Size matters (and so does experience):

How personal experience with a fine influences behavior

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Abstract

In this paper, we disentangle the effects of new information from the effects of personal experience to describe how personal experience changes behavior. We examine personal experience with one of the most ubiquitous managerial and policy tools: the monetary fine. We demonstrate that experience with a fine, controlling for the effect of learning new information, significantly boosts future compliance. We also show that experience with a large fine boosts compliance more than experience with a small fine, but that the influence of experience with both large and small fines decays sharply over time. We report longitudinal analyses of approximately 10,000 video-rental customers over a period of two years. We show that direct experience with a late fee significantly decreases the likelihood that customers will incur a late fee during their next rental. This is true even for renters who had incurred a late fee for a prior rental and had complete information about the late-fee policy. Our findings have broad implications for understanding how information and experience influence behavior over time.

Size matters (and so does experience):

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After renting the movie ‘Apollo 13,’ Reed Hastings misplaced his video cassette. He found the cassette six weeks later and faced a $40 late fee. The experience of paying this late fee was so aversive for Hastings, that it motivated him to take an action that would fundamentally change the entire video-rental industry: In 1997, Hastings founded Netflix (Zipkin, 2006).

Even though Hastings was aware of the late-fee policy, it was the experience of paying the fine that motivated him to change his behavior. In this paper, we examine the unique influence of personal experience on subsequent behavior.

Economic models of behavior assume that new information changes behavior (e.g., Becker, 1968; 1976). These models have considered the content and reliability of new information, but have largely ignored the influence of how new information is obtained. Recent work, however, has found that how individuals receive information matters. In particular, an emerging body of research suggests that information gained from *experience* may be particularly influential (e.g., Simonsohn, Karlsson, Loewenstein & Ariely, 2008; Harvey & Fischer, 2005; Weber, Shafir & Blais, 2004; Barron & Erev, 2003). For example, a prospective diner may be more likely to avoid a restaurant after experiencing poor service there than after reading a review of the poor service others have had at that restaurant.

Several scholars, however, have argued that much of the extant research that examines how personal experience changes behavior has confounded how information is acquired with the nature of information acquired (e.g., Rakow, Demes & Newell, in press; Newell & Rakow, 2007; Fox & Hadar, 2006). For example, the experience of being arrested may deter criminals from reoffending (e.g., Smith & Gartin, 1989). It is not clear, however, whether the experience itself (i.e., the personal experience of getting arrested) or new information (e.g., new information about the subjective probability of being caught) deters crime.

In the current work, we explore how experience influences behavior. We introduce a novel methodological approach to disentangle the effects of learning new information from the effects of personal experience. We examine experience with one of the most ubiquitous policy tools—the monetary fine. We demonstrate that personal experience with a fine powerfully influences behavior. This is true even when people have complete information. Our results also describe the mechanics of the relationship between experience and future behavior. We show that larger fines change behavior more than smaller fines, and we show that the effects of personal experience with a fine decay quickly over time.

Information and Behavior

In this paper, we disentangle the effects of experience from the effects of information. Information campaigns are often used to change individual behavior, and an extensive body of research suggests that individuals, as rational actors, will respond to new information (e.g., Prescott & Rockoff, 2008; Cutler, Huckman & Landrum, 2004; Jin & Leslie, 2003; Nelson, 1974). For example, Cutler, Huckman and Landrum (2004) found that the introduction of a hospital “report card” system influenced patient decisions; cardiac admissions fell by 10% at hospitals that received a “high mortality” label. Similarly, Jin and Leslie (2003) found that publicizing the hygiene ratings of Los Angeles restaurants led consumers to shift their dining preferences in favor of the most hygienic restaurants.

