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DO CREDIT CARD COMPANIES SCREEN FOR BEHAVIORAL BIASES?

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ABSTRACT

We look at the supply side of the credit card market to analyze the pricing and marketing strategies of credit card offers. First, we show that card issuers target less-educated customers with more steeply back-loaded fees (e.g., lower introductory APRs but higher late and over-limit fees) compared offers made to educated customers. Second, issuers use rewards programs to screen for unobservable borrower types. Conditional on the same borrower type, cards with rewards, such as low introductory APR programs, also have more steeply backloaded fees. In contrast, cards with mileage programs, which are offered mainly to the most-educated consumers, rely much less on back-loaded fees. Finally, using shocks to the credit risk of customers via increases in state-level unemployment insurance, we show that card issuers rely more heavily on back-loaded and hidden fees when customers are less exposed to negative cash flow shocks. These findings are in line with the recent behavioral contract theory literature.

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1. Introduction

Over the last three decades, the US has experienced a rapid expansion of retail financial products, especially among middle- and lower-income households. At the same time, the heterogeneity and complexity of the products and the terms that are offered to consumers increased dramatically; see, for example, Merton (1992), Miller (1993), or Tufano (2003). Recent papers by Phillipon (2012) and Greenwood and Scharfstein (2013) suggest that these emerging trends were accompanied by increased rents for intermediaries in the financial industry. Many policy makers are concerned that these rents come at the expense of consumers, particularly if less financially sophisticated consumers are targeted with especially onerous or hidden fees. For a summary of the policy implications of consumers that are not fully rational, see Thaler and Sunstein (2008) or Campbell et al (2011).

In this paper, we aim to establish whether and how financial institutions take the sophistication of their customers into account by examining the US credit card industry. We document three main findings: First, credit card terms that are offered to more financially sophisticated consumers differ significantly from those offered to unsophisticated customers, where sophistication is measured as educational attainment, holding other observable household characteristics constant. [1] Less-sophisticated households are much more likely to be offered back-loaded or hidden fee structures, such as low introductory (or teaser) rates. However, after the introductory period, these cards have higher rates, late fees and over-limit fees. In contrast, cards that are offered to

[1] We will discuss these findings in the context of behavioral contract theory models in which a lack of financial literacy is often modeled as the inability to understand contract terms, e.g., Gabaix and Laibson (2007), or to forecast one's own demand for credit, e.g., Heidhues and Koszegi (2010) or Grubb (2010).

sophisticated customers rely much less on back-loaded fees and instead have higher upfront fees, such as annual fees. We also show that the worse the credit terms, the more likely they are to appear either in small font or on the last pages of the offer letter. Similarly, offer letters with back-loaded terms contain more photos and less text.

Second, we find that even when holding constant the observable characteristics of customers, card issuers attempt to screen households based on *unobservable* characteristics by offering a menu of cards with varying degrees of back-loaded fees and different rewards programs. Cards with rewards programs that appeal to less-sophisticated consumers also have more back-loaded terms. While cards with miles programs that appeal mainly to sophisticated consumers have more front-loaded fees.

This explicit targeting of less-sophisticated households with more back-loaded or shrouded credit terms is concerning because a number of prior studies on the demand side of the credit card industry have shown that credit card users suffer when they choose these contracts. For example, Agarwal et al (2008) and (2015) show that, on average, households that choose cards with back-loaded terms are subject to higher fees and carry higher balances. In light of this evidence, our results suggest that less-sophisticated consumers are more likely to bear the costs of increased credit term complexity.

Third, we document an important trade-off between borrower sophistication and credit risk that has not been previously explored in the literature. A lending strategy that selects for less-sophisticated customers via back-loaded or shrouded attributes might increase rents from these consumers over the short run, but it might also expose the lender to higher credit risk over the long run if these customers do not understand the true cost of credit. We find that banks proactively increase their reliance on back-loaded terms when the credit risk of consumers decreases. Using a difference-in-difference estimator, we show that when states increase unemployment insurance (UI), which protects and stabilizes households' cash flows on the downside, banks increase their use of back-loaded fees and introductory APR (teaser) offers.

The credit card industry is an ideal environment in which to analyze how financial institutions target more (or less) sophisticated consumer groups because the majority of credit cards are sold via pre-approved credit card solicitations sent by mail.[2] This means that the same information that customers receive is observable to the researcher once we obtain the card solicitations .[3] We use detailed information from Compremedia on the almost one million individual credit card offers that were sent to a set of representative households in the US between 1999 and 2011.[4] Compremedia selects the sample of households to mirror the information credit card issuers observe when targeting customers. These data allows us to observe the supply side of the credit card market, i.e., the types of offers that customers receive. Using complete PDF versions of the actual offer letters, we created algorithms to extract the card information and features of the offer. We classify the "hard" information in the offers such as the APRs, fees, and reward programs. However, we also observe what we call the "soft" features of the offers, for example, the use of

[2] During our sample period, the majority of applications were solicited via mailers. Only in the last five years have online applications become predominant. Therefore, we focus on the period before 2008. We repeated the analyses using data up to Jan 2016, and the results are qualitatively unchanged.

[3] For almost all other retail financial products, the customer's choice is intermediated by sales agents or advisors, for example, insurance brokers and financial advisors. This process makes it difficult to observe the actual information consumers receive, as these agents might alter the information or even product features in a way that is unobservable to the researcher.

[4] Compremedia collects monthly information on all credit card mailers sent to a set of approximately 4000 representative households that work with Compremedia across the US. These households provide a representative sample of US credit card owners. The goal of the data collection is to help card issuers monitor each other's offers and product innovations.

photos, color, font size, and whether information about an offer is provided at the beginning or the end of the letter.[5]

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

We first provide evidence that credit card issuers target unsophisticated customers with more back-loaded or hidden card features than sophisticated ones, holding all other observable characteristics constant. Our measure of sophistication is the educational attainment of a household. The education levels are some high school, high school, some college, college education, and more than college.[6] We regress different card features on dummies for educational attainment while controlling for income level, age, gender, and marital status, as well as for the monthly fed funds rate and state-level fixed effects. Lower educational attainment is correlated with higher late fees, higher over-limit fees and higher default APRs, but these customers are more likely to receive low introductory APR offers and no annual fees. The reverse is true for sophisticated consumers. We show that these results hold even if we control for bank fixed effects in the regressions. This means that these differences in targeting strategies are not a cross-bank phenomenon where different banks target different customer groups, as the pattern holds even within a given bank.

[5] As financial institutions in the US have to follow TILA (Truth in Lending Act) rules, all the information concerning the card must be included in the pre-approved mailer. In addition, the mandatory Schumer box discloses most of the main card features included in the letter. However, issuers can choose how they display the information that they highlight in the main text.
[6] For a subset of observations, we can also control for FICO scores.

Since credit card terms are not offered to customers one by one but as a bundle, we carefully explore the correlation structure of terms across cards. We find strong positive correlations among all back-loaded card features (late fees, over-limit fees, default APRs and low introductory APRs), and these features are negatively correlated with front-loaded card features (annual fees and regular APR). A principal component analysis allows us to sort cards into more forward- or back-loaded fee structures. We find that the first principal component loads positively on all the back-loaded terms and negatively on front-loaded ones, again suggesting that banks consistently sort cards into front- versus back-loaded categories. We then regress the loading of each card on the first principal component on our sophistication measure, controlling for personal characteristics. We find that consistent with prior results, less-sophisticated households are more likely to receive card offers that offer a bundle of back-loaded characteristics.

To explore the relationships between individual card features, we also regress front-loaded features, such as the regular APR or the annual fee, on the back-loaded fees, e.g., late fees, and an interaction between late fees and a dummy for the sophistication level of the household. The results show that the trade-off between back- and front-loaded card features is much steeper for less-sophisticated households. In other words, the less sophisticated the household, the more back-loaded are the credit terms that are offered to them. We repeat this analysis for the remaining back- and front-loaded card features.

To understand whether these different card features actually affect the pricing of the cards, we follow the approach in Ausubel (1991) and use changes in the federal funds rate as shocks to the banks' cost of funding. This allows us to analyze which card features banks use to pass these costs on to consumers. If issuers never expected to collect late fees or over-limit fees from (unsophisticated) customers, we would not expect them to change these card features. However, we see that when the FFR increases, credit cards that target less-sophisticated consumers, respond strongly in their late fees and over-limit fees but not in their upfront fees (regular APR and annual fees). In contrast, the regular APRs and annual fees of cards offered to sophisticated consumers are more sensitive to a FFR increase than are the back-loaded terms. This pattern supports our prior finding that the pricing of the first set of cards is conducted via back-loaded fees, while cards offered to sophisticated consumers are priced via the regular APR.

A second important dimension of the credit card market is that even conditional on borrowers' observable characteristics, they might differ in their sophistication along ex ante unobservable dimensions. Our data allows us to observe the menu of card offers that issuers send to the same household in order to screen for unobservable borrower types. This means we can compare the pricing of different cards while holding constant the borrower fixed effect. It appears that issuers use rewards programs to screen for unobservable differences between borrowers. We show that cards that have rewards programs, such as low introductory APRs, cash back or points, rely more on back-loaded pricing terms such as lower regular APR and higher late and over limit fees. In contrast, cards with airline miles programs, which are mainly offered to the most educated groups in the population (less than 9% of cards offer airline miles), have significantly higher regular APRs and often carry an annual fee, but they have low late fees and over-limit fees. The results of these screening regressions hold even if we control for bank fixed effects, which means that two credit cards offered by the same issuer show these differences in pricing strategy. These findings suggest that card issuers try to use different rewards programs to separate more-sophisticated from less-sophisticated borrowers. As more-sophisticated borrowers might be able to avoid back-loaded fees, it is not in the interest of the card issuers to offer them features such as low introductory teaser rates.

