

## **Adverse Selection in the Credit Card Market: Evidence from a Natural Experiment\***

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### **Abstract**

Using a unique data from multiple large-scale randomized marketing trials of pre-approved credit card solicitations, we find that consumers responding to the lender's *inferior* solicitation offers have poorer credit quality attributes. This finding supports the argument that riskier type borrowers are liquidity or credit constrained, and thus have a higher reservation loan interest rate. After controlling for a cardholder's observable risk type, demographic characteristics, and adverse economic shocks, we find that for unobservable reasons cardholders who responded to the inferior credit card offers are significantly more likely to default *ex post*. Moreover, we also find that *ex post* default is significantly correlated with unobserved risk types. Overall, these results indicate that the lender faces higher-than-expected loss due to adverse selection.

JEL Classification: D12, D82, G2

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In his seminal paper, Akerlof (1970) shows that in a market with asymmetric information between buyers and sellers, adverse selection is likely to result. Over the years, numerous papers have extended Akerlof's theory. For example, Stiglitz and Weiss (1981) show how asymmetric information can prevent a credit market from clearing and lead to the rationing of credit. Bester (1985) shows that endogenously chosen collateral may offset the problem of information asymmetry and the market can clear. Empirical evidence of asymmetric information in the consumer credit markets includes<sup>1</sup>: credit cards (Ausubel, 1999), home mortgage and automobile loans (Edelberg, 2003), home equity credit (Agarwal et al., 2006), sub-prime automobile loans (Adams et al., 2008) and personal loans (Karlan and Zinman, 2008).

In this paper, we test for adverse selection using a unique data from multiple large-scale randomized marketing trials of pre-approved credit card solicitations by a large financial institution that issues credit cards nationally. Our paper is closely related to Ausubel (1999) in which we test to see whether, for unobservable reasons, inferior offer types chosen by applicants *ex ante* experience a higher default rate *ex post*. However, we extend our empirical study by following the approach used in Adams et al., (2007) to construct a cardholder's unobservable risk type by regressing the cardholder's internal behavior score on his/her external FICO risk score in the first month after the credit card was issued, and then use the residual from this risk score regression (henceforth, risk score residual) as a proxy for the cardholder's unobservable risk type.<sup>2</sup>

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<sup>1</sup> Numerous studies have tested for the role of asymmetric information in the auto and health insurance markets. For example, Genesove (1993) analyzed the market for used cars and found weak evidence for adverse selection, while Chiappori and Salanie (2000) examined the French market for automobile insurance and found no evidence of adverse selection. Altman, Cutler and Zeckhauser (1998) studied the health insurance market and found evidence of adverse selection.

<sup>2</sup> While we use the risk score residual, Adams et al (2007) use the residual from the down payment regression.

We then test for adverse selection by estimating the likelihood of a cardholder defaulting on his credit card debt as a function of solicitation offer type, the risk score residual, and the interaction between the inferior offer indicator and the risk score residual, while controlling for information on a cardholder's initial loan amount (balance transfer), other risk attributes observed by the lender at the time the card was issued, demographic characteristics (e.g., age, gender, marital status, and income), and the extent to which a cardholder faces adverse economic shocks ex post.

To preview our results, we find that consumers who responded to the lender's credit card solicitation exhibit significantly higher risk attributes than those who did not respond. When we compare the credit risk characteristic of responders across contract offer types within a marketing trial, we find that consumer who responded to the *inferior* offer types (e.g., higher APR offer) exhibit poorer credit quality characteristics than those responding to *superior* offer types. These patterns are quite striking, and support the argument that higher risk consumers, assuming that consumers are aware of their own credit risk type, have fewer options for acquiring funds to smooth consumption (i.e., liquidity or credit constrained). And therefore, they have a higher reservation credit card interest rate. Taken together, these observations provide preliminary evidence that the lender may be susceptible to potential adverse selection problems.

After controlling for a cardholder's observable risk type, as well as demographic characteristics and adverse economic shocks, we find that cardholders with a higher debt balance transfer are significantly more likely to default. Moreover, we also find that for unobservable reasons cardholders who responded to the *inferior* credit card offers are significantly more likely to default ex post. We also find a significant correlation between

the risk score residual and cardholders' default risk. Overall, our results provide evidence on the existence of adverse selection in the credit card market.

