Do Credit Card Companies Screen For Behavioral Biases?

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We analyze the supply side of credit card markets, and the pricing and marketing strategies of issuers. First, card issuers target less-educated customers with more steeply back-loaded and hidden fees (e.g. higher late and over-limit fees). Second, issuers use rewards programs to screen for unobservable borrower types. Finally, we use increases in state-level unemployment insurance (UI) as positive shocks to creditworthiness and show that issuers rely more on back-loaded (hidden) fees when UI increases, especially for less-educated customers. This result documents a novel trade-off: card issuers weigh short-term fee maximization against increases in credit risk, when using back-loaded fees.

Over the last three decades, the U.S. has experienced a rapid expansion of retail financial products, especially among middle- and lower-income households. At the same time, the heterogeneity and complexity of the products and the terms that are offered to consumers increased dramatically; see, for example, Merton (1992), Miller (1993), or Tufano (2003). Recent papers by Phillipon (2012) and Greenwood and Scharfstein (2013) suggest that these emerging trends were accompanied by increased rents for intermediaries in the financial industry. Many policy makers are concerned that these rents come at the expense of consumers, particularly if less financially sophisticated consumers are targeted with onerous or hidden fees.

In this paper, we look at the supply side of the US credit card market to document whether and how financial institutions take the sophistication of their customers into account. We document three main findings: First, when looking at the observable characteristics of households, we show that less-educated (financially less sophisticated) households are more likely to be offered more back-loaded or hidden fee structures that rely on low introductory (or teaser) rates and no annual fees but high penalty rates, late fees, and over-limit fees. We also document the use of shrouding. In particular, offers with worse credit terms are more likely to only display these terms either in small font or on the last pages of the offer letters. Furthermore, offer letters sent to less-educated households are more likely to be shrouded by showing back-loaded terms only on the last pages of the offers.

Second, we find that even after controlling for the observable characteristics of customers, card issuers attempt to screen households based on unobservable characteristics by offering a menu of cards with varying degrees of back-loaded fees and different rewards programs. Cards with rewards programs that appeal to less-sophisticated consumers (e.g., zero introductory annual percentage rate

(APR)) also have more back-loaded terms. While cards with miles programs that appeal mainly to sophisticated consumers have more front-loaded fees.

Third, we document an important trade-off between borrower sophistication and credit risk that has not been previously explored in the literature. A lending strategy that selects for less-sophisticated customers via back-loaded or shrouded attributes can increase rents from these consumers over the short run, but might also expose the lender to higher credit risk over the long run: If these card features attract customers who do not understand the true cost of credit, the issuer might end up with an adversely selected pool of borrowers who cannot pay their charges. We find that banks seem to take this trade-off into consideration, since they rely less on back-loaded and hidden terms when the credit risk of consumers is higher. Using a difference-in-difference estimator, we show that when states increase unemployment insurance (UI), which protects and stabilizes households' cash flows on the downside, banks increase their use of back-loaded fees and zero introductory APR (teaser) offers, especially for less-educated households.

This explicit targeting of less-sophisticated households with more back-loaded or shrouded credit terms is important to understand, because a number of prior studies on the demand side have shown that credit card users pay higher fees and carry higher balances when they choose these contracts, see for example, Agarwal et al. (2008) and (2015). In other words, households do not seem to be able to avoid the higher fees imbedded in these contracts.

The credit card industry is an ideal industry to analyze the strategies of financial institutions because the majority of credit cards are sold via pre-approved credit card solicitations sent by mail. This means the same information that customers receive is observable to the researcher once we obtain the card solicitations. We use detailed information from Comperemedia on almost one million individual credit card offers that were sent to a set of representative households in the US between 1999 and 2011. Comperemedia records the households' demographics

to mirror the information credit card issuers observe when targeting customers. These data allows us to observe the supply side of the credit card market, i.e., the types of offers that customers receive. Using complete PDF versions of the actual offer letters, we created algorithms with optical character recognition (OCR) to extract the card information and features in the offer. We classify the "hard" information in the offers such as the APRs, fees, and reward programs. Moreover, we also observe the "soft" features of the offers, for example, the use of photos, color, font size, and whether information about an offer is provided at the beginning or the end of the letter.

A typical credit card in the US combines a broad set of complex features that constitute a three-part tariff: a regular APR is often combined with a low introductory APR (i.e., a lower rate for a limited time), very high late and over-limit fees, and (low) annual fees. Approximately 50% of cards also include a rewards program, such as cash back, points, or airline miles.

We first provide evidence that credit card issuers target unsophisticated customers with more back-loaded or hidden card features than sophisticated ones, holding all other observable characteristics constant. Our measure of sophistication is the educational attainment of a household, such as high school, college education, and more than college. We run hedonic regressions of different card features on dummies for educational attainment while controlling for income level, age, gender, and marital status, as well as for the monthly fed funds rate and state-level fixed effects. Lower educational attainment is correlated with higher late fees, higher over-limit fees and higher default APRs, but these customers are more likely to receive low introductory APR offers and zero annual fees. The reverse is true for sophisticated consumers. We show that these results hold even if we control for bank fixed effects in the regressions. This means that these differences in targeting strategies are not a cross-bank phenomenon, but even a given bank differentially targets different customer groups. We also show

that the design of card offers that are sent to less-educated consumers are more likely to display back-loaded terms like late fees, over-limit fees, or default APRs on the last pages of the offer letters, but not in the main text.

Since credit card terms are offered to customers as a bundle, we carefully explore the correlation structure of terms across cards. We find strong positive correlations among all back-loaded card features (late fees, over-limit fees, default APRs and low introductory APRs), and these features are negatively correlated with front-loaded card features (annual fees and regular APR). Similarly, a principal component analysis allows us to sort cards into generally more forward- or back-loaded fee structures. When regressing the loading of each card on the first principal component on our sophistication measure, we find consistent with prior results that less-sophisticated households are more likely to receive card offers with a bundle of back-loaded characteristics.

To document that these card terms affect the pricing of the cards, we follow the approach pioneered in Ausubel (1991) and use changes in the federal funds rate (FFR) as shocks to the banks' cost of funding. This allows us to analyze which card features banks use to pass their costs on to consumers. We again find a strong asymmetry: credit cards that are offered to less-sophisticated consumers, strongly increase their late fees and over-limit fees when the FFR increases, but not their upfront fees. In contrast, cards offered to sophisticated consumers show a greater response of the front-loaded terms when the FFR increases than are the back-loaded terms. This pattern supports our prior finding that the pricing of the first set of cards is conducted via back-loaded fees, while cards offered to sophisticated consumers are priced via the regular APR.

Second, we find that even conditional on borrowers' observable characteristics, credit card issuers use rewards programs to screen borrowers for unobservable differences in sophistication by offering them a menu of cards. This means we can compare the pricing of different cards while holding constant the borrower fixed

effect. We show that cards that have rewards programs, such as low introductory APRs, cash back or points, rely more on back-loaded fees. In contrast, cards with airline miles programs, which are predominantly offered to the most educated groups in the population, have significantly higher upfront-fees but lower back-loaded fees. These results hold even if we control for bank fixed effects, which means that banks run mini-experiments to separate more-sophisticated from less-sophisticated borrowers. It is in the interest of card issuers to separate these two groups when using a back-loaded pricing strategy, since more-sophisticated borrowers might be able to avoid back-loaded fees and only benefit from the low upfront rates, e.g. teaser rates.

Third, we show that banks seem to understand that reliance on back-loaded or shrouded features can affect the credit risk of their borrower pool because it changes which customers take up these credit cards. This trade-off has previously not been analyzed in the literature. If borrowers do not understand all the credit terms or miss the hidden fees in the offer, this strategy could attract customers who ultimately cannot afford the credit they take on and default when the fees come due. This risk creates risks to the bank and limits how heavily lenders should rely on these strategies.

To test if banks are more willing to rely on back-loaded features when unsophisticated borrowers are more credit-worthy, we look at exogenous shocks to customer creditworthiness. This approach also helps us to differentiate the role of credit risk from sophistication. In particular, we use changes in state-level unemployment insurance (UI). UI increased in a staggered fashion across several US states over the last decade by providing higher levels of insurance and longer benefit periods. By reducing the impact of employment loss on an employee's cash flows, increases in UI also reduce a lender's exposure to one of the largest economic shocks that households can experience. We use a standard difference-in-difference estimator to regress changes in card features on UI changes across

states. Our results show that increases in UI levels lead to an increase in the fraction of card offers with low introductory APRs but high back-loaded fees, such as late fees, default APRs and over-limit fees. Interestingly, we also find that offer letters use more colors and move back-loaded features to the last pages of the letter in response to an UI change. In line with our hypothesis, we find that the back-loadedness of card terms increases especially for less sophisticated households, by interacting the UI dummy with the education level of the households. Taken together, these results suggest that credit card companies realize that there is an inherent trade-off in the use of back-loaded features in credit card offers: They might induce customers to take on more (expensive) credit, but at the same time, they expose the lender to greater risk, if those consumers do not anticipate the true cost of credit.

How can we interpret the results documented above? On the side of the behavioral contract theory literature, there are several recent models of the credit card market that are in line with our findings. These models suggest that the three-part tariff we see in the credit card market can be optimal if customers do not understand their actual cost of credit. These consumers will demand credit as if they were facing only the low (introductory) APR but not the back-loaded fees. A rational consumer who understands the full cost of credit would instead reduce borrowing to avoid late fees or over-limit fees, but this practice is not optimal for card issuers if consumers are rational because it reduces the infra-marginal rents they can extract. The mistakes consumers make can either be due to not understanding the contract terms (myopia) or their own demand. Gabaix and Laibson (2006) suggest that companies can attract myopic consumers by offering low base prices but break-even by charging high prices for hidden, or shrouded features. Heidhues and Koszegi (2010, 2016) derive similar predications but assume that borrowers have self-control issues and underestimate the likelihood of being tempted in the future. Or Grubb (2009) proposes that consumers cannot

forecast the variance of their future demand. These models do not assume that issuers earn excess rents, since, in a competitive market, the salient terms of contracts (e.g. the teaser rate) might be driven below marginal costs and the late fees would be used to break even in expectations.

