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). Finally, we use increases in state-level unemployment insurance (UI) as positive shocks to consumer 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.

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Over the past three decades, the U.S. has experienced a rapid expansion in the level and heterogeneity of retail financial products. Similarly, the complexity of contract terms offered to consumers has increased dramatically.[1] With the emergence of big data, machine learning tools and much more detailed customer information, firms are able to design products that are more personalized to their customers' preferences. But it potentially also allows for greater targeting of consumers' behavioral biases.

In this paper, we analyze how credit card issuers target different customer groups with a variety of terms and shroud unappealing features of card offers. It is often challenging to differentiate behavioral explanations from preference-based ones. But the combination of hard contract terms with detailed metrics of the design of the offer letters, such as the font size, location of information on the page, or the complexity of the language, allows us to shed light on these different margins.

A typical credit card in the US is comprised of a three-part fee: a regular interest rate or annual percentage rate (APR), an upfront fee such as annual fee, and finally backloaded fees, such as late fees, high default APR or over-limit fees. These fees serve different functions: The APR is the price of taking out credit and varies with the credit risk of the customer. The annual fee is the price for rewards programs that come with the credit card. And late fees allow for contingent pricing if the credit situation of a customer changes. A rational, financially-sophisticated household should consider all the fees independent of their form or how the information is presented in the offer. In contrast, if some consumers are not financially-sophisticated or are subject to behavioral biases, it opens an opportunity for banks to design offers that load on the fees that are more difficult for people to understand, see for example Gabaix and Laibson (2006). Of the three types of fees, the backloaded fees are most difficult to understand for many consumers. They are likely to be ignored by financially unsophisticated households, since they do not come due at the time of signing up for a credit card such as annual fees or APR.

We show that backloaded fees are more likely to be shrouded than other fees. In general, less appealing features of a card are shrouded more, which suggests that at least a subset of the population is subject to behavioral biases. Shrouding can take several forms, including differences in where information is placed, the font size, or complexity of the language. Without information

[1] Recent papers by Tufano (2003), Phillipon (2012) and Greenwood and Scharfstein (2013) suggest that these trends were accompanied by increased rents for intermediaries in the financial industry, which raises concerns among policy makers that these rents come at the expense of consumers, particularly for less financially sophisticated ones.

about the particular preferences of a customer, it is often difficult for empirical research to determine what should be the optimal trade-off between these fees. For example, a household might rationally choose a low upfront teaser rate, even with the prospect of high back-loaded fees, if it is severely credit constrained but faces increased cash flows in the future. Alternatively, the households might just not understand the cost of these fees.[2] We show that cards with backloaded fee structures are more likely to be offered to less educated customers, even controlling for credit constraints and risk. Similarly, financially less sophisticated households receive offers with more shrouded designs and are more likely to receive even strictly dominated offers.

In addition, we document an important trade-off between borrower sophistication and credit risk that has previously not been explored in the literature. A lending strategy that selects for less-sophisticated customers via back-loaded or shrouded attributes can increase rents 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. Our analysis confirms that card issuers take this trade off into account.

The credit card industry is an important arena to analyze the targeting strategies of financial institutions given the magnitude of this market. The majority of cards are sold via pre-approved card solicitations sent by mail, which means the researchers can observe not only the hard contract terms of the offer but also the "mechanics" by which certain terms in the offer are shrouded. We create metrics for how prominent information is displayed in the offer, based on location, font size, color choice and even the complexity of the language that is used. We use detailed information from Comperemedia on more than 1.3 million individual credit card offers that were sent to a set of representative households in the US between 1999 and 2016. Comperemedia records the households' demographics to mirror the information credit card issuers observe when targeting customers. These data allow us to observe the supply side of the credit card market, i.e., the types of offers customers receive. Using complete PDF versions of the actual offer letters, we created algorithms with optical character recognition (OCR) to extract card information and features in the offers. We then classified "hard" information in the offers such as the APRs, fees, and reward

[2] This explicit targeting of less-sophisticated households with more back-loaded or shrouded credit terms is important, because prior studies on the demand side have shown that older or less sophisticated households pay higher fees and carry higher balances when they choose these contracts, see for example, Agarwal et al. (2008) and (2015).

programs. We also extract the "soft" features of the offers, e.g., the use of photos, color, font size, the location where information is displayed, and measure of the complexity of the language.

