult. In making social judgments, a readily accessible guide is the self (Ross, Greene & House, 1977). Although self-knowledge can helpfully inform social knowledge (Krueger, 2003; Dawes & Mulford, 1996), it is an incomplete guide. Social insight requires not only that people know what part of their own preferences are idiosyncratic ("I have to remember not everyone thinks cilantro tastes like soap"), but also that they actually expend the effort to adjust from their own egocentric perspective (Epley, Keysar, Van Boven & Gilovich, 2004). And other research—especially in the gift giving literature—has shown people display systematic biases when estimating what others prefer to receive. For instance, gift givers overweight thoughtfulness, cost, and uniqueness. In actuality, gift recipients prefer gifts they explicitly ask for, or simply money (Gino & Flynn, 2011).

Although past research documents clear challenges in understanding what others *like*, we posit there is a special challenge in predicting what others are likely to *choose.* This differentiation may seem odd. After all, there are not clear normative reasons to differentiate preferences and choice: It is almost axiomatic that people choose what they would prefer to receive. And here, we don't challenge this tautology. Instead, we suggest that the task of estimating others' choices naturally calls to mind a heuristic that—unless put under greater

scrutiny—is likely to be leaned upon when answering the difficult question of "Will people choose A or B?"

A hallmark of a heuristic is that it involves attribute substitution, reliance on an imperfectly valid but readily accessible cue when making a difficult, potentially intractable judgment (Kahneman, 2003; Kahneman & Frederick, 2002). We propose that in estimating others' choices of A or B, people lean on a *prevalence heuristic*— their intuitive sense of the relative prevalence of A over B. Our proposal rests on the recognition that this attribute is deceptively similar to the question of interest. The greater prevalence of vanilla ice cream over tiramisu does indeed reflect that the plain frozen treat has been *chosen to be eaten* more often than the Italian delicacy. But this does not imply that people are likely to choose vanilla ice cream over tiramisu when given the choice between the two. After all, vanilla ice cream is not merely a more common dessert choice, it is (for a variety of reasons) more commonly offered as an option to begin with.

Although the prevalence heuristic has not been identified or tested to date, several lines of research support the tenability of our hypotheses. First, various psychological literatures show that when X (e.g., positive events) is known to cause Y (e.g., positive mood), Y leads to an invalid inference of X (Johnson & Tversky, 1983; Mayer, Gaschke, Braverman, & Evans, 1992). This leap is invalid when X is not the *only* cause of Y. That is, the choice of an item (X) does lead to the prevalence of that item (Y), but merely observing an item is prevalent (Y) does not reveal the context in which (X) was chosen. If more grocery stores carry vanilla ice cream than tiramisu, it means that vanilla ice cream may be chosen by shoppers more often, but not chosen *over* tiramisu.

Second, another property of prevalence makes it enticing as a cue to social forecasts: its external observability. People prefer—and often are forced—to make forecasts about others using their observable behavior instead of their (often inaccessible) internal states (Pronin, 2008; Pronin, Berger, & Molouki, 2007). Reliance on observable behavior is what makes social forecasts frequently superior to self forecasts. That is, social forecasts benefit from leaning on others' (informative) past performance, whereas self forecasts give weight to the self's (overly-)lofty ambitions (Helzer & Dunning, 2012). It is notable that in the present research, we depart from this tradition by highlighting how reliance on observable behavior can be a source of error instead of accuracy.

If people do lean on the prevalence heuristic when forecasting choice, it should lead to systematic biases when two forces are in opposition: the (perceived) prevalence and inherent likeability of options. The prevalence heuristic should lead people to overestimate the extent to which others will choose commonplace but bland options (e.g., vanilla ice-cream, black dress shoes, daisies) over rare but enticing options (e.g., tiramisu, blue dress shoes, dragon snaps). We test whether the prevalence heuristic correctly anticipates such forecasting errors, directly assess the attribute substitution account of our effects, identify what it is about the forecasting task that encourages reliance on the prevalence heuristic, and then ultimately probe an applied implication of the bias.

Study 1

Method

Participants and design. One hundred ten undergraduates at the University of California, Berkeley completed this and other unrelated studies as part of an hour-long session for which they received course credit. Seven participants failed at least one of two attention

checks—one that asked for the sum of 2 and 2, one that asked what the study was about (see Supplemental materials for details). The remaining 103 participants are included in the results below.

For Study 1, we aimed to collect at least 100 participants. Because we had key manipulations in Studies 2 and 3, we knew we needed a larger sample size. Instead of prespecifying a specific sample size, we prespecified an amount of time to run the study. Research assistants recruited as many participants as they could for their scheduled hours and continued to run the experiment until the end of the academic semester. For Study 4, our sample size was based on how many other MTurk studies the lab planned to run that month as well as the lab's monthly MTurk budget at the time. In this way, Study 4 used the largest sample size that the budget permitted.

