In Search of a Risk-free Asset: 
Search Costs and Sticky Deposit Rates *

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October 18, 2017

Abstract

To attract time deposits, more than 6,000 banks post their offer rates. I document large and persistent cross-sectional dispersion, on average negative spreads over Treasuries, and asymmetric rigid adjustments in these rates. Estimates of an oligopoly model reveal a large fraction of high search cost, and a small declining fraction of low search cost investors. Despite estimates of high intertemporal elasticity of substitution and recent technological innovations, the non-declining fraction of high search cost depositors, likely elderly households, grants banks significant monopoly power and allows for sluggish pass-through of increases in the Federal funds rate into deposit rates.

JEL Classification: D83, D91, G12, G21
Keywords: Deposit rates, Rate rigidity, Rate dispersion, Interest rate pass-through, Search Costs, Bank-affiliated money market mutual funds, Limited deposit insurance

*First draft: April 23, 2012
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1 Introduction

Since the seminal work by Stigler [1961], it is well understood that even small search costs can generate first-order effects in the behavior of prices, quantities, and welfare in otherwise homogeneous product markets with potentially large number of competitors. I study the systematic violation of the law of one price in the market for FDIC insured certificates of deposit (CD) or time deposits—a large and important component of the M2 monetary aggregate, and a close substitute for a Treasury security. On average, banks pay significantly lower rates on time deposits as compared to matched maturity Treasury bonds. Furthermore, within narrowly defined geographic markets, there is an economically significant rate dispersion. Finally, deposit rates adjust rigidly and asymmetrically to changes in market rates—deposit rates respond sluggishly to increases and adjust flexibly to decreases in Treasury yields. These patterns can be observed in Figure (1) and are documented in detail in Section (2).

To rationalize the observed rate dispersion, I examine a model of oligopolistic competition for deposits with heterogeneous search cost investors. The presence of search costs allows banks to sustain rate dispersion as a mixed strategies equilibrium of Burdett and Judd [1983]. Differences in search costs lead to market segmentation according to investors’ search intensity. Segments with high search costs remain rationally uninformed about the presence of better returns. The relative size of uninformed investors determines the equilibrium price dispersion, monopoly profits, and the degree of interest rate pass-through to deposit rates.

Maximum likelihood estimates of the model reveal a bimodal distribution of search costs with two distinct groups of investors—an uninformed group with large search costs and an informed group with low search costs. More than one third of investors implied by the model are uninformed investors. These investors have search costs ranging from 30 basis points to as high as 140 basis points. Depending on the marginal value of search, a significant fraction of high search cost investors switch between examining one offer and comparing rates of at most two banks.

Informed investors have low enough search costs, and are able to identify and act upon the best rates in their market. This segment gradually declines during the sample period from slightly above 10 percent in 1997 to below 5 percent in 2016. The trend is puzzling as, over the period, there has been rapid introduction of information technologies such as the Internet or mobile banking that should have eased information gathering and reduced transaction costs. Elderly households, who form the bulk of investors in time deposits, have

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1. A large and growing theoretical and empirical literature rationalizes the observed price dispersion in homogeneous product markets with the presence of costly information acquisition. An excellent summary can be found in Baye, Morgan, and Scholten [2006].
Figure 1: The cross-sectional distribution of CD yield offers

3-month

12-month

Note: The light gray shaded area represents offer rates between the 1st and 99th percentile. The dark gray shaded area are offer rates within the interquartile range. The black line is the median of the distribution and the dashed red lines mark the 5th and the 95th percentiles of the offer distribution.

Source: RateWatch and Federal Reserve H.15 Selected Interest Rates
adopted the Internet at a much slower pace and their Internet use remains low relative to younger households.

The exit of low search cost investors implied by the structural estimates of the model is related to Hortaçsu and Syverson [2004] who document the existence of sizable dispersion in fees charged by retail mutual funds. Hortaçsu and Syverson [2004] attribute the fee dispersion to the presence of search costs and recent entry of high search cost novice investors. These developments in the retail mutual fund industry could be related to the exit of low information cost investors from time deposits and their entry into mutual funds where these novice investors face large information costs. I provide evidence that banks used their affiliated money market mutual funds to price discriminate between high search cost depositors, who continue to invest in time deposits, and the active segment of investors, who are likely steered into bank-affiliated funds.

The documented stylized facts extend results from previous empirical studies on deposit rates. In particular, Diebold and Sharpe [1990] examine the pass-through of wholesale interest rates into the pricing of retail deposit rates in the immediate post-Regulation Q period and are the first to document the rigid response of retail deposit rates to the variation in the wholesale market interest rates. Hannan and Berger [1991] and Neumark and Sharpe [1992] document the asymmetric rigidity of deposit rates to changes in the marginal cost of funds of banks and relate the magnitude of these rigidities to the degree of local market competition. Driscoll and Judson [2013] extends this literature to test theories on price rigidity. Their conclusion is that the existing models based on firm menu costs face a challenge in fitting some of the unique characteristics of the price setting behavior of deposit rates. A recent paper by Honka, Hortaçsu, and Vitorino [2016] examines the effect of advertisement on shopping for bank deposits. Their modeling strategy, however, requires them to work with extreme value type I distribution of interest rates, which does not match the empirical distribution of rates. Furthermore, their survey data are limited to a single point in time in a low rate environment with compressed dispersion. As a result their search cost estimates are biased to be very low.

Building on this existing literature, first, I introduce a much more detailed micro-level data. Second, I provide a theoretical framework that can rationalize the pricing facts. Unlike previous research on deposit pricing and interest pass-through, the focus in this paper is on the resulting rate dispersion, and its time-variation, both of which have not been previously explored.

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2 The Depository Institutions Deregulation and Monetary Control Act of 1980 gradually removed all restrictions on interest rates paid on savings accounts and time deposits by 1986. The prohibition to pay interest on demand deposits was only repealed in 2010 by the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. In addition, in 1990, changes in Regulation D lifted the requirement for banks to hold reserves against time deposits.
2 Stylized facts on deposit pricing

2.1 Data

Information on deposit rates comes from a proprietary database constructed from weekly industry surveys gathered by RateWatch since 1997. The data contain branch level deposit rates of close to 6,000 FDIC insured commercial banks in over 60,000 branch offices located in over 10,000 cities covering all major Metropolitan Statistical Areas (MSA). The survey represents more than 90 percent of deposits in FDIC insured banks. I supplement these data with information on industry concentration, number of banks and branches from the Summary of Deposit database (SOD). Balance sheet and income statement information is constructed from the Reports of Condition and Income (also known as Call Reports), as well as from the consolidated bank holding company reports (FR Y-9C). The Survey of Consumer Finances (SCF) provides information on the allocation of deposits across financial institutions. MSA level demographic and income information is obtained from the Census Bureau. Data on pricing of money market mutual funds is obtained from iMoneyNet.³

2.2 Deposit pricing within banking conglomerates

Deposit pricing within multi-branch and multi-market banking organizations is decentralized. Special rate-setting branches determine the rates for all branches in well-defined geographic areas. Table (1) shows the coverage of the rate-setting branches of the ten largest bank holding companies in 2007. Rate-setting branches are a small number relative to the total number of branches. For example, Bank of America designates 33 branches to set the rates for the remaining 5,370 branch locations and, on average, a rate-setting branch sets the rates in 160 branch locations. Most banks designate one rate-setting branch per state. The average deposit-weighted distance between a rate-setting branch and its subordinate locations is relatively short, ranging between 38 km (23 mi) to about 150 km (93 mi). As a result of this decentralized pricing, there is no dispersion in rates among the branches of the same bank within a metropolitan statistical area (MSA). For the rest of the analysis, I define a geographic market to correspond to a MSA area.⁴

⁴See also Becker [2007] for a discussion on the degree to which deposit markets are geographically segmented and the appropriateness of MSA as a well-defined geographic deposit market.
Table 1: Rate-setting branches in 2007

<table>
<thead>
<tr>
<th>Institution (BHC)</th>
<th>Rate-setting branches</th>
<th>Coverage of rate-setting branches</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>Locations (2) MSA (3) States (4) Distance (km) (5)</td>
</tr>
<tr>
<td>Bank of America</td>
<td>33</td>
<td>159.1</td>
</tr>
<tr>
<td>JPMorgan</td>
<td>43</td>
<td>58.5</td>
</tr>
<tr>
<td>Wachovia</td>
<td>50</td>
<td>46.4</td>
</tr>
<tr>
<td>Wells Fargo</td>
<td>36</td>
<td>86.8</td>
</tr>
<tr>
<td>Citigroup</td>
<td>14</td>
<td>37.6</td>
</tr>
<tr>
<td>USB</td>
<td>113</td>
<td>18.8</td>
</tr>
<tr>
<td>Suntrust</td>
<td>27</td>
<td>67.1</td>
</tr>
<tr>
<td>National city</td>
<td>65</td>
<td>36.1</td>
</tr>
<tr>
<td>Regions</td>
<td>40</td>
<td>77.0</td>
</tr>
<tr>
<td>BB&amp;T</td>
<td>14</td>
<td>99.9</td>
</tr>
</tbody>
</table>

Note: Distance is a weighted-average distance with weights equal to the branch location total deposits reported in SOD at the end of June. Source: RateWatch and Summary of Deposits (FDIC)

2.3 Dispersion

To understand the sources of dispersion documented in Figure (1), first, let us define the offer rate of the branches of bank \( j \in \{1, 2, ..., N_t\} \), located in geographic market \( m \in \{1, 2, ..., M\} \) in period \( t \) as \( R_{j,m,t} \), where \( N_t \) is the number of banks in period \( t \) and \( M \) is the number of markets. Next, let us define the overall \( \bar{R}_t \), the bank \( \{\bar{R}_{j,t}\}_{j=1}^{N_t} \), and the market-level \( \{\bar{R}_{m,t}\}_{m=1}^{M} \) average offer rates. Then, the total variation in rates at a point in time, defined as the sum of squared deviations of each bank rate from the overall mean \( W_t = \sum_{m,j} (R_{j,m,t} - \bar{R}_t)^2 \), can be decomposed in two ways

\[
W_t = \begin{cases}
\sum_{m,j} (R_{j,m,t} - \bar{R}_{j,t})^2 + M \sum_j (\bar{R}_{j,t} - \bar{R}_t)^2 & \text{Bank decomposition} \\
\sum_{m,j} (R_{j,m,t} - \bar{R}_{m,t})^2 + N_t \sum_m (\bar{R}_{m,t} - \bar{R}_t)^2 & \text{Market decomposition.}
\end{cases}
\]

