**Race, Ethnicity, and Credit Card Marketing**

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This Version: September, 2011

**Abstract**

This paper examines the relative probability of Black and Hispanic households in the U.S. receiving credit card offers in the mail from five large credit card lenders. We use a proprietary data set composed of mail received by a sample of U.S. households between August 2009 and October 2010. This data set allows us to analyze credit offers, as opposed to credit use, which is a result of combined decisions about the supply and demand for credit. We explore a puzzle that was first identified in aggregate data by Han, Keys, and Li (2011) in their study of credit access: Blacks were approximately 27% less likely to receive offers from these lenders during the sample period, even after controlling for variables such as credit history, household income, and local economic conditions. Hispanics were 17% less likely to receive an offer, after including controls. The discrepancy is robust to inclusion of a large number of explanatory variables. Examination of patterns by lenders shows differences in marketing strategies by card type, as well as variation among the five lenders of credit card offers. There are multiple possible explanations for this discrepancy, including but not limited to the existence of omitted variables, model misspecification, or disparate impact in lenders' marketing strategies. Due to the magnitude and robustness of these patterns, further study is merited.

## I Introduction and Literature Survey

We find unexplained discrepancies in credit card marketing to Black and Hispanic consumers. We analyze a data set created by Mintel Comperemedia composed of mail sent to 78,156 individuals in a total of 41,470 households from August 2009 to October 2010. Mintel Comperemedia coded detailed information on each piece of mail received by these households during a month, gathered extensive information about the households, and merged this data with information on the credit records of all individuals living in these households. This unique data set allows us to study credit card marketing to different demographic groups with an unusually rich set of controls. Even after including an extensive set of controls for income, education,

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geography, and credit history, we find economically and statistically significant unexplained discrepancies in marketing by four of five U.S. credit card lenders. This discrepancy's robust presence presents an interesting puzzle.

Han, Keys, and Li (2011) find a relationship between race, ethnicity, and credit card marketing at the aggregate level as part of their study of post-bankruptcy access to credit card markets. We extend this result by adding a wealth of additional controls, and focusing on individual lenders' marketing strategies. Harrison (2001) discusses the importance of lender heterogeneity in studies of discrimination in the mortgage market. As discussed below, we model the probability of receiving any offer from one of five large lenders, the number of offers received from these lenders, and the probability of receiving an offer from specific lenders. We show that the relationship between race, ethnicity, and the probability of receiving a credit card offer varies substantially by the lender. We also find that lenders' marketing strategies differ along several other dimensions, including individuals' income, history of bankruptcy, credit rating, length of credit history, and education.

There is a long history of analysis of the relationship between race, ethnicity, and the credit markets. Much research has focused on mortgage credit, partially due to the availability of data that includes borrowers' race and ethnicity.[2] Studies of the relationship between race, ethnicity, and credit other than mortgages are hampered by a lack of data that combines individuals' demographic characteristics with credit information. There are a few notable exceptions. Blanchflower et al (2006) uses the 1993 and 1998 National Surveys of Small

[2] Most U.S. lenders are required to submit data every year under the Home Mortgage Data Act (HMDA) on mortgage applications and originations, including the applicants' race, gender, and ethnicity. Each year's release of HMDA data creates a new round of analysis of whether protected classes have equal access to mortgage credit. See Ross and Yinger (2002) for a review of this literature. Much recent work has focused on the incidence of higher-cost mortgages among Black and Hispanic borrowers and in communities where Blacks and Hispanics are the majority of the population. See, for example, Calem, Gillen, and Wachter (2004), and Pence and Mayer (2008).

Business Finances to study minorities' use of business loans. Edelberg (2007) uses Survey of Consumer Finance data from 1989 to 2004 to study whether Blacks pay higher interest rates for consumer credit, and finds some evidence that Blacks pay more for automobile loans and credit cards, even after controlling for differences in default risk. Cohen-Cole (2010) uses credit record data to analyze the relationship between Blacks' share of a borrower's neighborhood and their use of credit. He defines access to credit as the total credit lines available, less whatever is utilized, and finds a strong negative relationship. Brevoort (2009) shows that the effect in Cohen-Cole (2010) is largely due to an inappropriately censored sample and miscoded income.

Our paper expands our understanding of consumer credit because we analyze individual lenders' offers of credit, while other studies often aggregate all lenders' credit. Our analysis of offers also features advantages over the studies which use data on credit usage. Credit *usage* depends on strategic decisions by both the borrower and lender. Borrowers may voluntarily sort themselves into different kinds of credit products, and different groups of borrowers may shop differently for credit products. Yezer, et al (1994) discuss how simultaneity bias and self-selection can create biased estimates in the case of mortgage markets. In contrast, studying credit *marketing* avoids potential biases in analysis of joint decisions by the lender and borrower.

Our study adds to a growing literature on credit card markets. Ausubel (1999) analyzes an apparent failure of price competition in the U.S. credit card market, along with extremely large profits for card lenders. Gross and Souleles (2002) document a large response in consumption to changes in credit limits and interest rates using a panel data set on credit card accounts. Karlan and Zinman (2009) study the effect of moral hazard and adverse selection in credit card markets using data on a credit marketing campaign in South Africa. Han, Li, and

Keys (2011) use the same Mintel Comperemedia data as this study to analyze consumers' access to credit cards after they have declared bankruptcy.

There are several limitations to our analysis. We can only study credit card marketing, and not the broader issue of access to credit. Would-be borrowers may seek credit on their own initiative or due to other forms of marketing such as advertising in the media, marketing of store-branded cards while they shop for goods, or e-mail offers, and may have different propensities to respond to offers. This paper cannot measure whether credit cards are more or less available to any particular group in general, only whether particular groups are more or less likely to receive mailed offers. Our data is limited to only fourteen months, and this period was a particularly turbulent time in the credit markets, when credit card lenders might have been especially conservative in their marketing. We only have data on offers, and cannot analyze how many borrowers returned these offers, or how many of the returned applications were finally approved for credit. We also do not observe the final terms or conditions actually granted to borrowers.

Based on conversations with lenders, we have learned that direct credit card direct mail marketing by large lenders typically uses more extensive data that than available to us. Lenders also make decisions based on a fairly complex set of predictions. Further details are provided in Section II. Using only a subset of the data actually used in lenders' decisions may lead to omitted variable bias, which could potentially explain the results in this study regarding race, ethnicity, and credit card marketing. In addition, we only observe the final product of a series of strategic decisions by lenders, which means that misspecification might explain these results. There are also certain differences between our data and the national population. Nonetheless, we think that the robust economic and statistical significance of these discrepancies is puzzling, and worthy of further investigation.

Section II discusses common industry practices in direct mail credit card marketing. Section III discusses the data used in this study, while Section IV describes the methodology used. Section V discusses the effects of controls for various borrower characteristics on credit card marketing, including differences in strategy by lender and card type. Section VI discusses our results on the relationship between race, ethnicity, and credit card marketing, including analysis by card type and lender, as well as the effect of geographic controls on the results. Section VII concludes.

## II Industry Practices in Credit Card Direct Mail Marketing

We had numerous conversations about this study with many industry experts, all of whom wished to remain anonymous. In this section, we provide background about general practices in direct credit card marketing as conducted by large lenders, based on these conversations. Lenders typically identify an eligible population through two primary routes: partnerships with other firms, and other sources. In the case of partnerships, a lender may partner with, for example, an airline or retailer. The partner provides data on customers, typically gathered in conjunction with a loyalty program, to the lender. The data includes contact information and the degree of engagement between the partner and individuals in the data set. Lenders send solicitations to individuals within the data set, sometimes without obtaining additional information, beyond confirming that the individuals have not opted out of receiving mailings. Cards marketed through this channel typically include some kind of rewards, such as frequent flier miles, that encourage individuals who use the cards to continue or strengthen their relationship with the partner.

In the case of other sources, lenders obtain lists of potential customers. These lists may come from requests made to credit bureaus or other means. In this case, lenders will typically obtain data such as credit record information, any internal data available from existing customer relationships with the individuals on the list, as well as other data sources. Such data sources might include public records of derogatory information, whether the individuals have requested to opt out of receiving mailings or other resources, as well as fraud detection services. Lenders also try to exclude individuals who are underage or deceased from mailings. Data from these sources is typically used to drop a large proportion of the potential recipients. One lender said that over 90% of individuals in the US are eliminated through such screens.

Lenders apply various models to potential recipients who are not eliminated through initial screens. Such models are typically designed to predict:

- Whether the recipient will respond to a solicitation;
- Credit risk associated with the recipient; and
- How profitable a card held by the recipient would be to the lender.

Of particular interest to many lenders is whether the recipient is likely to revolve balances or pay them off every month. Lenders also focus on whether the recipient is likely to shift existing balances due to a low introductory rate. Lenders offering multiple credit card products will typically estimate the expected profit received from a relationship with the customer through each of the products, and will send a solicitation for the products with highest expected profit. Lenders typically use the combination of these models to rank order individuals for solicitation. The actual number of solicitations sent depends on the marketing budget available for direct mail at a given point in time.

We only have access to a subset of the information available to lenders. Of note, we have no information on existing customer relationshipsor relationships with marketing partners, [3]

[3] As discussed below, we attempt to control for existing customer relationships through the distance between the individual's location and the nearest bank branch affiliated with the lender, where lenders have a network of

whether the individuals have opted out of receiving direct mail, or what fraud detection services say about the individuals in the sample. In addition, we lack data required to estimate separate models for the likelihood of response to solicitations, credit risk, and expected profitability. Our data is limited to survey information provided by the individuals in our study, plus their credit records and a proprietary credit score. We also only observe whether an individual receives a mailing or not, and cannot impute the likelihood or their response or expected profitability.

## III Data

We use a proprietary data source which combines detailed information on households' demographic characteristics, credit history, and the mailings they receive from credit card lenders. Information on credit card mailings comes from the Mintel Comperemedia© database. Mintel Comperemedia selects a sample of households from a list managed by a national survey management corporation. Households that elect to participate in the survey send in a month's worth of mail.[4] A fresh sample of households sends mail every month. Mintel Comperemedia gathers information on the households, including income, race, ethnicity, location, and household composition, and codes a wide variety of information about each piece of mail, including the sender, type of card, terms of the offer, and even the size of the envelope used.

The Mintel Comperemedia database on mailings and household demographic characteristics is merged with 313 credit record variables from a major credit bureau, plus the VantageScore© credit score. VantageScore is a proprietary credit score from a model developed by the three major credit bureaus. It predicts the likelihood of a consumer account going

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branches. We also re-estimate our model excluding campaigns focused on marketing partner lists and find it does not affect our results.

[4] Households who participate are entered in a lottery, where they can receive prizes such as large-screen televisions.

delinquent 90 days or more, and is scaled from 501 to 990, with higher scores indicating a lower probability of default. Note that we consider information on individuals, but all data other than that received from the match with credit records is at the household level. For example, a person other than a head of household in our sample will have their own distinct credit score, but we use data on race, education, and income from the head of household for that individual.

For all descriptive statistics and econometric analysis, we use weights provided by Mintel Comperemedia that are intended to make the survey nationally representative. Mintel Comperemedia divides the shares of the US population by permutations of geography, age, income, and homeownership. These permutations create 80 possible 'cells,' and observations in each cell are weighted to match the national distribution across these cells. The data with weights differs from national averages with respect to other variables. See Table 1 of Han, et al (2011) for a comparison of the Mintel Comperemedia data to the 2007 Survey of Consumer Finances. A broader concern with the data is that households who agree to participate in national surveys and are willing to turn over their mail to a third party may differ in some unobserved manner from the national population, and that these differences could affect our results. Our concerns are mitigated by the fact that Mintel Comperemedia created and maintains the data with the purpose of analyzing trends in credit card marketing. The firm engages in continual quality control, and consults with important participants in the direct mail business to confirm that its results reflect actual business practices.

Our data includes information on mailings received by 78,156 individuals in a total of 41,470 households from August 2009 to October 2010.[5] We focus on five lenders with large

[5] The number of mailings per month varied from 4,378 to 5,951. We eliminated mail to individuals that, according to credit record data, were deceased.

credit card portfolios.[6] Each lender's mailings included a variety of products. These offers varied in a number of ways, including APR, special introductory rates for purchases or balance transfers, rewards, and the presence of annual or, more rarely, monthly fees. Offers varied with regard to variation in APR on purchases; some offered the same purchase APR to all individuals, and others offered different borrowers one of up to seven APR levels for purchases. Some of the products had only a single APR offer in one month, and then offered multiple levels of APR in subsequent months.

Mintel Comperemedia divides cards into four segments. Cards which have neither an annual or monthly fee, and do not offer rewards are called 'vanilla.' Those that do not have such fees and offer rewards such as points that can be redeemed for travel or cash back are called 'general.' Cards that have a fee but do not offer rewards are known as 'credit building.' Cards that have a fee and offer rewards are known as 'premium rewards.' Figure 1 shows the distribution of type of card by lender. Lender #4 was the only of the five lenders to market credit building cards, and also offered vanilla and general cards. Lender #1 almost exclusively marketed general cards, with no fee and rewards. Lender #2 largely marketed a mix of general and premium rewards cards. Lender #3 and Lender #5 marketed a mix of vanilla, general, and premium rewards cards.

Figure 2 shows the distribution of income for the full sample, as well as just Black and Hispanic borrowers. Greater shares of both minority groups were low income. Table 1 shows other descriptive statistics for the full sample, as well as for the Black and Hispanic subsamples. We were unable to obtain credit information for 24% of the full sample.[7] About three-quarters



[6] Data on credit card loan portfolios is from americanbanker.com's list as of June 30, 2010. Published on line December 3, 2010.

[7] The match with credit record data was based on name and address only, and did not include matching based on social security number. A match based on additional data would likely have yielded a higher match rate.

of the full sample were homeowners, while this was true for only half of Blacks and less than two-thirds of Hispanics. For 36% of the full sample, the head of household completed at least a four-year college degree, while this level of education was attained by the head of household for 30% of Blacks and 32% of Hispanics. Blacks were also substantially less likely to be married.

Figure 3 shows the distribution of credit scores, where available, for the full sample, Blacks, and Hispanics. Blacks and Hispanics were more likely to have worse credit scores than the full sample. Table 2 shows data for the portion of the sample that had credit records. 7% of the sample had a history of filing for bankruptcy. Consistent with the pattern for credit scores, Blacks and Hispanics were more likely to have a history of filing for bankruptcy, have a recent delinquency, and utilize a large portion of their available credit. Blacks were less likely to have a high level of debt to income, possibly due to their lower homeownership rates, which results in a smaller mortgage burden. Both Blacks and Hispanics were more likely to have a relatively short credit history, as measured by the share of the group whose oldest credit trade line is less than five years old.

In Table 3, we analyze the share of the sample receiving a credit card offer from one of five lenders. For Lender #1 and Lender #2, Blacks were approximately one-third as likely to receive offers as someone selected randomly from the full sample. Lender #4's rates of mailings to minorities were more representative of the full sample. A randomly selected Black or Hispanic was 82% and 89% as likely to receive offers from Lender #4 as an individual pulled from the sample.

Table 4 shows the raw probability of receiving a credit card offer by card type. As explained above, there are four segments: vanilla (no annual or monthly fee, no rewards), general (no annual or monthly fee, rewards), premium rewards (annual or monthly fee, rewards), and credit building (annual or monthly fee, no rewards). The most commonly received credit card offer type in the data was the general card offer, which 19% of the overall sample received. Blacks were half as likely to receive vanilla, general, or premium rewards card offers, but were 47% more likely to receive a credit building card offer. Hispanics were between 62% and 79% as likely to receive a vanilla, general, or premium rewards card offer, but were 60% more likely to receive a credit building card offer.

The raw data show discrepancies in receiving mailings, but key characteristics of the population that lenders likely used in marketing differ between the two populations. We now use econometric analysis to see if differences in individual characteristics can explain the discrepancy. We also consider a variety of explanations for the raw disparity, including differences in local home price dynamics or unemployment and neighborhood demographic composition. We use data on unemployment at the MSA level from the US Bureau of Labor Statistics, home prices at the county level from CoreLogic©, the 2000 US Census data on census tract income and minority composition to analyze these potential explanations for discrepancies. We also use Federal Reserve data on the location of bank branches, for those lenders with networks of branches.

