Time Inconsistency in the Credit Card Market

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Abstract

This paper analyzes a unique dataset, which is results of a large-scale experiment in the credit card market. Two strange phenomena that suggest time inconsistency in consumer behavior are observed. First, consumers are very reluctant to switch, and even those consumers who have switched before fail to switch again later. Second, consumers prefer an introductory offer which has a lower interest rate with a shorter duration to that of a higher interest rate with a longer duration, even though they would benefit more should they choose the latter. A simple theoretical model is studied to show that the standard exponential time preferences without uncertainty can not explain the observed phenomena, whereas the hyperbolic time preferences can. The main focus of this paper to estimate a structual model which incorporates both time preferences and realistic random shocks. Estimation results show that consumers have severe self-control problem with a present-bias factor $\beta = 0.8$ and the average switching cost is \$150. With estimated parameters, the dynamic model can replicate quantitative features of the data.

1 Introduction

Does consumer behavior exhibit time inconsistency? This is an essential, yet difficult question to answer. Since the pioneering contribution of Samuelson (1937), it has become a standard assumption that consumers have an exponential time discount function $\{1, \delta, \delta^2, ...\}$, which implies that consumers behave *time consistently.* A significant body of evidence, however, has been gathered in experimental psychology and economics studies, that consumers discount future hyperbolically, not exponentially. The essential feature of hyperbolic discounting is that consumers are *time inconsistent.* In the last decade, many researchers have applied hyperbolic discounting to explain various economic anomalies, such as procrastination, retirement, addiction and credit card borrowing.[1] In particular, the quasi-hyperbolic discount function $\{1, \beta\delta, \beta\delta^2\}$ is widely studied,[2] which shall be simply referred as hyperbolic discounting in later discussion.

Regardless of its enormous impact, the hyperbolic discounting is criticized for lack of convincing empirical evidence.[3] An ideal test is to compare consumers' long run plans with their later actions, which will be consistent for exponential consumers, however inconsistent for hyperbolic consumers. In the real world, it is rare to be able to track both under controlled conditions. This paper examines time inconsistency using a large-scale randomized experiment in the credit card market, with which we have a unique opportunity to conduct an almost ideal test of hyperbolic discounting.

In the experiment, 600,000 consumers are randomly mailed one out of six different credit card offers, denoted as Market Cell A to F. The six offers have different introductory interest rates and different durations: Market Cell A (4.9% for 6 months), B (5.9% for 6 months), C (6.9% for 6 months), D (7.9% for 6 months), E (6.9% for 9 months) and F (7.9% for 12 months). All other characteristics of the solicitations are identical across the six market cells. Consumer responses and subsequent usage of respondents for 24 months are observed.

There are two phenomena in this dataset suggestive of time inconsistency. First, consumer switching behavior is not consistent over time. The majority of borrowers (60%) stay with this

[1] See Akerlof (1991), Diamond and Koszegi (1998), Gruber and Koszegi (2001), Harris and Laibson (2001), Laibson (1997), Laibson *et al.* (1998), O'Donoghue and Rabin (1999,2001).

[2] The quasi-hyperbolic discounting accomodates three different hyperbolic time preferences as special cases:naive, sophisticated and partial naive. We will dicuss their difference in more detail later.

[3] For example, Rubinstein (2000).

bank after the introductory period, while their balances remain at the same level as when they accepted this card. Given the same debt level, it should be worthwhile to switch a second time since it was optimal to accept this offer before.[4] Second, significantly more consumers in Market Cell A are found to accept their offers than in Market Cell F. This *ex ante* preference is puzzling after observing that respondents, *ex post*, keep on borrowing on this card well after the introductory period.

There are two important factors which can be associated with consumer behavior that on the surface appears to be time inconsistent. First, consumers are subject to realistic random shocks, the *ex post* realizations of which can generate divergences between consumers' initial plans and later actions, even if their preferences are time consistent. Second, consumers directly behave in a time inconsistent fashion, since they discount at a higher rate in the short run than in the long run ($\beta < 1$). In this paper, we develop a dynamic model which incorporates both factors. Consumers are assumed to have two kinds of time preferences. And three important random processes are taken into account. First, consumer income path has both persistent and transitory shocks. Second, receiving new introductory offers is probabilistic. Third, every time accepting a new offer, consumers incur a switching cost which is a random draw from a known distribution.

Estimation results show that the first puzzle can be explained by the stochastic nature of switching costs, which are normally assumed to be constant. The random switching cost is actually a more realistic treatment of individual consumers because it captures the fluctuations due to many unknown subjective, psychological factors that strongly affect the realized switching costs.[5] Respondents of this experiment accepted the offers due to their low realized switching costs at the time of solicitation. However, their mean switching costs are much higher, which can be partially inferred from the low response rate (1%). This high mean will keep the majority of respondents from switching a second time after the introductory periods. There are some empirical studies to estimate the magnitude of consumer switching costs, such as Sorensen (2001) and Kim, Kliger and

[4] Obviously, there would be no puzzle if the respondents did not receive new low-rate solicitations from other banks after the end of the introductory period. However, the number of solicitations averaged three per qualified household per month during this period. The typical solicitation included a 5.9% introductory interest rate for 6 months for the observed issuer, and the vast majority of respondents remained creditworthy, which will be discussed in more detail in the data section.

[5] Loewenstein (1996) studied emotional influences on people's behavior.

Vale (2003). However, they fail to identify the randomness of the cost due to the fact that, unlike this one, they don't have an individual-level transaction dataset.

Regarding to the second puzzle, we find that it is impossible to reconcile low switching rates and preference for the shorter offer in an exponential model even with realistic random shocks. An exponential individual may, *ex ante*, choose a wrong plan based on the realized *ex post* random shocks. However for a sufficiently large group of exponential consumers, as we observe, they always prefer such a credit offer that *on average* provides the most interest saving.

Hyperbolic time preferences are applied after the standard exponential model fails to offer a satisfactory explanation. There are two kinds of hyperbolic preferences which are widely studied, *sophisticated* and *naive*. Our studies show that both preferences are able to explain the second puzzle, however, the underlying economic stories are different. A sophisticated hyperbolic consumer who recognizes her time inconsistency problem would like to precommit from overspending in the future. Accepting a shorter introductory offer, rather than a longer one, serves as a commitment device, even though she would pay less interest if she accepted the longer offer. A naive hyperbolic consumer, however, trades the longer offer for a shorter one because she underestimates the amount she will borrow after the current period. This underestimation is due to the fact that she naively believes that her future preference would be as patient as she desires now.

There have been many empirical studies in support of hyperbolic discounting, both from lab experiments and field studies, as will be discussed in detail in the following section. Our study has two advantages compared with previous studies. First, the dataset provides a neat angle to identify hyperbolic preferences. Consumer relative preferences between credit card offers with different durations convey information about their borrowing plans for subsequent 12 months, which are determined by their expected future time preferences at solicitation. We can also infer time discounting functions they actually used after acceptance, since we observe the subsequent borrowing behavior of respondents. The second advantage is that consumers are subject to realistic random shocks. A realistic dynamic model is required because some researchers argue that exponential discounting can explain anomalies if "even a small degree of" uncertainty is incorporated,[6] which we show is not the case.

The paper is organized as follows. In section 2 we give a brief review of previous empirical studies

[6]See Fernandez-Villaverde (2002).

of hyperbolic discounting and the comparison with this paper. In section 3, the unique dataset is introduced and the two interesting puzzles are elaborated. Section 4 provides basic intuition that hyperbolic discounting can simultaneously explain consumer responses and respondents' behavior, by analyzing a three-period model with complete information. The dynamic model with incomplete information, which accommodates both exponential and hyperbolic time preferences, is presented in Section 5. The estimation strategy and results are discussed in section 6, 7 respectively. Lastly, we conclude this study in section 8.

2 Related Empirical Studies of Hyperbolic Discounting

The most cited empirical evidence is from laboratory experiments.[7] One major problem with laboratory evidence is that most experiments only elicit consumer time preferences once. In Ainslie and Haendel (1983), experimental subjects are asked the following two questions:

Question 1: Would you rather receive $50 today or $100 in 6 months?

Question 2: Would you rather receive $50 in one year or $100 in 1 year plus 6 months?

