The Cost of Being Late: The Case of Credit Card Penalty Fees

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January 2006

We thank the Social Sciences Research Council of Canada (SSHRC) and the National Research Program on Financial Services and Public Policy, at Schulich School of Business, York University for financial assistance. We also thank the Payments Cards Center at the Philadelphia Federal Reserve for providing us with the Terms of Credit Card Plans (TCCP) database, as well as Christopher Ody, Dan Bernhardt, David Humphrey, Greg Udell James McGrath, Linda Allen, Loretta Mester, Mark Furletti, Mitchell Berlin, Peter Burns and Robert Hunt and Tahir Choulli for helpful discussions. Saif Ullah and David Hou provided excellent research assistance.

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ABSTRACT

The size of credit card penalty fees and their potential impact on low income households has attracted considerable attention from politicians and regulators alike. In particular, there is concern that card penalty fees –late fees and overlimit fees— are exploitive and reflect card providers' market power over consumers. Despite their size and importance, no paper has examined either the determinants of these fees or their impact on the consumer. Ours is the first paper to examine such issues. Using a unique data base we find that credit card penalty fees are reflective of consumer default risk and that the level of these fees is negatively correlated with card interest rates. Moreover, we find no evidence that a card provider's market share impacts the size of these fees or that the burden of penalty fees fall more on consumers from poorer areas in the US. In general, our results question the need to impose additional regulatory restrictions on the level of card fees.

"As families go deeper into debt just to stay afloat, their pockets are sometimes picked by deceptive and abusive credit card practices". Senator John Kerry's Presidential Campaign (August 27, 2004).

"You would expect the credit card business to be somewhat more profitable than the rest of the industry, because it's riskier. It is an unsecured loan and so you would expect the returns to be a little higher" Edward Yingling, President of the American Bankers Association, PBS Frontline (2004).

INTRODUCTION

The US credit card market is one of the largest debt markets in the world. In 2003 total bank credit card debt in the US amounted to $400 billion (source: FDIC Statistics on Depository Institutions). In comparison, the total size of the US corporate bond market in 2003 was $2500 Billion (source: Bank for International Settlements). However, when examining how debt markets function and price risk, the existing literature has focused predominantly on corporate debt. Much less attention has been paid to consumer debt in general and credit card debt in particular, despite the size of the credit card market[1].

This is the first paper to examine the determinants of credit card penalty fees. The most important such fees are late fees and overlimit fees. The rising level of these fees and their impact has been prominent in recent public policy debates in the US. For example, as part of his 2004 Presidential campaign, John Kerry called for credit card penalty fees to be regulated. Furthermore in March 2005 the US senate rejected a

[1] Examples of papers that have examined issues related to consumer debt are Greer (1974), Benston (1977), Domowitz and Sartain (1999), and Kahn, Pennacchi, and Sopranzetti (2005) and Lustig andVan Nieuwerburgh (2005).

Democratic amendment to the Bankruptcy Bill (S 256) which, if passed, would have placed constraints on credit card providers' ability to charge penalty fees.

The key element in this public policy debate is the issue of whether credit card penalty fees can be explained by factors such as cardholder default risk, or whether such penalty fees are "abusive" or "exorbitant" as claimed by opponents. For example, in their defense of credit card penalty fees the American Bankers Association has claimed that penalty fees compensate banks' for the increased credit card risks they face. Until now, however, no formal study has been undertaken to validate or reject this claim.

Two different types of penalty fee are commonly charged by banks; late fees which are charged when borrowers repay after their due date and overlimit fees which are imposed when borrowers charge amounts that are larger than their pre-approved limits. For example, Chase Manhattan in 1998 charged a $20 overlimit fee and a $20 late fee while in 2002 it charged a $28 overlimit fee and a $28 late fee. A credit card borrower can be either late with a payment (i.e. a time dimension to the loan) or have charged an amount over their preauthorized limit (i.e. a dollar dimension to the loan) or both (in which case both the late and overlimit fees would be applied). It is important to note that in this paper we focus only on credit card *penalty fees* charged to consumers as a punishment for being late or overlimit and not other fees paid or received by credit card providers, such as the fixed annual fees paid up-front by credit card holders.

One reason for the increased focus on credit card penalty fees in recent public policy debates is the large dollar amounts involved. A recent survey found that penalty credit card fees in the US amounted to $13 billion in 2004 (RK Hammer Consulting Inc, 2004). Furletti (2003a) states that total late fee (i.e. not including overlimit fee) revenues in 2001 were $7.3 billion. As a proportion of bank credit card income, RK Hammer found that penalty fees accounted for 39% in 2004. Furletti (2003a) states that late fees (again not including overlimit fees) are the third largest revenue stream for card providers (following interest revenues and revenues received from merchants). These magnitudes clearly imply that credit card penalty fees are of substantial importance to both banks and their credit card borrowers.

Despite the significant public policy interest in card penalty fees as well as the large dollar magnitudes involved, this is the first paper in the literature to focus specifically on their determinants. Indeed, until now, the credit card literature has focused almost exclusively on credit card interest rates (e.g. Ausubel (1991), Brito and Hartley (1995), Calem and Mester (1995), Stango (2000), Stango (2002), Knittel and Stango (2003), Berlin and Mester (2004), Calem, Gordy and Mester (2005))[2]. Penalty fees, however, are determined in a very different way than interest rates. Specifically, they are imposed only when a consumer is late or overlimit *independent of time and dollar value*[3]. By comparison, card interest charges are increasing functions of both time and amount borrowed.

In section I of the paper, we provide further motivation for the importance of credit card penalty fees to banks (in addition to the evidence above on the large dollar revenues involved) by analyzing the impact of various proposed changes in card penalty fee regulations on the equity market values of US banks.

In section II of the paper, a theoretical model is used to motivate our empirical tests. The model provides four testable hypotheses. The first relates penalty fees to risk,

[2] Other papers have used Credit Card data to examine topics such as personal bankruptcy (Gross and Souleles (2002(a)) and Domowitz and Sartain (1999)), liquidity constraints (Gross and Souleles (2002(b)) and factors affecting the growth of bank credit cards (Peterson (1977)).

[3] Fees are generally for a fixed amount although Furletti (2003) reports that more recently some banks have imposed tiered fees based on outstanding balance.

the second relates to the substitutability of card penalty fees and interest rates, the third relates to the level of penalty fees and the level of consumer income and the fourth relates to the impact of credit card market share on penalty fees. Collectively, these hypotheses address the issues raised in the current public policy debate over the level and determinants of penalty fees. Specifically, it can be argued that if we find evidence that penalty fees are a function of (bank) market share, then public policy concerns could be raised regarding bank's potential use of their market share to extract economic rents. Furthermore, evidence that banks charge higher penalty fees in lower income states could buttress arguments similar to those of Senator Kerry's above. Alternatively, if we find evidence supporting penalty fees being based on consumer default risk and acting as substitutes for card interest rates, then this would provide support to the argument of the American Bankers Association that credit card penalty fees are determined by economic factors (e.g. risk and interest rates) and should not be subject to additional regulation.

In section III of the paper, we test these hypotheses using a unique data base developed from a number of primary sources. The core of our data base is the TCCP (Term of Credit Cards Plans) data base collected by the Federal Reserve. In addition we utilize a number of other data bases, including Bank Call Reports and the American Bankruptcy Institute consumer bankruptcy database, to derive measures of consumer risk, credit card market share and consumer income. Using three different econometric methodologies (2SLS, 3SLS and GMM) in order to control for endogeneity, we find strong support for our theoretical hypotheses concerning the effects of risk on penalty fees, as well as for the substitutability of penalty fees and interest rates. However, our evidence does not support the contention that consumers in poor (lower income) states pay higher penalty fees in comparison to those in rich states or that a higher bank market share leads to higher penalty fees. We do find, however, that market share (along with risk) does significantly impact the interest rates that banks charge on their credit cards. Thus, we can conclude that while the risk pricing argument of the American Bankers Association is broadly supported by the data on credit card fees, our data on credit card interest rates is consistent with both the risk pricing argument of the banks as well as the market share argument of bank critics.

I. CREDIT CARD PENALTY FEES AND BANKS' EQUITY MARKET VALUES

In order to motivate the importance of credit card penalty fees, we first analyze the impact on US bank equity market values of the US Supreme Court's Smiley v. Citibank case in 1996 which was a landmark decision regarding credit card penalty fee regulation. In addition, we analyze the equity market's response to Senator John Kerry's announcement concerning possible credit card penalty fee regulation, made during his 2004 Presidential campaign.

I.A. US Supreme Court Case: Smiley v. Citibank (1996)

The Smiley case concerned issues relating to the way banks had been imposing credit card penalty fees up until that date. The US Supreme Court had previously ruled, in the 1978 Marquette case, that the credit card interest rates charged by a bank in the specific state in which it was based, could be charged in all other states where the card was provided, regardless of where consumers resided. It is for this reason that many credit card issuers relocated to states such as South Dakota or Delaware (which had few if any usury or other restrictions on credit card issuers). Following the Marquette case, many banks had begun treating credit card penalty fees in the same way as credit card interest rates (i.e. overriding state specific restrictions). The Smiley case (Smiley v. Citibank, (1996)) concerned whether credit card penalty fees could be considered in the same fashion as interest rates in the context of the 1978 Marquette decision and thus whether banks could effectively ignore state specific restrictions on credit card penalty fees (see Toh (1996)).

To examine the impact of the Smiley Case we conducted an event study[4] to examine the market's interpretation of the Supreme Court's actions. Specifically, we analyzed three particular information events; (i) the day that the Supreme Court agreed to hear the case (19 January 1996), (ii) the day the case was argued (24 April 1996) and (iii) the day the ruling of the court was announced (3 June 1996). The event study tests were run on all 317 publicly traded banks for which stock return data were available. We find that on the days when the case was (i) accepted and (ii) argued, these banks had significantly negative abnormal returns of -0.24% (significant at the 5% level) and –0.16% (significant at the 5% level) respectively. These negative abnormal returns could be explained by bank investors' fears that by accepting and hearing the case, the Supreme Court might withdraw the ability of card providing banks to supersede state level restrictions on credit card penalty fees. Importantly, on the day that the Supreme Court ruled in favor of Citibank, (i.e. that credit card penalty fees were effectively free of state level restrictions) there was a significant positive abnormal return on bank stocks of 0.15% (significant at the 10% level) which reflected the good news this decision generated for bank card providers.