## IV Methodology

We use several methods to study the relationship between race, ethnicity, and the probability of receiving a credit card offer from one of the five credit card lenders. Many households in the sample received an offer from more than one lender. Consequently, we use a Poisson regression to estimate the number of offers received, as well as a logistic regression to estimate the probability of receiving at least one offer. Harrison (2001) discusses the importance of lender heterogeneity in studying discrimination in the mortgage market. In order to control for possible lender heterogeneity, we use five separate logistic regressions to estimate the probability of receiving an offer from each individual lender.[8]

All of our equations are of the form:

$$Pr(X_i) = F(B^B * I^B_i + B^H * I^H_i + B^Z * Z_i + E_i)$$

where $X_i$ is one of four variables, depending on the equation:

- How many of the five lenders sent offers, in the case of the Poisson regression; or
- Whether the individual received a offer from any of the five lenders, for the logistic regression where data on all five lenders is combined; or
- Whether the individual received an offer from a specific lender, for the lender-specific logistic regressions[9]; or

[8] While we focus on the results from these five large lenders, we also analyzed the probability of receiving a credit card offer from any firm. The results, which are available from the author upon request and are consistent with Han, Li, and Keys (2011), show that these unexplained discrepancies exist at the industry level.

[9] We also used Poisson regressions for the number of offers received during the month from an individual lender. In the interest of space, we do not include the results in this paper. The results, available upon request from the author, are consistent with the logistic regressions with regard to both economic and statistical significance.

- Whether the individual received a specific kind of offer (vanilla, general, premium rewards, or credit building) for logit regressions by individual credit card types.

$I^B_i$ and $I^H_i$ are indicators for whether the head of household is Black or Hispanic, and $Z_i$ is a vector of other demographic variables as well as information about the individual's credit history.

Explanatory variables in the vector $Z_i$ include a variety of household socioeconomic characteristics that are likely available to lenders, including the head of household's age, marital status, and education level, as well as household income. We also include the VantageScore credit rating plus a variety of data from the credit record, including the degree to which the borrower utilizes their available credit, the ratio of both total debt and revolving debt to household income, the age of the oldest trade line, and any history of filing bankruptcy. Demographic data is only available at the household level, while credit history data is available for individual household members.

We include a dummy variable indicating where households did not have a credit history. [10] Economic conditions vary by state and month, so we include dummy variables for both state and month. We include multiple individuals from the same household in our regressions, and the estimation controls for clustering of such error terms. Our focus is on the value of $B^B$ and $B^H$, which measure the relationship between Black and Hispanic status and the probability of receiving a credit card offer.



[10] 15% of individuals without credit records received an offer from at least one of the five credit card lenders. For such individuals, we assume that they have no debt burden, revolving debt burden, history of bankruptcy, or record of delinquencies. We assign such individuals the median credit score of individuals whose age of oldest trade is less than five years old, who are relatively new credit files. We repeated our analysis by replacing such missing credit values with the median for the entire sample; this had no effect on our results. We also tried the analysis dropping observations where the observation was not matched with a credit record. This left all key results unchanged. The data included a substantial number of observations which were not addressed to an individual household member, or to deceased individuals. Such observations were deleted from the data set.

## V Effects of control variables

*Poisson Regression*

Table 5 shows the coefficients from a Poisson regression, where the dependent variable is the number of offers received during a month from one of the five lenders. The coefficients for income and credit score are both consistent with a weakly monotonically increasing likelihood of receiving an offer as income and creditworthiness increase. Households whose credit balances are less than 10% of their total available credit were likely to receive offers from fewer lenders. Presumably such households pay less interest or fees and so generate less income for the credit card firms. Other groups that were likely to receive fewer offers include individuals with less education or a history of bankruptcy. Households with such characteristics may present a greater risk of default. Households located in states that were particularly hard hit by the financial crisis, such as Florida, Nevada and California, also received fewer offers,[11] again a likely effect of risk. Individuals without a credit score were likely to receive fewer offers, while those with a credit score whose age of oldest trade is less than five years were more likely to receive more offers.

*Individual Logit Equations by Lender*

The first column of Table 6 shows the coefficients from a logit regression of the probability of receiving an offer from at least one of the five lenders. The results from this estimation are similar to those of the Poisson regression, indicating that variables associated with the likelihood of receiving any offer are also related to the number of offers received. The other columns in this table show the results of individual logit equations for each of the lenders. Table

[11] This can be seen through the coefficients on state dummy variables, which are available from the author upon request.

7 shows odds ratios calculated based on these equations. A comparison of the differences in the odds ratios reveals some cross-sectional variation, indicating differences in the lenders' marketing strategies during this time. Figure 4 plots the odds ratios from the individual lender equations for the different income categories. We see that the probability of receiving a credit card offer was increasing for all lenders with respect to income, but the sensitivity of this probability to income differs. Lender #5's probability is the most sensitive; an individual living in a household with the highest income category was almost four times as likely to receive an offer as an individual in the lowest income bracket. For Lender #4, the highest income category was only 57% more likely to receive an offer.

Figure 5 shows the odds ratios by credit score category for the equations for individual lenders. The distribution of the probability of receiving an offer from Lender #4 is bimodal, with peaks at a VantageScore of between 650 and700, as well as at the highest level. This may indicate a composite strategy, where Lender #4 targeted one kind of product, likely the credit building cards (which charge an annual or monthly fee and don't offer rewards), to individuals with relatively low credit scores, and general cards (which offer rewards but don't charge a fee) to individuals with high credit scores. Lender #5 appeared to focus on borrowers with a VantageScore of approximately 800, while others' marketing focus appears to be weakly increasing with regard to the individual's credit score.

Other differences between the lenders include:

- Lender #2 focused on individuals living in households where the head of household was more educated.
- Lender #1 and Lender #3 were more likely to market themselves to homeowners, while Lender #4 and Lender #5 were relatively less likely to send offers to such households.

- Lender #1 focused more on individuals with high utilization of their available credit lines, and less on individuals whose total debt was a small portion of their household income.
- Lender #4 focused more on individuals with moderately high levels of the ratio of revolving debt to income, and who had had a delinquency within the past few years.
- Lender #5 was more likely to send offers to individuals with a high ratio of revolving debt to income.
- Lender #4 was much more likely to market to individuals who had filed for bankruptcy, compared to other lenders.

*Individual Logit Equations by Card Type*

Table 8 shows the logit equations for the probability of a household receiving at least one offer of each of the four kinds of cards: vanilla (no fee or rewards), general (no fee, no rewards), premium rewards (fee, rewards), and credit building (fee, no rewards). General and premium rewards cards were both marketed most heavily to individuals living in high income households. The odds ratios for our income categories from these equations are in Table 9. As shown in Figure 6, the probability of premium rewards cards being marketed to individuals in the highest household income category was six times that of the lowest household income category, while general rewards cards were twice as likely to be marketed to such households relative to the lowest household income category. Figure 7 shows differences in sensitivity to credit score. Credit building cards were marketed most heavily to individuals with VantageScores of approximately 650, and were much less likely to be marketed to those with very low scores or relatively high scores. The likelihood of receiving the other three kinds of cards was generally increasing in credit score, with vanilla cards more likely to be sent to borrowers with low credit scores than general or premium rewards cards.

Other observations from inspecting the coefficients include:

- Premium rewards cards were more likely to be marketed to individuals with more education.
- Credit building cards were most likely to be marketed to individuals with high revolving balances or recent delinquencies.
- Vanilla cards were most likely to be sent to individuals with credit histories less than five years old.

## VI Race, Ethnicity, and the Probability of Receiving Credit Card Offers

The overall pattern from consideration of the coefficients on “Black” and “Hispanic” identifiers across the various specifications indicates that, even after controlling for factors such as income, education, and credit variables, both minority groups were less likely to receive offers from large credit card lenders. With regard to card type, Blacks were less likely to receive any kind of offer, while Hispanics were less likely to receive cards offering rewards. While the magnitude and significance of these effects vary, they are always negative for Blacks and Hispanics.

Table 10 shows the raw disparities, compared to the odds ratios based on the individual logit equations. After including a large number of controls for geography, time, individual credit history, and household socioeconomic variables, Black and Hispanic individuals were approximately 25% less likely to receive credit card offers from one of the five lenders. We calculate the raw discrepancy as one minus the ratio of the raw probability of a Black or

Hispanic individual receiving an offer, relative to the entire population. For the adjusted discrepancy, we calculate one minus the odds ratio from the logit equation. Controls reduce the magnitude of the adjusted discrepancies compared to the raw discrepancies, typically by half. However, the discrepancies remain statistically significant with respect to Blacks for Lender #1, Lender #2, Lender #3, and Lender #5, and for Hispanics with respect to Lender #1 and Lender #2. After controls, Blacks and Hispanics were about two-thirds as likely to receive an offer from Lender #2. In no case were Blacks or Hispanics more likely to receive an offer from a particular lender.

With respect to card type, Blacks were less likely to receive cards that do not charge annual or monthly fees. The unexplained discrepancy is 24% for 'vanilla' cards, which don't charge a fee or offer rewards, and 31% for 'general' cards, which don't charge a fee but offer rewards. Hispanics were 37% less likely to receive offers of 'premium' cards, which charge an annual fee and offer rewards.

***Geographic Controls***

While our model includes state fixed effects, it is possible that differences in the geographic distribution of Blacks and Hispanics at a local level could explain these discrepancies. We consider the effect of Core Based Statistical Area (CBSA) level unemployment, county-level home price dynamics, and census tract-level demographic and socioeconomic variables on credit card marketing. As we show below, there were substantial differences between Blacks, Hispanics, and the rest of the sample with respect to local economic and demographic conditions. Seeming racial and ethnic discrepancies might actually be proxies for local variation. We find, however, that the significance and magnitude of the discrepancies are robust to the inclusion of geographic variables.

Table 11 shows descriptive statistics for the geographic variables we use for the entire sample, as well as that for just the Black and Hispanic subsamples.  Unemployment data at the CBSA level is from the Bureau of Labor Statistics.  We use the level of unemployment from 2009, as well as the change between 2008 and 2009.   CBSA unemployment was a median of 8.8% for individuals within the sample, and increased everywhere from 2009.  CBSA unemployment was slightly higher and increased slightly more on average for Hispanics than the rest of the sample.  This difference is likely due to Hispanics' concentration in California, Arizona, and Florida, which were particularly hit hard by the housing crash.

Home prices at the county level declined a median of 17% for the whole sample, and by 22% for Hispanics, again likely due to their geographic concentration.  Data on home prices is the change in the county level home price index from April 2007 to December 2009 according to CoreLogic.  These dates are approximately the peak and bottom of the change in home prices according to the Federal Housing Finance Agency national index

Data on census tract level median family income and minority share is from the US 2000 Census, the most recent version available.  Blacks and Hispanics were heavily concentrated in high minority areas.  62% of Blacks and 35% of Hispanics lived in majority minority census tracts, compared with 14% of the overall sample.  12% of Blacks lived in low-income tracts, as compared to just 2% of the whole sample.[12]

Table 12 shows the odds ratios for 'Black' and 'Hispanic' indicator variables and the odds ratios related to geographic variables from logistic regressions where geographic variables



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[12] Low Income Tract = Census tract median family income is less than 50% of metropolitan median family income. Moderate Income Tract = Census tract median family income <=50% of metropolitan median family income, < 80% metropolitan median family income.  Middle Income Tract = Census tract median family income is <=80% metropolitan median family income, <120% metropolitan median family income.  Tract level minority share includes all except non-Hispanic whites as minorities.

are included. In the interest of saving space, the full set of coefficients and odds ratios for other variables are not shown.[13] Inclusion of geographic variables does not generally have a significant effect on the coefficients on 'Black' and 'Hispanic.'[14] The odds ratios on variables other than 'Black' and 'Hispanic' are virtually unchanged by the inclusion of geographic information.[15]

As most borrowers rely on labor income to pay off consumer credit, local unemployment conditions are potentially important for credit risk. Table 12, Panels A and B show the odds ratios of models with the level of CBSA unemployment in 2009, as well as the change in unemployment from 2008 to 2009. We normalize the level of unemployment by the national statistics mean, so a change from one to two 'units' of unemployment in our data set would be a level that is double the national statistic. The probability of receiving an offer from any of the five credit card lenders, as well as that of receiving an offer individually from Lender #2, Lender #3, and Lender #4 were negatively related to both the level of unemployment and change in unemployment. The size of the effect on the probability of receiving an offer from Lender #4 is particularly large.

Our data set was collected during the aftermath of a historic decline in home prices, which had an enormous impact on consumer's assets. We consider the effect of changes in home prices on the probability of receiving an offer. Changes in home prices would likely affect homeowners differently than renters, so we include an interaction between an indicator variable for 'homeowner' and the change in the HPI. Results are in Panel C of Table 12. The odds ratio

[13] These are available upon request from the author.
[14] The one exception to this is an effect on the significance of the probability of receiving an offer from Lender #2. This is discussed below.
[15] Census tract median income was the sole geographic variable that had an appreciable effect on the coefficients of other variables in our specification. Inclusion of these tract-level variables reduced the effect of the individual's income on the probability of receipt for Lender #1, Lender #2, Lender #3, and Lender #5. For Lender #4, inclusion of the census tract median income variables increased the magnitude of the effect of individual income.

for the change in HPI is larger than one for all lenders, meaning that individuals in areas experiencing home price appreciation were more likely to receive an offer. The effect is only significant for Lender #2 and Lender #3. For Lender #2, the interaction between homeownership and the change in HPI is quite large and statistically significant, suggesting that the probability of receiving an offer from Lender #2 was especially sensitive to home price dynamics for homeowners

We estimate our equations with controls for census tract median family income, relative to the metropolitan median family income, and census tract minority share.[16] Data are from the US 2000 Census. Results are in Table 12, Panel D. The minority share of the census tract has a significant and negative effect on the probability of receiving an offer, regardless of the race or ethnicity of the recipients. An individual in a majority minority tract[17] was 26% less likely to receive an offer from Lender #2, 23% less likely to receive an offer from Lender #3, and 21% less likely to receive an offer from Lender #5.

The coefficients on indicators for census tract median family income are generally not significant. Interestingly, Lender #4, which as was shown in Figure 8 tended to cater to lower-income individuals more than the other lenders, was very unlikely to send offers to individuals in low income tracts. Lender #4 appears to have marketed cards to low-income borrowers, but not to those who live in low-income communities.

In general, neither the magnitude nor the significance of the coefficients on Black or Hispanic are affected by inclusion of any variables related to local conditions. The one exception is the effect of the coefficient on 'Black' for the probability of receiving an offer from Lender #2,

[16] 'Minority' for this purpose is all people other than non-Hispanic whites.
[17] We define a majority minority tract as one where the non-Hispanic white population is less than 50% of the census tract population.

when the census tract's demographic characteristics are included in the equation. In this case, the magnitude of the odds ratio for 'Black' is virtually unchanged, but it is no longer statistically significant. However, the minority share of the census tract population has a significant and negative effect on the probability of receiving an offer. Dropping the minority share of the census tract from the estimation restores the significance of the coefficient on 'Black' without changing the magnitude substantially.[18] For Lender #2, it appears difficult to separately identify the effect of minority composition of the area from the individual's minority status.

### *Affiliate Cards*

Some credit card lenders acquire accounts through 'affiliate' programs, where for example a union, sports team, or other organization helps market the card in return for some fee or share of the profits. It is possible that Blacks and Hispanics are less involved in organizations that have such arrangements with the five lenders. Examination of the data shows that during the sample period only the Lender #1 had a strong active affiliate program.[19] We ran logistic regressions separately for the probability of receiving a card, other than an affiliate card, from the Lender #1. The results, available from the author upon request, indicate that Blacks were 68% as likely to receive a credit card offer from the Lender #1, while Hispanics were 63% as likely, when affiliate cards are not counted as an offer. Both differences are statistically significant. These results indicate that unexplained discrepancies in marketing by race and ethnicity cannot be explained by affiliate programs.

### *Checking and Savings Accounts*

Banks may market credit cards more intensively to individuals with whom they already have a relationship. Cross-product marketing opportunities allow banks to benefit from

[18] This result is not shown, but is available upon request from the author.
[19] Lender #3 also sent a handful of solicitations for affiliate cards.

information unavailable to other lenders, a potentially important advantage in lending. Hogarth, Anguelov, and Lee (2005) show that Blacks and Hispanics are less likely to have checking or savings accounts, even after controlling for income, age, education, and credit history. It is possible that Blacks and Hispanics may be less likely to receive credit card offers due to a lower probability of holding checking or savings accounts with banks.