The paper proceeds as follows. Section 2 describes the market experiments and data, while section 3 compares the observable risk characteristics of responders to those of non-responders, and then compares the responder's risk type across credit card offers. Finally, we test for adverse selection on unobservable risk type in section 4 and provide concluding remarks in section 5.

## **2. Experiment Design and Data Description**

Our data comes from a large financial institution that issues credit cards nationally. As part of routine marketing campaigns between January and May 2001, the lender conducted several large-scale randomized trials of pre-approved credit card solicitations by mailing out seven distinct solicitation offers under three different marketing trials to a large random population of over 2.3 million consumers.

The first marketing trial (A) had three offers. The first offer (A1) was 0% interest on purchases for the first eight months with a go-to rate of 9.99%. The second offer (A2) was 0% interest on purchases for the first twelve months with a go-to rate of 9.99%. Finally, the third offer (A3) was 0% interest on purchases for the first eight months with a go-to rate of 8.99%. All three offers required a balance transfer (no minimum amount required), and the interest rate on the balance transfer (BT) was the go-to rate. Both offers A2 and A3 are clearly superior offers than A1 because (i) borrowers can have 4 additional months of 0% APR on purchases under the offer A2; and (ii) borrowers will face a 100 basis point lower go-to rate after eight months under the offer A3. It is not

possible to determine whether offer A2 is superior/inferior to offer A3 because both the duration for the 0% purchase and the go-to rates change. So for our purposes, we will only compare offer A1 to offer A2 and offer A1 to offer A3.

The second marketing trial (B) had two offers. The first offer (B1) provided a fixed 9.99% interest on purchases and balance transfer for life. The second offer (B2) provided a fixed 8.99% interest on purchases and balance transfer for life. In this case, offer B2 is clearly superior to offer B1 because it carries a 100 basis point lower interest rate. Finally, the third marketing trial (C) had two offers. The first offer (C1) provides a 0% interest on purchases, balance transfers, and cash advances for the first six months with a go-to rate of 12.99%. The second offer (C2) provides a 0% interest on purchases, balance transfers, and cash advances for the first six months with a go-to rate of 14.99%. Offer C1 is superior to offer C2 because its go-to rate is 200 basis points lower.

As previously mentioned, the bank mailed out 2.3 million solicitation offers over a five months period (January to May 2001) under the three marketing trials. By July 2001, a total of 6,448 (0.28%) consumers responded to the solicitations. Of these respondents, the bank rejected 1,389 (21.5%) applications due to deterioration in credit risk characteristics of the consumer, and issued a credit card to 5,059 consumers. For these booked accounts, we are able to track the debt repayment patterns of each cardholder over the next 24 months period (until July 2003) after lender issued the credit card.

Our data, in addition to capturing the ex post default behaviors of the cardholders, includes two additional key pieces of information: a cardholder's updated external (FICO) credit score and internal payment behavior score. A credit score, whether a

generic FICO score or an internal behavior score, is an index constructed to evaluate an individual's relative risk of default conditional on his/her credit profile. For example, a lower FICO score implies a higher probability of a consumer defaulting on his outstanding debt in the next 24 months. The FICO score captures the cardholder's repayment on all outstanding debt, while the internal behavior score captures the internal repayment patterns on this lender's credit card debt.

Scoring models lower underwriting and monitoring costs, increase productivity, and can provide more consistent underwriting guidelines; thus, they are a significant part of decision strategies in retail lending. In general, lenders cannot identify the specific borrower who will default. As a result, lenders rely on scoring models to rank-order the relative default risk of each borrower, and to develop an expectation of risk of loss on a pool-level by assuming a similar repayment behavior amongst borrowers with similar credit profiles.

The credit card lender in our study obtained an applicant's external credit risk (FICO) score at the time of credit application, and then updated a borrower's FICO score on a quarterly basis after credit issuance. In addition, the lender also developed an internal behavior scoring model to assess the likelihood that a credit account will become delinquent in the near future (e.g., the next 6 months). The quarterly updated FICO score captures a consumer's repayment behavior on all currently open credit trades, and therefore is informative of the extent to which the cardholder faced adverse economic shocks to his/her household portfolio and hindered his/her ability to meet debt obligations on all outstanding credit. The internal behavior score reveals the relative risk type of the

cardholder based on the internal repayment behavior with this credit card lender. These two risk scores summarize a cardholder's relative risk type to the lender.