Consistent with these predictions, we find that less-educated consumers are offered cards, where the prices of front-loaded or salient card features are driven down, while the contract features that consumers do not focus on are very high (e.g., late fees and over-limit fees). Conversely, in markets with predominantly sophisticated consumers, we do not find pricing below marginal cost because these consumers can see through add-on pricing and can avoid costly back-loaded features.

In contrast, how would models with rational consumers explain these findings? A plausible model with rational consumers would be one where consumers value back-loaded fee structures if they are very credit constrained today but expect to be less constrained in the future. These borrowers might be willing to trade low interest rates today for high fees and interest rates in the future. While such a model is in line with the basic (back-loaded) contract structure we document, several findings in our data are difficult to reconcile with this model: First, if rational, but credit constrained borrowers are looking for cards that allow them to delay interest payments, late fees and back-loaded fees should be very prominent in the contracts because they represent a service that consumers are selecting. This is not what we find: high late or over-limit fees are always printed in small font and on the last page sof the offer letter. This is especially prominent for offers made to less-educated consumers. Second, maybe most importantly, if back-loaded fees are a way to shift interest payments to the future, these fees should go down when customers become more credit worthy (via the shocks of UI increases). Instead, we find the opposite, which runs counter to the predictions of a rational model. Finally, the steep non-linearity of late fees

seems to run counter to the idea that the late fees are an interest rate because they do not take into account the actual balance that the borrower carries.

The rest of the paper is structured as follows. Section I provides a detailed literature review. In section II, we present the data used in the study, the variables we constructed for the paper, and the design of the sample. Section III summarizes the results for how credit card companies target consumers, while section IV focuses on credit card screening. In section V, we describe our difference-in-difference analysis using unemployment insurance shocks to borrower credit risk. Section VI concludes.

I. Literature Review

By focusing on the supply side of credit, our paper complements a growing literature in household finance on the demand side of the credit card market and credit card usage. Agarwal et al. (2008) analyze more than 4 million credit card transactions to show that customers, on average, pay significant fees (late payment fees and penalties) of approximately $14 per month, which does not include interest payments. These results confirm that fees indeed have a significant bite and that customers are not able to optimally avoid all the negative features of their cards. That paper also shows that customers seem to learn to reduce fees over time. However, this learning is relatively slow, as payments fall by approximately 75 percent after four years. Using a similar data set, Gross and Souleles (2000) show that consumers respond strongly to increases in their credit limits, especially to interest rate changes such as low introductory teaser rates. The long-run debt to interest rate elasticity is approximately -1.3, where more than one-half reflects net increases in total borrowing (rather than balance transfers). In related work, Agarwal et al. (2010) document that consumers who respond to inferior lender offers have poorer credit characteristics ex ante and

default more often ex post. Similarly, Agarwal et al. (2009) show that over the lifecycle, middle-aged households obtain the best credit terms, while older customers select worse credit terms. The authors conjecture that deterioration in cognitive ability could explain why older people choose worse terms. These papers provide important confirmation that credit cards with disadvantageous features are being taken up and have a significant impact on the borrower's cost of capital. Similarly, in the context of health club memberships, DellaVigna and Malmendier (2004) provide convincing evidence that consumers systematically choose contracts that lead them to overpay per gym visit because they are overconfident about their actual health club attendance.

Our study is related to a number of papers documenting considerable heterogeneity in the pricing of retail financial products, even in the face of increasing competition. For example, the seminal paper by Ausubel (1991) documents that credit card companies have very low pass-through rates for changes in their cost of capital. Hortacsu and Syverson (2004) and Bergstresser et al. (2009) show that wide dispersion in fees in the mutual fund industry is related to changes in the heterogeneity of the customer base. More recently, Sun (2014) and Celerier and Vallee (2015) show that even with the introduction of increased competition, price dispersion does not decrease and product complexity might increase. 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 because customers seem to be insufficiently price sensitive. Similarly, Gurun, Matvos and Seru (2016) show that areas with large house price increases and expanding mortgage origination saw increases in marketing expenses and marketing solicitations. Similarly, a recent paper by Agarwal et al. (2016) follows our methodology and analyzes the back-ward loading of mortgage contracts in areas with increased banking competition. These results suggest that firms

compete on nonfinancial dimensions, such as advertising, to substitute for price competition.

Finally, a large literature in economics and marketing has looked at how individuals respond to how product features are displayed when choosing 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 color Yellow Pages ads are viewed longer and more often than black-and-white ads. Similarly, Lohse and Rosen (2001) suggest that the use of colors, photos or graphics increases the perceived quality of the products being advertised and enhances the credibility of the claims made about the products compared with non-color advertisements. Heitman et al. (2014) document that how prices and add-on features are displayed significantly affects how well people choose among products. Besheres, Choi, Laibson and Madrian (2013) show that even when subjects are presented with information about mutual funds that is very transparent and easy to digest, they select dominated savings vehicles. Bertrand et al. (2010) show that the advertising content can indeed have a significant impact on product take-up and even willingness to pay. They set up a field experiment as part of a consumer lender's direct mailing campaign in South Africa and found that advertising content that appeals to emotions (such as a woman's face versus a man's) or more simply displayed choices leads people to accept much more expensive credit products. We build on this earlier literature by analyzing whether firms deliberately incorporate these behavioral biases when designing credit card offers.

Han, Keys and Li (2013) use a very similar data set but focus on a complementary topic. The authors use Comperemedia data between 2007 and 2011 to document the large expansion in the supply of credit card debt in the 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 rather than sub-prime customers. In addition, they show that even customers who have previously declared bankruptcy have a high likelihood of receiving offers, but these offers are more restrictive.

II. Data and Summary Statistics

A. Data Description

We use a comprehensive dataset from Mintel (also known as Comperemedia) that contains information on the types of credit card offers that customer with different characteristics receive in the US. These data are based on a monthly consumer panel of more than 4000 households, which are paid to collect all direct credit card mailers and send the originals to Mintel. For this data collection effort, Mintel selects households based on their demographic and economic characteristics in order to create a representative sample of the population of US credit card holders. 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, and zip code. Each month, Mintel collects all credit solicitation mailers received by the household, such as credit cards, home equity loans and mortgage offers. We only observe offers to the entire household, usually to the head of the household.

After gathering the physical credit card offers from the households, Mintel manually scans the mailers to produce PDF versions and electronically enters some key information, which is usually contained in the Schumer box: regular purchase APRs, balance transfer APRs, cash advance APRs, default APRs, credit limits, annual fees, late fees (penalties), over-limit fees, etc. We manually check the quality of the dataset and find that all the variables are adequately collected, except default APRs, which have many missing values.

Our data covers the period from March 1999 to February 2011. However, we also repeated our analysis excluding the post-2007 data to abstract from the impact of the financial crisis and the CARD Act. The results are unchanged. For each month, there are approximately 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. 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 confirm the quality of the Mintel data. We find that most variables are coded accurately. One exception is the default APR, which seems to have many missing entries.

We also create a second data set based on the Mintel information by using all the scanned 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 is located on the mailers. However, Mintel only keeps scanned images of approximately 80% of the credit card offers (approximately 803,285 out of the 1,014,768 scanned credit card offers are complete). Mailers are more likely to be missing in the first two years of the sample, and there are also later offers with randomly missing images. However, we verify that, with the exception of the time trend, the missing observations do not seem to have any observables biases.

We extract information on reward programs and soft information on the design of the mailer itself from these scanned images. First, we use OCR software to transfer all the images into Word documents. The OCR software we use is OmniPage Professional version 18.0, a leading document imaging software that is accurate and fast. The OCR software separates the characters and graphics/background patterns from the original documents (i.e., the scanned credit card offers), recombines them based on original digital documents' design and turns them into editable Word documents. Then, we use a keyword searching algorithm to search for the reward programs in each offer. We are able to identify

8 commonly used reward programs: cash back, points, airline mileage, car rental insurance, purchase protection, warranty protection, travel insurance, and zero introductory APRs.

Moreover, because we keep the formatting information for each character in the offer, we can also record the format design of these reward programs. Using Word in VBA, we are able to identify the fonts. We collect the size and color of each reward program when they were mentioned in the offer letter, as well as whether they were highlighted with bold or italic text. Additionally, we count the number and size of the pictures on each page. To check the quality of the OCR and keyword searching algorithm, we randomly select some offers and check them manually, the accuracy is over 90%. As we previously mentioned, there are some values for default APRs missing from Mintel's hand-collected database. To address this missing data, we use the keyword searching algorithm to search for the default APRs stated in the offers. Usually, the Schumer box contains the default APRs, which is sometimes called the penalty APR. We extract default APRs from the scanned images of all credit card offers using our algorithm and compare them to the rates collected by Mintel. The accuracy of our algorithm is approximately 98%. In this way, we are nearly able to complete the default APRs data. Because only 80% of the sample includes the scanned offers, our variables for reward programs and format are limited to this 80% sample.

B. Descriptive Statistics

Table 1 describes the summary statistics of the main variables used in the paper. In Table 1, the first twelve variables are based on our full sample of 1,014,768 mail offers from Mintel. APR is the regular purchase APR listed in the credit card offer. If the regular APR is a range, we pick the midpoint as the APR. The mean APR of the 982,767 total mailings received by consumers is 12.65%. 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 19.89% and the standard deviation is 4.28%. For the default APR, instead of default APR levels in the offers, we use the dummy for whether the credit card offer has default APR or not. The reason is that approximately 30% of the credit card offers don't have default APRs. For the offers with default APRs, the mean is at 26.51%, which is higher than all other APRs. The high default APRs is not surprising because 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 compounded monthly.

