The Free Installment Puzzle†

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Abstract

This paper studies the effect of interest rates on consumers' demand for installment credit using a new dataset on borrowing decisions by a sample of customers of a credit card company. Customers can pay for individual purchases on installment credit over terms up to 12 months at an interest rate that depends on the customer's credit score and the duration of the installment loan. We show that conventional econometric methods (including regression, instrumental variables, and matching estimators) produce implausible results, and often predict that the demand for installment credit is an *increasing* function of the interest rate. We exploit a novel feature in our data to make more credible inferences about the effect of interest rates on the demand for credit: *free installments* — customers are more or less randomly offered installment loan opportunities at a zero percent interest rate as a promotional device to increase market share. We exploit these free installment offers as a *quasi-random experiment* to help identify the demand for credit using a new flexible "behavioral" discrete choice model of installment credit decisions that accounts for censoring (choice based sampling) in observed free installments. Despite the significant censoring, we show that it is possible to identify consumers' choice probabilities and the probability they are offered free installments. The estimated model results in a downward sloping demand curve for installment credit. While our analysis solves one puzzle, it also raises a new one. The *free installment puzzle* results from our finding that less than 3% of the transactions in our sample were made as free installments, even though the model predicts that the average probability of being offered a free installment in our sample is 20%. Our model predicts a high incidence of "pre-commitment behavior" even among the minority of individuals who do take the free installment offers. For example, the model predicts that 88% of individuals who are offered a 10 month free installment offer will pre-commit at the time of purchase to pay off the balance in *fewer* than 10 installments. This pre-commitment behavior is puzzling since there are no pre-payment penalties, and traditional expected utility models predict that consumers should choose the maximum term offered when the interest rate is 0%. This puzzling consumer behavior also raises questions about the company's behavior: why does it make so many free installment offers if the response to them is so poor? We also present evidence that the increasing interest rate schedule the company offers to its customers may not be profit-maximizing.

Keywords: installment credit, credit cards, demand for credit, micro-borrowing decisions, behavioral finance, quasi random experiment, weak instruments, treatment effects, discrete choice model, pre-commitment 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 traditional *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 American and Asian countries. 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, and thus, 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 that determines the interest rate they would pay for installment loans payable over to 2 to 12 billing statements (months).

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 we study 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.

The 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 $\{2,\dots,12\}$).

To our knowledge there is no previous study that analyzes these sorts of micro-borrowing decisions, especially at the level of detail and with the huge number of observations 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 of their credit card and installment balances. 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. We show that the credit card company uses a particular non-linear increasing interest rate schedule that is *common* to all its customers. Thus, while the intercept of the interest rate schedule does shift to reflect consumer credit score and other credit history information, the schedule of interest rates for installment loans above a "base rate" for a 2 month loan is common to all customers. So, for example, the interest rate the company charges for a 12 month installment loan is 7 percentage points higher than the interest rate it charges to a customer for a 2 month installment loan and this differential is the same for all customers.

The main goal of this paper is to use these data to try to infer the credit demand function and determine its elasticity with respect to the interest rate charged. Unfortunately, we show that conventional reduced-form econometric approaches, including regression, instrumental variables, and matching estimators generate unstable and implausible estimates of the demand for credit. These methods typically predict that installment credit demand is an *upward sloping* function of the interest rate. Of course, we believe this is a spurious finding, a likely result of the failure to adequately control for unobserved factors that cause consumers who are worse credit risks. The higher riskiness induces the company to charge these customers higher interest rates, but at the same time, they may have higher needs for credit than consumers who have better credit scores or other lower cost borrowing opportunities, or who are otherwise not "liquidity constrained." Though we have reasonable instrumental variables such as the Certificate of Deposit or "CD rate" that lead to credible, exogenous variation in the company's cost of credit (and presumably to exogenous variation in the interest rates the company offers to its customers), in practice the "markup" the company charges to its customers over this CD rate is huge and highly variable and much more responsive to other factors such as credit card competition than it is to the relatively minor variations in the cost of credit to banks. As as result we find that the CD rate and other similar instrumental variables are actually very *weak instruments* that are nearly uncorrelated with actual interest rates the company charges its customers. To the extent there is any correlation at all, we find customer interest rates are actually slightly *negatively* correlated with the CD rate and other similar instruments designed to capture exogenous variation in the company's cost of credit. This negative correlation is one source of the spurious prediction that demand for credit is upward sloping.

To make more accurate inferences about the demand for credit, we estimate a behaviorally inspired discrete choice model of a consumer's choice of installment loan duration (i.e. the choice of the number of installments d over which the amount purchased is paid back). The model has a flexible specification, so depending on the value of its parameters, it can approximate a wide variety of rational as well as "behavioral" theories of decision making. The model also accounts for the increasing, time-varying and customer-specific interest rate schedules that are difficult to handle using conventional regression methods. Most importantly, it also enables us to exploit the quasi-random variability in the interest rates charged to consumers as a result of the interest-free installment opportunities that arise from promotions offered by the credit card company, sometimes in conjunction with merchants. We refer to these quasi-random zero interest offers as *free installments.*

However we confront econometric challenges due to significant *censoring* (choice-based sampling) in free installment offers. That is, we only observe a subset of free installment offers that customers actually chose: we do not observe offers that were not taken. Further, the company provided us with no data to independently estimate the probability distribution of how free installment offers were provided to customers over time and across different merchants. However dealing with the censoring problem creates new econometric challenges, since we show that correcting for the censoring results in a likelihood function that is akin to a mixture of choice probabilities that is potentially difficult to identify. However we show that the conditional probability of free installment offers can be separately identified from customers' choice probabilities, and that we can even identify the probability distribution of the maximum duration of different free installment offers. We show that our estimated model provides remarkably good predictions of the borrowing decisions of our sample of consumers, and can successfully control for the endogeneity of interest rates, resulting in a downward sloping demand for credit.

Though we find that the demand for credit downward sloping, there is substantial customer-specific heterogeneity and for most customers the demand for installment credit is highly inelastic and the take up rate for free installment offers is surprisingly low. We estimate that on average, the probability that customers who are offered free installment opportunities will actually take them is only 15%. Instead, in the vast majority of cases, customers choose to pay the purchased amount in full at the next statement date. The model predicts that the probability of purchasing on installment is an increasing function of the transaction amount, and individuals who we suspect are "liqudity constrained" are uniformly more likely to take advantage of free installment offers than individuals who do not appear to be liquidity constrained.

Our estimated model leads to an even more puzzling prediction: a large fraction of the customers who are offered and actually choose free installment offers engage in *pre-commitment behavior* in the sense of making an *ex ante* decision to pay off their purchase in *fewer installments* than the maximal number of installments allowed under the free installment offer. For example, the model predicts that 88% of individuals who were offered and who chose a 10 month free installment offer decided at the time of purchase to pay off their balance due in fewer than 10 installments. This pre-commitment behavior is puzzling since there is no pre-payment penalty in installment loans, so traditional economic theories predict that rational consumers should never pre-commit to a free installment offer for a term that is less than the maximum offered. We find that only a small minority of customers who are offered free installment loans would choose the maximum installment term offered to them (fewer than 1% of those offered 12 month loans, 12% of those offered 10 month loans, and approximately 10% of those offered 3 month free installment loans). The apparent aversion these customers have to taking advantage of zero interest loan opportunities constitutes what we call *the free installment puzzle.*

This aversion is very hard to explain using the standard economic model of behavior by rational individuals who maximize the expected discounted value of a time-additive utility with geometric discounting of future utilities. Early work by Strotz [1955] and subsequent contributions by Laibson [1997] and Gul and Pesendorfer [2001] and others on hyperbolic discounting, temptation, and self-control have shown that time-inconsistent behavior can arise in variety of extensions of the standard model of time-separable geometrically discounted utility maximization. Versions of these theories for "sophisticated" agents (i.e. agents who are self-aware of their time-inconsistent behavior) can explain a desire by some of these individuals to pre-commit to actions that restrain the options available to their "future selves". As Gul and Pesendorfer [2001] note, there are situations where pre-commitment can make these individuals "unambiguously better off when ex ante undesirable temptations are no longer available" (p. 1406).

Casari [2009] notes that "Although the implications of naïveté or sophistication are profound, the behavioral evidence is still quite limited" (p. 119). However there is some evidence, including laboratory evidence that Casari provides in his paper, that shows that "the demand for commitment was substantial" even though "Commitment always carries an implicit cost due to the uncertainty of the future." (p. 138).

Our findings are also puzzling in view of the conventional wisdom that many credit card customers are liquidity constrained and willing to borrow at usuriously high rates of interest. Indeed, at the same time as we infer large fractions of the customers in our sample forgoing free installment opportunities, other customers are paying very high rates of interest, averaging about 15%, to borrow varying amounts over varying lengths of time under traditional positive interest installment purchases. Indeed, the model predicts that even for a single customer, there is significant probability this customer could pay 15% to make an installment purchase for one transaction, yet turn down a free installment opportunity for another!

This seemingly internally inconsistent behavior, coupled with the highly inelastic demand response that we find to variations in interest rates is a puzzle, since we would expect that especially individuals who are liquidity constrained would have a strong motivation to use free installment credit opportunities at nearly every opportunity that is offered to them. Although we have no precise way of identifying customers in our sample who are liquidity constrained, there is substantial heterogeneity in the free installment take up rates in the customers in our sample. We tentatively identify the individuals with the highest take up rates as those who are potentially liquidity constrained, though some of them could also be the rational time-separable, geometric discounted expected utility maximizers — i.e. *homo economicus* — who are predicted to ruthlessly exploit every free installment opportunity that is presented to them.

Our results are also puzzling in view of the aggressive use of free installments by credit card companies as a marketing tool in an attempt to gain a larger share of the credit card market. Why do these companies use free installments so frequently if the take up rates of free installment offers are so low?

Section 2 reviews existing recent literature on credit card usage and borrowing decisions and shows that these studies provide results that are generally consistent with the puzzling behavior we uncover in this study. 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. Though we ultimately conclude that the take up of free installment offers is very low, 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 our discrete choice econometric model of installment choice and derives the likelihood function for the discrete choice model accounting 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 and the predicted installment credit demand function, as well as several counterfactual predictions of customer response to alternative installment credit policies. In particular, using the estimated demand system we 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, which suggests that the company may not behaving in profit-maximizing manner. We view this as a further puzzle raised by our analysis. Section 5 presents our conclusions and speculative comments about the underlying reasons for the free installment puzzle, as well as suggestions for future research that might solve this puzzle if additional data and particularly new experimental data could be gathered.

2 Previous Studies of Credit Card Borrowing

Recent studies of credit card spending and borrowing behavior have also obtained puzzling findings about credit card borrowing decisions similar to those we have uncovered in this study. For example, a number of previous studies have found that the demand for credit is remarkably inelastic including the recent paper by 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).

The fact that credit card borrowing is so high in most countries even though most credit card companies charge interest rates that are significantly higher than "traditional" sources of credit such as home mortgages or equity lines could be regarded as evidence that many credit card holders are at least "credit constrained" in the sense that they either do not have access to, or may have already fully exploited, other lower interest sources of credit and are therefore willing to borrow significant amounts on the margin at the much higher interest rates charged by credit card companies.[1]

Thus, one possible explanation for ADL's results is that their credit card customers are liquidity constrained and "trapped" in a *corner solution* so that neither decreases nor even increases in interest rates have a measurable impact on their borrowing. However, what we find even more puzzling is that ADL

[1] For example in the U.S. the average household credit card balance is over $15,000 and the average credit card interest rate is 14.65% according to creditcard.com, far higher than most other borrowing rates such as auto loans and other types of consumer credit.

found “no evidence of sensitivity to either a 1 or 3 percentage point increase (or the 3 percentage point decrease, cell 9) in our sample, even after conditioning on variables that are thought to be useful in characterizing *unconstrained* individuals.” (p. 21, italics added). This suggests that demand for credit is inelastic even among individuals who are not facing binding borrowing constraints, and we regard this as a much more puzzling finding and one consistent with the new evidence we present in this paper.

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 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 additional types puzzling behavior observed in a different credit card data set analyzed by Ausubel and Shui [2005]. They analyzed an experiment conducted by a large U.S. credit card company in 1995 that generated a mailing list of 600,000 consumers which 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 (including the opportunity to do balance transfers from other credit cards) at various low introductory rates for varying lengths of time. The most popular of these offers was the one offering the lowest interest rate, 4.9% for 6 months. However the response rate to these offers was uniformly small: only 1.07% of the customers who were offered the lowest interest rate actually responded and applied for the credit card, whereas the least popular offer, the one offering a 7.9% interest rate over a 12 month period, had a response rate of only 0.94% (a statistically significantly lower rate of acceptance).

Thus, while there is *prima facie* evidence of some level of consumer response to lower interest borrowing opportunities, the “take up rate” to the chance of a lower interest rate appears to be very small, and this is consistent with our findings of low response to free installment offers. Ausubel and Shui describe several other puzzling aspects of the behavior of the consumers who responded to these offers. The first puzzle is one 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 explanation for the rank reversal that Ausubel and Shui found is that customers who chose the most popular lowest interest offer tended to behave too *optimistically* — they tended to transfer and spend more and acquire higher balances during the introductory period, but failed to pay down these balances or switch to another credit card after the 6 month introductory period ended. At that point the interest rates on their cards reverted back to the normal high annual rates the company charged customers with similar credit scores, ranging from 14% to 16%. Thus, it would appear that the individuals who responded to the most popular offer would have been better off *ex post* if they had taken the least popular offer, i.e. to have borrowed at 7.9% at 12 months rather than 4.9% for 6 months.

The rank reversal puzzle appears to be intimately connected with another puzzle, namely that once customers decided to adopt these cards and start spending on them, the majority of these customers (60%) failed to cancel their accounts after the inroductory rates ended. As Shui and Ausubel 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 *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.[2]

However the puzzle we uncover cannot be so easily ascribed to large switching 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 interest rate installment opportunities (including "free installments") may be even more of a puzzle than the low response rates to low introductory interest rate opportunities that Ausubel and Shui found in their study.

[2]Shui and Ausubel argue that switching costs alone cannot fully explain the puzzles they find: they argue that the puzzling behavior of the customers they studied is best described by a hyperbolic discounting model than it is by a time-consistent dynamic programming model in the presence of switching costs.

3 Credit Card Data

Our data consist of six data files: sales, billing, revolving and collection, credit rating, and a final fiile defining merchant the classification codes that appear in the sales data. For sales data, we should note that there are three types of sales 1) sales payable in full at the next statement date, 2) sales payable in installments over two or more statement dates, and 3) cash advances. Cash advances can either be paid in full at the next statement date, or paid by installment over multiple future statements. Generally purchases and cash advances that are paid by installment are done at relatively high interest rates, except when customers are offered free installment options.

For each credit card purchase we have the following information: customer ID, types of credit card (regular card, gold card, platinum card, debit card, check card, and etc), NSS (number of the sales slip, the unique identifier for each transaction discussed above), the type of sale (including whether the sale is a return or reversal or cancellation), the date of sale (both the date of the actual sale and the date it was "posted" to the credit card), the merchant fee earned by the credit card company, and a code for the merchant type, which will be -1 for merchants that are not "in network" (i.e. for which the credit card company does not have a formal merchant agreement but does the transaction via a competing credit card's network and merchant agreement). The sales data also include the installment term chosen if the purchase was an installment sales transaction, and the up-front cash advance fees in case of cash advance transactions. Overall, we have a total of 182,742 credit card transaction observations for 884 customers, an average of 206 transactions per customer.

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. Thus, we define the "installment choice set" for a consumer as being $D = \{1, 2, \ldots, 12\}$ where a choice of $d = 1$ is equivalent to a regular charge that will be due at the next billing statement, a choice of $d = 2$ corresponds to equal installments payable in the next two billing statements, and so forth, so that $d = 12$ denotes an installment contract that is payable over the next 12 billing statements (which typically arrive monthly).

The vast majority of 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 formally allow for a pre-payment option, so that if a consumer does pre-pay an installment contract, 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 rates of internal rate of return on 8987 installment transactions in our credit card data set. The internal rate of return is the interest rate r that sets the net present value of the stream of cash flows involved in the installment transaction to 0, where the initial purchase is regarded as a cash outflow (from the credit card company) at time $t = 0$, and the successive payments (including interest) are treated as cash inflows at the successive statement dates $t_1, t_2, \ldots, t_d$. 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 orginally 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 rationalize these cases under a standard model of a rational, well-informed consumer. 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.[3]

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 compamy 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. Our data do not contain enough information for us to determine exactly which customers are offered free installments, so we model them as occurring probabilistically, depending on the merchant code where the customer makes a purchase, and dummies for the date of purchase (since some of these promotions tend to be offered at specific times in the year). The vast majority of interest-free installment loans have a term of 6 months or less. If a customer wishes to have a longer term than the one being offered, the customer generally must pay a positive interest rate for longer term installments, according to the schedule described below. In our analysis below, we will assume that when a customer is offered a interest-free installment purchase option, the maximum term is exogenously specified according to a probability distribution that we will estimate from our data.

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

[3]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 orginally 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.

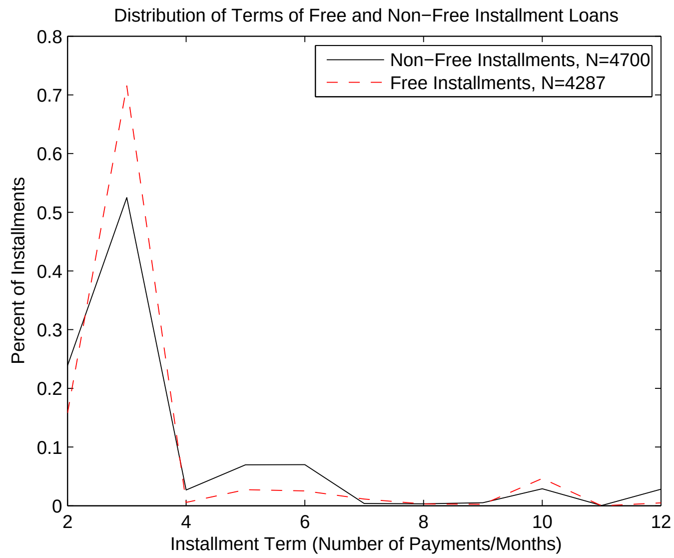
for the installment is typically not available at transaction time, though customers are informed of their installment interest rates on their monthly statements and via their accounts on the company's web site. In situations where the customer is offered a free installment opportunity, however, the cashier will typically inform the customer at the time of purchase. The free installment term is almost 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). The most common terms of free installments is 3 installments, though other maximum terms offered include 10 and 12 months. Free installments are also made available to the company's customers 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. The free installment 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.

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 by 4287 customers who took free installment offers. The distributions are roughly similar except that the mean installment term chosen by customers under positive interest installments, 3.66 payments/months, is longer than the 3.42 payments/months 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 payment terms, though the difference in the two distributions is not particularly striking.

