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The author explores how consumers anticipate product or service usage during the purchase deliberation and develops a descriptive model of the decision process in which consumers integrate their usage expectations into the choice between paying a flat fee for unlimited access or paying per use. The model helps explain why consumers habitually overestimate the likelihood of using enough to justify the flat fee and how this misperception depends on the perceived range of usage anticipated by the user.

A Cognitive Model of People's Usage Estimations

> Things have their due measure, there are ultimately fixed limits, beyond which, or short of which, something must be wrong
>
> —Horace, *Satires*

The idea of limitless consumption holds a special allure for many consumers Whether it means bellying up to the all-you-can-eat buffet, purchasing telephone service that allows an unrestricted number of calls, or subscribing to an online service that bills at a fixed monthly rate rather than by the hour, people generally like the idea of paying one fee for unlimited access. It is not unusual for a beginning tennis player to join a semiprivate club, a novice diver to buy rather than rent scuba equipment, or a recently enamored art aficionado to purchase a season pass to a local museum, each with the expectation that he or she eventually will use the product or service enough to justify the expense.

Yet a common phenomenon among consumers who prefer unlimited access is the tendency to pay a fixed fee that costs more than measured service would have cost, given their demonstrated demand. The inability to anticipate future usage and minimize expenditures accordingly has been dubbed the "flat rate bias" and has been observed in several studies of local telephone service (Train 1991).[1] In one study, 65% of customers who self-selected the flat fee would have saved money had they chosen the measured service billing option.[2] Conversely, only 10% of those who chose the measured service would have saved money with the flat fee (Kridel, Lehman, and Weisman 1993). In a more recent study involving an online grocery shopping and home delivery service, Nunes (1999) finds similar results. Of the service's 2600-plus subscribers in one Midwestern city, 59% of those who enlisted under the flat fee program paid more than they would have had they chosen a measured service pricing plan. Only 1% of those who chose the pay-per-use plan would have saved money with the flat fee.

Several motivational explanations might account for why people often intentionally buy more than they expect to use. First, people may expect their usage to increase simply because they want it to increase. This unwarranted expectation can be caused by wishful thinking (Einhorn and Hogarth 1986) Or, if there is a long-term benefit to increasing their usage, consumers can precommit by paying up front for unlimited access as an incentive to increase their consumption (Wertenbroch 1998). Second, people may not want to be encumbered by a pay-as-you-go plan. In addition to eliminating certain transaction costs, committing to the flat fee may free consumers from thinking about the cost each time they use a product or service (Clee and Wicklund

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[1]Kling and Van der Ploeg (1990) go so far as to incorporate a bias term when estimating a local usage distribution and calculating the expected consumer surplus (i e., the amount above the price paid that consumers would willingly pay, if necessary, to consume the units purchased) In their modeling efforts, they introduce the constant "bias" to capture a household's preference for the flat fee over measured service in the absence of factors of usage and pricing

[2]If consumer surplus, which accounts for risk aversion, is used as a decision rule, 50%–55% of flat rate customers would benefit by switching to local measured service.

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1980; Prelec and Loewenstein 1998). Finally, risk-averse consumers can ensure against any uncertainty with their bill by choosing to pay a preset fee with little or no incremental costs (Hayes 1987; Lee 1988).

This research examines a distinct cognitive explanation that can account for why people often unintentionally buy more than they use. In other words, faulty reasoning frequently leads consumers to overestimate the likelihood of using enough to justify the flat fee. This explanation is presented as a contributing and not an alternative one. Many biases (e.g., status quo bias, hindsight bias) have various causes that occur separately or in tandem, all of which contribute to their pervasiveness. The flat fee bias is no different. Cognitive errors can exacerbate motivational influences or occur independently, and they can help explain the severity and often the presence of the bias for many products and services for which motivational explanations are either not very compelling or simply break down.

The rest of this article is organized as follows. First, I review the relevant research regarding pricing and self-prediction. Next, I develop a model of the decision process that describes how two specific errors in reasoning can lead to a bias toward flat fee pricing. Study 1 demonstrates the robust nature of the flat fee bias, and the data reveal how consumers who favor the flat fee tend to foresee periods of higher-than-average usage as more common than periods of lower-than-average usage. The findings also illustrate how this perception is related to the consumer's foreseeable range of usage. The analysis of actual usage rates in Study 2 suggests that this perception is likely to be the opposite of what can be expected in the real world. In Study 3, I test directly and validate the link between the range of usage (i.e., minimum and maximum usage imaginable) and the flat fee bias. I conclude the article by reviewing some of the limitations of this work and offering suggestions for further research.

PRICING AND SELF-PREDICTION

Pricing is one of the most studied areas in marketing, yet nothing in the literature addresses flat fee pricing for unlimited access per se. Two somewhat related streams of research have explored how consumers process unit versus lump-sum prices. The first reveals how consumers are bad at identifying the best buy and commonly misjudge the price per unit when buying in quantity (Capon and Kuhn 1982; Nason and Della Bitta 1983; Russo 1977). The second shows how consumers can be less price sensitive when the price of a product is broken into smaller units (Estelami 1995; Gourville 1998; Morwitz, Greenleaf, and Johnson 1998). In this article, I examine the opposite phenomenon: consumers exhibiting less price sensitivity to a lump-sum price when the unit price is entirely unambiguous.

Economists think of flat fee and pay-per-use pricing schemes as special cases of two-part tariffs, in which the former includes a lump-sum fee plus a per-unit charge of zero, whereas the latter includes a positive per-unit fee with a lump sum that is at or near zero. Economic models (Wilson 1993) dictate that consumers abide by a self-selection process whereby heavy users prefer the pricing scheme with the high lump-sum and low per-unit cost (flat fee), whereas small-volume buyers prefer to pay a higher unit price on the smaller amounts they purchase (pay-per-use). Yet this self-selection constraint presumes that the users (1) can accurately assess their future usage rate at the time of purchase and (2) subsequently choose the pricing scheme that optimizes their allocation of resources. As Wilson (1993, p. 141) points out, "In practice ... customers are usually unable to predict exactly which optional two-part tariff will be best over the ensuing billing period."[3]

Behavioral research on the self-prediction of behavior is relatively scarce (for an exception, see Hoch 1985), whereas a relatively large amount of attention has been devoted to how people predict their preferences at some point in the future (for a review, see Kahneman 1994). A series of studies has shown that decision makers may not know, when making a decision at time t_0, how much they will enjoy the consumption of its consequences at time t_1 (Kahneman and Snell 1992; Kreps 1979; March 1978). But if purchasers end up not liking what they have bought, usage should taper off over time. Without a declining trend in consumption across consumers, this explanation cannot account for the flat fee bias.