Intro_APR_regular, Intro_APR_balance and Intro_APR_cash are dummies indicating whether the offer has 0% introductory APR (or very low introductory APR) for regular purchases, balance transfers and cash advances, respectively. Max Card limit is the natural log of the maximum credit card limit stated in the offers. We only have 526,949 observations for Max Card limit because many credit card offers do not specify a limit, especially after 2008.

Credit cards also have a number of different fee types; the dimensions that we observe in the data are the annual, late, and over-limit fees. Annual fees on average are $12.29 with a standard deviation of 31.99. The distribution of annual fees in our sample is quite skewed: 81.5% of the mailed offers have no annual fee, and the maximum annual fee is $500. Typically, cards that have annual fees offer mileage programs and other expensive value-added services. A late fee is the onetime charge incurred when the consumer does not pay at least the minimum monthly payment by the due date. This is a dollar value rather than a rate. In our sample, late fee has a mean of $33.83, a standard deviation of 6.17, and a max of $85. Its distribution is much less skewed than that of the annual fee. Approximately 90% of credit card offers have late fees ranging from $29 to $39. This fixed monthly fee comes due if the minimum payment has not been made,

independent of the size of the balance. Thus, this fee can be especially high for small balances.

Finally, an over-limit fee is charged when the consumers' credit card balance goes over the card limit. The mean of over-limit fee is $29.74 with a standard deviation of $10.16. The distribution of the over-limit fee is also concentrated: approximately 87% of the cards have over-limit fees ranging from $29 to $39. Although credit card companies usually charge no annual fee, they charge much more for late payments and over borrowing.

The remaining variables in Table 1 are based on the 80% sample of mail campaigns for which we have scanned images of the credit card offers. "Size" is the maximum size of the reward programs minus the average size of all characters on every page of each credit card offer. For example, if "cash back" appears in the offer 3 times, we pick the largest one. "Size" equals this largest number minus the average size of all characters on the same page. The size is drawn directly from Word document. The variable "Size" has a mean of 4.71 mean and a standard deviation of 5.49. The maximum value of Size is 143.63 because some offers use 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 use larger characters to emphasize the paragraphs that describe the reward programs compared to the nearby paragraphs. The size differences between them should be the measure highlighted. Moreover, "Color" is a dummy indicating whether the reward programs in the offer highlighted in color rather than in black and white. We focus on the characters describing the reward programs rather than on the entire offer because most credit card offers use some color, especially later in the study period. "Bold" is a dummy indicating whether the offer used bold to highlight its reward programs.

"Picture" is the file size of each page of the offer, which measures how many or how "fancy" the pictures in the offer are. We do not use an actual count of the

pictures or the size of the pictures because our algorithm considers the background of the page as a big picture (usually it is just a large, plain color picture). Using the storage size of each Word document, we can approximate the complexity of the page design. Other features, such as characters, also increase file size. However, pictures in Word documents usually take most of the file storage. Thus, we think that file size is a good measure of pictures in the credit card offers. The variable "Picture" is the file size, and the unit is megabytes (MB). The mean of "Picture" is 0.23 MB with a 0.26 MB standard deviation.

Finally, we are able to code the reward programs based on the PDF images. We define "Reward" as the number of reward programs, CASH, POINT and Car rental insurance, included in each offer. We choose these three reward programs because they are similar and most commonly used. CASH, POINT, MILE, Carrental, Purchaseprct are dummies indicating whether the offer includes these reward programs. Finally, FFR is the monthly average federal fund rate from January 1999 to December 2011. We merge FFR into our credit card dataset for each month.

[Place Table 1 here]

C. Credit Card Design

Table 2 summarizes the physical design of the credit card offers to document how and where certain features of the card are displayed in the letter. All credit card offers state late fees, default APRs, over-limit fees, and annual fees because their disclosure in the Schumer box is mandated. However, only 5.8% of the credit card offers mention late fees on the first page; 4.97% mention default APRs on the first page, and 6.96% mention over-limit fees on the first page. Not surprisingly, credit card offers usually do not mention fees, especially those that typically are back-loaded on the first page. On the other hand, 79.28% of the

credit card offers include annual fee information on the first page. However, as we will document below, annual fees are usually associated with cards that are offered to more-educated, higher-income customers. Similarly, reward programs are usually mentioned in the first page of the offers; 100% of cash back and mileage programs are mentioned in the first page. For point reward, car rental insurance, and zero introductory APRs, the likelihood of appearing on the first page is 93.51%, 80.48%, and 91.04%, respectively.

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

[Place Table 2 here]

III. Customer Characteristics and Credit Card Features

We start by analyzing how the offer features vary with the observable characteristics of the customers. In other words, how do credit card companies target their offers to customer types? The characteristics we observe in Comperemedia for people receiving these offers parallels the information that banks 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 stand for a bundle of characteristics. Because clients stay in the data set for only a limited time (they usually do not work for Mintel over many years) we follow not individuals but "cells" that can be thought of as bundles of characteristics. For example, we can observe the types of offers that a typical household in a middle-income group or a certain educational level receives over time or from different issuers. For each cell, we have several people

with the same characteristics in the sample who provide their information, and we are thus able to estimate their typical offer structure.

In Table 3, we run a simple hedonic regression model of card features, such as APRs, late fee, or reward programs, on customer characteristics. The characteristics of interest to us are the education levels of customers, which are measured as five distinct educational achievement dummies ranging from below high school to completed graduate school. We also consider nine income groups (annual household income) ranging from less than $15,000 to over $200,000. In these regressions, we also control for age group fixed effects of the customer, state fixed effect, dummies for household composition and credit card company fixed effects. Standard errors are clustered at the demographic cell, which is constructed by state, age, income, education and household composition.

[Place Table 3 here]

In Column (1) of Table 3, we start with the regular purchase APR as the dependent variable and report the coefficients on the education levels. Figure 1 plots the regression coefficients on education levels. Figure 2 plots the regression coefficients on income levels. The results show that the regular APR decreases significantly for higher-income groups, and the results are relatively monotonically increasing with income. The magnitude of the effect is quite large. Between the lowest and the fourth-highest income groups, the difference in mean APR is almost 0.6 percentage points, which is a significant difference. The relationship between APR and income drop off a little for the three highest income groups, but we 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 re-estimate the regression for the APRs on balance transfers and cash

withdrawals and obtain very similar results; these regressions are not reported but can be obtained from the authors. These results intuitively suggest that higher-income customers have lower credit risk and thus enjoy lower costs of capital. Interestingly, this is not true for more-educated customers, suggesting that people of similar educational achievement might vary considerably in their income and, thus, in their credit worthiness.

[Place Figure 1 and 2 here]

Interestingly, we find that late fees and the probability of having default APRs increase significantly with customer income but drop with higher educational attainment. For example, the difference in the late fees of the lowest and highest income groups is approximately $0.6. Thus, customers with higher incomes actually face higher late fees than those with lower incomes. The same pattern holds for default APR. In contrast, customers with more education receive card offers that have smaller late fees, lower probability of having default APRs, and lower over-limit fees. On the other hand, in Column (5), front-loaded annual fees are significantly higher for households with more education. These results are a first indication that interest rates and fees are set not just with an eye toward credit risk but also toward the sophistication of the customer. Moreover, we look at low introductory APR offers in Column (6). These usually expire after a few months (customarily after 6 to 12 months), and a higher interest rate then applies. Introductory APR programs are predominantly offered to less-educated or lower-income customers. A similar relationship holds for introductory APR rates on balance transfers.

We create a combined measure of how back-loaded a card is overall by calculating the first principal component of the card terms, including regular APR, over-limit fees, late fees, zero introductory APR dummy, and annual fee.

The results are presented in Appendix Table A2. The first principal component loads very negatively on front-loaded features, such as annual fees and APR, and positively on back-loaded fees, such as late fees and over-limit fees. When we estimate a hedonic regression on this combined measure that we called Backward. In column (7), we see the same very significant pattern: back-loadedness decreases significantly with the education level. Interestingly, the same is not true for income. In fact, richer people tend to receive more back-loaded card terms (controlling for education).

In Table 3 Column (8), we look at how mileage reward programs are offered to customers and observe a very different pattern compared to the Introductory APR program. In Column (8) the dependent variable is a dummy that equals one if the credit card offer contains a mileage program. 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 education group are more than six percentage points 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, education is dominant factor in explaining who receives a miles programs. It is important to remember that these regressions control for other household characteristics such as income or neighborhood effects which could potentially be correlated with education, which makes the strength of these results even more surprising.

In a next step, we now look at differences in how the information is displayed in the credit card offer across different consumers. In Table 3, Column (9), Format is a combined measure of a number of different dimensions of the layout of the offer letter: we look at the first principal component on font size, whether colors other than black is used, whether the text is in bold and the use of pictures and their size in the credit card offers. We believe that this measure captures how elaborate the offer looks like. We show that more-educated households are sent

more elaborately designed credit card offers, which usually use larger fonts, more colors, bold text, and more pictures to emphasize the reward programs. But when looking at where specific information about back-loaded fees is displayed, we find a differential approach for educated versus less-educated consumers. In Column (10), Back_LateFee is the dummy for whether the late fee information is displayed only at the back pages of the offer letters. We show that offers sent to less-educated households usually display late fees on the last pages of the offer letters. Column (11) repeats a similar analysis for default APR, and also shows that information about default APRs is displayed on the last pages of the offer letters. This evidence suggest that credit card companies tend to shroud the back-loaded pricing terms especially when sent to less-educated households.

Taken together, these results suggest that different reward programs and marketing strategies are used to target different customers groups. Introductory APR offers are primarily offered to less-educated and poor clients. Miles is the only reward program that is predominately targeted to richer and, importantly, more-educated customers. Credit card companies tend to hide the back-loaded pricing terms on the back pages of offer letters, especially for less-educated households.

