Competition and Customer Acquisition in the U.S. Credit Card Market

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Abstract

This paper presents an equilibrium model of credit card issuers' mail out decisions and estimates it using data on direct mail credit card offers. It finds that demand for cards is sensitive to the interest rate on purchases and to promotional rates and rewards programs, and that it is relatively insensitive to the inclusion of 'behavioral' fees on offered cards. In counterfactual experiments, it find that an increase in the Treasury rate (cost of funds) uniformly reduces consumers' propensity to receive offers as well as the range of rates on those offers, with little effect on average rates. Conversely, adding a hypothetical new competitor leads to a net increase in credit offers and in the dispersion of rates on those offers. Nevertheless, it deters incumbent lenders from making offers to individuals whom they might have otherwise found profitable, thus leading to a reduction in the supply of credit for some consumers.

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1 Introduction

Credit cards have become ubiquitous in the U.S. as tools for managing household balances. In 2010 nearly 2 in 5 households carried a credit card balance that averaged 2.9 percent of their household debt.[1] By July 2013, total unsecured revolving debt in the United States had risen to $849 billion, or 5.2 percent of 2012 GDP.[2] In addition to its growing size, the credit card market evolved considerably over recent decades. Technology adoption by banks during the 1990s reduced many of the informational asymmetries previously limiting competition. New found competitiveness, alongside improved screening and consumer targeting, induced lenders to launch complex new card products designed to simultaneously raise revenues, attract new customers, and be differentiated from competitors.[3] As a result, today's credit card market is dominated by lenders offering customized products to specific individuals. In doing so, these lenders consider consumers' tastes for different cards, how valuable they might be as customers, and other offers they might receive from competitors. Despite this evolution in credit card lending, there has been little recent empirical work studying the strategic interaction between lenders and how this interplay might affect the eventual supply of credit cards to consumers.

This paper studies how lenders compete for and acquire new customers. To this end, it sets out a framework with which to examine how lenders choose to offer their products to potential borrowers and then estimates it using rich individual level data on credit card mail-out offers. Rather than limiting price to a single interest rate, as done previously, this framework considers the overall contract, allowing consumers to have preferences over a large vector of price characteristics.[4] In doing so, it accounts for the fact that lenders offer a great variety of complex products to heterogeneous consumers who vary in their tastes for cards and in how valuable they are likely to be as customers, and who consequently face vastly

[1] More specifically, in 2010, 68 percent of U.S. households had at least one credit card, and 38 percent kept a balance averaging $7,100, or 2.9 percent of total household debt (Bricker et al., 2012)

[2] (FRB series G.19).

[3] Complex behavioral fee structures first appearing in the mid 1990's significantly increased revenues from fees, while various introductory offers and rewards programs simultaneously attracted new customers and differentiated the credit card from competitors' products.

[4] In addition to evaluating a uni-dimensional price vector, previous empirical work has been largely based on aggregate market outcomes, such as mean or modal interest rates offered by an issuer or in the entire market.

different choices when selecting a new card. Given limitations on available data mapping offers to consumer choice, this framework allows for the recovery of consumers' preferences over new cards as well as lenders' valuation of potential customers using solely data on lenders' offer decisions.

The framework in this paper characterizes lenders' underlying process in making offer decisions. The logic of the model is as follows. Lenders simultaneously decide whether or not to send credit card offers to specific consumers. For every potential customer, a lender selects the most profitable card from a pre-determined menu of its available products.[5] Facing a set cost for printing and mailing, a lender offers this product to the consumer if and only if it is profitable to do so. If there is no available product that yields positive expected profit, the lender does not offer any card to that consumer. Consumers receiving an offer are allowed to be inattentive. To this end, they can choose, with some probability, to be attentive to an offer and consider its contents. Take-up of, or demand for, an offered card is determined by the joint likelihood that a customer is attentive to the contents of the offer and that she prefers it to her alternatives.

The data on lenders' mail-out offers come from a national survey of consumer credit solicitations run by the market research company Mintel Comperemedia (Mintel). The survey is designed to inform financial firms of their competitors' mail out activities. It is a unique data source in that it documents offer decisions to specific individuals from all active credit card issuers. Consequently, these data serve as an excellent platform from which to study firms' supply decisions in this market. Because the survey is structured to provide information on lenders' offers decisions, take up of offers is not recorded: prices are observed but quantities are not.[6] Traditional industry models use both prices and quantities (either at the individual or market level) to estimate supply and demand.[7] Instead, the

[5]Note that a fixed menu implies that product location choice is held fixed in this game.

[6]This does not mean that only offers that were not accepted get forwarded. Individuals accepting offers are asked to forward the left over portion of accepted offers as well.

[7]Ideal data for this analysis would track the offers an individual receives from every lender and the subsequent take-up and usage of that individual. To my knowledge, there is no such data available. Although there exist data with information on choice sets and take-up, these are for only one lender (Ausubel, 1999; Shui and Ausubel, 2005). There are also data that span many lenders, and include information on the type of cards consumers hold, including the prices, terms, and subsequent usage (Agarwal et al., 2013; Stango and Zinman, 2009, 2013; Gross and Souleles, 2002). However, these data lack information regarding the choices consumers faced when taking up those cards.

analysis exploits the rich information on the sets of products offered to particular consumers (including the number, prices, and terms of offers) to jointly recover the entire profit function of the firm.[8] To the extent that these data can be interpreted as a collection of independent equilibrium outcomes generated by lenders strategically interacting in the market place, repeated observation of these outcomes recovers the primitives of the underlying game.

Model estimates suggest that consumers are very sensitive to interest rates and promotional programs, with a demand elasticity for the regular interest rate of approximately -10.[9] As is in line with the literature on salience and obfuscation (Ellison and Wolitzky, 2012; Gabaix and Laibson, 2006), model estimates further suggest that consumers are relatively less sensitive to the inclusion of delinquency fees on cards: adding late fees or over-limit fees to the card, for example, reduces take up by only 3 percent.[10] Lastly, low response rates, estimated on the order of 0.05 percent, are largely driven by consumers' inattentiveness as well as their strong preference toward their outside option.[11].

The model is used to explore the equilibrium effects of two changes in the market's competitive environment. The first looks at the impact of a rise in the one year Treasury rate (cost of funds). Given historically low interest rates following the Great Recession, this studies the equilibrium effects of a tightening market. The second looks at how adding competitors to the market might affect overall pricing and supply of cards to consumers. Over the past two decades the market consolidated significantly. However, this consolidation was coupled with reduced prices and profits. The purpose of this counterfactual is to determine the sensitivity of competitive outcomes to a reduction in concentration given today's market environment.

Counterfactual results indicate that an increase in the Treasury rate leads lenders to make

[8]There is some precedence for the analysis of seller behavior using data on prices without observing quantities. Thomadsen (2005) uses variation in geographical location of stores to estimate a model of competition for the fast food industry without quantity data. Brynjolfsson, Hu and Smith (2003) assess the impact of increased competition and product variety in the book market on consumer welfare observing only products on sale and posted prices.

[9]Demand elasticity for the length of promotional intro and balance transfer rates are on the order of 35 and 32, respectively. The result for balance transfers, for example, provides empirical support for the notion that consumers look to roll-over balances across cards and that this behavior is potentially lucrative to lenders looking to poach their competitors' customers (Drozd and Serrano-Padial, 2013)

[10]For example, this implies that increasing the late fee from \$0 to \$25 reduces take up by 3%.

[11]In other words, much of the draw for consumers away from accepting an offer (e.g. toward their outside option) cannot be explained by variation in their demographic characteristics

uniformly fewer and less heterogeneous offers. A 1 percent increase in the Treasury rate leads to a 46 percent decline in the proportion of individuals receiving offers. The average number of offers received, for those receiving offers, decreases by 16 percent. Nevertheless, average rates on received offers remains unchanged, though the range of rates on offered products declines by 30 basis points.[12] To the extent that individuals do not always choose the lowest rate offer, this reduction in dispersion might be a factor driving persistently low pass through of cost of funds to offered interest rates observed in this market. Unlike an increase in the cost of funds, an addition lender increases consumers' propensity to receive offers. However, this new lender deters existing incumbents from making offers to some consumers they might otherwise have found profitable. As a result, not all consumers benefit from this change. Moreover, an additional lender leads to greater dispersion in offered rates. As such, introducing a new lender to the market might lead some consumers to take up offers with higher rates than they might have previously.

The empirical literature studying the credit card industry is large and follows several strands. Much work has focused on testing for adverse selection (Agarwal, Chomsisengphet and Liu, 2010; Ausubel, 1999; Calem and Mester, 1995; Calem, Gordy and Mester, 2006; Ponce-Rodriguez, 2008) and on estimating behavioral bias in credit card use (Agarwal et al., 2006; Shui and Ausubel, 2005; Gabaix and Laibson, 2006; Kuchler, 2013; Meier and Sprenger, 2010). Others have looked at the impact of credit cards on consumers' household balance sheets. This includes the marginal propensity to consume out of new credit (Gross and Souleles, 2002), changes in debt repayment behavior due to temporary income shocks (Agarwal, Liu and Souleles, 2007), and dispersion in prices and the resulting cost of credit to users (Agarwal et al., 2013; Stango and Zinman, 2009, 2013). There has also been work analyzing network effects and the two sided nature of this market. This literature has studied the economic relationship between the issuing banks, clearing houses, and participating vendors (merchants)(Prager et al., 2009; Rysman, 2007).

To date, however, there have been few empirical papers studying competition and market structure in credit card lending. Moreover, existing papers focus on the credit card market

[12] On average, the minimum rate offer in individuals' mailbox increases by 13 basis points and the maximum rate offer decreases by about 17 basis points.

of the 1980s and early 1990s, before many of the technological improvements within the industry took effect. As a result, this literature largely considers price as a single rate that is the mean or modal regular interest rate in the market and abstracts away from the complexities of issuers' marketing decisions. The seminal paper in this literature is Ausubel (1991), which documents a failure of competition in this market during the 1980s and ascribes it to asymmetric information between lenders and time inconsistent borrowers. In contrast, Knittel and Stango (2003) argue that the lack of competition during that time might have instead resulted from tacit collusion by banks. Moving into the 1990s, Stango (2000) looks at issuers decision to set fixed vs. variable interest rates on cards, while Stango (2002) looks at pricing and consumer switching costs.

The remainder of the paper is organized as follows. The next section gives a brief description of the credit card market and its important features relevant to this analysis. Section 3 presents the data and relevant summary statistics, while section 4 introduces the model. Section 5 describes the parametrization and estimation procedure, section 6 discusses identification of the model, and section 7 presents the results. Section 8 concludes.

2 Direct Mail & the Credit Card Market

Direct mail is the most frequent channel by which credit card lenders acquire new customers. Today's lenders spend a substantial portion of their marketing budget on direct mail, sending out nearly 4 billion envelopes each year to American consumers.[13] Prior to the 1980s, credit cards were obtained at individual branches and credit offers were made face-to-face. Since that time, improvements in consumer reporting, facilitated in part by the rise of the three large credit bureaus (TransUnion, Experian, and Equifax), allowed lenders to economically and expeditiously access detailed credit histories for large sets of consumers.[14] Leading banks began leveraging their large branch networks and brand awareness to solicit customer applications through national mass mailing campaigns. Beginning in the 1990s, mail out

[13]Despite recent efforts by lenders to transition to Internet marketing, to date lenders continue to acquire new customers more often through direct mail than by any other means. For more detailed description of data and statistics on acquisition channels see appendix.

[14]Lenders could now purchase large mailing lists with consumers' names and addresses and match them via the credit bureaus to these consumers' credit histories.

volume increased sharply.[15] In addition, offers became increasingly complex and varied. By the close of the 1990s, potential customers were receiving rich and substantially differentiated mail offers, with greater frequency, from lenders with increasingly better information about them. These developments in lenders mail out activities reflect broader and more profound changes in the credit card market over the past three decades.

The credit card market of the 1980s was largely uncompetitive.[16] During this period, applicants' credit worthiness was assessed using simple metrics like debt to income ratios, and there was little variation across banks in the information and methods used to screen customers.[17] Consequently, issuers sold relatively homogeneous credit card products to similar consumers. Nearly every bank charged a 19.8 percent fixed interest rate and $20 annual fee, whereby fees were meant to compensate the lender for expenses associated with usage. Cards did not generally offer special introductory or balance transfer offers, bundled insurance products, or rewards. Information technology adoption by issuers during the 1990s improved their ability to gather and assess information on prospective consumers, spurring competition and giving rise to product and marketing innovations.[18] The roll out of complicated behavior based fee structures rolled out during the 1990s, for example, is viewed as issuers' attempt to recoup revenue lost as a result of competitive pressures.[19] In addition, to

[15]Between 1990 and 2001, the number of offers mailed annually increased by a factor of five, from 1 to 5 billion (Furletti, 2003). This number continued to grow, albeit at a lower rate until the Great Recession of 2008, at which point there was a sharp decline in mailed offers. Since 2010, however, the marketing of credit cards to consumers through direct mail has rebounded. Decidedly, the increase in direct mail was accompanied by a steep decline in consumer response rates. Prior to 1988, issuers might have expected response rates between 5 and 10 percent (Paige, 2003) However, between 1991 and 2012 the response rates for credit card direct mail solicitations decreased from 2.2 percent to 0.6 percent, hitting a low of 0.3 percent in 2005 (DMA, 2013).

[16]During this time the industry was large, unconcentrated, and competing lenders faced few barriers to entry or doing business across state lines. Still, mark-ups were high, prices were unresponsive to underlying cost, and lenders earned three to five times the ordinary rate of return in banking (Ausubel, 1991).

[17]Commercial credit scores such as Fair Isaac Corporation's FICO score, were not available until 1987.

[18]Improved screening technology eliminated many informational asymmetries limiting competition. As a result, prices decreased and became more responsive to underlying costs, profitability declined, and credit became more available to a broader range of consumers. By the end of 2008, consumer credit card debt rose to $990 billion, from $130 billion in 1989. Of this new debt, a substantial portion was acquired by lower income households. Between 1989 and 2007 the proportion of households below the 20th percentile of income holding credit card debt nearly doubled from 15.3 percent to 25.7 percent, while for households above the 90th percentile of income that proportion remained stable, moving from 40.5 to 40.6 percent (data are from the Survey of Consumer Finances). Moreover, because innovation was costly, this period was associated with substantial consolidation among lenders: by 2010, the largest 6 lenders held more than 90 percent of outstanding credit card balances (Grodzicki, 2013).

[19]This meant complicated over-limit and late fees that were scarcely charged up until then. As an example,

attract new customers and maintain their existing customer base, lenders introduced cards with low teaser rates, balance transfer incentives, rewards programs (like cash back and frequent flier miles), and bundled insurance products. These features were designed to simultaneously attract new customers and differentiate a lender from its competitors, thereby reducing the elasticity of its residual demand and further tempering competitive pressures.