A MODEL OF THE DECISION PROCESS

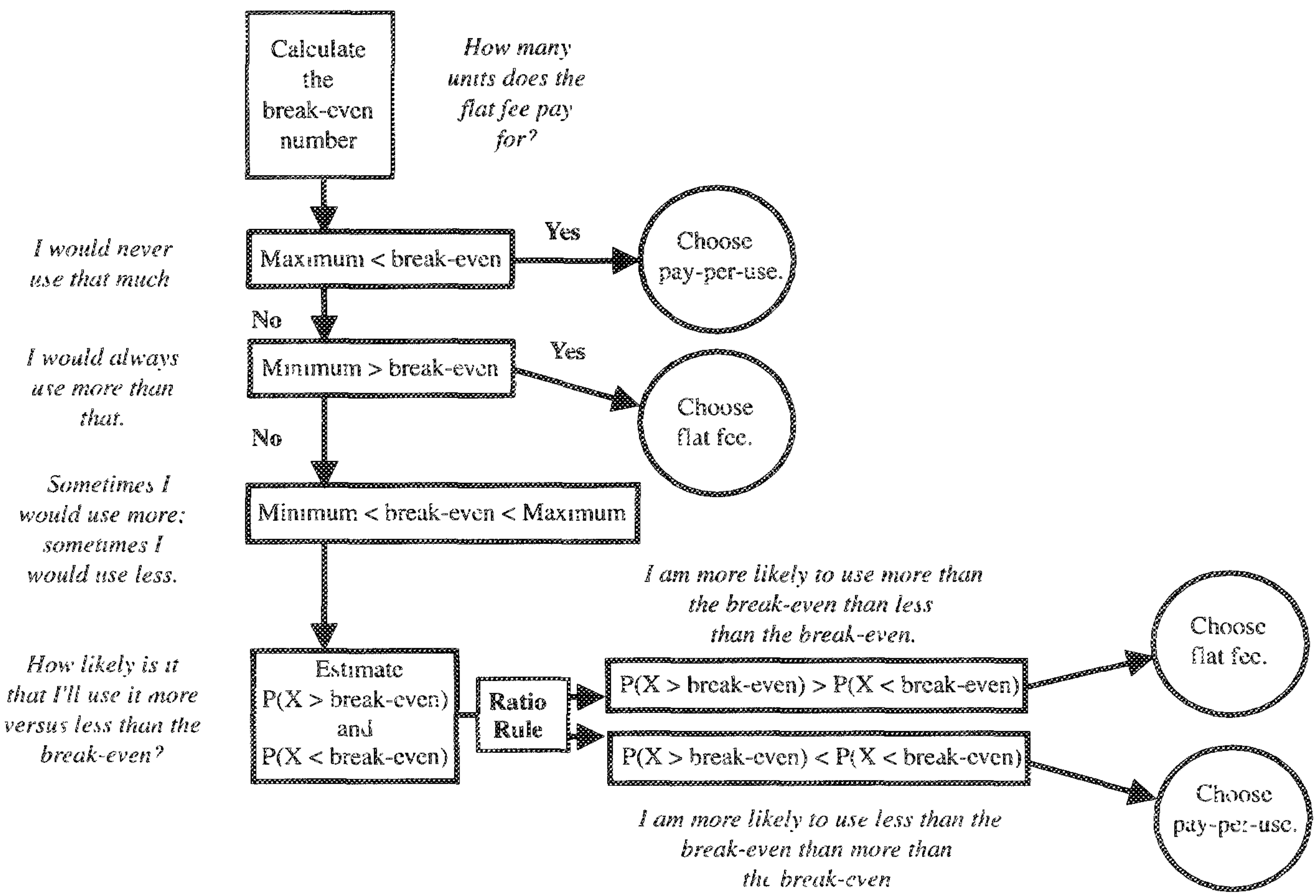
The proposed model assumes that, ceteris paribus, people choose the pricing schedule that offers the lowest total cost. In a pay-per-use situation, total cost is the per-use fee multiplied by the number of uses within a specified billing period. The flat fee ignores usage and is itself the total cost for that billing period. Comparing the total cost of each plan can be simple (e.g., buying a tuxedo versus renting one an anticipated number of times) or quite complex as the life of a product or the duration of a service becomes large or indeterminable (e.g., subscriptions, memberships, professional contracts). The process model outlined in Figure 1 applies largely to the initial choice, made before the first of many periods. It should be noted that this model is in line with both written and verbal protocols taken during Study 1 and several pilot studies.

Paying per use acts as the default option because it is far more prevalent in the real world, and it costs less at all levels of usage below some break-even number required to meet the flat fee. Consumers routinely begin the process by computing this break-even number. If they expect to use more than the break-even number, they would save money by opting for the flat fee. If they expect to use less, paying per use is the better deal. But what happens when a consumer expects to use more than the break-even number on some occasions and less on others (i.e., the break-even usage falls between the minimum and maximum usage imaginable)? The choice is not as simple.

While attempting to simplify matters, consumers frequently make two distinct errors in their reasoning. First, they frame the problem incorrectly. Consumers commonly base their decision on which of two outcomes they believe is more likely: (1) using more than the break-even number or (2) using less than the break-even number. If the former is expected to occur more frequently, they choose the flat

[3]Nonlinear pricing models include self-selection constraints, by which customers are assumed to select the tariff that minimizes the charge billed for their actual usage. Wilson (1993), recognizing that customers are generally unable to select the optimal plan, suggests that this "deficiency" can be "partially remedied" if the firm bills ex post according to the least costly option, something that neither Wilson nor I have seen in the real world.

Figure 1
PARAMORPHIC REPRESENTATION OF THE DECISION PROCESSES



fee. Otherwise, they pay per use. Frequency information often exerts undue influence for three reasons (Alba and Marmorstein 1987): (1) It is encoded easily, (2) awareness of an occurrence may be more salient or accessible than the details of what occurred, and (3) the marketplace fosters its use. Unfortunately, paying attention to frequencies (the number of sales at a store) and not magnitudes (the depth of the discounts) can result in poor decisions (Alba et al. 1994). This is true in this context as well. By simply comparing the expected frequency of the two competing outcomes, consumers fail to account for the absolute size of the savings or loss associated with the actual usage in each period. Consider the extreme example of consumers who use slightly more than the break-even number eight months of the year, but whose usage plummets to zero during the remaining months. Although these people appear twice as likely to use more than the break-even number, they may well pay much more with the flat fee.

The second error in reasoning entails consumers habitually overestimating the likelihood of using more than the break-even number. New and inexperienced users are unlikely to be able to assign probabilities to each possible level of usage or state of the world (S_1, .., S_n), which thereby creates a de facto distribution. Instead, they rely on what are salient but insufficient characteristics or cues (Brunswick 1956). The range, or number of possible states leading to each outcome, serves as an indicator of the likelihood of that outcome (Luce and Raiffa 1957).[4] The end result is identical to assigning equal probabilities to each state. Ellsberg (1961) has shown that when the probabilities of events are highly uncertain (i.e., ambiguity), people are resistant to making qualitative judgments such as $P(S_1) > P(S_2)$. Consequently, if the number of states on the right side of the break-even number is greater than the number on the left, the decision maker would perceive the likelihood of using more than enough to justify the flat fee as greater. This process is consistent with the fundamental principles under-

[4]According to the principle of insufficient reasoning first formulated by Jacob Bernoulli (1654–1705), if decision makers are completely ignorant (i.e., have no information about the likelihoods), they should behave as if each outcome is equally likely. Following this principle, also known as the Laplace Rule, would essentially be the same as relying on the range or number of outcomes. Each possible state would represent an outcome with equal probability assigned to each (i.e., a uniform distribution).

lying Parducci's (1965) range-frequency model.[5] Unfortunately, the diagnostic value of the number of states (e.g., using something between 0 and 4 times versus 4 and 21 times) is low because it says nothing about the specific probabilities of individual states.

It is critical to point out that any range of usage is truncated at zero by nature, people cannot use something less than zero times. Conversely, the right side of the range is limited only by the time available to consume as much or as many as possible. Consequently, the range or number of possible states greater than the break-even number can normally be expected to exceed the number less than the break-even number, which inflates the perceived likelihood of using more than enough to justify the flat fee. The truncated range contributes to the pervasiveness of people's preference for flat fee pricing and leads to the first formal hypothesis:

> H_1. A disproportionate percentage of consumers will prefer to pay a flat fee for unlimited access rather than pay per use, all else being equal.