We first show that credit card issuers target less financially sophisticated customers with more back-loaded or hidden card features than sophisticated ones, holding all other observable characteristics constant. These cards feature low introductory (or teaser) rates and no annual fees but high penalty rates, late fees, and over-limit fees. Our measure of sophistication is the educational attainment of a household, such as high school or college education. We estimate the relationship between different card features and educational attainment while controlling for income level, FICO, age, gender, and marital status, as well as for the monthly federal funds rate (FFR) and state-level fixed effects.[3] Households with lower educational attainment receive 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 customers. We show that these results hold even if we control for bank fixed effects, which means these differences in targeting strategies are not a cross-bank phenomenon, but even a given bank sophisticated consumers receive less shrouded offers than unsophisticated ones. Less sophisticated households also receive more *dominated* offers than educated households, i.e. all terms of the offer are worse than a competing offer from the same bank in the same time period. Banks would only engage in such a strategy if they believe that a household is extremely myopic or inattentive.

Moreover, the design of the card offers sent to less-educated consumers is more likely to display back-loaded terms such as late fees, over-limit fees, or default APRs on the last pages of the offer letters, but not in the main text. Similarly, card offerors use the complexity of the language in the offer letter to shroud unappealing contract features. We measure the complexity of the language used on a page with well-known linguistics programs, such as Coleman-Liau or Fog. In comparison to financially sophisticated customers, offer letters sent to less sophisticated agents, use simpler language on the front page but more complex language on the last page. Since the last page contains most of the information about the card, this indicates another strategy to make information less accessible to the consumer.

[3] We also find supporting evidence that especially very old people (and very young) are more likely to receive back-loaded or shrouded offers. Earlier research by Agarwal et al. (2009) suggests that age is a proxy for cognitive skills and financial literacy.

We confirm that the results on education are not just a proxy for the level of credit constraints of the household. Variables like household income and fico scores, have the opposite correlation with the backward loaded credit terms than education. E.g., richer people receive higher late fees, holding constant education; and people with high FICO scores receive more back-loaded features. This runs counter to an explanation where backloaded features target consumers who might be credit constraints.

Since credit card terms are offered to customers as a bundle, we also 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 APRs). 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 are important for the pricing of the cards, we follow the approach pioneered in Ausubel (1991) and use changes in the 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 offered to less-sophisticated consumers, strongly increase their late fees and over-limit fees, but not their upfront fees (e.g., annual fees and regular APRs), when the FFR increases. In contrast, cards offered to sophisticated consumers show a greater response of the front-loaded terms than the back-loaded terms when the FFR increases. 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 upfront fees.

Second, we analyze if banks perceive an inherent tension between targeting less-sophisticated customers via back-loaded terms, but at the same exposing themselves to greater credit risk: 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.

To test whether 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). In the past two decades, UI increased in a staggered fashion across several US states 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 reduce a lender's exposure to one of the largest economic shocks 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 and default APRs. 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 increase. In line with our hypothesis, we find that the back-loading 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 there is an inherent trade-off in the use of back-loaded features: 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.

In sum, our results support the intuition of behavioral contract theory models which suggest that the three-part tariff observed in the credit card market can be optimal if customers do not understand the true cost of credit. For example, Gabaix and Laibson (2006) suggest that companies can attract myopic consumers by offering low base prices (teaser rates) but break-even by charging high prices for hidden, or shrouded features. Myopic consumers will demand credit as if they were facing only low upfront teaser rate but no back-loaded fees. Bordalo et al. (2013, 2016), derive similar predictions if consumers overweigh the most salient features of a product. Or Heidhues and Koszegi (2010, 2017) assume that borrowers have self-control issues and underestimate the likelihood of being tempted in the future. In contrast, a rational consumer who understands the full cost of credit would reduce borrowing to avoid late fees or default APRs.

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. In Section IV, we describe our difference-in-difference analysis using UI shocks to borrower credit risk. Section V 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 of old people could explain this. 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. 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 (2017) show that even with the introduction of increased competition, price dispersion does not decrease and product complexity might increase. Similarly, Hastings, Hortacsu and Syverson (2017) 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 backward 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. Herrmann et al. (2014) document that how prices and add-on features are displayed significantly affects how well people choose among products. Beshears, 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 vs. 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. 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 2016. However, most of the analysis we report in the paper excludes the post-2007 data to abstract from the impact of the financial crisis and the CARD Act. The results are unchanged if we include data until 2016. For each month, on average, there are approximately 4,000 households and 7,000 credit card mail campaigns. In total, between March 1999 and December 2007, there are 849,672 mail campaigns, which consist of 141,628 different unique credit card offers. Credit card companies usually issue the same offer to many households at the same time. We use OCR software and our own extraction algorithms to confirm the quality of the Mintel data. We find that most variables are coded accurately.

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 75% of the credit card offers (approximately 638,458 out of the 849,672 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 observable 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 scanned credit card offer images, 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 (Visual Basic for Applications), 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%. 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 75% of the sample includes the scanned offers, our variables for reward programs and format are limited to this 75% sample.