With more information on potential customers, lenders today assess what types of cards specific consumers most like as well as how profitable these potential customers are likely to be. Moreover, the process by which lenders assess potential borrowers is more heterogeneous than before.[20] Consequently, the set of offered products varies greatly among consumers. This variation reflects lenders' differential beliefs over how much net revenue a consumer is likely to generate by using a card, the degree to which a consumer is in the market for a new card, what type of card features the consumer most prefers, and competing offers this consumer might have under consideration.[21]

Given these changes, aggregate measures of the regular interest rate on offered and/or held card products likely no longer provide an accurate characterization of supply decisions in this industry. Instead, it is important to consider the complexity of each product's price (including all rates, fees, and rewards), differences across lenders in the types of products they sell, and the variation across potential customers in the set of offers they receive.

average late fees assessed rose from $12 in 1994 to $29 in 2002 (Furletti, 2003).

[20] Unlike before, lenders now maintain and constantly update enormous amounts of information on potential borrowers. They analyze this information using sophisticated and proprietary behavioral credit scoring models to determine pre-screening and account marketing, pricing, account management, estimating losses from default, and predicting the profitability of individual accounts. Interestingly, lenders today might have good information regarding specific consumers' preferences and profitability, but they face increased uncertainty regarding the products potential borrowers might already be using as well the offers they may receive from competitors.

[21] Another important change in this industry, not discussed here, is a rise in lenders' securitization activities. Since being first introduced in 1987, credit card asset backed securities (ABS) have become an extremely popular way to finance unsecured credit. Between 1991 and 2001, annual issuance of credit card ABS grew nearly 160 percent ($25 billion to $58 billion). By the middle of 2002, about 60 percent ($400 billion of $712 billion) of total consumer revolving unsecured credit was securitized (Furletti, 2002).

3 Data & Summary Statistics

3.1 Data

The data used in this paper come from a national survey of mail out credit offers administered by the market research firm Mintel Comperemedia (Mintel). The survey is designed as a market research tool for lenders to learn about their competitors' mail out activities. As a result, it captures offer decisions for the entire market. In this survey, participating respondents are requested to forward to Mintel all financial mailings they receive.[22] In addition, respondents are asked to provide detailed demographic information such as their age, geographic location, income, home ownership status, occupation, and household composition. Mintel then matches respondents offers with their demographic information and their credit score.[23] The resulting data include, for each respondent, the terms of every offer they received (e.g. all relevant interest rates, rewards, fees, and pre-screened/pre-approved status of the offer), their demographic profile, and their credit score.

The survey is administered monthly, whereby each month a random sample of individuals are asked to participate.[24] On average, about one third of those invited choose to participate. The data thus comprise monthly repeated cross sections with between 1,500 and 2,300 respondents in each month. The unit of observation is a respondent by offer, resulting in between 7,000 and 9,000 monthly observations spanning the period January 2010 to July 2012.

For this analysis, the data are subset in the following ways. First, because credit score is collected only for the individual respondent, I restrict consideration to offers addressed specifically to the respondent; these offers are flagged by Mintel. As a result, the analysis that follows is carried out at the level of the individual respondent rather than the household. Second, I define a credit card offer to be a new acquisition credit card mailing that has

[22] These include offers for new credit cards, home equity loans, statements, loyalty mailings, and renewals.

[23] Mintel uses respondents *VantageScore*, which is a role up risk scoring algorithm designed by the credit bureaus as an alternative to the traditional FICO score. For more information on this score, how it measures consumer default, and its relationship to the more traditional FICO score, see CFPB (2012).

[24] Sampling is stratified according to household size and composition, age, education, geography, income, and risk. Groups with historically high non-response rates are over sampled to achieve better demographic coverage (e.g. young and high risk/low credit score households). Sampling weights are assigned to account for non-response.

been pre-screened. This accounts for 76.4 percent of new acquisition credit card mailings in the data that are addressed to respondents. Pre-screening implies that lenders obtain information from the credit bureaus on the individual prior to making an offer. Moreover, pre-screened offers provide a strong signal to individuals that this product is available to them. As a result, considering only pre-screened offers focuses the analysis to lenders making informed offer decisions, and consumers receiving clear signals regarding the availability of the product they are offered.[25] Lastly, I further restrict the analysis to mailings from the largest six lenders. These are *American Express*, *Bank of America*, *Chase*, *Capital One*, *Citibank*, and *Discover*. Mirroring the credit card market overall, the market for mail-outs during the sample period was highly concentrated among these issuers. As shown in figure 1, of the 151 lenders making offers in the data, mail outs from the largest six lenders account for nearly 90 percent of the screened offers sent to respondents.[26]

3.2 Summary Statistics

3.2.1 Respondents

Table 1 reports summary statistics for respondents in the data. The data comprise 63,496 individual respondents over the 31 month period between January 2010 and July 2012, inclusive. On average, respondents are 54 years old with a mean household income of $68,000.[27] About 7 percent of respondents have a credit score of below 700, termed *Vantage Grade C* , while 48 percent have a credit score between 700 and 800 and 44 percent have a credit score above 800. These latter groups are classified as *Vantage Grade B* and *Vantage Grade*

[25]Decisions to send general mailings may also confound lenders activities in learning about consumers' risk and taste preferences with the acquisition of customers through direct mail solicitations. Limiting the definition of offer to a mailing that has been pre-screened eliminates the possibility of counting offers which have been sent as part of customer experiments and/or the testing out of new products in the market. On the consumer side, accepting the offer might reflect a composition of demand response and consumers learning about what products are available to them. Also, the data suggest that products sent as pre-screened offers are unlikely to be sent simultaneously to other consumers as general mailings. As such there seems to be some separation between these two types of products. For a further discussion of the differences between pre-screened and general mailings see the data appendix.

[26]Moreover, an important fact of the data is that other firms do not consistently show up every month in the data as having sent offers.

[27]As compared to national averages, Mintel respondents are on average slightly older, poorer, and lower risk. For further discussion and comparison to population averages (e.g. CPS) see data appendix.

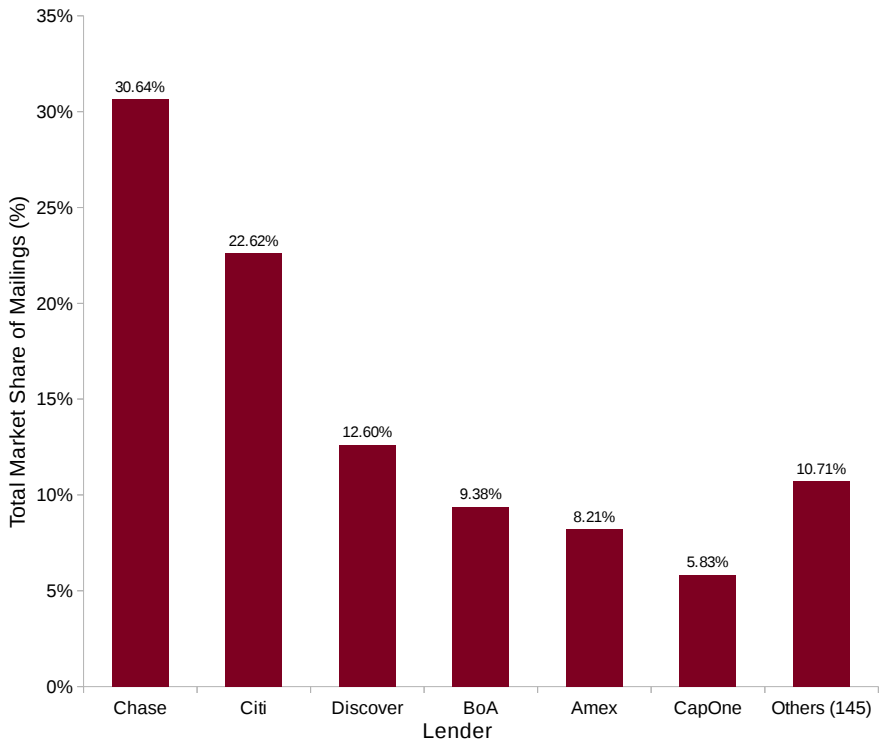

Figure 1: Market Shares of Screened Mailings (Jan 2010 - Jul 2012)

Notes: This figure plots the total market share of direct mail screened offers sent from each lender over the period Jan. 2010 to July 2012. Data are from the Mintel Comperemedia survey of credit solicitations and comprise monthly repeated cross section spanning the period Jan. 2010 to July 2012. An observation is an offer-recipient pair.

A, respectively.[28] Over 80 percent of respondents own their home and 40 percent live in a county located within one of the largest 25 metropolitan areas in the United States. Lastly, respondents from all census regions are well represented in the data. From the figure, about 18 percent of respondents are from the North East, 23 percent from the Midwest, 24 percent from the West, and 35 percent from the South.[29]

As aforementioned, survey participants are asked to forward all their financial mailings. In addition to new credit card offers, these include offers for home equity loans, loyalty

[28] *Vantage* score is reported in bins of about 10 points, with a minimum bound of 670 (e.g. reported as 670 or below) and a maximum bound of 835 (e.g. 835 of above). I classify respondents according the above three categories for two reasons. First, it is standard industry practice to separate individuals into coarse categories of credit worthiness for the purposes of offering credit. Second, the coarse reporting of credit scores does not allow for a more continuous distribution of scores to be used in the analysis.

[29] This distribution accords well with CPS statistics. For more details, see data appendix.

Table 1: Survey Respondents

	2010		2011		2012	
	Mean	IQR	Mean	IQR	Mean	IQR
Age	54	20	55	21	54	23
Annual HH Income ($1,000s)	68	55	66	55	68	55
Vantage Category (%)						
Vantage Grade C (< 700)	7		8		8	
Vantage Grade B (700 - 800)	48		50		52	
Vantage Grade A (> 800)	44		41		41	
Homeowners	83		83		83	
Living in Large Metropolitan Area	41		39		35	
Census Region (%)						
North East	18		18		18	
Midwest	23		23		23	
West	24		24		24	
South	35		35		35	
Existing Customers (%)						
American Express	5		4		3	
Bank of America	14		14		14	
Capital One	4		5		10	
Chase	22		21		12	
Citibank	13		14		15	
Discover	13		13		13	
Number of Individuals	24,450		26,258		12,788	

Notes: This table shows weighted summary statistics for survey respondents. Data are from the Mintel Comperemedia survey of credit solicitations and comprise monthly repeated cross section spanning the period Jan. 2010 to July 2012. An observation is an individual respondent.

mailings, informational statements, and cross selling offers, among others.[30] Although the analysis focuses on new credit card solicitations, these other mailings provide additional information about respondents' relationship with particular lenders. These likely affect lenders' offer decisions. More specifically, I classify a respondent as an existing customer of a lender if he or she receives any mailing categorized as a cross-sell, follow-up, loyalty, renewal, statement, or upgrade from that lender. The bottom panel of table 1 shows the percent of respondents who are counted as existing customers for each bank using the above mentioned definition. Note that the proportion of existing customers in each month varies from 3 to 22 percent. With the exception of Chase and Capital One, the proportion of existing customers by lender for the remains largely stable over time.

[30]In the data, each observations (respondent-offer) is categorized into mailing types.

3.2.2 Offers

The data reveal substantial variation in the individuals' offer sets. This includes both the number of offers considered by individuals in each month as well as types of offers made. Figure 2 shows the distribution of the number of monthly offers received by respondents in different credit bands. As shown in the figure, more than two thirds of all individuals never

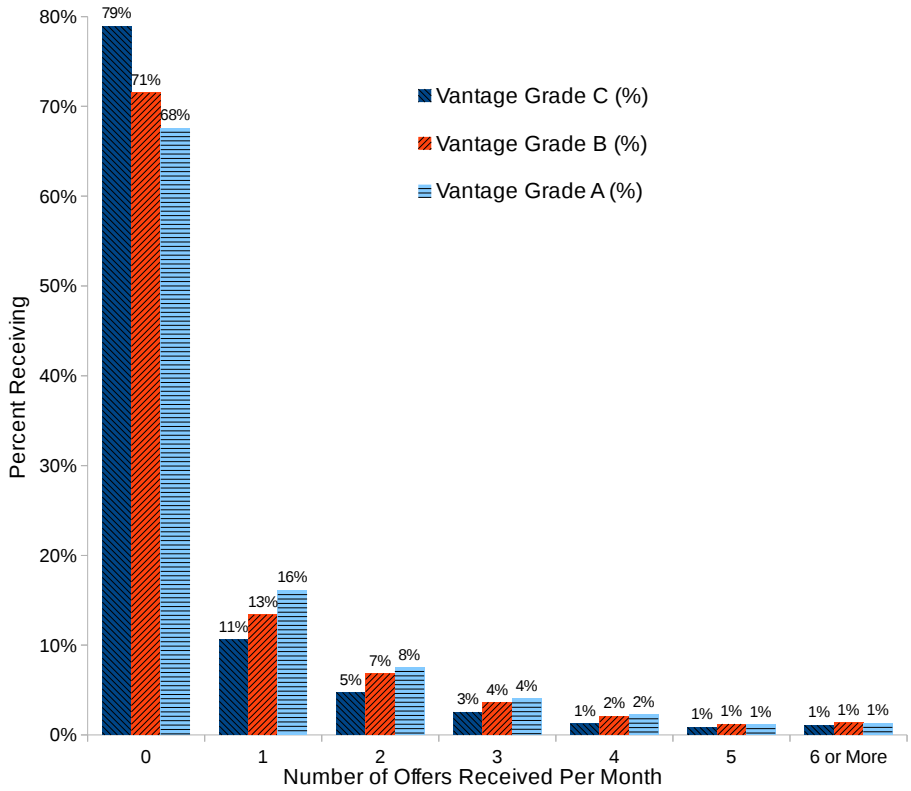

Figure 2: Number of Monthly Offers Received by Consumers

Notes: This figure plots distribution of the number of screened offers per month received by survey respondents from the largest 6 lenders over the period Jan. 2010 to July 2012. Data are from the Mintel Comperemedia survey of credit solicitations and comprise monthly repeated cross section spanning the period Jan. 2010 to July 2012. The unit of observation is a respondent in a given month.

receive any offer in any given month, and about fewer than in five receive one offer. Consequently, the vast majority of individuals consider one or fewer offers per month. Moreover, this propensity is monotonically decreasing in the number of offers, whereby about 1 percent receive six or more monthly offers. As would be expected, the distribution of number of offers received shifts to the right for individuals with higher credit scores. Nearly 80 percent of individuals with low credit scores receive no monthly offers while 68 percent of individuals

with high credit score receive no offers. Conversely, the propensity to receive one or more offers is increasing in individuals' credit scores.

