Precommitments for Financial Self-Control: Evidence from Credit Card Borrowing†

SungJin Cho
Seoul National University

John Rust
Georgetown University

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Abstract

We analyze a new data set on installment borrowing decisions of a sample of customers of a credit card company. In an attempt to increase its market share, the company more or less randomly offers its customers *free installments*, i.e. opportunities to finance credit card purchases via installment loans at a zero percent interest rate for durations up to twelve months. We exploit these offers as a *quasi-random field experiment* to better understand consumer demand for credit. Although there is considerable customer-level heterogeneity in installment usage, we show that the average take-up rate of free installment offers is low: customers choose them only 20% of time they are offered. Further, we provide evidence of pervasive precommitment behavior by individuals who do decide to take free installment offers. For example, we estimate that of the subset of 10 month free installment offers that are taken, only 18% are taken for the full 10 month term allowed under the offer. In the other 82% of these offers, customers precommit at the time of purchase to pay the balance in *fewer* than 10 installments. Thus, only 3.6% (18% $\times$ 20%) of all 10 month free installment offers are taken for the full 10 month duration. It is challenging to explain this behavior using standard expected utility models since there are no pre-payment penalties and the transactions costs involved in choosing these loans are small: rational customers should take every installment offer for the maximum allowed term when the interest rate is 0%. One explanation for this behavior is that consumers have financial self-control problems and resist the temptation to take interest-free loan offers. If they absolutely must borrow, most consumers choose repayment terms that are shorter than the maximum allowed term to avoid becoming excessively indebted.

Keywords: installment credit, credit cards, demand for credit, behavioral finance, field experiment, quasi-random experiment, discrete choice models, precommitment behavior, self-control, price discrimination, nonlinear pricing

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1 Introduction

This paper presents new findings on the demand for credit based on a unique new data set that allows us to observe "micro-borrowing" decisions made by a sample of customers of a major credit card company. Unlike *revolving credit* provided by most U.S.-based credit cards, the main type of credit offered by the company we study is *installment credit*, a contract that is commonly used by credit card companies in Latin America and Asia. Installment credit contracts require customers to make *ex ante* choices of the number of installments over which they will pay back the amount of *each purchase* made using their credit cards. Our data enable us to observe many thousands of these micro-borrowing decisions on a *transaction by transaction basis.* Customers are aware that they have this opportunity because it is described to them on each of their monthly statements, along with the interest rate schedule for installment loans with durations of 2 to 12 billing statements (months).[1]

In an attempt to increase its market share, the company more or less randomly offers its customers *free installments*, i.e. pre-approved installment loans at a zero interest rate for durations up to twelve months. We exploit these free installment offers as a *quasi-random experiment* to help identify the demand for credit using a flexible "behavioral" discrete choice model of installment credit decisions that accounts for censoring (choice based sampling of free installments). Despite the fact that we only observe free installment offers when consumers choose them, we show that it is possible to separately identify consumers' choice probabilities and the probability they are offered free installments. In particular, we can identify the probability that consumers will decline free installment offers, and the probability they will accept them but precommit to repay the loan in fewer installments than the maximum number allowed under the offer.

The average interest rate the company charges to consumers for positive interest installment loans is approximately 15%, so we would expect that free installment offers would have a high take-up rate. However we show that the take-up rate for these offers is actually very low: fewer than 3% of the transactions in our sample were made as free installments, even though we estimate that customers are offered free installments in approximately 15% of all transactions they make with this credit card, which imply an average take-up rate of only 20%. Further, we provide evidence of significant "suboptimal" precommitment

[1] In contrast, under revolving credit contracts, customers make borrowing decisions at the time they pay *each bill.* Revolving credit amounts to an option pay only part of their balance due, and to use a sequence of one month loans of endogenously chosen sizes (subject to an overall credit limit) to pay off their past purchase balances according to their own desired time path. The company did not offer revolving credit to its customers until 2005, and then only to a minority of its customers with the best credit scores. In the absence of revolving credit the full balance is due at each statement date unless the customer chose to pay for some of their previous purchases on installment.

behavior among the subset of individuals who do decide to take free installment offers. For example, we estimate that over 80% of the individuals who are offered and choose a 10 month free installment loan offer will precommit at the time of purchase to pay off the balance in *fewer* than 10 installments.

Since free installment offers are pre-approved, entail negligible transaction costs, and have no prepayment penalties, the frequent selection of "dominated alternatives" is difficult to explain using standard expected utility models: rational consumers should always choose to borrow for the maximum allowed term when the interest rate is 0%. However theories of time inconsistent decision making and decision making by individuals with self-control problems can explain this behavior. One interpretation for our findings is that consumers try to resist the temptation provided by interest-free loan offers because they have financial self-control problems and want to avoid becoming excessively indebted.

Though there is well established and influential *theoretical* literature on time inconsistency and self-control problems, there is not a great deal of empirical evidence supporting the predictions of these theories. As Bernheim and Meer [2012] note "Over the last twenty years, the concept of time inconsistency has emerged as a central theme in behavioral economics. As is well-known, any consumer sufficiently self-aware to notice her time-inconsistent tendencies will manifest a demand for precommitment technologies. At a minimum, consumers should acquire such self-awareness with respect to frequently repeated activities for which they consistently fail to follow through on prior intentions. Yet oddly, there is surprisingly little evidence that people actually value and exploit precommitment opportunities." (p. 1).

The main contribution of this paper is to provide evidence that the customers in our sample do actually value and exploit precommitment opportunities. However the various theories of time inconsistency or self-control problems may not be the only way to explain their behavior. There could be stigma associated with the decision to take a free installment offer, or consumers may believe that taking these offers could hurt their credit rating. While these latter explanations can explain low take-up rates, it is not clear that they can explain why customers precommit to repay interest-free loans faster than necessary.

There is independent evidence that individuals in the country we study do have financial self-control problems — at least in the aggregate. Just prior to the period of our sample, which covers the years 2003 to 2007, there was a large credit card "bubble and bust" that severely impacted the economy of this country.[2] Between the late 1990s and 2002 a combination of factors including government policy favoring credit

[2]Unfortunately confidentiality restrictions prevent us from revealing the country or the identity of the credit card company that provided the data.

cards to improve tax collection and the entry of new credit card issuers dramatically increased the number of individuals using credit cards and overall credit card spending. At the peak of the credit card "boom" in 2002, the average credit card customer had more than 3 credit cards, average credit card balances were in excess of $2000 per capita, and aggregate credit card debt amounted to nearly 15% of GDP.

Much of the aggressive expansion of credit card accounts and unsecured lending by the new non-bank entrants proved unwise and in 2003, the year preceding most of our data, there was a significant "credit card bust" with default rates in the credit card industry as a whole exceeding 25%. This lead to massive losses in the financial sector, several near bankruptcies of major banks and major non-bank companies that entered the credit card market, and a government bailout to prevent a wider financial panic from ensuing. The bailout was largely successful and in combination with adoption of better risk-management policies at the major credit card companies, average credit card balances and default rates rates declined rapidly after 2003. By 2005 the credit card default rate had fallen by more than 50% to just over 10%, per capita credit card balances had fallen to less than $700, or about one third of their peak in 2002 just before the crisis, and credit card debt as a fraction of GDP had fallen to a much more reasonable level of approximately 4%. By 2007, the last year of our data, the default rate on credit cards had fallen to less than 4%, roughly comparable to credit card default rates in other OECD countries.

In light of this history, an alternative explanation for reluctance of consumers to take free installment offers could be *stigmatization* and perhaps a degree of overreaction to the excessive borrowing and high credit card defaults in the boom and bust just prior to the period of our sample. However we stress that the low take-up rate of free installment opportunities cannot be ascribed to credit limits imposed by the company we are studying since interest-free loan offers are *pre-approved* and the company does not impose an explicit borrowing constraint on its customers as long as they are not delinquent. Thus, low take-up rate of interest-free installments can only be ascribed to a conscious choice by customers to forgo them.

Though we demonstrate that the decision to take free installments does *not* worsen a customer's credit score, we cannot rule the possibility that some customers *believe* that taking too many free installment offers could worsen their credit scores and limit their future borrowing options. So the behavior we observe might also be explained by an expected utility model, but one where consumers have *irrational beliefs*. In an era of rampant financial fraud, it may not be entirely irrational to suspect that there is some hidden "catch" in an interest-free loan offer, or a fear that borrowing will increase the risk of late payment penalties that could exceed interest savings on the amount borrowed. Even though we show that late payment penalties are small (at least by American standards) and the belief that taking free installment offers will degrade a credit score is incorrect, if enough consumers have these beliefs, it can constitute an alternative explanation as to why so many customer interest-free borrowing opportunities. Specifically, the behavior could reflect a *precautionary motive* by consumers who want to avoid compromising their credit score by using installment credit in non-critical situations in order to preserve their option to borrow in emergency situations that might arise in the future. A belief-based explanation for low take-up rates cannot explain why customers precommit to repaying interest-free loans faster than necessary unless they also believe that doing this helps their credit score somehow. Theories of *mental accounting costs* and "debt aversion" might be alternative ways to explain this behavior.

In section 2 we review the existing empirical literature on credit card borrowing and tests of consumer time-inconsistency and self-control issues and related studies that have shed some light on these questions. Section 3 describes the credit card data and documents the importance of merchant fees as a significant component of the profit that this company earns: we believe this is the main motivation for the company's frequent use of free installments — to incentivize increased spending by its customers in order to increase its own market share and profits. Though we find that the take-up of free installment offers is low, it does not follow that it is a bad idea for the firm to offer them to its customers. We show that individuals who are heavy installment spenders are also the individuals who are most likely to respond to free installment offers, and these individuals tend to be among the company's most profitable customers.

Section 4 introduces a flexible behavioral model of installment choice and derives the likelihood function for the choice of payment term for the 167,000 credit card transactions in our data set. The likelihood accounts for the censored, choice-based nature of our observations of free installment offers. We establish the identification of the structural parameters and present the estimation results, including an evaluation of the goodness of fit of the model. We show that the estimated model fits the data extremely well, and the borrowing behavior it predicts reflects a great deal of consumer-specific heterogeneity, and generally results in very inelastic estimated demand for installment credit. Most importantly, the model predicts the low take-up rate for free installment loan offers, and the high incidence of *ex ante* precommitment to loan terms that are shorter than the maximum term allowed under the loan offer. We test and strongly reject *strong and weak dominance restrictions* that constitute *a priori* restrictions on the behavioral model that rule out the anomalous precommitment behavior.

The low take-up rate of free installment offers raises questions about the cost-effectiveness and overall profitability of the aggressive use of free installments by the credit card company as a strategy for capturing a larger share of the credit card market. Why does this company use free installment offers so frequently if the take-up rates are so low? In section 5 we provide some evidence on the rationality of the company's behavior. We conduct a counterfactual exercise that uses the estimated demand system to search for alternative *consumer-specific* interest rate schedules that result in higher profits to the credit card company subject to the constraint that the expected utility of this alternative schedule to the customer is no lower than their utility under the company's current or *status quo* interest schedule. Our calculated optimal interest rate schedules differ significantly depending on customer characteristics and generally are very different from the particular schedule that the company has chosen. This suggests that the company may have suboptimal pricing and advertising policies, perhaps as a result of a limited understanding of the behavior and preferences of its customers.

Section 6 presents our conclusions. We view the primary contribution of this paper is to provide evidence that individuals do make "suboptimal" financial decisions — they frequently reject interest-free loan offers even though they are willing to pay very high interest rates to borrow on other occasions where the interest-free offer is not present. Further we have provided evidence that among the subset of individuals who do take interest-free offers, a large fraction of them precommit to paying the loan off over a shorter term than the maximum term allowed under the offer. It is a challenge to explain this behavior using standard expected utility theory, but this behavior is consistent with a variety of theories of individuals with time inconsistent preferences and self-control problems. Though there may be alternative models involving stigma, irrational beliefs, or "mental accounting costs" that can explain why consumers make these decisions, a secondary contribution of this paper is to introduce a simple behavioral model of installment credit decisions which is flexible enough to encompass a variety of theories of the underlying behavior of these customers. Though our econometric model is not rich or detailed enough to distinguish between alternative theories for the behavior we find (and we suspect that some of these theories may be nearly observationally equivalent), its ability to approximate the behavior and the high degree of heterogeneity we observe in this data set suggests that it could be a useful tool to enable firms to develop better models of the behavior of their customers, and potentially, to help them design more efficient/profitable loan contracts. However our ability to develop richer, more detailed behavioral models that might be able to distinguish different theories of customer behavior depends critically on the company's willingness to collect additional data and conduct experiments with their customers.

2 Existing Literature on Credit Cards and Self-Control Problems

The earliest work on time inconsistency and precommitment that we are aware of is by Strotz [1955], but much of the current interest in this area is due to subsequent contributions by Gul and Pesendorfer [2001], Fudenberg and Levine [2006], Laibson [1997], and others on hyperbolic discounting, temptation, and self-control. Versions of these theories for "sophisticated" agents (i.e. agents who are self-aware of their time-inconsistent behavior) can explain why individuals might precommit to actions that restrain the options available to their "future selves". As Gul and Pesendorfer [2001] note, there are situations where precommitment can make these individuals "unambiguously better off when ex ante undesirable temptations are no longer available" (p. 1406).

As we noted in the quote from Bernheim and Meer [2012] in the introduction, there has been comparatively little empirical work that finds behavior consistent with these theories, particularly with regard to whether individuals intentionally make costly precommitments to constrain their future selves. In their own empirical study, Bernheim and Meer [2012] conclude that "to our considerable surprise, we find no evidence that precommitment strategies affecting availability play meaningful roles in aggregate liquor consumption." (p. 12).

Most of the evidence that is consistent with these theories comes from laboratory experiments rather than "field data". Casari [2009] notes that "Although the implications of naïveté or sophistication are profound, the behavioral evidence is still quite limited" (p. 119). Casari's own experiment suggests that "the demand for commitment was substantial" even though "Commitment always carries an implicit cost due to the uncertainty of the future." (p. 138).[3]

Though there is a very old literature on installment credit going back to the U.S. during the Great Depression (see, e.g. Kisselgoff [1952]), and there have been several previous studies of credit card borrowing under revolving credit arrangements that are common in the U.S. (e.g. Gross and Souleles [2002]), to our knowledge there is no previous study that analyzes the type of *credit card installment borrowing* that we study in this paper, especially at the level of detail and with the large number of transactions that we have access to in this data set. In addition to having considerable data on the amount and type of the transaction, we also observe the company's proprietary credit scores for these customers, and we resolved problems of unobserved pre-sample balances (initial conditions) and were able to recreate the trajectories

[3]Other controlled laboratory experiments by Ariely and Wertenbroch [2002] provide evidence that costly precommitment (e.g. binding self-imposed deadlines) may have limited value as a self-control device to avoid procrastination.

of their credit card and installment balances. However an advantage of the data used by Gross and Souleles [2002] is that they observe usage and borrowing on *all* credit cards, whereas our study only allows us to study borrowing related to a *single* credit card.

Besides the low take rate of free installment loan offers, our estimated model predicts that the demand for credit is highly inelastic for most customers in our sample. This differs from the conclusions of Gross and Souleles [2002] who find a significant fraction of credit card consumers are liquidity constrained and are highly responsive to credit offers. For example Gross and Souleles [2002] find that "increases in credit limits generate an immediate and significant rise in debt" (p. 151). Further, Gross and Souleles [2002] find that "Unlike most other studies, we also found strong effects from account-specific interest rates." The high elasticity of credit demand they find is due to "net changes in total borrowing" rather than balance shifting across different credit cards (p. 182). Furthermore, they found that "The elasticity is larger than average for declines in interest rates, reflecting the widespread use of temporary promotional rates." (p. 182).

Perhaps the closest previous studies to our's is Ashraf et al. [2006] and Kaur et al. [2012] which provide evidence from field experiments that some individuals make voluntary choices that are suboptimal from the standpoint of expected utility theory. In Ashraf et al. [2006] randomly selected customers of a Phillippine bank were offered a savings precommitment option called "SEED" in order "to test whether individuals would open a savings account with a commitment feature that restricts their access to their funds but has no further benefits" (p. 636). Though they found a relatively small 28% take-up rate among the individuals who were offered the SEED savings plan, and the average bank balance was only $8.20 higher for those who chose it, Ashraf et al. [2006] argued that due to the relative poverty of the individuals in their sample that SEED had "a strong positive impact on savings." (p. 669). Further, Ashraf et al. [2006] asked subjects in the treatment group a set of hypothetical time-discounting questions designed to elicit whether the individual has time-inconsistent preferences. They found that individuals who exhibited evidence of time-inconsistent preferences were more likely to choose the SEED option.

Kaur et al. [2012] report the results of an experiment in which data entry workers in an Indian company were offered the choice of a *dominated contract.* The standard contract for these workers is a combination of a fixed wage plus a piece-rate bonus to create an incentive to enter data quickly but correctly. The experiment gave a subset of workers a choice of an alternative contract that provided only half of the piece rate bonus if they failed to reach a specified target level of output. Since the subjects only face a penalty for failing to reach the target but no extra bonus if they exceed it, expected utility models predict that no worker would choose these dominated contracts. Yet in their experiment, Kaur et al. [2012] found that "workers take-up the dominated contract by selecting a positive target 36% of the time when present." They found that total output was 2% higher for the subjects who chose the dominated contracts and the difference is statistically significant.

Our study can also be regarded as a field experiment, but where the "treatment" of interest is the free installment loan offer. However unlike Ashraf et al. [2006] and Kaur et al. [2012] who had the benefit of a direct randomized experiment with separate treatment and control groups, our study of installment offers is a *quasi-random experiment.* However our biggest econometric challenge is not the lack of perfect random assignment, but rather the significant censoring in our data. That is, we only observe the subset of individuals who were offered zero interest installments *and* chose them. We do not observe individuals who were offered interest-free installments and did not choose them. However we show how we can solve the censoring problem econometrically and exploit the free installment "quasi experiments" to learn a considerable amount from the data we have, despite some of its limitations.

Another closely related study to ours is Alan et al. [2011] (ADL) who analyzed data from a randomized experiment undertaken by a British credit card company. ADL find that "individuals who tend to utilize their credit limits fully do not reduce their demand for credit when subject to increases in interest rates as high as 3 percentage points." They interpret their finding as "evidence of binding liquidity constraints." (p. 1). Their finding of highly inelastic demand for credit differs from Gross and Souleles [2002] but is consistent with our empirical findings.[4] However ADL did not present evidence on whether the customers in their data exhibited a preference for costly precommitments which is the focus of this study.

The lack of sensitivity to interest rates may reflect some degree of "consumer inertia" either of the "rational inattention" variety (e.g. Sims [2003]) or the impact of *switching and information costs* including the costs of becoming informed about other ways to borrow at lower interest rates, and switching balances

[4]ADL argue that the random assignment of interest rates in their study enables them to get more credible estimates of the credit demand elasticity than Gross and Souleles [2002] found using non-experimental data "We show that estimating a standard credit demand equation with the nonexperimental variation in our data leads to seriously biased estimates, and that this is true even when we condition on a rich set of controls control variables and on individual fixed effects." (p. 27). However ADL only have access to data from a single credit card, whereas Gross and Souleles [2002] can observe borrowing over multiple credit cards. One would expect that due to substitution in balances across credit cards, that ADL should find more elastic demand than Gross and Souleles [2002] found. However the actual finding is precisely the reverse of this economically expected effect. Further, we would expect *a priori* that a failure to fully control for endogeneity in interest rates would lead Gross and Souleles [2002] to *underestimate* the demand elasticity. So the discrepancy between the findings from Gross and Souleles [2002] and ADL is doubly puzzling. While there is substantial heterogeneity in our estimated credit demand elasticities, the mean value is between the values estimated by ADL and Gross and Souleles [2002]: i.e. we find small but statistically significantly negative demand elasticities for installment credit.

to other credit cards in response to solicitations that offer consumers balance transfer opportunities at significantly lower interest rates.

This sort of inertia may explain puzzling behavior observed in a another field experiment analyzed by Ausubel and Shui [2005] (AS2005). They analyzed a marketing experiment conducted by a large U.S. credit card company in 1995 in which a mailing list of 600,000 consumers was divided into six subsets with approximately 100,000 individuals each. Customers in each subset were offered (via a letter delivered by mail) the opportunity to apply for a "pre-approved" credit card from this company with the opportunity to do balance transfers from other credit cards at various low introductory rates for varying lengths of time. The most popular offer was the one that offered the lowest interest rate but for the shortest duration, 4.9% for 6 months.

The take-up rate for these offers was uniformly small: 1% — a result consistent with our finding of low take-up rates for free installment offers. (AS2005) describe another puzzling aspect of the behavior of the subset of consumers who took these offers, which they call *rank reversal.* When they analyzed the actual *ex post* interest rate paid by customers for each of the six introductory offers over a 13 month period after the cards were adopted, the interest rate paid by customers who chose the least popular offer (7.5% for 12 months) was the *lowest* (just over 7.9%) whereas the interest rate paid by the customers who chose the most popular offer (4.9% for 6 months) was substantially higher (10.2%).

The rank reversal puzzle is a closely related to another puzzle, namely, that the majority of these customers (60%) failed to cancel their accounts after the introductory rates ended. As (AS2005) note, it is puzzling why these customers were not motivated to reduce their balances or switch out of these cards when the low interest rates period expired, given that the low interest rates were evidently one of their primary motivations to switch into these cards in the first place. These results suggest that either inattention or *switching costs* may be an important reason for the low response rates to the company's introductory low interest rate offers, and may explain the inertia that might be responsible for the relatively inelastic customer response to changes in interest rates overall. However (AS2005) argue that switching costs alone cannot fully explain the puzzles they find. Instead, they argue that a model of time inconsistent decision makers with hyperbolic discounting does a better job of explaining the behavior of the customers in their sample than a time-consistent dynamic programming model with switching costs.