Many subjects chose the smaller-sooner reward in the first question and the larger-later reward in the second. This phenomenon has been termed as "preference reversal." as empirical evidence against exponential discounting. The argument is that subjects apparently apply a larger discount rate for a six-month delay as the delay becomes closer, while exponential time preferences assume that consumers use the same discount rate for any equal-distance period. However, this "preference reversal" can also be explained by any predicted preference change in an exponential model.

The essential difference between an exponential and hyperbolic consumer is that whether "current self" and "future self" agree on the desired discount factor in the future, not whether the discount factor is exactly the same for any equal-distance period. An exponential consumer has the same discount factor (δ) between period t and $t+1$ no matter which period she is at. However, a hyperbolic consumer has a discount factor δ between period t and $t+1$ at period $\tau < t$, and a discount factor $\beta\delta$ at period t. Because of this, a hyperbolic consumer would like to revise her consumption plan made at period $\tau < t$ when period t arrives. This revision does not exist in

[7] For example, Ainslie and Haendel (1983), Loewenstein and Thaler (1989) and Thaler (1981).

the exponential model. Therefore, to identify hyperbolic discounting, it is vital to solicit consumer time preferences dynamically.

Several dynamic experiments have been studied, such as in Read and van Leeuwen (1998). Subjects are asked to choose between healthy and unhealthy food both in advance and immediately before the snacks are given. They find that subjects are more likely to make the unhealthy choice when asked immediately before the snacks are to be given than when asked a week in advance. However, this evidence is also questionable that subjects may not tell the truth when they are first asked, because they know they can always change their mind later[8].

Since eliciting consumer true time preferences from laboratories is difficult, if not impossible, some researchers start to infer consumer time preferences from their social economic behavior in the real world. They have analyzed consumer behavior in different markets, such as the credit card market (Laibson, Repetto and Tobacman (2000)), the health club market (Della Vigna and Malmendier (2001)), and the labor market (Fang and Silverman (2001) , Paserman (2001)).

Among them, the most related one is Della Vigna and Malmendier (2001), which utilizes a similar identification strategy. They identified consumer time inconsistency by comparing their initial contractual choices among an annual contract, a monthly contract and a pay-per-visit, with their later actual attendance. In the study, they focus on first-time users. The inexperienced users may choose the wrong contract because they have incorrect expectations about their future attendance. [9] For example, Miravete(2003) found that consumers chosen the wrong calling plan when they first faced with new choices. However they switched to the right calling plan after they learned more about their own telephone usage. Therefore, an experienced sample is very important when identifying consumer time-inconsistency from their behavior at different dates. In the next data section we will show that consumers in our sample are very familiar with credit card offers.

3 A Unique Dataset

A substantial portion of credit card marketing today is done via direct-mailed preapproved solicitations. The typical solicitation includes a low introductory interest rate for a known duration,

[8] See Besharov and Coffey (2003) for more details.

[9] Della Vigna and Malmendier (2001) shows that exponential inexperience users will choose a contract on average is right based on a strong assumption that they have correct expectation about the distribution of their attendence.

followed by a much higher post-introductory interest rate. Sophisticated card issuers decide on the terms of their solicitations by conducting large-scale randomized trials. The dataset used is results of such a "market experiment" conducted by a major United States issuer of bank credit cards in 1995. The issuer generats a mailing list of 600,000 consumers and randomly assigned the consumers into 6 equal-sized market cells (A-F). The market cells have different introductory offers as mentioned above but are otherwise identical (including the same post-introductory interest rate of 16%).

In each market cell, between 99860 and 99890 observations are actually obtained, out of the 100,000 consumers. About half of the missing observations are due to one known data problem: the approximately 5% of the individuals who have responded to the preapproved solicitation but are declined (due to a deteriation of credit condition or failure to report adequate information or income) are deleted from the dataset for unknown reasons. Nevertheless, over 99.8% of the sample is still included. Ausubel (1999) has offered statistical evidence that this is still a good random experiment among the remaining observations. Financial statistics of the remaining 599,257 consumers are observed at the time of solicitation and their responses to their offers are recorded.

Only for consumers who accepted their credit offers (respondents) we observe great details about their monthly account activities for subsequent 24 months. For a month t, we observe the amount that the account has paid at the beginning, the amount it has charged during the month, any finance charge (such as interest payment, late-payment fee and over-credit-limit fee) and the total balance owed at the end. Based on the information, we can accurately calculate monthly debt and the actual monthly interest rate on each account. Besides the quantitative measures, we also observe two interesting qualitative measures. The first measures the deliquency status: whether the account is delinquent this month or not and the duration of the delinquency. The second measures whether the account owner has filed for a personal bankruptcy or not. These two measures offer important information about the account credit status over time.

Important financial statistics of the whole sample and respondents are reported in Table 1. "Revolving Limit" is the total credit limit a consumer has on her revolving accounts.[10] "Revolving Balance" is the total balance on those revolving accounts, composed of convenience charges incur-

[10] Revolving accounts are the accounts on which consumers can borrow with no prespecified repayment plan. The majority of revolving accounts are credit cards.

ring no interest payments and debt. "Number of Past-due" is the nubmer of 30-day past-due in last 12 months. Most observables of respondents are statistically worse than the whole sample. Nevertheless, both groups are of good credit quality. Majority of consumers have more than ten-year credit history. Very few of them have ever passed due in last year. And none of them has had a sixty-day past due, which is considered to be a severe deliquency. For both groups, every consumer has at least one credit card before and 75% have more than two credit cards. For illustrate the quality of consumers, a *utilization rate* is introduced, defined as the ratio of revolving balance to its limit. The average utilization rate for the whole sample is only 16% and for respondents 27%.

The first puzzling phenomenon observed in this dataset is that respondents don't switch a second time even though their debts remain as the same level as before. We observe a stable debt distribution among respondents who borrow. The median debt among borrowers stables around \$2000 in the twenty-four months, shown in Fig.1. Not only the median, the first quartile remains around \$3500 and the third quartile is around \$500. The proportion of respondents who borrow doesn't decrease much over time. As shown in Fig.2, there are 60% respondents who borrow during introductory periods and 35% after two years. Of course, this is not a puzzle if respondents haven't received new offers after this one expires. Credit card companies will not send a consumer new solicitations if she is either more than 60-day past due or she declares a personal bankruptcy. Among respondents, about 1% have declared bankruptcy and 4% have passed due for more than 60 days. Apparently, this cannot explain why 35% respondents don't switch.

The second puzzle is that significantly more consumers in Market Cell A are found to accept their offers than in Market Cell F. However, respondents would have paid less interest in Market Cell F than in Market Cell A. This strange phenomenon is called "rank reversal" in Ausubel (1999). Consumer responses are recorded in the third column of Table 2. Only about one percent consumers accepted their credit card offers, which is also the average response rate for the whole economy in the sample period.[11] Among offer A, B, C and D, consumers optimally prefer a lower introductory interest rate given the same introductory duration. However, significantly more consumers have accepted the shorter offer A than the longer offers, E and F. This preference is suboptimal if comparing the prices –"effective interest rate"– under different offers. The effective interest rate is the annual interest rate respondents actually paid in each market cell, which is the ratio between

[11] According to BAI Global Inc., the response rate to solicitations is 1.4% in 195.

the total interest payment and the total credit card debt shown in the fifth column of Table 2. The effective interest rate is two percent points lower in Market Cell F than in Market Cell A and one percentage point lower in Market Cell E. Since the average debt among borrowers is $2000, an average respondent in Mark Cell A pays $40 more interest than in Market Cell F, and $20 more than in Market Cell E.

To make sure this "rank reversal" phenomenon is not driven by some strange outliers, we calculate a "what if" interest payment for each respondent, based on a formular which will be presented in the next section. We ask how much more or less a member of one market cell would pay if her account were repriced according to the formula of a different market cell. Consumer behavior is assumed unchanged under the new term. The average respondent of Market Cell A would save $27.31 dollars if she were in Market Cell F. This is less than $40 because this average is among all respondents. 41.61% of them would save more than $10.

