# Precommitments for Financial Self-Control? Micro Evidence from the 2003 Korean Credit Crisis[†]

SungJin Cho
*Seoul National University*
John Rust
*Georgetown University*

December, 2015

**Abstract**

We analyze installment borrowing decisions from two random samples of customers of a credit card company before and after the 2003 credit crisis in Korea. In an attempt to increase its market share, the company more or less randomly offers its customers *free installments,* i.e. opportunities to pay off card purchases in up to twelve monthly installments at a zero interest rate. We exploit these offers as a *quasi-random field experiment* to better understand consumer demand for credit. Despite censoring in the data (we observe free installment offers only when customers choose them), our econometric model is able to separately identify the probability a customer is offered a free installment opportunity from the probability they take it. We find that the company sharply reduced free installment offers after the crisis, while customer take-up rates increased from an average of 13% before the crisis to 20% after it. Among the minority of customers who take the interest-free loan offers, most precommit to repay the loan over a term that is *shorter* than the maximum allowed under the offer. This behavior is puzzling given that there are no pre-payment penalties and these offers can be easily accepted at the push of a button at the check out counter. Rational expected utility maximizers should take every interest-free loan offer for the maximum allowed term if the transaction cost of taking the offer is zero. A possible explanation of this behavior is that customers, in an exercise of financial self-control, resist the temptation of interest-free loan offers to avoid becoming excessively indebted.

**Keywords:** credit crisis, installment credit, credit cards, demand for credit, behavioral finance, quasi-random field experiment, discrete choice models, nested logit model, censoring, choice-based sampling, mixture models, precommitment behavior, self-control

---

[†]We are grateful to David McArthur for research assistance at an early stage of this project and to James J. Heckman and four anonymous referees for feedback on earlier versions of this paper. We are also grateful to comments from numerous attendees of workshop/seminar presentations of earlier versions of this paper, including the University of Maryland in fall 2010, the CEAR Workshop in Denver, January 2011, the State University of New York at Albany and Penn State University in September 2011, the 2012 Summer Meetings of the Econometric Society at Northwestern University, the 2015 Meeting of the American Finance Association in Boston, the Swiss Finance Institute at the University of Lausanne in 2015, the 2015 Meeting of the International Association for Applied Econometrics in Thessaloniki, the 2015 Sinapore Economic Review Conference, and the Sveriges Riksbank, University College London, and NHH in December 2015. Please send comments to SungJin Cho at Department of Economics, Seoul National University, Seoul, Korea, email: `sungcho@snu.ac.kr` or John Rust at Department of Economics, Georgetown University, Washington, DC 20057 e-mail: `jr1393@georgetown.edu`.

# 1 Introduction

It is well documented that financial markets can be inherently unstable, with recurrent cycles of booms, panics, and busts (see, e.g. Kindleberger [1978], Reinhart and Rogoff [2009], Mendoza and Terrones [2012], Smith et al. [1988], and Shiller [2015]). What is less clear is whether this instability is caused by "irrationality" of market participants as Shiller [2015] argues, or reflects the build up and bursting of "rational bubbles" that are among the multiplicity of equilibria possible in dynamic asset markets (see, e.g. Tirole [1985]). Regardless of the explanation, it is hard to escape the conclusion that many poorly regulated financial markets experience *periodic collective lapses of financial self-control.* In credit markets, the booms resemble a lemming-like rush to lend to increasingly less credit-worthy borrowers until leverage far exceeds historical norms. When the lemmings reach the precipice a financial panic occurs, and the boom turns into a bust with wave of defaults and an extended period of tight credit while de-leveraging occurs.

Korea experienced one of these cycles, starting with a boom in credit card lending between 1999 and 2002, a panic in 2003, followed by a bust from 2004 to 2007. Kang and Ma [2007] and Kang and Ma [2009] documented the Korean crisis as well as other similar crises elsewhere in Asia following the more severe and well known 1997 "Asian crisis". The 2003 Korean crisis bears striking similarity to the financial crisis in the U.S. in 2008, with the exception that the Korean crisis originated from excessive credit card lending, whereas the crisis in the U.S. was due to excessive mortgage lending. Also, unlike the U.S., the Korean central bank moved quickly to calm the panic and rescue a major lender, LG Card, so the real macroeconomic impact of the Korean crisis was comparatively minor. Otherwise the basic pattern of the Korean crisis is typical: "intensified competition in the high-yield, less prime, credit card lending business leading to reduced lending standards; a rapid build-up in household indebtedness; a disproportionate concentration of debt burdens among riskier cardholders; a sudden deterioration of asset quality; and a subsequent contraction in credit card receivables." (Kang and Ma [2007], p. 55).

At the peak of the credit card boom in 2002, the typical Korean had more than 3 credit cards with balances in excess of $2000, and aggregate credit card debt amounted to nearly 15% of GDP. In contrast, in the bust period after the 2003 panic, credit card debt rapidly fell to less than $700 per capita and 5% of GDP. However in the process of de-leveraging, "Many leading issuers suffered heavy losses from their card lending business. It is estimated that about one third of the entire card lending book at its peak eventually had to be written off." (Kang and Ma [2009], p. 103). While the broad outlines of financial crises have been well documented at the macro level, much less is known about what happens at the micro level. How does the behavior of individual lenders and borrowers change between the boom and bust periods on either side of a financial crisis? Who is most at fault for the crisis: the lenders who make unwise loans, or the customers who voluntarily take on too much debt?

This paper presents new findings on the supply and 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 Korean credit card company. The company (which has requested to remain anonymous) provided us with random samples of their customers before and after the 2003 crisis that enables us to analyze how it affected lending, spending, and borrowing behavior. While these shifts are consistent with the changes Kang and Ma documented using lower frequency macro data, our micro data enables us to analyze behavior that would be difficult to identify using macro data alone. In particular, contrary to the standard narrative that credit crises are caused by excessive borrowing by consumers, the customers in our samples appear to have exercised, if anything, *excessive financial self-control* — both before and after the crisis. Specifically, we find that customers in our samples had a surprisingly low propensity to take interest-free loan offers, and take up rates were significantly lower *before* the 2003 crisis than after it.

Unlike *revolving credit* provided by most U.S.-based credit cards, the main type of credit offered by the company we study is *installment credit,* a contract that is commonly used by credit card companies in Latin America and Asia. Installment credit contracts require customers to make an *ex ante* choice of the number of installments over which to pay back the amount of *each purchase* they make with their credit card. Our data allow us to observe hundreds of thousands of these micro-borrowing decisions on a *transaction by transaction basis.* Each monthly billing statement reminds the customer of the interest rate schedule applicable for installment loans payable over 2 to 12 billing statements (months).[1]

In an attempt to increase its market share, the company more or less randomly offers its customers *free installments,* i.e. pre-approved installment loans at a zero interest rate for durations up to twelve months. We exploit these free installment offers as a *quasi-random experiment* to help identify the demand for credit using a flexible “behavioral” discrete choice model of installment credit decisions that accounts for censoring (choice based sampling of free installments). Despite the fact that we only observe free installment offers when consumers choose them, we show that it is possible to separately identify consumers’

[1]In contrast, revolving credit contracts are similar to a *line of credit* that gives a customer the freedom to choose how quickly to pay off their past purchase balances. Revolving credit is a relatively new product for this company, offered only to a minority of its customers with the best credit scores. Customers who do not have revolving credit privileges must pay the full balance due at each statement date. The essential difference between installment and revolving credit is that installment loans are for fixed terms that must be chosen by the customer, *ex ante* at the time of *each purchase.*

choice probabilities and the probability they are offered free installments. In particular, we can identify the probability that consumers will decline free installment offers, and the probability they accept them but precommit to repay the loan in fewer installments than the maximum number allowed under the offer.

The average interest rate the company charges its customers for positive interest installment loans is approximately 15%, so we would expect that free installment offers would have a high take-up rate. However we show that the take-up rate for these offers is actually very low: fewer than 3% of the transactions in our post-crisis sample were made as free installments, even though we estimate that customers are offered free installments in approximately 15% of all transactions they made with this credit card. This implies an average take-up rate of only 20%. In the pre-crisis sample, 7.8% of all transactions were interest-free installments. However we estimate that customers were offered free installments in nearly 60% of all transactions before the crisis, so the take-up rate of these offers was actually *lower,* approximately 13%. This suggests that the company was pushing its customers to take on more credit card debt before the 2003 crisis, but customers exercised financial self-control by resisting these offers. After the crisis, the company dramatically reduced the number of interest-free loan offers to its customers, and it significantly raised its interest rates on positive-interest rate loans. This may explain why the customers in the post-crisis sample were more likely to take interest-free loan offers than those in the pre-crisis sample.

Our model also predicts that customers will sometimes choose a positive interest installment loan instead of an interest-free offer of shorter maximum duration, and it predicts significant "suboptimal" precommitment behavior among the subset of individuals who do decide to take free installment offers. For example, in the post-crisis sample, our model predicts that among the minority of customers who were offered *and took* a free installment loan offer with a 10 month maximum duration, 80% of them precommitted to pay off the loan in *fewer* than 10 installments. In the pre-crisis sample, the model predicts that nearly 88% of all customers precommitted to paying off installment loans faster than necessary.

Since free installment offers are pre-approved, entail negligible transaction costs, and have no prepayment penalties, the frequent selection of "dominated alternatives" is difficult to explain using standard expected utility models: rational consumers should always choose to borrow for the maximum allowed term when the interest rate is 0%. However theories of time inconsistent decision making and decision making by individuals with self-control problems can explain this behavior. One interpretation for our findings is that turning down an interest-free loan is not irrational, but rather an act of financial self-control. Customers resist the temptation of interest-free loan offers to avoid becoming overly indebted.

Though there is well established and influential *theoretical* literature on time inconsistency and self-control problems, (e.g. Strotz [1955], Gul and Pesendorfer [2001], Fudenberg and Levine [2006], and Laibson [1997]) there is not a great deal of *empirical evidence* supporting the predictions of these theories. As Bernheim et al. [2012] note “Over the last twenty years, the concept of time inconsistency has emerged as a central theme in behavioral economics. As is well-known, any consumer sufficiently self-aware to notice her time-inconsistent tendencies will manifest a demand for precommitment technologies. At a minimum, consumers should acquire such self-awareness with respect to frequently repeated activities for which they consistently fail to follow through on prior intentions. Yet oddly, there is surprisingly little evidence that people actually value and exploit precommitment opportunities.” (p. 1).

The main contribution of this paper is to provide evidence that the customers in our sample do exploit precommitment opportunities. They do this by *turning down* free installment offers or by taking them and precommiting to pay the amount due faster than necessary. Gul and Pesendorfer [2001] explain how these sorts of precommitments, which appear irrational from the context of standard dynamic decision theory, can make individuals who face repeated temptations “unambiguously better off” (p. 1406).

A more extreme precommitment would be to refuse to use a credit card in the first place. Since we we have a choice-based sample of *credit card customers,* we cannot estimate how many individuals could have applied for and received a credit card from this company (or other credit card) but chose not to. However we can directly observe a less extreme precommitment: namely, *a significant number of customers voluntarily requested the company to reduce the spending/borrowing limit on their credit card.* This direct evidence, combined with the the indirect evidence we provide on the low take up rate of interest-free installment offers and the high propensity of the minority of customers who do take these offers to precommit to repay theirs loan faster than necessary, constitute new evidence that suggests that some individuals use a range of precommitment strategies to deal with the temptations that credit cards create to overspend or borrow too much.

However existing theories of time inconsistency or self-control problems may not be the only way to explain this behavior. There could be stigma or *mental accounting costs* associated with the decision to take a free installment offer, or consumers may believe that taking these offers could hurt their credit rating. While these latter explanations can explain low take-up rates, it is not clear that they can explain why customers precommit to repay interest-free loans faster than necessary, or why take-up of free installments increased *after* the crisis, when presumably any stigma (or concerns about harm to their credit scores) associated with taking free installment offers would have been higher than in the boom before the crisis.