According to the proposed process model, the choice between pricing plans depends on whether consumers believe they are likely to use enough to justify the flat fee. In other words, people are predisposed to prefer the flat fee when they expect to use more than the break-even number. This leads to the second hypothesis:

> H_2. The likelihood of a person choosing the flat fee is directly related to the perceived likelihood of using more rather than less than the break-even number.

In turn, whether consumers believe that they are likely to use enough to justify the flat fee depends on the range of possible usage imaginable. The range is bounded by extreme values, or the perceived upper and lower limits of their consumption. If people rely on the number of possible states that lead to an outcome as a proxy for the probability of that outcome, it is the ratio or (maximum – break-even/break-even – minimum) that affects the perceived likelihood of an outcome and ultimately affects choice.

> H_3: The perceived likelihood of using more than the break-even number varies systematically with the distance between the maximum imaginable and the break-even numbers relative to the distance between the break-even and the minimum imaginable numbers.

In other words, the probability that a person will prefer the flat fee becomes larger as the perceived likelihood of using more than the break-even number grows. The perceived likelihood depends on the perceived boundaries of their usage and therefore the aforementioned ratio. The idea that this ratio influences choice will henceforth be called the "ratio rule." The ratio rule is an "as if" rule, and people who do not consciously follow the formula are predicted to act as if they did. The ratio rule implies that preferences are malleable and vary in some systematic way with the ratio or boundaries of expected usage. As such,

> H_4. Consumers whose ratios exceed 1.0 are more likely to favor the flat fee. As this ratio increases, so does the perceived likelihood of using more than the break-even number and consequently the propensity to select the flat fee. As the ratio gets smaller, people become more inclined to pay per use.

From a practical perspective, using the range as a proxy for probabilities is problematic only if it leads consumers to make faulty judgments. If people were truly apt to use more than the break-even number most often, the ratio rule might serve as a useful heuristic. The existence of a flat fee bias, however, implies that for most users, periods of relatively low consumption typically outnumber periods of relatively high consumption. Yet by definition, the ratio rule suggests that people expect the opposite to be true. This conflict leads to the following.

> H_5. By considering only the number of states and not the probabilities of each state, people typically perceive the distribution of their usage to be left-skewed (i.e., occasions of relatively high levels of consumption outnumber occasions of relatively low levels). This is the opposite of what can be expected most often in the real world.

Documenting the difference between what people perceive and what really happens is critical to this work, because this discrepancy contributes directly to making the flat fee bias such a widespread phenomenon. The empirical analysis of actual usage rates conducted in Study 2 explores whether people's perceptions are prone to reflect reality.

Implicit in the proposed model is the notion that consumers who rely on the ratio rule are new or light users who lack the data and the ability to process them that typically come with experience. Experienced users who have more data are expected to have a better understanding of the domain and thus to be better calibrated regarding their own usage patterns (how likely different levels of usage truly are). Therefore, as the amount and quality of information about usage increases, people are expected to be less apt to rely on the ratio rule, which diminishes any bias toward the flat fee. This leads to the following:

> H_6. As people accumulate better information about their own usage patterns (the true distribution), they will be less inclined to rely on the ratio rule and therefore less likely to be biased toward the flat fee.

The first three hypotheses are tested experimentally in Study 1, and the data support H_4 as well. In Study 2, secondary data are used to compare real and perceived usage and test H_5. Study 3 confirms the results of Study 1, while directly testing H_4 and H_6.

STUDY 1

Method

Subjects. Subjects were 100 regular shoppers at a large California grocery chain who indicated that they own a home computer and were interested in learning more about grocery shopping online. None of the respondents reported having shopped online before. A total of 69 women and 31 men completed the survey. Their average age was 32 years. Participation was voluntary, but those who completed the survey received a nominal gift.

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[5]The stages described here are somewhat analogous to the judgment strategies described by Parducci's (1965) range-frequency theory. The range principle would lead consumers to divide the range into two subcategories around the break-even number. States above this number are classified as savings, and states below as losses. The frequency principle would then lead them to divide the set into N equal groups or categories, each one corresponding to a state with equal proportions. Consumers who do this would compare the two sides to determine if the frequency of using more than the break even number is enough to justify the flat fee.

Stimuli and design. Respondents were shown printed pages from a leading online grocer's Web site before the survey began. The interviewer informed subjects of a plan to bring home shopping over the Internet to their area and explained two payment options supposedly being considered: (1) a monthly flat fee by which consumers could order as frequently as they liked and (2) a usage fee, which would apply each time the shopper placed an order. Respondents were told that the service only handled orders of $35 or more regardless of the pricing plan chosen and that the monthly service fee under either plan would be charged to subscribers' credit card automatically on the last day of the month.[6] It was also mentioned that delivery people were strictly forbidden from accepting tips. The rest of the survey was designed to collect respondents' estimations of their usage over a multiperiod event horizon and their preferences between pricing schedules.

First, respondents indicated how many times per month, on average, they currently spend more than $35 in a single shopping excursion. Respondents were also asked how many times per month, on average, they would expect to use the online service, if available, as well as the minimum and maximum number of times they could reasonably expect to use the service in any given month. Each respondent then chose between the per-use fee and the flat fee in a series of competing pricing schedules. The three focal per-use fees were $3, $4, and $6 (a pilot study indicated that a per-use rate of approximately $5 was appropriate). For these three choices, the interviewer surreptitiously calculated the competing flat fee separately for each subject on the basis of (1) the per-use fee, (2) the subject's previously reported usage rates (current, expected, and maximum), and (3) a premium of $12 over the product of the first and second factors. In this way, the flat fee was always greater than the amount the subjects would reasonably expect to pay if they paid per use. For example, if their reported current, expected, and maximum usage was four, three, and six, respectively, they were asked to choose among $6 per use or a $36 flat fee, $4 per use or a $24 flat fee, and $3 per use or a $30 flat fee. Each subject responded to all three focal choices, which were counterbalanced and separated by filler choices.

In the second part of Study 1, subjects were asked to estimate the likelihood (as a percentage of total usage occasions) that they would use the service exactly their expected amount in any given month. Subjects were also asked to estimate the likelihood that they would use more than average and less than average. The reported likelihoods were constrained to sum to one.

In this study, every attempt was made to control for motivational reasons that could lead people to favor the flat fee. First, in the online shopping context, it is unlikely that consumers want their usage to increase. There is simply no long-term benefit to shopping for groceries more often. Second, all subscribers pay at the end of each month in exactly the same way. Neither plan required more effort, and all "losses" were combined (i.e., integrated) automatically in accordance with mental accounting's principles of hedonic editing (Thaler 1985).[7] Third, the service was described as only handling orders of $35 or more, which forced consumers to think consciously about what they would spend every time they use the service. In other words, there was no freedom from thinking about costs, which often results when people pay a flat fee. Finally, the risk avoidance explanation is based on the assumption that risk-averse people are more likely to prefer the flat fee. To gauge each respondent's level of risk aversion, the following question, adapted from Lee (1988), was included in the survey:

> Imagine that you are at a community fair. You have just won a throwing game and are entitled to claim a $40 prize. The operator of the game offers a second, follow-up game with the prize money. In this game, you would spin a wheel with two colors, yellow and green. Your final prize depends on which color an arrow on the side is pointing to when the wheel stops spinning. If the pointer is on yellow, you win $60. If it comes up green, you get only $20. At what setting of the odds to win (percentage of the wheel that is yellow) would you agree to play the follow-up game? Answers can range from 1% to 100%.