A. Robustness Checks

One dimension that we do not have in our main data is the FICO score for individual borrower, since Mintel is not allowed to provide credit card information to individuals. To analyze the role of FICO scores for our analysis, we obtained Mintel data via the CFPB. While the data set available at the CFPB covers a shorter time period than ours (starting in 2000), they have the advantage of including FICO scores. The idea it to see whether the pricing relationships documented in our paper differ significantly when including FICO score. For this

purpose, in Table A5 in Appendix, we repeat our hedonic regressions of card features on customer characteristics, adding FICO scores as an additional explanatory variable. Adding the FICO scores does not add additional explanatory power to the regression. The R-squared of the regressions don't increase a lot, and all our results in Table A5 remain when including the FICO scores. Overall, it appears that the dimensions spanned by the FICO scores don't absorb the variations of the other observable characteristics used in the paper. These results alleviate concerns that we are missing an important, and un-spanned dimension of customer characteristics.

A second robustness check we undertake to confirm the results from our PCA, is to estimate directly how issuers trade off front-loaded and back-loaded credit card terms. In Table A4 in the Appendix, we regress regular APRs on late fees; we also control for the fed fund rate (FFR) in the month the offer was made. The tables shows that a $1 increase in the late fee is associated with an approximate 0.6 percentage point decrease in the regular APR. These results even when controlling for bank and borrower fixed effects. We also find that this trade-off is steeper for less-educated consumers, as suggested in the hedonic regressions in Table 3. We repeat this trade-off analysis between late fees and annual fees in Table A4B in Appendix and find very similar trade-off patterns.

IV. Screening and Pricing of Credit Cards

In a next step, we want to understand how the pricing of credit card offers changes when the cost of capital for the issuers changes. Specifically, we draw on the idea pioneered in Ausubel (1991), who uses changes in the Federal Fund Rate (FFR) as shocks to banks' cost of capital. This approach will allow us to understand which parts of the credit card contract are important for the issuer to receive rents from the borrower and to break even on the loan pool in expectation.

If cards that are offered to less-educated consumers are more reliant on back-loaded features, we should see that for these cards, back-loaded terms respond more strongly to shocks in the FFR than front-loaded features. The opposite should hold for cards offered to more-sophisticated consumers. Similarly, if cards with rewards programs, such as points, cash back or low introductory APRs, are used to screen for naïve consumers who pay via 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.

To test this relationship, in Table 4, our regression specification is:

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

$Y_{i,j,t}$ indexes the dependent variables we are interested in, such as regular purchase APRs, default APRs, late fees and over-limit fees. For example, $APR_{i,j,t}$ is the regular purchase APR offered by company i to consumer j at time t. FFR_M indexes the federal fund rate at month M. $LowEdu_{i,j,t}$ indexes the dummies indicating whether the education level of the household head is below college. We also control for fixed effects such state fixed effects, bank fixed effects, and household demographic cell fixed effects,[1] and t is at a daily frequency. We explore the sensitivity of APRs to the FFR by adding interaction terms between FFR and a dummy for less-educated borrowers.

We add bank fixed effects in all the specifications in Table 4. This allows us to control for the differences in pricing strategies between banks. So we test how different credit terms change for less versus more educated people in response to FFR changes for cards offered by the same bank. We cluster the standard errors at

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

the cell level. In Table 5, we then re-estimate the regression and interact FFR with dummies for different reward programs, such as miles and zero introductory APR programs. We also report the cash back and points reward program results in Appendix Table A3.

Education levels: In Table 4, we differentiate between cards that are issued to less- and more-educated borrowers. The low education dummy is equal to one for customers who have less than college education. The main coefficient of interest is the interaction term between FFR and the Low Education dummy. As discussed above, this approach follows Ausubel (1991) to test how different contract terms change with the FFR. We find a negative and significant coefficient on the interaction term, which means that the APRs offered to less-educated people are less sensitive to the FFR than those offered to more-educated consumers. In Column (2), we repeat the analysis using the annual fee of the card as our dependent variable. We again find that the estimated coefficient on the interaction term between the fed fund rate and the low education dummy is negative. In contrast, when looking at late fees and over-limit fees in columns (3) and (4) and default APR in column (5), we see that the interaction term is positive. This means that credit cards offered to less-educated people are more sensitive in these back loaded or hidden fees to changes in the Fed fund rate. The same is true for the use of introductory APR programs in column (6). Finally, we see that credit limits offered to less-educated people are less sensitive to changes in FFR in Column (7).

[Place Table 4 here]

These results support our hypothesis that for credit cards offered to less-educated households the back-loaded fees are the important pricing dimensions. Therefore, these back-loaded terms react to a change in the bank's cost of capital.

In contrast, for more educated customers the regular purchase APRs and annual fees of cards are much more sensitive to changes in the FFR. If more-educated people do not fall prey to back-loaded terms, a change in the cost of capital has to passed on through the regular purchase APR and annual fee.

Mileage Programs and Introductory APRs: In Table 5, Panels A and B, we focus on the pricing of cards with different rewards programs. The idea is to test whether cards with rewards program that are primarily offered to educated people, such as miles programs, show greater reliance on front-loaded terms, such as APRs and annual fees, while rewards programs offered mainly to less-educated people, such as low introductory APRs, rely on back-loaded pricing. These regressions parallel those in Table 4. We follow the same set of specifications as in Table 4 but interact FFR with the reward programs. In Table 5, Panel A, we find that cards that have miles programs have significantly higher regular APRs, much higher annual fees and much lower late fees or over-limit fees than cards without these programs. Again, it is important to note that these results hold even when we control for cell and bank fixed effects. Thus, we are identifying the variation in two different card offers sent to the same borrower type. Consistent with the results in Table 4, when we add an interaction term of FFR*MILES, we find that APR and annual fees are very sensitive to changes in FFR if the card has a mileage program, but late fees and over-limit fees are less sensitive. When we repeat these specifications in Panel B for cards with low introductory APR programs, we obtain the opposite results. For these cards, back-loaded terms (late fees and over-limit fees) are more sensitive to the FFR.[2] This confirms that

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[2] In Table A3 in appendix, we show that credit cards with cash back or points programs have pricing structures similar to those with introductory APR programs.

mileage programs are not priced via back-loaded features but via regular APRs and annual fees because sophisticated consumers see through add-on pricing.

[Place Table 5 here]

V. Shocks to Borrower Credit Risk: Unemployment Insurance

Finally, we 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 suggest that there is a countervailing force to how much card issues can rely on naiveté-based price discrimination. If back-loaded or shrouded card features attract not only myopic or present-biased but also lower credit quality customers, these can have an adverse effect on the card issuers. 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. However, this endogenously limits the extent to which banks should rely on this strategy.

To test whether banks take this dynamic into account, we use changes in the (state) unemployment insurance (UI) programs as exogenous shocks to the credit risk of customers. UI has increased in a staggered fashion across several US states over the last two decades. These changes provided higher levels of unemployment insurance and longer benefits periods. By providing households with a cash flow stream in cases of negative shocks, UI also reduces a lender's exposure to one of the largest negative economic outcomes that customers might suffer. We obtain data on the level of unemployment insurance (UI) from the US 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 to our credit card dataset. Following Hsu, Matsa and Melzer (2014), we use maximum UI benefits as the measure of unemployment protection. We define maximum UI

benefits as the product of the maximum weekly benefit amount (WBA) and the maximum number of weeks allowed. For example, in January 2000, Alabama allowed a maximum of 26 weeks of unemployment insurance over a 52-week period, and the maximum weekly benefit amount (WBA) was $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" as an increase equal to or greater than 10% within a year.

This allows us to use a standard difference-in-difference estimator to regress changes in card features on UI changes across states and over 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 small changes in a following year; 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. For example, 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 control for time fixed effects, cell fixed effects, and bank fixed effects. We re-estimated these regressions using other time windows, e.g., two-year windows, around the change, and the results are qualitatively and quantitatively very similar.

Table 6, Panel A presents the one-year difference-in-difference regression results between 1999 and 2007. We drop the years following the financial crisis of 2008. Because economic conditions worsened significantly in the years following the crisis, changes in UI after 2008 are likely to be endogenous to the economic distress of a state, and there may be concerns that other hidden variables drive our results. Overall, we find that card issuers rely more heavily on back-loaded and

shrouded terms when UI is increased and thus the riskiness of the borrowers is reduced. In Column (1), the dependent variable is the regular APR. The coefficient on the UI dummy is negative but not significant. However, in Column (3), we see that an increase in UI leads to a large and significant increase in late fees. In contrast, Column (4) shows that annual fees do not change significantly around UI changes, while in Column (5), 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*, to indicate whether the credit card offer has zero intro APRs for regular purchases, balance transfers, or cash advances. We find that card issuers indeed use more intro APR programs after UI increases have been implemented. In Column (6), we again use the first principal component as a summary of all the front- and back-loaded features as the dependent variable. We find that UI increases lead to significantly more use of back-loaded features. Overall, these results strongly support the idea that with the increase in UI issuers use a greater reliance on back-loaded payment features. Finally, in the last three columns of Table 6, Panel A, we look at the "softer" dimensions of the credit card offer. We see that after a UI increase, issuers are more likely to use colorful mailers. At the same time, the offers are more likely to move information about late fees and default APRs from the front of the offer letter to the end.

In Table 6, Panel B, we interact the UI dummy with dummy of less-educated households and with dummy of low income households. The coefficients of the interaction term between UI and less-educated households are significantly negative for regular APRs and significantly positive for default APR dummy, late fees, and first principal component "Backward". This suggests that, for less-educated households, increases in UI lead to more back-loaded pricing terms. In other words, when UI increases, banks tend to lower down the front-loaded terms while increase the back-loaded terms, especially for less-educated households.

[Place Table 6 here]

In addition, when we repeat all the regressions without the bank fixed effects, the results are quite similar to those in Table 6, and the estimated coefficients barely change. 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 within bank variation in decisions to change pricing policies based on UI changes.

