Do Credit Card Companies Screen for Behavioral Biases?[1]

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Abstract

We look at the supply side of the credit card market to analyze the pricing and advertising strategies of credit card offers. We show that credit cards which have reward programs have lower regular APR but rely more heavily on backward loaded and more hidden payment features such as late fees, default APR or over limit fees. Issuers target different reward programs at different types of the population: Programs such as miles, cash back and points are offered to richer and more educated customers, while low intro APR offers are offered to poorer and less educated customers. The results support the idea put forward in models of behavioral contract theory that credit card companies use reward programs to either shroud aspects of a card offer or exploit their time inconsistency. Our results also suggest that card features that are mainly demanded by sophisticated consumers cannot be shrouded and need to be priced upfront. Finally, using shocks to the credit worthiness of customers via increases in state level unemployment insurance, we show that card issuers rely more heavily on backward loaded credit terms when customers are more protected.

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1. Introduction

Retail financial products have grown in the heterogeneity and complexity of the terms they offer over the last two decades. A few recent papers have documented this growth of the retail financial sector, see for example Tufano (2003), Phillipon (2012) and Greenwood and Scharfstein (2013). But there are widely diverging views about the reasons behind this proliferation of new products and services. On the one side is a "functionalist" view as suggest by Merton (1992) or Miller (1993) or more recently Cochrane (2013). Greater product heterogeneity is seen as a reflection of increased financial innovation, which allows companies to better accommodate consumer demands and tailor products to their preferences. On the other side is a concern that the proliferation of new products and features aims to exploit consumers' behavioral biases and add complexity, which could make it difficult for consumers to compare prices and across products. This view has been summarized in Thaler and Sunstein (2008) or Campbell et al (2011).

While a large empirical literature over the last thirty years has documented different ways how consumers might make mistakes in choosing financial products, much less work has focused on how firms respond to these biases when designing product features and optimal pricing strategies. Recent advances on the theory side explore optimal supply side responses and equilibrium implications, if firms face consumers with behavioral biases. For an overview of the theoretical approaches see for example, Dellavigna (2009) or Koszegi (2013).

In this paper we focus on the credit card industry to shed light on the pricing and product design strategies that credit card issuers use to attract and screen customers. We show that credit card issuers use different credit card features to separate more sophisticated from less sophisticated customers. For example, low introductory rates are offered to less educated and poorer customers, while miles are offered to more educated and richer customers. Conditional on the reward program, the pricing of the cards then differs significantly. Reward programs that are offered to less educated consumers, have more expensive, backward loaded and hidden pricing features, compared to those offered to more sophisticated customers. In addition, cards with reward programs respond less to changes in the banks' cost of funds, which suggests that consumers are less sensitive to the pricing of these cards. Overall our findings suggest that credit card issuers screen for behavioral biases of customers in order to maximize the rents they extract from (unsophisticated) the customers. But we also document that card companies take into account the interaction between a customer's credit risk and heavily relying on a person's behavioral biases. Using exogenous shocks to the credit worthiness of customers via increases in state level unemployment insurance, we show that card issuers rely more heavily on backward loaded credit terms when customers are more protected.

Our results draw on the recent theory literature that explores optimal supply responses when consumers have behavioral biases. Nonlinear pricing models under adverse selection a la Mussa and Rosen (1978) or Maskin and Riley (1984) cannot explain the typical three-part tariffs, which are prominent for credit cards contracts: the typical card has a low APR or even lower introductory APR and backward loaded fee structures with very high late fees and overdraft fees.[2] These models predict marginal cost pricing for the last unit of consumption and suggest that the highest demand consumer will pay the lowest marginal price. The intuition is that under adverse selection firms do not want to distort the quantity chosen by the highest demand users in order to maximize the infra-marginal rents they can extract from these customers. Backward loaded credit card features with high late fees can only be optimal if customers do not understand their actual cost of credit, since in that case they will demand credit as if they were facing only the low APR. The two most prominent approaches of modeling behavioral biases in the credit card market focus either on self-control and time inconsistency problems of customers, or alternatively on myopic consumers who for example are not able to value more complex product features.

An application of the first set of biases is the work by Heidhues and Koszegi (2010) or Grubb (2009) that derives the optimal credit contract if borrowers have self-control issues but naively underestimate their likelihood to be tempted in the future. The profit-

[2] See for example Grubb (2009) for further discussion of this point.

maximizing contract for the issuer uses a three-part tariff with low introductory rates to make it look more attractive to consumers who underestimate their propensity to have self-control issues in the future. This contract maximizes the consumer's mistake, since it entices consumers to take on more debt than they optimally would. In contrast, sophisticated consumers will correctly forecast their propensity to have self-control issues and thus choose a less backward loaded contract. Similarly, Grubb (2009) suggests that three part tariff are an optimal response for firms that face consumers who are overoptimistic about how well they can forecast the variance of their future demand when choosing a card.

A prominent example of firm responses to myopic consumers is the influential paper by Gabaix and Laibson (2006) on shrouded attributes. It suggests if myopic consumers have difficulty understanding the price of add-on features of a product, companies can attract these consumers by charging a low base price or offering other enticing features, which are very visible to consumers. But then charging them high prices via hidden features. In the credit card context that would translate into features such as late fees, high default APRs or overdraft fees. As a result myopic or unsophisticated consumers transfer rent to the firm and also to more sophisticated consumers who avoid the expensive add-on features. The theory also suggests that products or features that are mainly demanded by sophisticated consumers are difficult to shroud and have to be priced at cost[3].

However, there are two additional implications of the model that have not been discussed in the literature, but as we will show, are important for the credit card industry. First, Gabaix and Laibson (2006) model a pooling equilibrium, since their firms have no other tool to separate customers. However, in their model firms would like to separate the sophisticated from the unsophisticated consumers, since part of the rents extracted from unsophisticated consumers go to the sophisticated consumers, since they avoid the costly

[3] Carlin (2013) suggests a related model where heightened product complexity increases the market power of financial institutions because it prevents some consumers from becoming knowledgeable about prices. Here complexity works as a (negative) externality on all customers, rather than being targeted at particular subsets of the population.

add-ons and therefore access the product at a price below cost. We show that credit card companies seem to take into account that cross subsidy and design reward programs to separate sophisticated from unsophisticated customers.

Second, the model does not take into account credit risk, since it was written for one shot product market interactions. However, in credit contracts an excessive reliance on shrouding and backward loading of payments, could change the credit risk of customers. In the extreme these pricing strategies could attract customers who cannot afford the products that are offered, since they do not understand the features. Or the backward-loaded nature of the contract could entice them to take on too much leverage that they ultimately cannot afford. This creates an endogenous limit in how heavily lenders can rely on these strategies. Our analysis suggests that banks are aware of this trade-off when designing credit card offers and rely more heavily on these backward loaded features when the credit risk of borrowers improves.

To test the importance of these models for the retail finance market we use data on preapproved credit card offers and their contract features from the US credit card industry. Credit cards are an ideal testing ground to observe whether and how firms use communication and product features to target different customers, since the majority of credit cards in the US are sold via pre-approved credit card solicitations done by mail. This means that the information that customers get is also observable to researcher, once we obtain the card solicitation that customers received. In contrast in almost all other retail financial areas customer choices are intermediated by advisors who might change the information or even product features in ways that are unobservable to the research. The data for this study are obtained from Compremedia (Mintel) a company that collects monthly information on all credit card mailers sent to a set of about 7000 representative households, which work with Compremedia across the US. These clients are chosen to represent the demographic and economic distribution of the US credit card owning population. Customer characteristics are parallel with the type of information that credit card issuers observe when targeting customers. This data allows us to observe the supply side of the credit card market, i.e. the type of offers that customers receive. Our data set covers the time period between 1999 and 2011.

Based on the pdf data that we receive from Compremedia, we created algorithms to extract card information and the features of the offer. We can classify the hard information of the offer such as APRs, fees, and reward programs. But we also can observe what we call the "soft" features of the offer, for example the use of photos, color, font size or amount of information provided in the mailer that the customer receives.[4]

We show that credit card issuers use different card features to target especially educated versus uneducated customers, and rich versus poor customers. Less educated customers and poorer customers receive more card offers with backward loaded payment features: Low introductory APRs but high late fees, penalty interest rates and over-limit fees. In contrast richer and more educated people receive almost no offers with introductory low APRs, and instead are more likely to receive card offers with cash back programs and points. And especially miles programs are targeted at more educated customers: Only 8% of offers have a miles program and they are exclusively offered to the highest income and educational groups.

We then analyze the pricing structure of credit cards conditional on having different reward programs. First, we find that cards that either have cash back or points programs have lower regular APR. But at the same time these cards display much higher late fees as well as higher over limit fees. The same relationship holds when looking at cards that have introductory APR programs as rewards. Regular APRs are negatively associated with late fees, but cards that have an intro APR program show a significantly larger trade-off between regular APRs and late fees. These results go through when controlling for person specific and even bank fixed effects, which holds constant the credit risk of the person and the cost of credit for the bank. In this regression we de facto rely on the

[4] Since financial institutions in the US have to follow TILA (the Truth in Lending Act) we know that all the information concerning the card have to be on the pre-approved mailer. In addition the mandatory Schumer box regulates the disclosure of most of the main card features that have to be included in the letter. However, issuers can choose how they display the information that they highlight in the main part of the text.

variation that comes from the fact that banks randomly send several offers to the same type of households to find out whether the customer responds to the backward loaded or shrouded features of the card. Therefore, we can estimate how banks on average change the pricing strategy of a card when using rewards programs such as miles, cash back and others.

Following the approach in Ausubel (2001) we also show that these card features are associated with lower sensitivity of regular APR of credit cards to changes in fed fund rate. However, we find that late fees and default APR are more sensitive to changes in the Fed fund rate. These results suggest reward features might be used to lower the sensitivity of customers to the price of the cards, either by screening for customers with behavioral biases or by shrouding the less attractive features of a credit card offer.

One interesting exception are miles programs, which we show are mainly offered to the most educated and richer groups of the population: These cards have *significantly higher* regular APR but lower late fees, and show a much smaller trade-off between the regular APR and backward loaded fees. We argue that this finding is in line with the idea in Gabaix and Laibson (2006) that product features which are demanded by more sophisticated (in our case measured as more educated) consumers cannot be easily shrouded and thus have to be priced upfront.

Finally, we test whether credit card issuers rely more heavily on backward loaded or shrouded features, when the ultimate credit risk of customers is lower and thus the borrower's mistake in picking the high-priced product, does not significantly affect credit risk. For that purpose we look at exogenous shocks to customer creditworthiness, in particular changes in state level unemployment insurance (UI) in the US over the last decade.[5] UI was increased in staggered fashion across several US states over the last decade. These changes all went in the direction of providing higher levels of unemployment insurance as well as longer time period. By reducing the impact on

[5] We follow Agrawal and Matsa (2013) in using changes in the state level unemployment insurance limits as a source of variation in employees risk exposure.

consumer cash flows in the case of negative shocks, it reduces also a lender's exposure to one of the largest negative economic shock that customers might suffer. This allows us to run a standard Difference in Difference estimator to regress changes in card features on UI changes across states and across income groups. Our results show that he credit conditions of the borrower indeed affect the willingness of card issuers to rely on shrouding and backward loaded features. We find that increases in the UI levels leads to an increase in the fraction of offers that have low intro APRs and also an increase in other reward programs. But at the same time we see an increase in the late fees and default APR. Taken together these results suggest that credit card companies realize that there is an inherent trade off in the use of backward loaded features of credit card offers: They might help in inducing customers to take on more (expensive) credit, but at the same time they expose the lender to people who pose a greater risk.