### **3. Observable Information**

Table 1 compares the average credit risk characteristics of: (i) responders versus non-responders for each offer type within a marketing trial; and (ii) responders across offer types within a marketing trial for six credit bureau variables. Specifically, we focus on the following risk attributes: (i) total credit card line amount (for all credit cards); (ii) total credit card utilization rate (total credit withdrawn as a fraction of total credit availability on all credit cards); (iii) account age (the length of time the customer's credit file has existed at the credit bureau); (iv) delinquency behavior (30+days past due); and (v) FICO score.

#### **3.1 Responders vs. Non-Responders**

The third and fourth columns of Table 1 compare the number and percentage of responders and non-responders for each offer type in a given marketing trial. First, the results show that the lender offered a disproportionately higher percentage of inferior offers within each marketing trial (A1, B1, and C2). Of the 951,651 solicitations under marketing trial A, for example, the lender sent 646,370 (68%) A1 offers to consumers, but only sent 150,643 (15.8%) A2 offers and 154,548 (16.2%) A3 offers.

Furthermore, the response rate for superior offers (A2, A3, B2, and C1) is lower than that for the inferior offers. Consumers were more than twice as likely to choose offer A2 over offer A1 (0.56% response rate for A2 offer versus a 0.27 % point response rate

for A1 offer), which suggests that consumers for marketing trial A are more sensitive to the duration of the teaser offer than the interest rate. The difference in the response rate for A1 and A3 offers, however, are insignificant (respectively, 0.27% and 0.29% response rate). Consumers for marketing trial B with fixed rate for life on purchases and balance transfers are more than twice as likely to choose B2 over B1 (response rates of 0.47% and 0.19% points respectively for B2 and B1). Similarly, consumers for marketing trial C are twice as likely to choose C1 over C2 (response rates of 0.44% and 0.19% points respectively for C1 and C2).

In terms of their credit risk characteristics, responders and non-responders are strikingly different. Responders across all product-offerings have significantly lower FICO score (30-points on average) than non-responders. Looking at more specific credit risk attributes, responders for offers in the marketing trials A (with the exception of offer A2) and B have higher credit limit (on all open and active credit cards) than non-responders, while responders for offers in the marketing trial C have lower credit limit than non-responders. Across all offer types, the average credit utilization rate (on all open and active credit cards) is higher for responders (about 14% average across offers) than non-responders (about 8% across offers). In addition, the average length of credit history with the bureau is 89 months for responders, while that for non-responders is 129 months. Finally, responders across all offer types experienced significantly higher delinquency incidences (30 + days past due) in the 12 months prior to responding to the lender's solicitation.

### **3.2 Responders' Choice on Offer Types**

Now we look at the risk characteristics of the responders by their choice of offer type within each marketing trial. The first market trial (A) has three offer types (A1, A2, and A3). As previously mentioned, offers A2 and A3 are clearly superior to A1 but it is unclear whether A2 or A3 is the superior offer amongst the two. The results show a statistically insignificant difference in risk type between responders choosing the inferior offer A1 relative to the superior offer A2 (average FICO score of 742 and 744, respectively) or in risk type between responders choosing the inferior offer A1 and the superior offer A3 (average score of 742 and 744, respectively). On the other hand, other risk measures show that responders to the inferior offer A1 may be more credit or liquidity constrained, or riskier than responders to the superior offers A2 or A3. For instance, responders of the inferior offer A1 have on average a significantly lower credit line available on all open and active credit cards than the responders of the superior offers A2 or A3. Moreover, the percentage of prior 12-month delinquency amongst the inferior offer A1 responders is significantly higher than that of those amongst the superior offers A2 or A3 responders.

Similarly, while the average FICO scores of responders of the inferior offer B1 are insignificantly different from that of responders of the superior B2 offer, and the average FICO scores of responders of the inferior offer C2 are insignificantly different from that of responders of the superior offer C1, other risk measures risk characteristics (such as the credit line available on all cards and prior 12-month delinquency incidences) show that responders to the inferior offers B1 or C2 may be liquidity or credit constrained relative to the responders of the superior offers B2 and C1, respectively.

Thus far, our results show that the risk characteristics of responders are statistically different from those of non-responders. These results indicate that higher risk consumers, assuming that consumers are aware of their own credit risk-type, have fewer outside options for acquiring funds to smooth consumption. These liquidity or credit constrained borrowers therefore have a higher reservation credit card interest rate. Taken together, these observations provide preliminary evidence that the lender may be susceptible to potential adverse selection problems.

