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. Along with advertising, branch density, marital status, race and income are very significant drivers of awareness. We also find that consumers face non-trivial search/consideration costs that lead the average consumer to consider only 2.2 banks out of the 6.7 they are aware of. Conditional on consideration, branch density, the consumer's current primary bank (i.e. inertia), interest rates and education are the primary drivers of the final choice.

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, 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 dollars 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 dollars per year on advertising¹, 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

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

profile containing information on demographics, attitudes towards different banks, advertising recall, reasons for opening a new bank account (with 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 fees and interest rates for the most common account types for all banks over the same time period as the first set of data. Advertising expenditure data were gathered from Kantar Media’s *AdSpender* database. Kantar tracks advertising expenditures in national media as well as advertising expenditures in local media at the Designated Media Area (DMA) level. Lastly, we collected information on consumers’ average balances in each account type by demographic group from the Survey of Consumer Finances of the Federal Reserve. 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 6.7 banks and consider 2.2 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 (83 percent of consumers), savings accounts (57 percent) and credit cards (25 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 2 miles of the consumer’s home lies between 50 and 75 percent or 50 and 80 percent, respectively.

We develop a structural model of the three stages of the consumer’s purchase process, namely, 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 fees and 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 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 (2013) 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 average consumer search costs (measured in interest-rate percentage points) are of 0.15 percent. 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, our detailed demand side results can be utilized in a large number of counterfactual analyses, including evaluating the effects of proposed mergers and advertising regulations, and measuring the impact of banks’ decisions to expand/contract their branch networks.

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 the next two sections, 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, 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. 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 et al. 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 2013).

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, van Nierop et al. 2010, while examples of the latter include Mehta, Rajiv, and Srinivasan 2003, Kim, Albuquerque, and Bronnenberg 2010, Honka 2013, Honka and Chintagunta 2013. 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 2013) 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 be-

havior 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 don’t know the specific dates in which the survey was conducted for each respondent, 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, attitudes towards different banks, advertising recall, 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).

For tractability reasons, we focus on the 19 largest financial institutions in the United States which have a combined market share of 56 percent (measured in total deposits). The left column in

²There 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.

Table 1 shows the list of included banks. This constraint forces us to drop all respondents who had at least one institution in their consideration sets that was not among the 19 institutions. Further, we also removed all respondents with invalid zip codes. This resulted in a final sample of 2,320 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 data as well as for the two subgroups of respondents: “shoppers” (2,045 consumers) and “non-shoppers” (275 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. 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 regard 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, 8 percent of respondents have a high school degree or less, while the remaining 92 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 are less educated.

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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 within 2 months of switching. On average, shoppers opened 2.19 account types with a minimum of 0⁴ and a maximum of 10 account types. Table 4 contains the percentages of shoppers that opened

³The 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.

⁴39 shoppers opened zero account types from among the types of accounts listed in the survey. These respondents may have opened some other type of account not listed (for example, a retirement account). The number reduces to 19 if we consider all accounts opened within 12 months of establishing a relationship with a new bank.

different types of accounts. The most common account types consumers shop for are checking accounts (83 percent of consumers) followed by savings accounts (57 percent) and credit cards (25 percent).

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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, Union Bank of California 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 right 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 6.7 banks and consider 2.2 banks. There is a large variation in the sizes of consumers’ awareness and consideration sets which range from 1 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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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 Union Bank of California, 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 conversation 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, Sovereign Bank and Union Bank of California 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 2 miles of the consumer’s home lies between 34 and 73 percent or 38 and 77 percent, respectively (Table 5). The probabilities are even higher when the radius is expanded to 5 miles. Table 6 shows that the probability that a bank has a local branch within 5 miles of the respondents’ place of residence ranges from 41 to 97 percent for consideration and 45 to 98 percent for purchase.

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3.2 Price Data

We observe two sets of prices: the fees charged on checking accounts and the interest rates paid on savings deposits.

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. This data, provided by RateWatch, tracks the rates and fees offered on various deposit products at the branch level. The

data is in panel format, i.e. for the same branch and account type there are multiple measurements over time. We focus on the data that was collected during the reference period.

We combine the price data with the individual-level data to obtain a measure of the rates and fees 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 set. 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 for each bank to calculate the median (over time) interest rate for each bank in the 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. We also use the RateWatch information to estimate the distribution of prices expected by the consumer prior to searching. Table 7 reports sample statistics for the interest rates associated with the most popular 2.5K savings account for each bank.

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Insert Table 7 about here

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3.3 Advertising Data

Advertising expenditure data were gathered from Kantar Media’s “AdSpender” database. Kantar tracks advertising expenditures in national media (e.g. network TV and national newspapers) as well as advertising expenditures 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 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 8 reports average advertising expenditures at the DMA level and the total expenditures at the national level for each bank during the reference period.