One separate reason why card issuers might use rewards programs which aim to increase the transaction volume of the card, e.g. miles, cash back or points, is that card issues get paid by the payment processors (visa and master card) based on how much vendor fees a card generates. While the incentive related to rewards programs surely are important, our results suggest that they are orthogonal to the channel we document in the paper. While one might argue that providing consumers with rewards (that are valuable) justifies an increase in the overall fees of the card, it does not explain why the form of the price increase should be via backward-loaded features, as we find in the case of points, cash back or introductory APR. In addition, as discussed before, we do see that reward programs that target more educated and richer people, like miles, have the opposite effect on the shape of the fee structure.

The rest of the paper is structured as follows. Section 2 provides a detailed literature discussion. In section 3 we lay out the data used in the study as well as variables we constructed for the paper and the design of the sample. Section 4 summarizes our results and Section 5 concludes.

2. Literature Review

Our paper builds on a large literature in economics and marketing that has looked at how individuals respond to information about product features is displayed when choosing between complex contracts such as retail financial products, medical insurance contracts or even cell phone plans. For example, Lohse (1997) demonstrates in an eye-tracking study that colored Yellow Pages ads are viewed longer and more often than black-and-white ads. Similarly, Lohse and Rosen (2001) suggests that the use of color and photos or graphics increases the perception of quality of the products that are being advertised and enhances the credibility of the claims made about the products when compared with non-color advertisements. Heitman et al (2014) documents that the way prices and add-on features are displayed, significantly affects how well people choose between products. Besheres, Choi, Laibson and Madrian (2010) show that even when subjects are presented with very transparent and easy to digest information about different mutual funds, they select dominated savings vehicles. Bertrand et al (2010) show that the advertising content indeed can have significant impact on product take up and even willingness to pay. They set up a field experiment with a consumer lender's direct mailing campaign in South Africa and find that advertising content which appeals to emotions (such as a woman's versus a man's face) or a simpler display of choices leads people to accept much more expensive credit products. We build on this earlier literature by analyzing if firms deliberately incorporate these behavioral biases when designing credit card offers.

There is also a growing literature in household finance that has looked at credit card usage of borrowers to document that people make non-optimal choices. Agarwal et al (2008) analyze more than 4 million transactions of credit card customer to show that customers on average pay significant fees (late payment and penalty fees) of about $14 per month, which does not include interest payments. These results confirm that fees indeed have significant bite and customers are not able to optimally avoid all the negative features of their cards. The paper also shows that customers seem to learn to reduce fees over time. But this learning is relatively slow, payments fall by about 75 percent after four years of account life. Using a similar data set, Gross and Souleles (2000) show that consumers respond strongly to an increase in their credit limit and especially to interest rate changes such as low introductory teaser rates. The long-run elasticity of debt to the interest rate is about -1.3 of which more than half reflects net increases in total borrowing (rather than just balance switches). In a related work, Agarwal et al (2010) document that consumers who respond to the inferior offers of a lender have poorer credit characteristics ex ante and also end up defaulting more ex post. Similarly, Agarwal et al (2009) show that over the lifecycle middle-aged households get the best credit terms, while older customers select worse credit. The authors conjecture that deterioration in cognitive abilities could be a reason why older people choose worse terms.[6] These papers provide important confirmation that credit cards with disadvantageous features are being taken up and have a significant impact on borrowers cost of capital.

Finally, we relate to a number of papers, which have documented large heterogeneity in the pricing or retail financial products even in the face of increasing competition. See for example the seminal paper by Ausubel (1991) which documents that credit card companies have very low pass through rates of any changes in their cost of capital. Hortacu and Syverson (2004) or Bergstresser et al (2009) show wide dispersion in fees for the mutual fund industry that is related to changes in the heterogeneity of the customer base. More recently Sun (2014) and Celerier and Vallee (2014) show that even with the introduction of increased competition price dispersion does not go down and product complexity might go up. Similarly, Hastings, Hortacsu and Syverson (2012) look at the introduction of individual savings accounts in Mexico and show that firms that invested more heavily in advertising had both high prices and larger market shares, since customers seem to not be sufficiently price sensitive. Similarly, Gurun, Matvos and Seru (2014) show that areas with large house price increases and expansion of mortgage originations, saw an increase in marketing expenses and amounts of marketing solicitations being sent out. These results suggest that firms seem to compete on nonfinancial dimensions such as advertising to substitute for price competition.

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[6] Hastings and Mitchell (2011) use a large-scale, nationally representative field survey from Chile to directly relate impatience and financial literacy relate to poor financial decisions within a savings context. The results show that impatience is a strong predictor of wealth. Financial literacy is also correlated with wealth though it appears to be a weaker predictor of sensitivity to framing in investment decisions.

A paper that uses a very similar data set is Han, Keys and Li (2013), but focus on a complementary topic. The authors use Mintel data between 2007 and 2011 to document the large expansion in the supply of credit card debt in the time period leading up to the financial crisis and after the crisis. The results show that the expansion prior to crisis was particularly large for consumers with medium credit scores as supposed to sub-prime customers. In addition they show that even customers who had previously gone through a bankruptcy still have a high likelihood of receiving offers, but that these offers are more restrictive.

3. Data and Summary Statistics

3.1. Data Description

We use a comprehensive dataset from Mintel Comperemedia that contains comprehensive information on the types of credit card offers that customer with different characteristics receive in the US. This data is based on panel conduced with more than 4000 households monthly where the household collects all mailings of direct (preapproved) credit mailing and send this original information to Mintel. For this data collection effort Mintel selects the households based on their demographic and economic characteristics in order to be representative of the distribution of the US credit card owning population. For each household, Mintel collects detailed demographic information including the age and education of household head, and household income, composition, races, zip code, etc. Each month, Mintel receives from the household all credit solicitation mails, such as credit card, home equity loan and mortgage offers that these selected households received during the month. We only observe offers to the entire households usually to the head of the household.

After gathering the physical credit card offers from the households, Mintel manually scans the actual mailers in PDF format and electronically enters some key information which usually are contained in the Schumer box: regular purchasing APRs, balance transfer APRs, cash advantage APRs, default APRs, maximum credit limits, annual fees, late fees (penalty fees), over limit fees and so on. We manually check the quality of the dataset and find that all the variables are very well collected except default APRs which has many missing values.

The data sample ranges from March 1999 to February 2011. For each month, there are about 4,000 households and 7,000 credit card mail campaigns on average. In total, there are 1,014,768 mail campaigns which consist of 168,312 different credit card offers. This is because credit card companies usually issue the same offer to many households at the same time.

Our second data resource from Mintel is the scanned images of all pages of the credit card offers. However, Mintel only keeps scanned images of about 80% of the credit card offers. Therefore, 803,285 out of the total 1,014,768 credit card offers have complete scanned images of each page.

We extract information of reward programs and any soft information about the design of the mailer itself from these scanned images. First, we use OCR (Optical character recognition) software to transfer all the images into Word documents. The OCR software we use is OmniPage Professional version 18.0. It is one of the leading document imaging software which is accurate and fast. The OCR software separates the characters and graphics/background patterns from the original documents (scanned credit card offers), recombines them together based on original digital documents' design and turns it into editable Word documents. After that, we use keyword searching algorithm to search the reward programs in each offer. We are able to identify 8 commonly used reward programs: cash back, point reward, flight mileage, car rental insurance, purchase protection, warranty protection, travel insurance and zero introductory APRs.

Moreover, because we keep format information of each character in the offers, we can also get the format design of these reward programs. By using Word application in VBA, we are able to identify the font of the characters. We collect the size and color of each reward program when they were mentioned in the offer as well as whether they were highlighted with bold or italic. Also, we count the number and size of pictures on each page. To check the quality of the OCR and keyword searching algorithm, we randomly select some offers to manually check the accuracy which turns out to be over 90%. As we mention before, there are some missing values for default APRs from Mintel's hand collect database. To deal with it, we also use keyword searching algorithm to search the default APRs stated in the offers. Usually, the Schumer box contains default APRs which sometimes called penalty APRs. We extract default APRs for all credit card offers with scanned images by using our algorithm and compare them with the ones collected by Mintel. The accuracy of our algorithm is about 98%. In this way, we are able to add back some of the missing values to almost complete the default APRs data. Because we only have 80% samples with scanned offers, our variables for reward programs and format are limited to these 80% sample.

3.2. Descriptive Statistics

Table 1 is the summary statistics. FFR is the monthly average federal fund rate from January 1999 to December 2011. We merge FFR into our credit card dataset by month. In Table 1, variables from APR to Intro_APR_cash are based on our entire 1,014,768 mail campaigns from Mintel. APR is the regular purchasing APRs in the credit card offers. Sometimes, regular APR is a range and we pick the middle point as the APR. The mean of APR is 12.64% among 982,796 total mailings received by consumers. The APRs for balance transfer has a mean of 11.33% and standard deviation of 3.34%. The cash advance APR has a mean of 19.88% and the standard deviation is 4.28%. For default APRs, the mean is much 26.51% which is higher than all other APRs. The credit card companies charge very high default APRs which may be applied to all outstanding balances of a credit card if a consumer pays the monthly bill late (usually in 60 days). All these APRs are monthly couponed. Intro_APR_regular, Intro_APR_balance and Intro_APR_cash are the dummies of whether the offer has 0% introductory APR for regular purchase, balance transfer and cash advance respectively. "Max Card limit" is the nature log of the maximum credit card limit stated in the offers. We only have 526,949 observations for "Max Card limit" since many credit card offers don't have it, especially during later years.

Credit cards also have a number of different fee types, the dimensions that we observe in the data are annual fee, late fee and over limit fee in our sample. Annual fee on average are $12.28 with a standard deviation of 31.99. The distribution of annual fee in our sample is pretty skewed. 81.5% of the mailing offers have zero annual fee and the maximum annual fee is $500. Typically the types of cards that have annual fees associated with them, offer mileage programs and other expensive value added services. Late fee is the onetime payment if the consumer misses paying at least their minimum monthly payment by the due date. In our sample, late fee has a mean of $33.83 and a standard deviation of 6.17. It is much less skewed than annual fee. About 90% of the credit card offers have late fee from $29 to $39. Since this is a fixed monthly fee that comes due if the minimum payment has not been, one can imagine that the cost of this fee structure can be very high especially when customers carry small balances.

Finally, over limit fee is the fee charged when consumers' credit card balance goes over the card limit. The mean of over limit fee is $29.7 with a standard deviation of 10.16. The distribution of over limit fee is also concentrated: about 87% of the cards has over limit fee from $29 to 39$. Although credit card companies usually charge zero annual fee, they do charge much more from late payment and over borrowing.

In Table 1, variables from "Size" to "Purchaseprct" are from 80% of 1,014,768 total mail campaigns which have scanned images of credit card offers. "Size" is the maximum size of the reward programs minus the average size of all characters in every pages of each credit card offer. For example, if the letters "cash back" appear 3 times in the offer, we pick the largest one. "Size" equals this largest number minus the average size of all characters on the same page. The unit of size is directly from Word document. The variable "Size" has 4.71 mean and 5.49 standard deviation. The maximum value of Size is 143.6 because some offers will print very large characters to highlight reward programs. The 90th percentile of variable Size is 10.99. We use this relative size measurement because credit card companies tend to enlarge the reward program characters' size relatively to the paragraphs nearby in order to highlight the reward programs. The size differences between them should be the measure of highlight.

Moreover, “Color” is the dummy of whether reward programs in the offer use color other than black/white. We only focus on the characters of reward programs rather than the entire offer since almost every credit card offers use some colors, especially during later years.[7] “Bold” is the dummy of whether the offer use bold to highlight reward programs.