What we cannot tell at this point is whether the lower frequency of the longer duration installments by individuals who chose free installments were a result of these individuals choosing to take the installments for shorter durations than the maximum term that was offered to them, or if the credit card company was simply offering very few 10 and 12 month free installment opportunities to its customers.

Note that due to censoring we are not always able to observe the full duration of installment transactions. For example we observe some installment NSS codes in our billing data for which the date of the initial installment purchase is not in our sales table. This is why, although we can identify 11175 installment transactions in our billing data, when we eliminate censored observations we obtain a smaller set of 8987 *uncensored* observations of installments where we can match the transaction NSS in the billing table to the NSS of the original sale in the sales table. The reason we want to make such matches is because the

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

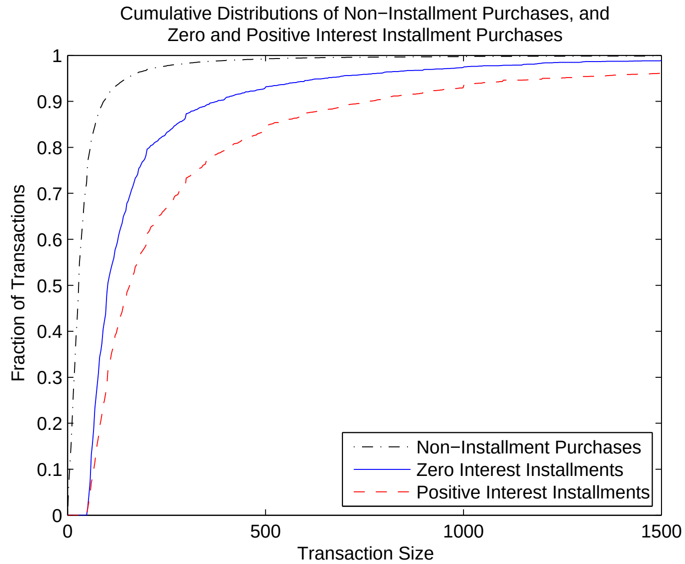


information on the merchant fee charged is only available in the sales table, not in the billing table. As we will show below, the merchant fee contributes a huge amount to the overall rate of return that the credit card company earns on installments. However the rates or return on installments quoted above are *net* of the merchant fee. That is, these are the effective rates of interest that the customer paid for the installment loan. The company earns a much larger rate of return when we also factor in the merchant fee it earns at the time of the installment transaction.

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 example, the median installment at positive interest rates is nearly 60% larger than the median installment done at a zero interest rate. Thus already we can see 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

Figure 2: Cumulative Distributions of Credit Card Transaction Amounts



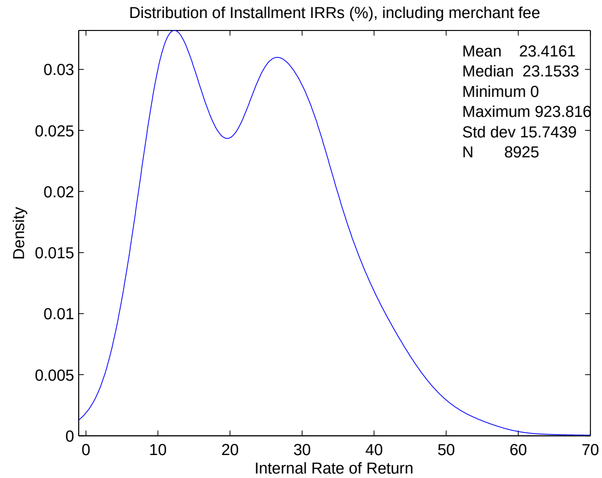
a zero interest rate. Economic intuition would suggest that installments done at a lower interest rate, and particularly at a *zero* interest rate should be signficantly *larger* than those done at a positive interest rate.

In summary, the vast majority of transactions in our sales dataset, 87%, are regular (non-installment) credit card purchase transactions. These tend to be smaller in size with an average size of $50. 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. Specifically, for the subset of installment transactions that we are able to match to the billing table (which enables us to determine the interest rates actually paid, which are not contained in the sales table), approximately 47% of the installments are at zero interest and the remaining ones are done at a positive rate of interest.

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%.

Figure 3 shows that when we include the merchant fee into the IRR calculation, the distribution of

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



returns is shifted significantly to the right. Even with the free installments transactions included, the company 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%. Of course, 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. Overall, we conclude that at least for this company, installment loans are excellent investments that offer very high rates of return with relatively low risk of default.

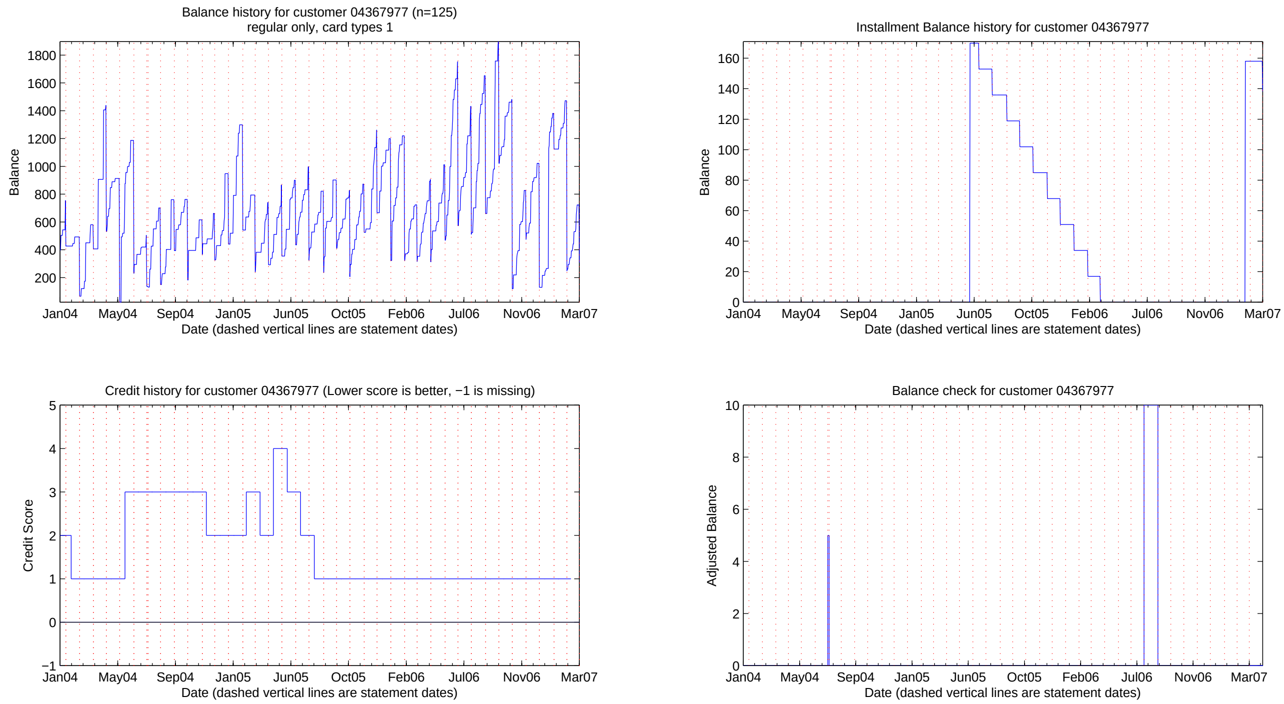
The high rates of return from installments point to the profitability of the company's non-installment credit card purchases as well. The average duration between a purchase and repayment of a non-installment purchase transaction is about 50 days. The average merchant fee that the company earns on its 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).

3.2 Customer-specific returns and profitability

In order to make customer-specific profit and rate of return calculations and analyze time patterns of credit card spending and installment usage, we had to assemble the data that were contained on customers in the sales, billing, and collections tables into a *longitudinal format* that would enable us to track the evolution of both credit card and installment balances on a *day by day basis.* We emphasize that the credit card company did not provide us with these latter data, rather we had to *construct the longitudinal data from the information we were provided.* While at first it may seem to be a relatively trivial exercise in stock/flow accounting to reconstruct these *balance histories* from the sales, billing and collection data, we faced a signficant *initial conditions problem.* That is, we were not given the outstanding installment and credit card balances at any initial date. Instead the collections table would tell us the *statement amount* and information on dates of collection and amounts received, but without knowing an initial balance, it was not always easy to determine if a customer had unpaid balances that needed to be carried over from previous statement dates. We could obtain some indirect evidence of the presence of such overdue balances from late fees charged, but without going into more detail, it proved to be a rather challenging accounting exercise to infer the initial balances of the customers in our sample accounting for the variable left and right censoring in the data.

Figure 4 plots our constructed longitudinal balance history for one of the customers in our data set. We chose this example because the customer made only a single installment transaction and this makes it very easy to understand how the constructed balance histories behave. The top left panel of figure 4 is the overall creditcard balance for this customer. We start observing this customer making a charge of $118.30 on December 12, 2003. However we did not know what the outstanding balance was for this customer at this date since the first statement date for the customers was on January 20, 2004. We were able to determine in this case that this customer had no outstanding unpaid balances and we were able to allocate all charges the customer made in the sales table to matching entries in the billing table and thus track this customer with an accurate determination of the customer's initial balance at the first installment date. Thus, the top right panel of figure 4 displays our inferred balance for this customer, $427.24, on the first statement date we observe for this customer, January 20, 2004.

Figure 4: Balance and credit history of customer 125



The dashed vertical lines in the figures represent the statement dates. Because this company has links to its customers' bank accounts and auto-debits the amount due on each statement date, its customers almost always pay the full balance due *exactly* on each statement date, unlike most American credit card companies where customers may mail in a check or pay online so the date a payment is received and credited frequently differs from the statement date by several days. Thus, this feature leads to the inverted sawtooth appearance of balances in the top right hand panel of figure 4: balances tend to grow monotonically (though stochastically) between successive statement dates representing the spending the customer is doing on their credit card, then it drops discontinuously on each statement date representing the payment of the balance due.

Note that the discontinuous drops in the credit card balance at each statement date do not bring balances exactly to zero. The reason is that the credit card company assigns to each purchase a particular statement date at which that purchase will be due (unless it is an installment, which leads to a different treatment we will discuss shortly) and therefore any purchases a customer makes that are sufficiently close to an upcoming statement date will be assigned as due and payable by the company to the *following* statement date. Thus, the level of credit card balances just after a statement date reflects the sum of all purchases made prior to that statement date that the company assigned to be due and payable at the next statement date. This implies that a person's credit card balance will almost never be exactly zero, even on a statement date — at least for customers who are sufficiently active users of their credit card.

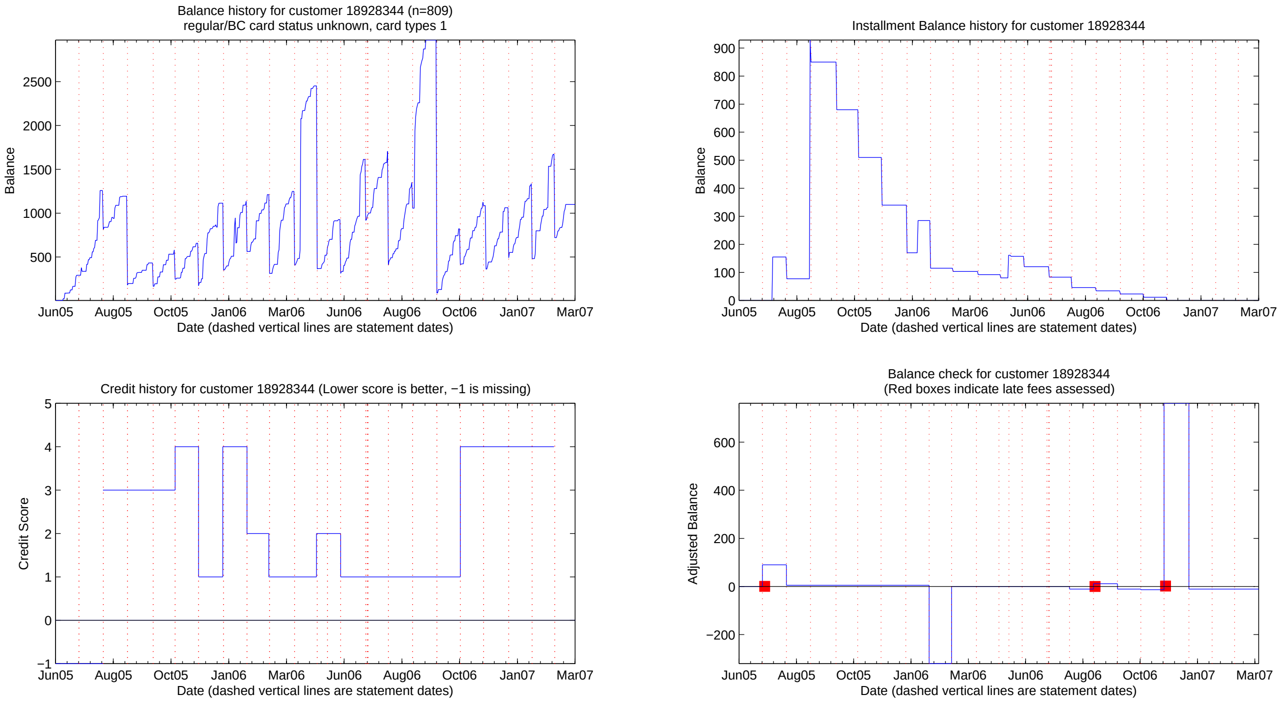
Note the "balance check" in the lower right panel of figure 4. The balance check should be identically zero if we had correctly inferred the customer's initial balance and perfectly tracked all charges and fees. However there were some small charges and payments that we could not reconcile or ascribe to any late charge, annual fee or so forth. These appear as the spikes in the lower right panel of figure 4. In some cases the balance check will be non zero due to a pre-payment or some slightly mis-timed or out of sync payment but shortly after the balance check returns to zero showing that we have basically correctly calculated the full balance history for this customer.

Now consider the top right panel of figure 4, which shows the *installment balance history* for the customer. We keep two separate accounts for the customer, 1) the credit card balance and 2) the installment balance. In this case, we see that the customer did not charge anything on installment until May 31, 2005 when the customer made an installment purchase in the amount of $169.90. This is reflected by the discontinuous upward jump in the installment balance in the top right panel of figure 4. We can see from the graph that this balance was paid off in 10 equal installments of $16.99. This installment also happened to be an interest-free installment and so at each of the 10 succeeding statement dates after the item was purchased on May 31, 2005 the installment balance decreased by $16.99 until the balance was entirely paid off at the statement date of March 20, 2006. Note that on each such statement date, the amount currently due on the customer's installment balance is debited from the customer's installment balance and added to the customer's credit card balance.

The final, lower left panel of figure 4 plots the credit score that the company maintained on this customer. Credit scores are integers on a scale from 1 to 10 with 1 being the best possible credit score and 10 being the worst. This customer generally had excellent credit scores, though for reasons that are not entirely clear from figure 4, the customer had periods of time (particularly May to September 2004 and May to July 2005) where the customer's credit score deteriorated for some reason. We see that the customer's worst credit scores appear to have coincided with the customer's installment purchase in May 2005.

We present another balance history for a more interesting customer, customer 809, in figure 5. This customer generally maintained larger credit card balances and also larger installment balances than cus-

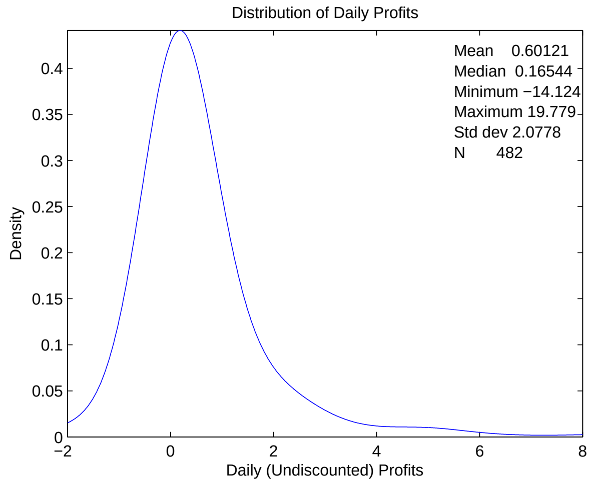
Figure 5: Balance and credit history of customer 809



tomer 125, and we see that this customer also tends to have uniformly worse credit scores than customer 125 had. The red boxes in the lower right panel of figure 5 indicate that the customer was late in making payments and was assessed late payments on three occasions. Because balances due are automatically debited from the customer's bank account, this means that on these three occasions the customer's bank account was *overdrawn* and the credit card company was unable to collect the full statement amount due. While the customer may have also been charged penalties by his/her bank, the late payment penalties charged by this credit card on these three occasions were trivially small by American standards: \$0.18 in each case. The main penalty seems to be a degradation of the credit score, though the late fee of \$0.45 that the customer was assessed on September 4, 2006 did not seem to have any effect on the credit score around that time.

Now that we have shown how we were able to construct the spending and payment patterns and thus the balances histories of our sample of customers, we are now in a position to calculate returns and profitability on a *customer by customer basis.* In terms of profits, we can think of the primary cost of a customer is the company's *cost of credit*, i.e. the credit card company's borrowing cost or opportunity cost of capital.

Figure 6: Distribution of Daily Profits per Customer



In the case of customers who default, the company also loses the uncollectible balance of their loan to the customer. The revenues include annual fees, late fees, interest and service charges, and merchant fees. We note that our measure is one of *gross profits*, i.e. we do not know the cost of things such as 1) rewards programs, 2) advertising costs, and 3) other fixed operating costs such as billing and collection costs and wages and salaries and payments to other credit card companies for out of network transactions.

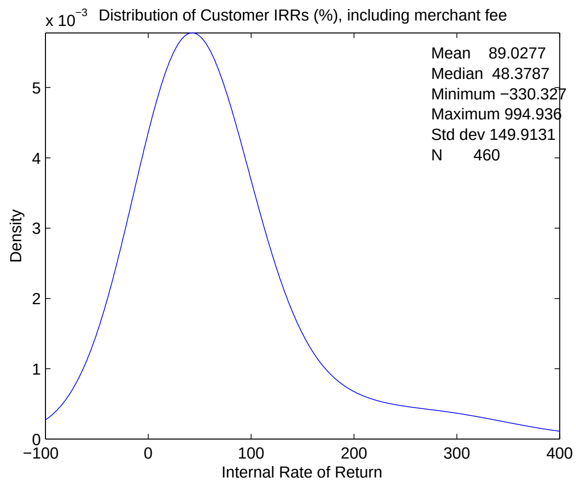
Figures 6 and 7 below calculate the gross profits and rates of return that the company earns on a *per customer* basis. The internal rates of return are calculated based on treating each full customer record as a stream of cash inflows and outflows, with outflows corresponding to purchases made by the customer and inflows being payments received from merchant and from the customer when the customer pays balances due and other fees on the statement dates.