Though we show that taking free installments does *not* worsen a customer's credit score, we cannot rule out the possibility that some customers *believe* this to be the case. So the behavior we observe might also be explained by an expected utility model, but one where consumers have *irrational beliefs.* On the other hand, in an era of rampant financial fraud, it may not be irrational to suspect that there is some hidden catch in an interest-free loan offer. For example late payment penalties could wipe out any interest savings on the amount borrowed. However credit card payments are made automatically via electronic debit from the customer's bank account, so there is no risk of late payments provided the customer's checking account balance is not overdrawn. Also the company we study is a large, reputable company, so it is far from a "fly by night" operation that would lead its customers to distrust its interest-free offers. Nevertheless, given the relatively small size and short duration of most installment loans, many customers may rationally believe that the transactions costs associated with using and exploiting these loans (e.g. investing the funds in higher yield securities) outweigh the benefits from doing so.

Lusardi and Mitchell [2014] summarize evidence of "financial illiteracy" that might also explain customers' failure to take interest-free offers as a result of sheer ignorance. For example they note that "the least financially savvy incurred high transaction costs, paying higher fees and using high-cost borrowing." (p. 23). They survey other studies that show "that the less financially literate were substantially more likely to use high-cost methods of borrowing, a finding that is particularly strong among young adults (age 25 to 34)" and "many borrowers do not know what interest rates were charged on their credit card or mortgage balances" (p. 23). However we find that the customers who are most likely to take free installment offers are the ones with the worst credit scores, which seems inconsistent with the positive correlation between measures of financial illiteracy and poor credit scores and default behavior that Lusardi and Mitchell [2014] discuss, and the finding that financially illiterate customers "frequently fail to take advantage of other, cheaper opportunities to borrow" (p. 25).

While there may be multiple ways to explain why customers in our samples pass up interest-free loan offers so frequently, unfortunately our data are not rich enough to enable us to distinguish between these various possible explanations of the anomalous behavior we find. Even though we cannot identify the ultimate explanation for this behavior (and different explanations could apply to different people), the main contribution of this paper is simply to show this behavior exists and to use it to improve our understanding of the causes and consequences of the 2003 Korean financial crisis. To the extent that the financial crisis as a whole represents a temporary loss of “financial self-control” our results suggest the it was the credit card company, not its customers, that experienced the most evident loss of self-control. The company “binged” on high rates of free installment offers before the crisis, but dramatically cut back on these offers after the crisis. The customers in our sample did reduce their credit card balances — by about 50% comparing pre and post-crisis samples — but we are unable to tell whether this was a voluntary reduction or one forced on them via reductions in credit card borrowing limits by the company.

Section 2 describes our credit card data and shows that merchant fees make up a large share of company profits. We believe merchant fees and network externalities in credit card competition motivate the use of free installments: companies incentivize customer spending and borrowing to increase their own market share and profits. Section 4 introduces a flexible behavioral model of installment choice that forms the basis of our empirical analysis of customers’ choice of payment term that accounts for the censored, choice-based nature of our data sets. We show that the estimated model fits the data extremely well, and the borrowing behavior it predicts reflects a great deal of consumer-specific heterogeneity, but generally very inelastic demand for installment credit. Most importantly, the model predicts the low take-up rate for free installment loan offers, and the high incidence of *ex ante* precommitment to loan terms that are shorter than the maximum term allowed under the loan offer. We test and strongly reject *strong and weak dominance restrictions* that constitute *a priori* restrictions on the behavioral model that rule out the anomalous precommitment behavior. Section 5 presents our conclusions and the insights our analysis provides into the question of whether excessive lending by credit card companies or excessive borrowing by credit card customers are most responsible for the credit boom and subsequent bust in Korea.

## 2 Credit Card Data

A credit card company provided us with data on all purchases, billing statements, and payments made by two random samples of its customers: a pre-crisis sample of 4990 customers followed from August 2000 to June 2003, and a post-crisis sample of 938 customers followed from 2004 to spring 2007. We have transactions for some customers in the post-crisis sample as early as 2001, but not enough to be able to make reliable inferences on the behavior of a single cohort over the entire pre and post crisis period, 2001 to 2007. Both samples were drawn as “stock samples” i.e. random samples of the company’s customers before and after the crisis, which is generally acknowledged to have come to a head shortly after the unexpected failure of SK Global in March 2003. Company executives told us that there were no major changes in the eligibility criteria to obtain a credit card before or after 2003. Thus, we are confident that any differences in spending or borrowing behavior we observe in these two samples are due to a change in behavior rather than systematic differences in the types of customers in our two samples.

Table 1 summarizes the transaction numbers and volumes (in dollars) in the two samples. In terms of number of transactions, the most common transaction is a "sale" — i.e. the usual type of credit card transaction where the customer is expected to repay the amount in full at the next statement date to which the transaction is assigned. The credit card company collects the balance due on the statement date automatically via a direct electronic debit from the customer's bank account. Sales transactions are the default type of credit provided by the credit card company and involve "free float" — the mean time from transaction to repayment (with no interest charges) is an average of 37 and 32 days in the pre- and post-crisis samples, respectively.

Besides ordinary sales transactions, the company extends longer term loans to its customers via three other transaction types: 1) installments, 2) cash advances, and 3) revolving purchases. Revolving purchases are the default type of transaction in the U.S. and most European countries, and provide customers wide discretion on how and when to pay these balances. Revolving accounts are a relatively new product in Korea, and we can see from table 1 they constitute only a small fraction of the credit extended by the company, both in terms of share of transactions, and the share of the total funds it lends. The main sources of credit the company provides are cash advances and installment loans. We can see from table 1 that cash advances constituted the largest share of funds the company loaned to its customers, both before and after the crisis. However cash advances dramatically contracted, from 71% before the crisis to 45% afterwards. The share of lending done via installment loans increased after the crisis, but much more moderately, from 10% before the crisis to 13% afterwards. However as a share of all *transactions,* installments and cash advances fell dramatically, from approximately 30% of all transactions prior to the crisis to about 11% afterwards.

Table 2 displays the average transaction sizes and interest rates charged for each type of credit that the company provides to its customers. Sales transactions involve a 0% interest rate and are smaller, averaging $54.27 before the crisis and $51.49 afterwards. The average transaction sizes of the other types of loans are much larger but also have substantial interest rates. Cash advances are particularly large and expensive, carrying an average interest rate of 21.5% before the crisis and 24% afterwards. Installments are the next

Table 1: Summary of the Pre and Post-Crisis Credit Card Samples

| Item | Pre-crisis | Post-crisis |
|---|---|---|
| Customers | 4990 | 938 |
| Period | Aug 2000 to Jun 2003 | Sep 2001 to Jun 2007 |
| By number of transactions | | |
| Sales | 228613 (66.3%) | 151225 (76.4%) |
| Cash advances | 73903 (21.4%) | 12460 (6.3%) |
| Installments | 30614 (8.8%) | 9658 (4.9%) |
| Revolving | 11657 (3.3%) | 24503 (12.4%) |
| By total value ($ millions) | | |
| Sales | 13.1 (16.8%) | 7.6 (37.8%) |
| Cash advances | 55.6 (71.5%) | 9.1 (45.3%) |
| Installments | 8.3 (10.7%) | 2.6 (12.9%) |
| Revolving | 0.8 (1.0%) | 0.8 (4.0%) |

Table 2: Average transaction sizes and interest rates in the pre and post-crisis credit card samples

| Item | Pre-crisis | Post-crisis |
|---|---|---|
| Sales | $54.27, 0.00% | $51.49, 0.00% |
| Cash advance | $752.80, 21.48% | $732.38, 23.96% |
| Installment | $348.13, 12.93% | $287.20, 15.25% |
| Revolving | $73.73, 13.70% | $30.87, 27.17% |

largest in terms of average transaction size and carry a lower average interest rate, though this is partly due to interest-free installment loan offers that we will discuss in more detail shortly.

The company imposes a credit limit on its customers: the sum of each customer's installment balance and credit card balance cannot exceed a specified credit limit, which depends on the customer's credit score and history (including spending patterns) with this company. Unfortunately the company did not provide us with information on the credit limits for the customers in our sample. Customers are not allowed to use their credit cards for further spending when their combined credit card and installment balances exceed their credit limit: they must pay part of these balances so they are below their credit limit to restore their charging privileges. Thus, by virtue of the fact that we observe credit card transactions, we can infer that the customer's credit card limit is higher than the sum of the balances in their credit card and installment accounts, which we can track on a daily basis given the information the company provided us.

In the rest of this paper we focus on the choice of transaction type, but ignore revolving transactions and cash advances. Cash advances are a different type of loan motivated by an immediate need for cash that are typically done for shorter terms than installment loans. For example the average duration of a cash advance loan was 39 days in the pre-crisis sample and 45 days in the post-crisis sample, compared to 90 and 120 days, respectively, for installments.

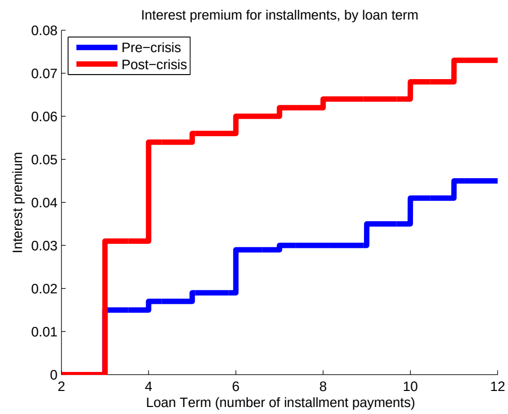
## 2.1 Installment Loans and Interest Rates

With rare exceptions, the maximum term of an installment loan is 12 months. Every credit card transaction other than revolving purchases or cash advances requires an *ex ante* choice of the installment term by the customer. That is, the customer can choose to pay the purchase amount in full at the next billing statement (which we denote as the choice $d = 1$) or to pay it off in installments over 2 to 12 subsequent billing statements (which we denote as a choice $d$ from the set $\{2, \ldots, 12\}$). The primary focus of this paper is to understand how customers decide whether to pay for individual purchases as a "regular purchase" (i.e. as payable at the next statement date to which the transaction is assigned, $d = 1$) or as an installment purchase in which case the payment is spread out over 2 to 12 future statement dates, i.e. a choice $d \in \{2, \ldots, 12\}$. Our goal is to understand how the installment interest rate afects the customer's choice of installment term.

The most popular term is $d = 3$, chosen in 61.5% of all of the installment purchases in our post-crisis sample. The maximum installment term we observe is 12 months, chosen in nearly 2% of the cases. Other commonly chosen terms are 2 months (20% of cases), 5 months (5%), 6 months (5%), and 10 months (4%). Almost all installments are paid off in $d$ equal payments. For example, if a consumer purchases an amount $P$ under an installment with a term of $d$, the customer pays back the "principal" $P$ in $d$ equal installments of $P/d$ over the subsequent $d$ billing statements. When interest is charged, it is billed separately at the successive $d$ statement dates. Installments with unequal payments are usually a result of late payments or pre-payments.

We calculated the realized internal rates of return on 30614 installment transactions in our pre-crisis sample and 9658 transactions in the post-crisis sample. In the pre-crisis sample, two thirds of the transactions had a zero interest rate, whereas in the post-crisis sample, only 48% of the installments carried a zero interest rate. These zero interest or "free installments" are usually a result of special promotions that are provided either at the level of individual merchants (via agreement with the credit card company to help promote sales at particular merchants), or via general offers that the credit card company offers to all customers during specific periods of time either to encourage more spending, increased customer loyalty,

Figure 1: Interest Premium for Installment Purchases as a function of the Installment Term




or as a promotion to attract new customers.

Though the company does not publish its schedule for setting interest rates, we were able to econometrically infer the company's policy for setting installment credit interest rates by regression. The high $R^2$ of this regression, 0.99, indicates that we were successful in uncovering the actual formula the company uses to set interest rates for its customers. Interest rates not only depend on the credit score of the customer, but also on the duration of the installment loan. The credit card company uses a particular non-linear increasing interest premium schedule for loans over two months in duration that is *common* to all its customers, but with a base rate or intercept that varies with customer characteristics, particularly the customer's credit score. For example, the interest rate premium the company charges customers for a 12 month installment loan is 7 percentage points and, interestingly, this differential is the *same for all customers.*

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

$$r_t(d,x) = r_0(x,t) + r_1(d,t), \tag{1}$$

where the effects of time-varying macroeconomic and market conditions are captured by the time effect $t$ and the characteristics of the particular consumer $x$ only enter via the intercept term $r_0(x,t)$. The term $r_1(d,t)$ represents the *interest premium* for installments longer than $d = 2$ months. Our regression results reveals that this term does not depend on $x$ but only $d$ and $t$. Figure 1 graphs the interest premium customers must pay for various installment terms $d > 2$.

