BANK FOR INTERNATIONAL SETTLEMENTS

BIS Working Papers

No 842

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Monetary and Economic Department

February 2020

JEL classification: G02, G1, G21, G23.

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This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

Do Credit Card Companies Screen for Behavioral Biases?

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September 5, 2019

Abstract

Using granular data on the contract terms and design details of more than 1.3 million credit card offers, we document how card issuers shroud unappealing, back-loaded features of an offer (e.g., high default APRs, late or over-limit fees) via the position of the information, font size, or complexity of the language used. More heavily shrouded offers that rely on back-loaded fees are also more likely to be offered to less-educated consumers. In addition, we document a novel interaction between behavioral screening and adverse selection: Using changes in state-level unemployment insurance (UI) as positive shocks to consumer creditworthiness, we show that issuers rely more on shrouded and back-loaded fees when UI increases, especially for less-educated consumers. Card issuers weigh short-term rent maximization against increased credit risk when targeting consumers' behavioral biases.

Keywords: Credit Card, Shrouding, Back-loaded

JEL Classification: G02, G1, G21, G23

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1. Introduction

Over the past three decades, the U.S. has seen a rapid expansion in the heterogeneity of retail financial products and the complexity of contract terms offered to consumers (see, for example, Tufano (2003) or Campbell et al. (2011)).[1] With the emergence of big data, machine learning tools, and much more detailed customer information, firms can design products that are more personalized to their customers' preferences and reduce adverse selection. However, these tools potentially also allow for greater targeting of consumers' biases, such as inattention or time inconsistency.[2]

In this paper, we document how credit card issuers use the structure of hard contract terms, such as fees and interest rates, in combination with the design of the offer letter to target different customer groups. Using the unique data of the mailers from more than 1.3 million credit card offers, we can extract the combination of hard contract terms with detailed metrics of the design of the offer letters. This approach allows us to test which features of a card are explicitly highlighted to customers and which are hidden via the design choices. In other words, we can provide evidence of the production function of shrouding. In the US, a key dimension along which credit card contracts differ is how much they rely on back-loaded terms. For example, many cards offer low introductory teaser rates coupled with high late fees and over-limit fees, while other cards are more front-loaded and charge annual fees and regular APRs. The growing behavioral contract theory literature suggests that back-loaded fees appeal to consumers with myopic or time-inconsistent preferences. For example, DellaVigna and Malmendier (2004), Gabaix and Laibson (2006) or

[1] Recent papers by Phillipon (2015) and Greenwood and Scharfstein (2013) suggest that these trends were accompanied by increased rents for intermediaries in the financial industry.
[2] Previous studies on the demand side of retail credit 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)).

Heidhues and Koszegi (2010) suggest that companies can attract myopic or time-inconsistent consumers by offering low base prices (teaser rates) and break-even by charging high prices for hidden or shrouded features. It is often challenging to distinguish behavioral explanations from preference-based explanations since back-loaded card terms might also appeal to a rational customer with severe credit constraints. However, our unique ability to measure how information is displayed in the offer letter allows us to differentiate these explanations. If back-loaded terms were explicitly targeted at credit-constrained customers who are shopping for a card that allows them to delay payments, we would expect these terms to be displayed clearly. If instead, these terms are used to target customers' behavioral biases, we would expect these features to be shrouded.

We first show that back-loaded card fees, such as high late fees, over-limit fees, or penalty APRs, are indeed more likely to be shrouded, while attractive features such as low introductory teaser rates are highlighted. Shrouding can take several forms, including differences in where information is placed in the offer letter, the font size, or the complexity of the language used to describe the specific terms. To further support the idea that this back-loaded fee structure aims to target consumers' behavioral biases, we show that cards that are offered to less-educated consumers, tend to rely more heavily on back-loaded terms with more shrouded designs, even after controlling for household income and credit risk. Less-educated consumers are also more likely to receive strictly dominated offers, even from the same financial institution.

Second, 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 consumers via shrouded and back-loaded card terms can increase rents for the lender over the short run, but it might also expose the lender to higher credit risk over the long run.

Specifically, if these card features attract consumers 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 or default. Our analysis confirms that card issuers take this trade-off into account and are more likely to send shrouded offers once consumers had an improvement in their credit risk.

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., different offers received by various types of customers. Using complete PDF versions of the actual offer letters, we create algorithms with optical character recognition (OCR) to extract card information and features on each page in an offer. We then classify "hard" information in the offers such as the APRs, fees, and reward programs. We also create metrics for how prominently information is displayed from the "soft" features of the offers, e.g., the use of color, font size, the location where information is displayed, and measures of the complexity of the language. The credit card industry is an important arena in which to analyze the targeting strategies of financial institutions given the magnitude of this market. It has the additional unique advantage that the majority of cards are sold via pre-approved card solicitations sent by mail, which means that researchers can observe not only the hard contract terms of the offer but also the "mechanics" of how information is shrouded.

We first show that credit card issuers use the design features that we measure to highlight the attractive parts of an offer but shroud the unattractive parts. More than 90% of the card offers in our sample display late fees, default APRs, or over-limit fees only on the back pages of the offer, usually in small font. We also show that the only times these payment terms are mentioned on the front page is if they are particularly low. In contrast, reward programs such as miles, points, or cash back offers, as well as low introductory teaser rates are almost always mentioned on the front page of the offer and in large font. This analysis confirms that our design metrics allow us to classify the dimensions of an offer that the issuer either wants to shroud or highlight to consumers.

In a second step, we then use these metrics to analyze how card issuers target different consumers. We show that less financially sophisticated customers receive more back-loaded and shrouded card offers compared to sophisticated consumers, holding all other observable characteristics constant. 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 attainments 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] Consumers with lower educational attainment receive significantly more back-loaded payment terms. For example, relative to the consumers with the lowest educational attainment (i.e., below high school), the most educated consumers (with graduate degrees and above) receive offers with 2% lower late fees, or 4% lower over-limit fees, but a 11% lower likelihood of having low introductory APRs (teaser rates). Additionally, these back-loaded fees, when offered to less educated consumers, are more likely to be displayed only on the back pages of the offer letters and in small font, not in the main text. The reverse is true for sophisticated consumers who receive offers with front-loaded payment terms, e.g., they have 11.7% higher upfront annual fees as well as less shrouding in the design.

[3] We also find supporting evidence that very old people in particular (and very young people) 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.