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⁵Whenever zip code data for a specific bank in the respondent’s consideration set was not available, we used data from branches located in adjacent zip codes.

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. We use the approach suggested by Horsky, Misra, and Nelson (2006) and include observed consumer attitudes towards banks in the utility function to lessen the need to control for unobserved heterogeneity. 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 spending, 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 a bank is offering and charging, 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 $i = 1, \dots, N$ who open an account with of J banks indexed by $j = 1, \dots, J$. Consumer i 's awareness of bank j is a function of bank fixed effects ς_{0j} , advertising adv_{ij} , demographic variables D_i , local bank branch presence b_{ij} , strength of local presence l_{ij} and an error term ξ_{ij} and can be written as

$$A_i = \varsigma_{0j} + \varsigma_{1j}adv_{ij} + D_i\varsigma_2 + b_{ij}\varsigma_{3j} + l_{ij}\varsigma_{4j} + \xi_{ij} \quad \forall j \neq j_{PB} \quad (1)$$

where A_i is a vector of dummy variables indicating whether consumer i is aware of bank j . adv_{ij} denotes consumer- and company-specific advertising because this variable includes both national and DMA-level advertising (with the DMA being dependent on where the consumer resides). D_i are observed demographic variables (age, gender, etc.), b_{ij} are dummy variables indicating whether

there is a branch of bank j within 2 miles of consumer i 's zip code's centroid and l_{ij} is the percentage of branches that belong to bank j within 2 miles of consumer i 's zip code's centroid. $\theta_1 = (\varsigma_0, \varsigma_{1j}, \varsigma_2, \varsigma_{3j}, \varsigma_{4j})$ are the parameters to be estimated. We assume that the error term ξ_{ij} follows a multivariate Gumbel distribution thus allowing for correlations among the unobservables of the banks consumer i is aware of.

Note that we exclude the consumer's primary bank j_{PB} from the model since we assume that consumers are aware of their current 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 those banks.

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

Consumer i 's indirect utility for company j is given by

$$u_{ij} = \alpha_j + \beta_1 p_{ij} + \beta_2 I_{ijPB} + \beta_3 adv_{ij} + \beta_4 b_{ij} + \beta_5 l_{ij} + Z_{ij}\beta_6 + \epsilon_{ij} \quad (2)$$

where ϵ_{ij} is observed by the consumer, but not by the researcher. We assume ϵ_{ij} follows an EV Type I distribution. 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. Note that in the following we use the terms "price" and "interest rate" interchangeably.

I_{ijPB} is a dummy variable indicating whether bank j is consumer i 's primary bank, b_{ij} is a dummy variable indicating whether there is a branch of bank j within 2 miles of consumer i 's zip code's centroid, l_{ij} is the percentage of branches that belong to bank j within 2 miles of consumer i 's zip code's centroid and Z_{ij} contain consumer i 's reported attitudes towards bank j .⁶ $\theta_2 = (\alpha_j, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$ are the parameters to be estimated.

4.3 Consideration

We model consumers' search as in Honka (2013). Search is simultaneous and interest rates follow an EV Type I distribution with location parameter η_j and scale parameter μ . Consumers know the

⁶The last two variables are not included in the preliminary estimation results reported in this version of the paper.

distributions of interest rates in the market, but search to learn the specific interest rate a bank will offer them. The means of the interest rate distributions are company-specific; the standard deviation is not (for a more detailed discussion of this assumption please refer to the next subsection). Given these assumptions, utility (from the consumer's perspective) u_{ij} is an EV Type I distributed random variable with location parameter $a_{ij} = \alpha_j + \beta_1\eta_j + \beta_2I_{ijPB} + \beta_3adv_{ij} + \beta_4b_{ij} + \beta_5l_{ij} + Z_{ij}\beta_6 + \epsilon_{ij}$ 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

$$E[u_{ij}] = \alpha_j + \beta_1 E[p_j] + \beta_2 I_{ijPB} + \beta_3 adv_{ij} + \beta_4 b_{ij} + \beta_5 l_{ij} + Z_{ij}\beta_6 + \epsilon_{ij}. \quad (3)$$

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. We implement this requirement by assuming that the variance of the interest rate distributions is identical across companies. Further, we also impose a second restriction on the simultaneous search models in order to be able to use Chade and Smith (2005): we assume that search costs are *not* company-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

$$\Gamma_{ik} = E \left[\max_{j \in R_{ik}} u_{ij} \right] - kc_i \quad (4)$$

where c_i denotes consumer i 's search costs. We model search costs c_i as a function of a constant c_0 , demographics and the number of account types the consumer is planning to open.⁷ 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.