B. Descriptive Statistics

Table 1 describes the summary statistics of the main variables used in the paper. Each observation is an offer sent to a specific consumer, where consumers are drawn to represent a bundle of personal characteristics, or "cells". These cells span the distribution of the US credit card population. 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 1, the first twelve variables are based on our sample of 849,672 mail offers from Mintel between March 1999 and December 2007. 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 825,118 total mailings received by consumers is 12.42%. The APRs for balance transfer has a mean of 11.00% and standard deviation of 3.30%. The cash advance APR has a mean of 19.47% and the standard deviation is 4.33%. For the default APR, besides default APR levels in the offers, we also 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 26.13%, 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 level of the maximum credit card limit stated in the offers. We only have 494,255 observations for Max Card limit because many credit card offers do not specify a limit.

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 \$11.03 with a standard deviation of 28.52. The distribution of annual fees in our sample is quite skewed: 82.62% of the mailed offers charge zero 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 monthly fixed charge incurred when the consumer does not pay at least the minimum monthly payment by the due date, independent of the size of the balance. Thus, this fee can be especially high for small balances. In our sample, late fee has a mean of \$33.19, a standard deviation of 6.16, and a max of \$85. Its distribution is much less skewed than that of the annual fee. Approximately 92% of credit card offers have late fees ranging from \$29 to \$39. 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 $30.16 with a standard deviation of $8.71. The distribution of the over-limit fee is also concentrated: approximately 89% 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 for over borrowing.

The remaining variables in Table 1 are based on the 75% 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 4.52 mean and a standard deviation of 5.29. The maximum value of Size is 131.30 because some offers use very large characters to highlight reward programs. The 90th percentile of variable Size is 10.10. 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 0.22 MB with a 0.26 MB standard deviation. We are also able to code the reward programs based on the PDF images. CASH, POINT, MILE, Carrental, Purchaseprct are dummies indicating whether the offer includes these reward programs. We merge monthly average FFR into our credit card dataset.

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 6% of the credit card offers mention late fees on the first page; 3.87% mention default APRs on the first page, and 7.27% 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, 78.02% 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 on the first page of the offers; 100% of cash back and mileage programs are mentioned on the first page. For point reward, car rental insurance, and zero introductory APRs, the likelihood of appearing on the first page is 93.68%, 88.35%, and 89.69%, respectively. We also compare the format design of card features between the first page and back pages of the offers. Panel B of Table 2 compares 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

A. Card Terms by education levels

We now analyze how credit card companies vary offer terms based on customer characteristics. The characteristics collected in Comperemedia are parallel to the information that banks obtain by buying mailing lists from firms that sell consumer data. In Table 3, we run simple hedonic regression models of card features, such as APRs, fees, or reward programs, on customer characteristics. Our main variable of interest is the educational attainment of customers, as a proxy for the financial literacy, measured as five distinct levels ranging from high school to completed graduate school. But it is important to control for other characteristics that might correlate with education, such as income. In fact, we will show below that the correlation of contract terms with income is very different from education. We also control for age, state fixed effect, household composition, and credit card company fixed effects in all regressions. Standard errors are clustered at the demographic cell.

Table 3 shows that card companies target customers with lower education levels with more shrouded and back-loaded card features. Column (1) looks at APR levels and surprisingly there is no monotonic pattern between the regular APR and education levels. While the lowest education group has a slightly higher APR, for the rest of the groups the relationship is flat. This would be very surprising if education was just another proxy for income or credit risk. In fact when looking at the coefficients for the income bins in the same regression, see Appendix Table A4 for the coefficients, we see that there is a significant decline in APR with income, which probably reflects lower credit risk.

However, we see significant differences in the shape of the offers. In columns (2), (3) and (4) we look at late fees, default APR and over-limit fees, respectively. We see a strong negative relationship between higher educational attainment and the magnitude of these (backloaded) fees, controlling for income. In contrast, these fees tend to increase with income, again suggesting that education and income pick up different underlying factors. When looking at forward-loaded features of the cards, like annual fees, in Column (5), we find that these fees are significantly higher for households with more education, but very low for less educated customers. Similarly, Column (6) shows that low introductory APR programs are predominantly offered to less-educated customers, while highly educated consumers almost never receive them. In contrast in Column (8) we see that reward programs like miles, are typically are only offered to more educated people. These results are a first indication that less educated customers receive distinctly more back-ward loaded and shrouded card offers than educated customers.