The first decomposition is the sum of within-bank variation across different markets and variation in average offer rates across different banks. Analogously, the second decomposition breaks down total variation into within and across-markets variation. Table (2) shows that more than 90 % of the overall variation in rates can be attributed to differences in rates across banks, and less than 10 % can be attributed to differences in rates of the same bank across different markets. Similarly, the market based decomposition shows that most of the total variation is due to dispersion in rates across banks within the same market, and less than 20 % of variation in rates is due to differences in median rates across markets.
Table 2: Decomposition of total variation, 2007

<table>
<thead>
<tr>
<th>Fraction of total variation:</th>
<th>3-mo</th>
<th>6-mo</th>
<th>12-mo</th>
<th>24-mo</th>
<th>36-mo</th>
<th>60-mo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Across market variation</td>
<td>0.17</td>
<td>0.16</td>
<td>0.17</td>
<td>0.18</td>
<td>0.19</td>
<td>0.17</td>
</tr>
<tr>
<td>Within market variation</td>
<td>0.83</td>
<td>0.84</td>
<td>0.83</td>
<td>0.82</td>
<td>0.81</td>
<td>0.83</td>
</tr>
<tr>
<td>Across bank variation</td>
<td>0.92</td>
<td>0.92</td>
<td>0.91</td>
<td>0.92</td>
<td>0.92</td>
<td>0.91</td>
</tr>
<tr>
<td>Within bank variation</td>
<td>0.08</td>
<td>0.08</td>
<td>0.09</td>
<td>0.08</td>
<td>0.08</td>
<td>0.09</td>
</tr>
</tbody>
</table>

SOURCE: RateWatch

To measure the economic significance of rate dispersion, the first four columns of Table (3) show the quartiles and the weighted averages of the median rates across markets and for different maturities. The last four columns present the same summary statistics for the difference between the 95th and the 5th percentiles of rates within markets. Compared to the median rate, within-market rate dispersion is economically significant. For example, the weighted average 12-month rate is 375 basis points whereas the range of rates between the 95th and the 5th percentiles is as high as 222 basis points. An investor starting with an offer in the 5th percentile, can gain $222 in interest income on every $10,000, if she could identify and deposit at the bank in the 95th percentile. Although the median rate increases and rate dispersion decreases with maturity, incentives to search are even higher for longer maturities. For the 5-year CD, the weighted-average within-market difference between the 95th and the 5th percentiles implies an overall gain in interest payments of $765 on every $10,000.

Table 3: Dispersion across and within markets, 2006

<table>
<thead>
<tr>
<th>Maturity</th>
<th>Median rate</th>
<th>Rate dispersion $P(0.95) - P(0.05)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25th</td>
<td>50th</td>
</tr>
<tr>
<td>3-mo</td>
<td>2.50</td>
<td>2.75</td>
</tr>
<tr>
<td>6-mo</td>
<td>3.00</td>
<td>3.27</td>
</tr>
<tr>
<td>12-mo</td>
<td>3.69</td>
<td>3.84</td>
</tr>
<tr>
<td>24-mo</td>
<td>3.75</td>
<td>3.98</td>
</tr>
<tr>
<td>60-mo</td>
<td>4.05</td>
<td>4.25</td>
</tr>
</tbody>
</table>

NOTE: † Weighted-mean across markets with weights equal to the total deposits in the market.
SOURCE: RateWatch and Summary of Deposits (FDIC)
2.4 Pass-through and monopoly power

Banks’ monopoly power is large, time-varying, and increasing with higher market rates. This fact is illustrated in Figure (2) which plots the spread over 3-month Treasury and a measure of dispersion for the 3-month CD against the level of the target Federal funds rate.

**Figure 2:** Target Federal funds rate, spreads, and dispersion

In the high interest rate environments of 1997-2000 and 2006-07, when the target Federal funds rate is five percentage points or higher, the average spread on the 3-month CD is negative 100 basis points or lower, and the difference between the 95th and the 5th percentiles exceeds 150 basis points.\(^5\) These negative spreads translate into sizable profits. For example, based on the outstanding amounts on banks’ balance sheets and the corresponding spreads over Treasuries, collectively banks earned at least $15 billion in profits from time deposits alone or 11 percent of their total net income in 2006 as compared to a situation in which time deposits were priced at Treasury rates.\(^6\) This calculation is a lower bound as

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\(^5\)An incomplete pass-through in deposit rates is present to an even higher degree for other deposit categories such as savings and interest checking accounts as documented by Driscoll and Judson [2013] and Drechsler, Savov, and Schnabl [2017].

\(^6\)Most time deposits have remaining maturity below one year which justifies the treatment of outstanding
it does not take into account the fact that time deposits likely fund much higher yielding assets than Treasuries.

2.5 Rigidity

The negative correlation of deposit spreads and the positive correlation of dispersion with the level of the Federal funds rate are a direct consequence of an asymmetric rigidity of rate adjustments. While, deposit rates adjust relatively flexibly when the target Federal funds rate decreases, adjustments are rigid in periods when the target increases. This fact is summarized in Table (4) which shows the quartiles of durations between rate adjustments observed across banks for three regimes of monetary policy: decreasing, constant, and increasing target Federal funds rate.

<table>
<thead>
<tr>
<th>Fed Fund Target</th>
<th>decreased p25</th>
<th>p50</th>
<th>p75</th>
<th>constant p25</th>
<th>p50</th>
<th>p75</th>
<th>increased p25</th>
<th>p50</th>
<th>p75</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-month</td>
<td>0</td>
<td>3</td>
<td>11</td>
<td>1</td>
<td>7</td>
<td>20</td>
<td>1</td>
<td>6</td>
<td>16</td>
</tr>
<tr>
<td>6-month</td>
<td>0</td>
<td>2</td>
<td>7</td>
<td>2</td>
<td>6</td>
<td>17</td>
<td>2</td>
<td>5</td>
<td>12</td>
</tr>
<tr>
<td>12-month</td>
<td>0</td>
<td>2</td>
<td>6</td>
<td>1</td>
<td>5</td>
<td>15</td>
<td>1</td>
<td>5</td>
<td>11</td>
</tr>
<tr>
<td>24-month</td>
<td>0</td>
<td>2</td>
<td>6</td>
<td>1</td>
<td>5</td>
<td>14</td>
<td>1</td>
<td>5</td>
<td>12</td>
</tr>
<tr>
<td>60-month</td>
<td>0</td>
<td>1</td>
<td>5</td>
<td>0</td>
<td>3</td>
<td>12</td>
<td>0</td>
<td>3</td>
<td>12</td>
</tr>
</tbody>
</table>

**Note:** Durations are measured in weeks. The sample period is 1-January-1997 - 30-June-2011.

**Source:** RateWatch

The Median duration of rate adjustments is 6 weeks during periods of increasing target, slightly lower than the 7 weeks during periods when the target remains unchanged. In contrast, when the target decreases, the median duration is 3 weeks. All maturities display asymmetric adjustments. However, longer maturities are more flexible in all three regimes. A further observation from this table is fact that rate adjustments vary considerably among banks. Some banks adjust their rates quite flexibly while others adjust even more rigidly. For example, the 75th percentile bank kept its rates on 3 month CDs unchanged for as long as 16 weeks during monetary policy tightening, while the 25th percentile bank adjusted deposit rate with a lag of one week.

Although all banks face the same aggregate shocks related to variation in market interest rates, there is little synchronization in deposit rate adjustments. During periods of tightening, the median fraction of adjusters is around 12 percent, only slightly higher than amounts as flows over an annual horizon.
the 11 percent in periods of constant target Federal funds rate. This fraction increases to 20 percent during periods of monetary policy easing. Unlike the durations of rate adjustments, synchronization of rate adjustments are about the same across maturities.

Table 5: Synchronization of rate adjustments

<table>
<thead>
<tr>
<th>Fed Fund Target</th>
<th>decreased p25</th>
<th>p50</th>
<th>p75</th>
<th>unchanged p25</th>
<th>p50</th>
<th>p75</th>
<th>increased p25</th>
<th>p50</th>
<th>p75</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-month</td>
<td>0.13</td>
<td>0.20</td>
<td>0.28</td>
<td>0.08</td>
<td>0.11</td>
<td>0.13</td>
<td>0.10</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>6-month</td>
<td>0.16</td>
<td>0.26</td>
<td>0.36</td>
<td>0.09</td>
<td>0.13</td>
<td>0.16</td>
<td>0.12</td>
<td>0.14</td>
<td>0.16</td>
</tr>
<tr>
<td>12-month</td>
<td>0.18</td>
<td>0.27</td>
<td>0.36</td>
<td>0.11</td>
<td>0.14</td>
<td>0.17</td>
<td>0.13</td>
<td>0.14</td>
<td>0.17</td>
</tr>
<tr>
<td>24-month</td>
<td>0.16</td>
<td>0.25</td>
<td>0.36</td>
<td>0.10</td>
<td>0.13</td>
<td>0.16</td>
<td>0.12</td>
<td>0.13</td>
<td>0.14</td>
</tr>
<tr>
<td>60-month</td>
<td>0.15</td>
<td>0.24</td>
<td>0.34</td>
<td>0.09</td>
<td>0.11</td>
<td>0.14</td>
<td>0.09</td>
<td>0.11</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Note: The table computes the quartiles of the fraction of synchronized rate changes within a week.
Source: RateWatch

The heterogeneity and lack of synchronization of rate adjustments across banks constantly changes the ranking of banks’ offers even as many banks keep their rates unchanged. Therefore, to identify the best rates investors cannot rely on past information and need to conduct search.

The pricing of deposits resembles that of retail goods. For example, Lach [2002] documents that the pricing of homogeneous retail goods in Israel exhibits persistent price dispersion and constant repositioning of shops’ price rankings. Similarly, Kaplan and Menzio [2015] present evidence based on U.S. household-level transactions data that there is persistent price dispersion even for identical retail goods across stores and over time within the same store. They also document heterogeneity in shopping behavior across different households based on age and employment status reflecting heterogeneity in search costs based on marginal value of time.

2.6 Demand for certificates of deposit

Given the high dispersion in rates, do households search for better return on their savings? Is search distinct from other characteristics such as risk aversion, degree of intertemporal elasticity of substitution, planning horizon, use of financial advisor, and overall financial sophistication? Household demand for and investments in CDs offer a laboratory to disentangle those different aspects of savings behavior. A certificate of deposit is a relatively simple financial instrument that has undergone little financial innovation over the years.
Therefore, it requires little financial sophistication to evaluate the desirability of the offer of one bank over another. With deposit insurance, the decision should be entirely based on the offered rate. However, if there are costs of acquiring information on offer rates at different banks, households would not necessarily be able to pick the best return on their savings. Even if a household could observe all relevant information, they could still decide to stick with their main bank if transaction and convenience costs are too high to open an account with another bank.