While the premium for longer duration installment loans is approximately the same for all customers, it does shift over time. Figure 1 shows that the company significantly raised this premium after the 2003 Korean credit crisis. The higher interest rates for installment loans may be one of the factors that caused the significant reduction in installment balances and installment loan usage that we document in figure 4 below. Note that one of the individual-specific factors that we did *not* include in the $x$ vector is the customer's installment balance, or other measures of usage of installment loans. These variables are not statistically significant predictors of the interest rate charged to consumers after we include other customer characteristics, particularly the credit score and number of late payments.

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

## 2.2 Interest-free Installment Loans

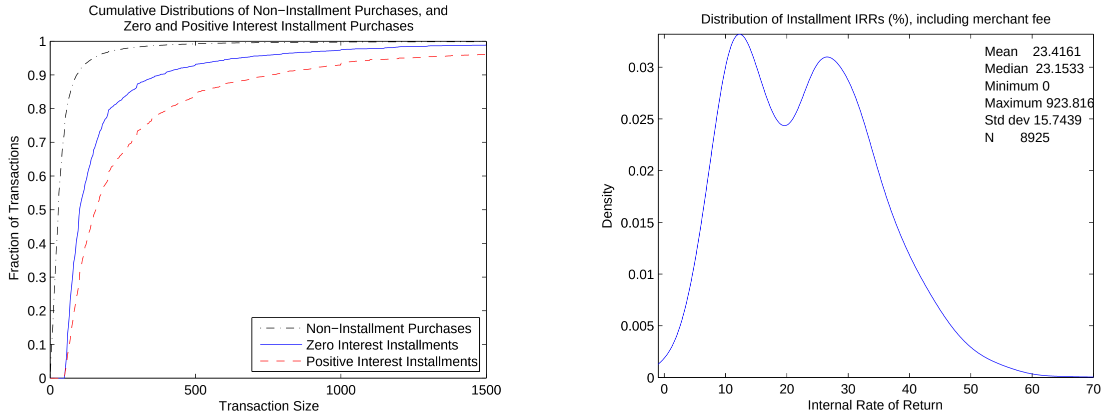
We already noted in the introduction that the credit card company uses interest-free loans as a marketing device to attract new customers and to incentivize its current customers to stay with the firm and to spend more using its credit card instead of using credit cards of its competitors. This company is very profitable and merchant fees associated with credit usage contribute in an important way to the overall profitability of the firm. Specifically, for our pre-crisis sample we found that merchant fees amounted to 36% of the total revenues received from these customers. In the pre-crisis sample, 22% of total revenues were from merchant fees, whereas customer finance charges constituted the largest share, 68%. Due to the structure of electronic payments in Korea, success in the credit card market depends on having a dominant market share. 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 them to charge higher merchant fees. The company views interest-free installment loan offers as a critical part of its strategy to increase its market share and be successful in this market.

The company does not keep a record of when, where, and to whom interest-free installment offers were made. Instead, we can only learn about them indirectly via customers who chose them, since the company obviously does record the choices its customers make in order to bill them. Although they keep no central records, company management told us that it was their impression that after the crisis customers were offered free installments in 10 to 20% of all transactions they made with the company's credit card, and most of these offers had a maximum term of 3 months.

Company management confirmed that interest-free offers are *universal* in the sense that they are made to all customers regardless of their credit score, installment balance, or other customer-specific characteristics. The only way customers may have differential access to free installment offers is due their shopping patterns (since free installments are offered with different probabilities at different merchants and vary by time of year) and the possibility that installment-prone customers might actively seek out free installment offers. Free installments are sometimes made available to *all* of the company's customers regardless of where they shop, but for limited periods of time. These opportunities are announced on the company's web site, or in flyers or ads that are included in the monthly statements that it mails to its customers. Management also confirmed that the maximum term of the offer is independent of the characteristics of the customers, or other variables such as merchant type, or time of year.

Installment term is chosen at purchase time, at the checkout counter via a pin pad, or by notifying the checkout clerk. Customers are informed of the installment interest rate schedule on their monthly statements and via their account on the company's web site. When customers receive interest-free installment offers, the maximum term is part of the offer, and is not a variable that the customer can choose (unlike the case of positive interest rate installments), except that customers are allowed to precommit to pay off the installment in *fewer* than the maximum number of payments allowed under the offer. If a customer wishes

Figure 2: Distributions of Transaction Amounts and Rates of Return




to borrow for a longer term than the one offered, it must be done at a positive interest rate according to the customer-specific interest schedule described above.

Figure 2 plots the cumulative distribution of regular purchases (i.e. $d = 1$), as well as zero and positive-interest installments in the post-crisis sample. 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 we can see what we have called the *free installment puzzle* in figure 2: the average size of a positive interest rate installment is more than 75% larger than the average installment done under a zero interest rate. Economic intuition (e.g. the hypothesis of a downward sloping demand for installment credit) would suggest that installments done at a lower interest rate — and particularly those done at a *zero* interest rate — should be significantly *larger* than those done at a positive interest rate.

The right panel of Figure 2 plots the distribution of internal rates of return that the credit card company earned on its installment loans in the post-crisis sample. These returns are inclusive of 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%.

The merchant fee shifts the distribution of returns significantly to the right. Even with the interest-free installment transactions included, the company earned an average rate of return of 23% on its installment loans. Note that even the most frequent transaction, ordinary sales, earn a 24% average rate of return for the company when we factor in the merchant fee, which averages 2.3% for this company. For the positive interest installment loans the average internal return inclusive of the merchant fee is even higher, 31.4%.[2] Overall, we conclude that at least for this company, installment loans are excellent investments that offer very high rates of return. Further, the customers in our post-crisis sample had relatively low risk of default.

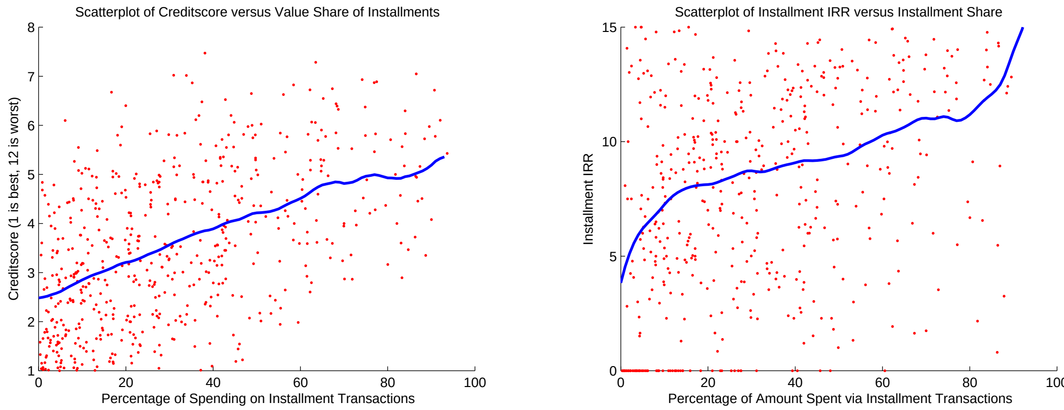
These high rates of return explain why credit card companies are so interested in a variety of promotional devices, including use of free installment offers. By increasing the number of customers, spending per customer, and extending its network of merchants, the company's market power is significantly enhanced and this can enable it to raise its merchant fee, which is a significant component of its revenues and profits. If the company were able to raise its average merchant fee from 2.3% to 4%, the rate of return it earns on ordinary sales transactions nearly doubles, to 42% (assuming the same average delay between purchase and repayment on non-installment purchases).

### 2.3 Characteristics of Installment-Prone Customers

We constructed longitudinal balance histories for the customers in our sample to calculate returns and profitability on a *customer by customer basis.* 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. In the case of customers who default, the company also loses the uncollected balance of their loan. Revenues include annual fees, late fees, interest and service charges, and merchant fees. We measure *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.

[2] 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 the post-crisis 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 2 would not significantly diminish the returns the company earns.

Figure 3: Customer-specific credit scores and rates of return by installment share




Our analysis reveals a substantial degree of heterogeneity across credit card customers in their profitability and their propensity to use of installment loans, and we find that the best single measure of this propensity is the mean share of credit card purchases paid for by installment, something we refer to as the *installment share.* We now document that installment-prone customers, i.e. those who pay for most of their credit card spending on installment, are both more profitable but also more risky as reflected by worse credit scores. In turn, customers who have worse credit scores also have higher default rates.

The left hand panel of figure 3 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 up to their credit limit (which we do not observe in either sample). 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 that customers who rely more on installment spending tend to have worse credit scores.

Figure 3 suggests that customers with poor credit scores have a *high demand for credit* perhaps reflecting credit constraints, such as if their poor credit score flags them as poor credit risks to other lenders, forcing them to make heavier use of installment credit at relatively high rates. In contrast, customers with the best credit scores are the least likely to use installment credit, which may indicate that they are not liquidity constrained such as having access to lower cost sources of credit elsewhere.[3]

[3] We also find that the incidence of late payments and seriously late payments (i.e. payments that are 90 or more days past due,

As we noted previously, there is a clear direction of causality in terms of the positive correlation between the installment share and the credit score: high installment use *per se* does not degrade the credit score, rather individuals with poor credit scores have the highest demand for installment credit. In a separate scatterplot (also not shown due to space limitations) we find that the installment share is also strongly positively correlated with the fraction of installment transactions done at zero interest rates. This suggests that customers who pay for most of their credit card purchases on installment are relatively desperate for credit, which explains why they are significantly more likely to take free installment offers.

For the heaviest installment users in our post-crisis sample, nearly 20% of their installment transactions are interest-free installments. If we assume that the heaviest installment users have a take-up rate for free installments close to 100%, the fact that 20% of all installment transactions for these individuals are free installments provides an estimate of the probability that free installments are offered to customers, an estimate that squares with the one provided by company executives for the post-crisis sample and is consistent with the estimated offer rate from our econometric model that we present in the next section.

The right hand panel of figure 3 relates customer-level profitability (as measured by the overall customer-specific "rate of return", i.e. the calculated internal rate of return the company earns on all transactions for each customer) to the installment share. We see that the most installment prone customers are also the most profitable, and this is due largely to the higher rate of interest the company earns on these customers due to their poorer credit scores. We have already suggested that the company's use of free installment offers seems motivated by a desire to increase its customers' use of its credit cards. However we have also shown that the customers who are most likely to take the free installment offers are more likely to have worse credit scores and make late payments. As such, the use of free installments as a promotional device has the perverse effect of offering free credit to the company's least creditworthy customers, a group most likely to default. Thus, the strategy of offering interest-free installment loans may increase its expected returns, but also its risk of default.

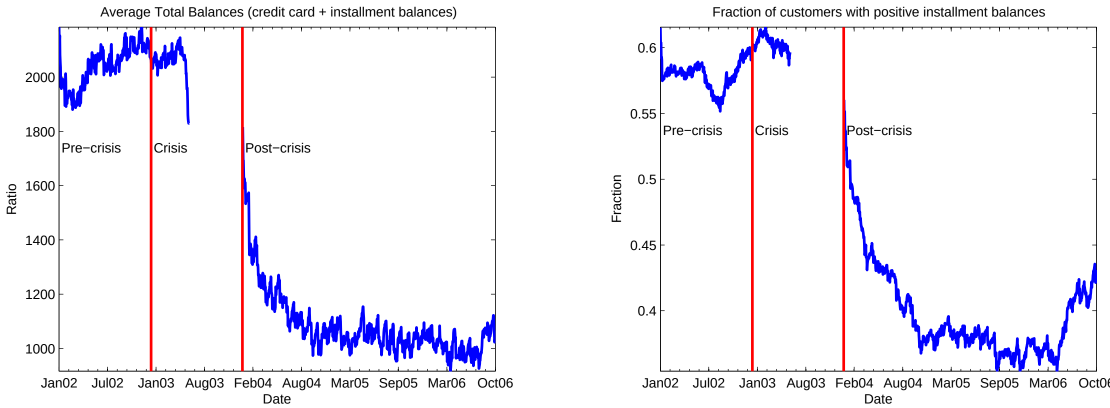
### 2.4 Changes in credit card spending and balances before and after the crisis

We aggregated the individual balance histories in our samples to reveal overall changes in spending and balances before and after the 2003 crisis. Figure 4 plots the average total credit card balances (i.e. the

---

or at about the threshold where the company suspends credit card charging privileges) and defaults are also positively correlated with the installment share, confirming that customers who are the heaviest installment spenders tend to be the worst credit risks.