Procedure and materials. We constructed 11 pairs of items. Each pair was comprised of two options—one relatively prevalent (or common), one relatively rare—from the same category. These materials are presented in the left half of Table 1. To make certain that the items did indeed differ on perceived prevalence, we conducted a pretest on Amazon's Mechanical Turk with 120 subjects. Nine participants failed one of two attention checks (see Supplemental materials for details). The remaining 111 were used for analyses. For all 11 pairs, the common item was indeed identified as more common for people to use or partake in than the rare item, all ts > 10.97, ps < .001. Participants completed two sets of measures in a randomized order:

Choices. For each pair, participants were asked to consider having a choice between two options. For example, one item read, "If you had the choice of the following two options for lunch tomorrow, which would you choose?" For this item, the rare option was "curry" and the

common option was “a sandwich.” The order of the two options was randomized, as was the order of the 11 choice pairs.

Forecasts. Participants were asked to forecast the choices of their fellow participants. For exploratory purposes, we elicited such forecasts in one of two normatively-equivalent formats (see Critcher & Dunning, 2013). Some participants were asked to answer, “How many of the 100 other people taking this study would choose one option vs. the other?” Others were instead asked to estimate how likely it was that a specific randomly-selected participant would choose one option or the other (e.g., “what is the percentage chance that Participant 71 would choose one option vs. the other?”) Each question included two sliding scales, one for each item in the pair, that had to add up to 100%. The order of the two items within each pair was randomized, as was the order of the 11 choice pairs.

Results

On average, participants chose the common (but bland) over the rare (but exciting) option 50.22% of the time. Did participants realize that others choices would be evenly split between the two options? As predicted by the prevalence heuristic, participants believed that others would gravitate toward the common item (M = 59.12%, SD = 8.57%)—a significant overestimation, $t(102) = 10.53$, $p < .001$, $d = 1.04$. The results by item are listed in Table 1. Participants’ forecasts depended neither on the nature of the target (random-selected individual vs. population) nor on the order with which participants indicated their own choice vs. forecasted others choices, Fs < 1.

Table 1.

Predicted and Actual choice of the common (vs. rare) options (Study 1)

Category	Common Option	Rare Option	Predicted, Common (%)	Actual, Common (%)	Forecasting Bias (Predicted - Actual)
Dinner beverage	Budweiser	Japanese imported beer	55.94	27.18	28.76***
Dinner	pizza	Thai food	47.13	20.39	26.74***
Dessert 1	assorted cookies	crème brulee	38.36	19.41	18.95***
Breakfast beverage	orange juice	passion fruit juice	68.19	54.37	13.82***
Weeklong vacation	Hawai'i	The Galápagos	65.35	54.37	10.98***
Flowers	daisies	snapdragons	64.14	54.37	9.77***
Lunch	sandwich	curry	63.31	55.34	7.97***
Dessert 2	vanilla ice cream	tiramisu	50.31	46.6	3.71
Office wall paint color	white	bright blue	70.32	69.9	0.42
Birthday celebration (with friends)	dinner	improv comedy	62.26	67.96	-5.70**
Concert	classical piano	classical harp	65.09	82.52	-17.43***
	Average:		59.13	50.22	8.91***

Note. Evidence consistent with the prevalence heuristic is seen when the predicted choice of the common item is greater than the actual choice. The significance level of each prediction bias is based on a one-sample *t* test on the predicted value compared against the actual value.

** $p < .01$, *** $p < .001$

Study 2

Study 2 replicated Study 1, but extended on it in two ways. First, we conducted a more direct test of the prevalence heuristic. More specifically, we estimated that choice forecasts would lean on the perceived prevalence of the options, even when controlling for how much participants thought others would be pleased to receive each option. Second, we had some participants reflect on both the prevalence and others' liking for each options *before* they made their forecasts. If people use the prevalence heuristic because they explicitly believe prevalence

to be a valid cue to choice (or to liking, which predicts choice), this manipulation should have no effect. But if the prevalence heuristic is merely an attribute substitution driven by the cue's accessibility and not its perceived helpfulness, then calling special attention to these two cues should encourage people to lean on the more normatively-defensible liking instead of prevalence (see Critcher & Rosenzweig, 2014, for similar logic).

Method

Participants and design. Two hundred twenty-five undergraduates at the University of California, Berkeley completed this and other unrelated studies as part of an hour-long session for which they received course credit. Fourteen participants failed at least one of two attention checks—one that asked for the sum of 2 and 2, one that asked what the study was about (see Supplemental materials for details). Data from the 211 remaining participants are included in analyses reported below. Participants were randomly assigned to a *salience* or a (non-salience) *control* condition.