We see from figure 6 that though the average gross daily profits that the company earns per customer is about 60 cents per day, there is huge variability, and the company can incur large losses (amounting to as much as $14 per day) for the customers who default, but balanced by profits as high as $19 per day for some of the most profitable customers. [4]

Figure 7 plots the distribution of profitability of different customers in terms of the gross internal rate of

[4]Note that we calculated the daily profits only for a subsample of customers for which we could observe at least several hundred transactions over an account duration of at least 3 months, so we do not believe the maximum and minimum gross profit values are likely to be results of sampling noise from customers who made only a few transactions and were observed only over short periods of time. For the 23 customers whose accounts were suspended and in collection, we assumed that the total ending balances were uncollectible, and hence these accounts were in complete loss. Often some partial recovery can be obtained for some accounts that have gone into collection after a considerable delay but collection costs typically imply that the company only recovers a small fraction of the amount owed to it for most defaulted accounts.

Figure 7: Distribution of Customer-specific Internal Rates of Return, Including Merchant Fee



return the company makes on them. Here again we see the large degree of variability in return, reflecting that the credit card business does represent an "investment" that has both risk and return. However the most important conclusion to take away from these figures is the huge effect merchant fees have on the overall profitability of this firm. Without merchant fees, the company is already earning a respectable 29% rate of return on its customers, however when we include merchant fee the mean return increases to 89%! Thus, merchant fees account for more than a third of total revenues in our sample, and they account for an even greater share of total profits and the overall high rates of return earned by the firm. The reason for this, of course, is that the merchant fee is a cash flow the company receives right away at the time of each transaction, and there is virtually no risk associated with this stream of revenues. This is why even modest merchant fees equal to 2% of the transaction price contribute so importantly to the bottom line of this company.

Already, our simple exploratory analysis of the credit card data leads to a number of key conclusions. First, we already see the "free installment puzzle" emerging by comparing the distributions of expenditures for zero interest installments to the corresponding distribution of positive interest installments. We showed that the latter distribution stochastically dominates the former distribution, so that at every quantile in the distribution, these customers are spending more on installments that come with a large interest rate than for installments that are offered at an interest rate of zero.

Secondly, we showed that the company is highly profitable and that merchant fees 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. We believe that the company sees merchant fees as a major component of its profits. 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 accepted by more merchants and this in turn enables these firms to charge higher merchant fees.

We believe that the high profitability of customers, particularly profits from merchant fees, provides a strong incentive for credit card companies to try to attract new customers and to stimulate the credit card spending of its existing customers by offering free installment opportunities to their customers. However this only heightens the basic puzzle: if consumers appear to be spending *less* per transaction on the free installment opportunities they are offered in comparison to their average transaction sizes when they pay the full interest rate, what evidence is there that free installments are really stimulating spending or enabling the company to attract a significant number of new customers?

Our analysis is limited by an important *sample selection bias:* our data do not allow us to observe all transactions a customer makes using the various possible means of payment at their disposal, including paying in cash, and paying using an alternative credit card. As a result, our data are not informative as to whether the possibility of free installments induces customers to make a *greater number of transactions* even if the average size of a free installment is less than installments done at a positive interest rate. We do not observe whether customers are aware of the free installment opportunity *prior* to undertaking any purchase using their credit card, and thus, whether this option caused them to make an extra purchase, or switch from paying in cash or using another credit card to making the purchase using the company's credit card under the free installment option.

However what we can learn from our data is the likelihood, conditional on being presented with a free installment opportunity, that a customer is willing to take this opportunity when it is offered to them. We believe it is reasonable to assume that all customers are aware that they can make purchases under installment at a positive interest rate, since this information (and the interest rate schedule they are facing) is part of their monthly statements. Further, customers are usually informed about the option to do an installment on an interest-free basis at the checkout counter, though there are some interest-free installment options that are offered by any merchant during a specific interval of time, and the creditcard company usually heavily advertises these special promotional periods, including in flyers included in customers' monthly statements. Thus, we think that it is plausible that the customers we are studying are fully aware of the various options that they have for making a purchase, including to purchase under a free installment option when it is available.

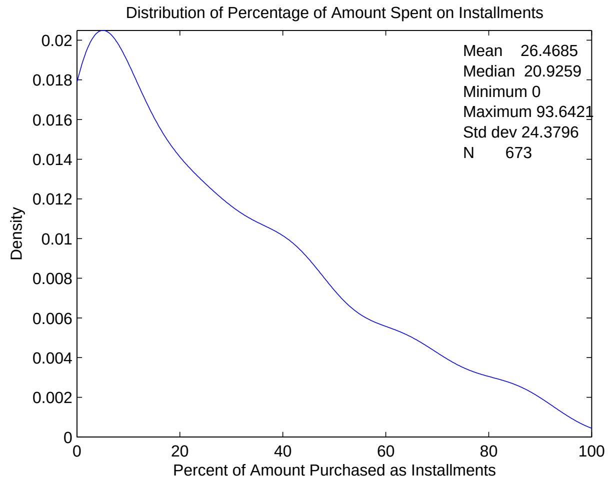
Thus, our data allows us to ask and hopefully answer questions such as, "conditional on deciding to make the purchase, how does the magnitude of the interest rate affect the likelihood the customer will pay for the item on installment?" While our data do not allow us to identify the complete *demand curve for credit*, if we can use our data to provide answers to the questions raised above, we can at least gain new insights into the *conditional demand for credit*, i.e. how interest rates affect the probability that the consumer will borrow (via deciding to pay the amount on installment) conditional on their having made a decision to buy a given item (or spend a given amount on a bundle of goods).

3.3 Characteristics of Installment-Prone Customers

Before we introduce the model and embark on a more structured empirical analysis directed at the specific issue of attempting to estimate the conditional demand for credit we find it useful to present some additional scatterplots that reveal some additional key facts and features and correlates of installment purchase decisions. In particular, we are interested in understanding the degree of customer heterogeneity in our sample, and in particular the question "which types of purchases are made via installment credit, and which types of individuals are the most likely users of installment credit?"

Figure 8 shows the distribution of the *share of all credit card spending* done as installment purchases over the different consumers in our sample. Not shown, due to space limits, is the comparable distribution of the *fraction of credit card transactions* done as installments. The two distributions are similar, though the distribution of the installment share is substantially more skewed and heavy tailed than the distribution of the fraction of transactions done on installment. We see that while installments are less than 9% of all credit card transactions, they account for more than 25% of all credit card spending. Of course, this is due to the fact that the average credit card purchase is $74 while the average installment purchase is $364. Thus, not surprisingly, consumers generally pay for much larger items (or more expensive baskets) on installment, but choose to pay smaller amounts in full at the next statement date. The distribution of transaction sizes (not shown due to space limitations) reveals much greater skewness in the distribution of installment purchases relative to that of credit card purchases as a whole.

Figure 8: Distribution of the Share of all Credit Card Spending done as Installments

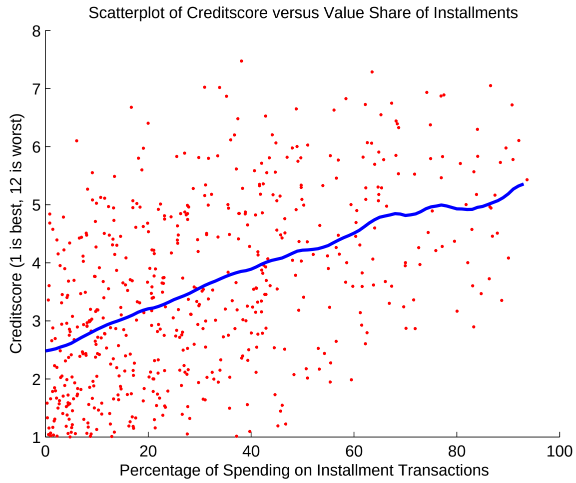


Our analysis reveals a substantial degree of heterogeneity across credit card customers in their propensity to make use of installments to pay for their credit card purchases. Overall our analysis suggests that the best single measure of the propensity to use installments is not the mean fraction of transactions done via installment, but rather the mean share of credit card purchases paid for by installment. Hereafter we will refer to the latter measure as the *installment share.* Now we will turn to a series of scatterplots that relate the installment share to other covariates we observe in our credit card data set.

Figure 9 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 generally negative correlation between the credit score and the installment share (remember that higher credit scores indicate worse credit, so the relationship in figure 9 is actually positively sloped).

We see figure 9 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

Figure 9: Customer-Specific Credit Scores by Installment Share



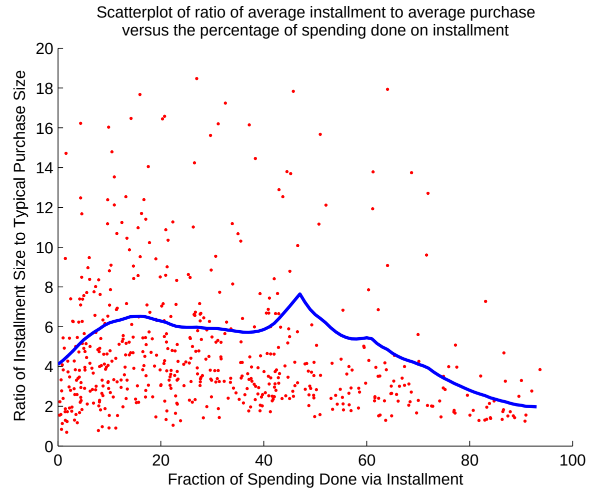
best credit scores also generally the least heavy users of installment, which could be an indication that they are not liquidity constrained, or have other lower cost sources of access to credit elsewhere.

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 the main message from figure 9, namely, that customers who are heavy users of installment spending are also worse credit risks.

Figure 10 presents a scatterplot of the ratio of the size of a typical installment purchase to the typical credit card purchase. As we noted previously, credit card customers generally pay for only relatively large purchases on installment, and pay for the smaller transactions in full at the next statement date. We see that as a function of the installment share, the low intensity installment users tend to buy items on installment that are between 4 and 6 times as large at their typical credit card purchase. However for the heaviest users of installment spending this ratio falls to less than 3, which potentially indicates they are more credit-dependent individuals who are more likely to pay for smaller "everyday" items by installment.

Figure 11 shows that the fraction of installment transactions done as free installments is positively correlated with the 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 11 is consistent with this

Figure 10: Ratio of Installment Size to Typical Purchase Size by Installment Share

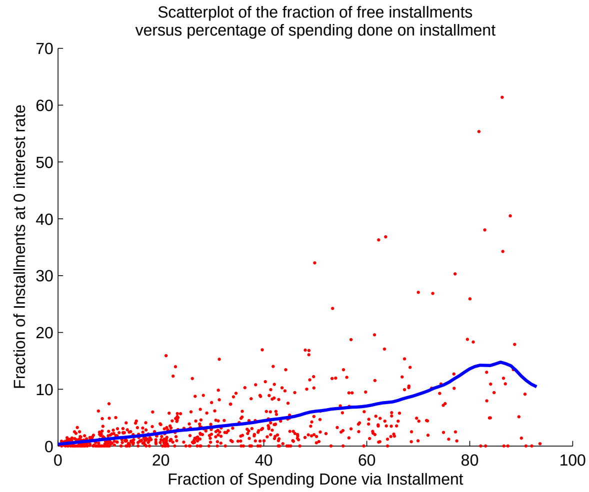


interpretation, and shows that the heaviest installment users are doing as much as 20% of their installment purchase transactions as free installments.

Finally, we conclude this section with figures 12 and 13 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 in an attempt to increase its credit card market share, since doing this increases its leverage in setting merchant fees, which we showed are a major component of the high profitability of this company. However we have also shown that the customers who are most likely to take the free installment offers are those with worse credit scores and higher incidence of 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 credit-worthy 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.

Figure 12 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 that it counteracts the effect of their greater propensity to take free installments, so that overall average installment interest rates paid by its customers increase monotonically as a function of the installment share. Of course the reason for this is likely to be related to the fact that the customers

Figure 11: Fraction of Installment Transactions done as Free Installments by Installment Share



with high installment shares 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. customers with higher scores, which indicate worse credit risks, pay higher interest rates).

Figure 13 plots the average daily profits for each consumer against the installment share. This figure indicates a pronounced upward sloping relationship between the installment share and the profitability of customers. If we believe this is the relevant figure to focus on, then the company's free installment marketing policy seems rational and well targetted: it appears to be succeeding in having the biggest impact on the most profitable customers, but these customers also happen to have worse credit scores and present higher credit risks.

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 one way or the other about the wisdom of free installments at this point. As we noted in the previous section, we cannot address with our data 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? Recall that we are doing our analysis *conditional* on the decision to purchase 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 likelihood of using the company's credit instead of paying for the item using a competing credit card or cash.

Figure 12: Average Internal Rates of Return on Installments by Installment Share

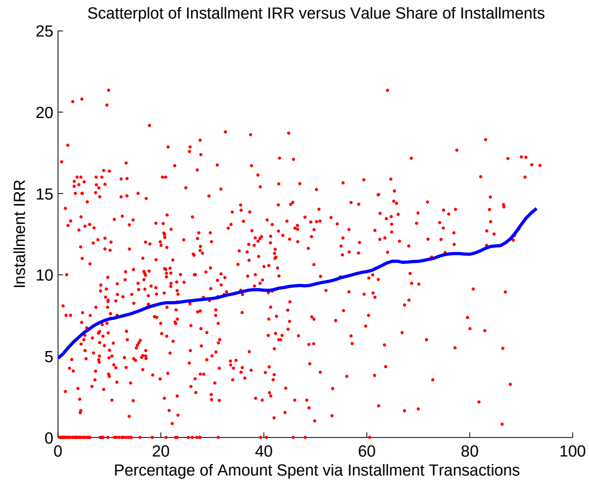
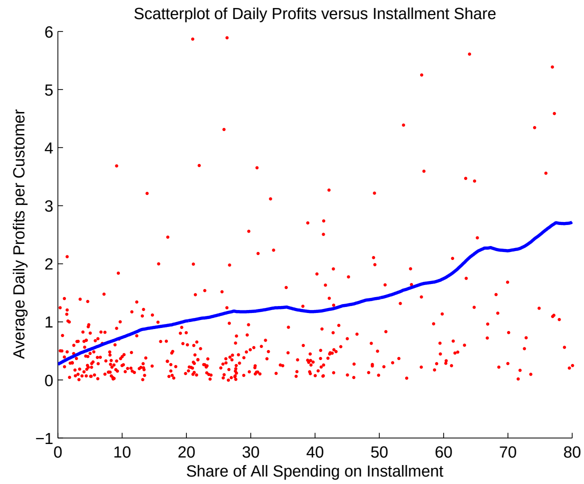


Figure 13: Customer-level Daily Profits by Installment Share



4 Exploiting the Quasi-Random Nature of Free Installment Offers

The goal of this section is to develop econometric methods to make reliable inferences about *the conditional demand for credit.* We do this by formulating a behavioral model of the installment credit decision that enables us to exploit the free installment offers the company provides to its customers as a type of quasi-random experiment. Free installment offers provide a much greater degree of variation in interest rates than what the company's customers would be exposed to if the company only offered its customers the much more limited (and higher) range of positive interest rates in its standard customer-specific installment interest rate schedules. While our credit card data provide a wealth of information on how customers choose different installment terms, and may enable us to determine how their choices are affected by the existence of a free installment offer, we must also be aware of the limits placed on our analysis by the self-selected nature of these data. In particular, we can only study the decision of installment term conditional on the customer's decision to buy a given item in the first place. It is also conditional on the customer's decision to use company's credit card instead of paying by cash or using an alternative card.

4.1 The Conditional Demand for Installment Credit

To order to provide a more precise defintion of the conditional demand for credit, we introduce a bit of notation. Let c denote the decision by the consumer to pay using the company's credit card (as opposed to paying by cash, or using some other credit card). Let r be the interest rate charged to a customer with observed characteristics x for purchasing via installment credit. As we show in more detail below, we should actually interpret r as an entire *interest rate schedule* since the customer can ordinarily choose the term of the installment loan and thus faces an individualized "term structure" of interest rates. Consider the demand for credit via the company's credit card c over a specific interval of time, say one month. The (unconditional) expected demand for credit by a single customer with characterics x, $ED(r,x,c)$ (where x includes variables such as the customer's credit score, spending history, and might also include information on interest rates offered by competing credit cards or interest rates for other sources of credit) can be written as follows

$$ED(r,x,c) = \left[\int_0^\infty a[1-P(1|a,r,x,c)]\,f(a|x,r,c)da\right]\pi(c|r,x)EN(x,r). \tag{1}$$

where $P(1|a,r,x,c)$ is the probability that a customer will choose to pay for a purchase amount a in full at the next statement date given the interest schedule r, the consumer characteristics x and the decision to use the company's credit card c to carry out the transaction. We use $\pi(c|r,x)$ to denote the probability that the customer will use the company's credit card c to pay for the transaction, and $f(a|x,r,c)$ denotes the density of the amount purchased using the company's credit card during any given shopping trip. Finally $EN(x,r)$ denotes the expected number of shopping trips that the customer makes during the specified interval of time. The total unconditional expected demand for credit from all customers who use credit card c is then just a sum over the customer-specific expected demand curves $ED(r,x,c)$ weighted by the number of customers with characteristics x.

The data we have are not sufficient to estimate the objects $\pi(c|r,x)$ or $EN(x,r)$. Separate survey data would have to be collected that would enable us to study the purchase habits of a sample of the company's customers, and how something like free installment offers during a given period of time might affect the number of shopping trips they make (thereby helping us to estimate $EN(x,r)$), or the likeilihood that they will use the company's credit card c to pay for the purchase (providing additional variation to help us to estimate $\pi(c|r,x)$). The objects $EN(x,r)$ and $\pi(c|r,x)$ are also likely to depend on the interest rate schedules and free installment offers and other special incentives provided by other competing credit cards, as well a household-specific financial considerations such as the health and employment status and asset and debt values (including bank account balances) that are not well captured in the more limited set of customer characteristics x that we have in our data. We would require much more extensive survey data that records a much richer set of customer "state variables" x and possibly the use of consumer diaries to record various competing offers and credit opportunities in order to obtain good estimates of π and EN.