4 Identification

In this section, we will analyze a three-period model with complete information to provide an intuitive idea that the "rank reversal" suggests that consumers discount future hyperbolically. This model shows when choosing between different credit offers, exponential agents will always choose the one which provides the most interest saving. However, hyperbolic agents, both naive and sophisticated, will not always behave so rationally. Besharov and Coffey (2003) concluded that hyperbolic time preferences are not identifiable using financial rewards. The rewards they considered is a specific type: giving a certain amount of money to agents at different dates, which is commonly observed in laboratory experiments. The model below provides an example that hyperbolic discounting is identifiable, if the formula of financial rewards is carefully designed. Our later estimation work, which is based on a realistic dynamic model, shows that this identification still holds when uncertainty is incorporated.

In addition, this example will illustrate how to solve a general life-cycle model, which incorporates both hyperbolic and exponential time preferences. In the next section, a multiple-period dynamic model will be presented, which is solved numerically using a similar method.

The representative agent lives for three periods. At the beginning of period τ, she chooses an optimal consumption level by maximizing a weighted sum of her utilities from this period on:

$$\max_{C_\tau} u\left(C_\tau\right) + \beta_0 \sum_{t=\tau+1}^{3} \delta^{t-\tau} u\left(C_t\right), \tag{1}$$

where the relative weights are determined by her *current* discount function. δ is the long-term discount factor, which is consistent over time, and β_0 represents "a bias for the present", how much the agent favors this period versus later. Note when $\beta_0 < 1$ the agent is time inconsistent. The agent at period τ has a smaller discount factor $(\beta_0\delta)$ between period τ and period $\tau+1$ than between any two consecutive periods in the future (δ). In other words, the desired discount factor between period τ and period $\tau+1$ decreases from δ to $\beta_0\delta$ as period τ arrives. $u\left(C_t\right)$ is a concave instantaneous utility function.

She receives one unit of income every period and she has to pay off her previous debt. The gross interest rate for her debt during period t is r_t. She can borrow as much as she desires to increase her consumption, but she is assumed not to save for simplicity.[12]

$$C_t = 1 + L_t - r_{t-1}L_{t-1}, \tag{2}$$

where $L_t \geq 0$ and $t = 1, 2, 3$. The boundary condition is that she pays off all her debt in the third period, i.e. $L_3 = 0$. For simplicity, we assume the initial debt (r_0L_0) is zero. The interest rates (r_1, r_2) are determined by her credit card choice in the first period.

Let C denote all financially feasible consumption plans. Strotz (1956) showed that only when $\beta_0 = 1$, the agent's behavior would be described as a straightforward maximization problem, namely to select a consumption plan in C such that Eq.(1) is maximized at period 1. And this plan remains optimal at all subsequent periods. When the agent is not time consistent $(\beta_0 < 1)$ and she cannot precommit her future behavior, a plan selected this way will not be followed later. Later selves would like to revise the consumption plan based on her own Eq.(1). To describe consumer behavior under this situation, Strotz (1956) proposed to choose "the best plan among those he will actually follow". Based on this concept, a dynamic consumption problem is modeled as an interpersonal game, in which the agent at different periods, self τ, are players. The solution of this problem is that each self chooses a level of consumption which maximizes her own utility (Eq.(1)) given

[12]The story will remain the same if the saving interest rate is less than the borrowing rate.

the utility maximizing strategies of all future selves, which is formally defined as *a Strotz-Pollak equilibrium* in Peleg and Yaari (1973).

The *expectation of the strategies of future selves*are determined by the expected discount function, which is assumed to be $\{1, \beta_1\delta, \beta_1\delta^2, ...\}$ for all subsequent periods. Depending on the expected strategies, the hyperbolic model has three interesting special cases, which have been commonly studied[13]. When $\beta_0 = \beta_1 = \beta < 1$, the agent (sophisticate hyperbolic) has a correct expectation about her future. Self τ realizes that the discount factor between period t and period $t+1$ will become $\beta\delta$ when period t arrives, which is less what she desires (δ). Thus she wants to constrain herself from overspending in later periods. When $\beta_0 < \beta_1 = 1$, the agent is called a naive hyperbolic agent since she has an incorrect expectation about her future. She naively believes that she would behave herself from the next period on ($\beta_1 = 1$), thus has no desire for self-commitment. In between the sophisticate and naive hyperbolic agent, a partially naive agent can be defined when $0 < \beta_0 < \beta_1 < 1$. Such an agent underestimates the impatience she has in the later periods like a naive agent. However, she anticipates a difference between today's desired patience and tomorrow's actual one. Therefore she also has some incentive to precommit her behavior.

We apply backward induction to solve for the equilibrium of the above four types. Start from period 2, self 2 maximizes Eq.(1) subject to the constraint Eq.(2). The problem that Self 1 faces is more complicated. In order to chooses C_1, she first solves for the *expected* C_2 , i.e. maximizing Eq.(1) for self 2 where β_1 is used instead of β_0. Based on the expected C_2 self 1 selects the optimal $C_1$by maximizing Eq.(1).

In the first period, she receives two introductory offers A, B. A offers a low introductory interest rate for the first period r_1^A. After that, the interest rate jumps to a much higher post-intro interest rate r_2^A. B offers introductory the same interest rates for two periods $r_1^B = r_2^B$, however the rate is higher than A. She chooses the credit card offer which gives her the larger utility based on her debt at period one and her *expected* debt at period two.

We shall discuss the relationship between time preferences and the "rank reversal" phenomenon. **Definition:***The "rank reversal" phenomenon is that the agent chooses offer A at the first period*

[13]In particular, naive and sophisticated hyperbolic models have been studied. Strotz (1956) and Phelps and Pollak (1968) carefully distinguished the two assumptions, and O'Donoghue and Rabin (1999) studied different theoretic implications from these two. Laibson (1994, 1996, 1997) assumed consumers are sophisticated. On the other hard, Akerlof (1991) adopted the naive hyperbolic assumption.

and $PDV_{A,B}\left(L_1^A, L_2^A\right) > PDV_{B,B}\left(L_1^A, L_2^A\right)$*, where* $\left\{L_1^A, L_2^A\right\}$ *denote the debt the agent borrows under offer A and* $PDV_{i,j}\left(L_1, L_2\right) = L_1\left(r_1^i - 1\right)/r_1^j + L_2\left(r_2^i - 1\right)/\left(r_1^j r_2^j\right)$.

Here, we define "pay a larger interest payment under offer A than under offer B" as the present discounted interest payment under A is larger than that under B.

Proposition:*If* $PDV_{A,B}\left(L_1^A, L_2^A\right) > PDV_{B,B}\left(L_1^A, L_2^A\right)$*, the consumption stream defined by* $\left\{L_1^A, L_2^A\right\}$ *is also feasible under contract B.*

The proof is simple. Applying the definition of $\left\{C_t^A\right\}$, it can be shown that the inequality is equivalent to the definition of C, the finanically feasible consumption set. More details can be found in Shui (2003).

For an exponential agent, *the "rank reversal" is impossible.* If she pays more interest under A, the optimal consumption plan under A is also financially feasible under B. Therefore the optimal consumption plan under B should be no worse than that under A, which is in contradictory to the fact that she prefers A at the first period. Note the optimal consumption plan for the exponential agent is chosen by maximizing over all feasible consumption plans.

However, the possibility exits for a hyperbolic agent. To give some intuition for this result, we describe numerical examples where hyperbolic agents, both sophisticated and naive, behave in this way. Assume $u(c) = C^{1-\rho}/(1-\rho)$ and $\rho = 2$. Offer A carries an interest rate of 5% for the first period and 20% for the second period. Offer B has a flat interest rate schedule: 10% for both periods.

A naive agent exhibits "rank reversal" because she underestimates her future borrowing. For example, suppose $\beta = 0.8$ and $\delta = 1$. In the first period, she prefers offer A because she expects that $L_1 = 0.08466$ and $L_2 = 0$. However, when the second period arrives she gives in to her instantaneous desire and borrows $L_2 = 0.05802$. Base on her actual behavior, she has made a suboptimal choice in the first period.