Our data set does not include information on whether an individual has a checking or savings account, let alone at which institution individuals have accounts. While Blacks and Hispanics are less likely to have a checking or savings account, analysis shows that this relationship is strongly affected by household income. We use the variation in this relationship to explore whether differences in the probability of having a checking or savings account with any institution might explain the discrepancy in credit card marketing.[20] Data limitations prevent us from analyzing whether an institution-specific relationship can explain the discrepancies in credit card marketing.

In January, 2009 the US Census Bureau included a supplement in the Current Population Survey to identify the 'unbanked' population, where unbanked is defined as having neither a checking nor a savings account.[21] Figures 9 and 10 show the share of Black and Hispanic individuals who are unbanked by household income compared to the share of unbanked non-Black and non-Hispanic individuals. The gap is quite pronounced for individuals in households earning less than $50,000. For example 39% of Hispanic individuals in households earning

[20] An alternative method would be to estimate a model of the probability of having a checking or savings account using data from the Current Population Survey Supplement Data or the Survey of Consumer Finances, use the coefficients from this model to assign the probability of having a checking or savings account to our sample, and include this assigned probability as an explanatory variable in our analysis. Concerns about separately identifying discrepancies in the deposit account and credit markets, multicolinearity, and measurement error led us to choose this simpler approach.

[21] The supplement was sponsored by the Federal Deposit Insurance Corporation. See http://www.fdic.gov/householdsurvey/ for more information.

between $15,000 and $20,000 are unbanked, as compared to 18% of non-Hispanic individuals living households with similar income. However, the gaps are much less pronounced for individuals in households earning more than $50,000, ranging from 6% to less than 1%.

If the difference in probability of receiving a credit card offer were driven by differences in the likelihood of having a checking or savings account, then we would expect to see the discrepancy shrink for higher income levels, where the gap in the likelihood of having a checking or savings account is much smaller. Table 13 shows the odds ratios from individual logit equations where we limit the sample to individuals living in households with household income of at least $50,000. The magnitude of the odds ratios is largely unchanged, increasing in some cases and decreasing in others.[22] As with the full sample, the discrepancy for Blacks is statistically significant for four of the five lenders, in spite of the fact that reducing sample size generally increases standard errors. While this test is imperfect, it does not support the hypothesis that differences in banking relationships can be explained by gaps in the probability of having a checking or savings account.

***Credit Score Threshold***

For a large part of the credit score spectrum, very few individuals receive an offer from any of the issuers, with the exception of Lender #4. Individuals with a history of bankruptcy in their credit record might also not receive offers from the major lenders. It is possible that inclusion in our sample of many individuals with a low probability of receiving an offer could bias our results. We consequently estimate our equations, limiting the sample to individuals who have a credit score, whose score is in excess of a cutoff. We used a VantageScore of 750 as a



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[22] We also ran the full model with an interaction between an indicator variable for income less than $50,000 and 'Black' or 'Hispanic.' This is another approach to testing if the relationship between race, ethnicity and credit card marketing varies by income. The interaction terms were generally not statistically significant, suggesting that this relationship does not vary. This is consistent with results from estimation with the subsample where household income is $50,000 or more.

minimum for this exercise. Our choice was motivated by dividing the sample into subsamples of individuals defined by ranges of ten VantageScore points each. For all buckets above 750, each lender sent an offer to at least 3% of the subsample. In contrast, for the lowest credit scores subsamples, some lenders sent offers to less than 0.2% of individuals.

Table 14 shows the odds ratios from estimates of the equations on this censored sample. The sample is reduced almost by half, to 41,920 observations. This mechanically increases the standard errors, which would tend to decrease the number of significant results. Lender #3's discrepancy in marketing to Blacks is much smaller and no longer significant on this subsample. For this subsample, Lender #1, Lender #2, and Lender #5 have significant unexplained discrepancies with regard to their marketing to Blacks, and Lender #1 and Lender #2 have significant unexplained discrepancies with respect to Hispanics. Other coefficients are generally not changed with respect to magnitude or significance when the equations are estimated on the subsample. The one exception of having a delinquency reported on the credit record within the past twelve months, whose sign and significance increases.

***Proximity to Branches***

Certain of the lenders we study have national branch networks. It is possible that lenders focus their marketing on individuals living in close proximity to a branch. We use geographic information on the household location determine the distance from the household to the nearest bank branch for these lenders, and then include dummy variables indicating whether the closest branch for the lender is within three, ten, or fifty miles of the household. The median distance to one's primary bank branch, according to Amel, Kennickel, and Moore (2008), was three miles.

In the interest of maintaining the confidentiality of the lender identities, we do not disclose for which lenders we performed these tests. Geocoding was successful for 50,208 individuals.  In no case were the variables for distance from bank branch significant at less than a 5% level.  The magnitude and significance of other variables, including the indicators for Black and Hispanic, were not significantly affected by inclusion of this variable.

## VII Conclusion

We use a new data set to study the relationship between race, ethnicity, and credit card marketing.  We find that Blacks were only half as likely to receive offers from five credit card lenders during our fourteen month sample period; the corresponding figure for Hispanics is less than three-quarters.  Controlling for multiple characteristics, including household income, the head of household's education, credit score, and multiple other credit characteristics, explains only a portion of this gap.  Incorporating such controls shrinks the difference in likelihood of receiving an offer to 27% for Blacks and 17% for Hispanics.  The result for Blacks holds for four of the five credit card lenders and for two of the five lenders for Hispanics.  Blacks were also significantly more likely to receive offers of cards that charge annual fees.

Industry experts assert that it is unlikely that the discrepancies found in this paper are due to disparate treatment of minority borrowers, as there would be substantial legal and reputational risk for inclusion of such characteristics in models or business rules.    They also note that the decision to send a credit card offer to an individual is a result of a multi-stage process.  Lenders obtain lists of possible households, often from third party vendors.  They may use models on these lists to separately predict the probability of an individual accepting an offer of credit, the risk of a borrower defaulting on their credit, and the profitability of an account, conditional on it not defaulting.  All of these predictions affect the probability of receiving an offer.  Some of these models use hundreds of explanatory variables.  As we only observe the joint outcome of these decisions, possible biases may arise from misspecification. While recreating each lender's set of models used in the marketing process is impractical, we have attempted to include key variables of interest in our model. In addition, lenders use more information than available to us, including data on whether individuals have opted out from receiving mailings, output from fraud detection techniques, and history from existing customer relationships. All of these omitted variables could bias our results in ways that are impossible to detect with existing information.

As discussed in the introduction, our study covers a time of crisis in the credit card industry where lenders were generally reducing the amount of marketing. Figure 10 shows the volume of credit card offers over the past ten years. The period we study is marked by the red box. As the figure shows, offers were at a historical low during our study period and began to recover by the end. This may affect the generality of our results. An additional caveat related to our study is that we analyze only one form of marketing, and cannot determine whether the offers of credit actually led to the extension of credit. Our data set, while more complete than others used to study this issue, does not incorporate all factors used in credit card marketing. Finally, the fact that our data is limited to those households that volunteer to participate in the study may affect the generality of our results.

With all of the limitations to our study, we find that this statistically robust relationship and economically significant between race, ethnicity, and credit card marketing is puzzling and noteworthy. The patterns may be due to disparate impact, omitted variable bias, model misspecification, or the special nature of the sample. We have attempted to control for these factors, where possible. Our study suggests that further analysis of the relationship between race, ethnicity, and credit card marketing is warranted.

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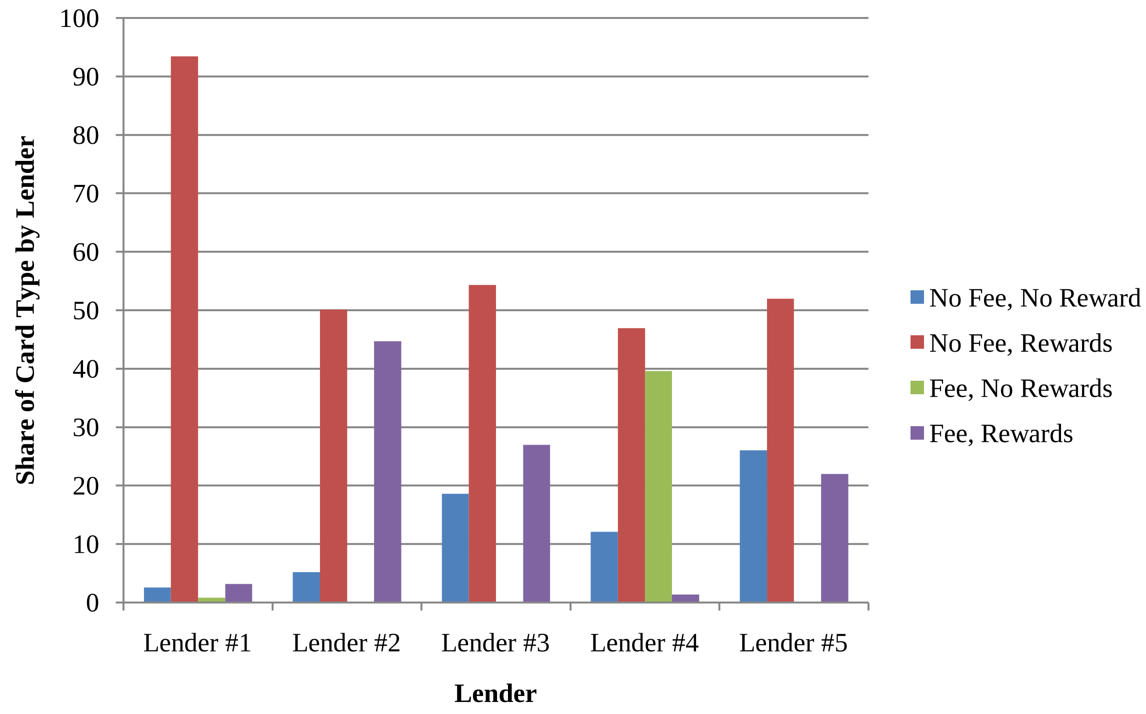
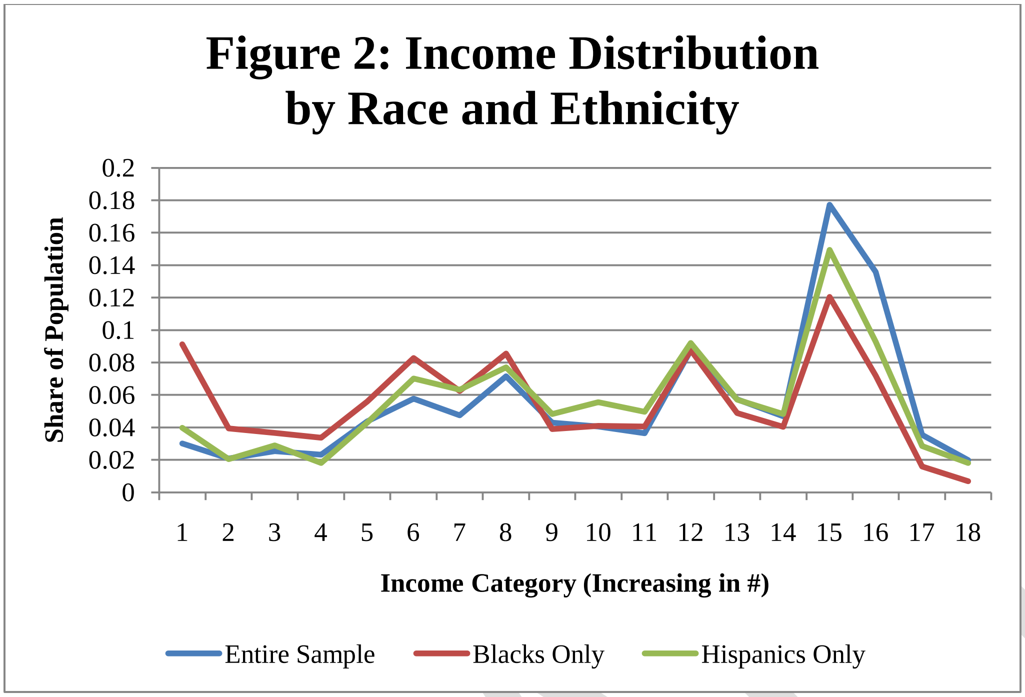
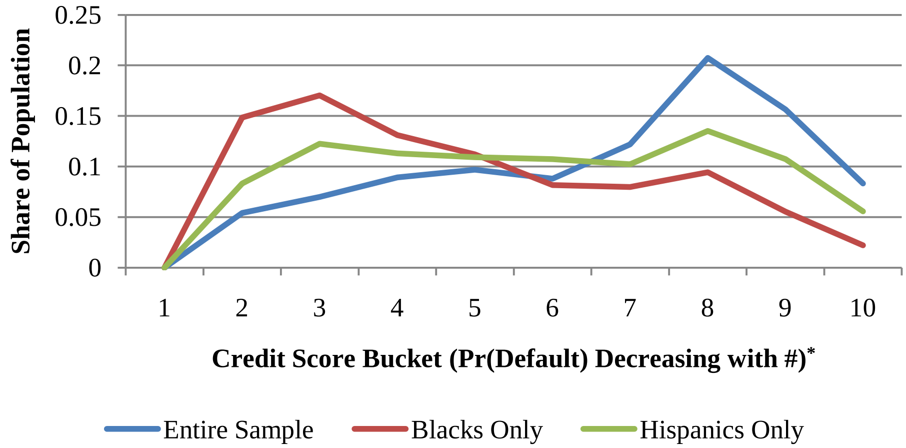
**Figure 1: Card Type by Lender**



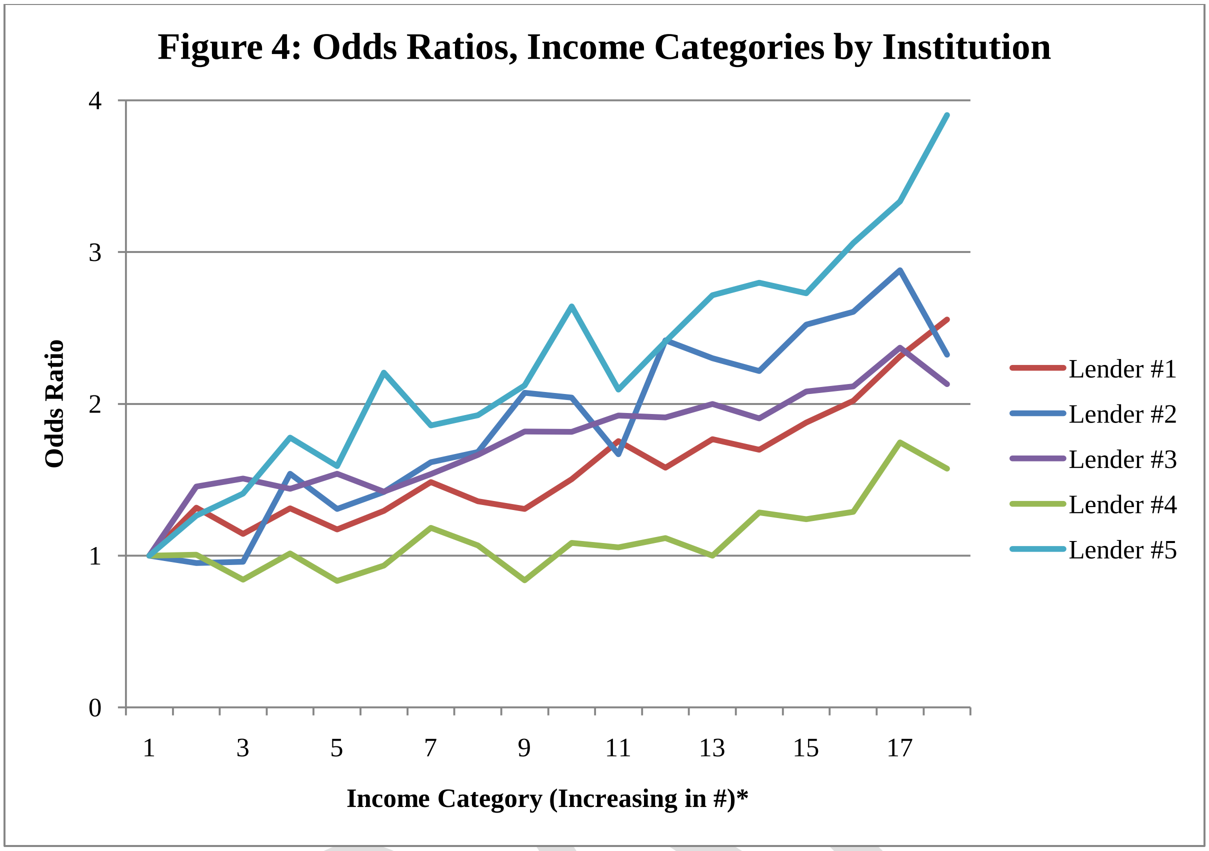



| *Household Income Categories for Figure 2 | |
|---|---|
| **Income Category** | **Range of Values** |
| 1 | $0 - $7,500 |
| 2 | $7,500-9,999 |
| 3 | $10,000-12,499 |
| 4 | $12,500-14,999 |
| 5 | $15,000-19,999 |
| 6 | $20,000-24,999 |
| 7 | $25,000-29,999 |
| 8 | $30,000-34,999 |
| 9 | $35,000-39,999 |
| 10 | $40,000-44,999 |
| 11 | $45,000-49,999 |
| 12 | $50,000-59,999 |
| 13 | $60,000-69,999 |
| 14 | $70,000-74,999 |
| 15 | $75,000-99,999 |
| 16 | $100,000-149,999 |
| 17 | $150,000-199,999 |
| 18 | $200,000+ |

