Recurring Goals and Learning: 
The Impact of Successful Reward Attainment on Purchase Behavior

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ABSTRACT

This research examines the impact of successfully attaining a goal on future effort directed at attaining the same goal. Using data from a major frequent flier program, we demonstrate empirically how success contributes to an increase in effort exhibited in consecutive attempts to reach a goal. We replicate the effects in a laboratory study that shows the impact of success is significant only when the goal is challenging. We also show how progress enhances perceptions of self-efficacy but successfully completing the task provides an added boost, supporting the notion that self-learning is the principal mechanism driving our results.

Keywords: Loyalty Programs, Rewards, Goals, Learning, Self-efficacy
Consumers possess voracious appetites for rewards. The enticement of earning a reward and its impact on purchase behavior has helped spur American companies to create more than 2,000 loyalty programs (Berman 2006). More consumers are engaging with brands through rewards programs than ever before. In 2009, approximately 1.8 billion memberships were on record in the U.S. alone, up from 1.3 billion in 2006, according to a Loyalty Census by research firm Colloquy (Ferguson and Hlavinka 2009). Further, the census found households actively participate in an average of 6.2 programs, up from 4.7 in 2007. The authors stressed the immense influence of rewards programs on business, noting that rewards have become “…the cost of entry for new credit and debit products” (p. 6), the hotel industry “is united in its belief that reward programs continue to offer the best platform for retaining profitable customers” (p. 9), and specialty retailers are fighting back against Wal-Mart and other mass-merchant discounters through the use of successful reward programs such as Best Buy’s renowned Reward Zone® program (p. 11).

Research generally supports a positive connection between loyalty programs built on rewards and customer retention (Lewis 2004; Taylor and Neslin 2005; Nunes and Drèze 2006a, 2006b). However, the efficacy of rewards programs has its critics. Shugan (2005) argued many programs trade short-term revenues (purchases) for long-term liabilities (promises of future rewards) rather than invest in the customer. And a number of empirical studies suggest loyalty programs generate small effects (Verhoef 2003) or no effect on purchase behavior (DeWulf, Odekerken-Schroder, and Iacobucci 2001; Mägi 2003). Our research approaches the question of impact with respect to loyalty programs and their rewards much differently than previous research. Rather than model the impact of membership in a firm’s loyalty program on share-of-
wallet, we look at the impact of successfully attaining a reward within a loyalty program on future effort directed at attaining the same reward within the same program.

Most loyalty programs are comprised of rewards that can be earned repeatedly, such as free tickets on an airline, free nights at a hotel, or discount certificates at specialty retailers such as Best Buy. These rewards are what we refer to as *recurring goals* because consumers often work toward a goal (reward) that, once attained, continues to serve as a goal toward which they can work again. It is not clear from previous research what impact successfully earning a reward would have on consumers’ motivation to direct future purchases toward the reward-granting firm. While not conclusive, work by Kivetz, Urminsky, and Zheng (2006) provides preliminary insight.

With loyalty programs that involve discrete purchases, effort toward achieving a goal or earning a reward is frequently measured by evaluating interpurchase times (Neslin, Henderson, and Quelch 1985; Kivetz and Simonson 2002; Nunes and Drèze 2006b). Kivetz et al. (2006) conducted a field study at a university café in which participating customers were required to make 10 coffee purchases in order to earn a free coffee. They found that for customers who earned the first reward, purchase rates slowed as they began working toward their second reward. More specifically, it took 2.1 days between the ninth and tenth purchases — the final purchases necessary for the first reward. This was significantly shorter than the 3.1 days it took between the first and second purchases toward the second reward. The authors dubbed this slowdown in the interpurchase times between attaining the reward in the first attempt and the initial purchases toward the second attempt as *post-reward resetting*.

Kivetz et al. (2006) relied on post-reward resetting to rule out learning, or habituation, as an explanation for the acceleration in purchases observed as consumers approach a reward, otherwise known as the goal-gradient phenomenon. The deceleration they observed (from 2.1 to
3.1 days) would imply whatever was learned had been suddenly forgotten. In Figure 1a, we see effort increasing monotonically over time depicted with a convex function consistent with the goal-gradient phenomenon (Hull 1932; Brown 1948; Nunes and Drèze 2006b; Kivetz et al. 2006). Yet once past the goal, output continues to rise in an unrealistic fashion. After one learns the basic steps necessary to reach a reward, procedural learning, or learning about how things work (e.g., how many miles does one get per flight, how to check accrual levels, etc.), should abate. Otherwise, the consumer would continue accelerating purchases indefinitely. Hence, we expect a slowdown in effort after the goal is achieved the first time.

Figure 1b illustrates the opposite extreme, where there is an absence of any learning. As soon as the goal is achieved, effort reverts back to its original base rate, increasing exactly as it had before as the consumer approaches the goal the second time. While post-reward resetting suggests the goal gradient phenomenon is not due to procedural learning, it does not preclude other forms of learning from taking place. We posit consumers accelerate purchases as they near a reward and decelerate after attaining the reward. However, they do learn something from successfully reaching a goal. This learning results in a reassessment of one’s own likelihood of success that manifests itself as observable increases in effort upon reengagement with a recurring goal (Bandura 1988).

Accordingly, in this research, we expect to observe acceleration in purchases consistent with the goal-gradient phenomenon observed by others. As consumers approach the goal (reward), the effort they direct toward reaching that goal will increase. This is stated formally as hypothesis 1.
H1  The effort exerted toward reaching a goal increases with progress towards the goal. We also expect a post reward reset (i.e., deceleration). If progress toward the goal drives effort, once the goal is reached and in the absence of any learning, one might expect effort to return to its original level. However, if learning occurs while striving for or when reaching the goal (we discuss different types of learning in the next section), we would expect this knowledge to impact behavior. Consequently, consumers should exhibit more effort when commencing successive attempts at reaching recurring goals. Although Kivetz et al. (2006) noted a “markedly similar acceleration pattern” (p. 47) whether participants were working toward their first or second free coffee, the interpurchase times observed after customers reengaged were slightly lower than those observed the first time around (3.1 < 3.2; 2.7 < 2.8), consistent with a partial post reward reset. The authors did not test for significance as the extent of resetting was not their concern. In the presence of learning, we expect consumers to exhibit partial post-reward resetting rather than full post-reward resetting. This leads to hypotheses 2a and 2b.

H2a  After reaching a goal, there will be a decline in effort when initiating a successive attempt to achieve the same goal (i.e., a post goal reset).

H2b  The effort exerted initially toward achieving a recurring goal will be greater following successful goal attainment then it was previously (a partial post goal reset).

Any boost in effort exhibited initially toward a recurring goal would undoubtedly be of interest to managers of rewards programs responsible for assigning rewards and reward levels. A partial reset could occur for two reasons involving two different types of learning. First, Figure 1c illustrates the case of goal attainment leading to learning from experience (Hoch and Ha 1986). This occurs when the benefits associated with attaining a goal (i.e., the reward) are vague until
experienced. Consider airlines that provide premier status to frequent fliers. Status comes with a variety of benefits such as priority boarding and complimentary upgrades that are sometimes difficult to appreciate until experienced. Frequent fliers should be more engaged after reaching the goal because only then will they have the experience necessary to understand exactly what to expect if and when they reach the goal (earn status) again. Note that once a flier has experienced the benefits of status once (i.e., a year with status), there is little more to learn. Therefore, a partial reset after the first successful reward redemption reflects the notion of learning from experience, and subsequent resets should return to this newly elevated level.