A sophisticated agent does not behave suboptimally because of her incorrect expectation, rather she has no ability to precommit her future behavior. Since the self-control problem is realized, the sophisticated agent may do one of two things to align her future behavior with her current preference. She may reduce her debt in period one to take account of overspending in period two. Or she may constrain herself in period two by choosing the shorter offer A. A much higher post-introductory interest rate will damp her desire to borrow, which conforms to her preference in period one. The two strategies are called *the strategy of consistent planning* and *the strategy of precommitment* respectively in Strotz (1956). However, these two strategies can only partially solve her self-control problem, she can not behave as optimal as if she has full commitment ability. We will illustrate the two strategies by numerical examples.

Still suppose $\beta = 0.8$ and $\delta = 1$. If she can commit her future behavior, she will choose offer A and $L_1 = 0.08466$ and $L_2 = 0$, which is the same as the naive agent's expectation. However, she anticipates that this plan will not be followed in the second period. She decides to still accept offer A but borrow less at period one ($L_1 = 0.05617$) to accommodate tomorrow's borrowing (the strategy of consistent planning). Based on her reduced debt, the interest payment under A is more than B. However it is not optimal to choose B since this consumption plan will not be followed if B is chosen.

To illustrate the strategy of precommitment, suppose $\beta = 0.56$ and $\delta = 0.8$. If the sophisticated agent can commit, she would choose offer B since she would like to borrow in both periods. However, she decides to choose A, $L_1 = 0.2637$ and $L_2 = 0.243$, even though she has to pay more interest. If she were to choose B, the best plan is $L_1 = 0.254$ and $L_2 = 0.2742$, which is worse than A.

To summarize,we plot the rank reversal region for both naive and sophisticated hyperbolic agents in Fig.3. The rank reversal region is plotted in (β, δ) space since there is only one β for both models. The rank reversal region is defined by two lines which represents the two conditions. Below the horizontal line (FDG) $PDV_{A,B}\left(L_1^A, L_2^A\right) > PDV_{B,B}\left(L_1^A, L_2^A\right)$. The agent accepts B to the left of the vertical line (CDE) and A to the right. When choosing between A and B, the agent compares interest saving in the first period and that in the second period. Obviously, she should prefer A if her debt path declines greatly over time, which implies a higher δ (the long-run discount factor) and a lower β (the present bias factor). The sophisticated agent accepts A in a larger region than that of the naive agent, where the strategy of precommitment is implemented. Nevertheless, the rank reversal region is very similar for both models. The debt level is also similar across the two models within this region. This similarity is due to the fact that the sophisticated agent lacks strong self-commitment device in this three-period model. She couldn't solve her self-control problem even though she anticipates it.

5 Modeling Credit Card Acceptance and Borrowing Decisions

A realistic dynamic model, which captures consumer decision problem in the market experiment, is presented in this section. It will be applied to empirical data in later sections. The model is inspired by standard "buffer-stock" life-cycle models.[14] Four realistic institutional features have been included to give a better description of consumer behavior in this particular experiment.

This model is set in discrete time. One period in the model represents one quarter in the real world.[15] The consumer lives for T periods. The boundary condition is that the consumer consumes all her cash-on-hand at the final period. The consumer receives stochastic income every period. She can either save in her liquid account or borrow on credit cards to smooth her consumption. However, she is liquidity constrained in two respects. First, she is restricted in her ability to borrow. The upper bound is the total credit limit of her credit cards, denoted as $\bar{L}$, which is exogenously given. However nothing prevents her from accumulating liquid assets. Second, she faces different interest rates depending on whether she is savings (r^s) or borrowing ($r > r^s$), and r is the regular interest rate on credit cards.

The consumer can reduce the interest payment on her debt if she accepts an introductory offer. At the beginning of period 1, the credit card company that conducted this market experiment, denoted as Red, offers the consumer an introductory interest rate $r^r < r$ with a duration τ^r periods, and a credit limit l. The consumer may also receive credit card solicitations from other credit card companies which are not observed in this dataset. These unobservable companies are simplified as one company, Blue. Blue provides an introductory interest rate $r^b < r$ with an introductory duration of τ^b and the credit limit l. In every period, the consumer receives a Blue offer with a probability q, which is positive and finite if the consumer has no current introductory offer from Blue, otherwise zero.[16]

Simultaneously with the acceptance of credit card offer(s), the consumer decides how much to consume at the beginning of period t. There is a switching cost, k_t, associated with accepting every introductory offer. The switching cost is indexed by t because it is assumed that the consumer has

[14] See Carroll (1992, 1997a), and Deaton (1991).

[15] The data is monthly. However, a quarter is chosen as a time unit to save computation time.

[16] This assumption effetively excludes the event that consumers have more than one introductory offers from Blue. We believe relaxing it will not change our conclusion.

a time-varying switching cost. This assumption is required to explain the first puzzle, as mentioned in the introduction. The switching cost captures the expected time and effort required in filling out an application for a new card. It is assumed that there is no extra cost for transferring balance after the consumer accepts a new offer. Once she accepts introductory offer(s), she has immediate access to the credit. In addition, the consumer's total credit limit $\bar{L}$ is held constant even after accepting a new offer to simplify computation.

The consumer in period t maximizes a weighted sum of utilities from current period on, which is a generalization of Eq.(1).

$$\begin{aligned} &\max_{C_t, d_t^b, d_t^r} \tfrac{C_t^{1-\rho}}{1-\rho} - d_t^b k_t - d_t^r k_t + \beta_0 \delta E\left\{V_{t,t+1}\left(\Lambda_{t+1}\right)\right\}, \quad &&\text{for } t = 1, \\ &\max_{C_t, d_t^b} \tfrac{C_t^{1-\rho}}{1-\rho} - d_t^b k_t + \beta_0 \delta E\left\{V_{t,t+1}\left(\Lambda_{t+1}\right)\right\}, &&\text{for } t \geq 2. \end{aligned} \tag{3}$$

The instantaneous utility is the sum of the consumption utility and the disutility (the switching cost) from accepting an introductory offer. C_t and d_t^b are the consumption choice and the decision to accept an introductory offer from Blue at period t respectively. d_1^r is the decision to accept the Red offer at period 1. k_t is the current switching cost. The consumption function is assumed to be CRRA and ρ is the coefficient of relative risk aversion. The difference between Eq.(3) and Eq.(1) is that here $V_{t,t+1}$ represents all utilities of self t from period t+1 on. Λ_{t+1} denotes the vector of state variables: $\left\{X_{t+1}, \varphi_{t+1}, k_{t+1}, \tau_{t+1}^b, \Gamma_{t+1}^r, s_{t+1}\right\}$. X_{t+1} is cash-on-hand at the beginning of period t+1 which is a sum of income y_{t+1} and wealth A_{t+1}. φ_{t+1} is the realized persistent income shock at period t+1, which will be discussed in more detail later. k_{t+1} is the realized switching cost in period t+1. τ_{t+1}^b and Γ_{t+1}^r denote the number of introductory periods left at period t+1 on the Blue and Red card respectively. s_{t+1} denotes whether a new introductory offer is received at period t+1, where $s_{t+1} = 1$ for receiving an offer and $s_{t+1} = 0$ for no offer. The expectation is taken with respect to the distributions of y_{t+1}, φ_{t+1}, k_{t+1} and s_{t+1}.

$V_{t,t+1}$ is a weighted sum of self t's excepted future utilities and the weights are determined by self t's long-run preference δ. It is recursively defined as:

$$V_{t,t+1}\left(\Lambda_{t+1}\right) = \quad u_{t+1}^* + \delta E\left\{V_{t+1,t+2}\right\} \tag{4}$$

u_{t+1}^* is the optimal utility of "expected self t+1", which is decided by maximizing Eq.(3) where β_1 is used instead. Note $V_{t+1,t+2}$ is used instead of $V_{t,t+2}$ because they are the same. Self t and self

$t+1$ have the same expectation about periods later than $t+1$ and they also agree on the desired time preferences among them. This is a special feature of quasi-hyperbolic discount function.

In the estimation described below this consumer problem is solved numerically by backward induction (iterating Eq.(3) and Eq.(4)).[17]

6 Estimation Strategy

The parameters of the model are estimated by matching empirical moments with simulated moments from the dynamic model. The estimation method used is*Simulated Minimum Distance Estimator* (SMD), proposed in Hall and Rust (2002).[18] One important feature of this method which deserves mentioning is that It recognizes the fact that there is endogenous sampling at the first period, i.e. we only observe respondents' subsequent borrowing behavior.

