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. First, we show that card issuers target poorer and less educated customers with more steeply backward loaded fees (lower introductory APR but much higher late- and over-limit fees), compared to cards offered to educated and richer customers. Second, issuers use rewards programs to screen for unobservable borrower types. Conditional on the same borrower type, cards with rewards such as low Introductory APR, Cash back or Points programs, also have more steeply backward loaded fees, than cards without these salient rewards. In contrast, cards with Miles programs, which are offered only to the most educated and richest consumers, rely much less on backward loaded fees. These findings are in line with predictions from behavioral contract theory that shrouded (or backward loaded) pricing should occur in markets with naïve consumers while products offered to 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 and hidden fees when customers are less exposed to negative cash flow shocks.

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1. Introduction

Retail financial products have grown in the heterogeneity and complexity of their terms over the last two decades, see for example Tufano (2003), Phillipon (2012) or Greenwood and Scharfstein (2013). But there are widely diverging views about the reasons behind this proliferation of new products and services. The classical view of efficient product differentiation is that these trends represent improved customization of products to heterogeneous consumers, for an early discussion see Merton (1992) or Miller (1993). On the other side is a behavioral view which suggests that added features or complexity aim to exploit consumers' behavioral biases, for a summary see Thaler and Sunstein (2008) or Campbell et al (2011).

In this paper we use detailed information about almost 1 million individual credit card offers that were sent to a set of representative consumers in the US. We describe how card issuers use contract structures to target and screen potential borrowers based on their observable and unobservable characteristics. The typical credit card in the US combines a complex set of features that broadly constitute a three-part tariff: it has a regular APR (annual percentage rate) often combined with a very low introductory APR for a limited amount of time, very high late fees and over-limit fees, and usually a (low) annual fee. About 50% of the cards also carry a rewards program, such as cash back, points, or miles.

A recent theory literature in behavioral contract theory has made important advances in characterizing the equilibrium contract structures that arise in competitive markets when rational lenders interact with customers who have behavioral biases, what Heidhues and Koszegi (2015) call "naiveté based price discrimination". We will rely on the predictions from these models in our empirical analysis to test the relevance of behavioral screening models against a null hypothesis where contracts serve to solve adverse selection problems with rational agents.[2] Standard adverse selection models with nonlinear pricing a la Mussa and Rosen (1978) or Maskin and Riley (1984) cannot easily explain the typical credit card contract. These models predict that the last unit of consumption should be priced at marginal cost so that the highest demand consumer will pay the lowest

[2] For a detailed overview of the theoretical models see for example, DellaVigna (2009) or Koszegi (2013).

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. For example in the case of credit cards that would suggest not relying punitive late fees but extracting consumer rents via a fixed fee like an annual fee.[3]

In contrast, behavioral models of the credit card market suggest that this type of three-part tariff can 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 (not including the add on pricing). The mistakes in estimating the cost of credit could either be due to a lack of understanding of the contracts, or a lack of understanding of their own demand. A prominent example of the former is the model is the model by Gabaix and Laibson (2006) on shrouded attributes. It suggests that companies can attract myopic consumers by offering a low base price or other enticing features, but then break even by charging high prices for hidden, add-on features[4]. Heidhues and Koszegi (2010) provide a micro foundation that derives the optimal credit contract if borrowers have self-control issues but naively underestimate their likelihood to be tempted in the future.[5] The profit-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. Grubb (2009) derives very similar results for consumers with overoptimistic about how well they can forecast the variance of their future demand.

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

[4] 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.

[5] We do not aim to differentiate myopia from present bias, since the two traits can be intimately linked for the purpose of credit card issuers. Borrowers who have present bias might be happy not to be confronted with the late fees, even if they are not naïve about the contract features. And alternatively shrouding certain features of the card might aggravate a consumer's time inconsistency.

Independent of the specific form of naiveté, these models provide a number of common predictions for price discrimination with naïve consumers. First, when consumers are naïve, prices of forward loaded or salient features are driven down, while the features of the product that consumers do not concentrate on are very high (e.g., late fees and over-limit fees). In competitive markets, the salient features might even be offered below marginal cost to attract the naive consumers, but the firm breaks even by charging high add-on fees. This leads to a participation distortion, since consumers take on more credit than they rationally would. In reverse, in markets where consumers are predominantly sophisticated, we do not expect to find below marginal cost pricing, since these consumers can see through the add on pricing and avoid the costly features. Second, in a competitive market with both naïve and sophisticated agents, where firms cannot ex ante separate consumers, there is cross-subsidy from naïve to more sophisticated agents. Firms would find it optimal to reduce this subsidy to ideally capture these rents themselves.

We provide evidence in support of a view where credit card companies take into account the expected sophistication or naiveté of their customers. First, we show that credit card issuers target sophisticated customers with very different product features than unsophisticated ones. Sophistication is proxied for by borrower education (controlling for income levels). Not surprisingly, we find that the average APR and credit limits are more favorable for borrowers who look to be better credit types[6]. But we also show that credit cards that are offered to less sophisticated consumers on average have more steeply backward loaded (and hidden) fee structure, compared to those offered to more sophisticated customers. The former, for example, have higher late fees and over-limit fees but are more likely to receive low introductory APR offers (for a limited time period) and no annual fee. The reverse is true for sophisticated consumers.

Second, even conditional on their observable characteristics, borrowers might differ in their naïveté or sophistication along ex ante unobservable dimensions. We find that

[6] We ran hedonic regressions and show that interest rates are lower for potential borrowers with higher income, more education, living in richer zip codes, are home owners.

issuers use in particular rewards programs to screen for naïve versus sophisticated borrowers by offering the same borrower a menu of contracts that vary in how much they appeal to their myopia (or present-bias). Cards that have low introductory APR, cash back or points programs, have lower regular APR but much higher late fees and over limit fees than cards without these salient rewards. In contrast, cards with miles programs, which we show are mainly offered to the most educated and richer groups of the population (less than 9% of the cards offer miles), have significantly higher regular APR and often carry a high annual fee, but lower late fees and over-limit fees. We argue that this finding is in line with the predications of the behavioral contract theory literature: Backward loaded or salient features are used to screen for naïve or myopic consumers. But products which are offered predominantly to more sophisticated consumers cannot be easily shrouded and thus have to be priced upfront. In these screening regressions we can control for person and even bank fixed effects, which holds constant the credit risk of the person and the cost of credit for the bank. In fact, we rely on the variation that comes from the fact that banks send a menu of different offers to the same household in order to screen for unobservable borrower types.

Third, following the approach in Ausubel (2001) we look at changes in the Fed Fund rate as shocks to the cost of funding for banks in order to analyze how banks pass on these costs to consumers. When the cost of capital for lenders changes, credit cards that carry rewards programs like cashback or points, which are the ones targeted to less sophisticated consumers, respond much more strongly in their late fees but not the upfront fees (APR and annual fees). Cards with miles programs show the opposite behavior. This again supports our prior finding that the pricing of the first set of cards is done via the backward loaded fees, while in the miles cards via the regular APR. This also goes against the idea that the late fees are just a way for borrowers to signal that they are never going to use them, since then they should not change with cost of capital of the bank.

Fourth, we analyze at a dimension of pricing that has largely been ignored in most behavioral contract models of the credit market, i.e. the interaction between naiveté based pricing and credit risk. 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. This creates an endogenous limit to how heavily lenders can rely on these strategies.

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.[7] 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 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.