The answers were used to calculate a constant absolute risk aversion (CARA) coefficient for each respondent under the assumption of constant risk aversion.[8] If risk aversion is responsible for the flat fee bias, the coefficient would be expected to be significantly larger for respondents who favor the lump-sum fee.

Results

A significant majority (87%) of subjects favored the flat fee, even though it always exceeded what they would pay per use, given their current rate of monthly $35-plus shopping trips. This makes sense, because respondents reported expecting to use the online service less often than they currently visit a grocery store (3.58 versus 3.98 times; $t_{99} = 3.76$, $p < .01$). Yet almost the same proportion (85%) preferred the flat fee even when it exceeded what they would pay per use given their lower expected rate of usage. These results support H_1, and the flat fee bias does not depend on any expectation of increasing future usage in this case. Likewise, it did not depend on any real or expected differences in usage. The average number of shopping trips did not differ significantly between subjects who favored the flat fee and those who favored paying per use (see Table 1). In addition, subjects who favored the flat fee were no more risk averse than those who were content to pay per use. The average risk-aversion coefficient did not differ significantly between those who chose the flat fee and those who preferred to pay per use (.25 and .226, respectively; $t = .58 < t_{25, 23} = 2.069$).

The proportion of people that preferred the flat fee fell dramatically (to a mere 5%) when it was calculated on the

[6]This figure was chosen to reflect the average consumer expenditure at a retail grocery store, which is $34 according to the Irving, Tex., research firm M/A/R/C Group (*Promo* 1998).

[7]More important, Thaler and Johnson (1990) find little empirical evidence to support the prediction that people actively try to integrate losses. Nevertheless, the losses (per-use fees) would be integrated automatically and billed as a lump sum.

[8]Assuming risk aversion and that most people have a positive willingness to insure against risk, I used the following utility function: $U(x) = a - be^{-rx}$, where r is the risk-aversion coefficient under CARA. If w denotes wealth, and because $e^{-r(w+x)}$ ($= e^{-rw}e^{-rx}$) is proportional to e^{-rx} for any w, it follows that changing initial wealth w does not affect economic decisions. In other words, CARA implies zero wealth effects.

Table 1
STUDY 1: REPORTED PREFERENCES BASED ON USAGE

Reported Usage	*Percentage Who Favored Flat Fee*	*Reported Usage: All Subjects*	*Reported Usage: Those Who Prefer Flat Fee*	*Reported Usage: Those Who Prefer Pay Per Unit*	*Per-Unit Fee*	*Average Flat Fee**	*Average Break-Even Number**
Current	87%	3.98	3.97	4.17	$6	$36	6.0
Expected	85%	3.58	3.57	3.67	$4	$26	6.6
Maximum	5%	6.1	6.13	5.93	$3	$30	10.0
Minimum		.94	.92	1.08			

*Notes: Flat fees were calculated for all subjects using their individual reported usage. The formula was (per-unit fee × reported usage) + $12. Therefore, the flat fee and break-even number differed for each subject on the basis of usage.

basis of the maximum usage imaginable. This precipitous drop suggests that the vast majority of respondents were conscious of the upper bound of their usage, and when the break-even outgrew the maximum imaginable usage, the flat fee ceased to be an attractive option.

In addition to the previous analysis, I employed forward stepwise logistic regression to determine which explanatory variables corresponded most closely to the choice between pricing plans (i.e., were the best independent variables). Choice was the dependent variable, whereas the subject's reported maximum, minimum, and expected usage and the ratio (maximum – break-even)/(break-even – minimum) were all included as independent variables. Each subject's risk-aversion coefficient was included as well. The results indicate that the ratio was the only variable significant at the .05 level ($\chi^2 = 5.0168$, $p = .025$). Backward stepwise regression provided similar results. This analysis suggests that the preference between pricing plans can best be predicted by the ratio alone.

Also, the subjective likelihood of using more than average exceeded the subjective likelihood of using less than average for half of those who chose the flat fee ($n = 85$, ratio = 1.37) but for only one person who preferred to pay per use ($n = 15$, ratio = .78). These asymmetries suggest that respondents who favored the flat fee perceived the distribution of their usage to be left-skewed. The ratios defined by the ratio rule (maximum – break-even)/(break-even – minimum) averaged 1.16 for those favoring the flat fee and .56 for those favoring paying per use and were highly correlated ($r = .48$) with the previous ratios of subjective likelihoods.

Discussion

Study 1 illustrates how people are generally willing to pay a hefty premium for unlimited access, even when neither their current nor their expected usage can justify it. This supports H_1. The marked drop in consumers who favor the flat fee when it is calculated with their maximum usage suggests that people have an upper bound in their minds as to what they are willing to pay for unlimited access, and they do not make reckless decisions.

The data also reveal that (1) users tend to believe that periods of higher-than-normal usage are more likely than periods of lower-than-normal usage and (2) users who favor the flat fee are more inclined to maintain such perceptions. The likelihood of a person choosing the flat fee seems to be directly related to the perceived likelihood of using more rather than less than the break-even number, in support of H_2.

The correlation between the ratio of the range and the ratio of the perceived likelihood of periods of higher- versus lower-than-average consumption (symmetry) was quite high. This suggests that perceptions regarding future usage vary with the distance between the maximum imaginable and the break-even usages compared with the distance between the break-even and the minimum imaginable usages, in support of H_3. Together, the results suggest that choice is affected by respondents' perceptions regarding the shape of the distribution of their usage (i.e., skewness), which depends on the perceived range of possible outcomes. Therefore, the results of Study 1 support H_1, H_2, H_3, and, in many respects, H_4.

At this point, it is important to explore whether respondents' perceptions regarding the shape of the distribution of their usage (i.e., skewness) reflect reality. In other words, is it reasonable for them to expect incidences of higher-than-average usage to be more common, such that usage rates as represented in a histogram would be typically left-skewed in their distribution?

STUDY 2: REAL VERSUS PERCEIVED USAGE RATES

An Empirical Investigation

For all durable goods and services, there exists some time interval between one usage occasion and another. This interval might range from one minute to one hour for a telephone call, one day to one week for a health club, or one day to one month for an online grocery service. The Poisson distribution is the simplest and most widely used probability distribution applied to the number of events occurring in a given time interval. Consumer purchases, customers arriving at a store, and telephone calls to a complaint department have all been modeled effectively by means of Poisson distributions at the individual level. For frequently purchased goods, the Poisson assumption has a long-validated history (Ehrenberg 1972; Morrison and Schmittlein 1981; Schmittlein, Morrison, and Colombo 1987).[9] It seems reasonable, therefore, to model other discrete events, such as product or service usage, with the same type of model (Ehrenberg 1959).

[9]For a detailed discussion of the Poisson process in modeling purchasing patterns, see Chatfield, Ehrenberg, and Goodhardt (1966). The Poisson purchasing process has not gone unchallenged. The Poisson process implies exponentially distributed interpurchase times, and Chatfield and Goodhardt (1973) have questioned the Poisson assumption on grounds that the intertemporal purchase times might be better fitted by an Erlang distribution of order two.

The most widely used compound model in marketing, which will be applied here, posits that events at the individual level follow a Poisson distribution with mean λ. The mixing distribution follows the flexible gamma distribution, which yields a negative binomial compound distribution (NBD model).