The low take-up rates we find cannot be so easily ascribed to large switching or transaction costs since the ability to borrow on installment credit is an opportunity offered to customers *after* they have received their credit card and this opportunity is available for *every customer and for nearly every transaction.* Thus, there is no additional onerous paperwork that must be filled out to apply for the installment loan, and there is no issue about an installment loan being denied: these loans are essentially pre-approved and can be done at the check out counter at very low marginal cost in terms of time and effort. Since installment transactions are designed to be easy and are not subject to credit limits (provided the customer is in good standing), our finding that customers are not very responsive to low free installment offers may be more compelling evidence of a desire for precommitment than the low response rates to low introductory interest rate opportunities that (AS2005) found in their study.

3 Credit Card Data

A credit card company provided us with data on all purchases, billing statements, and payments made by a sample of 938 of its customers from late 2004 to spring 2007. We observe over 180,000 individual purchase transactions for these customers over this period, and the vast majority of these transactions involved customer-level micro borrowing decisions about the whether to pay for the purchased amount in full at the next billing statement (which we denote as the choice $d = 1$) or to make the purchase under installment credit over 2 to 12 subsequent billing statements (denoted as a choice d from the set $\{2, \dots, 12\}$).

The primary focus of this paper is to understand how customers decide whether to pay for individual purchases as a "regular purchase" (i.e. as payable at the next statement date to which the transaction is assigned) or as an installment purchase in which case the payment is spread out over 2 to 12 future statement dates. We are particularly focused on identifying the effect of the installment interest rate on the customer's choice of installment term. Although the availability of installment credit can potentially affect the customer's decision whether to purchase a given item or not, or to purchase via credit versus cash or some other credit card, as we discuss below, our data are of limited usefulness for studying these other related effects on interest rates on spending and credit card usage decisions.

3.1 Installment Loans and Interest Rates

In our data we observe installment purchases of varying lengths, from 2 to 12 months. The most commonly chosen term is 3 months: 61.5% of all of the installment purchases we observe have a 3 month term. The maximum installment term we observe is 12 months, which is chosen in 1.7% of the cases. Other frequently chosen terms are 2 months (20.0% of cases), 5 months (5.0%), 6 months (4.9%), and 10 months (3.7%). There are no installment purchases with a term of 1 month, since this is equivalent to a regular charge, i.e. a payment due at the next billing statement. The vast majority of all transactions, 93% in our data set, involve the default option of paying the balance in full at the next statement date, $d = 1$.

Almost all installment purchases are paid off in a series of equal payments. For example, if a consumer purchases an amount P under an installment contract with a total of d installments payments, then the consumer will pay back the "principal" P in d equal installments of P/d over the next d billing periods. If the consumer is charged interest for this installment purchase, the credit card company levies additional interest charges that are due and payable along with the installment payment at each of the successive d statement dates. However in some cases there are unequal payments, sometimes as a result of late payments, or pre-payments. The installment agreement does not have a pre-payment option, so that if a consumer does pre-pay an installment loan, the credit card company still charges principal and interest at the successive d statement dates, as if the customer had not pre-paid.

We calculated the realized internal rates of return on 8987 installment transactions in our credit card data set. This is the interest rate that sets the net present value of the cash flows in the installment transaction to zero. There were only 141 cases out of the 8987 installment transactions where the customer did not follow the original installment contract by paying in the d installments that the customer originally agreed to pay. There were pre-payments in 127 cases, i.e. where the customer paid off the installment balance more quickly than necessary under the original installment agreement. Given that there is no direct benefit to the customer from pre-paying the installment (since the credit card company will continue to collect interest from the customer as if the installment loan had not been pre-paid), it seems hard to explain why a rational, well-informed consumer would do this. In 31 of these cases, the customer was given a 0% installment loan, and yet still pre-paid. One possible explanation is that these customers were not aware that they had what was in effect an interest-free loan, and not aware that there was no benefit to pre-paying. These customers might have believed (incorrectly) that by paying off their installment balance more quickly they were saving interest charges, or perhaps some other explanation such as "mental accounting" (e.g. the desire to be free of the mental burden of having a large outstanding installment balance to pay), that might explain this behavior.[5]

[5] There were only 17 cases where the number of installment payments were greater than the number of installments originally agreed to in the original installment transactions. These do not appear to be "defaults" since the total amount collected in each of these cases equals the initial amount purchase. The delay in payment was typically only one billing cycle more than the originally

Most installment purchases have a positive internal rate of return, but in nearly half of all installment purchases we observed (47.7%) the internal rate of return was 0, so the customers were in effect given an interest-free loan by the credit card company. These zero interest or "free installments" are usually a result of special promotions that are provided either at the level of individual merchants (via agreement with the credit card company to help promote sales at particular merchants), or via general offers that the credit card company offers to selected customers during specific periods of time either to encourage more spending, increased customer loyalty, or as a promotion to attract new customers. We will discuss these offers in more detail in the next subsection.

Though the company does not publish its schedule for setting interest rates, We were also able to uncover (econometrically) the formula the company uses for setting installment credit interest rates, and we show that these interest rates not only depend on the credit score of the customer, but also on the duration of the installment loan. The credit card company uses a particular non-linear increasing interest premium schedule for loans over two months in duration that is *common* to all its customers, but with a base rate or intercept that varies with customer characteristics, particularly the customer's credit score. For example, the interest rate premium the company charges customers for a 12 month installment loan is 7 percentage points (i.e. the interest rate on a 12 month installment is 7 percentage points higher than the interest rate it charges for a 2 month installment loan) and this differential is the *same for all customers.*

3.2 Interest-free Installment Loans

We already noted in the introduction that the credit card company uses interest-free loans as a marketing device to attract new customers and to incentivize its current customers to stay with the firm and to spend more using its credit card instead of using credit cards of its competitors. This company is very profitable and merchant fees associated with credit usage contribute in an important way to the overall profitability of the firm. Specifically, when we computed the (undiscounted) revenues of the firm for the 938 customers we analyzed, we found that merchant fees amounted to 36% of the total revenues received from these customers. Due to the structure of payments in this country, the company places great importance on rapid growth, both in absolute and in terms of its market share, as the key to its future success. A combination of increasing returns to scale and network externalities cause the cards offered by the dominant firms to be

agreed number of installments. For this reason, we believe that these cases might reflect the effect of holidays (such as where a payment is allowed to be skipped since a statement falls on a special holiday) or some other reason (e.g. an agreed *ex post* modification in the installment agreement). Since there are so few of these cases, we basically ignore them in the analysis below.

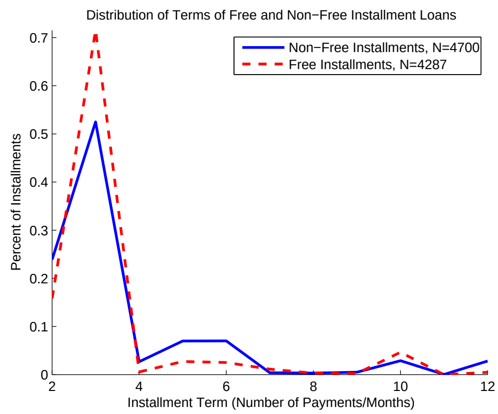
accepted by more merchants and this in turn enables them to charge higher merchant fees.

The credit card company does not keep a record of when and where and to whom interest-free installment offers are made. Instead, we can only learn about them indirectly via customers who chose them, since in these cases the choice is recorded in the company database at time of purchase. Although they keep no central records, company management told us that it was their impression that between 10 to 20% of all credit card transactions involve free installment offers, and the majority of these involve a maximum term of 3, i.e. the installment loan is paid off in equal payments in the subsequent three statement dates.

Company management confirmed that interest-free offers are *universal* in the sense that they are made to all customers regardless of their credit score, installment balance, or other customer-specific characteristics except for customers who are not in good standing, i.e. customers whose accounts have been classified as in collection for having unpaid balances for more than 6 months. The only way customers may have differential access to free installment offers is due their shopping patterns (since free installments are offered with different probabilities at different merchants and vary by time of year) and the possibility that installment-prone customers might actively seek out free installment offers. Free installments are sometimes made available to *all* of the company's customers regardless of where they shop for limited periods of time announced on the company's web site, or in flyers or ads that are included in the monthly statements that it mails to its customers. Management also confirmed that the maximum term of the offer is not determined in any systematic fashion, and is also independent of the characteristics of the customers, or other variables such as merchant type, or time of year. We will estimate the probability distribution for the maximum term of the free installment offer as an additional "nuisance parameter" in section 4.

Installments are typically decided upon at the time of purchase, where the customer notifies the cashier of their intention to have the purchase be done on installment over their chosen term. The interest rate applicable for positive interest installment loans is typically not displayed to the consumer at transaction time, though customers are informed of their installment interest rates on their monthly statements and via their accounts on the company's web site. In situations where the customer is offered a free installment, the cashier will typically inform the customer of the availability of this option at the time of purchase. The free installment term is always determined as part of the free installment offer, and thus is not a variable that the customer can choose (unlike the case of positive interest rate installments), except that customers are allowed to precommit to pay off the installment in *fewer* than the maximum number of payments allowed under the offer. If a customer wishes to borrow for a longer term than the one offered, it must be done

Figure 1: Durations of Free and Non-Free Installment Loans



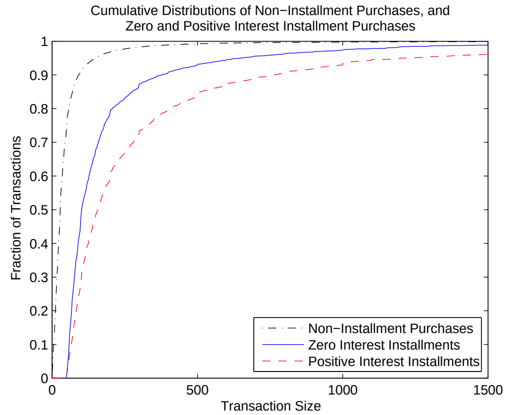
at a positive interest rate according to a customer-specific schedule for positive interest installment loans presented in section 4.2.

Figure 1 plots the distributions of installment terms for 4700 installment transactions made by customers who chose positive interest rate installments, and also the distribution of installment terms chosen in 4287 transactions where customers chose free installment offers. The distributions are roughly similar except that the mean installment term chosen by customers under positive interest installments, 3.66 payments, is greater than the 3.42 payments offered to customers who chose free installment options. We see that when customers choose installments with a positive interest rate, they are generally more likely to choose longer duration loans, though the difference in the two distributions is not particularly striking. What we cannot tell at this point is whether the lower frequency of longer duration interest-free installments is a result of consumer choice, or due to the fact that the company makes relatively few longer duration free installment offers.

Figure 2 plots the cumulative distribution of non-installment purchases, as well as zero and positive-interest installments. We see a striking pattern: the distribution of positive-interest installments *stochastically dominates* the distribution of zero-interest installments, and this in turn stochastically dominates the distribution of non-installment purchases. The latter finding is not surprising: we would expect consumers to put mainly their larger expenditures on installment and the remaining smaller charges as regular, non-installment credit card charges.

However the surprising result is that installments done at a positive rate of interest are substantially larger than installments done at a zero interest rate, at *every quantile* of the respective distributions. For

Figure 2: Cumulative Distributions of Credit Card Transaction Amounts

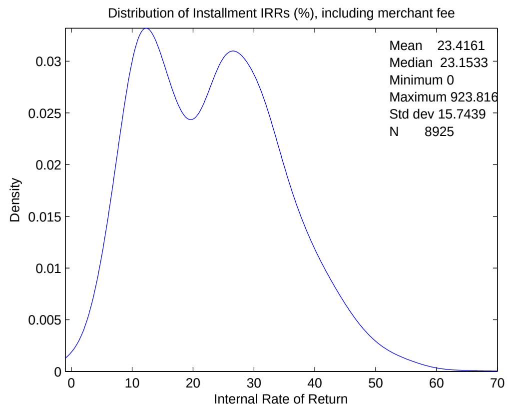


example, the median installment at positive interest rates is nearly 60% larger than the median installment done at a zero interest rate. Thus we can see what we have called the *free installment puzzle* in figure 2: the average size of a positive interest rate installment is more than 75% larger than the average installment done under a zero interest rate. Economic intuition (e.g. the hypothesis of a downward sloping demand for installment credit) would suggest that installments done at a lower interest rate — and particularly those done at a *zero* interest rate — should be significantly *larger* than those done at a positive interest rate.

In summary, the vast majority of transactions in our sales dataset, 87%, are regular (non-installment) credit card purchase transactions (93% if we exclude cash advance transactions). These tend to be smaller in size, about $50 per transaction. The remaining transactions consist of cash advances (7% of the transactions) and installments (6% of the transactions). The installments we observe are roughly equally divided between zero interest and positive interest transactions. The most common installment term is 3 and the mean size of an interest-free installment transaction is approximately $200 whereas the mean size of a positive interest installment transaction is $350.

Figure 3 plots the distribution of internal rates of return that the credit card company earns on these installment sales, including the merchant fee. Due to space limitations, we do not plot the distribution of internal rates of returns that exclude the merchant fee. This distribution is effectively the distribution of interest rates charged to the company's customers. It is a pronounced bi-modal distribution reflecting the fact that roughly 50% of installment purchases are done at a zero percent interest rate and the other half of positive interest installments are done at a mean interest rate of 15.25%. When we include the merchant fee, the distribution of returns shifted significantly to the right. Even with the interest-free installment

Figure 3: Distribution of Rates of Return on Installments, Including Merchant Fee



transactions included, the company earned an average rate of return of 23% on its installment loans. For the positive interest installment loans the average internal return inclusive of the merchant fee is 31.4%.[6] Overall, we conclude that at least for this company, installment loans are excellent investments that offer very high rates of return. Further, in this post-financial crisis era, the sample of customers we analyzed exhibited relatively low risk of default.

The high rates of return from installments point to the profitability of the company's non-installment credit card purchases as well. Due to billing lags, the average duration between a purchase and repayment of a non-installment purchase transaction is about 50 days. The average merchant fee that the company earns on its purchase is 2% which implies that the company *earns an average gross return of 15% even on its regular credit card transactions even when it is giving its customers a 50 day interest-free loan*! This may be why the credit card company might be interested in a variety of promotional devices, including use of free installment offers, aimed at increasing its number of customers, the spending per customer, extending the network of merchants that accept the company's card, and ultimately in raising the merchant fee that the company can charge. If the company were able to raise its average merchant fee to 4%, then the rate of return it earns on ordinary purchases more than doubles, to 29.8% (assuming the same average delay between purchase and repayment on non-installment purchases).

[6]These calculations do not include *defaults.* However fortunately for the credit card company we studied, there were only 23 individuals out of the 938 in our sample who defaulted and whose credit card accounts were sent to collection. We cannot determine the amount of the unpaid balances that the company was ultimately able to recover from these 23 individuals, however even if all 23 were declared complete losses, factoring these losses into the distribution in figure 3 would not significantly diminish the returns the company earns.

3.3 Characteristics of Installment-Prone Customers

Our analysis reveals a substantial degree of heterogeneity across credit card customers in their propensity to use of installment loans, and we find that the best single measure of this propensity is not the mean fraction of transactions done via installment, but rather the mean share of credit card purchases paid for by installment, something we refer to as the *installment share.*

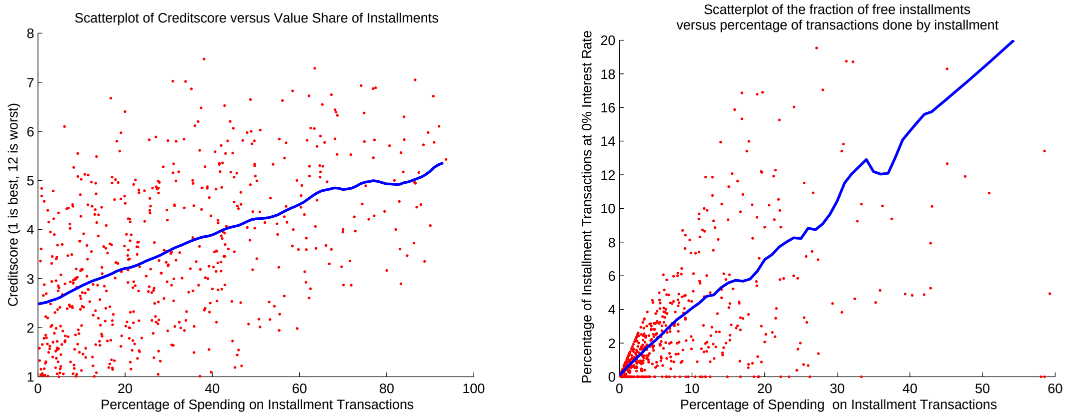
The left hand panel of figure 4 presents a scatterplot (with the conditional mean of the data indicated by a local linear regression fit to the data) that shows how the installment share relates to creditworthiness as reflected by the company's internal (proprietary) credit scoring system where a score of 1 represents the best possible creditworthiness and 12 is the worst. Customers who have credit scores in this range are still allowed to borrow on installment and face no credit limits. However consumers who are in the process of collection will have their credit card borrowing and spending privileges suspended and they show up in our data set as having a credit score of 0. We see a positive relationship between the credit score and the installment share so individuals with higher installment spending tend to have worse credit scores.

We see figure 4 as a potential first indication of possible credit constraints, or at least *high demand for credit* among the customers that are heavy installment spenders. Perhaps their poor credit score indicates that they are also regarded as poor credit risks to other lenders, and as a result of this, they are forced to make heavier use of installment credit at relatively high rates. On the other hand, the customers with the best credit scores also generally the least heavy users of installment, which could be an indication that they are not liquidity constrained, or have other lower cost sources of access to credit elsewhere.

Other scatterplots (not shown) show that both the incidence of late payments and seriously late payments (i.e. payments that are 90 or more days past due, or at about the threshold where the company suspends credit card charging privileges) are also positively correlated with the installment share. These figures confirm that customers who are heavy installment spenders are also worse credit risks.

The right hand panel of figure 4 shows that the fraction of installment transactions done as free installments is positively correlated with the installment share suggesting that the take-up rate for free installments is an increasing function of installment share. Taken as a whole, the main impression that we draw from these figures is that the heavy installment spenders are relatively desperate for credit, and thus, it would seem logical that they are the ones who would be most likely to take the greatest advantage of free installment opportunities when they are offered. The upward sloping relationship in figure 4 is consistent with this interpretation, and shows that for the heaviest installment users as many as 20% of their install-

Figure 4: Customer-specific credit scores and share of free installments by installment share



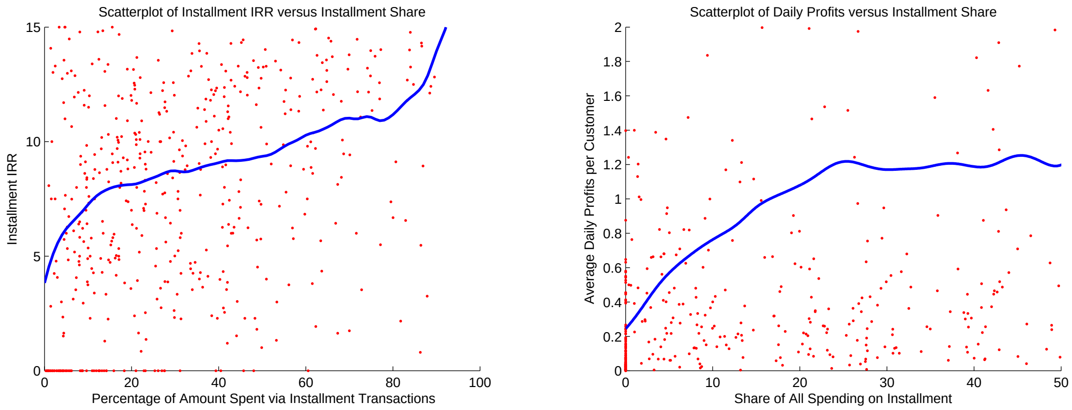
ment purchase transactions are free installments. If the heaviest installment users had a take-up rate for free installments of nearly 100%, the fact that 20% of all installment transactions for these individuals are free installments is consistent with the company estimates that free installments are offered to customers in about 10 to 20% of all credit card transactions.[7]

We conclude this section with figure 5 that give us some insight into the profitability of the "free installment marketing strategy" used by this firm. We have already suggested that the company's use of free installment offers seems motivated by a desire to increase its customers' use of its credit cards. However we have also shown that the customers who are most likely to take the free installment offers are more likely to have worse credit scores and make late payments. As such, the use of free installments as a promotional device may have the perverse effect of offering free credit to the company's least creditworthy customers, and this group may be the most likely to default. This creates the possibility that free installments might be a relatively ineffective and/or highly costly means of increasing credit card usage.

The left hand panel of figure 5 plots the average internal rate of return on all installment transactions (including free installments) against the installment share. We see that this curve is upward sloping, which indicates that even though the "installment addicts" are the ones most likely to be taking up the free installment opportunities, the interest rates that they pay on their positive interest installment transactions are rising sufficiently fast with the installment share to more than offset their higher take-up of free installments. Of course the reason for this is that customers with high installment shares are worse credit risks

[7] In fact, if the most installment prone customers either actively seek out free installment opportunities, or cancel transactions where a free-installment opportunity is not offered, then their personal share of free installment transactions could exceed the general rate at which free installments in the overall population.