Finally, one might ask whether there are dynamic adverse selection models with rational agents that can explain this set of results? These models could fall into one of two categories: First, one could imagine consumers who value a backward loaded fee structure if they are very credit constrained today, but expect to be much less constrained in the future. This is equivalent to having a very high discount factor. As a result these

[7] 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.

borrowers would be willing to trade off very low interest today against high interest in the future. In this case, the borrower is fully prepared to pay the future high costs and the bank is able to price late fees to break even on the product.[8] But several of the findings in our data do not support this interpretation: First, the steep non-linearity of the late fees, seems to run counter to the idea that the late fees are an interest rate, since it does not take into account the actual balance that the borrower is carrying. Second, in a world where rational consumers are looking for cards that allow them to shift backward their interest payments, late fees and backward loaded fees should be very prominent in the contract, since it is a service that consumers are selecting on.[9] This is not what we find, since fees are always in small print and on the last page of the offer. In addition, the results from the UI analysis suggests that an improvement in the credit risk of borrowers leads to more hiding of fees on the last page. Since the UI shock does not alleviate the credit constraints of the borrowers but only their potential downside risk, this alternative cannot explain the increased hiding of fees.

An alternative rational model would be one where very price sensitive and low risk borrowers signal their (high) type to the bank by selecting a contract with low APR but very high backward loaded penalty rates. The expectation on both sides would be that the borrower will never incur any late fees and always pay on time, on the equilibrium path. But the assumption of this model are not supported by our findings either. First, as before, we would expect penalty rates in such a situation to be prominently displayed in the contract, since it is a desirable feature of the contract. Second, we show that credit cards with rewards that have particularly steep backward loaded fees, react very strongly in the size of late fees (but not regular APR), when there is a shock to the cost of capital to the bank. If banks were never expecting to get paid via these late fees, funding shocks should not affect them. And finally we can draw on several papers that have looked at the

[8] One caveat for such a model would be that banks have to get the timing just right, since highly credit constraint borrowers typically have high default propensity so that the backward loaded fees coincide with the borrowers ability to pay.

[9] One might want to argue that even a rational agent would not look at the future fees since they intend to default if fees are too high. But this could not be an equilibrium since then banks would not be able to break even.

usage behavior of credit cards, see for example Agrawal et al (2008), which find that borrowers who take up credit cards with high late fees, do indeed often pay them.[10]

One separate reason why card issuers might use rewards programs is to increase the transaction volume of the card, e.g. miles, cash back or points, since 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 these additional revenues might be shared via reward programs with the borrowers, it does not explain why these rewards should be associated with more backward-loaded pricing terms.

To test these models in the context of the credit card market we use data on preapproved credit card offers and their contract features from the US credit card industry between 1999 and 2011. 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 4000 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.

[10] A related behavioral version of this argument might suggest that borrowers demand high late fees to self-commit against over-spending or falling late on the card, see for example DelaVigna and Malmendier (2004). However, if this was true we would again expect late fees to be prominently featured on the offer letter.

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.[11]

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 on how credit card companies target consumer and section 5 on credit card screening. In section 6 we describe our Difference in Difference analysis using Unemployment Insurance shocks to borrower credit risk, and Section 7 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

[11] 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.

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 (demand side) 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. [12] 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.

[12] 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.

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.

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 (also known as Compremedia) 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 consumer panel conduced with more than 4000 households monthly, where these households are paid to collect all direct credit card mailers and send the originals 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 the head of the household, household income, household composition, family status, zip code, etc. Each month, Mintel receives from the household all credit solicitation mails, such as credit cards, home equity loans 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 into 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 well collected except default APRs which has many missing values.

Our data covers the time period from March 1999 to February 2011. But we also repeated all our analysis where we excluded the data post 2009 to abstract from the impact of the financial crisis and the CARD Act. The results are not changed. 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. We use OCR (Optical character recognition) software and our own extraction algorithms to reconfirm the quality of the data Mintel coded. We find that the coding of most variables is of high accuracy, but one exception is default APR where there seem to many missing variables.

We also create a second data set based on the Mintel information by using the scanned images of all pages of the credit card offers. These allow us to analyze the actual structure and design of the offer, e.g. where information about the card are located on the mailers. However, Mintel only keeps scanned images of about 80% of the credit card offers (about 803,285 out of the total 1,014,768 credit card offers have complete scanned images of each page). Mailers that are more likely to be missing in the first two years of the sample and there are also some later offers where images seem to be randomly missing. But we verified that besides the time trend the missing observations seem to not have any observables biases.

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 described the summary statistics of the main variables used in the paper. In Table 1 the first twelve variables are based on our full sample including 1,014,768 mail offers 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 higher (26.51%) which is higher than all other APRs. The high default APRs is not surprising since it is conditional on the borrower being more than 60 days late. The default APR may be applied to all outstanding balances of a credit card if a consumer pays the monthly bill late. All these APRs are monthly.

Intro_APR_regular, Intro_APR_balance and Intro_APR_cash are the dummies of whether the offer has 0% introductory APR (or very low 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 do not specify the limit.

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, 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. This is a dollar value not a rate. In our sample, late fee has a mean of $33.83, a standard deviation of $6.17, and a max of $89. It is much less skewed than annual fee. About 90% of the credit card offers have late fee from $29 to $39. This is a fixed monthly fee that comes due if the minimum payment has not been made, independent of the size of the balance. So especially for small balances this can be very high.

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 have 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.

The remaining variables in Table 1 are based on the 80% sample with mailing campaigns for which we 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.[13] "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.

Finally, we are able to code the reward programs based on the PDF images. 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. Finally, FFR is the monthly average federal fund rate from January 1999 to December 2011. We merge FFR into our credit card dataset by month.

3.3 Credit Card Design

Table 2 summarize the physical design of the credit card offers to document how and where in the letter certain features of the card are displayed. All credit card offers state late fees, default APRs, over-limit fees, and annual fees since it is mandated by the

[13] 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.

Schumer box. But only 5.8% of the credit card offers mention late fees in the first page of the offers; 4.97% mention default APRs in the first page, and 6.96% mention over-limit fees in the first. Not surprisingly, credit card offers usually do not mention fees, especially those that typically are backward loaded on 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 of the offer. But as we will document below, annual fees are usually associated with cards that are offered to more educated and higher income customers. Similarly, 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 zero introductory APRs, the likelihood to be on the first pages are 93.51%, 80.48%, and 91.04%, respectively.

Panel B of Table 2 compares the size of credit card terms conditional on being mentioned on the first page or not. Late fee, over-limit fee, and annual fee are lower if they are mentioned on the first page of the offer, than for the offers when they are mentioned in the back. Again, it is not surprising that issuers would highlight features that they perceive as very competitive.

Table 2B shows the correlation among different reward programs. The numbers are the percentage of the credit card offers with both reward programs. For example, 6.30% of the credit card offers have both cash back and point reward programs. We see that there are not so many overlaps among different reward programs. Mileage program, for instance, is not usually offered with cash back or point reward programs. Only 1.15% of the cards have both mileage and cash back programs together.

Finally, in figures 1 to 4, we plot the monthly time trend of reward programs and the main design features of credit card offers that we can measure from March 1999 to February 2011. We see that the uses of size, color and pictures in credit card offers increased significantly overtime and show slight cyclicality, i.e. there was a slightly drop following the 2001 stock market crash and the 2008 financial crisis. Also, the number of reward programs increases overtime and also appears to have a similar cyclical patter.

This increase in the “polish” or complexity of the offers might be driven by reduced production cost of mailers or an outcome of increased market competition. But it suggests that it is important to control for time trends in the analysis.