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

VI. Conclusions

The results in this paper suggest that credit card companies target and screen sophisticated and naïve creditors differently by offering these groups of different reward programs and pricing structures. In line with the behavioral contract theory literature, the results show that cards offered to less-sophisticated customers rely more on back-loaded and shrouded terms. In contrast, more-sophisticated customers who would be able to avoid back-loaded terms while benefitting from lower introductory fees are offered more front-loaded terms in order for the lender to break even. These results support the insights of behavioral contract theory models, in particular, Gabaix and Laibson (2006), Heidhues and Kozsegi (2010) and, Grubb (2010), which suggest that card issuers will not offer shrouded terms on products that are demanded mainly by sophisticated consumers because they can undo these terms and thus reduce the rents that accrue to the firm. We find that issuers use reward programs to effectively segregate these

groups. Cards with miles programs, which appeal to educated consumers, are predominantly offered to sophisticated consumers and have front-loaded pricing. In contrast, cards with introductory APR programs are mainly issued to less-sophisticated consumers and carry more back-loaded pricing.

Finally, our analysis highlights an important dimension of the use of naiveté-based discrimination that has not been previously explored in the literature. The interaction between behavioral screening and classic adverse selection is more complex than noted in the prior theoretical literature. There appears to be a built-in trade-off between the immediate benefits of using naiveté-based price discrimination and the impact on the credit risk of the customer pool. By attracting customers who do not understand the credit terms that they are offered, the issuer might ultimately end up with a borrower pool that has a higher chance of not being able to afford the credit and thus of defaulting. Using changes in state-level unemployment insurance, which reduces the credit risk of borrowers, we show that card issuers rely more heavily on back-loaded terms when borrowers' credit risk is reduced. These findings suggest that card issuers are aware of the above trade-off.

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TABLE 1 – SUMMARY STATISTICS

Variable	Mean	Std. Dev.	Min	Max	Obs
FFR	2.68	2.14	0.07	6.54	156
APR	12.65	4.18	0.00	79.90	982,767
Max Card limit	10.05	1.37	6.21	15.42	526,949
APR_Balance	11.33	3.34	0.00	29.90	749,264
APR_CASH	19.89	4.28	0.00	79.90	942,430
Default APR Dummy	0.71	0.45	0.00	1.00	1,014,768
Annual_fee	12.29	31.99	0.00	500.00	1,003,977
Late_fee	33.83	6.17	0.00	85.00	1,001,221
over_limit_fee	29.74	10.16	0.00	79.00	898,636
Intro_APR_regular	0.47	0.50	0.00	1.00	1,014,768
Intro_APR_balance	0.47	0.50	0.00	1.00	1,014,768
Intro_APR_cash	0.06	0.23	0.00	1.00	1,014,768
Size	4.71	5.49	0.00	143.63	644,865
Color	0.32	0.47	0.00	1.00	644,865
Bold	0.36	0.48	0.00	1.00	644,865
Picture	0.23	0.26	0.00	4.10	803,285
Reward	0.68	0.77	0.00	3.00	803,285
CASH	0.21	0.41	0.00	1.00	803,285
POINT	0.24	0.43	0.00	1.00	803,285
MILE	0.09	0.28	0.00	1.00	803,285
Carrental	0.23	0.42	0.00	1.00	803,285
Purchaseprct	0.23	0.42	0.00	1.00	803,285

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 program in the offer, we put missing value to Size, Color, and Bold. Picture is the file storage size of the credit card offer images. The unit is megabyte (MB). We drop the year before 2003 due to a lot of missing scanned images of credit card offers. 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 Schumerbox.

TABLE 2 – DESCRIPTIVE STATISTICS FOR FORMAT DESIGN OF CREDIT CARD OFFERS

Panel A	Late fee	Default APR	Over limit fee	Annual fee	CASH	POINT	MILE	Carrental	Intro APR
% of cards that have	100.00%	100.00%	100.00%	100.00%	21.05%	23.83%	8.79%	22.74%	51.64%
Is term mentioned on 1st page	5.80%	4.97%	6.96%	79.28%	100%	93.51%	100%	80.48%	91.04%
Font size 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 if not mentioned on 1st page	9.57	9.63	9.50	13.76	10.62	10.80	9.91	10.04	10.62
Font color if mentioned on 1st page	33.98%	37.88%	27.73%	66.86%	40.13%	42.84%	47.12%	24.34%	32.28%
Font color if not mentioned on 1st page	24.67%	26.19%	27.73%	44.35%	37.24%	38.45%	29.47%	23.31%	32.29%
Font bold if mentioned on 1st page	38.59%	27.77%	35.07%	79.01%	47.24%	43.90%	56.34%	10.56%	53.15%
Font bold if mentioned on 1st 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
Panel B									
If term is on first page	29.38	28%	27.59	7.69					
If term is in the back (Schumer box)	35.10	27%	30.11	33.22					

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 envelope and the first page letter of credit card offers

TABLE 3 – CREDIT CARD FEATURES AND DEMOGRAPHICS

Dependent Variable	1 APR	2 Late Fee	3 Default APR Dummy	4 Over-limit Fee	5 Annual Fee	6 IntroAPR	7 Backward	8 MILE	9 Format	10 Back_LateFee	11 BackAPRDefault	12 LogMax CardLimit
FFR	0.352***	-0.242***	-0.041***	0.173***	-0.565***	-0.026***	-0.028***	0.008***	-0.014***	-0.011***	0.027***	0.005***
	(0.004)	(0.006)	(0.001)	(0.010)	(0.024)	(0.000)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)
Education_2	-0.046	-0.118***	-0.014***	-0.472***	-0.551***	-0.002	0.006	0.013***	0.070***	-0.005***	0.002	0.095***
	(0.030)	(0.045)	(0.003)	(0.051)	(0.162)	(0.003)	(0.007)	(0.002)	(0.007)	(0.002)	(0.003)	(0.009)
Education_3	0.026	-0.323***	-0.039***	-0.592***	-0.068	-0.015***	-0.032***	0.019***	0.075***	-0.009***	-0.008**	0.103***
	(0.032)	(0.045)	(0.004)	(0.056)	(0.169)	(0.003)	(0.008)	(0.001)	(0.008)	(0.002)	(0.003)	(0.009)
Education_4	-0.073**	-0.277***	-0.040***	-1.118***	0.352**	-0.026***	-0.076***	0.046***	0.160***	-0.013***	-0.002	0.205***
	(0.033)	(0.047)	(0.004)	(0.059)	(0.176)	(0.003)	(0.008)	(0.003)	(0.008)	(0.002)	(0.004)	(0.009)
Education_5	-0.004	-0.541***	-0.067***	-1.561***	1.326***	-0.049***	-0.140***	0.064***	0.190***	-0.017***	-0.017***	0.242***
	(0.035)	(0.052)	(0.004)	(0.068)	(0.201)	(0.003)	(0.009)	(0.004)	(0.009)	(0.002)	(0.004)	(0.010)
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	942,397	961,247	972,260	872,831	963,283	972,260	870,029	777,192	629,637	750,855	750,855	496,063
R-squared	0.253	0.157	0.148	0.177	0.233	0.159	0.008	0.075	0.080	0.235	0.145	0.607

Note: Table 3 shows the OLS regressions to estimate relationship between credit card features and consumer's demographics between 1999 and 2011. Data is restricted to offers we have scanned pictures from column 6 to 11. Format is the first principal component of reward programs' size, color, bold and the picture sizes on the credit card offers. Backward is the first principal component of regular APR, annual fee, late fee, over limit fee, and intro_APR after taking out the bank fixed effects and monthly fixed effects. Back_LateFee is the dummy for whether the late fee information is displayed only at the back of the offer letter. Back_APR_Default is the dummy for whether the default APR information is displayed only at the back of the offer letter. Education_2 is dummy for household head whose highest education is high school. Education_3 is for some college. Education_4 is for graduated college. Education_5 is for post college graduate. The missing category is the household head with education below high school. Standard errors in parentheses are clustered by demographic cells, which are based on states, age, income, education and household composition. Regressions are controlled by income fixed effects, age fixed effects, household composition fixed effects, state fixed effects and bank fixed effects.

TABLE 4 – RELATIONSHIP BETWEEN APRS/FEES AND EDUCATION

Dependent Variable	1 APR	2 Annual Fee	3 Late Fee	4 Over-Limit Fee	5 Default APR Dummy	6 Intro_APR	7 LogMaxCardLimit
FFR	0.755***	0.671***	0.007	-0.424***	-0.061***	-0.014***	0.013***
	(0.005)	(0.033)	(0.011)	(0.011)	(0.001)	(0.001)	(0.002)
LowEdu	0.163***	1.148***	0.007	-0.042	0.030***	0.011***	-0.053***
	(0.032)	(0.158)	(0.043)	(0.047)	(0.004)	(0.003)	(0.009)
LowEdu*FFR	-0.050***	-0.440***	0.101***	0.173***	0.003**	0.003***	-0.012***
	(0.008)	(0.048)	(0.014)	(0.016)	(0.001)	(0.001)	(0.003)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	785,950	800,546	798,936	749,306	808,430	808,430	463,490
R-squared	0.318	0.252	0.208	0.199	0.162	0.146	0.586

Note: OLS regressions to estimate relationship between education and credit card APRs and fees. Data period is from 1999 to 2007. Regressions in column 1 to 7 are controlled by household demographic cell fixed effects based on states, age, income, and household composition. We also control for bank fixed effects. LowEdu is a dummy for household head's education level below college (highest degree is high school). Standard errors in parentheses are clustered by cells.