Finally, we show that banks seem to understand that reliance on back-loaded or shrouded features can affect the credit risk of their borrower pool because it changes which customers take up these credit cards. If borrowers do not understand all the credit terms or mistakenly believe that they will never incur the back-loaded fees, these pricing strategies could attract customers who cannot afford the credit cards that are offered and who then default when the fees come due. This risk creates an endogenous limit to how heavily lenders can rely on these strategies.

To test whether banks proactively take this effect into account, we look at exogenous shocks to customer creditworthiness, in particular, changes in state-level unemployment insurance (UI) in the US over the last decade.[7] UI has increased in a staggered fashion across several US states over the last decade. These changes provide higher levels of unemployment insurance and longer UI benefits periods. By reducing the impact on consumer cash flows in the event of negative shocks, increases in UI also reduce a lender's exposure to one of the largest negative economic shocks that customers can experience. This policy change allows us to use a standard difference-in-difference estimator to regress changes in card features on UI changes across states. Our results show that these shocks to borrowers indeed affect the willingness of card issuers to rely on back-loaded and shrouded features. We find that increases in UI levels lead to an increase in the fraction of offers with low intro APRs and other reward programs. However, we also see a significant

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

increase in late fees and default APRs. Interestingly, we also find that when the UI level increases, offer letters use more colors and move back-loaded features to the back of the letter. Taken together, these results suggest that credit card companies realize that there is an inherent trade-off in the use of back-loaded features in credit card offers: They might induce customers to take on more (expensive) credit, but at the same time, they expose the lender to greater risk, if those consumers do not anticipate the true cost of credit.

Our results are in line with the predictions of several recent behavioral models of the credit card market.[8] These models suggest that the three-part tariff we see in the credit card market might be optimal if customers do not understand their actual cost of credit. These consumers will demand credit as if they were facing the low APRs but not the back-loaded fees. A rational consumer who understands the full cost of credit would instead reduce borrowing to avoid late fees, but this practice is not optimal for card issuers because it reduces the infra-marginal rents they can extract.[9] The mistakes consumers make in estimating their costs of credit can be due to misunderstandings about either the contract (myopia) or their own demand (self-control). A prominent example of the former is the model by Gabaix and Laibson (2006) on shrouded attributes. It suggests that companies can attract myopic consumers by offering low base prices or other enticing features but break even by charging high prices for hidden, add-on features.[10] Heidhues and Koszegi (2010, 2015) provide a micro foundation for these contracts if borrowers have self-control

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[8] For a detailed overview of the theoretical models, see for example, DellaVigna (2009), Koszegi (2013) or Heidhues and Koszegi (2015).

[9] Standard adverse selection models with nonlinear pricing a la Mussa and Rosen (1978) or Maskin and Riley (1984) predict that the last unit of consumption should be priced at marginal cost so that the highest demand consumer will pay the lowest marginal price. For a discussion of these points, see Grubb (2015).

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

issues but naively underestimate the likelihood of being tempted in the future.[11] Grubb (2010) derives very similar results for consumers with overoptimistic evaluations of how well they can forecast the variance of their future demand.

Our results are also consistent with recent papers on salience, see for example Bordalo et al (2013, 2016), which suggest that consumers overweigh the most salient features of a product and try to maximize the quality-price ratio of the goods they purchase. This can lead to "quality salient equilibria" where firms compete by differentiating themselves along a quality dimension rather than price. In our context of the credit card market, this could be interpreted as customers viewing reward programs as the perceived quality dimension of a credit card choice.

Independent of the specific form of mistake, these models provide a number of common predictions that are confirmed by our findings. First, when consumers are naïve, the prices of front-loaded or salient card features are driven down, while the prices of features that consumers do not focus on are very high (e.g., late fees and over-limit fees). This leads to participation distortion because consumers take on more credit than they rationally should. Conversely, in markets with predominantly sophisticated consumers, we do not expect to find pricing below marginal cost because these consumers can see through add-on pricing and can avoid costly back-loaded features. Second, in a competitive market with both naïve and sophisticated agents where firms cannot ex ante separate consumers, there is cross-subsidy from naïve to more-sophisticated agents. Ideally, firms would find it optimal to reduce this subsidy to capture these rents themselves.

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

We do not want to rule out that it might not be possible to write dynamic adverse selection models with rational agents that can explain our set of results. However, there are a number of findings that seem challenging to explain in a purely rational framework. First, one could imagine consumers who value a back-loaded fee structure if they are very credit constrained today but expect to be much less constrained in the future. As a result, these borrowers would be willing to trade a very low interest today for a high interest in the future.[12] However, several findings in our data do not support this interpretation: On the one hand, the steep non-linearity of late fees seems to run counter to the idea that the late fees are an interest rate because they do not take into account the actual balance that the borrower carries. On the other hand, in a world where rational consumers are looking for cards that allow them to shift their interest payments to the future, late fees and back-loaded fees should be very prominent in contracts because they represent a service that consumers are selecting.[13] This is not what we find: fees are always in printed in small fonts on the last page of the offer letter.

Second, an alternative rational model could be one where very price-sensitive and low-risk borrowers signal their (high) type to the bank by selecting contracts with low APRs but very high back-loaded penalty rates. The expectation on both sides would be that the borrower will never incur any late fees and always pay on time, on the equilibrium path. However, this interpretation is also difficult to reconcile with our findings. First, as before, we would expect penalty rates in such a situation to be prominently displayed in the

[12] One caveat for such a model would be that banks have to get their timing just right, as highly credit constrained borrowers typically have high default propensities such that the back-loaded fees coincide with the borrower's ability to pay.

[13] One could argue that even a rational agent would not look at the future fees because they intend to default if fees are too high. This is not an equilibrium because banks would not be able to break even.

contract because they would be desirable features of the card. Second, we show that credit cards with rewards that have particularly steep back-loaded fees react very strongly in the size of the late fees (but not the regular APRs) when there is a shock to the bank's cost of capital. If banks were never expecting to be paid via late fees, funding shocks should not affect them. Finally, we draw on several papers that have looked at the usage behavior of credit cards; see, for example, Agrawal et al (2008), which finds that borrowers who take up credit cards with high late fees indeed often pay them.[14] Thus, this rational signaling model is difficult to reconcile with our difference-in-difference results using UI changes. If consumers use high late fees to signal their price sensitivity and ability to manage credit, this should not change when their credit risk is reduced.[15]

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 for how credit card companies target consumers, while section 5 focuses on credit card screening. In section 6, we describe our difference-in-difference analysis using unemployment insurance shocks to borrower credit risk. Section 7 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

[14] A related behavioral version of this argument suggests that borrowers demand high late fees to prevent themselves from over-spending or falling behind on card payments; see, for example, DelaVigna and Malmendier (2004). In this case, we would also expect late fees to be prominently featured in the offer letter.

[15] We thank Michael Grubb for alerting us to this argument.

that customers, on average, pay significant fees (late payment fees and penalties) of approximately $14 per month, which does not include interest payments. These results confirm that fees indeed have a significant bite and that customers are not able to optimally avoid all the negative features of their cards. That paper also shows that customers seem to learn to reduce fees over time. However, this learning is relatively slow, as payments fall by approximately 75 percent after four years. Using a similar data set, Gross and Souleles (2000) show that consumers respond strongly to increases in their credit limits, especially to interest rate changes such as low introductory teaser rates. The long-run debt to interest rate elasticity is approximately -1.3, where more than one-half reflects net increases in total borrowing (rather than balance transfers). In related work, Agarwal et al (2010) document that consumers who respond to inferior lender offers have poorer credit characteristics ex ante and default more often ex post. Similarly, Agarwal et al (2009) show that over the lifecycle, middle-aged households obtain the best credit terms, while older customers select worse credit terms. The authors conjecture that deterioration in cognitive ability could explain why older people choose worse terms.[16] These papers provide important confirmation that credit cards with disadvantageous features are being taken up and have a significant impact on the borrower's cost of capital. Similarly, in the context of health club memberships, DellaVigna and Malmendier (2004) provide convincing evidence that consumers systematically choose contracts that lead them to overpay per gym visit because they are overconfident about their actual health club attendance.

[16] Hastings and Mitchell (2011) use a large-scale, nationally representative field survey from Chile to directly relate impatience and financial literacy to poor financial decisions in a savings context. The results show that impatience is a strong predictor of wealth. Financial literacy is also correlated with wealth, although it appears to be a weaker predictor of sensitivity to framing in investment decisions. Agarwal et al (2016) show similar demand responses to credit card contracts.

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. Hortacu 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 (2014) show that even with the introduction of increased competition, price dispersion does not decrease and product complexity might increase. Similarly, Hastings, Hortacsu and Syverson (2012) look at the introduction of individual savings accounts in Mexico and show that firms that invested more heavily in advertising had both high prices and larger market shares because customers seem to be insufficiently price sensitive. Similarly, Gurun, Matvos and Seru (2016) show that areas with large house price increases and expanding mortgage origination saw increases in marketing expenses and marketing solicitations. Similarly, a recent paper by Agarwal et al (2016) follows our methodology and analyzes the back-ward loading of mortgage contracts in areas with increased banking competition. These results suggest that firms compete on nonfinancial dimensions, such as advertising, to substitute for price competition.