4. Customer characteristics and credit card features

We start by analyzing how the features of offers vary with the observable characteristics of the customers. In other words, how do credit card companies target offer to customers types. The characteristics of the people receiving the offers that we observe in Mintel is parallel to the information that banks can obtain by buying mailing lists from gatekeepers or other firms that sell consumer data. Each observation in our data set is an offer sent to a specific consumer, where consumers here stand for a bundle of characteristics. Since clients stay in the data for only a limited time period (they usually do not work for Mintel over many years) we cannot follow individuals in the data but “cells” which can be thought of as bundles of characteristics. For example, we can observe the type of offers that a typical household in a middle income group and a certain education level etc. receives over time or from different issuers. For each of the cells, we have several people with the same characteristics in the sample who are collecting information and thus are able to estimate their typical offer structure.

In Table 3 we run a simple hedonic 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.

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 drop 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 such enjoy a lower cost of capital. Interestingly the same is not true for more educated customers, maybe suggesting that people of similar educational achievement might have a lot of variance in their income and thus their credit worthiness. When we 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 find that limits increase with higher education bins, but again the increase is even steeper with income categories.

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. These results might be a first indication that these interest rates are not just set with and eye to credit risk, but also take into account the sophistication of the customers.

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 six 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.

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.

Robustness Check: 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 un-spanned dimension of customer characteristics.

5. Screening with Different Credit Card Offers

5.1. Trade-off between card features

We now explore the menu of credit card contracts that a given consumer with a given set of characteristics is offered. In particular, we want to understand how issuers trade-off font loaded terms such as regular APR and annual fees with back loaded terms such as late fees. In Table 4 we therefore regress the regular APRs on late fees; we also control for the level of the fed fund rat (FFR) in the month the offer was made. One should understand this estimated coefficient purely as a correlation between late fees and regular APR, not a causal estimate in any sense. But we prefer this specification since it allows us to easily control for cell and bank fixed effects. In Column (1) we first report the cross sectional correlation between late fees and APR. Therefore we only control for state and year fixed effects and find that cards which have $1 higher late fee also have 0.6% lower regular APRs. We then add controls for cell fixed effects (column 2) and cell and bank fixed effects (column 3) successively. The variation in this last specification holds constant the borrower type and the bank. This variation exists in the data since banks experiment with sending credit card holders different contracts to screen for their types. This means we can identify the menu of contract structures that a given bank is sending the same customer. We find that the negative correlation between regular APRs late fees also holds at the individual level, and magnitudes are similar. Customers have to trade-off between lower upfront fees and high late fees or vice versa.

In the next step we analyze whether this trade off changes with other features of the cards, specifically the reward programs. If reward programs that are aimed at less sophisticated consumers screen for more myopic or present-biased consumers, we would expect the terms of the credit card to become more backward loaded. However, rewards that are sent predominantly to sophisticated consumers should not show the same structure. As suggested in Gabaix and Laibson (2006), these consumers can see through the add on pricing and avoid it. To test these ideas, in column (4) and (5) we add a number of reward programs of cash back, point, and car rental insurance (which we saw are targeted at all income and education levels) in each offer and interact it with late fees. Again in column (4) we control for the cell fixed effect and in (5) for both cell and bank fixed effects. We find a significantly negative coefficient on this interaction term, which means that the trade-off between upfront fees (APR) and late fees becomes steeper for cards with these rewards. We repeat the same regressions using an indicator variable for whether the card has a low introductory APR program in column (6) and (7). The results are qualitatively similar but larger in quantity.

Finally, in the last two columns of Table 4, we now look at the use of mileage programs and find a distinctly different pattern. Interestingly, we see that the interaction term of mileage programs with late fees is strongly positive and significant, which suggests that cards that this cards have a much flatter trade-offs between late fees and regular APRs. In other words these cards have much less backward loaded fee structure, which is in line with the idea that cards which are offered to more sophisticated people cannot be backward loaded since they can undo the backward loaded features.

In Table 4B we repeat the same regressions as in Table 4 but use as the LHS variable a dummy for whether the firm charges an annual fee. We confirm that the results are parallel to the findings when using regular APR. In unreported regressions (can be requested from the authors), we also confirm that the trade off between late fee and regular APR (or annual fees) becomes steeper when customers are less educated, which confirms the results reported in Table 3.

In sum these results are consistent with a model where credit card companies offer a menu of contracts to potential customers (conditional on their observable characteristics) to screen between naïve and sophisticated customers along unobservable dimensions. To separate myopic or present-biased consumers from more sophisticated ones, issuers seem to offer terms that have low APR and annual rate but very high late fees. These cards are usually combined with rewards programs such as low introductory rate APR, or cash back and points. Interestingly, we see that credit cards with rewards programs which are only offered to more sophisticated borrowers (miles) do not have the same backward loaded fee structure, since customers would undo the add on pricing.

5.2. Pricing of credit cards

In a next step we now want to understand how the pricing of credit card offers changes when the cost of capital for the issuers changes, more specifically, which terms of the card are more sensitive to the issuer's cost of capital. This will allow us to understand which parts of the credit contract are important for the issuer to receive rents from the borrower, i.e. break even on the loan pool in expectations. We follow the general idea pioneered in Ausubel (1991) to assume that APR should be very sensitive to the Fedfund Rate (FFR) since this is the rate at which the banks can raise capital. If cards with rewards programs such as points, cash back or low introductory APR indeed are used to screen for naïve consumers who pay via the incurred late fees, then we should see late fees respond particularly strongly when the FFR changes. The reverse should be true for miles cards which we have shown are mainly offered to sophisticated consumers.

Our 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 for fixed effects such state fixed effects, bank fixed effects, and household demographic fixed effects. [14] 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.

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

Point and Cash Back Rewards: In Table 6 Panel A, we focus on cards with points programs. 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 cell fixed effects but not bank fixed effects. We see that the coefficient on FFR is positive (0.314), 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 regular APR, which confirms our findings from Table 4. In column (2) 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 factor of 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 again in line with the screening effects we found in Table 4.

In column (3) and (4) we now repeat the same analysis but use as our dependent variable the late fees of the card. We find as expected from our prior results that late fees are significantly higher for cards with point programs, compared to those without. This relationship again holds when holding constant the person and bank fixed effects. And finally in column (5) and (6) we look at annual fees.

In the last three columns of the table we now follow Ausubel (1991) and test how different contract terms (APR, Annual fee and late fee) change with the FFR if the card has a point program (interact Points * FFR). We see that APR and annual fee are much less sensitive to changes in FFR if the card has a point program. But late fees are much more sensitive to FFR if the card has a points program. These results confirm the idea that late fees are an important dimension for the pricing of the card and as a result react to a change in the bank's cost of capital. In contrast APR and annual fees are much less sensitive to changes in the FFR.

In Panel B of Table 5 we repeat the same set of regressions but look at the interaction with cash back programs and obtain very similar results.

Mileage Programs and Introductory APR: In Table 6 Panel A, we focus on the cards that have mileage programs. We again follow exactly the same set of specifications as in Table 6 Panels A and B. We find that the pricing of these cards is exactly reversed from all the other rewards programs. Cards that have miles programs associated with them have significantly higher regular APR, much higher annual fees and much lower late fees than cards without these programs. Again it is important to note, that these results always hold, when we control for cell and bank fixed effects, so we are identifying off the variation from two different card offers being sent to the same borrower type. But interestingly when we add an interaction term of FFR * MILES in the last three columns of the table, we see that APR is very sensitive to changes in FFR if the card has a mileage program, but late fees and annual fees are not. This again confirms the idea that mileage programs are not priced via the backward loaded features but via the regular APR, since sophisticated consumers see through the add on pricing.