[4]We used a one factor market model to test the impact of different announcements on bank stock prices. The model is: $R_{i,t} = a_i + b_i R_{M,t} + e_{i,t}$, where $R_{i,t}$ is the return on the common stock of the i^{th} bank in a sample of all public banks with usable data at time t; $R_{M,t}$ is the return on the equally-weighted Market Index (CRSP) at time t and $e_{i,t}$ is the error term. Return data for each sample firm was obtained from CRSP Standardized abnormal returns were calculated following Patell (1976). The market model was estimated over a 255-day period, ending 46 days before the event day.

Credit cards (and their penalty fees) have a varying degree of importance across banks. Consequently, we repeated the above event study by separating the sample based on whether the bank's ratio of credit card receivables to total assets was either above or below the median ratio. The card receivables to total asset ratio was calculated using Call Report balance sheet data from the FDIC for bank holding companies in 1996. As expected, we find that the impact of the Smiley case was significantly stronger for those banks with an above median level of card receivables/assets ratio, on both the days that the case was argued and decided. On the day the case was argued, the above median credit card banks had an average negative abnormal return of -0.47% (significant at 1% level) while the below median banks had no significant abnormal returns on average. Similarly, on the day that the case was decided, the above median credit card banks on average had a positive abnormal return of 0.25% (significant at the 10% level) while on the other hand, the below median credit card banks had no significant abnormal returns on average.

I.B. John Kerry's Credit Card Penalty Fee Announcement (2004)

We also examined equity market concerns relating to John Kerry's announcement on 27 August 2004, that if elected President he would regulate penalty fees. Specifically, the Associated Press reported that to curb credit card penalty fees, Kerry wanted to restrict banks charging overlimit fees (27 August 2004). On the day of this announcement bank abnormal returns were negative i.e. –0.22% (significant at the 0.1% level) for the 608 publicly traded banks for which data were available. In terms of market capitalization, the –0.22% negative abnormal return implied a loss in these banks' equity market values of more than $2.5 billion on that day.

As in the case of the Smiley event studies, we also examine the impact of this announcement on banks with an above or below median credit card receivables/assets ratio. As in the Smiley case, we find that the negative impact of this event on the above median credit card banks is greater on average (-0.23% at the 5% significance level) than the impact on below median credit card banks (-0.16% at the 10% significance level).

II. THE MODEL AND HYPOTHESES

Given the importance of credit card penalty fees for bank profitability and consumer welfare, this section develops a model to examine the economic factors that determine penalty fees. The section that follows (section II.B.) develops the hypotheses directly derived from the model.

II.A. The Model

Our model captures a number of important features of credit card markets[5], in particular: (i) banks face uncertainty regarding the ability of consumers to pay their balances on time, (ii) credit card banks engage in price discrimination based on the credit constrained nature of customers, (iii) credit card companies differentiate themselves through nonprice features (e.g. frequent flier miles) and (iv) consumer demands for credit card services are price elastic. Our model is based on a spatial search model in a monopolistically competitive credit card market. This reflects the fact that the top 10 credit card issuers have a large market share. In 1997 the top 10 credit card issuers

[5] Our model ignores the role of VISA and MasterCard because these companies do not have any role in determining any specific credit card characteristics (such as penalty fees and interest rates), nor do they bear any cost of consumer default or late payment etc. VISA and MasterCard only receive payment for clearing facilities from to the issuer banks and merchants.

controlled 57% of the market (Card Industry Directory (1999)), while by 2002 this had grown to 85% (Card Industry Directory (2004))[6].

Our theoretical model bears some similarity to a model by Sarangi and Verbrugge (2000) --henceforth SV-- designed to explain penalty fees in the video rental market where late penalty fees from video cassette rentals can sometimes exceed the actual rental fee itself. SV (2000) show that a monopoly video supplier will price discriminate when consumers face stochastic shocks impacting their ability to return items on time. However, our model is different from SV (2000) along a number of dimensions. Specifically, SV assume a monopoly video market, while we consider a spatial search model with monopolistic bank competition. This better characterizes the credit card industry for the following two reasons. First, as explained above, the credit card market is mostly a competitive market and this is captured by the monopolistic competition assumption. Second, consumers usually search for a credit card that is more convenient to them in terms of price and familiarity with the bank card provider; this is captured by the spatial search model. In addition, we model a variety of possible repayment behaviors including (i) paying on time, (ii) being late or over limit and (iii) defaulting on payment. It should be noted that banks usually price discriminate among subgroups of consumers based on their payment behavior. For example, they will impose a penalty fee on all

[6] Our modeling approach for credit card contract is therefore, different from the literature of information asymmetry in incomplete debt contracts, e.g. Bester (1985), Boot, Greenbaum and Thakor (1993), Boot, Thakor and Udell (1991), Gale and Hellwig (1985). Credit card loans are different from other debt contracts (e.g. corporate loans) in many respects: the nature of the contract, relationship between borrowers and lenders and the degree of information asymmetry between borrowers and lenders. For example, the contracts for credit cards loan are mostly standardized and payments have a grace period. By comparison, no standardized contracts exist for corporate loans and there is no grace period on payment. In addition, the relationship between borrowers and lenders play a major role in the likelihood of successful corporate loan application and on the degree of information asymmetry between the borrowers and lenders.

consumers who fail to pay on time. This feature of price discrimination is also captured in our theory model.

Our model is also related to the banking literature which uses spatial search models to capture bank competition (e.g. Matutes and Padilla (1993), Chiappori, Perez-Castrillo and Verdier, (1995), Massoud and Bernhardt (2002)). These models have focused on issues such as a bank's decision as to whether to employ compatible ATM technologies (Matutes and Padilla (1993)); how banks price discriminate in the market for ATMs service according to system and membership (Massoud and Bernhardt (2002)); how banks compete in providing different types of service such as deposits and loans, (Chiappori et al. (1995)). Thus, in addition to being the first paper to examine empirically credit card fees (see below), our paper is also the first to model banking competition in the credit card market in which banks price discriminate when consumers face stochastic shocks to their income which then impacts their repayment choices (i.e. pay on time, pay late, or default on payment).

We consider a spatial search economy in which a measure, two, of bank consumers are uniformly distributed on the perimeter of an island with circumference two. There are two banks, A and B, each with one branch. Bank A has a branch located at 0 and bank B has a branch located on the opposite side of the island at location 1, see Figure 1. Each bank provides a credit card service to its customers.

Each consumer is distinguished by her/his initial spatial location, d. Based on her search, a consumer must obtain a credit card at one bank or the other. The consumer is free to choose the bank at which she obtains her credit card. That is each consumer may receive an invitation from each bank to become a credit card holder. Each consumer receives incremental utility M from obtaining a credit card from her bank. M is assumed to be sufficiently large that in equilibrium, all consumers will obtain a credit card. To obtain a credit card, a consumer must search for the cheapest credit card provider. The search cost is captured by the distance between the consumer's initial location and the location of a bank branch on the circle[7]. A consumer located at ***d*** who chooses to obtain a credit card from a bank branch located at *h* incurs a search cost *T(d-h)****,*** where ***T > 0.***

As is standard in the spatial search modeling literature, the consumer's spatial location does not necessarily have to represent an actual geographic location[8]. In our context, the spatial location can be thought of as representing consumers' heterogeneity in their search ability, while the bank's location can be thought of as representing bank characteristics including card prices. In other words, the spatial search model introduces heterogeneity because both consumer search ability and bank characteristics differ.

Each consumer chooses to spend *$x* on their credit card to finance their expenses/purchases. The credit card contract gives consumers a grace period for the payment of their outstanding balance, during which they are subject to two sequentialy dependent income shocks, see the binomial tree in Figure 2. The first income shock is drawn from a binomial distribution $\{L_1, H_1\}$, with respective probabilities $\Pr(L_1) = 1-\phi$ and $\Pr(H_1) = \phi$**,** where $L_1 > 0$ and $H_1 < 0$. When a consumer receives the negative income shock, H_1, her net income decreases dramatically to the extent that she will be unable to pay the outstanding balance on her credit card on time (and is therefore late). On the other hand, when the consumer receives a positive income shock, L_1, she will immediately pay her outstanding balance (and is therefore paying on time).

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[7] A variety of papers have examined credit card interest rates based on search costs including Ausubel, (1991), Calem and Mester (1995) and Berlin and Mester (2004).

[8] We recognize that geographical closeness is not necessarily a principal factor in determining card choice. For example, a consumer in North Dakota may choose Citigroup over a small local provider based on card price, name familiarity and other characteristics.

Conditional on the outcomes of the first income shock, consumers receive a second income shock. The second conditional income shock is also drawn from binomial distribution $\{L_2, H_2\}$ with respective probabilities $\Pr(L_2) = q$ and $\Pr(H_2) = 1 - q$, where $L_2 > 0,\ H_2 < 0$ and $|H_2| \gg |H_1|$. When a consumer receives a positive income shock L_2 she will *not* default on her credit card payment. However, when she receives a negative income shock H_2 she will default on her credit card payment.

If the outcome of the first income shock is L_1, see Figure 2, then the value of the conditional probabilities are $\left(\Pr(L_2 \mid L_1) = 1\right)$ and $\left(\Pr(H_2 \mid L_1) = 0\right)$. This implies that the chance of default is zero. However, if the outcome of the first income shock is H_1 then the value of the conditional probabilities are $\left(\Pr(L_2 \mid H_1) = \mu\right)$ and $\left(\Pr(H_2 \mid H_1) = (1-\mu)\right)$ such that $1 > \mu > 0$[9].

Accordingly, there are three, mutually exclusive, possible outcomes: (1) a consumer pays her credit card balance on time (with probability $1-\phi$), (2) a consumer delays on her credit card payment (with probability $\phi\mu$) and (3) a consumer defaults on her credit card payment (with probability $\phi(1-\mu)$). We assume there is no uncertainty about the distribution of shocks in the economy and that consumers are endowed with income ***y*** before they make their purchasing decisions. In our model, the consumer's choice of credit card purchases is determined by her expected income.