⁷The results when search costs vary with observed heterogeneity will be added to the next version of this paper.

$$j = \arg \max_{j \in S_i} u_{ij} \quad (5)$$

where p_{ij} is now 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 (2013). The identification of the parameters capturing differences in brand intercepts, the effects of advertising, price and observed brand preferences 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

$$P_{ij} = P_{iA_i} \cdot P_{iS_i|A_i} \cdot P_{ij|S_i} \quad (6)$$

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

Given our assumption on the error term ξ_{ij} , we estimate Equation 1 as a multivariate logit regression using the approach suggested by Russell and Petersen (2000). The probability that consumer i is aware of bank j is given by

$$P_{iA_i} = \frac{\exp(\varsigma_{0j} + \varsigma_{1j}adv_{ij} + D_i\varsigma_2 + b_{ij}\varsigma_{3j} + l_{ij}\varsigma_{4j})}{1 + \exp(\varsigma_{0j} + \varsigma_{1j}adv_{ij} + D_i\varsigma_2 + b_{ij}\varsigma_{3j} + l_{ij}\varsigma_{4j})} \quad (7)$$

where A_i is a vector of indicator variables capturing whether consumer i is aware of bank j . Russell and Petersen (2000) have shown that a multivariate logit regression can be estimated by maximizing the sum of the loglikelihoods of separate univariate binary logit regressions where each univariate logit regression describes whether consumer i is aware of bank j for $j = 1 \cdots J$. In order for this approach to be equivalent to the estimation of a multivariate logit regression, we must include consumer i 's awareness of all banks other than j as regressors in the univariate binary logit regressions.

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 2013, Honka and Chintagunta 2013) 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 (2013) has shown that the following condition has to hold for any searched set

$$\min_{j \in S_i} (E[u_{ij}]) \geq \max_{j' \notin S_i} (E[u_{ij'}]) \quad \cap \quad \Gamma_{ik} \geq \Gamma_{ik'} \quad \forall k \neq k' \quad (8)$$

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

$$P_{iS_i|\epsilon} = \Pr \left(\min_{j \in S_i} (E[u_{ij}]) \geq \max_{j' \notin S_i} (E[u_{ij'}]) \cap \Gamma_{ik} \geq \Gamma_{ik'} \quad \forall k \neq k' \right) \quad (9)$$

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

$$P_{ij|S_i,\epsilon} = (u_{ij} \geq u_{ij'} \quad \forall j \neq j', \quad j, j' \in S_i) \quad (10)$$

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 9 and conditional purchase probability given by Equation 10.

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

$$L = \prod_{i=1}^N \left[\prod_{h=1}^H P_{iA_i}^{v_{ih}} \right] \cdot \left[\int_{-\infty}^{+\infty} \prod_{l=1}^L \prod_{j=1}^J P_{iS_i|A_i,\epsilon}^{\vartheta_{il}} \cdot P_{ij|S_i,\epsilon}^{\delta_{ij}} f(\epsilon) d\epsilon \right] \quad (11)$$

where v_{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 in equation (9) nor the purchase probability as shown in equation (10) have a closed-form solution. Honka (2013) describes how to estimate this simultaneous search model in detail and we follow her estimation approach.

7 Results

7.1 Awareness

We start by discussing our results on consumer awareness for retail banks. Table 9 shows the estimates from four multivariate logit regressions: Model (A1) includes bank fixed effects and demographics. In Models (A2) and (A3), we subsequently add advertising and bank branch dummies, respectively. And, finally in Model (A4), we also include the relative strength of local bank presence ("Branch strength") and allow for bank-specific effects of advertising.

In all four models, all bank fixed effects (except Union Bank of California) are significant. As expected, the big-4 banks (Bank of America, Citi, Chase, Wells Fargo) have relatively high brand

awareness fixed effects compared to their more regional counterparts. In Model (A2), we find a small positive coefficient of advertising (measured in \$1,000) and it further decreases once we control for local bank branch dummies in Model (A3). The effects of local bank branch dummies are large and positive. In Model (A4), we additionally control for the strength in local bank presence compared to competitors and find the effects of local bank branch dummies to decrease significantly in magnitude as a consequence. Further, we also see quite a bit of heterogeneity in the effects of advertising across banks. While most banks show significant positive effects of advertising (a noticeable exception is Wells Fargo), the effects vary considerably in magnitude ranging from 0.005 for Citibank to 0.615 for Union Bank of California.