Hypothesis 2b, however, does not limit the increase in effort to occurring only one time. In addition to procedural learning and learning from experience, successful goal attainment can lead to self-learning, resulting from an enhanced sense of proficiency. Experiencing success can enhance proficiency in at least two ways (Gonzalez and Dowrick 1982). It provides clear information regarding how to proceed the next time around (learning from experience), while also strengthening beliefs in self-efficacy (self-learning). Self-efficacy refers to an individual’s perception of how well he or she can execute various courses of actions to deal with different prospective situations (Bandura 1982). It is important to point out that we are neither interested in, nor do we measure general self-efficacy or GSE, which is not domain specific. Instead, our focus is on specific self-efficacy or SSE, which centers on efficacy in a specific task (Chen, Gully, and Eden 2001). In this research, that task is attaining a reward.

Consumers must often orchestrate their buying behavior in very specific ways, scheduling and steering purchases in a deliberate manner in order to successfully attain a reward. Research on reasoned action and self-efficacy (Dzewaltowski, Noble, and Shaw 1990) as well as aspiration (Ryan 1970) suggests that, if the task’s difficulty is high enough that one success does not
necessarily guarantee future success, individuals will reassess their self-efficacy after each success. If self-learning occurs, we would expect to see the situation depicted in Figure 1d; each successive goal attainment leads to a reassessment, and in turn, an increase in base effort, provided the task is challenging enough. This leads to hypotheses 3a and 3b.

H3a  Repeated successes result in recurring partial post-reward resets (i.e., each reset occurs at a higher level).

H3b  For a “partial” rather than a full reset to occur, the goal must be challenging.

We therefore expect to observe the impact of success on subsequent effort more than once, which does not rule out learning from experience but does support the incidence of self-learning. We should point out self-learning impacts one’s subjective assessment of one’s likelihood of success, which is consistent with work on goals relying on “expectancy-value” models (see Klein 1991 for a review). Much of the work on goal-directed behavior is based on the premise that effort is frequently a function of: (1) external inducements (e.g., rewards), and (2) the likelihood of success in reaching the goal. Mento, Cartledge, and Locke (1980) showed individuals are more likely to work toward a goal when they have a high rather than low expectation of reaching it. Learning from experience leads to a reassessment of the value of the reward. Self learning leads to a re-assessment of the likelihood of attaining the reward. Both types of learning lead to an increase in expected value of the reward after successful task completion and thus warrant
exerting more effort toward reaching the reward, but learning from experience would lead to a
one time reassessment, while self learning would lead to reoccurring reassessments.

The predicted impact of successful goal attainment on perceptions of self-efficacy leads to
our next two formal hypotheses.

H4a Marked progress toward a goal impacts one’s assessment of self-efficacy.

H4b Successful task completion has an additional impact on self-efficacy over and above marked progress alone.

The remainder of this paper is organized as follows. We commence by presenting a real-
world illustration of partial resetting in order to demonstrate the magnitude of the effect and its
importance. Study 1 is comprised of two parts intended to test hypotheses 1, 2 (a and b), and 3a.
Using data from a leading international carrier’s frequent flier program, we illustrate partial post-
reward resetting utilizing elite status as the goal and the rate of miles flown as reflective of effort.
In Study 2, we test hypotheses 1, 2 (a and b), and 3b in a laboratory setting. The results replicate
Study 1 with strict controls while revealing how goal difficulty factors in, demonstrating that only
in cases where the reward is challenging does the impact of success affect future effort. In Study
3, we test hypotheses 4a and 4b and in doing so document the impact of self-learning, the
principle mechanism driving our results. By partitioning a task differently and thus reframing the
task as either successfully completed or not, we show that progress enhances perceptions of self-
efficacy, but successfully completing the task provides an added boost. We conclude by pointing
out some of the limitations of this work and suggesting avenues for future research.
Study 1: Empirical Evidence of the Effect of Success on Effort

Part I

We utilize frequent flier program data obtained from a major U.S.-based international airline. The airline that provided the data offers frequent fliers three tiers of status. Tier 3 is reached after flying 25,000 miles within a given year, Tier 2 after flying 50,000 miles, and Tier 1 after flying 100,000 miles. Only miles actually flown qualify for annual status; bonus miles or miles earned through third parties such as hotels or credit cards do not count. Each tier entitles members access to special privileges and, once earned, is valid until the end of the following year. The airline provides Tier 3 status for life to those who have earned one million miles during the course of their membership and Tier 2 status for life to those who have earned more than two million miles. All earned miles, through flying or other means such as credit card purchases and hotel stays, count toward reaching the one million and two million marks.

The airline does not offer Tier 1 status for life; this level of status can only be earned by flying 100,000 miles or more in a single year. In light of the structure of this airline’s status programs, we restrict our study in Part I to a distinct subset of program members who have earned at least two million miles and who, at the time of the study, possessed at least 200,000 miles in their frequent flier account. For each traveler, we possess 18 months of detailed flight activity; the beginning of the data coincides with the beginning of the 2005 status year (status years are slightly offset from calendar years). These restrictions allow us to accomplish two important things.

First, a significant bank of miles suggests these fliers are unlikely to see earning the 25,000 miles necessary for a free ticket as a meaningful goal. Their primary goal in earning miles is likely to be earning Tier 1 status. Of course, restricting our analysis as such does not guarantee
that they care only about status. The average flier in our sample spent two-thirds of his/her lifetime earnings in miles. These fliers use their miles and must therefore value them as a pathway to free flights or other perks (e.g., first class upgrades or lounge access). Our intent was to select those fliers for whom accumulating miles for free flights was of less or little relative importance as compared to attaining Tier 1 status, the primary goal.

Second, each flier has earned more than two million miles and consequently possesses Tier 2 status for life. The only meaningful status goal left is earning Tier 1 status. Further, as a Tier 2 status holder, they understand the benefits associated with status; any change in behavior associated with reaching Tier 1 status will likely be due to self-learning rather than learning from experience (we tease apart the effects of self-learning from learning from experience more directly in Part II). It is critical to note that Tier 1 and Tier 2 fliers accrue miles toward rewards and status at the exact same rate; possessing Tier 1 status in 2005 does not facilitate earning Tier 1 status the following year.

We expect the propensity to fly among this particular subset of program members to increase as they near the Tier 1 status goal (100,000 miles), consistent with the goal gradient phenomenon (Kivetz et al. 2006; Nunes and Drèze 2006b). In addition, for those who have actually reached Tier 1 in 2005, we expect the propensity to fly at the beginning of the subsequent year to be higher than at the beginning of the current year, but lower than it was prior to reaching the goal of Tier 1 status (i.e., partial post-reward resetting after goal-re-engagement). This pattern is exhibited graphically in Figure 2.
Model

To model the propensity to fly in a way that is consistent with our model and our hypotheses, we build a random effects proportional hazard rate model. The basic Weibull proportional hazard rate model with covariates is parameterized as:

\[ h(t, \beta) = \gamma \alpha (\alpha t)^{\gamma-1}, \]

with \( \alpha = e^{X\beta} \),

where:

- \( h \) is the hazard function,
- \( t \) is the duration events that are being modeled (in our case the inter-flight time),
- \( \gamma \) is the Weibull shape parameter,
- \( \alpha \) is the Weibull scale parameter,
- \( X \) is a set of covariates,
- \( \beta \) is the vector of parameters to be estimated.