To summarize the various aspects of financial sophistication, I construct a financial sophistication score using data from the Survey of Consumer Finances (SCF). The surveys collect information on households' financial decisions and resulting portfolios. The score is calculated as the first principal component of a set of quantitative and qualitative characteristics of households. The set of variables included are: Excellent understanding of the SCF questions; Reliance on advice from a financial professional; Willingness to undertake above average financial risks; Financial budgeting horizon exceeding 5 years; Direct ownership of stocks or stock mutual funds; Ownership of a brokerage account; Ownership of money market mutual funds or other mutual funds; Diversity of asset holdings. Table (6) provides summary statistics for households grouped by the quartiles of the financial sophistication score from the lowest in column 1 to the highest in column 3. As a comparison, column 4 examines the group of households who own a CD and column 5 shows the characteristics of the average household in the survey.

High financial sophistication households are slightly older, twice as likely to have a college degree, have substantially higher average incomes and net worth, and earn a higher share of their income from financial assets. By construction of the score, those households have excellent understanding of the SCF questionnaire, have more diverse portfolios of financial assets, hold higher shares of risky assets such as stocks and corporate bonds, and are more willing to take above-average financial risks.

In comparison, households who invest in CDs are near retirement age and 10 years older than the average. Even though some CD holders have high sophistication scores, the average for this group is around the median of the score distribution. While CD holders have higher incomes and net-worth than average, they are much less wealthy than the high sophistication group. CD holders are also significantly less likely to take above average financial risks and hold much higher share of their financial assets in deposits. Only a fifth of these households report preference for great deal of shopping for investment return which is about the same as the average. In addition, only a quarter of CD holders report using the Internet for investment decisions compared to close to half of investors in the high group.

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7Gabaix, Agarwal, Laibson, and Driscoll [2010] examine the role of age-related cognitive decline for quality of financial decisions and document an inverse U-shaped relationship between age and optimality of financial decisions with peak performance around age 54.
The results from this analysis lead to the conclusion that the preference for search for higher return is distinct from financial sophistication. Furthermore, different investors have different preferences for search technology—most notably the use of the Internet.

Table 6: Financial sophistication, financial assets, and deposit accounts

<table>
<thead>
<tr>
<th>Financial Sophistication Score</th>
<th>Q1 (low)</th>
<th>Q1-Q4</th>
<th>Q4 (high)</th>
<th>Own CD</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>50</td>
<td>50</td>
<td>54</td>
<td>60</td>
<td>50</td>
</tr>
<tr>
<td>College education</td>
<td>18</td>
<td>40</td>
<td>72</td>
<td>47</td>
<td>35</td>
</tr>
<tr>
<td>Income</td>
<td>38,764</td>
<td>85,777</td>
<td>278,051</td>
<td>121,404</td>
<td>88,162</td>
</tr>
<tr>
<td>—Share income from financial assets</td>
<td>1</td>
<td>3</td>
<td>15</td>
<td>8</td>
<td>3</td>
</tr>
<tr>
<td>Net worth (Assets–Debt)</td>
<td>124,349</td>
<td>476,309</td>
<td>2,830,072</td>
<td>1,047,925</td>
<td>583,351</td>
</tr>
<tr>
<td>Leverage (Debt/Assets)</td>
<td>32</td>
<td>32</td>
<td>17</td>
<td>15</td>
<td>30</td>
</tr>
<tr>
<td>Bankruptcy</td>
<td>14</td>
<td>13</td>
<td>3</td>
<td>6</td>
<td>12</td>
</tr>
<tr>
<td>Homeowner</td>
<td>52</td>
<td>75</td>
<td>93</td>
<td>85</td>
<td>69</td>
</tr>
<tr>
<td>Financial assets/total assets</td>
<td>24</td>
<td>30</td>
<td>44</td>
<td>42</td>
<td>29</td>
</tr>
<tr>
<td>—Share deposits/financial assets</td>
<td>72</td>
<td>32</td>
<td>11</td>
<td>45</td>
<td>43</td>
</tr>
<tr>
<td>—Share MMMF/financial assets</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>—Share equity/financial assets</td>
<td>0</td>
<td>5</td>
<td>16</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>—Share risky/financial assets</td>
<td>0</td>
<td>7</td>
<td>39</td>
<td>12</td>
<td>8</td>
</tr>
<tr>
<td>—Share retirement and life ins./fin. assets</td>
<td>22</td>
<td>50</td>
<td>39</td>
<td>35</td>
<td>40</td>
</tr>
<tr>
<td>Own CD</td>
<td>10</td>
<td>18</td>
<td>26</td>
<td>100</td>
<td>16</td>
</tr>
<tr>
<td>—owned jointly [Own CD==1]</td>
<td>43</td>
<td>60</td>
<td>60</td>
<td>57</td>
<td>57</td>
</tr>
<tr>
<td>—above FDIC limit [Own CD==1]</td>
<td>8</td>
<td>11</td>
<td>18</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>Deposits above FDIC limit</td>
<td>3</td>
<td>7</td>
<td>21</td>
<td>24</td>
<td>7</td>
</tr>
<tr>
<td>Own money market mutual fund</td>
<td>0</td>
<td>4</td>
<td>31</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>Own mutual fund</td>
<td>0</td>
<td>7</td>
<td>77</td>
<td>20</td>
<td>11</td>
</tr>
<tr>
<td>Number of institutions</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>—Number of banks</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Take above average financial risks</td>
<td>5</td>
<td>25</td>
<td>50</td>
<td>20</td>
<td>21</td>
</tr>
<tr>
<td>Budgeting horizon over 5 years</td>
<td>13</td>
<td>50</td>
<td>72</td>
<td>47</td>
<td>40</td>
</tr>
<tr>
<td>Great deal shopping for investment</td>
<td>17</td>
<td>23</td>
<td>22</td>
<td>23</td>
<td>21</td>
</tr>
<tr>
<td>Use Internet for investment decisions</td>
<td>21</td>
<td>32</td>
<td>46</td>
<td>25</td>
<td>30</td>
</tr>
<tr>
<td>Use professional investment advice</td>
<td>24</td>
<td>46</td>
<td>54</td>
<td>50</td>
<td>40</td>
</tr>
<tr>
<td>Excellent understanding of SCF</td>
<td>36</td>
<td>52</td>
<td>71</td>
<td>53</td>
<td>48</td>
</tr>
<tr>
<td>Financial Sophistication Index percentile</td>
<td>0.1</td>
<td>0.5</td>
<td>0.9</td>
<td>0.5</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Note: Columns 1 through 3 present the averages for the households belonging to the lowest quartile, the interquartile range, and the highest quartile of the financial sophistication index, respectively. Column (4) presents averages for the group of households who own a certificate of deposit (CD). Column (5) presents averages for the full sample. All averages are weighted with the survey sampling weights. Source: Survey of Consumer Finances, 2007

The notion that search is a distinct activity is collaborated by evidence in Honka, Hortaçsu, and Vitorino [2016]. They use confidential survey data to breakdown shopping for deposit rates into distinct stages—an awareness phase, a search phase, and choice phase. On
average, households are aware of close to 7 banks operating in their local geographic market and examine offers of at least 2 banks. Consistent with active search, Honka, Hortaçsu, and Vitorino [2016] document that 52 percent of consumers end up choosing the bank with the highest interest rate while 31 percent of consumers choose the second highest interest rate bank.

Figure 3: Allocation of CD holdings across contracts and banks

---

**Note**: The size of the circle presents the relative amount of the allocation based on the survey weights and deposit amounts. In the public version of SCF, the number of CD contracts and the number of institutions are top coded at 20 and 10, respectively. **Source**: Survey of Consumer Finances, 2007

Search for better return implies that depositors should be willing to buy CDs from banks different from their main checking account bank. According to Figure (3), this indeed appears to be the case for many households in the SCF. While most households hold one CD with a single bank, about 45 percent invest in a CD with a bank different from their main checking account bank. In addition, around 20 percent of households hold multiple CDs with more than one bank.

An additional reason for having multiple accounts with different banks is the FDIC insurance limit. If an investor’s total deposits at a bank exceed the limit, she faces the credit risk of the bank for the uninsured portion. Opening additional accounts with different banks allows to diversify this credit risk as each new account is insured up to the limit. For example, an investor with $500,000 in a single bank account will have half of that amount uninsured. By opening and placing $250,000 in a second bank, a depositor can achieve
Table 7: Certificate of deposit accounts with multiple banks

<table>
<thead>
<tr>
<th></th>
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<th></th>
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<tr>
<td>Age 65 plus</td>
<td></td>
<td>0.187***</td>
<td>−0.006</td>
<td>−0.023</td>
<td>0.089**</td>
<td>0.100**</td>
<td>0.168***</td>
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<td></td>
<td></td>
<td>(0.048)</td>
<td>(0.048)</td>
<td>(0.051)</td>
<td>(0.045)</td>
<td>(0.043)</td>
<td>(0.056)</td>
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<tr>
<td>College degree</td>
<td></td>
<td>0.158***</td>
<td>0.088*</td>
<td>0.087</td>
<td>0.116**</td>
<td>0.018</td>
<td>−0.046</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.049)</td>
<td>(0.048)</td>
<td>(0.053)</td>
<td>(0.047)</td>
<td>(0.045)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>log(Assets)</td>
<td></td>
<td>0.072***</td>
<td>−0.025</td>
<td>0.034**</td>
<td>0.051***</td>
<td>0.082***</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.016)</td>
<td>(0.017)</td>
<td>(0.016)</td>
<td>(0.015)</td>
<td>(0.016)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Deposits exceed FDIC limit</td>
<td></td>
<td>−0.014</td>
<td>0.407***</td>
<td>0.244***</td>
<td>0.223***</td>
<td>0.135**</td>
<td>0.495***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.056)</td>
<td>(0.056)</td>
<td>(0.056)</td>
<td>(0.051)</td>
<td>(0.059)</td>
<td>(0.079)</td>
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<tr>
<td>CD held jointly</td>
<td></td>
<td>−0.159***</td>
<td>−0.074</td>
<td>−0.120**</td>
<td>0.136***</td>
<td>0.087**</td>
<td>0.366***</td>
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<tr>
<td></td>
<td></td>
<td>(0.047)</td>
<td>(0.047)</td>
<td>(0.048)</td>
<td>(0.042)</td>
<td>(0.040)</td>
<td>(0.053)</td>
</tr>
<tr>
<td>Take above average financial risks</td>
<td></td>
<td>0.011</td>
<td>−0.009</td>
<td>−0.221***</td>
<td>0.015</td>
<td>−0.036</td>
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<td></td>
<td></td>
<td>(0.056)</td>
<td>(0.057)</td>
<td>(0.058)</td>
<td>(0.049)</td>
<td>(0.052)</td>
<td>(0.067)</td>
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<tr>
<td>Great deal shopping for investment</td>
<td></td>
<td>−0.019</td>
<td>0.055</td>
<td>0.215***</td>
<td>0.135***</td>
<td>0.226***</td>
<td>0.235***</td>
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<tr>
<td></td>
<td></td>
<td>(0.052)</td>
<td>(0.052)</td>
<td>(0.053)</td>
<td>(0.046)</td>
<td>(0.044)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>Use Internet for investment decisions</td>
<td></td>
<td>−0.024</td>
<td>0.045</td>
<td>0.025</td>
<td>0.007</td>
<td>0.312***</td>
<td></td>
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<td></td>
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<td>(0.064)</td>
<td>(0.059)</td>
<td>(0.047)</td>
<td>(0.043)</td>
<td>(0.056)</td>
<td></td>
</tr>
<tr>
<td>Financial Sophistication</td>
<td></td>
<td>0.085***</td>
<td>0.101***</td>
<td>0.098***</td>
<td>0.040*</td>
<td>0.093***</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.022)</td>
<td>(0.023)</td>
<td>(0.025)</td>
<td>(0.022)</td>
<td>(0.023)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td>−0.812***</td>
<td>0.205</td>
<td>−0.334</td>
<td>−0.920***</td>
<td>−1.133***</td>
<td>−0.610**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.205)</td>
<td>(0.222)</td>
<td>(0.204)</td>
<td>(0.204)</td>
<td>(0.203)</td>
<td>(0.260)</td>
</tr>
</tbody>
</table>