Procedure and materials. Like before, participants made judgments about 11 unique choice pairs. For each, participants indicated which option they would choose (choice), what percentage of other participants would choose one option or another (forecast), how prevalent or common each item was in people's lives (prevalence), and how much other participants in the study would like to receive each option (liking). Participants in the salience condition completed the perceived prevalence and perceived liking measures (in a counterbalanced order) *before* completing the choice and forecasting measures (also in a counterbalanced order). Those in the (non-salience) control condition completed the prevalence and liking measures *after* the choice and forecasting measures. Details on these measures are offered below:

Choices. These measures were equivalent to those used in Study 1, except we substituted out two choice pairs and added in two new choice pairs. In place of the questions about wall paint color and musical concerts, we asked participants to choose either an apple or a guava for their next snack and either a traditional landscapes or abstract/modern exhibit for their next art show attendance.

Forecasts. Given in Study 1 it did not matter whether forecasts were elicited for all other participants or a randomly-chosen other participant, all participants in Study 2 estimated what percentage of other participants would select one option or another.

Prevalence. Participants were asked to rate the commonness of having each item when partaking of or consuming an option in the relevant category. For example, participants indicated how common it was to eat curry when having lunch. Ratings were made on a 1 to 10 scale, from 1 (relatively uncommon) to 10 (relatively common). The order of the 22 items was randomized.

Liking. Presumably others' choices will largely (if not entirely) be a function of whether they would like or be pleased to receive one option vs. another. We aimed to measure perceptions of how much others would like to receive each item without invoking the language of choice (which we believe encourages reliance on the prevalence heuristic). We asked participants, "How pleased do you think people in this study would be if the following choices were made for them?" Judgments responded to items like "that their next lunch will be curry" on a 1 to 10 scale, from 1 (not at all pleased) to 10 (very pleased). The order of the 22 items was randomized.

Results

First, we tested whether we replicated the forecasting error encouraged by the prevalence heuristic. Overall, participants actually chose the common (but bland) option instead of the rare

(but exciting) option 44.94% of the time. As the prevalence heuristic would predict, participants overestimated how often others would choose the common option (M = 54.40%, SD = 9.75%), $t(210) = 14.10$, $p < .001$, $d = .97$.

Of course, this directional bias is merely consistent with, but does not offer direct evidence of the prevalence heuristic. To provide a more direct test, we wanted to connect people's perceptions of prevalence to their forecasts of choice. But prevalence may be a cue to choice for perfectly normative reasons: The commonness of an item *can* be a valid cue that it is preferred and thus likely to be chosen. Chocolate ice cream is more prevalent than jalapeño ice cream in part because people actually like—and thus would likely choose—a chocolate-flavored dessert. Our hypothesis is bolder: that prevalence (an assessment of what has been chosen) predicts forecasts of choice above and beyond such perceptions of liking.

To test these ideas, we began by defining two variables: *relative-prevalence* and *relative-liking.* Each reflected a participant's rating of the common item minus the participant's rating of the rare item, for a particular choice pair. For example, if a participant thought liking for assorted cookies would be an 8, but for crème brulee would be a 9, the relative-liking score for this participant for this choice pair would be -1. Relative-prevalence and relative-liking were Level-1 variables that were nested within participant in a random-slope, random-intercept model predicting choice forecasts. This permitted the effects of prevalence and liking to vary for each participant (random-slope), and allowed for differences between participants in how often they thought common items would be chosen (random-intercept). We also included a random effect of choice pair to account for variation between the 11 pairs in how often it was assumed others would choose the common item. Finally, given the robust phenomenon of projection—that

people look to the self as a guide for what others will choose—we included participants' own choice as an additional Level-1 predictor (Alicke, Dunning & Krueger, 2005; Krueger, 2000.)

Unsurprisingly, there was a main effect of relative-liking on choice forecasts, B = 3.62, *SE* = 0.21, *t*(176.71) = 17.23, *p* < .001. In other words, the more participants thought that others would like to receive the common as opposed to the rare item, the more they forecast others would make choices reflecting those preferences. But important for our purposes, there was a residual main effect of relative-prevalence, B = 0.99, *t*(276.49) = 5.64, *p* < .001. That is, prevalence predicted forecasts of choice above and beyond what would be clearly normatively defensible—i.e., a reliance on prevalence only to infer liking.

Do people intentionally lean on the prevalence heuristic because they embrace it as a valid cue for forecasting choice, or is it the mere accessibility of perceived prevalence that prompts mindless reliance on this attribute substitution? To disentangle these possibilities, we added several terms to our model. First, we included our two between-subjects conditions as Level-2 variables: *salience* (+1: prevalence and liking made salient before forecast; -1: none) and *order* (+1: forecast before choice ; -1: choice before forecast). We also included the Salience X Order interaction. Then crucially, we included two more interaction terms: Salience X Relative-Prevalence and Salience X Relative-Liking. This would permit us to test whether calling special attention to prevalence and liking shifted how much participants relied upon them when forecasting others' choice.