Figure 5: Customer-specific rates of return and daily profits installment share



and have significantly worse credit scores, and as we will show in section 4, the interest rates that customers pay is a monotonically increasing function of their credit score (i.e. with higher scores indicating worse credit risks).

The right hand panel of figure 5 plots the average daily profits for each consumer against the installment share. This figure also shows a monotonic relationship but one that is concave, with daily profits flattening out for the more installment-prone customers. Though these customers pay higher interest rates on average, the volume of their spending is not as high as customers with lower installment shares, accounting for the flattening out of daily profits for the most installment-prone customers.

Casual inspection of Figure 5 suggests that the company's free installment marketing policy is rational and well targeted: it tends to attract customers with higher credit risk but these customers are also more profitable. However given the relatively small number of observations and the relatively large number of outliers, we think it is hazardous to come to any definite conclusion about the wisdom of interest-free installments at this point. As we noted in the previous section, we are missing a crucial missing piece of information that would be needed to provide a fuller answer to this question: to what extent does the knowledge of free installments cause customers to increase their spending? Our analysis is *conditional* on the decision to purchase a given amount at a given item. We would need additional information to determine whether the existence and knowledge of free installment opportunities causes the company's customers to go to stores more often, purchase more at a given store than they otherwise would, or increase their use the company's credit card instead of paying for items using a competing credit card or cash.

4 Exploiting the Quasi-Random Nature of Free Installment Offers

We now present a simple, flexible behavioral model of customers' choice of installment loans that can exploit the quasi-random nature of free installment offers. Our original motivation was to use free installments as an *instrumental variable* to help identify the effect of interest rates on consumer demand for credit. When we regress the size of installment loans on the interest rate the company charges its customers, we usually obtain an *upward sloping* estimated demand curve. The positive slope is spurious, due to the endogeneity of the interest rate: customers with high demand for installment credit also tend to have worse credit scores and therefore are charged higher interest rates as we showed in section 3. Several obvious choices of instrumental variables such as the aggregate daily CD or Call rates (which affect the banks' opportunity cost of credit and thus serve as exogenous shifters of the interest rates they charge to their customers) turn out to be *weak instruments* due to the huge, highly variable markups that swamp the small variations in the CD or Call rates). As a result, instrumental variables approaches fail to provide reliable estimates of credit demand. We reasoned that the occasional and often unpredictable interest-free installment offers that this company makes to its customers could function as a *quasi-random experiment* (QRE) since these offers are made to everyone equally regardless of their characteristics or credit scores.

It is useful to contrast how our use of free installments, treated as a QRE, differ from *randomized controlled experiments* (RCEs) that have been used in previous work discussed in section 2 such as Alan et al. [2011], Ashraf et al. [2006] and Kaur et al. [2012]. RCEs require the cooperation of enlightened companies that are willing to incur significant costs to better understand their customers' demand for credit (or savings behavior in the case of Ashraf et al. [2006], or employees' behavior in the case of Kaur et al. [2012]).[8]

Consider some of the benefits and costs of using a RCE to estimate the average treatment effect of free installment offers on overall credit card usage. Since the company already offers free installments to its customers, a RCE would require a treatment group of customers who are randomly selected to be *denied* all such offers. The main benefit of a RCE is that measuring the average treatment effect requires few assumptions or econometric modeling: we simply compare mean credit card spending and installment usage for customers assigned to the treatment group (i.e. those who no longer receive any free installment offers) to those in the control group. Further, if the company could record all instances where individuals

[8] Ausubel and Shui [2005] analyzed data from a randomized experiment, but it was not a standard RCE since there was no "control group" against which they could measure the effect of the various "treatments" (i.e. the six introductory offers).

in the control group were offered but did not take free installment offers (or take them but not for the maximum term offered), then it would also be straightforward to directly estimate both the take-up rate and the fraction of customers who accept these offers but choose a repayment horizon that is shorter than the maximum term allowed.

However there are significant technological and logistical obstacles to the company's ability to conduct such an experiment. For example many interest-free installments are offered by merchants and advertised via store-wide promotions. Customers in the treatment group would have to be issued special credit cards and merchant data systems would have to be reprogrammed to make these cards *ineligible* for any interest-free installment offers. At the same time, customers in the treatment group would have to be convinced that these cards are identical in all other respects to their existing credit card. Recording responses to interest free offers would seem to be an easier task (i.e. record events where a free installment was offered but not taken, or taken for less than the maximum term), but it would involve software changes in a huge variety of merchant payment terminals — something much easier said than done.

While the company we analyze has not conducted RCEs to our knowledge (perhaps due to the practical difficulties discussed above), they were willing to share some of their data with us. So our only option was to see if it is possible to successfully exploit the company's interest-free installment promotions as a QRE. However in a QRE we cannot do simple comparisons of responses (e.g. demand for credit) of "control" and "treatment" groups. In particular, while we can be sure that individuals who accepted free installments were offered the "treatment", we cannot simply assume that individuals who did not choose free installments are in the "control group" (i.e. were not offered free installments) since some of these individuals might have been offered free installment opportunities, but decided not to accept them. Therefore, in order to fully exploit the information provided by the existence of free installment offers, we have to undertake some additional modeling and make some additional assumptions.

Thus, the main econometric problem we face is *censoring:* the company's data systems only record free installment offers when customers actually choose them. For all other transactions, we do not know whether the customer was offered a free installment opportunity and chose not to take it. Since we are willing to make some reasonable assumptions and put some additional structure on the credit choice problem, we can provide econometric solutions to the censoring problem. The model we present in the next section will enable us to *infer* the probability customers are offered free installments, and to predict how these offers affect their choices.

4.1 A Flexible Behavioral Model of Installment Loan Choice

We hypothesize that customers with characteristics x makes a simple cost/benefit calculation about whether to pay for a given transaction in full ($d = 1$) or choose to pay for the transaction amount a on installment ($d \in \{2,\ldots,12\}$). We assume that customers choose the payment alternative d that offers the highest *net value* of benefit less cost, where the cost includes the interest cost of the installment credit (except for $d = 1$ or interest-free loan offers where this cost is zero), less the cash equivalent value of any additional psychic *transactions cost* involved in choosing a payment option d besides the "default option" $d = 1$.

A customer of type x faces an interest rate $r(x,d)$ for an installment loan involving d equal payments. By default, $r(x,1) = 0$, i.e. all customers get an "interest-free loan" if they choose to pay the transaction amount a in full on the next statement date. We normalize the value of this "pay in full" option, $d = 1$, to 0. However for the installment purchase options $d = 2,3,\ldots,12$ we assume that the net value has the form

$$v(a,x,r,d) = ov(a,x,d) - c(a,r,d) \tag{1}$$

where $c(a,r,d)$ is the *cost of credit* equal to the (undiscounted) interest that the customer pays for an installment loan of amount a over duration d at the interest rate r and $ov(a,x,d)$ is the *option value* to a customer with characteristics x of paying for the purchase amount a over d months rather than paying the amount in full a the next statement date (which has an option value normalized to 0 as indicated above, $ov(a,x,1) = 0$). The option value is net of any transactions costs of choosing one of the non-default options $d \in \{2,\ldots,12\}$ and specific functional forms for these functions will be discussed in more detail shortly. Thus $v(a,x,r,d)$ reflects a simple cost/benefit calculation that the customer makes for all of the installment alternatives $d \in \{2,\ldots,12\}$ each time he/she makes a transaction with their credit card. The consumer chooses the alternative d that has the highest value $v(a,x,r,d)$.

We also allow for transitory unobserved factors that affect consumers' decisions about installment term by incorporating additive random shocks $\varepsilon(d)$ so that the net utility of installment choice d observed by the customer (but not the econometrician) is $v(a,x,r,d) + \varepsilon(d)$, $d = 1,2,\ldots,12$. Examples of factors affecting a person's choice that might be in the $\varepsilon(d)$ term is whether there is a long line at checkout (so the customer feels uncomfortable weighing the options $d = 2,\ldots,12$ relative to doing the "default" and choosing $d = 1$), or other time-varying but serially uncorrelated factors such as transitory or unexpected financial shocks that affect the customer's valuations of the net benefits of the other installment choices $d = 2,\ldots,12$.

Our baseline specification is that the "error terms" $\{\varepsilon(d), d \in \{1, \dots, 12\}\}$ are *IID* Type I (Gumbel) extreme value random variables, though we will also estimate specifications where ε is from the Generalized extreme value family (GEV) that allows for correlation in the random variables $\varepsilon(d)$ (see McFadden [1981]). This correlation can reflect "similarity" in unobserved factors affecting consumer choices that violates the *Independence from Irrelevant Alternatives* (IIA) property that holds when the error terms are independently distributed.

Specifically, since $v(a,x,r,d) = ov(a,x,d)$ when $r = 0$, if the option value function is nonnegative and monotonically increasing in the loan duration d for each (a,x), then in the absence of a random error term, this simple cost-benefit model predicts that consumers should always choose the maximum duration $\delta \in \{2, \dots, 12\}$ allowed in any interest-free installment loan offer. However when there are random, unobservable factors affecting consumers' utility of different installment choices, there is a possibility that the model could predict that a *dominated alternative* $d < \delta$ could be chosen by a customer because the realized value of $\varepsilon(d)$ is sufficiently greater than $\varepsilon(\delta)$ so that $ov(a,x,d) + \varepsilon(d) > ov(a,x,\delta) + \varepsilon(\delta)$, even though $ov(a,x,\delta) > ov(a,x,d)$. Under the GEV specification for ε, we can allow for correlation in $\varepsilon(d)$ for d in the set of interest-free alternatives $\{1, \dots, \delta\}$, and in the limiting case of perfect correlation in these random components, the model predicts that the probability of choosing any of the "dominated" interest-free alternatives $d \in \{1, \dots, \delta - 1\}$ will be zero.

In addition, we are able to estimate the scale parameter σ for these random components of the value of different installment choices. The σ parameter is proportional to the standard deviation of these shocks. We will show that the maximum likelihood estimate of the σ parameter is very small, so that the predictions of this model are driven by the properties of the $v(a,x,r,d)$ function rather than the distribution of the unobserved components $\varepsilon(d)$. Thus, any evidence we find for choices of dominated alternatives are not artifacts of a high probability of large shocks that lead to random "irrational" choices of dominated alternatives.

We can integrate out the unobserved components of the values of the different installment alternatives to obtain *conditional choice probabilities.* In the case where the shocks have independent Type 1 extreme value distributions with scale parameter $\sigma \geq 0$, these probabilities are given by the well known *multinomial logit formula.* When we allow for correlation in the unobserved components of the value of the interest-free alternatives, we get a *nested logit model* (McFadden [1981]). We will provide formulas for these below.

Let $P_+(d|x,a)$ be the probability that a customer with characteristics x will choose to pay for a purchase of amount a on installment at a positive interest rate over a term of d billing months, where $d \in \{2,3,\ldots,12\}$. We omit the interest rate r since as we show below, the interest rate charged to a consumer with characteristics x for an installment loan with term d is $r(x,d)$. Thus, substituting this into the value function, the model predicts that the net utility of choosing a term of d is $v(a,x,r(x,d),d)+\varepsilon(d)$, and when we integrate out over the distribution of ε we obtain a conditional choice probability $P_+(d|x,a)$ that is a function of (x,a) only.

Now consider a consumer who is offered a free installment opportunity to spread a purchase a over a maximum of $\delta > 1$ payments. We let $P_0(d|x,a,\delta)$ denote the conditional choice probability for the installment term in this situation. This case is similar to the choice problem for a consumer who does not have any free-interest installment offer, except that $c(a,r,d) = 0$ for $d \in \{1,\ldots,\delta\}$ in this case, whereas $c(a,r,d) = 0$ only for $d = 1$ in the absence of a free installment offer. Presumably, the presence of the free installment option δ should have a major impact on a consumer's choice of installment alternative, and this is reflected by the presence of the maximum term of the free installment offer δ as an additional argument in the conditional choice probability $P_0(d|x,a,\delta)$.

Our empirical analysis will focus on testing a key *dominance assumption* implied by expected utility theory: namely all customers should strictly prefer a free installment opportunity of duration δ over any positive interest rate installment of *shorter* duration, $d = 2,3,\ldots,\delta-1$. The dominance assumption implies that the probability of choosing any positive interest rate alternative $d < \delta$ is zero.

Strong Dominance Assumption

$$P_0(d|x,a,\delta) = 0 \text{ if } d \in \{1,\ldots,\delta-1\}. \tag{2}$$

We also consider and test a slightly weaker version of the dominance assumption.

Weak Dominance Assumption

$$P_0(d|x,a,\delta) = 0 \text{ if } d \in \{2,\ldots,\delta-1\}. \tag{3}$$

The weak dominance assumption allows the possibility that the consumer may choose to pay for the transaction amount a in full at the next billing cycle, $d = 1$, rather than take the free installment offer. This behavior is not completely consistent with expected utility theory, but may be consistent with a behavioral theory of *habit formation* in which consumers are used to taking the default action $d = 1$. Consumers may perceive a "transactions cost" associated with taking one of the other free installment alternatives, $d \in \{2, \ldots, \delta\}$, and this could explain why consumers frequently choose $d = 1$ over any of the options $d \in \{2, \ldots, \delta\}$. Thus, we single out the default choice $d = 1$ as constituting a special case. Even though it is technically a "dominated alternative" when a free installment offer is present, a variety of theories including habit formation or several of the theories of choice in the presence of self-control problems may explain why the strong dominance assumption would be violated.

The weak dominance assumption allows for the possibility a customer might choose the default alternative $d = 1$. However there may be situations where transactions costs are not too high where the consumer prefers one of the interest-free alternatives $d \in \{2, \ldots, \delta\}$ to the default choice $d = 1$. The weak dominance assumption states that whenever this is the case the consumer will only want to choose $d = \delta$, i.e. the maximum term allowed under the free installment offer, and not precommit to repaying over a shorter term $d \in \{2, \ldots, \delta - 1\}$.

To see how the weak dominance condition can hold when the strong dominance condition fails, even when the option value function $ov(a,x,d)$ is strictly monotonically increasing in d, assume that there is a small positive transaction cost associated with choosing any alternative $d \in \{2, \ldots, 12\}$, whereas the value of the default choice $d = 1$ is normalized to $v(a,x,r,1) = 0$. Then it can be the case that the transaction cost is greater than the option value of installment credit for sufficiently small transactions a, making it optimal for the consumer to choose $d = 1$ in these cases. Thus, even in the absence of any random shocks to utility, this model is flexible enough to predict that consumers will sometimes choose the dominated alternative $d = 1$ instead of $d = \delta$.

However if $ov(x,a,d)$ is monotonic in d and a, then if $ov(x,a,\delta) > 0$ for sufficiently large values of a, the weak dominance condition will hold, i.e. the consumer would never find it optimal to choose an interest free alternative $d \in \{2, \ldots, \delta - 1\}$. Thus both the weak and strong dominance assumptions rule out the possibility that consumers make the suboptimal precommitment decisions, i.e. choosing an interest-free installment offer for less than the maximum allowed term δ.

Notice that neither the weak or strong dominance assumptions rule out the possibility that consumers might choose a positive interest loan duration $d \in \{\delta + 1, \ldots, 12\}$. It may happen that a consumer has a need for credit for a duration longer than the maximum term δ allowed under the free installment offer, and every customer has this option if they are willing to pay a positive interest rate.

In the remainder of this section we will focus our attention on estimation of an *unrestricted model* of consumer choice, that does not impose either the weak or strong dominance assumptions. In the unrestricted model, consumers always have the full choice set $\{1,2,\ldots,12\}$ and can choose to take a free installment loan offer for a shorter duration than the maximum term allowed under the offer. In the unrestricted model, it will generally be the case that $P_0(d|x,a,\delta) > 0$, even when d is in the set of "dominated alternatives" $\{2,3,\ldots,\delta-1\}$. The weak and strong dominance restrictions do emerge as limiting cases of the unrestricted model when the scaling parameter σ for the extreme value unobservables affecting consumer choice of installments takes the value $\sigma = 0$. The strong dominance assumption emerges as a limiting outcome if $ov(a,x,d) > 0$ and $ov(a,x,d)$ is non-decreasing in d, since in the limit as $\sigma \downarrow 0$ the consumer will choose the interest-free alternative with the highest option value, and this will be $d = \delta$ for the reasons discussed above.

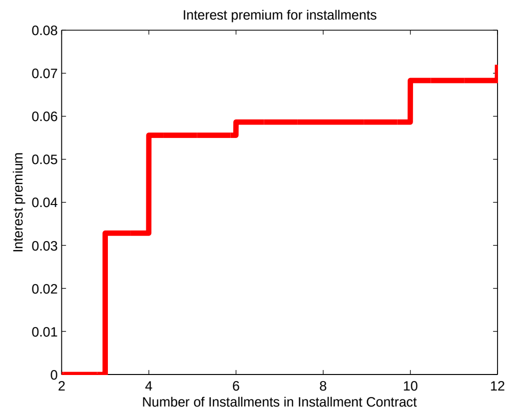
Further, as we show below, the Strong and Weak Dominance Assumptions can also hold in the GEV specification even when $\sigma > 0$. In this case there is an additional correlation parameter σ_1 applicable to the subset of interest-free alternatives. We derive the nested logit choice probabilities below and show that the Strong and Weak Dominance assumptions can hold when $\sigma > 0$ provided that $\sigma_1 = 0$ and the option value function $ov(a,x,d)$ satisfies monotonicity and positivity restrictions.

4.2 Nonlinear Customer-Specific Interest Schedules

A key piece of information required in order to estimate the model is the interest rate schedule offered to customers. The company does not publish its schedule for setting interest rates, which are determined according to a rather complex, proprietary, proprietary function of a) the consumer's credit score and payment history (including the number of recent late payments), b) the number of installment payments, and c) the current economic environment, including the level of overall interest rates and dummy variables capturing current economic conditions. Though the credit card company does not publish this schedule and did not provide us with the formula it uses to set interest rates on installment loans, we were able to uncover it from our data econometrically.

As we described in section 3, we were able to calculate the internal rate of return for each installment loan contract in our data. For the subset of installment contracts where a positive internal rate of return was calculated, we regressed this internal rate of return on the customer specific variables, as well as time and merchant dummies in order to uncover the formula the company uses to set interest rates. Our regression resulted in an extremely good fit, with an R^2 value of 0.99, indicating that we were successful

Figure 6: Interest Premium for Installment Purchases as a function of the Installment Term



in econometrically uncovering the interest formula the company uses to set interest rates to its customers.

Let $r_t(d,x)$ denote the *installment interest rate schedule* offered on calendar day t to a customer with characteristics x who desires to finance an installment purchase with d installments. Our regression analysis revealed that this schedule has the form

$$r_t(d,x) = \rho_0(x,t) + \rho_1(d), \tag{4}$$

where the effects of time-varying macroeconomic and market conditions are captured by the time effect t and the characteristics of the particular consumer x only enter via the intercept term $\rho_0(x,t)$. The term $\rho_1(d)$ represents the *interest premium* for installments longer than $d = 2$ months. Our regression results reveals that this term does not depend on x or t but only d. Figure 6 graphs the interest premium customers must pay for various installment terms $d > 2$.

Note that one of the individual-specific factors that we did *not* include in the x vector is the customer's installment balance, or other measures of usage of installment loans. These variables are not statistically significant predictors of the interest rate charged to consumers after we include other customer characteristics, particularly the credit score and number of late payments. However as we discussed in the introduction, there is a possibility that customers could be reluctant to take installments (both free installments and installments at a positive interest rate) out of a concern that a high installment balance would compromise their credit score. Company management assured us that the company does not penalize customers for installment borrowing by degrading their credit score. However when we regress the company's 12 point integer-valued credit score on a variety of customer-specific characteristics x including the various measures of installment usage such as the change in installment balances, it does emerge as a significant predictor of credit scores, and in the expected direction — an increase in installment balances predict worse (higher) credit scores. However this finding is not robust to the inclusion of other customer-specific covariates such as the number of late payments. This suggests that the positive correlation between changes in installment balances and credict scores reflects *spurious causality* and omitted variable bias due to information that we do not observe that the company uses to set credit scores that is correlated with installment balances. We ran fixed-effect regressions to try to get further evidence as to the effect of installment spending on credit scores, and found no significant effect of changes in installment balances on changes in credit score. This confirms the company's claim that usage of installments does not cause them to degrade credit scores. The most important predictor of credit scores is the number of late payments, and measures of how large and how late these balances are.

In summary, our regression analysis of actual interest rates charged to customers confirms our discussion with company management, namely, that the interest premium captured by the ρ_1 term is, to a first approximation, independent of t and x and thus is a time-invariant function that is also common to all of the company's customers. We found that the most important factors determining the customer-specific intercept term $\rho_0(x,t)$ are factors a) and b) above. In particular, we found that consumer characteristics determine the "base interest rate" for an installment loan with $d = 2$ payments. It is a puzzle why the company would choose an interest rate schedule $r_t(d,x)$ of this particular form, with a duration premium $\rho_1(d)$ that is both *time invariant* and *common to all consumers.* We will return to this question and try to shed more light on the optimality of this interest rate schedule in section 5.