Observations | 3,473 | 3,557 | 3,405 | 4,175 | 4,382 | 2,621 |
Log Likelihood | −2,304.044 | −2,306.954 | −2,149.179 | −2,778.135 | −2,839.386 | −1,658.086 |
Akaike Inf. Crit. | 4,628.089 | 4,635.908 | 4,320.358 | 5,578.270 | 5,700.771 | 3,338.171 |

* p<0.1; ** p<0.05; *** p<0.01

Note: A probit regression on an indicator whether a household owns certificates of deposit with more than one bank or with a bank different from their main checking account bank. The survey provided weights are used as regression weights.

Source: Survey of Consumer Finance

full deposit insurance.\textsuperscript{8} Even in the case of households looking to place large deposits in multiple banks to increase insurance coverage, they should optimally choose banks offering higher rates.

To disentangle the two motives for multiple deposit accounts, Table (7) presents results from a probit regression on whether a household owns CDs with one or several banks

\textsuperscript{8} Shy, Stenbacka, and Yankov [2016] present evidence for demand of multiple deposit accounts due to the partial deposit insurance design and examine the effect of the partial insurance design on competition.
different from their main checking account bank. Households with total deposits exceeding the deposit insurance limit are indeed more likely to hold CDs with multiple banks, and, up to 2004, less likely to hold multiple accounts if they have a joint account which increases the effective coverage.\footnote{FDIC allows the insurance coverage to be extended to joint account ownership for a single institution (see http://www.fdic.gov/deposit/). The insurance limit per deposit account per bank was set to $100,000 from 1980-2008. It was then raised to $250,000 in 2008.} The results are consistent with the limited deposit insurance motive. Conditioning on this motive, higher financial sophistication and the preference for shopping a great deal for investment returns both increase the likelihood that a household buys CDs from multiple banks. The use of the Internet for investment decisions only appears significant in the 2013 survey. It indicates that more tech savvy households are more likely to have multiple deposit accounts, likely reflecting both lower search costs and also lower transaction costs of maintaining multiple accounts with different banks.

Figure 4: Financial sophistication, shopping for return, and number of bank accounts

A. Low financial sophistication

B. High financial sophistication

\begin{center}

\begin{figure}[h!]
\centering
\includegraphics[width=\textwidth]{figure4}
\caption{Financial sophistication, shopping for return, and number of bank accounts}
\end{figure}
\end{center}

\textbf{Source:} Survey of Consumer Finances

Using SCF data, it is not possible to link a particular household to its local deposit market and examine the effect of rate dispersion on deposit allocations. However, variation over time in rate dispersion should affect those allocations. Panel A of Figure (4) shows that low sophistication households who have preference for great deal of shopping for investment return are more likely to have more bank accounts in the high dispersion years of 1998 and 2007 as compared to the low dispersion years of 2004 or 2013. In contrast, Panel B shows that high sophistication households have higher number of bank accounts irrespective of their preference for shopping for investment return or rate dispersion. The average number of bank accounts for the financial sophisticates increases following the 2007 survey in the low dispersion environment of 2008-15.
3 Model

Banks compete for deposits by announcing simultaneously their offer rates. Deposit insurance rules out bank runs as in Diamond and Dybvig [1983]. In case of a bank failure, a deposit insurance fund subsidized by the government covers the whole amount of the deposit contract including the accrued interest.

3.1 Depositors

3.1.1 Consumption-savings decision

Each period a unit mass of investors enters the market for time deposits with $A_0$ liquid wealth stored in a checking account with a bank. Depositors choose how much assets to leave in a liquid checking account which yields utility through funding current consumption $c_0$, and how much to save $A_\tau$ to fund consumption in some future period $\tau \geq 1$. The optimal consumption-savings problem is

$$
\nu_\tau(R, A_0) = \max_{A_\tau} u(c_0, c_\tau)
$$

subject to:

$$
c_0 = A_0 - A_\tau,
$$

$$
c_\tau = R_\tau A_\tau,
$$

where utility takes the following constant elasticity of substitution form

$$
u_\tau(R, A_0) = \max_{A_\tau} u(c_0, c_\tau) = \left\{
\begin{array}{ll}
\left\{c_0^{\frac{1}{\sigma}} + \beta^\tau \left(\frac{1}{1-\gamma}\right)^{\frac{1}{1-\gamma}}\right\} \frac{\sigma}{\sigma - 1} & \text{if } \sigma \neq 1 \\
\ln c_0 + \beta^\tau \ln \left(\frac{1}{1-\gamma}\right) \frac{1}{1-\gamma} & \text{if } \sigma = 1.
\end{array}
\right.
$$

The utility specification depends on three parameters: discount factor $0 < \beta < 1$; relative risk-aversion $\gamma > 0$; and the inter-temporal elasticity of substitution (IES) $\sigma > 0$. If an investor invests in a risky asset, her wealth and consumption are stochastic and $\left(\frac{1}{1-\gamma}\right)$ captures the certainty equivalent of a risky-asset lottery.

**Proposition 1** The solution of the consumption-savings problem takes the following closed form

$$
c_0 = h_\tau(R) \times A_0,
$$

$$
c_\tau = R(1 - h_\tau(R)) \times A_0,
$$

$$
A_\tau = (1 - h_\tau(R)) \times A_0.
$$

The marginal propensity to consume $h_\tau(R)$ is
• for insured deposits

\[
h^d(R) = \frac{1}{1 + \beta^\sigma R^\sigma - 1}
\]  

(4)

• for a risky asset with log-normal returns \(\log(R^r) \sim N(\bar{R}^r, \nu^2_r)\)

\[
h^r(\bar{R}^r) = \frac{1}{1 + \beta^\sigma \left(\bar{R}^r e^{-\frac{1}{2} \nu^2_r}\right)^{\sigma - 1}}
\]  

(5)

Indirect utility is linear in financial wealth

\[
\nu_r(R, A_0) = \phi^i_r(R) A_0,
\]  

(6)

where marginal utility of wealth \(\phi^i_r(R) = h^i_r(R) \frac{1}{1 - \sigma}\) for \(i \in \{d, r\}\) is a monotone increasing \((\phi'(\cdot) > 0)\). If \(\sigma < 2\), then \(\phi(\cdot)\) is concave.

**Proof** The results are straightforward to show and rely on the homogeneity of degree one of the utility function\(\square\)

If \(\sigma\) exceeds one, then the substitution effect dominates the income effect and the marginal propensity to consume is decreasing in the interest rate. Conversely, if \(\sigma < 1\), the income effect dominates and the marginal propensity to consume is increasing in \(R\).

### 3.1.2 Costly search

Although investors are aware of the offer distribution, they have no prior information about the specific rates of each bank.\(^\text{10}\) Information gathering is costly as each depositor faces search cost \(\xi \geq 0\) per bank offer. Search costs are distributed among investors according to a known population distribution \(F_\xi(\xi)\) over a range \([0, \infty)\). Investors search non-sequentially by optimally choosing a fixed sample of bank offers.\(^\text{11}\) The first offer is costless which ensures that there is full participation even for depositors with very high search costs. The total search cost for a sample of \(n\) offers is \((n - 1) \times \xi\).

Let us define the highest rate in a random sample of \(n\) rates as \(R_{\text{max}}(n)\). The cumulative probability function of \(R_{\text{max}}(n)\) is \(\text{Pr}(R_{\text{max}}(n) \leq R) = F_R(R)^n\). It is easy to show that the

\(^{10}\)The assumption that an investor knows the distribution of offers is rather strong. Rothschild [1974] relaxes this assumption and shows that optimal search strategies under unknown price distribution are qualitatively similar to strategies when the price distribution is known. However, Koulayev [2013] shows that not accounting for the uncertainty in price distribution could result in biases in search cost estimates.

\(^{11}\)The assumption of non-sequential search could be justified by the presence of economies of scale of search. Also recent evidence in De los Santos, Hortacsu, and Wildenbeest [2012] shows that the non-sequential fixed sample search model better describes actual search behavior. Morgan and Manning [1985] derive conditions under which different modes of search are optimal.
expected value of $R_{\text{max}}(n)$ is increasing in the sample size $n$, while its variance is decreasing in $n$. Optimal search selects the sample size that maximizes the expected utility

$$n^*(\xi) = \arg\max_{1 < n \leq N} \left\{ \int_{R_{\text{min}}}^{R_{\text{max}}} \phi(R)n F_R(R)^{n-1} f_R(R) dR - (n - 1) \times \xi \right\},$$

where search costs enter linearly in the utility and are assumed proportional to wealth $A_0$. Optimal search is determined by a trade-off between the disutility of search captured by the search costs and the gains in utility from both a higher expected rate as well as lower uncertainty about the rate when sampling more offers. Let us define the marginal value of information from increasing the sample size by an extra offer given that $k$ offers have been sampled

$$\Delta_k = \int_{R_{\text{min}}}^{R_{\text{max}}} \phi(R) \left\{ (k + 1) F_R(R)^{k} - k F_R(R)^{k-1} \right\} f_R(R) dR.$$ \hfill (8)

Integration by parts leads to an equivalent representation

$$\Delta_k = \int_{R_{\text{min}}}^{R_{\text{max}}} \phi'(R) \left\{ 1 - F_R(R) \right\} F_R(R)^k dR \hfill (9)$$

which clearly reveals that the marginal value of information $\Delta_k$ is a decreasing sequence in $k$ since $F_R(R) \leq 1$ and $\phi'(\cdot) > 0$.