Credit card products consist of many rates and terms. As a result, individuals can be offered a wide range of products for consideration. Table 2 organizes and characterizes the different parts of the card product used in the analysis. Broadly, a credit card is made

Table 2: Offer Structure

Interest Rates (1)	Fees (2)	Benefits (3)
Regular Rate on Purchases	Bal. Transfer Fee	Credit Insurance
Intro. Rate (Period)	Late Payment Fee	Purchase Insurance
Bal. Transfer Rate (Period)	Overlimit Fee	Fraud Insurance
Rate Given Default	Cash Advance Fee	Rebates
Cash Adv. Rate	Min. Finance Charge	Points
	Foreign Transaction Fee	Miles
	Annual Fee	Cash Back

up of three parts. These are interest rates, fees, and benefits. Interest rates, column (1), include the regular rate on purchases, the introductory and balance transfer offers, and the rates given delinquency. Introductory and balance transfer offers consist of an interest rate charged as well as a period for which that rate is valid.[31] Introductory and/or balance transfer promotions are nearly always offered with 0 percent interest for some predetermined period of time - the promotional period. However, lenders vary in the length for which they offer these promotions. Consequently, I restrict consideration to the length of the promotion period (e.g. 12 or 18 months). Fees, column (2), generally include a balance transfer fee, delinquency fees (late payment, over-limit, cash advance, and minimum finance charges), and usage fees (foreign transaction and annual fees). Benefits, column (3), include bundled insurance and reward programs. As with introductory and balance transfer promotions, fee levels do no vary much across cards (both within and across lenders). Also, the data do not

[31] For example, an introductory rate offer might give you 0 percent on purchases for 12 months.

contain specific information on the generosity of rewards and insurance products. As such, the analysis treats all fees and rewards as either being offered/charged in the product or not.[32]

Table 3 shows the variety of products appearing in the data and how offered products differ by risk category. As shown in the table, the mean regular rate on purchases for offered

Table 3: Offered Products

Variable	*Vantage* Score Grade C (1)	Grade B (2)	Grade A (3)
Non-Introductory Rate on Purchases			
Mean	13.47	13.28	13.10
Std. Dev.	2.57	2.55	2.41
Introductory Rate Period (Months)	13.26	13.34	13.48
Balance Transfer Period (Months)	15.37	15.45	15.76
Card Fees (% With)			
Late Payment Fees	96.41	96.41	96.64
Overlimit Fee	69.91	67.60	62.57
Cash Withdrawal Fee	97.03	96.78	95.12
Minimum Finance Charge	49.31	50.44	56.83
Fee on Balance Transfers	89.41	89.06	89.32
Foreign Transactions Fee	96.21	95.50	93.58
Annual Fee Fee	2.30	1.89	3.15
Insurance Products (% With)			
Travel	3.59	5.25	7.40
Credit	62.24	61.14	56.21
Purchase	16.44	17.34	18.45
Fraud	40.44	40.51	39.94
Rewards (% With)			
Rebates/Points	26.11	29.15	32.84
Miles	4.12	4.95	6.69
Cashback	50.22	48.6	47.60

Notes: This table summarizes the types of offers sent. Data are from the Mintel Comperemedia survey of credit solicitations and comprise monthly repeated cross section spanning the period Jan. 2010 to July 2012. An observation is an offer made to a specific respondent. *Vantage* Grade C refers to respondents with *Vantage* scores below 700. *Vantage* Grade B refers to respondents with *Vantage* scores between 700 and 800. *Vantage* Grade A refers to respondents with *Vantage* scores greater than 800.

cards is decreasing with credit score. However, the decrease is modest. Consumers with *Vantage* scores below 700 are, on average, offered rates that are 37 basis points, or ∼3 percent

[32]See table 4 in section 5 for more details.

of the average rate, lower. The average length of an introductory rate promotion is just over one year and is increasingly modestly in consumers' credit scores, a trend is similar to that of balance transfer promotions. Most cards include a fee on balance transfers, which is nearly always 3% of the transferred balance, as well as a fee on foreign transactions. In contrast to fees on balance transfers, however, the propensity to offer cards with foreign transaction fees is decreasing in consumers credit scores. Interestingly, not all cards include delinquency fees (late payment fee, over-limit fee, cash withdrawal fee, and a minimum finances charge). Generally, consumers with higher credit scores receive cards with fewer delinquency fees than consumers with lower credit scores. One exception is that the propensity to receive cards with minimum finance charges is increasing in consumers credit score.

There are four types of insurance products classified in the data: repayment, travel, purchase, and fraud insurance.[33] As would be expected, travel insurance is offered more often to those with high credit scores while repayment insurance is offered more often to those with low credit scores. Looking at rewards programs, note that rebates/points and miles are offered most often to those with high credit scores, while cash back is offered (modestly) more often to high risk customers. This trend is congruent with credit worthy individuals being offered fewer products with foreign transaction fees and more products with travel and/or purchase insurance.

4 Model

Credit card lenders' supply decision can be divided in two parts. In the first part, lenders select their portfolio of available products (contracts), their menu.[34] In the second, they choose which of these products they would like offer, mail out, to potential customers. The model that follows characterizes the second part of the decision, whereby lenders choose how to offer products from their pre-determined menu to prospective customers.[35]

The decision to offer a card is treated in the context of a simultaneous move discrete

[33] Credit insurance is an insurance over the inability to repay debt given illness or separation from employment.

[34] This is similar to players location choices in a standard oligopoly game.

[35] The menu formation decision is not modelled in this paper (e.g. lenders' location choices are held fixed).

game with incomplete information (Bresnahan and Reiss, 1990, 1991*a*,*b*; Seim, 2006). As such, lenders in this model simultaneously choose which of their existing products they would like to offer to prospective customers in order to maximize their expected profit. Their decision rule is summarized as follows. For every potential customer, a lender selects the most profitable card from a pre-determined menu of its available products. Facing a set cost for printing and mailing, the lender mails an offer to the consumer if it is profitable to do so. If there is no available product yielding positive profit, the lender does not offer any card to that customer.

The profit function of the firm broadly consists of two parts. The first is the demand, or take-up. This is the probability that a customer takes-up an offered card. The second is the value. Value is defined as the lifetime net revenue a potential customer is expected to generate by using a particular card.[36] Customers vary in their likelihood of responding to different offers and in how valuable they are to each lender. This depends on the type of card offered, customers' demographic characteristics, and the degree to which lenders are competing for their business. When making offer decisions, lenders are perfectly informed of the number of competitors they face, the set of potential products those competitors might offer, and the set of potential customers in the market. However, each lender is only partially informed of how valuable a potential customer is to its competitors. As a result, lenders form expectations over what their competitors' might decide to offer. An equilibrium in offers for each potential consumer is then characterized as a distribution over lenders' propensity to mail out an offer such that every lender is maximizing its profit.

More formally, let $\mathscr{L} = \{1, ..., L\}$ be the set of lenders active in the market, and let the set (or menu) of products lender $\ell \in \mathscr{L}$ holds be $\mathcal{H}_\ell$. Then $h_\ell \in \mathcal{H}_\ell$ is a specific card product available to ℓ. The set of potential customers is $\mathscr{I} = \{1, ..., I\}$, with $i \in \mathscr{I}$ denoting a specific individual. As described above, lenders simultaneously choose which of their products h_ℓ they wish to offer i, or to make no offer at all. Moreover, each lender is completely informed of the identity of its competitors $(-\ell)$, the menus of products held by them $(\mathcal{H}_{-\ell})$, and individuals potentially receiving offers $(\mathscr{I})$.

[36]Net revenue is gross revenue less cost. Moreover, it includes the probability of default as an implicit cost of providing the card.

4.1 Demand (Take-Up)

Demand for cards is modelled as a two part process. First, upon receiving an offer in the mail, a consumer need be attentive to the offer - e.g. open the envelope and consider its contents. Once attentive, the consumer must then decide whether or not she prefers this offer to her alternatives. As such, demand for cards comprises the joint likelihood that consumers are attentive to an offer and that they prefer it over their alternatives.[37]

4.1.1 Forming Consideration

Credit card products are complex and comprise a substantial set of trade-offs for the consumer. Due to this, it may be costly for the consumer to read, analyze, and compare the contents of each offer. A consumer then might not fully consider all available alternatives. Upon receipt, an offer might be tossed unopened into the trash.[38] The manner of consumer inattention is thus defined explicitly within the model.[39] Specifically, consumers select a most preferred option from a set of alternatives according to a two stage choice rule (Manzini and Mariotti, 2012; Masatlioglu, Nakajima and Ozbay, 2012; Lleras et al., 2010).[40] First the consumer sets a probabilistic choice rule over which offer to consider, whereby it is assumed the consideration set contains at most one offer. Once under consideration, an offer is taken up if it is preferred to the consumer's outside option.[41] Lastly, it is assumed that consumers' first stage choice rule is determined prior to observing an offers' contents and does not depend on consumer's demographic characteristics or unobserved taste for cards(Manzini and Mariotti,

[37]This view of the consumer's problem follows a growing literature of consumer choice under limited attention in which consumers form *consideration sets* and in which sellers compete to be included in them (Goeree, 2008; Eliaz and Spiegler, 2011; De los Santos, Hortacsu and Wildenbeest, 2012).

[38]Data from Strategic Business Intelligence's (SBI) Macro Monitor shows that between 2010 and 2012 fewer than 1 in 5 consumers opened more than half of the credit card offers they received. Moreover, about half opened 'almost none'. For more information see data appendix.

[39]Because I only observe offer decisions, there it is not possible to identify the manner of consumer inattention directly from the data.

[40]This is in contrast to a sequential procedure as in Mandler, Manzini and Mariotti (2012).

[41]As an example, consider a consumer initially sets a rule regarding which days of the week she is willing to think about new credit card offers and only considers the first offer received on that day. Alternatively, the consumer could each day choose whether or not to entertain offers with some independent probability. Furthermore, note that in the data the majority of consumers receive one or fewer offers each month (figure 2). Consequently, the vast majority of individuals will be choosing the first offer from a set of at most one.[42] She then takes up that offer if she prefers it to her outside option. The outside option could be interpreted as what she already has, what she might expected will become available in the future, or some combination of the two.

2014).[43] Given the above, let the probability of an offer being considered be expressed as a function of the number of offers received whereby

$$Pr(open\ letter \mid n) = r(n\,;\,\alpha) \tag{1}$$

where $r(\cdot)$ is a probability mass function in the number of offers $n \in 0 \cup \mathbb{N}$ and α is a parameter measuring the weight of more or fewer received offers on the probability of being in the consideration set.

4.1.2 Choice Under Consideration

As aforementioned, the choice rule is set such that consumers consider at most one offer at a time. Given this, choice under consideration is treated as a standard discrete choice for the consumer. Let individual i's indirect utility from taking up offer h_ℓ be given by the function

$$u_{ih_\ell} = u(X_{h_\ell},\, Z_i;\, \beta) + \eta_{ih_\ell} \tag{2}$$

where X_{h_ℓ} is a vector of product characteristics (e.g. interest rates, rewards, and fees), Z_i is a vector of the recipient's characteristics, β is the parameter on i's indirect utility from taking up the offer, and η_{ih_ℓ} is an idiosyncratic taste shock that is distributed i.i.d type-I extreme value across i and h_ℓ. Individual i's indirect utility from not taking up offer h_ℓ is given by

$$u_{i0} = s(Z_i;\, \gamma) + \eta_{i0} \tag{3}$$

where γ is the parameter on i's outside option. The probability of preferring a considered offer to the outside option is then

$$pr(take\ up \mid considered) = \frac{e^{u(X_{h_\ell}, Z_i;\, \beta)}}{e^{s(Z_i, \gamma)} + e^{u(X_{h_\ell}, Z_i;\, \beta)}} \tag{4}$$

As consumers' choice to consider a card does not depend on the contents of the card, their demographic characteristics, or their unobserved tastes for a particular card, the probability

[43] This is the case if, for example,'attentive afternoons' and the order of received mail are independently distributed in the population.

of an offer being considered is independent of it being chosen once under consideration. More formally,

Assumption 1 *(Independence of taste and consideration): Consumers' propensity to open and consider an offer is independent of their idiosyncratic taste shock, their demographic characteristics, and the offer characteristics:* $r(\cdot) \perp \eta_{ih_\ell},\ X_{h_\ell},\ Z_i$.

It follows from assumption 1 that the probability of recipient i taking up offer h_ℓ, conditional on the number of offers received (n) can then be written as

$$pr(take\ up|n) = \frac{e^{u(X_{h_\ell}, Z_i;\beta)}}{e^{s(Z_i,\gamma)} + e^{u(X_{h_\ell}, Z_i;\beta)}} \cdot r(n;\alpha) \tag{5}$$

In contrast to standard discrete choice models, the above demand structure describes consumers who open each offer with some probability which, once viewed, is assessed individually. An important implication of this approach is that lenders in this model compete against each other for customers' attention. Once under consideration, a lender becomes a monopolist for the consumer. Own prices then matter because they affect the probability this consumer prefers the card to her outside option. Competitors' prices matter because they affect the expected number of offers received by an individual, and thus the likelihood that an offer is considered.[44]

This approach has the benefit that it incorporates consumer inattention, which is an important feature in this market. Moreover, it allows for a tractable model of lender decisions.[45] This is because the above implies that lenders care only about the number of offers in a customer's mailbox, and not what is contained in those offers, simplifying significantly the computation of an equilibrium. There are two major drawbacks to this approach. First,

[44]The data provide some cursory evidence in favor of this view. As shown in Table 5, the number of offers received by competitors is predictive of the propensity for an issuer to make an offer. Nevertheless, as shown in table 6, it is uncorrelated with the interest rate on sent offers. This stands in contrast to standard models of competition which would predict a that banks expecting more competition for a particular consumer would offer lower interest rates.

[45]As will become clear below, a key feature of this market is that lenders are uncertain about the set of alternatives a prospective customer could face. As a result, the lender takes an expectation over the possible sets of alternatives, whereby an equilibrium is characterized as a fixed point of the distribution over possible sets. It follows that the number of possible sets becomes large very quickly with the total number of products in the market. In the data there are between 70 and 160 products each month (Table 7). So the number of possible subsets of a set of products could be on the order of 2^{100}. As a result, the dimensionality of the equilibrium object becomes intractably large.

it makes fairly strong assumptions regarding consumers' decision making process. Second, it eliminates the possibility of investigating consumers' response to a change in the mix of offers they receive. Nevertheless, tractability of the lender's problem now allows for the direct analysis of equilibrium supply decisions under alternative market scenarios.

4.2 Value (Net Revenues)

In deciding what type of offer to make to individual i, lender ℓ assesses the value of i for each of their available products $h_\ell \in \mathcal{H}_\ell$. This value is measured as the discounted net revenue generated by i were she to take up an offer for a particular product h_ℓ. It is a function of the product characteristics (X_{h_ℓ}), individual characteristics (Z_i), the overall market environment (M) and an additively separable private signal ($\epsilon_{i\ell}$)

$$V_{ih_\ell}(X_{h_\ell},\, Z_i,\, M,\, \epsilon_{i\ell}\,;\, \psi) = v(X_{h_\ell},\, Z_i,\, M;\, \psi) + \epsilon_{i\ell} \tag{6}$$

where $\epsilon_{i\ell}$ is specific to individual i and bank ℓ, and therefore common across all products $\mathcal{H}_\ell$ that ℓ could potentially offer.