4.3 Choice Probabilities and Likelihood Function

Consider a consumer who is about to pay for a transaction for an amount a_t but who is not offered a free installment option. The consumer chooses installment term $d \in D = \{1,2,\ldots,12\}$ if and only if

$$v(a_t,x_t,r_t(d,x),d) + \varepsilon(d) \geq \max_{d' \in D} \left[v(a_t,x_t,r_t(d',x),d') + \varepsilon(d') \right]. \tag{5}$$

The extreme value assumption implies that the conditional choice probability is given by the standard multinomial logit model

$$P_+(d|a_t,x_t) = \frac{\exp\{v(a_t,x_t,r_t(d,x_t),d)/\sigma\}}{\sum_{d' \in D} \exp\{v(a_t,x_t,r_t(d',x_t),d')/\sigma\}}, \tag{6}$$

where the $+$ subscript denotes a situation where no interest-free installment offer is present, so the consumer can must pay positive interest rates $r_t(d,x) > 0$ for all installment choices $d \in \{2,\ldots,12\}$.

The consumer's choice problem is slightly more complicated when the consumer is offered an interest-free installment option. Suppose this consumer is offered an interest-free installment option with a maximum duration of δ payments (months) where $\delta \leq 12$. The consumer can either to choose to pay in full, $d = 1$, or purchase the item via the interest-free installment option but over any number of installments $d \in \{2,\ldots,\delta\}$, or to pay over even longer installment durations $d \in \{\delta+1,\ldots,12\}$, but at the cost of paying a positive interest rate on these installment balances. The consumer will choose a free installment option $d \in \{2,\ldots,\delta\}$ that satisfies

$$v(a,x,0,d)+\varepsilon(d) = \max\left[\max_{d\in\{1,\ldots,\delta\}} v(a,x,0,d)+\varepsilon(d), \max_{d'\in\{\delta+1,\ldots,12\}}\left[v(a,x,r_t(d',x),d')+\varepsilon(d')\right]\right], \quad (7)$$

where for simplicity we omitted the t subscripts on the a and x variables.

A customer may also choose a *positive* interest rate installment option $d \in \{\delta+1,\ldots,12\}$. The customer will do this if they obtain a greater net benefit for borrowing for a longer term than the maximum term δ allowed under the free installment offer. This will occur when

$$v(a,x,r_t(d,x),d)+\varepsilon(d) = \max\left[\max_{d'\in\{1,\ldots,\delta\}} v(a,x,0,d')+\varepsilon(d'), \max_{d'\in\{\delta+1,\ldots,12\}}\left[v(a,x,r_t(d',x),d')+\varepsilon(d')\right]\right], \quad (8)$$

with the understanding that the set of positive interest rate choices $\{\delta+1,\ldots,12\}$ is empty if $\delta = 12$. The implied choice probability is denoted by $P_0(d|x,a,\delta)$ and is given by

$$P_0(d|x,a,\delta) = \frac{\exp\{v(a,x,r_t(d,x),d)/\sigma\}}{\sum_{d_0=1}^{\delta}\exp\{v(a,x,0,d_0)/\sigma\}+\sum_{d_+=\delta+1}^{12}\exp\{v(a,x,r_t(d_+,x),d_+)/\sigma\}}, \quad (9)$$

if $d \in \{\delta+1,\ldots,12\}$, i.e. the consumer chooses an installment term longer than the maximum free installment duration offered, δ, or

$$P_0(d|x,a,\delta) = \frac{\exp\{v(a,x,0,d)/\sigma\}}{\sum_{d_0=1}^{\delta}\exp\{v(a,x,0,d_0)/\sigma\}+\sum_{d_+=\delta+1}^{12}\exp\{v(a,x,r_t(d_+,x),d_+)/\sigma\}}, \quad (10)$$

if $d \in \{1,\ldots,\delta\}$, i.e. the consumer chooses to pay the amount purchased a in full at the next statement date, or chooses one of the free installment options.

The probabilities given above are the multinomial logit probabilities that are implied by the Type 1 Extreme value assumption for the unobserved components $\{\varepsilon(d)|d \in \{1,\ldots,12\}\}$. We also estimate an alternative model where the unobserved components $\varepsilon(d)$ have a GEV distribution to allow for the possible correlation among the components $\varepsilon(d)$ in the subset of interest-free alternatives $d \in \{1,\ldots,\delta\}$. Following the discussion above, if we regard $d = 1$ as the "default payment option" it may be reasonable to assume that the unobserved component $\varepsilon(1)$ corresponding to this alternative does not reflect the same pattern of similarity as for the unobserved components $\varepsilon(d)$ for $d \in \{2,\ldots,\delta\}$. So we will consider two variants of the GEV distribution, one in which we allow for correlation in the unobserved components $\varepsilon(d)$ of the value all of the interest free alternatives $d \in \{1,\ldots,\delta\}$, and the other where we allow for correlation in $\varepsilon(d)$ for $d \in \{2,\ldots,\delta\}$. When the unobserved components $\varepsilon(d)$ of the values of these alternatives are perfectly correlated, which holds when $\sigma_1 = 0$, then the Strong and Weak Dominance Assumptions will hold for the respective nested logit models.

Following McFadden [1981], let $\sigma_1 \geq 0$ be a parameter indexing the degree of correlation or "similarity" in the GEV distribution for the unobserved components $\varepsilon(d)$ of the values of the interest-free alternatives (either including or excluding the alternative $d = 1$). McFadden showed that this results in nested logit choice probabilities given by

$$P_0(d|x,a,\delta) = \left[\frac{\exp\{v(a,x,0,d)/\sigma_1\}}{\sum_{d_0\in\{1,\ldots,\delta\}}\exp\{v(a,x,0,d_0)/\sigma_1\}}\right] P_0(\{1,\ldots,\delta\}|x,a,\delta) \tag{11}$$

for $d \in \{1,\ldots,\delta\}$ where

$$P_0(\{1,\ldots,\delta\}|x,a,\delta) = \left[\frac{\exp\{I_1(x,a,\sigma_1)/\sigma)\}}{\exp\{I_1(x,a,\sigma_1)/\sigma\} + \sum_{d_+\in\{\delta+1,\ldots,12\}}\exp\{v(a,x,r(d_+,x),d_+)/\sigma\}}\right] \tag{12}$$

and $I_1(x,a,\sigma_1)$ is the *inclusive value* given by

$$I_1(x,a,\sigma_1) = \sigma_1 \log\left(\sum_{d\in\{1,\ldots,\delta\}}\exp\{v(a,x,0,d)/\sigma_1\}\right). \tag{13}$$

The probability of choosing a positive interest installment $d \in \{\delta+1,\ldots,12\}$ is given by

$$P_+(d|x,a,\delta) = \left[\frac{\exp\{v(a,x,r(d,x),d)/\sigma)\}}{\exp\{I_1(x,a,\sigma_1)/\sigma\} + \sum_{d_+\in\{\delta+1,\ldots,12\}}\exp\{v(a,x,r(d_+,x),d_+)/\sigma\}}\right]. \tag{14}$$

If the value functions $v(a,x,0,d)$ are non-negative and strictly monotonically increasing in d, it is not hard to show that in the limit as $\sigma_1 \to 0$, that $P_0(d|x,a,\delta)$ will satisfy the Strong Dominance Assumption, i.e. $P_0(d|x,a,\delta) = 0$ for $d \in \{1,\ldots,\delta-1\}$.

The choice probabilities given above are for the case where the unobserved components of all of the interest-free alternatives $d \in \{1,\ldots,\delta\}$ are correlated with scale parameter σ_1. We also consider an alternative nesting where we assume that the correlation in the $\varepsilon(d)$ components is limited to the set $\{2,\ldots,\delta\}$. In this case we have

$$P_0(1|x,a,\delta) = \left[\frac{1}{1+\exp\{I_2(x,a,\sigma_1)/\sigma\} + \sum_{d_+\in\{\delta+1,\ldots,12\}}\exp\{v(a,x,r(d_+,x),d_+)/\sigma\}}\right] \tag{15}$$

and

$$P_0(d|x,a,\delta) = \left[\frac{\exp\{v(a,x,0,d)/\sigma_1\}}{\sum_{d_0\in\{2,\dots,\delta\}}\exp\{v(a,x,0,d_0)/\sigma_1\}}\right] P_0(\{2,\dots,\delta\}|x,a,\delta) \tag{16}$$

for $d \in \{2,\dots,\delta\}$ where

$$P_0(\{2,\dots,\delta\}|x,a,\delta) = \left[\frac{\exp\{I_2(x,a,\sigma_1)/\sigma)\}}{1+\exp\{I_2(x,a,\sigma_1)/\sigma\}+\sum_{d_+\in\{\delta+1,\dots,12\}}\exp\{v(a,x,r(d_+,x),d_+)/\sigma\}}\right] \tag{17}$$

and $I_2(x,a,\sigma_1)$ is the inclusive value given by

$$I_2(x,a,\sigma_1) = \sigma_1 \log\left(\sum_{d\in\{2,\dots,\delta\}}\exp\{v(a,x,0,d)/\sigma_1\}\right). \tag{18}$$

The probability of choosing a positive interest installment $d \in \{\delta+1,\dots,12\}$ is given by

$$P_+(d|x,a,\delta) = \left[\frac{\exp\{v(a,x,r(d,x),d)/\sigma)\}}{1+\exp\{I_2(x,a,\sigma_1)/\sigma\}+\sum_{d_+\in\{\delta+1,\dots,12\}}\exp\{v(a,x,r(d_+,x),d_+)/\sigma\}}\right]. \tag{19}$$

If the value functions $v(a,x,0,d)$ are strictly monotonically increasing in d, it is not hard to show that in the limit as $\sigma_1 \to 0$, that $P_0(d|x,a,\delta)$ will satisfy the Weak Dominance Assumption, i.e. $P_0(d|x,a,\delta) = 0$ for $d \in \{2,\dots,\delta-1\}$.

The parameters to be estimated are $\theta = (\sigma,\sigma_1,\phi,\alpha,\beta)$ where ϕ are parameters of consumers' value functions. The parameter subvector α represents parameters characterizing the probability $\Pi(z|\alpha)$ that a customer is offered a free installment offer (where z are variables characterizing the date and merchant category), and β are parameters of the distribution of the maximum term of free installment offers $f(\delta,\beta)$. Note that z does not contain any customer-specific variables x, but does include dummies indicating the date of the purchase and the type of merchant the customer is purchasing the item from, since as we noted above, the main determinants of the interest-free installment option are a) the time of year, and b) the type of merchant (since different merchants can negotiate interest-free installment deals with the credit card company as a way of increasing their sales). We now present a likelihood function for our observations that accounts for the fact that in certain situations we do not observe whether or not a customer is offered a free installment opportunity.

Consider the likelihood function for a specific customer who makes purchases at a set of times $T = \{t_1,\dots,t_N\}$. Of these times, there is a subset $T_I \subset T$ where the customer purchased under installment, i.e. where $d > 1$. The complement T/T_I consist of times where the customer purchased without installment, i.e. where $d = 1$. We face a censoring problem that in many cases where $d = 1$, we do not know if the consumer was eligible for an interest-free installment purchase option or not. Even when $d > 1$, we only know if the consumer was offered an interest-free installment purchase option when the customer actually chose that alternative. However it is possible that in some cases customers may have been offered an interest-free installment purchase option with term δ but decided to choose an installment with a longer term than δ but pay a positive interest rate. Our likelihood must be adjusted to account for these possibilities and to "integrate out" the various possible interest-free installment options that the consumer could have been offered and did not choose, and therefore (given the company's failure to record offers made by not taken) which we do not observe.

Let T_0 be the subset of purchase dates T where the customer did choose the installment option and we observe that this was an interest-free installment option (we can determine this by observing that the consumer never made interest payments on the installments as described above). For this subset, the component of the likelihood is

$$L_0(\theta) = \prod_{t \in T_0} P(d_t|x_t, z_t, a_t, \theta) \tag{20}$$

where

$$P(d|x,z,a,\theta) = \sum_{\{\delta|d \leq \delta\}} P_0(d|x,a,\delta,\phi) f(\delta,\beta) \Pi(z|\alpha), \tag{21}$$

where for each transaction in the set of times T_0, d_t is less than or equal to the free installment (maximum) term δ_t offered to the customer under the interest-free installment option and of course $d_t > 1$ (otherwise the consumer would have chosen to pay the amount a_t in full at the next statement date). When the Strong or Weak Dominance assumptions hold, we have $P_0(d_t|x_t, a_t, \delta_t, \phi) = 0$ if $d_t \in \{2, \ldots, \delta_t - 1\}$, and the customer always chooses the maximal loan duration permitted under the free installment offer. In that case we have $d = \delta$ and

$$P(d|x,z,a,\theta) = P_0(d|x,a,d,\phi) f(d,\beta) \Pi(z|\alpha). \tag{22}$$

Now consider the likelihood for the cases, $t \in T/T_0$, where we do not know for sure if the customer was offered the interest-free installment option or not. There are two possibilities here: a) the consumer chose not to purchase under installment, b) the consumer chose to purchase under installment but paid a positive interest rate, rejecting the free installment offer. Consider first the probability that $d = 1$, i.e. the consumer chose to pay the purchased amount a in full at the next statement date. Let $P(1|x,z,a,\theta)$ denote the probability of this event, which is given by

$$P(1|x,z,a,\theta) = \Pi(z|\alpha) \left[\sum_{\delta \in \{2,\ldots,12\}} P_0(1|x,a,\delta,\phi) f(\delta,\beta) \right] + [1 - \Pi(z|\alpha)] P_+(1|x,a,\phi). \tag{23}$$

The other possibility is that the customer chose to pay under installment for a duration of d months, for $d \in \{2,\dots,12\}$ but at a positive rate of interest. In the case where $d = 2$, i.e. where the consumer pays a positive interest to pay the purchased amount a over two installments, we deduce that the customer could *not* have been offered a free installment opportunity of 2 or more months due to the company's procedures which essentially force the customer into the free installment offer any time then chosen duration is less than or equal to the maximum duration of the free installment opportunity that it offers to the customer. This implies that $P(2|x,z,a)$ is given by

$$P(2|x,z,a,\theta) = [1-\Pi(z|\alpha)]P_+(2|x,a,\phi). \tag{24}$$

The other cases $d \in \{3,\dots,12\}$ are where the customer chose a positive interest rate installment option but we cannot be sure whether the customer was offered a free installment or not. In this case we have

$$P(d|x,z,a,\theta) = \Pi(z|\alpha)\left[\sum_{\delta<d} P_0(d|x,a,\delta,\phi)\, f(\delta,\beta)\right] + [1-\Pi(z|\alpha)]P_+(d|x,a,\phi). \tag{25}$$

The summation term in the formula for $P(d|x,z,a)$ above reflects the company's billing constraint: the customer is not allowed to choose a positive interest installment option d if the customer had been offered a free installment option of duration δ greater than or equal to d. Let $L_1(\theta)$ denote the component of the likelihood corresponding to purchases that the consumer makes in the subset T/T_0, i.e. purchases either that were not done under installment, or which were done under installment but at a positive interest rate. This is given by

$$L_1(\theta) = \prod_{t \in T/T_0} P(d_t|x_t,z_t,a_t,\theta), \tag{26}$$

where $d_t = 1$ if the customer chose to purchase an item at time t without installment, and $d_t > 1$ if the customer chose to purchase via installment, but with a positive interest rate.

The full likelihood for a single consumer i is therefore $L_i(\theta) = L_{i,0}(\theta)L_{i,1}(\theta)$ where $L_{i,0}(\theta)$ is the component of the likelihood for the transactions that the consumer did under free installment offers (or $L_{i,0}(\theta) = 1$ if the consumer had no free installment transactions), and $L_{i,1}(\theta)$ is the component for the remaining transactions, which were either choices to pay in full at the next statement, $d_{i,t} = 1$, or to pay a positive interest rate for a non-free installment loan with duration $d_{i,t} > 1$. The full likelihood for all consumers is then

$$L(\theta) = \prod_{i=1}^{N} L_{i,0}(\theta)L_{i,1}(\theta). \tag{27}$$

4.4 Model Specification

We estimated flexible functional forms for the value function $v(a,x,r,d)$ that can capture behavior implied by a variety of theories, as well as the substantial heterogeneity in consumer behavior that our analysis in section 3 revealed. Recall that $v(a,x,r,d) = ov(a,x,d) - c(a,r,d)$ where $ov(a,x,d)$ represents the value to a consumer with observed characteristics x of the option to borrow an amount a for d periods (billing periods, roughly equal to months). We assumed that the option value is a linear function of the amount borrowed, but there may be "transaction costs" involved in choosing non-default alternatives $d > 1$. Thus, we estimated the following specification for $ov(a,x,d)$

$$ov(a,x,d) = a\rho(x,d) - \lambda(x,d) \tag{28}$$

where $\rho(x,d)$ is the percentage "shadow interest rate" that a customer with characteristics x is willing to pay for a loan of duration d months and $\lambda(x,d)$ represents the fixed transaction costs of deciding and undertaking an installment transaction at the checkout counter. Note that the transaction cost $\lambda(x,d)$ does not depend on the amount purchased a whereas the option value, $ov(a,x,d) = a\rho(x,d)$ is assumed to be a linear function of the amount purchased. If $\lambda(x,d) > 0$, then consumers will not want to pay for sufficiently small credit card purchases on installment since the benefit of doing this, $a\rho(x,d)$, is lower than the transactions cost $\lambda(x,d)$. We can also think of λ as capturing potential stigma associated with purchasing on installment, as well as "mental accounting costs" such as any apprehension customers might have that adding to their installment balance increases their risk of making a late payment on their installment account in the future, or beliefs that installments have adverse effects on their credit score, and so forth.

Notice that we assume the option value of having the benefit of extended payment does not depend on the interest rate the credit card company charges the customer, and the customer-specific interest rate schedule $r_t(d,x)$ only enters via the cost function $c(a,r,d)$ which is a known function that does not have to be estimated. Combined with the location normalization that $v(a,x,r,1) = 0$, this simple cost-benefit specification for $v(a,x,r,d)$ is an important identifying assumption because it fixes both the location and scale of the value functions and thereby enables us to identify both scale parameters (σ,σ_1). Typically neither the location or scale parameters of the unobserved components $\varepsilon(d)$ of the value or utility functions are identified, so they are arbitrarily normalized. However McFadden [1981] showed that the value of σ_1 can be identified relative to any normalization for σ.

We assume that the financial cost that a customer perceives due to purchasing an item under installment equals the excess of the total payments that the customer makes over the term of the agreement less the current cost a of the item. That is, we assume c equals the difference between the total payments the customer makes under the installment agreement *cumulated with interest to the time the installment agreement ends* less the amount the customer purchased, a, discounted back to the date t when the customer purchased the item. This value can be shown to be

$$c(a,r,d) = a\left(1 - \exp\{-rt_d/365\}\right), \tag{29}$$

where t_d is the elapsed time (in days) between the next statement date after the item was purchased and the statement date when the final installment payment is due. The interest rate r is the internal rate of return on the installment loan, and is given by $r = r_t(d,x)$. Obviously, for interest-free installment opportunity, $r = 0$ and so $c(a,r,d) = 0$ as well. To a first approximation (via a Taylor series approximation of the exponential function) we have $c(a,r,d) = r_t(d,x)at_d/365$, so the cost of the installment loan equals the product of the duration of the loan, the amount of the loan, the interest rate offered to the consumer, and the fraction of the year the loan is outstanding.

Recall that the parameters of the model are $\theta = (\sigma, \sigma_1, \phi, \alpha, \beta)$. We are interested in the α and β parameters only to the extent that we are interested in learning the conditional probability $\Pi(z,\alpha)$ and the distribution of the maximum terms of free installment offers. We present the β parameters below (since there are only 10 of them required to estimate the 11 probabilities $f(\delta,\beta)$ for $\delta \in \{2,\ldots,12\}$), but due to space constraints we omit the maximum likelihood estimates of the 26 α parameters.

Table 1 presents the maximum likelihood estimates of $(\sigma, \sigma_1, \phi, \beta)$ for three specifications. The first column, Unrestricted NMNL, presents estimates without any restriction on the ϕ, σ or σ_1 parameters.[9]

The column labeled “Strong Dominance” corresponds to a nested logit specification where alternative $d = 1$ is included in the set of interest-free alternatives in the lower nest of the choice tree, under the additional restriction that $\sigma_1 = 0$. As we noted above, when $\sigma_1 = 0$, there is perfect correlation in the unobserved components $\varepsilon(d)$ of the value of the interest-free alternatives, so the consumer chooses the alternative $d \in \{1,\ldots,\delta\}$ with the highest option value $ov(a,x,d)$ with probability 1.

The remaining column labeled “Weak Dominance” corresponds to a nested logit specification where the default payment option $d = 1$ is not included in the set of interest-free payment alternatives in the

[9] We also estimated a multinomial logit specification, which is a special case of the nested logit model when we impose the restriction $\sigma_1 = \sigma$, but due to space constraints we do not present these estimates in Table 1. However we will discuss the differences in the estimates and fit of the NMNL versus the MNL model in section 4.5.

lower level nest of the choice tree, and with the additional restriction $\sigma_1 = 0$. As noted above, this implies that consumers will choose the alternative $d \in \{2,\dots,\delta\}$ with the highest option value $ov(a,x,d)$ with probability one, but the unobserved random components of the value of the default pay in full alternative $d = 1$, or any of the positive interest alternatives $d \in \{\delta+1,\dots,12\}$ have the common positive scale parameter $\sigma > 0$, which implies these shocks have a positive (though small) variance.