[Place Table 3 here]

To provide an overall measure of how back-loaded a card is, we calculate the first principal component of all 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 A3. The first principal component loads very negatively on front-loaded features, such as annual fees and regular APR, and positively on back-loaded fees, such as late fees and over-limit fees. In Column (7), we then rerun our hedonic regression for the overall metric of "backward" loadedness, and find that it decreases significantly with the education level of the household. Interestingly, the same is not true for income. Richer people tend to receive more back-loaded card terms after controlling for education.

B. Offer Letter and Display

In a next step, we now look at differences in how the information is displayed in the credit card offer across different consumers. Specifically, we look at where specific information about back-loaded fees and default APR are displayed. If offer terms are only displayed on the last page of an offer it will it much less likely that a consumer will see the information. We already showed in Table 2 that on average the less enticing terms of the card are typically on the last page. But in the following analysis we also find a differential approach for educated versus less-educated consumers. In Column (9), Back_LateFee is the dummy for whether the late fee information is displayed only on the last page of the offer letters, this is usually in the Shumer box, which mandates the display of the offer terms at least on the last page. We show that offers sent to less-educated households are more likely to display late fees on the last pages of the offer letters. The difference is very significant. For the most educated group the likelihood of having the late fees displayed in the front of the offer is four percent higher than less educated households. Since the base rate probability of having a negative term displayed in the front is only eight percent, education explains almost 50% of the difference. Column (10) 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 they are sent to less-educated households. Since these households also receive worse back-loaded features, these results suggest that credit card companies tend to hide the back-loaded pricing terms on the back pages of offer letters, especially for less-educated households.

C. Dominated Offers

Finally, we also take a different approach to test if credit card issuers assume that less educated people are more prone to making financial mistakes. We analyze if the same card issuer sends a given person different offers in the same time period, where one card strictly dominates the other. Such a strategy would only be profitable if consumers are unable to accurately compare cards and make mistakes. In contrast for a consumer who pays attention to all card features, an issuer would not want to use such a strategy since they would either just ignore the dominated card. Or they might even get annoyed at the company for trying to trick them.

We had previously constructed demographic cells of borrowers by state, age, income, education, and household composition. For each cell and year, we mark the offer as "Dominated" when the households in the cell receive another credit card offer with strictly better terms in all 14 dimensions that we can measure (i.e., all types of APRs, fees, reward programs, and credit limit etc). We also define the "Worst" offers which is the subsample of dominated offers where all these individual 14 terms are the worst among all offers in the same cell and year. In Table 4, Panel B we first show that the magnitudes of the differences in card terms are not small between the dominated and other offers. For example, the difference in regular APRs between the dominated offers and the better offers a household receives are approximately three percentage points higher.

In Panel B we show that households in the lowest education bin (i.e., high school, versus college and more) receive significantly more "Dominated" and "Worst" offers. We divide the sample into three bins for those who For households in the lowest education bin 16% of their offers are dominated by another offer they receive from the same bank. This is 40% higher than for more educated households. The results confirm the idea that dominated offers are more likely to be sent to less educated people who might be less attentive or more myopic when choosing a card.

D. Robustness Check with Subsample

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 whether including FICO scores affects 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), it is otherwise identical. The idea it to see whether the pricing relationships documented in our paper differ significantly when including FICO score. For this purpose, in Table A6 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 A6 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. We also perform another robustness test by controlling for zipcode fixed effects. The patterns are very similar as in Table 3. These results alleviate concerns that we are missing an important, and un-spanned dimension of customer characteristics.

Moreover, we identify each credit card offer campaigns by year, bank, and reward program. In particular, for each year we consider card offers belong to the same campaign if they have the same reward programs and same issuers. We find the similar results by controlling for this campaign fixed effects. This means that these differences in targeting strategies are not a cross-bank-campaign phenomenon, but even a given campaign of a bank differentially targets different customer groups.

IV. Is Pricing of Cards Asymmetric in Borrower Sophistication

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 price a card 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:

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

, where $Y_{i,j,t}$ indexes the dependent variables we are interested in, such as regular purchase APRs, annual fees, 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 bank fixed effects and household demographic cell fixed effects, and t is at a daily frequency.

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

Education levels: In Table 4, we explore the sensitivity of APRs to FFR by interaction terms between FFR and a dummy for less-educated borrowers. The main coefficient of interest is β_2 for the interaction term. 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 FFR and the low education dummy is negative. In contrast, when looking at late fees, over-limit fees, and default APR between Columns (3) and (5), the interaction terms are significantly 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 FFR. The same is true for the use of introductory APR programs in Column (6).

[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 pass 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. 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.[4] This confirms that 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

[4] In Table A5 in Appendix, we show that credit cards with cash back or points programs have pricing structures similar to those with introductory APR programs.