Similarly, the complexity of the language in the offer letter is used to shroud unappealing contract features. We measure the complexity of the language used on a page with well-known linguistics programs, such as Fog and Coleman-Liau indexes. Offer letters sent to less sophisticated consumers, use simpler language on the front pages but more complex language on the back pages, which contains most of the critical information about card terms. In contrast, sophisticated customers receive letters that have more complex language on the front pages, but simpler language on the back page. This reversal in the use of language suggests that card offers to less sophisticated people deliberately shroud the more onerous card features.

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; even within a given bank, sophisticated consumers receive less shrouded offers than unsophisticated consumers. Less sophisticated households also receive more dominated offers than educated households, i.e., all the terms of the offer are worse than a competing offer from the same bank in the same period. Banks would only engage in such a strategy if they believe that a household is extremely myopic or inattentive.

We confirm that the results regarding education are not just a proxy for the level of credit constraints of the household. Variables such as household income and FICO scores have the opposite correlation with back-loaded credit terms than education. For example, wealthier 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 that back-loaded features target consumers who might be credit constrained.

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. Furthermore, we compare transactions credit cards with true credit cards. The credit card industry differentiates between cards that are used for payment convenience by consumers who typically do not carry any balances (transaction cards) and the cards that are used by consumers who carry balances (true credit cards). We can differentiate these cards in our data by the rewards they offer. The transaction cards usually have rewards that target spending, such as miles, points, or cash back. While true credit cards have rewards that are back-loaded, such as zero introductory APRs for a limited time. True credit cards should be more transparent regarding their credit features since this is what people intend to use the card for. Instead, we again find that true credit cards have less transparency with regard to these features compared to transaction cards.

Third, we analyze whether banks perceive an inherent tension between targeting less-sophisticated consumers via back-loaded and shrouded offers while at the same time exposing themselves to higher credit risk: If these card offers attract consumers 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 shrouded and back-loaded features when unsophisticated borrowers are more creditworthy, 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-differences (DID) estimator to regress changes in card features on UI changes across states.

Our DID regressions show that increases in UI levels lead to an 18.9% increase in the fraction of card offers with low introductory (teaser rate) APRs but significantly higher back-loaded fees (e.g., a 2.7% increase in late fees). Interestingly, we also find that offer letters use more colors, move back-loaded terms, such as late fees and default APRs, to the back pages of the letter with smaller font sizes, and highlight low introductory APRs on the front page in response to UI increases. Moreover, following UI increases, the language becomes simpler on the front pages but more complex on the back pages where most of the back-loaded terms are displayed. In line with our hypothesis, we also find that these increases in the back-loading and shrouding of card terms following UI increases are more pronounced for less sophisticated consumers 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. As a result, card issuers use shrouding more aggressively once the credit risk of the customers is reduced.

In sum, our results support the intuition of behavioral contract theory models, which suggests that the structure of back-loaded contract terms and explicit shrouding, as we documented in the paper, can be optimal if customers do not understand the true cost of credit. For example, Gabaix and Laibson (2006) suggest that myopic or inattentive consumers will demand credit as if they were facing only low upfront teaser rates but no back-loaded fees. Bordalo et al. (2013, 2016), derive similar predictions if consumers overweigh the most salient features of a product. DellaVigna and Malmendier (2004) 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 2 provides a detailed literature review. In Section 3, we present the data used in the study, the variables we constructed for the paper, and the design of the sample. Section 4 summarizes the results of how credit card companies target consumers. In Section 5, we describe our DID analysis using UI shocks to borrower credit risk. Section 6 concludes.

2. 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 do 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% after four years. Using a similar data set, Gross and Souleles (2002) 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 the cognitive ability of old people could explain this phenomenon. 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 (2006) 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 significant house price increases and expanding mortgage originations saw increases in marketing expenses and marketing solicitations. Similarly, a recent paper by Agarwal et al. (2017) 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 body of literature in economics and marketing has examined 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 advertisements 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 how the display of prices and add-on features 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 advertising content can indeed have a significant impact on product take-up and even willingness to pay. The authors 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. Finally, Meier and Sprenger (2010) use a field experiment to show that more present biased consumers tend to have more credit debt even after controlling for other household circumstances. 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 dataset 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 before the crisis was particularly large for consumers with medium credit scores rather than sub-prime customers. In addition, the results show that even customers who have previously declared bankruptcy have a high likelihood of receiving offers, but these offers are more restrictive.

3. Data and Summary Statistics

3.1. Data Description

We use a comprehensive dataset from Comperemedia (also known as Mintel) that contains information on the types of the credit card offers that consumers with different characteristics receive in the US. These data are based on a monthly consumer panel of more than 4,000 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 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 every page in 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.

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 2008 financial crisis and the Credit Card Accountability Responsibility and Disclosure Act (CARD) in 2009. The main results are qualitatively and quantitatively very similar if we include data until 2016. For each month, on average, there are approximately 4,000 households and 7,000 credit card mail offers received by them. In total, between March 1999 and December 2007, there are 849,672 mail offers, which consist of 141,628 different unique credit card campaigns. Credit card companies usually issue the same offer (campaign) to many households at the same time. We use OCR software and design Python algorithms to extract information for credit card terms to confirm the quality of Mintel coded variables. We also manually check the quality of the dataset and find that all the variables are adequately collected by Mintel, except default APRs, which have many missing values. Our algorithms also allow us to extract the granular information for how card features are displayed in the offer letters.

More specifically, we first 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 pricing terms and reward programs in each offer. Moreover, because we keep the formatting information for each character in the offer, we can also record the format design of these card features. Using Visual Basic for Applications (VBA) in Word, we can identify the fonts of characters in mailers. We collect the size and color for each reward program and for each pricing term when they were mentioned in the offer letter at the page level. Also, we perform the text analysis for each page of credit card offers. In particular, based on the contents of a page, we calculate several standard measurements of text readability (e.g., Fog Index and Grade index).[4]

To check the quality of the OCR and keyword searching algorithm, we randomly select some offers and check them manually, and the accuracy is over 90%. However, Mintel only keeps scanned images of approximately 75% of the credit card offers (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 offers with randomly missing images in later years. Nevertheless, we verify that, except for the time trend, the missing observations do not seem to have any observable biases.

Based on our algorithms, we create a second dataset on the Mintel information by using all the scanned pages of credit card offers. These allow us to analyze the design of the offer letter, e.g., where and how information about the card and its individual features is located on the mailers. We extract information on card terms and reward programs and soft information on the design of the mailer itself from these scanned images. For example, we can identify eight commonly used reward programs: cash back, points, airline mileage, car rental insurance, purchase protection, warranty protection, travel insurance, and zero introductory APRs.