Finally, in Panel B of Table 6, we confirm that credit cards with low introductory APR programs, have a pricing structure similar to cash back and points programs.

6. Shocks to borrower credit risk: Unemployment insurance

We now analyze the effect of an exogenous shock to the credit worthiness of customers, in particular their risk of default, on credit card terms and reward programs. We conjecture that naiveté based price discrimination can possibly lead to an adverse effect on issuers if by shrouding credit features these contracts draw in not only myopic or present-biased but also lower credit quality customers. For example, if customers who are drawn in by zero APR introductory programs truly do not expect that they ever have to pay interest on the credit, they might have to default once the introductory period expires. This however endogenously limits the extend to which banks should rely on this strategy.

To test this idea we use changes in the (states') unemployment insurance as an exogenous shock to the credit risk of customers. 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 a window of one year before and after the UI increase to estimate the effect. 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 a follow-on year. So we did not want to confound the impact of the UI change with small subsequent changes. In addition, we see in the data that credit card companies on average react very quickly to changes in the market. E.g. if one issuer introduces a new product feature in the market, other firms adopt this change within a few months. We also include dummies to control for a possible pre-trend three or six months before the UI change. All regressions use control year fixed effects, cell fixed effects, and bank fixed effects. We also repeated these regressions using other time windows, e.g. two year windows around the change and the results are qualitatively and quantitatively very similar.

Table 7 Panel A is the one year Diff-in-Diff regression results between 1999 and 2007. We drop the years following the financial crisis of 2008. Since economic conditions worsened significantly in those years following the crisis, changes in UI after 2008 might be very endogenous to the economic distress of a state and there could be a concern that other hidden variables drive our results. In column 1, the dependent variable is regular APR. The coefficient on the UI dummy is negative but not significant. But in column (2) we see that an increase in UI leads to a large and significant increase in the late fees. In contrast, Column (3) shows that annual fees do not change significantly around UI changes, while in column (4) 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 find that indeed card issuers use more intro APR programs after UI increases have been implemented. Overall these results strongly support the idea that with the increase in UI issuers are using a greater reliance on backward-loaded payment features. Finally in the last four columns of Table 7 Panel A we look at "softer" dimensions of the credit card offer. We see that after a UI increase issuers are relatively more likely to use more colorful mailers and more pictures. At the same time the offers tend to be more likely to put information about late fees and default APR from the front of the offer letter to the end. In addition, when we re-ran all the regressions but dropping the bank fixed effects, the results are quite similar to Table 7 and estimated coefficients change barely. 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. We then repeat the same analysis in Table 7 Panel B but across our entire sample period (1999 to 2011). The regression results in Panel B are very similar to Panel A.

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.

7. Conclusions

The paper shows that credit card issuers use different card features to separate customer groups with higher or lower sophistication versus naiveté. 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 an important dimension of the use of naiveté based discrimination that has been largely ignored in the literature. The interaction between behavioral screening and classic adverse selection is 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 naiveté based price discrimination and their impact on the credit risk of the customer pool. By drawing in customers who do not understand the credit terms that they are offered the issuer might end up with borrowers who have a higher chance that they can ultimately not afford the credit and default.

The results in this paper provide evidence that credit card companies do target and screen sophisticated and naïve creditors differently, via the type of reward programs and pricing structures that are offered to customers. Issuers offer customers a menu of contracts to choose from; so rational customers on average can find contracts with less hidden charges. However naïve customers will also be able to find contracts that cater to their behavioral problems. But we can see that on average the menu of cards that is offered to more educated and richer customers contains fewer cards with hidden charges than the one offered to less educated and poorer customers. This means the latter group has to work harder to pick their card.

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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

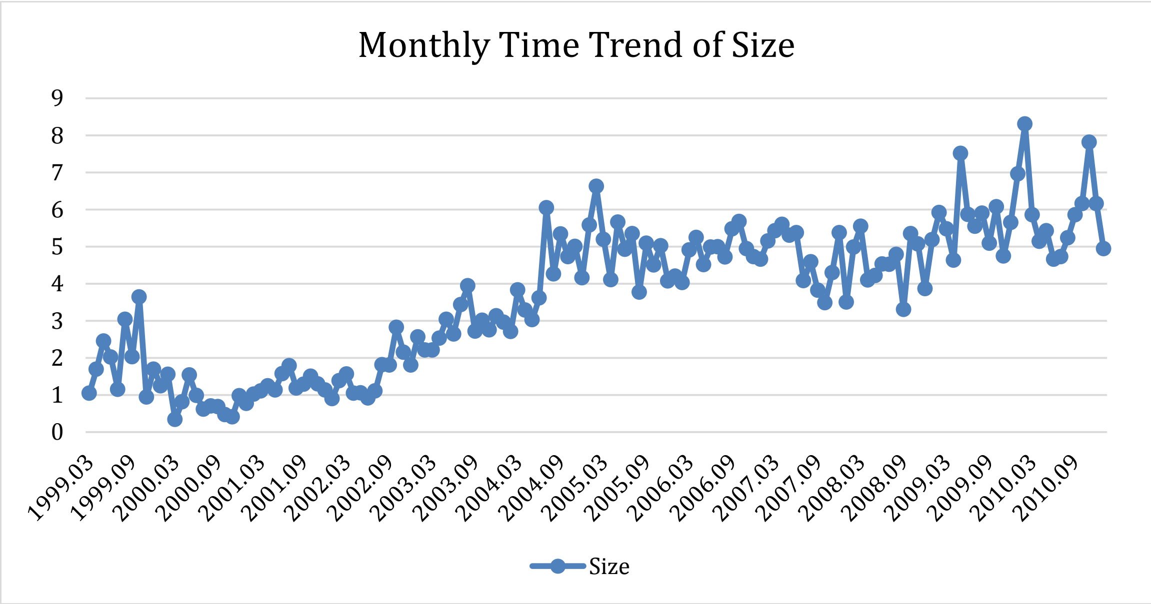


Figure 2 is the plot of monthly time trend of variable "Size". Size is the maximum size of the reward programs minus the average size of all characters in every pages of each credit card offer. For each month, we calculate the average "Size" of the credit card offers.