We specified $ov(a,x,d) = a\rho(x,d)$ where

$$\rho(x,d) = \frac{1}{1+\exp\{h(x,d,\phi)\}} \tag{30}$$

where

$$\begin{aligned} h(x,d,\phi) \quad = \quad & \phi_0 I\{d \geq 2\} - \sum_{j=3}^{12} \exp\{\phi_{j-2}\} I\{d \geq j\} + \phi_{11} ib + \phi_{12} \mathit{installshare} \\ & + \phi_{13} \text{creditscore} + \phi_{14} \text{nlate} + \phi_{15} I\{r = 0\}. \end{aligned} \tag{31}$$

The fixed transaction cost of choosing an installment term at the checkout counter, $\lambda(x,d)$, is specified as

$$\lambda(x,d) = \exp\left\{\phi_{16} I\{r=0\} + \phi_{17} \mathit{installshare} + \sum_{j=2}^{10} \phi_{16+j} I\{d=j\} + \phi_{27} I\{d > 10\}\right\}. \tag{32}$$

The variable *creditscore* is the interpolated credit score for the customer at the date of the transactions (the company only periodically updates its credit scores so we only observed them at monthly intervals), and *nlate* is the number of late payments that the customer had on his/her record at the time the transaction was undertaken, and *ib* is the customer's installment balance at the time of the transaction. Note that due to the large variability in spending on credit cards by different customers, we normalized both *a* and *ib* as *ratios of each customer's average statement amount.*

4.5 Estimation Results

The estimation results are presented in table 1. Note that in general, most though not all of the parameters are estimated very precisely — something we would expect given the large number of observations in our sample. Due to the large number of α parameters (26) and because they are not of central interest to this paper, we omit them from table (1). However we note that the estimated probabilities of receiving a free installment offer $\Pi(z,\hat{\alpha})$ vary rather significantly over our sample, from a low of 1.41×10^{-4} to a high of 0.527. The variability justifies our treatment of free installments as quasi-random experiments since there appears to be no easy way to predict when and where free installments will be offered to consumers. Note

Table 1: Maximum Likelihood Parameter Estimates, Dependent variable: installment term, d

Model	Unrestricted Nested Logit		Strong Dominance		Weak Dominance	
Parameter	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
σ_1	0.027	2.8×10^{-4}	0.0	0.0	0.0	0.0
σ	0.033	3.6×10^{-4}	0.048	7.0×10^{-4}	0.042	5.8×10^{-4}
$\phi_0\ I\{d \geq 2\}$	-3.553	0.015	-3.374	0.020	-3.428	0.018
$\exp\{\phi_1\}\ I\{d \geq 3\}$	0.282	0.013	0.293	0.017	0.271	0.015
$\exp\{\phi_2\}\ I\{d \geq 4\}$	0.212	0.025	0.196	0.036	0.018	0.033
$\exp\{\phi_3\}\ I\{d \geq 5\}$	0.083	0.027	0.117	0.038	0.102	0.035
$\exp\{\phi_4\}\ I\{d \geq 6\}$	0.112	0.011	0.124	0.016	0.129	0.015
$\exp\{\phi_5\}\ I\{d \geq 7\}$	1.9×10^{-27}	0.022	1.98×10^{-27}	4.05×10^{-6}	1.98×10^{-27}	4.7×10^{-6}
$\exp\{\phi_6\}\ I\{d \geq 8\}$	0.105	0.036	0.099	0.047	0.087	0.036
$\exp\{\phi_7\}\ I\{d \geq 9\}$	0.076	0.035	0.101	0.052	0.087	0.042
$\exp\{\phi_8\}\ I\{d \geq 10\}$	0.072	0.022	0.045	0.026	0.072	0.026
$\exp\{\phi_9\}\ I\{d \geq 11\}$	3.7×10^{-16}	0.058	1.98×10^{-16}	0.088	2.72×10^{-16}	0.076
$\exp\{\phi_{10}\}\ I\{d = 12\}$	0.207	0.058	0.088	0.222	0.213	0.076
$\phi_{11}\ (ib)$	-0.056	0.0002	-0.061	0.001	-0.058	0.001
$\phi_{12}\ (installshare)$	-2.254	0.028	-2.513	0.033	-2.585	0.032
$\phi_{13}\ (creditscore)$	-0.002	0.001	-0.005	0.001	-0.002	0.001
$\phi_{14}\ (nlate)$	-0.020	0.001	-0.035	0.001	-0.027	0.001
$\phi_{15}\ (I\{r = 0\})$	-0.841	0.016	-0.819	0.017	-0.805	0.017
$\phi_{16}\ (installshare)$	-0.218	0.012	-5.498	0.099	-5.303	0.066
$\phi_{17}\ (I\{r = 0\})$	-1.501	0.014	-1.129	0.018	-1.263	0.017
$\phi_{18}\ (I\{d = 2\})$	-1.721	0.014	-1.304	0.017	-1.438	0.016
$\phi_{19}\ (I\{d = 3\})$	-1.046	0.020	-0.688	0.023	-0.823	0.023
$\phi_{20}\ (I\{d = 4\})$	-1.220	0.016	-0.853	0.019	-0.980	0.019
$\phi_{21}\ (I\{d = 5\})$	-1.181	0.015	-0.724	0.019	-0.858	0.018
$\phi_{22}\ (I\{d = 6\})$	-0.966	0.019	-0.720	0.019	-0.854	0.018
$\phi_{23}\ (I\{d = 7\})$	-0.849	0.025	-0.459	0.032	-0.597	0.031
$\phi_{24}\ (I\{d = 8\})$	-0.850	0.024	-0.513	0.029	-0.625	0.029
$\phi_{25}\ (I\{d = 9\})$	-1.181	0.015	-0.767	0.020	-0.906	0.019
$\phi_{26}\ (I\{d = 10\})$	-0.934	0.017	-0.556	0.021	-0.691	0.020
$\phi_{27}\ (I\{d > 10\})$	-1.974	0.045	-0.407	0.115	-1.129	0.083
$f(2,\beta)$	0.028	0.006	0.159	0.005	0.153	0.005
$f(3,\beta)$	0.576	0.019	0.697	0.007	0.706	0.006
$f(4,\beta)$	0.007	0.009	0.006	0.001	0.006	0.001
$f(5,\beta)$	0.017	0.011	0.029	0.002	0.028	0.002
$f(6,\beta)$	6.2×10^{-16}	0.028	1.4×10^{-17}	0.004	1.4×10^{-17}	0.004
$f(7,\beta)$	0.078	0.047	0.039	0.005	0.038	0.005
$f(8,\beta)$	2.00×10^{-15}	0.048	0.003	8.2×10^{-4}	0.003	8.0×10^{-4}
$f(9,\beta)$	1.30×10^{-15}	0.014	0.002	7.2×10^{-4}	0.002	7.1×10^{-4}
$f(10,\beta)$	0.192	0.212	0.054	11.71	0.053	19.81
$f(11,\beta)$	1.26×10^{-16}	0.265	1.11×10^{-17}	11.71	1.1×10^{-17}	19.81
$f(12,\beta)$	0.101	0.016	0.009	0.001	0.008	0.001
Log-likelihood	-45716.9		-49350.8		-48518.8	

that the prior information we obtained from company management — namely that free installment offers do not depend on consumer characteristics — provides a powerful and *justified* exclusion restriction that helps us to identify the model. The exclusion restriction is that $\Pi(z,\alpha)$ depends only on merchant and time time dummies z but not on any customer characteristics x.

Over our entire sample, the average estimated probability that customers in our sample receive free installment offers at check-out time of is 15%. We obtained this estimate by simulating the model conditioning on the observed transaction data and tabulating the fraction of all simulated transactions that resulted in free installment offers. This estimate appears to be reasonable in light of our discussions with the credit card company executives and is in the midpoint of the 10% to 20% range that they provided as their rough expectation of the fraction of all transactions in which free installments are offered. While the simulations display considerable customer-specific heterogeneity in take-up rates for free installment offers, the average take-up rate over all consumers and transactions in our simulations is 18%.

Note that the simulations allow us to "observe" phenomena that we cannot observe in the actual data due to the censoring. Specifically, in the simulations we can see the number of times where customers were offered but did not choose free installment offers, and the overall fraction of times consumers do accept these offers, which is 18%. Taking the product of the 15% rate at which free installments are offered on average times the 18% average take-up rate results in the prediction that 2.7% of the transactions in our simulated data are free installments. This is the same percentage of free installment transactions that we do observe in the actual data set.

Now consider the question of whether the individuals in our sample make suboptimal precommitment decisions, by choosing one of the "dominated" interest free alternatives $d \in \{1,\ldots,\delta-1\}$. We do a Likelihood Ratio test the Weak and Strong Dominance Assumptions, which rule out the possibility that customers make these suboptimal precommitment decisions, *and the data overwhelmingly reject both of these assumptions.* Recall that the Strong Dominance Assumption holds in the nested logit specification given by the choice probabilities in equations (15) to (19) when the similarity parameter $\sigma_1 = 0$, which corresponds to the case where all the unobserved components of the value of the interest-free alternatives $d \in \{1,\ldots,\delta\}$ are perfectly correlated with each other.

The second column of Table 1 presents the parameter estimates when the Strong Dominance Assumption is imposed and we see that doing this causes the maximal attainable value of the likelihood function to fall considerably, from -45716.9 for the unrestricted nested logit model to -49350.8 when the Strong Dominance condition holds. Under the null hypothesis that $\sigma_1 = 0$, the likelihood ratio test has an asymptotic Chi-square distribution with 1 degree of freedom, and the Chi-square statistic, -2 times the log-likelihood ratio value, equals 7267, which is so far out in the tail of the Chi-square distribution that we can reject the null hypothesis at any reasonable significance level.

The third column of Table 1 presents the maximum likelihood estimates of the parameters when the Weak Dominance Assumption is imposed. Recall that under the Weak Dominance Assumption, we allow for the possibility that consumers might treat the default choice to pay for a transaction in full, $d = 1$, as having unobserved characteristics that are not perfectly correlated with the remaining interest-free alternatives $d \in \{2,\ldots,\delta\}$. The Weak Dominance Assumption holds for a nested logit model where we allow for perfect correlation in the unobserved values $\varepsilon(d)$ of the alternatives $d \in \{2,\ldots,\delta\}$ when $\sigma_1 = 0$, but allows the unobserved component $\varepsilon(1)$ for the default choice $d = 1$ to be independently distributed of the common $\varepsilon(d)$ value for the other interest-free alternatives.

We see from Table 1 that while the Weak Dominance Assumption results in a significantly higher log-likelihood value than we can achieve under the Strong Dominance Assumption, -2 times the log-likelihood ratio is still 5604 in this case, so we can also easily reject the Weak Dominance Assumption at any reasonable significance level.

Though we do not report it due to space limitations, we also estimated the standard Multinomial Logit specification where the unobserved components $\varepsilon(d)$ of the values of all alternatives are assumed to be independently distributed. The maximized log-likelihood value of this model, is -45727.9 which is much closer to the maximized value of the unrestricted, best fitting nested logit model. However we can also test and reject the multinomial logit model, which corresponds to the null hypothesis $H_o : \sigma = \sigma_1$. The product -2 times the loglikelihood ratio, 21.4, is much smaller but also has an asymptotic Chi-square distribution with 1 degree of freedom under the null hypothesis. The P-value the likelihood ratio statistic under H_o is 3.7×10^{-6}, so we can also reject the MNL specification at any reasonable significance level.

However from a behavioral and overall model fit perspective, there is not a huge difference in predicted behavior between unrestricted nested logit model and the MNL model, whereas the difference in the behavior implied by the Weak or Strong Dominance Specifications is huge. Also, imposing these assumptions has significant implications for the estimated probabilities of free installment offers $\Pi(z,\alpha)$ and the probability distribution of maximum free installment terms offered.

In particular, when we impose either the Weak or Strong Dominance Assumption, the model predicts implausibly low average probabilities of being offered free installment offers — far below 10%, the lower bound that company management suggested in their range of expectations of the fraction of transactions where free installments are offered. Under the Weak Dominance Assumption, the model predicts that free installments are offered on average in only 4% of all transactions, but in order to be consistent with the 2.7% of transactions where we observe free installment offers being chosen by customers in our sample, the model estimates a much higher average take-up rate of 75%. Under the Strong Dominance Assumption, the model predicts that *every* free installment offer is taken, so the take-up rate is 100% and the model predicts that free installments are offered on average in only 2.7% of the transactions in our sample.

We can also see directly from table 1 that the estimated distributions of the maximum duration of free installment term offered, $f(\delta,\beta)$ are very different under the Weak and Strong Dominance Assumptions relative to the unrestricted nested logit parameter estimates. In particular, since we observe very few customers choosing free installment loans with a 12 month duration, the model predicts that almost no free installments with a 12 month duration are offered (otherwise there would be too many customers who take them, which would be inconsistent with what we observe), whereas the unrestricted nested logit model predicts that 10% of the company's free installment loan offers have 12 month maximum duration.

The model explains the fact that fewer than 1% of all observed free installment loan choices have a 12 month duration by predicting that consumers have a high probability of choosing installment terms that are shorter than 12 months. In particular, in our simulations of the model we see strong preference for installment loans of shorter durations, particularly for 3 installments. Only 8% of the customers who took the 12 month free installment offer chose the full 12 installment maximum. The most popular option was 3 installments, chosen by 38% the customers who accepted interest-free installment offers with a maximum of 12 installments.

We now discuss the parameters of interest, the ϕ parameters entering the option value function $\rho(x,d,\phi)$ and the fixed cost function $\lambda(x,d,\phi)$ that are two key "behavioral objects" underlying our discrete choice model. Note that due to the large variability in spending across different consumers, we normalized each customer's credit card spending and installment balances to be ratios of their average statement amounts (the monthly balance due on their credit card bill). Thus, a purchase amount $a = 2$ denotes a purchase that is twice as large as the average amount of that customer's average credit card balance on each statement date. The installment balance, *ib*, of 3 corresponds toan installment balance that is 3 times as large as the average of the customer's credit card statement balance.

Consider first the estimation results for the parameters entering the option value function $\rho(x, d, \phi)$. We did not include a constant term in our specification in equation (31) since the sum of the installment duration dummy variables $I\{d \geq j\}$, $j = 2, \ldots, 12$ adds up to the constant term on the set of relevant choices, $d \in \{2, \ldots, 12\}$ since we have normalized the option value for the decision $d = 1$ to equal zero. Therefore, we allowed the parameter ϕ_0 to be unconstrained and take positive or negative values in order to to play the effective role of the constant term. However we did constrain the coefficients of $I\{d \geq j\}$ for $j = 3, \ldots, 12$ to be positive by writing them as exponential functions of the underlying parameters ϕ_j, $j = 1, \ldots, 10$.[10] This constrains $\rho(x, d, \phi)$ to be a non-decreasing function of d.

The two largest coefficients (in absolute value) after ϕ_0 are ϕ_{12} the coefficient of the *installshare* variable, and ϕ_{15}, the coefficient of a dummy variable indicating that the transaction was done as a free installment. The latter coefficient indicates that customers perceive free installments to have even *higher* option value than installments done at positive interest rates. We are not quite sure of how to interpret this finding, but the data are clearly telling us that it needs to make the option value of a free installment extra high, otherwise the model would have difficulty in explaining the number of free installment chosen in our sample, since the take-up rate is already low. This finding suggests that customers evaluate free installments differently than regular positive interest installment offers. We also included the $I\{r = 0\}$ dummy in the transaction cost function λ and find that it has a strong significantly negative coefficient there as well.

The estimated parameters imply that consumers perceive lower transactions costs for free installment offers than regular positive-interest installments, a result that is inconsistent with a stigma explanation for the low take up rate of free installments. We found that we could significantly increase the likelihood by including the $I\{r = 0\}$ dummy in both the ρ and λ functions, which suggests that not only do customers regard free installment offers has having lower transactions costs than regular positive-interest installment transactions, but they also find free installment offers to be more valuable than positive interest installments in a manner that is proportional to transaction size a.

This finding is hard to explain using traditional expected utility models, where the consumer's evaluation of the option value of credit is independent of the cost of credit. Here we find that customers regard the option to borrow to be more valuable to them if this option is "free" than if it was costly. Of course the model already factors the cost of credit into customers' calculations by deducting the actual cost of credit

[10] In table 1 we report the exponentiated values instead of the parameters themselves, and used the delta method to calculate the implied standard errors.

as given by the $c(a,r,d)$ function. The estimation results tell us that the fact that $c(a,r,d) = 0$ for free installment offers is not sufficient incentive for customers according to a traditional cost-benefit calculation with a fixed option value function $ov(a,x,d)$ that is independent of the interest rate r. The model fit is significantly improved when we allow a significantly higher option value $ov(a,x,d)$ for borrowing opportunities where $r = 0$ compared to the default case situations where $r = r_t(x,d)$. One possible explanation is that customers realize that free installment opportunities are "fleeting chances" which they value more highly because they are transitory opportunities to borrow under the best possible terms.

The most important x variable turned out to be *installshare,* the share of creditcard spending that the customer does under installment. We included *installshare* because it serves as an important observable indicator of unobserved preference heterogeneity, as well as an observed indicator about which consumers are most likely to be liquidity constrained. We found that neither *creditscore* nor the number of late payments *nlate* are as powerful as the *installshare* variable in enabling the model to fit the data and capture the high degree of customer-specific heterogeneity that we found in our analysis in section 3. We think that *installshare* is a better indicator of customers who are "credit constrained" than the *creditscore* or *nlate* variables, though it may also capture customers who are "installment addicts" who make frequent use of installment credit.

The large negative and strongly statistically significant estimated coefficient of the *installshare* variable ϕ_{12} indicates, not surprisingly, that customers with high installment shares have uniformly higher estimated option values, and thus a higher proclivity to take installments, both those at zero and those at positive interest rates. As we discussed previously in section 3, *installshare* is the most important single factor affecting differential take-up of free installment offers across customers in our sample, as shown in the right hand panel of figure 4. We use *installshare* as a covariate in our model as a convenient, low-dimensional means of capturing unobserved heterogeneity in the behavior of the consumers in our sample.

An alternative estimation strategy would be to replace *installshare* by a random parameter τ representing *unobserved heterogeneity* with the interpretation that lower values of τ indicate customers who are more desperate for liquidity and thus have a higher subjective willingness to pay for loans of various durations, $\rho(x,d,\tau,\phi)$. We also experimented with alternative ways of capturing unobserved heterogeneity such as the approach of Heckman and Singer [1984] but found it computationally infeasible to estimate the model.[11]

[11] A random effects approach requires integration over the distribution of possible types of preference parameters for the

We had much more success in capturing customer-specific heterogeneity using a *fixed effects approach.* Since we have (unbalanced) panel data, we have a subset of customers for whom we observe sufficiently many transactions to be able to estimate subsets of the ϕ parameters on a *customer by customer basis.* For example, we observe more than 100 credit card transactions for 470 of the 611 customers in our estimation sample (the maximum number of observations for any single customer was 1981). Though it is not realistically possible to estimate all 29 of the ϕ parameters on a customer by customer basis, even for the subset of 470 customers for whom we have more than 100 transaction observations, we did find it was possible to estimate *customer-specific constant terms* in the $h(x,d,\phi)$ and $\lambda(x,d,\phi)$ functions given in equations (31) and (32) above. Specifically, for the subsample of the 470 customers for whom we have at least 100 observations per customer, we estimated customer-specific constants $\hat{\phi}_{i,12}$ and $\hat{\phi}_{i,16}$, where i indexes this subset of 470 customers, $i = 1,\ldots,470$, so in effect we estimated a total of 27 ϕ parameters that were common to all individuals, plus an additional $940 = 2*470$ customer-specific intercept terms in the h and λ functions.[12]

We found that although there is a substantial amount of customer-specific differences in the estimated $\hat{\phi}_{i,12}$ and $\hat{\phi}_{i,16}$ coefficients, *the estimated coefficients were well approximated by a simple linear functions of the installshare variable.* That is, we found that

$$\hat{\phi}_{i,12} = \hat{\phi}_{12} installshare_i + u_i \tag{33}$$

$$\hat{\phi}_{i,16} = \hat{\phi}_{16} installshare_i + e_i \tag{34}$$

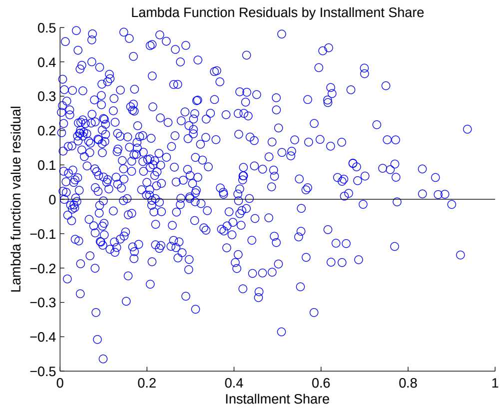
where $\hat{\phi}_{12}$ is the maximum likelihood estimate of the coefficient ϕ_{12} in equation (31) and $\hat{\phi}_{16}$ is the maximum likelihood estimate of the coefficient ϕ_{16} in equation (32), and, as we will show below $\{u_i\}$ and $\{e_i\}$ are "residuals" that turned out to have approximate mean zero and are mean-independent of the *installshare* variable.

Thus, while some readers may worry about the problem of "endogeneity" by including the *installshare* variable as an explanatory variable into the model of installment choice, it is actually just a parsimonious

likelihood function for each individual consumer. For many customers in our sample we have hundreds of transactions which implies that the customer-specific likelihoods — the product of their probabilities of choosing various payment options for their many observed transactions — are very small probabilities. We had great difficulty doing the numerical integration in an accurate and reliable manner. When we try to maximize the log-likelihood we ended up having to take logs of probabilities that turned out to be too small to be reliably computed on 64 bit computers.

[12]For identification purposes, we normalized $\phi_0 = 0$ and $\phi_{27} = 0$ to do these customer-specific fixed-effect estimations, since the sum of the installment loan duration variables equals a constant term and thus, the customer-specific intercepts would not be identified without such additional normalizations. Further, in the cases where a customer does no installment spending, the customer-specific intercepts are not identified, so we were unable to estimate these for the small number of individuals who did no installment spending.