Although Mintel generally code variables for card features adequately, there are still some missing observations. For example, some values for default APRs are 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,

[4] The Gunning Fog Index was developed in 1952 to measure text readability based on the number of words in sentences and the ratio of complex words. The formula is $0.4\left[\left(\frac{words}{Sentences}\right)+100\left(\frac{Complex\ words}{Words}\right)\right]$. We also calculate the grade of texts which is based on several readability scores (e.g., Fog index, Coleman-Liau index, ARI, Flesch Kincaid Grade level, Flesch Reading Easy score, SMOG index, Dale-Chall Readability score, and Linsear-Write score).

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.

3.2. Descriptive Statistics

Table I 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 I, we first list variables that are based on our sample of 849,672 mail offers from Mintel between March 1999 and December 2007. For example, *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 value for *APR*. The mean *APR* of the 825,118 total mailings received by consumers is 12.42%. The balance transfer APRs 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 do not 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 introductory APR (usually very low and mostly zero) for regular purchases, balance transfers, and cash advances, respectively. *Intro_APR_All* is the dummy for whether the offer has any types of introductory APRs.

Credit cards also have several 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 fees, 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, the 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 the 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. We merge monthly average FFR into our credit card dataset.

The remaining variables in Table I are based on the 75% sample of mail campaigns for which we have scanned images of the credit card offers (totally 638,458 offers). For the reward programs captured by our algorithms, *CASH*, *POINT*, *MILE*, *CarRental*, *Purchaseprct* are dummies indicating whether the offer includes these reward programs. For example, 18%, 22%, and 8% of the credit card offers have cash back, point, and mileage programs, respectively.

Also, we obtain the variables for offer designs in several dimensions. For example, *Size* is the maximum size of the reward programs (i.e., cash back, point, mile, car rental insurance, and purchase protection) minus the average size of all characters on every page of each credit card offer. For example, if "cash back" appears in the offer three times, we pick the largest one. *Size* equals this largest number minus the average size of all characters on the same page. *Size* is drawn directly from Word documents. 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 huge characters to highlight reward programs. The 90th percentile of *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.

Similarly, *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. Since we know the exact page on which a specific term is displayed, we can classify the pages into front vs. back pages. The front page includes the envelope and the first page of the credit card offer letter, and the rests are back pages. *Back_LateFee* is the dummy for whether the back fee is mentioned only on back pages, and 79% of the credit card offers do so. Similarly, the mean of *Back_APR_Default* is 0.47, which means that 47% of the offers mention default APRs only on back pages. Moreover, *Fog* and *Grade* are two measurements for readability. The average

Fog index is 14.02 with the standard deviation of 1.63. The average *Grade* is 8.54, which means that the average readability level of the credit card offers is around 8th to 9th grade level.

[Place Table I about here]

3.3. Credit Card Design

Table II summarizes the physical design of the credit card offers to document how and where certain features of the card are displayed in the letter. Panel A shows that almost all credit card offers state regular APRs, late fees, default APRs, over-limit fees, and annual fees because their disclosure in the Schumer box is mandated after 2000. However, only 6.06% of the credit card offers mention late fees on the front page; 3.87% mention default APRs on the front page, and 7.27% mention over-limit fees on the front page. Even for regular APRs, only 27.95% of the offers display them on the front page. Not surprisingly, credit card offers usually do not mention fees, especially those that typically are back-loaded on the front page. On the other hand, 78.02% of the credit card offers include annual fee information on the front 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 front page of the offers; 100% of cash back and mileage programs are mentioned on the front page. For point reward, car rental insurance, and zero introductory APRs, the likelihood of appearing on the front page is 93.68%, 88.35%, and 89.69%, respectively.

We also compare the format design of card features between the front page and the back pages of the offers. Panel B of Table II compares the credit card terms conditional on whether they are mentioned on the front page. Late, over-limit, annual fees, and regular APRs are lower if they are mentioned on the front 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 II about here]

4. Customer Characteristics and Credit Card Features

4.1. Card Terms by Education Levels

We now analyze how credit card companies vary offer terms based on consumer characteristics. The characteristics collected in Mintel are parallel to the information that banks obtain by buying mailing lists from firms that sell consumer data. In Table III, we run simple hedonic regression models of card features on consumer characteristics at the credit card mail offer level. Formally, the regression can be expressed as follows:

$$Y_{i,j,t} = \beta_1 \times Education_{j,t} + \beta_2 \times FFR_t + Control_{i,j,t} + FE + \varepsilon_{i,j,t} \quad (1)$$

where $Y_{i,j,t}$ indexes the card features we are interested in, such as APRs, fees, reward programs, card designs, or text readability. For example, $APR_{i,j,t}$ is the regular purchase APR offered by credit card offer *i* to consumer *j* at month *t*. Our main variable of interest is the educational attainment of consumers, as a proxy for the financial literacy, measured as five distinct levels ranging from some high school to completed graduate school. We follow the earlier literature that has shown education to be a good proxy for financial literacy, see for example Lusardi and Mitchell (2007), Lusardi et al (2011), or Hastings and Mitchell (2018). Specifically, $Education_{j,t}$ is the matrix of four dummies for whether consumer *j*'s education level is at high school, some college, complete college, or post graduate, respectively. The lowest educational attainment is below high school, which is the missing category in the hedonic regression. FFR_t indexes the federal fund rate at the month *t*. We also 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, household composition, state fixed effect, and credit card company fixed effects in all regressions. Standard errors are clustered at the demographic cell level.

Panel A of Table III 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 mostly flat. This would be very surprising if education was simply 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 A1 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 pricing structure 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 back-loaded fees, controlling for income. For example, the coefficient of *Education_5* is -0.652, -0.279, and -1.179 in columns (2), (3), and (4), respectively, with the 1% significance level. This suggests that relative to the consumers with the lowest educational attainment (i.e., below high school), the most educated consumers (i.e., graduate degrees) receive offers with 2% lower late fees (0.652/33.19), 1% lower default APRs (0.279/26.13), or 4% lower over-limit fees (-1.179/30.16). In contrast, late fees tend to increase with income, as shown in Table A1, again suggesting that education and income pick up different underlying factors.