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) 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 UI 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 UI from the US Department of Labor for each state. Based on this information, we calculate semi-annual changes in UI in January and July of each year from 1999 to 2007 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 which is 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 UI over a 52-week period, and the maximum WBA was \$190. We use \$4,940 (26×\$190) 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. Column (4) shows that annual fees do not change significantly around UI changes either. In contrast, in Column (3) and (5), we see that an increase in UI leads to a large and significant increase in late fees and in the use of intro APR programs. 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. In Column (7) to (9), 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. Conclusion

The results in this paper suggest that credit card companies target sophisticated and naïve creditors differently by offering these groups different contract terms, pricing structures, and reward programs. In line with the behavioral contract theory literature, the results show that cards offered to less-educated 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 Koszegi (2010) or Grubb (2009), 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..

Finally, our analysis highlights an important new 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 UI, 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
APR	12.42	4.26	0.00	44.90	825,118
APR Balance	11.00	3.30	0.00	27.75	604,580
APR CASH	19.47	4.33	0.00	35.99	787,166
Default APR Dummy	0.70	0.46	0.00	1.00	849,672
Annual Fee	11.03	28.52	0.00	500.00	839,987
Late Fee	33.19	6.16	0.00	85.00	837,657
Over-limit Fee	30.16	8.71	0.00	79.00	774,284
Intro_APR_Regular	0.44	0.50	0.00	1.00	849,672
Intro_APR_Balance	0.46	0.50	0.00	1.00	849,672
Intro_APR_Cash	0.06	0.24	0.00	1.00	849,672
Size	4.52	5.29	0.00	131.30	494,562
Color	0.28	0.45	0.00	1.00	494,562
Bold	0.32	0.47	0.00	1.00	494,562
Picture	0.22	0.26	0.00	4.10	638,458
CASH	0.18	0.38	0.00	1.00	638,458
POINT	0.22	0.42	0.00	1.00	638,458
MILE	0.08	0.27	0.00	1.00	638,458
Carrental	0.21	0.41	0.00	1.00	638,458
Purchaseprct	0.23	0.42	0.00	1.00	638,458

Note: Variables are based on Mintel's credit card's direct mail campaigns from March 1999 to December 2007. Variables from "Size" to "Purchaseprct" are from 75% of 849,672 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). 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 level 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 are usually displayed in Schumer box.

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	Intro APR
% of cards that have	100.00%	100.00%	100.00%	100.00%	17.53%	22.44%	8.23%	67.86%
Is term mentioned on 1st page	6.06%	3.87%	7.27%	78.02%	100%	93.68%	100%	89.69%
Font size if mentioned on 1st page	9.56	9.39	9.82	13.39	12.12	10.98	16.56	13.43
Font size if not mentioned on 1st page	9.56	9.64	9.52	14.47	10.62	10.80	9.91	11.50
Font color if mentioned on 1st page	32.92%	32.29%	25.53%	64.42%	44.97%	41.40%	60.89%	58.30%
Font color if not mentioned on 1st page	23.69%	24.96%	21.82%	44.53%	37.24%	38.45%	29.47%	43.84%
Font bold if mentioned on 1st page	38.91%	25.58%	34.18%	77.82%	53.84%	39.06%	72.70%	75.78%
Font bold if mentioned on 1st page	42.71%	10.66%	32.97%	53.78%	36.58%	29.97%	18.08%	63.09%
# Obs	611,797	611,797	611,797	611,797	611,797	611,797	611,797	611,797
Panel B								
If term is on first page	27.89	27.56%	28.38	5.95				
If term is in the back (Schumer box)	34.63	27.75%	30.62	26.12				

Note: The dataset is based on Mintel's credit card's direct mail campaigns from March 1999 to December 2007. Descriptive statistics are based on 75% of 849,672 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 611,797 offers since we have missing pages of Schumer box where these terms usually appear. Intro_APRs contains all introductory APR programs: regular intro APR, balance transfer Intro APR and cash advance Intro APR. Size is the maximum size of the reward programs in credit card offer. Color is the dummy of whether reward programs in the offer use color other than black/white in the offer. Bold is the dummy of whether the offer use bold to highlight reward programs. Picture is the file size of each page of the offer which is the measurement of how many or how large are pictures in the offer. Penal B is the descriptive statistics of credit card terms when they mentioned on the first page or not. "First page" includes the envelop and the first page letter of credit card offers.