Figure 7: λ function residuals $\{e_i\}$ by Installment Share



way of capturing the considerable degree of customer-specific parameter heterogeneity in our estimated model. Even though there is some degradation in the likelihood resulting from using $\hat{\phi}_{12}$*installshare*$_i$ instead of $\hat{\phi}_{i,12}$, and $\hat{\phi}_{16}$*installshare*$_i$ instead of $\hat{\phi}_{i,16}$, there were major computational savings resulting from having to estimate only 26 ϕ parameters instead of $965 = 940 + 25$ (here we account for the 28 ϕ parameters less the two identifying normalizations discussed in footnote 11 above), and we found that our estimates of the other ϕ parameters did not change significantly as a result using this more parsimonious specification for capturing unobserved heterogeneity in the model.

Figure 7 plots the estimated "residuals" $\{e_i\}$ that capture customer-specific heterogeneity in the λ function above and beyond the heterogeneity captured by $\hat{\phi}_{16}$*installshare*$_i$ (see equation (34) above). The fact that there is no obvious trend in these residuals and that they are approximately mean zero and mean independent of *installshare* shows that the pattern of heterogeneity in the estimated customer-specific constant terms $\hat{\phi}_{i,17}$ is well approximated by the simple linear specification $\hat{\phi}_{17}$*installshare*$_i$.

The residuals for the h function (see equation (33) above) are similar, though the variance is larger. We take this as very good evidence that our simplified 28 ϕ parameter specification given in Table 1 is a very good one, and that the *installshare* variable is successful in capturing the majority of the customer-specific heterogeneity we observe in our data in a very parsimonious manner.

Other points to note about the estimated parameters of ρ is that counterintuitively, we find that the option value *increases* the larger the customer's existing installment balance is (see ϕ_{11} the coefficient of *ib*). While this could be a spurious estimate due to potential endogeneity of the installment balance, we believe that we have already controlled for the effect of installment via the inclusion of the *install-*

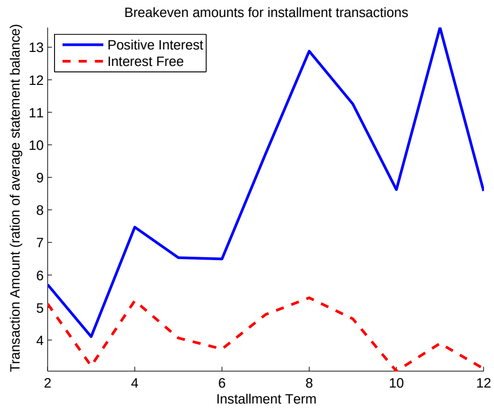
share variable. Further, the coefficient of ϕ_{11} remains negative when we exclude *installshare* and estimate customer-specific constant terms in h and λ. The positive coefficient on *ib* may reflect periods of persistently high need for credit or a consumer who faces tighter credit constraints in other aspects of his/her financial life (recall that there are no explicit borrowing constraints for the credit card we study). In such situations, the consumer will borrow more under installment (and thus have a higher value of *ib*) and will also have a higher option value for credit. Thus, *ib* may be proxying for *time-varying* needs for installment credit that are not captured by the time invariant *installshare* variable.

A more intuitive finding is that the option value is an increasing function of *creditscore* which means customers with worse (i.e. higher) credit scores are predicted to have higher option values for installment credit. Similarly, another indicator of credit problems, the number of late payments that the customer has on his/her record *nlate* also increases the option value and thus the value of installment credit.

We now turn to a discussion of the estimated parameters of the fixed cost function $\lambda(x,d,\phi)$. The first point to note is that the estimated transactions costs are *non-monotonic in loan duration* d. Though we also estimated specifications where we imposed monotonicity (or completely exclude the dummy variables for various installment terms d), we can strongly reject both of these restrictions on the model. The results show that transaction costs are lowest for loan with either $d = 3$ or $d \in \{6,7,8\}$ installments, but are significantly higher for the shortest duration $d = 2$, or the longest durations $d \in \{11,12\}$. As a result of the non-monotonicity in transactions costs, it is possible to get violations of the Weak and Strong Dominance assumptions for some transaction sizes a even when $\sigma_1 = 0$ and even though we have restricted $\rho(x,d)$ to be a monotonically increasing function of d. Whether the non-monotonicity of $\lambda(x,d)$ in d really reflects variations in transactions costs or is indirectly reflecting a specific preference for particular durations d is not entirely clear. However the finding shows a key avenue in which the model captures both the low take up and high incidence of choice of dominated repayment durations $\{2,\ldots,\delta-1\}$ for free installment loan offers, and our finding is not just an artifact of random noise in the unobserved components $\varepsilon(d)$ of the values of the various interest-free alternatives.

Generally, the model estimates that consumers perceive high fixed costs to choosing any installment transactions other than the "default" choice $d = 1$. These "costs" may reflect perceived "stigma" associated with taking installment transactions. From anecdotal evidence, the people in the country we are studying regard installment purchases as a sign of "weakness" especially in view of the bad experience that these people had several years prior to the period we studied where there had been a credit bubble and

Figure 8: Estimated breakeven amounts $\overline{a}(x,d)$ for installment transactions



a high frequency of credit card defaults. Thus, the individuals may have been chastised or even scarred by that prior experience and had resolved themselves to try to avoid the use of installment credit whenever possible.

One might ask why this scarring effect and aversion to installments doesn't show up in lower estimated option values. We believe that the fixed costs play an important role in explaining a clear pattern in our data where generally only sufficiently expensive purchases are made under installment. The reason is that while the average non-installment credit card purchase is \$50, the average (positive interest) installment purchase is \$350. The fixed costs are estimated to be large in order to explain differential pattern of spending.

Figure 8 illustrates this by plotting the "cut-off" value of spending $\overline{a}(x,d)$ for which the net benefit of borrowing on installment equals the fixed cost of undertaking it, i.e.

$$\overline{a}(x,d) = \frac{\lambda(x,d,\phi)}{\rho(x,d,\phi) - c(a,r(x,d),d)}. \tag{35}$$

This figure was calculated for an individual with a *creditscore=5* (i.e. about average credit) with *installshare=.1* and $ib = 0$ and *nlate=4*. We see that for positive interest loans, the breakeven ratio (i.e. the amount is expressed as a ratio of the average credit card statement balance) is generally over 5 and is as high as 12 or 13 for the less popular (and more expensive) installment loan durations, $d = 8$ and $d = 11$. Notice that ϕ_{17}, the coefficient of $I\{r = 0\}$ is *negative and strongly statistically significant* indicating that consumers perceive free installments to have lower fixed costs, which reinforces the effect of free installments on the option value, as captured by the estimate of $\hat{\phi}_{15}$ discussed above. Together, these coefficients suggest that consumers regard free installments as "special" in the sense that they are perceived to have extra option value and a lower transaction cost than low but positive interest loan offers. Despite this effect, it is a puzzle as to why the model still predicts a low take-up rate of free installments. Without the $I\{r=0\}$ dummy included in the h and λ function, the model fit would deteriorate and it would predict an even lower take-up rate of free installments than the 15% rate that the current specification predicts.

In any event, the net effect of free installment offers on credit decisions is not immediately clear since we have found that the free installment lowers the option value but also zeros out the cost of the loan which has ambiguous effects on the denominator of (35). As we have seen above, the fixed costs of taking an installment loan are estimated to be lower if the loan is a free installment offer, and this reduces the numerator of (35). Even though the effect of free installments on the cutoff level $\overline{a}(x,d)$ is ambiguous in general, we see from figure 8 that for the particular customer that we plotted, the net effect is to uniformly lower the threshold at which the customer decides to undertake the installment transaction. The effect is particularly pronounced for loans of duration $d=8$ and higher: under a free installment offer the cutoff point is less than 5 and as low as 3 times their average statement amount, whereas the cutoffs are over 10 for positive interest installment loans.

This is how the model explains the fact (see figure 2 in section 3) that the distribution of free installment transaction sizes is stochastically dominated by the distribution of positive interest transaction sizes. The model is telling us that the "acceptance threshold" $\overline{a}(x,d)$ for undertaking an installment transaction is lower for free installment offers than for installments done at positive interest rates. The gap between these thresholds is particularly pronounced at higher loan durations. Thus, the model predict that customers are more likely to choose to pay under installment for smaller size transaction when the installment is free than when it is at a positive interest rate. This implies that the distribution of transaction amounts for positive interest installments stochastically dominates the distribution of transaction amounts for free installments that we observed in figure 2.

In simulations of the model the mean sizes of transactions done as positive interest and free installment transactions, respectively, closely match the values we observe in our data set. If we measuring transactions as a ratio of the average statement balance, transactions that are not done on installment ($d=1$) average 9% of the average statement balance, free installments are 36% of the average statement balance and positive interest installments are 49% of the average statement balance. In our simulations the corresponding percentages are 9%, 38% and 53%, respectively. Given the standard errors of these percentages in our simulations, we cannot reject the hypothesis that the simulation estimates equal the true percentages at the 5% significance level.

The final comment we have about the estimated λ function is that the coefficient ϕ_{16} of the *installshare* variable is a large negative number that is very precisely estimated. Thus, we find that the model captures the systematically higher use of installment credit by individuals with high values of *installshare* by increasing the option value of the loan and by reducing the fixed cost of undertaking the transaction. This is how the model explains the fact that the ratio of the typical installment purchase to the typical credit card (non-installment) purchase decreases as *installshare* increases.

4.6 Model Identification

Given the high degree of censoring in our data (i.e. the fact that we observe free installments in only 2.7% of all transactions), it may seem surprising that we can separately identify the consumer choice probabilities $P_+(d|x,a)$, $P_0(d|a,x,\delta)$ from the probability that customers are offered free installments $\Pi(z,\alpha)$ and also identify the probability distribution $f(\delta,\beta)$ of the maximum term of free installment offers. How is it that the model can enable us to infer so much about customer behavior in the 97.3% of transactions where we cannot observe whether a free installment was offered or not?

We start by observing that the model *is* identified. Our model is a fully parametric one and we are also greatly assisted by the *a priori* exclusion restriction that the probability $\Pi(z,\alpha)$ that a customer is offered a free installment does not depend on customer characteristics x. As we have noted above, this is a strong piece of identifying information but one that is completely justified by virtue of quasi random nature of the free installment offers. Company management confirmed to us that customers *are* offered free installments without regard to their characteristics x and we relied on this prior information and imposed this exclusion restriction as a powerful source of identification of our model.

For fully parametric models, lack of identification can only show up in two ways: 1) locally flat likelihood, or 2) two or more isolated global maximums of the likelihood function. The fact that we can numerically calculate the hessian matrix of the log-likelihood function and confirm that this matrix is well conditioned means that we can rule out possibility 1). We also conducted a thorough search of the parameter space and cannot find any evidence of two or more isolated global maxima for our model. From standard results in differential topology, there is essentially no chance of a failure of identification of type 2): almost all smooth, *regular* functions (i.e. those that have only isolated critical points) have a unique global maximum. Thus, if there is any lack of identification, it will show up in the form of a singular hessian matrix for the log-likelihood at the maximum likelihood parameter estimates.

Even in cases where the hessian is technically invertible, a nearly flat or poorly identified model reveals itself in the form of huge standard errors, since these are calculated from the negative of the inverse of the hessian matrix of the log-likelihood function. As we can see from table 1, nearly all of the parameters of the model have very small estimated standard errors and most parameters are statistically significantly different from zero.

The parameters that are the least well identified are the β parameters of the distribution $f(\delta,\beta)$ of the maximum terms of free installment offers. Particularly under the Weak and Strong Dominance Assumptions, the standard errors of the estimated probabilities $f(10,\hat{\beta})$ and $f(11,\hat{\beta})$ are indeed huge, and reflect the fact that very few installments of these durations where chosen in our dataset. For example, there are only 5 cases where $d = 11$ and none of these were free installment ofers. As a result the maximum likelihood point estimates for $f(11,\hat{\beta})$ is virtually zero but the standard errors are huge due to the very small number of observations.

However further evidence that the model is identified comes from the fact that we can decisively reject both the Weak and Strong Dominance Assumptions. If the model was not well identified, it would be possible to fit the data under these restrictions nearly as well as without them, since these assumptions only restrict customer behavior in situations we do not observe. Yet we are able to decisively reject these assumptions because the model is unable to fit the data as well when the Weak and Strong Dominance Assumptions hold. Why? The reason is that there are two different ways to predict the small fraction of free installment transactions. One way is to predict that very few of these offers are made, but the take up rate is relatively high. The other way is to predict that free installments are made at a higher rate but the take up rate is lower. The data favors the former explanation since the latter explanation results in low option values for installment credit (to explain the low take up rate), but the low option values cause the model to underpredict the number of positive interest installment offers chosen.

However the other explanation that the data prefer, namely to have the model predict high take-up rate, but a low probability of being offered a free installment, has its own difficulties fitting all of the data. In this case, the model overestimates the number of free and positive installment offers taken. For example, under the Weak Dominance Assumption, simulations of the model result in 3.3% of all transactions being done as free installments and 4.1% as positive interest installments, whereas in the data the corresponding percentages are 2.7% and 3.7%, respectively.

The unrestricted nested logit model has additional flexibility that is lacking under the Weak and Strong

Dominance assumptions that help it fit the data. Though the unrestricted model can also explain low rate of free installments in two different ways (e.g. low offer rate and high take-up rate, or higher offer rate and low take-up rate), the second explanation provides a significantly better fit to the data. The additional flexibility comes from not requiring the unobserved components of the values of the various interest-free alternatives to be perfectly correlated with each other. The increased flexibility provides more ways for the model to explain the relative number and durations of free versus positive interest installment transactions. For example, simulations of the unrestricted nested logit model result in 2.8% of all transactions being done as free installments and 3.8% as positive interest installments. These are quite close to the actual percentages and well within the standard deviations of these percentages accounting for simulation noise and estimation error.

Thus, it is *not* the case that the various ways of explaining the 2.7% fraction of free installments and the 3.7% fraction of positive interest installment transactions in our data are observationally equivalent or even nearly so. The likelihood clearly favors the unrestricted nested logit model and with an explanation that involves a relative high offer rate but low take-up rate of free installments offers. Further evidence that the model is identified is provided by the fact that, as we show in section 4.7, we are unable to reject the unrestricted nested logit model specification in Chi-square goodness of fit tests of the model, whereas we can strongly reject the specifications in which the Weak and Strong Dominance assumptions are imposed.

Furthermore, we do not think that any of our key conclusions are artifacts of particular parametric functional form assumptions. In fact, we have established *sufficient conditions* for the *non-parametric partial identification* of the model. Though it beyond the scope of this paper to provide a full analysis of the non-parametric identification of the model under the weakest possible conditions, in appendix 1 we prove the following theorem.

Theorem *Suppose there are a finite number of possible values of observed consumer types x, transaction sizes a, and merchant types/time dummies z and that if we denote* $\overline{z}$*,* $\overline{x}$ *and* $\overline{a}$ *as the number of possible values for z, x and a respectively, then we assume that* $\overline{z} > 1$ *and* $\overline{ax} > 7$*. Further, if* $f(a,x,z)$ *is the population proportion for cell* (a,x,z) *we assume that for each z that* $f(a,x,z) > 0$ *for all possible values of a and x, i.e. the conditional density* $f(a,x|z)$ *has full support for each possible value z. Define the structural objects* Γ *of the installment model as the following probabilities* $\Gamma = \{f(\delta), P(z), P_+(d|a,x), P_0(d|a,x,\delta)\}$ *where* $f(\delta)$*,* $\delta \in \{2,\ldots,12\}$ *is the probability distribution for the maximum term of a free installment offer,* $P(z)$ *is the conditional probability that a free installment offer is made to customers purchasing at merchant/time* *z, $P_+(d|a,x)$ is the conditional probability of choosing payment term $d \in \{1,2,\dots,12\}$ by a consumer of observed type x making a transaction of amount a who was not offered a free installment, and $P_0(d|a,x,\delta)$ is the probability a consumer of observed type x making a transaction amount a will choose payment option $d \in \{1,2,\dots,12\}$ given that they are offered a free installment with maximum term $\delta \in \{2,\dots,12\}$. Suppose the following conditions hold: 0) the model is correctly specified, i.e. there is an underlying true structure Γ^* that generates the (censored) data (d,x,z) we observe (i.e. that a free installment offer is only observed for customers that choose them), 1) $\exists z\, \Pi(z) = 0$, and 2) $\forall \delta \in \{2,\dots,12\}\ \exists (a,x)\ P_0(\delta|a,x,\delta) = 1$. Then the following structural objects in Γ are identified: $f(\delta)$, $\delta \in \{2,\dots,12\}$, $P(z)$ for all z, and $P_+(d|a,x)$ for all (a,x). The choice probabilities $P_0(d|x,a,\delta)$ are partially identified. We can identify $P_0(3|a,x,2)$ and $P_0(12|a,x,12)$ for all (a,x) and the following weighted averages of the remaining values $P_0(d|a,x,\delta)$ for all (a,x):*

$$\begin{aligned} &\sum_{\delta=2}^{12} P_0(d|a,x,\delta) f(\delta) \quad d \in \{1,\dots,12\} \\ &\sum_{\delta=2}^{d-1} P_0(d|a,x,\delta) f(\delta) \quad d \in \{3,\dots,12\} \\ &\sum_{\delta=d}^{12} P_0(d|a,x,\delta) f(\delta) \quad d \in \{3,\dots,12\}. \end{aligned} \tag{36}$$

Note that Assumption 1) in the Theorem states that there is at least one merchant/time period z' where there is zero probability of a free installment offer. We believe this is a reasonable assumption given that certain merchants such as fast food restaurants or newspaper stands sell items where the transaction sizes are too small to justify the use of free installments as a promotional device. Indeed our estimates of the parametric probability $\Pi(z,\hat{\alpha})$ resulted in values very close to zero and we are unable to reject the hypothesis that $\Pi(z,\alpha^*) = 0$ for many merchants/time periods z.

Assumption 2) states that there *exists at least one "installment taker"* i.e. a type of customer that always takes free installments when they are offered. We wish to make clear that this assumption does *not* state that *all* customer types are "installment takers" since a customer who is an installment taker necessarily satisfies the Strong Dominance Assumption, which our empirical analysis in section 4.5 has strongly rejected. However note rejecting the hypothesis that *all* customers satisfy the Strong Dominance Assumption does *not* rule out the possibility that *some* customers might be installment takers. Indeed, we have found a great deal of heterogeneity in consumer behavior and our empirical analysis does show that there a small fraction of "installment avoiders" who, paradoxically, behave as "installment takers" for sufficiently large transaction amounts. That is, there are customers who have no apparent liquidity constraints or need for installment credit but who are rational and who *will* take a free installment offer at the maximum term offered δ for transactions a that are sufficiently large.

The Theorem shows that most of the structural objects in Γ^* are uniquely identified non-parametrically, but that we can only partially identify $P_0(d|a,x,\delta)$. We can exactly identify two values of these probabilities for any (a,x), $P_0(3|a,x,2)$ and $P_0(12|a,x,12)$, but we cannot uniquely identify the remaining values of $P_0(d|a,x,\delta)$ but only the weighted averages of these probabilities given in equation (36).

Note that the non-parametric identifiability of $P_0(12|a,x,12)$ is enough information to make the Strong Dominance Assumption testable under very weak assumptions. Note that the Strong Dominance Assumption implies thate $P_0(12|a,x,12) = 1$. Since, the fraction of all free installment offers with the maximum term of 12 payments, $f(12)$, is identified, we can test Strong Dominance by estimating the fraction of customers in any (a,x) cell who choose free installment offers of duration $d = 12$. If this estimated probability is less than $f(12)$ then we can reject the Strong Dominance Assumption. Thus, the Strong Dominance Assumption is one that can be tested under very weak assumptions, and with sufficient data, it can be tested on "cell by cell" basis, i.e. separately for each possible value of (a,x).

However it appears that some additional prior information must be imposed to test the Weak Dominance Assumption, and to be able to make more detailed predictions of how free installment offers affect customers' choices when the data are censored. We believe the simple model of choice of payment terms that we introduced in section 4.1 does not rely on implausible or highly restrictive *a priori* assumptions, yet this additional parametric structure allows us to make the more detailed predictions of how consumers react to the presence of free installment offers that we cannot directly observe. In particular, we not not believe that any of our main empirical conclusions are artifacts of functional form assumptions, and are robust to reasonable modifications of the assumed functional forms for the value functions $v(a,x,r,d)$ or the distributions of unobserved components of these values, $\varepsilon(d)$, $d \in \{1,\dots,12\}$.

4.7 Model Fit

We now discuss the fit of the model. Figures 9, 10, and 11 summarize the ability of the structural model to fit the credit card data. Of course the predominant choice by consumers is to pay their credit card purchases in full by the next installment date: this is the choice made in 93.57% of the customer/purchase transactions in our data set. When we simulate the estimated model of installment choice, taking the x and purchase amounts a as given for the 167,946 observations in our data set, we obtain a predicted (simulated) choice of paying in full at the next statement (i.e. to choose $d = 1$) of 93.56% (this is an average over 10 independent simulations of the model).

Of more interest is to judge the extent to which the model can predict the installment choices made by the customers in our sample, i.e. to predict the incidence of choices $d > 1$. Figure 9 plots the predicted versus actual set of *all* installment choices made the customers in our sample. We see that the model provides a nearly perfect fit of actual installment choices. Figure 10 compares the actual versus predicted choices for the subsample of individuals (both simulated and actual) who chose positive interest installments. We see that once again, the model predicts the outcome we observe nearly perfectly.