However since we do observe all of the purchase amounts that a given consumer makes during any given shopping trip where the customer uses the company's credit card, we can potentially estimate the conditional distribution of spending, per shopping trip, using the company's credit card $f(a|x,r,c)$. Further, since we also observe customers' choices of whether to purchase on installment or whether to pay the amount a in full at the next statement date conditional on having decided to use the company's credit card, we can potentially estimate the *installment choice probability* $P(d|a,r,x,c)$, where the option $d=1$ indicates a choice to pay the purchase amount a in full at the next statement date. If so, then by segregating customers' purchases into those that are paid in full at the next statement date and those that are paid on installment, we can estimate two conditional densities, $f_0(a|x,r,c)$ (i.e. the distribution of purchase amounts that are paid in full at the next statement date) and $f_1(a|x,r,c)$ (the distribution of purchase amounts that are paid for by installment).

$$
\begin{aligned}
f_0(a|x,r,c) &= \frac{P(1|a,r,x,c)\,f(a|x,r,c)}{\int_0^\infty P(1|a,r,x,c)\,f(a|x,r,c)da} \\
f_1(a|x,r,c) &= \frac{[1-P(1|a,r,x,c)]\,f(a|x,r,c)}{\int_0^\infty [1-P(1|a,r,x,c)]\,f(a|x,r,c)da}.
\end{aligned} \tag{2}
$$

We have already used our data to plot the unconditional versions of f_0 and f_1 in figure 2 of section 3, where we showed that f_1 stochastically dominates f_0 (i.e. consumers spend more on installment at every quantile of the distribution). We also computed the unconditional version of f_1 for the case $r = 0$ (free installments) and showed, counterintuitively, that the distribution of spending under free installments is stochastically dominated by the distribution of installment spending under positive interest rates, providing the first indication of the free installment puzzle that we will provide further insight on below.

Thus, we can at least use our data to estimate the *conditional expected demand for installment credit* $ED_I(r,x,c)$ which we define as

$$
ED_I(r,x,c) = \int_0^\infty a f_1(a|x,r,c)da. \tag{3}
$$

Note that $ED_I(r,x,c)$ measures the average size of an installment purchase, *conditional on the choice to make the purchase on installment credit.* However there is also a closely related notion of the conditional demand for installment credit that is probably more relevant from the credit card company's perspective. Define the quantity $P(1|r,x,c)$ as the probability that the customer chooses to pay a purchase in full (i.e. not to use installment credit) *not conditioning on the purchase amount a*.

$$
P(1|r,x,c) = \int_0^\infty P(1|a,r,x,c)\,f(a|x,r,c)da. \tag{4}
$$

Then the other more relevant notion of the "conditional demand for installment credit" is the *per transaction demand for installment credit* $ED_T(r,x,c)$ given by

$$
ED_T(r,x,c) = [1-P(1|r,x,c)]ED_I(r,x,c) = \int_0^\infty a[1-P(1|a,r,x,c)]\,f(a|x,r,c)da. \tag{5}
$$

$ED_T(r,x,c)$ is the product of the expected size of an installment purchase and the probability that the transaction is done as an installment. Since $[1-P(1|r,x,c)]$ represents the share of transactions done under installment, $ED_T(r,x,c)$ represents the expected installment spending *per transaction* by a customer of card c with characterics x whereas $ED_I(r,x,c)$ represents the expected size of an *installment transaction.*

From the definition of the conditional demand function $ED(r,x,c)$ in equation (1) we see that

$$
ED(r,x,c) = ED_T(r,x,c)\pi(c|r,x)EN(x,r), \tag{6}
$$

so the conditional demand for installment credit from credit card c is the product of the demand for credit per transaction taken, $ED_T(r,x,c)$, times the probability the transaction will be done using credit card c, $\pi(r,x,c)$, times the expected number of transactions (shopping trips) per unit of time, $EN(x,r)$. We have already noted that we cannot estimate the objects π and EN from our data, but it may be possible to estimate $ED_T(r,x,c)$, and from this piece alone, we may be able to gain considerable insight into the overall demand for credit. In particular, we would expect that under very general conditions, π should be increasing in r, since higher interest rates would increase the probability that a customer will pay using cash or with other credit cards that offer a potentially lower interest rate. Similarly, it seems reasonable to assume that the expected number of transactions $EN(x,r)$ is either independent of r or a weakly decreasing function of r (which could occur if consumers decide to make a special shopping trip to take advantage of a low interest purchase opportunity). If so, then the issue of whether the conditional demand for credit is upward or downward sloping in r depends on whether the function $ED_T(r,x,c)$ is downward sloping in r.

We might also expect that the conditional demand for installment credit $ED_I(r,x,c)$ to be a downward sloping function of r if customers spend more on installment when the interest rate is lower. Even if the distribution of purchase sizes was unaffected by r (i.e. if $f(a|x,r,c)$ was not a function of r), a downward sloping demand would still follow if the probability that a customer chooses to pay the purchase amount a in full at the next statement date is an increasing function of r (in which case the customer's credit demand is nothing beyond that inherent in the typical "float" i.e. the lag between buying an item with a credit card and paying for it at the next statement date). However we emphasize that it is logically possible for $ED_T(r,x,c)$ to be a *decreasing* function of r even if $ED_I(r,x,c)$ is an *increasing* function of r. This happens when the average size of an installment transaction increases in r, but the probability of purchasing under installment $[1-P(1|r,x,c)]$ decreases sufficiently quickly in r to outweigh the positive effect of r on the average size of an installment transaction.

However since $ED_I(r,x,c)$ is a conditional expectation, it is natural to restrict attention to the subset of transactions that a customer purchases on installment credit, since this implies that for this subset of the data we have the regression equation

$$\tilde{a}_i = ED_I(r,x,c) + \tilde{\varepsilon}_i \tag{7}$$

where $\tilde{a}_i$ is the amount borrowed in the i^{th} installment transaction made by the customer, and $\tilde{\varepsilon}_i$ is a residual satisfying $E\{\tilde{\varepsilon}_i|r,x,c\} = 0$. We can use the regression equation (7) to estimate the conditional demand curve for installment credit, and it seems like a natural place to start is to estimate this regression by ordinary least squares. However rather than attempt to specify parametric functional forms for the underlying components of the regression function $ED_I(r,x,c)$, i.e. the probability $P(1|a,r,x,c)$ and the density $f(a|x,r,c)$ which would result in a more complicated specification that is nonlinear in the underlying parameters, we start by estimating a flexible linear-in-parameters approximation to $ED_I(r,x,c)$.

However, perhaps not surprisingly, when we did these regressions, regardless of the specification we tried, we always found that the regression predicted a strong, and statistically significant *positive relationship* between the expected amount of installment borrowing and the interest rate r. Thus, the regression results predict that the *conditional (expected) demand for credit is upward sloping!*

The question is whether we should believe the regression results or not. We have already seen from figure 2 in section 3 that the unconditional distribution of installment spending at positive interest rates stochastically dominates the distribution of spending at a zero interest rate, and this would be consistent with an upward sloping conditional demand for installment credit. However, there is an equally compelling reason to believe that the ordinary least squares regression results are spurious due to the *endogeneity of the interest rate.*

That is, there are good reasons to suspect that there *unobserved characteristics* of consumers that affect both their willingness/desire to make purchases on credit and the interest rate they are charged. In particular, we would imagine that customers who are *liquidity constrained* and who might exhibit *bad characteristics* that can lead them to simultaneously wish to borrow more but at the same time constitute a *higher credit risk* will have worse credit score and therefore face a higher rate of interest, but will still have a higher propensity to borrow due to liquidity constraints resulting from an absence of alternative lower interest borrowing options. Indeed, figure 9 in section 3 shows that there is a strong correlation between the fraction of spending on installment credit and the credit score: individuals with worse credit scores tend to do a higher fraction of their credit card purchases on installment. Given the monotonic relationship between credit scores and installment interest rates, it is plausible that the large positive and statistically significant regression estimate of the installment interest rate could be completely spurious — a consequence of our failure to adequately control for the potential correlation between r and the error term in our regression equation.

We attempted to deal with the endogeneity problem using the standard arsenal of “reduced form” econometric techniques, including *instrumental variables.* In particular, we have access to daily interest rates that measure the “cost of credit” to the bank for the loans it makes to its customers, including 1) *the* *certificate of deposit CD rate* and 2) *the call rate.* The latter is an interbank lending rate for "one day loans." Both the CD rate and the call rate change on a daily basis. We use these rates as instrumental variables on the theory that in a competitive banking market, no single bank can affect the CD or call rates, and thus changes in these rates can be regarded as exogenous changes in the cost of credit that the credit card companies ultimately "pass on" to their credit card customers. However the instrumental variables (two stage least squares) estimate of the coefficient of the interest rates the company charges its customers is *statistically insignificant.* The coefficient estimates of the interest rate r are highly sensitive to whether we include all installment transactions (including those with $r = 0$) or just those with $r > 0$. We obtain a highly negative but statistically insignificant point estimate in the former case, and positive and statistically insignificant estimate in the latter.

In view of the failure of the various reduced form methods that we tried in the previous section we started to think "outside the box" for other ways to provide more credible and econometrically valid estimates of the conditional demand for credit. Our goal was to develop an approach was that is capable of exploiting the information contained in the company's use of free installment offers as a *quasi random experiment.*

A natural way to do this is to apply one of the standard approaches in the "treatment effects" literature, such as the use of *matching estimators.* Unfortunately the matching estimators were all strongly statistically and economically significant, but with the *wrong sign.* Specifically, the matching estimators, which compare the average installment spending at positive interest rates with a set of matched "controls" where customers purchased under a free installment offer, result in the prediction that "treatment effect" is *negative:* i.e. the average size of a free installment purchase is smaller than for a positive interest installment purchase. We have already seen this result foreshadowed in figure 2 of section 3. The matching estimator shows that even when we attempt to pair specific positive interest installment purchases with corresponding "matching" free installment purchases (including when we use individuals with sufficient numbers of installment transactions as "self-controls", i.e. comparing the average size of positive and zero interest purchase amounts for the *same* individual), the treatment effect is negative. These results from the matching estimator can be interpreted as implying a positively sloped demand curve for installment credit.

Although the quasi-random nature of the way the credit card company offers free installment offers to its customers does provide a strong degree of *prima facie* plausibility for the validity of the key conditional independence assumption that justifies the use of matching estimators, the fact that individuals *self-select* whether or not to take free installment offers suggests that there may be an important problem of *selection on unobservables* that could invalidate a key *conditional independence assumption* that is used to establish the consistency of the matching estimator. However we will also show that a more fundamental reason is that the regression, instrumental variables, and matching estimators are providing a misleading inferences of the demand for credit because they are focusing on estimating the *wrong object* $ED_I(r,x,c)$. We will show below that this function *can* be positively sloped in r under certain conditions, and there is a very natural explanation of why this should be so. But in our opinion, the relevant demand function is not $ED_I(r,x,c)$ but rather $ED_T(r,x,c) = [1-P(1|r,x,c)]ED_I(r,x,c)$, and we will show this function *is* always decreasing in r. However in order to calculate $ED_T(r,x,c)$ we also need to estimate customers' probabilities of choosing various installment terms. Doing this requires some additional econometric modeling that we will turn to now.

4.2 The Discrete Choice Model

We now present an approach that can exploit the quasi random nature of free installment offers that is also robust to the possibility of selection on unobservables and which enables us to estimate customer choice probabilities, and thus both of the objects $ED_I(x,r,c)$ and $ED_T(x,r,c)$. However, in the absence of further data, or without the ability to conduct randomized, controlled experiments, our ability to exploit free installments as a quasi random experiment does require some degree of modeling and assumptions.

Consider first what would be possible if had data from a *randomized controlled experiment* (RCE). Though the company we are studying has not done this to our knowledge, one could imagine that the company could be convinced to undertake such a study to get better estimates its customers' demand for installment credit. For example the ADL 2011 study (Alan et al. [2011] discussed in the introduction) is an example where an enlightened credit card company did choose to undertake a large scale RCE to better understand its customers' demand for credit. In a classical RCE the company would randomly assign a subset if its customers to a control group and a treatment group. Individuals in the control group would continue to receive the same interest rates for installments that they receive under the *status quo* while individuals in the treatment group would be offered randomly assigned alternative installment interest rates. The alternative interest rates could be either higher or lower, or even zero, and by comparing the demand for installment loans for the treatment and control groups, we could essentially use the random assignment as a valid "instrument" to help solve the problem of endogeneity in the interest rate, and make valid inferences about the conditional demand for credit.[5]

In order to exploit the free installment promotions the credit card offers as a type of *quasi random experiment* (QRE) we can no longer 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 do have to undertake some additional modeling and make some additional assumptions.

In particular, the self-selected nature of customers' decisions to take advantage of free installment offers is compounded by another potentially serious measurement issue, namely *censoring.* That is, *our data only allows us to observe free installment offers when customers actually choose them, however for all other non-free installment transactions, we cannot observe whether the customer was not offered a free installment opportunity, or if the customer was offered a free installment opportunity but the customer 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 and self-selection problems, enabling us to infer how interest rates affect the choice of installment term and the conditional demand for credit.

Assume that a customer with characteristics x evaluates each transaction in terms of the *net utility* of postponing the payment of the purchase over a term of d months. The customer faces an interest rate $r(x,d)$ for borrowing over a term of d months, except that $r(x,1)=0$, i.e. all customers get an "interest free loan" if they choose to pay the purchase amount a in full on the next statement date. We normalize the net utility 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 utility is of the form $v(a,x,r,d)=ov(a,x,d)-c(a,r,d)$ where $ov(a,x,d)$ 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

[5]Note that Ausubel and Shui [2005] analyzed data from a randomized experiment, but it was not a RCE since there were no "controls" corresponding to the subjects who were offered the "treatments" (i.e. the six introductory offers). However to a certain extent the individuals who were offered different introductory offers could be regarded as controls. For example the individuals who were offered a 7.9% 12 month introductory offer could serve as controls for the individuals who were offered the 4.9% 6 month introductory offer, but doing this only allows us to test how customers respond to one of these offers relative to the other one. They cannot tell us how the customers who accepted either of these introductory offers behaved relative to customers who were not offered either introductory offer: the company would have have to have included an explicit control group to do this —- i.e. a 7th group of customers who decided to sign up for the credit card without being offered any special introductory offer.

above, $ov(a,x,1) = 0$).

The function $c(a,r,d)$ 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. The net utility

$$v(a,x,r,d) = ov(a,x,d) - c(a,r,d) \tag{8}$$

can therefore be regarded as capturing an elementary cost/benefit calculation that the customer makes each time he/she makes a transaction with their credit card.

We add onto each of the net utilities $v(a,x,r,d)$, $d = 1,2,\ldots,12$ an additional Type I (Gumbel) extreme value error component $\varepsilon(d)$ that represent the effect of "other idiosyncratic factors" that affect an individual's choice of installment term that are independent across successive purchase occasions, so that the overall net utility of choosing to purchase an amount a on an installment of duration d months is $v(a,x,r,d) + \sigma\varepsilon(d)$, where $\sigma > 0$ is a scale parameter that determines the relative impact of the "idiosyncratic factors" $\varepsilon(d)$ relative to the "systematic factors" affecting decisions as is captured by $v(a,x,r,d) = ov(a,x,d) - c(a,r,d)$.[6] 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 if a customer has time-varying but uncorrelated psychological uncertainty about what other bills or payments may be due at various upcoming months $d = 2,\ldots,12$.

As is well known, when we "integrate out" these unobserved components of the net utilities we obtain a multinomial logit formula for the conditional probability that a consumer will choose an installment term $d \in \{1,\ldots,12\}$. For consumers who are not offered any free installment purchase opportunity, their choice set is the full set of 12 alternatives $d \in \{1,2,\ldots,12\}$. However for a consumer who is offered a free installment opportunity to spread a purchase a over a maximum of $\delta > 1$ payments, we will test a key *dominance assumption*, namely that all customers strictly prefer a free installment opporunity 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.

We consider and test two versions of the dominance assumption. The *strong dominance assumption* is the one described above, namely that a customer who is offered any free installment offer of maximum

[6] Specifically, we assume that $\varepsilon(d)$ are "standardized" Type I extreme value random variables, standardized to have scale parameter equal to 1, so $\sigma\varepsilon(d)$ is then a Type I extreme value random variable with scale parameter σ.

duration δ will never choose any duration $d < \delta$ including the option of paying in full for the amount purchased at the next statement date, which is the choice of alternative $d = 1$. 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 in the limit as $\sigma \downarrow 0$, since for any free installment offer we will have $c(a,r,d) = 0$ for $d \leq \delta$ where δ is the maximum allowed duration of the free installment offer. As $\sigma \downarrow 0$, the implied choice probabilities from the discrete choice model will assign probability 0 any choice $d < \delta$, though it does not rule out the possibility that a sufficiently liquidity constrained consumer could pay a positive interest rate for a installment loan of longer duration than the maximum term δ offered under the free installment option.

We will show shortly that we can strongly reject the strong dominance assumption. In particular. while the credit card does not keep records that can enable it to precisely estimate what the overall probability of free installment offers is, company employees we did speak to are quite certain that the rate is significantly higher than 2.6%. which is the fraction of transactions we observe being done under free installment offers, and would constitute an estimate of the average probability of free installment offers in our sample if the strong dominance assumption held.

Therefore we consider and test an alternative *weak dominance assumption.* Under the weak dominance assumption, we assume that there may be "mental accounting costs" that might deter a customer from taking an installment offer, even if it were free, but if a customer finds it optimal to incur these mental accounting costs and choose the free installment option, then these customers will always choose a loan duration d equal to the maximum loan duration δ permitted by the company under the free installment offer. After all, since there is no pre-payment penalty, if *ex post* events make it optimal for the customer to pay off the installment balance faster than over the δ months allowed under the free installment offer, the customer is always free to do so. As we noted in the introduction, it is very hard for standard economic theories to explain why an individual would pre-commit to taking the installment for any shorter term $d \in \{2,\ldots,\delta-1\}$ when there is no apparent cost to choosing the maximal allowed term δ and choosing the maximal term gives the customer the option that has the maximal *ex post* flexibility in terms of uncertain future events that may affect his/her ability to pay off their account balance.

We do not test a third variant of the dominance assumption, namely, that if a customer were to choose an installment loan of shorter duration than the maximum duration offered, $1 < d < \delta$, the customer would always choose this loan to be at a zero interest rate rather than at positive interest rate. We cannot test this even weaker variant of the dominance assumption because the credit card company *forces* customers to choose the zero interest installment option over the positive interest installment option whenever the duration of their installment loan is less than the maximum duration offered, δ. However customers do always have the option to choose installment loans of *longer* duration than the maximum duration of the free installment offer δ (unless $\delta = 12$) and then in such cases the customer would pay a positive interest rate to choose one of the longer installment durations $d \in \{\delta+1,\dots,12\}$. As we will see, the model allows for this possibility and predicts that it will occur, though the probability that it happens is small.

If we observed whether consumers had a free installment option *regardless of whether or not they choose the free installment option* our life would be much simpler. Then we could write a *full information likelihood function* that is the product of the probablity of whether or not the customer is offered a free installment option or not on any specific purchase occasion times the probability of their choice of installment term (where the choice probability is conditional on whether they are offered a free installment option or not). This would result in a relatively easy estimation exercise, where we could use a flexible parameterization for the option value function and estimate the model no differently than most static discrete choice models are estimated.