We can group investors into segments according to the intensity of their search $\{q_k\}_{k=1}^N$. Investors with search costs higher than $\xi > \Delta_1$ optimally choose not to shop for rates and sample only one bank. Investors with search costs in the range $\Delta_k \leq \xi < \Delta_{k-1}$ examine offers of $k$ banks. Finally, investors with search costs lower than $\xi < \Delta_{N-1}$ choose to examine the offers of all banks. Given a search cost distribution, we can compute the size of each segment

$$q_1 = 1 - F_\xi(\Delta_1)$$
$$q_k = F_\xi(\Delta_{k-1}) - F_\xi(\Delta_k) \hfill (10)$$
$$q_N = F_\xi(\Delta_{N-1}) = 1 - \sum_{j=1}^{N-1} q_j.$$

Once incurred search costs are sunk and investors can always choose an outside option. I assume full participation and, as shown in the lemma below, this implies that the reservation deposit rate is common to all investors and independent of their idiosyncratic search costs.
Lemma 1 If a randomly drawn deposit rate from the offer distribution \( F_R(R) \) is preferred to investing in an outside option, then the reservation deposit rate and the choice to participate do not depend on individual search costs.

Proof The results follow from the linearity of the indirect utility with respect to wealth and the zero cost of observing one offer. Let the outside option have indirect utility \( V^0 \) while \( V^d_1 \) be the expected utility from one deposit offer. The indirect utility of optimal search \( V^d_{\alpha^*}(\xi) \) for any search cost \( \xi \) weakly dominates \( V^d_1 \). The condition for participation can be written as \( V^d_{\alpha^*}(\xi) \geq V^d_1 \geq V^0 \). Participation in the deposit market, therefore, does not depend on the individual search cost \( \xi \). □

It is easy to compute that the reservation rate for a log-normally distributed risky asset with expected return \( \bar{R} \) and return variance \( \nu^2 \) is \( \dot{R} = \bar{R} \times e^{-\frac{1}{2} \times \nu^2} \). I do not take a stance on what an outside option of a CD investment is. However, it is useful to point out that the reservation rate for a risky asset likely depends on the expected return and its variance but also on the relative risk aversion of investors. To the extent that CD investors are highly risk-averse, they would accept very low deposit rates.

3.2 Deposit demand

Suppose that a bank posts a rate \( R \) above the reservation rate \( \dot{R} \). Investors who sample \( k \) offers choose this bank’s offer if the other \( k - 1 \) offers are inferior. The probability of this event is \( F_R(R)^{k-1} \). Since each bank is sampled randomly, the individual bank demand from the segment with search intensity \( k \) is \( (1 - h(R)) \frac{k}{N} F_R(R)^{k-1} q_k \). Summing over all market segments and normalizing aggregate wealth to one, deposit demand is

\[
D(R|F_R(R), \{q_k\}_{k=1}^N) = \begin{cases} (1 - h^d(R)) \frac{k}{N} \sum_{k=1}^N k F_R(R)^{k-1} q_k & \text{if } R \geq \dot{R} \\ 0 & \text{if } R < \dot{R}. \end{cases}
\]  (11)

A bank’s deposit demand is composed of two elements—an intensive margin which determines how much is saved and an extensive margin which determines the mass of depositors a bank is expected to attract with an offer rate \( R \).

3.3 Deposit pricing

The marginal cost of funds \( \ddot{R} \) is assumed common to all banks. The Federal Reserve directly controls the interest on reserves and determines to a large extent the effective rate at which banks borrow and lend at interbank markets.\(^1\) Let us define \( \psi(R, \ddot{R}) = (\ddot{R} - R)(1 - h^d(R)) \)

\(^1\) This assumption could be relaxed. For example, Reinganum [1979] and MacMinn [1980] develop models with costly search in which the observed price dispersion is derived from an underlying distribution of marginal costs.
to be the profit per captured depositor, then the deposit profit is

$$\pi(R|F_R(R), \{q_k\}_{k=1}^N) = \psi(R, \tilde{R}) \frac{1}{N} \sum_{k=1}^N kF_R(R)^{k-1}q_k. \quad (12)$$

To price deposits, banks follow symmetric mixed strategies as in Burdett and Judd [1983]. In this equilibrium, every bank is indifferent between posting any rate along the support $S = [R_{\text{min}}, R_{\text{max}}]$ of an equilibrium offer rate distribution. In expectation, banks earn equal nonzero profits and any rate outside the equilibrium support leads to strictly lower profit

$$\pi(R|F_R(R), \{q_k\}_{k=1}^N) = \begin{cases} \pi^* & \text{if } R \in S \\ < \pi^* & \text{if } R \notin S. \end{cases} \quad (13)$$

In order to sustain equal profits, the following trade-off is at work. Higher rates generate lower profits per captured depositor but attract a larger mass of investors. The two effects exactly offset each other in equilibrium. On one hand, even if a bank posts the highest offer rate, it would not capture the entire market as only a fraction of investors observes this rate. On the other hand, banks that offer the lowest rate still attract depositors—those with high search costs $q_1$ who choose to sample only one offer and happen to be unlucky to obtain this low rate.

The lower bound of the support of the equilibrium distribution is the largest between the monopoly rate $R_{\text{m}} = \arg\max R\psi(R, \tilde{R})$ and the reservation rate, $R_{\text{min}} = \max\{\tilde{R}, R_{\text{m}}\}$. A bank would not post a rate lower than the reservation rate or the monopolistic deposit rate, as it would either attract no depositors or fail to fully maximize profits. The upper bound of the support is derived as follows.

**Lemma 2** The maximum rate that a bank would post in equilibrium is

$$R_{\text{max}} = \begin{cases} \psi^{-1}(\psi(R_{\text{min}}, \tilde{R}) \frac{q_1}{\sum_{k=1}^N kq_k}) & \text{if } \sigma \neq 1 \\ \tilde{R} - (\tilde{R} - R_{\text{min}}) \times \frac{q_1}{\sum_{k=1}^N kq_k} & \text{if } \sigma = 1. \end{cases} \quad (14)$$

**Proof** In equilibrium, profits at the two ends of the support of the distribution must be equal $\pi(R_{\text{max}}) = \pi(R_{\text{min}})$. Using this equality, one can solve for $R_{\text{max}}$. A unique solution is guaranteed by the fact that $\psi(R, \tilde{R})$ is a monotone decreasing function in $R$.

The degree of monopoly power is determined by the share of high search cost investors $q_1$. To see this, let us examine the ratio of the mark-ups over marginal costs for the two ends
of the support
\[
\frac{\hat{R} - R_{\text{max}}}{\hat{R} - R_{\text{min}}} = \frac{q_1}{\sum_{k=1}^{N} k q_k} \times \frac{(1 - h^d(R_{\text{min}}))}{(1 - h^d(R_{\text{max}}))}.
\] (15)

If all investors consider only one offer \(q_1 = 1\), then the offer rate distribution is degenerate at the monopoly price equilibrium \(R_{\text{max}} = \max\{\hat{R}, R^m\}\). This is consistent with the so-called “Diamond paradox” described in Diamond [1971]. If all investors observe only one rate, banks can sustain monopoly equilibrium by charging the monopoly rate. Since there is no price dispersion, investors have no incentives to search which confirms the equilibrium. This equilibrium is overwhelmingly ruled out by the data.

Alternatively, if the share of the uninformed investors is zero \(q_1 = 0\), then each investor observes and compares rates from at least two banks. In this environment, each bank competes in prices with at least one more bank and has incentives to enter into a Bertrand competition. The offer rate distribution becomes degenerate at \(R_{\text{min}} = \hat{R}\). However, this is not an equilibrium outcome as the lack of price dispersion does not rationalize the existence of costly search to begin with. Hence, \(q_1 = 0\) cannot be an equilibrium.

For a dispersed price equilibrium to exist, there should be some investors who examine only one offer \(0 < q_1 < 1\), and others who sample more than one offer \(q_k > 0\) for some \(k = 2, 3, ..., N\). We can characterize the dispersed price equilibrium as the sub-game perfect equilibrium in symmetric mixed strategies.

**Definition** The set \(\left( F_R(R), R_{\text{min}}, R_{\text{max}}, \pi^*, h(R), \{q_k\}_{k=1}^{N} \right) \) is a dispersed equilibrium if for a given distribution of investor types \(F_\xi(\xi)\), reservation rate \(\hat{R}\), and marginal cost \(\hat{R}\):

a) Given an equilibrium distribution of offer rates \(F_R(R)\), \(\left( h^d(R), \{q_k\}_{k=1}^{N} \right) \) is a solution to the optimal consumption-savings and search problems of investors in which some investors observe only one deposit offer \(0 < q_1 < 1\), while others observe and compare \(k\) offers \(q_k \geq 0\) for some \(k = 2, 3, ..., N\).

b) \(\left( F_R(R), R_{\text{min}}, R_{\text{max}}, \pi^* \right)\) is a deposit pricing equilibrium in symmetric mixed strategies given optimal consumption-savings and non-sequential search. The mixed strategies equilibrium distribution \(F_R(R)\) is implicitly defined by the indifference condition (13).

The model differs from the original Burdett-Judd model along two dimensions—search costs are heterogeneous and demand is price-elastic.\(^{13}\) The elasticity of demand is determined

\(^{13}\)Reinganum [1979] shows that, in the presence of homogeneous search costs, heterogeneity in marginal costs and price-elastic demand are sufficient for a dispersed equilibrium. Unlike the model of Reinganum [1979], banks are assumed to have a common marginal cost and consumers have heterogeneous search costs.
by $\sigma$. We can show that even with consumer search cost heterogeneity and the presence of interest-elastic demand, the equilibrium rate distribution has the same properties as in the case of homogeneous search costs and unit demand of Burdett and Judd [1983].

**Proposition 2** Given consumer search characterized by $\{q_k\}_{k=1}^N$ such that $0 < q_1 < 1$, there exists a unique offer distribution $F_R(R)$ which is a solution to the equilibrium condition (13). $F_R(R)$ is continuous and with connected support.