**Figure 3: VantageScore Distribution by Race and Ethnicity**

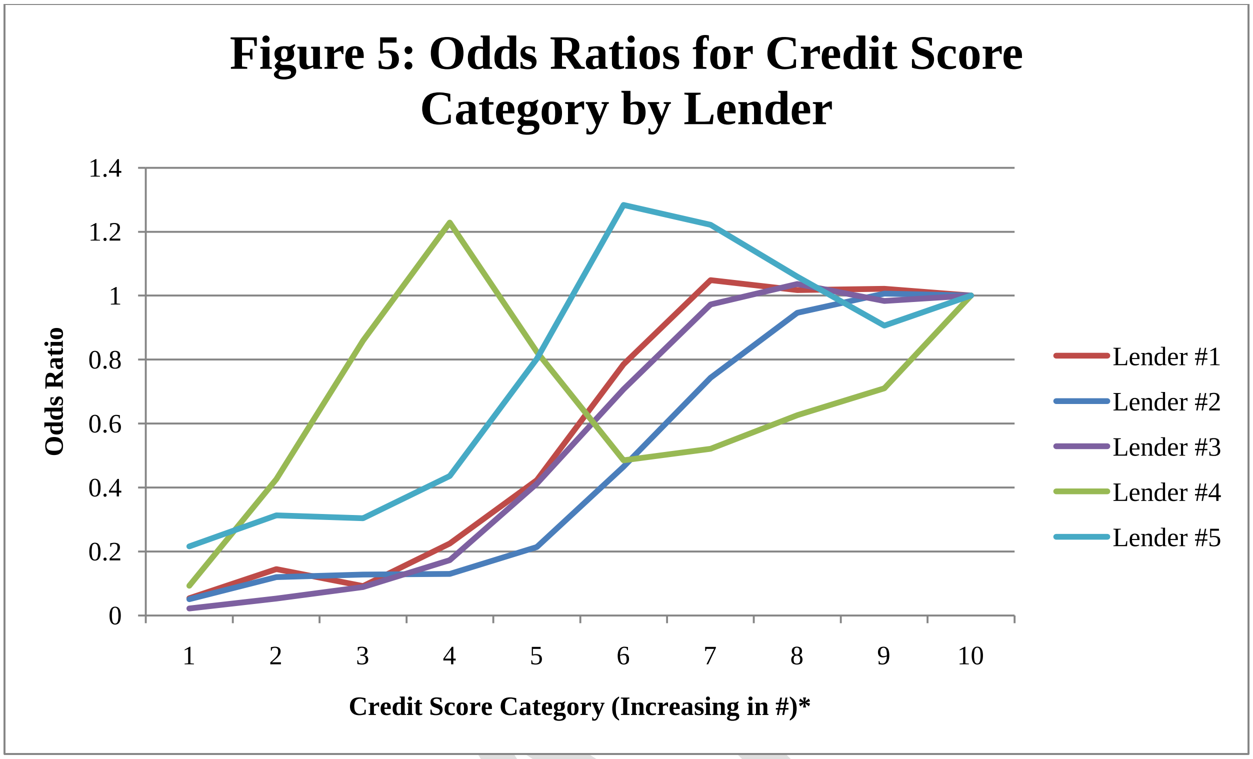



| *Vantage Score Categories for Figure 3 | |
|---|---|
| Vantage Score Category | Range of Values |
| 1 | 501-550 |
| 2 | 551-600 |
| 3 | 601-650 |
| 4 | 651-700 |
| 5 | 701-750 |
| 6 | 751-800 |
| 7 | 801-850 |
| 8 | 851-900 |
| 9 | 901-950 |
| 10 | 951-990 |



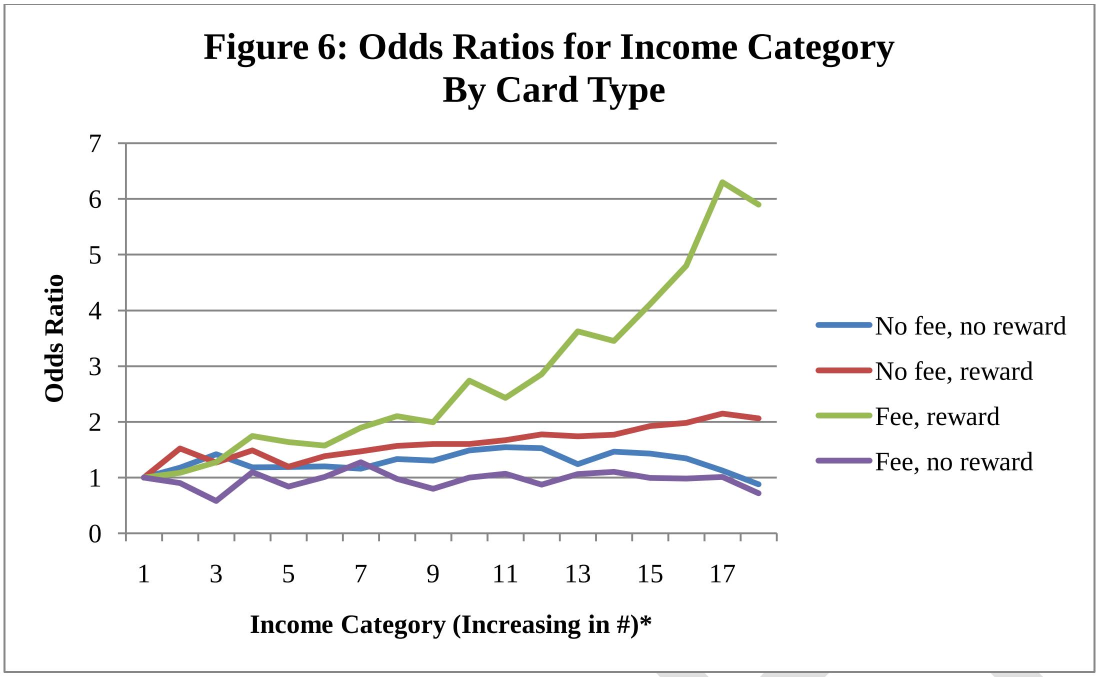

Odds ratios from individual logit equations for the probability of receiving a credit card offer from each of the credit card lenders.

| ***Household Income Categories for Figure 4** | |
|---|---|
| **Income Category** | **Range of Values** |
| 1 | $0 - $7,500 |
| 2 | $7,500-9,999 |
| 3 | $10,000-12,499 |
| 4 | $12,500-14,999 |
| 5 | $15,000-19,999 |
| 6 | $20,000-24,999 |
| 7 | $25,000-29,999 |
| 8 | $30,000-34,999 |
| 9 | $35,000-39,999 |
| 10 | $40,000-44,999 |
| 11 | $45,000-49,999 |
| 12 | $50,000-59,999 |
| 13 | $60,000-69,999 |
| 14 | $70,000-74,999 |
| 15 | $75,000-99,999 |
| 16 | $100,000-149,999 |
| 17 | $150,000-199,999 |
| 18 | $200,000+ |



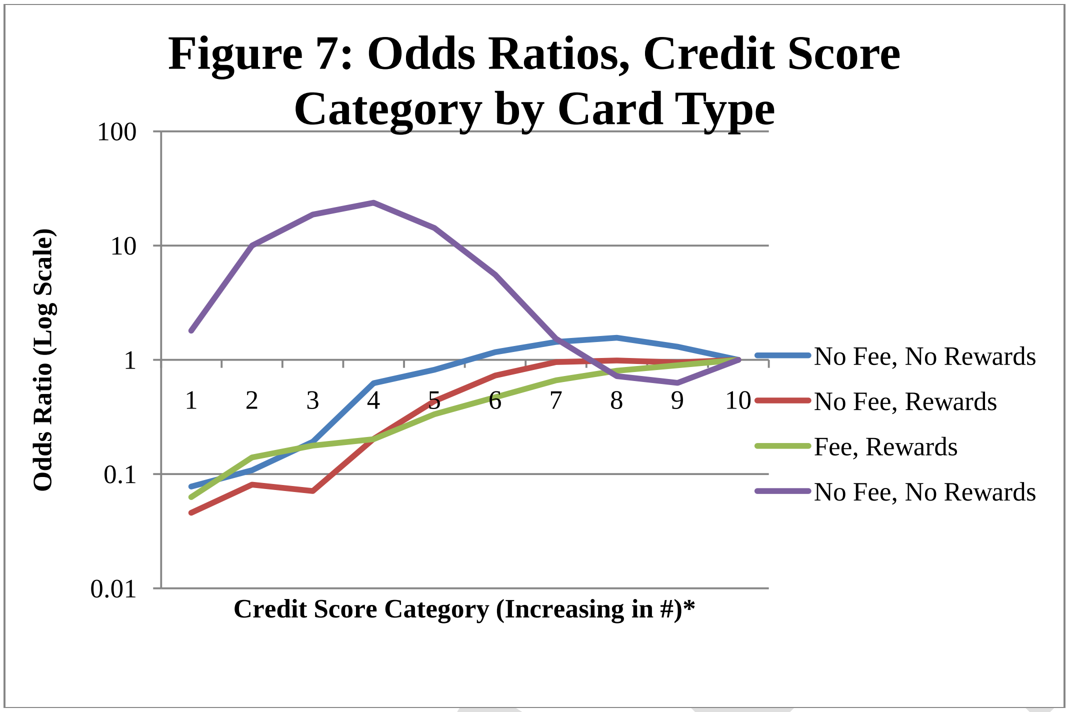

Odds ratios from individual logit equations for the probability of receiving a credit card offer from each of the credit card lenders. Odds ratios are based on estimates from the subsample of borrowers with credits scores. These estimates are available from the author upon request. Odds ratios from estimates based on the full sample are very similar.

| ***Vantage Score Categories for Figure 5** | |
|---|---|
| **Vantage Score Category** | **Range of Values** |
| 1 | 501-550 |
| 2 | 551-600 |
| 3 | 601-650 |
| 4 | 651-700 |
| 5 | 701-750 |
| 6 | 751-800 |
| 7 | 801-850 |
| 8 | 851-900 |
| 9 | 901-950 |
| 10 | 951-990 |




Odds ratios from individual logit equations for the probability of receiving a credit card offer from one of the credit card lenders by card type.

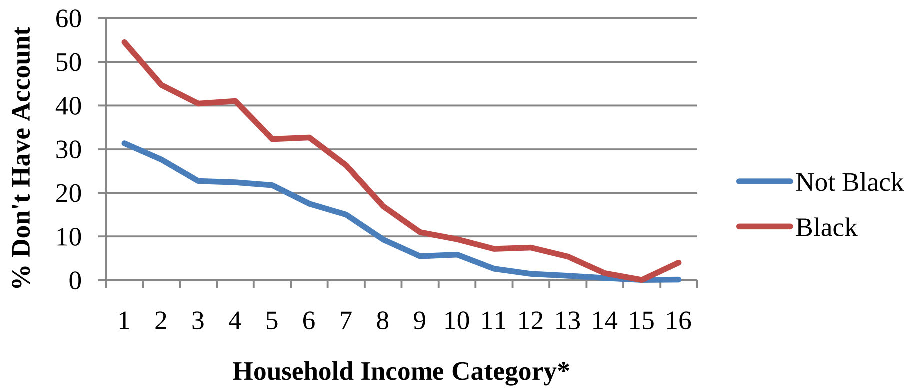
| *Household Income Categories for Figure 6 | |
|---|---|
| **Income Category** | **Range of Values** |
| 1 | $0-$7,500 |
| 2 | $7,500-9,999 |
| 3 | $10,000-12,499 |
| 4 | $12,500-14,999 |
| 5 | $15,000-19,999 |
| 6 | $20,000-24,999 |
| 7 | $25,000-29,999 |
| 8 | $30,000-34,999 |
| 9 | $35,000-39,999 |
| 10 | $40,000-44,999 |
| 11 | $45,000-49,999 |
| 12 | $50,000-59,999 |
| 13 | $60,000-69,999 |
| 14 | $70,000-74,999 |
| 15 | $75,000-99,999 |
| 16 | $100,000-149,999 |
| 17 | $150,000-199,999 |
| 18 | $200,000+ |




Odds ratios from individual logit equations for the probability of receiving a credit card offer from one of the credit card lenders, by card type. Odds ratios are based on estimates from the subsample of borrowers with credits scores. These estimates are available from the author upon request. Odds ratios from estimates based on the full sample are very similar.

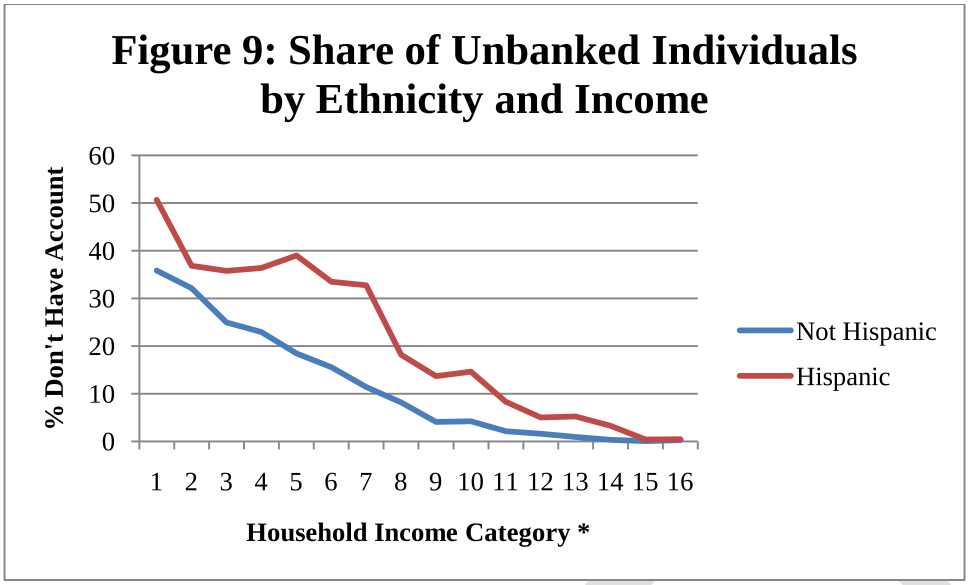
| *Vantage Score Categories for Figure 7 | |
|---|---|
| **Vantage Score Category** | **Range of Values** |
| 1 | 501-550 |
| 2 | 551-600 |
| 3 | 601-650 |
| 4 | 651-700 |
| 5 | 701-750 |
| 6 | 751-800 |
| 7 | 801-850 |
| 8 | 851-900 |
| 9 | 901-950 |
| 10 | 951-990 |

**Figure 8: Share of Unbanked Individuals by Race and Income**




Source: Analysis of January 2009 Supplement to US Census Current Population Survey. 151,652 observations. Share of individuals within household income category reporting not having a checking or savings account.

| *Household Income Categories for Figures 8 & 9 | |
|---|---|
| **Income Category** | **Range of Values** |
| 1 | <$5,000 |
| 2 | $5,000 - $7,499 |
| 3 | $7,500 - $9,999 |
| 4 | $10,000 - $12,499 |
| 5 | $12,500 - $14,999 |
| 6 | $15,000 - $19,999 |
| 7 | $20,000 - $24,999 |
| 8 | $25,000 - $29,999 |
| 9 | $30,000 - $34,999 |
| 10 | $35,000 - $39,999 |
| 11 | $40,000 - $49,999 |
| 12 | $50,000 - $59,999 |
| 13 | $60,000 - $74,999 |
| 14 | $75,000 - $99,999 |
| 15 | $100,000 - $149,999 |
| 16 | $150,000 or more |