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 (spending measured in \$1,000) is increased by 1 percent, the average probability (across all banks and consumers) of a consumer being aware of a bank increases by 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 expenditure. For example, in Model (A2), we find that Citibank’s brand fixed effect is 0.136 points above Bank of America’s. Using the estimated advertising coefficient of 0.01, this means the “brand value gap” between Citi and BofA is \$13,600 in advertising expenditure ($0.136/0.01$ multiplied by \$1,000). Moreover, note that the “branch presence” indicator coefficients are between 10 to 110 times the advertising coefficient (based on Model A4 estimates, focusing on significant coefficients), suggesting that the presence of a branch is worth around \$10-\$100,000 in ad spend (assuming, of course, that the advertising effect is linear throughout its domain).

At this point in time, we speculate that the insignificant and, in the case of Wells Fargo even significantly negative, effects of advertising might be due to diminishing returns of advertising as we observe banks which spend more on advertising 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.

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Insert Table 9 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 Blacks are aware of fewer banks than Whites and consumers with higher income (above \$100,000) have larger awareness sets.

7.2 Consideration and Purchase

Model (LI-1) in Table 10 shows the estimates for the consideration and purchase parts of the model. Similarly to the results on awareness, we find almost 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 0.316 for Regions Bank to 0.804 for Citizens Bank. Among the variables entering consumers’ utility function, local bank presence is the second-largest utility shifter after inertia (i.e. whether the consumer chooses to open an account with the bank he already has established a relationship with). Also, the estimated coefficients for local bank presence are much larger in magnitude than the advertising coefficient and the coefficient on interest rates. Being a consumer’s primary bank, having high interest rates on savings accounts and high advertising spending increase consumer’s utility for a bank. Inertia has the largest effect on the consideration and purchase stages with a coefficient of 1.126. This supports the notion that consumers enjoy the convenience of “one-stop-shopping,” i.e. having to deal with only one institution when it comes to all of their financial matters. 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 10 about here

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We find consumer search costs for retail banks (measured in interest-rate percentage points) to be 0.15 percentage points (15 basis points) per bank searched, which translates to about \$3.75 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 appear to be an important factor of demand in this market. Although the coefficient estimate on Primary Bank is somewhat larger than the coefficient estimates for local bank presence, (multiple) branch closures have the potential to lead to switching to a different bank.

7.3 Comparison with a Model under Full Information

In the previous sections, we developed and estimated an elaborate 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 10. Compared to the

results from the model under limited information, the coefficient estimates for local bank presence are three 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 19 banks in the retail banking sector and that consumers, on average, only consider 2.2 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 19 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.

7.4 Interest Rate Elasticities

Table 11 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 own-interest rate elasticity under full information is -0.03. The negative sign of the interest rate elasticity is counterintuitive and comes from the negative interest rate coefficient reported in Table 10.

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Insert Table 11 about here

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8 Robustness Checks

We conduct a variety of checks to test the robustness of our results. First, we include different definitions of 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 2 miles of the consumer's zip code's centroid. We also estimated our model using an alternative definition of local bank presence, namely, a count variable capturing the number of bank branches within 2 miles of the consumer's zip code's centroid. The results are shown in Model (LI-2) in Table 10. As expected, we find (smaller) positive significant effects of the number of bank

branches close by. The estimates for the other variables remain very similar. Thus we conclude that our results are robust to different definitions of local bank presence.⁸

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 all different types of 2.5K savings account for each bank. But we also experimented using data on the top 2.5K savings accounts that each bank has and the results did not change significantly.

9 Limitations and Future Research

There are a few 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.

10 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, 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 0.15 percentage points in interest rate terms. Switching costs also appear to be an important factor

⁸We are currently testing the robustness of our results using a 5-mile and 10-mile radius.

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 into 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.

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

Institution	Aware	Considered	Chosen
BB&T	17.11	5.69	3.28
Bank Of America	94.40	44.22	12.80
Capital One	30.43	6.55	3.28
Chase/WaMu	73.02	31.81	12.24
Citibank	63.10	18.02	7.16
Citizens Bank	23.66	7.28	4.31
Comerica Bank	11.77	1.90	0.95
Fifth Third Bank	24.05	7.33	3.36
HSBC	20.30	7.28	2.84
Keybank	22.89	5.56	2.72
M&T	8.23	4.09	2.37
PNC/National City Bank	32.72	10.43	4.31
Regions Bank	20.78	5.91	3.02
Sovereign Bank	16.25	4.31	2.03
Suntrust Bank	30.26	11.42	7.33
TD Bank	19.91	8.45	3.66
U.S. Bank	32.89	13.49	8.53
Union Bank Of California	10.34	2.93	2.16
Wells Fargo/Wachovia	87.63	35.56	13.66