“Picture” is the file size of each page of the offer which is the measurement of how many or how “fancy” the pictures are in the offer. We don’t use actual count of the pictures nor the size of the pictures because our algorithm considers the background of the page as a big picture as well (usually it is just a big plain color picture). Using storage size of each Word document, we can approximate how complicated the design of the page is. Other information such as characters also use some storage. However, Pictures in Word documents usually take most of the storage room. We think that file storage size is a good measurement of the pictures in the credit card offers. The variable “Picture” is the file storage size and the unit is megabyte (MB). The mean of “Picture” is 0.23MB with 0.26MB standard deviation. In the appendix, we plot two samples of the credit card offers. Figure A.1 is the sample of simple visual offer, which doesn’t use big font, flashy colors, or pictures to highlight the reward programs. Figure A.2 is the sample of high visual offer with many fancy designs.

Moreover, we define “Reward” as the number of reward programs of CASH, POINT and Car rental insurance in each offer. We choose these three reward programs because they are similar and most commonly used. CASH, POINT, MILE, Carrental, Purchaseprct are dummies of whether the offer has these reward programs respectively.

Table 2 summarize the design of the credit card offers. All credit card offers state late fees, default APRs, over-limit fees, and annual fees. Only 5.8% of the credit card offers mention late fees in the first page of the offers. 4.97% of the credit card offers mention default APRs in the first page of the offers. 6.96% of the credit card offers mention over-limit fees in the first page of the offers. Basically, credit card offers usually don’t mention

[7] To construct the format variables such as Size, Color, and Bold, we only focus on the reward programs fonts which include cash back, point rewards, mileage, car rental insurance, purchase protection, and low intro APR programs.

backward loaded terms in the first page of the offer. On the other hand, 79.28% of the credit card offers put annual fees information on the first page which is considered to be the front loaded term. Moreover, reward programs are usually mentioned in the first page of the offers; 100% of the cash back program and mileage programs are mentioned in the first page. For point reward, car rental insurance, and 0 introductory APRs, the changes to be put on the first pages are 93.51%, 80.48%, and 91.04% respectively. Panel B of Table 2 compares the credit card terms when they are mentioned on the first page or not. It is clear that late fee, over-limit fee, and annual fee are much lower in the offers when they are mentioned on the first page than in the offers when they are mentioned in the back.

Timetrend: In figure 1 to figure 4, we plot the monthly time trend of reward programs and variables of credit card design from March 1999 to February 2011. As we can see, the number of reward programs increases overtime and appears cyclical. For example, there is a drop of reward program numbers during the recent crisis. The uses of size, color and pictures in credit card offers also increase overtime and have cyclical patterns.

4. Results

4.1. Customer Characteristics and credit card features

We start by analyzing how the features of offers vary with the characteristics of the customers. The analysis allows us to understand whether specific credit card features are used to target different client groups. But the exercise also allows us to see if the relationships in the data are intuitive. For that purpose in Table xx we run a simple regression model of card features, such as card APR, late fees or reward program on customer characteristics. The characteristics of interest for us are the education levels of customers, which are measured as six distinct educational achievement dummies ranging from some high school to graduate school. And nine different income groups ranging from the lowest income group of less than $15,000 to the highest of over $200,000. In these regressions we also control for the age group fixed effects of the customer, the state fixed effect, dummies for household composition and credit card company fixed effects. Standard errors are clustered at the month level. It is important to note that these customer characteristics are also the same ones that credit card companies observe when they send out mailing campaigns.

In column 1 of Table 3 we start with the mean APR as the dependent variable and report the coefficients on the education and income bins. The results show that regular APR decreases significantly for higher income groups and the results are relatively monotonically going up with increasing income. The magnitude of the effect is quite large. Between the lowest and the third highest income groups there is a difference in mean APR of almost 0.561 percentage points which is a significant difference. The relationship between APR and income levels off a little for the highest two income groups, but we will show that these groups also have different product features. In contrast there is no significant relationship between the regular APR and education. The estimated coefficients are all close to zero and insignificant. We repeat the same regression for APR on balance transfers and APR on cash withdrawals and get very similar results. The regressions are not reported but can be obtained from the authors. These results intuitively suggest that higher income customers are better credit risk and as a result enjoy a lower cost of capital. Interestingly the same is not true for more educated customers.

We now use the logarithm of the maximum credit balance as the left hand side variable and repeat the same regression set up as in column (1). We see that limits increase with higher education bins, but the increase is even steeper with income categories. It is intuitive to think that credit card companies are more comfortable increasing their exposure to customers with higher income and better educational attainment since this might be correlated with increased future earnings potential.

Interestingly in columns (3) and (4) these results reverse when we look at Default APR and late fee. These are backward loaded fees which become due when the customer is either 30 days late or becomes more than 90 days delinquent. Very surprisingly we find that late fees and default APR increase significantly with customer income, but drop with higher educational attainment. For example the difference in default APR between the lowest and the highest income group is about 0.543 percentage points. So customers with higher income actually face higher default interest rates than those with lower income. The same pattern holds true for late fees. In contrast, customers with higher education receive card offers that have smaller late fees and lower default APR. This result is very puzzling: If default APR or late fees are a means to manage customer default risk, it is not clear why customers with higher income would be a higher default risk conditional on falling late, compared to customers with lower income. These results might be a first indication that these interest rates are set with a different set of considerations in mind.

In a next step we look at how reward programs are offered to customers. In column (5) the dependent variable is a dummy equal one if the credit card offer contains a cash back program. We see that there is a strong positive correlation with income, between the highest and lowest income group there is a 4 percent difference that a card has cash back program. This is economically very substantive since only 21 percent of card offers contain a cash back program. In contrast we do not see any relationship between educational levels and the likelihood of receiving a credit card offer with a cash back program. In column (6) we see a very similar result for points programs. Again there is a statistically and economically significant increase in the likelihood of receiving an offer with a points program for households that have higher income levels. But there is no relationship with educational levels.

We observe a very different relationship when looking at miles programs. In column (7) we show that the likelihood of receiving a card offer with a miles program increases significantly with the education level of the household. Households in the second to last highest income group are more than percent more likely to receive an offer with a miles program compared to a household in a the lowest educational bin. Since only eight percent of credit card offers include a miles program in the first place, education seems to be a very important dimension in receiving miles programs. We also see that miles programs increase with the income level of the customer. The final reward program we look at are low introductory APR offers. These usually expire after a few months (customarily between six to 12 months) and then a higher interest rate kicks in. In column (8) we see that introductory APR programs are predominantly offered to less educated and lower income customers. A similar relationship holds for introductory APR rates on balance transfers.

Moreover, in Table 3 Column 9, “Format” is the first principal component of reward programs' size, color, bold and the picture sizes on the credit card offers. We show that more educated households or high income households can get fancier designed credit card offers which usually use bigger font size, more colors, more bold, and more pictures to emphasize the reward programs.

As discussed above, the detailed customer information in the Mintel data allows us to analyze how credit card issuers target customers with different characteristics, for example across the income and educational attainment distribution. However, one dimension that we do not have in our data, are the FICO scores for individual borrowers. To analyze if the lack of FICO scores in our data is a significant limitation, we obtained Mintel data via the CFPB. While the data covers a shorter time period than ours, starting only from 2007, it has the advantage of containing also FICO scores.

The idea it to see if credit card features differ significantly by FICO scores, after controlling for all the other observable characteristics of the customer. This is equivalent to asking whether card issuers use FICO scores to screen a different dimension of the borrowers from all the other characteristics. For that purpose we repeat our waterfall regressions where we regress card features on the different customer characteristics and then add FICO scores as an additional explanatory variable. Adding the customers’ FICO scores does not add any additional explanatory power to the regression. The adjusted R-squared of the regressions are unchanged and none of the coefficients on other RHS variables change when including the FICO scores. So, overall it appears that the dimensions spanned by the FICO scores are jointly spanned by the other observable characteristics. These results reduce the concern that we are missing an important, and separate screening dimension.

Taken together these results suggest that different reward programs are used to target different customers groups. Introductory APR offers are primarily offered to less educated and poor clients. In contrast points and cash back programs are offered to richer customers but independent of their educational level. Finally, miles is the only reward program that are predominately targeted to richer and importantly to more educated customers. We plot the coefficients from Table 3 in Figure 5 and 6 to make the patterns more clear. Figure 5 plots the estimated coefficients of the education on credit card terms and reward programs. Figure 6 plots the estimated coefficients of the income level on credit card terms and reward programs.

4.2. Pricing of credit cards

In a next step we now want to understand how the pricing of credit card offers changes with reward programs. The idea is to test if these reward programs are used in combination with more backward loaded credit card features or different pricing levels. If indeed rewards are used to attract customers who are more prone to shrouding we would expect more pricing of hidden features and more backward loading. For that purpose we will investigate the different reward programs separately. We follow the general idea pioneered in Ausubel (1991) to assume that APR should be very sensitive to the Fedfundrate since this is the rate at which the banks can raise capital. Parallel to Ausubel (1991) we will interpret any elasticity between the APR and FFR that is much below 1 as an indication that credit card issuers are insulated from competition. But in our case we want to understand whether the use of reward programs allows issuers to react less strongly to changes in the FFR and also use more backward loaded fee structures.

Our first regression specification is

$$Y_{i,j,t} = \beta_1 \times FFR_M + \beta_2 \times RP_{i,j,t} + FE_{i,j,t} + \varepsilon_{i,j,t}$$

$Y_{i,j,t}$ indexes the dependent variables we are interested in such as regular purchasing APRs, default APRs, late fee and over limit fee. For example, $APR_{i,j,t}$ is the regular purchasing APR of the credit card offer issued by company i to consumer j at time t.

FFR_M indexes the federal fund rate at month M. $RP_{i,j,t}$ indexes the dummy of certain reward program in the credit card offer such as cash back, point reward, flight mileage and zero introductory APRs. We also control the fixed effects such state fixed effects, bank fixed effects, and household demographic fixed effects. [8] t is at daily frequent.

Also, we explore the sensitivity between APRs and FFR by adding interaction terms of FFR and reward programs:

$$Y_{i,j,t} = \beta_1 \times FFR_M + \beta_2 \times RP_{i,j,t} + \beta_3 \times RP_{i,j,t} \times FFR_M + FE_{i,j,t} + \varepsilon_{i,j,t}$$

We cluster the standard errors at the cell level.

3.2.1. Points Programs

In Table 4 Panel A, we focus on the use points programs. Ex ante there is no obvious reason why a credit card offer should even be linked with a points program, since the credit card company could rather offer a lower interest rate. In column (1) we regress the regular APR on the FFR and an indicator for whether the credit card contains a points program. In this first column we only control for state fixed effects but no person specific characteristics. We see that the coefficient on FFR is only 0.326, while the coefficient is highly significant it indicates that there is less than perfect pass through of the cost of capital to customers. We also see that those cards that have a points program have lower APR. But in this baseline specification the negative coefficient could be driven by a composition effect, since was we saw in the prior Table only higher income customers receive credit cards with points. Therefore, in column (2) we include cell fixed effects in the regression. This means we control for every consumer cell, which is a unique combination of the customers' income bin, educational attainment, household composition, age and the state that she lives in. This specification allows us to test how credit card offers that have points programs are priced compared to those without a points program holding constant the customer characteristics. As we see in column (2) the coefficient on Points stays negative and only drops by about 10 percent, which means

[8] We construct the household demographic cells by age, education, income, household composition, and the states.

that it cannot be driven by the customer's observable credit type but has to be specific to the pricing strategy of a given card.

In column (3) of Table 4 Panel A we now add bank fixed effects to the regression. This allows us to control for the differences in pricing strategies between banks. We see that with bank fixed effect the coefficient on Points drops by a huge factor, almost ten! This result suggests that banks differ significantly in their use of point programs and those issuers which use point programs extensively are also those that charge lower APR rates. However, in this most stringent specification, we still find a negative and significant coefficient on the POINT dummy. This means that when two credit cards are sent to the same person by the same bank, but one card offers a reward program with points to the customer and the other does not, the one with the points program has a lower APR affiliated with it. This is very surprising since the production of points is most likely not costless and thus we need to ask how the card company will break even on the production of such points.