To account for the way status is earned in loyalty programs, we need to make some adjustments to the simple model presented in Figure 1d. We need to account for the fact that status is earned based on calendar years. If someone reaches 100K miles during year \( y \), he or she gains Tier 1 status for the remainder of the year \( (y) \) and for the totality of the following year \( (y + 1) \). Miles accrued after earning Tier 1 status during year \( y \) do not count toward earning Tier 1 status in year \( y + 1 \) (there is no carry-over effect). Hence, for travelers who reach 100K miles in a given year, we would expect effort to drop after reaching 100K miles and remain low until the beginning of the next year (post-goal dip; see Figure 2). We state this more formally as hypothesis 5:
H5  Effort will be reduced after goal completion until the next goal becomes active.

Further, in a status program, as in any program with a time limit, there is the ability to fail by not reaching the goal in time. In a traditional buy-10-get-one-free type program, one never really fails, there is always the possibility one will buy more and eventually reach the ten purchases needed for the reward. Failure would not lead to positive self-learning and could even lead a consumer to see himself or herself as less efficacious. Thus, one would expect a full-reset (or even worse) at the beginning of the new year in the case of a failure to reach the goal in time.

Figure 2 illustrates the predicted effects for those who are successful in reaching Tier 1 (for the unsuccessful ones, we expect their effort to follow the pattern in Figure 1b, substituting the advent of the new year for the goal). Our model considers the following: (a) a goal gradient effect leading up to the goal (H1), (b) a post goal dip between the time the goal has been reached and the beginning of the next year (H5), (c) a possible gradient between goal attainment and the beginning of the next year in case the traveler has other goals in sight, and (d) a partial reset when starting the second year (H2a, H2b). We also incorporate random effects coefficients to account for heterogeneity in members’ base propensity to fly and how the goal gradient motivates people differently (i.e., individual rates of acceleration). Our full set of covariates is as follows:

\[ X_{iyt} \beta = \beta_0 + \beta_1.NMiles_{iyt} + \beta_2.NMiles_{iyt}.Tier_{iy} + \beta_3.NPGMiles_{iyt} + \beta_4.Post_{iyt} + \beta_5.Year_{iy} + \beta_6.Year_{iy}.Tier1_{iy} + \beta_7.Tier1_{iy} + z_i + zz_i.NMiles. \]

Where:

- \( NMiles_{iyt} \) is the number of pre-goal miles flown in year \( y \) by traveler \( i \) before taking flight \( t \),
\( NPGMiles_{iyr} \) is the number of post-goal miles flown in year \( y \) by traveler \( i \) before taking flight \( t \),

\( Post_{iyr} \) is an indicator variable that is set to 1 if traveler \( i \) has reached Tier 1 status in year \( y \) by flight \( t \) and 0 otherwise,

\( Year_{iyr} \) is an indicator variable that is set to 0 for the first flights taken in the first year of the data set and 1 for the second year,

\( Tier1_{iyr} \) is an indicator variable that is set to 1 if traveler \( i \) reaches Tier 1 status in year \( y \).

The variables \( NMiles_{iyr} \), \( NPGMiles_{iyr} \), and \( Post_{iyr} \) are reset to 0 at the beginning of the year. The variable \( NMiles_{iyr} \) accrues miles for every flight flown until Tier 1 status is reached; \( NPGMiles_{iyr} \) accrues miles for every flight flown in the year when Tier 1 status is reached after earning Tier 1 status. Thus, \( NMiles_{iyr} + NPGMiles_{iyr} \) is the total miles flown by \( i \) up to flight \( t \) in year \( y \). To scale the parameters so that they are easier to interpret, we divide the number of miles flown by 100K. Thus, when reaching the miles necessary to reach Tier 1 status, \( NMiles_{iyr} \) is equal to 1.

The random coefficients \( z_i \) and \( zz_i \) allow for traveler level heterogeneity in both base propensity to travel \( (z_i) \) and goal gradient sensitivity \( (zz_i) \). To allow for the fact that goal gradient sensitivity might be correlated with base propensity of flying (those travelers who fly more might be less sensitive to the goal gradient) we model the random effects as a correlated bivariate normal:

\[
(z_i, zz_i) \sim N(0, \Sigma),
\]
Using our model specification, a negative and significant $\beta_1$ ($NMiles$) parameter will provide support for H1 (increased effort results in shorter interpurchase times for flights, and thus translates into negative parameters). A positive $\beta_4$ ($Post$) parameter provides support for H5. As we have rescaled the number of miles flown to be equal to 1 when 100K miles are flown, a $\beta_6$ ($Year$ by $Tier1$ interaction) parameter that is significantly smaller than $\beta_1 + \beta_2$ would provide support for post goal resetting (H2a). Further, if it is also significantly greater than 0, it would provide support for partial rather than full resetting (H2b). In other words, $\beta_6=0$ indicates a full reset while $0 < \beta_6 < \beta_1 + \beta_2$ indicates a partial reset.

In terms of the other parameters of the model, $\beta_0$ is the base propensity of traveling at the beginning of the year for an average flyer who will not reach Tier 1 in year 1. As such, $\beta_0 + \beta_7$ is the base propensity of flying for those who do reach Tier 1 in year 1. $\beta_2$ is the base difference in the goal gradient for those fliers who reach Tier 1. $\beta_3$ reflects any possible post-goal gradient for those who reach Tier 1; this allows for the possibility of a gradient existing for other goals. $\beta_5$ is a year intercept that allows for a different propensity to fly in year 2 versus year 1.

The model is estimated using PROC NLMIXED in SAS. Our sample includes more than 400,000 flights taken by about 7,000 travelers who fly on average slightly above 85,000 miles per year. To test the robustness of our model, we also fit a fixed-effect version of the model, we tried using the number of trips flown rather than the number of miles accrued as a marker of progress, and we fit the model using only those travelers who had earned Tier 1 status in year 2004 (and thus possessed status throughout 2005). The results were substantively the same across all model (i.e., all models led to the same conclusions about the hypotheses and when comparable, the parameters were of the same sign and magnitude). Thus we only report the random effects model.
Results

The parameter estimates for our model are shown in Table 1. As this is a time-to-failure model, negative coefficients are indicative of a higher propensity to fly and positive coefficients are indicative of a lower propensity to fly. For the sake of brevity, we do not report on the individual random effects. One should note however that the individual level intercept ($z_i$) and goal gradient ($zz_i$) parameters are negatively correlated ($\sigma_{z,zz} = -0.0696, p < .0001$, implies that $\rho_{z,zz} = -.59$); this indicates that those with a higher propensity to fly (and thus more likely to reach the goal) exhibit a smaller goal gradient effect.

We find support for H1 ($\beta_{NMILES} = -0.2269, p < .0001$). We also find that those who reach Tier 1 in 2005 not only exhibit a higher base propensity to fly ($\beta_{TIER1} = -0.0886, p < .0001$), they also exhibit a stronger goal gradient effect ($\beta_{NMILES*TIER1} = -0.1392, p < .0001$). At $-0.3661(-0.2269 – 0.1392)$, the goal gradient exhibited by the Tier 1 recipients is more than 50% larger than for other travelers.

We find support for H5 ($\beta_{POST} = 0.2223, p < .0001$). This large decrease in propensity to fly validates that reaching Tier 1 status is a goal travelers strive for. A test of parameters actually fails to reject the hypothesis that the drop in propensity to fly is equal to the increase in propensity to fly brought by the goal gradient ($\beta_{NMILES} = - \beta_{POST}, p < .55$). There is evidence, however, that this is not the only goal they have in mind. Those who reach Tier 1 have a significantly higher goal gradient than those who do not ($\beta_{NMILES*TIER1} = -0.1392$). This increase in gradient persists after Tier 1 is reached ($\beta_{NPGMILES} = -0.1393, p < .0001$). A test of parameters fails to reject that these two parameter are different ($\beta_{NMILES*TIER1} = \beta_{NPGMILES}, p = .49$). This implies that some of
those who reach Tier 1 might have a secondary goal that becomes active after Tier 1 status is reached.