When looking at front-loaded features of the cards, like annual fees, in column (5), we find that these fees are significantly higher for households with higher education but very low for less-educated consumers. Similarly, column (6) shows that low introductory APR programs are predominantly offered to less-educated consumers, while highly educated consumers are significantly less likely to receive them. For example, the coefficient of *Education_5* is -0.048, with the 1% significance level. This suggests that relative to the consumers with the lowest educational attainment (i.e., below high school), the most educated consumers (i.e., graduate degrees) receive offers that are 11% less likely to have low introductory APRs (0.048/0.44). In contrast, in column (8), we see that reward programs like miles, are offered primarily to more educated consumers. These results are the first indication that less-educated consumers receive distinctly more back-loaded and shrouded card offers than educated consumers.

[Place Table III about 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 A2. 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, over-limit fees, and the dummy for introductory APRs. In column (7) of Table III, we then rerun our hedonic regression for the overall metric of "backward" loads and find that it decreases significantly with the education level of the household. Interestingly, the same is not true for income, as shown in Table A1. Richer people tend to receive more back-loaded card terms after controlling for education.

4.2. 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 back pages of an offer, it will be much less likely that a consumer sees the information. We have already shown in Table II that on average the less enticing terms of the card are typically on the back pages. In the following analysis, we also find a differential approach for educated versus less-educated consumers. In column (9) of Table III, *Back_LateFee* is the dummy for whether the late fee information is displayed only on the back pages of the offer letters (i.e., not on the front pages), this is usually in the Schumer box, which mandates the display of the offer terms at least on the back pages. We show that offers sent to less-educated consumers are more likely to display late fees on the back 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 2.6% higher than less educated consumers. Since the base rate probability of having a negative term displayed in the front is only 6%, as shown in Table II, 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 back pages more often for less-educated consumers. Since these less-educated consumers also receive higher back-loaded fees, 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 consumers.

Moreover, 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 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 are 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 A3 of the Appendix, we show that households in the lowest education bin (i.e., below high school) receive significantly more "Dominated" and "Worst" offers. 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.

4.3. Readability

In a next step, we are also able to explore how the language used in the card offer varies across consumers and even across given pages within a specific offer letter. This allows us to analyze if card issuers use more complex language to shroud onerous terms of an offer. In Panel B of Table III, we perform hedonic regressions of text readability on consumer characteristics. In particular, we use the Fog index, Grade index, and *Readability* (i.e., the first principal component of various readability measurements) to capture the difficulty level of the text on each page of the offer.[5] The higher the indexes, the more difficult to read the text. Furthermore, we calculate these readability measurements for front pages vs. back pages and regress them on education levels.

In column (1) to (3), the Fog index, Grade index, and *Readability* of the text on the front pages are mostly flat across consumers with different education levels, except for the higher readability

[5] Readability is the first principal component from the principal component analysis of Fog index, Coleman-Liau index, ARI, Flesch Kincaid Grade level, Flesch Reading Easy score, SMOG index, Dale-Chall Readability score, and Linsear-Write score.

levels for the highest education bin (i.e., graduate degree). In contrast, in column (4) to (6), we find that the text readability levels of back pages significantly decrease with education levels. These results suggest that offers sent to less-educated people use more complex language, especially on the back pages where the more important pricing and payment terms of the card are explained. In columns (7) to (9), we use the differences in the readability indexes of the front pages versus the back pages of the same offer as the dependent variable. The results confirm that the difference in the readability between the front and back pages is significantly larger for the consumers with lower education. In short, the language on the back pages of a credit card offer is more difficult, especially for less-educated consumers.

Moreover, in columns (10) and (11), we find that the font sizes of introductory APRs are significantly larger for less-educated consumers. This means that for financially unsophisticated consumers, the card issuers tend to use the large fonts to get their attention on the front-loaded features, along with the simpler languages on front pages.

In summary, compared to financially sophisticated consumers, offer letters sent to less sophisticated consumers use simpler language on the front pages but more complex language on the back pages. Since the back pages contain most of the information about the card, such as detailed notes of pricing terms, this constitutes another strategy of how credit card issuers can shroud information and make informational contents less accessible to their customers, especially the less-educated ones.

4.4. Transaction Card vs. Credit Card

Furthermore, we classify cards to transactions credit cards vs. true credit cards. The credit card industry differentiates between cards that are used for payment convenience by consumers (transaction cards) who typically do not carry balances and the cards that are used by consumers for borrowing (true credit cards). In our data, we can differentiate these cards by various reward programs in the offers. On the one hand, we define the transaction cards as the ones with any of miles, points, or cash back reward programs since these rewards target consumer spendings. On the other hand, we define the true credit cards as the ones with any introductory APRs since consumers can carry balances for low costs for a limited time. We exclude the cards with both reward programs for spending and introductory APRs to have a clean stratification. There are total 76,667 transaction cards and 242,104 true credit cards in our sample.

In Table IV Panel A, we compare the card pricing terms between transaction and credit cards. The front-loaded costs such as APR and annual fee are significantly lower for the credit cards than the transaction cards. In contrast, the back-loaded costs such as late fees and over-limit fees are significantly higher for the credit cards than the transaction cards. In short, credit cards have more back-loaded fee structures than transaction cards. In Panel B, we compare the readability of the text in the offers between these two types of cards. We find that all readability indexes for the back pages such as Fog and Grade are significantly higher for the credit cards than the transaction cards. Moreover, in Table V, we repeat the hedonic regressions for transaction cards and true credit cards, respectively. For credit cards in Panel A, the less-educated consumers have significantly higher back-loaded fees, which are also significantly more shrouded than the offers for well-educated consumers. These patterns are much weaker or insignificant for transaction cards, as shown in Panel B.

[Place Table V and VI about here]

In summary, if card issuers were expecting true credit cards to be mainly taken up by rational but very credit constraint consumers, we would expect these cards to be more transparent on the credit features since this is what people intend to use the card for. Instead, we again find that true credit cards have less transparency on the credit relevant payment terms than transaction cards, especially for less-educated consumers. Again this supports the idea that card issuers use the back-loaded pricing structure and shrouding of these terms to exploit consumer behavioral biases.

4.5. Robustness Check with Subsample

One dimension that is missing in our main data is the FICO score for individual borrowers since Mintel is not allowed to provide such information to individual researchers. To analyze whether including FICO scores affect our analysis, we obtained Mintel data via the Consumer Financial Protection Bureau (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 is to see whether the pricing relationships documented in our paper differ significantly when including FICO score. For this purpose, in Table A4 in Appendix, we repeat our hedonic regressions of card features on consumer 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 do not increase a lot, and all our results in Table A4 remain when including the FICO scores. Overall, it appears that the dimensions spanned by the FICO scores do not absorb the variations of the other observable characteristics used in the paper. We also perform another robustness test by controlling for zip code fixed effects. The patterns are very similar as in Table III. These results alleviate concerns that we are missing an important and un-spanned dimension of consumer 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 the same issuers. We find 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.