In the remaining columns of the table we now analyze how this relationship correlates with other card features. First in column (4) we follow Ausubel (1991) and interact Points * FFR to test if credit cards that offer points are less sensitive to changes in the FFR. The results suggest that this is indeed true, since the coefficient on the interaction term is minus 0.244 and significant at the one percent level. This means that credit cards that have points programs do not need to adjust as quickly to changes in the FFR. However, maybe more interestingly in the context of our analysis in column (5) we now use the Default APR as a dependent variable. We repeat the same regression as in columns (2) regressing Default APR on FFR and Points controlling for cell fixed effects. We show that Default APR increases significantly with Points, again keep in mind that this is holding constant all the characteristics of the recipient of the offer. When we now interact Points * FFR in column (6) we again find that the there is a large and significantly negative coefficient suggesting that Points programs allow credit card issuers to maintain higher default APRs and not pass on any changes in their cost of capital to consumers. And finally we repeat the same regression specifications in columns (8) to (10) but using late fees as the dependent variable. Again we see a very strong increase in late fees for cards that have a point program. But in this case the reward program is associated with higher sensitivity of late fees to underlying changes in the FFR. This could indicate that late fees are an important way to make adjustments for the banks changing cost of capital.

4.2.2. Cash back Program

In Table 4 Panel B, we focus on the use cash back programs. In column (1) we regress the regular APR on the FFR and an indicator for whether the credit card contains a cash back program. As before, we first only control for state fixed effects but no person specific characteristics. We see that the coefficient on FFR is only 0.312, while the coefficient is highly significant it indicates that there is less than perfect pass through of the cost of capital to customers. We also see that those cards that have a cash back program have lower APR. Parallel to before, in column (2) we include cell fixed effects in the regression. This specification allows us to test how credit card offers that have cash back programs are priced compared to those without a cash back program holding constant the customer characteristics. As we see in column (2) the coefficient on cash back stays negative and only drops by about 8 percent. In column (3) of Table 4 Panel B we now add bank fixed effects to the regression. This allows us to control for the differences in pricing strategies between banks. We see that with bank fixed effect the coefficient on cash back drops by a factor of three. This result suggests that banks differ significantly in their use of cash back programs and those issuers which use cash back programs extensively are also those that charge lower APR rates.

We now analyze how this relationship correlates with other card features. First in column (4) as before we follow Ausubel (1991) and interact cash back * FFR to test if credit cards that offer cash back are less sensitive to changes in the FFR. The results suggest that this is indeed true, since the coefficient on the interaction term is minus 0.363 and significant at the one percent level. However, maybe more interestingly in the context of our analysis in column (5) and (6) we now use the Default APR as a dependent variable. When we interact cash back * FFR in column (6) we again find that the there is a large and significantly negative coefficient suggesting that cash back programs allow credit card issuers to maintain higher default APRs and not pass on any changes in their cost of capital to consumers. And finally we repeat the same regression specifications in columns (8) to (10) but using late fees as the dependent variable. Again we see a very strong increase in late fees for cards that have a cash back program. But in this case the reward program is associated with higher sensitivity of late fees to underlying changes in the FFR. This could indicate that late fees are an important way to make adjustments for the banks changing cost of capital.

4.2.3. Mileage Programs

In Table 5 Panel A, we focus on the use of mileage programs. In column (1) we regress the regular APR on the FFR and an indicator for whether the credit card contains a mileage program. Again, we only control for state fixed effects but no person specific characteristics. Moreover, we see a very strong increase in APR for cards that have a mileage program. The coefficient on MILE is 1.698, significant at one percent level. In column (2) we again include cell fixed effects in the regression. As we see in column (2) the coefficient on mileage stays significantly positive and increases by about 24 percent.

In column (3) of Table 5 Panel A, we now add bank fixed effects to the regression. This allows us to control for the differences in pricing strategies between banks. We see that with bank fixed effect the coefficient on mileage stays almost the same. This result suggests that banks don’t differ significantly in their use of mileage programs.

In the remaining columns of the table we now analyze how this relationship correlates with other card features. First in column (4) we follow Ausubel (1991) and interact mileage * FFR to test if credit cards that offer mileage are less sensitive to changes in the FFR. The results suggest that this is indeed true, since the coefficient on the interaction term is minus 0.363 and significant at the one percent level. In column (5) and (6) we now use the Default APR as a dependent variable. We find similar results as regular APRs in column (1) and (2). Finally we repeat the same regression specifications in columns (8) to (10) but using late fees as the dependent variable. Again we see a very strong increase in late fees for cards that have a mileage program. But in this case the reward program is associated with higher sensitivity of late fees to underlying changes in the FFR. This could indicate that late fees are an important way to make adjustments for the banks changing cost of capital.

4.2.4. Zero Introductory APR

In Table 5 Panel B, we focus on the use zero introductory APRs programs. In column (1) we regress the regular APR on the FFR and an indicator for whether the credit card contains a zero introductory APRs program. Again, we only control for state fixed effects but no person specific characteristics. We see that the coefficient on FFR is only 0.397, while the coefficient is highly significant it indicates that there is less than perfect pass through of the cost of capital to customers. We also see that those cards that have a zero introductory APRs program have lower APR. But in this baseline specification the negative coefficient could be driven by a composition effect, since was we saw in the prior Table only higher income customers receive credit cards with zero introductory APRs. Therefore, in column (2) we include cell fixed effects in the regression. This specification allows us to test how credit card offers that have zero introductory APRs programs are priced compared to those without a zero introductory APRs program holding constant the customer characteristics. As we see in column (2) the coefficient on zero introductory APRs stays negative and only drops by about 4 percent, which means that it cannot be driven by the customer's observable credit type but has to be specific to the pricing strategy of a given card.

In the remaining columns of the table we now analyze how this relationship correlates with other card features. First in column (3) we follow Ausubel (1991) and interact zero introductory APRs * FFR to test if credit cards that offer zero introductory APRs are less sensitive to changes in the FFR. The results suggest that this is indeed true, since the coefficient on the interaction term is minus 0.566 and significant at the one percent level. However, maybe more interestingly in the context of our analysis in column (4) and (5) we now use the Default APR as a dependent variable. When we interact zero introductory APRs * FFR in column (6) we again find that the there is a large and significantly negative coefficient suggesting that zero introductory APRs programs allow credit card issuers to maintain higher default APRs and not pass on any changes in their cost of capital to consumers. And finally we repeat the same regression specifications in columns (8) to (10) but using late fees as the dependent variable. Again we see a very strong increase in late fees for cards that have a zero introductory APRs program. But in this case the reward program is associated with higher sensitivity of late fees to underlying changes in the FFR. This could indicate that late fees are an important way to make adjustments for the banks changing cost of capital.

4.2.5. Format of the reward programs

In Table 6, we focus on the design of the credit card offers. We use the font size, color, and bold of the reward programs on the offers. We also use the picture sizes to measure the design of the credit card offers. “Format” is the first principal component of reward programs' size, color, bold and the picture sizes on the credit card offers. In column (1) we regress the regular APR on the FFR and Format. Again, we only control for state fixed effects but no person specific characteristics. We see a very strong increase in APR for cards with fancier design. The coefficient on Format is 0.374, significant at one percent level. In column (2) we again include cell fixed effects in the regression. As we see in column (2) the coefficient on Format stays significantly positive and increases by about 2 percent.

In column (3) of Table 6, we now add bank fixed effects to the regression. This allows us to control for the differences in pricing strategies between banks. We see that with bank fixed effect the coefficient on Format stays almost the same. This result suggests that banks don’t differ significantly in their use of mileage programs.

In the remaining columns of the table we now analyze how this relationship correlates with other card features. First in column (4) we follow Ausubel (1991) and interact mileage * FFR to test if credit cards with fancier design are less sensitive to changes in the FFR. The results suggest that the sensitivity doesn’t change significantly with Format. In column (5), (6) and (7) we now use the Default APR as a dependent variable. We find similar results as regular APRs in column (1) and (3). However, in column (7), we find that default APRs of credit cards with fancier design are significantly less sensitive to changes in the FFR. Finally we repeat the same regression specifications in columns (8) to (10) but using late fees as the dependent variable. Again we see a very strong increase in late fees for cards with fancier design. Format again is associated with lower sensitivity of late fees to underlying changes in the FFR. This could indicate that fancy designs such as big colorful font, can make back loaded terms less sensitive to banks cost of capital.

In sum these results suggest that the majority of reward programs are designed to allow the company to backward load a lot credit card payments to a later time period when credit terms are very expensive. For example through the use of late fees and default APRs. At the same time credit cards with point programs are even in the current time less sensitive to the ups and downs of the FFR. A similar relationship holds for cash back program. It is interesting that both of these programs are used in combination with backward loading of payments, since schemes like points or cashback are not inherently depending on the time factor. This might point to the idea that these reward programs are used to shroud the more expensive aspects of a card program. Similarly cards with introductory APR offers have almost by definition more backward loaded payment features.

The one big exemption are cards with mileage programs. These cards seem to be predominately targeted at more educated customers. These cards are associated with a higher mean APR rate but much lower late fees and default APR.

4.3. Trade-off between regular APRs and late fees

From above, we see that credit card companies use different reward programs with different pricing strategies and target different consumer groups. We explore the pricing trade-offs between font loaded terms such as regular APR and back loaded terms such as late fees. In Table 7 column (1), we first look at the trade-offs between regular APRs and late fees by regressing regular APRs on late fees. We only control state fixed effects in column (1). We find that a $1 increase in late fee is associated with a 0.06% increase in regular APRs. When we control for cell fixed effects and bank fixed effects in column (2) and (3), we still find that regular APRs are negatively associated with late fees. This suggests that credit card companies usually choose to decrease regular APRs and increase late fees to make the terms more backward loaded or choose to increase regular APRs and decrease late fees to make the terms front loaded.

Moreover, we interact the reward programs (cash back, point, and car rental insurance programs) with late fees in column (4) and find significantly negative coefficient on the interaction term. This suggests that more reward programs led to significantly more trade-offs between late fees and regular APRs. Then, we compare the heterogeneous effects of mileage program and intro APR program on credit card pricing strategy. In Table 7 column (5) and (6), we find that intro APR programs led to significantly more trade-offs between late fees and regular APRs. Interestingly, in Table 7 column (7) and (8), we find that mileage programs led to significantly fewer trade-offs between late fees and regular APRs. This is consistent with our previous findings; Intro APR programs led to more backward loaded terms but not the mileage program which usually targets the well-educated consumers.

4.4. Unemployment Insurance

We now analyze the effect of changes in the unemployment insurance's effects on credit card terms and reward programs. The idea is to use an exogenous shock to the credit worthiness of customers, in particular their risk of default.

UI was increased in staggered fashion across several US states over the last decade. These changes all went in the direction of providing higher levels of unemployment insurance as well as longer time period. By buffering consumer cash flow in the case of negative shocks, it reduces also a lender's exposure to one of the largest negative economic shock that customers might suffer. We obtain data on the level of unemployment insurance (UI) from the U.S. Department of Labor for each state. Based on this information we calculate annual changes in UI at the beginning of each year from 1999 to 2012 and match them into our credit card dataset. Following, Hsu, Matsa and Melzer (2012) we use the maximum UI benefits as the measure of unemployment protection. We define the maximum UI benefits as the product of the maximum weekly benefit amounts (WBA) and the maximum number of weeks allowed. For example, in January 2000, Alabama allows a maximum of 26 weeks unemployment insurance during 52 week period and the maximum weekly benefit amounts (WBA) is $190. We use $4,940 (26 weeks times $190 WBA) as the level of UI. For each state, we then calculate the annual percentage increase of UI. We use 10% annual growth as the cut-off and define a UI “jump” if it increases more or equal to 10% within a year.