**Proof** To show uniqueness of the equilibrium distribution $F_R(R)$, we need to examine the equilibrium condition (13). The equilibrium profit for any offer rate $R \in [R_{\text{min}}, R_{\text{max}}]$ must equal the profit achieved at the minimum rate $R_{\text{min}}$. We can express this condition as follows

$$ \sum_{k=1}^N kq_kF_R(R)^{k-1} = \frac{(\tilde{R} - R_{\text{min}})(1 - h^d(R_{\text{min}}))q_1}{(R - R)(1 - h^d(R))}. $$

(16)

Note that the left-hand side is monotone increasing function in $F_R$ and the right hand side is a monotone increasing function in $R$ as $(\tilde{R} - R)(1 - h^d(R))$ is a monotone decreasing function in $R$. Therefore, there exists a monotone increasing function $\Phi(\cdot)$ such that

$$ F_R(R) = \Phi\left(\frac{(\tilde{R} - R_{\text{min}})(1 - h^d(R_{\text{min}}))q_1}{(R - R)(1 - h^d(R))}\right). $$

(17)

The rest of the results follow from slight modification of arguments in Burdett and Judd [1983] □

Although Proposition (2) guarantees the existence of a unique offer distribution given search behavior, for this offer distribution to be an equilibrium, we need to also verify that search behavior is consistent with it. Search behavior is determined by the distribution of search costs and the critical search cost thresholds $\{\Delta_k\}_{k=1}^{N-1}$. A change of variables $z = F_R(R)$ and $R(z) = F_R^{-1}(z)$ allows us to express the indifference points (8) as

$$ \Delta_k = \int_0^1 \phi(R(z)) (k+1)z^k - k z^{k-1} dz, \text{ for } k = 1,.., N-1. $$

(18)

With some abuse of notation, let us define $\Delta_N = \sup\{\xi : F_\xi(\xi) = 0\}$ and $\Delta_0 = \inf\{\xi : F_\xi(\xi) = 1\}$.

$$ R(z) = \psi^{-1}\left(\psi(R_{\text{min}}) \frac{1 - F_\xi(\Delta_1)}{\sum_{k=1}^N k z^{k-1}(F_\xi(\Delta_{k-1}) - F_\xi(\Delta_k))}\right). $$

(19)
The system of equations (18) and (19) is a mapping between the unknown search cost distribution evaluated at the critical points \( \{ \Delta_k \}_{k=1}^{N-1} \) and the observed offer rate distribution \( F_R(R) \). Solving this system of non-linear equations using global numerical methods leads to unique solutions for most parameterizations of the search cost distribution and the coefficient of intertemporal substitution.  

4 Model estimation

4.1 Maximum likelihood estimation

The dispersed equilibrium implies a likelihood of observing a particular offer rate given an underlying search cost distribution, IES, marginal cost, and reservation rate of depositors.

**Proposition 3** The model implies a well-defined likelihood of observing a deposit offer rate

\[
f_R(R|\Theta) = \begin{cases} 
\frac{-\psi'(R, \tilde{R})}{\psi(R, \tilde{R})} \times \frac{\sum_{k=1}^{N} k q_k F_R(R)_{k-1}}{\sum_{k=1}^{N} k(k-1) q_k F_R(R)_{k-2}}, & \text{for } R \in [R_{\min}, R_{\max}] \\
0, & \text{otherwise,}
\end{cases}
\]

where the equilibrium offer rate distribution \( F_R(R) \) is implicitly defined in (16), and \( \Theta = (F_\xi(\cdot), \sigma, \tilde{R}, \dot{R}) \) are primitives of the model.

**Proof** The probability density function is derived by applying the implicit function theorem to equation (16). For \( \sigma < 2 \), the derivative of the profit function is negative \( \psi'(R) < 0 \) which guarantees that the likelihood is non-negative.

Following Hong and Shum [2006] and Moraga-González and Wildenbeest [2008], one can obtain maximum likelihood estimates of the market segments \( \{ q_k \}_{k=1}^{N} \)

\[
\max_{\{ q_k \}_{k=1}^{N}} \left\{ \frac{1}{N} \sum_{j=1}^{N} \ln f_R(R_j|\sigma, \{ q_k \}_{k=1}^{N}) \right\}
\]

where \( F_R(R_j) \) solves

\[
\sum_{k=1}^{N} k q_k F_R(R_j)_{k-1} = (\tilde{R}_j - R_{\min})(1 - h^d(R_{\min})) q_1, \quad \text{for } j = 1, \ldots, N.
\]

Moraga-González, Sándor, and Wildenbeest [2017] apply the Brouwer fixed point theorem to show that an equilibrium exists in a Burdett-Judd model with heterogeneous search cost consumers. They show uniqueness under a specific parameterization of the search cost distribution and draw the conclusion that the lack of uniqueness in the original Burdett-Judd model is likely due to the homogeneity of search costs. Deriving the conditions for the existence of a unique equilibrium in this model is beyond the scope of this paper.
The marginal cost of funds is derived from the equilibrium indifference condition \( \pi(R_{\min}) = \pi(R_{\max}) \) and plugged into the likelihood function

\[
\hat{R} = \frac{R_{\max}(1 - h(R_{\max})) \sum_{k=1}^{N} kqK - R_{\min}(1 - h(R_{\min}))q_1}{(1 - h(R_{\max})) \sum_{k=1}^{N} kqK - (1 - h(R_{\min}))q_1}.
\]  

(23)

The estimation starts with the support of the equilibrium offer distribution. The minimum and maximum offer rates are estimated with their sample equivalents

\[
\hat{R}_{\min} = \min\{R_{j,m,t}\}_{j=1}^{N} \quad \text{and} \quad \hat{R}_{\max} = \max\{R_{j,m,t}\}_{j=1}^{N}.
\]

Given a set of estimates \( \{\hat{q}_k\}_{k=1}^{N} \), the indifference points of the search cost distribution \( \{\Delta_k\}_{k=1}^{N-1} \) are computed using (18). The values of the cumulative density function of the search cost distribution at those points are solved from (10)

\[
\hat{F}_{\xi}(\Delta_k) = 1 - \sum_{j=1}^{k} \hat{q}_k \quad \text{for} \quad k = 1, 2, \ldots, N - 1.
\]

(24)

The upper percentiles of the search cost distribution are identified up to \( \Delta_1 \). Therefore, higher percentiles are extrapolated using non-decreasing Hermite polynomials.

### 4.2 Estimation of the intertemporal elasticity of substitution

The coefficient of intertemporal elasticity of substitution \( \sigma \) is estimated independently from the search cost distribution using the relationship

\[
A_{\tau} = (1 - h(R))A_0.
\]

Taking derivatives with respect to the deposit rate and using the fact that

\[
\frac{\partial h(R)}{\partial R} = (1 - \sigma)\frac{h(R)}{R}(1 - h(R)),
\]

one arrives at an empirical specification which relates the growth in time deposits to the growth in rates

\[
\Delta \log(A_{\tau,t+1}) = \alpha_0 + (\sigma - 1)(1 - s_{\tau,t}) \times \Delta \log(R_t) + \epsilon_t,
\]

(25)

where \( s_{\tau,t} = \frac{A_{\tau,t}}{A_{0,t}} \) is the share of time deposits in total deposits at a point in time and \( \Delta \hat{R}_t \) is the percent change in the time deposits rate. This empirical specification differs from the standard regression analysis based on an Euler equation introduced by Hall [1988]. In particular, regression (25) does not relate next period consumption to expected interest rates. Instead, it assumes a stable relationship between expected next period consumption and deposits. Such stable relationship could be easily rationalized with the presence of a cash-in-advance constraint for certain types of lumpy expenditures such as a downpayment required for the purchase of a car or a house. Substitution of demand deposits for

\[\text{The substitution of the marginal costs introduces dependence among rate observations. Moraga-González and Wildenbeest [2008] show using Monte Carlo methods that the dependence has minimal effects on the estimates due to the super-consistent rate of convergence of \( \hat{R}_{\min} \) and \( \hat{R}_{\max} \) to their true values.}\]
## Table 8: Estimates of the coefficient of intertemporal elasticity of substitution

<table>
<thead>
<tr>
<th>Dependent variable: Growth in time deposits</th>
<th>OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>6-month</td>
<td>12-month</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>σ</td>
<td>1.190***</td>
<td>1.202***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.012***</td>
<td>0.011***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Observations</td>
<td>73</td>
<td>73</td>
</tr>
<tr>
<td>R²</td>
<td>0.319</td>
<td>0.315</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.309</td>
<td>0.306</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>0.028 (df = 71)</td>
<td>0.028 (df = 71)</td>
</tr>
<tr>
<td>Weak instruments</td>
<td>0.007***</td>
<td>0.007***</td>
</tr>
<tr>
<td>Wu-Hausman</td>
<td>0.163</td>
<td>0.325</td>
</tr>
<tr>
<td>Sargan</td>
<td>0.010**</td>
<td>0.003***</td>
</tr>
</tbody>
</table>

*p<0.1; **p<0.05; ***p<0.01

### Note:
The instrumental variable (IV) regressions use two instrumental variables and their lags. The first set is the current and lagged value of the unexpected component of changes in the target Federal funds rate identified from the Federal funds futures market following Kuttner [2001]. The second is the second lag of the growth rate in time deposits. Standard errors are based on Newey and West [1987] heteroskedasticity and autocorrelation consistent estimator.

time deposits, therefore, is an intertemporal choice equivalent to postponement of current consumption and relaxation of cash-in-advance constraints in future periods.

Estimates of the IES are presented in Table (8). The regressions use the 6-month and the 12-month CD rates. The first two columns present the OLS estimates of σ and the last two columns use an instrumental variables (IV) approach. Since the growth in time deposits and the change in deposit rates are jointly determined, the IV regressions use exogenous variation in deposit rates coming from unexpected movements in the target Federal funds rate identified from the Federal funds futures following Kuttner [2001]. A second instrument is the second lag of the growth rate in time deposits. The estimates of σ from all specifications are statistically larger than one and lower than two. These estimates imply that the substitution effect dominates the income effect. The marginal propensity to save is increasing in the rate while the marginal utility of wealth is increasing and concave in rates.
4.3 Structural estimates

The search cost distribution is estimated using data from 234 Metropolitan Statistical Areas (MSA) in which there are at least 20 banks at a point in time. The remaining markets have between 20 and 257 banks. This selection guarantees meaningful price dispersion and good coverage of banks’ branch networks. Since the average outstanding maturity of time deposits on banks’ balance sheets is 10 months, estimates are based on the 12-month CD and the IV estimate $\hat{\sigma} = 1.276$ in column 4 of Table (8).

Figure 5: Model implied marginal cost of funds, 12-month CD

Note: The figure plots deposit-weighted average estimate of the model implied marginal cost of funds computed from equation (23) as well as the deposit-weighted estimate of the maximum rate for the 12-month CD. These estimates are contrasted with the 12-month USD LIBOR rate.