In particular, we would then be able to directly observe violations of the weaker version of the dominance assumption, namely we could observe situations where a customer was offered a free installment opportunity of duration $\delta > 2$ and nevertheless, the customer chose a free installment of a shorter duration $d < \delta$. Even though we cannot directly observe such violations of the dominance assumption in our data set, we are able to estimate the probability that they occur, and thereby test the hypothesis that the weaker form of the dominance assumption holds empirically.

However to do this, we need to recognize the difficulties imposed by the fact that our observations of free installment opportunities are censored resulting in econometric problems that are very similar to those that arise under *choice based sampling.* In such a situation, how is it possible to infer the probability that customers are offered free installment options? More importantly, how can we estimate the probability that customers do not choose the free installment option when it is offered to them? We show that we can solve the problem by forming a likelihood function that accounts for the censoring, by treating the possible existence of a free installment option as a type of *unobserved choice set* for the customer. We can calculate the probability that customers will face various installment credit choice sets, and this results in a likelihood function that takes the form of a *mixture model* where the probability of being offered a free installment option is a key part of the *mixing probabilities* (there are additional component corresponding to a probability distribution over the duration δ offered to customers who are offered free installment options).

Though there are well know econometric diffficulties involved in identifying mixture models, and the degree of censoring in our application is very high (we only observe free installments being chosen in 2.6% of the 167,946 customer-purchase observations used in our econometric analysis), we show that under reasonable but *parametric* assumptions about the forms of the probability function governing free installment options and for flexibly parameterized functional forms for customers' option value functions $ov(a,x,d)$, we are able to separately identify the probability of being offered a free installment, $\Pi(z)$, (which depends on a set of variables z including time dummies and merchant class code dummies) from consumers' conditional choice probabilities for installments $P(d|a,r,d,x)$.

Thus, we are able to show that the small, 2.6% frequency of free installments in our sample is not explained by a low offer rate Π and a high acceptance rate P (for example, the extreme where every customer takes free installments whenever they are offered, and the 2.6% frequency of free installments is due to the company offering them only 2.6% of the time) from the case we actually find, which is that customers are offered free installments on average 17% of the time but they take these free installments on average only 15% of the time. We will discuss how our model is able to distinguish between these two cases below, but intuitively, we are able to dismiss the first explanation on the grounds that if free installments were so likely to be chosen, then our model also implies that positive interest installments would be much more likely to occur than the 2.8% rate we observe in our sample.

We find that the model fits the data well, but implies a highly inelastic demand for credit. In particular, we find a relatively limited degree of consumer responsiveness to free installment options: the probability of turning down these options is relatively high even though we estimate that for our sample customers are offered free installments approximately 20% of the time, Thus, on average customers take free installments in only 15% of the times that they are offered them. We refer to this low take-up rate of what would appear to be a "costless" option for an interest-free loan as the *free installment puzzle.*

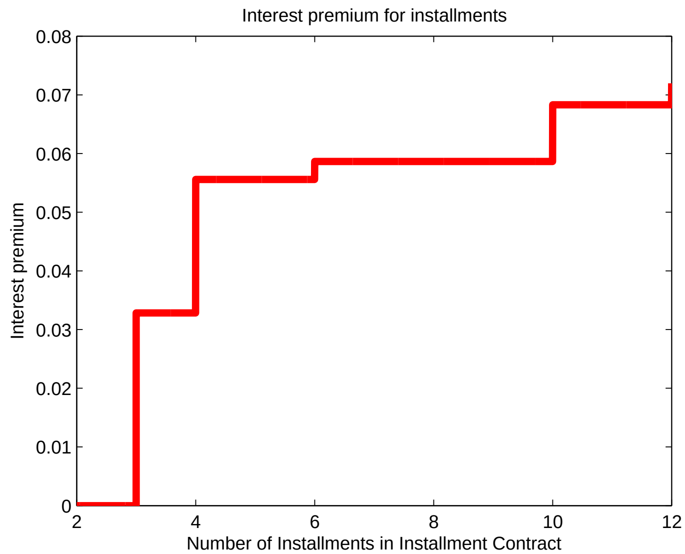
Our data are not sufficiently detailed to enable us to delve a great deal further and uncover a more detailed explanation for the reasons *why* customers appear so unwilling to take up free installments and why their demand for credit is so inelastic. Our model attributes the reasons for this low takeup rate to a combination of a relatively low option value of credit relative to the cost of credit and to relatively high fixed transactions costs associated in undertaking each installment purchase transaction. However these "transactions costs" could also be interpreted as capturing *stigma* associated with installment transactions, and the low option value may be associated with a fear (whether rational and well-founded or not) that installment credit balances could undermine one's credit rating, or that there are some unspecified hidden future fees or "gotcha's" associated with installment loans beyond the interest rate (e.g. an unfounded belief that there are pre-payment penalties, or a concern that an installment balance could lead to a higher risk of missed future payments and thus late fees). Unfortunately, we are unable to delve further to determine which of these various more subtle psychological explanations is the dominant explanation of the free installment puzzle.

4.3 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. We will show that there is not a single schedule but instead customers are offered individualized interest rate schedules. These schedules are determined according to a rather complex 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 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 above 0.99, indicating that we were successful in econometrically uncovering the interest formula the company uses to set interest rates to its customers. We found that the most important factors determining the customer-specific interest rates are factors a) and b) above. In particular, we found that consumer characteristics a) determine the "base interest rate" for an installment loan with $d = 2$ payments, but there is a step-wise increasing schedule that is *common to all consumers* that determines successive increases in the interest rate offered for longer installment terms $d > 2$. Figure 14 graphs the interest "premiums" customers must pay for successively longer installment terms d.

Figure 14: Interest Premium for Installment Purchases as a function of the Installment Term



Let $\overline{r}_t(d,x)$ 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. By our discussion above, this schedule has the form

$$\overline{r}_t(d,x) = \rho_0(x,t) + \rho_1(d), \tag{9}$$

where the effects of time-varying macroeconomic and market conditions are captured by t, and the characteristics of the particular consumer x only enter via the "intercept" term $\rho_0(x,t)$, and $\rho_1(d)$ represents the *interest premiums* for installments longer than $d = 2$ months. Thus $\rho_1(d) = 0$ for $d \leq 2$ and $\rho_1(d) > 0$ is given by the function graphed in figure 14 for $d \geq 2$. Note that our regression analysis of actual interest rates charged to customers confirms that the ρ_1 function 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.

Consider a consumer with characteristics x_t who is interested in purchasing a given item that costs an amount a_t on calendar day t. We take as a given that the consumer is going to make the purchase and focus on modeling the customer's choice of installment term, i.e. whether to pay the balance a_t in full at the next statement ($d = 1$), or request an installment purchase option with $d > 2$ installments at an interest rate of $r = \overline{r}_t(d,x)$. Later, we will consider separately the question of how interest rate schedule affect the size of the transaction by estimating the conditional distribution $f(a|x,r,c)$ in equation (1) above.

4.4 Likelihood Function

The consumer chooses installment term $d \in D = \{1,2,\ldots,12\}$ if and only if

$$v(d,x_t,a_t,\overline{r}_t(d,x)) + \varepsilon(d) \geq \max_{d' \in D} \left[v(d',x_t,a_t,\overline{r}_t(d',a)) + \varepsilon(d') \right]. \tag{10}$$

The extreme value assumption implies that the conditional probability of observing the consumer choose installment term d is (after integrating out the unobserved components of utility $\{\varepsilon(d')|d' \in D\}$ is given by the standard multinomial logit model

$$P_+(d|a_t,x_t) = \frac{\exp\{v(d,x_t,a_t,\overline{r}_t(d,x_t))/\sigma\}}{\sum_{d' \in D} \exp\{v(d',x_t,a_t,\overline{r}_t(d',x_t))/\sigma\}}, \tag{11}$$

where the $+$ subscript denotes a choice situation where the consumer can only choose from installment that have positive interest rates, $\overline{r}_t(d,x) > 0$ for $d \in \{2,\ldots,12\}$. The choice set D in this case is just the set $D = \{1,2,\ldots,12\}$ where choice $d = 1$ denotes the decision to pay the amount of the purchase a in full at the next statement date, and choices $d = 2,3,\ldots,12$ denote the decision to spread out the payment over d installments over the next d statement dates, though at the cost of a positive interest rate on the outstanding installment balance.

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_0 payments (months) where $\delta_0 \leq 12$. 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 $d \in \{2,\ldots,\delta_0\}$, or to pay over even longer installment durations $d \in \{\delta_0+1,\ldots,12\}$, but at the cost of paying a positive interest rate on these installment balances. The consumer will choose a free installment option $d \in \{2,\ldots,\delta_0\}$ that satisfies

$$v(d,x,a,0) + \varepsilon(d) = \max \left[\max_{d \in \{1,\ldots,\delta_0\}} v(d,x,a,0) + \varepsilon(d), \max_{d' \in \{\delta_0+1,\ldots,12\}} \left[v(d',x,a,\overline{r}_t(d',a)) + \varepsilon(d') \right] \right], \tag{12}$$

where for simplicity we omitted the t subscripts on the a and x variables (and will continue to do this below).

However a customer may also choose a *positive* interest rate installment option $d \in \{\delta_0+1,\ldots,12\}$. The customer will do this if they obtain a greater net benefit for borrowing for a longer term than the maximum term δ_0 allowed under the free installment offer. This will occur when

$$v(d,x,a,r(d_+,a)) + \varepsilon(d) = \max \left[\max_{d' \in \{1,\ldots,\delta_0\}} v(d',x,a,0) + \varepsilon(d'), \max_{d' \in \{\delta_0+1,\ldots,12\}} \left[v(d',x,a,\overline{r}_t(d',a)) + \varepsilon(d') \right] \right], \tag{13}$$

with the understanding that the set of positive interest rate choices $\{\delta_0+1,\ldots,12\}$ is empty if $\delta_0=12$. The implied choice probability is denoted by $P_0(d|x,a,\delta_0)$ and is given by

$$P_0(d|x,a,\delta_0)=\frac{\exp\{v(d,x,a,\overline{r}_t(d,x))/\sigma\}}{\sum_{d_0=1}^{\delta_0}\exp\{v(d_0,x,a,0)/\sigma\}+\sum_{d_+=\delta_0+1}^{12}\exp\{v(d_+,x,a,\overline{r}_t(d_+,x))/\sigma\}}, \tag{14}$$

if $d\in\{\delta_0+1,\ldots,12\}$, i.e. the consumer chooses an installment term longer than the maximum free installment duration offered, δ, or

$$P_0(d|x,a,\delta_0)=\frac{\exp\{v(d,x,a,0)/\sigma\}}{\sum_{d_0=1}^{\delta_0}\exp\{v(d_0,x,a,0)/\sigma\}+\sum_{d_+=\delta_0+1}^{12}\exp\{v(d_+,x,a,\overline{r}_t(d_+,x))/\sigma\}}, \tag{15}$$

if $d\in\{1,\ldots,\delta_0\}$, 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 to pay the amount a over 2 to up to δ_0 installments.

The parameters to be estimated are $\theta=(\sigma,\phi,\alpha,\beta)$ where ϕ are parameters of consumers' utility/value functions $v(d,a,x,r,\phi)$. For notational simplicity, we will include the extreme value scale parameter σ as part of the ϕ vector, so the implied choice probabilities when a consumer is offered a free installment offer of duration δ_0, $P_0(d|a,x,\delta_0,\phi)$, and the choice probability when the consumer is not offered a free installment offer, $P_+(d|a,x,\phi)$, are both functions of an unknown vector of parameters ϕ to be estimated. 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 characterizing the distribution of offered durations of free installment offers $f(\delta_0|z,\beta)$. We use the method of maximum likelihood to estimate these parameters. We now have the probability notation that allows us to write a likelihood function 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 $T=\{t_1,\ldots,t_N\}$. 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_0 but decided to choose a longer term option at a positive interest rate. Our likelihood must be adjusted to account for these possiblities and to "integrate out" the various possible interest-free installment options that the consumer could have been offered but which we did not observe.

As noted above, $\Pi(z_{it}|\alpha)$ is the probability that a customer i who makes a credit card purchases at date t is offered an interest-free installment opportunity. The vector z_{it} does not contain any customer-specific variables x, but does include dummies indicating the date of the purchase and the type 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). Conditional on being offered an interest-free installment purchase option, let $f(\delta_0|z,\theta)$ be the conditional distribution of the installment term that is associated with the interest-free installment option. Note that $f(1|z,\theta) = 0$: by definition an installment payment plan must have 2 or more future payment dates. Equivalently, by default every consumer has the option to pay in a single installment, and they get what amounts to an interest free loan covering the duration between the date of purchase until the next billing date.

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

$$L_0(\theta) = \prod_{t \in T_0} P(d_t|x_t, z_t, a_t, \theta) \tag{16}$$

where

$$P(d|x,z,a,\theta) = \sum_{\{\delta_0|d \leq \delta_0\}} P_0(d|x,a,\delta_0,\phi) f(\delta_0|z,\beta)\Pi(z|\alpha), \tag{17}$$

where for each transaction in the set of times T_0, d_t is less than or equal to the free installment (maximum) term $\delta_{0,t}$ 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 (weak) dominance assumption holds, we have $P_0(d_t|x_t, a_t, \delta_{0,t}, \phi) = 0$ if $d_t \in \{2, \ldots, \delta_{0,t} - 1\}$, i.e. the customer always chooses the maximal loan duration permitted under the free installment offer. In that case we have $d = \delta_0$ and

$$P(d|x,z,a,\theta) = P_0(d|x,a,d,\phi) f(d|z,\beta)\Pi(z|\alpha). \tag{18}$$

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

$$P(1|x,z,a,\theta) = \Pi(z|\alpha)\left[\sum_{\delta_0 \in \{2,\dots,12\}} P_0(1|x,a,\delta_0,\phi)\,f(\delta_0|z,\beta)\right] + [1-\Pi(z|\alpha)]P_+(1|x,a,\phi). \tag{19}$$

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

$$P(2|x,z,a,\theta) = [1-\Pi(z|\alpha)]P_+(2|x,a,\phi). \tag{20}$$

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

$$P(d|x,z,a,\theta) = \Pi(z|\alpha)\left[\sum_{\delta_0 < d} P_0(d|x,a,\delta_0,\phi)\,f(\delta_0|z,\beta)\right] + [1-\Pi(z|\alpha)]P_+(d|x,a,\phi). \tag{21}$$

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_0 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

$$L_1(\theta) = \prod_{t \in T/T_0} P(d_t|x_t,z_t,a_t,\theta). \tag{22}$$

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 transations 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

$$L(\theta) = \prod_{i=1}^{N} L_{i,0}(\theta)L_{i,1}(\theta). \tag{23}$$

4.5 Model Specification

We maximize the log-likelihood with respect to θ for various "flexible functional forms" for $v(d,x,a,r)$ that are designed to capture the net "option value" to the customer of purchasing an item under installment. We assume that $v(d,x,a,r)$ has the additively separable representation given in equation (8) above. Thus, we can view consumers as making "cost-benefit" calculations where they compare the benefit or option value $ov(a,x,d)$ of paying a purchase amount over $d > 1$ installments with the interest costs $c(a,r,d)$. For free installments, we have $c(a,r,d) = 0$, but this does not necessarily imply that customers will necessarily always take every free installment option. One reason is due to the randomly distributed *IID* extreme value shocks $\varepsilon(d)$ representing unboserved idiosyncratic factors that affect a consumer's choice of the installment term. In some cases these shocks will be sufficiently negative to cause a consumer not to take a free installment offer even if $ov(a,x,d)$ is positive (and thus higher than the utility of paying the purchase in full at the next statement date, which is normalized to 0). Another reason is that we specify the option value function as follows

$$ov(a,x,d) = a\rho(x,d) - \lambda(x,d) \tag{24}$$

where we can think of $\rho(x,d)$ as the percentage rate 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 this component is assumed not to be a function of the amount purchased a whereas the other component of the option value, $a\rho(x,d)$ is a linear function of the amount purchased. This implies that *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 costs" 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 that undertaking another installment transaction will 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 $\overline{r}_t(d,x)$ only enters via the cost function $c(a,r,d)$. This is an important identifying assumption. Furthermore 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

$$c(a,r,d) = a\left(1-\exp\{-rt_d/365\}\right), \tag{25}$$

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 $r = \overline{r}_t(d,x)$. Recall that this is the positive interest rate that company offers to the customer for an installment purchase with term d. Notice that if $d = 1$ and the consumer chooses not to do an installment then $c(a,r,1) = 0$. Notice also that for any 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 $c(a,r,d) = \overline{r}_t(d,x)at_d/365$, 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.

Notice that the $c(a,r,d)$ function has no unknown parameters to be estimated. The parameters to be estimated are the parameters ϕ entering the option value function, $ov(a,x,d,\phi)$, the scale parameter σ of the Type I extreme value distributions for the unobserved components of the $v(a,x,r,d,\phi)$ functions, and α, the parameters of the probability of being offered a free installment, $\Pi(z,\alpha)$, and β, the parameters of the probability distribution over the maximum term of the free installment offers that are offered to consumers, $f(d|z,\beta)$.

Let $\theta = (\sigma,\phi,\alpha,\beta)$ be the full set of parameters to be estimated. Table 1 presents the maximum likelihood estimates of (σ,ϕ) Clearly, the parameters of interest are (σ,ϕ). We are interested in the α

parameters only to the extent that we are interested in learning the conditional probability $\Pi(z,\alpha)$ that credit card customers are offered free installment options when shopping at different merchants at different periods of time. Thus, due to space constraints we omit the maximum likelihood estimates of the 26 α parameters.

To understand the parameter estimates, note that we have specified $ov(a,x,d) = a\rho(x,d)$ where

$$\rho(x,d) = \frac{1}{1+\exp\{h(x,d,\phi)\}} \tag{26}$$

where

$$\begin{aligned} h(x,d,\phi) \quad = \quad & \phi_0 I\{d \geq 2\} - \sum_{j=3}^{12} \exp\{\phi_{j-2}\} I\{d \geq j\} + \phi_{11}\text{ib} + \phi_{12}\text{installshare} \\ & +\phi_{13}\text{creditscore} + \phi_{14}\text{nlate} + \phi_{15} I\{r=0\}. \end{aligned} \tag{27}$$

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

$$\lambda(x,d) = \exp\left\{\phi_{16} I\{r=0\} + \phi_{17}\text{installshare} + \sum_{j=2}^{10} \phi_{16+j} I\{d=j\} + \phi_{27} I\{d>10\}\right\}. \tag{28}$$

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.*

The most important variable of the *x* variables 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 *nlate* are as powerful as the *installshare* variable in enabling the model to fit the data can capture the large degree of customer-specific heterogeneity that we found.