#### **4. Adverse Selection**

To investigate the existence of adverse selection, we conduct two types of analysis. First, we examine whether there are any changes in the cardholders' credit quality immediately after the lender issued the credit card, and if yes, whether the changes differ by solicitation offer types. Specifically, we look at the quarterly updated external credit score (FICO score) and the lender's quarterly updated internal credit risk score (behavior score) 12 months and 24 months after booking.

Second, we test for adverse selection on unobservable risk type by estimating the likelihood of a cardholder defaulting as a function of a solicitation offer type indicator, a proxy for the risk type unobserved by the lender *ex ante*, and the interaction between the inferior offer indicator and unobservable risk type, while controlling for information on consumer's demographic characteristics (e.g., age, gender, marital status, and income), the consumer's risk type observed by the lender at the time the card was issued, and the extent to which a cardholder faces adverse economic shocks *ex post*.

#### **4.1 Changes in Cardholders' Credit Quality after Booking**

In Table 2, we assess the extent to which a cardholder's FICO score and internal behavior score changed in the 12- and 24-months after the lender issued the credit card to the consumer. If the credit quality of the cardholder declined significantly and the cardholders did *not* face adverse economic shocks to the family's portfolio ex post, the lender may likely face higher than expected default risk due to adverse selection. If the true risk of a cardholder is hidden from the lender at the time of credit issuance, we expect a more severe deterioration ex post in the credit quality of the booked accounts of inferior offer types relative to superior offers.

Table 2 reports the average FICO score and the internal behavior score for the cardholders (who did not attrite)<sup>3</sup> at 12 and 24 months after the lender issued the borrower a credit card. Both credit scores measure the relative credit risk of an individual account. However, given that a FICO score comes from the credit bureaus and reflects the account-holder's credit and debt repayment activities across all credit products he/she holds, it can be informative of the extent to which the borrower faced adverse economic hardships that hindered his/her ability to make the minimum payment on other held credit cards or on other loans. The behavior score, on the other hand, reveals the debt repayment behavior of the cardholder with this lender who issued this credit card.

The results show that across all offer types, the average FICO scores at the 12 or 24 months subsequent to the issuance of this credit card remains similar as at the time of the card issuance. Hence, there was no (economically or statistically) significant deterioration of a cardholder's FICO score; this finding is consistent across offer types.

These findings suggest that on average cardholders across all offer types did not experience major adverse economic shocks to the extent that hindered their ability to meet debt obligations on other credit outstanding. On the other hand, the behavior scores are significantly lower for cardholders of a particular offer type. More distinctively, the behavior scores are significantly lower for cardholders who responded to and were issued the *inferior* offer types. The results on the changes in the FICO and behavior scores provide us with a preliminary indication that the lender may be face higher than expected default rate do to unobservable risk type at the time of credit issuance.

#### **4.2 Unobservable Risk Type and Cardholders' Ex Post Default**

Following the empirical methodology in Adams et al., (2007)<sup>4</sup>, we construct our measure of unobservable risk type by regressing a cardholder's internal behavior score on his/her external FICO risk score in the first month after the credit card was issued<sup>5</sup>, and then use the residual from this risk score regression (Risk Score Residual) as a measure of the cardholder's private risk type that is unobservable at the time the lender issued the card. A positive risk score residual implies that a cardholder is less risky than the lenders actual estimate. Thus, if the lender faces adverse selection problems due to unobservable risk type ex ante, we should find a positive risk score residual to have significantly negative impact on cardholders' default behaviors ex post *ceteris paribus*.

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<sup>3</sup> Attrition refers to accounts that were closed. Voluntary attrition is defined as cardholders who requested to close their accounts. Involuntary attrition is defined as whose account was closed by the lender, for instance, due to fraud.

<sup>4</sup> Adams et al., (2007) estimate a consumer's loan demand.

<sup>5</sup> Specifically, we estimate the following regression model:  $\text{Behavior Score}_{i1} = \alpha + \beta \text{FICO}_{i1} + \varepsilon_{i1}$ . Where  $i$  denotes a booked account at month 1. Next, the Risk Score Residual = predicted Behavior Score- actual Behavior Score.