Assumption 2 *(Independent symmetric private values): Private profitability signals ($\epsilon_{i\ell}$) are independent and identically distributed across individuals i and lenders ℓ. For every $i \in \mathscr{I}$, each lender receives an independently and identically drawn private value from a common continuously differentiable distribution with cdf $F(\cdot)$ and pdf $F'(\cdot) = f(\cdot)$.*

Unobserved heterogeneity in lenders' valuation of potential customers ($\epsilon_{i\ell}$) comes from two sources. The first is differences across lenders in the input data used to calculate the value of potential customers. The second is differences in the modelling technology used by them. To asses potential customers, lenders pull and reconcile data from the large credit bureaus (TransUnion, Equifax, and Experian). These data vary from day to day (as they update regularly) and across bureaus (as they may update at different times). Consequently, there is substantial heterogeneity in the input data used to asses customers.[46] These differences

[46]For example, a firm pulling Equifax data on a pool of borrowers on Tuesday is likely to get different estimates than another firm pulling data from TransUnion on a similar pool on Thursday. Moreover, if data is pulled from more than one bureau, as is often the case, lenders vary in how they reconcile these data and incorporate them into their assessments.

depend on consumers' actions on a particular day (e.g. purchase, payment, default) and the point at which those actions are incorporated into their file by the bureau. It follows that variation across lenders in the content of their information on prospective customers is largely random and uncorrelated with observables used to determine value. Lenders assess prospective customers with sophisticated behavioral scoring models. These models are quantified using historical data, which can lead to differences across lenders in the weights attributed to various characteristics used to determine value. These differences are also assumed to be independently and identically distributed across lenders and uncorrelated with the observables used to determine value.

Assumption 3 *(Independence of take-up and value): For any given offer h_ℓ, consumers' idiosyncratic taste shock η_{ih_ℓ} (and propensity to consider the offer $r(n\,;\,\alpha)$), are independent of lenders' private value signals $\epsilon_{i\ell}$.*

Assumption 3 implies that any selection is priced into the observable portion of consumers' assigned value.[47] Let $\theta = (\beta,\, \gamma,\, \alpha,\, \psi)$ and let $\Lambda = (X_{h_\ell},\, Z_i,\, M)$. Given the above assumptions, ℓ's expected profit from sending an offer h_ℓ to i can be written as the product of the take-up and the value minus a set cost (c) of printing and mailing the offer

$$\pi_{ih_\ell}(\Lambda,\, \epsilon_{i\ell};\, \theta|\, n) \;=\; pr(take\ up\,|\, n_{i,\ell} + n_{i,-\ell}) \cdot V_{ih_\ell} - c$$

$$= \left[\frac{e^{u(X_{h_\ell}, Z_i;\, \beta)}}{e^{s(Z_i,\gamma)} + e^{u(X_{h_\ell}, Z_i;\, \beta)}} \cdot r(n_{i,\ell} + n_{i,-\ell}; \alpha)\right] \cdot [v(\Lambda;\, \psi) + \epsilon_{i\ell}] - c \qquad (7)$$

where $n_{i,\ell}$ is the number of offers sent by lender ℓ, $n_{i,-\ell}$ is the number of offers sent by her competitors $-\ell$, and $n = n_{i,\ell} + n_{i,-\ell}$.

Lender ℓ observes her own value for individual i. However, because ℓ does not observe her competitors' ($-\ell$) private value signals for i, she faces uncertainty regarding the number of offers i might receive from them.

[47] In fact, having discussed this issue with industry participants, I have learned that this is actually quite true in reality. Lenders have robust models for determining take-up, and robust models for determining value. However, they do not have a good way to combine these two models. They are aware that a certain degree of adverse selection still exists. As a result, they end up 'pricing-in' this adverse selection through other means, such as reducing fixed costs of operations.

Assumption 4 *Each lender ℓ offers at most one product to each prospective customer i. In other words, $n_{i,\ell} \leq 1 \; \forall \; i \; \in \mathscr{I}$ and $\ell \in \mathscr{L}$.*

This assumption serves to simplify the calculation of an equilibrium and is largely empirically driven. In the data, there are few cases in which individuals receive more than one offer from a particular bank in one month.[48]

Given assumptions 2 through 4, let $\boldsymbol{P_{i,-\ell}}$ be an $L-1$ dimensional vector of probabilities representing ℓ's belief over each competitor's likelihood of sending an offer. Then let ξ be an vector valued function of $\boldsymbol{P_{i,-\ell}}$, whereby $\boldsymbol{P^n_{i,-\ell}} = \xi(\boldsymbol{P_{i,-\ell}})$ is an L dimensional vector of probabilities representing ℓ's subsequent belief regarding the number of offers i receives from all competitors (0 to $L-1$ offers). Without loss of generality, for lender $\ell = 1$ write $\boldsymbol{P^n_{i,-1}} = \xi(\boldsymbol{P_{i,-1}})$ as

$$
\begin{aligned}
P^n_{i,-1}(0) &= \prod_{j=2}^{L}(1 - P_{ij}) \\
P^n_{i,-1}(1) &= \sum_{j=2}^{L}\left[P_{ij}\prod_{k=-j}(1 - P_{ik})\right] \\
P^n_{i,-1}(2) &= \sum_{j=2}^{L}\sum_{j_2=j+1}^{L}\left[P_{ij}P_{ij_2}\prod_{k=-j,j_2}(1 - P_{ik})\right] \\
&\cdot \\
&\cdot \\
&\cdot \\
P^n_{i,-1}(L) &= \prod_{j=2}^{L}P_{ij}
\end{aligned}
\tag{8}
$$

Lender ℓ then uses her expectations over the number of offers i might receive from competing lenders to calculate overall expected profits from sending offer h_ℓ to individual i. Because of the above independence assumptions $\ell's$ profit, unconditional of the number of offers received, is given by

[48]If the data provided greater variation regarding the number of offers sent to each consumer, it would be straight forward to relax this assumption and allow lenders to send multiple offers.

$$\pi_{ih_\ell} = \left[\frac{e^{u(X_{h_\ell}, Z_i; \beta)}}{e^{s(Z_i,\gamma)} + e^{u(X_{h_\ell}, Z_i; \beta)}} \cdot \sum_{n_{-\ell}=0}^{N_{-\ell}} r(1 + n_{i,-\ell}; \alpha) \cdot P^n_{i,-\ell}(n_{-\ell}) \right] \cdot [v(\Lambda;\, \psi) + \epsilon_{i\ell}] - c \tag{9}$$

4.3 The Lender's Problem & Equilibrium

Lenders' supply decision can be summarized as follows. For each i, ℓ ranks all its available products from $\mathcal{H}_\ell$ in order of decreasing profitability for that customer. She then offers i that product yielding the greatest profit from i if and only if it is positively profitable to do so. This means that, given $\boldsymbol{P_{i,-\ell}}$ and $\mathcal{H}_\ell$, ℓ first chooses

$$h_\ell \text{ s.t. } \pi_{ih_\ell} > \pi_{ih'_\ell} \;\; \forall \;\; h'_\ell \neq h_\ell, \;\; h_\ell,\; h'_\ell \in \mathcal{H}_\ell$$

and then offers h_ℓ to i if and only if $\pi_{ih_\ell} > 0$.

Note that profit is not observed by the econometrician. Nevertheless, profit ordering can be inferred by using the assumption that $\epsilon_{i\ell}$ is common across all products lender ℓ might offer i. Let $\omega(\cdot)$ be an inversion of the profit function under the cut-off rule of positive profits. In other words, when $\epsilon_{i\ell}$ is additively separable in lenders' value function and $\pi_{ih_\ell} > 0$ we can derive

$$\omega(\cdot)_{ih_\ell} \equiv c \cdot \left[\frac{e^{u(X_{h_\ell}, Z_i; \beta)}}{e^{s(Z_i,\gamma)} + e^{u(X_{h_\ell}, Z_i; \beta)}} \cdot \sum_{n_{-\ell}=0}^{N_{-\ell}} r(1 + n_{i,-\ell}; \alpha) \cdot P^n_{i,-\ell}(n_{i,-\ell}) \right]^{-1} - v(X_{h_\ell},\, Z_i,\, ;\, \psi) < \epsilon_{i\ell} \tag{10}$$

Then, because $\epsilon_{i\ell}$ is common across $\mathcal{H}_\ell$ for i it follows that

$$\{h_\ell | \omega_{ih_\ell} = min(\omega_{i1_\ell}, ..., \omega_{iH_\ell})\} \iff \{h_\ell | \pi_{ih_\ell} = max(\pi_{i1_\ell}, ..., \pi_{iH_\ell})\} \; \forall \; i \; \in \; I$$

In other words, the product that yields the lowest ω_{ih_ℓ} will also be the product that yields the greatest π_{ih_ℓ} for every i.

For each i, let $h^i_{\ell,\, min(\omega)} = \{h_\ell | \omega_{ih_\ell} = min(\omega_{i1_\ell}, ..., \omega_{iH_\ell})\}$ and express ℓ's best response

(BR_ℓ) as a cut-off rule whereby

$$BR_\ell = \begin{cases} \text{offer product } \ h^i_{\ell,\,min(\omega)} & \text{if } min(\omega_{i1_\ell}, ..., \omega_{iH_\ell}) < \epsilon_{i\ell}, \\ \text{make no offer} & \text{otherwise} \end{cases} \tag{11}$$

The equilibrium concept is a Bayesian Nash Equilibrium (BNE) in which lender ℓ maximizes her profit conditional on her beliefs regarding competitors' mail out decisions. This equilibrium can thus be characterized as a probability distribution $\boldsymbol{P^*_i}$ over the number of offers received by each $i \in \mathscr{I}$. Denote $\omega_{i\ell} = \{\omega_{i1_\ell}, ..., \omega_{iH_\ell}\}$, and re-express ℓ's best response as the probability of offering $h^i_{\ell,min}$ to i by

$$Pr(\text{offer } h^i_{\ell,min})_{i\ell} = P_{i\ell} = 1 - F(\min_{h_\ell} \ \omega_{i\ell}(\xi(\boldsymbol{P_{i,-\ell}}), X_{h_\ell}, Z_i, c;\, \theta)) \tag{12}$$

where F is the common CDF from which the $\epsilon_{i\ell}$ are drawn. An equilibrium $\boldsymbol{P^*_i}$ can then be expressed as the solution to the following L equations in L unknowns

$$\begin{aligned} P^*_{i1} &= 1 - F(\min_{h_1} \ \omega_{i1}(\xi(\boldsymbol{P^*_{i,-1}}), X_{h_1}, Z_i, c;\, \theta)) \\ P^*_{i2} &= 1 - F(\min_{h_2} \ \omega_{i2}(\xi(\boldsymbol{P^*_{i,-2}}), X_{h_2}, Z_i, c;\, \theta)) \\ &. \\ &. \\ &. \\ P^*_{iL} &= 1 - F(\min_{h_L} \ \omega_{iL}(\xi(\boldsymbol{P^*_{i,-L}}), X_{h_L}, Z_i, c;\, \theta)) \end{aligned} \tag{13}$$

for each individual i with demographic characteristics Z_i.

Existence follows from an application of Brouwer's fixed point theorem. Note that because F is an atomless continuous distribution, the best response probability is a function mapping from observables to a probability of sending the offer for each ℓ. Moreover, this mapping is continuous on $P: \ [0,1]^L \rightarrow \ [0,1]^L$. As a result, existence of an equilibrium follows from Brouwer's theorem. For uniqueness, note that lenders' best response probabilities

are monotonically decreasing in their competitor's response given CDF F. As an illustration consider the case of two lenders. Suppose lenders are in equilibrium. Any increase in lender 1's propensity to offer a card results monotonically in a decrease of lender 2 offering a card. As a result, given any move away from an equilibrium, there is no convergence to a new equilibrium point.[49]

5 Estimation

This section details the parametric functional form used in the empirical exercise and the procedure used for estimating the relevant parameters.

5.1 Functional Form

The equation to be estimated (π_{ih_ℓ}) can be separated into four distinct parts. These are the utility over the offered product ($u(X_{h_\ell}, Z_i;\, \beta)$), the utility over the outside option ($s(Z_i;\, \gamma)$), the probability of being considered ($r(n;\, \alpha)$), and lenders' value equation ($v(X_{h_\ell}, Z_i, M;\, \psi)$). In the following, let $u(X_{h_\ell}, Z_i;\, \beta)$ be a linear function of the product characteristics, or

$$u(X_{h_\ell};\, \beta) = X'_{h_\ell}\beta \tag{14}$$

where I allow for the interest rate to vary by credit score by including two interaction terms in the function. Under this restriction, the utility parameter β can be interpreted as relative preference weights consumers place on the different features of the card at the time they take it up. Similarly, preferences over the outside option are linear according to

$$s(Z_i;\, \gamma) = Z'_i\gamma \tag{15}$$

Demographics are chosen to resemble as closely as possible information lenders use to assess potential customers.[50] Table 4 shows detailed definitions of included variables. As discussed

[49] I have not verified this analytically for the general case with L lenders. However, in numerical simulations, the equilibrium has shown to be unique.

[50] For example, income and race are conspicuously missing from this vector of characteristics. This is because household income is not directly observed lenders (e.g. it is not in customers' credit reports) and

Table 4: Variable Definitions

Variable	Definition
Product Characteristics ($X_{h\ell}$)	
Rate	Non-introductory rate on purchases
Introductory Offer Period	Length (in years) of introductory rate promo period
Balance Transfer Offer	Length (in years) of balance transfer rate promo period
Delinquency Fees	Count of delinquency fees (e.g. over balance, late payment) on card
Balance Transfer Fees	Indicator for whether card charges balance transfer fees
Foreign Transaction Fee	Indicator for whether card charges a foreign transaction fee
Annual Fee	Indicator for whether card charges an annual fee
Repayment Insurance	Indicator for whether card offers repayment (credit) insurance
Other Insurance	Count of other bundled insurance products offered on card (e.g. fraud/travel)
Non-Cash Rewards	Indicator for whether card offers non-cash (e.g. miles/rebates) rewards
Cashback Rewards	Indicator for whether card offers cashback rewards
FE	Lender fixed effect
Individual Characteristics (Z_i)	
Middle Age	Indicator for whether respondent is between 35 and 65 years old
Older Age	Indicator for whether respondent is over 65 Years Old
Vantage Grade B	Indicator for whether respondents' *Vantage* score is between 700 and 800
Vantage Grade A	Indicator for whether respondents' *Vantage* score is greater than 800
Homeowner	Indicator for whether the respondent owns their home
Metropol	Indicator for whether the respondent lives in a large metro area
Existing Customer	Indicator for whether the respondent is an existing customer
Macroeconomic Environment (M)	
Yield	Monthly 1 year Treasury rate at constant maturities

in section 3, for the sake of parsimony offer characteristics $X_{h\ell}$ other than *Rate* are introduced as indicators of a product offering this type of fee and/or promotion. For example, as can be seen in the table, *Rewards* takes a value of 1 if the card offers rewards.[51] Moreover, to allow for flexibility in the effect of demographics on demand and value, age and credit score categories are present as individual dummies. Consequently, the relevant base group is defined as consumers younger than 35 with low credit scores that do not own their home or live in a large metropolitan area and that do not have a relationship with the lender.

thus is not used in determining whether or not to make an offer. It illegal for lenders to use race at all in their assessments.

[51] This is true for $\sim$ 70 percent of cards.