TABLE 5 – MILEAGE PROGRAM VS. ZERO INTRODUCTORY APR PROGRAM

Panel A	1	2	3	4	5	6	7	8	9
	APR	APR	APR	Annual Fee	Annual Fee	Late Fee	Late Fee	Over-Limit Fee	Over-Limit Fee
FFR	0.796***	0.741***	0.728***	0.364***	0.213***	0.264***	0.385***	-0.226***	-0.096***
	(0.005)	(0.005)	(0.005)	(0.030)	(0.029)	(0.008)	(0.007)	(0.011)	(0.010)
MILE	2.009***	2.096***	1.526***	22.429***	15.681***	-1.654***	3.755***	-10.266***	-4.126***
	(0.022)	(0.023)	(0.042)	(0.231)	(0.453)	(0.057)	(0.092)	(0.089)	(0.186)
MILE*FFR			0.163***		1.918***		-1.539***		-1.756***
			(0.013)		(0.127)		(0.037)		(0.053)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	597,489	597,489	597,489	609,055	609,055	607,868	607,868	570,300	570,300
R-squared	0.114	0.321	0.321	0.281	0.281	0.240	0.251	0.297	0.303

Panel B									
	APR	APR	APR	Annual Fee	Annual Fee	Late Fee	Late Fee	Over-Limit Fee	Over-Limit Fee
FFR	0.797***	0.725***	0.897***	0.401***	1.101***	0.050***	-0.245***	-0.344***	-0.455***
	(0.005)	(0.004)	(0.005)	(0.026)	(0.035)	(0.008)	(0.009)	(0.009)	(0.012)
Intro_APR	-1.199***	-0.925***	0.285***	-9.088***	-4.047***	1.133***	-0.988***	1.969***	1.223***
	(0.013)	(0.014)	(0.023)	(0.096)	(0.153)	(0.020)	(0.028)	(0.032)	(0.045)
Intro_APR*FFR			-0.394***		-1.640***		0.690***		0.244***
			(0.006)		(0.045)		(0.010)		(0.015)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	785,950	785,950	785,950	800,546	800,546	798,936	798,936	749,306	749,306
R-squared	0.116	0.317	0.324	0.265	0.267	0.214	0.223	0.207	0.208

Note: Panel A shows OLS regressions to estimate relationship between mileage reward programs and credit card APRs and fees. Panel B shows OLS regressions to estimate relationship between zero intro APR reward programs reward programs and credit card APRs and fees. Data period is from 1999 to 2007. Data is restricted to offers we have scanned pictures in Panel A. Panel B includes the entire credit card offer sample with and without scanned pictures. Regressions in column 1 to 9 are controlled by household demographic cell fixed effects based on states, age, income, education, and household composition. Regressions in column 2 to 9 are controlled by bank fixed effects. MILE is the dummy of whether the credit card offer has mileage reward program or not. Intro_APR is the dummy of whether the credit card offer has 0 intro APR for regular purchase or not. Standard errors in parentheses are clustered by cells.

TABLE 6 – UNEMPLOYMENT INSURANCE AND CREDIT CARD FEATURE

| Panel A | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
	APR	Default APR Dummy	Late Fee	Annual Fee	Intro_APR_All	Backward	Color	DefaultAPR MainPage	LateFee MainPage
FFR	0.421***	-0.048***				0.006			
	(0.043)	(0.003)				(0.005)			
UI	-0.276	0.044	0.909**	0.271	0.123**	0.061*	0.027**	-0.011***	-0.012**
	(0.353)	(0.028)	(0.389)	(0.454)	(0.056)	(0.035)	(0.012)	(0.003)	(0.005)
UI_Pre_3M	-0.005	0.022	0.655***	-0.036	0.140*	0.050	0.015	-0.005	-0.010
	(0.120)	(0.021)	(0.185)	(0.361)	(0.077)	(0.040)	(0.017)	(0.005)	(0.009)
UI_Pre_6M	0.156	-0.068***	-0.204	-0.159	0.066	0.058**	0.012	-0.004	-0.001
	(0.269)	(0.024)	(0.450)	(0.714)	(0.043)	(0.024)	(0.008)	(0.004)	(0.010)
UI_Small	-0.052	-0.015	0.125	-1.321	0.065	0.020	0.010	-0.006	0.012
	(0.158)	(0.015)	(0.402)	(0.925)	(0.042)	(0.034)	(0.012)	(0.004)	(0.010)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,224	93,491	92,876	93,215	93,940	90,700	81,968	46,161	46,161
R-squared	0.263	0.410	0.179	0.193	0.121	0.100	0.038	0.054	0.029

Note: OLS regressions to estimate unemployment insurance effects on credit card features at 6 month frequency. Data includes the credit card offers from 1999 to 2007. All columns are controlled by year fixed effects, bank fixed effects, and cell fixed effects based on states, age, income, education and household composition. UI is the dummy which equals 1 if unemployment 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 pre-trend of the UI jumps. UI_Pre_6M is the dummy for 6 month pre-trend of the UI jumps. UI_Small is the dummy of the UI increases below 10% which are mainly due to inflation adjustments. In Panel B, LowEdu is a dummy for household head's education level below college (highest degree is high school). LowIncome is the dummy for households with annual income below 35k. Column 8 and 9 are OLS regression on whether default APR/late fees are mentioned on the main page of the credit card offers. Standard errors are clustered at the state level.

(*To be continued*)

TABLE 6 – UNEMPLOYMENT INSURANCE AND CREDIT CARD FEATURE - *CONTINUED*

Panel B	1 APR	2 Default APR Dummy	3 Late Fee	4 Annual Fee	5 Intro_APR_All	6 Backward	7 Color	8 DefaultAPR MainPage	9 LateFee MainPage
FFR	0.425***	-0.048***				0.005			
	(0.044)	(0.003)				(0.005)			
UI	-0.038	0.030	0.867**	0.695	0.135**	0.035	0.036***	-0.014***	-0.016***
	(0.304)	(0.030)	(0.354)	(0.432)	(0.053)	(0.037)	(0.010)	(0.005)	(0.006)
UI*LowEdu	-0.324***	0.021***	0.215**	-0.597	-0.013	0.059**	-0.006	0.005	0.006
	(0.109)	(0.006)	(0.100)	(0.487)	(0.019)	(0.028)	(0.007)	(0.005)	(0.006)
UI*LowIncome	-0.048	-0.004	-0.295**	-0.062	-0.013	-0.009	-0.025*	-0.001	0.000
	(0.127)	(0.017)	(0.119)	(0.590)	(0.018)	(0.031)	(0.013)	(0.006)	(0.011)
UI_Pre_3M	0.004	0.021	0.648***	-0.028	0.140*	0.048	0.015	-0.005	-0.010
	(0.118)	(0.020)	(0.187)	(0.360)	(0.076)	(0.040)	(0.017)	(0.005)	(0.009)
UI_Pre_6M	0.174	-0.070***	-0.216	-0.129	0.067	0.055**	0.012	-0.004	-0.002
	(0.281)	(0.024)	(0.454)	(0.725)	(0.042)	(0.024)	(0.008)	(0.005)	(0.011)
UI_Small	-0.041	-0.015	0.130	-1.306	0.066	0.018	0.010	-0.007	0.012
	(0.159)	(0.015)	(0.400)	(0.923)	(0.042)	(0.034)	(0.012)	(0.005)	(0.010)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,224	93,491	92,876	93,215	93,940	90,700	81,968	46,161	46,161
R-squared	0.263	0.410	0.179	0.193	0.121	0.100	0.039	0.054	0.029

Note: OLS regressions to estimate unemployment insurance effects on credit card features at 6 month frequency. Data includes the credit card offers from 1999 to 2007. All columns are controlled by year fixed effects, bank fixed effects, and cell fixed effects based on states, age, income, education and household composition. UI is the dummy which equals 1 if unemployment 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 pre-trend of the UI jumps. UI_Pre_6M is the dummy for 6 month pre-trend of the UI jumps. UI_Small is the dummy of the UI increases below 10% which are mainly due to inflation adjustments. In Panel B, LowEdu is a dummy for household head's education level below college (highest degree is high school). LowIncome is the dummy for households with annual income below 35k. Column 8 and 9 are OLS regression on whether default APR/late fees are mentioned on the main page of the credit card offers. Standard errors are clustered at the state level.

FIGURE 1

Figure 1 plots the estimated coefficients on education when we regress individual card features on dummies for different education levels (as provided by Mintel). The regression results are reported in Table 3.