5. Shocks to Borrower Credit Risk: Unemployment Insurance

Finally, we analyze the effect of an exogenous shock to the creditworthiness of consumers, in particular, their risk of default, on credit card terms, and reward programs. We suggest that there are countervailing forces on 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 consumers, these can have an adverse selection on the card issuers. For example, if consumers 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 back-loaded pricing and shrouding.

5.1. Estimation 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 consumers. 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 consumers 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-differences (DID) 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 the following years; 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 and roll out new mailing campaigns every 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, demographic 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.

5.2. UI, Credit Card Pricing, and Design

Table VI, Panel A presents the one-year DID regression results between 1999 and 2007. Consistent with our prior analysis, 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. Overall, we find that card issuers rely more heavily on back-loaded and shrouded terms when UI is increased, and the riskiness of the borrowers is reduced. We see that front-loaded terms like APR or annual fees do not change, e.g., in column (1), we find a negative but not significant effect of UI changes on APR. Column (4) shows similarly that annual fees do not change after the UI changes. In contrast, in columns (3) and (5), we see that an increase in UI leads to a substantial and significant increase in late fees and in the use of intro APR programs. In particular, the coefficients of *UI* are 0.909 and 0.123 in column (3) and (5), respectively, with the 5% significance level. This means that a jump in UI leads to an 18.9% increase in the fraction of card offers with low introductory (teaser rate) APRs (0.123/0.65), and a 2.7% increase in late fees (0.909/33.19). In column (6), we again use the first principal component (i.e., "*Backward*") 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 suggest that with the increase in UI issuers rely more heavily on back-loaded payment features.

In a next step, we look at how the back-loaded terms are displayed in the offer letter after the UI change. Column (7) shows how default APRs are mentioned in the front page or back pages of the offer. *DefaultAPR_MainPage* is the dummy for whether the default APR is displayed on the front page or not. The coefficient of UI is -0.011 at the 1% significance level. Column (8) shows the same pattern for late fees. This means that following UI increases, card issuers are more likely to push the relevant pricing information to the back pages of offers.

In Table VI, Panel B, we interact the UI dummy with the dummy of less-educated households (i.e., below college) and also control for UI times a dummy for low-income households (i.e., below 35k annual income). 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 the backloading effect we found in Panel A is even more pronounced for less-educated households following UI increases.

[Place Table VI about here]

In Table VII, we repeat this DID analysis for the readability of the language. When again looking of *Fog*, *Grade*, and *Readability* indexes in columns (1) to (3), we see that for all these metrics of difficulty of the language, there is a decline in the complexity of the front pages after the increases in UI, the coefficients of the readability indexes on UI are all significantly negative. In contrast, columns (4) to (6) look at the changes in the readability of the back pages. Here we find that the coefficients of *UI* are not significant and close to zero, but the coefficients on the interaction terms with the low education dummy are significantly positive for *Fog_Back* and *Readability_Back*. This means that although the language on the front pages becomes easier to read, the language on the back pages becomes harder to understand, especially for less-educated households. Since the back pages of the offer are the place where the actual payment terms are displayed in detail, we interpret this again as an indication of more shrouding.

[Place Table VII about here]

We also repeat all the regressions without the bank fixed effects, and the results are very similar to those in Tables VI and VII; 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 and shrouding strategies based on UI changes.

Taken together, these results suggest that when a consumer's credit risk goes down after a UI increase, credit card companies tend to use more back-loaded pricing contracts. At the same time, they also engage in more shrouding of these terms, as highlighting by the use of more complicated language on the back pages and pushing them to the back of the offer letter. In other words, card issuers rely more heavily on naiveté-based targeting when then credit risk of the consumer is reduced which supports the idea that they understand the trade-off between short term rent extraction from targeting consumers' behavioral biases and the long-run possibility of increased credit risk if people do not understand their full cost of credit.

6. Conclusion

The results in this paper suggest that credit card companies use an array of different design features of the offer letter to shroud aspects of the credit card contract that are unappealing to myopic or time-inconsistent consumers. In addition, card issuers target sophisticated and naïve consumers 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, such as Gabaix and Laibson (2006), Heidhues and Koszegi (2010), or Grubb (2009).

Finally, our analysis highlights an important new dimension of the use of naiveté-based targeting 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 I
Summary Statistics

Table 1 presents the summary statistics of the main variables in the empirical analysis. Variables are based on 849,672 Mintel's credit card's direct mailings from March 1999 to December 2007. Variables from *CASH* to *Grade* are from 638,458 total mailing offers with 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 colors other than black/white in the offer. *Bold* is the dummy of whether the offer uses bold to highlight reward programs. If there are no reward programs in the offer, we put missing value to *Size*, *Color*, and *Bold*. *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. *Annual_fee, Late_fee*, and *OverLimit_fee* are fees charged by credit card companies, which are usually displayed in the Schumer box.

Variable	Mean	Std. Dev.	Min	Max	Obs
FFR	3.17	1.73	0.98	6.54	849,672
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	26.13	4.01	0.00	41.00	592,855
Default APR Dummy	0.70	0.46	0.00	1.00	849,672
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
Intro_APR_All	0.65	0.48	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
OverLimit_fee	30.16	8.71	0.00	79.00	774,284
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
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
Back_LateFee	0.79	0.41	0.00	1.00	611,797
Back_APR_Default	0.47	0.50	0.00	1.00	611,797
Fog	14.02	1.63	2.40	27.87	626,033
Grade	8.54	1.12	2.00	17.00	625,583

Table II
Descriptive Statistics for Format Design of Credit Card Offers

Table II presents the design of the credit card features in the offer letters. The dataset is based on 638,458 Mintel's credit card's direct mailing offers with scanned images from March 1999 to December 2007. Penal A is the descriptive statistics of format information of credit card terms and reward programs. In Panel A, APR, 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_APR_All* 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 colors other than black/white in the offer. *Bold* is the dummy of whether the offer uses bold to highlight reward programs. Panel B shows the descriptive statistics of credit card terms when they mentioned on the front pages or not. "Front page" includes the envelope and the first page in the letter of credit card offers.