Totally 216 moments are used, 36 for each market cell. The 36 moments are the response rate plus five debt distribution statistics for seven quarters: proportion of consumers who borrow, mean, median, forty and sixty percentiles among borrowers. The debt statistics for the first quarter is omitted because they are exceptionally low due to the fact that it takes about 2-3 months to transfer debt into this account. This time lag is not modeled in the dynamic model.

To make estimation feasible, we calibrate a subset of parameters, using related literature and our dataset, and make assumptions about exogenous variables' distributions.

The income process is modeled as a time series with changes in two possible states: a good state and a bad state.[19] In a given state, income is a random draw from a lognormal distribution $LN\left(\eta^j, \varepsilon^j\right)$, where $j \in \{g, b\}$. The distribution parameters depend on whether it is in the good state or the bad state. The evolution of the two states is governed by a discrete random variable, $\varphi_t \in \{1, 0\}$, where 1 and 0 represent the good and bad state respectively. φ_t is a two-state Markov chain with transition probabilities: $\{p_{i,j}\}$, where $i, j \in \{1, 0\}$, $p_{i,j} = prob(\varphi_t = i|\varphi_{t-1} = j)$. To get

[17]Interested readers can find more computational details in Shui (2003).

[18]This method is similiar to Simulated Moments Estimator (SME) of McFadden (1989) and Pakes and Pollard (1989).

[19]The standard way of modeling the income randomness is as a sum of a persistent and transitory shock. In this study, the persistent income shock is modeled as a two-state Markov process, rather than as an AR(1). The method was introduced in Laibson *et al.* (2000) to save computation time.

reasonable estimates for the income distribution, we use estimates from Laibson et al. (2000) as a starting point. we describe this calibration process in more details in Appendix.

We assume consumer switching cost k_t is an identical and independent random draw from a uniform distribution with a mean value k. We assume at the time of solicitation consumer liquid asset (or credit card debt) follows a normal distribution with a mean μ and a variance ϵ^2.[20]

We calibrate the total credit limit $\overline{L}$ and the credit limit for each credit card l (recall that they are assumed the same), using the information in the dataset. The calibrated $\overline{L}$ are \$15,000 and l is $\$6,000$. In addition, the regular interest rate for credit cards r is assumed to be 1.16, and the saving interest rate $r_s = 1.01$. The relative risk aversion coefficient, ρ, is assumed to be 2.

The introductory interest rates r^r and durations of the Red offers τ^r are given in the dataset. However, we don't observe introductory offers consumers received in subsequent periods. We assume the duration for the Blue offer is 6 months, which is the typical duration in the company we observed. The interest rate on the Blue offer is assumed to be 1.08.

We assume consumers have a probability of 90% to receive Blue offers. As argued before, we believe respondents should receive new offers every quarter with a probability of almost one in the sample period. It is assumed 1% consumers have an ongoing Blue offer at the time of the Red solicitation which the average response rate to credit card solicitations at the sample period.

Given the calibrated parameters and the distribution assumptions, we estimate remaining parameters by minimizing a weighted[21] distance between simulated moments of consumers' behaviors and their empirical counterparts. We estimate parameters for three models: exponential, naive and sophisticated hyperbolic. The estimated parameters are the time discount factors, β and δ, the switch cost distribution parameter k, and the parameters of the liquid asset distribution at the beginning of period 1, the mean μ and the variance ϵ^2. For the exponential model, $\beta = 1$. For the naive model, $\beta_1 = 1$ and $\beta_0 = \beta$ is estimated. For the sophisticated model, $\beta_1 = \beta_0 = \beta$.

[20] We observe the "revolving balance" for every consumer at the time of solicitation, which unfortunately includes not only the credit card debt but also the convenience charge.

[21] The weighting matrix is chosen by the authors, which gives much weight to the response rate. Shui (2003) provides more detail on this.

7 Estimation Results

Estimation Results for the dynamic model are reported in Table 3. "Goodness-of-Fit" is the weighted distance between empirical moments and simulated moments. Allowing for hyperbolic time preferences significantly improves model prediction, reducing the distance to half. As argued above, the failure of exponential discounting is determined by two apparently contradictory facts:First, *ex ante* more consumers accept the short offer A than the longer offer E and F, which implies that consumers expect to behave patiently in the future. Second, thirty-five percent of respondents, *ex post*, continually borrow an average of \$2000 on this card, paying a 16% annual interest rate, which suggests that consumers are impatient in the current period.

A close inspection of Table 3 shows that all parameters are estimated precisely. The parameters for both hyperbolic models are very close, whereas those of the exponential model are quite different. The similarity of naive and sophisticated models is expected because consumers in this model has very limited ability to constrain themselves. They receive new introductory offers almost every quarter and they have large spare credit limit. Without self-commitment device, sophisticated consumers behave similarly to naive consumers. The small difference is that given β and δ, naive consumers borrow more since they expect their debt to be temporary and are eager to accept new offers since they don't realize their self-control problem. Therefore, the naive model needs a larger β to match the consumer debt level and a larger switching cost to keep consumers from switching out.

However, exponential consumers have a much larger switching cost (\$861 vs. \$150). Such a large k is required to better match the debt path over time. In Fig.4, the predicted debt paths of Market Cell A, E and F by three models are compared with empirical data. Comparing to the exponential model, the two hyperbolic model match the debt path much better, which is the reason why their "Goodness-of-Fit" are much lower. Despite a very large switching cost, the predicted debt path by the exponential model declines much faster than the data. Exponential consumers borrow too much at the beginning, an average of \$3500 compared with \$2700 empirically, and too little at the end, an average of \$900 instead of \$2600 empirically. Such a debt path is because that exponential consumers are so patient ($\delta = 0.9999$) that they will pay off their debt even without switching. However such a large δ is required to match consumer responses to the six offers.

Consumer responses to six different introductory offers are shown in Table 4. All three models match the response rates because we put a large weight on this moment. Hyperbolic models are better than the exponential model because they also match the relative preferences among the six offers.

The magnitude of k deserves some discussion. Is the average switching cost \$150 outrageously high? The magnitude of k here is consistent with anecdotal evidence in the credit card market. First, credit card issuers spend lots of money to acquire one customer. Credit card companies send out billions of solicitations every year and 99% of them end up in trash cans. Many solicitations offer a very low introductory rate, as low as 0%. The behavior of issuers will only be rational if majority consumers don't switch. Second, it is a widespread view that switching between different financial products is more hassle than it's worth. A 2002 survey by WHICH? revealed that 66% respondents kept the same credit card and majority of them said that they thought it was too difficult to change. the k captures not only the time it takes to fill out one application form, but also any psychological disutility that consumers associate with the whole process.

A close inspection of Fig.4 reveals that there are two features of the data, which are not explained by the hyperbolic models. First, there are only 65% respondents borrowed during introductory duration. However both hyperbolic models predict that almost all respondents borrow at the beginning. Second, the predicted debt distribution is more concentrated than the empirical data, because there are significantly more respondents borrow more than the sixty percentile, about 75%. We suspect this is due to the restrictive assumption of homogenous consumers. We observe that there are 20% respondents are convenience users, who never borrowed even in the introductory period. Their time preferences must be different from those revolvers, who borrow even under 16% interest rate. In the future research, we plan to explore the effect of consumer heterogeneity.

8 Conclusion

This study uses a rich individual-level dataset in the credit card market to answer the question: whether consumers are time consistent not. From this unique dataset, two puzzles are identified. First, the majority of respondents do not switch out after the expiration of their introductory offers, even though their debt remains at the same level as when they accept the offer. Second, at the time of solicitation, consumers prefer an offer with a lower introductory interest rate (4.9%) and a shorter duration (6 months), to an offer with a higher introductory interest rate (7.9%) but a longer duration (12 months). The relative preference is puzzling since consumers would benefit more, *ex post*, from the longer introductory offer.