We observed a negative Salience X Relative-Prevalence interaction, B = -0.44, *SE* = 0.14, *t*(185.90) = -3.09, *p* = .002. Consistent with our attribute substitution account, once special attention was called to both prevalence and liking, they reduced their reliance on prevalence as a cue. But also, calling special attention to prevalence and liking increased reliance on perceived

liking, as reflected by a positive Salience X Relative-Liking interaction, B = 0.51, *SE* = 0.20, *t*(146.17) = 2.61, *p* = .010. These shifted weights are depicted in Figure 1. In short, the prevalence heuristic seems to emerge because prevalence is a spontaneously accessible cue; reliance on prevalence drops (and perceived liking increases) when both cues are made salient in forecasters' minds (see Rosenzweig & Critcher, 2014). In the Supplemental Materials, we provide additional analyses that demonstrate that perceived relative liking is indeed a more diagnostic cue than perceived relative prevalence; we also explore how our salience manipulation affects forecasting precision and bias.

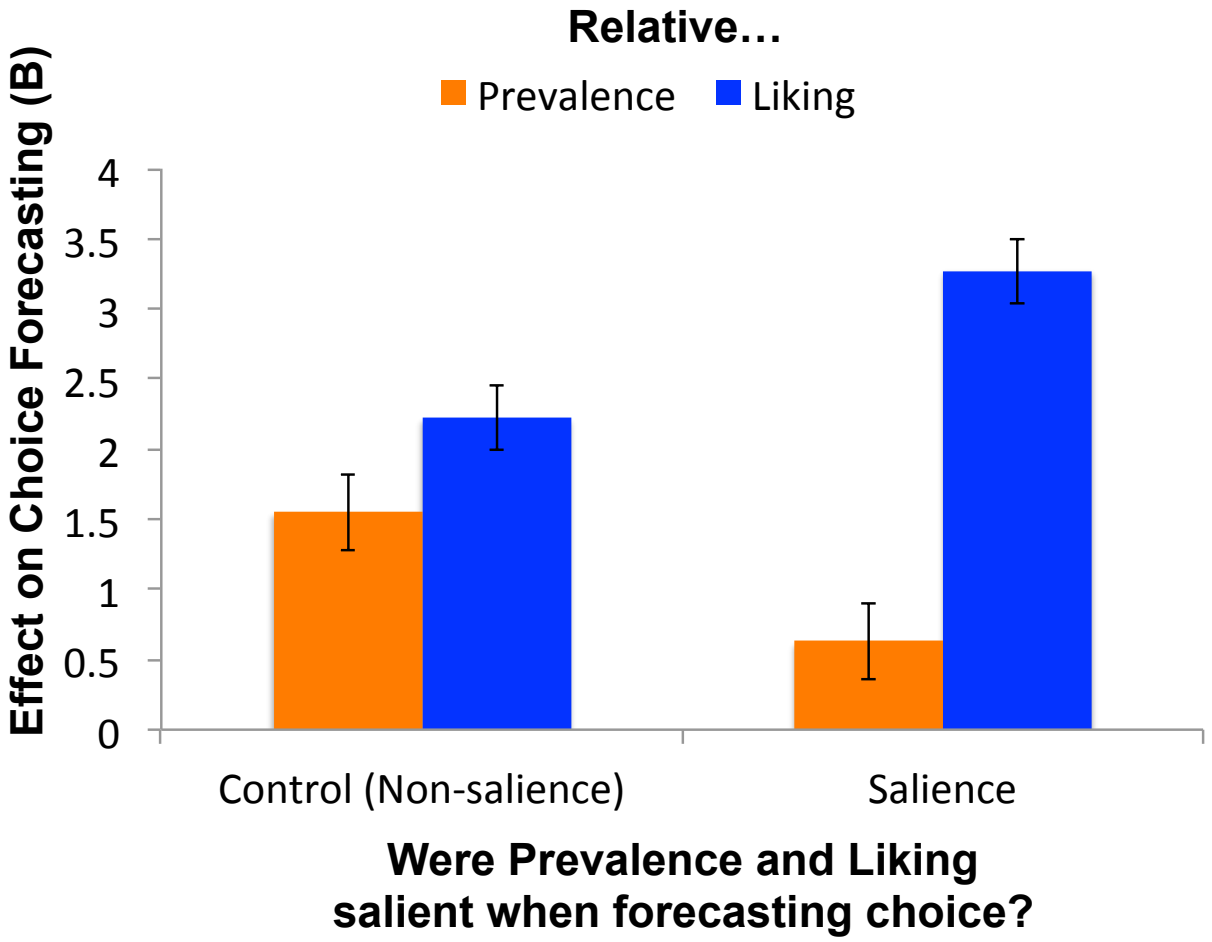

Figure 1. The independent influence of relative perceived prevalence and relative perceived liking on forecasts of others' choice. The depicted values are betas (and ±1 standard errors) from the model described in the text. Positive betas reflect that the more that a common items was

seen to be more prevalent than or liked more than a rare item, the more it was assumed others would choose the common item. (Study 2)