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

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

3. Data and Summary Statistics

3.1. Data Description

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

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

Our data covers the period from March 1999 to February 2011. However, we also repeated our analysis excluding the post-2007 data to abstract from the impact of the financial crisis and the CARD Act. The results are unchanged. For each month, there are approximately 4,000 households and 7,000 credit card mail campaigns, on average. In total, there are 1,014,768 mail campaigns, which consist of 168,312 different credit card offers. Credit card companies usually issue the same offer to many households at the same time. We use OCR (optical character recognition) software and our own extraction algorithms to confirm the quality of the Mintel data. We find that most variables are coded accurately. One exception is the default APR, which seems to have many missing entries.

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

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

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

3.2. Descriptive Statistics

Table 1 describes the summary statistics of the main variables used in the paper. In Table 1, the first twelve variables are based on our full sample of 1,014,768 mail offers from Mintel. APR is the regular purchase APR listed in the credit card offer. If the regular

APR is a range, we pick the midpoint as the APR. The mean APR of the 982,767 total mailings received by consumers is 12.65%. The APRs for balance transfer has a mean of 11.33% and standard deviation of 3.34%. The cash advance APR has a mean of 19.89% and the standard deviation is 4.28%. For the default APR, the mean is much higher at 26.51%, which is higher than all other APRs. The high default APRs is not surprising because it is conditional on the borrower being more than 60 days late. The default APR may be applied to all outstanding balances of a credit card if a consumer pays the monthly bill late. All these APRs are compounded monthly.

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

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

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

The remaining variables in Table 1 are based on the 80% sample of mail campaigns for which we have scanned images of the credit card offers. "Size" is the maximum size of the reward programs minus the average size of all characters on every page of each credit card offer. For example, if "cash back" appears in the offer 3 times, we pick the largest one. "Size" equals this largest number minus the average size of all characters on the same page. The size is drawn directly from Word document. The variable "Size" has a mean of 4.71 mean and a standard deviation of 5.49. The maximum value of Size is 143.63 because some offers use very large characters to highlight reward programs. The 90th percentile of variable Size is 10.99. We use this relative size measurement because credit card companies tend to use larger characters to emphasize the paragraphs that describe the reward programs compared to the nearby paragraphs. The size differences between them should be the measure highlighted. Moreover, "Color" is a dummy indicating whether the reward programs in the offer highlighted in color rather than in black and white. We focus on the characters describing the reward programs rather than on the entire offer because most credit card offers use some color, especially later in the study period.[17] "Bold" is a dummy indicating whether the offer used bold to highlight its reward programs.

"Picture" is the file size of each page of the offer, which measures how many or how "fancy" the pictures in the offer are. We do not use an actual count of the pictures or the size of the pictures because our algorithm considers the background of the page as a big picture (usually it is just a large, plain color picture). Using the storage size of each Word document, we can approximate the complexity of the page design. Other features, such as characters, also increase file size. However, pictures in Word documents usually take most of the file storage. Thus, we think that file size is a good measure of pictures in the credit card offers. The variable "Picture" is the file size, and the unit is megabytes (MB). The mean of "Picture" is 0.23 MB with a 0.26 MB standard deviation.

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

3.3 Credit Card Design

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

Table 2 summarizes the physical design of the credit card offers to document how and where certain features of the card are displayed in the letter. All credit card offers state late fees, default APRs, over-limit fees, and annual fees because their disclosure in the Schumer box is mandated. However, only 5.8% of the credit card offers mention late fees on the first page; 4.97% mention default APRs on the first page, and 6.96% mention over-limit fees on the first page. Not surprisingly, credit card offers usually do not mention fees, especially those that typically are back-loaded on the first page. On the other hand, 79.28% of the credit card offers include annual fee information on the first page. However, as we will document below, annual fees are usually associated with cards that are offered to more-educated, higher-income customers. Similarly, reward programs are usually mentioned in the first page of the offers; 100% of cash back and mileage programs are mentioned in the first page. For point reward, car rental insurance, and zero introductory APRs, the likelihood of appearing on the first page is 93.51%, 80.48%, and 91.04%, respectively.

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

Table 3 provides a correlation matrix for the different reward programs, as indicated along the vertical and horizontal axes. The numbers are the percentage of credit card offers with both reward programs. For example, 6.30% of the credit card offers have both cash back and point reward programs. We see that there is little overlap among reward programs. Mileage programs, for instance, are not usually offered with cash back or points programs. Only 1.15% of cards have for example both mileage and cash back programs. Similarly, mileage programs are rarely offered with other reward programs or zero APRs. However, more than 50% of cards with airline miles carry an annual fee. In contrast, cards with cash back, points or zero APRs are almost never combined with annual fees.

4. Customer Characteristics and Credit Card Features

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

In Table 4, we run a simple hedonic regression model of card features, such as APRs, late fee, or reward program, on customer characteristics. The characteristics of interest to us are the education levels of customers, which are measured as six distinct educational achievement dummies ranging from some high school to completed graduate school. We also consider nine income groups (annual household income) ranging from less than $15,000 to over $200,000. In these regressions, we also control for age group fixed effects of the customer, state fixed effect, dummies for household composition and credit card company fixed effects. Standard errors are clustered at the demographic cell, which is constructed by state, age, income, education and household composition.

In Column (1) of Table 4, we start with the regular purchase APR as the dependent variable and report the coefficients on the education and income bins. The results show that the regular APR decreases significantly for higher-income groups, and the results are relatively monotonically increasing with income. The magnitude of the effect is quite large. Between the lowest and the fourth-highest income groups, the difference in mean APR is almost 0.607 percentage points, which is a significant difference. The relationship between APR and income drop off a little for the three highest income groups, but we show that these groups also have different product features. In contrast, there is no significant relationship between the regular APR and education. The estimated coefficients are all close to zero and insignificant. We re-estimate the regression for the APRs on balance transfers and cash withdrawals and obtain very similar results; these regressions are not reported but can be obtained from the authors. These results intuitively suggest that higher-income customers have lower credit risk and thus enjoy lower costs of capital. Interestingly, this is not true for more-educated customers, suggesting that people of similar educational achievement might vary considerably in their income and, thus, in their credit worthiness.

Interestingly, we find that late fees and default APRs increase significantly with customer income but drop with higher educational attainment. For example, the difference in the default APRs of the lowest and highest income groups is approximately 0.543 percentage points. Thus, customers with higher incomes actually face higher default interest rates than those with lower incomes. The same pattern holds for late fees. In contrast, customers with more education receive card offers that have smaller late fees, lower default APRs, and lower over-limit fees. On the other hand, in Column (5), front-loaded annual fees are significantly higher for households with more education. These results are a first indication that interest rates and fees are set not just with an eye toward credit risk but also toward the sophistication of the customer.

In a next step, we look at how reward programs are offered to customers. In Column (6), the dependent variable is a dummy that equals one if the credit card offer contains a cash back program. We see that there is a strong positive correlation with income; between the highest and lowest income groups, there is a 4 percent difference in the presence of a cash back program. This difference is economically substantive because only 21 percent of card offers contain a cash back program. In contrast, we do not see any relationship between education and the likelihood of receiving a credit card offer with a cash back program. In Column (7), we see a very similar result for points programs. Again, there is a statistically and economically significant increase in the likelihood of receiving an offer with a points program for households at higher income levels. However, there is weak relationship with education.

We observe a very different relationship when looking at miles programs. In Column (8), we show that the likelihood of receiving a card offer with a miles program increases significantly with the education level of the household. Households in the second to last highest income group are more than six percent more likely to receive an offer with a miles program compared to a household in a the lowest educational bin. Because only eight percent of credit card offers include a miles program, education seems to be a very important dimension in receiving miles programs. We also see that miles programs increase with the income level of the customer. Finally, we look at low introductory APR offers. These usually expire after a few months (customarily after 6 to 12 months), and a higher interest rate then applies. In Column (9), we see that introductory APR programs are predominantly offered to less-educated or lower-income customers. A similar relationship holds for introductory APR rates on balance transfers.

In Table 4, Column (10), *Format* is the first principal component of reward programs' font size, colors used, bold text and picture size in the credit card offers. We show that more-educated households or high-income households can obtain more elaborately designed credit card offers, which usually use larger fonts, more colors, more bold text, and more pictures to emphasize the reward programs.

Finally, we create a combined measure of how back-loaded a card is overall by calculating the first principal component of the card terms, including regular APR, over-limit fees, late fees, zero introductory APR dummy, and annual fee. The results are presented in Appendix Table A2. The first principal component loads very positively on front-loaded features, such as annual fees and APR, and negatively on back-loaded fees, such as late fees and over-limit fees. When we estimate a hedonic regression on this combined measure that we called *Backward*. In column (11), we see the same very significant pattern: back-loadedness decreases significantly with the education level. Interestingly, the same is not true for income. In fact, richer people tend to receive more back-loaded card terms (controlling for education).

Taken together, these results suggest that different reward programs are used to target different customers groups. Introductory APR offers are primarily offered to less-educated and poor clients. In contrast, points and cash back programs are offered to richer customers independent of their educational level. Finally, miles is the only reward program that is predominately targeted to richer and, importantly, more-educated customers. We plot the coefficients from Table 4 in Figures 1 and 2 to clarify the patterns. Figure 1 plots the estimated coefficients of education on credit card terms and reward programs. Figure 2 plots the estimated coefficients of income on credit card terms and reward programs.

Robustness Check: One dimension that we do not have in our data is the FICO score for individual borrower, since Mintel is not allowed to provide credit card information to individuals. To analyze the role of FICO scores for out analysis, we obtained Mintel data via the CFPB. [18]. While the data set available at the CFPB covers a shorter time period than ours (starting in 2007), they have the advantage of including FICO scores. The idea it to see whether the pricing relationships documented in our paper differ significantly when including FICO score. For this purpose, we repeat our waterfall regressions of card features on customer characteristics, adding FICO scores as an additional explanatory variable. Adding the FICO scores does not add additional explanatory power to the regression. The adjusted R-squared of the regressions are unchanged, and none of the coefficients on other RHS variables change when including the FICO scores. Overall, it appears that the dimensions spanned by the FICO scores are orthogonal to the other observable characteristics used in the paper. These results alleviate concerns that we are missing an important, and un-spanned dimension of customer characteristics.