Figure 3

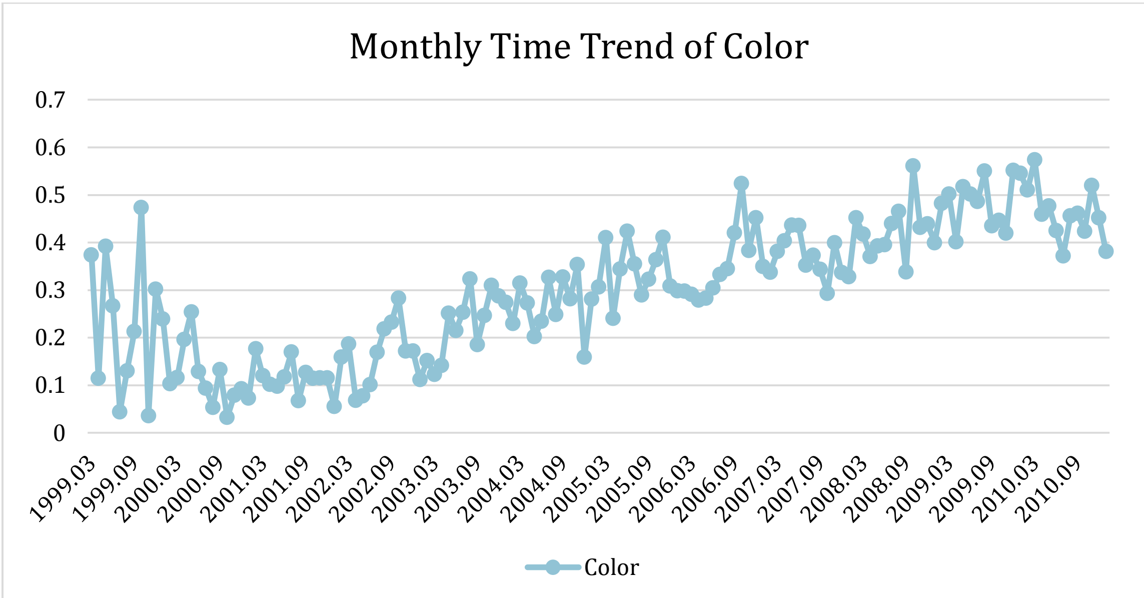


Figure 3 is the plot of monthly time trend of variable "Color". "Color" is the dummy of whether reward programs in the offer use color other than black/white. For each month, we calculate the average "Color" of the credit card offers.

Figure 4

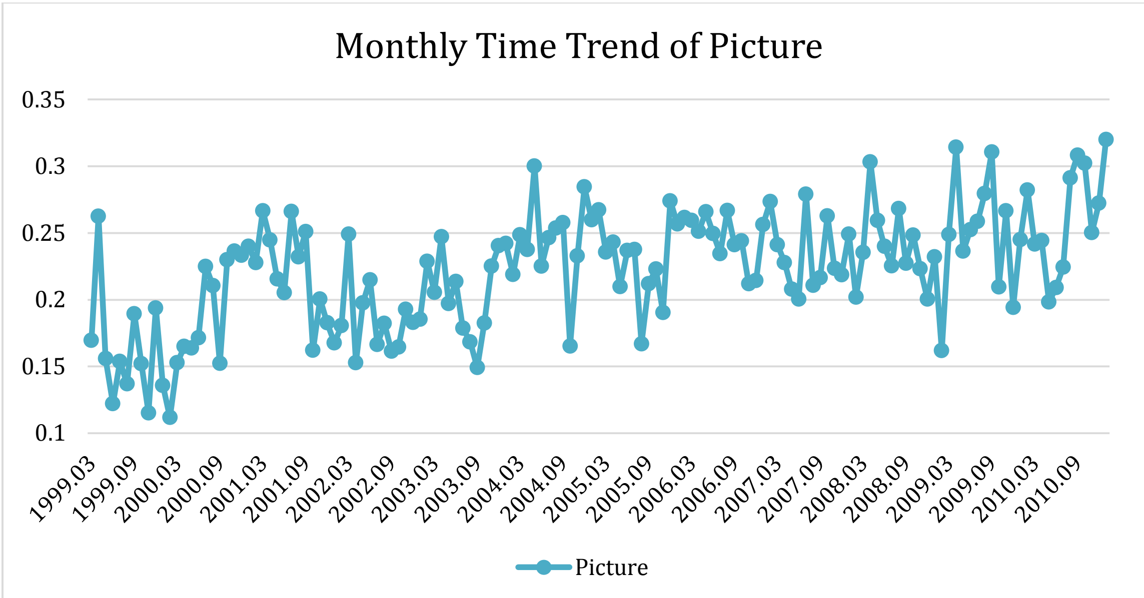
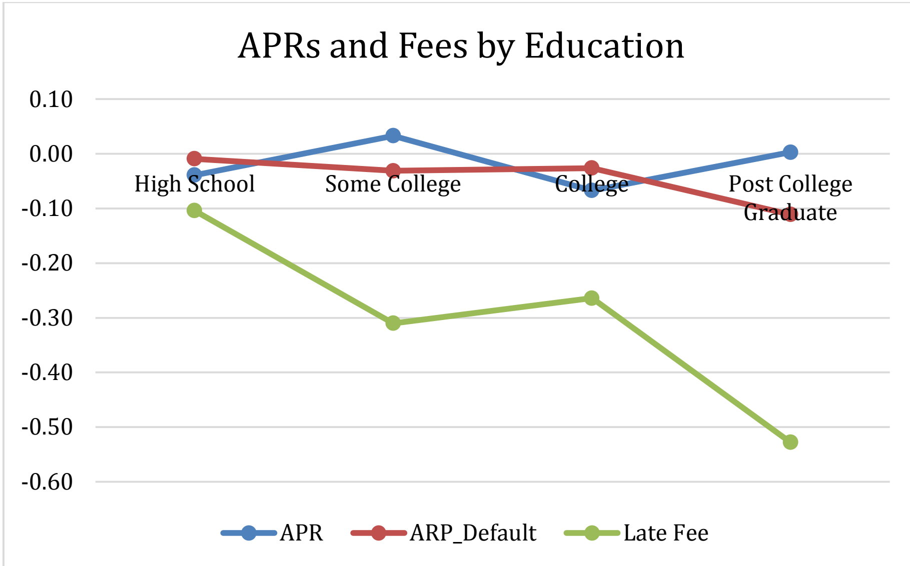


Figure 4 is the plot of monthly time trend of variable "Picture". “Picture” is the file storage size of scanned images of credit card offers. The unit is megabyte (MB). For each month, we calculate the average "Picture" of the credit card offers.

Figure 5



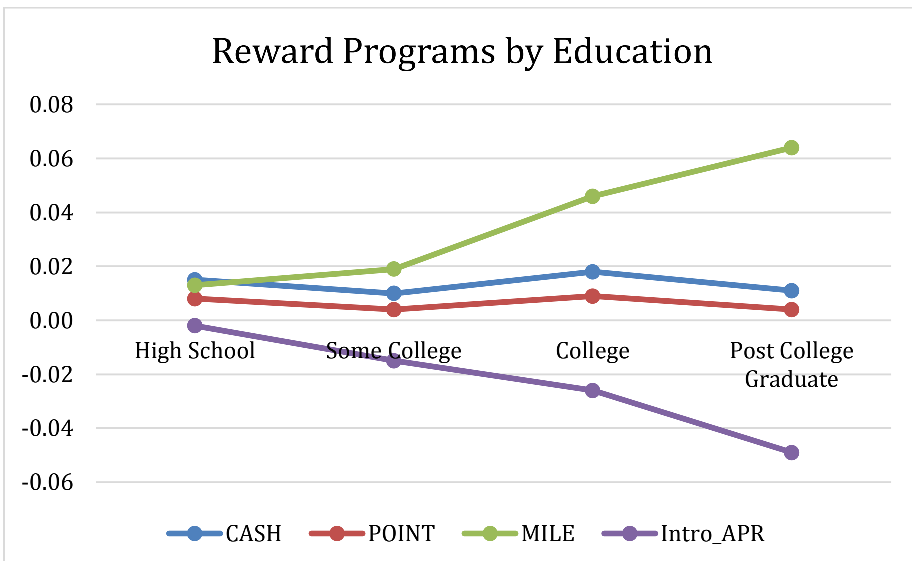
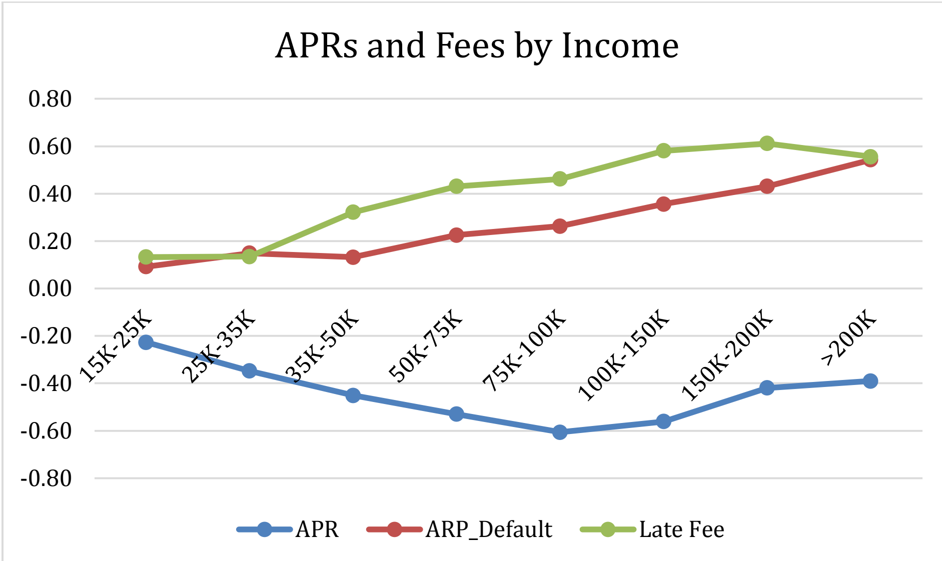