An alternative 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, $\rho(x,d,\tau,\phi)$. However, we have had considerable difficulty in estimating specifications with unobserved heterogeneity due to the fact that we have an unbalanced panel where for some consumers we observe many hundreds of transactions. Conditioning on τ, the likelihood for these hundreds of conditionally independent choices of installment duration is typically a *very very small number.* Unobserved heterogeneity specifications require us to take averages (i.e. integrate over the distribution of τ) of these very small numbers and we often found that when we tried to take the logarithm of the resulting *mixture probability* it was sufficiently small to be below the "machine epsilon" i.e. the lowest positive number a computer is capable of representing, even on 64-bit machines.

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 have more than 100 transaction observations 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 (27) and (28) 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 $\hat{\phi}_{i,17}$, 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.[7]

We found that although there is a substantial amount of customer-specific differences in the estimated $\hat{\phi}_{i,12}$ and $\hat{\phi}_{i,17}$ coefficients, *the estimated coefficients were well approximated by a simple linear functions of the installshare variable.* That is, we found that

$$\hat{\phi}_{i,12} = \hat{\phi}_{12}\text{installshare}_i + u_i \tag{29}$$

$$\hat{\phi}_{i,17} = \hat{\phi}_{17}\text{installshare}_i + e_i \tag{30}$$

where $\hat{\phi}_{12}$ is the maximum likelihood estimate of the coefficient ϕ_{12} in equation (27) annd $\hat{\phi}_{17}$ is the maxi-

[7]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.

mum likelihood estimate of the coefficient ϕ_{17} in equation (28), 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, we think it is actually quite harmless and merely a parsimonious way of approximating the estimated parameter heterogeneity in our estimated model. Even though there is some degradation in the likelihood resulting from using $\hat{\phi}_{12}\text{installshare}_i$ instead of $\hat{\phi}_{i,12}$, and $\hat{\phi}_{17}\text{installshare}_i$ instead of $\hat{\phi}_{i,17}$, there were major computational savings resulting from having to estimate only 29 ϕ parameters instead of $965 = 940 + 25$ (here we account for the 27 remaining parameters less the two identifying normalizations discussed in footnote 7 above), and we found that our estimates of the other ϕ parameters were not significantly changed as a result of our use of this convenient approximation and computational simplification.

4.6 Identification

It is not immediately obvious that the econometric model we introduced in this section is identified. The likelihood function we derived in section 4.4 can be regarded as a type of *mixture model* since the conditional probabilities $P(d|x,z,a,\theta)$ entering the likelihood function are themselves mixtures of the underlying choice probabilities $P_0(d|x,a,\delta,\phi)$ and $P_+(d|x,a,\phi)$ that constitute the probabilities of choosing different installment terms with and without the presence of a free installment offer with maximum duration δ, respectively. As is well known, it is very difficult to identify econometric models that are formulated as mixtures of probabilities, since a wide variety of probability distributions can be well-approximated by convex combinations of a given a set of probabilities (also known as "components"), and there are generally many different ways to do this. For example, Henry et al. [2011] note that "Without further assumptions there is of course no way to identify the mixture weights and components" (p. 2).

Identification can be especially problematic when we relax the weak dominance assumption, since then both of the conditional probabilities P_+ and P_0 have the same support $\{1,\dots,12\}$, and the conditional probabilities entering the likelihood are mixtures of these two conditional probabilities. If we view the identification problem from the lens of "multicollinearity", another way to state the concern about identification is that it is far from obvious that probabilities P_0 and P_+ are sufficiently different from each other to rule out the possibility that are many different ways to represent the "reduced-form" probabilities $P(d|x,z,a,\theta)$ that enter the likelihood in terms of various convex combinations of the "structural" probabilities P_+ and P_0.

Despite these concerns, we find that the model *is* identified and surprisingly, the method of maximum likelihood is able to distiguish between the alternative explanations for the low take up rate of free installments. In particular, we are easily able to reject the hypothesis that the low take up rate of free installments is simply an indication of a very low probably of being offered free installments for the reasons already discussed in section 4.2. Note that the model is fully *parametric* and the standard argument for identification of parametric involves showing that the expectation of the log-likelihood function, $E\{\log(P(\tilde{d}|\tilde{x},\tilde{z},\tilde{a},\theta))\}$ is uniquely maximized at a value θ^* in the parameter space.

As is well known, in the case of the multinomial logit model, the expectation of the log-likelihood is *concave* in the underlying parameters, and identification amounts to verifying additional conditions that imply that this function is also *strictly concave.* However the concavity property generally no longer holds when the expected log-likelihood function involves mixtures of multinomial logit models. When a parametric model is unidentified, there are typically two ways in which the identification condition fails: either 1) the expected log-likelihood function is "flat" in a neighborhood of the global maximum (so there is a continuum of values of θ that maximize the likelihood), or 2) each local maximum of the expected log-likelihood is "regular" in the sense that the hessian matrix at each local maximum is negative definite (implying that there are a finite number of isolated local maxima, each one is unique within a sufficiently small neighborhood of each local maximum point) but there are two or more distinct local maxima that happen to have the same exact value of the expected log-likelihood, so the set of such distinct global optima are observationally equivalent and the model is unable to distinguish them.

Given the large number of observations in our sample, $N = 167,946$, the empirical log-likelihood $\log(L(\theta))/N$ (where $L(\theta)$ is the likelihood function defined in equation (23) above) provides a very good approximation to its expectation $E\{\log(P(\tilde{d}|\tilde{x},\tilde{z},\tilde{a},\theta))\}$ by the uniform law of large numbers. Therefore it is sufficient to show that the sample log-likelihood function has a unique maximizer since for the very large sample size we have in this case, the probability is very high that sample log-likelihood is uniformly close to its expectation. Therefore the continuous mapping theorem implies that if the sample log-likelihood has a unique maximizer (or equivalently each local maxima that we find are "regular" — the type 2 case discussed above), then we can rule out the most obvious type of non-identification, i.e. namely that the expected log-likelihood is locally flat in a neighborhood of the global maximum. We have indeed verified this numerically: at each local maximum we found in the course of a thorough search of the likelihood over the parameter space, we found that the hessian of the sample log-likelihood function was negative definite.

Further, though we did encounter multiple local maxima of the likelihood function in the course of running our estimation algorithm, we we unable to find distinct local maximizers that resulted in the *identical* values of the sample log-likelihood function. Instead we found a single "global optimum" $\hat{\theta}$ that resulted in a significantly higher sample log-likelihood than for any of the local optima we encountered in our thorough search for a global optimum of the likelihood. Although we are not aware of any general argument that we can rely to provide a mathematical proof that there are no other values of θ besides the value we found $\hat{\theta}$ that result in the same or a higher value of the sample log-likelihood function, we feel that our numerical experience in maximizing the likelihood does at least provide strong evidence suggesting that the parameters of the model is in fact identified.

Identification of the parameters β probabilities of the maximum durations of free installment offers, $f(d|z,\beta)$ is more problematic than the estimation of the probability of receiving a free installment offer itself, $\Pi(z,\alpha)$, since when we relax the strong dominance assumption, if we observe a customer taking a free installment offer of duration d the customer could have been offered a free installment with a maximum duration δ for any $\delta \in \{d,\ldots,12\}$. This gives considerable freedom to how the model might "explain" the particular set of installment durations that consumers actually choose. For example, one possibility is to set $f(12|z,\beta) = 1$, so that the maximum duration of every free installment offer is 12, and the pronounced peak we observe in free installments at a duration of $d = 3$ is purely a result of consumers pre-commiting and choosing their most popular loan duration $d = 3$ rather than choosing the full $\delta = 12$ month loan duration. Although this explanation might seem a bit implausible on its face, recall figure 1, which showed that $d = 3$ is the most likely term of installment loan for individuals who choose to do installments at a positive interest rate.

Though we have independent evidence that in fact most free installment loans that are offered to consumers have a maximum of $\delta = 3$ installments, how can the likelihood distinguish between the case where all free installments offered have a maximum of $\delta = 12$ installments versus the case where all free installments have a maximum of $\delta = 3$ installments? One easy way that the latter hypothesis can be rejected is by virtue of the fact that we do observe a small number of free installments that did involve 12 payments. This enables us to conclude that not all free installment offers could have a maximum of $\delta = 3$ installments. However, beyond, this, the precise identification of the probabilities $f(d|z,\beta)$ seems more tenuous, since due to the censoring, we never directly observe someone being offered a free installment with a maximum of δ installments and choosing to take the installment for $d < \delta$ installments.

We do note that we made several implicit *exclusion restrictions* that assist in the identification of the parameters of the model. First, we assume that the z variables that affect the probability of being offered a free installment opportunity do not enter the choice probabilities P_+ and P_0. This is because z contains dummy variables for merchant codes and calendar time intervals that are relevant for predicting whether a free installment is offered but do not seem directly relevant for predicting a consumer's choice of installment term. Conversely, the customer specific variables x do enter these choice probabilities but can be plausibly excluded from the probabilities that a customer would be offered a free installment opportunity. Finally, we also assume that the probabilities of being offered free installments of various maximum durations are independent of z, so only 10 parameters are necessary to estimate these 11 probabilities. Following our pragmatic approach to identification, we verified numerically that various convex combinations of the choice probabilities P_0 (where the duration probabilities $f(d|\beta)$ are the mixture weights) do not result in the same reduced-form probability $P(d|x,z,a,\theta)$. Otherwise the likelihood function would be flat in a neighborhood of any optimum, and this in turn would imply that the log-likelihood function has a singluar hessian matrix at any such point. However we found in fact that the hessian is strictly negative definite at the maximum. Further evidence is provided by the fact that if we fix the β parameters at arbitrary values and maximize over the remaining parameters (ϕ,α), the value of the likelihood falls significantly below the value we attain when we also free up β and allow the maximum likelihood algorithm to optimize over (ϕ,α,β) simultaneously.

In summary, the identification of the model results from a combination of 1) *exclusion restrictions* and 2) *parametric functional form assumptions.* We have not investigated conditions under which the "structural objects" in the model $\{P_+, P_0, \Pi, f\}$ are *non-parametrically identified* however recent work by Henry et al. [2011] and others may represent promising avenues for further investigation. For this study, we feel that are exclusion restrictions are well-justified and our specification of the option value function ρ and fixed cost functions λ are sufficiently flexible that none of our conclusions are fragile, or depend on arbitrary or hard to justify assumptions. We can verify that the model is locally identified since the hessian matrix of the log-likelihood is non-singular at the maximum likelihood estimates. A formal proof of global is much harder since it requires us to prove that no other local maximum of the likelihood that has the same or higher value of the likelihood than we were able to find after an extensive and careful numerical search.

4.7 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. Over our entire sample, the average estimated probability that a given transaction was subject to a free installment offer is 17%. This estimate appears to be reasonable from our discussions with the credit card company executives. As we see below, it implies that the "take up rate" of free installments is low: although the model predicts substantial consumer-specific heterogeneity in take up rates, on average only 15% of the individuals who are offered free installment opportunities actually take them.

The free installment probabilities vary over the calendar year and across merchants, and the combination of merchant and time dummies enabled us to capture the high degree of variability of free installment options, both over time and across merchants. The variability also 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.

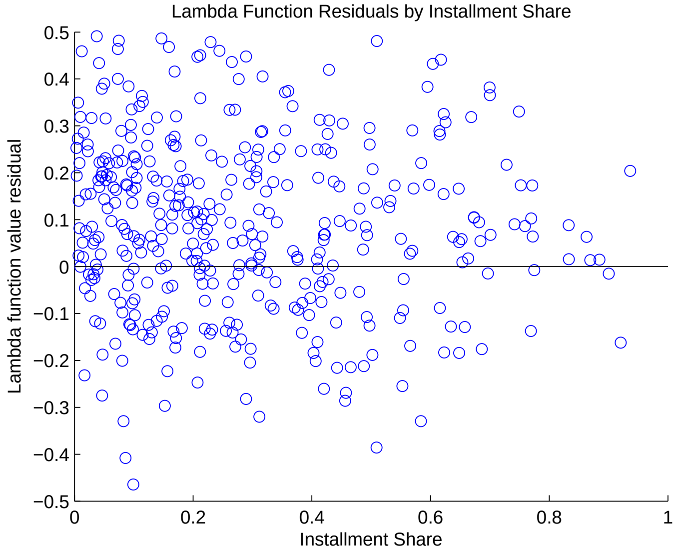
We now turn to the parameters of interest, the ϕ parameters entering the option value function $\rho(x,d,\phi)$ and the fixed cost function $\lambda(x,d,\phi)$ that are two key "behavioral objects" underlying our discrete choice model. Note that due to the large variability in spending across different 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, and and installment balance, denoted as *ib*, equal to 3 would denote an installment balance that is 3 times as large as the average of the customer's credit card balance due.

Consider first the estmation 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 (27) since the sum of the installment duration dummy variables $I\{d \geq j\}$, $j = 2,\dots,12$ adds up to the constant term on the set of relevant choices, $d \in \{2,\dots,12\}$ 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

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

$\rho(x,d,\phi)$ (option value)	Estimate	Standard Error
σ	0.066	3.97×10^{-4}
$\phi_0\ I\{d\geq 2\}$	-3.693	0.025
$\exp\{\phi_1\}\ I\{d\geq 3\}$	0.227	0.018
$\exp\{\phi_2\}\ I\{d\geq 4\}$	0.251	0.179
$\exp\{\phi_3\}\ I\{d\geq 5\}$	0.067	0.049
$\exp\{\phi_4\}\ I\{d\geq 6\}$	0.136	0.026
$\exp\{\phi_5\}\ I\{d\geq 7\}$	2.265×10^{-25}	0.072
$\exp\{\phi_6\}\ I\{d\geq 8\}$	4.430×10^{-14}	0.092
$\exp\{\phi_7\}\ I\{d\geq 9\}$	0.156	0.079
$\exp\{\phi_8\}\ I\{d\geq 10\}$	0.082	0.053
$\exp\{\phi_9\}\ I\{d\geq 11\}$	9.070×10^{-15}	0.180
$\exp\{\phi_{10}\}\ I\{d=12\}$	0.281	0.180
ϕ_{11} (ib)	-0.087	0.001
ϕ_{12} (installshare)	-2.202	0.040
ϕ_{13} (creditscore)	-0.207	0.005
ϕ_{14} (nlate)	-0.015	0.002
$\phi_{15}\ (I\{r=0\})$	-2.166	0.061
$\lambda(x,d,\phi)$ (fixed cost)	Estimate	Standard Error
ϕ_{16} (installshare)	-0.941	0.015
$\phi_{17}\ (I\{r=0\})$	-0.246	0.011
$\phi_{18}\ (I\{d=2\})$	-0.740	0.010
$\phi_{19}\ (I\{d=3\})$	-1.006	0.009
$\phi_{20}\ (I\{d=4\})$	-0.297	0.016
$\phi_{21}\ (I\{d=5\})$	-0.487	0.012
$\phi_{22}\ (I\{d=6\})$	-0.208	0.018
$\phi_{23}\ (I\{d=7\})$	-0.106	0.024
$\phi_{24}\ (I\{d=8\})$	-0.106	0.022
$\phi_{25}\ (I\{d=9\})$	-0.462	0.012
$\phi_{26}\ (I\{d=10\})$	-0.215	0.014
$\phi_{27}\ (I\{d>10\})$	-2.166	0.061
$f(d,\beta)$ (maximum installment term)	Estimate	Standard Error
$f(2,\beta)$	0.695×10^{-15}	0.003
$f(3,\beta)$	0.594	0.290
$f(4,\beta)$	1.717×10^{-12}	0.025
$f(5,\beta)$	5.362×10^{-13}	0.022
$f(6,\beta)$	1.356×10^{-14}	0.044
$f(7,\beta)$	3.314×10^{-14}	0.112
$f(8,\beta)$	2.358×10^{-16}	0.150
$f(9,\beta)$	1.565×10^{-11}	0.108
$f(10,\beta)$	0.256	0.425
$f(11,\beta)$	3.252×10^{-16}	0.436
$f(12,\beta)$	0.149	0.024
Log-likelihood, number of observations	$\log(L(\theta))=-46561.3$	$N=167,946$

Figure 15: λ function residuals $\{e_i\}$ by Installment Share



$j = 3, \ldots, 12$ to be positive by expressing these as exponential functions of the underlying parameters ϕ_j, $j = 1, \ldots, 10$.[8] It is easy to see that this is equivalent to constraining the option value function $\rho(x, d, \phi)$ to be non-decreasing as a function of d.

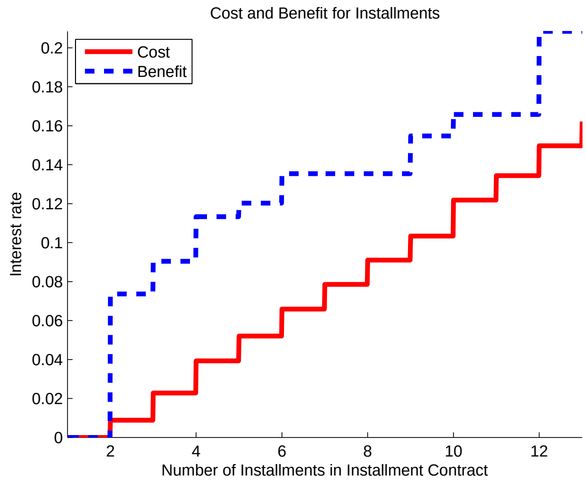
Figure 15 plots the estimated "residuals" $\{e_i\}$ representing customer-specific heterogeneity in the λ function above and beyond the heterogeneity captured by $\hat{\phi}_{16}\text{installshare}_i$ (see equation (30) above). The fact that there is no obvious trend in these residuals as a function of the *installshare* and that they are approximately mean zero and mean indepdent 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 $\hat{\phi}_{17}\text{installshare}_i$.

The residuals for the h function (see equation (29) above) are similar, though the variance is larger. We take this as very good evidence that our simplified 29 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.

Figure 16 plots the estimated option value function and compares it to the $c(a, r, d)$ function (which, recall, has no unknown parameters in it). However the $c(a, r, d)$ function does depend on the set of interest rates, $r(x, d)$, which do depend on customer characteristics x. We plotted these figures for an illustrative

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

Figure 16: Estimated option value $\rho(x,d,\phi)$ function relative to $c(a,r,d)$ function

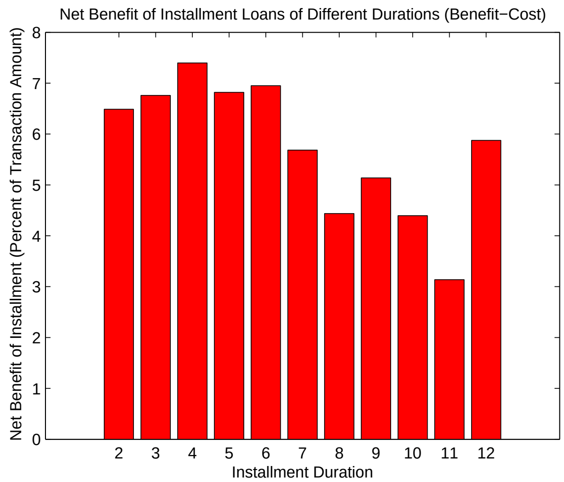


consumer with a creditscore of 2, $ib = 2$, and an installment share of 30%. From figure 16 we see that indeed, the estimated ρ function is non-decreasing in d and it is everywhere above the cost of credit function $c(a,r,d)$, signalling a clear net benefit of purchasing under installment credit. The $\rho(x,d,\phi)$ function has its largest jumps at $d = 3$ and $d = 12$.