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[18] We thank Jialan Wang at the CFPB for making this data available to us, and VIkram Jialabuti for running the analysis for us.

5. Screening with Different Credit Card Offers

5.1. Trade-offs between card features

We now explore the menu of credit card contracts that a consumer with a given set of characteristics is offered. In particular, we want to understand how issuers trade-off front-loaded terms, such as regular APR and annual fees, with back-loaded terms, such as late fees. In Table 5, we regress regular APRs on late fees; we also control for the fed fund rate (FFR) in the month the offer was made. One should understand this estimated coefficient purely as the correlation between late fees and regular APR rather than as a causal estimate in any sense. However, we prefer this specification because it allows us to easily control for household demographic cell fixed effects and bank fixed effects. In Column (1), we first report the cross-sectional correlation between late fees and APRs. Therefore, we only control for state and year fixed effects. We find that a $1 increase in the late fee is associated with a 0.6 percentage point decrease in the regular APR. We then add controls for bank fixed effects in Column (2). The specification holds the borrower type and bank constant. This variation exists in the data because banks experiment with sending credit card holders different contracts to screen for their types. This means we can identify the menu of contract structures that a given bank sends the same customer. We find that the negative correlation between regular APRs and late fees also holds at the individual level. Customers have to trade-off between lower upfront fees and high late fees, or vice versa.

In the next two columns, (3) and (4), we analyze whether this trade-off is steeper for less-educated consumers, as suggested in the hedonic regressions in Table 4. Therefore, we interact late fees with a dummy indicating whether a customer is in the top half of the education distribution (some college and above) or in the bottom half of the education distribution. We see that the trade-off between late fees and APR indeed becomes more negative, i.e., steeper, for less-educated borrowers.

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

Then, in Columns (7) and (8) of Table 5, we look at the use of mileage programs and find a distinct pattern. Interestingly, we see that the interaction term between mileage programs and late fees is strongly positive and significant, which suggests that these cards have a much flatter trade-offs between late fees and regular APRs. In other words, these cards have a much less back-loaded fee structure, which is in line with the idea that cards that are offered to more-sophisticated people cannot be back-loaded because they can overcome back-loaded features. In Table 5B, we reestimate the regressions in Table 5 using annual fees as our dependent variable. We confirm that the results are parallel to the findings for regular APRs.

Finally, in the last two columns of Table 5, we explore the role of the marketing material itself. The algorithm we use to process the offer letters allows us to rank offer letter by how much they rely on pictures rather than text. This variable, *Picture*, indicates the size of the file and of the images in each credit card offer. To test whether offer letters that have more pictures and flashier advertising material also rely more on back-loaded fee structures, we reestimate our trade-off regressions but interact late fees with the *Picture* variable. The results in Columns (9) and (10) show a very significant and negative coefficient on the interaction term. This suggests that offer letters that employ flashier communications also have more back-loaded fees.

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

5.2. Pricing of credit cards

In a next step, we want to understand how the pricing of credit card offers changes when the cost of capital for the issuers changes. Specifically, we analyze which terms of the card are more sensitive to the issuer's cost of capital. We draw on the idea pioneered in Ausubel (1991), assuming that APRs should be very sensitive to the Federal Fund Rate (FFR) because this is the rate at which the banks can raise capital. This approach will allow us to understand which parts of the credit card contract are important for the issuer to receive rents from the borrower and to break even on the loan pool in expectation. If cards that are offered to less-educated consumers are more reliant on back-loaded features, we should see that for these cards, back-loaded terms respond more strongly to shocks in the FFR than front-loaded features. The opposite should hold for cards offered to more-sophisticated consumers.

Similarly, we should find that if cards with rewards programs, such as points, cash back or low introductory APRs, are indeed used to screen for naïve consumers who pay via late fees, then we should see late fees respond particularly strongly when the FFR changes. The reverse should be true for miles cards, which we have shown are mainly offered to sophisticated consumers.

To test this relationship, in Table 6, our regression specification is:

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

$Y_{i,j,t}$ indexes the dependent variables we are interested in, such as regular purchase APRs, default APRs, late fees and over-limit fees. For example, $APR_{i,j,t}$ is the regular purchase APR offered by company i to consumer j at time t. FFR_M indexes the federal fund rate at month M. $LowEdu_{i,j,t}$ indexes the dummies indicating whether the education level of the household head is below college. We also control for fixed effects such state fixed effects, bank fixed effects, and household demographic cell fixed effects,[19] and t is at a daily frequency.

Additionally, we explore the sensitivity of APRs to the FFR by adding interaction terms between FFR and a dummy for less-educated borrowers:

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

We cluster the standard errors at the cell level. In Table 7, we then re-estimate the regression and interact FFR with dummies for different reward programs, such as miles and zero introductory APR programs. We also report the cash back and points reward program results in Appendix Table A3.

Education levels: In Table 6, we differentiate between cards that are issued to less- and more-educated borrowers. Again, the low education dummy is equal to one for customers who have no college education. In Column (1), we regress the regular APR on the FFR and an indicator for low education. In this first column, we control for cell fixed effects but not bank fixed effects. We see that the coefficient on FFR is positive (0.813). While the coefficient is highly significant, it indicates that there is less than perfect pass-through of the cost of capital to customers. We also see that cards that are offered to less-educated people have higher regular APRs, which confirms our findings in Table 4. In Column (2), we add bank fixed effects to the regression. This allows us to control for the differences in pricing strategies between banks. We see that with bank fixed effects, the coefficient on Low education drops significantly. This result suggests that banks differ

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

significantly in their targeting of less-educated consumers, and issuers that target less-educated consumers extensively also charge lower APRs. In Column (3), we add the interaction term between FFR and the Low Education dummy. As discussed above, this approach follows Ausubel (1991) to test how different contract terms change with the FFR. We find a negative and significant coefficient on the interaction term, which means that the APRs offered to less-educated people are less sensitive to the FFR than those offered to more-educated consumers.

In Columns (4) and (5), we repeat the analysis using the annual fee of the card as our dependent variable. We find, as expected from our prior results, that annual fees are significantly lower for cards offered to less-educated people. This relationship holds when holding constant person and bank fixed effects. Parallel to the results in Column (3) for the APR, we find that the interaction term between the Fed fund rate and the Low education dummy is negative.

In contrast, when looking at late fees and over-limit fees in columns (7) and (9), respectively, we see that the interaction term is positive. This means that credit cards offered to less-educated people are more sensitive in the late fees and over-limit fees to changes in the Fed fund rate.

These results support our hypothesis that back-loaded fees, such as late fees and over-limit fees, are the important pricing dimensions of cards offered to less-educated people. Therefore, these back-loaded terms react to a change in the bank's cost of capital. In contrast, the regular purchase APRs and annual fees of cards offered to more educated people are much more sensitive to changes in the FFR. If more-educated people do not fall prey to back-loaded terms, a change in the cost of capital affects the regular purchase APR and annual fee.

Mileage Programs and Introductory APRs: In Table 7, Panels A and B, we focus on the pricing of cards with different rewards programs. The idea is to test whether cards with rewards program that are primarily offered to educated people, such as miles programs, show greater reliance on front-loaded terms, such as APRs and annual fees, while rewards programs offered mainly to less-educated people, such as low introductory APRs, rely on back-loaded pricing. These regressions parallel those in Table 6. We follow the same set of specifications as in Table 6 but interact FFR with the reward programs. In Table 7, Panel A, we find that cards that have miles programs have significantly higher regular APRs, much higher annual fees and much lower late fees or over-limit fees than cards without these programs. Again, it is important to note that these results hold even when we control for cell and bank fixed effects. Thus, we are identifying the variation in two different card offers sent to the same borrower type. Consistent with the results in Table 6, when we add an the FFR*MILES interaction term, we find that APR and annual fees are very sensitive to changes in FFR if the card has a mileage program, but late fees and over-limit fees are less sensitive. When we repeat these specifications in Panel B for cards with low introductory APR programs, we obtain the opposite results. For these cards, back-loaded terms (late fees and over-limit fees) are more sensitive to the FFR.[20] This confirms that mileage programs are not priced via back-loaded features but via regular APRs and annual fees because sophisticated consumers see through add-on pricing.

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

6. Shocks to borrower credit risk: Unemployment insurance

Finally, we analyze the effect of an exogenous shock to the credit worthiness of customers, in particular, their risk of default, on credit card terms and reward programs. We suggest that there is a countervailing force to how much card issues can rely on naiveté-based price discrimination. If back-loaded or shrouded card features attract not only myopic or present-biased but also lower credit quality customers, these can have an adverse effect on the card issuers. For example, if customers who are drawn in by zero APR introductory programs truly do not expect that they ever have to pay interest on the credit, they might have to default once the introductory period expires. However, this endogenously limits the extent to which banks should rely on this strategy.