Panel A

	APR	Late fee	Default APR	Over limit fee	Annual fee	CASH	POINT	MILE	Intro_APR_All
Percentage of cards that have this term	97.31%	100.00%	100.00%	100.00%	100.00%	17.53%	22.44%	8.23%	67.86%
Term mentioned on front page	27.95%	6.06%	3.87%	7.27%	78.02%	100%	93.68%	100%	89.69%
Font size of term if mentioned on front page	13.02	9.56	9.39	9.82	13.39	12.12	10.98	16.56	13.43
Font size of CC term if NOT mentioned on front page	10.57	9.56	9.64	9.52	14.47	10.62	10.80	9.91	11.50
Font color of CC term if mentioned on front page	33.48%	32.92%	32.29%	25.53%	64.42%	44.97%	41.40%	60.89%	58.30%
Font color of CC term if NOT mentioned on front page	23.79%	23.69%	24.96%	21.82%	44.53%	37.24%	38.45%	29.47%	43.84%
Font bold of CC term if mentioned on front page	54.97%	38.91%	25.58%	34.18%	77.82%	53.84%	39.06%	72.70%	75.78%
Font bold of CC term if NOT mentioned on front page	51.71%	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

	APR	Late fee	Default APR	Over limit fee	Annual fee
if term is on front page	11.17%	27.89	27.56%	28.38	5.95
if term is in the back (e.g., Schumer box)	12.71%	34.63	27.75%	30.62	26.12

Table III
Credit Card Features and Demographics

Table III presents the OLS regressions of credit card features on consumer demographics. The dataset is based on 849,672 Mintel's credit card's direct mailing offers between 1999 and 2007. In Panel A, we restrict the sample to the offers we have scanned pictures from columns 8 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. Panel B is for the card readability and design. *Education_2* is the dummy for the 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. We control for the household income, age of the household head, household composition. We also control for the bank fixed effects and state fixed effects. Standard errors in parentheses are clustered by demographic cells, which are based on states, age, income, education, and household composition. *, **, and *** indicate the significance at 10%, 5%, and 1% levels, respectively.

Panel A										
	1	2	3	4	5	6	7	8	9	10
Dependent Variable	APR	Late Fee	Default APR	Over-limit Fee	Annual Fee	Intro_APR_regular	Backward	MILE	Back_LateFee	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)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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

(To be continued)

Table III
Credit Card Features and Demographics – *continued*

Panel B

	1	2	3	4	5	6	7	8	9	10	11
Dependent Variable	Fog_Front	Grade_Front	Readability_Front	Fog_Back	Grade_Back	Readability_Back	Fog_Front-Back	Grade_Front-Back	Readability_Front-Back	Intro_APR_Size	Intro_Balance_Size
FFR	-0.020***	0.038***	0.014***	0.056***	0.004***	0.054***	-0.022***	0.052***	-0.009***	-0.229***	-0.554***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.004)	(0.013)
Education_2	-0.020	-0.002	-0.007	-0.066***	-0.018**	-0.033***	0.044***	0.014	0.025**	-0.013	-0.140*
	(0.013)	(0.011)	(0.009)	(0.011)	(0.007)	(0.007)	(0.015)	(0.012)	(0.010)	(0.024)	(0.073)
Education_3	-0.012	0.008	0.008	-0.086***	-0.019**	-0.038***	0.068***	0.024*	0.042***	0.004	-0.145*
	(0.014)	(0.011)	(0.009)	(0.011)	(0.007)	(0.007)	(0.016)	(0.013)	(0.011)	(0.026)	(0.076)
Education_4	-0.013	0.016	0.012	-0.124***	-0.045***	-0.058***	0.109***	0.059***	0.069***	-0.038	-0.138*
	(0.014)	(0.012)	(0.009)	(0.012)	(0.007)	(0.008)	(0.017)	(0.014)	(0.011)	(0.026)	(0.078)
Education_5	0.033**	0.041***	0.048***	-0.138***	-0.039***	-0.060***	0.174***	0.080***	0.109***	-0.085***	-0.239***
	(0.015)	(0.013)	(0.010)	(0.013)	(0.008)	(0.008)	(0.018)	(0.015)	(0.012)	(0.030)	(0.082)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	561,053	559,397	561,053	593,717	592,784	593,717	556,456	554,307	556,456	166,279	146,041
R-squared	0.084	0.038	0.062	0.121	0.111	0.105	0.091	0.034	0.063	0.272	0.063

Table IV
Transaction vs. Credit Card

Table IV presents the statistics for the comparison between the transaction cards and true credit cards. We define the transaction cards as the ones with any of miles, points, or cash back rewards, and there are 76,667 transaction cards in total. We define the true credit cards as the ones with any introductory APRs (i.e., introductory APR for regular purchase, balance transfer, and cash advance). There are 242,104 true credit cards in our sample. We exclude the cards with both reward programs and introductory APRs. In Panel A, we compare the credit card pricing terms (e.g., APR, annual fee, late fee, and over-limit fee) between the transaction and credit cards. In Panel B, we compare the readability and design of the offer letters between the transaction and credit cards. We report the results of the standard t-tests with the differences and t-stats. *, **, and *** indicate the significance at 10%, 5%, and 1% levels, respectively.

Panel A: Pricing Terms

	Credit		Transaction			
	N	Mean	N	Mean	Difference	t-stats
APR	242,009	11.61	64,751	13.40	-1.79***	-110.00
Annual Fee	241,635	6.37	75,765	33.91	-27.54***	-230.00
Late Fee	241,440	34.55	75,329	32.18	2.37***	83.20
Over-limit Fee	240,241	32.25	57,307	24.26	7.99***	202.37

Panel B: Design

	Credit		Transaction			
	N	Mean	N	Mean	Difference	t-stats
Fog_Back	239,376	14.79	76,049	14.29	0.50***	65.84
Grade_Back	239,143	8.85	76,009	8.68	0.16***	31.06
PC1_Read_Back	239,376	0.47	76,049	0.27	0.20***	38.62
Fog_Front-Back	224,637	-2.07	71,982	-1.76	-0.31***	-26.15
Grade_Front-Back	223,669	-0.94	71,883	-0.71	-0.23***	-23.94
PC1_Read_Front-Back	224,637	-1.46	71,982	-1.20	-0.25***	-32.89
Back_Default APR	231,182	0.49	72,752	0.34	0.15***	69.70
Back_LateFee	231,182	0.83	72,752	0.73	0.10***	57.51

Table V
Credit Card Features and Demographics (Credit vs. Transaction)

Table V presents the OLS regressions of credit card features on consumer demographics. The dataset is based on 849,672 Mintel's credit card's direct mailing offers between 1999 and 2007. In Panel A, we restrict the sample to the credit cards with any introductory APR programs (i.e., introductory APR for regular purchase, balance transfer, and cash advance), and there are 242,104 true credit cards in our sample. In Panel B, we restrict the sample to the transaction cards that are cards with any of the cash back, miles, or point reward programs, and there are 76,667 cards in total. 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 the dummy for the 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. We control for the household income, age of the household head, household composition. We also control for the bank fixed effects and state fixed effects. Standard errors in parentheses are clustered by demographic cells, which are based on states, age, income, education, and household composition. *, **, and *** indicate the significance at 10%, 5%, and 1% levels, respectively.