Table 2: Comparison of demographics

	Data set	
	All Respondents	Selected Sample
	($n = 4,246$) %	($n = 2,320$) %
<i>Gender</i>		
Female	60.0	61.3
Male	40.0	38.8
<i>Age</i>		
19-29	17.0	17.8
30-44	30.4	32.1
45-59	34.0	32.9
60+	18.7	17.3
<i>Household Income</i>		
Under \$49,999	36.5	36.5
\$50,000-\$99,999	38.0	37.3
\$100,000 and over	25.5	26.2
<i>Race</i>		
White	81.3	78.2
Black	5.0	5.5
Asian	7.5	9.2
Hispanic	3.9	4.9
Other	2.3	2.2
<i>Education</i>		
High school or less	8.5	7.6
Some College	32.2	31.4
College graduate	29.4	30.9
Postgraduate	29.9	30.0
<i>Marital Status</i>		
Single/Divorced	33.4	33.2
Married/Partner	63.7	64.4
Widowed	2.9	2.4
<i>Region</i>		
New England	5.6	5.9
MidAtlantic	22.9	26.5
Midwest	10.5	6.5
North Central	10.9	8.4
Southeast	8.1	8.4
South Central	4.1	3.3
Texas	4.1	4.5
Florida	8.8	10.2
Southwest	6.3	5.8
Northwest	4.3	4.6
California	12.8	15.1
Other	1.6	0.9

Table 3: Demographics by Respondent Type

	Respondent Type		
	Shopper %	Non Shopper %	All %
<i>Gender</i>			
Female	61.3	60.7	61.3
Male	38.7	39.3	38.8
<i>Age</i>			
19-29	19.5	5.1	17.8
30-44	34.0	17.5	32.1
45-59	31.3	44.7	32.9
60+	15.2	32.7	17.3
<i>Household Income</i>			
Under \$49,999	35.0	47.6	36.5
\$50,000-\$99,999	37.9	32.4	37.3
\$100,000 and over	27.0	20.0	26.2
<i>Race</i>			
White	77.2	85.8	78.2
Black	5.7	4.0	5.5
Asian	9.8	4.4	9.2
Hispanic	5.3	1.8	4.9
Other	2.0	4.0	2.2
<i>Education</i>			
High school or less	6.9	12.7	7.6
Some College	30.9	35.6	31.4
College graduate	31.5	26.9	30.9
Postgraduate	30.7	24.7	30.0
<i>Marital Status</i>			
Single/Divorced	33.6	30.2	33.2
Married/Partner	64.2	66.2	64.4
Widowed	2.2	3.6	2.4
<i>Region</i>			
New England	6.2	3.6	5.9
MidAtlantic	27.6	18.5	26.5
Midwest	5.2	16.0	6.5
North Central	7.9	12.0	8.4
Southeast	8.5	7.6	8.4
South Central	3.0	5.1	3.3
Texas	4.4	4.7	4.5
Florida	10.6	7.6	10.2
Southwest	5.6	7.3	5.8
Northwest	4.5	5.1	4.6
California	15.7	10.2	15.1
Other	0.7	2.2	0.9

Table 4: Account types opened (shoppers only)

Account type	% Respondents Opening	Account type	% Respondents Opening
<i>Deposit Accounts</i>		<i>Borrowing Accounts</i>	
Checking	83.33	Credit Card	25.04
Savings	56.92	Mortgage	8.85
Certificate of Deposit	11.39	Home Equity Loan	5.87
Money Market Account	11.83	Personal Loan	7.92
<i>Investment Accounts</i>			
Mutual Funds	4.25		
Stocks/Bonds	3.91		

Table 5: Respondents with bank branches within 2 miles of their home conditional on them having Considered/Chosen each bank (Shoppers only) (%)

Institution	Considered	Chose
BB&T	53.08	52.70
Bank Of America	68.14	66.80
Capital One	54.30	52.00
Chase/WaMu	72.92	77.46
Citibank	49.03	53.70
Citizens Bank	47.13	47.73
Comerica Bank	64.29	70.00
Fifth Third Bank	55.90	63.77
HSBC	34.36	38.33
Keybank	57.26	51.72
M&T	63.22	57.45
PNC/National City Bank	62.17	57.95
Regions Bank	65.91	66.15
Sovereign Bank	69.47	73.81
Suntrust Bank	61.63	66.87
TD Bank	73.20	73.49
U.S. Bank	65.62	70.52
Union Bank Of California	67.16	69.39
Wells Fargo/Wachovia	70.74	73.36

Table 6: Respondents with bank branches within 5 miles of their home conditional on them having Considered/Chosen each bank (Shoppers only) (%)

Institution	Considered	Chose
BB&T	83.85	83.78
Bank Of America	84.85	85.48
Capital One	65.56	62.67
Chase/WaMu	87.11	90.16
Citibank	68.84	75.93
Citizens Bank	58.60	59.09
Comerica Bank	85.71	85.00
Fifth Third Bank	78.88	85.51
HSBC	41.10	45.00
Keybank	85.48	91.38
M&T	83.91	82.98
PNC/National City Bank	84.78	88.64
Regions Bank	87.12	89.23
Sovereign Bank	78.95	80.95
Suntrust Bank	85.27	87.12
TD Bank	89.69	92.77
U.S. Bank	81.60	87.86
Union Bank Of California	97.01	97.96
Wells Fargo/Wachovia	88.56	91.39