To test whether banks take this dynamic into account, we use changes in the (state) unemployment insurance (UI) programs as exogenous shocks to the credit risk of customers. UI has increased in a staggered fashion across several US states over the last two decades. These changes provided higher levels of unemployment insurance and longer benefits periods. By providing households with a cash flow stream in cases of negative shocks, UI also reduces a lender's exposure to one of the largest negative economic outcomes that customers might suffer. We obtain data on the level of unemployment insurance (UI) from the US Department of Labor for each state. Based on this information, we calculate annual changes in UI at the beginning of each year from 1999 to 2012 and match them to our credit card dataset. Following Hsu, Matsa and Melzer (2012), we use maximum UI benefits as the measure of unemployment protection. We define maximum UI benefits as the product of the maximum weekly benefit amount (WBA) and the maximum number of weeks allowed. For example, in January 2000, Alabama allowed a maximum of 26 weeks of unemployment insurance over a 52-week period, and the maximum weekly benefit amount (WBA) was $190. We use $4,940 (26 weeks times $190 WBA) as the level of UI. For each state, we then calculate the annual percentage increase of UI. We use 10% annual growth as the cut-off and define a UI "jump" as an increase equal to or greater than 10% within a year.

This allows us to use a standard difference-in-difference estimator to regress changes in card features on UI changes across states and over time. We use a window of one year before and after the UI increase to estimate the effect. The reason to use this short cut-off is that some states have a large increase in UI in one year and small changes in a following year; we did not want to confound the impact of the UI change with small subsequent changes. In addition, we see in the data that credit card companies, on average, react very quickly to changes in the market. For example, if one issuer introduces a new product feature in the market, other firms adopt this change within a few months. We also include dummies to control for a possible pre-trend three or six months before the UI change. All regressions control for time fixed effects, cell fixed effects, and bank fixed effects. We reestimated these regressions using other time windows, e.g., two-year windows, around the change, and the results are qualitatively and quantitatively very similar.

Table 8, Panel A presents the one-year difference-in-difference regression results between 1999 and 2007. We drop the years following the financial crisis of 2008. Because economic conditions worsened significantly in the years following the crisis, changes in UI after 2008 are likely to be endogenous to the economic distress of a state, and there may be concerns that other hidden variables drive our results. Overall, we find that card issuers rely more heavily on back-loaded and shrouded terms when UI is increased and thus the riskiness of the borrowers is reduced. In Column (1), the dependent variable is the regular APR. The coefficient on the UI dummy is negative but not significant. However, in Column (2), we see that an increase in UI leads to a large and significant increase in late fees. In contrast, Column (3) shows that annual fees do not change significantly around UI changes, while in Column (4), look at whether credit card issuers use more intro APR programs when UI increases. For that purpose, we build a dummy variable, *Intro_APR_All*, to indicate whether the credit card offer has zero intro APRs for regular purchases, balance transfers, or cash advances. We find that card issuers indeed use more intro APR programs after UI increases have been implemented. In Column (5), we again use the first principal component as a summary of all the front- and back-loaded features as the dependent variable. Overall, these results strongly support the idea that with the increase in UI issuers use a greater reliance on back-loaded payment features. Finally, in the last four columns of Table 7, Panel A, we look at the “softer” dimensions of the credit card offer. We see that after a UI increase, issuers are more likely to use colorful mailers. At the same time, the offers are more likely to move information about late fees and default APRs from the front of the offer letter to the end. In addition, when we repeat all the regressions without the bank fixed effects, the results are quite similar to those in Table 7, and the estimated coefficients barely change. This means that the results are not driven by banks differentially selecting to offer credit cards in states with UI changes. Our results are driven by within bank variation in decisions to change pricing policies based on UI changes. We then repeat the analysis in Table 8, Panel B across our entire sample period (1999 to 2011). The regression results in Panel B are very similar to Panel A.

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

7. Conclusions

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

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

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Appendix

Table A1

Demographic Distribution

Panel A: Income

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

Panel B: Education

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

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

Table A2

Principal Component Analysis on Credit Card Pricing

Panel A

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

Panel B

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

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

Table A3

Cashback and Points Reward Programs

Panel A	1	2	3	4	5	6	7	8	9
	APR	APR	APR	Annual Fee	Annual Fee	Late Fee	Late Fee	Over-Limit Fee	Over-Limit Fee
FFR	0.301***	0.255***	0.347***	-0.908***	-1.162***	-0.108***	-0.140***	0.338***	0.008
	(0.005)	(0.005)	(0.005)	(0.032)	(0.041)	(0.007)	(0.007)	(0.013)	(0.014)
CASH	-0.453***	-0.165***	0.718***	-11.943***	-14.450***	0.849***	0.536***	-2.514***	-5.969***
	(0.013)	(0.012)	(0.019)	(0.086)	(0.155)	(0.022)	(0.026)	(0.053)	(0.094)
CASH*FFR			-0.352***		1.003***		0.125***		1.295***
			(0.006)		(0.044)		(0.010)		(0.027)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	753,690	753,690	753,690	771,535	771,535	769,923	769,923	693,714	693,714
R-squared	0.019	0.214	0.219	0.228	0.228	0.221	0.221	0.194	0.202

Panel B									
	APR	APR	APR	Annual Fee	Annual Fee	Late Fee	Late Fee	Over-Limit Fee	Over-Limit Fee
FFR	0.315***	0.258***	0.298***	-0.783***	-0.298***	-0.132***	-0.246***	0.379***	0.428***
	(0.005)	(0.005)	(0.005)	(0.032)	(0.028)	(0.007)	(0.008)	(0.013)	(0.014)
POINT	-0.673***	-0.062***	0.393***	1.240***	6.109***	1.511***	0.362***	-2.315***	-1.692***
	(0.013)	(0.012)	(0.021)	(0.120)	(0.268)	(0.015)	(0.023)	(0.050)	(0.087)
POINT*FFR			-0.165***		-1.783***		0.421***		-0.218***
			(0.006)		(0.076)		(0.008)		(0.028)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	753,690	753,690	753,690	771,535	771,535	769,923	769,923	693,714	693,714
R-squared	0.022	0.214	0.215	0.212	0.213	0.227	0.230	0.193	0.194

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

References

Agarwal, Sumit, Itzhak Ben_David and Vincent Yao, "Systematic Mistakes in the Mortgage Market and Lack of Financial Sophistication," *Journal of Financial Economics*, forthcoming, 2016.

Agarwal, Sumit, John C. Driscoll, Xavier Gabaix, and David Laibson, "Learning in the credit card market," NBER Working Paper No. 13822, 2008.

Agarwal, Sumit, Souphala Chomsisengphet, and Chunlin Liu, "The Importance of Adverse Selection in the Credit Card Market: Evidence from Randomized Trials of Credit Card Solicitations," *Journal of Money, Credit, and Banking*, 42 (2010), 743-754.

Agarwal, Sumit, Souphala Chomsisengphet, Chunlin Liu, and Nicholas S. Souleles, "Do Consumers Choose the Right Credit Contracts?," *Review of Corporate Finance Studies*, 2015.

Agarwal, Sumit, Xavier Gabaix, John C. Driscoll, and David Laibson, "The Age of Reason: Financial Decisions over the Life Cycle and Implications for Regulation," *Brookings Papers on Economic Activity*, (2009), 51-117.

Agarwal, Sumit, Changcheng Song and Vincent W. Yao, "Banking Competition and Shrouded Attributes: Evidence from the US Mortgage Market", Working Paper, (2016).

Agrawal, Ashwini K., and David A. Matsa, "Labor unemployment risk and corporate financing decisions," *Journal of Financial Economics*, 108 (2013), 449-470.

Ausubel, Lawrence M., "The failure of competition in the credit card market," *American Economic Review*, 81 (1991), 50.

Bergstresser, Daniel, John M. R. Chalmers, and Peter Tufano, "Assessing the Costs and Benefits of Brokers in the Mutual Fund Industry," *Review of Financial Studies*, 22 (2009), 4129-4156.

Bertrand, Marianne, Dean Karlan, Sendhil Mullainathan, Eldar Shafir, and Jonathan Zinman, "What's Advertising Content Worth? Evidence from a Consumer Credit Marketing Field Experiment," *Quarterly Journal of Economics*, 125 (2010), 263-306.

Beshears, John, James J. Choi, David Laibson, and Brigitte C. Madrian, "Simplification and saving," *Journal of Economic Behavior & Organization*, 95 (2013), 130-145.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, “Salience and Consumer Choice” *Journal of Political Economy* (2013) 121 (5): 803-843.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, “Competition for Attention” *Review of Economic Studies* (2016) 83 (2): 481-513.

Campbell, John Y., Howell E. Jackson, Brigitte C. Madrian, and Peter Tufano, "Consumer Financial Protection," *Journal of Economic Perspectives*, 25 (2011), 91-114.

Carlin, Bruce I., "Strategic price complexity in retail financial markets," *Journal of Financial Economics*, 91 (2009), 278-287.

Cochrane, John H., "Finance: Function Matters, Not Size," *Journal of Economic Perspectives*, 27 (2013), 29-50.

DellaVigna, Stefano, "Psychology and Economics: Evidence from the Field," *Journal of Economic Literature*, 47 (2009), 315-372.

DellaVigna, Stefano, and Ulrike Malmendier, "Contract Design and Self-Control: Theory and Evidence," *Quarterly Journal of Economics*, 119 (2004), 353-402.

Gabaix, Xavier, and David Laibson, "Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets," *Quarterly Journal of Economics*, 121 (2006), 505-540.

Greenwood, Robin, and David Scharfstein, "The Growth of Finance," *Journal of Economic Perspectives*, 27 (2013), 3-28.

Gross, David and Nicholas Souleles, "Consumer Response to Changes in Credit Supply: Evidence from Credit Card Data," Center for Financial Institutions Working Papers 00-04, Wharton School Center for Financial Institutions, University of Pennsylvania, 2000.

Grubb, Michael D., "Selling to Overconfident Consumers," *American Economic Review*, 99 (2009), 1770-1807.

Gurun, Umit G., Gregor Matvos, and Amit Seru, "Advertising Expensive Mortgages," *Journal of Finance*, 2016.