This allows us to run a standard Difference in Difference estimator to regress changes in card features on UI changes across states and across time. We use one year before and after the UI jumps to perform the Difference in Difference regressions. The reason to use this short cut off is that some states have a large increase in UI in one year and then small changes in follow on year. So we did not want to confound the impact of the UI change with small subsequent changes. Table 8 Panel A is the one year Diff-in-Diff regression results across our entire sample period (1999 to 2011). In column 1, the coefficient of UI jump is not significant. This suggests that an increase in the UI doesn’t have significant effects on regular APRs. But in column (2) and (3) we see a greater reliance on backward-loaded payment features such as a very strong increase in the late fees and balance transfer APRs. Column 4 is for annual fees. UI doesn’t have significant effects on annual fees. In the last column, we also look at whether credit card issuers use more intro APR programs when UI increases. For that purpose we build a dummy variable “Intro_APR_All” for whether the credit card offer has either zero intro APR for regular purchases, balance transfer, or cash advance. We see in column (5) that indeed card issuers use more intro APR programs after UI increases have been implemented. We control year fixed effects, cell fixed effects, and bank fixed effects. We also repeated this regression set up using other time windows, e.g. two year windows around the change and the results are qualitatively and quantitively very similar.

We now repeat the same analysis in Table 8 Panel B but from 1999 to 2007. A lot of UI increases happened between 2008 and 2010. Since many other things also happened during this crisis period, there is a concern that other hidden variables drive our results. In order to mitigate this concern, we drop years after 2007 and only focus the period from 1999 to 2007 in Panel B. The regression results in Panel B are very similar with Panel A; Balance transfer APR, late fee, and zero intro APR increase after the UI jump. Moreover, when we drop the bank fixed effects, the regression results are quite similar with Table 8. This means that the results are not driven by banks differentially selecting to offer credit cards in states with UI changes. Our results are driven by the variation within bank decisions to change pricing policies based on the UI changes.

Taken together these results suggest that credit card companies realize that there is an inherent trade off in the use of backward loaded or shrouded features of credit card offers: They might help in inducing customers to take on more (expensive) credit, but at the same time they expose the lender to people who pose a greater risk. Therefore we observe a greater reliance on these features when the customer pool has an (exogenous) improvement in credit quality.

5. Conclusions

The paper shows that credit card issuers use different card features to separate customer groups with higher or lower propensity for behavioral biases. We show that less educated and poorer customers receive more card offers with backward loaded payment features, and they are also less likely to receive rewards programs that are targeted at richer and more educated people, especially miles but also points and cash back programs. In contrast, richer and more educated people receive more card offers with miles, cash back and points, but are much less likely to receive offers with low intro APR. This latter customer group gets on average better terms: lower interest rate and fees. Interestingly we find that cards with rewards that are predominantly offered to richer and more educated people do not show backward-loaded pricing structures. These results are in line with the insight of Gabaix and Laibson (2006) that suppliers will not offer shrouded terms on products which are mainly demanded by sophisticated consumers, since they can undo the shrouding and as a result hurt the profits of the firm.

Finally our analysis highlights and important dimension of the use of shrouding and backward loading that has previously been ignored in the literature. It is beneficial for banks to maximize shrouding and backward loading of payments if this does not change the credit risk of customers. However, at an extreme these pricing strategies could attract customers who cannot afford the products that are offered. Using shocks to unemployment insurance, which reduce the credit risk of especially poorer customers, we show that banks are well aware of this trade off. They are willing to extend more backward loaded or “shrouded” credit to these customers when their overall credit risk is lower.

The results in this paper provide evidence that credit card companies do screen for behavioral biases via the type of reward programs and low introductory APRs that are offered to customers. However, the interaction between behavioral screening and classic adverse selection is much more complex than the prior theory literature has taken into account. There appears to be an inbuilt trade off between the immediate benefits from using shrouded terms to charge higher cost of capital (via a combination of interest rates and fees) and their impact on increasing the credit risk of the customer pool by drawing in customers who do not understand the credit terms that they are offered and thus have a higher chance that they can ultimately not afford them.

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Figure 1

Figure 1 is the plot of monthly time trend of variable "Reward". Reward equals to how many reward programs the offer has out of Cash back, point and car rental insurance program. For each month, we calculate the average "Reward" of the credit card offers.

Figure 2

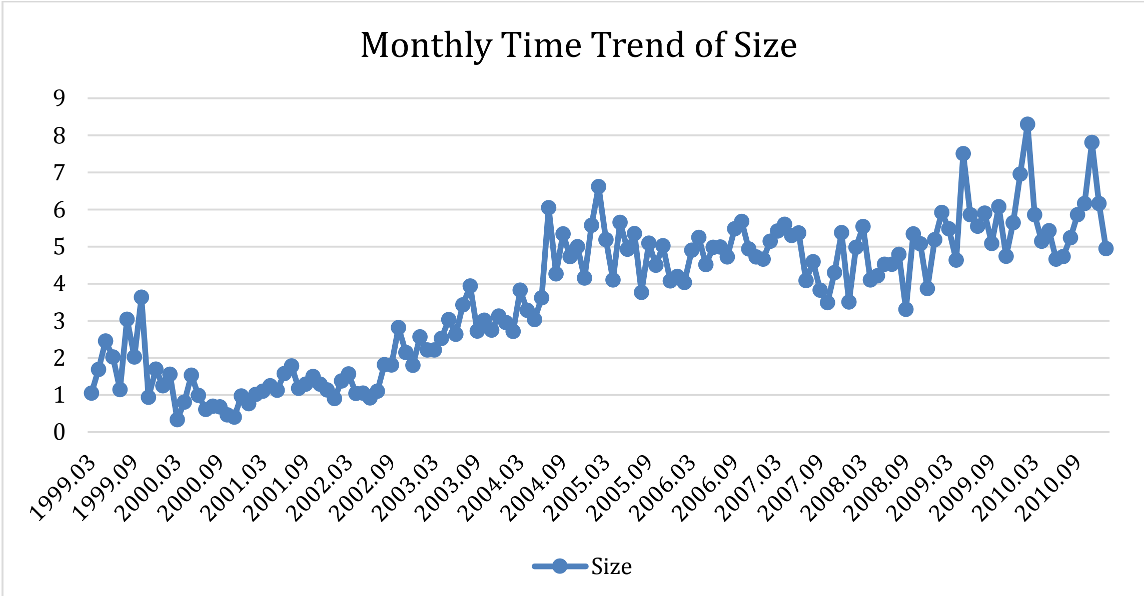


Figure 2 is the plot of monthly time trend of variable "Size". Size is the maximum size of the reward programs minus the average size of all characters in every pages of each credit card offer. For each month, we calculate the average "Size" of the credit card offers.

Figure 3

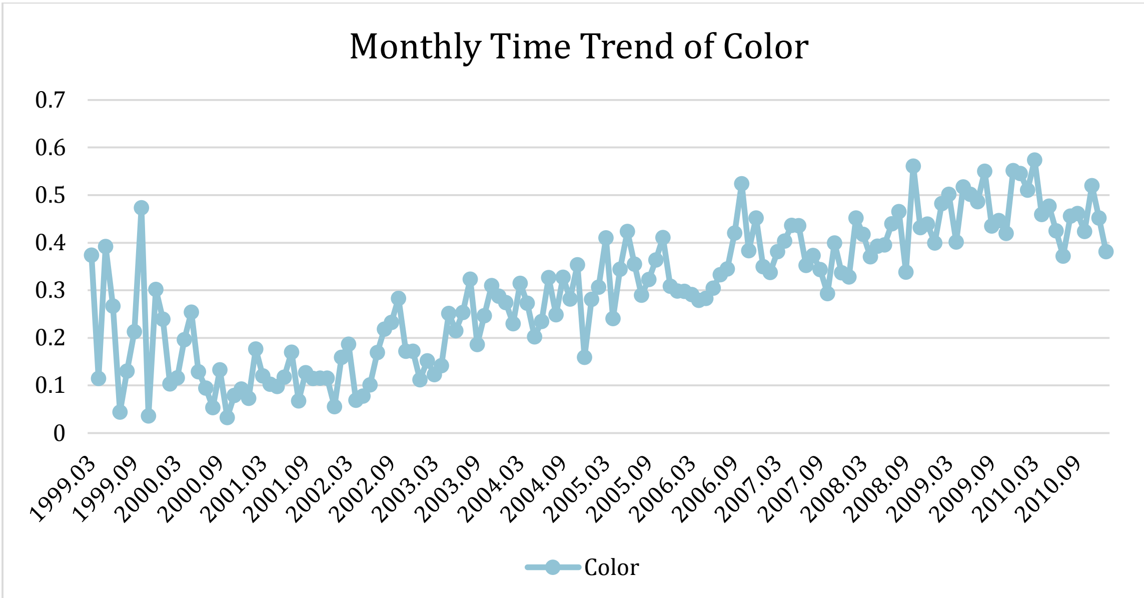


Figure 3 is the plot of monthly time trend of variable "Color". “Color” is the dummy of whether reward programs in the offer use color other than black/white. For each month, we calculate the average "Color" of the credit card offers.

Figure 4

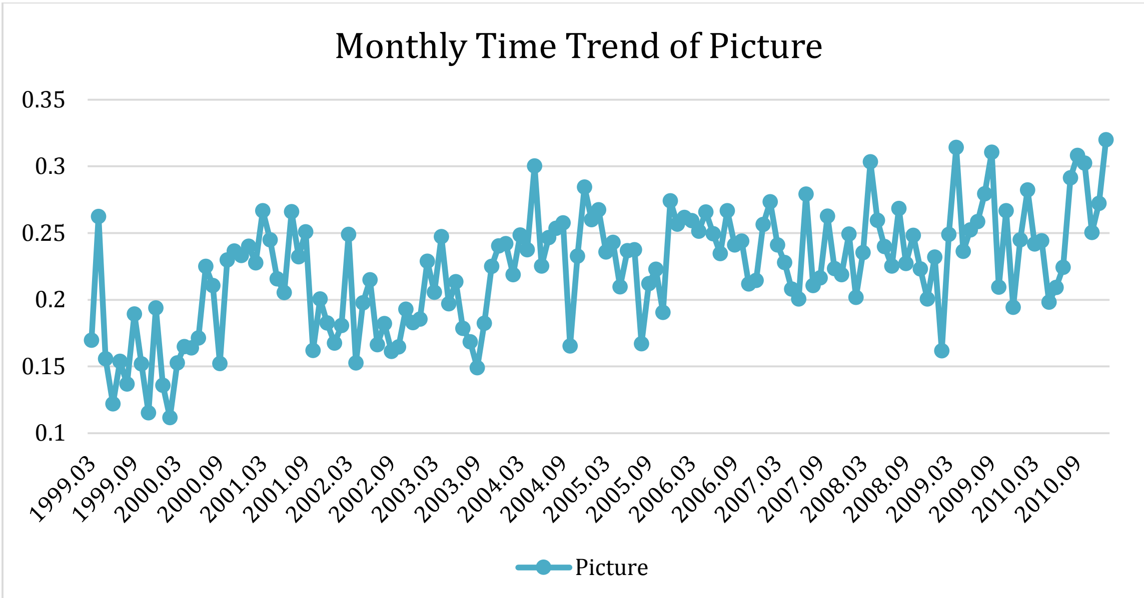
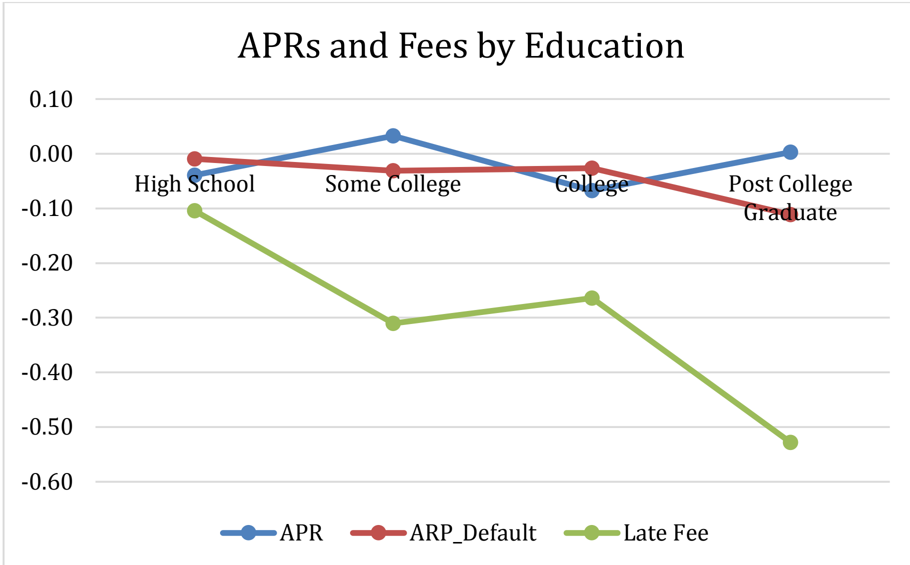


