Advertising, Consumer Awareness and Choice: Evidence from the U.S. Banking Industry *

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Abstract

Does advertising serve to (i) increase awareness of a product, (ii) increase the likelihood that the product is considered carefully, or (iii) does it shift consumer utility conditional on having considered it? We utilize a detailed data set on consumers' shopping behavior and choices over retail bank accounts to investigate advertising's effect on product awareness, consideration, and choice. Our data set has information regarding the entire "purchase funnel," i.e., we observe the set of retail banks that the consumers are aware of, which banks they considered, and which banks they chose to open accounts with. We formulate a structural model that accounts for each of the three stages of the shopping process: awareness, consideration, and choice. Advertising is allowed to affect each of these separate stages of decision-making. Our model also endogenizes the choice of consideration set by positing that consumers undertake costly search. Our results indicate that advertising in this market is primarily a shifter of awareness, as opposed to consideration or choice. We view this result as evidence that advertising serves a primarily informative role in the U.S. retail banking industry.

Keywords: advertising, banking industry, consumer search, demand estimation

JEL Classification: D43, D83, L13

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1 Introduction

In his classic book, Chamberlin (1933) argued that advertising affects demand because (i) it conveys information to consumers with regard to the existence of sellers and the prices and qualities of products in the marketplace and (ii) it alters consumers' wants or tastes. This led to the distinction between the "informative" and the "persuasive" effects of advertising in the economics literature (as surveyed, for example, in Bagwell 2007). The marketing literature refines the Chamberlinian framework by positing the "purchase funnel" framework for the consumer's shopping process: consumers first become "aware" of the existence of products; then they can choose to "consider" certain products investigating their price and non-price characteristics carefully; and, finally, they decide to choose one of the considered alternatives. In this framework, advertising can affect each of these three stages: "awareness," "consideration," and, finally, "choice."

This paper uses detailed survey data to empirically disentangle the roles of advertising on the different stages (awareness, consideration, and choice) of the consumer's purchase process when opening a bank account. More specifically, we measure how much advertising influences consumer behavior directly as a utility shifter vs. as a way of increasing consumers' awareness of the brand or of inducing the consumer to consider a bank. We conduct our measurement through a fully-specified structural model that contains the awareness-consideration-choice stages and, in particular, endogenizes the "choice" of consideration set by each consumer using a costly-search framework. The value of the structural approach is that it allows us to consider the impact of various (counterfactual) managerial policies in a logically consistent fashion.

Our paper also contributes to our understanding of demand for retail banking products and services, a very large and growing sector of the economy. With its $14 trillion of assets, 7,000 banks, and more than 80,000 bank branches, the U.S. banking sector comprises a very important portion of the "retail" economy with significant attention from regulators and policy-makers. Despite the importance of the banking sector, structural demand analyses to date (e.g. Dick 2008, Mólnar, Violi, and Zhou 2013, Wang 2010) have only utilized aggregated market share data on deposits. There has been very little research using detailed consumer level data to characterize consumers' heterogeneous response to drivers of demand. Moreover, although the banking and financial industry spends more than $8 billion per year on advertising,[1] there is little academic research that investigates the precise way through which advertising affects consumer demand in this important industry. Some recent exceptions in the literature are Gurun, Matvos, and Seru (2013) on the marketing of mortgages and Hastings, Hortaçsu, and Syverson (2013) on retirement savings products; however, neither of these studies can differentiate between the awareness and the utility-shifting functions of advertising.

Our study is based on individual-level survey data on consumers' (aided) awareness for banks, the set of banks the consumer considered, and the identity of the bank the consumer decided to open one or more new bank accounts with. In addition, we observe a nearly complete customer profile containing information on demographics and reasons for opening a new bank account (with

[1] http://kantarmediana.com/intelligence/press/us-advertising-expenditures-increased-second-quarter-2013

their current primary bank or with a new bank) or for switching banks. We complement this data with three additional sets of data on the retail banking industry. Data provided by RateWatch contain information on interest rates for the most common account types for all banks over the same time period as the first set of data. Advertising data were gathered from Kantar Media's *Ad$pender* database. Kantar tracks the number of advertisements and advertising expenditures in national media as well as both measures of advertising in local media at the Designated Media Area (DMA) level. Lastly, we collected information on the location of bank branches from the Federal Deposit Insurance Corporation (FDIC).These data give us a detailed picture of consumers' shopping and purchase processes and of the main variables affecting them.

Our data show that consumers are, on average, aware of 6.8 banks and consider 2.5 banks and that there is large variation in the size of consumers' awareness and consideration sets. Further, the correlation between the size of consumers' awareness and consideration sets is low indicating a distinct difference between the two stages. This difference is further reflected in the large variation across consumers in what concerns which banks enter consumers' awareness and consideration sets. There are also large differences in the conversion rates from awareness to consideration and from consideration to purchase across banks. Looking at the consumers' decision process, the most common account types consumers shop for are checking accounts (85 percent of consumers), savings accounts (98 percent) and credit cards (26 percent). Finally, our data also show the crucial importance of local bank presence – i.e., bank branches – in the consumer decision process: given that a consumer decides to consider or purchase from a bank, we find that the probability that a bank has a local branch within 5 miles of the consumer's home lies between 42 and 90 percent or 47 and 93 percent, respectively.

We develop a structural model of the three stages of the consumer's purchase process: awareness, consideration, and choice. Our model reflects the consumer's decision process to add one or more bank accounts to his existing portfolio and includes his costly search for information about interest rates. Awareness is the result of bank advertising, local bank presence, and demographic factors. A consumer searches among the banks he is aware of. Searching for information is costly for the consumer since it takes time and effort to contact financial institutions and is not viewed as pleasant by most consumers. Thus a consumer only investigates a few banks that together represent his consideration set and makes the final decision to open one or more new accounts with a bank from among the ones in the considered set. Our utility-maximizing modeling approach contains all three outcome variables: the set of banks the consumer is aware of, the consumer's decision of which banks to include in his consideration set given his awareness set, and the decision of which bank to open one or more accounts with given his consideration set. To estimate our structural model we enhance the approach developed by Honka (2014) by including the awareness stage.

We are able to disentangle the effects of advertising from the effects of local bank presence, as our advertising measure does not include in-branch advertising. As expected, we find a positive effect of local bank presence on consumers' awareness of a bank. Our results show that advertising has a large effect on consumer awareness for a bank but affects consumers' consideration and final choice decisions only marginally. This suggests that, in the retail banking industry, advertising's primary role is to inform the consumer about the existence and availability of retail banks and their offerings. This finding stands in contrast to other recent research that has also investigated consumers' demand for financial products. For example, Gurun, Matvos, and Seru (2013) and Hastings, Hortaçsu, and Syverson (2013) suggest a persuasive effect of advertising for mortgages and retirement savings products, respectively.

The estimates from the consideration and choice stages indicate that the average consumer search cost rationalizing the amount of search conducted by consumers within their awareness sets is about 9 basis points (0.09%). Our results also show that convenience is the major driver in the consumers' shopping and account-opening process. Convenience is captured by the fact that consumers are more likely to open bank accounts with banks with which they already have a relationship and that have branches located in proximity to their place of residence. Inertia towards the consumer's primary bank supports the convenience factor of one-stop-shopping – i.e., consumers only having to deal with one bank for all of their financial matters. The positive effect of local bank presence shows that, in spite of the widespread availability and convenience of online banking, consumers still value having the possibility of talking to a bank employee in person.

The main positive result of our empirical analysis is that the role played by advertising in the retail banking sector is largely informative as opposed to persuasive. Beyond this finding, we will use our detailed demand side results to conduct two counterfactuals: In the first one, we will quantify the socially optimal amount of informative advertising. In the second one, we will investigate the effects of free interest rate comparisons provided by an internet bank.

The remainder of the paper is organized as follows: In the next section, we discuss the relevant literature. In Section 3, we describe our data. Then we introduce our model and discuss identification in the following two sections. We present our estimation approach in Section 6 and show our results in Section 7. In Section 8, we consider two counterfactual scenarios, the first investigating how much the observed amount of informative advertising deviates from the socially optimal amount of informative advertising. The second counterfactual considers the scenario where one of the banks allows consumers to compare the interest rates offered by competitors. Next, we present robustness checks and discuss limitations of our work and suggest opportunities for future work. Finally, we conclude by summarizing our findings in the last section.

2 Relevant Literature

This paper is related to four streams of literature, namely, on advertising, multi-stage models of consumer demand, consumer search and consumer purchase behavior for financial services.

Since Chamberlin's (1933) seminal paper in which he described the informative and persuasive effects of advertising, several empirical researchers have tried to distinguish between these two effects of advertising in a variety of industries. For example, Ackerberg (2001) and Ackerberg (2003) investigate the roles of advertising in the yogurt market. Narayanan, Manchanda, and Chintagunta

(2005), Chan, Narasimhan, and Xie (2013) and Ching and Ishihara (2012) study the pharmaceutical market and Lovett and Staelin (2012) investigate entertainment (TV) choices. Clark, Doraszelski, and Draganska (2009) use data on over three hundred brands and find advertising to have a positive effect on awareness but no significant effect on perceived quality. Our focus is on financial products and, more specifically, retail banking. There is little academic research that investigates the precise way through which advertising affects consumer demand for financial products. Gurun, Matvos, and Seru (2013) and Hastings, Hortaçsu, and Syverson (2013) explore the effects of advertising in the mortgage and social security markets but neither of these studies can differentiate between the awareness and the utility-shifting functions of advertising. Because we observe consumers' (aided) awareness of, consideration of and purchase from individual banks, we can distinguish between advertising affecting consumer's information and advertising shifting consumer's utility.

While it is well-known that consumers go through several stages (awareness, consideration and choice) in their shopping process before making a purchase decision (as discussed, for example, in Winer and Dhar 2011, p. 111), most demand side models maintain the full information assumption that consumers are aware of and consider all available alternatives. This assumption is mostly driven by data restrictions as information going beyond the purchase decision is rarely available to researchers. Among the set of papers that explicitly acknowledge and model the different stages of the consumer's shopping process a crucial distinction relates to the data and identification strategy used. A first group of papers models at least two stages, usually consideration and choice, and uses purchase data for estimation purposes (e.g., Allenby and Ginter 1995, Siddarth, Bucklin, and Morrison 1995, Chiang, Chib, and Narasimhan 1998, Zhang 2006, van Nierop et al. 2010, Terui, Ban, and Allenby 2011). A second, smaller group of papers, also models at least two stages, but makes use of available data on each of the shopping stages by incorporating it directly in the estimation (e.g., Franses and Vriens 2004, Lee et al. 2005, Abhishek, Fader, and Hosanagar 2012, De los Santos, Hortaçsu, and Wildenbeest 2012 and Honka 2014).

Further distinction should be made between papers that have estimated consumers' consideration sets and papers that have also modeled *how* consumers form their consideration sets. Examples of the former set of papers include Allenby and Ginter (1995), Siddarth, Bucklin, and Morrison (1995), Chiang, Chib, and Narasimhan (1998), Zhang (2006), Goeree (2008), van Nierop et al. (2010), while examples of the latter include Mehta, Rajiv, and Srinivasan (2003), Kim, Albuquerque, and Bronnenberg (2010), Muir, Seim, and Vitorino (2013), Honka (2014), Honka and Chintagunta (2014). The latter set of papers is also part of a growing body of literature on consumer search. While earlier literature developed search models without actually observing search in the data (e.g., Mehta, Rajiv, and Srinivasan 2003, Hong and Shum 2006), in the most recent search literature, search is observed in the data either directly through data on the consumers' consideration sets (e.g. De los Santos, Hortaçsu, and Wildenbeest 2012, Honka 2014) or indirectly through other variables (e.g., Kim, Albuquerque, and Bronnenberg 2010). In this paper, we develop a structural model of all three stages of the consumer's purchase process where consumers form their consideration sets through search and we estimate the model using data on awareness, consideration and choice.

And finally, our paper is also related to the literature examining consumer purchase behavior for financial services and products. Hortaçsu and Syverson (2004) study consumer purchase behavior for S&P 500 index funds and Allen, Clark, and Houde (2012) look at consumer behavior when buying mortgages. There is also a stream of literature on consumer adoption and usage of payment cards (e.g. Rysman 2007, Cohen and Rysman 2013, Koulayev et al. 2012, see Rysman and Wright 2012 for an overview). Somewhat surprisingly, and despite its size and importance for both consumers and the economy, the literature on consumer demand for retail banks and their products is very sparse. Dick (2008) and Wang (2010) develop aggregate-level, structural models of consumer demand for retail banks. Dick (2007) and Hirtle (2007) investigate branching structures and Dick (2007) and Mólnar, Violi, and Zhou (2013) study competition in retail banking. Similar to Dick (2008) and Wang (2010), we estimate demand for retail banks, but in contrast to the before mentioned papers, our model describes consumer shopping and purchase behavior using consumer-level data.