A surprising number of studies, however, have found that people are often insensitive to information. For example, health workers in Africa claimed that “we could talk about germs until we were blue in the face, and it didn’t change behavior” (Duhigg, 2008). In a different domain, college administrators tried to curtail alcohol consumption by providing students with new information, but these attempts completely failed to influence drinking behavior (Clapp et al., 2003). Other informational campaigns, ranging from listing nutritional information of food in supermarkets to spreading awareness of the hazards of smoking, have had only modest effects on behavior (McKenna & Williams, 1993; Russo et al., 1986).

These discrepant findings regarding the efficacy of providing individuals with new information have prompted scholars to investigate conditions under which people are more or less likely to react to new information. For example, Chu and Chu (1990) found that feedback consistency is important in determining whether new information will affect judgments and decisions. Others have considered how social-cognitive factors, such as goals and norms, moderate the influence of new information (e.g., Cialdini, 2003; Kunda, 1990). More recent work has begun to consider how the mode of communication moderates the influence of new information.

In practice, people can learn information in several different ways. For example, a driver may learn about the hazards of receiving a speeding ticket by hearing someone tell a story about how she received a fine for speeding (information via description), by witnessing another driver receive a fine for speeding (information via observation), or by actually receiving a fine for speeding (information via personal experience). Each of these sources (description, observation, or personal experience) may convey the same factual information. Although most information studies (e.g., Di Tella & Schargrodsky, 2003; Kessler & Levitt, 1999) have focused on the informational *content* of the message (e.g., whether or not an individual learns that she may face a $100 fine for speeding), recent work suggests that the mode of communication matters (Simonsohn et al., 2008). In particular, information gained from *experience* may be particularly powerful in influencing judgments and behavior.

Experience

People often receive more information when they learn from experience. Although different sources of information may convey the same factual content, personal experience can convey affective information that other modes of communication lack (Nisbett & Ross, 1980). For example, information learned from someone else's description of receiving a speeding ticket may lack the affective (and typically awful) feeling that is part of the experience of receiving a speeding ticket.

Even if the factual content is held constant, the addition of affective information gained through experience may change how people react to new information. Prior work has found that people often make mistakes when they forecast how they are likely to feel about specific outcomes in the future (Mellers, 2000; Loewenstein & Schkade, 1999; Gilbert et al., 1998). While some research has found that individuals overpredict how badly they will feel following negative outcomes (e.g., Mellers, 2000; Gilbert et al., 1998), research using behavioral measures suggests that individuals may actually underpredict these negative emotions (e.g., Read & Loewenstein, 1999; Christensen-Szalanski, 1984, see also Loewenstein & Schkade, 1999). Following a personal experience, individuals may be able to improve their affective forecasts relative to the forecasts individuals make following described or observational accounts. For example, a driver who learns about someone else's speeding ticket may mispredict just how awful she will feel when she receives a speeding ticket of her own.

Recent research has attempted to isolate the effects of personal experience from other types of accounts. Much of this research contrasts the influence of information gained from personal experience with the influence of information gained from a description. This work has found that the informational source matters (e.g., Yechiam & Busemeyer, 2005; Weber, Shafir & Blais, 2004; Barron & Erev, 2003). For instance, Hertwig et al. (2004) found that decision makers overweight small probabilities when they are given the actual probability distribution, but underweight these same probabilities when they gain information about the probability distribution from their own experience. Even when people receive information from multiple sources (e.g., when an outcome is first described, then experienced; Yechiam, Barron & Erev, 2005; Inzana et al., 1996) people tend to place a great deal of weight on their personal experience.

While a growing body of evidence suggests that personal experience is important, this work has routinely confounded the source of the information with the factual information conveyed (Rakow, Demes & Newell, in press; Newell & Rakow, 2007; Fox & Hadar, 2006; see Simonsohn et al., 2008 for an exception). For example, compared to peers who might hear second hand accounts about street crime, victims of street crime are more likely to engage in actions to prevent future victimization (e.g., Skogan, 1987). It is unclear, however, whether the personal experience of the crime adds only affective information, or whether it adds factual information as well, such as information about the subjective probability of being accosted. By confounding both affective and other types of information, we cannot be sure that experience itself uniquely affects behavior.