Figure 4 is the plot of monthly time trend of variable "Picture". "Picture" is the file storage size of scanned images of credit card offers. The unit is megabyte (MB). For each month, we calculate the average "Picture" of the credit card offers.

Figure 5



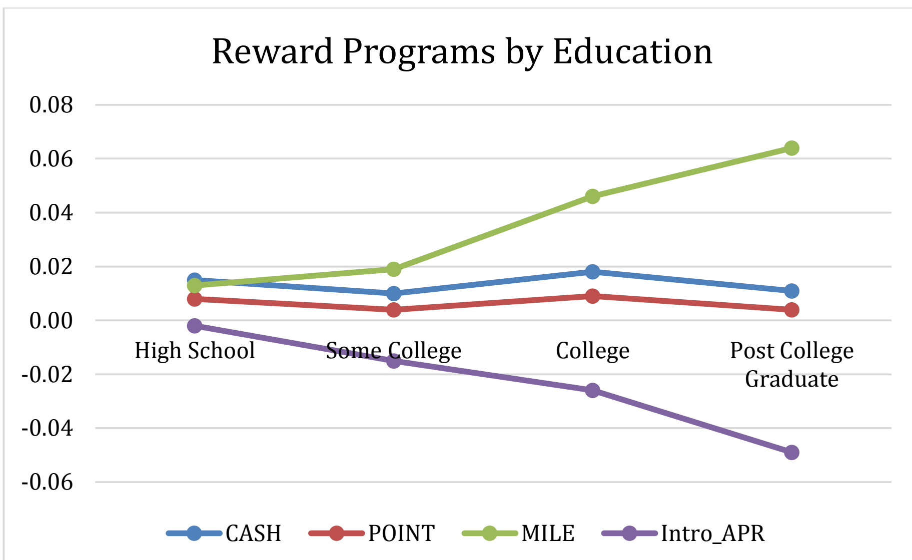
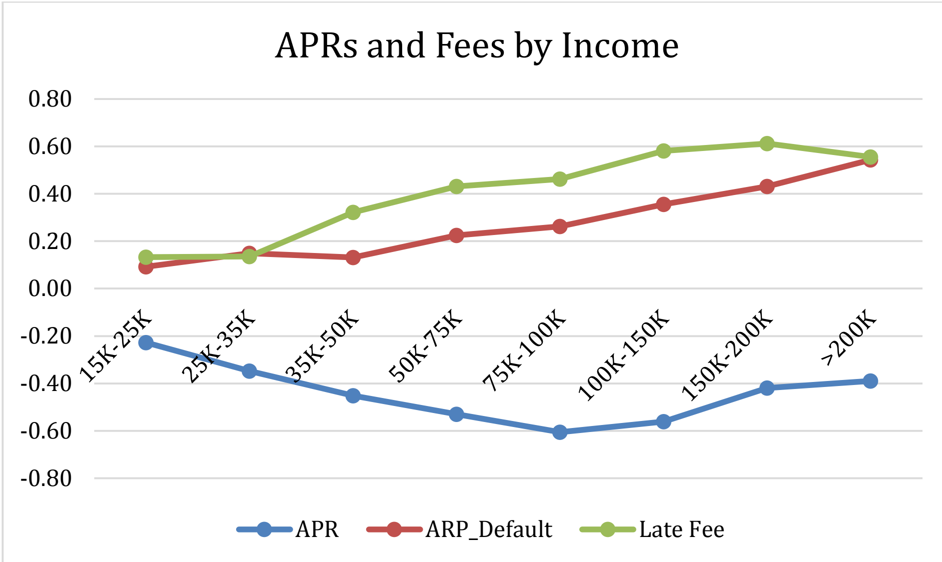


Figure 5 plot the estimated coefficients on the education from a regression where we regress individual card features on dummies for different education levels (as provided by Mintel). The regression results are reported in table 3. We omitted the highest education bin (graduate school) since it is very rare and noisy.

Figure 6



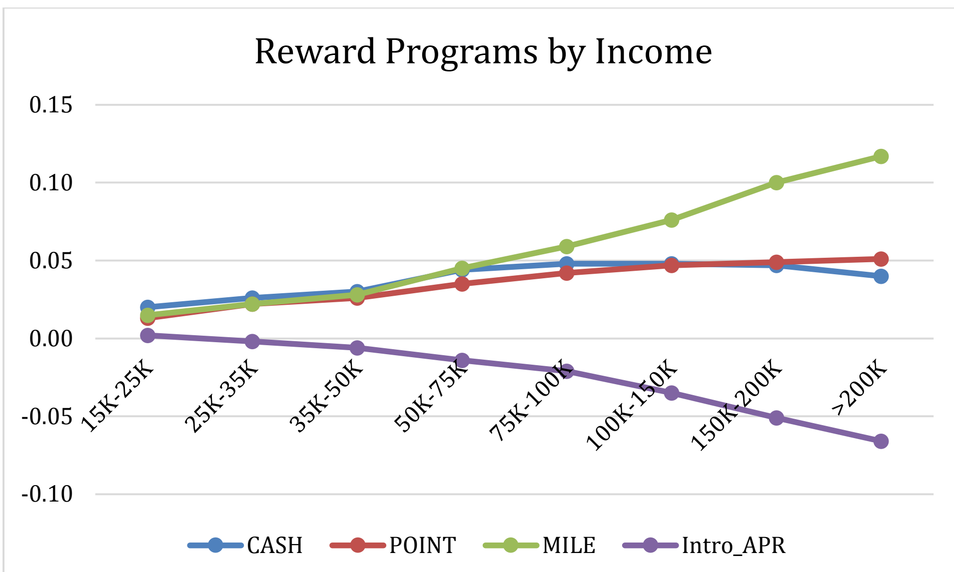


Figure 6 plot the estimated coefficients on the income from a regression where we regress individual card features on dummies for different income levels (as provided by Mintel). The regression results are reported in table 3.

Table 1
Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
FFR	156	2.676708	2.137708	0.070645	6.544516
APR	982767	12.64551	4.180521	0	79.9
Max Card limit	526949	10.05231	1.366279	6.214608	15.42495
APR_Balance	749264	11.33406	3.341435	0	29.9
APR_CASH	942430	19.88759	4.282504	0	79.9
ARP_Default	721393	26.51097	3.970656	0	41
Annual_fee	1003977	12.28505	31.99156	0	500
Late_fee	1001221	33.8348	6.165273	0	85
over_limit_fee	898636	29.74222	10.15561	0	79
Intro_APR_regular	1014768	0.467421	0.498938	0	1
Intro_APR_balance	1014768	0.473942	0.499321	0	1
Intro_APR_cash	1014768	0.056262	0.230427	0	1
Size	644865	4.709489	5.491711	0	143.6293
Color	644865	0.321094	0.466897	0	1
Bold	644865	0.355845	0.478769	0	1
Picture	803285	0.229046	0.263854	0.001715	4.10319
Reward	803285	0.676207	0.767116	0	3
CASH	803285	0.210522	0.40768	0	1
POINT	803285	0.238283	0.426033	0	1
MILE	803285	0.08788	0.283121	0	1
Carrental	803285	0.227403	0.419155	0	1
Purchaseprct	803285	0.234071	0.423417	0	1

Note: FFR is the federal fund rate at monthly frequency. Other variables are based on Mintel's credit card's direct mail campaigns from March 1999 to February 2011. Variables from "Size" to "Purchaseprct" are from 80% of 1,014,768 total mail campaigns which have scanned images of credit card offers. Size is the maximum size of the reward programs minus the average size of the whole page in credit card offer. Color is the dummy of whether reward programs in the offer use color other than black/white in the offer. Bold is the dummy of whether the offer use bold to highlight reward programs. If there is no reward programs in the offer, we put missing value to Size, Color, and Bold. Picture is the file size of each page of the offer which is the measurement of how many or how large are pictures in the offer. Reward is the number of reward programs of CASH POINT and Car rental insurance in each offer. CASH, POINT, MILE, Carrental, Purchaseprct are dummies of whether the offer has these reward programs respectively. Intro_APR_regular, Intro_APR_balance and Intro_APR_cash are the dummies of whether the offer has 0% introductory APR for regular purchase, balance transfer and cash advance respectively. APR is the regular purchase APR of the credit card offer which is the middle point if APR is a range in the offer. Card Limit is the log of maximum credit card limit stated in the offer. Annual fee, late fee and over limit fee are fees charged by credit card company which usually are in shumerbox.

Table 2

Descriptive Statistics for Format Design of Credit Card Offers

Penal A

	Late fee	Default APR	Over limit fee	Annual fee	CASH	POINT	MILE	Carrental	Intro APR
Percentage of cards that have this term	100.00%	100.00%	100.00%	100.00%	21.05%	23.83%	8.79%	22.74%	51.64%
Term mentioned on 1st page	5.80%	4.97%	6.96%	79.28%	100%	93.51%	100%	80.48%	91.04%
Font size of term if mentioned on 1st page	9.49	9.28	9.80	13.24	11.16	11.47	14.12	10.27	11.27
Font size of CC term if NOT mentioned on first page	9.57	9.63	9.50	13.76	10.62	10.80	9.91	10.04	10.62
Font color of CC term if mentioned on first page	33.98%	37.88%	27.73%	66.86%	40.13%	42.84%	47.12%	24.34%	32.28%
Font color of CC term if NOT mentioned on first page	24.67%	26.19%	27.73%	44.35%	37.24%	38.45%	29.47%	23.31%	32.29%
Font bold of CC term if mentioned on first page	38.59%	27.77%	35.07%	79.01%	47.24%	43.90%	56.34%	10.56%	53.15%
Font bold of CC term if NOT mentioned on first page	49.00%	19.59%	34.53%	53.20%	36.58%	29.97%	18.08%	13.08%	39.99%
# Obs	776,624	776,624	776,624	776,624	803,285	803,285	803,285	803,285	776,624

Penal B

	Late fee	Default APR	Over limit fee	Annual fee
if term is on first page	29.38247	28.20%	27.58632	7.691491
if term is in the back (schumer box)	35.10307	27.01%	30.11493	33.22181

Note: The dataset is based on Mintel's credit card's direct mail campaigns from March 1999 to February 2011. Descriptive statistics are based on 80% of 1,014,768 total mail campaigns which have scanned images of credit card offers. Penal A is the descriptive statistics of format information of credit card terms and reward programs. In Penal A, late fee, default APR. over limit fee and annual fee appears in 776,624 offers since we have missing pages of Schumer box where these terms usually appear. Intro_APRs contains all introductory APR programs: regular intro APR, balance transfer Intro APR and cash advance Intro APR. Size is the maximum size of the reward programs in credit card offer. Color is the dummy of whether reward programs in the offer use color other than black/white in the offer. Bold is the dummy of whether the offer use bold to highlight reward programs. Picture is the file size of each page of the offer which is the measurement of how many or how large are pictures in the offer. Penal B is the descriptive statistics of credit card terms when they mentioned on the first page or not. "First page" includes the envelop and the first page letter of credit card offers.