A dynamic model is developed to explain consumer behavior, in which consumers have both time consistent (exponential) and time inconsistent (hyperbolic) preferences and they are subject to realistic random shocks. According to the estimation results based on this dynamic model, a time-varying switching cost is required to explain the first puzzle. Accepting one offer only implies that respondents have low switching costs at the time of acceptance. Most of the time consumers face much higher switching costs. Therefore majority of them fail to switch a second time even though their debt remains large. And only the hyperbolic model can explain the second puzzle. The failure of the exponential model is because that time consistent consumers would always prefer an offer which provides the most interest saving. We have explored two extreme types of hyperbolic discounting: naive and sophisticated. Both of them can explain the data, however the underlying stories are different. Naive consumers mistakenly prefer the shorter offer because they underestimate their future borrowing. Sophisticated consumers prefer the shorter offer because it offers a self-commitment device. Unfortunately, the two hyperbolic models are indistinguishable in this experiment.

Consumer time consistency is an important question since different answers have vastly different normative implications. For example a consumer piles up debt on her credit cards. She may do so because the pleasure of consumption today outweighs the interest payment tomorrow. Or she may do so because she has impulsive to overspend which is not valued from the long-run perspective, like the sophisticated agent. The two stories have totally different public policy conclusions. The first consumer just borrows the right amount. However, the second consumer would like somebody to bind her hands. It is crucial to distinguish between the two hypothesis.

Consumer behavior identified here also facilitates the understanding of two competition anomalies in the credit card market. The first one is that consumer credit card loans earn a higher capital return than other bank assets, and credit card interest rates are excessively downward sticky compared with fund costs, which is well established in Ausubel (1991). The other is, instead of lowering interest rates, credit card issuers fiercely compete with each other by sending out "junk mails". Consumer irresponsiveness to interest rates has been offered as a reason for this in Ausubel (1991). This study not only provides individual-level evidence of this inertia, but also identify two separate forces behind it: self-control problem and high switching cost.[22]

[22] Calem and Mester (1995) finded that consumers have high switching cost in the credit card market.

Appendix

Laibson *et al.* (2000) models the idiosyncratic income shock, ξ_t, as a sum of a persistent shock, μ_t, and a transitory shock, ν_t. The persistent shock follows an AR(1) process with a coefficient α.

$$\xi_t = \mu_t + \nu_t,$$
$$\mu_t = \alpha\mu_{t-1} + \varepsilon_t,$$

where $\varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right)$ and $v_t \sim N\left(0, \sigma_v^2\right)$. He estimated α, σ_ε^2, σ_v^2 for three different education levels. The parameters for "completed college" are used in the estimation.

Define a quarterly income shock, η_q, such that $\xi_t = \sum_{q=4(t-1)+1}^{4t} \eta_q$.

$$\eta_q = s_q + \epsilon_q,$$
$$s_q = f s_{q-1} + \gamma_q,$$

where s_q is a quarterly persistent shock with a coefficient of f. $\gamma_q \sim N\left(0, \sigma_r^2\right)$ and $\epsilon_q \sim N\left(0, \sigma_\epsilon^2\right)$.

It can be shown that:

$$4\sigma_\epsilon^2 = \sigma_v^2$$
$$\frac{1}{1-\alpha^2}\sigma_\varepsilon^2 = (4 + 6f + 4f^2 + 2f^3)\frac{\sigma_r^2}{1-f^2}$$
$$\frac{\alpha}{1-\alpha^2}\sigma_\varepsilon^2 = (f + 2f^2 + 2f^3 + 4f^4 + 3f^5 + 2f^6 + f^7)\frac{\sigma_r^2}{1-f^2}$$

After obtaining parameters for the quarterly shock, I use a two-state Markov process to replace the s_q which follows an AR(1), following Laibson *et al.* (2000). The Markov process is symmetric taking two values $\{\theta, -\theta\}$, where $\theta = \sqrt{\frac{\sigma_r^2}{1-f^2}}$ and the transition probability $p = \frac{1+f}{2}$. In this way the Markov process matches the variance covariance of s_q.

Recall the income process in the dynamic model, $y_t = \varphi_t y_t^g + (1-\varphi_t)\, y_t^b$. y_t^j is lognormal random variable, where $j \in \{g, b\}$ and φ_t is a signal whether the income state is good or bad.

$$\log\left(y_t^g\right) = c + \theta + \epsilon_t$$
$$\log\left(y_t^b\right) = c - \theta + \epsilon_t$$

where c is a constant to capture the permanent income. To determine c, I assume the mean income is \$10,000 per quarter.

In summary, the income process in the good state has a mean of 10,000 and a variance of 3.5×10^5. The income process in the bad state has a mean of 7645 with a variance of 2.05×10^5. The transition probability matrix is:

$$p = \begin{pmatrix} 0.9939 & 0.0061 \\ 0.0061 & 0.9939 \end{pmatrix}.$$

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Table 1: Sample Statistics[a]

	N	Months On File	Number of Past-due	Revolving Balance	Revolving Limit	Credit Score	Number of Credit Cards	Income
All[b]	599,257	174	0.0197	$2,509	$17,481	643	3.77	NA
		(71)	(0.139)	(4058)	(11388)	(89)	(1.88)	
A	1073	126	0.0308	$3,927	$15,473	584	3.94	$44,180
		(76)	(0.1727)	(4979)	(10573)	(96)	(2.057)	(24051)
B	903	128	0.0266	$3,474	$15,137	592	3.81	$43,170
		(79)	(0.1609)	(4725)	(11112)	(96)	(2.101)	(25175)
C	687	114	0.0247	$3,543	$14,230	579	3.598	$42,253
		(77)	(0.1555)	(4901)	(11268)	(95)	(2.068)	(24437)
D	645	112	0.0248	$3,584	$14,075	582	3.557	$41,215
		(76)	(0.1557)	(4988)	(11703)	(104)	(2.07)	(25274)
E	992	125	0.0363	$3,694	$15,176	590	3.729	$43,830
		(76)	(0.1871)	(5066)	(11313)	(100)	(2.076)	(28733)
F	944	123	0.0222	$4,042	$15,107	581	3.807	$43,697
		(77)	(0.1476)	(5469)	(10688)	(100)	(1.98)	(26725)

[a]Standard deviations are in parentheses.

[b]Sample statistics are reported for all six market cells to save space. Due to randomization, the statistics are similiar across different market cells.

Table 2: Rank Reversal[a]

Market Cell	Number of Observations	Effective Response Rate	Rank by Response Rate	Effective Interest Rate	Rank by Interest Rate
A: 4.9% 6 months	99,886	1.073% (0.00033)	1	10.23%	3
B: 5.9% 6 months	99,872	0.903% (0.00030)	4	11.35%	4
C: 6.9% 6 months	99,869	0.687% (0.00026)	5	11.86%	5
D: 7.9% 6 months	99,880	0.645% (0.00025)	6	12.35%	6
E: 6.9% 9 months	99,890	0.992% (0.00031)	2	9.23%	2
F: 7.9% [b] 12 months	99,860	0.944% (0.00031)	3	8.32%	1
T-TEST		P-VALUES			
A vs. E		7.23%			
A vs. F		0.29%			

[a]Source: Ausubel (1999) 'Adverse Selection in the Credit Card Market'. Standard errors in parentheses.

[b]It should be briefly be explained why the calculated effective interest rate for market cell F (8.32%) slightly exceeded the stated APR of 7.9%. First, the author's calculations incorporated the first 13 months of the potential life of the account, in order to deal with some timing problems in the data. Second, the APR is twelve times the monthly interest rate and, so, omits monthly compounding. Third, the introductory interest rate is conditional on the card holder remaining current on his account; each market cell includes customers who went delinquent and lost the introductory rate.