Figure 4: Effect of crisis on credit card balances and installment usage

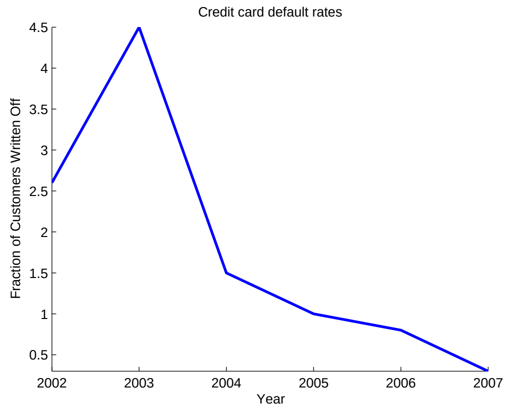



sum of the balance currently due plus the installment balance) for the pre and post-crisis samples and the fraction of customers in these samples who had positive installment balances. We only plotted the averages when we had sufficiently large number of observations, and the lack of sufficient observations in the latter part of 2003 causes the gap in the lines during the crisis period, 2003. However our data are sufficient to show the striking decline in credit card balances after the crisis: total balances fell by half from approximately \$2000 per customer before the crisis to an average of \$1000 after the crisis.

The biggest contributor to the decline in balances was the drop in non-installment (currently due) balances, from \$1400 in the pre-crisis sample to \$700 in the post-crisis sample. Average installment balances also fell by half, from \$600 before the crisis to \$300 afterwards. The right hand panel of figure 4 shows that the share of customers who carried installment balances declined by a third, from 60% before the crisis to under 40% afterwards. However for the subset of customers who carried positive installment balances, the ratio of installment to credit card balances increased after the crisis: from an average ratio of 1 before the crisis to 1.5 afterwards. This increase was not caused by increased installment spending, rather customers were quick to reduce their balances in their credit card accounts but reduced installment balances more slowly. This is why credit card balances of installment users fell by half but their installment balances fell by a third.

Figure 5 plots the trend in default rates for the customers in the combined pre and post-crisis samples. Default rates rapidly rose and peaked in 2003, the year of the crisis, and then rapidly declined thereafter. Note that default rates in 2003 are likely to be underestimated due to the fact that our pre-crisis sample ends in June 2003, so there could potentially have been many more defaults between July and December

Figure 5: Effect of crisis on default rates




2003 that are not reflected in figure 5.

The $2000 average balance of the customers in our pre-crisis sample is the same value that Kang and Ma [2007] report as the per capita credit card balance in Korea in 2002. Overall the changes in our micro data sets are consistent with the changes Kang and Ma [2007] and Kang and Ma [2009] documented using lower frequency macro data. What is particularly striking is how quickly Koreans reduced their credit card balances, and how quickly default rates dropped after 2003. What is less clear is what were the factors that drove the rapid buildup and peak in default rates in 2003 and the rapid decline in balances and default rates afterwards.

Some of the reductions in credit card spending were due to reductions in credit limits. Some of these were imposed by the company in response to deteriorating credit scores of certain customers, but significant number of reductions were done *voluntarily at the request of the customer.* The company honored significant numbers of voluntary requests by its customers to reduce their credit limits *without providing any compensation or reward for doing this.* This is precisely the sort of "suboptimal precommitment" behavior that is difficult to explain using standard expected utility models. In the next section we provide evidence of other puzzling precommitments by customers: turning down free installment offers, and precommiting to pay them off faster than necessary.

# 3 Exploiting the Quasi-Random Nature of Free Installment Offers

We now present a simple, flexible behavioral model of customers' choice of installment loans that allows us to exploit the quasi-random nature of free installment offers. Our original motivation was to use free installments as an *instrumental variable* to help identify the effect of interest rates on consumer demand for credit. When we regress the size of installment loans on the interest rate the company charges its customers, we obtain an *upward sloping* estimated demand curve. Of course, the positive slope is spurious, due to the endogeneity of the interest rate: customers with high demand for installment credit also tend to have worse credit scores and therefore are charged higher interest rates. Several obvious choices of instrumental variables such as the aggregate daily CD or call rates (which affect the banks' opportunity cost of credit and thus serve as exogenous shifters of the interest rates they charge to their customers) turned out to be *weak instruments* due to the huge, highly variable markups that swamp the small variations in the CD or Call rates.

We also tried to infer the causal effect of the interest rate on the demand for credit using a *matching estimator* which involves comparing the average size of installment transactions made at positive interest rates to the average size of installment transactions when the interest rate is zero.[4] But for the reasons discussed in section 2.2, the matching estimator also implies an upward sloping demand for credit, i.e. the mean size of an installment done at a positive interest rate is *larger* than the mean size of an installment done at a zero interest rate. As a result, both the instrumental variables and "treatment effects" approaches result in the unreasonable conclusion that the demand for credit is *increasing in the interest rate.*

We reasoned that the occasional and often unpredictable interest-free installment offers that this company makes to its customers could function as a *quasi-random experiment* (QRE) since these offers are made to all customers regardless of their characteristics or credit scores. We will now show how it is possible to identify the demand for credit by exploiting the quasi-random nature of free installment offers. The main econometric problem we face is *censoring:* the company's data systems only record free installment offers when customers actually choose them. For all other transactions, we do not know whether the customer was offered a free installment opportunity and chose not to take it. Since we are willing to make some reasonable assumptions and put some additional structure on the credit choice problem, we can provide econometric solutions to the censoring problem. The model we present next enables us to *infer* the probability customers are offered free installments, and to predict how these offers affect their choices.

[4] We have sufficiently many transactions on individual consumers that we can use them as *self-controls* and compare the mean size of specific types transactions (e.g. for specific merchant codes) by the same consumer for transactions done at positive interest rates and comparable transactions done at zero interest rates.

### 3.1 A Flexible Behavioral Model of Installment Loan Choice

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

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

$$v(a,x,r,d) = ov(a,x,d) - c(a,r,d) \tag{2}$$

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

We also allow for transitory unobserved factors that affect consumers' decisions about installment term by incorporating additive random shocks $\varepsilon(d)$ so that the net utility of installment choice $d$ is $v(a,x,r,d) + \varepsilon(d)$, $d = 1,2,\ldots,12$. Examples of factors that affect a customer's choice that might be in the $\varepsilon(d)$ term include whether there is a long line at checkout (so the customer feels time pressured and unable to carefully weigh the net benefits of options $d = 2,\ldots,12$ relative to the "default action" of choosing $d = 1$), or other time-varying but serially uncorrelated factors such as transitory or unexpected financial shocks that affect the customer's valuations of the net benefits of the other installment choices.

We assume that the "error terms" $\varepsilon = (\varepsilon(1),\ldots,\varepsilon(12))$ are *IID* Generalized extreme value (GEV) random vectors. The GEV family allows for correlation in the random variables $\varepsilon(d)$ (see McFadden [1981]) that reflect "similarity" in unobserved factors affecting consumer choices that violates the *Independence from Irrelevant Alternatives* (IIA) property that holds when the error terms are independently distributed, which is the case for the *multinomial logit model.* We estimate a version of the GEV distribution that results in a *nested logit model* of customer installment choices.

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

We are able to estimate the scale parameters $\sigma$ and $\sigma_1$ of the GEV distribution. The parameter $\sigma$ indexes the level of similarity in the positive interest choices, whereas $\sigma_1$ indexes the level of similarity in the interest-free choices in the cases where the customer is offered an interest-free installment offer. We find that the maximum likelihood estimates of $\sigma$ and $\sigma_1$ are very small, so that the predictions of this model are driven by the properties of the $v(a,x,r,d)$ function rather than by the distribution of the unobserved components $\varepsilon(d)$.

Let $P_+(d|x,a)$ be the choice probability for a customer with characteristics $x$ who does *not* have an interest-free installment offer. This customer must pay a positive interest rate for any choice $d \in \{2,3,\dots,12\}$. In our notation for the choice probability we omit the interest rate $r$ since as we show below, the interest rate charged to a consumer with characteristics $x$ for an installment loan with term $d$ is $r(x,d)$. Substituting $r(x,d)$ into the value function we see that the net utility of choosing a term of $d$ is $v(a,x,r(x,d),d)+\varepsilon(d)$, and when we integrate out over the distribution of $\varepsilon$ we obtain a conditional choice probability $P_+(d|x,a)$ that is a function of $(x,a)$ only.

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

In an online appendix to this paper we derive the formulas for $P_+$ and $P_0$ implied by the nested logit specification for the errors terms, $\{\varepsilon(d)|d \in \{1,\dots,12\}\}$, as well as the likelihood for the data. The likelihood accounts for the censoring of the free installment offers: i.e. it accounts for the fact that we only observe a free installment offer in the case where a customer takes it, but not in cases where the customer does not take the offer. The likelihood depends on two additional objects that we estimate in addition to the customer value functions $v(a,x,r,d)$: the probability that a customer receives a free installment offer, $\Pi(z)$, and a probability distribution $f(\delta)$, $\delta \in \{2,\dots,12\}$ for the maximum allowed term of this free installment offer. We use the variable $z$ to denote variables that shift the probability of receiving a free installment offer. There are two types of variables entering $z$: 1) time dummies, and 2) merchant dummies. These are included to reflect the fact that free installments vary considerably over different types of merchants and at different times of the year.

The likelihood has the structure of a *mixture model* since the probability of observing a particular choice such as $d = 1$ is a mixture over different ways this choice could have been made. For example the person could have been offered a free installment with maximum term $\delta = 10$ but chose $d = 1$ instead. Or the customer may not have received a free installment offer and still chose $d = 1$. The probability of observing $d = 1$ is thus a weighted sum of the choice probabilities $P_0(1|a,x)$ and $P_+(1|a,x,\delta)$ weighted by the probability that the customer receives a free installment offer $\Pi(z)$ as well as by the probabilities $f(\delta)$ for the different possible maximum terms of a free installment offer, $\delta \in \{2,\dots,12\}$.

It is important to note that our specification assumes that the probability of being offered a free installment, $\Pi(z)$, and the distribution of the maximum term $f(\delta)$, do not depend on $x$, the characteristics of the customer. The company verified that this is the case, and it is due to the nature of the information technology for credit cards: there is no two way dialog between the pin pad at the checkout counter and the company's customer database that enables the company or a merchant to condition a free installment offer on the characteristics $x$ of a particular customer.[5] Thus, we have a credible *exclusion restriction* that enables us to separately identify the value function $v(a,x,r,d)$ (which determines the probabilities $P_0$ and $P_+$) from $(\Pi(z), \{f(\delta)\})$.

### 3.2 Testing the Dominance Assumption for Free Installment Offers

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

**Strong Dominance Assumption**

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

**Weak Dominance Assumption**

$$P_0(d|x,a,\delta) = 0 \text{ if } d \in \{2,\ldots,\delta-1\}. \tag{4}$$

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

Notice that neither the weak or strong dominance assumptions rule out the possibility that consumers might choose a positive interest loan duration $d \in \{\delta+1,\ldots,12\}$. It may happen that a consumer has a

[5] When the consumer swipes the credit card, the credit card company does check if the sum of their credit card and installment balances exceeds their credit limit, and it so, the transaction is refused. In principle the company could condition its interest free installment offers on customer-specific characteristics and deny these offers to specific types of customers, but company executives confirmed to us that they do not engage in this type of discrimination.

need for credit for a term longer than the maximum term $\delta$ allowed under the offer, and every customer has this option by paying a positive interest rate for terms $d > \delta$.

In the remainder of this section we will focus our attention on estimation of an *unrestricted model* of consumer choice, that does not impose either the weak or strong dominance assumptions. In the unrestricted model, consumers always have the full choice set $\{1,2,\ldots,12\}$ and can choose to take a free installment loan offer for a shorter duration than the maximum term allowed under the offer. In the unrestricted model, it will generally be the case that $P_0(d|x,a,\delta) > 0$, even when $d$ is in the set of "dominated alternatives" $\{2,3,\ldots,\delta-1\}$. The weak and strong dominance restrictions emerge as limiting cases of the unrestricted model when the scaling parameter $\sigma_1$ for the extreme value unobservables affecting consumer choice of installments takes the value $\sigma_1 = 0$, where $\sigma_1$ is the similarity parameter for the "lower level nest" of interest-free alternatives. We estimated two different specifications of the GEV model, one where the lower level nest is the full set $\{1,2,\ldots,\delta\}$ and the other where the lower level nest is the set $\{2,\ldots,\delta\}$ that excludes alternative $d = 1$. Strong and weak dominance hold in these respective nestings when $\sigma_1 = 0$. We estimate the unrestricted GEV model (where $\sigma$ and $\sigma_1$ are free parameters both estimated by maximum likelihood), and we strongly reject the hypothesis that $\sigma_1 = 0$ for either nesting. Thus the data strongly reject both the weak and strong dominance assumptions.