3 Data

To conduct our analysis we combine several data sets. We describe these data sets below before turning to the presentation of our model and to the empirical results.

3.1 Consumer-Level Data

We benefit from access to survey data collected by a major marketing research company during March and April of 2010 for a representative sample of 4,280 respondents. Respondents were asked to refer to their bank shopping experiences during the previous 12 months. Given that we do not know the specific dates when the respondent was shopping for banks, the period studied refers to bank activities (across all respondents) from March 2009 to April 2010 (herein referred to as "reference period").

In this data, we observe a consumer's previous and current primary bank;[2] the majority of account types the consumer has with his primary and other banks; the banks the consumer considered during his search process; the accounts the consumer moved from his previous to his current primary bank or opened with another (non-primary) bank. In addition, we observe a nearly complete customer profile containing information on demographics and reasons for opening a new bank account (with their current primary bank or with a new bank) or for switching primary banks. We use the respondents' 5-digit zip code information to find their zip code centroid and calculate the distance to the different institutions in their neighborhood using branch-location data obtained from the Federal Deposit Insurance Corporation (FDIC).

[2]There are many ways to define "primary financial institution" – by the assets held, number of accounts, types of accounts, frequency of transactions, or some combination of these. In our survey data, a definition of "primary bank" was not provided to respondents, but most respondents indicated that this was the bank they had their primary checking account with.

For tractability reasons, we focus on the 18 largest financial institutions in the United States which had a combined national market share of 56 percent (measured in total deposits) in 2010. The leftmost column in Table 1 shows the list of included banks. We drop all respondents that have at least one institution in their consideration sets that is not among the 18 institutions listed. Further, we also remove all respondents with invalid zip codes. This resulted in a final sample of $2,076$ consumers. To ensure that dropping consumers did not introduce a selection problem, we compare the demographics of the initial and final set of respondents in Table 2. The descriptives show that the final data set contains consumers with similar demographics to those in the initial data.

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Table 3 shows descriptive statistics for all respondents in our final sample as well as for the two subgroups of respondents: "shoppers" ($1,832$ consumers) and "non-shoppers" (244 consumers). Shoppers are consumers who shopped and opened one or more new accounts, and non-shoppers are consumers who neither shopped nor opened new accounts during the reference period. We see that 61 percent of respondents are female; 65 percent are between 30 and 59 years old; 78 percent are white; 33 percent are single/divorced and 64 percent are married/with partner. With respect to income, households are almost equally distributed among the three categories "Under \$49,999," "\$50,000 – \$99,999" and "\$100,000 and over" with the last category having a slightly smaller percentage of respondents than the other two. And, finally, regarding education, 7 percent of respondents have a high school degree or less, while the remaining 93 percent of respondents are evenly split among the "Some College," "College Graduate" and "Postgraduate" categories. Looking at shoppers and non-shoppers separately, we find non-shoppers to be older and to have lower income and less education.

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Insert Table 3 about here

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We also observe the number and type(s)[3] of bank account(s) the consumer opened during the reference period. Figure 1 shows the distribution of the number of account types shoppers opened

[3]The types of accounts considered in the survey fall into 3 groups. "Deposit accounts" include Checking, Savings, CD and Money Market Accounts. "Borrowing accounts" include credit cards, mortgages, home equity loans or home equity lines of credit and personal loans (including auto loans and student loans). Lastly, "Investment accounts" include Mutual funds/annuities and Stocks/bonds.

within 2 months of switching. On average, shoppers opened 2.25 different types of accounts with a minimum of 1 and a maximum of 10 account types. Table 4 contains the percentages of shoppers that opened different types of accounts. The most common account types consumers shop for are checking accounts (85 percent of consumers) followed by savings accounts (55 percent) and credit cards (26 percent).

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Insert Table 4 about here

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Table 1 displays the percentages of respondents who are aware of, consider or choose a bank. The percentage of consumers aware of a given bank ranges from around 90 percent for the largest banks such as Bank of America and Wells Fargo/ Wachovia to around 10 percent for the smaller banks in our data such as M&T, and Comerica Bank. Similarly, the percentage of consumers considering a given bank varies from around 40 percent for the larger banks to around 1–2 percent for the smaller banks. And finally, the rightmost column in Table 1 shows the percentage of consumers who chose to open an account with each of the banks listed in the table. The purchase shares range from less than 1 percent to more than 13 percent.

Figures 2 and 3 show histograms of the awareness and consideration set sizes, respectively. Consumers are aware, on average, of 6.8 banks and consider 2.5 banks. There is a large variation in the sizes of consumers' awareness and consideration sets which range from 2 to 15 and 2 to 9, respectively. Further, the relationship between the size of consumers' awareness and consideration sets is weak (see Figures 3 and 4). This suggests that there are distinct differences between how the sets are formed and that looking at one of the stages may not be enough to understand consumers' choices.

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Insert Figure 3 about here

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The differences between the awareness and consideration stages are further reflected in the large variation across consumers in what concerns which specific banks enter consumers' awareness and consideration sets. There are also large differences in the conversion rates from awareness to consideration and from consideration to purchase across banks (see Table 1). For example, while Bank of America, Chase/WaMu, M&T and TD Bank can get about 40 to 50 percent of consumers who are aware of these banks to consider them, Capital One, Keybank and Sovereign Bank can only get 20 to 30 percent of consumers who are aware of these banks to consider them. Similarly, while U.S. Bank, Suntrust Bank and Citizens Bank have conversion rates between 60 and 75 percent from consideration to purchase, the conversion rates for Bank of America, Chase/WaMu, HSBC and WellsFargo/Wachovia lie between 30 to 40 percent. Interestingly, it is not true that banks with the largest conversion rates from awareness to consideration also have the largest conversion rates from consideration to purchase. For example, Bank of America has a very high conversion rate from awareness to consideration and a very low conversion rate from consideration to purchase. We see that the opposite is true for Comerica Bank and Keybank, for example. This holds true even when we compare banks with similar market shares. The market shares of HSBC, Keybank, M&T and Sovereign Bank all lie between 2 and 3 percent. But the awareness probabilities for this set of banks range from 8 to 23 percent indicating that predicting awareness from choice (and vice versa) is hard.

Finally, our data also show the crucial importance of local bank presence – i.e., bank branches location – in the consumer's decision process: given that a consumer decides to consider or purchase from a bank, we find that the probability that that bank has a local branch within 5 miles of the consumer's home lies between 42 and 90 percent or 47 and 93 percent, respectively (Table 5).

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Insert Table 5 about here

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3.1.1 Sample Representativeness

The focus of the shopping study conducted by the marketing research company were shoppers, i.e. consumers that opened new accounts. We correct for the over-sampling of shoppers by using weights in the model estimation so that the results are representative and accurately reflect the search and switching behavior of the overall U.S. population of retail banking consumers.

We re-weigh shoppers and non-shoppers in our data using information from another survey conducted by the marketing research company. This last survey does not contain the same level of detail as the data described in section 3.1 but has a much larger scale (around $100,000$ respondents) and a sampling design that ensures population representativeness. This allows us to calculate the representative weights needed for the model estimation.

3.2 Price Data

Previous papers (e.g. Dick 2008) have imputed price data from deposit revenues (in the case of checking accounts) and from deposit expenses (in the case of savings deposits) given that data on actual interest rates is typically only available from small-sample surveys. We benefit from access to a comprehensive database with branch-level deposit product prices. These data, provided by RateWatch, track the rates and fees offered on various deposit products at the branch level. The data are in panel format,; i.e., for the same branch and account type there are multiple measurements over time. We focus on the data that were collected during the reference period.

We combine the price data with the individual-level data to obtain a measure of the interest rates that each consumer faced while shopping for a bank account. From the survey data we know which respondents have checking and savings accounts with each bank and which banks were part of the respondents' consideration sets. Since we do not observe what types of checking or savings accounts respondents have, we use information on the most popular type of 2.5K savings account[4] for each bank to calculate the median (over time) interest rate for each bank in each respondent's zip code.[5] We believe that the rates calculated using this method are a good proxy for the rates that each respondent obtained upon searching over the banks in his consideration set. Table 6 reports summary statistics for the interest rates associated with the most popular 2.5K savings account for each bank. We also use the RateWatch information to estimate the distribution of prices expected by the consumer prior to searching.

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3.3 Advertising Data

Advertising data were gathered from Kantar Media's "Ad$pender" database. Kantar tracks advertising expenditures and number of advertisements (also called "units" or "placements"[6]) placed in national media (e.g., network TV and national newspapers) as well as in local media (e.g., spot TV and local newspapers) at the Designated Media Area (DMA) level. A DMA is a geographic region where the population can receive the same (or similar) television and radio station offerings.

We calculate total advertising expenditure and placements by institution and DMA over the period from March 2009 until April 2010 (the reference period). Respondents' locations are identified by zip code and not DMA, so we match each respondent's zip code to a specific DMA to find how much each bank spent on advertising in each respondent's DMA. We add the advertising spending at the national level to the DMA–level advertising for each bank. Table 7 reports average advertising expenditures and placements at the DMA level for each bank during the reference period. In the estimation we focus on placements as a measure of advertising intensity. This is so

[4]A 2.5K savings account is a type of savings account that requires a minimum balance of $2,500 average monthly to avoid any fees associated with the account.

[5]Whenever zip code data for a specific bank in a respondent's consideration set were not available, we used data from branches located in adjacent zip codes.

[6]According to Kantar, "units" are simply the number of advertisements placed. These data are reported by Kantar without any weighting (based on spot length, size, etc.).

that we have a measure of advertising that is independent of the cost of advertising and that thus can be more easily compared across DMAs and banks.

In Figures 7 and 8 we display the geographic distribution of DMA-level advertising expenditures and placements for all the banks in our sample in the reference period and across the 206 DMAs in the U.S. The maps clearly shows that there is significant variation in advertising spending across DMAs. This regional variation will be useful to identify the effects of advertising on bank awareness and choice.

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3.4 Data Limitations

While our data are well suited to study consumers' shopping and purchase process for retail bank accounts because we observed (aided) awareness, consideration and choice, the data have a few limitations. First, our data are cross-sectional. As a consequence, our ability to control for consumer-level unobserved heterogeneity, beyond the factors that are observable and that we use in the estimation, is limited. Second, our data do not contain information on credit unions, which have a significant share of the retail banking sector in the U.S. Third, our data on interest rates/prices relies on assumptions regarding the consumer's account size, and the timing of the account opening. Hence our interest rate/price data is a proxy for the actual interest rate/price observed by the consumers.

4 Model

Our model describes the three stages of the purchase process: awareness, consideration, and choice. We view awareness as a passive occurrence; i.e., the consumer does not exert any costly effort to become aware of a bank. A consumer can become aware of a bank by, for example, seeing an ad or driving by a bank branch. We model awareness as a function of banks' advertising intensity, local bank presence, and consumers' demographic variables. Consideration is an active occurrence;

i.e., the consumer exerts effort and incurs costs to learn about the interest rates and fees offered and charged by a bank, respectively. The consumer's consideration set is thus modeled as the outcome of a simultaneous search model given the consumer's awareness set. And finally, purchase is an active, but effortless occurrence in which the consumer chooses the bank which gives him the highest utility. The consumer's purchase decision is modeled as a choice model given the consumer's consideration set.

4.1 Awareness

There are N consumers indexed by $i = 1, \ldots, N$. Consumer i lives in market m ($m = 1, \ldots, M$) and his awareness of bank j ($j = 1, \ldots, J$) is a function of bank fixed effects ς_{0j}, advertising adv_{jm}, demographic variables D_i, local bank branch presence b_{jm} and an error term ξ_{ij}, and can be written as

$$a_{ijm} = \varsigma_{0j} + \varsigma_{1j} adv_{jm} + D_i \varsigma_2 + b_{ij} \varsigma_{3j} + \xi_{ij}, \qquad \forall j \neq j_{PB}, \tag{1}$$

where a_{ijm} is the latent awareness score for consumer i that lives in market m. We assume that consumer i is aware of bank j if his awareness score for bank j is larger than 0 and unaware otherwise. adv_{jm} denotes bank j's advertising intensity in market m (where consumer i resides). A market is defined as a DMA. D_i are observed demographic variables (age, gender, etc.) and b_{ij} are dummy variables indicating whether there is a branch of bank j within 5 miles of consumer i's zip code's centroid. $\theta_1 = (\varsigma_0, \varsigma_{1j}, \varsigma_2, \varsigma_{3j})$ are the parameters to be estimated.