We assume consumers have a quadratic utility function for the demand for credit card debt. An advantage of this assumption is that it is consistent with the consumer

[9] Accordingly, $\Pr(L_2) = q = \Pr(L_2 \mid L_1).\Pr(L_1) + \Pr(L_2 \mid H_1).\Pr(H_1) = 1.(1-\phi) + \mu.\phi$. This shows the dependence of the two sequential income shocks.

demand for credit card debt being a decreasing function of income. This is because the quadratic utility function displays increasing absolute risk aversion (Huang and Litzenberger (1988)). Furthermore, Sarangi and Verbrugge (2000) use a similar utility function to examine late fees for video rentals. Accordingly, we assume the following utility function[10]:

$$u_j(x_j) = \begin{cases} ax_j - \frac{1}{2}x_j^2 - P_j - r_j x_j & \text{if outstanding balance NOT paid on time and} \\ & \text{NO default (i.e. a penalty fee is paid)} \\ ax_j - \frac{1}{2}x_j^2 - kx_j & \text{if outstanding balance NOT paid on time and} \\ & \text{DEFAULT (i.e. NO penalty fee is paid)} \\ ax_j - \frac{1}{2}x_j^2 - cx_j & \text{if outstanding balance paid on time,} \end{cases} \tag{1}$$

where x_j is the dollar value of purchases that are financed by a credit card issued by bank j $(j = A, B)$, P_j is a fixed penalty late/over-limit[11] fee that is charged by bank j, r_j is the interest rate charged by bank j, c denotes the random utility cost of paying the credit card outstanding balance on time and k is the random net utility cost of defaulting, e.g. the cost of the inability to borrow in the future, and a is a fixed coefficient, such that $a > 0$. Consumers must make their purchasing decisions before the realization of the income shock. Accordingly, the consumer's expected utility from financing her purchases using the credit card is:

$$E[u_j(x_j \mid \phi, \mu)] = ax_j - \tfrac{1}{2}x_j^2 - \phi\mu P_j - \phi\mu r_j x_j - (1-\phi)cx_j - \phi(1-\mu)kx_j. \tag{2}$$

The Timing of the game:

- At stage one, at the beginning of time period one, banks set prices for their credit card service, i.e. interest rates and penalty fees.

[10] Our specification of a consumer utility function is similar to the Sarangi and Verbrugge (2000) video market model. Other specifications of utility functions, e.g. natural log of intertemporal consumption provide qualitatively similar results but complicate the analysis and the presentation.

[11] For simplicity we assume the bank charges the same penalty fee for either being late or going over limit. In reality this is frequently the case.

- At stage two, given their location and the vector of prices set by each bank, each consumer chooses a bank at which to obtain a credit card.
- At stage three, each consumer decides her use of the credit card (i.e. expenditures), given prices and her expectation of income.

Equilibrium:

We solve for equilibrium outcomes recursively, beginning with the choice of a consumer to finance her $x purchases using her credit card.

Stage three: The optimal solution to the consumer's problem is given by[12]:

$$x_j^* = a - \phi\mu r_j - \phi(1-\mu)k - (1-\phi)c. \qquad (3)$$

Stage two: At this stage, consumers choose where to obtain the credit card. A consumer located at ***d*** who obtains a credit card at bank ***A,*** expects at the next stage to receive expected utility:

$$E[U_A(x_A^* \mid d)] = M + E[u(x_A^* \mid \mu, \phi)] - T(d). \qquad (4)$$

If she sets up a bank account at bank *B*, instead, she expects to receive expected utility:

$$E[U_B(x_B^* \mid d)] = M + E[u(x_B^* \mid \mu, \phi) - T(1-d)]. \qquad (5)$$

The location of the consumer, d_A, who is indifferent between obtaining a credit card from banks A and B is:

$$d_A = \frac{E[u(x_A^* \mid \mu, \phi)] - E[u(x_B^* \mid \mu, \phi)] + T}{2T}. \qquad (6)$$

[12] Given that $a > \phi\mu r_j + \phi(1-\mu)k + (1-\phi)c$.

Consumers who are located closer to bank *A* than d_A optimally choose to obtain a credit card from bank *A* and those located closer to *B* obtain a credit card from bank *B*, see Figure 1. The total number of consumers who obtain a credit card from bank *j* is

$$N_A = 2d_A \qquad N_B = 2(1-d_A) \tag{7}$$

Stage One: Bank *j's* expected profit is: [13]

$$E[\pi_j(P_j, r_j \mid x_j^*, \mu, \phi)] = \mu\phi N_j\left(P_j + r_j x_j^* - \eta\right) - (1-\mu)\phi N_j\left(\psi_1 + x_j^*(1+\psi_2)\right) + (1-\phi)N_j x_j^*\delta, \tag{8}$$

where η is the marginal cost of providing a credit service to credit card holders, ψ_1 is the fixed legal cost and administrative costs related to defaulting consumers, ψ_2 is the marginal costs related to defaulting consumers (this includes the marginal cost of providing the credit card service) and δ is the marginal cost/profit from providing the credit card service for card holders who pay, in full, their balance on time. The first term in equation (8) is bank *j's* expected profit from those consumers who do not pay their outstanding balances on time. The second term is bank *j's* expected losses from consumers who default on their card payments. The last term is bank *j's* expected profits/losses from consumers who pay their outstanding credit card balance on time.

Equilibrium solution

To solve for equilibrium outcomes we derive the first order conditions for profit maximization and then solve for the pricing outcomes[14].

[13] Here for presentation purposes we assume the costs functions for the two banks are the same, however, all results are robust if we relax this assumption by considering a case in which one Bank has lower costs related to credit card service, e.g. cost of funds or administrative cost are lower.

[14] The analysis was conducted using Mathematica.

The first order conditions for profit maximization with respect to bank *j's* strategic pricing choices: i.e. card penalty fees (P_j) and card interest rates (r_j) are:

$$\frac{\partial E(\pi_j)}{\partial P_j} = \mu\phi \frac{\partial N_j}{\partial P_j}\left(P_j + r_j x_j^* - \eta\right) + \mu\phi N_j - (1-\mu)\phi \frac{\partial N_j}{\partial P_j}\left(\psi_1 + x_j^*(1+\psi_2)\right) + (1-\phi)\frac{\partial N_j}{\partial P_j}\delta x_j^* = 0 \tag{9}$$

$$\frac{\partial E(\pi_j)}{\partial r_j} = \left\{\begin{array}{l} \mu\phi \frac{\partial N_j}{\partial r_j}\left(P_j + r_j x_j^* - \eta\right) + \mu\phi N_j \left(x_j^* + r_j \frac{\partial x_j^*}{\partial r_j}\right) - (1-\mu)\phi \frac{\partial N_j}{\partial r_j}\left(\psi_1 + x_j^*(1+\psi_2)\right) \\ -(1-\mu)\phi N_j \frac{\partial x_j^*}{\partial r_j}(1+\psi_2) + (1-\phi)\frac{\partial N_j}{\partial r_j}\delta x_j^* + (1-\phi)N_j \delta \frac{\partial x_j^*}{\partial r_j} = 0 \end{array}\right\}, \tag{10}$$

where $\frac{\partial N_j}{\partial P_j} = \frac{-\phi\mu}{T}$, $\frac{\partial N_j}{\partial r_j} = \frac{-\phi\mu}{T}\left(a - \phi(1-\mu)k - (1-\phi)c - \phi\mu r_j\right)$, $\frac{\partial x_j}{\partial r_j} = -\phi\mu$, and $\frac{\partial x_j}{\partial P_j} = 0$. We solve equations (9) and (10) for the equilibrium values of P_j and r_j, where $j = A$ and B. Proposition 1 summarizes the equilibrium outcomes.

Proposition 1: *Equilibrium always exists and the equilibrium is symmetric. In equilibrium,*

- *The interest rate (r_j) that banks charge to credit card holders for carrying a positive outstanding balance is:*

$$r_j = \frac{(1-\mu)}{\mu} + \frac{(1-\mu)}{\mu}\psi_2 - \frac{(1-\phi)}{\phi\mu}\delta. \tag{11}$$

- *The Penalty fee (P_j) for being late or for going over limit is:*

$$P_j = \frac{T}{\phi\mu} + \eta + \frac{(1-\mu)}{3\mu}\psi_1. \tag{12}$$

- *The dollar value of purchases financed using credit cards (x_j^*) is*

$$x_j^* = a - \phi(1-\mu)\left(1+\psi_2\right) + (1-\phi)\delta - \phi(1-\mu)k - (1-\phi)c. \qquad (13)$$

The equilibrium outcome and the comparative static predictions of the model are next reflected in the four hypotheses specified in section II. B. below:

II.B. HYPOTHESES

H1. The Risk Pricing Hypothesis:

The penalty fee and the interest rate charged on the outstanding balances of the credit card are positively related to default risk, $\frac{\partial P_j}{\partial(1-\mu)} > 0$ and $\frac{\partial r_j}{\partial(1-\mu)} > 0$ [15].

Here default risk is measured by the second income shock in our model. That is the shock that increases default risk.

H2. The Substitution Hypothesis:

The model predicts that credit card interest rates and penalty fees are substitutes since $\frac{\partial r_j}{\partial P_j} < 0$.

H3. The Average Income Hypothesis:

A marginal increase in an income shock that makes the average customer wealthier (an increase in $1-\phi$, which, in turn, increases the probability of paying the outstanding balance on time) has a positive effect on penalty fees, $\frac{\partial P_j}{\partial(1-\phi)} > 0$.

More specifically, the hypothesis implies that bank credit card price discrimination is more severe when banks operate in markets where the average consumer is wealthier.

[15] Given that $\delta \le 0$.

H4. The Market Share Hypothesis:

Banks with Larger market share charge higher fixed fees. Specifically, a direct extension of the basic model above predicts that banks with greater market share charge a higher fixed penalty fee. This extension is shown in Appendix A of the paper. In this extension, we allow Bank A to have greater market share than Bank B (Bank A has 2 branches in comparison to the 1 branch of the bank B). It is shown there that Bank A (which has the larger market share) charges higher fixed penalty fees.

II.C. ENDOGENEITY

In addition to these hypotheses, the theoretical model has important implications for the way we structure our empirical tests. The endogenous variables in the theoretical model are: the bank's optimal choice of two card prices (interest rates and penalty fees); the consumer's optimal choices of credit card provider (which determine each bank's market share); and the consumer's optimal choice of the dollar amount of the loan and the dollar amount of default (which determines the bank's default/loan ratio). Thus penalty fees, interest rates, market share and the default/loan ratio are treated as endogenous in our empirical tests below [16].

III. DATA SOURCES, METHODOLOGY AND EMPIRICAL RESULTS

III.A. DATA SOURCES

In this section we discuss the data used to test the four hypotheses specified above. We first describe the endogenous variables from the above model (card penalty

[16] Stango (2000) also argues that bank losses from credit card default and bank market share are endogenous.

fees, card interest rates, bank market share and bank default/loan ratio) and then the exogenous control variables (systematic impacts on consumer default rates, average consumer income levels, open market interest rates etc.).