### 3.3 Model Specification

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

$$ov(a,x,d) = a\rho(x,d) - \lambda(x,d) \tag{5}$$

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

Notice that we assume the option value of having the benefit of extended payment does not depend on the interest rate the credit card company charges the customer, and the customer-specific interest rate schedule $r_t(d,x)$ only enters via the cost function $c(a,r,d)$ which is a known function that does not have to be estimated. Combined with the location normalization that $v(a,x,r,1) = 0$, this simple cost-benefit specification for $v(a,x,r,d)$ is an important identifying assumption because it fixes both the location and scale of the value functions and thereby enables us to identify both scale parameters $(\sigma,\sigma_1)$ of the GEV distribution. Typically neither the location or scale parameters of the unobserved components $\varepsilon(d)$ of the value or utility functions are identified, so they are arbitrarily normalized. However McFadden [1981] showed that the value of $\sigma_1$ can be identified relative to any normalization for $\sigma$.

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

$$c(a,r,d) = a\left(1 - \exp\{-rt_d/365\}\right), \tag{6}$$

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

The parameters of the model are $\theta = (\sigma, \sigma_1, \phi, \alpha, \beta)$ where $\alpha$ is a vector of parameters determining the probability of receiving a free installment offer, $\Pi(z, \alpha)$, and $\beta$ is a vector of parameters characterizing the probability distribution for the maximum term of a free installment offer, $f(\delta, \beta)$, $\delta \in \{2, \ldots, 12\}$. We present the $\beta$ parameters below (since there are only 10 of them required to estimate the 11 probabilities $f(\delta, \beta)$ for $\delta \in \{2, \ldots, 12\}$), but due to space constraints we omit the maximum likelihood estimates of the $\alpha$ parameters ($\alpha$ is a $26 \times 1$ vector of coefficients for a set of time and merchant class dummies).

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

$$\rho(x,d) = \frac{1}{1 + \exp\{h(x,d,\phi)\}} \tag{7}$$

where

$$\begin{aligned} h(x,d,\phi) \quad = \quad & \phi_0 I\{d \geq 2\} - \sum_{j=3}^{12} \exp\{\phi_{j-2}\} I\{d \geq j\} + \phi_{11} ib + \phi_{12} \mathit{installshare} \\ & + \phi_{13} \text{creditscore} + \phi_{14} \text{nlate} + \phi_{15} I\{r = 0\}. \end{aligned} \tag{8}$$

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

$$\lambda(x,d) = \exp\left\{ \phi_{16} I\{r = 0\} + \phi_{17} \mathit{installshare} + \sum_{j=2}^{10} \phi_{16+j} I\{d = j\} + \phi_{27} I\{d > 10\} \right\}. \tag{9}$$

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.*

### 3.4 Estimation Results

Table 3 presents the maximum likelihood estimates of $(\sigma, \sigma_1, \phi, \beta)$ for the unrestricted GEV specifications for the pre and post-crisis data sets, respectively.[6] The nesting that results in the highest likelihood is the one where the lower level nest consists of the interest-free alternatives $\{1, \ldots, \delta\}$ when an interest-free

[6] We also estimated a multinomial logit specification, which is a special case of the nested logit model when we impose the restriction $\sigma_1 = \sigma$, but due to space constraints we do not present these estimates in Table 3 since we strongly reject the restriction $\sigma = \sigma_1$.

installment offer is present. The maximum likelihood parameter estimates for this nesting are presented in table 3. The parameters $\sigma$ and $\sigma_1$ are precisely estimated and a Wald test decisively rejects the restriction $\sigma_1 = 0$. Similarly, for the alternative nesting where the lower level nest is the set $\{2,\ldots,12\}$ (not shown due to limited space), $\sigma_1$ is also very precisely estimated and a Wald test also decisively rejects the hypothesis $\sigma_1 = 0$ so we decisively reject the Weak Dominance Assumption as well.[7] While we can easily reject the restriction $\sigma_1 = 0$, we do find that our estimated $\sigma_1$ is significantly smaller than $\sigma$ which indicates that individuals find the interest-free alternatives $d \in \{2,\ldots,\delta\}$ to be significantly more "similar" to each other in terms of unobserved factors $\varepsilon(d)$ than for the default choice $d = 1$ or for any of the positive interest alternatives $d \in \{\delta+1,\ldots,12\}$.

In addition to the decisive rejection of the weak and strong dominance assumptions, the model predicts a surprisingly low takeup of free installment offers, both before and after the 2003 crisis. Figure 6 plots the average rate at which free installments were offered before and after the crisis (i.e. the average of the estimated $\Pi(z,\alpha)$ probabilities, where this probability differs across merchants and time periods), and the implied take up rate of these offers, i.e. the average probability $\sum_{d=2}^{\delta} P_0(d|x,a,\delta)$ which is the probability that a customer of type $x$ takes the offer, although possibly not for the maximum allowed term $\delta$.

In the pre-crisis sample the average probability of receiving a free installment offer was over 50%, rising rapidly and eaking at nearly 80% by mid 2003 as the credit crisis reached fever pitch. In the post-crisis period, the probability of receiving free installment offers fell dramatically. In the immediate aftermath of the crisis in January 2004, interest-free installments were offered in only 10% of all transactions, though offers slowly increased to about 20% by 2007. Note that these estimates are within the range of probabilities that the company executives told us would be their best guess of likely values in effect after the 2003 crisis. Company executives also confirmed that prior to the crisis the company had been very aggressive in its use of free installment offers, and additionally, merchants were much more likely to partner with the company to sponsor interest-free installments as part of sales promotions. Thus, our findings square with independent evidence provided by company executives.

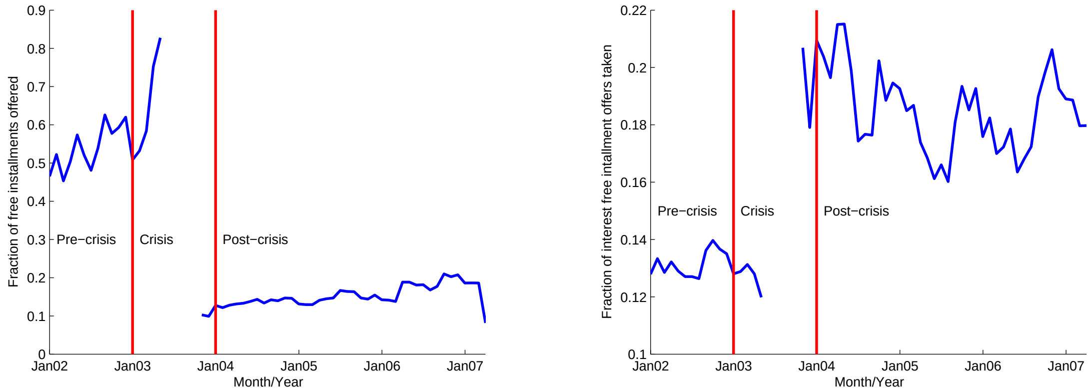
The right hand panel of figure 6 plots the average probabilities that customers took these free install-

[7] The Weak and Strong Dominance Assumptions are also decisively rejected by likelihood ratio tests, where we estimated the two nestings imposing the restriction that $\sigma_1 = 0$ in each case. For example for the alternative nesting that includes alternatives $\{2,\ldots,\delta\}$ in the lower level nest for the choice probability $P_0$ in the presence of a free installment offer, the unconstrained nested logit maximum likelihood value in the post-crisis sample is -45717. When we maximize the likelihood function subject to the constraint $\sigma_1 = 0$ the likelihood is -49351. The likelihood ratio statistic, distributed as $\chi^2(1)$ under the null hypothesis of Weak Dominance $H_o : \sigma_1 = 0$, is 7268. Thus we can strongly reject $H_o$ at any reasonable significance level. The Strong Dominance restriction is rejected even more decisively by likelihood ratio tests in both the pre and post-crisis samples.

Table 3: Maximum Likelihood Parameter Estimates, Dependent variable: installment term, $d$

| | Pre-Crisis | | Post-Crisis | |
|---|---|---|---|---|
| Parameter | Estimate | Std. Error | Estimate | Std. Error |
| $\sigma$ | 0.1175 | $2.2 \times 10^{-3}$ | 0.053 | $7.5 \times 10{-}4$ |
| $\sigma_1$ | 0.021 | $3.7 \times 10^{-4}$ | 0.012 | $5.0 \times 10^{-4}$ |
| $\phi_0\ I\{d \geq 2\}$ | -3.115 | 0.031 | -3.289 | 0.021 |
| $\exp\{\phi_1\}\ I\{d \geq 3\}$ | 0.260 | 0.022 | 0.317 | 0.017 |
| $\exp\{\phi_2\}\ I\{d \geq 4\}$ | 0.107 | 0.014 | 0.200 | 0.029 |
| $\exp\{\phi_3\}\ I\{d \geq 5\}$ | 0.044 | 0.016 | 0.087 | 0.031 |
| $\exp\{\phi_4\}\ I\{d \geq 6\}$ | 0.059 | 0.007 | 0.116 | 0.017 |
| $\exp\{\phi_5\}\ I\{d \geq 7\}$ | $1.6 \times 10^{-27}$ | 0.012 | $2.0 \times 10^{-27}$ | 0.009 |
| $\exp\{\phi_6\}\ I\{d \geq 8\}$ | 0.239 | 0.019 | 0.110 | 0.050 |
| $\exp\{\phi_7\}\ I\{d \geq 9\}$ | 0.017 | 0.008 | 0.088 | 0.052 |
| $\exp\{\phi_8\}\ I\{d \geq 10\}$ | $1.1 \times 10^{-16}$ | 0.004 | 0.049 | 0.018 |
| $\exp\{\phi_9\}\ I\{d \geq 11\}$ | $1.8 \times 10^{-16}$ | 0.004 | $3.5 \times 10^{-16}$ | 0.103 |
| $\exp\{\phi_{10}\}\ I\{d = 12\}$ | 0.349 | 0.017 | 0.248 | 0.102 |
| $\phi_{11}$ $(ib)$ | -0.042 | 0.001 | -0.072 | 0.001 |
| $\phi_{12}$ $(installshare)$ | -1.642 | 0.025 | -2.320 | 0.034 |
| $\phi_{13}$ $(creditscore)$ | — | — | -0.003 | 0.001 |
| $\phi_{14}$ $(nlate)$ | -0.036 | 0.002 | -0.023 | 0.001 |
| $\phi_{15}$ $(I\{r = 0\})$ | 0.004 | 0.017 | -0.472 | 0.057 |
| $\phi_{16}$ $(installshare)$ | -0.882 | 0.009 | -0.821 | 0.016 |
| $\phi_{17}$ $(I\{r = 0\})$ | -1.697 | 0.013 | -1.591 | 0.042 |
| $\phi_{18}$ $(I\{d = 2\})$ | -0.113 | 0.021 | -1.024 | 0.017 |
| $\phi_{19}$ $(I\{d = 3\})$ | -0.617 | 0.021 | -1.228 | 0.016 |
| $\phi_{20}$ $(I\{d = 4\})$ | 0.213 | 0.022 | -0.572 | 0.022 |
| $\phi_{21}$ $(I\{d = 5\})$ | 0.002 | 0.021 | -0.744 | 0.018 |
| $\phi_{22}$ $(I\{d = 6\})$ | -0.143 | 0.021 | -0.711 | 0.018 |
| $\phi_{23}$ $(I\{d = 7\})$ | 0.386 | 0.023 | -0.483 | 0.021 |
| $\phi_{24}$ $(I\{d = 8\})$ | 0.389 | 0.023 | -0.376 | 0.030 |
| $\phi_{25}$ $(I\{d = 9\})$ | 0.384 | 0.023 | -0.369 | 0.025 |
| $\phi_{26}$ $(I\{d = 10\})$ | 0.160 | 0.022 | -0.696 | 0.018 |
| $\phi_{27}$ $(I\{d > 10\})$ | 0.278 | 0.021 | -0.463 | 0.020 |
| $f(2,\beta)$ | 0.004 | 0.001 | 0.076 | 0.007 |
| $f(3,\beta)$ | 0.168 | 0.010 | 0.664 | 0.013 |
| $f(4,\beta)$ | 0.030 | 0.008 | 0.011 | 0.006 |
| $f(5,\beta)$ | 0.002 | 0.003 | 0.033 | 0.007 |
| $f(6,\beta)$ | $5.4 \times 10^{-16}$ | 0.052 | $1.9 \times 10^{-16}$ | 0.015 |
| $f(7,\beta)$ | 0.337 | 0.053 | 0.060 | 0.017 |
| $f(8,\beta)$ | $1.4 \times 10^{-14}$ | 0.005 | $8.2 \times 10^{-16}$ | 0.013 |
| $f(9,\beta)$ | $8.0 \times 10^{-18}$ | 0.009 | $2.8 \times 10^{-16}$ | 0.001 |
| $f(10,\beta)$ | 0.203 | 0.011 | 0.123 | 0.099 |
| $f(11,\beta)$ | 0.007 | 0.003 | $3.9 \times 10^{-17}$ | 0.107 |
| $f(12,\beta)$ | 0.247 | 0.007 | 0.032 | 0.005 |
| Log-likelihood, N | -110111,N=242594 | | -45257,N=167946 | |