Source: Analysis of January 2009 Supplement to US Census Current Population Survey. 151,652 observations. Share of individuals within household income category reporting not having a checking or savings account.

| *Household Income Categories for Figures 8 & 9 | |
|---|---|
| **Income Category** | **Range of Values** |
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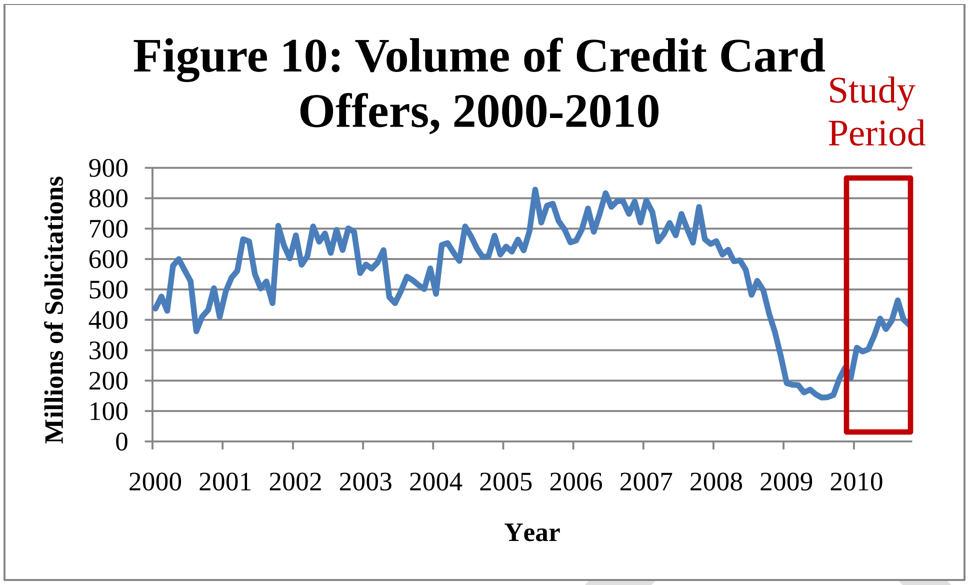
| 7 | $20,000 - $24,999 |
| 8 | $25,000 - $29,999 |
| 9 | $30,000 - $34,999 |
| 10 | $35,000 - $39,999 |
| 11 | $40,000 - $49,999 |
| 12 | $50,000 - $59,999 |
| 13 | $60,000 - $74,999 |
| 14 | $75,000 - $99,999 |
| 15 | $100,000 - $149,999 |
| 16 | $150,000 or more |




Source: Mintel Compermedia© Database

Includes all US lenders.

**Table 1: Demographics, Full Sample**

| Variable | Full Sample Mean | Black Mean | Hispanic Mean |
|---|---|---|---|
| Thin Credit File | 0.24 | 0.28 | 0.26 |
| Married | 0.58 | 0.33 | 0.55 |
| High School Graduate | 0.32 | 0.29 | 0.29 |
| Completed Some College | 0.22 | 0.28 | 0.26 |
| College Graduate | 0.36 | 0.30 | 0.32 |
| Homeowner | 0.73 | 0.49 | 0.61 |
| Number of Observations | 78,156 | 4,337 | 4,150 |

Descriptive statistics for entire sample. Numbers are weighted, using weights provided by Mintel Comperemedia.

**Table 2: Credit Variables, Sample With Credit Data**

| Variable | Full Sample | Black | Hispanic |
|---|---|---|---|
| Credit Utilization <=10% | 0.39 | 0.28 | 0.30 |
| 10% <Credit Utilization <=25% | 0.14 | 0.08 | 0.14 |
| 25% <Credit Utilization <=50% | 0.18 | 0.15 | 0.18 |
| 50% <Credit Utilization <=75% | 0.15 | 0.18 | 0.18 |
| Credit Utilization >75% | 0.15 | 0.30 | 0.21 |
| Debt to Income <=10% | 0.32 | 0.32 | 0.27 |
| 10%<Debt to Income <=25% | 0.09 | 0.11 | 0.09 |
| 25%<Debt to Income <=50% | 0.09 | 0.11 | 0.11 |
| 50%<Debt to Income <=75% | 0.06 | 0.07 | 0.07 |
| Debt to Income >75% | 0.43 | 0.39 | 0.46 |
| Revolving Debt to Income <=10% | 0.72 | 0.71 | 0.70 |
| 10%<Revolving Debt to Income <=25% | 0.12 | 0.13 | 0.13 |
| 25%<Revolving Debt to Income <=50% | 0.08 | 0.08 | 0.09 |
| 50%<Revolving Debt to Income <=75% | 0.03 | 0.04 | 0.03 |
| Revolving Debt to Income >75% | 0.05 | 0.05 | 0.06 |
| Bankruptcy Filer | 0.07 | 0.10 | 0.09 |
| Date of Most Recent Delinquency <= 12 months | 0.11 | 0.22 | 0.18 |
| 12 < Date of Most Recent Delinquency < =24 months | 0.05 | 0.09 | 0.06 |
| 24 < Date of Most Recent Delinquency < =36 months | 0.04 | 0.08 | 0.05 |
| 36 < Date of Most Recent Delinquency < =48 months | 0.04 | 0.06 | 0.04 |
| 48 < Date of Most Recent Delinquency | 0.05 | 0.08 | 0.07 |
| Age of Oldest Trade <= 5 Years | 0.05 | 0.09 | 0.08 |
| Number of Observations | 59,601 | 3,171 | 3,122 |

Descriptive statistics for portion of sample that was matched to credit records. Numbers are weighted, using weights provided by Mintel Comperemedia.

Credit Utilization=Outstanding Debt/Sum of Available Credit

Debt to Income=Total Debts/Annual Household Income

Revolving Debt to Income=Total Revolving Debts/Annual Household Income

**Table 3: Raw Relative Probability of Receipt of Credit Card Offer by Lender**

| Lender | Black Ratio | Hispanic Ratio |
|---|---|---|
| Lender #1 | 0.36 | 0.43 |
| Lender #2 | 0.38 | 0.61 |
| Lender #3 | 0.44 | 0.70 |
| Lender #4 | 0.82 | 0.89 |
| Lender #5 | 0.52 | 0.85 |
| Any Offer from the 5 Lenders | 0.54 | 0.75 |

The final two columns show the ratio of the raw probability of a random Black or Hispanic individual receiving an offer to the probability of an individual randomly selected from the full sample receiving an offer.  Numbers are weighted, using weights provided by Mintel Comperemedia.

**Table 4: Raw Probability of Receipt of Credit Card Offer by Card Type**

| Card Type | Rewards? | Annual Fee? | Full Sample | Blacks | Hispanics | | Black Ratio | Hispanic Ratio |
|---|---|---|---|---|---|---|---|---|
| Vanilla | No | No | 0.04 | 0.02 | 0.03 | | 0.49 | 0.79 |
| General | Yes | No | 0.19 | 0.08 | 0.12 | | 0.43 | 0.66 |
| Premium Rewards | Yes | Yes | 0.06 | 0.03 | 0.04 | | 0.47 | 0.63 |
| Credit Building | No | Yes | 0.02 | 0.03 | 0.03 | | 1.47 | 1.60 |

The probability of receiving a credit card offer by card type.  Numbers are weighted, using weights provided by Mintel Comperemedia.  The final two columns show the ratio of the raw probability of a random Black or Hispanic individual receiving an offer to the probability of an individual randomly selected from the full sample receiving an offer.  The first two columns show what distinguishes the card types.  A value of ‘Yes’ for the ‘Rewards?’ column indicates that the use of the card gives the borrower rewards such as airline miles, cash back, or points redeemable for some good or service.  A value of ‘Yes’ for the ‘Annual Fee’ column indicates that there is an annual (or rarely) monthly fee charge for having the card, aside from any interest charges or late fees.

**Table 5: Poisson Regression, Number of Offers Received**
***Part I, Demographic and Economic Variables***

| Parameter | Estimate | SE |
|---|---|---|
| Intercept | -1.24*** | 0.18 |
| Black | -0.25*** | 0.04 |
| Hispanic | -0.14*** | 0.04 |
| Married | 0.06*** | 0.02 |
| Head Age | 0.01 | 0.00 |
| Head Age^2 | 0*** | 0.00 |
| Graduated High School | 0.06* | 0.03 |
| Some College | 0.03 | 0.03 |
| Graduated College | 0.17*** | 0.03 |
| Homeowner | 0.11*** | 0.03 |
| Income ($7,500-9,999) | 0.23** | 0.10 |
| Income ($10,000-12,499) | 0.18* | 0.09 |
| Income($12,500-14,999) | 0.33*** | 0.09 |
| Income ($15,000-19,999) | 0.21** | 0.08 |
| Income ($20,000-24,999) | 0.32*** | 0.08 |
| Income ($25,000-29,999) | 0.37*** | 0.08 |
| Income ($30,000-34,999) | 0.4*** | 0.08 |
| Income ($35,000-39,999) | 0.41*** | 0.08 |
| Income ($40,000-44,999) | 0.51*** | 0.08 |
| Income ($45,000-49,999) | 0.47*** | 0.08 |
| Income ($50,000-59,999) | 0.54*** | 0.07 |
| Income ($60,000-69,999) | 0.56*** | 0.08 |
| Income ($70,000-74,999) | 0.57*** | 0.08 |
| Income ($75,000-99,999) | 0.63*** | 0.07 |
| Income ($100,000-149,999) | 0.67*** | 0.07 |
| Income ($150,000-199,999) | 0.75*** | 0.08 |
| Income ($200,000+) | 0.75*** | 0.08 |

Poisson regression for number of the five lenders sending credit card offers to the individual. Includes fixed effects for state and month, not shown. Table continues on next page. Weighted, using weights provided by Mintel Comperemedia. *significant at 10% level; **significant at 5% level; ***significant at 1% level

**Table 5: Poisson Regression, Number of Offers Received**
***Part II, Credit Variables***

| Parameter | Estimate | SE |
|---|---|---|
| Missing Credit Score | -0.24*** | 0.06 |
| Vantage Score <550 | -2.26*** | 0.13 |
| Vantage Score (550<600] | -1.43*** | 0.08 |
| Vantage Score (600<650] | -1.16*** | 0.06 |
| Vantage Score (650<700] | -0.76*** | 0.05 |
| Vantage Score (700<750] | -0.48*** | 0.04 |
| Vantage Score (750<800] | -0.17*** | 0.04 |
| Vantage Score (800<850] | 0.01 | 0.03 |
| Vantage Score (850<900] | 0.02 | 0.03 |
| Vantage Score (900<950] | -0.03 | 0.02 |
| Filed for Bankruptcy | -0.96*** | 0.07 |
| Utilization Ratio 10<25 | 0.08*** | 0.02 |
| Utilization Ratio 25<50 | 0.15*** | 0.02 |
| Utilization Ratio 50<75 | 0.16*** | 0.03 |
| Utilization Ratio >75 | 0.14*** | 0.04 |
| Debt Balance to Income Ratio (0-.1] | -0.09*** | 0.02 |
| Debt Balance to Income Ratio (.1<.25] | -0.04 | 0.03 |
| Debt Balance to Income Ratio (.25<.5] | 0.03 | 0.03 |
| Debt Balance to Income Ratio (.5<.75] | 0.08** | 0.03 |
| Revolving Balance to Income Ratio(0-.1] | 0.01 | 0.04 |
| Revolving Balance to Income Ratio(.1<.25] | 0.1** | 0.04 |
| Revolving Balance to Income Ratio (.25<.5] | 0.03 | 0.04 |
| Revolving Balance to Income Ratio(.5<.75] | 0.03 | 0.05 |
| Delinquency within Past 12 Months | -0.17*** | 0.03 |
| Delinquency within (12, 24] Months | -0.08** | 0.04 |
| Delinquency within (24, 36] Months | -0.16*** | 0.04 |
| Delinquency within (36, 48] Months | 0.05*** | 0.05 |
| Delinquency more than 48 Months Ago | 0.04*** | 0.04 |
| New File | 0.04*** | 0.04 |
| | | |
| QIC | 96, 988.11 | |

Poisson regression for number of five lenders sending credit card offers to the individual. Includes fixed effects for state and month, not shown. 78,156 observations. Weighted, using weights provided by Mintel Comperemedia. *significant at 10% level; **significant at 5% level; ***significant at 1% level. Table continued from previous page.

**Table 6, Single Logit Equations, Whether Household Received an Offer from Any Lender, or from Individual Lenders**
***Part I, Demographic and Economic Variables***

| | Any Offer | | Lender #1 | | Lender #2 | | Lender #3 | | Lender #4 | | Lender #5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** |
| Black | -0.32*** | 0.00 | -0.4*** | 0.00 | -0.39*** | 0.00 | -0.23*** | 0 | -0.10 | 0.3 | -0.32*** | 0.00 |
| Hispanic | -0.19*** | 0.00 | -0.31*** | 0.00 | -0.55*** | 0.00 | -0.11 | 0.13 | 0.00 | 0.97 | -0.05 | 0.58 |
| Married | 0.10*** | 0.00 | -0.03 | 0.50 | 0.18*** | 0.00 | 0.00 | 0.9 | 0.15*** | 0.00 | 0.02 | 0.58 |
| Head Age | 0.01 | 0.15 | -0.01 | 0.19 | 0.08*** | 0.00 | 0.01* | 0.08 | -0.02* | 0.07 | -0.04*** | 0.00 |
| Head Age^2 | 0.00*** | 0.00 | 0.00 | 0.25 | 0.01*** | 0.00 | 0.00 | 0.13 | 0.00 | 0.11 | 0.00*** | 0.00 |
| Graduated High School | 0.08* | 0.06 | 0.12 | 0.12 | 0.23** | 0.01 | 0.07 | 0.23 | 0.06 | 0.40 | -0.10 | 0.18 |
| Some College | 0.03 | 0.51 | 0.13 | 0.13 | 0.31*** | 0.00 | 0.01 | 0.85 | -0.02 | 0.84 | -0.12 | 0.13 |
| Graduated College | 0.24*** | 0.00 | 0.36*** | 0.00 | 0.48*** | 0.00 | 0.22*** | 0.00 | 0.05 | 0.49 | 0.07 | 0.35 |
| Homeowner | 0.17*** | 0.00 | 0.2*** | 0.00 | 0.09 | 0.22 | 0.22*** | 0.00 | 0.05 | 0.46 | -0.01 | 0.91 |
| Income ($7,500-9,999) | 0.25** | 0.03 | 0.27 | 0.28 | -0.05 | 0.88 | 0.37** | 0.04 | 0.01 | 0.97 | 0.23 | 0.36 |
| Income ($10,000-12,499) | 0.12 | 0.26 | 0.13 | 0.57 | -0.04 | 0.89 | 0.41** | 0.02 | -0.17 | 0.38 | 0.34 | 0.16 |
| Income($12,500-14,999) | 0.36*** | 0.00 | 0.27 | 0.24 | 0.43 | 0.11 | 0.37** | 0.03 | 0.01 | 0.94 | 0.58** | 0.01 |
| Income ($15,000-19,999) | 0.14 | 0.15 | 0.16 | 0.44 | 0.27 | 0.28 | 0.43*** | 0.01 | -0.18 | 0.31 | 0.46** | 0.03 |
| Income ($20,000-24,999) | 0.30*** | 0.00 | 0.26 | 0.20 | 0.35 | 0.13 | 0.35** | 0.02 | -0.07 | 0.69 | 0.79*** | 0.00 |
| Income ($25,000-29,999) | 0.37*** | 0.00 | 0.39** | 0.05 | 0.48** | 0.04 | 0.43*** | 0.01 | 0.17 | 0.34 | 0.62*** | 0.00 |
| Income ($30,000-34,999) | 0.37*** | 0.00 | 0.31 | 0.11 | 0.52** | 0.02 | 0.51*** | 0.00 | 0.06 | 0.7 | 0.65*** | 0.00 |
| Income ($35,000-39,999) | 0.42*** | 0.00 | 0.27 | 0.18 | 0.73*** | 0.00 | 0.6*** | 0.00 | -0.18 | 0.31 | 0.75*** | 0.00 |
| Income ($40,000-44,999) | 0.5*** | 0.00 | 0.41** | 0.04 | 0.71*** | 0.00 | 0.6*** | 0.00 | 0.08 | 0.65 | 0.97*** | 0.00 |
| Income ($45,000-49,999) | 0.5*** | 0.00 | 0.56*** | 0.01 | 0.51** | 0.02 | 0.65*** | 0.00 | 0.05 | 0.77 | 0.74*** | 0.00 |
| Income ($50,000-59,999) | 0.55*** | 0.00 | 0.46** | 0.02 | 0.88*** | 0.00 | 0.65*** | 0.00 | 0.11 | 0.5 | 0.88*** | 0.00 |
| Income ($60,000-69,999) | 0.55*** | 0.00 | 0.57*** | 0.00 | 0.83*** | 0.00 | 0.69*** | 0.00 | 0.00 | 1.00 | 1.00*** | 0.00 |
| Income ($70,000-74,999) | 0.58*** | 0.00 | 0.53*** | 0.01 | 0.8*** | 0.00 | 0.64*** | 0.00 | 0.25 | 0.16 | 1.03*** | 0.00 |
| Income ($75,000-99,999) | 0.69*** | 0.00 | 0.63*** | 0.00 | 0.92*** | 0.00 | 0.73*** | 0.00 | 0.22 | 0.18 | 1.00*** | 0.00 |
| Income ($100,000-149,999) | 0.76*** | 0.00 | 0.7*** | 0.00 | 0.96*** | 0.00 | 0.75*** | 0.00 | 0.25 | 0.12 | 1.12*** | 0.00 |
| Income ($150,000-199,999) | 0.86*** | 0.00 | 0.84*** | 0.00 | 1.06*** | 0.00 | 0.86*** | 0.00 | 0.56*** | 0.00 | 1.2*** | 0.00 |
| Income ($200,000+) | 0.78*** | 0.00 | 0.94*** | 0.00 | 0.84*** | 0.00 | 0.76*** | 0.00 | 0.45** | 0.02 | 1.36*** | 0.00 |

First column is a logit regression for if any of the number of the five lenders sent a credit card offer to the individual. The next four columns are logit regressions for if the individual institution sent an offer. 78,156 observations. Estimation includes fixed effects for state and month, and standard errors are clustered at the household level. Weighted, using weights provided by Mintel Comperemedia. *significant at 10% level; **significant at 5% level; ***significant at 1% level. Table continues on next page.