Unlike purchase rate studies, the goal of this analysis is not to predict aggregate behavior in the future. Instead, the value lies in specific deductions that might be made from certain features of the Poisson distribution. In particular, the Poisson's skewness is always positive (right-skewed), which is the opposite of how most respondents perceived their usage in Study 1. As the mean of a Poisson shifts right (as it would for heavy users), the distribution spreads out, gradually approximating a normal (symmetric) distribution. Thus, light users tend to use less than average more often, with occasional surges in usage. If these light users prefer the flat fee because they perceive the distribution of their usage as left-skewed (many incidences of high usage versus few incidences of low usage) whereas in reality it is right-skewed, this misperception would contribute to the pervasiveness of the flat fee bias

The data The data consist of 429 health club visitation records from a residential health club in Chicago.[10] The only way to be certain that each visit recorded represented a single usage for a single person was to rely on only the 140 account records for individuals. Eleven records were eliminated because the users had six or more months with zero attendance. The final analysis was based on attendance records for 129 individual regular users, some of whom had less than all 12 months of data recorded, which accounted for a total of 1433 data points rather than the expected 1548 These 129 users visited the health club an average of 61 times per year. Coincidentally, the annual membership cost $610 if paid up front ($99 per month if paid monthly). The 79 users who visited less than 61 times (median = 51) could have chosen to pay a one-time $10 guest fee each time they visited the club. Residents who used the facility less than 61 times averaged 38 visits for the year, which resulted in an average premium of $230 more than they would have paid had they elected to pay per visit. This is not to say that there were no motivational reasons for these residents to choose membership (it has its privileges, such as prestige). Instead, this analysis looks at the pattern of usage among those people who have the greatest incentive to frequent the club (i.e., those most likely to be heavy users).

Analysis. Let x_{cm} be equal to the number of days customer c uses the facility in month m, and let $x_{cm} | \lambda_c$ be an observation from month m from customer c who has mean λ_c. Although it is impossible to truly determine the distribution for each user, it is even more difficult given that the data include heterogeneous users with limited, and sometimes different, amounts of data ($x_{cm}, _{m = 1, \ldots, M_c}$) for each user. It is hypothesized that X is a random variable such that $x_{cm} \sim$ Poisson (λ_c). If $x_{cm} \sim$ Poisson (λ_c) and $\lambda_c \sim$ gamma (r, α), then the likelihood of seeing the data collected, or L(data), is $P(X, \lambda) = P(X/\lambda)P(\lambda)$. The strategy for testing the Poisson assumption at the individual level was consequently one of constructing the conditional likelihood for each user with the gamma distribution mixed in and maximizing the resulting overall likelihood function (see Appendix), which is

$$(1) \qquad LL = \sum_c \left[\ln \Gamma\left(\sum_m x_{cm} + r - \ln\right)\Gamma(r) - \sum_m \ln(x_{cm}!) + r\ln(\alpha) - \left(\sum_m x_{cm} + r\right)\ln(\alpha + M_c)\right].$$

Maximizing this function provides the para meters for the expected NBD (s = 2, p = .27) used to generate the expected data, which is then compared with the actual data. Both the actual and expected values are plotted in Figure 2. The NBD model thus far appears to fit exceptionally well ($\chi^2_{29} = 36.83 < \chi^2_{critical} = 42.56$, a = .05).

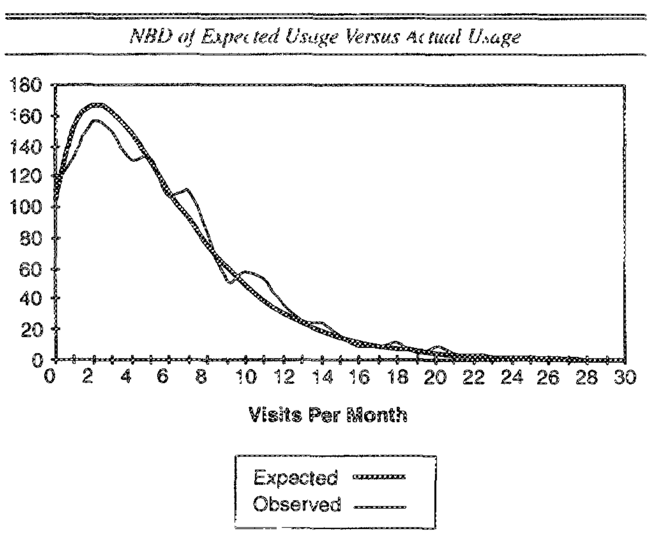
From the parameters of the NBD, the associated gamma function can be estimated In turn, the gamma (2, 2 7) is fitted to the λs using the capability procedure in SAS, and it appears as if the predicted curve is a reasonable approximation as well ($\chi^2_7 = 10\ 20 < \chi^2_{critical} = 14.07$, a = .05).

These results support the notion that successive uses of a product or service behave like independent samplings from a Poisson distribution, but this idea can also be tested without depending on the precise form of the compounding distribution (Chatfield, Ehrenberg, and Goodhardt 1966). The second test involves comparing the theoretical and observed standard deviations of the differences in purchases across two time periods. This comparison was made 11 times across the 12 months of data. The mean deviation of the individual differences was .16, which shows close agreement and again supports the Poisson part of the NBD model.

Two distinct analyses suggest that usage rates at the individual level can be well represented by a Poisson distribution, even for people most likely to be heavy users (i.e., members). Therefore, it seems reasonable to assume that in many, if not most, cases real usage rates are right-skewed.

Figure 2

COMPARISON OF THE EXPECTED USAGE FROM THE NBD (2, 27) AND THE DISTRIBUTION OF ACTUAL OR OBSERVED USAGE ACROSS ALL USERS



[10]Note that an inherent selection bias exists in the data because these records include only those members who chose to pay the flat fee (i e, become members) This hardly seems problematic, as the population selected is entirely consistent with the goal of studying overpurchasing

similar to the Poisson distribution. As demonstrated in Study 1, however, people often act as if their usage rates are left-skewed. If misperceptions regarding the distribution of a customer's usage depend on the range of possible outcomes, altering the range of usage (minimum and maximum, holding the break-even usage constant) should affect people's expected usage and therefore their choice of pricing plans. This is tested explicitly in Study 3.

STUDY 3

This study demonstrates how people's choices between pricing plans can change in accordance with the perceived boundaries of their usage. Both the minimum and maximum usage were manipulated in an attempt to affect the subjective likelihoods respondents assign to using more versus less than the break-even usage. The ratio rule predicts that these likelihoods will affect choice. Also, inexperience, or an information deficit regarding the true distribution of their usage, is predicted to lead consumers to depend on faulty cues, such as the range. Consequently, these effects should disappear if consumers are provided with enough information to understand the true shape of the distribution of their usage.

Method

Subjects. Subjects were 520 undergraduate and graduate students at a large state university in the Midwest who voluntarily completed the survey in exchange for a nominal gift (a candy bar).

Stimuli and design. Subjects were told to imagine that they had just moved into a new apartment building that maintains a pool for residents, who can pay an additional fee for access. Residents pay either (1) a flat fee of $60 per month or (2) $5 each time they use the pool. Subjects were informed that regardless of the pricing schedule chosen, they would be billed at the end of each month. They were then given historical information regarding their usage at their last building, where, they were told, they had lived for three years. All subjects were told that they had averaged 12 visits per month. The break-even number (12 or $60/$5) was deliberately set to match the long-term average of their usage. Consequently, subjects should not expect to spend any more or less with either pricing plan and, all else being equal, should be relatively indifferent between the two. The primary dependent variable was their choice of pricing schedule, but subjects were also asked to estimate their likelihood of using the pool exactly 12 times in any one month, more than 12 times in one month, and less than 12 times in one month. In this way, any asymmetry in how subjects perceived the shape of the distribution of their usage could be detected.