Figure 5 plot the estimated coefficients on the education from a regression where we regress individual card features on dummies for different education levels (as provided by Mintel). The regression results are reported in table 3. We omitted the highest education bin (graduate school) since it is very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

Figure 6



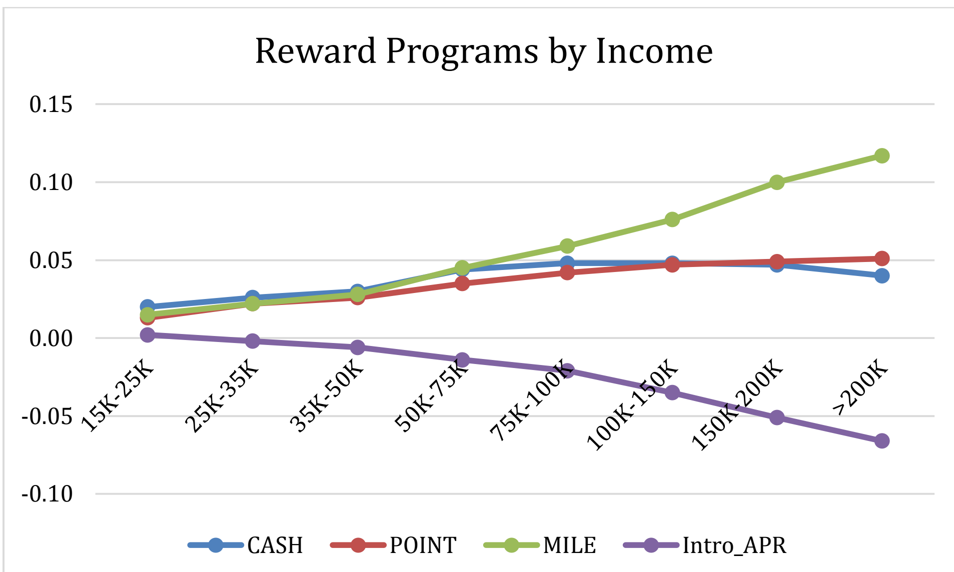


Figure 6 plot the estimated coefficients on the income from a regression where we regress individual card features on dummies for different income levels (as provided by Mintel). The regression results are reported in table 3.

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 2B
Correlation among credit card features

Both	CASH	POINT	MILE	CAR	PurchasePrct	Intro_APR	Zero Annual fee
CASH	21.10%	6.30%	1.15%	4.62%	3.37%	11.67%	20.76%
POINT	6.30%	23.80%	0.28%	7.55%	6.71%	9.39%	19.93%
MILE	1.15%	0.28%	8.80%	2.26%	0.76%	2.40%	4.27%
CAR	4.62%	7.55%	2.26%	22.70%	10.76%	10.91%	16.46%
PurchasePrct	3.37%	6.71%	0.76%	10.76%	23.40%	14.54%	17.37%
Intro_APR	11.67%	9.39%	2.40%	10.91%	14.54%	48.80%	43.17%
Zero Annual fee	20.76%	19.93%	4.27%	16.46%	17.37%	43.17%	80.80%

Note: The dataset is based on Mintel's credit card's direct mail campaigns from March 1999 to February 2011. Statistics are based on 80% of 1,014,768 total mail campaigns w hich have scanned images of credit card offers. The numbers on diagonal are the percentage of credit card offers w ith the rew ard program. For example, 21.10% of the credit card offers have cash back program. The numbers in other cells are percentage of the credit card offers w ith both programs accordingly. For example, 6.3% of the credit card offers have both cash back and point rew ard programs.

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
Regular APR vs. Late Fees

	1	2	3	4	5	6	7	8	9
Dependent Variable	APR	APR	APR	APR	APR	APR	APR	APR	APR
FFR	0.571***	0.568***	0.459***	0.809***	0.671***	0.493***	0.424***	0.761***	0.666***
	(0.015)	(0.013)	(0.011)	(0.010)	(0.010)	(0.013)	(0.011)	(0.011)	(0.009)
LateFee	-0.066***	-0.057***	-0.016***	-0.024***	0.023***	-0.029***	0.030***	-0.077***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Reward				1.945***	2.069***				
				(0.056)	(0.056)				
LateFee*Reward				-0.065***	-0.057***				
				(0.002)	(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	Yes
State Fixed Effects	Yes	No	No	No	No	No	No	No	No
Cell Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	No	Yes	No	Yes	No	Yes
Observations	975,486	936,641	936,641	773,694	749,983	936,641	936,641	749,983	749,983
R-squared	0.165	0.150	0.332	0.172	0.329	0.173	0.348	0.168	0.347

Note: OLS regressions to estimate relationship betw een regular APR and late fees in credit card offers. Data is restricted to offers w e have scanned pictures in column 4, 8 and 9. Regressions in column 1 is controlled by state fixed effects. Regression in column 2 to 9 are controlled by demographic cell fixed effects based on states, age, income, education and household composition. Regressions in column 3, 5, 7, and 9 are controlled by bank fixed effects. Rew ard is the number of rew ard programs of CASH POINT and Car rental insurance in each offer. MILE is the dummy of w hether the credit card offer has mileage rew ard program or not. Intro_APR is the dummy of w hether 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 4 B
Annual Fees vs. Late Fees