The present research

In this paper, we describe how personal experience, controlling for new information, changes behavior. We examine this question within the context of one of the most ubiquitous policy tools: the monetary fine. We report results from a field setting with approximately 10,000 customers who made video-rental decisions over a two-year period.

We test the effects of personal experience with a late fee on future rental behavior. Specifically, we examine how paying a late fee influences how punctual people will be in returning their next rental. We use a semiparametric econometric method to compare the behavior of renters who experience a late fee with those who do not while controlling for individual-specific effects.

In this setting, the late-fee policy is simple and explicit, and we report analyses on individuals who had and had not paid a late fee for a previous rental. In this way, we can study the influence of experience in a domain in which the experience (of paying a late fee) does not communicate new factual information.

Our dataset is longitudinal. This allows us both to control for individual differences in experience-based behaviors and to explore how the effects of experience decay over time. Our ability to look at individual-level effects helps us to make direct comparisons between described consequences (e.g., being informed of the late return policy) and direct experience of these consequences (e.g., actually being assessed a late fee).

We test four hypotheses. These hypotheses describe a specific set of relationships between personal experience and subsequent behavior.

Experience curtails late returns. Our first hypothesis predicts that the experience of paying a fine will influence how punctual an individual will be in returning their next rental. We conceptualize the experience of paying a fine as having both an informational and an affective component. That is, personal experience can provide individuals with new information and trigger specific feelings. In our context, renters who return materials late lose money and experience negative feelings.

The experience of paying a fine is associated with negative affect (Novemsky & Kahneman, 2005; Kahneman & Tversky, 1979). Consistent with prior work (Read & Loewenstein, 1999; Christensen-Szalanski, 1984), we expect renters in our sample to mispredict affective experiences. Specifically, we expect renters to be surprised by the negative affect they experience when they actually pay a fine.

Having experienced a fine, we expect renters to improve their affective forecasts. Specifically, when forecasting the consequences of returning their next rental late, individuals who experienced a fine will incorporate both the loss of money and the very negative feelings associated with a late return. By accurately anticipating the negative affect associated with paying a fine, we expect renters who returned a movie late in one time period (and paid a fine) to be less likely to return a movie late on their subsequent visit.

Hypothesis 1: Individuals who incurred a late fee in one period will be more likely to return their materials on time in future periods than will individuals who did not incur a late fee.

The influence of experiences decays over time. Recent experiences are more salient and more affectively charged than distant experiences (Hertwig et al., 2004; Ariely, 1998; Varey & Kahneman, 1992). This is particularly true for negative experiences. Although both positive and negative memories decay over time, the memory of negative experiences decays particularly quickly (e.g., Mitchell et al., 1997).

The experience of paying a late fee triggers negative affect. We expect this negative affect to influence subsequent behavior. Over time, however, we expect the memory of negative experiences to decay and we expect the influence of experience on behavior to decay. Specifically, we expect experience with a fine to influence short-term behavior far more than it influences long-term behavior.

Hypothesis 2: The effects of personal experience on subsequent behavior will decay over time.

Size matters. We expect larger fines to influence behavior more than smaller fines. This is likely to be true for two reasons. First, although all losses are aversive, larger losses are more painful than smaller losses (Kahneman & Tversky, 1979). As a result, the discrepancy between anticipated and experienced negative affect will grow with the size of the fine. The larger the late fee, the stronger the relationship between experience and future behavior.

Second, larger fines are more salient than smaller fines. The salience of information can influence behavior (e.g., Hertwig et al., 2004), and as a result, we expect larger fines to influence behavior more than smaller fines. Taken together, we predict the following:

Hypothesis 3: Compared to smaller fines, larger fines are more likely to decrease the likelihood of a late return on a subsequent visit.