Figure 6: Free Installment Offer and Takeup Rates

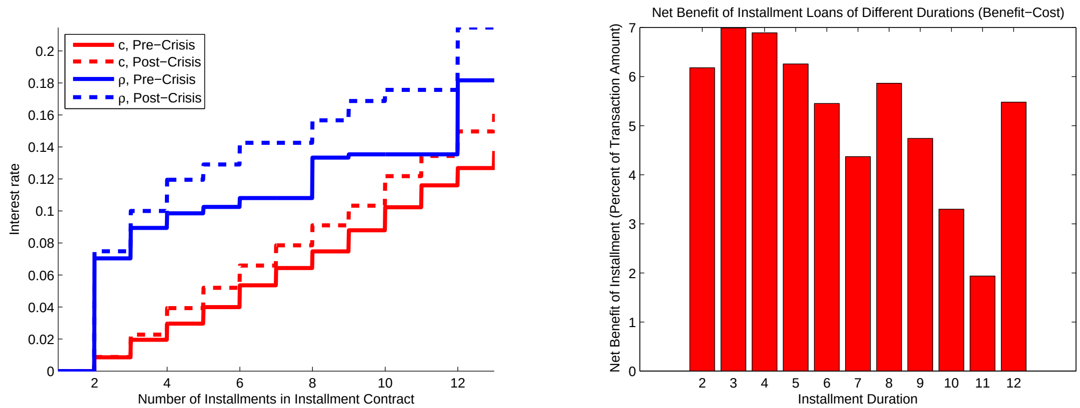



ment offers before and after the 2003 crisis. We see that the estimated takeup rates are quite low, averaging about only 13% in the pre-crisis sample, and about 20% in the post-crisis sample. Note that the average probabilities that free-installments are offered and taken are *inferred* from our econometric model. However the product of these two probabilities equals the fraction of installment transactions that are done at a zero interest rate and this is something we *observe* directly in our data. Our model accurately predicts that the incidence of interest-free installments increased from about 6% in January 2002 to 10% by June 2003, but then collapsed to just 2% by January 2004 and cycled between 2% and 3% from 2004 to 2007.

The model captures the increase in takeup rates in the post-crisis sample in two ways: a) the estimates imply that customer option values for credit are higher in the post-crisis sample, and b) the transactions costs associated with choosing alternatives $d > 1$ are significantly lower for customers in the post-crisis sample. As we noted in section 2, the credit card company significantly raised its interest rates after the 2003 crisis. The combination of the rise in interest rates and the drop in estimated transactions costs explains why there was simultaneously a significant drop in the number of positive interest installment transactions in the post-crisis sample, while at the same time takeup free installment offers increased.

The left hand panel of Figure 7 illustrates the upward shift in both customers' valuations of credit and in the cost of credit after the 2003 crisis. The blue lines plot the estimated subjective "opportunity cost of credit" $\rho(x,d)$ for an illustrative customer $x$ with a creditscore of 2, $ib = 2$, and an installment share of 30%. From figure 7 we see that the estimated subjective interest rates $\rho$ are non-decreasing in $d$ and are everywhere above the interest rates the credit card company charges $r(x,d)$, signaling a clear net benefit of purchasing under installment credit. The $\rho(x,d,\phi)$ functions has its largest jumps at $d = 3$ and $d = 12$.

Figure 7: Estimated $\rho(x,d,\phi)$, $r(x,d)$, and $\rho(x,d) - r(x,d)$




The dashed blue line plots the estimate of $\rho(x,d)$ in the post-crisis sample, whereas the solid blue line plots the estimate of $\rho(x,d)$ from the pre-crisis sample We see that there is a noticeable increase in $\rho(x,d)$ in the post-crisis sample, particularly for longer loan terms $d$. The red lines plot the interest premium function $r_1(d,t)$ for the pre and post-crisis samples respectively. The company did not raise interest rates for longer term loans as much as customers' subjective values for these longer duration installment loans increased, so this should have induced a shift in demand towards installment loans of longer duration. However we do not observe a shift toward longer duration loans in the post-crisis data set. Why?

The right hand panel of figure 7 provides insight into this paradox. Recall that customers are hypothesized to choose the installment term $d$ which as the largest *net gain* between the customer's subjective opportunity cost or option value of the of the funds $ov(a,x,d) = a\rho(x,d) - \lambda(x,d)$ and the cost the company charges for this credit, $c(a,r,d)$, which is approximately equal to $ar(x,d)d/12$. The difference between $ov(a,x,d)$ and $c(a,r,d)$ is proportional to the difference $\rho(x,d) - r(x,d)$, and we see that while $\rho(x,d)$ did "tilt" to provide higher option values for longer duration loans in the post-crisis sample, it is still the case that the highest difference between $\rho(x,d)$ and the interest rate $r(x,d)$ occurs at shorter terms such as $d = 3$. Thus in the absence of any stochastic shocks (and assuming that $\lambda$ is not too high to make the choice of an installment worthwhile to the customer), the utility maximizing choice of installment term is $d = 3$ which is also the most popular loan term as we noted above.

However $d = 3$ is also the most frequently chosen term when customers are offered free installments. How does the model explain this? When $r = 0$ the monotonicity of the option value function in $d$ suggests that customers should always be choosing the maximum term offered to them, $\delta$. The left hand panel of

Figure 8: Estimated $\lambda(x,d,\phi)$ and $f(\delta)$

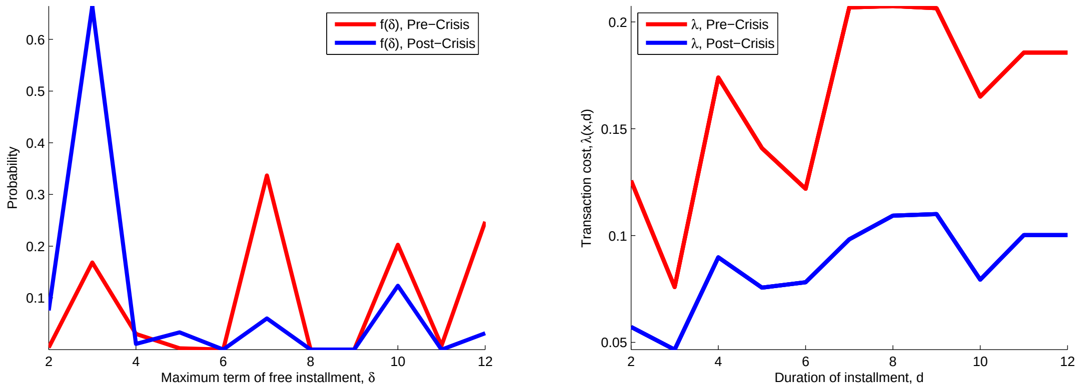



figure 8 shows that prior to the 2003 crisis, the company was much more likely to offer its customers free installment offers of longer maximum duration $\delta$ than after the crisis. We see that there was nearly equal probability of receiving a free installment offer with maximum term $\delta$ in the set $\{3,7,10,12\}$ whereas after the crisis two thirds of all free installment offers had a maximum term of only $\delta = 3$ months. The right hand panel of figure 8 shows that the transaction cost associated with choosing installment terms $d \in \{2,\ldots,12\}$ *decreased* in the post-crisis sample. Thus, we conclude that while the company offered its customers many more opportunities to take longer term free installment offers prior to the 2003 crisis, customers chose to forgo most of these offers, and the model captures this effect via higher psychic transactions costs, i.e. a higher $\lambda(x,d)$. The higher transactions costs increase the probability of choosing $d = 1$ or $d = 3$ even in the presence of a free installment offer with a maximum term $\delta > 3$.

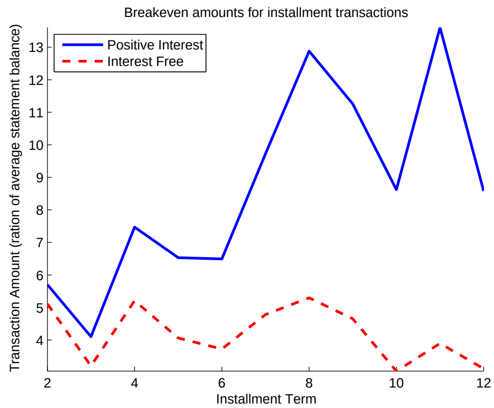
After the crisis, customers had less aversion to choosing installments, as reflected in the downward shift in the estimated transactions cost function $\lambda(x,d)$, but by then the company was no longer offering as many longer term free installment offers. Most of these offers involved a maximum term of $\delta = 3$ and customers were more likely to take them when offered than the customers in the pre-crisis sample. Thus, the model not only predicts a low takeup rate for interest-free installments, it predicts that takeup increased after the crisis, and it predicts that among those customers who do take interest-free offers, there is a very high probability that the customers will *precommit to a term that is less than the maximum term* $\delta$ *allowed under the offer.* In the post-crisis sample, the model predicts that only 8% of the customers who received a 12 month free installment offer chose the loan for the full 12 installment maximum term. The most frequently chosen option was to precommit to pay off the loan in just 3 installments. This option was chosen by 38% in our simulation of customers who accepted these interest-free installment offers with a maximum allowed term of $\delta = 12$ installments. In the pre-crisis sample, only 2.6% of simulated customers who were offered an interest-free loan for 12 months chose to take this offer for the full 12 month maximum term. The most popular term was also $d = 3$ and this was chosen by 50% of the individuals who took these offers.

The estimated model also predicts that a small fraction of customers choose installment durations $d > \delta$, i.e. they choose to pay a positive interest rate to borrow for a term longer than the maximum term $\delta$ allowed under the free installment offer. For example simulations of the model for the pre-crisis sample show that for the set of customers offered a $\delta = 3$ month free installment offer, 9% take the offer for the full term, i.e. $d = \delta = 3$, 1% choose $d = 2$, and 1% choose a term $d > 3$ and pay a positive interest rate. The remaining 88% choose $d = 1$, paying the purchase amount in full at the next statement date.

Our finding that the presence of a free installment offer increases the customer's option value for credit (at least in the post-crisis sample) is hard to rationalize using traditional expected utility models, which predict that a consumer's option value of credit should be independent of the cost of credit. In order to fit the data, our estimated model has to allow customers' option values to depend on the cost of credit, so that interest-free offers are regarded as more valuable than the already present option to borrow at a positive interest rate. Of course the model already factors the cost of credit into customers' calculations by deducting the actual cost of credit given by the $c(a,r,d)$ function. However model fit is significantly improved when we allow the option value function $ov(a,x,d)$ to depend on $r$, and particularly to be significantly higher when a free installment option is present. A possible explanation for this finding is that customers realize that free installment opportunities are "fleeting chances" that may not come again for a while. In the pre-crisis sample free installments were common, offered in nearly 60% of all transactions, and in this sample there is no statistically significant effect of free installment offers on the option value of credit. However in the post-crisis sample, the probability of receiving free installment offers had declined precipitously and it is in that sample where we find that presence of a free installment offer significantly increases the customer's perception of the option value of credit.