Let the probability of being considered, $r(n;\, \alpha)$, be a continuously differentiable function in both n and α such that

$$r(n;\, \alpha) = \frac{1}{\alpha_0 + \alpha_1\, n} \tag{16}$$

Finally, let $v(\cdot)$ be linear function of X_{h_ℓ}, Z_i, and the 1 year Treasury yield M such that

$$v(X_{h_\ell}, Z_i, M;\, \psi) = [X'_{h_\ell}\; Z'_i\; M']\psi \tag{17}$$

where elements of X_{h_ℓ}, Z_i are as above and M is the one year constant maturity Treasury rate.[52]

5.2 Estimation Procedure

The parameter of interest is $\theta = (\beta,\, \gamma,\, \alpha,\, \psi,\, \sigma)$, whereby σ is the shape of F. Estimation is carried out using a nested maximum likelihood procedure. This procedure is as follows. For each parameter value, the model is solved to obtain $\boldsymbol{P_i^*}$ for each $i \in \mathscr{I}$. Note that each $i \in \mathscr{I} \equiv Z_i$ so that individuals of the same demographic type are treated as identical by lenders. As such, the model is solved separately for each distinct Z_i for every θ. $\boldsymbol{P_i^*}$ is used as an input into a likelihood function which is then maximized over the relevant parameter space.

Let $Pr(\text{offer})_{i\ell}$ be the probability of ℓ sending an offer to i, as a function of the data and parameters, can be written as

$$Pr(\text{offer})_{i\ell} = 1 - F(\min_{h_\ell} \omega_{i\ell}(\boldsymbol{P^*}, X_{h_\ell}, Z_i, M, c;\, \theta)) \tag{18}$$

whereby $Pr(\text{offer})_{i\ell}$ is a function of parameters and data. Since lenders make at most one offer, the likelihood of the data can be expressed as a sequence of Bernoulli trials with probability of success $Pr(\text{offer})_{\ell,i}$. Moreover, because private values ($\epsilon_{i\ell}$) are independently drawn for i and ℓ, these trials are independent across each consumer and lender pair. Write

[52] One year Treasury rate is used as a proxy for issuers' cost of funds. To the extent that a credit card is an offer of a line of credit, higher rates increase the cost of providing funds for the card (e.g. holding open a line of credit) and subsequently the excess returns on this asset (which thus determine the price at which the asset can be sold as a security, should the issuer choose to do so).

the likelihood as

$$\mathcal{L} = \prod_{t \in T} \prod_{i \in \mathscr{I}} \prod_{\ell \in \mathscr{L}} \Big[Pr(\text{offer})_{i\ell} \Big]^{y_{i\ell}} \Big[1 - Pr(\text{offer})_{i\ell} \Big]^{1-y_{i\ell}} \tag{19}$$

where y_{il} is an indicator that equals 1 if ℓ sent an offer to i. The outcome, or dependent variable, is thus an indicator for whether or not it was profitable for ℓ to make an offer to i. This is a function of the products available to ℓ, her competitors' offer decisions, customers' demographic traits, the macroeconomic environment (M), and the set cost of printing and mailing the offer (c). Given that the data is a series of repeated monthly cross sections, spanning the period Jan 2010 to July 2012, let a market be defined as one month ($t \in T$) in the data, and assume independence across markets. The estimation then maximizes the likelihood of individuals receiving offers from heterogeneous lenders, whereby the propensity to receive an offer is a function of the above mentioned factors.

Finally, let $\epsilon_{i\ell}$ be normally distributed with mean zero and variance σ^2. The cost of printing and mailing (c) is set at \$0.40. This cost is calculated using the Direct Marketing Association's 2013 Factbook (DMA, 2013), which estimates the cost of printing at about \$0.25 and mailing cost (from commercial standard mail rates of the United States Postal Service) at \$0.15. It follows that the log of the likelihood function is given by

$$\mathcal{LL} = \sum_{m \in \mathscr{M}} \sum_{i \in \mathscr{I}} \sum_{\ell \in \mathscr{L}} y_{i\ell} \cdot ln \Big[Pr(\text{offer})_{\ell,i} \Big] + (1 - y_{i\ell}) \cdot ln \Big[1 - Pr(\text{offer})_{\ell,i} \Big]$$

$$= \sum_{m \in \mathscr{M}} \sum_{i \in \mathscr{I}} \sum_{\ell \in \mathscr{L}} y_{i\ell} \cdot ln \Big[1 - \Phi(\frac{1}{\sigma} \min_{h_\ell} \omega_{ih_\ell}(\cdot)) \Big] + ln \Big[\Phi(\frac{1}{\sigma} \min_{h_\ell} \omega_{ih_\ell}(\cdot)) \Big] \tag{20}$$

6 Identification

As discussed in section 3, the data comprises a large set of independent equilibrium outcomes of lenders interacting in the market place. This model of lender interaction is set out in section 4, whereby different banks can choose a different strategy for each different type of potential customer. In this section I discuss how variation in the data can separately

identifies the parameters of this model.

6.1 Variation in Offer Sets

The main source of identification is in the variety of offer sets faced by potential consumers. Because different offers consumers receive in their mailbox each month are equilibrium observations of lenders' offering game, variation in the number and characteristics of the products offered to different individuals by different banks thus identifies the underlying primitives in the model. For example, suppose there are two types individuals: low risk and high risk. The model predicts that low risk types get product A from lender ℓ with probability x and high risk types get product B from ℓ with probability y. In the data, some low risk types receive A and some do not, while some high risk types receive B and some do not. To the extent that high types receive product A while low types receive product B, along with differences in their respective propensities to receive these products (x, y), provide moments for identification.

Table 5 expresses systematic differences in prospective customers' propensities to receive offers from different lenders. The table shows results from a seemingly unrelated regression (SUR) system of 6 linear equations. In each equation, the dependent variable is an indicator of whether or not a prospective customer received an offer from a particular lender. Each equation relates prospective customers' propensity to receive an offer to their risk (*Vantage* score), demographics, and the number of offers received from other banks. In the regressions, coefficients on demographics and risk are restricted to be the same across equations. Coefficients on the existing customer status, the number of offers received from competitors, a measure of an individual's competitiveness, and the number of products held by the lender, are allowed to vary across equations. The unit of observation is a respondent in a month. Regressions include month fixed effects.

As indicated in the table, there is substantial variation among different types of consumers in their propensity to receive offers from different lenders. More specifically, lenders are more likely to make offers to younger consumers with higher credit scores. Moreover, home owners are more likely to be offered a new card, while those living in large urban areas are made fewer offers. As might be expected, consumers identified as having an existing relationship

Table 5: Probability of Making an Offer

Dendent Variable =	Offer Received From					
Linear SUR	Amex	BoA	CapOne	Chase	Citi	Discover
	(1)	(2)	(3)	(4)	(5)	(6)
	Parameters Restricted Across Equations					
Vantage Grade B	0.0101**					
	(0.0014)					
Vantage Grade A	0.0183**					
	(0.0014)					
Between 35 and 65 Years Old	-0.0082**					
	(0.0012)					
Older than 65	-0.0193**					
	(0.0013)					
Homeowner	0.0101**					
	(0.0010)					
Large City	-0.0030**					
	(0.0007)					
	Unrestricted Parameters					
Existing Customer	-0.0319**	-0.0274**	-0.0134**	-0.0324**	0.0084**	-0.0597**
	(0.0042)	(0.0026)	(0.0033)	(0.0031)	(0.0032)	(0.0027)
Num. of Competing Offers	0.0349**	0.0381**	0.0164**	0.0931**	0.0847**	0.0531**
	(0.0007)	(0.0007)	(0.0006)	(0.0012)	(0.0011)	(0.0008)
Num. Products in Menu	0.0019*	0.0008	-0.0019**	0.0010*	-0.0010*	-0.0041**
	(0.0009)	(0.0006)	(0.0005)	(0.0003)	(0.0004)	(0.0010)
Observations	63,496	63,496	63,496	63,496	61855	61855
Adjusted R^2	0.0363	0.0381	0.0277	0.0289	0.0472	0.0484
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows parameter estimates from a SUR system of six linear probability models relating lenders' propensity to offer a card to customers demographic and risk characteristics as well as their competitiveness. Data are from the Mintel Comperemedia survey of credit solicitations and comprise monthly repeated cross section spanning the period Jan. 2010 to July 2012. The top panel shows parameter estimates that restricted to be the same across equations. The bottom panel shows parameter estimates which are bank specific and are free to vary across equations. The unit of observation is a survey respondent. Robust standard errors in parentheses. $^{+}$ $p < .1$, * $p < .05$, ** $p < .01$.

with the lender are less likely to be made offers in a month, suggesting that lenders are careful to not cannibalize their own business. Finally, lenders' likelihood of sending an offer is on net increasing in the number of competing offers received by a customer, suggesting a counter-balance to the mail-box stuffing effect discussed above. This fact that holds true even after controlling for the size of the set of products lenders could potentially offer (their menu).

Table 6 indicates how offered products are customized to different consumer types. The table shows six ordinary least squares regressions relating product price characteristics to consumers' demographic profiles. As aforementioned (section 3), *Rate* is a continuous variable indicating the level of the interest rate on regular purchases, *Intro* and *Bal. Trans.*

Table 6: Interest Rate & Other Price Characteristics

	Rate	Intro	Bal.Trans	Delinq. Fees	Other Ins.	CashBack
	(1)	(2)	(3)	(4)	(5)	(6)
Vantage Grade B	-0.1954**	0.0051	0.0005	-0.0054	0.0061	0.0033
	(0.0472)	(0.0055)	(0.0054)	(0.0101)	(0.0127)	(0.0086)
Vantage Grade A	-0.4364**	0.0270**	0.0248**	-0.0121	0.0267*	-0.0071
	(0.0471)	(0.0056)	(0.0055)	(0.0102)	(0.0129)	(0.0087)
Respondent is a Homeowner	-0.4001**	0.0026	0.0141**	-0.0102	-0.0213*	-0.0023
	(0.0313)	(0.0036)	(0.0034)	(0.0065)	(0.0086)	(0.0054)
Large City	-0.0232	0.0063*	0.0119**	-0.0035	-0.0110+	-0.0119**
	(0.0204)	(0.0026)	(0.0026)	(0.0047)	(0.0061)	(0.0040)
Existing Customer	0.0334	0.0181	-0.0027	0.0087	-0.0038	-0.0011
	(0.0985)	(0.0196)	(0.0114)	(0.0326)	(0.0319)	(0.0041)
Num. of Competing Offers	-0.0199**	0.0036**	-0.0003	-0.0019	-0.0100**	-0.0012
	(0.0065)	(0.0008)	(0.0008)	(0.0014)	(0.0019)	(0.0013)
BoA FE.	-3.7734**	0.1887**	-0.3790**	0.7232**	-1.1169**	0.5787**
	(0.0396)	(0.0037)	(0.0052)	(0.0073)	(0.0120)	(0.0091)
CapOne FE	-1.8864**	-0.0625**	-0.0998**	-1.9587**	-1.3106**	-0.1604**
	(0.0521)	(0.0051)	(0.0077)	(0.0182)	(0.0121)	(0.0095)
Chase FE	-4.1643**	0.0839**	-0.4686**	0.1500**	-0.5966**	0.2670**
	(0.0307)	(0.0030)	(0.0049)	(0.0086)	(0.0117)	(0.0086)
Citi FE	-2.8967**	0.2015**	-0.2036**	-0.3715**	0.1293**	-0.1631**
	(0.0326)	(0.0040)	(0.0050)	(0.0078)	(0.0129)	(0.0082)
Discover FE	-5.6763**	-0.1775**	-0.5586**	-0.4970**	-0.3107**	0.7221**
	(0.0316)	(0.0043)	(0.0050)	(0.0096)	(0.0122)	(0.0078)
Amex FE	17.3636**	1.0234**	1.6090**	3.2976**	1.2648**	0.2888**
	(0.0580)	(0.0065)	(0.0073)	(0.0132)	(0.0176)	(0.0119)
Observations	40014	40014	40014	40014	40014	40014
Adjusted R^2	0.389	0.288	0.410	0.647	0.425	0.425
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows parameter estimates from six OLS regressions relating product characteristics to consumer's demographic and risk characteristics. Each regression includes bank and month-year fixed effects. Data are from the Mintel Comperemedia survey of credit solicitations and comprise monthly repeated cross section spanning the period Jan. 2010 to July 2012. The unit of observation is an offer sent to a survey respondent. Robust standard errors clustered are in parentheses. $^{+}$ $p < .1$, * $p < .05$, ** $p < .01$.

are continuous variables referring to the length of the respective promotional period, *Delinq. Fees* and *Other Ins* are discrete variables referring to the count of fees on the card, and *CashBack* is a binary variable indicating the inclusion the program on the card. The unit of observation is a product offered to an individual.

As might be expected, offers sent to consumers with higher credit scores have lower interest rates, are more likely to offer longer promotional periods, and are more likely to include bundled insurance products. Moreover, there is little difference in the propensity to get cash back offers among higher and lower credit score consumers. Similarly, lenders are more likely to send home-owners and urban consumers offers with lower rates and longer

promotional periods; they are less likely to send them them offers with introductory rates, balance transfer promotions, or offers that carry foreign transaction fees. Furthermore, home-owners and urban consumers are less likely to be sent offers with bundled insurance products, a fact not observed for other consumer types. Although lenders are less likely to send offers to existing customers (Table 5), they do not seem to distinguish between existing customers and new customers when deciding which offer to send.

6.2 Product Line Heterogeneity

The analysis in this paper takes as given lenders' product location choice. In other words, the menu of available products (product-line) for each respective lender is assumed to be fixed. Despite this lenders' product lines are of substantial size and variety, such that lenders retain considerable choice over which products to offer to which consumers. As shown in table 7, in

Table 7: Differences in Sent Offers

Variable	Type	Amex	BoA	CapOne	Chase	Citi	Discover
	Avg. Mean	16.74	13.05	15.20	13.02	13.90	11.08
Rate	$\mathbb{E}$(Min)	13.04	11.07	11.60	9.96	11.41	10.38
	$\mathbb{E}$(Max)	18.05	17.88	21.34	20.6	20.44	12.93
Intro Rate Period (Years)	Avg. Mean	1.07	1.25	1.04	1.14	1.25	0.89
Bal. Transf. Period (Years)	Avg. Mean	1.66	1.27	1.54	1.18	1.39	1.07
Delinquency Fee (Count)	Avg. Mean	3.26	4.00	1.38	3.42	2.93	2.85
Bal Transf. Fee (% with)	Avg. Mean	0.97	1.00	0.31	0.86	1.00	0.78
Foreign Transaction Fee (% with)	Avg. Mean	1.00	0.99	0.48	0.96	0.97	1.00
Annual Fee (% with)	Avg. Mean	0.04	0.02	0.09	0.04	0.03	0.00
Repayment Insurance (% with)	Avg. Mean	0.67	0.04	0.00	0.41	0.93	0.94
Other Insurance (Count)	Avg. Mean	1.17	0.16	0.05	0.63	1.31	0.97
Non-Cash Rewards (% with)	Avg. Mean	0.70	0.13	0.81	0.08	0.62	0.00
CashBack Rewards (% with)	Avg. Mean	0.30	0.83	0.10	0.53	0.11	1.00
Menu Size	Mean	12	12	11	30	33	11

Notes: This table shows characteristics of the menu of products held by each lenders. Means are taken across months in the data. Avg. Mean refers to the average monthly mean, $\mathbb{E}$(Min) is the average monthly minimum, and $\mathbb{E}$(Max) is the average monthly maximum. Data are from the Mintel Comperemedia survey of credit solicitations and comprise monthly repeated cross section spanning the period Jan. 2010 to July 2012. The unit of observation is an offer sent to a survey respondent.

an average month the number of products in a menu ranges from 11 for Discover and Capital One to 30 for Chase and 33 for Citi. In addition, lenders hold a wide portfolio of products. On average, the interest rate on purchases for offered products can range from below 10

percent to more than 20 percent. Moreover, for other characteristics, it is the case that for the most part lenders vary in the products they offer. For example, Citi on average provides more generous introductory rate promotions, while Amex provides more generous balance transfer promotions. Citi always includes a fee on transfered balances, while on average one third of CapOne's products include a fee on balance transfers. Similarly, Chase always offers cards with a rewards program and cards without, while Discover only offers cards with CashBack rewards, their signature program.[53] Overall, the table suggests substantial variation in products offered both across and within banks which will be used to identify the parameters in the model.