The study had a 2 × 2 × 3 completely randomized factorial design, in which the independent variables were minimum usage (0 or 8), maximum usage (16 or 24), and the presentation format of prior usage information (range, tabular, distribution). In the range format condition, subjects were told only the boundaries of their usage (e.g., "At most, you used the pool 16 times in one month, but there were months when you never used it.") In the tabular format condition, subjects saw a list of 36 numbers, each one representing a single month's usage. In the distribution format condition, subjects saw a histogram of their prior usage (see Figure 3). The specific numbers were selected so that the mean always equaled 12.[11] Set apart from these 12 cells was a control condition in which subjects were simply told that their average usage equaled 12. In this condition, subjects were asked to estimate realistic minimum and maximum usage rates.

If the ratio rule applies, the largest proportion of respondents should prefer the flat fee when the ratio is the largest (range is 8–24, [(24 – 12)/(12 – 8)], ratio = 3) and the lowest when the ratio is smallest (range is 0–16, ratio = 1/3). The two remaining conditions, 8–16 and 0–24 (ratio = 1 in both), should fall somewhere in between and should not differ significantly. This should be the case in the range and tabular format conditions, but not the distribution format condition. A histogram displays numerical information differently, using spatial relations that convey complex information rapidly for easier absorption (Guthrie, Weber, and Kimmerly 1993). When subjects are presented a histogram that illustrates the distribution of their usage over time, the diagram should support some easy perceptual inferences, such as the likelihood of using more or less than a particular point on the graph (Larkin and Simon 1987), through a comparison of the shaded areas to the left and right of 12 (see Figure 3). Therefore, respondents should have an easier time assessing the true likelihood of using more versus less than the break-even number in the distribution format condition.

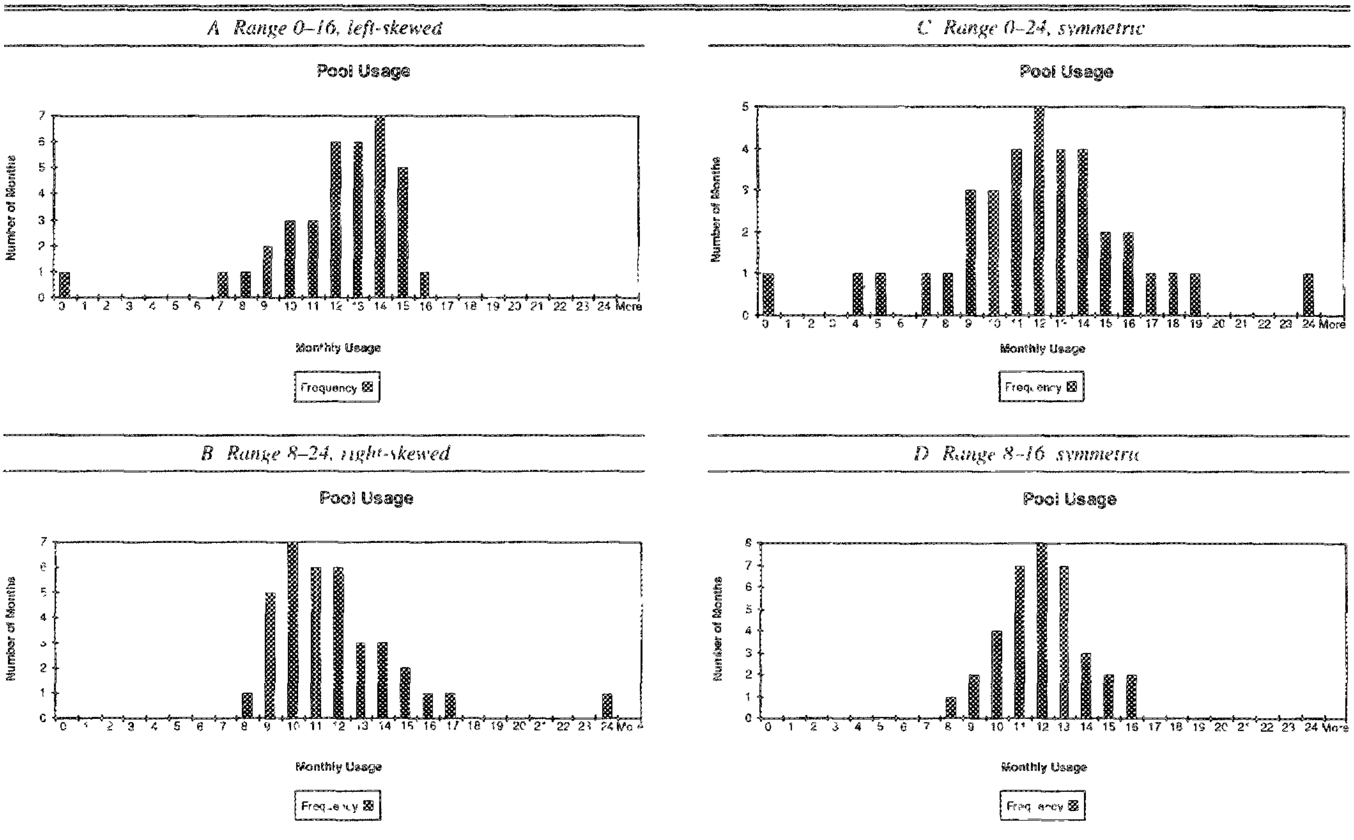
But as Larkin and Simon (1987) duly note, nothing about a diagram ensures that the inferences made will be useful in solving the problem at hand. Respondents in the distribution format condition should no longer need to rely on the range to formulate the likelihood of using more versus less than the break-even number (the second error in reasoning). But nothing prevents the first error in reasoning—comparing likelihoods—from occurring. Consequently, preferences would be expected to correspond to the correct relative likelihoods; the highest percentage of respondents will favor the flat fee when the range is 0–16, and the lowest when the range is 8–24, whereas the remaining respondents remain somewhere in between.

The control condition was included to determine how people would behave when the boundaries (i.e., minimum and maximum) were not explicit. Respondents in the control group were expected to imagine a minimum at or near 0, as the range is naturally truncated at that point, and a maximum of no greater than 30 or 31 (the number of days in a month). In other words, without experience or other information, people generally assess a range at or near the extremes, which in this case results in a ratio ≈ 1.50. Thus, the proportion of people preferring the flat fee in the control condition is predicted to be less than the proportion when the range is 8–24 (ratio = 3) but greater than the three remaining conditions (ratios all ≤ 1).

As many competing explanations as possible were either controlled or tested for in this study. All subjects were told that they would be billed at the end of the month. Neither pricing plan required more effort. In addition, subjects were asked whether they could imagine wanting their average usage to increase. More than 95% of the respondents said no, which ruled out wishful thinking and precommitment as sig-

[11] Given the premise that the underlying distribution of a person's usage is well represented by a Poisson, the numbers were drawn from a data set randomly generated from a Poisson with mean 12.

Figure 3
STUDY 3 STIMULI (DISTRIBUTION FORMAT CONDITION)



nificant drivers of choice. Risk-averse consumers presumably prefer the flat fee because then they know exactly what they will spend from month to month. There is no reason this desire to budget ahead of time should vary with the ratio, but it should be affected by the variability of usage. Therefore, if risk aversion is at work, the proportion of respondents preferring the flat fee would be expected to be highest when the variance is largest (range = 0–24, see Figure 3) and to be lowest when the variance is smallest (8–16). The ratio rule predicts something quite different. Preferences among these two groups will not differ significantly

Finally, choice could be affected by loss aversion (Kahneman and Tversky 1979) if the potential to lose money (i.e., using more than the break-even number while paying per use) looms larger than the potential to save money (i.e., using less than the break-even number while paying per use). If subjects were to exhibit loss aversion, an increase in the number of ways to lose money (the range is extended from 8–16 to 8–24) when consumers pay per use should have a more profound effect on choice than an equivalent decrease in the number of ways to save money (range is shortened from 0–24 to 8–24). In other words, the number of subjects that prefers the flat fee in the 0–24 and 8–16 (symmetric) conditions should differ significantly. The ratio rule predicts the opposite (both have ratios = 1.0).