ENDOGENOUS VARIABLES

III.A.a. Credit Card Pricing (Penalty Fees and Interest Rates)

For data on credit card penalty fees and interest rates, we use the twice yearly survey undertaken by the Federal Reserve. This survey (called "Terms of Credit Card Plans" or TCCP) has data from 1990 to 2002 and covers approximately 150 banks per survey. In this survey, each bank reports on the card specific details of its most popular credit card[17]. These details include pricing variables (interest rate, late fee, overlimit fee) details of the characteristics of the card (gold/standard, Visa/MasterCard), geographic/market size variables (the specific US states where each card is marketed) as well as a large variety of other variables related to the benefits available to users of the card (insurance discounts, travel rewards, rebates, extended warranty etc…). The data set is an unbalanced panel, since some bank cards appear in different bi-annual surveys while others do not. In total there are 2, 592 usable data points in the sample.

An important institutional factor concerning card penalty fees is that it is common practice for most banks that issue multiple credit cards, to charge the same overlimit fees and the same late fees for all of their different credit cards[18]. Thus the overlimit fee and late fee data, as reported by the TCCP, on each bank's most popular card can be

[17] The TCCP database does not provide information on the number of cards issued by provider.

[18] We are grateful to Mark Furletti of the Payments Card Center of the Philadelphia Federal Reserve for pointing this institutional factor out to us.

considered to represent the penalty fees charged on all the cards issued by that particular bank.

III.A.b. Consumer Loan and Default Choices (Chargeoff Ratio)

Our theoretical model examines the link between consumer choices (regarding amount of card loans and whether or not to default) and penalty fees. Our empirical proxy for these choices is the credit card default/loan ratio. The default/loan ratio is the standard metric used in the banking industry (Furletti (2003b)) to measure bank specific risk due to the loan and default choices made by the consumers of that bank.

Following Furletti (2003b) our proxy measure of a bank's default/loan ratio is its credit card chargeoff/credit card receivables ratio[19]. This variable is calculated from banks Report of Condition and Income (Call Reports), which are matched with the TCCP survey data by using bank specific (FDIC code numbers) attached to both data sources. The chargeoff ratio has also been widely used in the literature on credit cards as a measure of the default loss associated with a particular bank's credit card portfolio (e.g. Ausubel (1991), Stavins (2000), Stango (2000), Stango (2002), etc)[20].

[19] An issue relating to the use of the chargeoff ratio as a measure of risk, concerns the effects of credit card receivable securitization, (see Furletti (2003b)). Our measure of risk (credit card chargeoffs on the income statement, divided by total credit card receivables remaining on the balance sheet after securitization) is an appropriate measure of the credit card risk "retained" by each individual bank assuming that those credit card loans are securitized without recourse. Furletti (2003b) also describes how in the period from 1991 to 2000 (covering most of our sample period), there is a very high correlation between aggregate on-balance-sheet chargeoffs and off-balance-sheet (securitized) chargeoffs on credit card loans.

[20] Furletti (2003b) describes in detail the importance of the chargeoff ratio as a measure of loss in the credit card industry, as well as the method of its calculation. Our measure of the chargeoff ratio matches the method described by Furletti (2003b). Furthermore, in the FDIC Call Report data, both the series on credit card chargeoffs as well as credit card receivables are reported in "year to date" format. Because we have to match our Call Report data with the TCCP data (which is twice annual data based on surveys in January and July), we standardize our data so that all FDIC data is for a full calendar year, ending on the date of the TCCP survey (either January or July). We also take into account bank mergers as well as the fact that some banks have international credit card portfolios.

III.A.c. Bank Market Share

Our empirical proxy for the credit card market share for each bank is each bank's total credit card receivables per year (taken from FDIC call report balance sheet data) divided by the total credit card receivables in the US for that year (The Card Industry Directory, various years). The reason we use total US receivables as the denominator in our market share variable is that since the Marquette Supreme Court decision of 1978, interstate-banking restrictions have essentially been eliminated on card provision. The credit card market can thus legally be considered a national market, with banks facing no legal barriers to entry into the national market (even though some banks still choose to market their cards in a subset of states only and in some cases a single state only). It is important to note that in this paper we only focus on the impact of the size of a bank as measured by its market share[21].

Further evidence to support our nationally based measure of market share can be seen by examining the TCCP database. This database reports the interest rate and fees that banks charge for the same credit card across the different states where each card is marketed. The TCCP database shows that all banks charge the same interest rates and penalty fees for each particular card across *all* the states where it is marketed. If the credit card market was regionally segmented then the data would have shown the same card with different prices in different regions or states[22].

An alternative argument against our national definition of market share is that the market could be segmented across banks based on customer risk (i.e. separate markets for high and low risk borrowers). We argue however, that any such risk based market

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[21] As is well known in the IO literature, the issue of market power is subject to significant measurement difficulties (Office of Fair Trading, UK Government (1999)).

[22] Because the data shows that specific cards have the same fees across states, the variability in our data occurs because different cards are marketed in very different combinations of states in different times.

segmentation is porous, both at the bank level as well as the consumer level. At the bank level many of the largest credit card issuers are active in both the high and low risk markets[23], for example Chase, Citibank and MBNA[24]. At the consumer level, it can also be argued that based on their income shocks, individual consumers can face rapid changes in their risk profiles, which would impact their access to different types of cards (high or low risk) over time. For these reasons, when considering bank market share, we argue that it is preferable to consider the credit card market as a single national market, and not a segmented market based on risk.

EXOGENOUS VARIABLES

III.A.d. Income Shocks and Default Risk

In order to test our hypotheses, we require a measure of exogenous systematic income shocks that impact a consumer's probability of default, $(1-\mu)$ in our theory model, see Figure 2. As described in our model, such shocks determine the probability of the consumer defaulting. Our proxy for consumer default risk is consumer bankruptcy filings per capita in the appropriate geographical area where each card is made available in each year. For each card in the TCCP credit card database, we know specifically which of the various US states the card is marketed and made available. For example, bank 1 may market its credit card in one state (e.g. New York), bank 2 may market its card in some states (e.g. California, Washington and Oregon) and bank 3 may market its card in all 50

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[23] The high-risk market is often called the market for "sub-prime" borrowers.

[24] We are grateful to Mark Furletti of the Payments Card Center of the Philadelphia Federal Reserve for pointing this institutional factor out to us.

states (i.e. nationally)[25]. Because we have data on which states each card for each bank is made available in, we are able to match the TCCP data with data on state level bankruptcy per capita, provided by the American Bankruptcy Institute. If a card is made available in, say, three states, then we measure the number of consumer bankruptcy filings in those three states and determine an average weighted by each state's population (i.e. average bankruptcies per capita). This generates an average level of bankruptcy applicable for each card. We use the American Bankruptcy Institute's measure of consumer bankruptcies rather than business bankruptcies for each US state for each year. The state level bankruptcy per capita variable can be considered to be exogenous, since it is unlikely that any individual bank's card pricing activities alone can significantly impact a state (or multi-state or national) level of the default risk measure.

III.A.e. Average Consumer Income

In the average consumer income hypothesis above (H3) we argued, based on our model, that the higher the *average* expected income of consumers, the higher are penalty fees. In order to test this hypothesis we use, as a proxy, a measure of the average state level income per capita for the specific states in which each card is marketed. In effect, this variable measures whether borrowers in poorer states pay higher (or lower) penalty fees than those in higher income states[26]. In calculating the state income (GDP) per capita variable, we use the same approach described above for determining state bankruptcies per capita – i.e. an average of state income for the relevant states where each credit card

[25]It should be noted that this geographical area only concerns the States where a card will be marketed and issued by a particular bank, but it does not affect the area where the consumer can use the card. Most US credit cards have no restrictions on whether the consumer can use the card nationally or even internationally.

[26] Because our data is based on state income levels, we cannot comment on how fees impact consumers of different income levels within a state.

is marketed, weighted by the state's population. These data were collected from Bureau of Economic Analysis statistics.

III.A.f. Other Control Data

We also include a large number of other control variables in our empirical models. A large amount of credit card specific data is made available from the same TCCP database. These data include the characteristics of the card (e.g. Gold/standard and Visa/MasterCard), as well as a large variety of benefits made available to consumers who own the card (e.g. rebates, insurance, discounts, warranty extension, whether an introductory interest rate is offered etc.).

Our final control variable is the average 1year CD rate. We use the same twice-yearly CD rate for all banks in each twice-yearly TCCP sample. The 1year CD rate can be considered as the measure of the marginal cost of open market funds for the credit card issuing banks.

III.B. ECONOMETRIC METHODOLOGY:

Our model has four endogenous variables (card penalty fees, card interest rates, card chargeoff ratio and card market share). In order to estimate this model, we use two stage least squares (2SLS), three stage least squares (3SLS) and generalized methods of moments (GMM) estimation. In order to verify the robustness of our results, we provide estimates based on all three of these methodologies (2SLS, 3SLS and GMM).

An additional issue concerns the two different types of credit card penalty fee we examine in this study – late fees and overlimit fees. For two reasons, we do not include both as endogenous variables in the *same* system of equations (i.e. having a system with *five* endogenous variables – late fee, overlimit fee, interest rate, chargeoff ratio and market share). The first reason is that our data on late fees runs for 12 years from 1990 to 2002, while our data on overlimit fees runs for only 6 years (from 1996 to 2002). Thus, by including both overlimit and late fees in the same equation system, we would lose half our dataset. A second and more fundamental reason is that when data on both late and overlimit fees became available (after 1996) a simple OLS regression between them over the 1996-2002 period resulted in a slope coefficient of 0.98 with a t-statistic of 208.6. In other words, the dollar levels of each of these two penalty fees tend to be highly similar for each bank-time data point. For example, as noted in the introduction, Chase Manhattan bank in 1998 charged a $20 overlimit fee and a $20 late fee while in 2002 it charged a $28 overlimit fee and a $28 late fee. For these reasons, in all our tests below we run two separate equation systems, with either late fees or alternatively overlimit fees as one of the four endogenous variables in the system.