Note that we exclude the consumer's primary bank j_{PB} from the model since we assume that consumers are aware of their primary bank. By this logic we should also exclude any other banks the consumer has accounts with since the consumer should be aware of those banks as well. Unfortunately, although the survey data contain information on whether a consumer has other accounts other than those with his primary bank it does not have information on the identities of the banks the consumer has (an) account(s) with.

And, lastly, note that we are not including interest rates when modeling consumers' awareness sets. The reason is that a consumer logically cannot have interest rate beliefs for banks he is not aware of.

4.2 Utility Function

Let u_{ijm} be the utility that consumer i that lives in market m obtains from bank j. Utility is specified as:

$$u_{ijm} = \alpha_j + \beta_1 p_{ij} + \beta_2 I_{ij_{PB}} + \beta_3 adv_{jm} + \beta_{4j} b_{ij} + \epsilon_{ij}, \tag{2}$$

where ϵ_{ij} is observed by the consumer, but not by the researcher. α_j are company-specific brand intercepts and p_{ij} denotes prices. One of the challenges of modeling the consumers' shopping process for retail bank accounts stems from the definition of "price". In most retail settings, price is the posted amount the consumer has to pay to acquire a product. When it comes to retail banking, the definition of price is not as straightforward as price can have multiple components such as fees and interest rates and consumers can have multiple account types. For the purpose of this paper, we define "price" as the interest rate on 2.5K savings accounts.[7] $I_{ij_{PB}}$ is a dummy variable indicating whether bank j is consumer $i's$ primary bank and b_{ij} is a dummy variable indicating whether there is a branch of bank j within 5 miles of consumer $i's$ zip code's centroid. $\theta_2 = (\alpha_j, \beta_1, \beta_2, \beta_3, \beta_{4j})$ are the parameters to be estimated.

4.3 Consideration

We model consumers' search as in Honka (2014). Search is simultaneous, and interest rates follow an EV Type I distribution with location parameter η and scale parameter μ. Consumers know the distribution of interest rates in the market, but search to learn the specific interest rate a bank will offer them. Given these assumptions, utility (from the consumer's perspective) u_{ijm} is an EV Type I distributed random variable with location parameter $a_{ij} = \alpha_j + \beta_1\eta + \beta_2 I_{ij_{PB}} + \beta_3 adv_{ijm} + \beta_{4j} b_{ij} + \epsilon_{ij}$ and scale parameter $g = \frac{\mu}{\beta_1}$. A consumer's search decision under simultaneous search depends on the expected indirect utilities (EIU; Chade and Smith 2005). Consumer $i's$ EIU, where the expectation is taken with respect to price, is then given by

$$E\left[u_{ijm}\right] = \alpha_j + \beta_1 E\left[p\right] + \beta_2 I_{ij_{PB}} + \beta_3 adv_{jm} + \beta_{4j} b_{ij} + \epsilon_{ij} \qquad \forall j \in A_i. \tag{3}$$

Consumer i observes the EIUs for every brand he is aware of (including ϵ_{ij}). To decide which companies to search over, consumer i ranks all companies according to their EIUs (Chade and Smith 2005) and then picks the top k companies to search. The theory developed by Chade and Smith (2005) on the optimality of the ranking according to EIUs only holds under the assumption of first-order stochastic dominance among the interest rate distributions. Since we assume that interest rates follow a market-wide distribution, the assumption is automatically fulfilled. Further, we also need to impose a second restriction on the simultaneous search model to be able to use Chade and Smith (2005): search costs *cannot* be bank-specific.

To decide on the number of companies k for which to obtain interest rate information, the consumer calculates the net benefit of all possible search sets *given the ranking of the EIUs*. A consumer's benefit of a searched *set* S_i is then given by the expected *maximum* utility among the searched banks. R_{ik} denotes the set of top k banks consumer i ranked highest according to their EIUs. For example, R_{i1} contains the company with the highest expected utility for consumer i, R_{i2} contains the companies with the two highest expected utilities for consumer i, etc. The consumer picks the size of his searched set S_i which maximizes his net benefit of searching denoted by Γ_{ik}, i.e. expected maximum utility among the searched companies minus the cost of search

$$\Gamma_{ik} = E\left[\max_{j \in R_{ik}} u_{ijm}\right] - kc_i \tag{4}$$

where c_i denotes consumer $i's$ search costs. We model search costs c_i as a function of a con-

[7] Henceforth we will use the terms "price" and "interest rate" interchangeably.

stant c_0, demographics and the number of account types the consumer is planning to open.[8] The consumer picks the number of searches k which maximizes his net benefit of search.

4.4 Choice

After a consumer has formed his consideration set and learned the interest rates of the considered banks, all uncertainty is resolved. At this stage, both the consumer and the researcher observe interest rates. The consumer then picks the company with the highest utility among the searched companies, i.e.

$$j = \arg\max_{j \in S_i} u_{ijm} \tag{5}$$

where u_{ijm} now contains the actual interest rate for consumer i by bank j and S_i is the set of searched banks.

5 Identification

The identification strategy of the search model parameters follows closely Honka (2014). The identification of the parameters capturing differences in brand intercepts, the effects of advertising, price and bank branches that vary across companies is standard as in a conditional choice model. These parameters also play a role in consumers' consideration set decisions.

The size of a consumer's consideration set helps pin down search costs. We can only identify a range of search costs as it is utility-maximizing for all consumers with search costs in that range to search a specific number of times. Beyond the fact that a consumer's search cost lies within a range which rationalizes searching a specific number of times, the variation in our data does not identify a point estimate for search costs. The search cost point estimate will be identified by the functional form of the utility function and the distributional assumption on the unobserved part of the utility.

The base brand intercept is identified from the consumer's decision to search or not to search. Intuitively speaking, the option not to search and not to open (an) account(s) is the outside option and allows us to identify the base brand intercept. So while the search cost estimate is pinned down by the average number of searches, the base brand intercept is identified by the consumer's decision to search or not.

6 Estimation

The unconditional purchase probability is given by

$$P_{ij} = P_{iA_i} \cdot P_{iS_i|A_i} \cdot P_{ij|S_i} \tag{6}$$

[8] The results when search costs vary with observed heterogeneity will be added to the next version of this paper.

where A_i is a vector of awareness probabilities for consumer i for all 18 banks. In the following three subsections, we discuss how each of these probabilities are estimated. Note that the awareness probability does not have any parameters or error terms in common with the conditional consideration and conditional purchase probabilities. Thus it can be estimated separately.

6.1 Awareness

If we assume the term ξ_{ij} to be EV Type I, we can estimate Equation 1 as a binary logit regression for each bank j separately. The probability that consumer i is aware of bank j is given by

$$P(a_{ijm} > 0) = \frac{\exp\left(\varsigma_{0j} + \varsigma_{1j} adv_{jm} + D_i \varsigma_2 + b_{ij} \varsigma_{3j}\right)}{1 + \exp\left(\varsigma_{0j} + \varsigma_{1j} adv_{jm} + D_i \varsigma_2 + b_{ij} \varsigma_{3j}\right)} \tag{7}$$

and the probability that consumer i is aware of the J banks is denoted by

$$P_{iA_i} = \prod_{j=1}^{J} P(a_{ijm} > 0). \tag{8}$$

6.2 Consideration Given Awareness

We start by pointing out the crucial differences between what the consumer observes and what the researcher observes:

1. While the consumer knows the distributions of prices in the market, the researcher does not.
2. While the consumer knows the sequence of searches, the researcher only partially observes the sequence of searches by observing which banks are being searched and which ones are not being searched.
3. In contrast to the consumer, the researcher does not observe ϵ_{ij}.

Since the researcher does not observe the price distributions, these distributions need to be inferred from the data. In other words, the typical assumption of rational expectations (e.g. Mehta, Rajiv, and Srinivasan 2003, Hong and Shum 2006, Moraga-González and Wildenbeest 2008, Honka 2014, Honka and Chintagunta 2014) is that these distributions can be estimated from the prices observed in the data. Given that the parameters of the price distributions are estimated, we need to account for sampling error when estimating the other parameters of the model (see McFadden 1986).

To address the second issue, we point out that partially observing the sequence of searches contains information that allows us to estimate the composition of consideration sets. Honka (2014) has shown that the following condition has to hold for any searched set

$$\min_{j \in S_i} \left(E\left[u_{ijm}\right]\right) \geq \max_{j' \notin S_i} \left(E\left[u_{ijm'}\right]\right) \qquad \cap \qquad \Gamma_{ik} \geq \Gamma_{ik'} \qquad \forall k \neq k' \tag{9}$$

i.e. the minimum EIU among the searched brands is larger than the maximum EIU among the non-searched brands *and* the net benefit of the chosen searched set of size k is larger than the net benefit of any other search set of size k'.

We account for the fact that the researcher does not observe ϵ_{ij} (point 3 above) by assuming that ϵ_j has an EV Type I distribution with location parameter 0 and scale parameter 1 and integrating over its distribution to obtain the corresponding probabilities with which we can compute the likelihood function. Then the probability that a consumer picks a consideration set $S_i = \Upsilon$ is

$$P_{iS_i|\epsilon} = \Pr\left(\min_{j \in S_i} (E\left[u_{ijm}\right]) \geq \max_{j' \notin S_i} \left(E\left[u_{ijm'}\right]\right) \quad \cap \quad \Gamma_{ik} \geq \Gamma_{ik'} \qquad \forall k \neq k'\right) \tag{10}$$

6.3 Purchase Given Consideration

We now turn to the purchase decision stage given consideration. The consumer's choice probability conditional on his consideration set is

$$P_{ij|S_i,\epsilon} = \left(u_{ijm} \geq u_{ijm'} \quad \forall j \neq j', \quad j, j' \in S_i\right) \tag{11}$$

where we now include the actual prices in the utility function. Note that there is a selection issue: given a consumer's search decision, the ϵ_{ij} do not follow an EV Type I distribution and the conditional choice probabilities do not have a logit form. We solve this selection issue by using SMLE when we estimate the conditional purchase probabilities.

In summary, the researcher estimates the price distributions, observes only partially the utility rankings, and does neither observe ξ_{ij} in the consumer's awareness nor ϵ_{ij} in the consumer's utility function. Given this, our estimable model has awareness probability given by Equation 7, conditional consideration set probability given by Equation 10, and conditional purchase probability given by Equation 11.

We maximize the joint likelihood of awareness set, consideration set, and purchase. The likelihood of our model is given by

$$L = \prod_{i=1}^{N} \left[\prod_{h=1}^{H} P_{iA_i}^{\upsilon_{ih}}\right] \cdot \left[\int_{-\infty}^{+\infty} \prod_{l=1}^{L} \prod_{j=1}^{J} P_{iS_i|A_i,\epsilon}^{\vartheta_{il}} \cdot P_{ij|S_i,\epsilon}^{\delta_{ij}} f(\epsilon)\, \mathrm{d}\epsilon\right] \tag{12}$$

where υ_{ih} indicates the awareness set, ϑ_{il} indicates the chosen consideration set, and δ_{ij} the bank with which the consumer chooses to open an account with. $\theta = \{\theta_1, \theta_2, c_i\}$ is the set of parameters to be estimated. Neither the consideration set probability as shown is equation (10) nor the purchase probability as shown in equation (11) have a closed-form solution. Honka (2014) describes how to estimate this simultaneous search model in detail, and we follow her estimation approach.

6.4 Advertising Endogeneity

One estimation concern is the potential endogeneity of the advertising intensity variable which may arise both in the awareness and utility equations (equations (1) and (2), respectively).

The correlation between advertising intensity and the unobserved portions of latent awareness and latent utility is caused by omitted variables: the econometrician does not observe all the factors that affect consumers' awareness or utility and that may be correlated with advertising intensity. For example, banks may set advertising levels according to their regional performance measured, for instance, as a function of levels of customer satisfaction. Since customer satisfaction is not observed by the researcher, but may be observed by the bank management, this can give rise to endogeneity concerns. Ideally, this advertising endogeneity issue could be addressed by including bank-specific regional fixed effects in the awareness and utility equations. Unfortunately, the number of respondents that we have for each bank-region combination does not allow us to follow this approach.

We allow for endogeneity in advertising intensity adv_{jm} and address the problem that ξ_{ij} in (1) and ϵ_{ij} in (2) may not be independent of adv_{jm} by using the control function approach (Heckman 1978, Hausman 1978, Petrin and Train 2010 and Blundell and Powell 2004). The idea behind the control function correction is to derive a proxy variable that conditions on the part of adv_{jm} that depends on ξ_{ij} and on ϵ_{ij} so that the remaining variation in the endogenous variable becomes independent of the errors.