We test for adverse selection on unobservable risk type by estimating the likelihood of a cardholder defaulting as a function of solicitation offer type indicator, the risk score residual, and the interaction between the inferior offer indicator and the risk score residual, while controlling for information on a cardholder's balance transfer amount, observable risk characteristics, demographic characteristics (e.g., age, gender, marital status, and income), and the extent to which a cardholder faces adverse economic shocks ex post. The lender faces adverse selection problems if, for unobservable reasons, cardholders who responded to an inferior credit card offer experienced a significantly higher default risk ex post.

Table 3 presents the results of a logit estimation of account-level default behaviors on a dummy indicator for offer type, risk score residual, the interaction between the risk score residual and offer types. Default is defined as 60-days past due. We control for the cardholder's FICO score at three months prior to default, the amount of debt on other credit card the cardholder initially transferred to this credit card (i.e., balance transfer), and other risk characteristics observed by the lender at the time of card issuance: total card and non-card credit utilization, total credit limit, number of credit cards held by the responder. In addition, we also control for the cardholder's demographic characteristics (age, gender, marital status, and income) and include zip code fixed effects to control for the general macro economic conditions (unemployment, exemption laws, divorce rates, etc.).

With respect to the demographic characteristics, our results reveal that while the cardholder's gender has no significant correlation with default behaviors, a cardholder who is younger, is married, or earns higher income is significantly *less* likely to default

on his/her credit card debt. Consistent with prior studies (Gross and Souleles, 2002; Agarwal, Chomsisengphet, Liu, and Souleles, 2008), we also find that cardholders with lower credit limit, higher utilization rate, higher number of credit cards open and active, or higher balance transfer are more likely to default. Moreover, cardholders who transfer a greater amount of debt from other credit card to this credit card are significantly more likely to default. And cardholders who face a decline in the external risk (FICO) score are significantly more likely to default. The results are consistent across all three marketing trials.

After controlling for the cardholder's demographic as well as risk characteristics that were observed at the time the lender issued the credit card and the cardholder's updated FICO score, we find evidence of adverse selection. For the marketing trial A, the negative coefficients on the A2 and A3 indicator dummies indicate that these superior offers are, respectively, 6 and 4 percent *less* likely to default. These findings imply that for unobservable reasons cardholders who responded the inferior offer (A1) are significantly more likely to default. In the case of marketing trials B and C, we also find a significantly negative correlation between superior offer types and default behaviors ex post. Furthermore, we find that across all three marketing trials the risk score residual (a proxy for risk type unobservable to the lender) is negatively and statistically correlated to default behaviors ex post. Moreover, the coefficient on the interaction term between the inferior offer type and the risk score residual is significantly negative. A positive coefficient on the interaction terms implies that the risk score residual for superior offer types is positive in relation to the inferior offer types. In combination, our results imply that some cardholders have ex ante private information about their risk type that was

unobservable to the lender. As a result, the lender faces ex post higher-than-expected default rate due to unobservable risk types.

## **5. Conclusion**

Our paper uses a unique data set that cover multiple large-scale randomized market trials of pre-approved credit card solicitations to test for adverse selection on unobservable risk type. First, our descriptive analysis reveal that consumers who respond to the lender's credit card solicitation exhibit significantly higher credit risk characteristics than those who did not respond, and consumers who respond to inferior offer types (e.g., higher APR) exhibit worse credit risk characteristics than those responding to superior offer types. Consistent with the argument that because higher risk consumers have fewer outside options for acquiring funds to smooth consumption (i.e., liquidity or credit constrained), they have a higher reservation loan interest rate. These results also provide us with the first preliminary evidence that the lender may be susceptible to adverse selection problems.

After controlling for a cardholder's initial balance transfer, observable risk types, demographic characteristics, and potential adverse economic shocks ex post, we find that cardholders who responded to the inferior credit card offers are significantly more likely to default for unobservable reasons. Moreover, we also find a significant correlation between unobservable risk types and default behaviors. Overall, our results provide evidence on the existence of adverse selection in the credit card market.