Results

Range condition. Data in the range condition were analyzed independently to test the basic premise of the ratio rule. The data were analyzed using the analysis of variance (ANOVA) categorical modeling procedure of the SAS statistical software package (CATMOD). As expected, people were not indifferent between pricing plans, and the results were in line with the ratio rule's predictions (Table 2). The proportion of respondents that preferred the flat fee was largest (93%) when the ratio was highest (8–24, ratio = 3) and was smallest (40%) when the ratio was lowest (0–16, ratio = 1/3). The percentages of subjects that favored the flat fee in the two symmetric middle conditions (8–16 and 0–24, ratio = 1) were 58% and 53%, respectively, and did not differ significantly ($\chi^2 = .202$, $p = .653$). This last result is in direct conflict with the predictions based on risk aversion and loss aversion, which suggests that they cannot help explain the results. The main effects for both maximum and minimum were highly significant, and so was their interaction (see Model 1 in Table 3).

More interesting, however, is how the proportion that prefers the flat fee appears closely related to the likelihoods subjects assigned to using more versus less than the break-even number. As the reported likelihood of using more than the break-even number increased relative to the likelihood of using less, so did the preference for the flat fee (Table 2). The reported likelihood of using more than the break-even number for each respondent was divided by the reported likelihood of using less to create a measure of perceived symmetry, henceforth called "symmetry." A separate ANOVA was run with symmetry as the dependent variable (see Model 2 in Table 3). Both main effects were highly sig-

Table 2
STUDY 3 REPORTED PREFERENCES AND SUBJECTIVE LIKELIHOODS

Format	*Range Ratio*	*Percentage Who Prefer Flat Fee*	*Subjective Likelihood of Using* *Less*	*More*	*Equal*	*Ratio of Likelihoods More/Less*
			Range			
0–16	(1/3)	40%	49%	32%	19%	66
0–24	(1)	53%	42%	42%	16%	99
8–16	(1)	58%	42%	39%	19%	94
8–24	(3)	93%	30%	47%	23%	1 55
			Tabular			
0–16	(1/3)	35%	48%	32%	20%	67
0–24	(1)	50%	38%	41%	21%	1 08
8–16	(1)	53%	40%	40%	20%	1 00
8–24	(3)	90%	34%	47%	19%	1 39
			Distribution			
0–16	(1/3)	88%	29%	50%	21%	1 72
0–24	(1)	48%	43%	39%	18%	91
8–16	(1)	53%	41%	41%	17%	1 00
8–24	(3)	30%	49%	30%	21%	62

Table 3
STUDY 3 RANGE FORMAT—SUBJECTIVE LIKELIHOOD (SYMMETRY) AS A MEDIATOR OF CHOICE

Dependent Measure		*Model 1 Choice (Percentage Flat Fee)*		*Model 2 Symmetry*		*Model 3 Choice (Percentage Flat Fee)*	
Independent Measures	*Degrees of Freedom*	*Chi-Square*	*Probability*	*Chi-Square*	*Probability*	*Chi-Square*	*Probability*
Intercept	1	9 44	0021	391 27	0000	26 43	0000
Minimum	1	14 59	0001	10 56	0012	2 75	0974
Maximum	1	11 06	0009	12 88	0003	11	7450
Minimum × Maximum	1	4 36	0369	1 76	1846	2 92	0873
Symmetry	1					31 73	0000

nificant, which suggests that changes in the minimum and maximum usage influenced the perceived likelihood of using more versus less than the break-even number. In addition, when symmetry was included in the original model (as in an analysis of covariance), the effects of minimum and maximum on choice disappeared (see Model 3 in Table 3). This suggests that the range affects choice by affecting people's estimations of the likelihood of using more versus using less than the break-even number (Baron and Kenny 1986) This is directly in line with the hypothesized choice process and the ratio rule.

Tabular and distribution conditions. The data from the tabular and distribution format conditions were subsequently addressed by adding them into the analysis. For simplicity, the independent variables minimum and maximum were eliminated and replaced by the singular ratio of the range (low = 1/3, medium = 1, high = 3). This resulted in a 3 (format) × 3 (ratio) design The results revealed that only the ratio ($\chi^2 = 6.53$, $p = .0381$) and format × ratio interaction ($\chi^2 = 40.31$, $p < .01$) were significant. This implies that the extent to which the ratio rule applies varies by format.

Previously, it was shown that the ratio rule works well when used to predict results in the range condition. The results for conditions in the tabular format were almost identical to those in the range format (see Table 2), in both magnitude and direction. It seems as if subjects could not filter through the 36 data points and relied on the same decision strategy as in the range condition Apparently, the ratio rule applies in the range and format conditions, but not in the distribution condition, in which the results for the two asymmetric conditions reversed themselves (see Table 2). When diagnostic information about the frequencies of competing outcomes is readily available and easily accessible (i.e , the histograms), the ratio rule is not needed to determine the likelihood of using more versus less than the break-even number. This is apparently what happened in the distribution format condition The reversal in preference among the asymmetric conditions suggests that even when people are clear about the distribution of their usage, they can still frame the problem wrong. In this case, they relied on the number of actual occurrences on each side of the break-even number instead of the number of possible states while assessing the likelihoods. Again, subjects were not indifferent between payment plans, rather, in the distribution condition, they relied on the true relative likelihoods when making their choices

In the control condition, 78% of the 40 subjects in this cell preferred the flat fee. These subjects assessed a range with a ratio only slightly greater than the predicted 1.5 (average reported range = 4.75 to 23.2, ratio = 1 52). Consequently, the proportion of people that preferred the flat fee fell below the proportion in the 8–24 range (95%, ratio = 3) and above the 8–16/0–24 ranges (65%/70%, ratio = 1), as predicted. Even when usage characteristics are not made salient, subjects seemed to behave in a manner consistent with the ratio rule.

DISCUSSION

Together, the results of Study 3 indicate that, when no other information is available, people indeed misjudge the shape of the distribution of usage rates and that this misjudgment can depend on the range of possible outcomes. Only when people have precise and easily interpretable information—in this case, when they see a histogram of the distribution—are their perceptions more accurate But the bias toward the flat fee does not dissipate; it simply reverses itself, and preferences are guided by actual and not perceived likelihoods. In all cases and across all formats, the preference for the flat fee was related to the perceived likelihood of using more versus less than the break-even number (symmetry). The symmetry, which varied depending on the possible range of usage in the range and tabular conditions, mediated choice These results support H_2, H_3, H_4, and H_6 and confirm the steps in the proposed decision process model (Figure 1), in which choice depends on perceptions of the skewness of the distribution of usage, and this symmetry depends on the range of possible outcomes In turn, the range depends on the imagined boundaries of their usage when more complete and easily accessible information is unavailable

CONCLUSION

In this research, I set out to show that people, unable to predict their future usage accurately, make two distinct errors when trying to decide between paying a flat fee for unlimited access or paying per use Instead of following a more normative procedure, which is simply to compare their average rate or long-term expectation of usage with the break-even usage, consumers compare the subjective likelihood of using more than the break-even number with the subjective likelihood of using less It is during this comparison that people often misjudge the shape of the distribution of their usage, overestimating the likelihood of incidents of higher-than-average usage. It has been shown that the actual distribution of usage rates, even for those most likely to be heavy users, is likely to be the opposite of people's perceptions of it. New and inexperienced users (i e , those who are poorly calibrated) are likely to overestimate the chances of using enough to justify the flat fee, thereby favoring this payment plan when they should not.