Study 3

Study 3 addresses a question that is typically neglected in the heuristics and biases research tradition: What about the judgment task encourages reliance on the prevalence heuristic? Study 3 used three different forecasting conditions. Some participants forecasted others' choice (as in Studies 1 and 2). Participants in the other two conditions forecasted how likely it was that another participant would be more pleased (i.e, prefer) to receive one item or the other. What differentiated these two conditions was whether the other participant knew (preference—known options condition) or did not know (preference—unknown options condition) which option they did not receive. If the prevalence heuristic stems from people blurring what has been chosen with what will be chosen, then only those in the choice forecasting condition should lean on the prevalence heuristic. If instead the prevalence heuristic is called to mind by considering a target who is contemplating two options—perhaps because this makes their relative commonness salient—then those in the preference—known condition should lean on the prevalence heuristic as well. Finally, if the prevalence heuristic is leaned upon merely to understand others' preferences, then those in all three conditions should lean on the prevalence heuristic.

Method

Participants and design. Two hundred eleven undergraduates at the University of California, Berkeley completed this and other unrelated studies as part of an hour-long session for which they received course credit. Participants were randomly assigned to one of three forecasting conditions: *choice forecasts*, *preference—known options, preference—unknown*

options. Nine participants failed the attention check that asked what the study was about (see Supplemental materials for details). Data from the 202 remaining participants are reported below.

Materials and procedure. All participants began by making forecasts in one of three forms (see below). After that, they completed measures that were identical to those used in Study 2: (self-)choices, prevalence, and liking (in a random order):

Choice Forecasts. These measures were nearly equivalent to the forecasts used in Study 2. Instead of predicting what percentage of other participants would choose the common vs. the rare item, participants estimated the percentage chance that a randomly-selected participant would choose one item or the other. The instructions fleshed out one example: "Participant A will see this question: 'If you had the choice of the following two options for lunch tomorrow, which would you choose?' Predict what percentage chance Participant A will choose one option vs. the other."

Preference—known options forecasts. Participants in the preference—known options condition were shown the same 11 choice pairs as those in the choice forecasts condition. Furthermore, they were told that Participant A would see these same pairs. But it was said a computer would randomly select the option Participant A would receive. Participants' task was thus not to forecast choice, but to forecast the percentage chance that Participant A would be more pleased to receive one item or the other.

Preference—unknown options forecasts. Participants in the preference—unknown options condition were given a similar forecasting task as those in the preference—known condition, except they were explicitly told that Participant A would not see the same pairs. This

meant Participant A could not compare the choices directly, and thus could not even hope for one of the two options.

Results

When expressing their own choices, participants picked the common item only 44.45% of the time. The extent to which participants' forecasts overshot this value (as predicted by the prevalence heuristic) depended on the specific forecast participants were asked to make, $F(2, 199) = 5.84$, $p = .003$, $\eta_p^2 = .06$ (see Table 2). When estimating what another participant would choose, participants thought there was a 54.10% (SD = 10.80%) chance the common item would be chosen. Once again, this estimate was significantly too high in the direction predicted by the prevalence heuristic, $t(51) = 6.45$, $p < .001$, $d = .89$.

But by asking participants to make estimates not of which item others would choose, but which they would be more pleased to receive, they seemed to have more insight into how likely each item was to be selected. That is, compared to those in the choice forecasts condition, other participants saw less appeal in the common option regardless of whether they were asked to forecast which of two known items another would be more pleased to receive (M = 49.66%, SD = 7.84%), $t(199) = 2.80$, $p = .01$, $d = .40$ or which of two unknown items another would be more pleased to receive (M = 48.83%, SD = 8.50%), $t(199) = 3.23$, $p < .001$, $d = .46$. Forecasts were similar regardless of whether the recipient knew the other options or not, $t < 1$.

Table 2.

Predictions (by forecasting condition) and Actual choice of the common (vs. rare) options (Study 3)

Category	Common Option	Rare Option	Predicted Choice, Common (%)	Predicted Preference (Known), Common (%)	Predicted Preference (Unknown), Common (%)	Actual Choice, Common (%)

Lunch	sandwich	curry	59.48[a]	54.18[a]	56.3[a]	47.53[b]
Dinner beverage	Budweiser	Japanese imported beer	49.87[a]	41.54[b]	44.69[b]	24.26[c]
Weeklong vacation	Hawai'i	The Galápagos	59.25[a]	58.14 [a]	56.99[a]	55.94[a]
Dinner	pizza	Thai food	49.25[a]	46.48 [a]	50.01[a]	27.73[b]
Fruit	apple	guava	63.31[a]	57.96[ab]	48.99[c]	56.93[b]
Birthday celebration (with friends)	dinner	improv comedy	63.56[a]	53.24[b]	51.87[b]	60.89[a]
Dessert 1	assorted cookies	crème brulee	35.08[a]	39.16[a]	35.39[a]	21.78[b]
Flowers	daisies	dragon snaps	57.37[ab]	53.21[b]	53.37[b]	58.91[a]
Dessert 2	vanilla ice cream	tiramisu	42.85[a]	41.04[a]	40.60[a]	34.16[b]
Breakfast beverage	orange juice	passion fruit juice	66.23[a]	54.20[b]	50.29[bc]	50.50[c]
Art Exhibit	Traditional paintings	Modern/ Abstract	48.92[ab]	47.14[b]	48.61[ab]	50.50[a]
	Average		54.10[a]	49.66[b]	48.83[b]	44.47[c]