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Table 1: Credit risk characteristics of responders and non-responders

Offer Type	Responders Nonresponders	Response Frequency	Response Rate (%)	Balance Transfer (\$)	Credit Line (\$) All Cards	Utilization (%) All Cards	Account Age	30+DPD prior 12 months	FICO Score
A1	Non-Responders	644624		0	21068	8	131	0.08%	773
	Responders	1746	0.27%	1503	19557**	13**	83**	0.31%**	742**
A2	Non-Responders	149800		0	20409	9	123	0.04%	772
	Responders	843	0.56%	1926	23506**	15**	92**	0.12%**	744**
A3	Non-Responders	154090		0	22429	9	137	0.04%	772
	Responders	458	0.30%	1922	22100	15**	94**	0.15%**	744**
B1	Non-Responders	542666		0	21354	8	132	0.18%	773
	Responders	1058	0.19%	363	15163**	14**	80**	0.28%**	740**
B2	Non-Responders	150118		0	20369	9	122	0.13%	772
	Responders	708	0.47%	538	18553**	16**	82**	0.10%**	742**
C1	Non-Responders	150076		0	20400	9	122	0.03%	772
	Responders	678	0.45%	3078	29479**	17**	98**	0.11%**	743**
C2	Non-Responders	493903		0	21868	8	135	0.07%	773
	Responders	957	0.19%	2464	27772**	14**	94**	0.19%**	743**
	T-test for Diff A1 & A2			-3.60	-4.45	-2.60	-2.79	-5.28	-1.24
	T-test for Diff A1 & A3			-2.87	-2.35	-2.12	-2.62	-3.89	-1.01
	T-test for Diff B1 & B2			-5.61	-4.05	-2.06	-0.53	-2.77	-1.05
	T-test for Diff C1 & C2			3.41	1.26	3.32	0.95	2.13	0.00

Notes: Offer A1 has an APR of 0% for purchases during the first 8 months with a balance transfer rate of 9.99%, and thereafter the APR on purchases goes to 9.99%. Offer A2 has an APR of 0% for purchases during the first 12 months with a balance transfer rate of 9.99% and thereafter the APR on purchases goes to 9.99%. Offer A3 has an APR of 0% for purchases during the first 8 months with a balance transfer rate of 8.99% and thereafter the APR on purchases goes to 8.99%. Offer B1 has no teaser rate offer but the APR on purchases and balance transfer are 9.99% for life. Offer B2 has no teaser rate offer but the APR on purchases and balance transfer are 8.99% for life. Offer C1 has an APR of 0% on purchases and balance transfer for the first 6 months and thereafter the APR on purchases goes to 12.99%. Offer C2 has an APR of 0% on purchases and balance transfer for the first 6 months and thereafter the APR on purchases goes to 14.99%.

Table 2 Credit scores of booked accounts by offer type

Offer Type	Frequency			FICO Score			t-stat	t-stat	Behavior Score			t-stat	t-stat
	at booking	at 12Mth	at 24Mth	at booking	at 12Mth	at 24Mth	1st 12Mth	2nd 12Mth	at 1Mnth	at 12Mth	at 24Mth	1st 12Mth	at 24Mth
<b>A1</b>	1329	729	645	744	740	737	-0.96	-0.74	722	711	701	-2.25	-2.17
<b>A2</b>	697	627	509	745	743	737	-1.61	-0.63	742	740	740	-0.72	0.05
<b>A3</b>	368	318	259	746	743	739	-0.91	-0.45	731	725	721	-1.04	-1.60
<b>B1</b>	765	702	658	743	737	735	-0.43	-0.34	732	721	712	-2.35	-1.91
<b>B2</b>	613	588	562	744	740	737	-0.37	-0.43	741	739	734	-0.54	-0.20
<b>C1</b>	560	479	462	743	739	739	-0.09	-1.03	739	736	737	-0.78	0.24
<b>C2</b>	727	501	395	744	741	738	-1.08	-0.92	730	721	710	-2.45	-2.06

Notes: Offer A1 has an APR of 0% for purchases during the first 8 months with a balance transfer rate of 9.99%, and thereafter the APR on purchases goes to 9.99%. Offer A2 has an APR of 0% for purchases during the first 12 months with a balance transfer rate of 9.99% and thereafter the APR on purchases goes to 9.99%. Offer A3 has an APR of 0% for purchases during the first 8 months with a balance transfer rate of 8.99% and thereafter the APR on purchases goes to 8.99%. Offer B1 has no teaser rate offer but the APR on purchases and balance transfer are 9.99% for life. Offer B2 has no teaser rate offer but the APR on purchases and balance transfer are 8.99% for life. Offer C1 has an APR of 0% on purchases and balance transfer for the first 6 months and thereafter the APR on purchases goes to 12.99%. Offer C2 has an APR of 0% on purchases and balance transfer for the first 6 months and thereafter the APR on purchases goes to 14.99%. Due to attrition (voluntary and involuntary), the number of accounts at the 12- or 24-month is less than at the time of booking.