In terms of the 2SLS and 3SLS methodologies, we specify a system, which has four endogenous variables (equations 14 to 17 below). The four endogenous variables are the credit card penalty fee ($P_{j,t}$), the credit card interest rate ($r_{j,t}$), the bank specific chargeoff ratio ($ov_{j,t}$) and the credit card market share ($m_{j,t}$). Exogenous variables include bankruptcies per capita ($rup_{j,t}$) and average income per capita ($inc_{j,t}$), both measured over the appropriate geographic area where each card is marketed. We also include in the equations, a vector Z of card, bank and market specific control variables, which are described above. Finally T is a vector of time fixed effects for each of the twice-yearly TCCP sample dates, in order to control for the possible time trends in these data.

$$P_{j,t} = \alpha_1 + \beta_1 r_{j,t} + \beta_2 ov_{j,t} + \beta_3 m_{j,t} + \beta_4 inc_{j,t} + \beta_4 rup_{j,t} + \beta_5 Z + \beta_6 T + \varepsilon_j, \tag{14}$$

$$r_{j,t} = \alpha_2 + \omega_0 P_{j,t} + \omega_2 ov_{j,t} + \omega_3 m_{j,t} + \omega_4 inc_{j,t} + \omega_4 rup_{j,t} + \omega_5 Z + \omega_6 T + e_j, \tag{15}$$

$$ov_{j,t} = \alpha_1 + \chi_0 P_{j,t} + \chi_1 r_{j,t} + \chi_3 m_{j,t} + \chi_4 inc_{j,t} + \chi_4 rup_{j,t} + \chi_5 Z + \chi_6 T + \eta_j \quad \text{and} \tag{16}$$

$$m_{j,t} = \alpha_4 + \gamma_0 P_{j,t} + \gamma_1 r_{j,t} + \gamma_2 ov_{j,t} + \gamma_4 inc_{j,t} + \gamma_4 rup_{j,t} + \gamma_5 Z + \gamma_6 T + \psi_j \tag{17}$$

In general, 3SLS may be asymptotically superior to 2SLS because a complete system is estimated simultaneously. However a problem with 3SLS, relative to 2SLS, is that any specification error in any part of the system will impact the whole system. Furthermore, if there is hetroskedacity in the data, then the GMM estimator can be considered a superior estimator (see Greene (2003)).

Thus, in addition to our 2SLS and 3SLS systems we also estimate a single equation GMM-Instrumental Variable estimator. The GMM-Instrumental Variable model is a single equation model that not only includes the dependent variable as endogenous, but also can include other variables as endogenous, which are instrumented for by other exogenous variables in the system (in this case bankruptcies per capita ($rup_{j,t}$), average income per capita ($inc_{j,t}$), the control variables in the Z vector described above, as well as the time fixed effects in the T vector). In the context of this paper, we are interested in a model with penalty fees (in both the late fee and the overlimit fee specifications) as a dependent variable but which also has interest rates, chargeoffs and market share as endogenous. This model has the following form:

$$P_{j,t} = \alpha_1 + \beta_1 r_{j,t} + \beta_2 ov_{j,t} + \beta_3 m_{j,t} + \beta_4 inc_{j,t} + \beta_4 rup_{j,t} + \beta_5 Z + \beta_6 T + \varepsilon_j. \tag{18}$$

This single equation model (equation 18) has the same basic format and variables as equation (14), the first equation is the system above, with penalty fees as the dependent variable.

III.C. RESULTS

Table 1 reports the descriptive statistics for the variables we use in our tests. We report results for models with either late fees or overlimit fees as an endogenous variable. The late fees results are in Tables 2 (2SLS), 3 (3SLS) and 6 (GMM). The overlimit fees results are in Tables 4 (2SLS), 5 (3SLS) and 6 (GMM). The four key hypotheses derived from our model concern the impact of four possible determinants (consumer risk of default, market interest rates, bank market share and consumer income) on credit card penalty fees. The results for these four hypotheses are discussed in turn below.

III.C.a. Risk Pricing Hypothesis (H1)

The risk pricing hypothesis is tested by examining the impact of the bankruptcy per capita variable on penalty fees. In terms of the current public policy debate, this hypothesis reflects the argument of the American Bankers Association that credit card penalty fees reflect the additional risk borne by banks. As can be seen in Tables 2 to 6, this variable is significant and positive, across all three of our econometric specifications (2SLS, 3SLS and GMM) and across both the penalty fee variables (late fees and overlimit fees). In other words these results are highly consistent with both the theoretical prediction of our model above, as well as the public policy stance of the American Bankers Association.

Besides the statistical significance of the bankruptcy per capita variable on penalty fees, it is also possible to determine its economic significance – i.e. by how much does the bankruptcy per capita variable influence credit card penalty fees charged by banks. Our estimated coefficients for this variable in the different models in Tables 2 to 6 range from 53,466 to 114,444. A one standard deviation increase in bankruptcy per capita leads to an increase in penalty fees ranging from $0.62 to $1.31 depending on which econometric specification is chosen. These values can be compared to the mean levels of penalty fees in our sample (mean late fee is $14.68 and mean overlimit fee is $17.54)[27]. Clearly therefore, exogenous systematic forces which impact consumer default/repayment behavior have both a statistical as well an economic impact on the penalty fees set by banks.

In addition to examining the impact of bankruptcy per capita on penalty fees, we can also examine empirically the impact of the chargeoff ratio on penalty fees, which captures the impact of bank specific risk (Furletti (2003)). We find that the chargeoff ratio variable is highly significant and positively signed in explaining penalty fees in all of our reported results, across both types of penalty fee and all three econometric methodologies. In other words, the greater the bank specific risk as measured by the chargeoff ratio (Furletti (2003), the higher the penalty fees charged by that bank.

In terms of the economic impact of the chargeoff ratio on penalty fees, our estimated coefficients in the different late fees models ranged from 7256 (3SLS) to 12630 (GMM), where penalty fees are measured in cents. A one standard deviation change in the chargeoff ratio will impact late fees in a range of $4.35 to $7.57 depending on

[27] Note that the means for late fees and overlimit fees are somewhat different because late fee data runs from 1990 to 2002, while the overlimit fee data runs from 1996 to 2002.

econometric methodology. Given that the mean level of late fees in our sample is $14.68, the impact of chargeoff ratio risk on late fees is clearly economically significant. Our estimated coefficients for the impact of the chargeoff ratio on overlimit fees are broadly similar.

III.C.b. Substitution Hypothesis (H2)

The substitution hypothesis predicts that card penalty fees and card interest rates are substitutes – i.e. higher credit card interest rates would have a negative impact on the size of penalty fees and vice versa. As in the case of the risk pricing hypothesis above, empirical evidence in favor of this hypothesis would support the case of those bankers arguing against increased regulation of credit card penalty fees, because substitution implies that card issuers avoid increasing both penalty fees and interest rates simultaneously.

In Tables 2 to 6 we show that the credit card interest rate variable has a significant and negative effect on penalty fees across all of our econometric specifications (2SLS, 3SLS and GMM) and across both types of penalty fee (late fees and overlimit fees).

In terms of economic significance, we find that the coefficient on the interest rate term in the different penalty fee models ranges from –0.78 (GMM overlimit fee model) to –4.4 (3SLS overlimit fee model). The interest rate is measured in basis points and the late fee is measured in cents, thus the impact of a 1 basis point reduction in card interest rates will result in an increase in penalty fees of between 0.88 and 4.11 cents. Given that in our sample the mean interest rate charged is 1633 basis points (or 16.33%) and the standard deviation is 273 basis points (or 2.73%), interest rates are clearly economically significant in impacting penalty fees. For example, a one standard deviation increase in credit card interest rates (i.e. 273 basis points) reduces late fees by at least $2.40 based on the coefficients from our different models.

III.C.c. Average Income Hypothesis (H3)

The average income hypothesis predicts that as the average income of its credit card consumers rises, the card providing bank will increase its penalty fees. If we find that banks in wealthier states charge higher penalty fees, then in terms of public policy implications we can conclude that banks are not systematically charging higher penalty fees to borrowers in poorer states, which is contrary to the assertion of many consumer activists.

Our results in Tables 2 to 6 show that the coefficient on the state income level per capita variable is positive and significant in all three of the late fee models, while it is significant and positive in only one of the three overlimit fee models. Thus, these results (while not being conclusive for the overlimit fee models), do provide some evidence in support of this hypothesis. In terms of the economic significance of our models, the estimated coefficients on those average income variables that are significant range from 0.035 to 0.052. This implies that a one standard deviation increase in the average per capita income in those states where each card is marketed will increase the penalty fee charged by between $1.16 and $1.73, depending on which econometric specification is chosen.

III.C.d. Market Share Hypothesis (H4)

The market share hypothesis predicts that banks with greater market share will be able to use that market share to charge higher penalty fees and thus extract rents. This hypothesis clearly has important public policy implications given the concern of regulators over increasing concentration in banking in general and in the credit card market in particular.

Our results in Tables 2 to 6 provide no support for this hypothesis for overlimit fees and little support for late fees (in only one of our three reported late fee models is the market share term significant). Thus, on the whole our results do not support the public policy position of those who would like to regulate credit card penalty fees because of issues relating to the market share of credit card providers.

III.D The Determinants of Credit Card Interest Rates

While the focus of this paper has been on the determinants of penalty fees, our 2SLS and 3SLS methodologies also allow us to use our data to examine the determinants of credit card interest rates. Our results in Tables 2 to 5 indicate that, as in the case with penalty fees, both our measures of risk (chargeoff ratio and bankruptcy per capita) are significant determinants of credit card interest rates. However, unlike the case of credit card fees, we also find that market share is significant in explaining interest rates, which implies that larger banks charge higher credit card interest rates. While both our risk measures are clearly significant for both penalty fees as well as interest rates, the fact that market share is also significant for explaining interest rates indicates that our results are inconsistent with the views of the banks that credit card pricing (both penalty fees and interest rates) is *only* a result of risk pricing.

IV. CONCLUSIONS

This paper examined, theoretically and empirically, the determinants of credit card penalty fees (i.e. late fees and overlimit fees). This is the first paper in the literature to examine this topic, even though the issue of credit card penalty fees has become very prominent in public policy debates. As part of his 2004 Presidential campaign, for example, John Kerry called for these fees to be regulated because they were "abusive". The American Bankers Association (ABA) responded that such penalty fees are charged by banks to compensate for consumer default risk. The debate between Senator Kerry and the ABA revolves around the extent to which the credit card market resembles standard descriptions of debt markets, (i.e. that debt pricing reflects default risk). Until now, however, no formal study has been undertaken to examine this issue.