Table 3
Credit Card Features and Demographics

	1	2	3	4	5	6	7	8	9
Dependent Variable	APR	LogMaxCardLimit	ARP_Default	Late Fee	CASH	POINT	MILE	Intro_APR	Format
FFR	0.352***	0.005	0.882***	-0.242*	-0.012***	0.010***	0.008***	-0.026***	-0.014
	(0.076)	(0.010)	(0.096)	(0.133)	(0.004)	(0.003)	(0.002)	(0.005)	(0.014)
Education_2	-0.039	0.095***	-0.009	-0.104**	0.015***	0.008***	0.013***	-0.002	0.069***
	(0.029)	(0.008)	(0.030)	(0.041)	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)
Education_3	0.033	0.103***	-0.031	-0.310***	0.010***	0.004	0.019***	-0.015***	0.075***
	(0.037)	(0.011)	(0.031)	(0.051)	(0.002)	(0.003)	(0.001)	(0.003)	(0.008)
Education_4	-0.067	0.206***	-0.026	-0.264***	0.018***	0.009***	0.046***	-0.026***	0.159***
	(0.045)	(0.013)	(0.040)	(0.055)	(0.003)	(0.003)	(0.003)	(0.004)	(0.011)
Education_5	0.003	0.242***	-0.111***	-0.528***	0.011***	0.004	0.064***	-0.049***	0.190***
	(0.047)	(0.015)	(0.039)	(0.078)	(0.003)	(0.004)	(0.004)	(0.004)	(0.014)
Education_6	0.043	0.003	-0.009	0.086	0.003	0.005	-0.003	0.003	-0.003
	(0.047)	(0.013)	(0.047)	(0.067)	(0.004)	(0.005)	(0.003)	(0.005)	(0.013)
Income_2	-0.227***	0.118***	0.092***	0.133*	0.020***	0.013***	0.015***	0.002	0.079***
	(0.036)	(0.011)	(0.029)	(0.074)	(0.003)	(0.002)	(0.002)	(0.004)	(0.010)
Income_3	-0.348***	0.178***	0.149***	0.135**	0.026***	0.022***	0.022***	-0.002	0.111***
	(0.050)	(0.013)	(0.035)	(0.066)	(0.003)	(0.003)	(0.002)	(0.004)	(0.011)
Income_4	-0.451***	0.228***	0.132***	0.322***	0.030***	0.026***	0.028***	-0.006	0.137***
	(0.056)	(0.014)	(0.040)	(0.077)	(0.003)	(0.003)	(0.002)	(0.005)	(0.011)
Income_5	-0.530***	0.301***	0.225***	0.431***	0.044***	0.035***	0.045***	-0.014***	0.200***
	(0.070)	(0.015)	(0.048)	(0.088)	(0.004)	(0.003)	(0.003)	(0.005)	(0.013)
Income_6	-0.606***	0.361***	0.263***	0.462***	0.048***	0.042***	0.059***	-0.021***	0.247***
	(0.078)	(0.016)	(0.060)	(0.098)	(0.005)	(0.003)	(0.003)	(0.006)	(0.014)
Income_7	-0.561***	0.380***	0.356***	0.581***	0.048***	0.047***	0.076***	-0.035***	0.291***
	(0.084)	(0.017)	(0.070)	(0.110)	(0.005)	(0.004)	(0.004)	(0.006)	(0.016)
Income_8	-0.419***	0.405***	0.431***	0.612***	0.047***	0.049***	0.100***	-0.051***	0.336***
	(0.095)	(0.018)	(0.081)	(0.131)	(0.006)	(0.005)	(0.006)	(0.008)	(0.020)
Income_9	-0.390***	0.419***	0.543***	0.556***	0.040***	0.051***	0.117***	-0.066***	0.380***
	(0.096)	(0.018)	(0.087)	(0.139)	(0.006)	(0.005)	(0.006)	(0.008)	(0.022)
Age Group fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Housholdhold Compoisition	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	942,397	496,063	713,882	961,247	777,192	777,192	777,192	972,260	629,637
R-squared	0.253	0.607	0.310	0.157	0.248	0.262	0.075	0.159	0.080

Note: OLS regressions to estimate relationship between credit card features and consumer's demographics. Data is restricted to offers we have scanned pictures from column 5,6,7, and 9. Format is the first principal component of reward programs' size, color, bold and the picture sizes on the credit card offers.Income_2 is the dummy for households whose annual income is from 15k to 25K. Income_3 is for 25k to 35k. Income.Income_4 is for 35k to 50k. Income_5 is for 50k to 75k. Income_6 is for 75k to 100k. Income_7 is for 100k to 150k. Inocme_8 is for 150k to 200k. Income_9 is for over 200k. Education_2 is dummy for household head whoes highest education is high school. Education_3 is for some college. Education_4 is for graduated college. Education_5 is for post college graduate. Standard errors in parentheses are clustered by month. Regressions are controlled by age fixed effects, household composition fixed effects, state fixed effects and bank fixed effects.

Table 4
Relationship Between APRs/Fees and Reward Program

Panel A										
	1	2	3	4	5	6	7	8	9	10
Dependent Variable	APR	APR	APR	APR	DefaultAPR	DefaultAPR	DefaultAPR	Late Fee	Late Fee	Late Fee
FFR	0.326***	0.314***	0.258***	0.373***	0.759***	0.808***	0.733***	-0.160***	-0.277***	-0.133***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.007)	(0.009)	(0.007)
POINT	-0.844***	-0.671***	-0.062***	0.007	0.750***	1.341***	0.429***	2.063***	0.869***	1.510***
	(0.013)	(0.013)	(0.012)	(0.023)	(0.013)	(0.025)	(0.012)	(0.018)	(0.024)	(0.015)
POINT*FFR				-0.244***		-0.197***			0.434***	
				(0.007)		(0.007)			(0.010)	
State Fixed Effects	Yes	No	No	No	No	No	No	No	No	No
Cell Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	No	No	No	Yes	No	No	Yes
Observations	778,497	753,690	753,690	753,690	616,957	616,957	616,957	769,923	769,923	769,923
R-squared	0.0282	0.0218	0.214	0.0241	0.116	0.118	0.313	0.0226	0.0258	0.227

Panel B										
	1	2	3	4	5	6	7	8	9	10
Dependent Variable	APR	APR	APR	APR	DefaultAPR	DefaultAPR	DefaultAPR	Late Fee	Late Fee	Late Fee
FFR	0.312***	0.301***	0.255***	0.395***	0.784***	0.846***	0.748***	-0.120***	-0.139***	-0.109***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.008)	(0.008)	(0.007)
CASH	-0.528***	-0.451***	-0.165***	0.472***	0.002	0.621***	0.587***	1.573***	1.381***	0.845***
	(0.012)	(0.013)	(0.012)	(0.020)	(0.015)	(0.027)	(0.015)	(0.019)	(0.026)	(0.022)
CASH*FFR				-0.363***		-0.238***			0.076***	
				(0.006)		(0.008)			(0.011)	
State Fixed Effects	Yes	No	No	No	No	No	No	No	No	No
Cell Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	No	No	No	Yes	No	No	Yes
Observations	778,497	753,690	753,690	753,690	616,957	616,957	616,957	769,923	769,923	769,923
R-squared	0.0236	0.0189	0.214	0.0242	0.109	0.111	0.315	0.0127	0.0128	0.221

Note: Panel A shows OLS regressions to estimate relationship between point reward programs and credit card APRs and fees. Panel B shows OLS regressions to estimate relationship between cash back reward programs and credit card APRs and fees. Data is restricted to offers we have scanned pictures. Regressions in column 1 is controlled by state fixed effects. Regression 2 to 8 are controlled by demographic cell fixed effects based on states, age, income, education and household composition. Regressions in column 3,7 and 10 are controlled by bank fixed effects. POINT is the dummy of whether the credit card offer has point reward program or not. CASH is the dummy of whether the credit card offer has cash back reward program or not. Standard errors in parentheses are clustered by cells.

Table 5
Mileage Program vs. Zero Introductory APR Program

Panel A

	1	2	3	4	5	6	7	8	9	10
Dependent Variable	APR	APR	APR	APR	DefaultAPR	DefaultAPR	DefaultAPR	Late Fee	Late Fee	Late Fee
FFR	0.314***	0.294***	0.241***	0.278***	0.783***	0.774***	0.742***	-0.125***	-0.028***	-0.107***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
MILE	1.698***	1.938***	1.971***	1.448***	0.332***	0.058	0.317***	-2.724***	0.128	-1.507***
	(0.018)	(0.019)	(0.020)	(0.028)	(0.024)	(0.044)	(0.017)	(0.063)	(0.090)	(0.051)
MILE*FFR				0.170***		0.100***			-0.992***	
				(0.010)		(0.012)			(0.034)	
State Fixed Effects	Yes	No	No	No	No	No	No	No	No	No
Cell Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	No	No	No	Yes	No	No	Yes
Observations	778,497	753,690	753,690	753,690	616,957	616,957	616,957	769,923	769,923	769,923
R-squared	0.0350	0.0368	0.234	0.0373	0.110	0.110	0.312	0.0176	0.0249	0.223

Panel B

	1	2	3	4	5	6	7	8	9	10
Dependent Variable	APR	APR	APR	APR	DefaultAPR	DefaultAPR	DefaultAPR	Late Fee	Late Fee	Late Fee
FFR	0.397***	0.391***	0.326***	0.664***	0.891***	0.774***	0.859***	-0.286***	-0.479***	-0.239***
	(0.004)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.009)	(0.007)
Intro_APR	-0.950***	-0.990***	-0.740***	0.560***	0.183***	0.058	0.571***	1.035***	-0.082***	1.105***
	(0.012)	(0.012)	(0.013)	(0.022)	(0.011)	(0.044)	(0.011)	(0.016)	(0.025)	(0.017)
Intro_APR*FFR				-0.566***		0.100***			0.411***	
				(0.006)		(0.012)			(0.010)	
State Fixed Effects	Yes	No	No	No	No	No	No	No	No	No
Cell Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	No	No	No	Yes	No	No	Yes
Observations	982,736	942,397	942,397	942,397	713,882	713,882	713,882	961,247	961,247	961,247
R-squared	0.0486	0.0452	0.238	0.0613	0.126	0.127	0.300	0.0148	0.0185	0.209

Note: Panel A shows OLS regressions to estimate relationship between mileage reward programs and credit card APRs and fees. Panel B shows OLS regressions to estimate relationship between zero intro APR reward programs reward programs and credit card APRs and fees. Data is restricted to offers we have scanned pictures in Panel A. Panel B includes the entire credit card offer sample with and without scanned pictures. Regressions in column 1 is controlled by state fixed effects. Regression 2 to 8 are controlled by demographic cell fixed effects based on states, age, income, education and household composition. Regressions in column 3,7 and 10 are controlled by bank fixed effects. MILE is the dummy of whether the credit card offer has mileage reward program or not. Intro_APR is the dummy of whether the credit card offer has 0 intro APR for regular purchase or not. Standard errors in parentheses are clustered by cells.