4.3.1 Goodness-of-fit

I use the two-sample Kolmogorov-Smirnov (KS) test to evaluate the goodness-of-fit of the model. The KS test is based on the maximal difference between the empirical distribution and the model generated evaluated at the MLE estimates. KS test statistic is computed for each MSA market and each period. According to p-values from this test, the model generated distribution is statistically close to the empirical for most of the MSA markets throughout the sample period. One fails to reject the null hypothesis of equality at 5 percent significance level for the majority of markets and the deposit-weighted average p-value exceeds 25 percent in all years of the sample. I focus the analysis on markets with p-values exceeding 5 percent. This excludes between 0 and at most 8 mostly small markets.
A further somewhat indirect test of the goodness-of-fit is presented in Figure (5) which plots the estimate of the marginal cost of funds $\tilde{R}$ along with the 12-month LIBOR rate and the weighed-average maximum rate. Remarkably, the model implied marginal cost tracks very closely the LIBOR rate. On average, however, the marginal cost estimate is slightly higher than LIBOR. The model estimates reflect higher marginal costs of smaller banks in the sample which are likely to face higher costs of accessing external finance in wholesale funding markets.

4.3.2 Estimates of search intensity and search costs

The estimates of the market segments $\{q_k\}_{k=1}^N$ vary across markets and over time. Panel A of Figure (6) presents the time series variation of the cross-section of estimates of the share of uninformed or inactive investors $q_1$. The weighted average share of inactive investors is large and hovers around 40 percent over the period from 1997 to 2004. The share increases in the low interest rate environment of 2001-04 to close to 50 percent. It then quickly drops to less than 30 percent in the increasing interest rate environment of 2005-07. As the level and dispersion in rates begin to decrease starting in 2008, the incentives to search diminish and the share of inactive investors increases across all markets to reach 60 percent for the average market in 2016.

Figure 6: Estimates of search intensity investor segments

A. Uninformed investors $q_1$
B. Active investors

Note: The shaded area in Panel A is the range between the 5th and the 95th percentiles of the cross-sectional distribution of $q_1$ estimates. Panel B shows the deposit-weighted average estimates of $q_2$ and $q_N$. The weighted average fraction of banks sampled shown in green is calculated as $\frac{1}{N} \sum_{k=1}^N kq_k$.

Panel B plots the time series of the weighed average estimates of $q_2$, $q_N$, and the average fraction of banks sampled $\frac{1}{N} \sum_{k=1}^N kq_k$. The two segments $q_1$ and $q_2$ combined comprise close to 80 percent of investors in most markets. The segments are also strongly negatively
correlated. For example, in contrast to $q_1$, $q_2$ increases in the high dispersion environment of 2004-07 and decreases during the low dispersion environment since 2008. This tight link between the two segments is due to variation in the marginal value of information $\Delta_1$ resulting from changes in rate dispersion. As $\Delta_1$ increases a mass of inactive investors find it worthwhile to search for rates and compare rates of two banks.

Table 9: Search intensity and market characteristics

<table>
<thead>
<tr>
<th>Dependent variable: Search intensity share $q_k$</th>
<th>$q_1$</th>
<th>$q_2$</th>
<th>$q_N$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share population age 65+</td>
<td>4.922***</td>
<td>1.559*</td>
<td>−2.320***</td>
</tr>
<tr>
<td></td>
<td>(0.547)</td>
<td>(0.871)</td>
<td>(0.743)</td>
</tr>
<tr>
<td>log(Population)</td>
<td>0.158*</td>
<td>0.249**</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.121)</td>
<td>(0.112)</td>
</tr>
<tr>
<td>HHI</td>
<td>14.102***</td>
<td>3.582</td>
<td>−10.033**</td>
</tr>
<tr>
<td></td>
<td>(3.921)</td>
<td>(5.130)</td>
<td>(4.644)</td>
</tr>
<tr>
<td>log(Population per bank)</td>
<td>13.290**</td>
<td>2.088</td>
<td>−10.471</td>
</tr>
<tr>
<td>log(Population per branch)</td>
<td>−8.892***</td>
<td>4.290</td>
<td>8.088**</td>
</tr>
<tr>
<td></td>
<td>(2.803)</td>
<td>(3.699)</td>
<td>(3.622)</td>
</tr>
<tr>
<td>log(Income per capita)</td>
<td>−2.983</td>
<td>−7.724**</td>
<td>−0.453</td>
</tr>
<tr>
<td></td>
<td>(2.521)</td>
<td>(3.582)</td>
<td>(3.330)</td>
</tr>
<tr>
<td>log(Deposits/Income)</td>
<td>−36.994***</td>
<td>−35.447***</td>
<td>16.207*</td>
</tr>
<tr>
<td>Range ($R_{max} - R_{min}$)</td>
<td>−7.540***</td>
<td>4.751***</td>
<td>2.049***</td>
</tr>
<tr>
<td></td>
<td>(0.410)</td>
<td>(0.393)</td>
<td>(0.234)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,414</td>
<td>2,414</td>
<td>2,414</td>
</tr>
<tr>
<td>R^2</td>
<td>0.075</td>
<td>0.241</td>
<td>0.041</td>
</tr>
</tbody>
</table>

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

**Note:** The monthly structural estimates are aggregated to annual averages for each market and merged with annual SOD data and Census demographic and income data. Wherever applicable variables are expressed as percentage points. All panel regressions include MSA market fixed effects. Standard errors are based on a robust variance-covariance matrix estimator with MSA level clustering (See Arellano [1987]).

The remainder 20 percent are active investors who search more than two banks. Of
those, the largest segment is the lowest search cost segment $q_N$ with search costs $\xi < \Delta_{N-1}$. Over the sample period from 1997 to 2007, this segment gradually decreases from around 10 percent to less than 5 percent. In lockstep with $q_N$, the average fraction of banks sampled also gradually decreases from around 20 percent to 10 percent.

Figure (6) reveals sizable differences across markets in the share of inactive investors. In 2006, the 5th percentile market has only 10 percent of inactive investors, while for the 95th percentile this share is above 50 percent. Table (9) examines how market characteristics such as the competitive structure, demographic composition, incomes, and deposit wealth relate to search intensities. Two sets of regressions with market fixed-effects are estimated for $q_1$, $q_2$, and $q_N$ each. The first regression does not condition on rate dispersion whereas the second does. With the exception of $q_N$, controlling for rate dispersion makes measures of market concentration such as the HHI and the number of banks and branches per capita statistically insignificant.

Even after conditioning on rate dispersion, the share of elderly households of age 65 and above continues to play economically large and statistically significant role in determining search intensity across markets. A higher share of this population is correlated with higher share of inactive investors $q_1$ and a lower share of active investors $q_N$ with no effect on $q_2$ when conditioning on rate dispersion. In addition to the share of elderly households, larger population size is also related to a higher share of inactive investors. In contrast, markets with higher incomes and higher deposit-to-income ratios have lower share of inactive investors $q_1$ and higher shares of investors who compare two bank offers. Markets with wealthier households are more likely to involve investors for whom the limited deposit insurance motive is a concern.

To understand the apparent dichotomy in the population of investors between inactive $q_1$ investors and those that sample two $q_2$ or all banks $q_N$, we need to first examine the variation in the marginal values of information for different sample sizes $\{\Delta_k\}_{k=1}^{N-1}$ and over time. Since $\{\Delta_k\}_{k=1}^{N-1}$ are expressed in utils, I convert them into interest rate equivalents. An interest rate equivalent expresses the marginal value of information as the increase in the expected best offer rate starting from a sample size $k$ and a particular reference rate. For $R_{\min}$ as reference rate, the interest rate equivalent $\Delta(R_{\min})_k$ for sample size $k$ is a solution to $\Delta_k = \phi'(R_{\min}) \Delta(R_{\min})_k$ or $\Delta(R_{\min})_k = \frac{\Delta_k}{\phi'(R_{\min})}$ for $k = 1, 2, ..., N-1$. Since $\phi''(R) < 0$, the interest rate equivalent evaluated at $R_{\min}$ is the lowest than any other reference rate.

Panel A of Figure (7) plots the time series variation of $\Delta(R_{\min})_k$ for a number of sample sizes. In 2006, the expected marginal increase in utility from sampling two banks instead of one is equivalent to close to 70 basis points increase in the expected rate. The interest rate equivalent $\Delta(R_{\min})_1$ is only 16 basis points in the low dispersion period of 2013. As the sample size $k$ increases, the marginal value of information decreases and so does its time
series variation.

Figure 7: Marginal value of information, rate dispersion, and search intensity

A. $\Delta_k$ variation over time

![Graph A](image)

B. $\Delta_k$ variation over sample size

![Graph B](image)

C. Rate dispersion and $\Delta_k$

![Graph C](image)

D. $\Delta_1$ and share of uninformed $q_1$

![Graph D](image)

Note: In panel C, the black line is a polynomial fit based on a weighted regression using the total deposits of an MSA market as weights.

This can be seen clearly in Panel B which plots the marginal value of information as a function of sample size for two periods—the high dispersion period of 2006 and the low dispersion period of 2016. The marginal value of information declines sharply with sample size in both periods. In 2006, $\Delta(R_{min})_1$ is as high as 70 basis points. The marginal value of information declines sharply with sample size. $\Delta(R_{min})_2$ is only 30 basis points. For sample sizes above 10 banks, the marginal value of information drops below 5 basis points and remains flat for higher sample sizes. In the low dispersion environment of 2016, the marginal values of information are uniformly lower across sample sizes. For example, $\Delta(R_{min})_1$ is around 18 basis points and $\Delta(R_{min})_2$ is slightly less than 10 basis points. However, for sample sizes exceeding 20 banks the marginal values of information remain roughly unchanged.
Marginal values of information increase with rate dispersion but this relationship declines with sample size. Panel C shows scatter plots of $\Delta(R_{min})_1$ and $\Delta(R_{min})_{N-1}$ against the range of rates. For some markets and time periods, the range is as large as 500 basis points and the marginal value of sampling two bank offers $\Delta(R_{min})_1$ is as high as 100 basis points. The relationship between rate dispersion and $\Delta(R_{min})_1$ is strong. However, as shown in Panel B, this relationship quickly flattens with sample size, so much so that $\Delta(R_{min})_{N-1}$ has little sensitivity to rate dispersion. This low sensitivity explains the relatively stable fraction of the most active investors $q_N$.

Finally, Panel D shows that the share of high search cost and inactive investors $q_1$ is a decreasing nonlinear function of the marginal value of information $\Delta(R_{min})_1$. The share of inactive investors $q_1$ declines faster starting from low levels of $\Delta(R_{min})_1$. The shape of this relationship is determined by the shape of the underlying search cost distribution which we describe next.