More formally, let the endogenous explanatory variable adv_{jm} be expressed as a linear function of all relevant exogenous variables entering the latent awareness and the utility function specifications, denoted as X; the variables Z that do not enter latent awareness or utility directly but affect adv_{jm} (also called instruments); and an unobserved term μ_{jm}:[9]

$$adv_{jm} = \alpha_j + X\beta_j + Z_{jm}\gamma_j + \mu_{jm}. \tag{13}$$

Substituting this expression for adv_{jm} into equations (1) and (2) the endogeneity issue becomes clear. While ξ_{ij}, ϵ_{ij} and μ_{jm} are independent of X and Z_{jm}, μ_{jm} is correlated with ξ_{ij} and with ϵ_{ij}. This correlation implies that adv_{jm} is correlated with ξ_{ij} and with ϵ_{ij}, which is the source of the endogeneity concern. More specifically, there may be bank-DMA specific variables that affect all consumers living in a given DMA and that are not observed by the researcher, such as branch regional performance as mentioned above. Note that we assume that μ_{jm} and ξ_{ij} and ϵ_{ij} are independent for all $k \neq j$.

Further, we specify ξ_{ij} in the awareness equation (1) to consist of a part that is correlated with adv_{jm} and that can be explained by a general function of μ_{jm} (a first order approximation can be $\lambda \cdot \mu_{jm}$) and a part that is iid EV Type I. In particular let

$$\xi_{ij} = CF(\mu_{jm}; \lambda_a) + \tilde{\xi}_{ij}; \tag{14}$$

similarly, for the utility equation (2) we can write

$$\epsilon_{ij} = CF(\mu_{jm}; \lambda_u) + \tilde{\epsilon}_{ij}, \tag{15}$$

[9]Note that the point of the advertising equation is not to model advertising-setting behavior but it is only a robust way of uncovering the true parameters of the awareness model (see Rivers and Vuong 1988, Villas-Boas 2007, Petrin and Train 2010).

where CF$(\cdot)$ denotes the control functions with parameters λ_a and λ_u and $\tilde{\xi}_{ij}$ and $\tilde{\epsilon}_{ij}$ are iid EV Type I.

The model is estimated in two steps: First, the advertising equation (13) is estimated and its residuals $\hat{\mu}_{jm}$ are retained. To estimate equation (13), we use as Xs variables that capture the bank presence across DMAs and that are similar to the bank presence variables included in the awareness and utility equations. Namely, we use an indicator variable for whether the bank has a branch present in the DMA and the number of branches it has in that DMA. As instruments (Z variables) we use the number of TV homes for each DMA (which captures the size of each market) and the cost of advertisements at the DMA- and bank-level. Market size and advertising costs act as exogenous shifters of advertising placement decisions because they are likely to be correlated with advertising intensity but uncorrelated with latent awareness or utility.[10]

Second, both the discrete awareness model and the consideration-choice model are estimated with these residuals entering as explanatory variables. These residuals are the control functions that are included to account for omitted attributes.

Because the second step uses an estimate of μ_{jm} from the first step, as opposed to the true μ_{jm}, the asymptotic sampling variance of the second-step estimator needs to take this extra source of variation into account. We implement a bootstrap procedure to address this issue.

7 Results

7.1 Awareness

We start by discussing our results on consumer awareness for retail banks. Table 8 shows the estimates from four multivariate logit regressions: Model (A1) includes bank fixed effects and demographics and Model (A2) also includes advertising intensity. In Model (A3), we subsequently control for bank branch presence. And, finally in Model (A4), we let the effects of advertising to be bank-specific.[11]

In all four models, all bank fixed effects other than Bank of America in Model (A4) are significant. As expected, the big-4 banks (Bank of America, Citi, Chase, Wells Fargo) have relatively higher brand awareness when compared to their more regional counterparts. In Model (A2), we find a small positive coefficient of advertising (measured in $1,000$ units/placements) which decreases in magnitude (but still remains significant) once we control for local bank branch dummies in Model (A3). The effects of local branch presence are large and positive. In Model (A4), we see that even after allowing for bank-specific coefficients on advertising the effects of local bank branch dummies remain similar to the ones found in Model (A3). Further, we also see quite a bit of heterogeneity

[10] Average advertising costs were calculated for each type of media by using total advertising expenditures and units across all industries for each market and media type. Then, because different banks have different allocation of advertising units across media, we calculated an average advertising cost per bank and DMA (weighted by the share allocated to each media). This means that advertising costs are not just market- but also bank-specific.

[11] In Table 8, we show the estimation results for the awareness stage after shoppers and non-shoppers have been re-weighted to our data to be representative of the population. We also estimated our model with the non-representative sample and our results are similar.

in the effects of advertising across banks. The effects of advertising vary considerably in magnitude ranging from 0.0113 for Capital One to 1.4796 for Comerica Bank. Most interestingly, the advertising coefficients for the big-4 banks (Bank of America, Citi, Chase, Wells Fargo) are all insignificant. At this point in time, we speculate that the insignificant effects of advertising might be due to diminishing returns of advertising as we observe banks which advertise more to have smaller coefficient estimates. We will test this hypothesis in the next version of the paper by also including squared advertising in the awareness function.

To quantify the effect of advertising, note that the average probability (across all banks and consumers) of a consumer being aware of a bank is 32.46 percent. When advertising (measured in $1,000$ units/placements) is increased by 1 percent, the average probability (across all banks and consumers) of a consumer being aware of a bank increases to 32.51 percent, i.e. an increase of 5 basis points. These estimates also allow us to quantify the "brand awareness" value of the banks in terms of advertising quantity. For example, in Model (A2), we find that Chase's brand fixed effect is 2.2458 points above Citibank's. Using the estimated advertising coefficient of 0.1624, this means the "brand value gap" between Citi and BofA consists of $13,829$ advertisements (2.2458/0.1624 multiplied by 1,000). Moreover, note that the "branch presence" indicator coefficients are between 1 to 16 times the advertising coefficient (based on Model A4 estimates, focusing on significant coefficients), suggesting that the presence of a branch is worth around 1,000 to 16,000 advertisements (assuming, of course, that the advertising effect is linear throughout its domain).

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Insert Table 8 about here

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Finally, we also control for consumer demographics and find that the more thoroughly we control for advertising and local bank presence, the fewer parameters associated with demographic variables are significant. In Model (A4), only three demographics are significant: Asians and Hispanics are aware of fewer banks than Whites and single/ divorced consumers have smaller awareness sets.

7.2 Consideration and Purchase

Models (LI-1) and (LI-2) in Table 9 show the estimates for the consideration and purchase parts of the model. In Model (LI-2), we allow the effects of local bank branches to be bank-specific.[12] Similarly to the results on awareness, we find all brand intercepts and bank branch dummies to be significant. As expected, local bank presence increases consumers' utility for a bank with the effects ranging from 0.3839 for US Bank to 1.2999 for Keybank. Among the variables entering consumers' utility function, local bank presence is the second-largest utility shifter after interest rates. Also, the estimated coefficients for local bank presence are much larger in magnitude than

[12]In Table 9, we show the estimation results for the consideration and purchase stages after shoppers and non-shoppers have been re-weighted to our data to be representative of the population. We also estimated our model with the non-representative sample and our results are similar.

the advertising coefficient and the coefficient on inertia (i.e. whether the consumer switches his primary bank). Being a consumer's primary bank, having high interest rates on savings accounts and local bank presence increase consumer's utility for a bank. While significant, the coefficient for advertising is small and advertising is by far the smallest utility shifter. Thus we conclude that advertising for retail banks only shifts consumer utility marginally.

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Insert Table 9 about here

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We find consumer search costs for retail banks (measured in interest-rate percentage points) to be 0.09 percentage points (9 basis points) per bank searched, which translates to about \$2.25 for a 2.5K account. Interestingly, this amount of search cost is comparable to other search cost estimates in the financial products industry. For example, Hortaçsu and Syverson (2004) found median search costs to be between 7 and 21 basis points for S&P 500 index funds, which are typically purchased by more financially sophisticated and higher-income individuals.

Based on the estimated coefficient for the "Primary Bank" dummy variable, switching costs with regard to a consumer changing his primary bank appear to be an important factor of demand in this market. The coefficient estimate on Primary Bank is about half of the coefficient estimates for local bank presence which implies that branch closures have the potential to lead to consumers switching their primary bank.

7.3 Does Advertising have an "Informative" or a "Persuasive" Role?

To compare the magnitudes of the effects of advertising across the different stages in the purchase process, we calculate advertising elasticities for awareness and choice. Table 11 shows the results. The average advertising elasticities for awareness and choice are 0.89 and 0.27, respectively. This finding indicates that advertising rather affects consumer awareness than choice conditional on awareness and that the role of advertising in the U.S. retail banking industry is primarily informative. Our results are similar to those found by previous literature albeit in different categories. For example, Ackerberg (2001) and Ackerberg (2003) find that advertising has a primarily informative role in the Yogurt market and Clark, Doraszelski, and Draganska (2009) also show that advertising has stronger informative effects in a study of over 300 brands.

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Insert Table 11 about here

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Looking at the bank-specific advertising elasticities for awareness and choice, we find that the advertising elasticities for awareness vary from 0.02 to 7.89, while the advertising elasticities for choice conditional on awareness range from 0.00 to 1.15. For most banks, the advertising elasticity for awareness is larger than that for choice. One important exception is Bank of America. Its advertising elasticity for choice is about five times larger than that on awareness.[13] Thus, for Bank of America, the role of advertising is primarily persuasive.

7.4 Comparison with a Model under Full Information

In the previous sections, we developed and estimated a complete three-stage model of the consumer's shopping and account opening process that accounts for a consumer's limited information. Doing so only makes sense when limited information is an important factor in the decision-making process and significantly influences results. To show the importance of accounting for limited information in the retail banking sector, we compare our estimates to those obtained from a model under full information. In the full information model, we assume consumers are aware of and consider all banks when deciding on the bank with which they would like to open (an) account(s) with (we also allow for an outside option). Further, consumers know the actual interest rate any bank in the data will offer them. Under these assumptions, the full information model can be estimated as a multinomial logit model. The results are shown as Model (FI) in Table 9. Compared to the results from the model under limited information, the coefficient estimates for local bank presence are two to five times larger, the coefficient estimate for primary bank is negative and, most importantly, the coefficient estimate on interest rates is also negative, i.e. consumers prefer savings accounts with lower than higher interest rates, under the full information assumption.

The reason for the negative interest rate coefficient is the following: Recall that there are 18 banks in the retail banking sector and that consumers, on average, only consider 2.5 banks. When demand is estimated under the full information assumption, in many cases consumers do not pick the option with the highest or one of the highest interest rates among the 18 banks. Under full information, this behavior is attributed to the consumer being insensitive to interest rates or, in this specific case, even preferring lower to higher interest rates (holding everything else constant). Under limited information, the model can distinguish between the consumer not picking a bank with a high interest rate because he does not know about it (due to not being aware of or not considering the bank) and the consumer being insensitive to interest rates. We conclude that it is essential to account for consumers' limited information in the retail banking sector to get meaningful demand estimates.

7.5 Interest Rate Elasticities

Table 10 shows the own-interest rate elasticities implied by our limited information model. The mean interest rate elasticity across all companies is 0.03 and the bank-specific interest rate elasticities vary from 0.00 to 0.09. A strong contrast is found when the interest rate elasticities calculated under limited information are compared to those estimated under full information. The average

[13] For Keybank and Capital One, the advertising elasticity for choice is also larger than that for awareness. But the difference in magnitudes is much smaller: In both cases, the advertising elasticity for choice is about twice as large as the advertising elasticity for awareness.

own-interest rate elasticity under full information is -0.01. The negative sign of the interest rate elasticity is counterintuitive and comes from the negative interest rate coefficient reported in Table 9 and discussed in the previous section.

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Insert Table 10 about here

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8 Counterfactuals

Note: We are currently working on the counterfactuals and results will be available in the next version of the paper.

Note that our model is a partial equilibrium model. Thus any counterfactuals only capture consequences on the demand side, i.e. we do not model interest rates or advertising spending adjustments on the supply side. The results can be interpreted as short-run market effects.

8.1 Welfare Analysis

While informative advertising is viewed as "good," there is some debate about whether persuasive advertising actually provides consumers with any "real" utility. If persuasive advertising does not yield any real utility, then we may ask what the socially optimal amount of informative advertising is given that there are costs to advertising. In this counterfactual, we will study three scenarios: First, we investigate what happens to market shares if either persuasive and/or informative advertising is shut down and interest rates are fixed. Next, we allow interest rates to adjust in the same scenarios. And finally, assuming that persuasive advertising does not yield any real utility to consumers, we quantify the socially optimal amount of informative advertising. We then compare this with the observed amount of informative advertising in the U.S. retail banking industry.