In terms of post-goal resetting, we find no year effect for those who have not reached Tier 1 status in 2005 ($\beta_{\text{YEAR}} = -0.0037, p = .74$). This shows support for a full reset at the beginning of the year for those who did not succeed. In contrast, there is a significant year by Tier 1 interaction ($\beta_{\text{YEAR} \cdot \text{TIER1}} = -0.0489, p < .0001$) such that those who reached Tier 1 status in 2005 kick off 2006 faster than they started 2005. This interaction term is smaller than the parameter for the goal gradient ($\beta_{\text{YEAR} \cdot \text{TIER1}} = -0.0489 < \beta_{\text{NMILES}} = -0.2269, p < .0001$). This indicates that the increased propensity to fly in 2006 is smaller than the increased propensity to fly observed when reaching the goal in 2005, thus providing support for a partial post-goal reset (H2a and H2b) for those who succeed. We also compared the reset to the Tier 1 by gradient interaction term to insure that the reason the reset is partial is not due to a second goal we might not know of still being active as the new year begins. We find that the reset is significantly smaller than the interaction term ($\beta_{\text{YEAR} \cdot \text{TIER1}} = -0.0489 < \beta_{\text{NMILES} \cdot \text{TIER1}} = -0.1392, p < .0001$), providing further evidence of a partial reset.

It bears repeating that the aforementioned effects are not due to innate differences in the propensity to fly across fliers (i.e., heterogeneity) as observed in the Kivetz et al. (2006) data. If it were simply that those who fly more often are more likely to reach Tier 1 status in 2005 and thus are also more likely to fly in 2006, the effect would be captured by the individual random effects and not by an intercept shift in 2006. Rather, what these variables indicate is that the attainment of Tier 1 status in 2005 leads to reduced or partial resetting at the beginning of 2006; it takes less time between the first and second ticket purchase for those who had successfully reached their goal of Tier 1 status the prior year than for those who did not.
To facilitate the interpretation of the coefficients we estimated, Figure 3 illustrates the predicted change in inter-flight time for a traveler who flies 10,000 miles per month and is average in terms of the random coefficients (i.e., $z_i = z_1 = 0$). Such a traveler reaches Tier 1 status 10 months into the year, and then goes two months without miles flown being applied towards reaching Tier 1 status again. The changes in inter-flight times are shown relative to the first flight. As Figure 3 reveals, by month 10, the reduction in time between flights has reached 31%. Upon reaching the goal of 100K miles, inter-flight time increases by 25% (from 0.69 to 0.87). As the new year starts, the inter-flight time resets, but not fully, going from 0.84 to 0.95 (13%).

**Part II**

In Part II, we look at the behavior of more than 40,000 frequent fliers to determine whether achieving status in one year impacts the number of miles flown on the same carrier the subsequent year. More specifically, we look at the number of base miles earned in one year (as in Part I, only miles actually flown qualify for status) and the likelihood of reaching status the following year, both for those who achieved status and for those who did not. Given differences across individuals in their propensity to fly (e.g., business vs. leisure travelers), the number of miles traveled in one year is likely to be correlated with the number of miles traveled the next.

In Part II, we focus on Tier 3 status. Compared to Tier 3 benefits, Tier 2 or Tier 1 might be seen as “more of the same.” One is more likely to be upgraded or to board first while possessing Tier 1 status, but the perks are similar to those accompanying Tier 3 status. Hence, we do not expect much learning from experience to occur when reaching Tier 1. In contrast, the difference in treatment between Tier 3 fliers and travelers without status is significant. Reaching Tier 3 for the first time opens the door to priority queues, free upgrades, bonus miles, and other perks that
make traveling far less onerous. Thus, one could expect the presence of both learning from experience and self-learning. However, learning from experience will only occur the first time the traveler reaches Tier 3 status, while self-learning can occur each time Tier 3 status is reached (Dzewaltowski et al. 1990). This allows us to distinguish between learning from experience and self-learning in this part of Study 1.

If one were to design an experiment to test for the presence of learning from experience or self-learning, one would need two groups of fliers, one that successfully attains status and one that does not but with random assignment to each group. Obviously, we could not implement such a field experiment and thus had to rely on actual travel records. This leads to potential confounds due to non-random assignment. Those who do not reach Tier 3 status might have a lower propensity to fly than those who do, they might not care about status and prefer splitting their travel across multiple airlines, or they might be less flexible in their travel plans. An established way to address the problem of non-random assignment to the treatment cells is to use a regression-discontinuity model (Hahn, Todd, and Van der Klaauw 2001; Busse, Silva-Risso, and Zettelmeyer 2006). To do so, we match people by comparing travelers who fly just shy of the 25,000 miles necessary for Tier 3 status to those who travel 25,000 miles or slightly more.

The basic idea behind this matching is that small differences in miles flown (a few hundred miles) are more likely due to the vagaries of flight distances and destinations than to a fundamental difference in travel needs. Given that the average flight on the airline we analyzed in Part I covers 1,248 miles and the minimum number of miles earned for a trip is 500, it is unlikely someone who travels 24,950 miles in a year has a basic demand that is fundamentally different from someone who travels 25,050.
We obtained the records of 43,548 travelers who flew between 20,000 and 30,000 miles. The data contain the number of miles flown for each member in 2004 and 2005 and whether they reached Tier 3 status in 2005 and any year prior. Let us call $X_i$ and $Y_i$ the number of base miles earned by traveler $i$ in 2004 and 2005 respectively. Further, let $Y_i^-$ be the number of miles flown in 2005 for a traveler who misses the 25,000 mile goal in 2004 by an infinitesimal margin and $Y_i^+$ the number of miles flown in 2005 for a traveler who flies exactly 25,000 miles in 2004. If we had enough such travelers, we could estimate the impact of gaining status as $E(Y^+) - E(Y^-)$. In the absence of a large enough sample size of people who barely missed or just made 25,000 miles, regression discontinuity estimates $Y^+$ and $Y^-$ in the following way. First, one constructs an interval of size $w$ around the goal (i.e., $[25,000 - w, 25,000 + w]$); and second, one estimates the following two linear regressions:

$$Y_i = \alpha^+ + \beta^+(X_i - 25000) + \epsilon_i, \forall X_i : 25000 \leq X_i < 25000 + w, \text{ and}$$

$$Y_i = \alpha^- + \beta^-(X_i - 25000) + \epsilon_i, \forall X_i : 25000 - w \leq X_i < 25000.$$

The impact of reaching status in 2004 on the number of miles flown in 2005 is then computed as $\alpha^+ - \alpha^-$. With such equations, increasing $w$ leads to more data points being included in the estimation. This helps produce estimates with small standard errors, but this is done at the expense of reducing the match between the consumers included in the $Y^+$ and the $Y^-$ regression. This may lead to biased estimates if the $\beta^+, \beta^-$ corrections do not properly account for changes in propensity to fly as one moves further away from 25,000 miles. To minimize this issue, one starts with a wide $w$ and then estimates the model with a smaller and smaller $w$ until there are too few data points to produce reliable estimates. In our case, we started with a $w$ of 5,000 miles and estimated the model in 100-mile decrements. Further, we estimated a single
nested model using a dummy variable to indicate whether 25,000 miles had been reached in the focal year. Thus, our model is:

\[ Y_i = \alpha^- + \alpha^+ I(X_i) + \beta^- |25000 - X_i| + \beta^+ |25000 - X_i|I(X_i) + \varepsilon_i, \]

\[ \forall X_i : 25000 - w \leq X_i < 25000 + w, \]

Where \( I(X_i) = 1 \) if \( X_i \geq 25000 \), and 0 otherwise.