Note. Evidence consistent with the prevalence heuristic is seen when the predictions are greater than the actual choice. Although forecasts in the two preference conditions did depart from actual choice, a more specific test showed participants in those conditions did not lean on the prevalence heuristic. Means in the same row that do not share a superscript are significantly different at the $p < .05$ level.

Of course, merely showing that participants in the two preference conditions showed less bias in their forecasts does not establish that they leaned less on the prevalence heuristic. We followed the procedure detailed in Study 2 to determine whether participants were indeed leaning on perceived prevalence when forecasting choice (consistent with the prevalence heuristic). We defined three Level-1 variables—*relative-prevalence*, *relative-liking*, and (*self-)choice*—and nested them within participant. The first two variables reflected the perceived prevalence or liking for the common item minus the rare item. The final variable controls for the

robust phenomenon of projection. Of greatest interest, we included a categorical variable of forecast (choice, preference—known options, preference—unknown options), as well as the Forecast X Relative-Prevalence and Forecast X Relative-Liking interaction terms. Finally, we included a random effect of *choice pair,* which accounted for differences among the 11 pairs in how popular the common vs. rare item was seen to be.

Unsurprisingly, we observed a strong main effect of relative-liking, $F(1, 147.50) = 193.92$, $p < .001$. That is, participants estimated that others were more likely to choose or be pleased to receive the common (vs. rare) item to the extent it was assumed others liked the common (vs. rare) item. Furthermore, this reliance on perceived liking did not vary by condition, $F < 1$. In contrast, we saw a more modest overall influence of perceived prevalence, $F(1, 220.01) = 13.52$, $p <.001$, in part because that influence varied by forecasting condition, $F(2, 160.76) = 8.01$, $p < .001$.

When we tested for reliance on prevalence by condition, we observed a pattern of results that nicely complemented our findings on forecasting bias. As expected, those who forecast others' choice leaned on perceived prevalence, B = 0.24, $t(47.18) = 4.19$, $p < .001$. In contrast, those who forecast what would make others more pleased did not lean on the prevalence heuristic. This was true regardless of whether forecasts were about those who did know about the counterfactual option, B = .01, $t < 1$, as well as those who did not know about that counterfactual option, B = .07, $t < 1$. In summary, even though it might seem tautological that others will select the options that they would be most pleased to receive, we found that reframing the forecasting task in this way encouraged more accurate forecasts of choice. This is because people leaned on (and were led astray by) the prevalence heuristic only when predicting others' *choice*, not what they would prefer to receive. This supports our account that the prevalence heuristic arises in part

from people inappropriately blurring what has been chosen (prevalence) with what people will choose (forecasts of choice).

Study 4

In our final study, we identified a context in which the prevalence heuristic can encourage literally costly mistakes. With the growth of on-line marketplaces and shopping communities, it is no longer only at garage sales that ordinary individuals play the role of sellers in economic exchange. Although some such marketplaces operate as auctions, for others sellers list specific prices for their goods. We developed a two-part marketplace simulation to test whether the prevalence heuristic would encourage sellers to misprice their goods by suboptimally raising (vs. lowering) prices for common (vs. rare) goods.

Method

Participants and Design. One hundred eight-two people were recruited on Amazon Mechanical Turk to complete the main study for pay. (An additional 100 people were recruited from the same pool for a pretest, described below, in which we determined the optimal, profit-maximizing price for every good.) Twelve participants failed the attention check that asked what the study was about (see Supplemental Materials for details). Fifteen other participants failed to follow instructions (e.g., by indicating they wished to both raise and lower the price of a given good). Data from the remaining 155 participants are reported below.

Materials and Procedure. Participants were told they were taking part in a market simulation, one that would have them play the role of a Mechanical Turk shopkeeper. As part of this simulation, participants' task was to determine how they wanted to price goods they might sell to fellow Turkers. Participants were given the goal of maximizing profits. As we pointed out,

raising prices typically reduces the number of items sold, but increases the profit margin made on each item sold. Lowering prices has the reverse effect: increasing sales, but reducing margins.