Table 7: Interest Rates by Institution

Institution	mean	sd	min	max	N
BB&T	0.050	0.000	0.050	0.050	132
Bank Of America	0.100	0.000	0.100	0.100	1026
Capital One	0.050	0.000	0.050	0.050	152
Chase/WaMu	0.010	0.000	0.010	0.010	738
Citibank	0.286	0.160	0.250	1.000	418
Citizens Bank	0.077	0.025	0.050	0.100	169
Comerica Bank	0.050	0.000	0.050	0.050	44
Fifth Third Bank	0.194	0.025	0.100	0.200	170
HSBC	0.050	0.000	0.050	0.050	169
Keybank	0.050	0.000	0.050	0.050	129
M&T	0.051	0.005	0.050	0.100	95
PNC/National City Bank	0.050	0.000	0.050	0.050	144
Regions Bank	0.100	0.000	0.100	0.100	137
Sovereign Bank	0.100	0.000	0.100	0.100	100
Suntrust Bank	0.050	0.000	0.050	0.050	265
TD Bank	0.106	0.028	0.100	0.250	196
U.S. Bank	0.100	0.000	0.100	0.100	313
Union Bank Of California	0.050	0.000	0.050	0.050	68
Wells Fargo/Wachovia	0.046	0.015	0.030	0.200	421

Note: Interest rates statistics are calculated using banks in respondents consideration sets (N is the number of respondents that considered a given bank). Rates are for 2.5K Savings accounts.

Table 8: Advertising Expenditures at DMA and National level by Bank (dols000)

Institution	DMA (mean)	National
BB&T	50.0	4957.7
Bank Of America	474.7	216846.0
Capital One	494.7	71364.1
Chase/WaMu	1143.7	129282.0
Citibank	655.3	98277.1
Citizens Bank	281.4	31394.1
Comerica Bank	68.2	6888.1
Fifth Third Bank	246.6	24626.8
HSBC	223.8	45165.4
Keybank	122.1	12143.1
M&T	56.2	5772.2
PNC/National City Bank	526.9	68691.8
Regions Bank	141.5	25005.8
Sovereign Bank	78.0	8755.2
Suntrust Bank	305.2	31765.8
TD Bank	369.5	38691.7
U.S. Bank	124.2	30469.8
Union Bank Of California	32.2	3308.7
Wells Fargo/Wachovia	458.3	78421.1

Note: National-level advertising expenditures are total expenditure over the entire reference period. DMA-level advertising expenditure is average of total advertising expenditures per DMA ($n = 99$).