In this model, \( \alpha^\pm \) provides the impact of reaching 25,000 miles in 2004 on the number of miles flown in 2005 directly. In addition to this linear model of miles flown in 2005, we estimated a logistic regression that modeled the likelihood of earning status in 2005 as a function of the number of miles flown in 2004.

We estimated the model in two steps. First, to get the cleanest test of whether successful goal attainment leads to an increase in effort in successive attempts, we only look at travelers who had never reached the status level prior to 2004. A positive and significant estimate for \( \alpha^\pm \) would provide support for the positive impact of success. However, it could be indicative of either learning from experience or self-learning (or both). To look at self-learning in the absence of learning from experience, we performed the same analysis for travelers who have attained status at some point before 2004. We believe that for such travelers, learning from experience would have occurred the first time they reached status (prior to 2004) and thus only self-learning would be experienced in 2004-2005. For these travelers, we add the number of times they have reached status in the past (\( \text{NSTATUS} \)) and its square (\( \text{NSTATUS}^2 \)) as covariates in the analysis. Per our theorizing about the positive impact of success on learning about one’s own abilities, we expect \( \text{NSTATUS} \) to be significant and positive; however, given self-learning can only be expected to increase one’s subjective likelihood of success up to a point, we expect \( \text{NSTATUS}^2 \) to be significant and negative.
The parameter estimates and associated statistics are shown in Table 2. The coefficients for $\alpha^\pm$ are positive and significant in all four models. Further, the coefficients for NSTATUS are positive and significant in both repeat status models. NSTATUS2 coefficients are negative and significant. None of the $\beta^-$ or $\beta^\pm$ parameters are significant, indicating that the number of miles flown in 2005 is not very sensitive to deviations from 25,000 miles. This is a good indication that the size of the interval we study ($w$) is not too wide.

The effect of reaching elite status on subsequent behavior is illustrated dramatically in Figure 4 where we display the empirical probability of reaching status again in 2005 as a function of the number of miles accrued in 2004.

For program members who had never earned status prior to 2004 (solid line), we see the likelihood of reaching 25,000 miles (earning status) in 2005 increases by 50% for those who barely attained the goal in 2004 as opposed to those who barely missed reaching the 25,000-mile goal. The effect is just as pronounced for members who have reached status in the past (dashed line, aggregated across all repeat earners) where the likelihood of earning status in 2005 means reaching the goal again. In the case of the first timers (solid line), the jump is due to a combination of learning from experience and self-learning. For the repeaters (dashed line), learning from experience is unlikely to occur as it is not the first time they have earned status. However, there is still evidence of self-learning.

It should be noted that in Part II, we cannot account for fliers who are behaving strategically, such that they possess a degree of flexibility that allows them to switch carriers as soon as, or shortly after they reach 25,000 miles. In this instance, these fliers may choose to
achieve Tier 3 status on another airline rather than Tier 2 status on this airline. While these fliers likely exist, and we cannot control for their behavior, we find it unlikely that they drive our effects. Nevertheless, we studies 2 and 3 control for this possibility.

Discussion

In Study 1, we demonstrate empirically how success contributes to an increase in effort exhibited in successive attempts to reach the same goal. By effort, like past research, we refer to consumers’ endeavors to orchestrate their buying behavior in very specific ways. In Part I, those who attained Tier 1 status exhibited a greater propensity to fly on the focal carrier as exhibited through partial resetting; after earning Tier 1 status, the time between flights slowed, but not to their original levels. In Part II, we observe a positive impact on the likelihood of earning Tier 3 status based on whether the flier has successfully earned status in the past and the number of times this goal was reached (more than once versus once).

It is crucial to note that all successes are not equal. Self-efficacy can be instilled and strengthened by experiencing success but only when success requires perseverance. Successes that come too easily are unlikely to lead people to update their sense of self-efficacy (Wood and Bandura 1989). Therefore, a program that hands out small rewards very frequently is unlikely to lead to self-learning. At the opposite extreme are goals that are too lofty. Creating larger rewards with higher purchase requirements should lead to more overall effort—but only up to a point. Studies have shown that motivation dissipates as the likelihood of task completion diminishes beyond the realm of possibility (Garland 1984; Mento, Cartledge, and Locke 1980). For firms utilizing reward programs, the amount of effort required and the size of the award can be scaled up or down, dictating the number of redemption opportunities available and the purchase activity required. A program’s divisibility, as we call it, determines how easy or difficult a reward is to
earn (e.g., 250 points leads to a $10 certificate vs. 1000 points leads to a $40 certificate). Our belief is that decreasing divisibility will serve to reinforce perceptions of self-efficacy to the extent that the individual believes he or she can successfully complete the task.

**STUDY 2: THE IMPACT OF DIVISIBILITY ON EFFORT**

In Study 2, we test hypothesis 3b in addition to revisiting hypotheses 1-3a. We do so by exploring consumer reactions to differing degrees of difficulty in attaining a reward. The results illustrate how self-learning diminishes with too much divisibility (rewards attained too easily) and motivation diminishes with too little divisibility (rewards seen as out of reach).

**Method**

*Respondents.* Participants in this study were 300 undergraduate business students who completed the survey voluntarily. Seven respondents failed to answer the questions, resulting in 293 usable surveys.

*Stimuli and design.* We utilized a 3 (divisibility: reward every $100, $500, or $1,000 spent) x 4 (accumulated spending: $25, $425, $525, or $925) between subjects, full factorial design. Participants were asked to imagine they had moved to a new city and there were two large grocery stores near their house carrying essentially the same assortment of goods. The stores were no different in terms of price, layout, cleanliness, or service. However, respondents were told the two grocers did differ significantly in their frequent shopper programs. Store B “offers a 10% cash refund on every dollar” spent at the store, which is issued immediately. For example, if a shopper spends $50, they would receive a $5 refund immediately (i.e., thereby only paying $45). Store A offers cash back at various increments. These increments or reward levels varied according to the degree of divisibility ($100, $500, or $1,000). It is important to note that the
cumulative rewards offered by the two stores are identical (10% of cumulative purchases); only the frequency at which the reward is dispersed differs.

The first question in the study asked the respondents which store they believed they would shop at more frequently. The study went on to describe their progress toward the goal at Store A. It explained that: “one store is near the freeway, which you often take to work, while the other is closer to a main surface street, which you take to and from work instead of the freeway when you leave during rush hour. While they are equal distances from your house, they are in opposite directions. As a result, you have shopped at both stores repeatedly during the past six months, as convenience has often been a factor.” We then manipulated accumulated spending by stating: “at store A you have currently accumulated $25 [$425, $525, or $925] in purchases. (Remember, when you reach an accumulated spending level of $100 [$500, $1,000] they will refund $10 [$50, $100].)” The scenario then told them that it was the weekend (rush hour would not be a factor) and asked them to imagine that they were heading out to buy $50 in groceries for a party they were planning that evening. They were asked to indicate at which store they would shop.