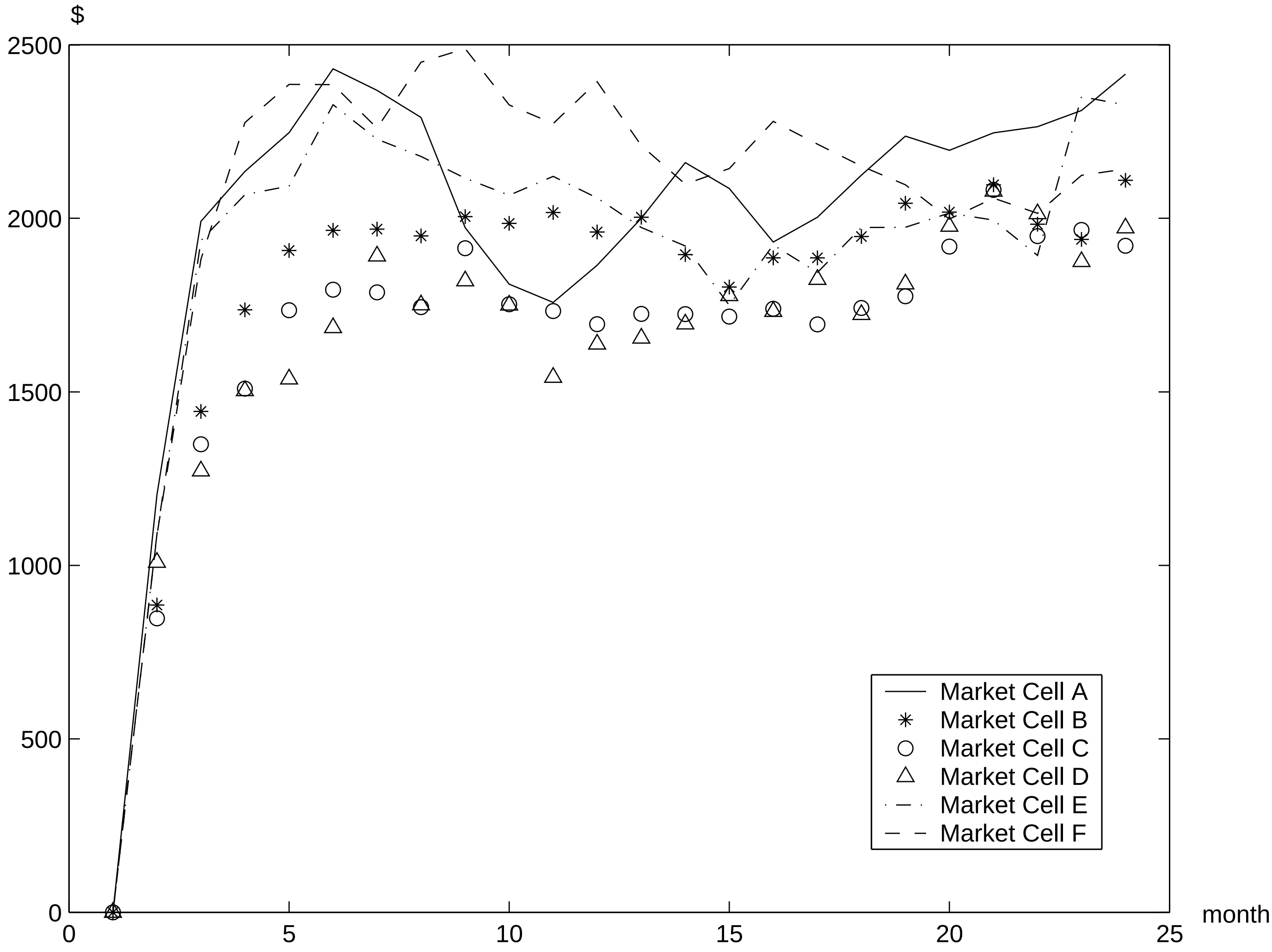

Figure 1: Medians of borrowers' debt distributions over time.

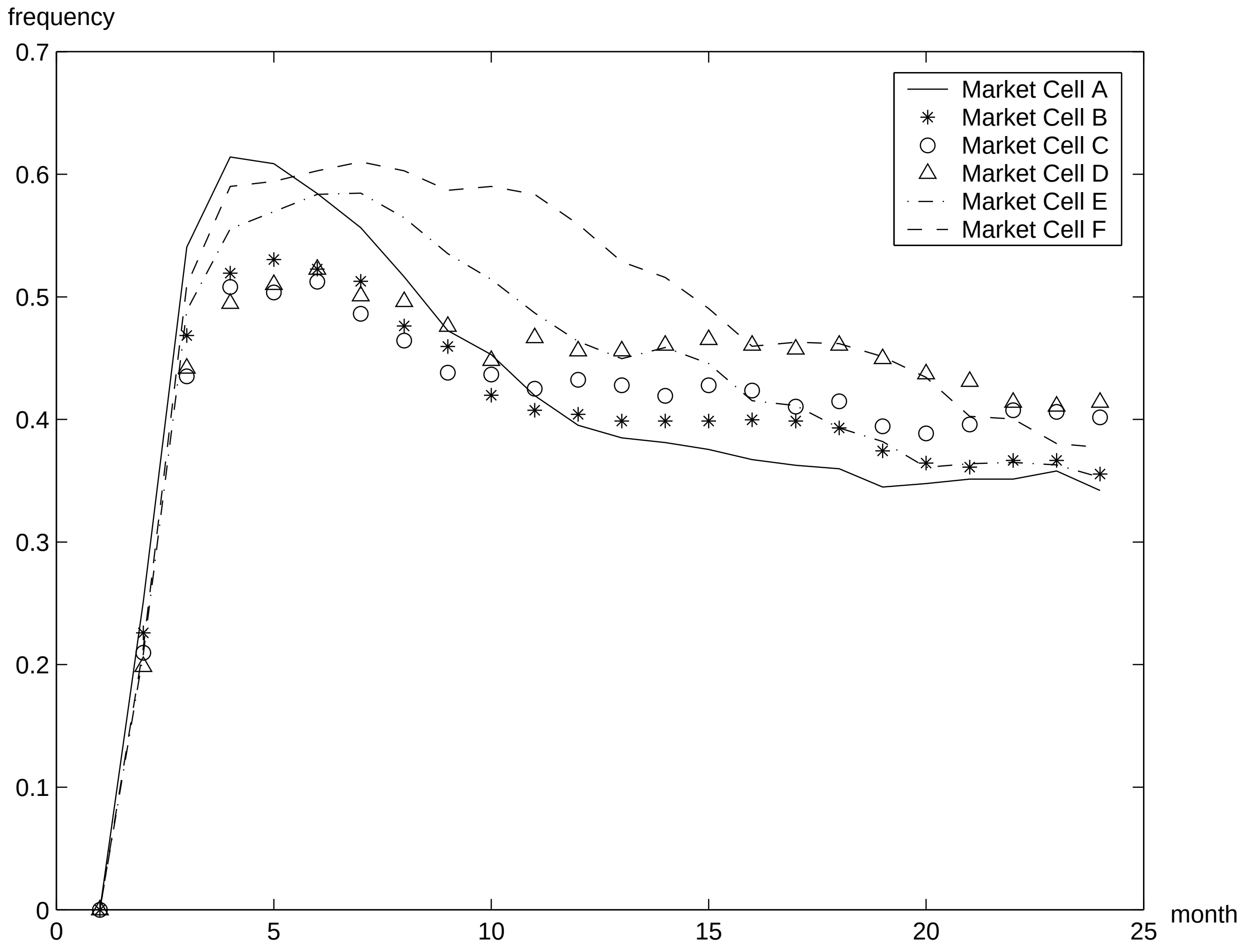

Figure 2: Borrowing Frequencies of respondents over time.