Table 3: Determinants of a cardholder's likelihood of defaulting

Panel A	Coeff Val	Std Err	T-stat	Marginal Effect
A2 Offer Indicator	-0.373	0.082	-4.52	-5.78%
A3 Offer Indicator	-0.171	0.067	-2.54	-4.41%
Risk Score Residual	-0.664	0.132	-5.02	-12.54%
Risk Score Residual*A2	-0.535	0.122	-4.37	-9.44%
Risk Score Residual*A3	-0.269	0.125	-2.16	-6.62%
FICO Score	-0.570	0.049	-11.58	-0.07%
Balance Transfer (\$)	0.028	0.010	2.79	0.01%
# of Credit Cards	0.323	0.066	4.90	0.14%
Utilization Rate (%)	0.788	0.286	2.76	0.48%
Credit Limit (\$)	-0.086	0.030	-2.89	-0.02%
Borrower Age	0.327	0.102	3.19	0.04%
Gender (Male=1)	0.342	0.192	1.78	3.84%
Marital Status (Married=1)	-0.276	0.068	-4.05	-6.74%
Ln(Income)	-1.057	0.290	-3.65	-7.88%
Zip Code Dummies	Yes			
Time Dummies	Yes			
Number of Obs/Defaults	1413/98			
Pseudo R-square	0.46			
Panel B	Coeff Val	Std Err	T-stat	Marginal Effect
B2 Offer Indicator	-0.322	0.132	-2.45	-5%
Risk Score Residual	-0.533	0.127	-4.21	-8.74%
Risk Score Residual*B2	-0.264	0.127	-2.07	-6.79%
FICO Score	-0.382	0.082	-4.67	-0.05%
Balance Transfer (\$)	0.028	0.010	2.73	0.02%
# of Credit Cards	0.314	0.065	4.85	0.17%
Utilization Rate (%)	0.770	0.279	2.76	0.35%
Credit Limit (\$)	-0.083	0.030	-2.83	-0.03%
Borrower Age	0.332	0.104	3.19	0.04%
Gender	0.338	0.191	1.77	3.86%
Marital Status	-0.284	0.068	-4.18	-6.84%
Ln(Income)	-1.057	0.293	-3.60	-7.92%
Zip Code Dummies	Yes			
Time Dummies	Yes			
Number of Obs/Defaults	1220/59			
Pseudo R-square	0.49			
Panel C	Coeff Val	Std Err	T-stat	Marginal Effect
C1 Offer Indicator	-0.534	0.168	-3.17	-4.18%
Risk Score Residual	-0.531	0.127	-4.19	-5.10%
Risk Score Residual*C1	-0.267	0.125	-2.13	-7.60%
FICO Score	-0.374	0.056	-6.63	-0.06%
Balance Transfer (\$)	0.028	0.010	2.72	0.01%
# of Credit Cards	0.320	0.066	4.85	0.15%
Utilization Rate (%)	0.759	0.278	2.73	0.42%
Credit Limit (\$)	-0.085	0.030	-2.89	-0.01%
Borrower Age	0.326	0.102	3.20	0.04%
Gender	0.344	0.190	1.81	3.91%
Marital Status	-0.285	0.069	-4.11	-6.92%
Ln(Income)	-1.051	0.293	-3.59	-7.92%

Zip Code Dummies	Yes			
Time Dummies	Yes			
Number of Obs/Defaults	857/67			
Pseudo R-square	0.47			

Notes: Default is defined as 60-days past due. The model is estimated as a logit. Panels A, B, and C present results from three different regressions for marketing trials A, B and C, respectively. The inferior offer type A1, B1 and C2 are the omitted type in marketing trial A, B and C respectively. Asymmetric information is captured by the risk score residual from the regression of behavior score on FICO score at month one of the account performance. FICO scores capture the credit risk characteristics three months prior to default (to avoid endogeneity). BT amount is the balance transfer amount, # of credit cards, utilization, credit limit all capture the credit risk characteristics of the borrower observed by the lender at the time of credit issuance. Finally the zip-code and time dummies capture the macroeconomic characteristics about the borrower.