Expertise matters. Experts, those with high levels of experience in a specific domain, are less susceptible to some cognitive and affective errors than are novices. For example, in collectables markets, List (2003) found that market experience mitigated the endowment effect. Experienced traders were less prone to the endowment effect than were less-experienced traders.

In our context, we expect customers with a great deal of rental experience to be less affected by late fees than less-experienced renters. Experienced renters are likely to have paid late fees in the past, and are likely to have gained information about the negative affect associated with paying a late fee. As a result, we expect experienced renters to make more accurate affective predictions than less-experienced renters.

Hypothesis 4: The influence of experience with a late fee on future compliance will be strongest for individuals with limited rental activity.

Study

Overview

We examine video rental behavior and compare the effects of described information (the late fee policy) to information gained through personal experience (actually paying a late fee) on future rental behavior. Using a semiparametric econometric technique in order to control for unobserved individual-specific effects in the dynamic process, we test whether paying a late fee affects the propensity to return videos late in future periods.

Data

We use a dataset on video store transactions received from a large, independent video store in Northern California. The data set includes all transactions made by over 10,000 distinct customers during a two-year period from January 1st, 2003 through December 31st, 2004.

Each observation involves the set of transactions by an individual on a given day. For each observation, we have the account number, date, type of rental (new release, etc.), rental cost, the amount of money paid to cover a late fee for a past rental, and payment method (credit, cash, check, gift card). Using the account number, we are able to follow the rental behavior for a given individual over the two-year period. We are unable to identify which accounts have multiple users; the added noise with regard to who actually receives the late fee makes for a more conservative test of our hypotheses.

The video store for which we have data classifies movies into two categories: new and old releases. New releases have a one-day rental period while old releases are five-day rentals. Each additional day beyond the rental period for which a movie is not returned is associated with a late fee of $3.00 for new releases and $1.00 for old releases. For each visit to the video store, we observe whether the customer paid money to cover a late fee associated with a previous rental (as opposed to observing which movies were returned late). The policy at this particular video store is that customers are asked to pay any late fees accrued from the previous rental whenever attempting to rent videos. If a customer returns a movie late and rents another movie in the same visit, they are asked at that time to pay the late fee. Thus, we associate paying a late fee in period t with movies returned late in period t-1. Occasionally, customers will return a movie late and decide to pay the late fee without renting any additional videos (2.6% of late fees are paid in this manner). Because they did not rent a movie when they paid the late fee, it will be impossible for them to have to pay a late fee during their subsequent visit. This behavior would mechanically provide evidence in favor of a premium placed on personal experience. To address this problem, we drop all observations which represent a visit to the video store in which a late fee was paid but no movie was rented.

Table 1 presents summary statistics for our data. The average person in our dataset rents 2.3 movies per visit and visits the video store 21 times during the two-year period. The movies are returned late 14% of the time causing the average individual to pay $16.50 in late fees over the two-year period.

Empirical Strategy

We use a semiparametric method for estimating dynamic, binary-response models (Honore & Kyriazidou, 2000; Chamberlain, 1985; Cox, 1958). Ordinarily, a fixed effects framework would be ideal to control for a situation in which there exists individual heterogeneity. However, since a lagged dependent variable is used as an explanatory variable, including dummy variables for each customer mechanically results in a negative coefficient on the lagged dependent variable (see Nickell, 1981). Unlike random-effects estimators, our method imposes less structure on the estimation.

Following Chamberlain (1985), we examine sequences of rental behavior (e.g., 101000 vs. 100100), where each number represents a visit to the movie store by a customer. A 1 represents that a late fee has been paid and 0 represents the absence of a late fee. In order to control for unobserved effects, we compare sequences with equal numbers of 1's and 0's, holding the initial and final observations constant. Within a sufficiency class and in the absence of first-order state dependence, we would expect all sequences of events to occur with equal probability. Thus, evidence of an effect of personal experience will emerge if late fees occur less often following a late fee in previous periods.