**Table 6, Single Logit Equations, Whether Household Received an Offer from Any Lender, or from Individual Lenders**
***Part II, Credit Variables***

| | Any Offer | | Lender #1 | | Lender #2 | | Lender #3 | | Lender #4 | | Lender #5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** |
| Missing Credit Score | -0.36*** | 0.00 | 0.11 | 0.53 | 0.7*** | 0.00 | 0.67*** | 0.00 | -1.09*** | 0 | -0.49*** | 0.00 |
| Vantage Score <550 | -2.53*** | 0.00 | -2.8*** | 0.00 | -2.81*** | 0.00 | -3.67*** | 0.00 | -2.34*** | 0 | -1.45*** | 0.00 |
| Vantage Score (550<600] | -1.63*** | 0.00 | -1.83*** | 0.00 | -1.98*** | 0.00 | -2.81*** | 0.00 | -0.83*** | 0 | -1.1*** | 0.00 |
| Vantage Score (600<650] | -1.31*** | 0.00 | -2.29*** | 0.00 | -1.93*** | 0.00 | -2.31*** | 0.00 | -0.13 | 0.26 | -1.13*** | 0.00 |
| Vantage Score (650<700] | -0.88*** | 0.00 | -1.42*** | 0.00 | -1.94*** | 0.00 | -1.67*** | 0.00 | 0.22** | 0.04 | -0.78*** | 0.00 |
| Vantage Score (700<750] | -0.57*** | 0.00 | -0.8*** | 0.00 | -1.47*** | 0.00 | -0.82*** | 0.00 | -0.18* | 0.07 | -0.18* | 0.06 |
| Vantage Score (750<800] | -0.27*** | 0.00 | -0.18** | 0.04 | -0.7*** | 0.00 | -0.29*** | 0.00 | -0.71*** | 0 | 0.28*** | 0.00 |
| Vantage Score (800<850] | -0.05 | 0.27 | 0.09 | 0.20 | -0.24*** | 0.00 | 0.02 | 0.76 | -0.64*** | 0 | 0.23*** | 0.00 |
| Vantage Score (850<900] | -0.01 | 0.85 | 0.05 | 0.44 | -0.01 | 0.86 | 0.07 | 0.19 | -0.46*** | 0 | 0.08 | 0.28 |
| Vantage Score (900<950] | -0.06 | 0.12 | 0.04 | 0.54 | 0.03 | 0.63 | 0.00 | 0.97 | -0.33*** | 0 | -0.09 | 0.21 |
| Filed for Bankruptcy | -1.01*** | 0.00 | -2.84*** | 0.00 | -2.03*** | 0.00 | -2.32*** | 0.00 | -0.12 | 0.18 | -1.74*** | 0.00 |
| Utilization Ratio 10<25 | 0.12*** | 0.00 | 0.18*** | 0.00 | 0.13** | 0.01 | -0.03 | 0.43 | 0.00 | 0.99 | 0.13** | 0.02 |
| Utilization Ratio 25<50 | 0.17*** | 0.00 | 0.25*** | 0.00 | 0.13** | 0.03 | 0.12*** | 0.01 | -0.04 | 0.54 | 0.21*** | 0.00 |
| Utilization Ratio 50<75 | 0.16*** | 0.00 | 0.18** | 0.02 | 0.10 | 0.23 | 0.17*** | 0.01 | -0.14* | 0.09 | 0.23*** | 0.00 |
| Utilization Ratio >75 | 0.18*** | 0.00 | 0.11 | 0.30 | 0.00 | 0.98 | 0.22*** | 0.01 | -0.02 | 0.84 | -0.06 | 0.54 |
| Debt Balance to Income Ratio (0-.1] | -0.04 | 0.19 | -0.27*** | 0.00 | -0.09 | 0.12 | 0.10** | 0.03 | 0.00 | 1 | -0.17*** | 0.01 |
| Debt Balance to Income Ratio (.1<.25] | 0.01 | 0.83 | -0.05 | 0.52 | 0.09 | 0.26 | 0.09 | 0.12 | -0.15* | 0.06 | -0.11 | 0.13 |
| Debt Balance to Income Ratio (.25<.5] | 0.10** | 0.01 | -0.04 | 0.60 | 0.01 | 0.86 | 0.15*** | 0.01 | 0.05 | 0.46 | 0.03 | 0.62 |
| Debt Balance to Income Ratio (.5<.75] | 0.14*** | 0.00 | -0.08 | 0.32 | 0.12 | 0.13 | 0.26*** | 0.00 | 0.07 | 0.41 | 0.07 | 0.38 |
| Revolving Balance to Income Ratio(0-.1] | 0.03 | 0.60 | -0.04 | 0.66 | -0.03 | 0.74 | 0.23*** | 0.00 | 0.25** | 0.03 | -0.17* | 0.06 |
| Revolving Balance to Income Ratio(.1<.25] | 0.12** | 0.04 | -0.01 | 0.89 | 0.01 | 0.96 | 0.08 | 0.39 | 0.33*** | 0.01 | 0.28*** | 0.00 |
| Revolving Balance to Income Ratio (.25<.5] | 0.06 | 0.32 | 0.03 | 0.80 | -0.18 | 0.14 | 0.13 | 0.17 | 0.01 | 0.96 | 0.25** | 0.01 |
| Revolving Balance to Income Ratio(.5<.75] | -0.01 | 0.93 | 0.13 | 0.28 | -0.25* | 0.09 | -0.02 | 0.87 | -0.14 | 0.41 | 0.37*** | 0.00 |
| Delinquency within Past 12 Months | -0.14*** | 0.00 | -0.32*** | 0.00 | -0.4*** | 0.00 | -0.4*** | 0.00 | 0.43*** | 0.00 | -0.5*** | 0.00 |
| Delinquency within (12, 24] Months | -0.09 | 0.11 | -0.02 | 0.84 | -0.05 | 0.69 | -0.5*** | 0.00 | 0.22** | 0.01 | -0.15 | 0.13 |
| Delinquency within (24, 36] Months | -0.18*** | 0.00 | -0.29*** | 0.01 | -0.33** | 0.02 | -0.35*** | 0.00 | 0.17* | 0.09 | -0.29*** | 0.01 |
| Delinquency within (36, 48] Months | -0.22*** | 0.00 | -0.13 | 0.25 | -0.24* | 0.06 | -0.44*** | 0.00 | -0.26** | 0.03 | -0.11 | 0.27 |
| Delinquency more than 48 Months Ago | -0.29*** | 0.00 | -0.18* | 0.07 | -0.48*** | 0.00 | -0.41*** | 0.00 | -0.4*** | 0.00 | -0.16* | 0.08 |
| New File | 0.36*** | 0.00 | -0.48*** | 0.00 | -0.10 | 0.51 | 0.2** | 0.03 | 0.78*** | 0.00 | -0.25** | 0.05 |
| AIC | 97,710..27 | | 33,348.86 | | 33,271.48 | | 51,674.91 | | 33,290.17 | | 35,581.77 | |

Table continued from previous page.

**Table 7: Odds Ratio Based on Estimates from Single Equations, Probability of Receiving a Credit Card Offer**

***Part I, Demographic and Economic Variables***

| | Odds Ratios | | | | | | Difference Between Lender and 'Any Offer' | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Any Offer** | **Lender #1** | **Lender #2** | **Lender #3** | **Lender #4** | **Lender #5** | **Lender #1** | **Lender #2** | **Lender #3** | **Lender #4** | **Lender #5** |
| Black | 0.73 | 0.67 | 0.68 | 0.79 | 0.9 | 0.73 | -0.06 | -0.05 | 0.06 | 0.17 | 0.00 |
| Hispanic | 0.83 | 0.73 | 0.58 | 0.90 | 1.00 | 0.95 | -0.10 | -0.25 | 0.07 | 0.17 | 0.12 |
| Married | 1.10 | 0.97 | 1.20 | 1.00 | 1.16 | 1.02 | -0.13 | 0.10 | -0.10 | 0.06 | -0.08 |
| Head Age | 1.01 | 0.99 | 1.09 | 1.01 | 0.98 | 0.96 | -0.02 | 0.08 | 0.00 | -0.02 | -0.04 |
| Head Age^2 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Graduated High School | 1.08 | 1.13 | 1.26 | 1.07 | 1.07 | 0.90 | 0.05 | 0.18 | -0.01 | -0.01 | -0.18 |
| Some College | 1.03 | 1.13 | 1.36 | 1.01 | 0.98 | 0.89 | 0.11 | 0.33 | -0.02 | -0.05 | -0.14 |
| Graduated College | 1.28 | 1.43 | 1.62 | 1.24 | 1.06 | 1.07 | 0.16 | 0.35 | -0.03 | -0.22 | -0.20 |
| Homeowner | 1.18 | 1.23 | 1.10 | 1.25 | 1.05 | 0.99 | 0.04 | -0.09 | 0.06 | -0.13 | -0.19 |
| Income ($7,500-9,999) | 1.28 | 1.32 | 0.95 | 1.45 | 1.01 | 1.26 | 0.03 | -0.33 | 0.17 | -0.28 | -0.02 |
| Income ($10,000-12,499) | 1.13 | 1.14 | 0.96 | 1.51 | 0.84 | 1.41 | 0.01 | -0.17 | 0.38 | -0.29 | 0.28 |
| Income($12,500-14,999) | 1.44 | 1.31 | 1.54 | 1.44 | 1.01 | 1.78 | -0.13 | 0.10 | 0.00 | -0.42 | 0.34 |
| Income ($15,000-19,999) | 1.15 | 1.17 | 1.31 | 1.54 | 0.83 | 1.59 | 0.02 | 0.16 | 0.39 | -0.32 | 0.44 |
| Income ($20,000-24,999) | 1.35 | 1.29 | 1.42 | 1.42 | 0.94 | 2.21 | -0.06 | 0.07 | 0.07 | -0.42 | 0.85 |
| Income ($25,000-29,999) | 1.45 | 1.48 | 1.62 | 1.54 | 1.18 | 1.86 | 0.04 | 0.17 | 0.09 | -0.27 | 0.41 |
| Income ($30,000-34,999) | 1.44 | 1.36 | 1.68 | 1.66 | 1.07 | 1.93 | -0.08 | 0.24 | 0.22 | -0.37 | 0.48 |
| Income ($35,000-39,999) | 1.52 | 1.31 | 2.07 | 1.82 | 0.84 | 2.12 | -0.21 | 0.55 | 0.3 | -0.68 | 0.60 |
| Income ($40,000-44,999) | 1.65 | 1.50 | 2.04 | 1.82 | 1.09 | 2.64 | -0.15 | 0.39 | 0.17 | -0.57 | 0.99 |
| Income ($45,000-49,999) | 1.65 | 1.76 | 1.67 | 1.92 | 1.05 | 2.09 | 0.11 | 0.02 | 0.27 | -0.6 | 0.44 |
| Income ($50,000-59,999) | 1.74 | 1.58 | 2.42 | 1.91 | 1.12 | 2.41 | -0.16 | 0.68 | 0.18 | -0.62 | 0.68 |
| Income ($60,000-69,999) | 1.74 | 1.77 | 2.30 | 2.00 | 1.00 | 2.72 | 0.03 | 0.56 | 0.26 | -0.74 | 0.98 |
| Income ($70,000-74,999) | 1.78 | 1.70 | 2.22 | 1.91 | 1.29 | 2.80 | -0.08 | 0.44 | 0.13 | -0.49 | 1.02 |
| Income ($75,000-99,999) | 1.98 | 1.88 | 2.52 | 2.08 | 1.24 | 2.73 | -0.11 | 0.54 | 0.10 | -0.74 | 0.74 |
| Income ($100,000-149,999) | 2.14 | 2.02 | 2.61 | 2.12 | 1.29 | 3.06 | -0.12 | 0.47 | -0.02 | -0.85 | 0.92 |
| Income ($150,000-199,999) | 2.37 | 2.31 | 2.88 | 2.37 | 1.75 | 3.33 | -0.05 | 0.51 | 0.00 | -0.62 | 0.97 |
| Income ($200,000+) | 2.19 | 2.56 | 2.32 | 2.13 | 1.57 | 3.90 | 0.37 | 0.14 | -0.06 | -0.61 | 1.72 |

First column is the odds ratio from a logit regression for if any of the number of the five lenders sent credit card offers to the individual. The next four columns are odds ratios from logit regressions for if the individual lender sent an offer. The final five columns are the difference between the odds ratio for the individual lender and the 'any offer' odds ratio. 78,156 observations. Continued on next page.