Figure 17 plots the net benefits from installment borrowing, $\rho(x,d,\phi) - c(a,r,d)$, 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 14. We will explain how the model is able to capture this peak when we describe the estimation results for the λ function below.

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 *installshare* variable. Further, the coefficient of ϕ_{11} remains positive when we exclude *installshare* and estimate customer-specific constant terms in h and λ. The positive coefficient on *ib* may reflect periods of persis-

Figure 17: Net benefit of installment Credit as a function of installment duration *d*



tently high need for credit or tigher credit constraints. 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.

The two largest (in absolute value) coefficients 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 in order to explain the (already low) take up rate of free installment opportunities.

Finally, the 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, whether free installments or at positive interest rates. As we discussed previously in section 4.5, we used the *installshare* as an observable indicator of unobserved heterogeneity, since we found it infeasible to implement a random effects approach to conrol for unobserved heterogeneity for the reasons already discussed in section 4.5. We view the *installshare* variable as capturing customers who are "credit constrained" in ways that are not well captured by the *creditscore* and *nlate* variables, though it may also capture customers who are for some other reason "installment addicts" who make frequent use of installment credit. Some of these could be consumers who behave like the textbook *homo economicus* with time-separable utilities and non-hyperbolic geometric discounting of future utilities that result in time-consistent intertemporal preferences and the prediction that these individuals would never pre-commit to choices that reduce their future options without any obvious compensation for doing so.

We now turn to a discussion of the estimated parameters of the fixed cost function $\lambda(x,d,\phi)$. 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 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.

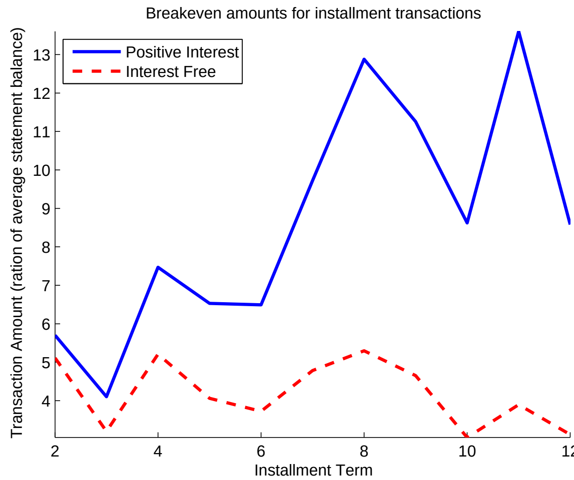
One might ask why this scarring effect and aversion to installments doesn't show up in lower estimated option values. We believe that the fixed costs play an important role in explaining a clear pattern in our data where generally only sufficiently expensive purchases are made under installment. The reason is that while the average credit card purchase is \$74, the average installment purchase is \$364, or nearly 5 times larger than the average credit card purchase. The fixed costs are estimated to be large in order to explain differential pattern of spending.

Figure 18 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.

$$\overline{a}(x,d) = \frac{\lambda(x,d,\phi)}{\rho(x,d,\phi) - c(a,r(x,d),d)}. \tag{31}$$

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

Figure 18: Estimated breakeven amounts $\overline{a}(x,d)$ for installment transactions



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 that nearly low but positive interest loan offers. Despite this effect, it is a puzzle that 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 (31). 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 (31). Even the effect of free installments on the cutoff level $\overline{a}(x,d)$ is ambiguous in general, we see from figure 18 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 installment loans.

This is how the model explains the puzzling finding given in figure 2 of 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 offer than for a transaction done at a positive interest rate. The gap between these thresholds is particularly pronounced at higher loan durations. Thus, the model predict that customers are more likely to choose pay under installment for smaller size transaction when the installment is free than when it is at a positive interest rated. This can imply that the distribution of transaction amounts for positive interest installments will stochastically dominate the distribution of transaction amounts for free installments that we observed in figure 2.

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 our finding in figure 10 that the ratio of the typical installment purchase to the typical credit card (non-installment) purchase decreases as *installshare* increases.

Finally, we discuss the estimated probabilities $f(d|\beta)$ representing the probability distribution over the maximum duration of a free installment offer, conditional on one being offered to a given customer. Recall that in section 4.6 we discussed concerns about our ability to identify this probability distribution with much precision. We see that fortunately, the estimation does not imply that all free installment offers involve a maximum of $\delta = 12$ installments, something we know is not the case from our discussions with the credit card company. Instead, the estimation results are very reassuring, since they show that the most commonly offered installment is for a maximum duration of 3 installments, something that we also believe is the case from discussion with executives of the credit card company. However we were surprised to see that the point estimates of the model imply that there is a near zero probability of being offered a free installment for a duration of $\delta = 6$ months.

The difficulty of identifying the $f(d|\beta)$ probabilities is indicated by the large estimated standard errors relative to the point estimates (again, the standard errors for $f(d|\hat{\beta})$, $d \in \{2,\ldots,12\}$ were computed from the standard errors for $\hat{\beta}$ using the delta method). The large standard errors reflect the uncertainty the model has in estimating these probabilities even with $N = 167,946$ observations. Given these large standard errors, there does appear to be a fairly wide range of distributions $f(d|\beta)$ that could be consistent with the installment choice data we observe. However these probabilities are not of direct interest to us in this study: instead, we are interest in consumer behavior and the uncertainty in the estimated β coefficients fortunately does not transmit and result in huge uncertainty in the key ϕ parameters entering the ρ and λ functions. As a result, we are confident that our inferences and key behavioral conclusions are robust to our uncertainty about the probailities $f(d|\beta)$.

We conclude this subsection with a discussion of our estimation results for the parameters of the distribution of purchases $f(a|x,r,c)$ that enters the expected demand curve for installment credit in formula (1) in section 6. Via initial non-parametric estimation for various consumers, we found that this distribution is well approximated as a log-normal probability density, so we estimated its parameters via regression using $\log(a)$ as the dependent variable. However for the reasons expressed above we were concerned about potential endogeneity in the consumer-specific interest rates. Therefore we conducted a series of regressions, focusing on fixed-effect regressions (e.g. regressing $\log(a)$ less customer-specific sample means of $\log(a)$) that are possible given the panel nature of our data and the fact that we observe many purchase transactions for each customer in our data set. We found that regardless of whether we did OLS or instrumental variable regressions (where similar to section 6 we used the CD rate as an instrumental variable for r) that the coefficient of r is extremely sensitive to the inclusion of time dummy variables in our regression. When time dummies are included, the coefficient of the interest rate is estimated to be near zero with a large standard error, allowing us to easily reject the hypothesis that r affects purchase amounts.

However when we omit the time dummies, then the coefficient of r is estimated to be negative and statistically significant in our two stage least squares regressions. However we do not believe this latter result is the correct one. Note that we have relatively few customer-specific variables x, and thus, the regression has no good way to account for macroeconomic shocks that affect credit card spending other than via the interest rate, which typically moves countercyclically. Thus, in in good times interest rates tend to be high and credit card spending tends to be high, whereas in bad times interest rates tend to be low and credit card spending is lower too. This suggests that interest rates should be *positively correlated* with credit card spending, however as we discussed in section 6, we also find that our instruments, such as the CD rate, is negatively correlated with customer-specific interest rates. As a result, the two stage least squares regression predicts a negative relationship between the instrumented consumer-specific interest rate and credit card spending.

However in the absence of adequate explanatory variables for income, employment and other factors that have strong direct effects on household spending decisions, including credit card spending, we believe that time dummies are a next best substitute for capturing macroeconomic shocks that affect all households.

Thus, when we include these time dummies, the estimated coefficient on the interest rate in our regressions falls to near zero and has a very large estimated standard error. Our conclusion is that it is plausible that credit card interest rates have negligible direct impact on credit card spending decisions, especially given that the vast majority of transactions (over 93%) are done without the benefit of any installment credit. In any event, we feel that the data at our disposal is not sufficiently rich in customer-specific covariates that we think are likely to have much stronger effects on credit card spending decisions than interest rates (such as family income, employment, and other unexpected spending shocks such as health shocks and so forth) that we do not trust results from regressions that have so many observations and so few covariates. We feel there is a strong likelihood that these regressions will reflect *spurious correlations* due classic ommitted variable bias. As a result, we have adopted as an initial working hypothesis that r does not enter as a significant shifter of the distribution $f(a|x,r,c)$, and thus we conclude that the key impact of r the demand for credit is its effect on customers' propensity to pay for a purchase via installment credit.

4.8 Model Fit

We now discuss the fit of the model. Figures 19, 20, and 21 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 19 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 20 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

Figure 19: Predicted versus Actual Installment Choices, All Installment Transactions

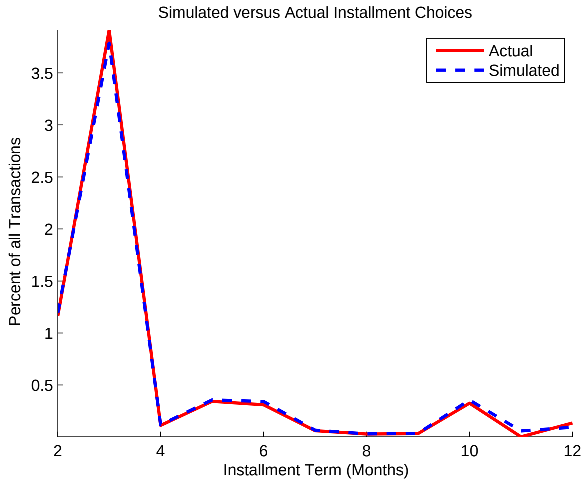


Figure 20: Predicted versus Actual Installment Choices, Positive Interest Installment Transactions

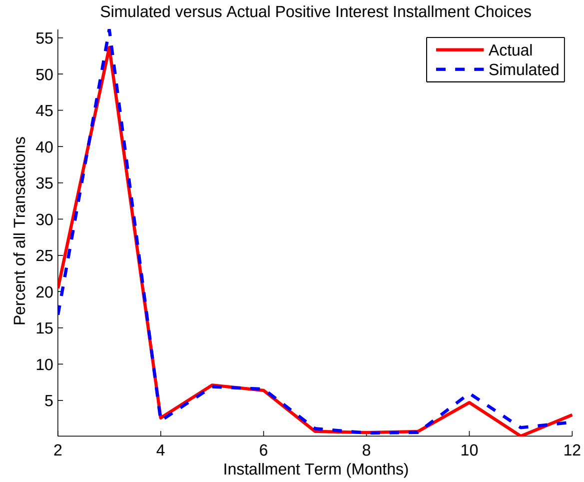
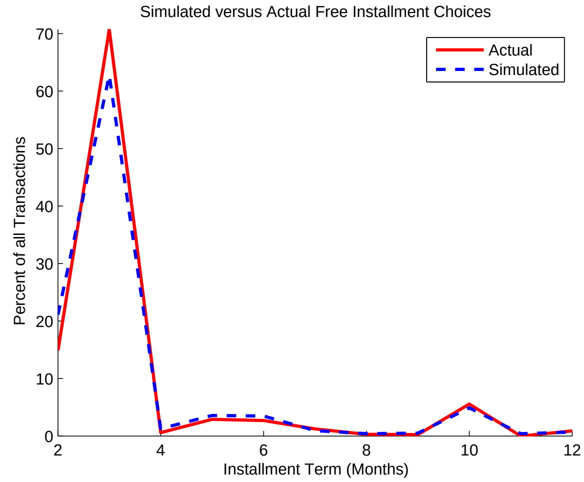


Figure 21: Predicted versus Actual Free Installment Choices



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 tranaction 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. 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 17% of 167,946 simulated customer-purchase transactions, the company offers customers free installment opportunities. This estimate strikes us as quite reasonable since figure 13 of section 3 shows that the most installment prone "addicts" with *installshare* values greater than 80% were were doing approximately 17% of all of their purchases as free installments. If we assume that the most installment-prone individuals would not pass up many opportunities to purchase items under free installment offers, then this provides independent evidence that our estimated average rate of free installment offers is reasonable.

4.9 Model Implications and Counterfactual Simulations

We conclude this section by providing some illustrative simulations of the model and calculating some counterfactual quantities to provide further insight into the model and into the behavior of the individuals in our sample — at least to the extent that the reader trusts that our model provides a good representation of choices consumers actually make.

Figures 22 and 23 illustrate the predicted installment borrowing behavior for two different individuals who are not offered free installment opportunities and so must borrow at an a positive interest rates. In figure 22 we illustrate an "installment avoider" who has an *installshare* of 0, and in figure 23 we illustrate an "installment addict" who has an *installshare* of 83.27%. The credit score happens to be the same for both individuals, equal to 3 (which is a reasonably since a score of 1 is the best possible), a moderate installment balance of $ib = 1.85$, and no late payments. Figure 22 shows that the installment avoider will never choose an installment term of more than three months, and it takes extraordinarily large purchases to motivate this customer to undertake any installment transactions. Even for purchases as large as 10 times the size of the customer's average statement balance, there is still a 30% chance that this customer will choose $d = 1$, i.e. to pay the purchased amount in full at the next statement date. Figure 23 shows that the installment addict is willing to select installment loans of duration $d = 12$ and this customer's choice probabilities are much more senstive to the size of the purchase amount. For small purchases, 20% of the size of this customer's typical statement amount, there is a 70% chance the customer will choose to pay in full at the next statement, $d = 1$, but a 30% chance of choosing some form of installment loan, with the choice $d = 3$ being the most likely alternative. However when the purchase amount equals the average statement amount for this customer, then there is less than a 10% chance this customer would choose $d = 1$, and the most likely installment terms the customer would choose would be either $d = 3$, $d = 6$, $d = 10$, or $d = 12$. For a purchase equal to 4 times the average statement amount, the chance this customer will select a 12 installment loan is over 60%, with the next most likely alternatives being $d = 10$ and $d = 6$.

Figures 24 and 25 illustrate how the choice probabilities of these two customers are affected when they are facing a 10 month free installment offer. The choice probabilities shift dramatically in the presence of the free installment offer, particularly for the installment avoider. 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

Figure 22: Choice probabilities for an “installment avoider” (*installshare=0*)

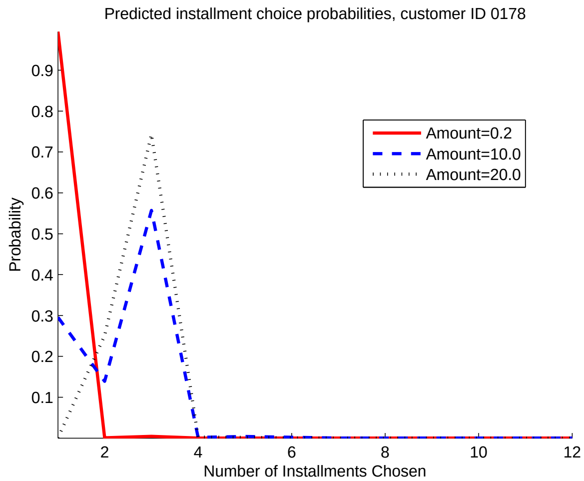
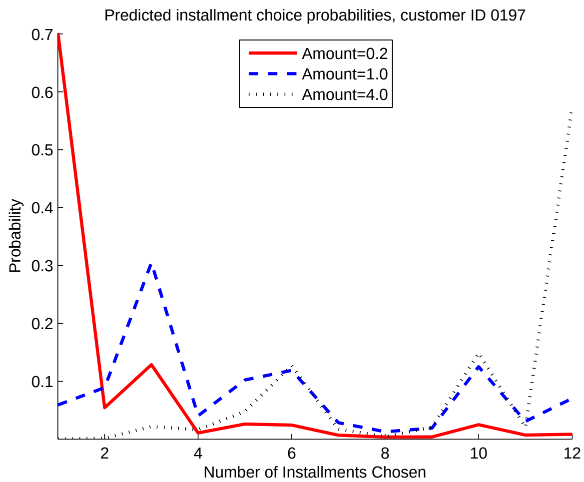


Figure 23: Choice probabilities for an “installment addict” (*installshare=0.83*)



offer starts to increase significantly with the size of the purchase amount a. When $a = 0.2$, 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.

This brings us to another key finding: *the model predicts that there is a significant probability that customers who choose a free installment will choose a term that is less than the maximum duration offered.* In figures 24 and 25 we see this clearly. For example the blue dashed line in figure 24 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 25 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 88% of individuals who were offered (and chose) a 10 month free installment offer also pre-commited at the time of purchase to pay the balance in *fewer* than 10 installments. This pre-commitment behavior, along with the fairly low probability that free installment offers are predicted to be chosen, constitutes what we have termed "the free installment puzzle." Although our econometric model enables us to show this puzzling behavior exists, 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

Figure 24: Choice probabilities for an "installment avoider" (*installshare=0*) with a 10 month free installment offer

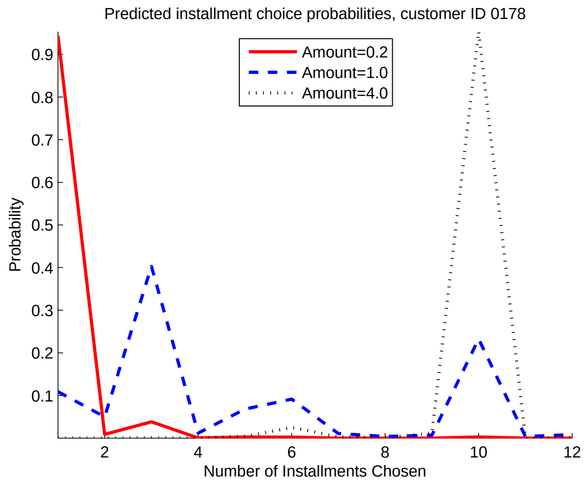
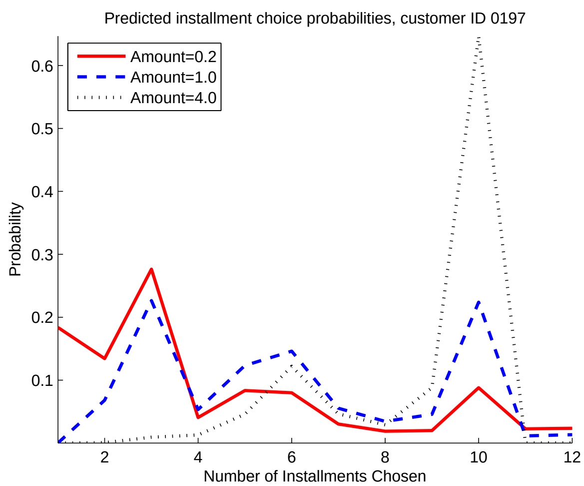


Figure 25: Choice probabilities for an "installment addict" (*installshare=0.83*) with a 10 month free installment offer



other psychological motivations more precisely.