FIGURE 2

APRS AND FEES BY INCOME
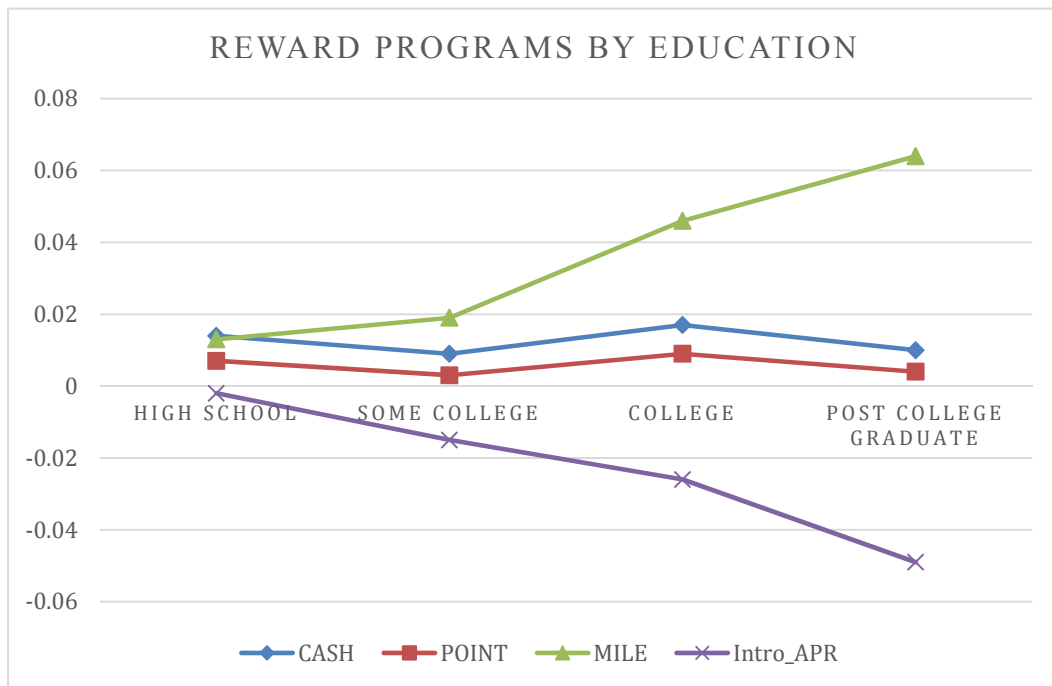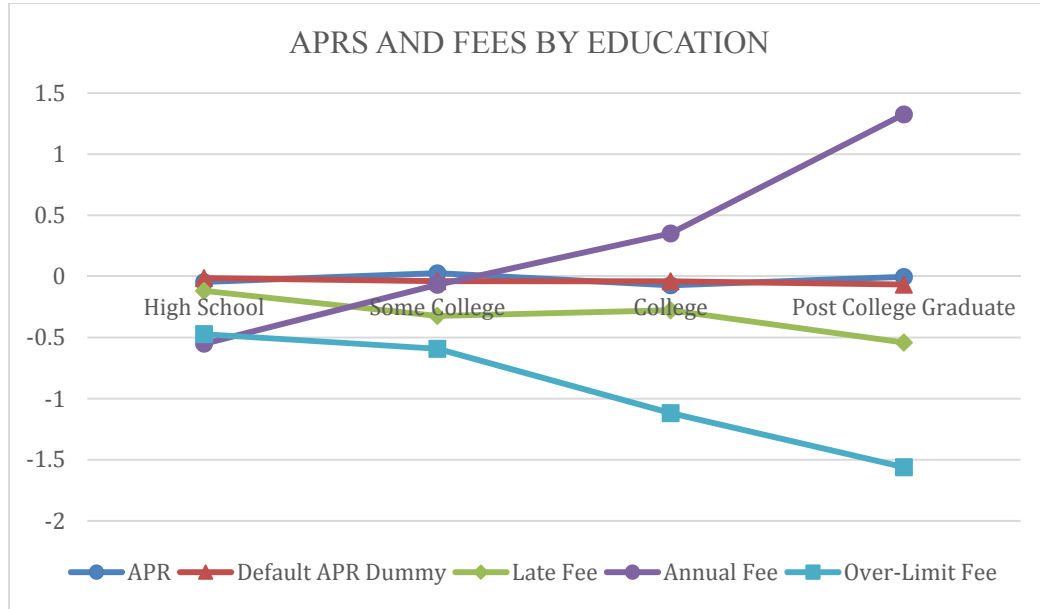
REWARD PROGRAMS BY INCOME
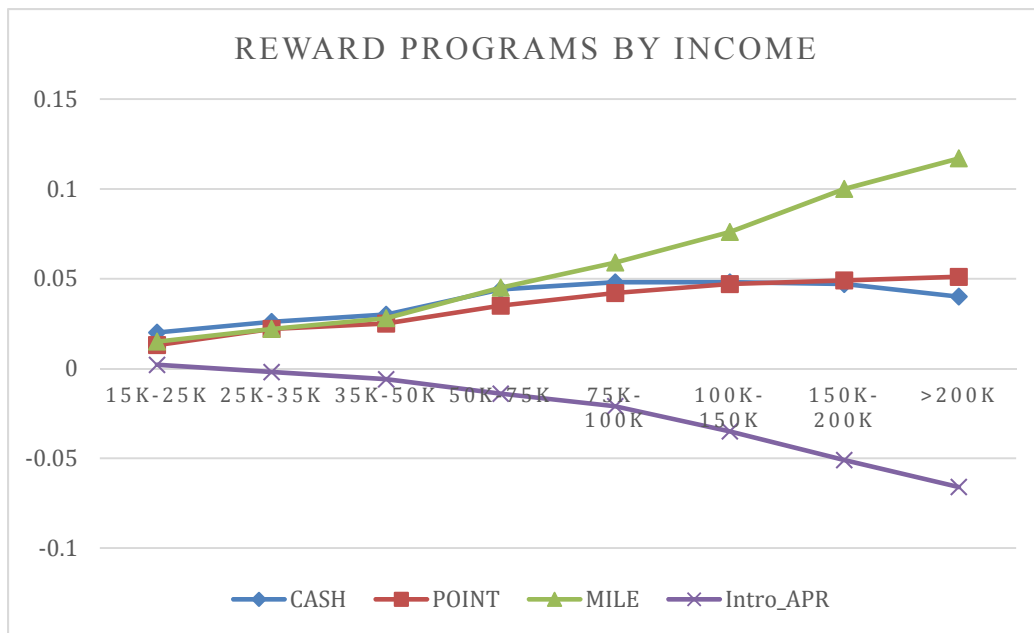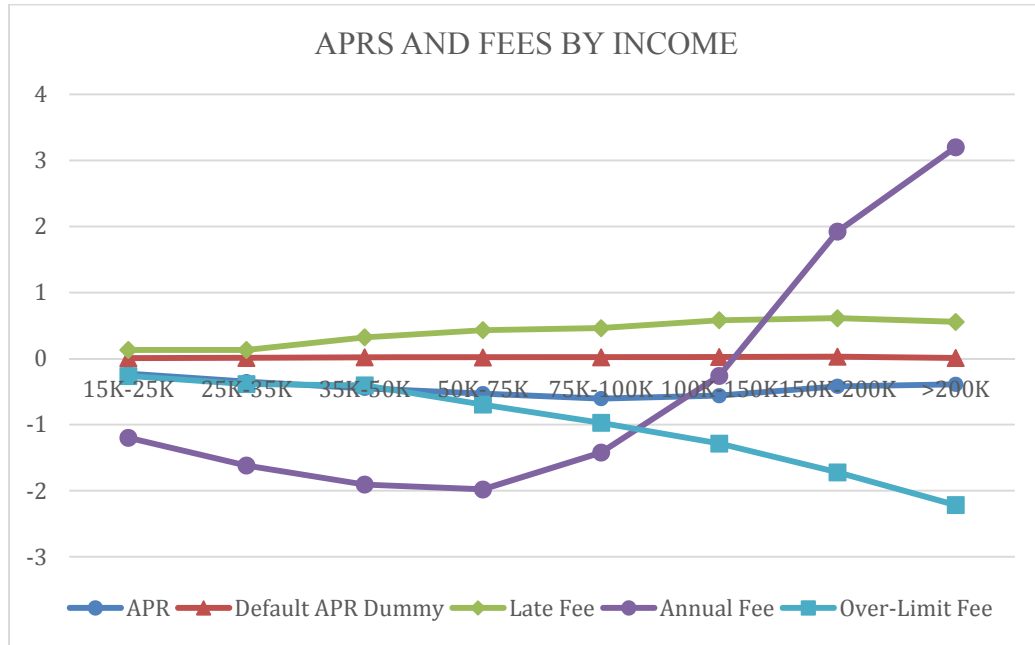
Figure 2 plots the estimated coefficients on the income when we regress individual card features on dummies for different household income levels (as provided by Mintel). The missing category is the household with annual income below USD 15,000.

APPENDIX

Panel A: Income

	Frequency	Percentage	Cum. Percentage
Less than $15,000	61,091	6.04	6.04
$15,000 - $24,999	78,154	7.72	13.76
$25,000 - $34,999	100,433	9.92	23.68
$35,000 - $49,999	150,700	14.89	38.57
$50,000 - $74,999	218,744	21.61	60.18
$75,000 - $99,999	197,131	19.48	79.65
$100,000 - $149,999	150,831	14.9	94.56
$150,000 - $199,999	34,653	3.42	97.98
Over $200,000	20,461	2.02	100
Total	1,012,198	100	

Panel B: Education

	Frequency	Percentage	Cum. Percentage
Below High School	74,167	7.63	7.63
Graduated High School	307,469	31.62	39.25
Some College	210,821	21.68	60.94
Graduated College	239,315	24.61	85.55
Post College Graduate	140,488	14.45	100
Total	972,260	100	

Note: Variables are based on Mintel's credit card's direct mail campaigns from March 1999 to February 2011. Mintel collects the income and education information from the households which receive the credit card offers. Income is the household annual income. Education is the household head education level.

Panel A

	Comp1	Comp2	Comp3	Comp4	Comp5
APR_res	-0.331	0.514	0.635	-0.468	-0.065
Annual Fee_res	-0.442	0.480	-0.106	0.642	0.389
Late Fee_res	0.405	0.607	-0.222	0.167	-0.625
Over-limit Fee_res	0.551	0.350	-0.160	-0.314	0.670
Intro_APR_res	0.477	-0.119	0.715	0.492	0.071
Eigenvalue	1.566	1.182	0.855	0.771	0.626
Variance Proportion	0.313	0.237	0.171	0.154	0.125
Cumulative Variance	0.313	0.550	0.721	0.875	1.000
Observations	895,633				

Panel B

	Comp1	Comp2	Comp3	Comp4	Comp5
APR	-0.425	0.481	0.122	0.737	-0.174
Annual Fee	-0.439	0.499	0.283	-0.517	0.460
Late Fee	0.437	0.572	0.142	-0.290	-0.615
Over-limit Fee	0.451	0.437	-0.558	0.187	0.510
Intro_APR	0.482	-0.050	0.757	0.266	0.347
Eigenvalue	1.839	1.093	0.785	0.712	0.571
Variance Proportion	0.368	0.219	0.157	0.142	0.114
Cumulative Variance	0.368	0.587	0.743	0.886	1.000
Observations	895,633				

Note: Panel A shows the principal component analysis on credit card regular APR, annual fee, late fee, over-limit fee, and intro APR dummy after taking out the bank fixed effects and monthly fixed effects. Column 1 to 5 are the eigenvectors of component 1 to 5 respectively. Panel B shows the principal component analysis on credit card regular APR, annual fee, late fee, over-limit fee, and intro APR dummy. Column 1 to 5 are the eigenvectors of component 1 to 5 respectively.