**Table 7: Odds Ratio Based on Estimates from Single Equations, Probability of Receiving a Credit Card Offer**

***Part II, Credit Variables***

| | Odds Ratios | | | | | | Difference Between Lender and 'Any Offer' | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Any Offer** | **Lender #1** | **Lender #2** | **Lender #3** | **Lender #4** | **Lender #5** | **Lender #1** | **Lender #2** | **Lender #3** | **Lender #4** | **Lender #5** |
| Missing Credit Score | 0.70 | 1.11 | 2.02 | 1.96 | 0.34 | 0.61 | 0.41 | 1.32 | 1.26 | -0.36 | -0.09 |
| Vantage Score <550 | 0.08 | 0.06 | 0.06 | 0.03 | 0.1 | 0.23 | -0.02 | -0.02 | -0.06 | 0.02 | 0.15 |
| Vantage Score (550<600] | 0.20 | 0.16 | 0.14 | 0.06 | 0.44 | 0.33 | -0.04 | -0.06 | -0.14 | 0.24 | 0.14 |
| Vantage Score (600<650] | 0.27 | 0.10 | 0.15 | 0.1 | 0.88 | 0.32 | -0.17 | -0.13 | -0.17 | 0.61 | 0.05 |
| Vantage Score (650<700] | 0.41 | 0.24 | 0.14 | 0.19 | 1.25 | 0.46 | -0.17 | -0.27 | -0.23 | 0.83 | 0.05 |
| Vantage Score (700<750] | 0.57 | 0.45 | 0.23 | 0.44 | 0.83 | 0.83 | -0.12 | -0.34 | -0.13 | 0.27 | 0.26 |
| Vantage Score (750<800] | 0.76 | 0.83 | 0.50 | 0.75 | 0.49 | 1.33 | 0.07 | -0.27 | -0.01 | -0.27 | 0.57 |
| Vantage Score (800<850] | 0.95 | 1.10 | 0.79 | 1.02 | 0.53 | 1.25 | 0.15 | -0.17 | 0.07 | -0.42 | 0.30 |
| Vantage Score (850<900] | 0.99 | 1.05 | 0.99 | 1.07 | 0.63 | 1.08 | 0.06 | 0.00 | 0.08 | -0.36 | 0.09 |
| Vantage Score (900<950] | 0.94 | 1.04 | 1.03 | 1 | 0.72 | 0.92 | 0.10 | 0.09 | 0.06 | -0.22 | -0.02 |
| Filed for Bankruptcy | 0.37 | 0.06 | 0.13 | 0.1 | 0.88 | 0.18 | -0.31 | -0.23 | -0.27 | 0.52 | -0.19 |
| Utilization Ratio 10<25 | 1.13 | 1.20 | 1.14 | 0.97 | 1 | 1.14 | 0.08 | 0.02 | -0.16 | -0.13 | 0.01 |
| Utilization Ratio 25<50 | 1.19 | 1.28 | 1.14 | 1.13 | 0.96 | 1.24 | 0.09 | -0.05 | -0.06 | -0.23 | 0.05 |
| Utilization Ratio 50<75 | 1.17 | 1.19 | 1.11 | 1.18 | 0.87 | 1.26 | 0.02 | -0.06 | 0.01 | -0.3 | 0.09 |
| Utilization Ratio >75 | 1.20 | 1.12 | 1.00 | 1.25 | 0.98 | 0.95 | -0.08 | -0.20 | 0.05 | -0.22 | -0.25 |
| Debt Balance to Income Ratio (0-.1] | 0.96 | 0.76 | 0.91 | 1.1 | 1 | 0.85 | -0.20 | -0.05 | 0.14 | 0.04 | -0.11 |
| Debt Balance to Income Ratio (.1<.25] | 1.01 | 0.95 | 1.09 | 1.1 | 0.86 | 0.89 | -0.06 | 0.08 | 0.09 | -0.15 | -0.12 |
| Debt Balance to Income Ratio (.25<.5] | 1.11 | 0.96 | 1.01 | 1.17 | 1.06 | 1.04 | -0.14 | -0.09 | 0.06 | -0.05 | -0.07 |
| Debt Balance to Income Ratio (.5<.75] | 1.15 | 0.93 | 1.12 | 1.3 | 1.07 | 1.07 | -0.22 | -0.02 | 0.16 | -0.07 | -0.08 |
| Revolving Balance to Income Ratio(0-.1] | 1.03 | 0.96 | 0.97 | 1.26 | 1.29 | 0.84 | -0.07 | -0.06 | 0.23 | 0.26 | -0.19 |
| Revolving Balance to Income Ratio(.1<.25] | 1.13 | 0.99 | 1.01 | 1.08 | 1.39 | 1.32 | -0.14 | -0.12 | -0.05 | 0.26 | 0.19 |
| Revolving Balance to Income Ratio (.25<.5] | 1.06 | 1.03 | 0.84 | 1.14 | 1.01 | 1.29 | -0.04 | -0.23 | 0.07 | -0.06 | 0.22 |
| Revolving Balance to Income Ratio(.5<.75] | 0.99 | 1.14 | 0.78 | 0.98 | 0.87 | 1.44 | 0.14 | -0.21 | -0.01 | -0.12 | 0.45 |
| Most Recent Delinquency within Past 12 Months | 0.87 | 0.72 | 0.67 | 0.67 | 1.53 | 0.61 | -0.15 | -0.20 | -0.2 | 0.66 | -0.26 |
| Most Recent Delinquency within (12, 24] Months | 0.92 | 0.98 | 0.96 | 0.6 | 1.25 | 0.86 | 0.06 | 0.04 | -0.31 | 0.33 | -0.06 |
| Most Recent Delinquency within (24, 36] Months | 0.84 | 0.75 | 0.72 | 0.71 | 1.19 | 0.75 | -0.09 | -0.12 | -0.13 | 0.35 | -0.08 |
| Most Recent Delinquency within (36, 48] Months | 0.80 | 0.88 | 0.79 | 0.64 | 0.77 | 0.89 | 0.08 | -0.02 | -0.16 | -0.03 | 0.09 |
| Most Recent Delinquency more than 48 Months Ago | 0.75 | 0.84 | 0.62 | 0.66 | 0.67 | 0.86 | 0.09 | -0.13 | -0.09 | -0.08 | 0.11 |
| New File | 1.43 | 0.62 | 0.90 | 1.22 | 2.17 | 0.78 | -0.81 | -0.53 | -0.21 | 0.74 | -0.65 |

First column is the odds ratio from a logit regression for if any of the number of the five lenders sent credit card offers to the individual. The next four columns are odds ratios from logit regressions for if the individual lender sent an offer. The final five columns are the difference between the odds ratio for the individual lender and the ‘any offer’ odds ratio. 78,156 observations. *significant at 10% level; **significant at 5% level; ***significant at 1% level. Continued from previous page

**Table 8, Single Logit Equations, Whether Household Received an Offer by Type of Card**
***Part I, Demographic and Economic Variables***

| | Vanilla Cards | | General Cards | | Premium Rewards | | Credit Building | |
|---|---|---|---|---|---|---|---|---|
| **Parameter** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** |
| Intercept | -4.63*** | 0.00 | -1.85*** | 0.00 | -4.11*** | 0.00 | -7.25*** | 0.00 |
| Black | -0.28** | 0.02 | -0.38*** | 0.00 | -0.18 | 0.13 | -0.02 | 0.89 |
| Hispanic | 0.01 | 0.94 | -0.21*** | 0.00 | -0.32*** | 0.00 | 0.23* | 0.06 |
| Married | 0.00 | 0.98 | 0.08*** | 0.00 | -0.05 | 0.25 | 0.08 | 0.33 |
| Head Age | 0.02** | 0.03 | 0.01* | 0.07 | 0.00 | 0.61 | 0.00 | 1.00 |
| Head Age^2 | 0.00*** | 0.00 | 0.00*** | 0.01 | 0.00 | 0.23 | 0.00 | 0.48 |
| Graduated High School | -0.05 | 0.55 | 0.10** | 0.03 | 0.39*** | 0.00 | -0.02 | 0.85 |
| Some College | -0.01 | 0.89 | 0.03 | 0.54 | 0.70*** | 0.00 | -0.21* | 0.08 |
| Graduated College | -0.01 | 0.87 | 0.14*** | 0.00 | 1.13*** | 0.00 | -0.32*** | 0.01 |
| Homeowner | 0.21*** | 0.00 | 0.24*** | 0.00 | -0.11* | 0.10 | 0.02 | 0.80 |
| Income ($7,500-9,999) | 0.17 | 0.51 | 0.42*** | 0.00 | 0.08 | 0.82 | -0.10 | 0.70 |
| Income ($10,000-12,499) | 0.35 | 0.12 | 0.24* | 0.06 | 0.25 | 0.47 | -0.54* | 0.05 |
| Income($12,500-14,999) | 0.17 | 0.47 | 0.40*** | 0.00 | 0.56* | 0.07 | 0.10 | 0.71 |
| Income ($15,000-19,999) | 0.17 | 0.42 | 0.18 | 0.12 | 0.49* | 0.09 | -0.18 | 0.45 |
| Income ($20,000-24,999) | 0.19 | 0.36 | 0.33*** | 0.00 | 0.46 | 0.11 | 0.01 | 0.97 |
| Income ($25,000-29,999) | 0.15 | 0.47 | 0.39*** | 0.00 | 0.64** | 0.03 | 0.25 | 0.28 |
| Income ($30,000-34,999) | 0.29 | 0.15 | 0.45*** | 0.00 | 0.74*** | 0.01 | -0.02 | 0.93 |
| Income ($35,000-39,999) | 0.27 | 0.19 | 0.47*** | 0.00 | 0.69** | 0.01 | -0.22 | 0.33 |
| Income ($40,000-44,999) | 0.4* | 0.05 | 0.47*** | 0.00 | 1.01*** | 0.00 | 0.00 | 1.00 |
| Income ($45,000-49,999) | 0.44** | 0.04 | 0.51*** | 0.00 | 0.89*** | 0.00 | 0.07 | 0.78 |
| Income ($50,000-59,999) | 0.42** | 0.03 | 0.58*** | 0.00 | 1.05*** | 0.00 | -0.13 | 0.55 |
| Income ($60,000-69,999) | 0.22 | 0.28 | 0.56*** | 0.00 | 1.29*** | 0.00 | 0.07 | 0.78 |
| Income ($70,000-74,999) | 0.38* | 0.07 | 0.57*** | 0.00 | 1.24*** | 0.00 | 0.10 | 0.68 |
| Income ($75,000-99,999) | 0.36* | 0.06 | 0.65*** | 0.00 | 1.41*** | 0.00 | -0.01 | 0.98 |
| Income ($100,000-149,999) | 0.3 | 0.13 | 0.69*** | 0.00 | 1.57*** | 0.00 | -0.02 | 0.94 |
| Income ($150,000-199,999) | 0.12 | 0.57 | 0.77*** | 0.00 | 1.84*** | 0.00 | 0.01 | 0.98 |
| Income ($200,000+) | -0.13 | 0.60 | 0.72*** | 0.00 | 1.77*** | 0.00 | -0.33 | 0.41 |

Logit regressions for if individual received a card type from one of the 5 lenders. Vanilla=no fee, no rewards. General=fee, rewards. Premium rewards=fee, rewards. Credit building=fee, no rewards. Includes fixed effects for state and month, not shown. Standard errors are clustered at the household level. Weighted, using weights provided by Mintel Comperemedia. 78,156 observations. Continued on next page

**Table 8, Single Logit Equations, Whether Household Received an Offer by Type of Card**

***Part II, Credit Variables***

| | Vanilla Cards | | General Cards | | Premium Rewards | | Credit Building | |
|---|---|---|---|---|---|---|---|---|
| **Parameter** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** | **Estimate** | **SE** |
| Missing Credit Score | -0.02 | 0.91 | 0.11 | 0.26 | 0.47** | 0.01 | -1.14*** | 0.00 |
| Vantage Score <550 | -2.45*** | 0.00 | -2.93*** | 0.00 | -2.64*** | 0.00 | 0.5 | 0.21 |
| Vantage Score (550<600] | -2.15*** | 0.00 | -2.38*** | 0.00 | -1.86*** | 0.00 | 2.23*** | 0.00 |
| Vantage Score (600<650] | -1.58*** | 0.00 | -2.52*** | 0.00 | -1.63*** | 0.00 | 2.86*** | 0.00 |
| Vantage Score (650<700] | -0.42*** | 0.01 | -1.5*** | 0.00 | -1.53*** | 0.00 | 3.12*** | 0.00 |
| Vantage Score (700<750] | -0.16 | 0.23 | -0.75*** | 0.00 | -1.04*** | 0.00 | 2.62*** | 0.00 |
| Vantage Score (750<800] | 0.19* | 0.09 | -0.25*** | 0.00 | -0.7*** | 0.00 | 1.68*** | 0.00 |
| Vantage Score (800<850] | 0.39*** | 0.00 | 0.01 | 0.82 | -0.37*** | 0.00 | 0.40 | 0.23 |
| Vantage Score (850<900] | 0.47*** | 0.00 | 0.03 | 0.53 | -0.19*** | 0.00 | -0.33 | 0.36 |
| Vantage Score (900<950] | 0.28*** | 0.00 | -0.03 | 0.46 | -0.09 | 0.12 | -0.46 | 0.21 |
| Filed for Bankruptcy | -0.64*** | 0.00 | -1.57*** | 0.00 | -2.04*** | 0.00 | -0.16* | 0.10 |
| Utilization Ratio 10<25 | 0.06 | 0.36 | 0.14*** | 0.00 | 0.00 | 0.94 | -0.16 | 0.32 |
| Utilization Ratio 25<50 | 0.18** | 0.01 | 0.2*** | 0.00 | 0.10 | 0.13 | -0.05 | 0.68 |
| Utilization Ratio 50<75 | 0.1 | 0.26 | 0.18*** | 0.00 | 0.13 | 0.11 | 0.01 | 0.92 |
| Utilization Ratio >75 | 0.15 | 0.19 | 0.26*** | 0.00 | 0.23** | 0.03 | -0.02 | 0.90 |
| Debt Balance to Income Ratio (0-.1] | -0.08 | 0.27 | -0.09** | 0.02 | 0.08 | 0.21 | -0.25** | 0.03 |
| Debt Balance to Income Ratio (.1<.25] | 0.02 | 0.82 | 0.01 | 0.78 | -0.03 | 0.75 | 0.05 | 0.70 |
| Debt Balance to Income Ratio (.25<.5] | 0.09 | 0.29 | 0.05 | 0.28 | 0.14* | 0.07 | 0.08 | 0.50 |
| Debt Balance to Income Ratio (.5<.75] | 0.17* | 0.07 | 0.11** | 0.04 | 0.09 | 0.29 | -0.02 | 0.87 |
| Revolving Balance to Income Ratio(0-.1] | 0.27** | 0.03 | -0.06 | 0.33 | 0.05 | 0.64 | 0.76*** | 0.00 |
| Revolving Balance to Income Ratio(.1<.25] | 0.11 | 0.41 | 0.02 | 0.71 | 0.13 | 0.27 | 0.53*** | 0.01 |
| Revolving Balance to Income Ratio (.25<.5] | 0.09 | 0.50 | -0.07 | 0.30 | 0.08 | 0.51 | 0.14 | 0.50 |
| Revolving Balance to Income Ratio(.5<.75] | -0.16 | 0.36 | -0.05 | 0.59 | 0.00 | 0.99 | 0.1 | 0.70 |
| Most Recent Delinquency within Past 12 Months | -0.34*** | 0.00 | -0.46*** | 0.00 | -0.17 | 0.11 | 0.88*** | 0.00 |
| Most Recent Delinquency within (12, 24] Months | -0.45*** | 0.00 | -0.2*** | 0.00 | -0.16 | 0.18 | 0.68*** | 0.00 |
| Most Recent Delinquency within (24, 36] Months | -0.19 | 0.19 | -0.3*** | 0.00 | -0.12 | 0.32 | 0.59*** | 0.00 |
| Most Recent Delinquency within (36, 48] Months | -0.4*** | 0.01 | -0.2*** | 0.01 | -0.39*** | 0.01 | 0.00 | 0.98 |
| Most Recent Delinquency more than 48 Months Ago | -0.62*** | 0.00 | -0.29*** | 0.00 | -0.45*** | 0.00 | -0.11 | 0.48 |
| New File | 1.2*** | 0.00 | 0.17** | 0.02 | -0.11 | 0.44 | 0.26** | 0.03 |
| AIC | 26, 205.32 | | 73,540.92 | | 33,475.93 | | 14,849.66 | |

Logit regressions for if individual received a card type from one of the 5 lenders. Vanilla=no fee, no rewards. General=fee, rewards. Premium rewards=fee, rewards. Credit building=fee, no rewards. Includes fixed effects for state and month, not shown. Standard errors are clustered at the household level. Weighted, using weights provided by Mintel Comperemedia. 78,156 observations. Continued from previous page