Han, Song, Benjamin J. Keys and Geng Li, "Unsecured Credit Supply over the Credit Cycle: Evidence from Credit Card Mailings", Working Paper, 2013.

Han, Song, Benjamin Keys, and Geng Li, “Information, Contract Design, and Unsecured Credit Supply: Evidence from Credit Card Mailings,” Finance and Economics Discussion Series, 2015-103. Washington: Board of Governors of the Federal Reserve System.

Hastings, Justine and Olivia S. Mitchell, “How Financial Literacy and Impatience Shape Retirement Wealth and Investment Behaviors.” NBER Working Paper No. 16740, 2011.

Hastings, Justine, Ali Hortaçsu and Chad Syverson, “Sales Force and Competition in Financial Product Markets: The Case of Mexico’s Social Security Privatization,” Working Paper, 2015.

Heidhues, Paul, and Botond Koszegi, "Exploiting Naivete about Self-Control in the Credit Market," *American Economic Review*, 100 (2010), 2279-2303.

Heidhues, Paul, and Botond Kőszegi, "Naïveté based discrimination,” Working Paper, 2015.

Heitmann, M., Johnson, Eric Johnson and Andreas Herrmann, “Pricing Add-Ons as Totals: How Changing Price Display Can Influence Consumer Choice,” Working Paper, 2014.

Hortacsu, Ali, and Chad Syverson, "Product Differentiation, Search Costs, and Competition in the Mutual Fund Industry: A Case Study of S&P 500 Index Funds," *Quarterly Journal of Economics*, 119 (2004), 403-456.

Hsu, Joanne, David A. Matsa, and Brian T. Melzer, “Positive Externalities of Social Insurance: Unemployment Insurance and Consumer Credit”, Working Paper, 2014.

Koszegi, Botond, "Behavioral Contract Theory," Journal of Economic Literature, 52 (2014), 1075-1118.

Lohse, Gerald L., "Consumer Eye Movement Patterns on Yellow Pages Advertising," Journal of Advertising, 26 (1997), 62-73.

Lohse, Gerald L., and Dennis L. Rosen, "Signaling Quality and Credibility in Yellow Pages Advertising: The Influence of Color and Graphics on Choice," *Journal of Advertising*, 30 (2001), 73-85.

Maskin, Eric, and John Riley, "Monopoly with incomplete information," *RAND Journal of Economics (RAND Journal of Economics)*, 15 (1984), 171-196.

Merton, Robert C, "Financial innovation and economic performance," *Journal of applied corporate finance*, 4 (1992), 12-22.

Miller, Merton H., "Financial Innovation: The Last Twenty Years and the Next," *Journal of Financial & Quantitative Analysis*, 21 (1986), 459-471.

Mussa, Michael, and Sherwin Rosen, "Monopoly and Product Quality," *Journal of Economic Theory*, 18 (1978), 301-317.

Shui, Hanyan and Lawrence M. Ausubel, “Time Inconsistency in the Credit Card Market,” Working Paper, 2005.

Thaler, Richard H., and Cass R. Sunstein., *Nudge: Improving decisions about health, wealth, and happiness*. (Yale University Press, 2008).

Tufano, Peter, "Securities innovations: a historical and functional perspective," *Journal of applied corporate finance*, 7 (1995), 90-104.

---, "Financial Innovation," in *Handbook of the economics of finance. Volume 1A. Corporate finance*, George M. Constantinides, Milton Harris, and Rene Stulz, eds. (Handbooks in Economics, vol. 21. Amsterdam; London and New York: Elsevier, North Holland, 2003).

Table 1

Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
FFR	2.68	2.14	0.07	6.54	156
APR	12.65	4.18	0.00	79.90	982,767
Max Card limit	10.05	1.37	6.21	15.42	526,949
APR_Balance	11.33	3.34	0.00	29.90	749,264
APR_CASH	19.89	4.28	0.00	79.90	942,430
ARP_Default	26.51	3.97	0.00	41.00	721,393
Annual_fee	12.29	31.99	0.00	500.00	1,003,977
Late_fee	33.83	6.17	0.00	85.00	1,001,221
over_limit_fee	29.74	10.16	0.00	79.00	898,636
Intro_APR_regular	0.47	0.50	0.00	1.00	1,014,768
Intro_APR_balance	0.47	0.50	0.00	1.00	1,014,768
Intro_APR_cash	0.06	0.23	0.00	1.00	1,014,768
Size	4.71	5.49	0.00	143.63	644,865
Color	0.32	0.47	0.00	1.00	644,865
Bold	0.36	0.48	0.00	1.00	644,865
Picture	0.23	0.26	0.00	4.10	803,285
Reward	0.68	0.77	0.00	3.00	803,285
CASH	0.21	0.41	0.00	1.00	803,285
POINT	0.24	0.43	0.00	1.00	803,285
MILE	0.09	0.28	0.00	1.00	803,285
Carrental	0.23	0.42	0.00	1.00	803,285
Purchaseprct	0.23	0.42	0.00	1.00	803,285

Note: FFR is the federal fund rate at monthly frequency. Other variables are based on Mintel's credit card's direct mail campaigns from March 1999 to February 2011. Variables from "Size" to "Purchaseprct" are from 80% of 1,014,768 total mail campaigns which have scanned images of credit card offers. Size is the maximum size of the reward programs minus the average size of the whole page in credit card offer. Color is the dummy of whether reward programs in the offer use color other than black/white in the offer. Bold is the dummy of whether the offer use bold to highlight reward programs. If there is no reward program in the offer, we put missing value to Size, Color, and Bold. Picture is the file storage size of the credit card offer images. The unit is megabyte (MB). We drop the year before 2003 due to a lot of missing scanned images of credit card offers. Reward is the number of reward programs of CASH POINT and Car rental insurance in each offer. CASH, POINT, MILE, Carrental, Purchaseprct are dummies of whether the offer has these reward programs respectively. Intro_APR_regular, Intro_APR_balance and Intro_APR_cash are the dummies of whether the offer has 0% introductory APR for regular purchase, balance transfer and cash advance respectively. APR is the regular purchase APR of the credit card offer which is the middle point if APR is a range in the offer. Card Limit is the log of maximum credit card limit stated in the offer. Annual fee, late fee and over limit fee are fees charged by credit card company which usually are in shumerbox.

Table 2

Descriptive Statistics for Format Design of Credit Card Offers

Panel A	Late fee	Default APR	Over limit fee	Annual fee	CASH	POINT	MILE	Carrental	Intro APR
Percentage of cards that have this term	100.00%	100.00%	100.00%	100.00%	21.05%	23.83%	8.79%	22.74%	51.64%
Term mentioned on 1st page	5.80%	4.97%	6.96%	79.28%	100%	93.51%	100%	80.48%	91.04%
Font size of term if mentioned on 1st page	9.49	9.28	9.80	13.24	11.16	11.47	14.12	10.27	11.27
Font size of CC term if NOT mentioned on first page	9.57	9.63	9.50	13.76	10.62	10.80	9.91	10.04	10.62
Font color of CC term if mentioned on first page	33.98%	37.88%	27.73%	66.86%	40.13%	42.84%	47.12%	24.34%	32.28%
Font color of CC term if NOT mentioned on first page	24.67%	26.19%	27.73%	44.35%	37.24%	38.45%	29.47%	23.31%	32.29%
Font bold of CC term if mentioned on first page	38.59%	27.77%	35.07%	79.01%	47.24%	43.90%	56.34%	10.56%	53.15%
Font bold of CC term if NOT mentioned on first page	49.00%	19.59%	34.53%	53.20%	36.58%	29.97%	18.08%	13.08%	39.99%
# Obs	776,624	776,624	776,624	776,624	803,285	803,285	803,285	803,285	776,624
Panel B									
If term is on first page	29.38	28%	27.59	7.69					
If term is in the back (schumer box)	35.10	27%	30.11	33.22					

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

Table 3

Correlation Among Credit Card Features

	CASH	POINT	MILE	PurchasePrct	Intro_APR	Zero Annual fee
CASH	0.21	0.06	0.01	0.03	0.12	0.21
POINT	0.06	0.24	0.00	0.07	0.09	0.20
MILE	0.01	0.00	0.09	0.01	0.02	0.04
CAR	0.05	0.08	0.02	0.11	0.11	0.16
PurchasePrct	0.03	0.07	0.01	0.23	0.15	0.17
Intro_APR	0.12	0.09	0.02	0.15	0.49	0.43
Zero Annual fee	0.21	0.20	0.04	0.17	0.43	0.81