TABLE 3 – CREDIT CARD FEATURES AND DEMOGRAPHICS

Dependent Variable	1 APR	2 Late Fee	3 Default APR	4 Over-limit Fee	5 Annual Fee	6 Intro_APR	7 Backward	8 MILE	9 Back_LateFee	10 Back_APR_Default
FFR	0.736***	0.067***	1.495***	-0.349***	0.515***	-0.013***	0.007***	0.016***	0.007***	0.086***
	(0.004)	(0.007)	(0.004)	(0.008)	(0.023)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Education_2	-0.156***	-0.169***	-0.151***	-0.272***	-0.528***	-0.007**	0.008	0.012***	-0.010***	-0.010***
	(0.030)	(0.048)	(0.025)	(0.047)	(0.168)	(0.003)	(0.008)	(0.001)	(0.002)	(0.003)
Education_3	-0.072**	-0.395***	-0.144***	-0.386***	-0.177	-0.019***	-0.008	0.015***	-0.014***	-0.022***
	(0.032)	(0.048)	(0.027)	(0.051)	(0.178)	(0.003)	(0.008)	(0.002)	(0.002)	(0.003)
Education_4	-0.234***	-0.366***	-0.217***	-0.790***	0.342*	-0.030***	-0.036***	0.041***	-0.020***	-0.022***
	(0.032)	(0.050)	(0.028)	(0.053)	(0.185)	(0.003)	(0.009)	(0.002)	(0.002)	(0.003)
Education_5	-0.137***	-0.652***	-0.279***	-1.179***	1.290***	-0.048***	-0.087***	0.055***	-0.026***	-0.037***
	(0.034)	(0.056)	(0.030)	(0.060)	(0.212)	(0.003)	(0.010)	(0.002)	(0.002)	(0.004)
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	785,950	798,936	586,259	749,306	800,546	808,430	746,656	613,629	587,292	587,292
R-squared	0.341	0.151	0.507	0.203	0.265	0.151	0.038	0.071	0.291	0.261

Note: Table 3 shows the OLS regressions to estimate relationship between credit card features and consumer's demographics between 1999 and 2007. Data is restricted to offers we have scanned pictures from column 6 to 10. 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. 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. The missing category is the households with income less than 15K. Standard errors in parentheses are clustered by demographic cells, which are based on states, age, income, education and household composition. All regressions control for income fixed effects, age fixed effects, household composition fixed effects, state fixed effects and bank fixed effects.

TABLE 3B – CREDIT CARD READABILITY AND DESIGN

VARIABLES	1 Fog_Front	2 Grade_Front	3 Fog_Back	4 Grade_Back	5 Fog Front-Back	6 Grade Front-Back	7 Intro_APR_Size _Front
FFR	-0.020***	0.038***	0.056***	0.004***	-0.022***	0.052***	-0.229***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.004)
Education_2	-0.020	-0.002	-0.066***	-0.018**	0.044***	0.014	-0.013
	(0.013)	(0.011)	(0.011)	(0.007)	(0.015)	(0.012)	(0.024)
Education_3	-0.012	0.008	-0.086***	-0.019**	0.068***	0.024*	0.004
	(0.014)	(0.011)	(0.011)	(0.007)	(0.016)	(0.013)	(0.026)
Education_4	-0.013	0.016	-0.124***	-0.045***	0.109***	0.059***	-0.038
	(0.014)	(0.012)	(0.012)	(0.007)	(0.017)	(0.014)	(0.026)
Education_5	0.033**	0.041***	-0.138***	-0.039***	0.174***	0.080***	-0.085***
	(0.015)	(0.013)	(0.013)	(0.008)	(0.018)	(0.015)	(0.030)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	561,053	559,397	593,717	592,784	556,456	554,307	166,279
R-squared	0.184	0.138	0.121	0.111	0.191	0.134	0.272

TABLE 4 – RELATIONSHIP BETWEEN APRS/FEES AND EDUCATION

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

Note: OLS regressions to estimate the sensitivity of credit card terms to Fedfundrate (FFR) interacted with household education. All regressions include controls for household demographic cell fixed effects based on state, age bins, income bins, 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). Data period is from 1999 to 2007. 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. All regressions include controls for household demographic cell fixed effects based on state, age bins, income bins, and household composition. Regressions in columns 2 to 9 also control for 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 APR	2 Default APR Dummy	3 Late Fee	4 Annual Fee	5 IntroAPR All	6 Backward	7 Color	8 DefaultAPR MainPage	9 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 regressions include controls for bank fixed effects, year fixed effects and household demographic cell fixed effects based on state, age bins, income bins, and household composition. UI is a 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 a dummy for 3 month pre-trend of the UI jumps. UI_Pre_6M is a dummy for 6 month pre-trend of the UI jumps. UI_Small is a 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.