8.2 Free Interest Rates Comparison

Online price comparison sites such as pricegrabber.com or pricewatch.com where consumers can costlessly see and compare product prices from different sellers are common for many products such as groceries, appliances, electronics, toys, furniture and many more. Price comparison sites are less common for financial services due to their complexity. Nevertheless, some innovative and largely internet-based companies in other financial services areas such as Progressive and Esurance for auto insurance are showing potential customers competitive price quotes on their own website thus allowing them to costlessly see and compare prices. In this counterfactual, we investigate the effects of the only internet bank, Capital One, newly introducing free local interest rate comparisons to all potential customers visiting its website or bank branch, i.e. all customers who consider Capital

One.[14]

We investigate three different scenarios. First, we study the effects of the interest rate comparison tool introduction by itself, i.e. without any changes to the other variables. Next, suppose Capital One accompanied the interest rate comparison tool introduction by doubling the number of advertisements they are showing. And finally, we investigate what the necessary increase in advertisements would be to triple Capital One's market share to 10 percent.

9 Robustness Checks

We conduct a variety of checks to test the robustness of our results. First, we change the radius for the local bank branch variable in the estimation. Currently, we control for local bank presence by including an indicator variable that reflects whether there is at least one bank branch within 5 miles of the consumer's zip code's centroid. We also estimated our model using an alternative radius of 10 miles from the consumer's zip code's centroid for local bank presence. The results are shown in Tables 12 for awareness and Table 13 for consideration and choice. For both awareness and consideration and choice, we find very similar and for most significant bank branch dummies slightly larger coefficients using the 10-miles radius compared to the 5-miles radius. The estimates for the other variables remain very similar. Thus we conclude that our results are robust to different definitions of local bank presence.

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Insert Table 12 about here
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Insert Table 13 about here
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Second, we also verified the robustness of our results to an alternative definition of interest rates. The current reported results are based on interest rate data calculated using information on the top 2.5K savings account for each bank. But we also experimented using data on all 2.5K savings accounts that each bank has, and the results did not change significantly.

And lastly, we check the robustness of our results with respect to a different measure of advertising. In our model, we operationalize advertising as the sum of national and DMA-level advertisements. In this robustness check, we only use the DMA-level advertising quantity in the estimation. We find that our results are qualitatively and largely also quantitatively robust to this alternative measure of advertising.

[14] Capital One only had 854 bank branches in the U.S. (in 2010), with over 70 percent of them being located in the states of New York, Texas and Louisiana.

10 Limitations and Future Research

There are several limitations to our research. First, our model describes the consumer's shopping and account opening process given the consumer's decision on account types he is considering adding or moving, i.e. we do not model jointly the consumer's choice of account types and the search among banks. Our model assumes that consumers first decide which account types to add/move and then begin the shopping process. It is left for future research to develop a model where consumers choose several products and search at the same time that they evaluate those products. Second, we use the interest rates for 2.5K savings account as a proxy for price. While this is a reasonable assumption, a more precise price measure potentially self-reported by consumers would further advance our understanding of consumers' shopping process for bank accounts.

Third, we assume consumers have rational expectations about the distribution of interest rates for all banks that they are aware of. A model that has information on consumer expectations for interest rates or is able to recover them would enable researchers to test the hypothesis of rational expectations. And lastly, more work is needed to enhance our understanding of the effectiveness of price promotions versus advertising in the retail banking industry. Advertisements stating, for example, that consumers can get $200 for opening a new checking account as advertised by Chase, are effectively price promotions and their effectiveness as compared to brand advertising is an open question. We leave it to future research to find the answer to this question.

11 Conclusion

In this paper, we utilize a unique data set with detailed info on consumers' shopping process for banking services. Using data on awareness and consideration sets and the purchase decision, we attempt to disentangle the informative and persuasive effects of advertising in the retail banking sector. We find advertising primarily informs consumers about the existence of banks and their products and does not shift consumers' utility for retail banking products. We also find that branch presence is a very effective driver of awareness and choice (upon consideration), reflecting the local nature of banking (consistent with the fact that banks that operate mostly through the internet have had very little penetration in the U.S.). Consumers face nontrivial search costs in this market, equivalent to 0.09 percentage points in interest rate terms. Switching costs away from the primary bank also appear to be an important factor of demand in this market, though with a similar order of magnitude to local bank presence – i.e. (multiple) branch closures would easily lead to switching to a different bank. We hope that our (still preliminary) results shed light on the drivers of demand in this very important sector of the economy, and we hope to seek further managerial and policy implications of our demand estimates in the near future.

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Tables and Figures

Figure 1: Number of Accounts Opened

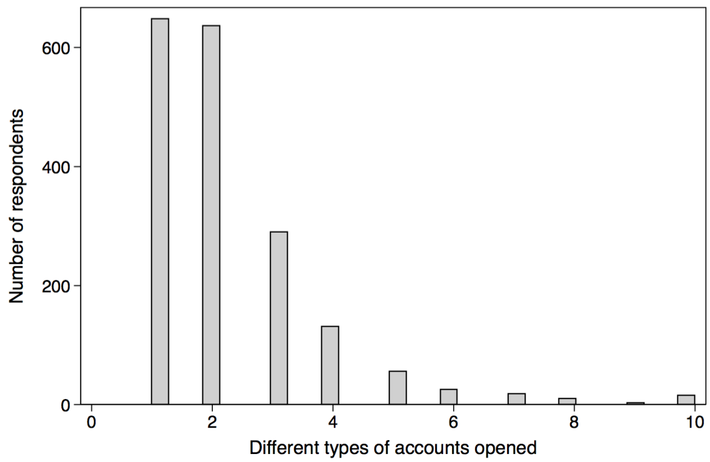


Figure 2: Size of awareness sets

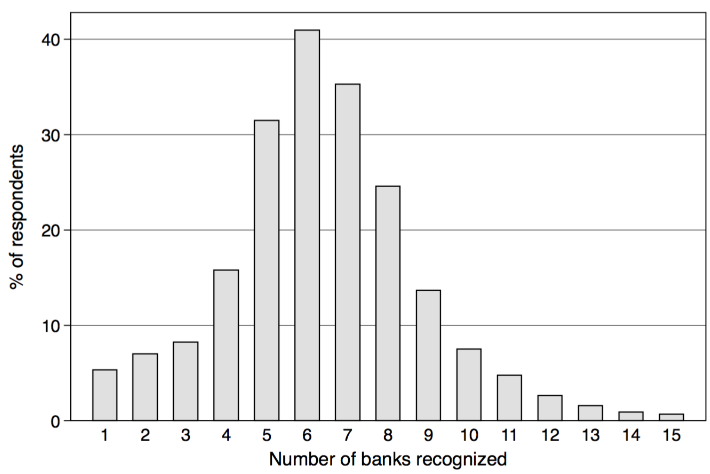


Figure 3: Size of shoppers' consideration sets

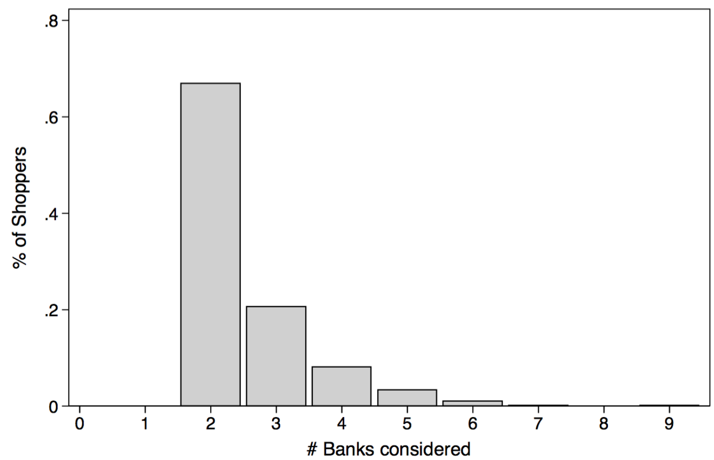


Figure 4: Awareness vs Consideration (Shoppers only)