Panel A	1	2	3	4	5	6	7	8	9
	APR	APR	APR	Annual Fee	Annual Fee	Late Fee	Late Fee	Over-Limit Fee	Over-Limit Fee
FFR	0.301***	0.255***	0.347***	-0.908***	-1.162***	-0.108***	-0.140***	0.338***	0.008
	(0.005)	(0.005)	(0.005)	(0.032)	(0.041)	(0.007)	(0.007)	(0.013)	(0.014)
CASH	-0.453***	-0.165***	0.718***	-11.943***	-14.450***	0.849***	0.536***	-2.514***	-5.969***
	(0.013)	(0.012)	(0.019)	(0.086)	(0.155)	(0.022)	(0.026)	(0.053)	(0.094)
CASH*FFR			-0.352***		1.003***		0.125***		1.295***
			(0.006)		(0.044)		(0.010)		(0.027)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	753,690	753,690	753,690	771,535	771,535	769,923	769,923	693,714	693,714
R-squared	0.019	0.214	0.219	0.228	0.228	0.221	0.221	0.194	0.202
Panel B									
	APR	APR	APR	Annual Fee	Annual Fee	Late Fee	Late Fee	Over-Limit Fee	Over-Limit Fee
FFR	0.315***	0.258***	0.298***	-0.783***	-0.298***	-0.132***	-0.246***	0.379***	0.428***
	(0.005)	(0.005)	(0.005)	(0.032)	(0.028)	(0.007)	(0.008)	(0.013)	(0.014)
POINT	-0.673***	-0.062***	0.393***	1.240***	6.109***	1.511***	0.362***	-2.315***	-1.692***
	(0.013)	(0.012)	(0.021)	(0.120)	(0.268)	(0.015)	(0.023)	(0.050)	(0.087)
POINT*FFR			-0.165***		-1.783***		0.421***		-0.218***
			(0.006)		(0.076)		(0.008)		(0.028)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	753,690	753,690	753,690	771,535	771,535	769,923	769,923	693,714	693,714
R-squared	0.022	0.214	0.215	0.212	0.213	0.227	0.230	0.193	0.194

Note: Panel A shows OLS regressions to estimate relationship between Cashback reward programs and credit card APRs and fees. Panel B shows OLS regressions to estimate relationship between Points reward programs reward programs and credit card APRs and fees. Data period is from 1999 to 2011. Data is restricted to offers we have scanned pictures in Panel A. Panel B includes the entire credit card offer sample with and without scanned pictures. Regressions in column 1 to 9 are controlled by household demographic cell fixed effects based on states, age, income, education, and household composition. Regressions in column 2 to 9 are controlled by bank fixed effects. MILE is the dummy of whether the credit card offer has mileage reward program or not. Intro_APR is the dummy of whether the credit card offer has 0 intro APR for regular purchase or not. Standard errors in parentheses are clustered by cells.

	1 APR	2 APR	3 APR	4 APR	5 APR	6 APR	7 APR	8 APR	9 APR	10 APR
FFR	0.568***	0.459***	0.553***	0.444***	0.809***	0.671***	0.761***	0.666***	0.768***	0.670***
	(0.013)	(0.011)	(0.014)	(0.012)	(0.010)	(0.010)	(0.011)	(0.009)	(0.011)	(0.010)
LateFee	-0.057***	-0.016***	-0.045***	-0.002	-0.024***	0.023***	-0.077***	-0.017***	-0.043***	0.008***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
LowEdu			1.678***	1.384***						
			(0.089)	(0.079)						
LateFee*LowEdu			-0.043***	-0.039***						
			(0.002)	(0.002)						
Reward					1.945***	2.069***				
					(0.056)	(0.056)				
LateFee*Reward					-0.065***	-0.057***				
					(0.002)	(0.002)				
MILE							-2.193***	-0.906***		
							(0.092)	(0.086)		
LateFee*MILE							0.115***	0.080***		
							(0.003)	(0.002)		
Picture									0.828***	1.045***
									(0.157)	(0.141)
LateFee*Picture									-0.022***	-0.024***
									(0.004)	(0.004)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	936,641	936,641	936,641	936,641	773,694	749,983	749,983	749,983	749,983	749,983
R-squared	0.150	0.332	0.164	0.348	0.172	0.329	0.168	0.347	0.146	0.327

Note: OLS regressions to estimate relationship between regular APR and late fees in credit card offers. Data is restricted to offers we have scanned pictures in column 5 to 10. Regression in column 1, 2, and 5 to 10 are controlled by demographic cell fixed effects based on states, age, income, education and household composition. Regression in column 3 and 4 are controlled by demographic cell fixed effects based on states, age, income, and household composition. Regressions in column 2, 4, 6, 8 and 10 are controlled by bank fixed effects. Reward is the number of reward programs of CASH POINT and Car rental insurance in each offer. MILE is the dummy of whether the credit card offer has mileage reward program or not. Picture is the file storage size of the credit card offer images. The unit is megabyte (MB). LowEdu is a dummy for household head's education level below college (highest degree is high school). All regressions are controlled by year fixed effects. Standard errors in parentheses are clustered by cells.

	1	2	3	4	5	6	7	8	9	10
	Annual Fee	Annual Fee	Annual Fee	Annual Fee	Annual Fee	Annual Fee	Annual Fee	Annual Fee	Annual Fee	Annual Fee
FFR	-0.824***	-0.609***	-0.748***	-0.571***	-1.076***	-1.116***	-1.261***	-1.283***	-1.148***	-1.148***
	(0.063)	(0.057)	(0.061)	(0.055)	(0.085)	(0.077)	(0.082)	(0.074)	(0.086)	(0.077)
LateFee	-0.625***	-0.061***	-0.520***	0.034***	-0.092***	0.279***	-1.235***	-0.573***	-0.515***	-0.100***
	(0.011)	(0.007)	(0.013)	(0.008)	(0.010)	(0.007)	(0.016)	(0.011)	(0.012)	(0.008)
LowEdu			12.399***	8.051***						
			(0.632)	(0.413)						
LateFee*LowEdu			-0.364***	-0.256***						
			(0.018)	(0.012)						
Reward					44.955***	32.936***				
					(0.699)	(0.512)				
LateFee*Reward					-1.242***	-0.921***				
					(0.018)	(0.014)				
MILE							-56.262***	-31.103***		
							(0.642)	(0.484)		
LateFee*MILE							2.362***	1.669***		
							(0.018)	(0.014)		
Picture									5.744***	1.927***
									(1.181)	(0.246)
LateFee*Picture									-0.162***	-0.059***
									(0.033)	(0.007)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	957,656	957,656	957,656	957,656	767,502	767,502	767,502	767,502	767,502	767,502
R-squared	0.032	0.226	0.036	0.234	0.049	0.232	0.109	0.285	0.031	0.223

Note: OLS regressions to estimate relationship between annual fees and late fees in credit card offers. Data is restricted to offers we have scanned pictures in column 5 to 10. Regression in column 1, 2, and 5 to 10 are controlled by demographic cell fixed effects based on states, age, income, education and household composition. Regression in column 3 and 4 are controlled by demographic cell fixed effects based on states, age, income, and household composition. Regressions in column 2, 4, 6, 8 and 10 are controlled by bank fixed effects. Reward is the number of reward programs of CASH POINT and Car rental insurance in each offer. MILE is the dummy of whether the credit card offer has mileage reward program or not. Picture is the file storage size of the credit card offer images. The unit is megabyte (MB). LowEdu is a dummy for household head's education level below college (highest degree is high school). All regressions are controlled by year fixed effects. Standard errors in parentheses are clustered by cell.

	1	2	3	4	5	6	7	8	9
Dependent Variable	APR	Late Fee	Default APR	Over-limit Fee	Annual Fee	Intro_APR	Backward	MILE	Format
FFR	0.684***	0.499***	1.412***	-0.286***	0.437***	0.009***	0.025***	0.019***	0.065***
	(0.004)	(0.008)	(0.004)	(0.012)	(0.031)	(0.001)	(0.002)	(0.000)	(0.001)
Education_2	-0.007	-0.075	-0.106***	-0.128**	0.031	-0.008**	-0.004	0.005***	0.031***
	(0.028)	(0.051)	(0.028)	(0.058)	(0.168)	(0.003)	(0.009)	(0.002)	(0.008)
Education_3	0.031	-0.086*	-0.091***	-0.144**	0.518***	-0.016***	-0.021**	0.011***	0.054***
	(0.030)	(0.047)	(0.030)	(0.063)	(0.181)	(0.003)	(0.010)	(0.002)	(0.009)
Education_4	0.065**	-0.071	-0.124***	-0.485***	1.379***	-0.027***	-0.074***	0.031***	0.110***
	(0.030)	(0.051)	(0.031)	(0.066)	(0.187)	(0.004)	(0.010)	(0.002)	(0.009)
Education_5	0.182***	-0.111*	-0.134***	-0.829***	2.518***	-0.039***	-0.146***	0.045***	0.147***
	(0.033)	(0.057)	(0.034)	(0.076)	(0.213)	(0.004)	(0.012)	(0.002)	(0.010)
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	509,958	521,614	451,020	486,060	522,116	526,641	484,736	447,719	354,235
R-squared	0.381	0.161	0.500	0.238	0.294	0.185	0.019	0.101	0.139

Note: Table A5 shows the OLS regressions to estimate relationship between credit card features and consumer's demographics between 2000 and 2007. Data is restricted to offers we have scanned pictures from column 8 and 9. Format is the first principal component of reward programs' size, color, bold and the picture sizes on the credit card offers. Backward is the first principal component of regular APR, annual fee, late fee, over limite fee, and intro_APR after taking out the bank fixed effects and monthly fixed effects. Education_2 is dummy for household head whose highest education is high school. Education_3 is for some college. Education_4 is for graduated college. Education_5 is for post college graduate. The missing category is the household head with education below high school. Standard errors in parentheses are clustered by demographic cells, which are based on states, age, income, education and household composition. Regressions are controlled by income fixed effects, age fixed effects, household composition fixed effects, state fixed effects and bank fixed effects as control variables. We also control for dummy variables for FICO score below 620, 620-660, 660-720, and above 720.