6.3 Restrictions

As noted above, lenders' profit functions consists of two parts: demand (take-up), and value (net revenues). Both of these parts depend on product (X_{h_ℓ}) and individual (Z_i) characteristics. Non-linearities imposed by the model ensure that X_{h_ℓ} and Z_i differentially impact eventual outcomes as a result of changes in take-up versus changes in value. However, I impose additional restrictions on the two equations to better parse out these effects.

The first, and most evident from the model, is that the number of offers received impacts take-up and thus but has no effect on the net-revenue stream generated by a consumer were they to take up the card. Second, I assume age is not used to determine consumers' value, but that it does enter demand. This restriction is in accordance with the Equal Credit Opportunity Act (ECOA) of 1974, which does not allow lenders to use age as information for directly determining the terms of credit; Lenders, however, are allowed to use age for marketing purposes. It follows that differences in offers by age are due solely to lenders' assessment of how likely individuals of different ages are to take-up their offers, rather than in how much net revenue they might generate. Third, I assume that brands preferences are i.i.d across consumers and uncorrelated with a products observed characteristics. As a result, I restrict time invariant lender heterogeneity (e.g. lender fixed effects) to the determination

[53] There are also differences in menus both within month across lenders and within lender across time, not shown here. This suggests substantial product space positioning by lenders, a process beyond the scope of this paper.

of value. For example, American Express and Discover might differentially value customers in ways that are time invariant and not explained by product characteristics or demographic traits (e.g. vendor fees). Lastly, I assume the Treasury rate is not salient to customers choosing a credit card. However, because Treasury yields determine the cost of raising the money to fund new lines of credit, changes in treasury yields are of first order importance to lenders in calculating the net revenue stream generated by a particular consumer.[54]

7 Results

7.1 Model Estimates

Table 8 shows estimates of the model parameters.[55] Columns (1) and (2) show estimates for the demand functions ($U(X;\beta)$, $s(Z;\gamma)$, $r(N;\alpha)$) , and columns (3) and (4) show estimates of lenders' value (net revenue) function.

7.1.1 Demand

Demand estimates suggest that consumers prefer lower interest rates, longer promotional periods, and more generous rewards programs. Moreover, consumers dislike card fees. As is in line with previous work (e.g. Ellison and Wolitzky (2012); Gabaix and Laibson (2006)), their demand is less sensitive to the inclusion of fees, which are seldom advertised, than to improved interest rate terms and more generous promotions.

Table 9 shows implied own price demand elasticities for continuous variables (e.g. rate and promotion period). As shown in the table, model estimates imply a high sensitivity of demand to the regular rate on purchases as well as to the length of promotional periods. Interest rate elasticity of demand is calculated at about -10.8. This means that a 1.2-1.6 percentage point increase in the interest rate, all else equal, reduces take-up rates by approximately 0.0045 percentage points.[56] Take up rates are also sensitive to the length of promotional periods. As shown in the table, elasticity of demand with regards to the

[54]Moreover, the Treasury rate affects the price at which new accounts can be sold as credit card asset backed securities.

[55]Definitions of variables used in the estimation are given in Table 4

[56]Mean estimated Demand (Take-Up) is 0.045% - or 1 in ∼2000 offers.

Table 8: Model Estimates

Variable	Parameter (1)	Std.Err. (2)	Parameter (3)	Std.Err. (4)
	Utility - $u(X;\beta)$		Value - $v(X,Z;\psi)$	
Constant			1834.22	(2.98)*
Rate	-0.910	(0.025)*	920.21	(3.37)*
Rate × *Vantage* Grade B	0.003	(0.031)		
Rate × *Vantage* Grade A	0.029	(0.033)		
Intro Period	0.371	(0.002)*	-405.82	(2.57)*
Balance Transfer Period	0.217	(0.002)*	-234.43	(0.96)*
Delinquency Fees	-0.037	(0.002)*	40.33	(3.62)*
Balance Transfer Fee	-0.054	(0.001)*	57.56	(0.99)*
Foreign Transaction Fees	-0.182	(0.003)*	204.76	(0.92)*
Annual Fee	-0.074	(0.006)*	80.45	(4.98)*
Repayment Insurance	0.006	(0.003)*	-4.72	(4.53)
Other Insurance	0.376	(0.005)*	-417.09	(0.75)*
Non-Cash Rewards	0.098	(0.001)*	-110.16	(0.70)*
Cashback Rewards	0.199	(0.003)*	-223.74	(0.48)*
	Outside Option - $s(Z;\gamma)$			
Constant	3.056	(0.002)*		
35 to 65 Years Old	0.004	(0.001)*		
Over 65 Years Old	0.008	(0.002)*		
Vantage Grade B	0.003	(0.003)	7.52	(1.84)*
Vantage Grade A	0.003	(0.006)	6.29	(1.17)*
Homeowner	-0.003	(0.001)*	-0.21	(1.30)
Metropol	-0.002	(0.001)	-3.30	(1.53)*
Existing Customer	0.004	(0.001)*		
	Pr(Open) - $r(N;\alpha)$			
Constant (α_0)	235.587	(0.721)*		
Number of Offers (α_1)	1.944	(1.340)*		
1-Year Treasury Bill Rate			1300.73	(2.61)*
$Var(\epsilon)$ - σ			25.78	(0.78)*
Lender FE (Base = Amex)			✓	
Observations		63,496		
Log Likelihood		-91,781.16		

Notes: This table shows model estimates of model parameters. Columns (1) and (2) show consumer demand parameters (standard errors) and columns (3) and (4) show lender value parameters (standard errors). Data are from the Mintel Comperemedia survey of credit solicitations and comprise monthly repeated cross sections spanning the period Jan. 2010 to July 2012. + p < 0.1, * p < .05.

promotional period is calculated as between 28.86 and 42.61, for the introductory rate period, and between 21.02 and 31.85, for the balance transfer period. This implies that, all else equal,

Table 9: Elasticity Estimates of Continuous Demand Variables

Var	Amex (1)	BoA (2)	CapOne (3)	Chase (4)	Citibank (5)	Discover (6)
$\bar{\epsilon}_{Rate}$						
Vantage Grade C	-10.79	-10.87	-10.77	-10.63	-10.74	-10.66
Vantage Grade B	-10.80	-10.81	-10.84	-10.80	-10.78	-10.76
Vantage Grade A	-10.74	-10.80	-10.77	-10.75	-10.82	-10.75
$\bar{\epsilon}_{Intro.}$	34.74	42.61	33.94	38.20	41.71	28.86
$\bar{\epsilon}_{Bal.}$	31.85	25.27	31.20	23.16	27.77	21.02
$\mathbb{E}(Rate)$	16.62	12.83	14.91	12.48	13.88	11.07
$\mathbb{E}(Intro)$ (Months)	12.48	14.83	11.90	13.46	15.20	10.27
$\mathbb{E}(Bal.)$ (Months)	19.61	15.05	18.74	13.97	17.31	12.76

Notes: This table shows own price elasticities for continuous price characteristics: Non-introductory interest rate (Rate), introductory period (Intro) and balance transfer period (Bal.). The bottom panel shows mean values of respective price characteristics on offers made during the sample period.

extending the introductory rate period by one week could increase take up by up to 0.014 percentage points.

Table 10 shows calculated demand elasticities for discrete characteristics, which include fees and rewards. These are defined as

$$\bar{\epsilon}_{x_i} = \begin{cases} \dfrac{1}{H}\displaystyle\sum_{h\in\mathcal{H}} \dfrac{P(x_i = md(x_i)+1, x_{-i}) - P(x_i = md(x_i), x_{-i})}{P(x_i = md(x_i), x_{-i})} & x_i \in \{\text{Dlq. Fees, Oth. Ins.}\} \\ \\ \dfrac{1}{H}\displaystyle\sum_{h\in\mathcal{H}} \dfrac{P(x_i = 1, x_{-i}) - P(x_i = 0, x_{-i})}{P(x_i = 0, x_{-i})} & \text{Otherwise} \end{cases}$$

where $md(x_i$ is the median value of characteristics x_i.

As aforementioned, delinquency fees are not as salient to consumers as other card characteristics. Including one more fee (e.g. going from a card with no late fees to one with a \$25 or \$39 late fee) reduces take up by only 3.3 percent (or 0.0015 percentage points).[57] This is similar for balance transfer fees, the inclusion of which reduces take up about 0.0025 percentage points. In contrast, consumers are more deterred by the inclusion of foreign transaction and annual fees, which are features the absence of which is often advertised in the mail out

[57]The median number of delinquency fees on a card is 3, the minimum is 0 and the maximum is 4.

Table 10: Arc-Elasticity Estimates of Discrete Variables

Characteristic	$\bar{\epsilon}$ (1)	$max(\epsilon)$ (2)	$min(\epsilon)$ (3)
Delinquency Fees	-3.31	-3.48	-2.77
Balance Transfer Fee	-4.77	-5.04	-3.98
Foreign Transactions Fee	-15.19	-16.04	-12.67
Annual Fee	-6.57	-6.91	-5.46
Repayment Insurance	0.52	0.44	0.55
Other Insurance	39.84	35.63	42.31
Non-Cash Rewards	9.36	7.67	9.96
Cash Rewards	19.84	15.93	21.10
Number of Competing Offers	-0.80	-0.81	-0.71

Notes: This table shows own price arc-elasticities for discrete price characteristics. Definition of elasticities is as shown in the text.

offer. As shown in the table, all else equal, including foreign transaction fees (usually set at 3% of purchases) reduces take up by 15.2 percent, while an annual fee reduces take up by a little less than half as much, 6.6 percent. On the benefit side, consumers are most responsive to bundled insurance products such as fraud, travel, and purchase insurance, whereby the inclusion of an extra insurance product increases take up by up to 42.3 percent.[58] Furthermore, including a non-cash rewards program on the card, such as points, rebates, or miles, increases take up, all else equal, by just under 10 percent. Including a cash back rewards program can increases take up by as much as 21.1 percent, or twice as much as a non-cash program. Overall, demand estimates suggest that consumers are much more responsive to rates and promotional characteristics such as introductory/balance transfer periods, bundled insurance products, and rewards. They care less about fees, especially to delinquency and balance transfer fees, which are characteristics that are seldom advertised.

The bottom panel of table 8 shows the effect of demographic characteristics on consumers' demand for new cards. As would be expected, older individuals are less likely to prefer taking up a new card, having a higher utility for their outside option. Moreover, lower risk individuals are also less likely to take up new cards, while home owners and individuals residing in large cities are more likely to take up a new card. Existing customers are less

[58]In contrast, consumers are on average much less responsive to the inclusion of repayment insurance products on the card. Lastly, consumers are very responsive to the inclusion of rewards programs on cards.

likely to take up offers for new cards. Note, however, a large coefficient on the constant in the equation. This suggests that, on average, consumers have a strong preference for their outside option that is not explained demographic differences.

Lastly, the weight parameters (α_0, α_1) on the inattention function $r(n; \alpha)$ indicate that, although consumers are largely inattentive to new offers, more offers in consumers' mailbox would not greatly impact their propensity to be attentive. For example, individuals receiving two offers are only $< 1\%$ less likely to open an envelope than those receiving only one offer. This implies that a high degree of inattention that is not explained by the 'mailbox stuffing' effect that lenders in this model are competing on. In other words, issuers struggle to get noticed even when consumers have few options to choose from in a given month.

7.1.2 Value

Columns (3) and (4) of table 8 shows lenders' net revenue (value) equation $v(X_{h_\ell}, Z_i, M; \psi)$. Parameter estimates are denominated in dollars. As shown in the table, higher interest rates increase revenues while longer promotional periods and more generous rewards and bundled insurance offers reduce net revenue. Moreover, more fees generate greater revenues for lenders.

Specifically, the table suggests that a 1 percentage point increase in the interest rate increases net revenue by about \$9, while adding a year to the intro period and/or the balance transfer period reduce net revenues by \$405 and \$234, respectively. Adding rewards and insurance products to the card is similarly expensive to the lender, while foreign transaction and annual fees are especially lucrative. These increase revenue by, all else equal, \$254 and \$80, respectively.

As might be expected, lower risk individuals are more profitable to issuers than higher risk individuals. Nevertheless, despite being more likely to take up a card, consumers living in large cities are less profitable to have as customers.[59] Finally, the model shows that increases in the cost of funds substantially reduce lenders net revenue from a potential account. A 1

[59] A result in the model then is that lender's decreased propensity to offer urban consumers new cards (Table 5) stems from these consumers' lower value rather than their lower take-up rates. City dwellers, for example, are perhaps less likely to hold high balances, use a new card, and/or might keep the account for a much shorter period of time.

percentage point increase in the Treasury rate reduces net revenue by \$13, which is about 1.3 percent of the average net revenue earned on accounts ($\sim$ \$1000).

7.2 Counterfactuals

In the following, I consider two market counterfactuals illustrating the equilibrium effects of changes in the market environment. In the first, I look at the potential short run impact of an increase in the cost of funds, measured as a rise in the one year constant maturity Treasury rate. Given historically low interest rates over the past years, this explores likely equilibrium effects of a tightening market. Moreover, this counterfactual sheds light on potential reasons for imperfect pass through in this market. I next explore the potential competitive effects of an additional market participant. In the past two decades, there has been substantial consolidation in credit card lending. This counterfactual studies what might be the potential cost of having too few competing lenders given today's market environment.

In each of the scenarios, I consider several outcomes. First I consider the proportion of individuals receiving offers under the baseline versus the counterfactual. I then compare the number of offers received and the rates on those offers. I calculate the mean over consumers i of the minimum, average, and maximum rate on offers received each month. On the lender side, I calculate changes in average response rates as well as expected profit from sending out an offer. For each outcome, I investigate separately the effect on four different types of consumers: (1) those who receive in both scenarios, (2) those who receive only in the baseline case, (3) those who receive only in the counterfactual, and (4) those who never receive.