What does this mean for the manager? Because people are influenced by the boundaries of their perceived usage, any efforts to alter the minimum or maximum number of times people believe they might use a product or service may affect choice. For example, a sales representative who hopes to increase the number of purchases as opposed to rentals (e.g , surfboards, ski equipment) should attempt to increase the maximum number of times people expect to use the product in the future, while also increasing the minimum number of uses deemed possible. This might be done by accenting all the different ways a customer can use the product. Another possibility is to describe the product or service as something that is both easy to access and important to use frequently. The health and fitness industry seems to thrive on the misperception that exercise can be easy and occur regularly (only ten minutes per day) if customers are given the right equipment (e g., abdominal machines, step platforms, videocassettes of workouts).

Consumers, in contrast, should seek out or be provided better information on the actual distribution of their product/service usage. This is reportedly what some telecommunication companies in Great Britain are doing: Customers receive detailed statistical reports on their past behavior from their present service provider's competitors, along with an explanation of how they can save money by switching companies. Without presenting these explicit calculations, consumers are not expected to be able to determine which company's pricing plan is optimal for them, given their idiosyncratic patterns of behavior.

Limitations and Future Research

It is critical to point out that forecasting error, or a reliance on the ratio rule, is only one of several possible factors that contribute to the flat fee bias. As always, the use of experiments to control for alternative explanations and isolate factors of interest involves a level of artificiality (i.e., realism). In Study 1, only inexperienced users participated. In Study 3, the information about past usage came from the "response context," when in reality consumers often rely on diagnostic information kept in memory, which is accumulated over time and stored as episodes or rates (Menon, Raghubir, and Schwarz 1995). It would be interesting to study whether consumers who gain experience with a product or service become better calibrated regarding their actual usage and incorporate this information into the decision process. In addition, when the stakes are relatively low, people may not dedicate as much time and energy to the decision as they do in the laboratory. Furthermore, consumers whose wealth enables them to pay a flat fee without any consideration might favor the lump sum regardless of other factors (a truly thoughtless decision).

Controlling for potentially confounding factors does not discredit competing motivational explanations or any combinatory effect, especially in the real world, where people often have more than one reason for making their choices. Therefore, when assessing the underlying causes of the flat fee bias in various domains, researchers must carefully consider many singular and joint explanations. Generalizations are bound by context, and the overall effect of poor forecasting may be diluted in many real-world scenarios In the future, it might be necessary to test the specific conditions under which the ratio rule applies. Similarly, testing whether the hierarchical structure proposed in Study 2 would fit as well onto data from another domain would strengthen the empirical results. Further research might also test the manager's ability to manipulate directly the parameters of the range and therefore choice.

Future work can also explore how the ratio rule might function in entirely different contexts in which the true underlying distribution is asymmetric. For example, can people's judgments regarding waiting times be influenced by the longest and shortest wait they have experienced? Imagine friends who are considering dining at a premiere restaurant, which does not accept reservations. They recall waiting 90 minutes to be seated one time, and their shortest wait was 20 minutes Now imagine that they do not want to wait more than 40 minutes, which is their recollection of the average wait. They may expect the probability of waiting longer than 40 minutes to be larger than it is in reality, simply because the number of possible waiting times between 40 and 90 is so much larger than the number between 20 and 40. Consequently, they may choose to dine elsewhere.

APPENDIX

Let x_{cm} be equal to the number of days customer c uses the facility in month m, and let $x_{cm} | \lambda_c$ be an observation from month m from customer c with mean λ_c. If x_{cm} is assumed to be distributed Poisson with mean λ_c, and if the flexible gamma distribution is used to account for the heterogeneity of consumers' average usage, then it turns out that $x_{cm} \sim$ NBD, which does not depend on the unobservable λ_c.

$$x_{cm}|\lambda_c \sim \text{Poisson} = \frac{e^{-\lambda_c}\lambda^{x_{cm}}}{x_{cm}!}.$$

$$\lambda_c \sim \text{gamma}(r,\alpha) = \frac{\alpha^r}{\Gamma(r)}\lambda_c{}^{r-1}e^{-\alpha\lambda_c}.$$

$$x_{cm} \sim \text{NBD}(s,p) = \binom{s + x_{cm} - 1}{x_{cm}} p^s(1-p)^{x_{cm}}.$$

$$p(x,\lambda|\alpha,\beta) = \frac{1\alpha^r}{\Gamma(r)x!}\lambda^{x+r-1}e^{-\lambda(1+\alpha)}.$$

Integrate to eliminate λ:

$$\int p = \int_0^\infty \left[\frac{\alpha^r 1}{\Gamma(r)x!}\right]\lambda^{x+r-1}e^{-\lambda(1+\alpha)}.$$

Using $\lambda^{x+r-1}e^{-\lambda(1+\alpha)}$ as the kernel of the gamma distribution,

$$= \left[\frac{\alpha^r}{\Gamma(r)x!}\right]\Gamma(x+r)\left(\frac{1}{1+\alpha}\right)^{x+r}$$

$$= \frac{\Gamma(x+r)}{\Gamma(r)}\frac{\left(\frac{1}{1+\alpha}\right)^{x+r}\alpha^r}{x!} = \binom{x+r-1}{x}\left(\frac{\alpha}{1+\alpha}\right)^r\left(\frac{1}{1+\alpha}\right)^x.$$

Solving for s and p of the NBD in terms of α and r, p = = $[\alpha/(1+\alpha)]$ and s = r.

These calculations do not take into account the multiple data points for each consumer. Therefore, the likelihood for a stream of uses for a given consumer is calculated under the assumption that the mean usage λ_c is distributed as a gamma (r, α) across the population

$$L_c(\text{data}|\lambda_c) = \prod_{m=1}^{M_c}\frac{\lambda^{x_{cm}}e^{-\lambda_c}}{x_{cm}!} = \frac{\lambda_c^{\sum_m x_{xm}} e^{-M_c\lambda}}{\prod_{m=1}^{M_c} x_{cm}!}$$

$$L(\text{data}) = \int_0^\infty \frac{\lambda_c^{\sum_m x_{xm}} e^{-M_c\lambda}}{\prod_{m=1}^{M_c} x_{cm}!}\frac{\alpha^r\lambda^{r-1}e^{-\alpha\lambda}}{\Gamma(r)}\partial\lambda$$

$$= \frac{\Gamma\left(\sum_{m=1}^{M_c} x_{cm} + r\right)\alpha^r}{\left[(\alpha+M_c)^{\sum_m^{M_c} x_{cm} + r}\right]\Gamma(r)\prod_{m=1}^{M_c} x_{cm}!}.$$

Consequently, the log-likelihood for the set of consumers ends up with the form

$$LL = \sum_c\Big[\ln\Gamma(\sum_m x_{cm} + r) - \ln\Gamma(r) - \sum_m \ln(x_{cm}!)$$
$$+ r\ln(\alpha) - (\sum_m x_{cm} + r)\ln(\alpha + M_c)\Big].$$

Values for r and α are easily obtained through the maximization routine Solver in Excel.

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