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

Panel B	1	2	3	4	5	6	7	8	9
	APR	Default APR Dummy	Late Fee	Annual Fee	IntroAPR All	Backward	Color	DefaultAPR MainPage	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

TABLE 7 – UNEMPLOYMENT INSURANCE AND CREDIT CARD DESIGN

	1	2	3	4	5	6
VARIABLES	Fog_Front	Grade_Front	Fog_(Back-Front)	Grade_(BackFront)	Main_Intro_APR	Back_Intro_APR
UI	-0.171*	-0.141**	0.183*	0.113	-0.014	0.004
	(0.100)	(0.058)	(0.092)	(0.095)	(0.026)	(0.032)
UI*LowEdu (Below College)	0.001	0.010	-0.024	0.033	0.041**	-0.033**
	(0.067)	(0.081)	(0.069)	(0.103)	(0.015)	(0.016)
UI*LowIncome (<=35K)	0.173*	0.153	0.246**	0.200*	-0.052**	0.045*
	(0.089)	(0.099)	(0.097)	(0.118)	(0.024)	(0.024)
UI_Pre_3M	-0.244**	-0.078*	-0.070	-0.003	-0.025	0.026
	(0.105)	(0.040)	(0.057)	(0.093)	(0.039)	(0.039)
UI_Pre_6M	-0.167	0.007	-0.163	-0.049	-0.024	0.009
	(0.151)	(0.079)	(0.189)	(0.090)	(0.026)	(0.028)
UI_Small	-0.419**	-0.214	-0.197	-0.110	-0.021	0.008
	(0.190)	(0.137)	(0.190)	(0.148)	(0.051)	(0.049)
Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	43,938	43,764	43,122	42,932	21,021	21,021
R-squared	0.058	0.058	0.068	0.038	0.035	0.031

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APPENDIX

TABLE A1 – DEMOGRAPHIC DISTRIBUTION

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.

Table A2- DISTRIBUTION OF DOMINATED OFFERS

Panel A: Cell*Year	Dominated Offers	Worst Offers
Below High School	1.38%	0.74%
High School	0.76%	0.41%
Some College	1.04%	0.53%
College	0.79%	0.42%
Post College	0.85%	0.43%

Panel B: Cell*Bank*Year	Dominated Offers	Worst Offers
Below High School	16.61%	10.07%
Graduated High School	12.11%	7.13%
Some College	13.81%	8.19%
Graduated College	12.47%	7.35%
Post College Graduate	12.47%	7.65%

Panel C: Magnitude of Dominance	Cell*Year	Cell*Bank*Year
APR	2.84%	1.62%
Default APR	1.59%	0.75%
Annual Fee	9.472343	4.063964
Late Fee	1.244025	0.8019464
Over-limit Fee	2.855747	1.62768
Intro_APR	-22.65%	-17.51%
MILE	-2.09%	-4.07%
MaxCardLimit	-19061.16	-5401.081

Note. This table shows the distribution of dominated offers across different education levels. Cell is based on households' states, age, income, education, and household composition. In Panel A, by each cell per year, we mark the offer as dominated when there is another offer in the group with strictly better terms in 14 dimensions; regular APR, balance transfer APR, cash advance APR, default APR, annual fee, late fee, over-limit fee, intro_APR, cash back, mile, points, car rental insurance, purchase protection, and credit limit. The worst offer is the subsample of dominated offers where all these individual 14 terms are the worst among all offers in each cell per year. In Panel B, we redefine the dominated and worst offers by cell, bank, and year. Panel A and B show the percentages of dominated and worst offers across five education levels. Panel C shows the magnitudes of the average differences of credit card terms between the dominated offers and other offers in the groups.

TABLE A3 – PRINCIPAL COMPONENT ANALYSIS ON CREDIT CARD PRICING

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.