	1	2	3	4	5	6	7	8	9
Dependent Variable	Annual Fee	Annual Fee	Annual Fee	Annual Fee	Annual Fee	Annual Fee	Annual Fee	Annual Fee	Annual Fee
FFR	-0.567***	-0.824***	-0.609***	-1.076***	-1.116***	-1.607***	-1.171***	-1.261***	-1.283***
	(0.102)	(0.063)	(0.057)	(0.085)	(0.077)	(0.064)	(0.057)	(0.082)	(0.074)
LateFee	-0.699***	-0.625***	-0.061***	-0.092***	0.279***	-0.397***	0.290***	-1.235***	-0.573***
	(0.024)	(0.011)	(0.007)	(0.010)	(0.007)	(0.013)	(0.009)	(0.016)	(0.011)
Reward				44.955***	32.936***				
				(0.699)	(0.512)				
LateFee*Reward				-1.242***	-0.921***				
				(0.018)	(0.014)				
Intro_APR						1.470***	8.297***		
						(0.499)	(0.389)		
LateFee*Intro_APR						-0.406***	-0.622***		
						(0.014)	(0.011)		
MILE								-56.262***	-31.103***
								(0.642)	(0.484)
LateFee*MILE								2.362***	1.669***
								(0.018)	(0.014)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	No	No	No	No	No	No	No	No
Cell Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	No	Yes	No	Yes	No	Yes
Observations	997,105	957,656	957,656	767,502	767,502	957,656	957,656	767,502	767,502
R-squared	0.036	0.032	0.226	0.049	0.232	0.071	0.264	0.109	0.285

Note: OLS regressions to estimate relationship betw een annual fees and late fees in credit card offers. Data is restricted to offers w e have scanned pictures in column 4, 8 and 9. Regressions in column 1 is controlled by state fixed effects. Regression in column 2 to 9 are controlled by demographic cell fixed effects based on states, age, income, education and household composition. Regressions in column 3, 5, 7, and 9 are controlled by bank fixed effects. Rew ard is the number of rew ard programs of CASH POINT and Car rental insurance in each offer. MILE is the dummy of w hether the credit card offer has mileage rew ard program or not. Intro_APR is the dummy of w hether 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 5
Relationship Between APRs/Fees and Reward Program

Panel A	1	2	3	4	5	6	7	8	9
Dependent Variable	APR	APR	Late Fee	Late Fee	Annual Fee	Annual Fee	APR	Late Fee	Annual Fee
FFR	0.314***	0.258***	-0.160***	-0.133***	-0.242***	-0.785***	0.373***	-0.277***	-0.300***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.037)	(0.032)	(0.005)	(0.009)	(0.028)
POINT	-0.671***	-0.062***	2.063***	1.510***	5.822***	1.235***	0.007	0.869***	6.108***
	(0.013)	(0.012)	(0.018)	(0.015)	(0.141)	(0.117)	(0.023)	(0.024)	(0.261)
POINT*FFR							-0.244***	0.434***	-1.785***
							(0.007)	(0.010)	(0.074)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes	No	Yes	No	No	Yes
Observations	753,690	753,690	769,923	769,923	771,535	771,535	753,690	769,923	771,535
R-squared	0.0218	0.214	0.0226	0.227	0.006	0.211	0.0241	0.0258	0.213

Panel B	1	2	3	4	5	6	7	8	9
Dependent Variable	APR	APR	Late Fee	Late Fee	Annual Fee	Annual Fee	APR	Late Fee	Annual Fee
FFR	0.301***	0.255***	-0.120***	-0.109***	-0.428***	-0.910***	0.395***	-0.139***	-1.165***
	(0.005)	(0.005)	(0.008)	(0.007)	(0.037)	(0.031)	(0.006)	(0.008)	(0.040)
CASH	-0.451***	-0.165***	1.573***	0.845***	-14.862***	-11.941***	0.472***	1.381***	-14.455***
	(0.013)	(0.012)	(0.019)	(0.022)	(0.089)	(0.084)	(0.020)	(0.026)	(0.151)
CASH*FFR							-0.363***	0.076***	1.006***
							(0.006)	(0.011)	(0.043)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes	No	Yes	No	No	Yes
Observations	753,690	753,690	769,923	769,923	771,535	771,535	753,690	769,923	771,535
R-squared	0.0189	0.214	0.0127	0.221	0.034	0.227	0.0242	0.0128	0.228

Note: Panel A show s OLS regressions to estimate relationship betw een point rew ard programs and credit card APRs and fees. Panel B show s OLS regressions to estimate relationship betw een cash back rew ard programs and credit card APRs and fees. Data is restricted to offers w e have scanned pictures. Regressions in column 1 to 9 are controlled by household demographic cell fixed effects based on states, age, income, education and household composition. Regressions in column 2, 4, 6 and 9 are controlled by bank fixed effects. POINT is the dummy of w hether the credit card offer has point rew ard program or not. CASH is the dummy of w hether the credit card offer has cash back rew ard program or not. Standard errors in parentheses are clustered by cells.

Table 6
Mileage Program vs. Zero Introductory APR Program

Panel A	1	2	3	4	5	6	7	8	9
Dependent Variable	APR	APR	Late Fee	Late Fee	Annual Fee	Annual Fee	APR	Late Fee	Annual Fee
FFR	0.294***	0.241***	-0.125***	-0.107***	-0.374***	-0.979***	0.278***	-0.028***	-0.897***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.036)	(0.030)	(0.005)	(0.007)	(0.030)
MILE	1.938***	1.971***	-2.724***	-1.507***	25.380***	25.654***	1.448***	0.128	27.948***
	(0.019)	(0.020)	(0.063)	(0.051)	(0.224)	(0.220)	(0.028)	(0.090)	(0.390)
MILE*FFR							0.170***	-0.992***	-0.804***
							(0.010)	(0.034)	(0.105)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes	No	Yes	No	No	Yes
Observations	753,690	753,690	769,923	769,923	771,535	771,535	753,690	769,923	771,535
R-squared	0.0368	0.234	0.0176	0.223	0.047	0.256	0.0373	0.0249	0.257

Panel B	1	2	3	4	5	6	7	8	9
Dependent Variable	APR	APR	Late Fee	Late Fee	Annual Fee	Annual Fee	APR	Late Fee	Annual Fee
FFR	0.391***	0.326***	-0.286***	-0.239***	-0.558***	-0.909***	0.664***	-0.479***	-1.262***
	(0.005)	(0.004)	(0.007)	(0.007)	(0.031)	(0.026)	(0.006)	(0.009)	(0.042)
Intro_APR	-0.990***	-0.740***	1.035***	1.105***	-12.211***	-12.477***	0.560***	-0.082***	-14.513***
	(0.012)	(0.013)	(0.016)	(0.017)	(0.098)	(0.106)	(0.022)	(0.025)	(0.185)
Intro_APR*FFR							-0.566***	0.411***	0.748***
							(0.006)	(0.010)	(0.047)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes	No	Yes	No	No	Yes
Observations	942,397	942,397	961,247	961,247	963,283	963,283	942,397	961,247	963,283
R-squared	0.0452	0.238	0.0148	0.209	0.037	0.248	0.0613	0.0185	0.249

Note: Panel A show s OLS regressions to estimate relationship betw een mileage rew ard programs and credit card APRs and fees. Panel B show s OLS regressions to estimate relationship betw een zero intro APR rew ard programs rew ard programs and credit card APRs and fees. Data is restricted to offers w e have scanned pictures in Panel A. Panel B includes the entire credit card offer sample w ith and w ithout scanned pictures. Regressions in column 1 is controlled by demographic cell fixed effects based on states, age, income, education and household composition. Regressions in column 2, 4, 6, and 9 are controlled by bank fixed effects. MILE is the dummy of w hether the credit card offer has mileage rew ard program or not. Intro_APR is the dummy of w hether the credit card offer has 0 intro APR for regular purchase or not. Standard errors in parentheses are clustered by cells.