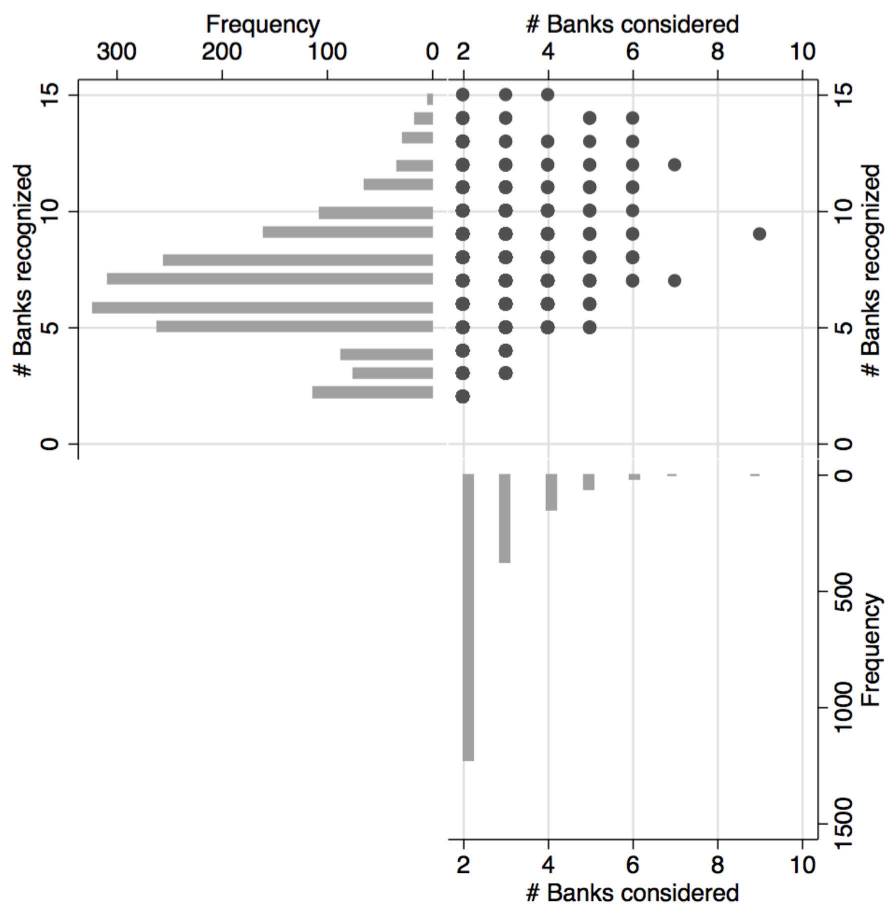


Figure 5: Size of awareness sets

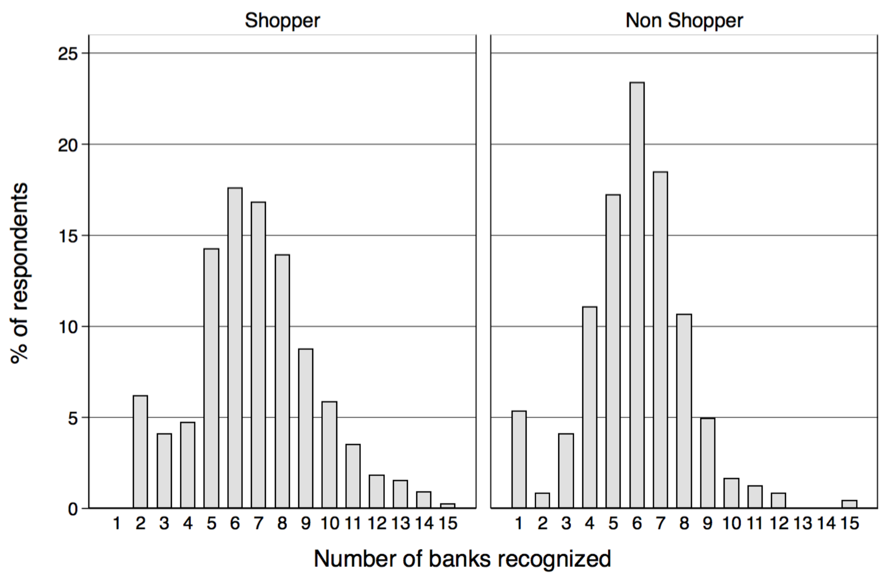
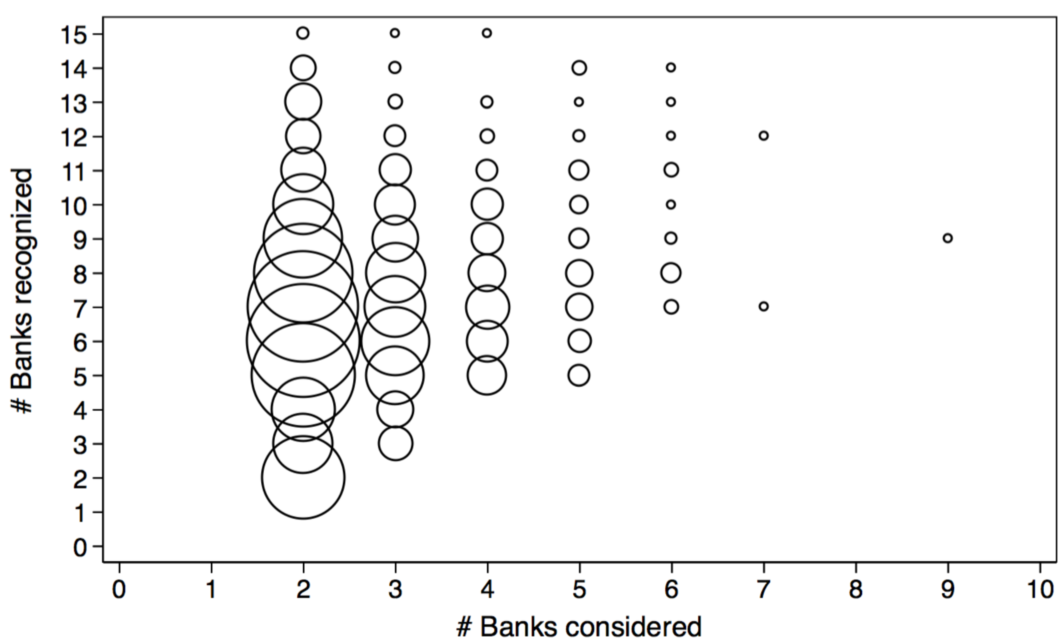


Figure 6: Awareness vs Consideration (Shoppers only)



Note: The area of each circle is proportional to the number of respondents for each combination of Awareness and Consideration Set sizes.

Figure 7: Geographic Distribution of Banks' DMA-level Advertising (Expenditures)

This map displays the spatial distribution of DMA-level advertising expenditure by banks in the 206 DMAs across the U.S. over the reference period. Areas in white correspond to DMAs for which Kantar Media does not collect data. Advertising numbers in the legend are represented in thousands.

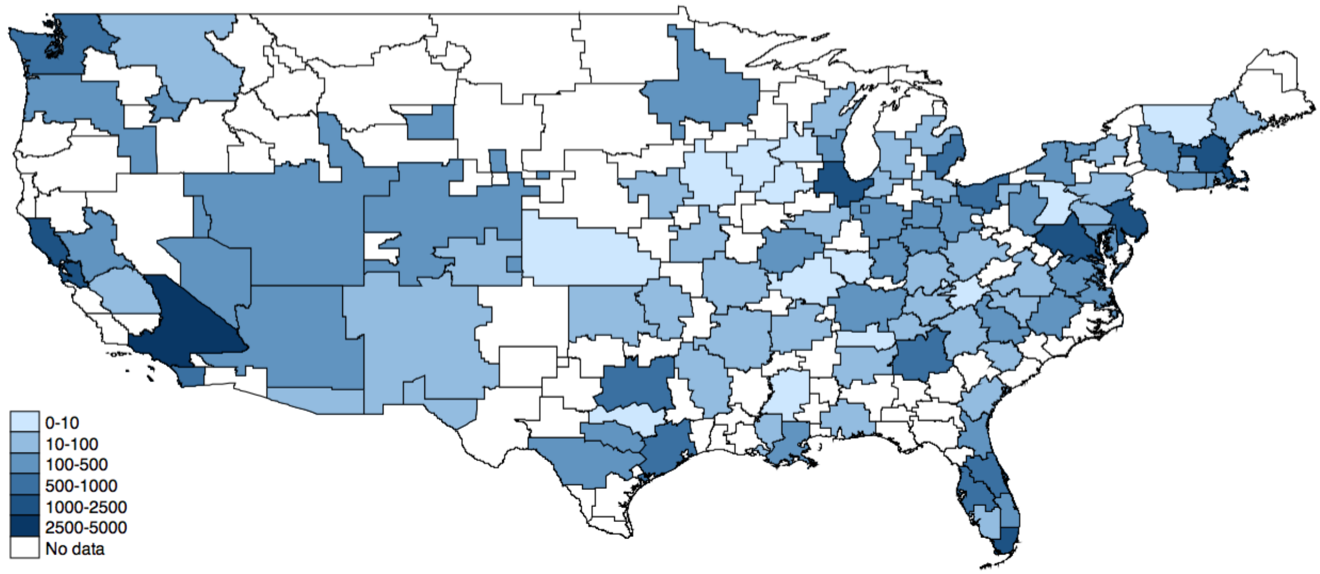


Figure 8: Geographic Distribution of Banks' DMA-level Advertising (Placements)

This map displays the spatial distribution of DMA-level number of advertising placements by banks in the 206 DMAs across the U.S. over the reference period. Areas in white correspond to DMAs for which Kantar Media does not collect data.

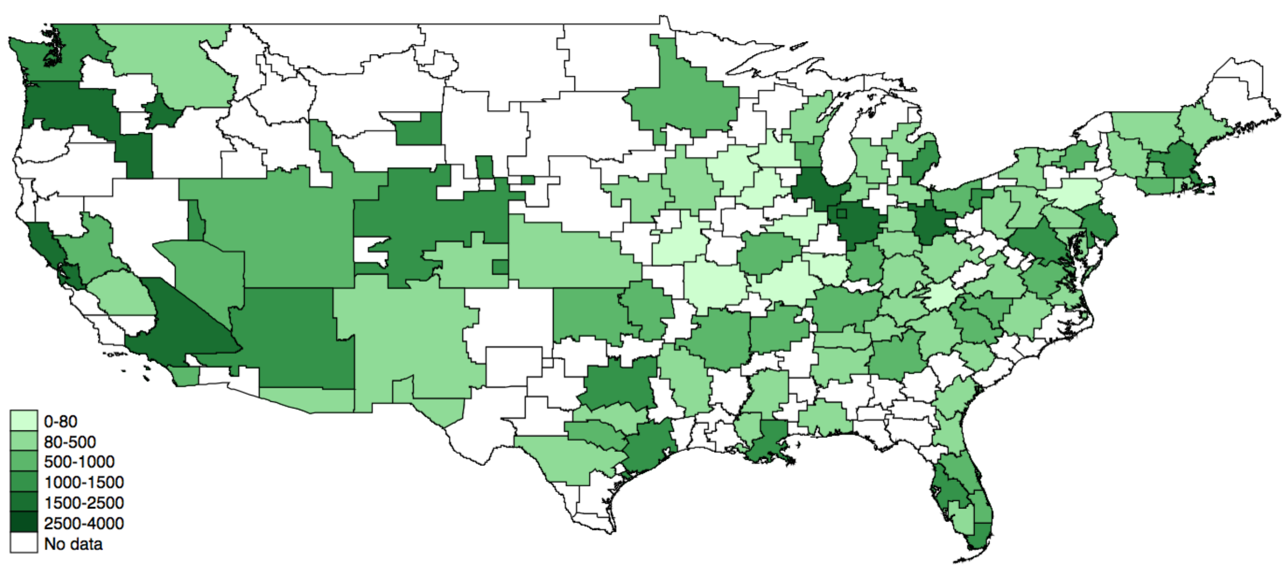


Table 1: Share of respondents that were Aware/Considered/Chose each Bank (%)

This table presents the percentage of respondents in the sample that were Aware, Considered or Chose each of the institutions listed.

Institution	Aware	Considered	Chose
BB&T	17.15	5.44	3.13
Bank Of America	95.18	44.27	12.52
Capital One	31.89	6.55	3.32
Chase/WaMu	73.94	32.18	12.62
Citibank	63.87	17.92	7.27
Citizens Bank	25.24	7.71	4.53
Comerica Bank	10.98	1.93	0.87
Fifth Third Bank	25.39	7.80	3.71
HSBC	21.53	7.56	3.03
Keybank	24.18	6.12	2.99
M&T	8.62	4.19	2.31
PNC/National City Bank	34.92	11.03	4.67
Regions Bank	21.10	5.97	3.08
Sovereign Bank	17.68	4.82	2.26
Suntrust Bank	31.12	11.66	7.61
TD Bank	21.48	8.96	4.05
U.S. Bank	31.21	13.01	8.33
Wells Fargo/Wachovia	87.24	34.39	13.68

Table 2: Demographics for full and selected samples

This table compares the demographics of the respondents in the selected sample with all of the survey respondents. Columns “All Respondents” and “Selected Sample” report the percentage of respondents in each of the demographic groups for all of the survey respondents and for the selected sample respectively.

	Data set	
	All Respondents ($n = 4,246$) %	Selected Sample ($n = 2,076$) %
Gender		
Female	60.0	60.8
Male	40.0	39.2
Age		
19-29	17.0	17.9
30-44	30.4	32.3
45-59	34.0	32.4
60+	18.7	17.4
Household Income		
Under $49,999	36.5	35.5
$50,000-$99,999	38.0	38.2
$100,000 and over	25.5	26.3
Race		
White	81.3	78.1
Black	5.0	5.6
Asian	7.5	9.3
Hispanic	3.9	5.0
Other	2.3	2.0
Education		
High school or less	8.5	7.2
Some College	32.2	31.0
College graduate	29.4	31.4
Postgraduate	29.9	30.4
Marital Status		
Single/Divorced	33.4	33.3
Married/Partner	63.7	64.5
Widowed	2.9	2.2
Region		
New England	5.6	6.5
MidAtlantic	22.9	28.3
Midwest	10.5	6.7
North Central	10.9	8.8
Southeast	8.1	8.0
South Central	4.1	3.1
Texas	4.1	4.6
Florida	8.8	10.8
Southwest	6.3	5.9
Northwest	4.3	4.5
California	12.8	12.7
Other	1.6	0.1

Table 3: Demographics by Respondent Type

This table reports descriptive statistics for all respondents in our final sample as well as for the two subgroups of respondents: "shoppers" (1,832 consumers) and "non-shoppers" (244 consumers). Shoppers are consumers who opened one or more new accounts and non-shoppers are consumers who did not open new accounts during the reference period.

	Respondent Type		
	Shopper	Non Shopper	All
	%	%	%
Gender			
Female	60.9	59.8	60.8
Male	39.1	40.2	39.2
Age			
19-29	19.6	5.3	17.9
30-44	34.2	17.6	32.3
45-59	30.8	43.9	32.4
60+	15.3	33.2	17.4
Household Income			
Under $49,999	34.0	47.1	35.5
$50,000-$99,999	38.9	32.8	38.2
$100,000 and over	27.1	20.1	26.3
Race			
White	76.9	86.9	78.1
Black	5.8	3.7	5.6
Asian	10.0	3.7	9.3
Hispanic	5.4	2.0	5.0
Other	1.8	3.7	2.0
Education			
High school or less	6.4	12.7	7.2
Some College	30.5	35.2	31.0
College graduate	32.0	26.2	31.4
Postgraduate	31.1	25.8	30.4
Marital Status			
Single/Divorced	33.7	30.7	33.3
Married/Partner	64.3	65.6	64.5
Widowed	2.0	3.7	2.2
Region			
Region			
New England	6.8	4.1	6.5
MidAtlantic	29.3	20.5	28.3
Midwest	5.6	15.6	6.7
North Central	8.2	12.7	8.8
Southeast	8.2	6.6	8.0
South Central	2.8	5.7	3.1
Texas	4.5	5.3	4.6
Florida	11.2	7.8	10.8
Southwest	5.8	6.6	5.9
Northwest	4.5	4.5	4.5
California	12.9	10.7	12.7
Other	0.2	0.0	0.1

Table 4: Account types opened (Shoppers only)

This table shows, for the subsample of shoppers, the types of new accounts opened during the reference period.

Account type	% Respondents Opening	Account type	% Respondents Opening
Deposit Accounts		*Borrowing Accounts*	
Checking	85.10	Credit Card	25.87
Savings	57.86	Mortgage	9.01
Certificate of Deposit	11.74	Home Equity Loan	6.28
Money Market Account	12.45	Personal Loan	8.02
Investment Accounts			
Mutual Funds	4.69		
Stocks/Bonds	4.26		

Table 5: Respondents with bank branches within 5 miles of their home (Shoppers only)

This table reports the percentage of shoppers in the sample with bank branches within 5 miles of their home conditional on them having Considered/Chosen each of the institutions listed.