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

Table 4
Credit Card Features And Demographics

	1	2	3	4	5	6	7	8	9	10	11
	APR	Late Fee	Default APR	Over-limit Fee	Annual Fee	CASH	POINT	MILE	Intro_APR	Format	Backward
FFR	0.352***	-0.242***	0.882***	0.173***	-0.565***	-0.012***	0.010***	0.008***	-0.026***	-0.014***	-0.057***
	(0.004)	(0.006)	(0.005)	(0.010)	(0.024)	(0.000)	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)
Education_2	-0.046	-0.118***	-0.008	-0.472***	-0.551***	0.014***	0.007***	0.013***	-0.002	0.070***	-0.002
	(0.030)	(0.045)	(0.031)	(0.051)	(0.162)	(0.002)	(0.002)	(0.002)	(0.003)	(0.007)	(0.007)
Education_3	0.026	-0.323***	-0.029	-0.592***	-0.068	0.009***	0.003	0.019***	-0.015***	0.075***	-0.035***
	(0.032)	(0.045)	(0.032)	(0.056)	(0.169)	(0.002)	(0.002)	(0.001)	(0.003)	(0.008)	(0.008)
Education_4	-0.073**	-0.277***	-0.025	-1.118***	0.352**	0.017***	0.009***	0.046***	-0.026***	0.160***	-0.067***
	(0.033)	(0.047)	(0.034)	(0.059)	(0.176)	(0.002)	(0.002)	(0.003)	(0.003)	(0.008)	(0.008)
Education_5	-0.004	-0.541***	-0.110***	-1.561***	1.326***	0.010***	0.004	0.064***	-0.049***	0.190***	-0.124***
	(0.035)	(0.052)	(0.038)	(0.068)	(0.201)	(0.003)	(0.002)	(0.004)	(0.003)	(0.009)	(0.009)
Income_2	-0.227***	0.133**	0.092**	-0.264***	-1.199***	0.020***	0.013***	0.015***	0.002	0.079***	0.033***
	(0.040)	(0.067)	(0.039)	(0.065)	(0.222)	(0.003)	(0.002)	(0.002)	(0.003)	(0.010)	(0.010)
Income_3	-0.349***	0.134**	0.149***	-0.386***	-1.620***	0.026***	0.022***	0.022***	-0.002	0.111***	0.051***
	(0.038)	(0.052)	(0.040)	(0.064)	(0.213)	(0.003)	(0.002)	(0.002)	(0.003)	(0.009)	(0.010)
Income_4	-0.452***	0.321***	0.132***	-0.406***	-1.908***	0.030***	0.025***	0.028***	-0.006*	0.137***	0.063***
	(0.037)	(0.052)	(0.038)	(0.063)	(0.207)	(0.002)	(0.002)	(0.002)	(0.003)	(0.009)	(0.009)
Income_5	-0.531***	0.430***	0.225***	-0.696***	-1.982***	0.044***	0.035***	0.045***	-0.014***	0.200***	0.067***
	(0.037)	(0.052)	(0.038)	(0.064)	(0.209)	(0.002)	(0.002)	(0.003)	(0.003)	(0.009)	(0.009)
Income_6	-0.607***	0.460***	0.263***	-0.973***	-1.423***	0.048***	0.042***	0.059***	-0.021***	0.247***	0.054***
	(0.039)	(0.056)	(0.041)	(0.070)	(0.220)	(0.003)	(0.002)	(0.003)	(0.003)	(0.010)	(0.010)
Income_7	-0.562***	0.580***	0.356***	-1.286***	-0.262	0.048***	0.047***	0.076***	-0.035***	0.291***	0.018*
	(0.041)	(0.060)	(0.043)	(0.076)	(0.236)	(0.003)	(0.003)	(0.004)	(0.004)	(0.010)	(0.010)
Income_8	-0.420***	0.611***	0.432***	-1.722***	1.924***	0.047***	0.049***	0.100***	-0.051***	0.336***	-0.040***
	(0.055)	(0.081)	(0.061)	(0.112)	(0.333)	(0.004)	(0.004)	(0.006)	(0.005)	(0.014)	(0.015)
Income_9	-0.391***	0.555***	0.543***	-2.218***	3.200***	0.040***	0.051***	0.117***	-0.066***	0.380***	-0.089***
	(0.063)	(0.093)	(0.073)	(0.147)	(0.422)	(0.004)	(0.004)	(0.006)	(0.005)	(0.018)	(0.018)
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	942,397	961,247	713,882	872,831	963,283	777,192	777,192	777,192	972,260	629,637	870,029
R-squared	0.253	0.157	0.310	0.177	0.233	0.248	0.262	0.075	0.159	0.080	0.307

Note: OLS regressions to estimate relationship between credit card features and consumer's demographics. Data is restricted to offers we have scanned pictures from column 6, 7, 8, and 10. Format is the first principal component of reward programs' size, color, bold and the picture sizes on the credit card offers. Backward is the first principal component of regular APR, annual fee, late fee, over limite fee, and intro_APR after taking out the bank and monthly fixed effects. 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 income less than 15k. Education_2 is dummy for household head whose highest education is high school. Education_3 is for some college. Education_4 is for graduated college. Education_5 is for post college graduate. The missing category is 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 age fixed effects, household composition fixed effects, state fixed effects and bank fixed effects.

Table 5

Regular APR vs. Late Fees

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

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

Table 5B

Annual Fees vs. Late Fees

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

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

Table 6

Relationships between APRs/Fees and Education

	1	2	3	4	5	6	7	8	9
	APR	APR	APR	Annual Fee	Annual Fee	Late Fee	Late Fee	Over-Limit Fee	Over-Limit Fee
FFR	0.813***	0.736***	0.755***	0.498***	0.671***	0.047***	0.007	-0.356***	-0.424***
	(0.005)	(0.004)	(0.005)	(0.025)	(0.033)	(0.008)	(0.011)	(0.008)	(0.011)
LowEdu	0.133***	0.009	0.163***	-0.213**	1.148***	0.320***	0.007	0.490***	-0.042
	(0.021)	(0.017)	(0.032)	(0.089)	(0.158)	(0.027)	(0.043)	(0.029)	(0.047)
LowEdu*FFR			-0.050***		-0.440***		0.101***		0.173***
			(0.008)		(0.048)		(0.014)		(0.016)
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	785,950	785,950	785,950	800,546	800,546	798,936	798,936	749,306	749,306
R-squared	0.103	0.318	0.318	0.251	0.252	0.208	0.208	0.198	0.199

Note: OLS regressions to estimate relationship between education and credit card APRs and fees. Data period is from 1999 to 2007. Regressions in column 1 to 9 are controlled by household demographic cell fixed effects based on states, age, income, and household composition. Regressions in column 2 to 9 are controlled by bank fixed effects. LowEdu is a dummy for household head's education level below college (highest degree is high school). Standard errors in parentheses are clustered by cells.

Table 7

Mileage Program vs. Zero Introductory APR Program

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

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

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

Table 8

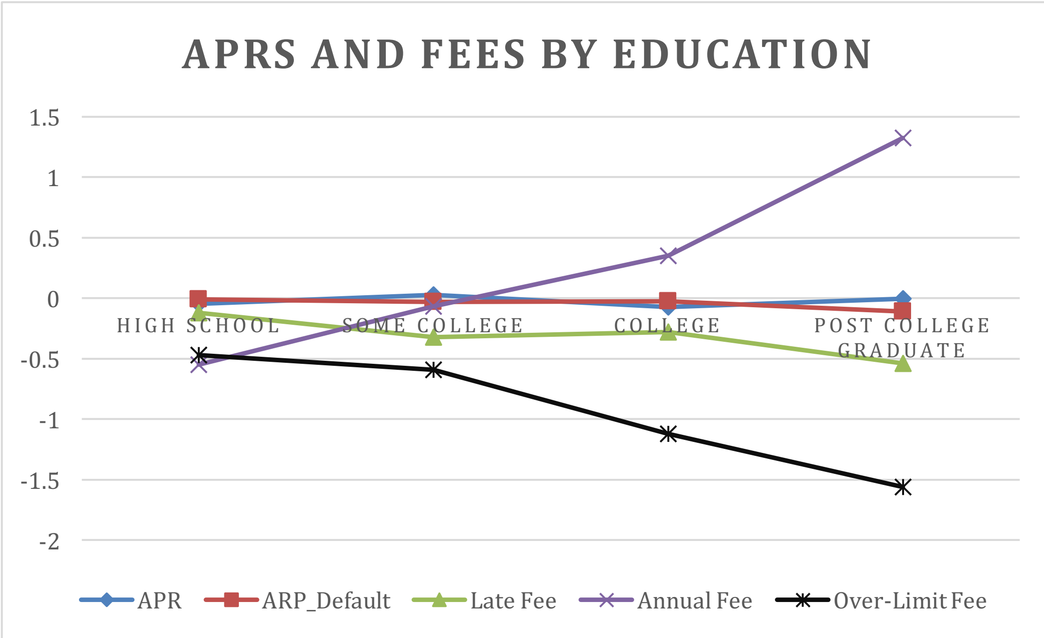
Unemployment Insurance and Credit Card Feature

Panel A	1	2	3	4	5	6	7	8	9
	APR	Late Fee	Annual Fee	IntroAPR _All	Backward	Color	Default APR MainPage	LateFee MainPage	Default APR Back
FFR	0.111***				-0.146***				
	(0.040)				(0.007)				
UI	-0.064	0.122**	0.163	0.053***	0.052*	0.011***	-0.011***	-0.009*	0.256**
	(0.114)	-0.053	(0.667)	-0.015	(0.031)	(0.004)	(0.003)	(0.006)	(0.115)
UI_Pre_3M	-0.182	0.17	-1.294***	0.070*	0.075***	0.008	-0.002	-0.007	0.010
	(0.118)	-0.12	(0.466)	(0.037)	(0.022)	(0.005)	(0.006)	(0.010)	(0.133)
UI_Pre_6M	-0.015	-0.215	0.379	0.004	0.009	0.003	-0.002	0.000	0.358***
	(0.114)	-0.14	(0.682)	(0.034)	(0.024)	(0.005)	(0.005)	(0.011)	(0.103)
UI_Small	-0.028	0.077	-0.625	-0.003	0.010	-0.002	-0.004	0.014	0.320***
	(0.092)	-0.086	(0.460)	(0.011)	(0.031)	(0.006)	(0.003)	(0.009)	(0.100)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102,735	103,342	103,820	105,380	97,449	91,783	48,592	48,592	12,895
R-squared	0.315	0.255	0.257	0.154	0.311	0.0413	0.0514	0.0301	0.324