The intuition for this identification is clear. To illustrate, suppose we compare the data series '101000' to the series '110000'. Each series describes a customer who has paid two late fees, but at different times: The first customer paid a late fee during the first and third visit to the store, while the second customer paid a fine in the first and second visits. If the first data series is found to be significantly more likely to occur than the second, this would suggest that receiving a late fee causes renters to be less likely to receive a late fee the following period. More generally, we are comparing individuals who receive the same overall number of late fees over a six period series and simply examining whether the order in which they receive these late fees varies in a systematic fashion.

For our analysis, we generate sequences of six observations so that we can estimate both first-order (i.e., behavior at period t) and second-order state dependence (i.e., behavior at t + 1). We created this data set by extracting the first six observations for each movie-rental customer and then continuing to extract the subsequent six observations for each customer provided that six additional observations exist. After obtaining these sequences, we further restricted the data set to include only the 44 sequences of six observations which are useful for the testing of state dependence. This procedure leaves us with 7,650 usable sequences of six observations. These sequences represent movie-rental behavior for 2,735 distinct customers. Table 2 presents counts for each of the 44 different sequences we used to test for first-order state dependence. A comparison of the counts for sequences within a sufficiency class suggests that negative state dependence is present in these data.

Results

We hypothesized that personal experience would have a larger effect on rental behavior than would other sources of information (Hypothesis 1). We find support for this hypothesis in our estimate of first-order state dependence (see Table 3), $\gamma = -.1067$, $p < .01$. This Logit coefficient can be used to calculate a marginal effect of paying a late fee in period t on paying a late fee in period t+1. The marginal effect implies that an individual is 1.3% (in absolute terms) less likely to pay a late fee during a visit if a late fee was paid during the last visit. This represents an 8.8% reduction from mean late fee rate of 14%.

We predicted that the effect of personal experience would decay over time (Hypothesis 2). In Table 3, we report estimates of second-order state dependence using the 1,648 sequences that include sets of rentals involving a late return followed by an on-time return. An example of two types of sequences that can be used to test for second-order state dependence is ‘101000’ and ‘100100’; second-order state dependence (the effect of paying a late fee in period t on compliance in t+2) predicts the second series to be more likely to occur than the first. Our estimate, $\gamma_2 = -.0510$, suggests that having paid a late fee two visits ago decreases the probability of paying a late fee during the current visit by 0.6% (4.3% reduction from the base rate of 14%). However, given the reduced sample size for testing second-order state dependence, this effect is not significantly different from zero (*p* = .27).

In Hypothesis 3, we predicted that larger fines influence behavior more than smaller fines. We test this hypothesis by comparing behavior across two types of sequences: Sequences that involved small late fees (fees between $1 and $3, which are typically caused by returning one movie past the deadline by one day), and sequences that involve large late fees (fees greater than $3; in these sequences the average late fee was $8.24).

We also restrict the samples for this analysis to sequences of six observations for which there were two late fees. In these sequences, the amount of the first late fee might influence subsequent late fee behavior. In sequences with multiple late fees, the sufficiency classes that test for first-order state dependence (e.g. 111000 vs. 110100) may not depend on the late fee amount in the first period. We report our analyses in columns (3) and (4) of Table 3. We find that the experience with a large fine influences behavior almost twice as strongly ($\gamma = -.1313$) as does experience with a small fine ($\gamma = -.0775$).

Expertise

We hypothesized that the experience of paying a fine would influence behavior more for individuals with limited rental histories than it would for individuals with long rental histories (Hypothesis 4). To test this hypothesis, we conducted separate analyses on populations with different rental histories. Specifically, we conducted analyses on customers who had previously rented at least 10, 20, and 40 times, respectively. We report results from these analyses in Table 4. We estimate the level of first-order negative state dependence in the data. Our results indicate that experience-based behavior is just as strong (if not stronger) for customers with long histories than it is for customers with short histories. Contradicting our fourth hypothesis, we find that experience with a fine influenced both seasoned and naïve renters alike.