7.2.1 Rise in the Cost of Funds

Table 11 shows the results from a 1 percentage point increase in the 1-year Treasury rate. The top panel of the table shows the proportion of individuals who receive offers (1) always, (2) only in the baseline case, (3) only in the counterfactual, and (4) in neither. Increasing the Treasury rate unambiguously reduces the propensity of receiving an offer. As is in line with the model, a uniform reduction in expected net revenues only affects firms' decision of whether or not to make an offer to a consumer (not which product to offer). As such,

Table 11: Increase in the Treasury Rate

		Proportion of Individuals Receiving			
		Always Receive (1)	Receive Only in Baseline (2)	Receive Only in Counterfactual (3)	Never Receive (4)
Percent	All	16.21	18.56	0	65.23
	Vantage C	10.27	15.07	0	74.66
	Vantage B	15.49	18.36	0	66.15
	Vantage A	18.02	19.39	0	62.59
		Offers Received			
		Always Receive Tbill+0% (1)	Always Receive Tbill+1% (2)	Receive Only in Baseline Tbill+0% (3)	Receive Only in Counterfactual Tbill+1% (4)
Num. Offers	All	1.29	1.08	1.11	0
	Vantage C	1.20	1.04	1.09	0
	Vantage B	1.27	1.07	1.10	0
	Vantage A	1.31	1.09	1.12	0
$\mathbb{E}$(Min Rate)	All	11.71	11.84	11.90	0
$\mathbb{E}$(Mean Rate)	All	11.91	11.90	11.98	0
$\mathbb{E}$(Max Rate)	All	12.12	11.95	12.06	0
Response	All	0.034	0.034	0.034	0
Profit	All	0.007	0.003	0.002	0

Notes: This table shows the estimated equilibrium effect of a 1% increase in the Treasury rate. $\mathbb{E}_i$(Mean Rate) is an average over consumers (i) of the mean non-introductory interest rates on all offers received by (i) in a given month. Similarly, $\mathbb{E}_i$(Min Rate) and $\mathbb{E}_i$(Max Rate) are the average over i of the minimum and maximum non-introductory interest rates, respectively, received by i in a given month. *Vantage* C refers to individuals with a *Vantage* score below 700, *Vantage* B refers to individuals with a *Vantage* score between 700 and 800, and *Vantage* A refers to individuals with *Vantage* scores above 800. The top panel shows percent of individuals who (1) receive in both scenarios, (2) receive only in baseline, (3) receive only in counterfactual, and (4) never receive. The bottom panel shows the number and type of offers received by individuals in who (1) receive in both scenarios under baseline (2) receive in both scenarios under counterfactual, (3) receive only in baseline under baseline (4) receive only in counterfactual under counterfactual.

the model predicts that an increase in the Treasury rate results in every individual receiving weakly fewer offers. From the table, note that there are no individuals who receive offers only in the counterfactual (column 3). In all, the proportion of individuals receiving offers falls by 46 percent. Moreover, this effect is decreasing in individuals' credit score. Riskier consumers, who are less profitable, are less likely to receive offers given a uniform rise in the cost of providing credit.

The bottom panel shows the effect of an increase in the Treasury rate on the number and types of offers received by consumers. As would be expected, for individuals receiving offers

in both cases, the average number of offers received declines by 16 percent (columns 1 and 2). Moreover, as compared to those always receiving offers, those receiving offers only in the base case receive on average fewer offers (column 3). Looking down the table, they are also less likely to respond and are substantially less profitable than other consumers.

Despite a drop in the number of mailed offers, the mean rate on received offers remains essentially unchanged. Nevertheless, the dispersion in offered rates declines substantially. The minimum rate on offers increases by 13 basis points and the max rate declines by 17 basis points. Facing an increase in the cost of providing credit, lenders whose preferred product carries especially high or especially low rates no longer find it profitable to send it out to. As a result, consumers see little change in the mean but rather a reduction in the range of interest rates (or products) offered to them. The above suggests that persistently observed low pass through of cost of funds to interest rates can in part result from the fact that higher cost impact dispersion more than average rates. In addition, as consumers do not always choose offered products with the lowest rates, we might perhaps observe little change, and potentially a decrease, in average rates on new accounts following a rise in the cost of funding accounts, even though the lowest rates offered in the market increase substantially following a rise in the cost of funds.

From the lender side, an increase in the Treasury rate does little to alter take-up rates, a result largely due to the importance of the outside option as a driver of low demand. Still, a negative shock to lenders' net revenue stream translates to a substantial decline in average profit from mailing an offer.

7.2.2 Adding a Competitor

Over the past two decades, the credit card market has consolidated substantially. In the late 1980s, the largest 10 lenders controlled about 10 percent of outstanding credit card debt. Today, the largest 5 lenders control more than 90 percent of outstanding credit card balances. Coupled with this consolidation, there has been a substantial decline in both average rates and industry profits (Grodzicki, 2013). These changes have led to the overall consensus that, over the past decades, the credit card market has become more competitive. This counterfactual investigates competitive effects of a reduction in concentration given today's

market conditions. To this end, I create a hypothetical lender called Citibank2. I do so by randomly assigning half of Citibank's existing customers to Citibank2 and making available to it the menu of products currently available to Citibank.[60]

Table 12 reports the results from this counterfactual. As shown in the table, adding another competitor on net increases the propensity to receive receive credit. In contrast to

Table 12: Adding a Competitor

		Proportion of Individuals Receiving			
		Always Receive (1)	Receive Only in Baseline (2)	Receive Only in Counterfactual (3)	Never Receive (4)
Percent	All	34.27	0.50	12.20	53.03
	Vantage C	25.00	0.34	10.51	64.15
	Vantage B	33.23	0.62	12.24	53.91
	Vantage A	37.03	0.38	12.44	50.15
		Offers Received			
		Always Receive L = 6 (1)	Always Receive L = 7 (2)	Receiving Only in Baseline L = 6 (3)	Receive Only in Counterfactual L = 7 (4)
Num. Offers	All	1.19	1.38	1.02	1.12
	Vantage C	1.13	1.28	1.00	1.08
	Vantage B	1.18	1.36	1.02	1.12
	Vantage A	1.21	1.40	1.02	1.12
$\mathbb{E}$(Min Rate)	All	11.81	11.72	11.72	11.99
$\mathbb{E}$(Mean Rate)	All	11.95	11.96	11.73	12.06
$\mathbb{E}$(Max Rate)	All	12.09	12.21	11.74	12.14
Response	All	0.034	0.034	0.034	0.034
Profit	All	0.004	0.005	0.000	0.002

Notes: This table shows the estimated equilibrium effect of adding a cometitor in the market. $\mathbb{E}_i$(Mean Rate) is an average over consumers (i) of the mean non-introductory interest rates on all offers received by (i) in a given month. Similarly, $\mathbb{E}_i$(Min Rate) and $\mathbb{E}_i$(Max Rate) are the average over i of the minimum and maximum non-introductory interest rates, respectively, received by i in a given month. *Vantage* C refers to individuals with a *Vantage* score below 700, *Vantage* B refers to individuals with a *Vantage* score between 700 and 800, and *Vantage* A refers to individuals with *Vantage* scores above 800. The top panel shows percent of individuals who (1) receive in both scenarios, (2) receive only in baseline, (3) receive only in counterfactual, and (4) never receive. The bottom panel shows the number and type of offers received by individuals in who (1) receive in both scenarios under baseline (2) receive in both scenarios under counterfactual, (3) receive only in baseline under baseline (4) receive only in counterfactual under counterfactual.

the above, however, it is not the case that all individuals receive weakly more or fewer offers.

[60] I choose Citibank because it has the largest product line, which gives it the most choice in targeting consumers, thus maximizing the potential competitive impact of an additional market player.

As shown in the table, about 0.15 percent of individuals no longer receive any offer once a new lender is added. This reflects the trade off between existing lenders making fewer offers as a result of more competition and new lenders making more offers. On net, because of the small weight on the inattention parameter (α_1), extra offers made by the new lender (Citibank 2) outnumber the reduction in offers from incumbents due to deterrence.

On the intensive margin, for individuals receiving offers in both case (e.g. with 6 and 7 lenders), an extra lender in the market increases the number of offers they receive by about 16 percent. For these individuals, the dispersion rises from 28 to 49 basis points, while the mean rate decreases remains largely the same. From table 7, note that Citibank has the greatest average menu size and offers a wide range of rates each month. The results above reflect the fact that, given these attributes of its menu, Citi is able to offer products with both lower and higher rates. Also, Citi's large menu size implies that it is more likely to find preferred products that are profitable, thus making more offers overall (a fact of the underlying data illustrated in figure 1). As such, with citi as the bench mark, we might expect the greatest increase in offers combined with the greatest change rates available to consumers.

Finally, looking at the lender side, an additional competitor does not change the underlying response rates or profitability of those always receiving an offer (columns 1 and 2). Individuals no longer receiving offers when a competitor is added are less likely to respond to offers and are only marginally profitable. This is similarly the case for individuals newly receiving offers when a competitor is added.

8 Conclusion

This paper has investigated how credit card lenders choose to offer their products to prospective borrowers. To this end, it has developed an equilibrium model of lenders' mail out decisions and estimated it using data on direct mail credit card offers. In contrast to previous work, this model has taken into account the fact that credit cards are complex products and that, as a result, there is a high degree of customization by banks in the offers they choose to send prospective customers. This subsequently leads to uncertainty by banks over the

choice sets of prospective customers, a salient fact in the data. The estimated model reveals that, as expected, consumers are more sensitive to promotions and rewards on cards than to delinquency fees such as late or over-limit fees.

With the estimated model, I have considered two market counterfactuals, one pertaining to possible market changes in the coming years and one which looks at the impact of consolidation on equilibrium market outcomes. I find that a market tightening, or uniform increase in the cost of providing credit, will likely lead lenders to make fewer and less varied offers. Although rising cost increases the lowest offered rates, it also leads lenders to stop making high rate offers, thus reducing dispersion in the market place. This reduction in overall price dispersion might be interpreted as a potential reason for persistently observed low pass through of the underlying cost of funds to interest rates. In contrast, adding a competitor increases the propensity to receive offers and the range of products sent to consumers. As a result price dispersion in the market increases substantially, despite little change in mean offered rates. Unlike in the above, some consumers will receive less credit.

There are several aspects of competition in this market that were not considered in the analysis. Most important of these is that the product line, or location choice, is held fixed and assumed to be separate from the offer decision. This location decision is a fundamentally dynamic process which will be treated in future work.

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A Mintel vs. Current Population Statistics

This appendix discusses differences between respondents in Mintel and population distributions as measured by the Current Population Survey (CPS). I compare distributions along three directly comparable dimensions. These are household income, respondents' age, and geographic location.

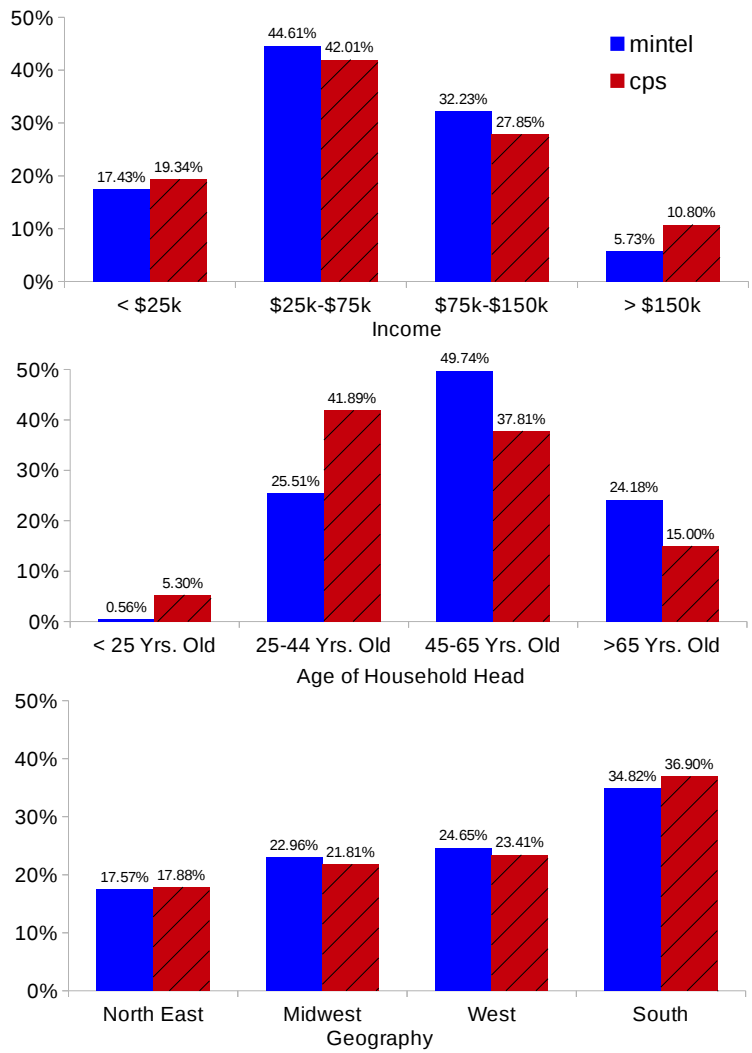

Figure 3: Mintel vs. CPS

Notes: This figure plots the distribution of household income, age, and geography for the Mintel respondents and Current Population Survey (CPS) respondents, respectively. Data are from the Mintel Comperemedia survey of credit solicitations for March of 2010, 2011 and 2012. March 2010, 2011, and 2012 CPS supplements, respectively.

Figure 3 shows the distribution of household income, age, and geographic location for

Mintel recipients in March of 2010, left columns, and the March 2010 CPS, right columns.

The top panel shows differences in the income distribution between Mintel and the population. Most notable in the figure is that Mintel respondents' household income is on average lower than in the CPS. Moreover, the variance in income is larger in the CPS. The second panel of figure 3 compares Mintel and CPS along the age dimension. As the figure shows, there is more difference between Mintel and the Population along this dimension. On average, mintel recipients are older. Finally, the bottom panel of figure 3 matches Mintel with the CPS along the geographic dimension. In contrast to comparisons of household income and age, the distribution of Mintel respondents by region matches well the population, as measured by the CPS.

Broadly, the figure suggests that Mintel respondents are somewhat well representative of the population as a whole. Nevertheless, there are some differences when looking across specific dimensions. For example, Mintel respondents are likely to be older and earn less income on average. Nonetheless, geographic distributions across these two samples match quite closely.