Participants completed 11 such simulations, corresponding to the 11 choice pairs used in Studies 2 and 3. In each, they were told to imagine they sold two items in a particular category to fellow Turkers. These categories and pairs of items were those used in Studies 2 and 3. We asked participants to envision Turkers coming into their store and deciding whether to buy one of their items (e.g., a sandwich or curry) or nothing at all (if all the prices were too high). We then showed participants the current price of each item. Unbeknownst to participants, such default prices were the optimal, profit-maximizing prices (as determined by a pretest described below and more fully in the Supplemental Materials). For each item, we asked participants, "Do you think it would be smart to **raise** the price, to **lower** the price, or to **not change** the price?" Participants indicated their responses by clicking an up arrow, a down arrow, or the price itself to indicate that they felt it would be smart to raise, low, or not change the price, respectively.

Finally, participants made forecasts of what a randomly-selected other in the study would do (like in Study 3). This permitted us to test whether suboptimal pricing decisions could be connected to the prevalence heuristic.

Determining the profit-maximizing price for each good. By setting the default price as the profit-maximizing price, we could classify any systematic desire by participants to raise or lower the price as a bias to overprice or underprice the item. To identify the optimal price for an MTurk store, we asked 100 participants on Amazon's Mechanical Turk to make two judgments about each of the 22 items. First, they estimated the maximum they would be willing to pay (WTP) for each item. We also had them estimate how much it would cost a store, on average, to supply each of these items (see Supplemental Materials for detail).

We leaned on participants' stated WTP to understand the distribution of demand. That is, for any given price, we could determine how many people would be willing to buy the good at that price. We used participants' median cost estimates merely to understand what the average Turker's belief was about the cost to supply each item. This estimate is important for calculating the estimated profit margin on each item sold. For each good, we calculated the profit-maximizing price by determining what price would maximize this expression: number of units sold at a given price * [price – cost]. Of course, the true validity of this procedure depends on participants' accurately reporting their true WTP. But even if this procedure systematically overestimates or underestimates the ideal price for each item, this should not prove problematic given our hypotheses focus not on a main effect of raising and lowering prices, but instead on a hypothesized difference in what pricing shifts participants will recommend for common vs. rare items.

Results

First, we determined whether a participant wanted to raise (+1), lower (-1), or leave unchanged (0) each price. Thus, for each pair of products, we calculated a *relative pricing strategy* composite by taking the participant's preferred pricing strategy for the common item and subtracting off the preferred pricing strategy for the rare item. Higher values on this composite reflect hypothesis-consistent results—i.e., a stronger tendency to want to overprice the common (as opposed to the rare) items.

To test our main hypothesis, we predicted the relative pricing strategy while including only a random effect of participant. As expected, the intercept was significantly greater than zero (B = 0.17), $t(154) = 3.97$, $p < .001$. This reflects that participants were more likely to pursue an inappropriately aggressive pricing strategy when considering common (vs. rare) items. Although

the results by item are provided in Table 3, the overall results showed participants were more likely to recommend raising the price on common (28.49%) than on rare items (23.50%), $p < .001$. In contrast, participants were more likely to recommend lowering the price on rare (45.14%) items than they were on common items (33.38%), $p < .001$. In short, participants' decisions to depart from the profit-maximizing prices was suggested by the distorting influence of the prevalence heuristic.

Table 3.

The percentage of participants who thought it wise to raise or lower the price for each common and rare item (Study 4)

Category	**Rare Option**	**Common Option**	**Rare, Raise Price (%)**	**Common, Raise Price (%)**	**Rare, Lower Price (%)**	**Common, Lower Price (%)**
Lunch	curry	sandwich	15.48[a]	23.23[a]	54.84[a]	39.35[b]
Dinner beverage	Japanese imported beer	Budweiser	20.13[a]	48.34[b]	48.32[a]	14.57[a]
Weeklong vacation	The Galápagos	Hawai'i	31.61[a]	44.52[b]	39.35[a]	27.74[b]
Dinner	Thai food	pizza	26.45[a]	21.94[a]	39.35[a]	49.03[a]
Fruit	guava	apple	16.13[a]	20.00[a]	45.81[a]	30.32[b]
Birthday celebration (with friends)	improv comedy	dinner	25.81[a]	39.35[b]	53.55[a]	21.94[a]
Dessert 1	crème brulee	assorted cookies	16.77[a]	21.94[a]	54.19[a]	38.71[b]
Flowers	dragon snaps	daisies	22.58[a]	18.71[a]	43.87[a]	50.32[a]
Dessert 2	tiramisu	vanilla ice cream	29.33[a]	21.19[a]	34.00[a]	39.07[a]
Breakfast beverage	passion fruit juice	orange juice	18.71[a]	24.52[a]	43.87[a]	16.77[b]
Art Exhibit	Modern/ Abstract	Traditional paintings	35.48[a]	29.68[a]	39.35[a]	39.35[a]
	Average		23.50[a]	28.49[b]	45.14[a]	33.38[b]

Note. Participants had the choice to raise, lower, or leave the price unchanged. This explains why the two rare percentages or two common percentages do not add to 100%. Means in the pairs of columns (i.e., raise rare and raise common, lower rare and lower common) in the same row that do not share a superscript are significantly different at the $p < .05$ level.