Prior Experience with a Fine

We conducted an even more conservative test of our primary thesis. In Table 4 (columns 4, 5, and 6), we report analyses for customers who had previously paid at least 2, 4, or 10 late fees. Notably, we find the same first-order effects for experience with a fine for customers who had paid a fine in the past.

Other behavioral effects

Our analyses focus on the relationship between experience with a late fee and whether or not customers return their next rentals on time or late. It is quite possible the experience with a late fee may influence other types of behavior as well (as it did for Reed Hastings).

In considering other types of behavior, we first test to see if individuals who paid a late fee decided not to visit the video store as often or decided to rent fewer movies on subsequent visits. Since a lagged dependent variable does not enter into the model anymore, we are able to use fixed effects to control for individual heterogeneity. As the dependent variables (days between rentals and movies rented) are both counts, we present fixed effects results from both OLS and Poisson models.

As we report in columns (1) and (2) of Table 5, after controlling for unobserved individual heterogeneity, paying a late fee is associated with an individual waiting 0.73 additional days before returning to the video store to rent another movie. This relationship appears to decay quickly over time. Paying a late fee two periods ago continues to be associated with a statistically significant longer waiting time before returning to the video store (0.48 days). However, paying a late fee three visits ago does not have a statistically significant effect on the number of days between rentals. In columns (3) and (4) of Table 5, we report results that test whether paying a late fee reduces the number of videos that the customer will rent during their subsequent visit. While the point estimates are all negative (customers rent fewer videos after paying a late fee), this relationship was not significant.

General Discussion

Personal experience changes behavior. Using a unique field setting and longitudinal data, we show that the personal experience of paying a late fee decreases the likelihood that customers will incur a late fee during their next rental period. Larger fines lead to greater behavioral effects than smaller fines, and recent experience matters. The influence of experience with a fine decays quickly over time. Surprisingly, personal experience affected the behavior of seasoned and novice renters alike. This was true even for customers who had previously paid fines. This provides powerful evidence in support of our thesis: the influence of personal experience extends beyond the factual information it conveys.

Our work makes a substantial contribution to the growing literature linking personal experience to cognition and behavior. Our methodological approach enables us to pinpoint the effects of direct experience in a context where the costs and benefits of either learning or failing to learn from experience are real. A particular benefit of our approach is that we observe actual behaviors rather than relying on surveys or self-reports.

Another strength of the current research lies in the longitudinal nature of our data. Aside from the benefits in terms of controlling for individual-specific effects, examining the effects of personal experience over time enables us to conduct the most conservative test of the influence of personal experience on behavior to date. In contrast to findings from laboratory experiments, we demonstrate that personal experience can affect behavior days or even weeks into the future. In light of the conservative nature of our tests, the effects of personal experience on behavior appear to be quite robust.

Our findings have implications for understanding information acquisition, both in workplace and educational settings. A substantial literature has developed comparing the efficacy of “passive” learning (e.g., learning through lectures or textbooks) to processes that give the learner more direct control and experience, such as experiential (Kolb, 1984) or active learning (e.g., Bell & Kozlowski, 2008; 2002). While the optimal information source may depend on the type of information being communicated (e.g., Ostroff & Kozlowski, 1992), research suggests that approaches offering learners a chance to experience information rather than simply absorb it often result in better performance in terms of adaptive learning and other relevant outcomes (e.g., Pfeffer & Sutton, 2006; see Salas & Cannon-Bowers, 2001 for a review). While passive and active learning approaches can vary greatly in the amount and type of information that they convey, the results we present here are consistent with the idea that learning through experience makes the information more salient and memorable.

Our findings inform a number of practical prescriptions. Across many domains, managers use fines to gain compliance. For example, managers not only impose fines to curtail smoking at work, but also to encourage healthy behaviors outside of work by fining employees who fail to meet specific health criteria (Costello, 2007). Our findings suggest that following a personal experience with a fine, employees will be particularly likely to comply with the desired behavior. Policies that regularly impose small fines are likely to be particularly effective in gaining compliance.