Panel A: Ture Credit Card

	1	2	3	4	5	6	7
Dependent Variable	Late Fee	Over-limit Fee	Default APR	Back_LateFee	Back_APR_Default	Fog_Back	Grade_Back
FFR	0.421***	0.415***	1.402***	0.010***	0.095***	0.072***	0.017***
	(0.010)	(0.008)	(0.006)	(0.001)	(0.001)	(0.003)	(0.002)
Education_2	-0.204***	-0.207***	-0.173***	-0.008***	-0.012***	-0.070***	-0.024**
	(0.050)	(0.047)	(0.032)	(0.003)	(0.005)	(0.015)	(0.010)
Education_3	-0.289***	-0.266***	-0.159***	-0.010***	-0.024***	-0.074***	-0.019*
	(0.054)	(0.051)	(0.035)	(0.003)	(0.005)	(0.016)	(0.011)
Education_4	-0.360***	-0.396***	-0.301***	-0.017***	-0.027***	-0.122***	-0.053***
	(0.056)	(0.052)	(0.036)	(0.003)	(0.005)	(0.017)	(0.011)
Education_5	-0.618***	-0.714***	-0.395***	-0.028***	-0.049***	-0.163***	-0.058***
	(0.063)	(0.060)	(0.040)	(0.004)	(0.006)	(0.018)	(0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	235,263	235,010	203,650	225,190	225,190	233,318	233,086
R-squared	0.201	0.247	0.452	0.169	0.231	0.128	0.126

(*to be continued*)

Table V
Credit Card Features and Demographics (Credit vs. Transaction) - *continued*

Panel B: Transaction Card							
	1	2	3	4	5	6	7
Dependent Variable	Late Fee	Over-limit Fee	Default APR	Back_LateFee	Back_APR_Default	Fog_Back	Grade_Back
FFR	-0.380***	-0.557***	1.405***	0.023***	0.064***	0.099***	0.045***
	(0.019)	(0.032)	(0.009)	(0.001)	(0.001)	(0.005)	(0.003)
Education_2	-0.209	-0.375*	-0.108*	-0.005	-0.003	-0.054*	-0.026
	(0.148)	(0.201)	(0.062)	(0.007)	(0.009)	(0.031)	(0.020)
Education_3	-0.126	-0.323	-0.134**	-0.015**	0.002	-0.097***	-0.037*
	(0.156)	(0.211)	(0.065)	(0.007)	(0.009)	(0.032)	(0.021)
Education_4	-0.158	-1.068***	-0.142**	-0.011	0.019**	-0.082***	-0.057***
	(0.157)	(0.212)	(0.064)	(0.007)	(0.009)	(0.032)	(0.020)
Education_5	-0.264	-1.048***	-0.188***	-0.017**	0.016*	-0.084**	-0.041*
	(0.166)	(0.225)	(0.066)	(0.007)	(0.010)	(0.033)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	71,506	0.647	36,850	68,776	68,776	72,401	72,366
R-squared	0.440	9.460	0.762	0.419	0.212	0.304	0.193

Table VI
Unemployment Insurance and Credit Card Feature

Table VI presents the DID regressions to estimate unemployment insurance effects on credit card features. Data include the credit card offers from 1999 to 2007. In Panel A, *UI* is the DID dummy at the semi-annual frequency, which equals to one if the unemployment insurance in the state increased by more than 10% in the year and equals to zero in the year before the jump. In Panel B, *LowEdu* is a dummy for the household head's education level below college (i.e., the highest degree is high school). *LowIncome* is the dummy for households with annual income below 35k. UI_Pre_3M is the dummy for three-month pretrend of the UI jumps. UI_Pre_6M is the dummy for six-month pretrend of the UI jumps. UI_Small is the dummy of the UI increases below 10%, which are mainly due to inflation adjustments. Column 8 and 9 show the DID regressions on whether default APR/late fees are mentioned on the main page of the credit card offers, and the sample is restricted to credit cards with scanned images. All columns are controlled by year fixed effects, bank fixed effects, and demographic cell fixed effects based on states, age, income, education, and household composition. Standard errors are clustered at the state level. *, **, and *** indicate the significance at 10%, 5%, and 1% levels, respectively.

Panel A								
	1	2	3	4	5	6	7	8
Dependent Variable	APR	Default APR Dummy	Late Fee	Annual Fee	Intro_APR_All	Backward	DefaultAPR MainPage	LateFee MainPage
FFR	0.421***	-0.048***						
	(0.043)	(0.003)						
UI	-0.276	0.044	0.909**	0.271	0.123**	0.080**	-0.011***	-0.012**
	(0.353)	(0.028)	(0.389)	(0.454)	(0.056)	(0.036)	(0.003)	(0.005)
UI_Pre_3M	-0.005	0.022	0.655***	-0.036	0.140*	0.059	-0.005	-0.010
	(0.120)	(0.021)	(0.185)	(0.361)	(0.077)	(0.037)	(0.005)	(0.009)
UI_Pre_6M	0.156	-0.068***	-0.204	-0.159	0.066	0.071***	-0.004	-0.001
	(0.269)	(0.024)	(0.450)	(0.714)	(0.043)	(0.024)	(0.004)	(0.010)
UI_Small	-0.052	-0.015	0.125	-1.321	0.065	0.017	-0.006	0.012
	(0.158)	(0.015)	(0.402)	(0.925)	(0.042)	(0.034)	(0.004)	(0.010)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,224	93,491	92,876	93,215	93,940	92,629	46,161	46,161
R-squared	0.263	0.410	0.179	0.193	0.121	0.121	0.054	0.029

(to be continued)