Finally, we note how the model is able to explain the counterintuitive finding that the distribution of transaction sizes of positive interest installment transactions stochastically dominates the distribution of interest-free transaction amounts that we discussed in section 2. If the "demand for credit" is downward sloping, one would expect that customers would purchase *more* when $r = 0$ than when $r > 0$. The way the

Figure 9: Estimated breakeven amounts $\overline{a}(x,d)$ for installment transactions




model resolves this paradox is illustrated in figure 9 where we plot 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.

$$\overline{a}(x,d) = \frac{\lambda(x,d,\phi)}{\rho(x,d,\phi) - c(a,r(x,d),d)}. \tag{10}$$

This figure was calculated for an individual in the post-crisis sample 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 $d = 11$.

The model predicts that fixed costs of taking an interest-free installment loan are lower than the costs of taking a positive interest installment and this reduces the numerator of (10). Even though the effect of free installments on the cutoff level $\overline{a}(x,d)$ is ambiguous in general, we see from figure 9 that for the particular customer that we plotted, the net effect is to uniformly lower the threshold at which the customer decides to undertake the installment transaction. The effect is particularly pronounced for loans of duration $d = 8$ and higher: under a free installment offer the cutoff point is less than 5 and as low as 3 times their average statement amount, whereas the cutoffs are over 10 for positive interest installment loans.

This is how the model explains the fact (see figure 2 in section 3) that the distribution of free installment transaction sizes is stochastically dominated by the distribution of positive interest transaction sizes. The model is telling us that the "acceptance threshold" $\overline{a}(x,d)$ for undertaking an installment transaction is lower for free installment offers than for installments done at positive interest rates. The gap between these thresholds is particularly pronounced at higher loan durations. Thus, the model predicts that customers are more likely to choose an installment ($d > 1$) for smaller size transaction if the installment is interest-free than when it is at a positive interest rate. This implies that the distribution of transaction amounts for positive interest installments stochastically dominates the distribution of transaction amounts for free installments that we observed in figure 2.

### 3.5 Capturing Heterogeneity in Installment Choices

Quantitatively, the most important $x$ variable in the model is *installshare,* the share of creditcard spending that the customer does under installment. We included *installshare* because it serves as an important observable indicator of unobserved preference heterogeneity, as well as an observed indicator about which consumers are most likely to be liquidity constrained. We found that neither *creditscore* nor the number of late payments *nlate* are as powerful as the *installshare* variable in enabling the model to fit the data and capture the high degree of customer-specific heterogeneity that we found in our analysis in section 2. The large negative and strongly statistically significant estimated coefficients of the *installshare* variable $\phi_{12}$ indicate, perhaps not surprisingly, that customers with high installment shares have uniformly higher estimated option values, and thus a higher proclivity to take installments, both those at zero and those at positive interest rates. In addition, the negative and significant estimated coefficients of the *installshare* variable entering the transaction cost function $\lambda(x,d)$ (see $\phi_{16}$ in table 3), indicate that individuals with high values of *installshare* have lower transactions costs associated with choosing installment alternatives $d > 1$ and thus are more likely to choose them.

In fact, it turns out that *installshare* is the most important single factor affecting differential take-up of free installment offers across customers in our sample. Thus, we found the *installshare* variable to be a convenient, low-dimensional means of capturing unobserved heterogeneity in the behavior of the consumers in our sample. An alternative estimation strategy would be to replace *installshare* by a random parameter $\tau$ representing *unobserved heterogeneity* with the interpretation that lower values of $\tau$ indicate customers who are more desperate for liquidity and thus have a higher subjective willingness to pay for loans of various durations, $\rho(x,d,\tau,\phi)$. For example, we tried to capture unobserved heterogeneity using the approach of Heckman and Singer [1984] but found it computationally infeasible to estimate the model.[8]

[8] A random effects approach requires integration over the distribution of possible types of preference parameters for the likelihood function for each individual consumer. For many customers in our sample we have hundreds of transactions which implies that the customer-specific likelihoods — the product of their probabilities of choosing various payment options for their

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 $\phi$ parameters on a *customer by customer basis.* For example, in the longer post-crisis sample we observe more than 100 credit card transactions for 470 of the 611 customers in our estimation sample and the maximum number of observations for any single customer was 1981. Though it is possible to estimate all 29 of the $\phi$ parameters on a customer by customer basis for the subset of 470 customers for whom we have more than 100 transaction observations, we found it easier to estimate *customer-specific constant terms* in the $h(x,d,\phi)$ and $\lambda(x,d,\phi)$ functions given in equations (8) and (9) above. Specifically, for the subsample of the 470 customers for whom we have at least 100 observations per customer, we estimated customer-specific constants $\hat{\phi}_{i,12}$ and $\hat{\phi}_{i,16}$, where $i$ indexes this subset of 470 customers, $i = 1,\ldots,470$, so in effect we estimated a total of 27 $\phi$ parameters that were common to all individuals, plus an additional $940 = 2*470$ customer-specific intercept terms in the $h$ and $\lambda$ functions.[9]

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

$$\hat{\phi}_{i,12} = \hat{\phi}_{12} installshare_i + u_i \tag{11}$$

$$\hat{\phi}_{i,16} = \hat{\phi}_{16} installshare_i + e_i \tag{12}$$

where $\hat{\phi}_{12}$ is the maximum likelihood estimate of the coefficient $\phi_{12}$ in equation (8) and $\hat{\phi}_{16}$ is the maximum likelihood estimate of the coefficient $\phi_{16}$ in equation (9), and, as we will show below $\{u_i\}$ and $\{e_i\}$ are "residuals" that turned out to have approximate mean zero and are mean-independent of the *installshare* variable.

Thus, while some readers may worry about the problem of "endogeneity" by including the *installshare* variable as an explanatory variable into the model of installment choice, it is actually just a parsimonious way of capturing the considerable degree of customer-specific parameter heterogeneity in our estimated

many observed transactions — are very small probabilities. We had great difficulty doing the numerical integration in an accurate and reliable manner. When we try to maximize the log-likelihood we ended up having to take logs of probabilities that turned out to be too small to be reliably computed on 64 bit computers.

[9]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.

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

### 3.6 Model Identification

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

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

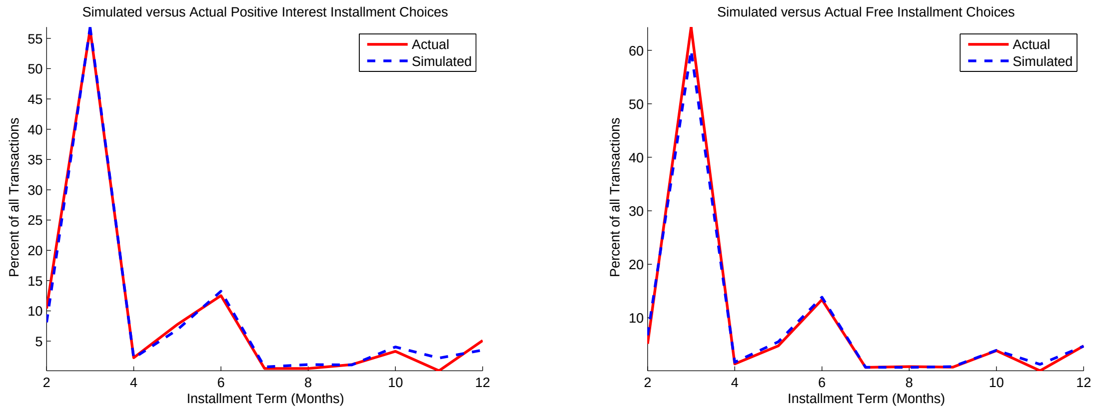
Additional evidence that the model is identified comes from the fact that we can decisively reject both the Weak and Strong Dominance Assumptions. If the model was not well identified, it would be possible to fit the data under these restrictions nearly as well as without them, since these assumptions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

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

Though it beyond the scope of this paper to provide a full analysis of the non-parametric identification of the model under the weakest possible conditions, an online appendix to this paper proves that the model is non-parametrically *partially identified.* We show that under weak assumptions, we can fully identify the probabilities of receiving a free installment offer $\Pi(z)$ and the distribution $f(\delta)$ of the maximum term of these offers separately from the consumer choice probabilities $P_+$ and $P_0$, *with no parametric restrictions on the underlying value/utility function* $v(a,x,r,d)$. However the cost is that we can only fully identify the choice probabilities $P_0$ for $d = 2$ and $d = 12$. For the other alternatives $d \in \{3,4,\ldots,11\}$ we can only identify a weighted average of $P_0$ (weighted by the probabilities $f(\delta)$ of receiving a free installment offer with a maximum term at least at great as $d$). However these partially identified probabilities are sufficient to enable us to provide a *non-parametric test of the Strong Dominance Assumption.* That is, the weighted average probabilities we can identify are sufficient to determine whether Strong Dominance holds.

However we choose to present flexible parametric estimates of these objects because the results are easier to understand and interpret and because we believe our model does not rely on implausible or highly restrictive *a priori* assumptions. The parametric structure provides more insight and detailed predictions of how consumers react to the presence of free installment offers that we cannot directly observe. But we do not believe that any of our main empirical conclusions are artifacts of functional form assumptions, and are robust to reasonable modifications of the assumed functional forms for the value functions $v(a,x,r,d)$ or the distributions of unobserved components of these values, $\varepsilon(d)$, $d \in \{1,\ldots,12\}$. The Strong Dominance Assumption can be decisively rejected even when we make *no assumptions* about the functional form about the value functions and the functional form of the distribution of unboservables $\varepsilon(d)$.

Figure 10: Predicted versus Actual Installment Choices, Pre-Crisis Sample




## 3.7 Model Fit

We now discuss the fit of the model. Figures 10, summarizes 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 vast majority 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 observations in our data sets, we obtain predicted (simulated) choices of paying in full at the next statement (i.e. to choose $d = 1$) that closely matches the observed frequency as well as all other installment choices $d > 1$. We show only figure 10 for the pre-crisis sample because of the two different samples, the model fits the pre-crisis data less well than the post-crisis data, as reflected by the average likelihood value per observation which is $-.45 = -110111/242594$ for the pre-crisis likelihood in table 3 versus $.27 = -45257/167946$ for the post-crisis sample. However as we can see from figure 10 the model fits the data extremely well even for the pre-crisis sample.

The model also closely matches the mean sizes of transactions done as positive interest and free installment transactions, respectively. Normalizing transactions as a ratio of the average statement balance, our data show that the smaller transactions that are not done on installment ($d = 1$) average 9% of the average statement balance, free installments are 36% of the average statement balance and positive interest installments are 49% of the average statement balance. The corresponding predictions of the model are 9%, 37% and 50%, respectively. Given the standard errors of these percentages, we cannot reject the hypothesis that the simulation estimates equal the sample values at the 5% significance level.

Overall, we feel that the model does an excellent job of capturing the key features that we observe in our credit card data. We also conducted a battery of Chi-squared goodness of fit tests using the random-cell Chi-squared test of Andrews [1988]. We tried several different choices of partitions and while particular values of the Chi-squared statistics are sensitive to how we choose these partitions, we found that with few exceptions the Chi-squared test was unable to reject the model at conventional levels of significance. At the same time the Chi-square tests generally decisively reject both the specifications where we impose the Weak and Strong Dominance assumptions. This is consistent with our Likelihood ratio tests, which also provided strong rejections of the Weak and Strong Dominance Assumptions.