We expect the average likelihood of going to Store A to increase as the program becomes less divisible, and the reward level increases from every $100 to every $500. We expect the average likelihood of going to Store A to decrease as the program becomes even less divisible; when the reward level increases from $500 to $1,000, the goal appears to many as unattainable. In addition, in accordance with the goal gradient effect (H1), when the only reward available is at $1,000, consumers will become increasingly inclined to go to Store A as their accumulated spending increases from $25 up to $925.

With regard to recurring goals and the impact of success on effort, for those in the $500 reward condition, we expect the likelihood of going to Store A to increase after successfully
reaching the goal (i.e., $500 in accumulated spending). Specifically, we expect the propensity to
go to Store A to be larger when accumulated spending is $525 (after one success) than when it is
$25 for those who earn $50 for every $500 spent even though the size of the rewards and the
effort needed to reach the goal is identical in both cases (H2b). In addition, we expect the
likelihood of going to Store A to be greater for those who have accumulated $925 in spending
than those who have accumulated $425, despite the fact that both groups are $75 away from
earning a $50 reward. This is due again to the fact that those who have spent $925 have
experienced success (H3a). Consistent with H3b, we do not expect to see an impact of success for
recurring goals in the $100 reward condition because the task is not challenging enough to prompt
self-learning.

Results

Only four of the 293 respondents (1.4%) indicated that they would regularly visit Store A,
suggesting that Store B was the preferred option in the absence of any accumulated spending.
Figure 5 depicts the reported probability of going to Store A for each of the three reward levels
($100, $500, and $1,000) and each of the four levels of accumulated spending ($25, $425, $525,
$925). As is evident from the graph, the likelihood of going to Store A is affected by both
divisibility—the level of reward redemptions—and accumulated spending.

As predicted, and in support of H3b, effort increased with a decrease in divisibility. The
average likelihood of going to Store A was greater in the $500 condition (57%), when shoppers
were paid $50 for every $500 in spending than in the $100 condition (11%), when shoppers were
awarded $10 for every $100 spent ($\chi^2 = 15.2, p < .01$). In addition, the average likelihood of
going to Store A decreased when divisibility decreased too much. The average likelihood of going
to Store A was lower (36%) when shoppers were offered $100 for every $1,000 spent than when
they were awarded $50 for every $500 spent \( (\chi^2 = 8.6, p < .01) \). In other words, the $500 reward level induced a higher likelihood of visiting Store A than either the $100 or $1,000 reward level.

Also, as expected, the likelihood of going to Store A increased monotonically in the $1,000 reward condition, consistent with the goal gradient effect and in support of H1. Tests of proportion revealed that those who spent $525 were more likely to choose Store A than those who spent only $25 (PA_{525} = 28\% versus PA_{25} = 4\%, \chi^2 = 3.9, p < .05), and those who spent $925 were more likely to go to Store A than those who spent $525 (PA_{925} = 100\% versus PA_{525} = 28\%, \chi^2 = 10.2, p < .01). Although the likelihood of choosing Store A in the $425 condition (16\%) falls halfway between those who spent $25 (4\%) and those who spent $525 (28\%), neither difference is statistically significant. Nevertheless, the overall pattern of results supports the notion that effort increases as participants near their goal.

Further, as expected, those in the $500 condition who accumulated $525 in spending were more likely to choose Store A than those who accumulated $25 in spending (44\% versus 12.5\%, respectively; \( \chi^2 = 5.35, p < .05 \)) in support of H2b. If success were not motivating, we would expect shoppers in both conditions who were $475 away from earning a $50 reward to be equally inclined to go to Store A. Likewise, we would expect the percentages to be equal in the $425 and $925 accumulated spending conditions (each $75 away from earning $50). This is not what occurred. In line with H3a, those who accumulated $925 were marginally more likely to choose Store A than those who accumulated $425 (96\% versus 76\%, respectively; \( \chi^2 = 3.11, p < .10 \)). It appears loyalty programs benefit from self-learning or people updating their perceptions of self-
efficacy—people take into consideration whether they have successfully reached the goal in the past when estimating whether they will reach it in the future. We tested whether the likelihood of going to Store A in the $100 reward condition varied with accumulated spending. An analysis of variance utilizing the CATMOD procedure in SAS found no difference across any of the four levels ($p = .95$). Again, consistent with H3b, for changes in effort to occur, the rewards must be challenging.

**Discussion**

Study 2 shows the importance of divisibility—the number of rewards and the level at which they are awarded—on self-learning. While the overall amount a shopper would receive remains constant for anyone spending $1,000, two effects are at play here. If one makes the program too divisible (but not perfectly, as in Store B), then success does not teach the consumer anything. In contrast, if the program is not divisible enough, it may offer great incentives, but only for those who are already committed to the program, and thus will be de-motivating to those who deem the reward level as too lofty. An adequate balance must be struck.

The key point made salient by this study is the impact of success on effort. Those respondents who were put into a hypothetical situation whereby they had confronted a challenging goal and succeeded were more likely to choose Store A. These results are consistent with our theorizing that goal-attainment, which is a function of divisibility, leads to a reassessment of one’s aptitude, which impacts future effort toward recurring goals. We should also highlight the relative size of the effect. For example, at the $525 level, the respondents in the $500 condition were actually more likely to go to Store A then the respondents in the $1,000 condition even though their accumulated spending toward the next reward was lower ($25 vs.
and they were striving for a reward that was smaller ($50 vs. $100). It appears success acted as a powerful motivator in Study 2.

While the scenario is hypothetical and we tell respondents what they have accumulated in spending, we do not believe that they are inferring which store they prefer from their level of past spending. If this were the case, we would see differences based on cumulative spending in the $100 condition (the more cumulative spending at store A, the more likely one is to pick it for the next trip). We do not see evidence of this as each accumulated spending level reflects the same level of preference for Store A. Admittedly, Study 2 does not isolate the mechanism but instead shows how self-learning depends on challenging goals or situations where there is something to learn. In Study 3, we examine the impact of successful goal attainment on self-learning and feelings of self-efficacy more directly.

**STUDY 3: THE IMPACT OF GOAL-ATTAINMENT ON SELF-PERCEPTIONS**

Study 3 was designed to gauge how task completion and the successful attainment of a reward impact perceptions of self-efficacy and thus self-learning. Our goal was to design a task difficult enough such that success would provide meaningful information to the participant about their ability to succeed. We also needed a task where we could control the success rate such that everybody succeeded (to keep sample size manageable), and succeeded at the exact same rate (to insure comparability of the treatment cells), but where participants would be oblivious to our manipulation of the outcomes. The study was presented as a game whereby the respondent’s goal was to determine whether the experimenter was lying by judging his or her facial expressions.

*Method*
Subjects. Respondents were 70 undergraduate business students who participated in this along with several other studies for course credit.

Stimuli and design. Respondents were brought into the lab individually under the premise that they were participating in a study on their ability to interpret facial expressions. It was explained that in business, just as in poker, people make judgments as to the credibility of a statement based on subtle facial cues. Each respondent was shown the eight of diamonds from a standard deck of cards. The experimenter explained that a card would be drawn randomly from a deck. Regardless of what card was drawn, the experimenter would say the card was “higher” than the eight of diamonds. This implied the card drawn was either a nine, 10, jack, queen, king, or ace. The respondent’s task was to determine whether the experimenter was lying (the card was actually a two, three, four, five, six, or seven). As there are an equal number of cards below and above the eight, on average their success rate should equal 50%. That is, it was explained, unless the person can detect a bluff. They were told expert poker players can identify when a person is bluffing on average two-thirds of the time, or in 66% of trials.