Institution	Considered	Chosen
BB&T	84.82	82.81
Bank Of America	85.52	86.26
Capital One	69.63	67.65
Chase/WaMu	88.08	90.58
Citibank	69.92	78.38
Citizens Bank	60.00	60.71
Comerica Bank	86.84	87.50
Fifth Third Bank	80.39	85.29
HSBC	42.38	47.37
Keybank	85.25	91.23
M&T	84.81	85.00
PNC/National City Bank	86.18	88.24
Regions Bank	88.33	91.67
Sovereign Bank	78.95	80.95
Suntrust Bank	86.02	87.50
TD Bank	90.76	92.68
U.S. Bank	82.00	88.24
Wells Fargo/Wachovia	88.65	91.44

Table 6: Interest Rates by Institution

This table reports summary statistics for the interest rates associated with the most popular 2.5K savings accounts for each bank. These rates proxy for the actual rates that each respondent obtained upon searching over the banks in his consideration set. Interest rates statistics are calculated using banks in respondents consideration sets and based on respondents' zip codes. N is the number of respondents that considered a given bank.

Institution	**mean**	**sd**	**min**	**max**	**N**
BB&T	0.050	0.000	0.050	0.050	113
Bank Of America	0.100	0.000	0.100	0.100	919
Capital One	1.101	0.439	0.050	1.290	136
Chase/WaMu	0.010	0.000	0.010	0.010	668
Citibank	0.290	0.169	0.250	1.000	372
Citizens Bank	0.050	0.000	0.050	0.050	160
Comerica Bank	0.050	0.000	0.050	0.050	40
Fifth Third Bank	0.200	0.000	0.200	0.200	162
HSBC	0.050	0.000	0.050	0.050	157
Keybank	0.050	0.000	0.050	0.050	127
M&T	0.050	0.000	0.050	0.050	87
PNC/National City Bank	0.050	0.000	0.050	0.050	136
Regions Bank	0.100	0.000	0.100	0.100	124
Sovereign Bank	0.100	0.000	0.100	0.100	100
Suntrust Bank	0.050	0.000	0.050	0.050	242
TD Bank	0.100	0.000	0.100	0.100	186
U.S. Bank	0.100	0.000	0.100	0.100	270
Wells Fargo/Wachovia	0.046	0.007	0.030	0.050	345

Table 7: DMA-Level Advertising Expenditures (dols000) and Placements by Bank

This table shows average advertising expenditures and average number of placements (also called “units”) by bank. It includes Spot TV, Newspapers, National Spot Radio, Internet Display, Outdoor at DMA-level. The averages are taken by dividing the total advertising expenditures/placements at the DMA-level over the entire reference period by the number of DMAs in which each bank had some advertising activity.

Institution	**Average per DMA**		**Number of DMAs**
	Expenditure	Units	
BB&T	207.0	188.9	23
Bank Of America	424.0	1859.0	101
Capital One	432.2	895.9	97
Chase/WaMu	1039.7	1376.0	98
Citibank	654.4	333.2	99
Citizens Bank	258.2	234.5	99
Comerica Bank	336.2	271.2	16
Fifth Third Bank	797.7	1526.3	30
HSBC	209.5	286.0	97
Keybank	415.6	1464.2	29
M&T	390.2	615.4	14
PNC/National City Bank	525.6	770.6	99
Regions Bank	254.2	353.4	43
Sovereign Bank	117.0	154.4	65
Suntrust Bank	336.3	501.7	83
TD Bank	848.5	810.2	43
U.S. Bank	154.1	183.2	79
Wells Fargo/Wachovia	433.2	1084.7	101

Table 8: Results from Awareness Stage

This table reports the results from four different model specifications for the Awareness stage. Panel A reports the Brand, Branches and Advertising Parameters and Panel B reports the parameters associated with the demographic variables. All four models include bank-specific fixed effects."Branch presence" is operationalized as a dummy variable that captures whether there is a branch of a given bank present within 5-miles of each respondent zip-code centroid. Advertising corresponds to the number of DMA placements. Advertising is not included in model (A1) and in Model (A4) is allowed to have coefficients that are bank-specific. The omitted demographic categories are Married/Partner, White, Income below 50k and High school or less for the variables Marital Status, Race, Income and Education, respectively. Standard-errors are reported in parentheses under coefficient estimates. (**) and (*) denote statistical significance for 5% and 10% levels respectively.

Panel A: Brand, Branches and Advertising Parameters

	(A1)	(A2)	(A3)		(A4)		
	Brand	Brand	Brand	Branch presence	Brand	Branch presence	Advert
Bank of America	-1.530**	-23.109**	-9.997**	0.385	-11.726	0.076	0.355
	(0.257)	(1.201)	(1.005)	(0.301)	(7.216)	(0.055)	(0.315)
BB&T	-5.141**	-5.363**	-5.475**	1.149**	-5.424**	0.300	1.147**
	(0.488)	(0.498)	(0.512)	(0.201)	(0.512)	(0.540)	(0.227)
Citibank	-2.399**	-7.171**	-4.709**	1.620**	-4.755**	0.064	1.615**
	(0.249)	(0.364)	(0.340)	(0.165)	(1.244)	(0.040)	(0.175)
Citizens Bank	-3.806**	-6.846**	-5.687**	1.732**	-15.985**	0.666**	1.434**
	(0.350)	(0.398)	(0.403)	(0.215)	(2.295)	(0.132)	(0.225)
Comerica	-5.010**	-4.882**	-5.817**	2.472**	-6.821**	1.480**	1.522**
	(0.556)	(0.545)	(0.581)	(0.206)	(0.632)	(0.198)	(0.238)
Fifth Third	-3.640**	-4.130**	-5.031**	2.919**	-5.321**	0.453**	2.198**
	(0.339)	(0.349)	(0.399)	(0.213)	(0.413)	(0.078)	(0.240)
HSBC	-4.028**	-9.118**	-6.022**	1.400**	-17.702**	0.392**	0.953**
	(0.380)	(0.472)	(0.453)	(0.228)	(3.160)	(0.089)	(0.268)
Chase	-3.525**	-4.925**	-4.209**	0.602**	-4.078**	0.046	0.654**
	(0.257)	(0.273)	(0.282)	(0.136)	(0.377)	(0.034)	(0.167)
Keybank	-3.083**	-3.457**	-4.225**	2.742**	-4.389**	0.222**	2.429**
	(0.311)	(0.319)	(0.347)	(0.179)	(0.354)	(0.050)	(0.202)
M&T	-7.354**	-8.218**	-8.540**	0.841**	-9.246**	0.822**	0.677**
	(0.711)	(0.753)	(0.785)	(0.260)	(0.827)	(0.171)	(0.267)
PNC/N. City Bank	-3.955**	-19.999**	-10.709**	1.582**	-8.330**	0.039	1.630**
	(0.295)	(0.930)	(0.774)	(0.147)	(2.677)	(0.027)	(0.153)
Regions	-4.266**	-5.041**	-5.516**	2.360**	-6.475**	0.300**	1.554**
	(0.398)	(0.406)	(0.438)	(0.199)	(0.482)	(0.035)	(0.225)
Sovereign	-4.693**	-4.891**	-5.468**	1.912**	-5.529**	0.108*	1.832**
	(0.422)	(0.415)	(0.450)	(0.216)	(0.484)	(0.065)	(0.230)
SunTrust	-3.401**	-3.907**	-5.131**	4.048**	-6.484**	0.898**	2.613**
	(0.329)	(0.338)	(0.393)	(0.267)	(0.476)	(0.134)	(0.334)
TD	-4.662**	-5.809**	-6.556**	2.406**	-6.964**	0.131**	2.077**
	(0.406)	(0.408)	(0.467)	(0.236)	(0.554)	(0.038)	(0.283)
US Bank	-2.491**	-3.013**	-4.596**	2.871**	-5.525**	0.366**	2.819**
	(0.306)	(0.311)	(0.363)	(0.183)	(0.512)	(0.123)	(0.192)
Wells Fargo/Wachovia	-3.314**	-7.087**	-5.288**	0.933**	-5.707**	0.081**	0.918**
	(0.260)	(0.335)	(0.339)	(0.190)	(0.732)	(0.032)	(0.202)
Capital One	-3.694**	-10.427**	-6.839**	1.586**	-4.781**	0.011	2.446**
	(0.310)	(0.491)	(0.456)	(0.264)	(0.465)	(0.008)	(0.279)
Advertising		0.162**	0.063**				
		(0.009)	(0.007)				

Table 8: Results from Awareness Stage (cont.)

Panel B: Demographics' Parameters

	(A1)	(A2)	(A3)	(A4)
Gender – Male	0.002	-0.004	-0.044	-0.045
	(0.038)	(0.038)	(0.041)	(0.041)
Age	-0.001	0.000	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Marital Status				
Single/ Divorced	0.004	-0.033	-0.090*	-0.094**
	(0.043)	(0.043)	(0.046)	(0.047)
Widow	-0.110	-0.167	-0.163	-0.154
	(0.123)	(0.126)	(0.133)	(0.135)
Race				
Black	-0.059	-0.063	-0.086	-0.103
	(0.080)	(0.081)	(0.087)	(0.088)
Asian	-0.101	-0.166**	-0.235**	-0.235**
	(0.067)	(0.069)	(0.073)	(0.074)
Hispanic	-0.140	-0.213**	-0.275**	-0.279**
	(0.088)	(0.091)	(0.097)	(0.097)
Other	-0.062	-0.096	-0.197	-0.188
	(0.130)	(0.133)	(0.141)	(0.142)
Income				
Income 50k - 100k	0.110**	0.050	0.040	0.029
	(0.044)	(0.045)	(0.048)	(0.048)
Income above 100k	0.163**	0.093*	0.030	0.027
	(0.052)	(0.053)	(0.056)	(0.057)
Education				
Some College	0.072	0.082	0.033	0.059
	(0.075)	(0.076)	(0.080)	(0.081)
College Degree	0.138*	0.141*	0.005	0.027
	(0.076)	(0.077)	(0.082)	(0.083)
Adv. Degree	0.133*	0.130*	-0.022	-0.002
	(0.077)	(0.078)	(0.083)	(0.083)

* $p < 0.10$; ** $p < 0.05$

Table 9: Results from Consideration and Purchase Stages

This table reports the results from three different model specifications for the Consideration and Purchase stages. Specification (FI) corresponds to a Full Information Model, equivalent to a traditional multinomial logit model, in which consumers are assumed to be aware and consider all banks and know what are banks' actual interest rates without engaging in search. Specifications (LI) correspond to models that account for consumers' Limited Information. In model (LI-1) branch presence is operationalized as a dummy variable that captures whether there is a branch of a given bank present within 5-miles of each respondent zip-code centroid and in model (LI-2) branch coefficients are allowed to be bank-specific. Standard-errors are reported in parentheses under coefficient estimates. (**) and (*) denote statistical significance for 5% and 10% levels respectively.