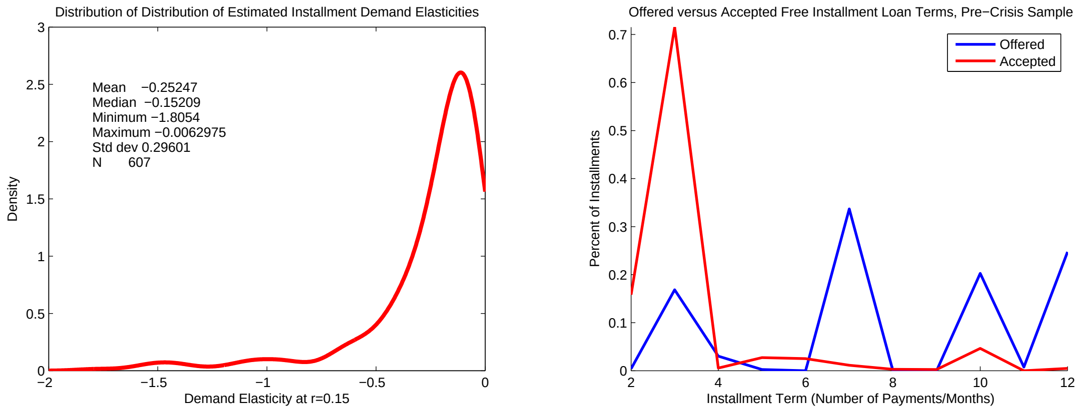
# 4 Implied Demand for Credit

Though it is not the main focus of this paper, we can use the estimated model of installment choice to calculate the implied *conditional demand curve* for installment credit (i.e. demand for credit conditional on the decision to purchase amount $a$ using this credit card $c$). Though a simple regression of the amount of installment borrowing on the interest rate charged results in an upward sloping estimated demand curve — a spurious result due to the endogeneity of the interest rate — the demand curves implied by our estimated discrete choice model are downward sloping, though fairly inelastic. We calculated the demand elasticities for our two illustrative customers — the "installment avoider" and the "installment addict" — at the average installment interest rate, 15%, and found in both cases their demand for credit is quite inelastic. The calculated elasticity for the installment addict is -0.074 whereas the demand elasticity of the installment avoider is -0.11. We find that the demand for installment credit is highly inelastic for virtually all of the individuals in our sample.

The left hand panel of figure 11 plots the distribution of estimated demand elasticities for 607 individuals in the post-crisis sample for whom we had enough data on purchases to calculate reasonable estimates of demand elasticities. We see a very skewed distribution with the lower tail containing a minority of individuals who have relatively elastic demand functions, but the vast majority of individuals have demand elasticities that are quite inelastic and concentrated near 0.

The right hand panel of figure 11 compares the distribution of the maximum terms of free installments that are *offered* to customers in the pre-crisis sample (blue line) to the distribution of terms of the free installment offers that were *chosen* (red line). We can now answer the question raised in section 3, namely whether pattern of chosen durations of free installment offers is supply-driven and determined by

Figure 11: Estimated Demand Elasticities and Durations of Offered and Accepted Free Installments




the company offering few interest-free installments with long payback terms, or whether these durations are demand-driven and a consequence of customer choices. We see that the distribution of offered terms is very different from the distribution of accepted terms. The maximum terms of company's offers were approximately equally distributed over terms of 3, 7, 10 and 12 payments. However the customers overwhelmingly preferred to borrow for shorter terms, with the most popular choices being 3 months (chosen by customers in 72% of all free installment offers that were taken) and 2 months (chosen by customers in 16% of all free installment offers that were taken). This graph illustrates rather starkly the key prediction of our model: customers who took free installment offers overwhelming chose to precommit to pay them off over a terms that was substantially shorter than the maximum term allowed under the offer.

This precommitment behavior, along with the fairly low probability that free installment offers are predicted to be chosen, constitutes a significant challenge to expected utility models, which generally predict that rational individuals should choose the maximum allowed term when offered an interest-free loan. In other words, expected utility models predict that individuals should satisfy the Strong Dominance Assumption, which our empirical findings have decisively rejected.

# 5 Conclusions

Using two new high frequency micro panel data sets on transactions of two random samples of customers of a major Korean credit card company before and after the 2003 Korean credit crisis, we offer evidence of pervasive *precommitment behavior* by Korean credit card holders that is difficult to explain using standard models of rational expected utility maximization. Specifically we find three different types of behavior that is difficult to explain using traditional economic theories: 1) customers voluntarily reduce their credit card borrowing limits without any compensation or reward for doing so,[10] 2) customers have a high probability of turning down interest-free installment loan offers, and 3) of the small fraction of customers who do accept interest-free loan offers, most precommit to pay off the loan over a shorter term than the maximum allowed term under the offer.

These behaviors can be explained by more recent economic theories of temptation and self-control. They can be interpreted as acts of *financial self control* where customers resist temptations to borrow and spend with their credit cards in order to avoid becoming excessively indebted. However there may be other explanations for these behaviors, though it not clear how plausible they are. For example, we discussed *stigma, transactions and mental accounting acounting costs, financial illiteracy,* and *irrational beliefs* as alternative explanations for the behavior we find. We have already expressed our doubts about the stigma explanation, and we are also skeptical that these behaviors reflect financial illiteracy, such as failing to understand the benefits of interest-free loan offers. We also have problems with the explanation that customers have irrational fears that borrowing will degrade one's credit score. For example, it seems reasonable that such fears would have increased after the crisis, but this does not square with the higher take-up of interest-free offers after the 2003 credit crisis. In our opinion, transactions and mental accounting costs are the most likely additional or alternative explanation for the behavior we find, though it is not clear how these models can explain why customers who take an interest-free loan offer fail to take it for the maximum term allowed.

Regardless of the underlying explanation for the behavior, or whether we classify the behavior as "rational" or "irrational", our findings are important for improving our understanding of the causes and consequences of the 2003 credit boom and bust in Korea. We conclude that the customers in our samples exercised a high degree of financial self-control by forgoing most interest-free borrowing opportunities that were offered to them. From our perspective, it is difficult to blame excessive spending and borrowing by these customers as the primary "cause" of the 2003 Korean credit crisis. Instead, to the extent we consider the crisis to be a result of a failure of financial self-control, we would inclined to place more of

[10]We do not have data on the actual numbers of customers of the company we study who voluntarily request reductions in their credit limit, but company executives told us that these requests happen frequently and their frequency increased after the 2003 Korean credit crisis. However another large Korean credit card company reported to us that each year approximately 24,000 of its customers voluntarily request to have their credit limits reduced without any compensation or reward for doing this. This amounts to nearly 1% of its customers who voluntarily make precommitments that are suboptimal from the perspective of rational expected utility theory.

the blame on the credit card company which "binged" by offering free installment offers to its customers at extremely high rates prior to the 2003 crisis, and then dramatically contracted its supply of credit after the crisis. The company sharply reduced its supply of credit in three different ways: 1) it sharply curtailed the rate at which it offered interest-free loans to its customers (from 80% at the peak of the crisis to 10% just after the crisis), 2) it reduced maximum term of interest-free offers, so that after the crisis most loans had a maximum term of three months, and 3) it significantly increased its interest rates across the board. The company may have also reduced the credit card borrowing limits of its customers, but unfortunately our data do not contain information on customer-specific credit limits.

Of course, we are not suggesting that this single company deserves to be blamed for the 2003 Korean credit crisis. The question is the extent to which this company and its customers are representative of the Korean market as a whole. Relative to the overall Korean credit card sector, the experience of this particular company was actually rather moderate. The company we study is a major bank that has been a long term player in the credit card market, and thus has considerable experience in credit evaluation. Though its default rates did peak in 2003, its losses due to defaults were modest compared to other credit card companies. Losses were generally much larger for the newer entrants that expanded too rapidly and made poor credit decisions. As Kang and Ma [2009] observed, nearly *one third* of all credit card debt outstanding at the peak in 2002 had to be written off and "Through either an understatement of the rules involved or the knowing acceptance of greater risks, the result was excessive lending and riskier credit card lending portfolios. Moreover, in addition to generally easier loan standards, there was a deliberate strategy to target the market for less prime and higher-yielding revolvers. Thus, competition for market share started moving down the credit spectrum. As a consequence, the composition of the cardholder base changed markedly, leading to larger and higher-risk card lending portfolios." p. 60

We noted that network externalities in the credit card market create strong increasing returns to scale and a "winner take all" aspect to competition in the Korean credit card market. The firm with the dominant market can charge the highest merchant fees and we have shown that these fees constitute nearly 40% of this company's profits. When credit deregulation in Korea enabled inexperienced firms to enter the credit card market and quickly gain significant market share by lending to increasingly risky customers, the company we study no doubt felt strong pressure to respond defensively to protect its own market share. This pressure could explain why it made so many free installment offers for longer durations prior to the 2003 crisis. After the crisis there was exit or sharp reductions in the operations of the less experienced new entrants, including a collective takeover of LG Card by a coalition of banks that was engineered by the Korean government. These factors could have dramatically altered the competitive landscape after the crisis, which could explain why the company raised interest rates and significantly reduced the number of free installment offers and reduced their maximum terms. Thus, we believe our results provide new insights into one mechanism by which *financial contagion* can occur, and how it can cause even the more prudent, well established banks to change their credit policy in response to actions of their competitors.

Overall we believe that a deeper understanding of *heterogeneity* — both at the firm level and at the customer level — is critical for understanding the dynamics of the Korean credit crisis. No doubt there was excessive lending to customers who were not creditworthy but most of this appears to have been done by the less experienced new entrants. However the reckless behavior of these new entrants forced the more prudent and experienced longer term players in this market, such as the company we studied, to also behave in a more aggressive and less prudent fashion and this is manifested in part by the high rates of free installment offers to its customers that we found in the pre-crisis sample. We showed that there is very significant heterogeneity in the company's customers, and the least creditworthy of these customers are the ones who were the most likely to take the free installment offers the company offered. This small minority of customers with the most elastic demand for credit were responsible for the peak in default rates that the company experienced in 2003.

Our study suggests that the various players in these markets have varying degrees of financial self-control and experience, and highlights how market forces can create strong incentives for herd-like behavior that can cause even the relatively more prudent and self-controlled actors to make unwise decisions. It is possible that imprudent behavior by a relatively small fraction of players in the market to lead to a lemming-like stampede that could have fairly serious collective consequences unless the stampede can be dissipated before it gets too large to be controlled and turn into a credit crisis that can have costly macroeconomic consequences. In their analysis of the macro data at a quarterly level Kang and Ma [2009] showed that the credit crisis "clearly caused the private consumption downturn in 2003" which suggests that the significant reduction in credit card balances of the customers in our sample was not just due to a shift in spending from one credit card to another (or spending in cash) but rather due to an overall reduction in consumption spending. Fortunately in the case of Korea, rapid action by the government prevented the crisis from turning into a serious recession unlike what happened in aftermath of the meltdown in the mortgage market in the U.S. in 2008.

# References

Donald W. K. Andrews. Chi-square diagnostic tests for econometric models: Theory. *Econometrica*, 56-6: 1419–1453, 1988.

B. Douglas Bernheim, Jonathan Meer, and Reva K. Novarro. Do consumers exploit precommitment opportunities? evidence from natural experiments involving liquor consumption. 2012.

Drew Fudenberg and David K. Levine. A dual-self model of impulse control. *American Economic Review*, 96-5:1449–1476, 2006.

Faruk Gul and Wolfgang Pesendorfer. Temptation and self-control. *Econometrica*, 69-6:1403–1435, 2001.

James J. Heckman and Burton Singer. A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica*, 52(2):271–320, 1984.

Tae Soo Kang and Guonan Ma. Recent episodes of credit card distress in asia. *BIS Quarterly Review*, June:55–68, 2007.

Tae Soo Kang and Guonan Ma. Credit card lending distress in korea in 2003. *BIS Papers*, 46:95–106, 2009.

Charles P. Kindleberger. *), Manias, Panics and Crashes: A History of Financial Crises*. New York: Basic Books, 1978.

David Laibson. Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics*, 112:443–477, 1997.

Annamaria Lusardi and Olivia S. Mitchell. The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, 52(1):5–44, 2014.

Daniel L. McFadden. Econometric models of probabilistic choice. In Charles F. Manski and Daniel L. McFadden, editors, *Structural Analysis of Discrete Data and Econometric Applications*, pages 198–272. Cambridge: The MIT Press, 1981.

Enrique G. Mendoza and Marco E. Terrones. An anatomy of credit booms and their demise. *NBER Working Papers*, 18379, 2012.

Carmen M. Reinhart and Kenneth S. Rogoff. *This Time is Different Eight Centuries of Financial Folly*. Princton University Press, 2009.

Robert J. Shiller. *Irrational Exuberance*. Princton University Press, 2015.

Vernon L. Smith, Gary L. Suchanek, and Arlington W. Williams. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica*, 56(5):1119–1151, 1988.

R. H. Strotz. Myopia and inconsistency in dynamic utility maximization. *Review of Economic Studies*, 23: 163–180, 1955.

Jean Tirole. Asset bubbles and overlapping generations. *Econometrica*, 53(6):1499–1528, 1985.