The design was a single factor experiment with two conditions: 10 trials or 30 trials (cards drawn). Those in the 10-trial (30-trial) condition were told that if they exceeded 66% correct in the task, or were successful in at least seven out of 10 trials (21 of 30), they would receive a $4 ($12) reward. What varied was the number of trials required to complete the task and not goal difficulty. There is no reason to believe that any more proficiency was required in either condition. In addition, the exact sequence of successes and failures was held constant across conditions (how this was accomplished will be described shortly). Hence, any change in self-efficacy would be the result of successfully completing the task and earning the reward.
Before commencing, respondents answered several questions regarding their perceived ability to determine whether someone is lying based on facial cues and their own subjective likelihood of success. Both groups answered the same questions after completing 10 trials (successfully completing the task for those in the 10-trial condition and one-third progress in the 30-trial condition). Those in the 10-trial condition were asked to repeat the task (creating a recurring goal) and both groups completed the questionnaire after 20 trials (two successful task completions and two-thirds progress, respectively).

Respondents rated their ability to determine whether someone is bluffing and their ability to read facial cues on an 11-point scale (-5 indicating much worse than average and +5 indicating much better than average). Respondents then rated their subjective likelihood of scoring 66% or better on subsequent trials, and thereby perform as well as professional poker players, on a seven-point scale where one indicated not at all likely and seven indicated extremely likely.

During the study, the experimenter utilized a screen to hide the cards drawn from the deck, which included a hidden pocket containing a pre-ordained sequence of cards. This was done to insure every participant had the same experience—each got seven of their first 10 responses correct, and seven of their second 10 responses correct in an identical fashion. Consequently, those in the 10-trial condition completed the task successfully twice while those in the 30-trial condition experienced the exact same sequence of success and failure in terms of trials but were only one-third and two-thirds of the way toward successfully attaining their goal when asked to assess their individual aptitude. Objectively, all respondents received identical feedback in terms of the number of trials they completed successfully. What differed was whether their progress thus far was framed as successfully completing the task. We should reiterate that respondents did
not know the experiment was rigged and believed that they were learning something about their lie detection abilities; no one during the debrief suggested any other reason for the study.

We expected an increasing number of successful trials to impact assessments of self-efficacy for all participants consistent with H4a. More importantly, however, in line with H4b, we predicted that those in the 10-trial condition who successfully reached their goals (7 of 10 and 14 of 20 correct) and received the rewards would believe they were learning more about their face-reading capabilities and thus experience a greater change in their perceptions of self-efficacy.

Results

Three participants in the 10-trial condition did not want to perform the task a second time; hence, we have 32 responses for the post-20 evaluation measures in that condition. Because the measures utilized different scales (-5 to +5 for “Bluffing” and “Facial” and 1 to 7 for “Success”), we standardized the data before starting the analysis. Further, we collapsed the three measures into one given the high degree of “agreement” between them (α = .83). To insure that the results were not driven solely by a reassessment of the likelihood of success (one measure), but were indeed driven by reassessment of ability (the other two measures), we also ran the analyses using only the two ability measures (α = .84). As the results were essentially identical, we only present the analysis done on the composite of the three measures.

To test for effective randomization, we compared the pre-measurement (self-assessments before beginning the task) across conditions. We do not find any significant differences across cells ($M_{10,pre} = -.49$ vs. $M_{30,pre} = -.61$, $F = .44$, n.s.). Our within-subject design allows us to normalize each subject’s score by subtracting each respondent’s pre-task measurement rating (their self-assessment before receiving any feedback) from later measurements (after 10 and after
20 trials) before making any comparisons across conditions. The average changes in ratings are shown in Figure 6.

An ANOVA reveals a change in perceptions of self-efficacy that varied across conditions ($M_{10} = .70$ vs. $M_{30} = .43$, $F = 13.68$, $p < .01$), a significant change in these perceptions as respondents completed more trials ($M_{pre}$ vs. $M_{+10}$ vs. $M_{+20}$, $F = 60.26$, $p < .01$) as well as a significant interaction between the two ($F = 3.74$, $p < .05$). Individual contrasts show that there is a significant improvement in perceived ability after 10 trials in both conditions ($M_{10,pre} = 0.0$ vs. $M_{10,+10} = .92$, $p < .01$; $M_{30,pre} = 0.0$ vs. $M_{30,+10} = .59$, $p < .01$). This supports H4a as progress toward the goal impacts one’s assessment of self-efficacy. As predicted, this increase is larger for those who viewed 70% correct after 10 trials as completing the task successfully than for those who viewed 10 trials as one-third progress toward the overall goal ($M_{10,+10} = .92$ vs. $M_{30,+10} = .59$, $p < .01$). This result supports H4b as successfully reaching the goal has an additional impact.

The gap in self-perceptions widens further after 20 trials, or between two successful task completions versus two-thirds completion ($M_{10,+20} = 1.17$ vs. $M_{30,+20} = .69$, $p < .01$). Further, the changes in ratings from 10 to 20 trials is marginally significant in the 10-trial condition ($M_{10,+10} = .92$ vs. $M_{10,+20} = 1.17$, $p = .056$) while it is not in the 30-trial condition ($M_{30,+10} = .59$ vs. $M_{30,+20} = .69$, $p = .42$). Finally, it is worth noting that the change for those in the 30-trial condition after 20 trials was less than the change for those in the 10-trial condition after only 10 trials, and this difference was marginally significant ($M_{30,+20} = .69$ vs. $M_{10,+10} = .92$, $p = .068$).
Discussion

In Study 3, we examined the impact of success as it pertains to self-learning. The only difference across conditions was whether the task was seen as completed or still in process. Despite identical sequences of successes and failures on individual trials, we find successfully reaching a goal and earning the reward differentially impacts self-efficacy. Successfully completing a task comprised of 10 trials (seven correct) did far more to boost both the participants’ perceptions of their own face-reading skills and likelihood of success in the future than a task in which completing 10 trials meant they had completed one-third of the task successfully. Successfully completing a task comprised of 10 trials did even more then successfully completing 20 trials in a 30-trial task. We find unequivocal support for H4a and H4b and our hypothesizing that successful goal attainment leads to self-learning or a change in beliefs about one’s capabilities (self-efficacy). This in turn increases one’s perceived ability of reaching the same goal again.

GENERAL DISCUSSION AND CONCLUSION

“If I did it once, I can do it again,” is a common mantra for those who have attained success. However, there is no indication regarding whether they will try as hard or harder the next time around. Not only can the successful do it again, but they will frequently work harder to help insure success happens again. This research illustrates how success in a recurring goal framework allows consumers to learn something about themselves and thus leads them to amplify their effort in successive endeavors toward the same reward.

We argue that the increase in effort brought on by successfully reaching a goal and earning a reward is due in part to self-learning. People feel success is a reflection of their ability
to coordinate their efforts, handle obstacles, and do whatever is necessary to succeed again. While we recognize that self-learning is likely only part of the story, its contribution is significant, as documented here, and worth noting. In Study 1, we utilized real world frequent flier program data to show how success fosters reengagement; successful fliers begin the new year flying more frequently. In addition, reaching the goal of earning status impacts a flier’s likelihood of success in subsequent attempts at earning status.