Table VI
Unemployment Insurance and Credit Card Feature- *continued*

Panel B

	1	2	3	4	5	6	8	9
Dependent Variable	APR	Default APR Dummy	Late Fee	Annual Fee	Intro_APR_All	Backward	DefaultAPR MainPage	LateFee MainPage
FFR	0.425***	-0.048***						
	(0.044)	(0.003)						
UI	-0.038	0.030	0.867**	0.695	0.135**	0.029	-0.014***	-0.016***
	(0.304)	(0.030)	(0.354)	(0.432)	(0.053)	(0.034)	(0.005)	(0.006)
UI*LowEdu	-0.324***	0.021***	0.215**	-0.597	-0.013	0.061**	0.005	0.006
	(0.109)	(0.006)	(0.100)	(0.487)	(0.019)	(0.027)	(0.005)	(0.006)
UI*LowIncome	-0.048	-0.004	-0.295**	-0.062	-0.013	-0.009	-0.001	0.000
	(0.127)	(0.017)	(0.119)	(0.590)	(0.018)	(0.031)	(0.006)	(0.011)
UI_Pre_3M	0.004	0.021	0.648***	-0.028	0.140*	0.044	-0.005	-0.010
	(0.118)	(0.020)	(0.187)	(0.360)	(0.076)	(0.039)	(0.005)	(0.009)
UI_Pre_6M	0.174	-0.070***	-0.216	-0.129	0.067	0.058**	-0.004	-0.002
	(0.281)	(0.024)	(0.454)	(0.725)	(0.042)	(0.023)	(0.005)	(0.011)
UI_Small	-0.041	-0.015	0.130	-1.306	0.066	0.021	-0.007	0.012
	(0.159)	(0.015)	(0.400)	(0.923)	(0.042)	(0.037)	(0.005)	(0.010)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,224	93,491	92,876	93,215	93,940	91,144	46,161	46,161
R-squared	0.263	0.410	0.179	0.193	0.121	0.100	0.054	0.029

Table VII
Unemployment Insurance and Credit Card Readability

Table VII presents the DID regressions to estimate unemployment insurance effects on credit card designs and readability of the language in the offer letters. Data include the credit card offers from 1999 to 2007. *UI* is the DID dummy at the semi-annual frequency, which equals to one if the unemployment insurance in the state increased by more than 10% in the year and equals to zero in the year before the jump. *LowEdu* is a dummy for the household head's education level below college (i.e., the highest degree is high school). *LowIncome* is the dummy for households with annual income below 35k. UI_Pre_3M is the dummy for three-month pretrend of the UI jumps. UI_Pre_6M is the dummy for six-month pretrend of the UI jumps. UI_Small is the dummy of the UI increases below 10%, which are mainly due to inflation adjustments. All columns are controlled by year fixed effects, bank fixed effects, and demographic cell fixed effects based on states, age, income, education, and household composition. Standard errors are clustered at the state level. *, **, and *** indicate the significance at 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6
Dependent Variable	Fog_Front	Grade_Front	Readability_Front	Fog_Back	Grade_Back	Readability_Back
UI	-0.192*	-0.123**	-0.154*	-0.019	-0.072	-0.080
	(0.111)	(0.051)	(0.090)	(0.048)	(0.058)	(0.057)
UI*LowEdu	0.054	-0.028	0.033	0.123**	0.025	0.081**
	(0.105)	(0.074)	(0.063)	(0.047)	(0.039)	(0.033)
UI*LowIncome	0.155	0.166*	0.090	-0.144*	-0.083*	-0.071
	(0.095)	(0.096)	(0.056)	(0.071)	(0.044)	(0.048)
UI_Pre_3M	-0.246**	-0.076*	-0.195*	-0.152	-0.086	-0.176
	(0.104)	(0.040)	(0.112)	(0.096)	(0.079)	(0.123)
UI_Pre_6M	-0.170	0.009	-0.072	-0.111	0.069	-0.059
	(0.152)	(0.079)	(0.099)	(0.092)	(0.056)	(0.047)
UI_Small	-0.420**	-0.214	-0.282*	-0.206**	-0.067	-0.147**
	-0.191	(0.137)	(0.146)	(0.076)	(0.047)	(0.062)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,938	43,764	43,938	45,219	45,145	45,219
R-squared	0.058	0.058	0.062	0.085	0.090	0.082

Appendix for "Do Credit Card Companies Screen for Behavioral Biases?"

Table A1
Credit Card Features and Demographics (Income)

Table A1 presents the OLS regressions of credit card features on consumer demographics. The dataset is based on 849,672 Mintel's credit card's direct mailing offers between 1999 and 2007. We restrict the sample to offers we have scanned pictures from columns 8 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. *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. We control for the household education, age of the household head, household composition. We also control for the bank fixed effects and state fixed effects. Standard errors in parentheses are clustered by demographic cells, which are based on states, age, income, education, and household composition. *, **, and *** indicate the significance at 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6	7	8	9	10
Dependent Variable	APR	Late Fee	Default APR	Over-limit Fee	Annual Fee	Intro_APR	Backward	MILE	Back_LateFee	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)
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)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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

Table A2
Principal Component Analysis on Credit Card Pricing

Table A2 presents the results of the principal component analysis on credit card pricing terms. The dataset is based on 849,672 Mintel's credit card's direct mailing offers between 1999 and 2007. 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
	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	849,672				
Panel B	1	2	3	4	5
	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	849,672				

Table A3
Distribution of Dominated Offers

Table A3 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.

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

Table A4
Credit Card Features and Demographics with FICO Scores

Table A4 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. *Format* is the first principal component of reward programs' size, color, bold, and 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. Education_2 is the dummy for the 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. We also control for dummy variables for FICO score below 620, 620-660, 660-720, and above 720. FICO score below 620 is the missing category. *, **, and *** indicate the significance at 10%, 5%, and 1% levels, respectively.

	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)
FICO (620-660)	-0.112***	0.106	-0.014	0.154***	-8.033***	0.014***	0.283***	0.005***	0.076***
	(0.040)	(0.103)	(0.034)	(0.056)	(0.268)	(0.004)	(0.012)	(0.002)	(0.010)
FICO (660-720)	-1.356***	-0.276***	-0.375***	-0.642***	-12.450***	0.019***	0.479***	0.026***	0.205***
	(0.033)	(0.037)	(0.028)	(0.055)	(0.225)	(0.004)	(0.010)	(0.002)	(0.009)
FICO (>720)	-2.260***	-0.671***	-0.742***	-1.488***	-15.325***	0.014***	0.517***	0.068***	0.362***
	(0.030)	(0.039)	(0.025)	(0.050)	(0.210)	(0.003)	(0.009)	(0.002)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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

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