The model does slightly overpredict the number of free installments chosen for durations of $d = 2$ installments, and underpredicts the number of $d = 3$ month installments chosen, but only slightly. Overall, we feel that the model does an excellent job of capturing the key features that we observe in our credit card data. In particular, when we use the simulated data to recreate analogs of the figures presented in section 5, we find that the model succeeds in capturing all of the key features that we observe in the actual data.

We also conducted a battery of Chi-squared goodness of fit tests using the random-cell Chi-squared test of Andrews [1988]. These tests are based on partitioning the dependent variables as well as the covariates entering the model into various "cells" and computing a quadratic form in the difference between the model's predicted probabilities of the customer's choices in the various cells in the partition to the actual frequency distribution of choices in each of the cells. The degrees of freedom depends on the number of cells in the partition less the number of estimated parameters in the model.

There are countless ways to partition the space $D \times A \times X \times Z$ where $D = \{1, \ldots, 12\}$ is the choice set, A is the set of (normalized) purchase amounts, X is the set of observed characteristics of customers and Z is a set of all possible merchant code and time dummies that entered the model to predict the probability of a free installment offer. For example, we could partition choices by purchases at various sets of merchants, or over various intervals of time, or on a partition of the amounts purchased (e.g. large transaction amounts versus small transaction amounts) and so forth. We have done this for many different choices of partitions and while particular values of the Chi-squared statistics are sensitive to how we choose these partitions, we found that with few exceptions the Chi-squared test was unable to reject the model at conventional levels of significance. At the same time the Chi-square tests generally decisively reject both the specifications where we impose the Weak and Strong Dominance assumptions. This is consistent with our Likelihood

Figure 9: Predicted versus Actual Installment Choices, All Installment Transactions

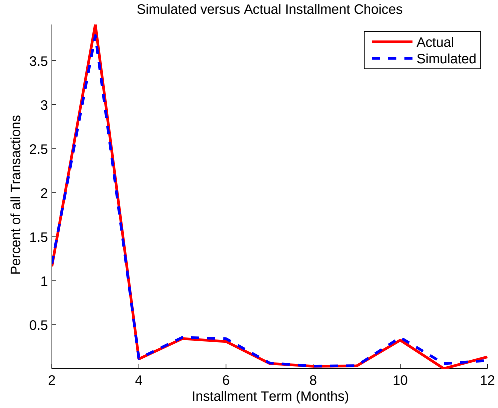


Figure 10: Predicted versus Actual Installment Choices, Positive Interest Installment Transactions

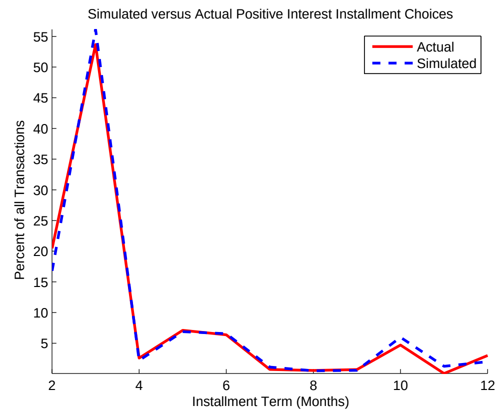
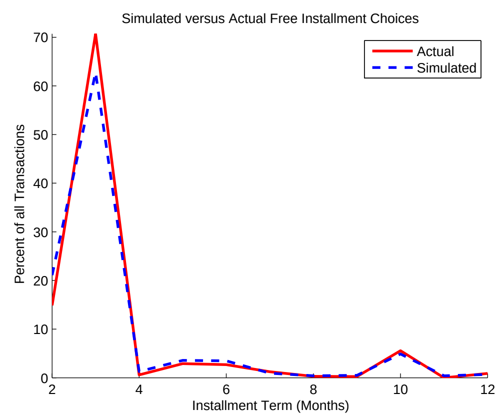


Figure 11: Predicted versus Actual Free Installment Choices



ratio tests, which also provided strong rejections of the Weak and Strong Dominance Assumptions. Given the length of the paper, we decided to omit presentation of the actual test statistics and the correspondence marginal significance values, but we are happy to provide this information upon request.

As we noted in the introduction and elsewhere, our simulations also predict something that we could not otherwise learn from our data without having a structural model: the model predicts that in 15% of 167,946 simulated customer-purchase transactions, the company offers customers free installment opportunities. This estimate strikes us as quite reasonable since figure 4 in section 2 shows that the installment ‘addicts” who do the highest share of their credit card spending on installment have the highest fractions of installment transactions that are done as free installments, and the average for this group is approximately 15%. Thus, if we assume that the most installment-prone individuals do not pass up opportunities to purchase items under free installment offers and have a take-up rate of nearly 100%, then this provides independent evidence that our estimated average rate of free installment offers is reasonable.

5 Model Implications and Counterfactual Simulations

The left hand panel of Figure 12 plots the estimated subjective interest rates $\rho(x,d)$ and compares it to the estimated interest rate schedule $r(x,d)$ for an illustrative consumer with a creditscore of 2, $ib = 2$, and an installment share of 30%. From figure 12 we see that the estimated subjective interest rates ρ are non-decreasing in d and are everywhere above the interest rates the credit card company charges $r(x,d)$, signaling a clear net benefit of purchasing under installment credit. The $\rho(x,d,\phi)$ function has its largest jumps at $d = 3$ and $d = 12$.

The right panel of Figure 12 plots the net benefits from installment borrowing, $\rho(x,d,\phi) - r(x,d)$, as a bar-plot. We see that for this particular customer, the highest net benefits occur at a duration of $d = 4$, where the customer experiences a net benefit to taking an installment, net of the cost of the installment, of about 7% of the transaction amount a. The net benefit of installments is generally the highest for shorter duration installment loans, for $d \in \{2,\ldots,6\}$, and then falls for the longer duration loans $d \in \{7,\ldots,11\}$ but increases again for $d = 12$ installment loans. This pattern of net benefits is generally consistent with the pattern of installment loan choices, although it does not show any pronounced peak at $d = 3$ that could explain the peak in installments at this duration that we observed in figure 6. We will explain how the model is able to capture this peak when we describe the estimation results for the λ function below.

Figure 12: Estimated $\rho(x,d,\phi)$, $r(x,d)$, and $\rho(x,d) - r(x,d)$

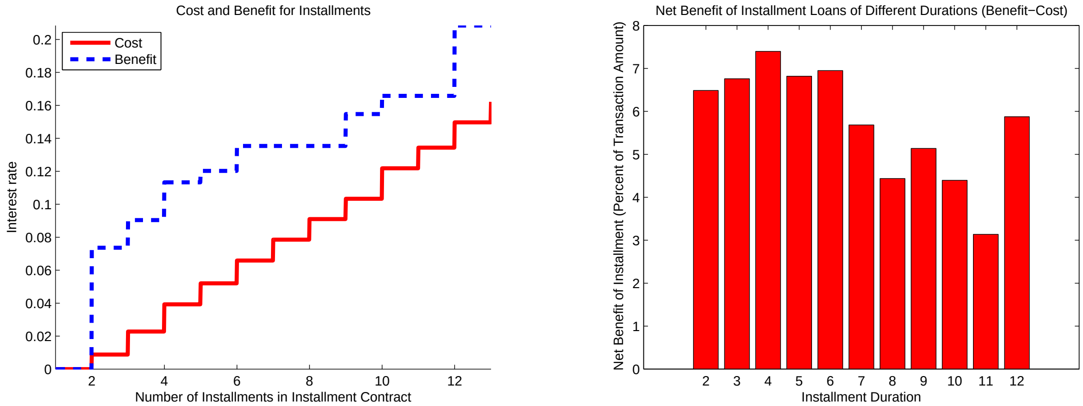
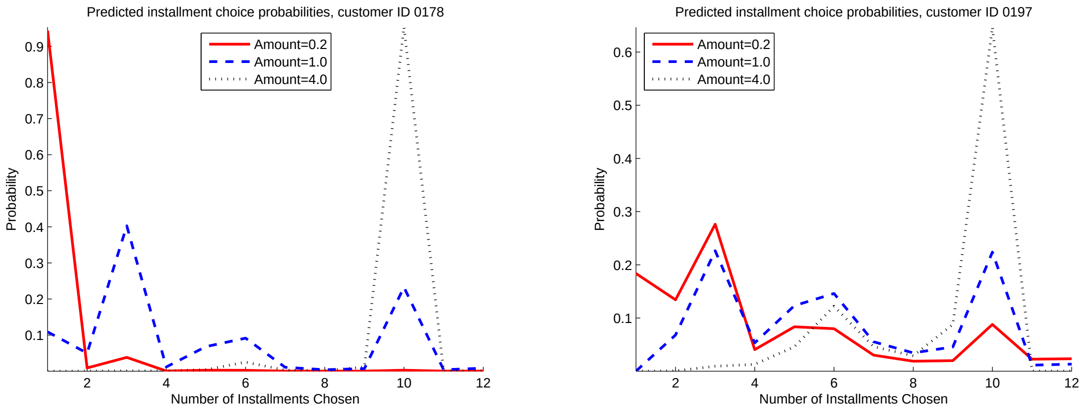


Figure 13 illustrates how the choice probabilities of two different customers — an installment "avoider" (*installshare=0*) and an installment "addict" (*installshare=0.83*) — are affected by the presence of a 10 month free installment offer. The choice probabilities shift dramatically in the presence of the free installment offer, particularly for the installment avoider. However the choice probabilities are also depend critically on the transaction size a/ This person had virtually no chance of choosing any installment duration greater than $d = 3$ when facing positive interest rates, however once a 10 month free installment offer is on the table, the customer's chance of taking the 10 month free installment offer starts to increase significantly with the size of the purchase amount a. When $a = 0.2$ (i.e. a transaction that is 20% of the size of the customer's average monthly balance due), the free installment option has very little effect on this consumer's choice probabilities. However when $a = 1.0$ the probability of choosing alternatives $d = 1$ and $d = 3$ fall significantly relative to the case where a free installment offer is not available, and the probabilities of choosing installment durations $d = 6$ and $d = 10$ increase significantly. For even larger purchases, such as $a = 4.0$, the probability of taking the full 10 month free installment offer rises to virtually 100%.

The story is similar for the installment addict, except that this person is motivated to take advantage of the free installment option at lower purchase amounts than we predict for the installment avoider. For a purchase of size $a = 0.2$, the probability of alternative $d = 1$ is only 20% when a 10 month free installment offer is present, compared to nearly 70% otherwise. It is interesting to note that the installment addict is less likely to choose the full 10 month duration of the free installment opportunity than the installment avoider.

Figure 13 summarizes the key finding of the paper, namely: *the model predicts that there is a significant*

Figure 13: Choice probabilities in the presence of a 10 month free installment offer



probability that customers who choose a free installment will choose a term that is less than the maximum duration offered. In figure 13 we see this clearly. For example, the blue dashed line in the left hand panel of figure 13 shows that if an installment avoider who is purchasing an item that equals the average size of his credit card statement, $a = 1.0$, is offered a free installment with a maximum duration of 10 months, the probability this person will actually choose the free installment at the maximum duration offered, $d = 10$, is less than 25%. Similarly, the solid red line in figure 13 shows that if an installment addict who is purchasing an item of amount $a = 0.2$ and is offered a free installment offer with a 10 month maximum duration, the probability the person will choose $d = 10$ is about 10%.

As we noted in the introduction, simulations of the model for our full sample leads to the prediction that 82% of individuals who were offered (and chose) a 10 month free installment offer also precommited at the time of purchase to pay the balance in *fewer* than 10 installments. This precommitment behavior, along with the fairly low probability that free installment offers are predicted to be chosen, constitutes a significant challenge to expected utility models, which generally predict that rational individuals should choose the maximum allowed term when offered an interest-free loan. In other words, expected utility models predict that individuals should satisfy the Strong Dominance Assumption, which our empirical findings have decisively rejected.

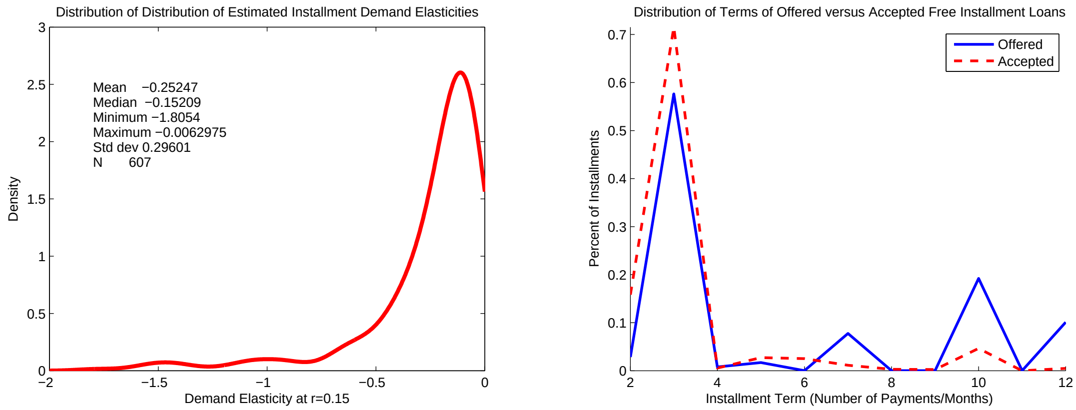
While our model is capable of explaining behavior inconsistent with expected utility maximization, the model is incapable of explaining *why* individuals in our sample are relatively reluctant to take (or fully exploit) free installment offers. Although we speculated that individuals might have some sort of stigma or fear about some hidden catch or cost associated with taking free installment offers, we simply do not have enough information to be able to isolate the underlying concerns, fears, or other psychological motivations more precisely.

However as we noted in section 4.5, our finding that a dummy variable for free installment offers, $I\{r = 0\}$, is a significant variable in both the h and λ functions of the option value function $ov(a,x,r)$ suggest that consumers regard free installments as "special deals" and there is little evidence that they feel stigmatized by these offers. This could suggest that the stigma explanation is less likely, and may suggest that our findings are more consistent with the time-inconsistent planning explanation we discussed in the introduction, where consumers avoid undertaking too much debt as a self-control device to constrain their "future selves."

Though it is not the main focus of this paper, we can use the estimated model of installment choice to calculate the implied demand curve for installment credit. Though a simple regression of the amount of installment borrowing on the interest rate charged results in an upward sloping estimated demand curve — a spurious result due to the endogeneity of the interest rate — the implied demand curves from the estimated discrete choice model are downward sloping, though fairly inelastic. We calculated the demand elasticities for our two illustrative customers — the "installment avoider" and the "installment addict" — at the average installment interest rate, 15%, and found in both cases their demand for credit is quite inelastic. The calculated elasticity for the installment addict is -0.074 whereas the demand elasticity of the installment avoider is -0.11. We find that the demand for installment credit is highly inelastic for virtually all of the individuals in our sample. The left hand panel of figure 14 plots the distribution of estimated demand elasticities for 607 individuals in our sample for whom we had enough data on purchases to calculate reasonable estimates of demand elasticities. We see a very skewed distribution with the lower tail containing a minority of individuals who have relatively elastic demand functions, but the vast majority of individuals have demand elasticities that are quite inelastic and concentrated near 0.

The right hand panel of figure 14 compares the distribution of the maximum terms of free installments that are *offered* to customers (blue line) to the distribution of terms that were *chosen* (red dashed line). We can now answer the question raised in section 3, namely whether pattern of chosen durations of free installment offers is supply-driven and determined by the company offering few interest-free installments with long payback terms, or whether these durations are demand-driven and a consequence of customer choices. We see that while the company does offer most of its interest-free loans at the most popular 3 month duration, it makes a significant share of interest-free loan offers at durations of 10 and 12 months,

Figure 14: Estimated Demand Elasticities and Durations of Offered and Accepted Free Installments



yet few customers take these offers at the maximum durations offered. Instead most customers who take these offers precommit to loan terms of 3 months, and this explains why 70% of customers in our sample chose interest-free installment loans for terms of 3 months, whereas we estimate that the company offers 3 month interest-free installment loans 57% of the time.

5.1 Customer Responses to Counterfactual Interest Rate Schedules

We conclude by examining the optimality of the credit card company's interest rate schedule in light of what we have learned about the demand for installment credit for this sample of customers. We argue that it is possible to obtain interesting insights into the optimality of company's particular nonlinear interest rate schedule even using our "partial" demand model for installment credit. Recall from section 4.2 that we found that the company sets customer specific interest rate schedules, but in a very particular way, namely, it offers the same "duration premium" shown in figure 6 to all customers, and engages in third degree price discrimination via the use of customer-specific intercepts which shift the entire interest rate schedule up and down in a parallel fashion.

We consider the effect on the firm's profitability from adopting alternative interest rate schedules, but we constrain our search to alternative installment interest rate schedules that guarantee that the customers' expected welfare is no lower under an alternative hypothetical interest rate than the expect under the *status quo.* That is, we solve the following problem

$$\max_{r_2,\dots,r_{12}} \int_0^\infty \sum_{d=2}^{12} [c(a,r_d,d) - c(a,R_t,d)] P_+(d|a,x,r_2,\dots,r_{12}) f(a|x) da \tag{37}$$

subject to:

$$\sigma \int_0^\infty \log\left(\sum_{d=1}^{12} \exp\{v(d,x,a,r_d)/\sigma)\}\right) f(a|x)da \geq \sigma \int_0^\infty \log\left(\sum_{d=1}^{12} \exp\{v(d,x,a,r_t(x,d))/\sigma)\}\right) f(a|x)da, \tag{38}$$

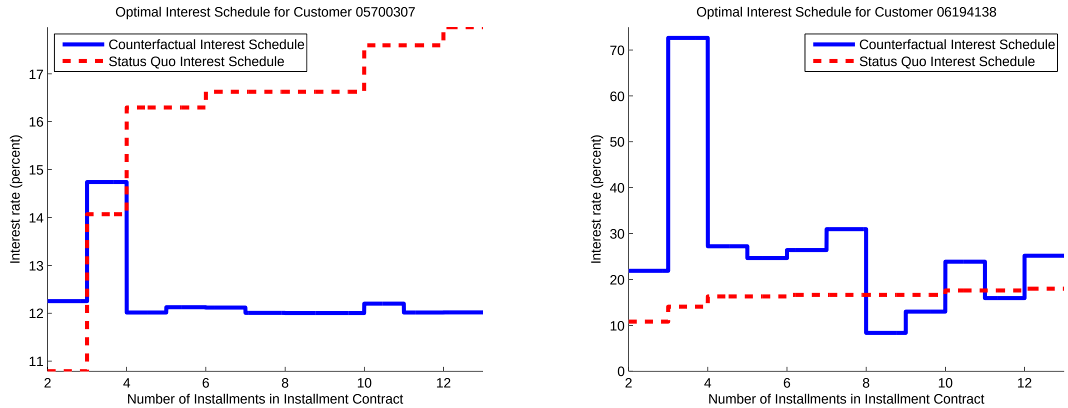
where R_t is the credit card company's opportunity cost of capital (i.e. the rate at which it can borrow) and $r_t(x,d)$ is the company's *status quo* interest schedule from equation (4) that we plotted in figure 6 above, and $f(a|x)$ is the conditional distribution of transaction amounts for purchases by a customer of characteristics x.[13] The choice probability $P_+(d|a,x,r_2,\ldots,r_{12})$ is the model's prediction of the probability that this customer would choose an installment loan of duration d when confronted with a hypothetical alternative interest rate schedule $(r_2,\ldots,r_{12})$. The constraint in inequality (38) simply states that the expected net benefit that the consumer expects from any alternative hypothetical interest rate schedule that the company might offer must be at least as high as the customer expects to receive under the *status quo* schedule.

While a fuller specification of the profit maximization problem for the company would probably relax this constraint and instead calculate overall company profits as a sum over all of its customers, accounting for the fact that raising interest rates too much for some customers might cause them to switch to other credit cards or close their accounts entirely, we feel that the constrained optimization problem (37) (38) does give us insight whether the company's interest schedule is at least optimal in a *second best* sense. After all, if we can find ways to increase company profits by changing interest rates to its customers without changing the expected welfare they expect from access to the installment borrowing opportunity, the company cannot be maximizing profits in a global sense, since by holding customer welfare constant, we have controlled for the effect of the proposed change in interest rates on the overall demand for and use of the company's credit card by its customers.

Figure 15 presents the optimal schedules that we calculated for the same two individuals that we have studied in our our analysis of predicted response to a 10 month free installment offer in section 4.7 (i.e. an installment "avoider" and and "addict", respectively). These are *customer-specific* interest rate schedules $(r_2,\ldots,r_{12})$ that increase the profits the company can expect to receive from these consumers while keeping both customers as well off in an expected utility sense as they are under the company's *status quo* increasing interest rate schedule. Since the company's interest rate schedules are already customer-

[13] We found that the distribution of transaction amounts is approximately lognormally distributed and used this specification for $f(a|x)$ in equation (38). We also empirically analyzed the effect of interest rate on the size of transactions and did not find any significant interest rate effect. For this reason the distribution $f(a|x)$ does not include the interest rate as an additional conditioning variable.

Figure 15: Optimal versus *status quo* installment interest rates schedules



specific, we believe it is feasible for the company to engage in third degree price discrimination and set alternative customer-specific schedules such as the ones suggested in figure 15.