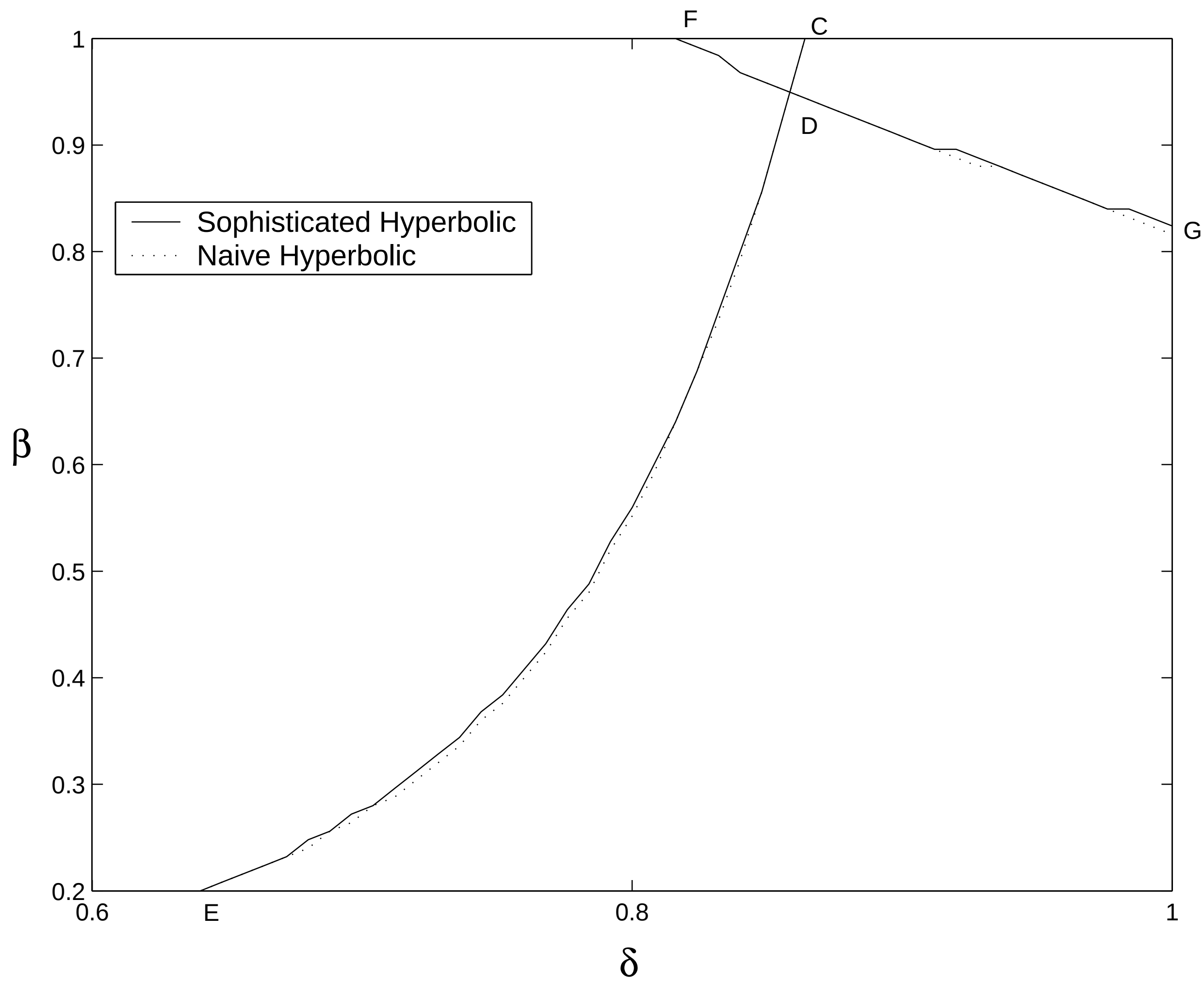

Figure 3: Rank Reverse Area of Sophisticated and Naive Hyperbolic Agents

Table 3: Estimated Parameters [a]

	(1) Sophisticated	(2) Naive	(3) Exponential
β	0.7863 (0.039)	0.8172 (0.02343)	
δ	0.9999 (0.003575)	0.9999 (0.002534)	0.9999 (0.000827)
k	0.02927 ($146) (0.006196)	0.0326 ($163) (0.00899)	0.1722 ($861) (0.004)
μ	1.0088 ($5044) (0.04485)	0.9584 ($4792) (0.02348)	1.5836 ($7918) (0.0098)
ϵ^2	0.831 ($2883) (0.0438)	0.8167 ($2858) (0.01913)	4.278 ($6541) (0.009812)
Goodness-of-Fit	$2.5202e-4$	$2.8183e-4$	$6.0534e-4$

[a] β,δ are discount factors. k is the switching cost parameter. A_1 is liquid assets at the time of solicitation. Standard errors are in parenthese.

Table 4: Simulated Response

Market Cell	Total	Empirical	Naive Hyperbolic	Sophisticated Hyperbolic	Exponential
A: 4.9% 6 months	99,886	1073	1013	1001	951
B: 5.9% 6 months	99,872	903	911	888	845
C: 6.9% 6 months	99,869	687	810	793	764
D: 7.9% 6 months	99,880	645	701	652	672
E: 6.9% 9 months	99,890	992	997	980	1005
F: 7.9% 12 months	99,860	944	978	947	1047

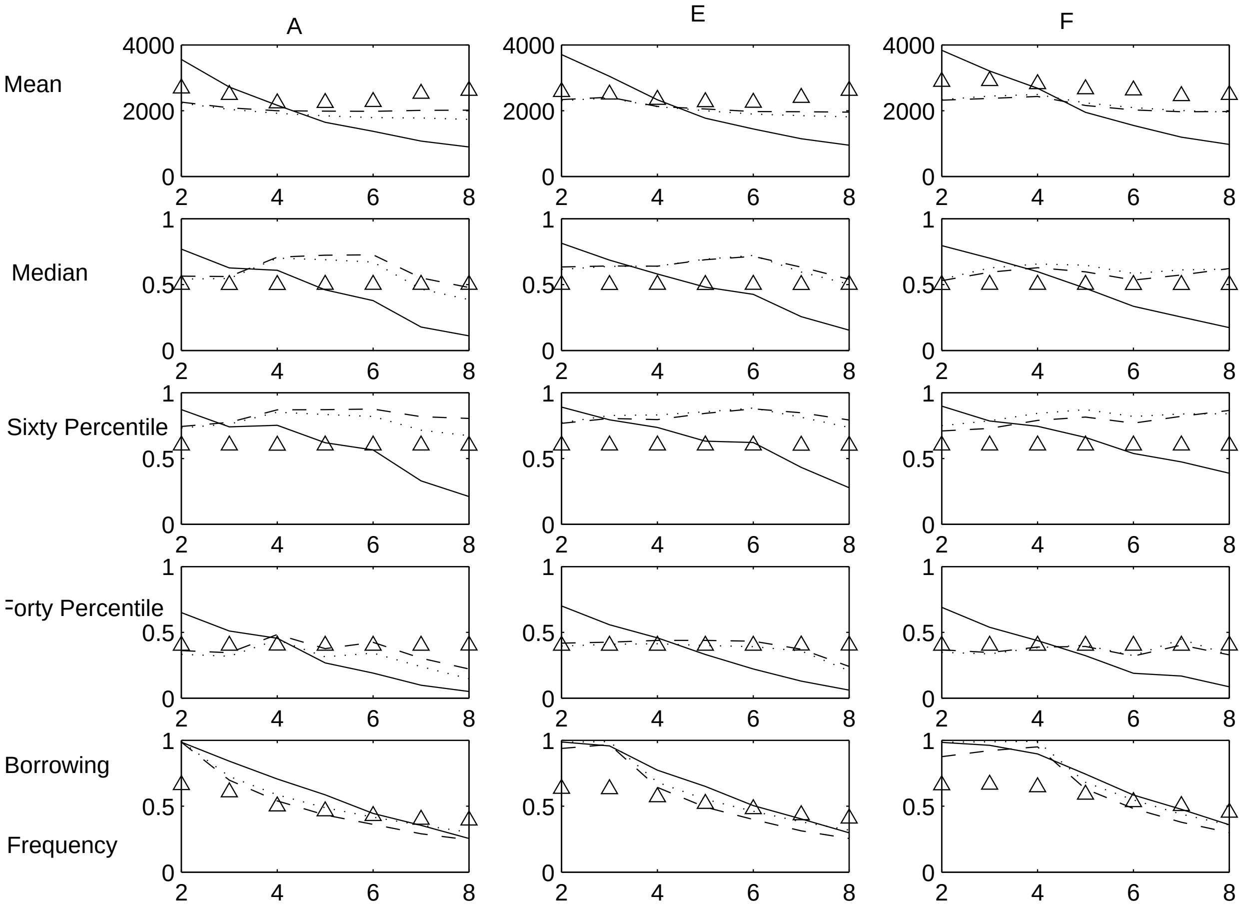

Figure 4: Simulated Debt Moments. The triangle line is the empirical data. The solid line, the dash line and the dotted line are predicted by the exponential, sophisticated and naive hyperbolic models respectively.