	(FI)		(LI-1)	(LI-2)	
	Brand	Branches	Brand	Brand	Branches
Bank of America	-2.266**	1.661**	-3.259**	-3.668**	0.682**
	(0.583)	(0.212)	(0.121)	(0.056)	(0.169)
BB&T	-2.694**	3.339**	-1.914**	-1.926**	0.920**
	(0.311)	(0.339)	(0.064)	(0.244)	(0.278)
Citibank	-1.793**	2.612**	-2.316**	-2.608**	1.133**
	(0.230)	(0.209)	(0.072)	(0.160)	(0.175)
Citizens Bank	-1.731**	2.271**	-1.801**	-1.826**	0.797**
	(0.197)	(0.236)	(0.070)	(0.197)	(0.246)
Comerica	-4.436**	4.091**	-2.712**	-3.191*	1.435
	(0.706)	(0.755)	(0.153)	(1.707)	(1.710)
Fifth Third	-2.760**	3.494**	-2.209**	-2.034**	0.685**
	(0.329)	(0.349)	(0.083)	(0.265)	(0.284)
HSBC	-2.038**	2.115**	-1.848**	-1.781**	0.462*
	(0.233)	(0.274)	(0.066)	(0.215)	(0.258)
Chase	-1.657**	2.503**	-1.951**	-2.261**	1.237**
	(0.234)	(0.237)	(0.061)	(0.189)	(0.191)
Keybank	-3.468**	4.001**	-2.215**	-2.563**	1.300**
	(0.453)	(0.473)	(0.080)	(0.271)	(0.301)
M&T	-3.321**	3.685**	-1.567**	-1.475**	0.826
	(0.415)	(0.449)	(0.167)	(0.684)	(0.725)
PNC/N. City Bank	-3.373**	2.828**	-3.028**	-3.526**	0.976**
	(0.475)	(0.342)	(0.060)	(0.198)	(0.230)
Regions	-3.509**	4.248**	-2.183**	-2.409**	1.110**
	(0.454)	(0.474)	(0.089)	(0.339)	(0.359)
Sovereign	-3.037**	3.329**	-2.101**	-1.819**	0.469
	(0.362)	(0.400)	(0.084)	(0.370)	(0.392)
SunTrust	-2.177**	3.884**	-1.688**	-1.861**	1.126**
	(0.241)	(0.256)	(0.096)	(0.397)	(0.404)
TD	-3.258**	3.859**	-1.819**	-1.687**	0.685*
	(0.416)	(0.429)	(0.111)	(0.349)	(0.358)
US Bank	-2.073**	3.039**	-1.910**	-1.445**	0.384
	(0.250)	(0.259)	(0.086)	(0.265)	(0.277)
Wells Fargo/Wachovia	-1.803**	2.439**	-2.263**	-2.680**	1.298**
	(0.261)	(0.248)	(0.069)	(0.184)	(0.188)
Capital One	-2.222**	2.706**	-2.622**	-2.672**	0.538**
	(0.407)	(0.298)	(0.119)	(0.201)	(0.228)
Other parameters					
Primary Bank	-0.763**		0.422**	0.415**	
	(0.090)		(0.038)	(0.060)	
Interest Rates	-0.107		0.950**	0.982**	
	(0.276)		(0.163)	(0.230)	
Advertising	0.009**		0.009**	0.014**	
	(0.004)		(0.001)	(0.006)	
Bank Branches			0.924**		
			(0.045)		
Search Cost Constant			0.001**	0.001**	
			(0.000)	(0.000)	

Table 10: Interest Rate Elasticities

This table reports the price (i.e. interest rate) elasticities that correspond to the model estimates reported in Table 9. Specification (FI) corresponds to a Full Information Model, equivalent to a traditional multinomial logit model, in which consumers are assumed to be aware and consider all banks and know what are banks' actual interest rates without engaging in search. Specification (LI-2) corresponds to a model that account for consumers' Limited Information in which branch presence is operationalized as a dummy variable that captures whether there is a branch of a given bank present within 5-miles of each respondent zip-code centroid. Elasticities are calculated for each respondent and bank and then averaged across respondents.

Brand	(FI)	(LI-2)
Bank of America	-0.01	0.06
BB&T	0.00	0.03
Citibank	-0.03	0.18
Citizens Bank	0.00	0.03
Comerica	-0.01	0.04
Fifth Third	-0.02	0.12
HSBC	-0.01	0.03
Chase	0.00	0.01
Keybank	0.00	0.03
M&T	0.00	0.03
PNC/N. City Bank	0.00	0.02
Regions	-0.01	0.06
Sovereign	-0.01	0.07
SunTrust	0.00	0.03
TD	-0.01	0.06
US Bank	-0.01	0.06
Wells Fargo/Wachovia	0.00	0.02
Capital One	-0.10	0.48
Average	-0.01	0.07

Table 11: Advertising Elasticities

This table reports the advertising elasticities that correspond to the model estimates reported in Tables 8 and 9. Elasticities are calculated for each respondent and bank and then averaged across respondents.

Brand	Awareness (4)	Choice (LI-2)
Bank of America	0.22	1.15
BB&T	0.02	0.00
Citibank	0.73	0.28
Citizens Bank	2.69	0.15
Comerica	0.14	0.02
Fifth Third	0.04	0.03
HSBC	7.89	0.34
Chase	0.14	0.08
Keybank	0.02	0.04
M&T	0.06	0.01
PNC/N. City Bank	0.85	0.84
Regions	0.27	0.08
Sovereign	0.10	0.04
SunTrust	0.52	0.03
TD	0.22	0.09
US Bank	1.45	0.03
Wells Fargo/Wachovia	0.23	0.20
Capital One	0.17	0.36
Average	0.89	0.27

Table 12: Results from Awareness Stage - Robustness

This table reports the results of robustness checks for two of the Awareness stage model results shown in table 8. Here "Branch presence" is operationalized as a dummy variable that captures whether there is a branch of a given bank present within 10-miles (as opposed to 5-miles) of each respondent zip-code centroid. Panel A reports the Brand, Branches and Advertising Parameters and Panel B reports the parameters associated with the demographic variables. Standard-errors are reported in parentheses under coefficient estimates. (**) and (*) denote statistical significance for 5% and 10% levels respectively.

Panel A: Brand, Branches and Advertising Parameters

	(A3-R)		(A4-R)		
	Brand	Branch presence	Brand	Branch presence	Advert
Bank of America	-8.024**	0.150	-13.291*	0.068	0.090
	(0.998)	(0.328)	(7.169)	(0.341)	(0.054)
BB&T	-5.560**	1.297**	-5.567**	1.304**	0.265
	(0.518)	(0.224)	(0.518)	(0.249)	(0.534)
Citibank	-4.464**	1.753**	-4.620**	1.731**	0.055
	(0.341)	(0.161)	(1.203)	(0.169)	(0.039)
Citizens Bank	-5.588**	1.709**	-15.958**	1.398**	0.658**
	(0.407)	(0.205)	(2.293)	(0.215)	(0.132)
Comerica	-6.202**	2.575**	-6.929**	1.365**	1.492**
	(0.594)	(0.224)	(0.629)	(0.273)	(0.214)
Fifth Third	-4.966**	2.812**	-5.310**	2.079**	0.476**
	(0.394)	(0.200)	(0.410)	(0.227)	(0.078)
HSBC	-5.685**	1.381**	-17.160**	0.991**	0.373**
	(0.453)	(0.212)	(3.174)	(0.248)	(0.089)
Chase	-4.143**	0.629**	-4.203**	0.609**	0.058*
	(0.285)	(0.138)	(0.374)	(0.164)	(0.033)
Keybank	-4.414**	2.541**	-4.557**	2.205**	0.218**
	(0.350)	(0.163)	(0.357)	(0.189)	(0.050)
M&T	-8.659**	0.995**	-9.533**	0.870**	0.873**
	(0.803)	(0.317)	(0.851)	(0.324)	(0.172)
PNC/N. City Bank	-9.666**	1.881**	-5.298**	1.990**	0.006
	(0.764)	(0.158)	(2.395)	(0.166)	(0.024)
Regions	-5.846**	2.801**	-6.588**	1.943**	0.256**
	(0.447)	(0.218)	(0.485)	(0.258)	(0.037)
Sovereign	-5.701**	2.136**	-5.672**	2.134**	0.055
	(0.457)	(0.223)	(0.488)	(0.247)	(0.068)
SunTrust	-5.337**	4.295**	-6.492**	2.959**	0.778**
	(0.404)	(0.271)	(0.480)	(0.355)	(0.141)
TD	-6.549**	2.596**	-6.788**	2.335**	0.097**
	(0.471)	(0.247)	(0.546)	(0.314)	(0.040)
US Bank	-5.078**	3.280**	-5.897**	3.220**	0.321**
	(0.384)	(0.204)	(0.529)	(0.213)	(0.126)
Wells Fargo/Wachovia	-5.128**	1.053**	-5.789**	1.029**	0.079**
	(0.347)	(0.200)	(0.722)	(0.214)	(0.031)
Capital One	-6.405**	1.956**	-4.684**	2.618**	0.007
	(0.453)	(0.242)	(0.463)	(0.257)	(0.008)
Advertising	0.049**				
	(0.007)				

Table 12: Results from Awareness Stage - Robustness (cont.)

Panel B: Demographics' Parameters

	(A3-R)	(A4-R)
Gender – Male	-0.036	-0.037
	(0.041)	(0.041)
Age	0.001	0.000
	(0.002)	(0.002)
Marital Status		
Single/ Divorced	-0.095**	-0.101**
	(0.047)	(0.047)
Widow	-0.179	-0.162
	(0.136)	(0.137)
Race		
Black	-0.142	-0.155*
	(0.088)	(0.088)
Asian	-0.260**	-0.258**
	(0.073)	(0.074)
Hispanic	-0.334**	-0.326**
	(0.097)	(0.098)
Other	-0.224	-0.207
	(0.141)	(0.142)
Income		
Income 50k - 100k	0.005	-0.002
	(0.048)	(0.048)
Income above 100k	0.020	0.024
	(0.057)	(0.057)
Education		
Some College	0.084	0.107
	(0.081)	(0.082)
College Degree	0.069	0.088
	(0.083)	(0.083)
Adv. Degree	0.040	0.052
	(0.083)	(0.084)

* $p < 0.10$; ** $p < 0.05$

Table 13: Results from Consideration and Purchase Stages - Robustness

This table reports the results of robustness checks for three of the Consideration and Purchase stages model results shown in table 9. Here, "Branch presence" is operationalized as a dummy variable that captures whether there is a branch of a given bank present within 10-miles (as opposed to 5-miles) of each respondent zip-code centroid. Standard-errors are reported in parentheses under coefficient estimates. (**) and (*) denote statistical significance for 5% and 10% levels respectively.

	(FI-R)		(LI-1-R)	(LI-2-R)	
	Brand	Branches	Brand	Brand	Branches
Bank of America	-2.213**	1.754**	-3.724**	-3.107**	0.749**
	(0.595)	(0.240)	(0.199)	(0.146)	(0.126)
BB&T	-3.130**	3.724**	-2.072**	-2.236**	1.171**
	(0.385)	(0.406)	(0.198)	(0.158)	(0.184)
Citibank	-1.849**	2.489**	-2.470**	-2.406**	0.955**
	(0.239)	(0.218)	(0.096)	(0.118)	(0.122)
Citizens Bank	-1.768**	2.184**	-1.997**	-1.784**	0.694**
	(0.203)	(0.239)	(0.149)	(0.125)	(0.153)
Comerica	-4.412**	3.744**	-2.812**	-2.474**	0.579*
	(0.711)	(0.759)	(0.135)	(0.304)	(0.342)
Fifth Third	-3.454**	4.101**	-2.315**	-1.988**	0.584
	(0.456)	(0.469)	(0.128)	(0.386)	(0.398)
HSBC	-1.988**	1.712**	-2.085**	-1.619**	0.352*
	(0.235)	(0.272)	(0.158)	(0.164)	(0.208)
Chase	-2.080**	2.849**	-2.075**	-2.355**	1.298**
	(0.301)	(0.304)	(0.096)	(0.151)	(0.153)
Keybank	-5.027**	5.385**	-2.355**	-3.247**	1.960**
	(1.002)	(1.010)	(0.131)	(0.143)	(0.165)
M&T	-5.082**	5.344**	-1.774**	-2.161*	1.456
	(1.003)	(1.015)	(0.562)	(1.254)	(1.262)
PNC/N. City Bank	-3.669**	3.209**	-3.394**	-3.029**	0.873**
	(0.527)	(0.429)	(0.258)	(0.284)	(0.284)
Regions	-15.837	16.500	-2.356**	-2.895**	1.540**
	(212.959)	(212.959)	(0.162)	(0.199)	(0.208)
Sovereign	-3.997**	4.224**	-2.254**	-2.005**	0.589*
	(0.582)	(0.603)	(0.095)	(0.298)	(0.306)
SunTrust	-2.926**	4.680**	-1.810**	-2.205**	1.471**
	(0.341)	(0.351)	(0.182)	(0.365)	(0.370)
TD	-4.331**	4.877**	-1.917**	-1.616**	0.636
	(0.711)	(0.719)	(0.123)	(0.452)	(0.469)
US Bank	-2.716**	3.599**	-2.023**	-1.581**	0.491**
	(0.343)	(0.349)	(0.086)	(0.236)	(0.237)
Wells Fargo/Wachovia	-2.203**	2.804**	-2.405**	-2.917**	1.602**
	(0.327)	(0.316)	(0.113)	(0.152)	(0.154)
Capital One	-2.592**	2.943**	-2.849**	-2.423**	0.571**
	(0.418)	(0.315)	(0.101)	(0.146)	(0.195)
Other parameters					
Primary Bank	-0.784**		0.460**	0.461**	
	(0.090)		(0.046)	(0.042)	
Interest Rates	0.047		0.872**	0.920**	
	(0.268)		(0.294)	(0.194)	
Advertising	0.008*		0.012**	0.008**	
	(0.004)		(0.001)	(0.001)	
Bank Branches			0.963**		
			(0.082)		
Search Cost Constant			0.001**	0.001	
			(0.000)	(0.000)	