We developed a theoretical model that captures important features of credit card markets and provides predictions about whether credit card penalty fees are related to default risk, credit card interest rates, income and market share. We tested these theoretical predictions using credit card level panel data across a large sample of credit cards from different US banks over time. The Federal Reserve's twice yearly "Terms of Credit Card Plans" survey provided data on credit card penalty fees, card interest rates and other card characteristics. In order to test the impact of default risk on credit card fees, we used (1) bank level risk of credit card default as measured by the chargeoff ratio from each bank's balance sheet, (from the FDIC), and (2) an exogenous measure of default risk as measured by bankruptcies per capita in the specific states where each card was marketed.

Overall, we find that card penalty fees do reflect the risk of consumer default and that these penalty fees are negatively related to card interest rates. Moreover, there is no strong evidence that banks with a large credit card market share charge higher penalty fees than those with a lower market share and, that higher penalty fees are charged to consumers from poorer states. We do, however find evidence that credit card interest rates are related to both risk of consumer default as well as market share. Importantly, many of these results are robust across a number of econometric specifications including 2SLS and 3SLS and GMM. In sum, our evidence supports the view that credit card penalty fees are significantly related to consumer default risk.

APPENDIX A

In this Appendix we explore how pricing of credit card services differs across banks of different market share (see hypothesis 4 in section II.B). We modify our model in the simplest way. The bank with larger market share (Bank A) has two branches while the other bank (Bank B) has only one branch. Accordingly, Bank A's branches are located at 0 and 4/3 and bank B's branches are located at 2/3 on the 2 unit circle. The other features of the model remain the same and the setup of the economy mirrors that of the homogeneous bank framework. Different bank sizes lead to asymmetries in bank strategies

Equilibrium:

Similar to our basic model, we solve for equilibrium outcomes recursively, beginning with the choice of a consumer to finance her $x purchases using her credit card.

Stage three: The optimal solution to the consumer's problem is given by:

$$x_j^* = a - \phi\mu r_j - \phi(1-\mu)k - (1-\phi)c. \tag{A.1}$$

Stage two: At this stage, consumers choose where to obtain the credit card. A consumer located at ***d*** who obtains a credit card at bank ***A,*** expects at the next stage to receive expected utility:

$$E[U_A(x_A^* \mid d)] = M + E[u(x_A^* \mid \mu, \phi)] - T(d). \tag{A.2}$$

If she sets up a bank account at bank *B*, instead, she expects to receive expected utility:

$$E[U_B(x_B^* \mid d)] = M + E[u(x_B^* \mid \mu, \phi)] - T\left(\tfrac{2}{3} - d\right). \tag{A.3}$$

The location of the consumer, d_A, who is indifferent between obtaining a credit card from banks A and B is:

$$d_A = \frac{E[u(x_A^* \mid \mu, \phi)] - E[u(x_B^* \mid \mu, \phi)]}{2T} + \frac{1}{3}. \qquad \text{(A.4)}$$

Consumers who are located closer to bank *A* than d_A optimally choose to obtain a credit card from bank A and those located closer to B obtain a credit card from bank B, see Figure A.1. The total number of consumers who obtain a credit card from bank *j* is

$$N_A = 2\left(d_A + \frac{1}{3}\right) \qquad \text{and} \qquad N_B = 2\left(\frac{2}{3} - d_A\right). \qquad \text{(A.5)}$$

Stage One: Bank *j's* expected profit is:

$$E[\pi_j(P_j, r_j \mid x_j^*, \mu, \phi)] = \mu\phi N_j\left(P_j + r_j x_j^* - \eta\right) - (1-\mu)\phi N_j\left(\psi_1 + x_j^*(1+\psi_2)\right) + (1-\phi)N_j x_j^*\delta, \qquad \text{(A.6)}$$

where η is the marginal cost of providing a credit service to credit card holders, ψ_1 is the fixed legal cost and administrative costs related to defaulting consumers, ψ_2 is the marginal costs related to defaulting consumers and δ is the marginal cost/profits from providing the credit card service to the customers who choose to pay their card outstanding balance, in full, on time. The first term is bank *j's* expected profit from consumers who do not pay their outstanding balances on time. The second term is bank *j's* expected losses from consumers who default on their card payments. The last term is bank *j's* expected profits/losses from consumers who pay their outstanding credit card balance on time.

Equilibrium solution

To solve for equilibrium outcomes we derive the first order conditions for profit maximization and then solve for the pricing outcomes[28].

The first order conditions for profit maximization with respect to penalty fees (P_j) and interest rate (r_j) are:

$$\frac{\partial E(\pi_j)}{\partial P_j} = \mu\phi\frac{\partial N_j}{\partial P_j}\left(P_j + r_j x_j^* - \eta\right) + \mu\phi N_j - (1-\mu)\phi\frac{\partial N_j}{\partial P_j}\left(\psi_1 + x_j^*(1+\psi_2)\right) + (1-\phi)\frac{\partial N_j}{\partial P_j}\delta x_j^* = 0, \tag{A.7}$$

$$\frac{\partial E(\pi_j)}{\partial r_j} = \left\{\begin{array}{l} \mu\phi\frac{\partial N_j}{\partial r_j}\left(P_j + r_j x_j^* - \eta\right) + \mu\phi N_j\left(x_j^* + r_j\frac{\partial x_j^*}{\partial r_j}\right) - (1-\mu)\phi\frac{\partial N_j}{\partial r_j}\left(\psi_1 + x_j^*(1+\psi_2)\right) \\ -(1-\mu)\phi N_j\frac{\partial x_j^*}{\partial r_j}(1+\psi_2) + (1-\phi)\frac{\partial N_j}{\partial r_j}\delta x_j^* + (1-\phi)N_j\delta\frac{\partial x_j^*}{\partial r_j} = 0 \end{array}\right\}, \tag{A.8}$$

where $\frac{\partial N_j}{\partial P_j} = \frac{-\phi\mu}{T}$, $\frac{\partial N_j}{\partial r_j} = \frac{-\phi\mu}{T}\left(a - \phi(1-\mu)k - (1-\phi)c - \phi\mu r_j\right)$, $\frac{\partial x_j}{\partial r_j} = -\phi\mu$, and $\frac{\partial x_j}{\partial P_j} = 0.$

For $j = A$ and B, we solve equations A.7 and A.8 for the equilibrium values of P_A, r_A, P_B, r_B. Proposition A.1 summarizes the equilibrium outcomes.

Proposition A.1*: An equilibrium always exists. In equilibrium,*

- *The difference in interest rate that banks charge to credit card holders for carrying a positive outstanding balance is:*

$$r_A - r_B = 0. \tag{A.10}$$

[28] The analysis was done using Mathematica.

- *The difference in the penalty fee for being late or for going over limit is:*

$$P_A - P_B = 0.22\ \frac{T}{\phi\mu}. \tag{A.11}$$

- *The dollar value of purchases financed using credit cards is*

$$x_A^* - x_B^* = 0. \tag{A.12}$$

- *The difference in market share of customers is*

$$N_A - N_B = 0.23. \tag{A.14}$$

In equilibrium, while the large Bank (Bank A, which has the larger market share) charges higher fixed penalty fees, both banks charge the same interest rate. The intuition behind this result is based on the relationship between the demand for credit card loans and two part pricing. A marginal increase in interest rates will lower the demand for credit card loans while a marginal increase in a fixed (quantity borrowed independent) penalty fee has no impact on the demand for credit card loans. Note that while the fixed penalty fee has no effect on consumers demand for credit card loans it plays a major role in choosing the credit card provider. Accordingly, banks with greater market share can extract rents more efficiently by increasing fixed penalty fees.

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Table 1: descriptive statistics

This Table includes descriptive statistics for the variables used in our analysis. These variables are taken from the following data sources: (1). Terms of Credit Card Plans (TCCP) twice annual survey from the Federal Reserve, (2). Call Reports bank balance sheet data from the FDIC, (3). Bankruptcy per Capita data from the American Bankruptcy Institute (4) CD Rate from the Federal Reserve. The TCCP survey has data from 1990 to 2002 which covers approximately 150 banks per survey twice annually, where each bank reports the card specific details of its most popular credit card.

Variable	Source	Obs	Mean	Std. Dev.	Min	Max
Overlimit Fee (cents)	Terms of Credit Card Plans	1,782	1,754.223	721.102	0	5,000
Late Fee (cents)	Terms of Credit Card Plans	2,969	1,468.108	720.976	0	5,000
Card Interest Rate (basis points)	Terms of Credit Card Plans	3,674	1,633.335	273.711	550	2,495
Market Share (Bank/ US Total Credit Card Receivables)	Call Reports/Card Industry Directory	3,415	0.003	0.007	0	0.066
Charge off Ratio (Credit Card Charge off/Receivables)	Call Reports	3,308	0.047	0.060	0.0004	0.964
Bankruptcy Average (filings per capita - State Weighted)	American Bankruptcy Institute	3,674	0.003	0.001	0.0001	0.011
State Income Per Capita ($ - State Weighted)	Bureau of Economic Analysis	3,674	20,080	3,334	12,395	35,113
National (all States) Market (Dummy)	Terms of Credit Card Plans	3,674	0.452	0.498	0	1
Regional (some states) Market (Dummy)	Terms of Credit Card Plans	3,674	0.321	0.467	0	1
State (single state) Market (Dummy)	Terms of Credit Card Plans	3,674	0.227	0.419	0	1
Premium/Gold Card (Dummy)	Terms of Credit Card Plans	3,674	0.067	0.253	0	2
Rebate on Purchases (Dummy)	Terms of Credit Card Plans	3,674	0.014	0.116	0	1
Extension of Manufacturer’s Warranty (Dummy)	Terms of Credit Card Plans	3,674	0.075	0.263	0	1
Purchase Protection (Dummy)	Terms of Credit Card Plans	3,674	0.080	0.271	0	1
Travel Accident Insurance (Dummy)	Terms of Credit Card Plans	3,674	0.284	0.451	0	1
Travel Discounts (Dummy)	Terms of Credit Card Plans	3,674	0.044	0.205	0	1
Car Rental Insurance (Dummy)	Terms of Credit Card Plans	3,674	0.109	0.312	0	1
Non-Travel Discounts (Dummy)	Terms of Credit Card Plans	3,674	0.020	0.140	0	1
Card Registration (Dummy)	Terms of Credit Card Plans	3,674	0.023	0.149	0	1
Other Plan Enhancements (Dummy)	Terms of Credit Card Plans	3,674	0.170	0.376	0	1
Visa Card (Dummy)	Terms of Credit Card Plans	3,674	0.645	0.479	0	1
Certificate of Deposit 1 year (Basis Points)	Federal Reserve	3,674	489.347	167.989	175	817
Reduced Introductory APR (Dummy)	Terms of Credit Card Plans	3,674	0.064	0.244	0	1

Table 2: Determinants Of Credit Card Late Fees **(2sls)** 1990-2002

Results from a 2SLS four equation system with the four endogenous variables derived from the theoretical model (Late Fees, Interest Rate, Chargeoff Ratio and Market Share). The full specification of the model is in equations (14) to (17). Our four hypotheses are all tested using estimated coefficients in the Late Fee equation (second column in bold). These include (i) the risk pricing hypothesis (model predicts positive relationship between bankruptcy per capita and late fees); (ii) substitution hypothesis (the model predicts a negative relationship between interest rates and late fees); (iii) average income hypothesis (the model predicts a positive relationship between state income and late fees) and (iv) market share hypothesis (the model predicts a positive relationship between market share and late fees).