In Study 2, we show that increasing divisibility (from $1,000 to $500), which reframes a larger task as several smaller tasks and disburses a reward in smaller increments, can boost people’s perceptions of self-efficacy. If they succeed once, albeit at reaching an easier goal, this tells them something about themselves. Conversely, too much divisibility ($100) was shown to be de-motivating. Therefore, loyalty programs that offer people multiple redemption opportunities must balance the attractiveness of an award with an appropriate level of difficulty in attaining success. If the only reward offered were a plasma television for one million points, this may prove too difficult and unattractive for most consumers. Conversely, offering magazine subscriptions for 100 miles may be uninspiring. We believe this is what American Express attempted to do at one time by highlighting that Am Ex Rewards points can be used at 160 stores for more than two million products. While this may encourage consumers to carry an Am Ex card, our work suggests that loyalty (i.e., share of wallet) may be better accomplished with more moderate divisibility, such that it is not so easy to cash out Rewards points, but when someone does, he/she feels successful.

Finally, in Study 3, we control the process such that participants experience the exact same sequence of success and failure on individual trials—their hit and miss rate remains constant. Yet, when we frame getting 70% correct in a sequence of 10 as the successful
completion of a task accompanied by an award, respondents elevated their perceptions of self-efficacy, showing that success does indeed lead to learning—learning about one’s abilities.

In all three studies, more than one success was shown to matter. Hence, not only does goal attainment result in increased effort the second time around, but successive successes further elevate effort. We show how the successful attainment of a goal and the accompanying reward serves to increase consumers’ efforts in subsequent undertakings and that this increase can endure after more than one or two successes.

This research is not without its limitations. We suggest goals or reward levels should be challenging to foster self-learning, but the precise level of difficulty will vary across situations. We do not offer a methodology for determining this level but only make managers aware of how changes in divisibility (i.e., adding or deleting reward levels) might impact their programs. While exploring how goal-attainment impacts self-efficacy, we did not examine the impact of success on people’s emotional response, such as the feelings of satisfaction and pleasure it should elicit (Isen 1987). It may be that affect regulation, or a process in which the positive affect associated with the reward is sought after, moderates persistence towards a goal. It is not clear, however, whether the positive feelings would encourage individuals to try again or whether individuals would attempt to protect the positive state associated with success by not trying again. Future research could examine the determinants of these opposing responses.

In Study 3, we show how successfully reaching a goal and earning a reward results in enhanced self-learning and thus self-efficacy, but we do this outside of the context of loyalty programs. We used a context pre-tested to insure our respondents had little previous experience and were uncertain about their abilities. We should point out that judging facial expressions is not entirely dissimilar to consolidating purchases in that perceived self-efficacy is not concerned with
the sub-skills necessary to achieve the goal (e.g., observing subtle facial cues, detecting a change in mannerisms, or interpreting gestures) but in whether the person feels efficacious. In other words, whether the task is determining if someone is lying on successive trials or purchasing successive flights to accumulate miles, each endeavor will include unpredictable and ambiguous elements.

From a practical perspective, all possible successes may not be entirely within the control of the firm. For example, frequent flier miles, the most ubiquitous alternative currency, are becoming interchangeable with several other alternative currencies and some can now be redeemed at numerous second-party vendors. This results in a myriad of outside rewards that might qualify as successes. Earning 25,000 miles for a free roundtrip ticket may no longer be the quintessential goal. Goals set by the firm and the associated self-learning may be diluted by such changes in the marketplace. Other firms, such as Southwest Airlines, are strategic in limiting the uses of their alternative currency by issuing credits in proprietary, non-divisible increments (flight segments). Fliers on Southwest quickly learn whether consolidating eight flights is something they can or cannot do repeatedly. Yet SWA’s less divisible currency (segments, as opposed to miles) limits their flexibility as a reward mechanism, which has led Southwest partners to begin issuing credits in partial segments. The objective of the firm is to identify the right amount of divisibility—that which engages high-value customers and allows them to reach their goals, thus keeping them coming back for more.
REFERENCES


### TABLE 1

**Study 1, Part I: Parameter Estimates for the Inter-flight Hazard Rate Model**

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<td>Random Coefficients</td>
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<tr>
<td>( \log(\sigma_z) )</td>
<td>-0.8302</td>
<td>0.01119</td>
<td>-74.18</td>
<td>&lt;.0001</td>
<td></td>
</tr>
<tr>
<td>( \log(\sigma_{zz}) )</td>
<td>-1.1980</td>
<td>0.03290</td>
<td>-36.42</td>
<td>&lt;.0001</td>
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<tr>
<td>( \sigma_{zz} )</td>
<td>-0.0777</td>
<td>0.00422</td>
<td>-18.43</td>
<td>&lt;.0001</td>
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<tr>
<td>Weibull Shape</td>
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<tr>
<td>Gamma</td>
<td>1.0220</td>
<td>0.00119</td>
<td>861.44</td>
<td>&lt;.0001</td>
<td></td>
</tr>
<tr>
<td>( n )</td>
<td>418,818</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Log Likelihood</td>
<td>-1,222,965</td>
<td></td>
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</tbody>
</table>

Note: The parameter for the intercept is omitted for confidentiality purposes.
Table 2

Study 1 Part II: Parameter Estimates for Regression Discontinuity Models

<table>
<thead>
<tr>
<th></th>
<th>1st Timers</th>
<th>Repeaters⁺</th>
<th>P(Reach 25K Miles)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>t-stat</td>
<td>Estimate</td>
</tr>
<tr>
<td>α⁻</td>
<td>XXX</td>
<td>21.02**</td>
<td>XXX</td>
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<tr>
<td>α⁺</td>
<td>1183.5</td>
<td>1.99*</td>
<td>2689.7</td>
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<tr>
<td>β⁻</td>
<td>-0.82</td>
<td>-1.38</td>
<td>0.48</td>
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<tr>
<td>β⁺</td>
<td>-0.13</td>
<td>-0.20</td>
<td>-1.08</td>
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<tr>
<td>NSTATUS</td>
<td></td>
<td></td>
<td>1322.2</td>
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<tr>
<td>NSTATUS2</td>
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<td></td>
<td>-57.7</td>
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<tr>
<td>w</td>
<td>1,300</td>
<td>1,200</td>
<td>900</td>
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<tr>
<td>N</td>
<td>15,845</td>
<td>8,478</td>
<td>9,956</td>
</tr>
<tr>
<td>Y⁻</td>
<td>11,682</td>
<td>13,979</td>
<td>9.2%</td>
</tr>
<tr>
<td>Y⁺</td>
<td>12,865</td>
<td>16,668</td>
<td>17.1%</td>
</tr>
</tbody>
</table>

* Significant at p = .05
** Significant at p = .01
⁺ For a traveler who has reached status once before
Note: The parameter for the intercept is omitted for confidentiality purposes.
Figure 1a: Procedural Learning

Figure 1b: Goal Gradient – No Learning
Figure 1c: Semantic Learning

Figure 1d: Self-learning
Figure 2: Propensity to Fly

- **Goal Reached**
- **New Year**
- **Effort/Output**
- **Post-goal dip**
- **Partial Post-reward Resetting**
- **Goal re-engagement**
Figure 3: Change in Inter-flight Times

- Partial Reset
- Post Goal Dip

Time between flights (Relative to first flight)

Months
Figure 4
Study 1 Part II: Empirical Probability of Attaining Status for Fliers Who Have and Have Not Succeeded Previously

Note: Probabilities expressed relative to the probability of reaching status for someone who had never reached status before 2004 and barely misses reaching 25,000 miles in 2004.
Figure 5
Study 2: Impact of Divisibility on Store Choice
Figure 6

Study 3: How Perceptions of Aptitude Change with Success