**Table 9, Odds Ratios from Single Logit Equations, Whether Household Received an Offer by Type of Card**

***Part I, Demographic and Economic Variables***

| | **Vanilla** | **General** | **Premium** | **Credit Building** |
|---|---|---|---|---|
| **Parameter** | **Odds Ratio** | **Odds Ratio** | **Odds Ratio** | **Odds Ratio** |
| Black | 0.76 | 0.69 | 0.84 | 0.98 |
| Hispanic | 1.01 | 0.81 | 0.73 | 1.26 |
| Married | 1.00 | 1.08 | 0.95 | 1.08 |
| Head Age | 1.02 | 1.01 | 1.00 | 1.00 |
| Head Age^2 | 1.00 | 1.00 | 1.00 | 1.00 |
| Graduated High School | 0.95 | 1.11 | 1.47 | 0.98 |
| Some College | 0.99 | 1.03 | 2.01 | 0.81 |
| Graduated College | 0.99 | 1.15 | 3.10 | 0.73 |
| Homeowner | 1.24 | 1.27 | 0.89 | 1.02 |
| Income ($7,500-9,999) | 1.18 | 1.52 | 1.09 | 0.90 |
| Income ($10,000-12,499) | 1.42 | 1.27 | 1.28 | 0.58 |
| Income($12,500-14,999) | 1.18 | 1.49 | 1.75 | 1.10 |
| Income ($15,000-19,999) | 1.19 | 1.20 | 1.64 | 0.84 |
| Income ($20,000-24,999) | 1.21 | 1.39 | 1.58 | 1.01 |
| Income ($25,000-29,999) | 1.16 | 1.47 | 1.90 | 1.28 |
| Income ($30,000-34,999) | 1.34 | 1.57 | 2.10 | 0.98 |
| Income ($35,000-39,999) | 1.31 | 1.61 | 2.00 | 0.80 |
| Income ($40,000-44,999) | 1.49 | 1.61 | 2.74 | 1.00 |
| Income ($45,000-49,999) | 1.55 | 1.67 | 2.43 | 1.07 |
| Income ($50,000-59,999) | 1.53 | 1.78 | 2.85 | 0.88 |
| Income ($60,000-69,999) | 1.24 | 1.74 | 3.63 | 1.07 |
| Income ($70,000-74,999) | 1.47 | 1.77 | 3.45 | 1.11 |
| Income ($75,000-99,999) | 1.43 | 1.92 | 4.11 | 1.00 |
| Income ($100,000-149,999) | 1.35 | 1.99 | 4.80 | 0.98 |
| Income ($150,000-199,999) | 1.13 | 2.15 | 6.30 | 1.01 |
| Income ($200,000+) | 0.88 | 2.07 | 5.90 | 0.72 |

Odds ratios from logit regressions for if individual received a card type from one of the 5 lenders. Vanilla=no fee, no rewards. General=fee, rewards. Premium rewards=fee, rewards. Credit building=fee, no rewards. 78,156 observations. Continued on next page

**Table 9, Odds Ratios from Single Logit Equations, Whether Household Received an Offer by Type of Card**
***Part II, Credit Variables***

| | Vanilla | General | Premium | Credit Building |
|---|---|---|---|---|
| **Parameter** | **Odds Ratio** | **Odds Ratio** | **Odds Ratio** | **Odds Ratio** |
| Missing Credit Score | 0.98 | 1.12 | 1.60 | 0.32 |
| Vantage Score <550 | 0.09 | 0.05 | 0.07 | 1.65 |
| Vantage Score (550<600] | 0.12 | 0.09 | 0.16 | 9.33 |
| Vantage Score (600<650] | 0.21 | 0.08 | 0.20 | 17.49 |
| Vantage Score (650<700] | 0.66 | 0.22 | 0.22 | 22.59 |
| Vantage Score (700<750] | 0.85 | 0.47 | 0.36 | 13.68 |
| Vantage Score (750<800] | 1.21 | 0.78 | 0.50 | 5.38 |
| Vantage Score (800<850] | 1.48 | 1.01 | 0.69 | 1.50 |
| Vantage Score (850<900] | 1.61 | 1.03 | 0.83 | 0.72 |
| Vantage Score (900<950] | 1.33 | 0.97 | 0.91 | 0.63 |
| Filed for Bankruptcy | 0.53 | 0.21 | 0.13 | 0.85 |
| Utilization Ratio 10<25 | 1.06 | 1.15 | 1.00 | 0.85 |
| Utilization Ratio 25<50 | 1.20 | 1.23 | 1.10 | 0.95 |
| Utilization Ratio 50<75 | 1.11 | 1.20 | 1.14 | 1.01 |
| Utilization Ratio >75 | 1.16 | 1.30 | 1.26 | 0.99 |
| Debt Balance to Income Ratio (0-.1] | 0.93 | 0.92 | 1.08 | 0.78 |
| Debt Balance to Income Ratio (.1<.25] | 1.02 | 1.01 | 0.97 | 1.05 |
| Debt Balance to Income Ratio (.25<.5] | 1.09 | 1.05 | 1.15 | 1.08 |
| Debt Balance to Income Ratio (.5<.75] | 1.19 | 1.11 | 1.09 | 0.98 |
| Revolving Balance to Income Ratio(0-.1] | 1.30 | 0.94 | 1.05 | 2.14 |
| Revolving Balance to Income Ratio(.1<.25] | 1.11 | 1.03 | 1.14 | 1.70 |
| Revolving Balance to Income Ratio (.25<.5] | 1.10 | 0.93 | 1.09 | 1.16 |
| Revolving Balance to Income Ratio(.5<.75] | 0.85 | 0.96 | 1.00 | 1.11 |
| Most Recent Delinquency within Past 12 Months | 0.71 | 0.63 | 0.85 | 2.41 |
| Most Recent Delinquency within (12, 24] Months | 0.64 | 0.82 | 0.85 | 1.98 |
| Most Recent Delinquency within (24, 36] Months | 0.83 | 0.74 | 0.89 | 1.80 |
| Most Recent Delinquency within (36, 48] Months | 0.67 | 0.82 | 0.68 | 1.00 |
| Most Recent Delinquency more than 48 Months Ago | 0.54 | 0.75 | 0.64 | 0.90 |
| New File | 3.34 | 1.18 | 0.89 | 1.29 |



Odds ratios from logit regressions for if individual received a card type from one of the 5 lenders. Vanilla=no fee, no rewards. General=fee, rewards. Premium rewards=fee, rewards. Credit building=fee, no rewards. 78,156 observations. Continued from previous page

**Table 10: Race, Ethnicity, and Credit Card Marketing:  Raw Probabilities and Odds Ratios**

| | Black | | | Hispanic | | |
|---|---|---|---|---|---|---|
| Lender or Card Type | Raw Prob. | Odds Ratio | % Discrepancy Explained | Raw Prob. | Odds Ratio | % Discrepancy Explained |
| Any Offer | 0.54 | 0.73*** | 42% | 0.75 | 0.83*** | 30% |
| | | | | | | |
| Lender #1 | 0.38 | 0.67*** | 47% | 0.61 | 0.73*** | 31% |
| Lender #2 | 0.36 | 0.68*** | 50% | 0.43 | 0.58*** | 26% |
| Lender #3 | 0.44 | 0.79*** | 62% | 0.70 | 0.90 | 67% |
| Lender #4 | 0.82 | 0.9 | 45% | 0.89 | 1.00 | 97% |
| Lender #5 | 0.52 | 0.73*** | 43% | 0.85 | 0.95 | 67% |
| | | | | | | |
| No Fee, No Rewards | 0.49 | 0.76*** | 53% | 0.79 | 1.01 | 97% |
| No Fee, Rewards | 0.43 | 0.69*** | 45% | 0.66 | 0.81 | 44% |
| Fee, Rewards | 0.47 | 0.84 | 69% | 0.63 | 0.73*** | 27% |
| Fee, No Rewards | 1.47 | 0.98 | 96% | 1.60 | 1.26 | 58% |

‘Raw probability’ is the ratio of the likelihood of a Black or Hispanic individual receiving a credit card offer from one of the five credit card lenders, relative to a random member of the entire sample.  Weights provided by Mintel Comperemedia are used in this calculation.  ‘Odds Ratio’ is the odds ratio coefficient for ‘Black’ or ‘Hispanic’ dummy variables from logit equations.  ‘% Discrepancy Explained’ is the ratio of the change in the absolute value in the discrepancy, divided by the absolute value of the initial discrepancy.  *significant at 10% level; **significant at 5% level; ***significant at 1% level.

**Table 11, Panel A: Geographic Variables by Race and Ethnicity, Continuous Variables**

| | Mean | Median | Min. | Max. | Std. Dev. | N Obs. |
|---|---|---|---|---|---|---|
| **CBSA Unemployment Level** | | | | | | |
| *Full Sample* | 9.23 | 8.80 | 4.00 | 28.20 | 2.13 | 64,797 |
| *Blacks* | 9.21 | 9.10 | 4.70 | 28.20 | 2.20 | 3,867 |
| *Hispanics* | 9.70 | 9.60 | 4.50 | 28.20 | 2.45 | 3,784 |
| **CBSA Change in Unemployment** | | | | | | |
| *Full Sample* | 3.47 | 3.50 | 0.70 | 9.00 | 0.98 | 64,797 |
| *Blacks* | 3.50 | 3.40 | 1.30 | 6.40 | 1.06 | 3,867 |
| *Hispanics* | 3.60 | 3.60 | 0.70 | 6.30 | 0.96 | 3,784 |
| **County Change in Home Prices** | | | | | | |
| *Full Sample* | -19.14 | -16.71 | -54.16 | 19.68 | 13.46 | 61,381 |
| *Blacks* | -19.03 | -16.37 | -54.16 | 12.51 | 14.21 | 3,516 |
| *Hispanics* | -23.71 | -22.46 | -54.16 | 15.23 | 14.81 | 3,574 |

**Table 11, Panel B: Geographic Variables by Race and Ethnicity, Discrete Variables**

| Variable | Full Sample | Black | Hispanic |
|---|---|---|---|
| Tract Minority % <=10% | 39.43 | 6.03 | 16.05 |
| 10% < Tract Minority % <=25% | 27.67 | 12.04 | 23.85 |
| 25% < Tract Minority % <=50% | 18.89 | 20.35 | 25.54 |
| 50 %< Tract Minority % | 14.01 | 61.57 | 34.56 |
| Low Income Tract | 1.74 | 12.50 | 3.31 |
| Moderate Income Tract | 14.73 | 36.28 | 22.90 |
| Middle Income Tract | 54.50 | 39.81 | 46.91 |
| High Income Tract | 29.03 | 11.41 | 26.88 |
| N Obs. | 58,533 | 3,044 | 3,064 |

Unemployment data is for 2009 and 2008 from the US Bureau of Labor Statistics. The 'level' is 2009 data, and the 'change' is from 2008 to 2009. Home price changes are based on the change in CoreLogic©'s home price index at the county level from April 2007 to December 2009, approximately the peak and bottom of home prices according to the FHFA national index. Data on tract-level minority share and income are from the US 2000 Census. The number of observations varies when different variables are added to the model due to changes in the success of geocoding at different aggregation levels, as well as differences in availability of geographic data. Low Income Tract = Census tract median family income is less than 50% of metropolitan median family income. Moderate Income Tract = Census tract median family income <=50% of metropolitan median family income, < 80% metropolitan median family income. Middle Income Tract = Census tract median family income is <=80% metropolitan median family income, <120% metropolitan median family income. The definition of minority in the calculation of tract level minority share includes all individuals except non-Hispanic whites as minorities. All statistics are weighted using weights provided by Mintel Comperemedia.

**Table 12, Panel A: Odds Ratios, Model with MSA Unemployment Level**

| | **Any Offer** | **Lender #1** | **Lender #2** | **Lender #3** | **Lender #4** | **Lender #5** |
|---|---|---|---|---|---|---|
| Black | 0.75*** | 0.68*** | 0.70*** | 0.81** | 0.91 | 0.77** |
| Hispanic | 0.82*** | 0.71*** | 0.61*** | 0.9 | 0.94 | 0.93 |
| MSA Unemployment | 0.68*** | 0.93 | 0.49*** | 0.66*** | 0.38*** | 0.87 |
| AIC | 68,073 | 25,487 | 24,495 | 38,536 | 25,361 | 27,083 |

Odds ratios from individual logit equations for the probability of receiving a credit card offer. MSA unemployment is for 2009 from the US Bureau of Labor Statistics. Unemployment numbers are normalized by the national unemployment level. 67,797 observations. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

**Table 12, Panel B: Odds Ratios, Model with CBSA Unemployment Annual Change**

| | **Any Offer** | **Lender #1** | **Lender #2** | **Lender #3** | **Lender #4** | **Lender #5** |
|---|---|---|---|---|---|---|
| Black | 0.75*** | 0.68*** | 0.70*** | 0.81** | 0.92 | 0.77** |
| Hispanic | 0.82*** | 0.71*** | 0.61*** | 0.90 | 0.93 | 0.92 |
| CBSA Change in Unemployment | 0.82*** | 1.07 | 0.76** | 0.71*** | 0.70** | 1.03 |
| AIC | 76,528 | 28,272 | 27,880 | 43,010 | 27,395 | 30,118 |

Odds ratios from individual logit equations for the probability of receiving a credit card offer. Core based statistical area (CBSA) unemployment is change from 2008 to 2009 from the US Bureau of Labor Statistics. 67,797 observations. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

**Table 12, Panel C: Odds Ratios, Model with % Change in County Home Price Index, Plus Indicator for Homeownership and Interaction between Change in County Home Price Index and Homeowner**

| | Any Offer | Lender #1 | Lender #2 | Lender #3 | Lender #4 | Lender #5 |
|---|---|---|---|---|---|---|
| Black | 0.76*** | 0.68*** | 0.73** | 0.82** | 0.88 | 0.78** |
| Hispanic | 0.83*** | 0.72*** | 0.63*** | 0.93 | 0.97 | 0.86 |
| Change in HPI | 2.47*** | 1.62 | 2.92* | 4.26*** | 1.59 | 1.57 |
| Homeowner | 1.15** | 1.09 | 1.36** | 1.13 | 1.15 | 0.93 |
| Change in HPI*Homeowner | 0.91 | 0.74 | 3.00** | 0.61 | 2.01 | 0.8 |
| AIC | 64,312 | 23,975 | 23,409 | 36,580 | 23,458 | 24,458 |

Odds ratios from individual logit equations for the probability of receiving a credit card offer. County home price index (HPI) is change from April 2007 to December 2009, which is approximately from the peak to the trough of the national FHFA home price index. Home price data is from CoreLogic. 61,381 observations. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

**Table 12, Panel D: Odds Ratios, Model with Fixed Effects for Census Tract Minority Share and Census Tract Median Family Income**

| | Any Offer | Lender #1 | Lender #2 | Lender #3 | Lender #4 | Lender #5 |
|---|---|---|---|---|---|---|
| Black | 0.75*** | 0.7** | 0.8 | 0.76** | 0.91 | 0.76** |
| Hispanic | 0.84*** | 0.76** | 0.57*** | 0.94 | 1.02 | 0.99 |
| Low Income Tract | 0.85 | 1.14 | 0.63 | 1.05 | 0.48** | 0.99 |
| Moderate Income Tract | 0.84* | 0.69*** | 0.89 | 0.85** | 0.77 | 0.92 |
| Middle Income Tract | 0.89 | 0.88 | 0.95 | 0.9 | 0.82 | 0.93 |
| 10% < Tract Minority % <=25% | 0.94** | 1.02 | 0.98 | 0.91** | 0.94 | 0.91* |
| 25% < Tract Minority % <=50% | 0.92** | 0.96 | 0.88* | 0.92 | 0.91 | 0.95 |
| Tract Minority % >50% | 0.84*** | 0.92 | 0.74*** | 0.77*** | 0.94 | 0.79** |
| AIC | 67,486 | 24,591 | 25,447 | 38,505 | 24,015 | 25,446 |

Low Income Tract = Census tract median family income is less than 50% of metropolitan median family income.

Moderate Income Tract = Census tract median family income <=50% of metropolitan median family income, < 80% metropolitan median family income.

Middle Income Tract = Census tract median family income is <=80% metropolitan median family income, <120% metropolitan median family income.

Tract level minority % includes all except non-Hispanic whites as minorities.

Tract-level data is from the US 2000 Census. 58,533 observations. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

**Table 13: Odds Ratios, Model Estimated on Subsample of Individuals with Household Income >=$50,000**

| | Any Offer | Lender #1 | Lender #2 | Lender #3 | Lender #4 | Lender #5 |
|---|---|---|---|---|---|---|
| Black | 0.68*** | 0.71** | 0.75** | 0.73*** | 0.75 | 0.80* |
| Hispanic | 0.87** | 0.86 | 0.58*** | 0.93 | 0.91 | 1.13 |

Odds ratios from individual logit equations for the probability of receiving a credit card offer. 19,946 observations. *significant at 10% level; **significant at 5% level; ***significant at 1% level.

**Table 14: Odds Ratios, Model Estimated on Subsample of Individuals with VantageScore >=750 and no History of Bankruptcy in Credit Record**

| | Any Offer | Lender #1 | Lender #2 | Lender #3 | Lender #4 | Lender #5 |
|---|---|---|---|---|---|---|
| Black | 0.77*** | 0.71** | 0.74** | 0.95 | 0.94 | 0.79** |
| Hispanic | 0.79*** | 0.74*** | 0.61*** | 0.92 | 0.84 | 0.94 |

Odds ratios from individual logit equations for the probability of receiving a credit card offer. 41,920 observations. *significant at 10% level; **significant at 5% level; ***significant at 1% level.