Panel B									
	APR	Late Fee	Annual Fee	IntroAPR _All	Backward	Color	Default APR MainPage	LateFee MainPage	Default APR Back
FFR	0.121***				-0.145***				
	(0.035)				(0.007)				
UI	-0.019	0.118**	-0.190	0.044***	0.065**	0.001	-0.008	-0.006	0.231***
	(0.111)	(0.060)	(0.700)	(0.015)	(0.029)	(0.009)	(0.006)	(0.007)	(0.089)
UI_Pre_3M	-0.121	0.168	-1.194**	0.062*	0.078***	0.003	-0.002	-0.010	0.038
	(0.123)	(0.113)	(0.494)	(0.037)	(0.021)	(0.006)	(0.005)	(0.011)	(0.136)
UI_Pre_6M	0.027	-0.230*	0.192	-0.003	0.010	0.003	-0.009*	-0.006	0.320***
	(0.121)	(0.138)	(0.742)	(0.030)	(0.022)	(0.006)	(0.005)	(0.012)	(0.080)
UI_Small	-0.007	0.090	-0.910	-0.010	-0.000	0.002	-0.003	0.003	0.386***
	(0.081)	(0.081)	(0.817)	(0.008)	(0.028)	(0.007)	(0.004)	(0.009)	(0.089)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,692	110,475	110,984	112,575	103,427	98,126	55,778	55,778	17,408
R-squared	0.307	0.275	0.237	0.153	0.305	0.0589	0.0852	0.0336	0.389

Note: OLS regressions to estimate unemployment insurance effects on credit card features at 6-month frequency. Panel A includes the credit card offers from 1999 to 2007. Panel B is from 1999 to 2011. All columns are controlled by 6 month fixed effects, bank fixed effects, and cell fixed effects based on states, age, income, education and household composition. UI is the dummy which equals 1 if unemployment insurances increase by more than 10% in this year and equals 0 in the year before the increase. UI_Pre_3M is the dummy for 3 month pre-trend of the UI jumps. UI_Pre_6M is the dummy for 6 month pre-trend of the UI jumps. UI_Small is the dummy of the UI increases below 10% which are mainly due to inflation adjustments. Column 7 and 6 are OLS regression on whether default APR/late fees are mentioned on the main page of the credit card offers. Column 9 is for the default APR level when it's on the main pages. Standard errors are clustered at the state level.

FIGURE 1



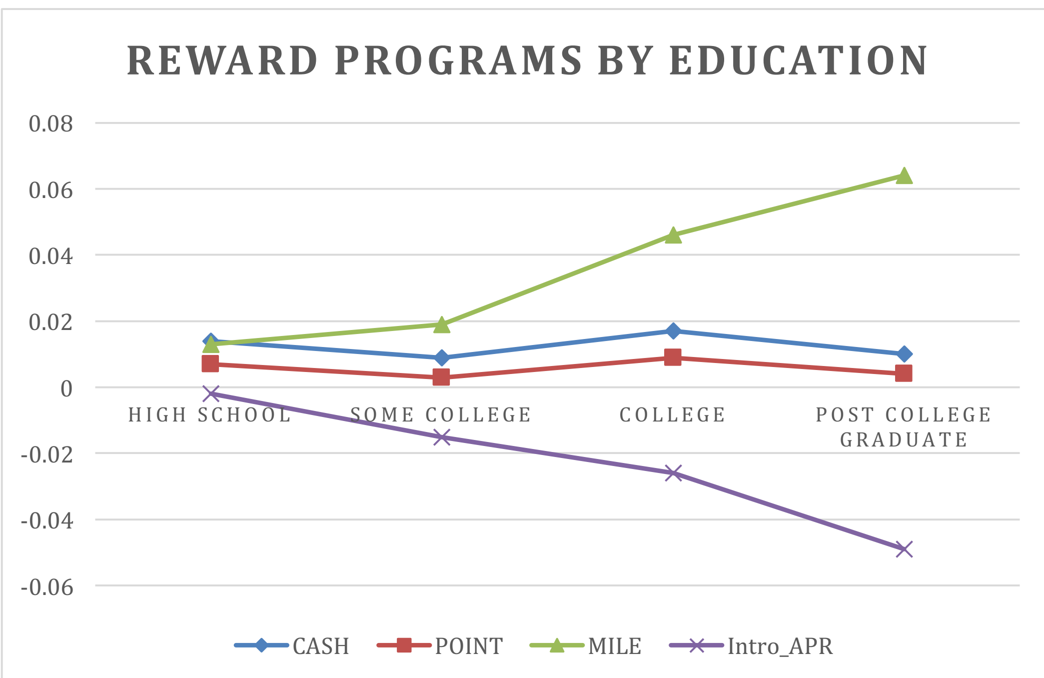
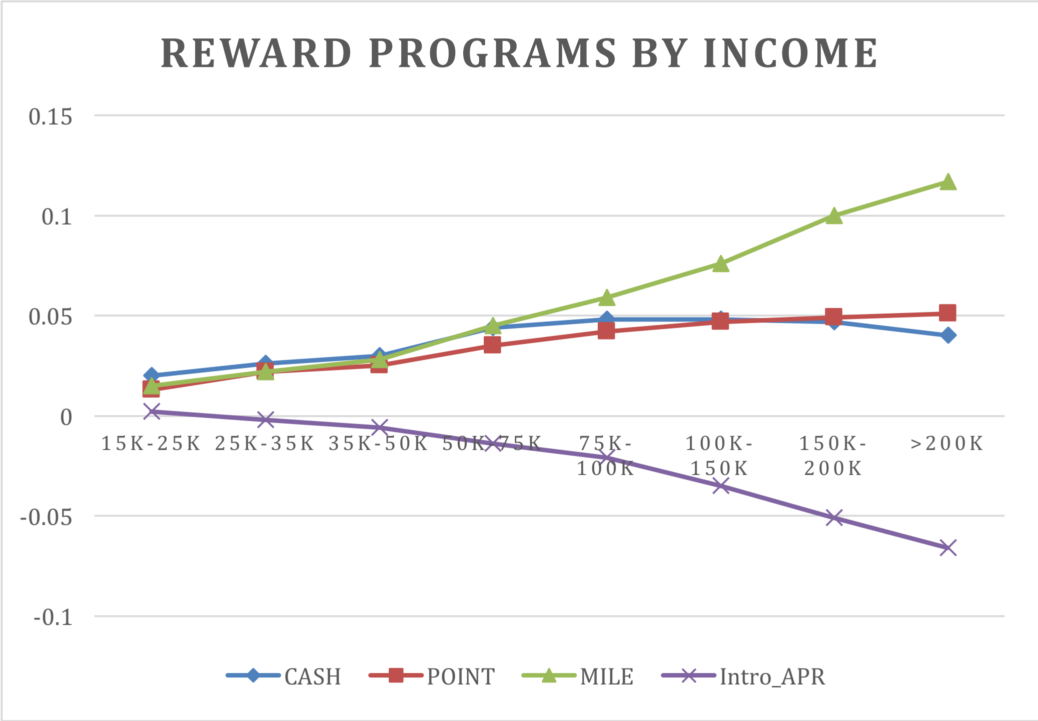


Figure 1 plots the estimated coefficients on education when we regress individual card features on dummies for different education levels (as provided by Mintel). The regression results are reported in Table 4.

FIGURE 2



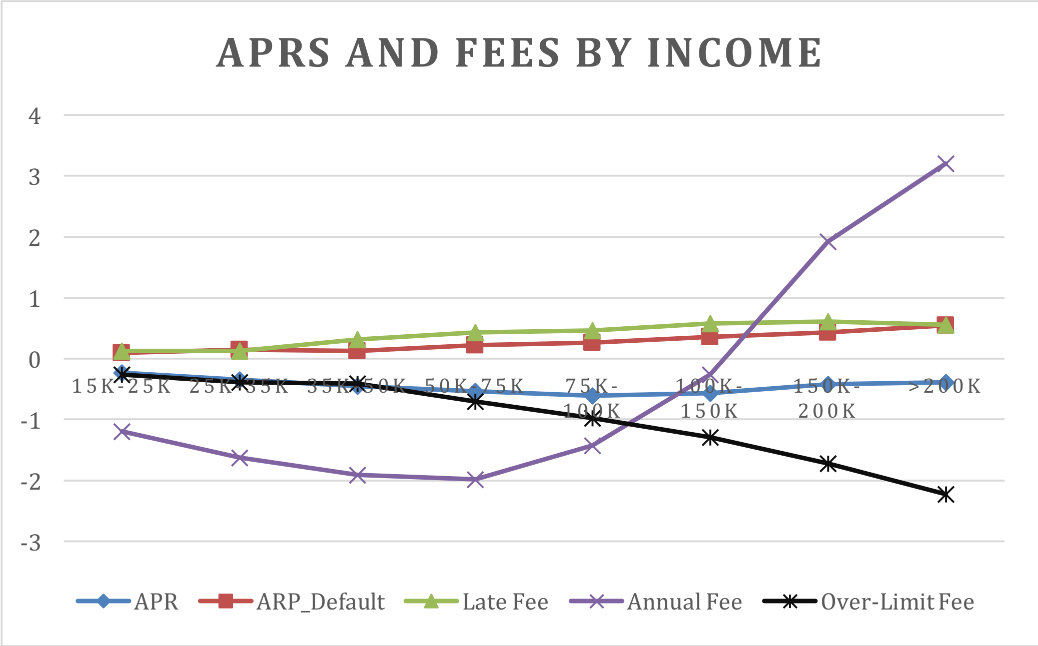


Figure 2 plots the estimated coefficients on the education when we regress individual card features on dummies for different household income levels (as provided by Mintel). The regression results are reported in Table 4.