In other cases, managers may wish to minimize the salience of fees they charge. Many businesses, such as credit-card companies, rely on various fees and penalties as a major source of income. These businesses may wish to implement policies that reduce the salience of the fees they charge to increase customer retention and satisfaction. Automatic withdrawal or prepaid late-fee accounts may reduce the impact of personal experience with a fine.

Our findings also inform prescriptions for public policy. For example, policymakers may be able to deter crime not only by adjusting punishment levels and detection rates, but also by changing the personal experience of potential criminals. Rather than giving a juvenile caught vandalizing a warning, an officer may deter future crime more effectively by meting out a punishment that involves a personal experience (e.g. briefly handcuffing the offender).

Conclusion

When it comes to motivating individuals, personal experience offers a unique vehicle for changing behavior. Importantly, personal experience even influences seasoned individuals with prior experience. Though we found that compliance effects decay over time, personal experience with a fine can motivate long-term behavior. In some cases, the influence of these changes can be profound. Just ask Reed Hastings and his competitors at Blockbuster.

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Table 1. Summary Statistics - By Individual

	Mean	Standard Deviation	Median	Min	Max
Visits (2-year period)	21.4	29.6	9	1	320
Avg Movies Rented (per visit)	2.3	1.1	2	1	12
Fraction of Time Movies are Returned Late	0.14	0.20	0.04	0	1
Late Fees Paid ($, per visit, conditional on paying a late fee)	4.24	3.34	3.3	1	44
Late Fees Paid ($, 2-year period)	16.5	45.1	2	0	1335
Total Number of Customers	10563	10563	10563	10563	10563

Notes: Summary statistics represent data from all video-store transactions made between Jan. 1, 2003 – Dec. 31, 2004. A visit represents all transactions that take place on a given day by a customer account number.

Table 2. Counts of Different Sequence Types Used For Testing First-order State Dependence

(1)	110000	266	(27)	011100	114
(2)	101000	307	(28)	001110	117
(3)	100100	317	(29)	010110	146
(4)	100010	288	(30)	011010	149
(5)	000011	287	(31)	111100	59
(6)	010001	322	(32)	111010	74
(7)	000101	339	(33)	110110	82
(8)	001001	345	(34)	101110	85
(9)	011000	300	(35)	001111	87
(10)	001100	330	(36)	011101	75
(11)	000110	341	(37)	010111	83
(12)	001010	328	(38)	011011	101
(13)	010010	346			
(14)	010100	347	(39)	100111	71
			(40)	110011	80
(15)	111000	103	(41)	111001	82
(16)	110100	120	(42)	110101	70
(17)	110010	123	(43)	101101	77
(18)	100110	125	(44)	101011	100
(19)	101100	128			
(20)	101010	137			
(21)	000111	123			
(22)	001011	112			
(23)	010011	135			
(24)	011001	137			
(25)	001101	138	**Total No.**		
(26)	010101	154	**of Sequences:**		7650

Notes: Each sequence type represents six consecutive visits by the same individual. 1's indicate that a late fee was paid during that visit and 0's indicate no late fee paid. Types (1) – (44) illustrate all sequences of six visits that are usable to test for first-order state dependence. Sequence types are separated into groups ((1)-(4), (5)-(8), etc.) which represent a given sufficiency class. The third and sixth columns provide counts for the number of times the sequence occurs in our data.