Variables	Endogenous Variables			
	Late Fee	**Interest Rate**	**Chargeoff Ratio**	**Market Share**
Chargeoff Ratio	**7,770(3.49)*** **	1,454.99(6.42)***	----	-0.034(-4.54)***
Bankruptcy per Capita	**109,308(2.18)** **	22,527.49(3.00)***	-12.27(-2.74)***	-0.451(-2.32)**
Interest Rate	**-4.1(-2.86)*** **	----	0.00(8.28)***	1.66E-5(4.17)***
Market Share	**108,279.60(1.04)**	12,227.76(2.01)**	-10.144(-3.33)***	----
State Income	**0.05(2.20)** **	0.002(0.57)	-5.08E-06(-1.94)*	-1.55E-7(- 1.24)
Late Fee	**----**	0.04(0.42)	9.9E-05(3.66)***	5.13E-6(4.10)***
National Dummy	**-228.82(-0.48)**	-90.84(-2.71)***	0.026 (1.43)	0.003(4.60)***
Regional Dummy	**117.08(0.88)**	-13.94(-0.60)	-0.009(-0.8)	4.74E-5(0.10)
Premium Dummy	**-134.13(-0.92)**	-8.80(-0.34)	0.01 (0.67)	0.001(2.24)**
Purchase Rebate	**-126.15(-0.30)**	----	----	----
Warranty Extension	**443.92(1.91)* **	----	----	----
Purchase Protection	**-489.18(-1.30)**	----	----	----
Travel Insurance	**-135.28(-1.19)**	----	----	----
Travel Discounts	**334.45(-1.06)**	----	----	----
Car Rental Insurance	**-137.45(-0.58)**	----	----	----
Non-Travel Discounts	**31.72 (0.06)**	----	----	----
Card Registration	**-97.49(-0.39)**	----	----	----
Other Plan Enhancements	**-30.20(-0.14)**	----	----	----
Visa Dummy	**----**	26.75(1.11)	-0.011(-0.8)	-0.001(-2.17)**
Certificate of Deposit (1yr)	**----**	1.97(18.25)***	----	----
Reduced Introductory APR	**----**	-109.46(-2.27)**	----	----
State Income Growth	**----**	----	----	-1.29E-7(-0.16)
Constant	**6,662.74(2.77)*** **	dropped	-0.733(-6.97)***	-0.026(-3.55)***
Observations	**2592**	2592	2592	2592
Time Fixed Effects Included	**Yes**	Yes	Yes	Yes

* significant at 10%; ** significant at 5%; *** significant at 1%
t statistics in parentheses

Table 3: Determinants Of Credit Card Late Fees **(3sls)** 1990-2002

Results from a 3SLS four equation system with the four endogenous variables derived from the theoretical model (Late Fees, Interest Rate, Chargeoff Ratio and Market Share). The full specification of the model is in equations (14) to (17). Our four hypotheses are all tested using estimated coefficients in the Late Fee equation (second column in bold). These include (i) the risk pricing hypothesis (model predicts positive relationship between bankruptcy per capita and late fees); (ii) substitution hypothesis (the model predicts a negative relationship between interest rates and late fees); (iii) average income hypothesis (the model predicts a positive relationship between state income and late fees) and (iv) market share hypothesis (the model predicts a positive relationship between market share and late fees).

Variables	Endogenous Variables			
	Late Fee	**Interest Rate**	**Chargeoff Ratio**	**Market Share**
Chargeoff Ratio	**7,256.55 (4.07)*** **	1,754.61(13.23)***	----	-0.039(-6.04)***
Bankruptcy per Capita	**114,444.83 (2.82)*** **	26,154.82(3.57)***	-14.73(-3.36)***	-0.554(-2.93)***
Interest Rate	**-3.94(-3.81)*** **	----	5.0E-5 (13.22)***	2.03E-5(5.65)***
Market Share	**102,078.07 (1.44)**	29,442.07(5.92)***	-18.912(-7.07)***	
State Income	**0.047 (2.21)** **	0.009(2.07)**	-5.9E-06(- 2.35)**	-1.78E-7(-1.51)
Late Fee	**----**	-0.177(-3.33)***	0.0001(6.19)***	5.92E-6(5.29)***
National Dummy	**-207.58(-0.59)**	-93.67(-3.31)***	0.05(3.37)***	0.003(4.42)***
Regional Dummy	**95.67 (0.88)**	8.23(0.42)	-0.01(-0.67)	-8.92E-5(- 0.19)
Premium Dummy	**-114.96(-0.85)**	-28.99(-1.14)	0.02(1.26)	0.001(2.49)**
Purchase Rebate	**203.06 (1.06)**	----	----	----
Warranty Extension	**-140.30(-1.03)**	----	----	----
Purchase Protection	**271.59 (1.06)**	----	----	----
Travel Insurance	**-5.15(-0.28)**	----	----	----
Travel Discounts	**-180.96(-0.95)**	----	----	----
Car Rental Insurance	**-50.85(-0.83)**	----	----	----
Non-Travel Discounts	**268.74(-1.06)**	----	----	----
Card Registration	**-33.66(-0.86)**	----	----	----
Other Plan Enhancements	**102.22 (0.98)**	----	----	----
Visa Dummy	**----**	14.426(0.83)	-0.01(-0.8)	-0.001(-1.89)*
Certificate of Deposit (1yr)	**----**	1.97(18.69)***	----	----
Reduced Introductory APR	**----**	-23.57(-1.1)	----	----
State Income Growth	**----**	----	----	5.71E-7(0.55)
Constant	**6,439.18 (3.87)*** **	dropped	-0.87(-10.1)***	-0.032(-4.90)***
Observations	**2592**	2592	2592	2592
Time Fixed Effects Included	**Yes**	Yes	Yes	Yes

* Significant at 10%; ** significant at 5%; *** significant at 1%
z statistics in parentheses

Table 4: Determinants Of Credit Card Overlimit Fees **(2sls)** 1996-2002

Results from a 2SLS four equation system with the four endogenous variables derived from the theoretical model (Overlimit Fees, Interest Rate, Chargeoff Ratio and Market Share). The full specification of the model is in equations (14) to (17). Our four hypotheses are all tested using estimated coefficients in the Overlimit Fee equation (second column in bold). These include (i) the risk pricing hypothesis (model predicts positive relationship between bankruptcy per capita and overlimit fees); (ii) substitution hypothesis (the model predicts a negative relationship between interest rates and overlimit fees); (iii) average income hypothesis (the model predicts a positive relationship between state income and overlimit fees) and (iv) market share hypothesis (the model predicts a positive relationship between market share and overlimit fees).

Variables	Endogenous Variables			
	Overlimit Fee	**Interest Rate**	**Chargeoff Ratio**	**Market Share**
Chargeoff Ratio	**6,781.94(3.04)*** **	1,195.84(4.90)***	----	-0.026(-3.23)***
Bankruptcy per Capita	**95,675.00(1.91)***	1,386.92(0.11)	-11.551(-1.80)*	-0.348(-1.78)*
Interest Rate	**-4.10 (-2.48)****	----	0.0004(7.21)***	9.12E-6(2.74)***
Market Share	**-58,261.25(-0.18)**	14,085.11(1.94)*	-10.48(-2.36)**	----
State Income	**0.02(0.66)**	-0.01(-0.77)	-2.3E-6(-0.60)	-6.25E-8(-0.51)
Overlimit Fee	**----**	0.12(1.12)	9.7E-5(3.11)***	2.47E-6(2.19)**
National Dummy	**482.65(50.37)**	-111.97(-2.38)**	0.027(1.01)	0.003(5.42)***
Regional Dummy	**292.03(0.96)**	-31.99(-0.97)	-0.009(-0.51)	4.0E-5(0.89)
Premium Dummy	**-101.15(-0.49)**	1.20(0.03)	0.004(0.18)	3.0E-5 (0.49)
Purchase Rebate	**346.24(0.37)**	----	----	----
Warranty Extension	**198.26(0.58)**	----	----	----
Purchase Protection	**17.87(0.02)**	----	----	----
Travel Insurance	**-321.46(-1.14)**	----	----	----
Travel Discounts	**-22.45(-0.05)**	----	----	----
Car Rental Insurance	**-254.09(-0.46)**	----	----	----
Non-Travel Discounts	**668.54(0.49)**	----	----	----
Card Registration	**-68.867(-0.17)**	----	----	----
Other Plan Enhancements	**277.25(1.62)**	----	----	----
Visa Dummy	**----**	-35.40(-0.73)	0.027(0.88)	0.001(1.04)
Certificate of Deposit (1yr)	**----**	2.82(11.97)***	----	----
Reduced Introductory APR	**----**	139.39(2.53)**	----	----
State Income Growth	**----**	----	----	-1.29E-7(-0.10)
Constant	**7,224.43(2.32)****	dropped	-0.659(-4.52)***	-0.014(-238)**
Observations	**1542**	1542	1542	1542
Time Fixed Effects Included	**Yes**	Yes	Yes	Yes

*significant at 10%; ** significant at 5%; *** significant at 1%
t statistics in parentheses

Table 5: Determinants Of Credit Card Overlimit Fees **(3sls)** 1996-2002

Results from a 3SLS four equation system with the four endogenous variables derived from the theoretical model (Overlimit Fees, Interest Rate, Chargeoff Ratio and Market Share). The full specification of the model is in equations (14) to (17). Our four hypotheses are all tested using estimated coefficients in the Overlimit Fee equation (second column in bold). These include (i) the risk pricing hypothesis (model predicts positive relationship between bankruptcy per capita and overlimit fees); (ii) substitution hypothesis (the model predicts a negative relationship between interest rates and overlimit fees); (iii) average income hypothesis (the model predicts a positive relationship between state income and overlimit fees) and (iv) market share hypothesis (the model predicts a positive relationship between market share and overlimit fees).