However as we noted above, the inclusion of a dummy for free installment offers, $I\{r=0\}$, in the h and λ functions of the option value function $ov(a,x,r)$ in equations (27) and (28) above, 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."

Even though the model predicts puzzling behavior that is inconsistent with standard theories of rational decision making by individuals time-separable discounted utility functions, figures 26 and 27 below show that the model nevertheless does predict downward sloping demand curves for installment credit. These figures present the implied demand curves for the same "installment avoider" and "installment addict" whose choice probabilities we illustrated above. These curves were calculated using the formula for the conditional demand curve for installment credit given by $ED_T(r,x,c)$ in equation (5) above, where $f(a|x,r,c)$ is the customer-specific log-normal distribution for the (relative) amount purchased on any given purchase occasion, conditional on the consumer's decision to use the company's credit card c to pay for the transaction. Note that from our empirical findings in section 4.8, we have no solid evidence that r affects the distribution of purchase amounts, so in calculating these demand curves we simply used customer-specific log-normal distributions $f(a|x,c)$ estimated by maximum likelihood but without including r as an explanatory variable since we found that it does have any statistically significant effect on a once we included time dummies in the model to control for macroeconomic shocks on spending.

Figure 26 shows that the demand for installment credit by the "installment avoider" is indeed negligible: regardless of the possible credit score, the demand for installment is only a fraction of 1 percent of the average amount of the customer's credit card statement balance. The "installment addict" on the other hand, does have a significant demand for installment credit amounting to approximately an order of magnitude greater than the installment avoider, in relative terms. Thus, depending on this person's credit score, the demand for installment credit in a typical purchase transaction could be anywhere from 10 to 17 percent of the average amount of this person's typical credit card statement amount.

While we have verified that the demand function $ED_T(x,r,c)$ is downward sloping for all customers and all values of x in our sample, as we discussed in section 4.1 above, it is possible that the *conditional* demand for installments can be *upward sloping in r* due to the "threshold effect" — the effect of interest

Figure 26: Estimated installment demand $ED_T(x,r,c)$ for an “installment avoider” (*installshare=0*)

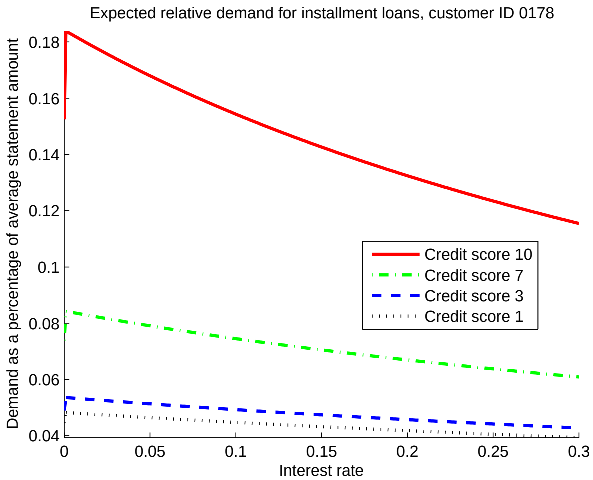


Figure 27: Estimated installment demand $ED_T(x,r,c)$ for an “installment addict” (*installshare=0.83*)

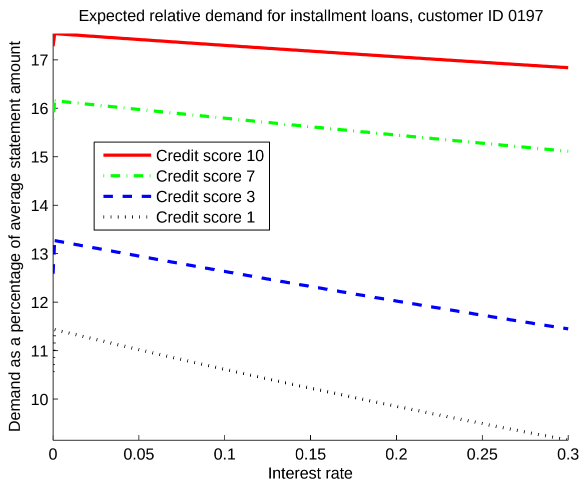
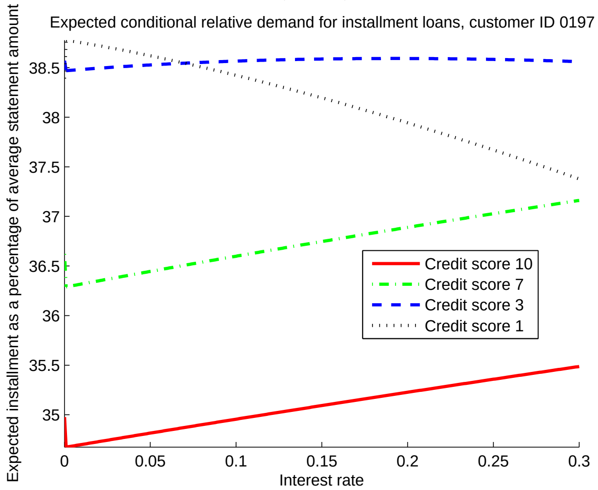


Figure 28: Conditional installment demand $ED_I(x,r,c)$ for an “installment addict” (*installshare=0.83*)



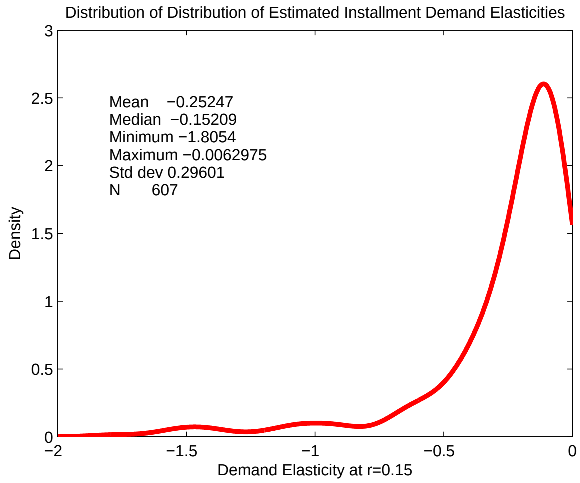
rates on the threshold $\overline{a}(x,c)$ at which consumers are willing to pay for a given purchase on installment given in equation (31) above. As we showed in figure 18 above, the threshold effect can cause consumers to be willing to pay for *smaller transaction amounts* on installment when the interest rate is lower. This can cause the average size of an installment transaction to fall with the interest rate, or in other words, it can imply that $ED_I(x,r,c)$ is *upward sloping in* r.

Figure 28 shows that this effect is predicted to occur in the estimated model, though not for all values of x. We show the calculated conditional installment demand curves $ED_I(x,r,c)$ for an installment addict (*installshare*=0.83) for different values of the credit score component of x. For the best credit scores, 10, 7 and 3, the $ED_I(x,r,c)$ is in fact downward sloping in r. However for the worst creditscore, 1, $ED_I(x,r,c)$ is indeed an upward sloping function of r.

However while simulations of the estimated model reproduce the pattern of stochastic domination in the unconditional distributions of non-installment transaction amounts, free installment transaction amounts, and positive interest installment amounts that we observe in the data (see figure 2), the main reason why the distribution of positive interest installment transactions stochastically dominates the distribution of free installment transaction sizes is that *free installments are unpredictable.* That is, customers are more or less randomly offered free installments for smaller purchases where the do not have strong incentive to take them, whereas since consumers always have the option to take positive interest installments, we see more frequent uss of positive interest installments for larger purchase amounts where free installment offers are not an option for the customer.

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. Thus, perhaps not surprisingly the installment avoider has a more elastic demand function than the installment addict, but the important point is both of them have highly inelastic demand curves for credit. This is true for virtually all of the individuals in our sample. Figure 29 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.

Figure 29: Distribution of Estimated Demand Elasticities



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. Although admittedly, there are hazards to doing an investigation since we do not have a complete model of the demand for credit as discussed in section 4.1 above, 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. We consider the effect on the firm's profitability from adopting alternative interest rate schedules, but constraining our search to alternative installlment 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

$$\max_{r_2,\ldots,r_{12}} \int_0^\infty \sum_{d=2}^{12} [c(a,r_d,d) - c(a,R_t,d)] P_+(d|a,x,r_2,\ldots,r_{12}) f(a|x) da \tag{32}$$

subject to:

$$\sigma \int_0^\infty \log\left(\sum_{d=1}^{12} \exp\{v(d,x,a,r_d)/\sigma)\}\right) f(a|x) da \geq \sigma \int_0^\infty \log\left(\sum_{d=1}^{12} \exp\{v(d,x,a,\overline{r}_t(x,d))/\sigma)\}\right) f(a|x) da, \tag{33}$$

where R_t is the credit card company's opportunity cost of capital (i.e. the rate at which it can borrow) and $\overline{r}_t(x,d)$ is the company's *status quo* interest schedule from equation (9) that we plotted in figure 14 above. 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 (33) 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 (32) (33) 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.

Figures 30 and 31 present the optimal schedules that we calculated for the same two individuals that we have studied in our other counterfactual calculations above. 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-specific, we believe it is feasible for the company to engage in *first degree price discrimation* and set alternative customer-specific schedules such as the ones suggested in figures 30 and 31 below.

From figure 30 we see that for the installment avoider, the model predicts 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%.

Figure 31 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,

Figure 30: Optimal versus *status quo* installment interest rates for the "installment avoider" (*install-share=0*)

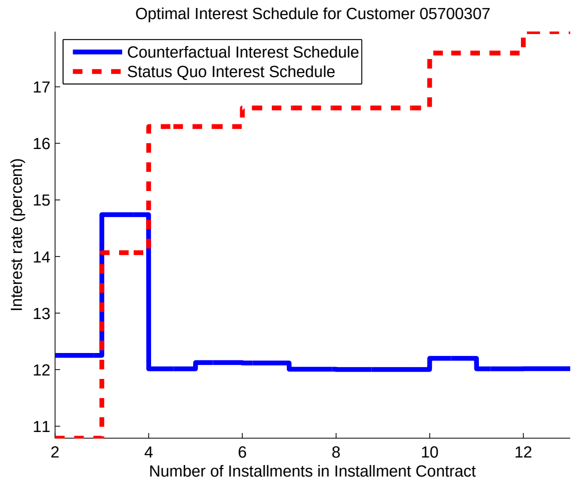
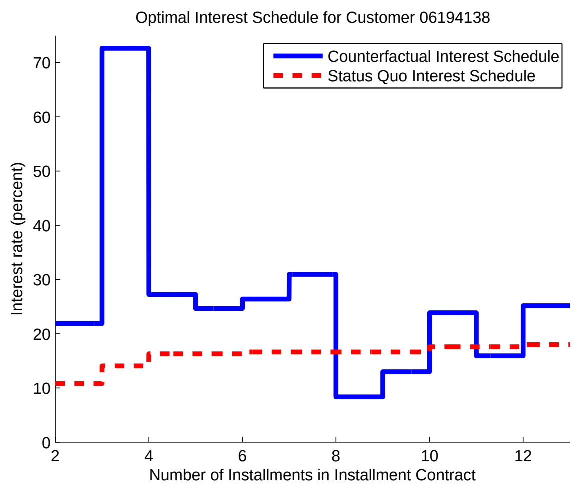


Figure 31: Optimal versus *status quo* installment interest rates for the "installment addict" (*install-share=0.83*)



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 significantlly 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 figure 44, 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 *per transaction.*

5 Conclusions

The main contribution of our paper is to introduce a new data set on credit card spending and payment decisions, and to study at a high level of micro detail the use of installment transactions, a topic that has not been well studied in previous theoretical and empirical work in economics. The objective of our analysis was to use this unique set of data to infer customers' demand for credit, since our data also enabled us to identify the *customer-specific* interest rate schedules that the credit card company charges. Unfortunately, due to endogeneity in the setting of customer-specific interest rate schedules (i.e. consumers with worse credit scores who often have the highest need and demand for credit also are assigned the highest interest rates), we found that the traditional "reduced form" econometric methods produced non-sensical estimates of the demand for credit that are *upward sloping* functions of the interest rate r. We found that the use of instrumental variables did not solve the problem since the credible instruments at our disposal (e.g. the CD rate and other meansures of the credit card company's cost of credit) are extremely *weak instruments* that do not succeed in producing in downward sloping estimated demand curves for credit.

In order to obtain more credible estimates of the demand for credit we exploited a novel feature of our data: *the company's frequent use of free installment offers.* We argued that the quasi-random way in which these offers are made to the company's customers can enable us to use them as instruments an approach that treats them as a *quasi random experiment* that creates extra variation that is helpful in identifying the slope of the demand for credit. Unfortunately, we showed that other standard econometric methods that are designed to exploit such quasi random variation such as *matching estimators* also result in upward sloping estimated demand curves for installment credit.

In response to these problems we introduced a flexible behavioral discrete choice model of the decision to purchase under installment credit. At each purchase occasion, the customer is modelled as choosing one of twelve installment alternatives, whether to pay the purchased amount in full at the customer's next credit card statement, $d = 1$ (an option that carries a default interest rate of zero), or to purchase the item under installment credit payable in d installments where $d \in \{2,\ldots,12\}$ at a positive interest rate that is customer-specific. We accounted for the free installment opportunity as a modification to the customer's choice set: a customer who is given the chance to take out a free installment loan of maximum duration δ may choose from the set $\{2,\ldots,\delta\}$ of *free interest options* or can choose to either pay in full, $d = 1$, or borrow for an even longer term $d \in \{\delta+1,\ldots,12\}$ at a positive interest rate. We modeled the choice probability as arriving from a simple cost-benefit tradeoff, where the customer experiences a benefit which we refer to as an *option value function* $ov(a,x,d) = a\rho(x,d)$ that reflects the benefit of the extra flexibility of being able to pay the purchased amount a over d installments.

Offsetting this benefit is a *cost of credit* $c(a,r,d) \simeq ar30d/365$ and additionally, we assumed that the customer might incur additional *fixed costs* $\lambda(x,d)$ in deciding among the various installment options at check-out time. We showed that the underlying functions ρ and λ can be flexibly specified so that the model can be consistent with a wide variety of rational and more "behavioral" theories of consumer behavior. In particular, the model results in a downward sloping demand for credit, even though we showed that for some customers the *conditional demand for installment credit* (i.e. the expected transaction size given that the transaction is an installment) *can* be an upward sloping function of the interest rate r. However we argued that this is not the main explanation for our finding that the distribution of positive interest installment transaction amounts stochastically dominated the distribution of zero interest installment transaction amounts. Instead, we have shown that the main explanation is that free installment offers are highly *unpredictable* and unlikely to be offered when customers really need them, whereas the option to purchase under installment at a positive interest rate is always available to customers.

Thus, we conclude that the positively sloped conditional demand curves for installment credit that the reduced-form econometric approaches predict are largely *spurious*, and a result of the lack of good instruments, and to properly control for the self-selected nature of installment transactions. However, we showed that it *is* possible to provide more credible estimates of the demand for credit by being willing to impose some reasonable modeling assumptions. We showed how to solve a major econometric challenge confronting the estimation of this model: namely, that our credit card data are heavily *censored* in the sense that we only observe free installment offers when consumers actually choose them, but the company has no record of other purchase situations where a customer is offered a free installment but did not choose it. Even though it would seem impossible to be able to separately identify the probability of being offered a free installment from the probability of choosing it, we showed that we can indeed separately identify these probabilities. What we found was surprising: even though only 2.6% of the transactions in our data set were done as free installments, the model predicts that consumers face free installment offers in approximately 20% of all the transactions they make.

The *free installment puzzle* results from this key finding, namely that customers in our data set are predicted to frequently pass up "free" borrowing opportunities. Further, we also showed that in the minority of cases (15%) where customers did choose the free installment offer, there was a very high probability (approximately 88% for a 10 month free installment offer) that the consumer would pre-commit to a choice of a loan duration that is *shorter* thatt the maximmum duration allowed under the offer. These decisions present a challenge to traditional economic models of rational, time-separable discounted utility maximization. Pre-committing to "suboptimal" choices can be evidence that individuals have more complicated *time inconsistent* preferences for which this type of pre-commitment can be welfare improving by constrains future options and the potential "temptations" that current borrowing poses for their welfare of their "future selves."

While we believe we have provided credible evidence that this type of pre-commitment behavior is common (something that few other non-experimental empirical studies have done so far, to the best of our knowledge) we still refer to our findings as the "free installment puzzle" since our data are not rich enough to delve deeper into the psychological rationale for these decisions. Besides time-inconsistent preference explanations, there are other potential "behavioral" explanations for this behavior, including social stigma against the use of installment credit and the scarring effect of past overuse of installment credit. Since installment credit decisions are made at the check out counter in a public setting, the potential stigmatization effect cannot be discounnted (similar to the way the use of food stamps at check out counters may be a source of embarrassment for consuers in the U.S.). Further, it is possible that due to the chastising effects of the growth and sudden bursting of a large "credit card bubble" in the country we studied just prior to the period of our data set could have significant *scarring effects* that might make many consumers hesitant to take advantage of installment credit opportunities given that excessive use of installment credit had created so many problems for this society in the very recent past.

However the parameter estimates of our model suggest that the stigma explanation is unlikely, since the parameters indicate that customers seem to have a especially high option value and lower transaction cost for undertaking free installment transactions in comparison to positive interest installment transactions. As such, our findings may constitute some of the most compelling “field evidence” in support of theories of individual behavior the involve problems of time-inconsistent planning and a consequent incentive for taking what would otherwise seem to be suboptimal precommitment choices (such as passing up free installment offers, or precommiting *ex ante* to pay off a free installment loan in fewer installments than the maximum allowed) as a means of self-control.

While we presented calculations that suggest that the credit card company’s interest rate schedule may not be optimal, we cannot provide any definite conclusions whether the company’s use of free installments is an effective policy or not. We did show that the people who are among most likely to respond to free installment offers — indidivuals with high values of the *installshare* variable — also tend to have worse creditscores but also tend to be more profitable customers. Although the response to free installment offers seems small even for individuals with high values of *installshare* our analysis is unable to address the question of whether the primary effect of free installment occurs if customers switch credit cards at the checkout counter in order to take advantage of free installment offer provided by one credit card but not another.

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. In the future, it would be important to study consumer choice over multiple alternative sources of payment similar to the study by Rysman [2007] who studied payment choices across 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.

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