Table 6

Relationship Between APRs/Fees and Credit Card Offer Design

	1	2	3	4	5	6	7	8	9	10
Dependent Variable	APR	APR	APR	APR	DefaultAPR	DefaultAPR	DefaultAPR	Late Fee	Late Fee	Late Fee
FFR	0.229***	0.232***	0.198***	0.198***	0.797***	0.738***	0.743***	-0.087***	-0.060***	-0.057***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.008)	(0.007)	(0.007)
Format	0.374***	0.393***	0.426***	0.420***	0.274***	0.208***	0.333***	0.160***	0.009	0.077***
	(0.004)	(0.005)	(0.004)	(0.007)	(0.005)	(0.005)	(0.008)	(0.009)	(0.009)	(0.010)
FormatFFR				0.002			-0.048***			-0.026***
				(0.002)			(0.002)			(0.005)
State Fixed Effects	Yes	No	No	No	No	No	No	No	No	No
Cell Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	623,476	608,946	608,946	608,946	510,788	510,788	510,788	627,119	627,119	627,119
R-squared	0.0297	0.0321	0.177	0.177	0.131	0.310	0.311	0.00176	0.186	0.186

Note: OLS regressions to estimate relationship between credit card offer design and credit card APRs and fees. Data is restricted to offers we have scanned pictures and reward programs. Regressions in column 1 is controlled by state fixed effects. Regression 2 to 8 are controlled by demographic cell fixed effects based on states, age, income, education and household composition. Regressions in column 3,7 and 10 are controlled by bank fixed effects. Format is the first principal component of reward programs' size, color, bold and the picture sizes on the credit card offers. Standard errors in parentheses are clustered by cells.

Table 7
Regular APR vs. Late Fees

	1	2	3	4	5	6	7	8
Dependent Variable	APR	APR	APR	APR	APR	APR	APR	APR
FFR	0.571***	0.809***	0.568***	0.493***	0.459***	0.424***	0.761***	0.666***
	(0.015)	(0.010)	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)	(0.009)
LateFee	-0.066***	-0.024***	-0.057***	-0.029***	-0.016***	0.030***	-0.077***	-0.017***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Reward		1.945***						
		(0.056)						
LateFee*Reward		-0.065***						
		(0.002)						
Intro_APR				0.837***		2.278***		
				(0.073)		(0.071)		
LateFee*Intro_APR				-0.059***		-0.094***		
				(0.002)		(0.002)		
MILE							-2.193***	-0.906***
							(0.092)	(0.086)
LateFee*MILE							0.115***	0.080***
							(0.003)	(0.002)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	No	No	No	No	No	No
Cell Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	No	No	Yes	Yes	No	Yes
Observations	975,486	773,694	936,641	936,641	936,641	936,641	749,983	749,983
R-squared	0.165	0.172	0.150	0.173	0.332	0.348	0.168	0.347

Note: OLS regressions to estimate relationship between regular APR and late fees in credit card offers. Data is restricted to offers we have scanned pictures in column 2, 7 and 8. Regressions in column 1 and 2 are controlled by state fixed effects. Regression in column 3 to 8 are controlled by demographic cell fixed effects based on states, age, income, education and household composition. Regressions in column 5, 6 and 8 are controlled by bank fixed effects. Reward is the number of reward programs of CASH POINT and Car rental insurance in each offer. MILE is the dummy of whether the credit card offer has mileage reward program or not. Intro_APR is the dummy of whether the credit card offer has 0 intro APR for regular purchase or not. All regressions are controlled by year fixed effects. Standard errors in parentheses are clustered by cells.

Table 8
Unemployment Insurance and Credit Card Features

Panel A

	1	2	3	4	5
Dependent Variable	APR	APR_Balance	Late Fee	Annual_Fee	Intro_APR_All
FFR	0.237***	0.459***			
	(0.029)	(0.104)			
UI	0.030	0.107***	0.160*	0.169	0.005*
	(0.047)	(0.039)	(0.088)	(0.266)	(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	127,697	63,134	128,778	129,344	131,025
R-squared	0.292	0.190	0.265	0.237	0.133

Panel B

	1	2	3	4	5
Dependent Variable	APR	ARP_Default	Late Fee	Annual_Fee	Intro_APR_All
FFR	0.223***	0.537***			
	(0.028)	(0.148)			
UI	-0.014	0.102**	0.179*	-0.016	0.008***
	(0.036)	(0.043)	(0.092)	(0.347)	(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	121,467	57,510	122,439	122,965	124,616
R-squared	0.297	0.197	0.258	0.245	0.132

Note.OLS regressions to estimate unemployment insurance effects on credit card features. Panel A includes the credit card offers from 1999 to 2011. Panel B is from 1999 to 2007. All regressions are controlled by year fixed effects, bank fixed effects and cell fixed effects based on states, age, income, education and household composition. UI is the dummy which equals 1 if unemployment insurance increases by more than 10% in this year and 0 in the year before the increase. Intro_APR_All is the dummy for whether the credit card offers have any of introductory APRs for regular purchase, balance transfer or cash advance. Standard errors are clustered at the state level.

Appendix

Figure A.1

XYZ Bank Credit Card

0% intro APR | *The new standard of excellence.*

Dear Sir/Madam,

Congratulations! You're Pre-Approved for this Credit Card! It is time to get the card you deserve! And you pay $0 Annual Fee.

Get Rewards on Every Purchase.

Your Credit Card rewards you more by earning:

- **2% reward points** for every dollar spent on restaurants, airfare and gas
- **1% reward points** on all other purchases

Points add up fast – make your purchases work for you.

Get the Privileges. Save the Fee.

With no annual fee, the value keeps coming. You will also receive a 0% introductory APR on purchases **and balance transfers for the first 12 months. Additionally,** we offer a Balance Transfer Fee that is only 3% of the amount.

The Credit Card is designed for people who are smart with their money, and want to enjoy the benefits.

Once you have the card, you can:

- Get **24/7 online** account access
- Ask for **e-alerts** to make sure you don't forget when payment is due
- Call us **anytime** with questions or concerns

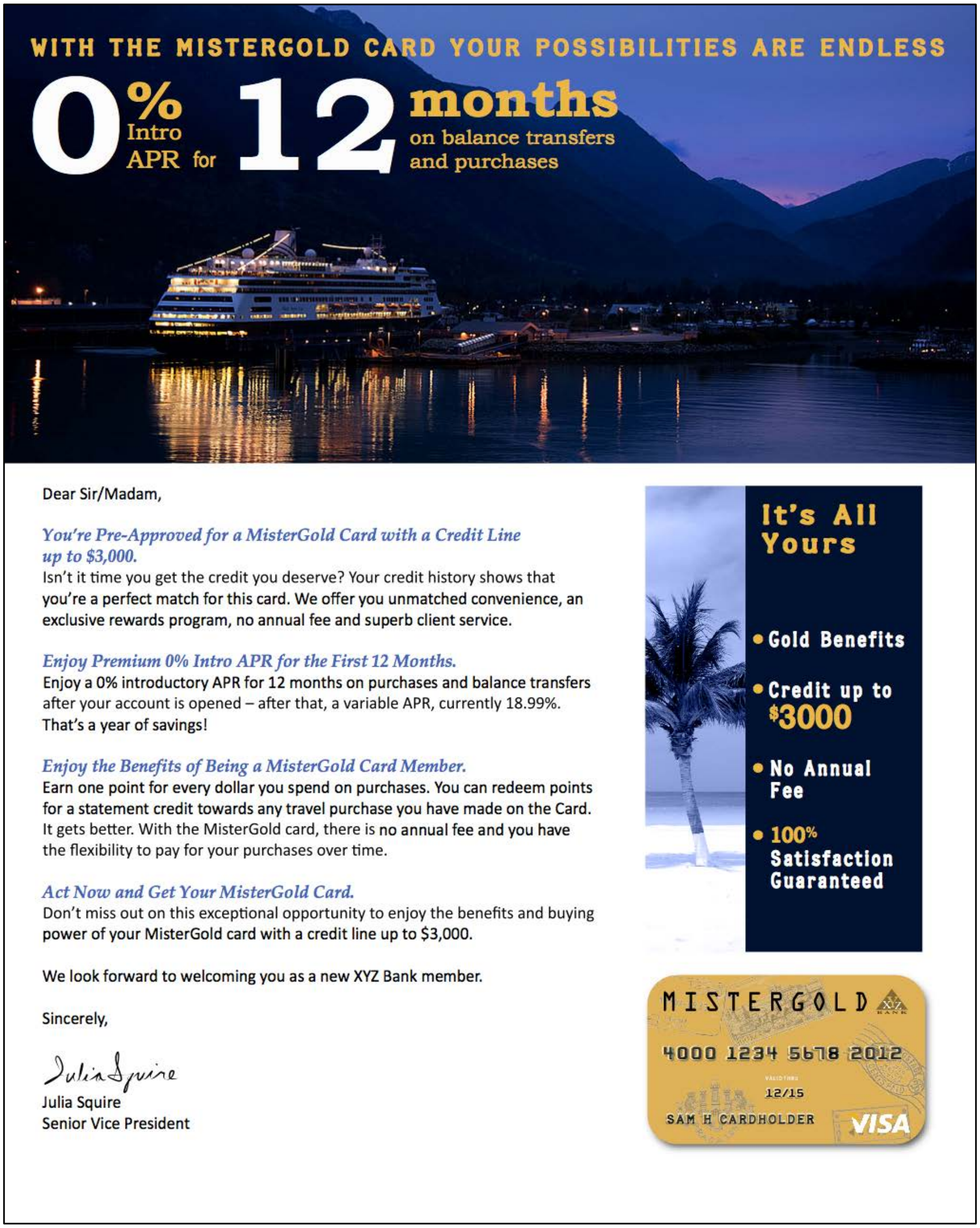
Request your card today, and let the rewards begin.

Sincerely,

David Hughes
Senior Vice President

Figure A.1 is the sample of simple visual credit card offers. It has relatively small font size to emphasis the reward programs. It doesn't have many colors or flashy pictures.

Figure A.2



WITH THE MISTERGOLD CARD YOUR POSSIBILITIES ARE ENDLESS

0% Intro APR for 12 months on balance transfers and purchases

Dear Sir/Madam,

You're Pre-Approved for a MisterGold Card with a Credit Line up to $3,000.
Isn't it time you get the credit you deserve? Your credit history shows that you're a perfect match for this card. We offer you unmatched convenience, an exclusive rewards program, no annual fee and superb client service.

Enjoy Premium 0% Intro APR for the First 12 Months.
Enjoy a 0% introductory APR for 12 months on purchases and balance transfers after your account is opened – after that, a variable APR, currently 18.99%. That's a year of savings!

Enjoy the Benefits of Being a MisterGold Card Member.
Earn one point for every dollar you spend on purchases. You can redeem points for a statement credit towards any travel purchase you have made on the Card. It gets better. With the MisterGold card, there is no annual fee and you have the flexibility to pay for your purchases over time.

Act Now and Get Your MisterGold Card.
Don't miss out on this exceptional opportunity to enjoy the benefits and buying power of your MisterGold card with a credit line up to $3,000.

We look forward to welcoming you as a new XYZ Bank member.

Sincerely,

Julia Squire

Julia Squire
Senior Vice President

It's All Yours

- Gold Benefits
- Credit up to $3000
- No Annual Fee
- 100% Satisfaction Guaranteed

Figure A.2 is the sample of high visual credit card offers. It has relatively big font size to emphasis the reward programs. It also has many colors and flashy pictures to draw consumers' attention.