Table 9: 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 2-miles of each respondent zip-code centroid. “Branch strength” is measured as the % of branches of a given bank as a function of the total number of branches in the same 2-mile radius. Advertising is not included in model (A1) and in Model (A4) is allowed to have coefficients that are bank-specific. 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) Brand	(A2) Brand	Brand	(A3) Branch presence	Brand	(A4) Branch presence	Branch strength	Advert
Bank of America	-1.670** (0.233)	-3.452** (0.285)	-2.934** (0.308)	0.483** (0.233)	-3.143** (0.376)	-0.281 (0.402)	0.036** (0.016)	0.007** (0.002)
BB&T	-5.093** (0.449)	-5.255** (0.464)	-5.308** (0.470)	0.904** (0.177)	-5.397** (0.478)	0.750** (0.260)	0.004 (0.009)	0.068* (0.036)
Citibank	-2.591** (0.231)	-3.316** (0.242)	-3.267** (0.251)	1.512** (0.209)	-3.245** (0.326)	0.348 (0.474)	0.096** (0.036)	0.005* (0.002)
Citizens Bank	-3.944** (0.339)	-4.171** (0.339)	-4.500** (0.352)	1.494** (0.222)	-5.379** (0.548)	0.266 (0.420)	0.042** (0.013)	0.033** (0.013)
Comerica	-5.233** (0.504)	-5.137** (0.501)	-5.450** (0.513)	1.627** (0.213)	-6.947** (0.583)	0.550* (0.314)	0.037* (0.020)	0.307** (0.035)
Fifth Third	-3.780** (0.311)	-3.810** (0.314)	-4.383** (0.346)	2.659** (0.257)	-5.259** (0.375)	1.596** (0.425)	0.007 (0.015)	0.074** (0.009)
HSBC	-4.139** (0.367)	-4.368** (0.365)	-4.320** (0.373)	1.702** (0.268)	-5.838** (0.630)	-0.470 (0.634)	0.251** (0.077)	0.036** (0.011)
Chase	-3.650** (0.234)	-4.708** (0.259)	-4.358** (0.264)	0.495** (0.130)	-3.653** (0.302)	0.383* (0.200)	0.009 (0.006)	-0.001 (0.002)
Keybank	-3.647** (0.295)	-3.522** (0.293)	-4.325** (0.320)	2.751** (0.211)	-4.582** (0.330)	1.298** (0.379)	0.061** (0.019)	0.069** (0.013)
M&T	-6.656** (0.647)	-6.803** (0.657)	-7.260** (0.691)	0.763** (0.243)	-7.590** (0.746)	0.431 (0.324)	0.014 (0.011)	0.063 (0.064)
PNC/N. City Bank	-3.990** (0.276)	-4.436** (0.278)	-4.701** (0.296)	1.596** (0.144)	-5.299** (0.459)	0.225 (0.237)	0.068** (0.010)	0.013** (0.005)
Regions	-4.486** (0.380)	-4.677** (0.384)	-5.110** (0.401)	2.111** (0.233)	-5.453** (0.459)	1.147** (0.385)	0.047** (0.018)	0.020** (0.010)
Sovereign	-4.707** (0.412)	-4.596** (0.406)	-5.006** (0.429)	1.648** (0.219)	-5.579** (0.506)	1.113** (0.305)	0.023* (0.014)	0.092** (0.033)
SunTrust	-3.696** (0.316)	-3.895** (0.320)	-4.711** (0.353)	3.439** (0.280)	-5.240** (0.424)	2.965** (0.441)	0.018 (0.015)	0.027** (0.008)
TD	-4.431** (0.377)	-4.674** (0.376)	-5.314** (0.406)	1.935** (0.209)	-7.105** (0.626)	0.725** (0.310)	0.059** (0.015)	0.051** (0.012)
US Bank	-2.041** (0.253)	-2.418** (0.260)	-3.010** (0.281)	1.614** (0.154)	-3.138** (0.325)	0.477* (0.247)	0.045** (0.008)	0.009 (0.007)
Union Bank of California	-24.725	-18.782 (71.895)	-18.618 (80.494)	0.914** (0.283)	-28.266 (1,520.255)	-0.319 (0.451)	0.037* (0.022)	0.615** (0.096)
Wells Fargo/Wachovia	-2.902** (0.234)	-3.818** (0.256)	-3.911** (0.277)	0.795** (0.177)	-2.946** (0.416)	0.581** (0.260)	0.011 (0.007)	-0.009** (0.005)
Capital One	-3.891** (0.293)	-4.550** (0.301)	-4.646** (0.315)	1.857** (0.253)	-4.457** (0.417)	1.063** (0.444)	0.055** (0.025)	0.004 (0.004)
Advertising		0.010** (0.001)	0.006** (0.001)					

Table 9: Results from Awareness Stage (cont.)

Panel B: Demographics Parameters				
	(A1)	(A2)	(A3)	(A4)
Male	0.005 (0.036)	-0.004 (0.036)	-0.034 (0.038)	-0.036 (0.039)
Age	-0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.000 (0.001)
Single/ Divorced	0.018 (0.041)	0.005 (0.041)	-0.053 (0.043)	-0.048 (0.044)
Widow	-0.069 (0.116)	-0.072 (0.116)	-0.092 (0.120)	-0.068 (0.122)
Black	-0.073 (0.076)	-0.096 (0.076)	-0.063 (0.079)	-0.105 (0.081)
Asian	-0.110* (0.065)	-0.121* (0.065)	-0.195** (0.068)	-0.222** (0.069)
Hispanic	-0.143* (0.086)	-0.177** (0.087)	-0.140 (0.090)	-0.193** (0.091)
Other	-0.034 (0.122)	-0.024 (0.122)	-0.024 (0.127)	-0.050 (0.129)
Income 50k - 100k	0.112** (0.042)	0.090** (0.042)	0.088** (0.044)	0.059 (0.045)
Income above 100k	0.149** (0.050)	0.132** (0.050)	0.097* (0.052)	0.089* (0.053)
Some College	0.081 (0.069)	0.079 (0.070)	0.044 (0.072)	0.058 (0.073)
College Degree	0.146** (0.071)	0.131* (0.071)	0.053 (0.074)	0.072 (0.075)
Adv. Degree	0.148** (0.072)	0.127* (0.072)	0.019 (0.075)	0.040 (0.076)