B Loan Channel of New Account Acquisition

This section incorporates data from Strategic Business Intelligence's (SBI) Macro Monitor. These data are from a biennial survey of roughly 4,300 households in which respondents are asked about their financial lives, attitudes, and how they interact with financial institutions. Specifically, one section of this survey asks respondents about their credit card use. In it they are asked if they have acquired a credit card in the past two years as well as the channel by which it was acquired. Figure 4 shows trends in the relative importance of various acquisition channels. The top panel looks at trends over time, comparing customers who were acquired between 2008 and 2010 to those acquired between 2010 and 2012. The bottom panel shows the relative importance of various acquisition channels by age. As shown in the figure, lenders acquire new customers most often through direct mail. Between 2008 and 2010, nearly half of all newly acquired customers applied through the mail, while fewer than a quarter applied online. Although this proportion declines for the period 2010 to 2012, it

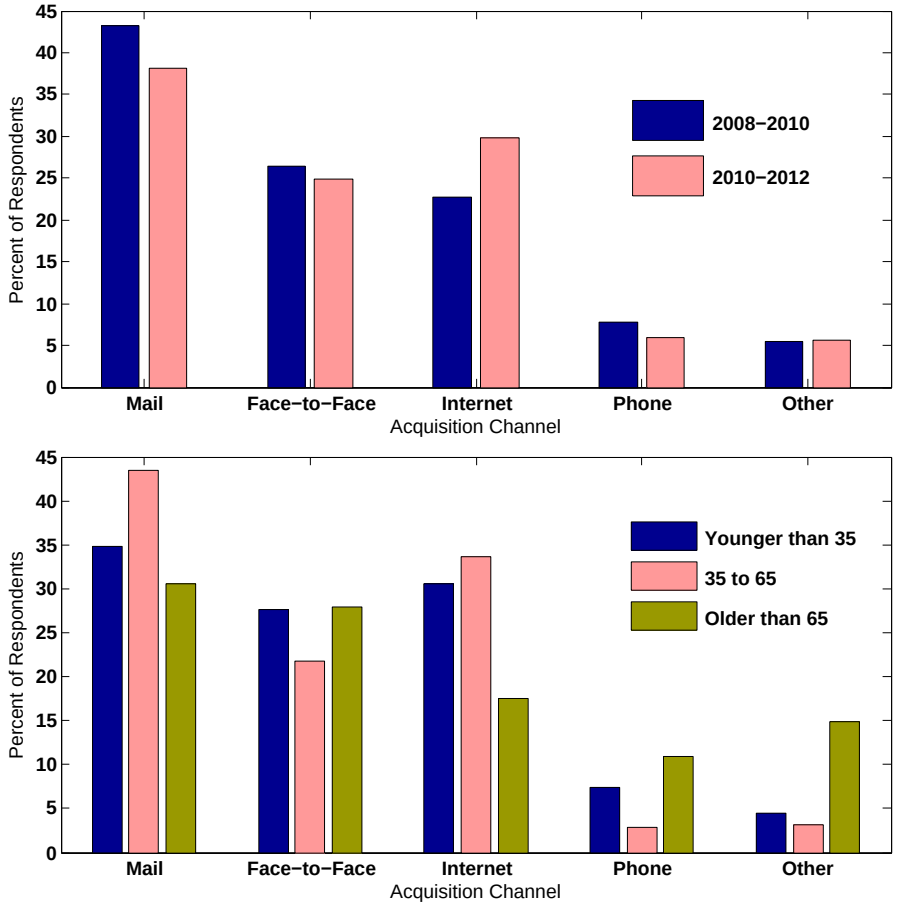

Figure 4: Customer Acquisition Channel 2008-2012

Notes: This figure plots the distribution of the channel by which credit card lenders acquire new customers. Data are from Strategic Business Insights's (SBI) MacroMonitor for waves 2010-2011 and 2012-2013. For more information see appendix.

is still more common for lenders to acquire customers through the mail than through any other means. Moreover, as compared to older customers, lenders are more likely to acquire younger customers via Internet applications. Nevertheless, among younger cohorts, direct mail remains a more prominent acquisition channel. As such, individuals across all age groups were more likely to be acquired via mail than via any other channel.

Importantly, these figures can be understood as a lower bound of the relevance of direct mail. For, although individuals may apply directly online, they are often times prompted to do by a direct mail offer. As described in a February 2011 interview in Direct Marketing News, Pam Girardo, a spokes person for Capital One was quoted as saying that "even in the

increasingly online-oriented marketplace, direct mail plays a role. We can send customized, pre-approved offers via mail with an option to respond online. We've made it as easy as possible for [customers] to use that channel with the full range of Capital One benefits available".

C Model Fit

In this section I compare the model implied market outcomes to those observed in the data. For this I look at how well the model performs in matching distributions of both the number and types of offers observed in the data.

Figure 5 shows distributions of the number of offers received consumers receive every month. The figures compares the distribution observed in the data to that implied by the

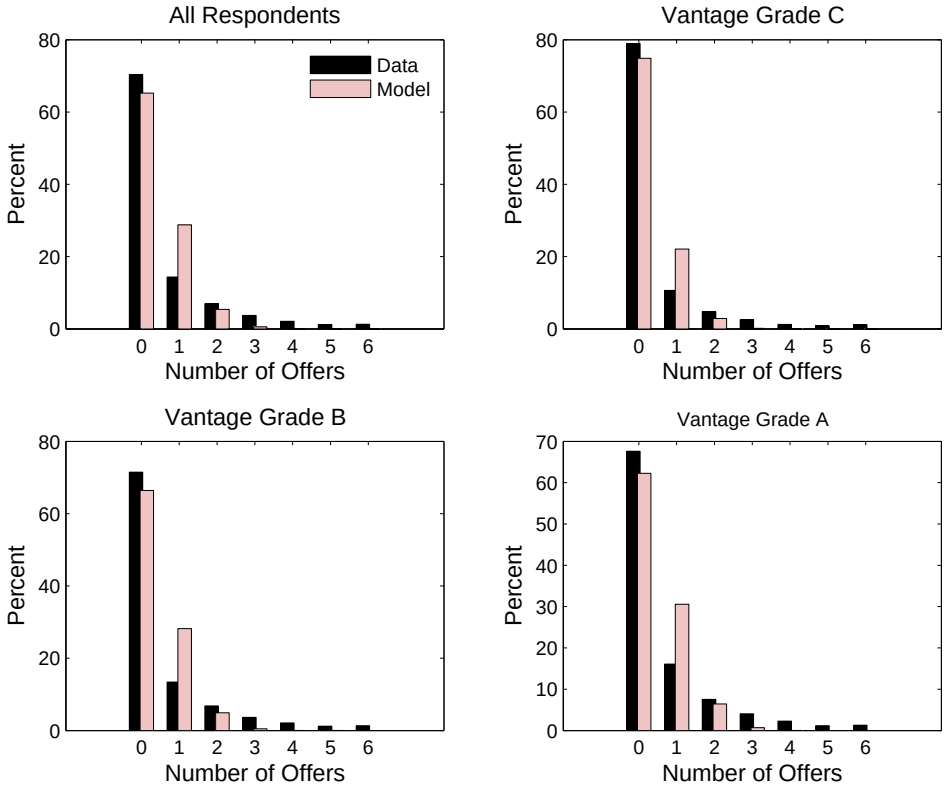

Figure 5: Model vs. Data Distribution in the Number of Offers

Notes: This figure compares the distribution of the number of monthly offers received by respondents observed in the data with that implied by the model. Data are from the Mintel Comperemedia survey of credit solicitations for Jan. 2010 to July 2012. An observation is an survey respondent in a given month.

model and shows how this comparison varies when conditioning on risk class. Just under 30 percent of individuals in the data receive at least one offer, a statistic largely echoed by the model. Moreover, like in the data, the model predicts that individuals with higher credit scores on average are more likely to receive offers. As the top right hand panel shows, only 20 percent of individuals with a Vantage score below 700 receive offers, while about 33 percent of individuals with Vantage scores greater than 800 receive offers. Still, the model predicts fewer offers received on average relative to the data. This discrepancy between the data and the model prediction is constant across credit scores.

Table 13 compares the types of offers observed in the data with those implied by the model. As shown in the table, both the mean and median non introductory rate implied by

Table 13: Model Vs. Data

	Data				Model			
	Mean	Std. Dev.	Median	Range	Mean	Std. Dev.	Median	Range
Rate	13.21	2.49	12.99	17.75	11.97	1.39	11.24	15.00
Intro Period (Years)	1.12	0.29	1.00	1.25	1.05	0.37	1.25	1.25
Bal. Transf Period (Years)	1.30	0.31	1.25	1.25	1.27	0.34	1.25	1.25
Delinquency Fees (Count)	3.11	0.75	3.00	4.00	3.06	0.89	3.00	4.00
Bal. Transf. Fee (% With)	0.89	0.31	1.00	1.00	0.88	0.32	1.00	1.00
Foreign Transaction Fees (% With)	0.95	0.23	1.00	1.00	0.95	0.22	1.00	1.00
Annual Fee (% With)	0.02	0.16	0.00	1.00	0.01	0.10	0.00	1.00
Repayment Insurance (% With)	0.59	0.49	1.00	1.00	0.50	0.50	0.00	1.00
Other Insurance (Count)	0.83	0.76	1.00	3.00	0.65	0.66	1.00	3.00
Non-Cash Rewards (% With)	0.31	0.46	0.00	1.00	0.32	0.47	0.00	1.00
Cashback Rewards (% With)	0.48	0.50	0.00	1.00	0.45	0.50	0.00	1.00

Notes: This table compares offers observed in the data with those implied by the model estimates. Data are from the Mintel Comperemedia survey of credit solicitations and comprise monthly repeated cross section spanning the period Jan. 2010 to July 2012. The unit of observation is an offer sent to a survey respondent.

the model are just over 1 percentage point lower than observed in the data, as are the range and standard deviation of offered rates. This implies that, on average the model implies lower rates and also lower dispersion in offered rates. Looking at other price characteristics of the offer, the model accords quite well with the data. For example, the model predicts that the median offer includes a mean introductory interest rate period of 1.05 years while in the data it is slightly higher at 1.12 years. Moreover, the dispersion in the length of the

introductory rate offer implied by the model is slightly higher than that observed in the data. Overall, the table shows that the distributions of offers sent as implied by the model largely matches those observed in the data.

D Implied Response Rates, Value, and Profits

Using the estimated model, I simulate data ($\epsilon_{i\ell}$'s) on firm decisions and back out implied take-up rates, customer value, and expected lender profits. These distributions are shown in Figures 6, 7, and 8, respectively. Figure 6 indicates that on average the take-up rate for new products implied by the model is 0.045 percent with a standard deviation of 0.0034 percent. This indicates that about 1 in 2000 offers sent out is taken up by consumers. Moreover,

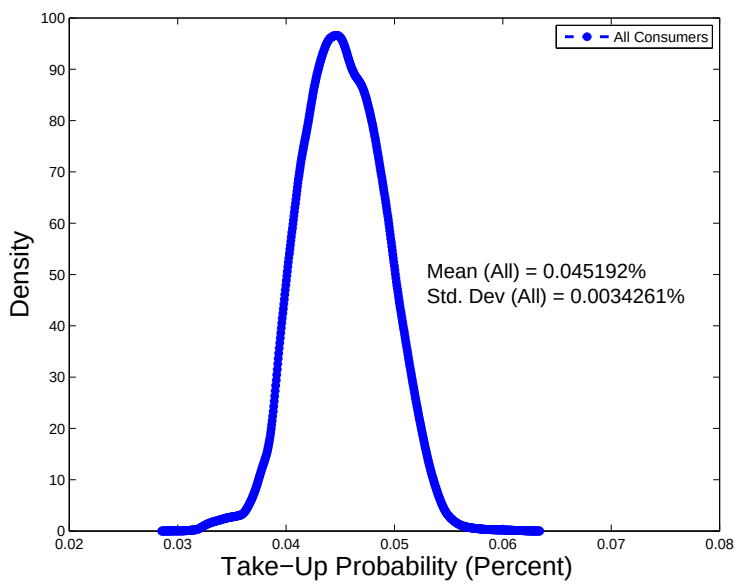

Figure 6: Model Implied Distribution of Take-up

Notes: This figure plots the model implied distribution of take-up for new cards This distribution is estimated using simulated data on lenders' mail out decisions.

as shown in figure 7, on average customers are worth \$909 in discounted net revenue over their lifetime, with a standard deviation of about \$68. Combining these elements, the model implies that, upon sending out an offer, lenders can expect to make about \$0.0087 (standard deviation of \$0.0085) from each offer they send. As such, lenders expect low margins on mail out offers.

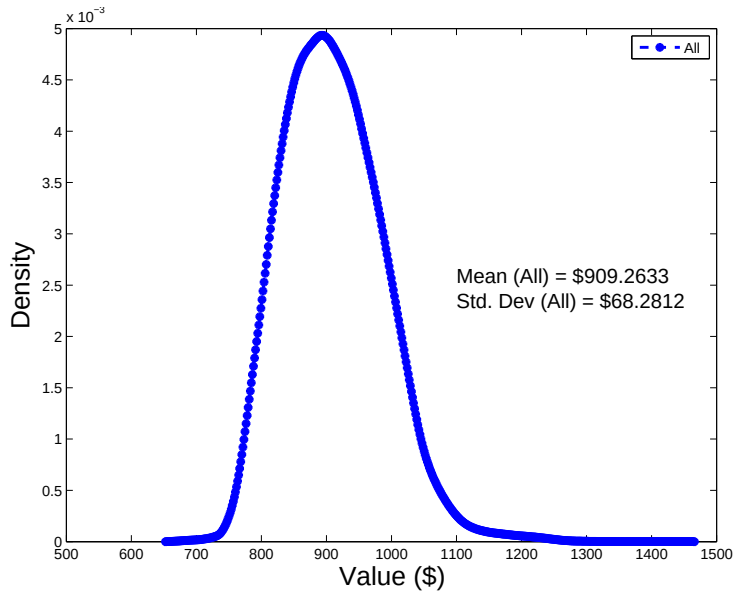

Figure 7: Model Implied Distribution of Customer Value

Notes: This figure plots the model implied distribution of customer value for lenders. This distribution is estimated using simulated data on lenders' mail out decisions.

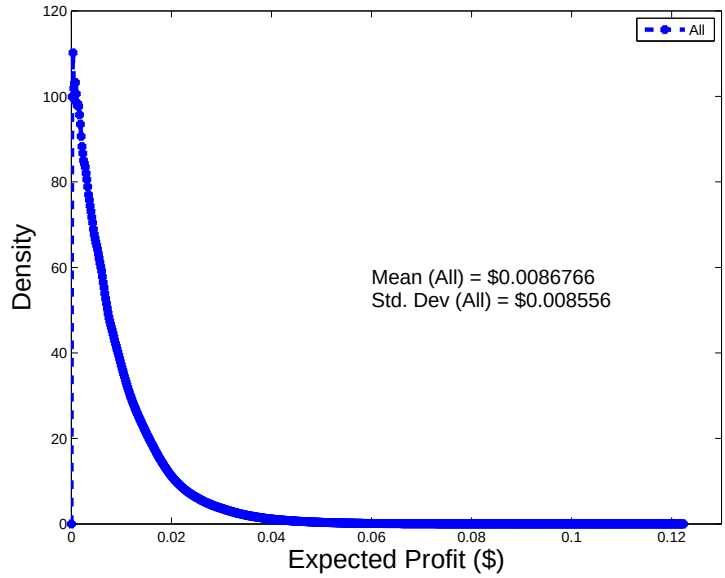

Figure 8: Model Implied Distribution of Expected Profits

Notes: This figure plots the model implied distribution of the expected profit from offering a product. This distribution is estimated using simulated data on lenders' mail out decisions.