TABLE A4 – CREDIT CARD FEATURES AND DEMOGRAPHICS

	1 APR	2 Late Fee	3 Default APR	4 Over-limit Fee	5 Annual Fee	6 IntroAPR	7 Backward	8 MILE	9 BackLateFee	10 BackAPR Default
Income_2	-0.274***	0.133*	-0.022	-0.220***	-0.818***	-0.002	0.027**	0.014***	-0.006**	-0.008**
	(0.041)	(0.075)	(0.032)	(0.059)	(0.232)	(0.004)	(0.011)	(0.002)	(0.003)	(0.004)
Income_3	-0.442***	0.143**	-0.024	-0.225***	-1.055***	-0.006*	0.057***	0.019***	-0.008***	0.002
	(0.039)	(0.056)	(0.033)	(0.057)	(0.224)	(0.004)	(0.011)	(0.002)	(0.003)	(0.004)
Income_4	-0.526***	0.342***	-0.023	-0.273***	-1.332***	-0.010***	0.068***	0.025***	-0.012***	0.004
	(0.038)	(0.055)	(0.031)	(0.056)	(0.217)	(0.003)	(0.010)	(0.002)	(0.002)	(0.004)
Income_5	-0.681***	0.406***	-0.049	-0.466***	-1.261***	-0.022***	0.071***	0.039***	-0.019***	0.005
	(0.037)	(0.056)	(0.032)	(0.057)	(0.219)	(0.003)	(0.010)	(0.002)	(0.002)	(0.004)
Income_6	-0.796***	0.411***	-0.065*	-0.689***	-0.686***	-0.028***	0.051***	0.051***	-0.023***	0.010**
	(0.039)	(0.060)	(0.034)	(0.061)	(0.231)	(0.004)	(0.011)	(0.002)	(0.003)	(0.004)
Income_7	-0.795***	0.498***	-0.034	-0.930***	0.422*	-0.040***	0.003	0.065***	-0.024***	0.015***
	(0.041)	(0.064)	(0.036)	(0.067)	(0.248)	(0.004)	(0.012)	(0.002)	(0.003)	(0.004)
Income_8	-0.735***	0.467***	-0.102**	-1.213***	2.440***	-0.055***	-0.047***	0.080***	-0.028***	0.025***
	(0.053)	(0.086)	(0.048)	(0.103)	(0.355)	(0.005)	(0.017)	(0.004)	(0.004)	(0.006)
Income_9	-0.723***	0.387***	-0.047	-1.562***	3.584***	-0.069***	-0.091***	0.095***	-0.029***	0.020***
	(0.059)	(0.101)	(0.056)	(0.129)	(0.428)	(0.006)	(0.021)	(0.005)	(0.005)	(0.008)
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	785,950	798,936	586,259	749,306	800,546	808,430	746,656	613,629	587,292	587,292
R-squared	0.341	0.151	0.507	0.203	0.265	0.151	0.038	0.071	0.291	0.261

Note: Table A4 shows the coefficients of income categories in OLS regressions in Table 3. 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. The missing category is the households with income less than 15K.

TABLE A5 – CASHBACK AND POINTS REWARD PROGRAMS

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 F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank F.E.	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 F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank F.E.	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. Standard errors in parentheses are clustered by cells.

TABLE A6 – CREDIT CARD FEATURES AND DEMOGRAPHICS WITH FICO SCORES

	1	2	3	4	5	6	7	8
	APR	Late Fee	Default APR	Over-limit Fee	Annual Fee	Intro_APR	Backward	MILE
FFR	0.684***	0.499***	1.412***	-0.286***	0.437***	0.009***	0.025***	0.019***
	(0.004)	(0.008)	(0.004)	(0.012)	(0.031)	(0.001)	(0.002)	(0.000)
Education_2	-0.007	-0.075	-0.106***	-0.128**	0.031	-0.008**	-0.004	0.005***
	(0.028)	(0.051)	(0.028)	(0.058)	(0.168)	(0.003)	(0.009)	(0.002)
Education_3	0.031	-0.086*	-0.091***	-0.144**	0.518***	-0.016***	-0.021**	0.011***
	(0.030)	(0.047)	(0.030)	(0.063)	(0.181)	(0.003)	(0.010)	(0.002)
Education_4	0.065**	-0.071	-0.124***	-0.485***	1.379***	-0.027***	-0.074***	0.031***
	(0.030)	(0.051)	(0.031)	(0.066)	(0.187)	(0.004)	(0.010)	(0.002)
Education_5	0.182***	-0.111*	-0.134***	-0.829***	2.518***	-0.039***	-0.146***	0.045***
	(0.033)	(0.057)	(0.034)	(0.076)	(0.213)	(0.004)	(0.012)	(0.002)
FICO (620-660)	-0.112***	0.106	-0.014	0.154***	-8.033***	0.014***	0.283***	0.005***
	(0.040)	(0.103)	(0.034)	(0.056)	(0.268)	(0.004)	(0.012)	(0.002)
FICO (660-720)	-1.356***	-0.276***	-0.375***	-0.642***	-12.450***	0.019***	0.479***	0.026***
	(0.033)	(0.037)	(0.028)	(0.055)	(0.225)	(0.004)	(0.010)	(0.002)
FICO (>720)	-2.260***	-0.671***	-0.742***	-1.488***	-15.325***	0.014***	0.517***	0.068***
	(0.030)	(0.039)	(0.025)	(0.050)	(0.210)	(0.003)	(0.009)	(0.002)
Fixed Effects	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

Note: Table A6 shows the OLS regressions to estimate the 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. 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. Dummy for FICO score below 620 is the missing category.