But is this asymmetry actually a consequence of the prevalence heuristic, or does it emerge for some other reason? Rare items' optimal price tended to be higher than common items' optimal price. Thus, if participants merely adopted a rule that the two items should be more evenly priced (for whatever reason), this could produce a pattern that misleadingly looked as if the prevalence heuristic produced this error. In order to address this concern, we examined whether individual variability in the extent to which participants displayed evidence of the prevalence heuristic on any given pair of items—i.e., the extent to which they thought others would prefer the common to the rare items—would explain their pricing strategy on that pair.

We added to our original model by defining a Level-1 variable, *prevalence heuristic,* that we nested within choice pair in a random-slope, random-intercept model. We also retained our random effect of participant. Consistent with hypotheses, those participants who showed the strongest evidence of the prevalence heuristic for any given choice pair (because they were most confident that the common item would be chosen over the rare item) were also those who incorrectly thought it wise to more aggressively price the common (compared to the rare) item, $t(10.76) = 5.66$, $p < .001$. In short, strategic pricing errors can be tied directly to the prevalence heuristic.

General Discussion

Predicting others' choices is not merely a tricky task, but one on which people systematically err. Across four studies, we find evidence that people lean on a prevalence heuristic: Their estimate of the likelihood that others will choose A over B is influenced by the perceived prevalence of A vs. B. That is, people forecast what others will choose in the future by

assessing what has been chosen before. But reliance on such a heuristic encourages overestimation of people's interest in commonplace, bland items (which may have been chosen in the past merely because they are commonly available) and underestimate interest in unusual, but exciting items (whose non-prevalence may reflect a lack of availability more than a lack of interest).

Studies 2 through 3 help explain why and when forecasters lean on the prevalence heuristic. Perceived prevalence was a spontaneously accessible guide to forecasts (an attribute substitution), not a cue on which participants put explicit weight upon conscious reflection (a faulty lay theory). Furthermore, the heuristic comes on-line when predicting others' *choices*, not merely what they would prefer to receive. This suggests that the origin of the prevalence heuristic may be the blurring of what has been chosen with what one will choose. Study 4 showed a practical consequence of this effect. Confusing the prevalence of commonplace but bland items with shoppers' interest in choosing them, virtual storeowners overpriced these items.

At first glance, reliance on the prevalence heuristic may appear inconsistent with a well-studied phenomenon: base-rate neglect. In a prototypical demonstration of that effect, judgments are disproportionately swayed by case-based information ("This rash looks remarkably similar to the one I saw in the dengue fever documentary!"). People fail to correct for just how uncommon (and thus improbable) such an attribution may be (Tversky & Kahneman, 1973; Bar-Hillel, 1980; Ajzen, 1977). The prevalence heuristic would seem to suggest that people are too embracing of base-rates. But there are two crucial differences between that literature and the present research.

First, we study the prevalence heuristic outside of contexts in which case-based information may have a deceptive allure. If we inserted case-based information that would seem

to imply interest in the rare, but exciting item, reliance on the prevalence heuristic might decline. Instead, participants are actually trying to *estimate* a base-rate ("What percentage of people will choose A over B?") and find it all too easy to consult another base-rate with which they have greater familiarity (prevalence). Second, and relatedly, prevalence is not the directly-applicable base-rate; it does not reflect how people select between A and B (but may instead reflect the relative supply or ease of attaining each). That said, some options A (e.g., Diet Coke, regular coffee) almost always co-occur with a corresponding option B (e.g., Coca-Cola, decaffeinated coffee). In those more limited circumstances, the prevalence heuristic might actually be a cue to accuracy.

A final question is whether perceptions of options' prevalence are themselves relatively accurate, or instead susceptible to biases. One possibility is that people lean on their own personal consumption experiences when estimating the broader prevalence of each option (Kahneman & Tversky, 1972). In Study 3, we asked participants how common it was for them personally to partake in or use each option (e.g., when having lunch, to eat a sandwich). We found that such personal experiences predicted participants' beliefs about the broader prevalence of the options $t(246.68) = 15.44$, $p < .001$. And although we found we could predict forecasts of choice from participants' own personal experience, this effect disappeared when we controlled for estimates of prevalence. This evidence is consistent with people leaning on a prevalence heuristic when forecasting choice, but being swayed by their own personal experience when forming impressions of options' prevalence.

In this paper, we have not only identified a heuristic that guides (and often misleads) forecasts of choice, but we have found hints of how to escape its influence. In many circumstances, we may be tempted to ask ourselves what someone else would choose. For

example, in deciding what to buy a friend for his birthday, we may ask what he would choose for himself. Reframing such questions as “Which would he be more pleased to receive?” may help to free us from the pull of an option’s mere prevalence, and spare us all many a melted scoop of vanilla ice cream along the way.

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