Table 7

Unemployment Insurance and Credit Card Feature

Panel A								
	1	2	3	4	5	6	7	8
Dependent Variable	APR	Late Fee	Annual Fee	Intro_APR	Color	DefaultAPR MainPage	LateFee MainPage	Default APR Back
FFR	0.111***							
	(0.040)							
UI	-0.064	0.122**	0.163	0.053***	0.011***	-0.011***	-0.009*	0.256**
	(0.114)	-0.053	(0.667)	(0.015)	(0.004)	(0.003)	(0.006)	(0.115)
UI_Pre_3M	-0.182	0.17	-1.294***	0.070*	0.008	-0.002	-0.007	0.010
	(0.118)	-0.12	(0.466)	(0.037)	(0.005)	(0.006)	(0.010)	(0.133)
UI_Pre_6M	-0.015	-0.215	0.379	0.004	0.003	-0.002	0.000	0.358***
	(0.114)	-0.14	(0.682)	(0.034)	(0.005)	(0.005)	(0.011)	(0.103)
UI_Small	-0.028	0.077	-0.625	-0.003	-0.002	-0.004	0.014	0.320***
	(0.092)	-0.086	(0.460)	(0.011)	(0.006)	(0.003)	(0.009)	(0.100)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102,735	103,342	103,820	105,380	91,783	48,592	48,592	12,895
R-squared	0.315	0.255	0.257	0.154	0.0413	0.0514	0.0301	0.324

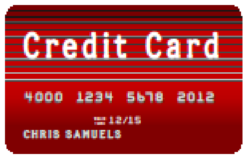
Panel B								
	1	2	3	4	5	6	7	8
Dependent Variable	APR	Late Fee	Annual Fee	Intro_APR	Color	DefaultAPR MainPage	LateFee MainPage	Default APR Back
FFR	0.121***							
	(0.035)							
UI	-0.019	0.118**	-0.190	0.044***	0.001	-0.008	-0.006	0.231***
	(0.111)	(0.060)	(0.700)	(0.015)	(0.009)	(0.006)	(0.007)	(0.089)
UI_Pre_3M	-0.121	0.168	-1.194**	0.062*	0.003	-0.002	-0.010	0.038
	(0.123)	(0.113)	(0.494)	(0.037)	(0.006)	(0.005)	(0.011)	(0.136)
UI_Pre_6M	0.027	-0.230*	0.192	-0.003	0.003	-0.009*	-0.006	0.320***
	(0.121)	(0.138)	(0.742)	(0.030)	(0.006)	(0.005)	(0.012)	(0.080)
UI_Small	-0.007	0.090	-0.910	-0.010	0.002	-0.003	0.003	0.386***
	(0.081)	(0.081)	(0.817)	(0.008)	(0.007)	(0.004)	(0.009)	(0.089)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,692	110,475	110,984	112,575	98,126	55,778	55,778	17,408
R-squared	0.307	0.275	0.237	0.153	0.0589	0.0852	0.0336	0.389

Note: OLS regressions to estimate unemployment insurance effects on credit card features at 6 month frequency. Panel A includes the credit card offers from 1999 to 2007. Panel B is from 1999 to 2011. All columns are controlled by 6 month fixed effects, bank fixed effects , and cell fixed effects based on states, age, income, education and household composition. UI is the dummy w hich equals 1 if unemployment insurances increase by more than 10% in this year and equals 0 in the year before the increase. UI_Pre_3M is the dummy for 3 month pretrend of the UI jumps. UI_Pre_6M is the dummy for 6 month pretrend of the UI jumps. UI_Small is the dummy of the UI increases below 10% w hich are mainly due to inflation adjustments. Column 6 and 7 are OLS regression on w hether default APR/late fees are mentioned on the main page of the credit card offers. Column 8 is for the default APR level w hen it's on the main pages. 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

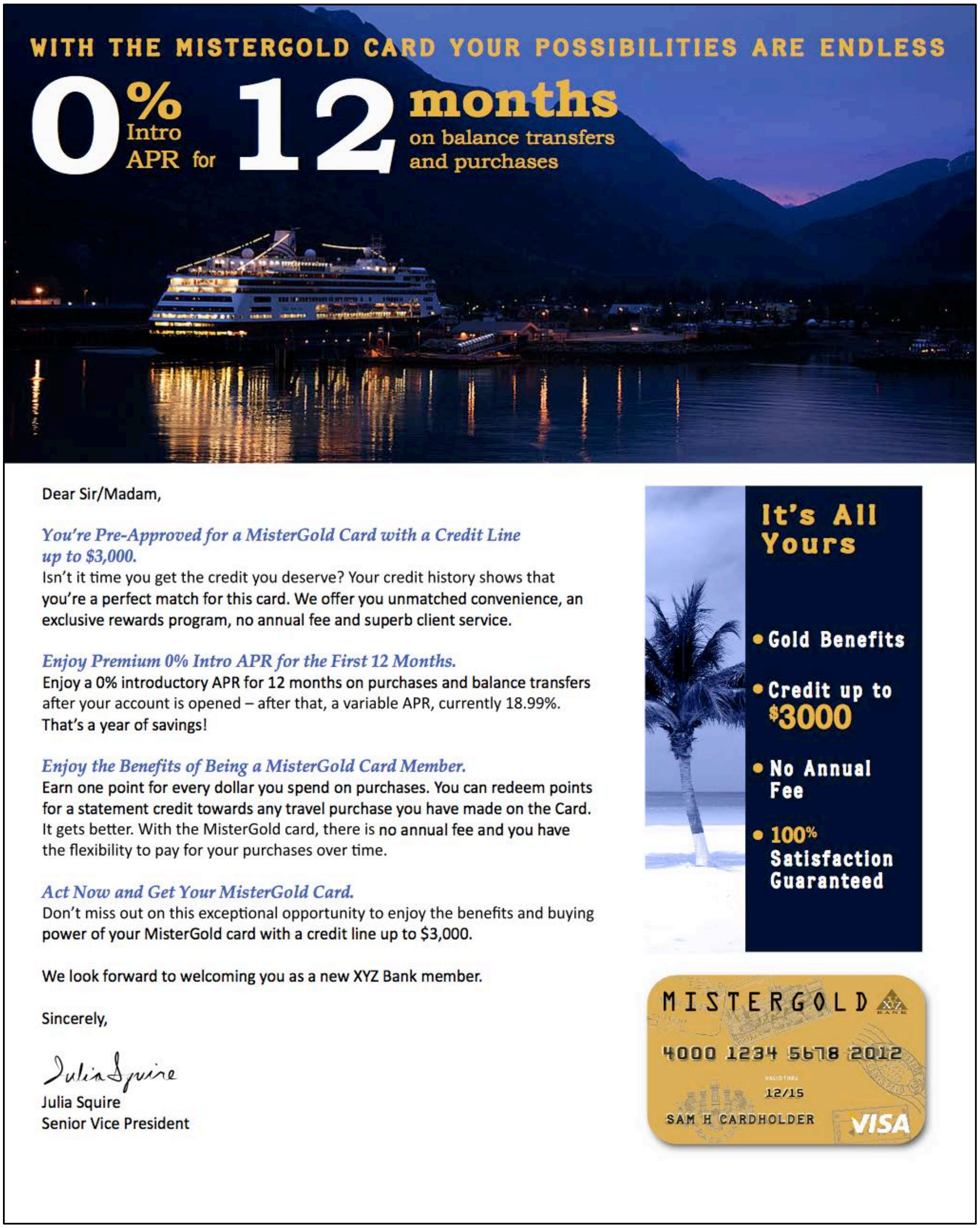


Figure A.2 is the sample of high visual credit card offers. It has relatively big font size to emphasis the reward programs. It also has many colors and flashy pictures to draw consumers' attention.