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

Table 10: 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 2-miles of each respondent zip-code centroid and in model (LI-2) it is operationalized as the number of branches of each bank in the same 2-mile radius. 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	Branches	Brand	Branches
Bank of America	-3.168** (0.379)	2.251** (0.147)	-2.032** (0.089)	0.757** (0.117)	-2.060 (0.003)	0.047** (0.003)
BB&T	-1.911** (0.137)	2.529** (0.138)	-1.925** (0.251)	0.569** (0.076)	-1.449** (0.045)	0.048** (0.002)
Citibank	-1.926** (0.206)	2.361** (0.147)	-1.866** (0.081)	0.686** (0.046)	-1.977** (0.023)	0.030** (0.002)
Citizens Bank	-1.931** (0.138)	2.468** (0.137)	-1.714** (0.060)	0.804** (0.219)	-1.501** (0.041)	0.028** (0.002)
Comerica	-3.005** (0.234)	2.158** (0.150)	-2.067** (0.369)	0.724** (0.158)	-2.116** (0.062)	0.043** (0.002)
Fifth Third	-1.979** (0.152)	2.334** (0.145)	-1.824** (0.032)	0.674** (0.166)	-1.672** (0.045)	0.033** (0.001)
HSBC	-2.203** (0.162)	2.407** (0.142)	-1.623** (0.156)	0.434** (0.063)	-1.637 (0.001)	0.041** (0.001)
Chase	-2.405** (0.238)	2.110** (0.157)	-1.737** (0.099)	0.650** (0.047)	-1.742** (0.024)	0.034** (0.001)
Keybank	-2.199** (0.151)	2.426** (0.139)	-2.097** (0.089)	0.412** (0.082)	-1.803** (0.048)	0.017** (0.001)
M&T	-2.197** (0.162)	2.487** (0.138)	-1.251** (0.131)	0.634** (0.110)	-0.887** (0.040)	0.058** (0.001)
PNC/N. City Bank	-2.582** (0.170)	2.341** (0.142)	-2.043** (0.058)	0.470** (0.056)	-1.786** (0.037)	0.015** (0.005)
Regions	-2.110** (0.149)	2.464** (0.141)	-2.146** (0.056)	0.316 (0.002)	-1.585 (0.002)	0.027** (0.002)
Sovereign	-2.461** (0.172)	2.627** (0.135)	-1.810** (0.180)	0.336** (0.057)	-1.872** (0.046)	0.035** (0.003)
SunTrust	-1.341** (0.116)	2.312** (0.140)	-1.534** (0.075)	0.326* (0.181)	-1.210** (0.045)	0.011** (0.003)
TD	-2.196** (0.146)	2.360** (0.143)	-1.668** (0.042)	0.390** (0.192)	-1.270 (0.004)	0.032** (0.004)
US Bank	-1.630** (0.118)	2.237** (0.155)	-1.679** (0.169)	0.380 (0.463)	-1.429** (0.035)	0.019** (0.001)
Union Bank of California	-2.144** (0.159)	2.332** (0.144)	-1.639** (0.151)	0.578** (0.218)	-1.398** (0.045)	0.011** (0.002)
Wells Fargo/Wachovia	-2.010** (0.158)	2.635** (0.138)	-1.869** (0.079)	0.464** (0.205)	-1.760** (0.041)	0.041** (0.001)
Capital One	-2.014** (0.347)	2.423** (0.145)	-2.233** (0.143)	0.525** (0.162)	-1.974** (0.050)	-0.016** (0.002)
Other parameters						
Primary Bank	-4.168** (0.409)		1.126		1.091	
Interest Rates	-0.368 (0.263)		0.351** (0.027)		0.489** (0.090)	
Advertising	0.009** (0.002)		0.001** (0.001)		0.003** (0.000)	
Search Cost Constant			0.001** (0.000)		0.001** (0.000)	

Table 11: Interest Rate Elasticities from Consideration and Purchase Stages

This table reports the price (i.e. interest rate) elasticities that correspond to the model estimates reported in Table 10. 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-1) 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 2-miles of each respondent zip-code centroid. Elasticities are calculated for each respondent and bank and then averaged across respondents.

Brand	(FI)	(LI-1)
Bank of America	-0.03	0.03
BB&T	-0.02	0.02
Citibank	-0.10	0.09
Citizens Bank	-0.02	0.03
Comerica	-0.02	0.02
Fifth Third	-0.07	0.06
HSBC	-0.02	0.02
Chase	0.00	0.00
Keybank	-0.02	0.02
M&T	-0.02	0.01
PNC/N. City Bank	-0.02	0.01
Regions	-0.03	0.03
Sovereign	-0.03	0.03
SunTrust	-0.01	0.01
TD	-0.03	0.03
US Bank	-0.03	0.03
Union Bank of California	-0.02	0.02
Wells Fargo/Wachovia	-0.02	0.01
Capital One	-0.35	0.02
Average	-0.03	0.03