Table 3. Fixed-Effects Estimates of State Dependence - Based on Semiparametric Conditional Logit Models

	Dependent Variable: Paid Fee in Period (t)			
	(1)	**(2)**	**(3)**	**(4)**
Paid Fee (t-1)	-0.1067		-0.0775	-0.1313
	(.0237)**		(.0416)†	(.0499)*
Paid Fee(t-2)		-0.0510		
		(.0464)		
First of Two Paid Fees $1-$3			X	
First of Two Paid Fees > $3				X
Log Likelihood	-18661	-1142	-6638	-3633
Total No. Observations	45900	9888	16614	9216
Total No. Chains of Six	7650	1648	2769	1536

Notes: Columns (1) – (4) provide maximum likelihood estimates of state dependence using the conditional log-likelihood functions given in Equations (9) and (11) – Equation (9) represents first-order state dependence and Equation (11) represents second-order state dependence. Standard errors are computed using a bootstrap routine with 1000 repetitions of full samples with replacement. Column (3) uses the subset of sequences which have exactly two late fees and where the first late fee paid is between $1 and $3. Column (4) uses the subset of sequences which have exactly two late fees and where the first late fee paid is greater than $3.
† significant at 10%; * significant at 5%; ** significant at 1%

Table 4. Estimating the Effects of Experience on First-Order State Dependence

	Dependent Variable: Paid Fee in Period (t)							
	Number of Previous Visits			Number of Previous Late Fees			First Half	Second Half
	>10	>20	>40	>2	>5	>10		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Paid Fee (t-1)	-0.1540	-0.1238	-0.2227	-0.1127	-0.1803	-0.1674	-0.1493	-0.1118
	(.0281)**	(.0327)**	(.0445)**	(.0284)**	(.0333)**	(.0411)**	(.0398)**	(.0386)**
Log Likelihood	-13451	-9859	-5456	-13620	-9736	-6010	-7131	-7157
Total No. Observations	33042	24300	13446	33690	24078	14784	17580	17580
Total No. Chains of Six	5507	4050	2241	5615	4013	2464	2930	2930

Notes: Columns (1) – (8) provide maximum likelihood estimates of state dependence using the conditional log-likelihood functions given in Equation (9) in the text. Standard errors are computed using a bootstrap routine with 1000 repetitions of full samples with replacement. Columns (1) – (3) restrict the sample by not creating sequences of six observations for each individual until the first 10, 20, and 40 visits to the video store have been deleted, respectively. Columns (4) – (6) restrict the sample by not creating sequences of six observations until the individual has paid 2, 5, and 10 late fees, respectively. Column (7) restricts the sample by only including the first half of sequences for any individual. Column (8) restricts the sample by only including the second half of sequences for any individual. In the event of an odd number of sequences for a given individual, the last sequence is deleted.

† significant at 10%; * significant at 5%; ** significant at 1%

Table 5. The Effect of Receiving a Late Fee on Time Between Rental Periods and Movies Rented Per Visit - OLS and Poisson Models

	Dependent Variable: Number of days between movie rental (t) and movie rental (t-1)		Dependent Variable: Number of movies rented during visit t	
	OLS	**Poisson**	**OLS**	**Poisson**
Late Fee (t-1)	0.732	0.051	-0.015	-0.006
	(.153)**	(.010)**	(.010)	(.003)†
Late Fee (t-2)	0.477	0.034	-0.009	-0.004
	(.150)**	(.010)**	(.010)	(.004)
Late Fee (t-3)	0.247	0.019	-0.017	-0.007
	(.152)	(.012)	(.010)	(.004)†
Individual F.E.	X	X	X	X
Observations	198,174	198,174	198,174	198,174

Notes: In Columns (1) and (2), the dependent variable is a count of the number of days between the current movie-rental visit (visit t) and the last time that the customer rented a movie (visit t-1). In Columns (3) and (4), the dependent variable is a count of the total number of movies that the customer rented in the current movie-rental visit (visit t). Columns (1) and (3) use ordinary least squares with customer fixed effects. Robust standard errors for these columns are presented in parentheses. Columns (2) and (4) run a Poisson conditional fixed effects model. Bootstrapped standard errors for these columns are presented in parentheses.
† significant at 10%; * significant at 5%; ** significant at 1%