Variables	Endogenous Variables			
	Overlimit Fee	**Interest Rate**	**Chargeoff Ratio**	**Market Share**
Chargeoff Ratio	**7,736(3.84)*** **	1,689(11.29)***	-----	-0.035(-4.63)***
Bankruptcy per Capita	**109,518(2.26)** **	20,712(2.00)**	-14.373(-2.30)**	-0.415(-2.17)**
Interest Rate	**-4.43(-3.68)*** **	-----	0.001(10.53)***	1.34E-5(4.33)***
Market Share	**43,161(0.16)**	34,427(5.27)***	-20.62(-4.98)***	-----
State Income	**0.025(0.78)**	0.003(0.43)	-2.7E-06(-0.71)	-9.6E-8(- 0.81)
Overlimit Fee	**-----**	-0.133(-2.02)**	0.0001(4.41)***	3.0E-6(2.72)***
National Dummy	**64.71(0.06)**	-117.685(-2.90)***	0.059(2.40)**	0.003(5.18)***
Regional Dummy	**178.95(0.70)**	-3.107(-0.11)	-0.005(-0.26)	3.0E-4(0.68)
Premium Dummy	**-81.97(-0.42)**	-8.187(-0.23)	0.006(-0.28)	0.001(0.79)
Purchase Rebate	**64.50(-0.09)**	-----	-----	-----
Warranty Extension	**98.10(0.38)**	-----	-----	-----
Purchase Protection	**-79.65(-0.09)**	-----	-----	-----
Travel Insurance	**-103.70(-0.53)**	-----	-----	-----
Travel Discounts	**4.03(0.01)**	-----	-----	-----
Car Rental Insurance	**-93.94(-0.23)**	-----	-----	-----
Non-Travel Discounts	**141.79(0.14)**	-----	-----	-----
Card Registration	**-7.22(-0.03)**	-----	-----	-----
Other Plan Enhancements	**123.49(1.49)**	-----	-----	-----
Visa Dummy	**-----**	-26.661(-0.6)	0.009(0.34)	0.001(1.34)
Certificate of Deposit (1yr)	**-----**	2.874(12.53)***	-----	-----
Reduced Introductory APR	**-----**	-29.876(-1.01)	-----	-----
State Income Growth	**-----**	-----	-----	-6.6E-7 (- 0.63)
Constant	**6,209.77(3.26)*** **	dropped	-0.748(-5.49)***	-0.02(-3.63)***
Observations	**1542**	1542	1542	1542
Time Fixed Effects Included	**Yes**	Yes	Yes	Yes

* significant at 10%; ** significant at 5%; *** significant at 1%
z statistics in parentheses

Table 6: Determinants Of Credit Card Late Fees And Overlimit Fees (GMM)

Results from two Separate GMM (Instrumental Variable) Estimations for each of Late Fees and Overlimit Fees as the endogenous variable. Each GMM-IV Equation also includes Chargeoff Ratio, Market Share and Interest Rate as additional endogenous variables. The specification of the models is in equation (18). Our four hypotheses are all tested using estimated coefficients in either the Late Fee or Overlimit Fee equations. These include (i) the risk pricing hypothesis (model predicts positive relationship between bankruptcy per capita and fees); (ii) substitution hypothesis (the model predicts a negative relationship between interest rates and fees); (iii) average income hypothesis (the model predicts a positive relationship between state income and fees) and (iv) market share hypothesis (the model predicts a positive relationship between market share and fees).

Variables	**Dependent Variable**	
	Late Fee	**Overlimit Fee**
Interest Rate	-0.88(-1.81)*	-0.781(-1.79)*
Chargeoff Ratio	12,630.19(3.97)***	12,673.43(4.19)***
Market Share	51,853.13(3.04)***	28,934.49(1.60)
Bankruptcy per Capita	53,466.60(1.90)*	87,055.09(4.00)***
State Income	0.039(2.22)**	0.035(2.50)**
National Dummy	-81.53(-0.60)	-26.00(-0.16)
Regional Dummy	137.59(2.26)**	197.88(2.62)***
Premium Dummy	-38.54(-0.46)	-21.82(-0.19)
Visa Dummy	29.10(0.38)	-23.08(-0.26)
Certificate of Deposit (1yr)	1.27(1.13)	2.24(1.62)
Constant	dropped	dropped
Observations	2592	1542
Time Fixed Effects Included	Yes	Yes

* significant at 10%; ** significant at 5%; *** significant at 1%
z statistics in parentheses

Figure 1: Location of Bank A, Bank B.
and the customer is indifferent between obtaining the credit card from bank A and B, d_A,
on the spatial circle

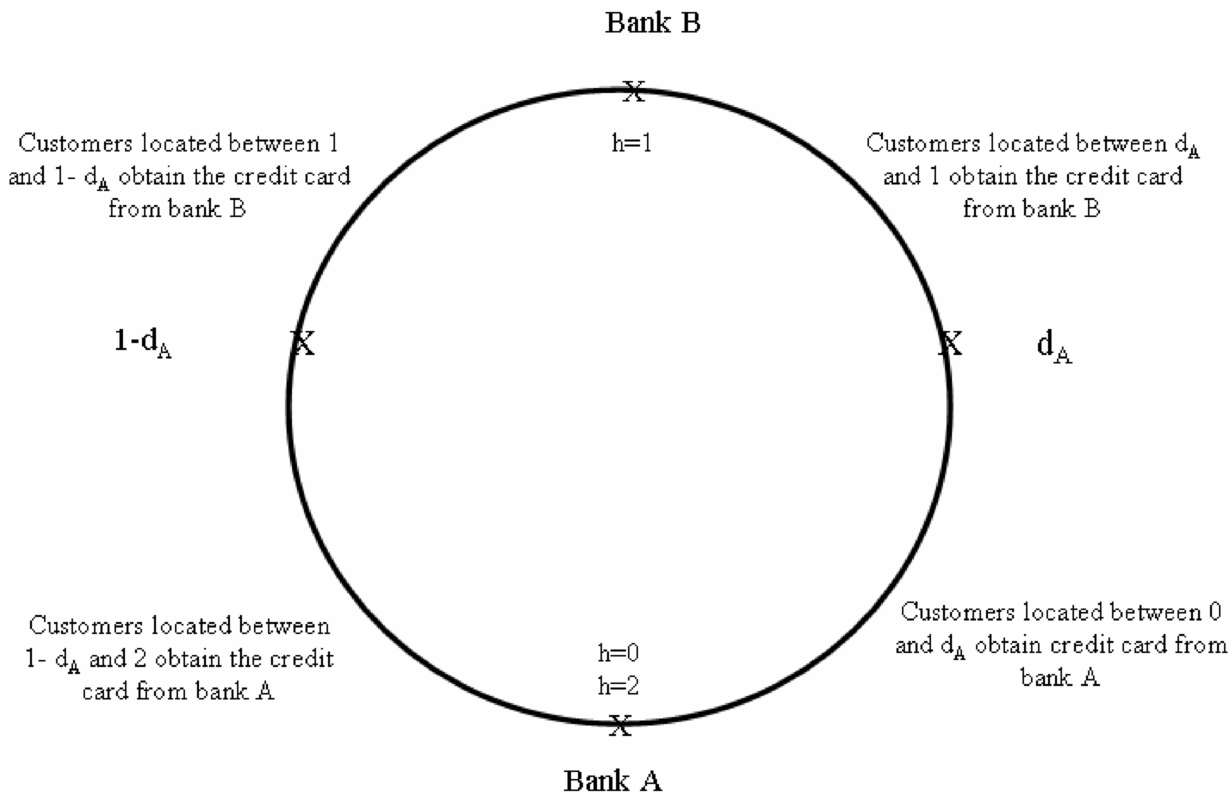

Figure 2: The distribution of the consumer's income shocks and their payoff from financing their purchases using a credit card at each state

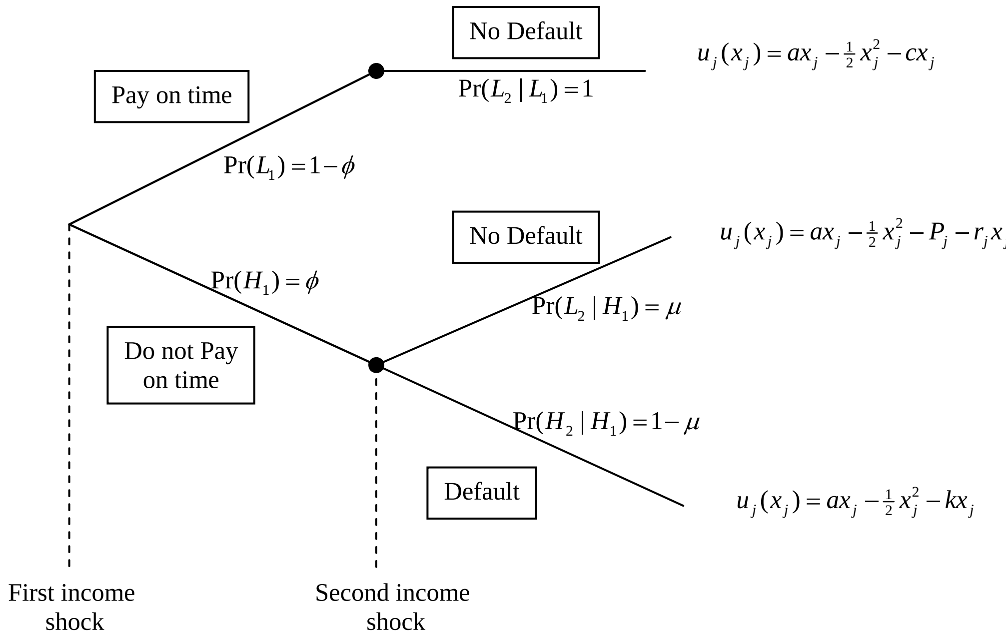

Figure A.1: Location of Bank A (2 branches), Bank B (1 branches) and the customer is indifferent between obtaining the credit card from bank A and B, d_A, on the spatial circle