From the left hand panel of figure 15 we see that for the installment avoider, the model predicts that the company could increase its profits by generally *lowering* its interest rates except for installment loans with $d = 2$ and $d = 3$ installments, for which its is optimal to increase these interest rates somewhat. The overall decline in interest rates keeps the welfare of this customer unchanged, while enabling the credit card company to extract more surplus from this customer over the durations that the customer is most likely to choose under the relatively infrequent occasions when the customer does do installment borrowing. Note that due to the low rate of use of installments by this customer, overall profits are very low, and even under the alternative interest rate schedule the profits the company can expect from installment loans from this customer are negligible, even though our alternative schedule does increase these (negligible) profits by 10%.

The right hand panel of figure 15 shows a more interesting case, the optimal schedule for the installment addict. Notice that in this case, the optimal interest rate schedule is generally *higher* than the *status quo* interest rate schedule, though the counterfactual schedule is lower at installment loan durations $d = 8$, $d = 9$ and $d = 11$, and the decreases in the rates at these durations are just enough to keep this consumer indifferent between this alternative interest schedule and the *status quo.* In this case, the higher rate of use of installment credit by this customer implies significantly higher profits for the credit card company relative to what it expects to earn from the installment avoider. We calculated profits under the *status quo*, as a fraction of the customer's average credit card statement amount, of 0.5 percent. By adopting the alternative interest schedule in the right hand panel of figure 15 we predict that the company can increase its expected profits by over 60% to 0.9 percent of the average statement amount for this customer on a *per transaction* basis.

These results suggest that the company may not be maximizing its profits since the particular interest rate schedule it uses, with a duration-based interest premium for installment terms that is common to all customers, seems hard to rationalize as an optimal schedule given that the company has the ability to (and does) set customer-specific interest rates. We conjecture that the company may not have a good understanding of the behavior and preferences of its customers, and may have failed to take full advantage of the strong preference of its customers for 3 month installment loans. Our counterfactual calculation suggests that the company can significantly increase its profits by increasing the interest rate it charges for this most popular installment loan duration.

6 Conclusions

We have analyzed a new data set on credit card transactions that enables us to observe micro-borrowing decisions by customers. Specifically, the main way that the credit card company that we study offers credit to its customers is via *installment credit*, which involves transaction by transaction decisions on whether to pay for a credit card purchase in full at the next statement ($d = 1$), or to spread out the payment in d equal monthly installments for $d \in \{2, \ldots, 12\}$.

In an attempt to increase its market share, the company more or less randomly offers its customers interest-free installment loan opportunities. These offers are made to all customers equally, without regard to their characteristics. We have treated these offers as a *quasi-random experiment* in order to overcome endogeneity in customer-specific interest rates and identify the demand for installment credit.

We have been able to circumvent another shortcoming in our data, namely, the fact that the observations on free installments are *censored* — we only observe whether a free installment was offered in the cases where customers chose them. We developed a flexible behavioral discrete choice model of installment credit demand. Despite the high degree of censoring, we have shown that it is possible to identify customer demand for credit, the probability that customers are offered interest-free installment opportunities, and the distribution of the maximum duration of these offers.

Our main empirical finding is that though we estimate that the company makes frequent use of interest-free installments — offering them in an average 15% of all transactions in our sample — the take-up rate for these offers is very low: customers accept them on average in only 18% of the transactions where they are offered. The product of the 15% offer rate times the 18% take-up rate equals the 2.7% fraction of free installment offers that we observe in our data set.

Further, we also find a high incidence of *suboptimal precommitments* among customers who do choose free installment loan offers. For example, of the customers who choose interest-free loan offers with a 10 month maximum duration, 82% of them precommit to repay the loan in *fewer* than 10 installments. These findings are hard to rationalize using standard expected utility models, but are consistent with theories of consumers who have self-control problems. Specifically, one interpretation of our findings is that some of the customers in our sample may have financial self-control problems and resist the temptation to take interest-free loan offers. If they absolutely must borrow, most consumers choose repayment terms that are shorter than the maximum allowed term to avoid becoming excessively indebted.

We have noted that due to the censoring in our data, we cannot directly observe this behavior: instead it is *inferred* from our econometric model of installment loan choice. We have proven that many of the unknowns underlying this model are non-parametrically identified, but a key choice probability that predicts how the presence of a free installment loan offer will affect their choice is only partially identified. Thus, our empirical "findings" depend on additional parametric functional form assumptions that enable us to predict how consumers respond to free installment offers that we cannot always observe. However we have argued that our findings are robust and are not sensitive to functional form assumptions. Further we are able to decisively reject the hypothesis that customers satisfy a "Strong Dominance Assumption" that is implied by standard expected utility theory, namely, that whenever a customer is offered an interest-free loan opportunity, if they do take this offer, then they will always take it for the maximum duration offered.

Why should we care whether consumers sometimes make "suboptimal" choices, or choices that are difficult to explain using traditional expected utility models? We have shown that while there is a significant *theoretical* literature on consumer consumers who have self-control problems or behave in a time-inconsistent fashion, there is relatively little empirical work that has shown consumers actually behave in the fashion predicted by these theories.

However besides providing new empirical results that suggest that these theories could be relevant to understanding consumer behavior, we have also demonstrated additional puzzling behavior by the credit card company itself. Specifically, why does the company rely so heavily on free installment offers as a marketing device if the take-up rates and overall response to them is so low? We have shown that the though the company engages in third degree price discrimination by setting customer-specific interest rate schedules, the particular schedule it uses is rather peculiar. It has a common duration premium for installment loans longer than 2 months (the same for all customers) and the price discrimination occurs only via a parallel customer-specific shift term in this common interest rate schedule.

If customer behavior is well approximated by our econometric model (and we find that the econometric model provides an extremely good fit to the data), then our counterfactual calculations in section 5 suggest that the interest rate schedule that the company uses is inefficient and cannot be profit-maximizing: we have shown that there are other non-monotonic and customer-specific interest rate schedules that are significantly more profitable for the firm. These alternative schedules involve significant increases in the most popular installment loan duration, 3 months, while lowering interest rates at other durations in order to keep overall customer welfare unchanged.

A final reason why we might care about these results is because our analysis is a step towards addressing the much bigger picture issue of whether consumer financial self-control problems can have macro effects and lead to financial instability in the country as a whole. We have noted in the introduction that there is evidence that consumers in the country we study had collective financial self-control problems since there was a credit card borrowing “boom and bust” in the years preceding our data set, with wave of defaults from excessive credit card debt that nearly lead to a financial collapse. This experience was not unlike the experience in the US in 2008, when a wave of mortgage defaults resulting from unwise lending and borrowing lead to the largest financial disaster since the 1929 stock market crash.

Due to competitive pressures to increase their market share resulting from a “winner take all” structure of payoffs to becoming a dominant firm (a result of substantial network externalities in the perculiar manner that merchant fees are collected in this country), credit card companies are locked into a fierce competition for market share and try to encourage their customers to increase their spending and borrowing via a variety of means, including the aggressive use of interest-free installment offers. The company we study does not impose any formal credit limit and relies on its customers to exercise their own self-control to avoid getting in over their heads in credit card debt.

Our analysis indicates that the customers in our study are exercising substantial self-control by frequently turning down attractive offers to borrow up to 12 months interest-free. We suspect that this behavior may reflect consumer “chastisement” and learning in response to the credit card crisis that just preceded the period of our study. What we do not know is whether consumer preferences and behavior shifted in response to the credit card crash, or if we had estimated our model using data from the credit card "boom" period we would have found far less evidence of self-control than we find in our post-crash data set.

These questions open up a number of interesting avenues for future research, particularly to determine the cause of the apparent collective failures of financial self-control: can these lapses be blamed entirely on consumers, or do banks and and government regulators also experience periodic lapses in their own financial self-control by making unwise loans or failing to impose reasonable borrowing constraints on their customers, or faling to provide adequate monitoring and supervision of the financial sector as whole? We need to better understand consumer preferences and financial decision making, and whether their behavior is stable, or subject to collective influences such as "herding behavior" that appear to be present during many financial "manias" as well as in the reactions (or overreactions) to these excesses in the crashes that follow.

A final contribution of our paper is methodological: to show how to make the most out of firm data when we are not lucky enough to have data gathered from randomized controlled experiments. In our opinion the empirical literature has gravitated towards a view that the only valid route to knowledge is to use data from RCEs and that empirical studies that use "observational data" and must necessarily make at least *some* econometric modeling assumptions to deal with problems and limitations in the data cannot be trusted.

We would certainly welcome the chance to analyze additional data, including data from well designed RCEs, but we have provided a number of reasons why it can be very costly and difficult for this firm to undertake RCEs on its customers. Howevver we feel that it would be a step backward to fail to analyze any data that does not meet the "gold standard" of being gathered from a RCE: there is a tremendous amount of information that can be exploited from observational data sets and not all econometric modeling assumptions will necessarily result in untrustworthy inferences.

All of the key findings from our analysis (namely the low take-up rate of free installment offer and the precommitment behavior we predict) could be easily independently verified via direct tabulations if the company were willing and able to record all instances where free installments are offered, whether chosen by customers or not. However we have discussed several compelling logistical reasons why it would be difficult for the company to record this information, so it may not be an easy task to independently validate many of the findings and predictions in this paper.

Besides this information, it is clear that a great deal more can be learned about the motivations, preferences, and behavior of the company's customers if it were willing to undertake more extensive data gathering and analysis. We have noted that a major limitation of this study is that our econometric model is not rich or detailed enough to distinguish between the deeper underlying explanations of why customers behave in the way our model predicts. We have argued that our results are more in line with theories of consumers with financial self-control problems rather than other belief-based or stigma explanations that we outlined in the introduction. However we believe that a considerable amount could be learned if it were possible to survey customers and ask them for their own reasons why they turn down free installment offers.

Further, if the company could be convinced to undertake RCEs, our paper provides some strong testable predictions about customer responses to alternative customer-specific interest rate schedules. We believe RCEs are most valuable when used *in conjunction* with econometric models instead of being used to *avoid* econometric modeling.

This point is connected to our final point, namely that an important limitation of our study is that our data only allows us to study credit decisions for customers of a single credit card company. Of course, customers have a choice of many different ways to pay at the check out counter, including using cash or other credit or debit cards. Though we did find that demand for installment credit is generally quite inelastic, it is important to remember that our finding is *conditional on the use of this particular credit card* and thus we have additional problems due to the choice-based nature of our sample of data.

This is why we believe it is critically important to study consumer choice over multiple alternative sources of payment similar to the studies by Gross and Souleles [2002] and Rysman [2007] who had access to customer-level transaction data from multiple different competing credit cards. It seems reasonable to suppose that the overall demand function for credit will be more elastic when we open up the analysis to consider all of the possible alternative means of payment. The company cannot really begin understand the behavior of its own customers until it knows more about their full array of payment options and the factors that lead the to choose one of these (e.g. the company's credit card) in preference to the others.

Appendix: Proof of the non-parametric identification of the model

Proof. In an analysis of identification we assume we have an unbounded number of observations and therefore can identify the "reduced form" i.e. the probability distribution of the data we observe, without any sampling error. What do we observe under the hypothesis of the Theorem? Observations can be written

(d,a,x,z,γ) where d is the consumer's choice of payment term, $d \in \{1,\ldots,12\}$, a is the transaction amount, x is a vector of characteristics of the customer including the customer's creditcard card and installment balances, credit score, and so forth, z is an indicator for the merchant and date at which the transaction occurs, and γ is an indicator of whether the transaction is a free installment or not, i.e. whether the interest rate on the transaction is 0% for installment sales alternatives $d \in \{2,\ldots,12\}$. Note that the information that the γ indicator conveys, i.e. whether an installment transaction was done at a positive interest rate or at a zero interest rate, is different from the observation of whether a consumer was *offered* a free installment. We only know that a customer was offered a free installment when the customer chose it, though as we have indicated the company allows customers to choose free installment offers for repayment terms that are shorter than the maximum allowed term, which we have denoted by δ.

Observations where $d = 1$ are always censored: we can never tell whether a customer who chooses to pay for a transaction in full at the next purchase date was offered a free installment and chose $d = 1$ rather than to choose any of the installment terms $d \in \{2,\ldots,\delta\}$ allowed under the free installment offer. However for the other alternatives $d \in \{2,\ldots,12\}$ we do observe the interest rate for the transaction, and $\gamma = 1$ indicates installment transactions that were done at positive interest rates given by $r = r(x,a)$ and $\gamma = 0$ indicates installment transactions where the customer was offered and chose a free installment offer and hence $r = 0$ in these cases.

For notational simplicity we combine the transaction amount a as part of the x vector. By the assumption of the Theorem there are finite number of x cells. Similarly there are a finite number of z cells, which indicate the merchant and date of the transaction. Let $P(1|x,z)$ be the probability that a customer with characteristics x choose to pay in full on transaction z. We assume this probability is known, as it could be consistently estimated by the fraction of all transactions in cell (x,z) where customers pay in full, given an unbounded number of observations. Thus, we can treat $P(1|x,z)$ as part of our "data" in the analysis of identification. Since the default option to pay in full always involves an interest rate of $r = 0$, we cannot tell whether these customers were offered free installments or not, and thus have not information γ in this case.

However for installment options $d \in \{2,\ldots,12\}$ we can observe the *ex post* interest rate for the installment transaction and thus we observe the γ indicator in this case. Let $P(d,\gamma|x,z)$ be the probability that a customer of type x doing a transaction at merchant z will choose installment option d and whether the installment is a free installment or not. These probabilities also constitute our "data" for the identification analysis.

Let $\overline{x}$ and $\overline{z}$ be the (finite) number of x and z cells, respectively. Then the knowledge of the censored data from the credit card company, via the probabilities $P(1|x,z)$ and $P(d,\gamma|x,z)$ for $d \in \{2,\dots,12\}$ and $\gamma \in \{0,1\}$ and $x \in \{1,\dots,\overline{x}\}$ and $z \in \{1,\dots,\overline{z}\}$ amounts to a total of $23\overline{xz}$ pieces of information, or "knowns" in our analysis of the non-parametric identification of the model. Of course we also assume that we know the joint distribution $f(x,z)$ of the fraction of customers making transactions in each (x,z) cell as well. For convenience, we will identify the cells by the corresponding integer labels so we treat x as an element of the set $\{1,\dots,\overline{x}\}$ and z as an element of the set $z \in \{1,\dots,\overline{z}\}$.

According to the Theorem, the "structure" is the set of objects $\Gamma = \{f(\delta),P(z),P_+(d|x),P_0(d|x,\delta)\}$ where $f(\delta)$ is the probability that the maximum term of a free installment is δ for $\delta \in \{2,\dots 12\}$, $P(z)$ is the probability that a customer will receive a free installment offer at merchant cell z, $P_+(d|x)$ is the conditional probability that a customer with characteristics x who does not receive a free installment offer will choose payment alternative $d \in \{1,\dots,12\}$, and $P_0(d|x,\delta)$ is the probability that a customer with characteristics x who receives a free installment offer with maximum term $\delta \in \{2,\dots,12\}$ will choose a payment alternative $d \in \{1,\dots,12\}$. Thus, Γ constitutes the set of "unknowns" in our analysis of identification.

By the assumptions of the Theorem, the model is correctly specified so that there is a "true structure" Γ^* and the set of censored observations are generated from this true model as the underlying data generating process. This implies that any structure Γ must satisfy the following set of equations that map the structural objects into the distribution of observables

$$\begin{aligned}
P(1|x,z) &= P_+(1|x)(1-P(z)) + P(z)\sum_{\delta=2}^{12} P_0(1|x,\delta)f(\delta) \\
P(2,\gamma=1|x,z) &= (1-P(z))P_+(2|x) \\
P(2,\gamma=0|x,z) &= P(z)\sum_{\delta=2}^{12} P_0(2|x,\delta)f(\delta),
\end{aligned} \tag{39}$$

and for $d \in \{3,\dots,12\}$ we have

$$\begin{aligned}
P(d,\gamma=1|x,z) &= (1-P(z))P_+(d|x) + P(z)\sum_{\delta=2}^{d-1} P_0(d|x,\delta)f(\delta) \\
P(d,\gamma=0|x,z) &= P(z)\sum_{\delta=d}^{12} P_0(d|x,\delta)f(\delta).
\end{aligned} \tag{40}$$

This is a system of $23\overline{xz}$ nonlinear equations in a total of $(22\overline{x}) + \overline{z} + 131$ unknowns, where we account for the fact that each of the structural objects in Γ are probabilities and so must sum to one, so we only count the total number of free parameters in these probabilities in our count of the total unknowns of the model.

Clearly the number of equations grows faster than the number of unknowns as $\overline{x}$ and $\overline{z}$ increase, and we assume that these are sufficiently large that total number of equations exceeds the number of unknowns. If $\overline{z} = 1$ then $\overline{x} > 132$. However if $\overline{z} > 1$ then

$$\overline{x} > \frac{\overline{z} + 131}{23\overline{z} - 22} \tag{41}$$

For sufficiently large values of $\overline{z}$ (e.g. $\overline{z} > 7$) this will be satisfied provided $\overline{x} > 1$. Further, by virtue of our assumption that the model is correctly specified, there is at least one solution to the system of nonlinear equations given in (39) and (40) above.

We now show that there even though we have a system of more equations than unknowns, it will have a unique solution for only some of the objects in Γ but there will generally be multiple solutions for the objects $P_0(d|x,\delta)$. That is, while some of the objects are non-parametrically identified, $P_0(d|x,\delta)$ is only partially identified.

First by the assumption that $\exists z'\ P(z') = 0$ it follows that we can identify $P_+(2|x)$ for all $x \in \{1, \ldots, \overline{x}\}$. For this z', it follows from the second equation in (39) that

$$P(2, \gamma = 1|x, z') = P_+(2|x), \tag{42}$$

since $P(z') = 0$. However this implies in turn that we can identify $P(z)$ for all other values of z from the equation

$$P(2, \gamma = 1|x, z) = (1 - P(z))P_+(2|x). \tag{43}$$

Further, we can identify the function $\sum_{\delta=2}^{12} P_0(2|x,\delta) f(\delta)$ from the third equation in (39)

$$P(2, \gamma = 0|x, z) = P(z) \sum_{\delta=2}^{12} P_0(2|x,\delta) f(\delta) \tag{44}$$

since we have shown we can identify $P(z)$. For similar reasons it follows from the second equation in (40) that we can identify $\sum_{\delta=d}^{12} P_0(d|x,\delta) f(\delta)$ for $d \in \{3, \ldots, 12\}$.

Further, since $\exists z'$ such that $\Pi(z') = 0$ it follows from the first equation in (40) that we can identify $P_+(d|x)$ for $d \in \{3, \ldots, 12\}$. From this and by adding the first and second equations in (40) it follows that we can identify $\sum_{\delta=2}^{d-1} P_0(d|x,\delta) f(\delta)$ and thus $\sum_{\delta=2}^{12} P_0(d|x,\delta) f(\delta)$ for $d \in \{3, \ldots, 12\}$.

Similarly, we can identify $P_+(1|x)$ from the first equation of (39) when we set $z = z'$ where $P(z') = 0$, and thus, it follows that we can also identify $\sum_{\delta=2}^{12} P_0(1|x,\delta) f(\delta)$.

We now show that we can identify $f(\delta)$ from knowledge of the functions $\sum_{\delta=2}^{12} P_0(d|x,\delta)f(\delta)$ for $d \in \{1,\ldots,12\}$ when assumption 2) of the Theorem also holds. Recall that this assumption states that for each $\delta \in \{2,\ldots,12\}$ there is at least one type of customer x' who is an *free installment taker,* i.e. $P_0(\delta|x',\delta) = 1$. However this implies that

$$\sum_{\delta=2}^{12} P_0(d|x,\delta)f(\delta) = f(\delta),\ \delta \in \{2,\ldots,12\}, \tag{45}$$

and since we have already shown that the right hand side of equation (45) is identified, it follows that we can identify $f(\delta)$, $\delta \in \{2,\ldots,12\}$.

It remains to show that the choice probabilities in the presence of free installment offers $P_0(d|x,\delta)$ are only partially identified, as claimed in the Theorem. We have already shown that the various weighted averages of $P_0(d|x,\delta)$ given in equation (36) are identified. The question is whether, given the knowledge of the probabilities $f(\delta)$, we can deconvolve these objects to identify the individual $P_0(d|x,\delta)$.

Unfortunately the general answer is no, i.e. it is not possible to identify all of the individual choice probabilities $P_0(d|x,\delta)$. To see this, for any fixed value x, it is not hard to see that after accounting for the adding up constraint that $\sum_{d=1}^{12} P_0(d|x,\delta) = 1$ for each $\delta \in \{2,\ldots,12\}$, there are a total of $121 = 11 \times 11$ unknown values for $P_0(d|x,\delta)$. However the number of identified weighted averages of these probabilities in equation (36) is 42, so we have a situation of a linear system with equations than unknowns, so in general there will be multiple solutions to the system (36).

However we can identify $P_0(3|x,2)$ and $P_0(12|x,12)$ for each x as claimed in the Theorem. Note that the third equation in (36) reduces to the equation

$$\sum_{\delta=d}^{12} P_0(d|x,\delta)f(\delta) = P_0(12|x,12)f(12) \tag{46}$$

when $d = 12$, and since the right hand side of equation (46) is identified and $f(12)$ is identified, it follows the $P_0(12|x,12)$ is identified.

Similarly, the second equation of the system (36) reduces to the equation

$$\sum_{\delta=2}^{d-1} P_0(d|x,\delta)f(\delta) = P_0(3|x,2)f(2) \tag{47}$$

and since the right hand side of equation (47) is identified and $f(2)$ is identified, it follows that $P_0(3|x,2)$ is also identified. $\square$

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