Figure 8: Estimated search cost distribution, 2006

Note: The figure is based on estimates of $(\Delta_k, F(\Delta_k))$ for June 2006 and for MSA markets with p-values exceeding 5 percent. Values outside these point estimates are extrapolated using monotone Hermite splines. The 5th and 95th percentiles of the search cost distributions are presented as a light gray shaded area. The blue dashed line is the median and the black line is the deposit-weighted average estimates of the cumulative density function of search costs.

The range of search costs and the shape of the search cost distribution are identified up to $\Delta_1$ and the corresponding cumulative density $F_\xi(\Delta_1)$. For search costs larger $\xi > \Delta_1$, the search cost distribution is extrapolated using monotone Hermite splines. Incorporating the heterogeneity in the estimates of $\Delta_1$ and $F_\xi(\Delta_1)$ across markets improves identification of the upper range and shape of the aggregate search cost distribution. Figure (8) presents the
5th and 95th percentiles along with the median and deposit-weighted cumulative densities of the search cost distributions estimated in 2006.

The aggregate search cost distribution is bimodal with two groups of investors. The first group has relatively low search costs of less than 15 basis points. This group is about a third of all investors. The cumulative search cost distribution remains flat between 15 and 30 basis points indicating few investors with search costs in this range. The second group has investors with search costs exceeding 30 basis points. The upper range of search costs for this group could be as high as 140 basis points or more. To illustrate how the search cost distribution determines search intensities, the red vertical line shows the weighted average $\Delta(R_{min})_1$. The marginal value of information for two bank offers stands at 69 basis points and implies an aggregate share of inactive depositors of about 30 percent. This is consistent with observations in Panel C of Figure (7). The blue vertical line shows the weighted average $\Delta(R_{min})_2$. It stands at 30 basis points and implies a share of investors who compare two bank offers $q_2$ of about 40 percent.

Keeping the search cost distribution fixed, variation in $\Delta_1$ changes the share of inactive investors $q_1$. For example, as rate dispersion increases, $\Delta_1$ increases and a mass of investors who previously would not have searched for rates decide to actively search and compare rates across banks. Since the marginal value of information and its correlation with dispersion drops precipitously for sample sizes of three or more banks, the bulk of those now active investors search at most two banks. The sharp decline in the marginal value of information explains the high share of $q_2$ investors and its strong negative correlation with $q_1$ documented in Figure (6).

Changes in search intensity are also determined by changes in the distribution of search costs. Arguably the distribution of search costs is more stable over time as compared to variation in marginal cost of funds. Search costs are related to an underlying set of technologies of gathering information and these technologies remain unchanged over long periods of time and across different generations of investors. The introduction and adoption of the Internet, however, is one such technological innovation that could have dramatically reduced search costs as well as other transaction costs of opening and maintaining accounts with different banks. According to a study of the Office of the Comptroller of the Currency, by the end of 2001, 50 percent of commercial banks offered some form of Internet banking services. Therefore, I use 2001 as a dividing line between the “pre-Internet” banking and the “Internet” banking period when examining search cost estimates.

To understand if the adoption of the Internet produced changes in the search cost distribution, panel A of Figure (9) compares the aggregate search cost distribution in the high dispersion environments of 2000 with that of 2006. Although, the median search cost is identical in the two periods of about 50 basis points, the search cost distribution in 2006...
features a higher share of low search cost investors and a lower share of investors with search costs exceeding 70 basis points. Panel B shows a similar comparison for two low dispersion years—2003 and 2010. The two search cost distributions are very similar in the lower percentiles. Although the median search cost in 2010 is about 5 basis points lower than in 2003, the two distributions are very similar.

Figure 9: Search cost distribution in high and low dispersion periods


B. Low dispersion: 2003 and 2010

Note: The search cost distributions are based on weighted averages of the estimates \((\Delta k, F(\Delta k))\) for MSA markets with p-values exceeding 5 percent. Values outside the point estimates are extrapolated using monotone Hermite splines.

All in all, Figure (9) indicates a reduction in search costs since 2000. However, this reduction is not as dramatic as one would have anticipated and, in particular, has not affected aggregate search intensity in a significant way. While this outcome may look surprising, it is consistent with surveys conducted by the Census Bureau on computer and Internet use by age groups. In particular, the 2010 survey shows that only 41 percent of elderly households of age 65 and above use a personal computer, and only 32 percent of these elderly households use the Internet.\(^\text{16}\) This result is also confirms the facts in Table (6), which documents that only a quarter of CD holders use the Internet to search for investment information, half as much as the usage reported by sophisticated investors. To the extent that elderly households constitute the bulk of the high search cost investors and are the largest segment investing in CD, the low adoption rate of the Internet contributed to the relatively unchanged search cost distributions.

\(^\text{16}\)Source: Computer and Internet Use in the United States (2010)
4.4 Effect on money markets

Another effect of differential adoption of information technologies not captured explicitly by the model is compositional. Although the model assumes full participation, investors can choose higher yielding investments other than CDs. With the introduction of the Internet, it became easier for more sophisticated investors to move money in and out of their checking accounts into non-deposit products such as mutual funds or brokerage accounts. As a result, even though the overall search and transaction costs may have significantly declined for younger and more sophisticated households, those households are also more likely to have exited the CD market for higher yielding alternatives.

The changing composition of CD investors towards less active elderly households further reinforces the exit of more active and sophisticated investors. Faced with a large mass of high search cost investors, banks are able to charge higher monopoly mark-ups reducing the incentives of active and sophisticated investors to participate in the CD market. Exit of low search cost investors from the CD market is corroborated by results in Hortaçsu and Syverson [2004] who document an increase in the fee dispersion and proliferation of S&P 500 index funds over the period 1995-2000. They attribute these trends to entry of novice investors with high search costs. Although their focus is on S&P 500 index funds, they document similar patterns of high fee dispersion in the retail money market mutual funds (MMF). MMFs compete with banks by providing access to a relatively safe and high interest-earning alternative to bank deposits. The exit of more sophisticated investors from the market for time deposits into MMFs could explain why advances in information technology surprisingly left the CD market intact. It could also explain the pricing of mutual funds documented in Hortaçsu and Syverson [2004]. The low information cost investors who exit the market for time deposits are the novice relatively high-search-cost investors in the more sophisticated and complex mutual fund markets.

Such hypothesis is not without empirical support. For example, Christoffersen and Musto [2002] provide evidence that money market mutual funds exploit the heterogeneity in price elasticities of investors to price discriminate between investors who withdraw from funds that increase fees and those who remain inactive. To the extent that these price elasticities are related to search costs, an inflow of novice investors in the MMF market presents an opportunity for retail MMFs to exploit a potentially less price elastic segment.

To test this hypothesis, I examine bank-affiliated MMFs. These are money funds that are advised, managed, and sponsored by major bank holding companies. Table (10) shows

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17 In fact, the MMF industry developed as a response to Regulation Q during the high-inflation period of the late 1970s when the ceiling on the deposit rates started to bind and investors were looking for alternatives. Since the 1970s banks have started to lose deposits to MMFs. This process continued in the post-Regulation Q era.

18 Kacperczyk and Schnabl [2013] document that many bank-affiliated funds received support from their
that in 2006 more than $300 billion of the $900 billion retail MMFs are in bank-affiliated funds. Bank-affiliated funds attract investors through distributional channels heavily dependent on the bank adviser and much less so on unaffiliated brokers or direct channels. In contrast, unaffiliated MMFs attract their investors either directly or through non-bank affiliated brokers and advisers. To the extent that the composition of distributional channels reveals that banks are steering some depositors to their affiliated funds, we should also observe differences in the fees charged by those fund. Indeed, bank-affiliated funds charge on average 10 basis points higher fees as compared to unaffiliated funds. The difference is even larger for direct investments. The dispersion in fees is also much smaller for unaffiliated funds relying on direct distributional channels. For example, for bank-affiliated funds, the difference between the 95th and the 5th percentile is 137 basis points, whereas for unaffiliated funds this difference is 63 basis points.

Table 10: Distribution channels, expense ratios, and bank-affiliation of MMFs

<table>
<thead>
<tr>
<th>Distribution channel</th>
<th>Bank-affiliated</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Funds count</td>
<td>AUM ($bn)</td>
</tr>
<tr>
<td></td>
<td>mean 5th 95th</td>
<td></td>
</tr>
<tr>
<td>Bank Affiliated</td>
<td>315 225 65 44 130</td>
<td>30 6 58 46 152</td>
</tr>
<tr>
<td>Broker</td>
<td>44 107 61 47 97</td>
<td>85 200 65 45 134</td>
</tr>
<tr>
<td>Direct (No Load)</td>
<td>29 9 60 14 151</td>
<td>68 293 35 13 75</td>
</tr>
<tr>
<td>Adviser</td>
<td>11 2 73 45 181</td>
<td>164 61 76 44 156</td>
</tr>
<tr>
<td>Other</td>
<td>12 1 80 51 140</td>
<td>21 8 84 37 201</td>
</tr>
<tr>
<td>Insurance</td>
<td>12 1 54 40 143</td>
<td>48 11 61 42 160</td>
</tr>
<tr>
<td>Retail total</td>
<td>423 345 63 41 123</td>
<td>479 608 53 32 160</td>
</tr>
<tr>
<td>Institutional total</td>
<td>488 627 27 15 98</td>
<td>408 496 27 12 81</td>
</tr>
</tbody>
</table>

Note: AUM stands for assets under management. The mean expense ratio is a weighted average based on the funds’ assets under management. Data are as of June 2006. Source: iMoneyNet

The statistics in Table (10) are suggestive of the presence of search costs and monopoly mark-ups exploited by retail money market funds which increase with bank affiliation. A further way to test this hypothesis is to contrast retail with institutional funds. The average asset-weighted fees charged to institutional investors are identical for bank-affiliated and unaffiliated funds, and significantly below retail fund fees. The weighted-mean fee is 27 basis points or more than half the average fee charged by retail funds. The magnitude of fee bank sponsors in the market turmoil following the failure of Lehman Brothers. Many funds also changed their names to incorporate the sponsor’s name and, thus, make the affiliation more salient.
dispersion is also similar between the bank-affiliated and unaffiliated funds. The reason for these differences is that Institutional funds are comprised of large investors with investments exceeding $1 million. For those funds, fee differentials of just a few basis points translate into large differences in returns. Even though fees are significantly lower than retail funds, there is still sizable fee dispersion. The dispersion may reflect differences in asset composition within prime funds and other product differentiation discussed in Hortaçsu and Syverson [2004]. Even with this fee dispersion, on an asset-weighted basis institutional investors invested in cheaper funds and paid significantly lower fees as compared to retail investors.

5 Conclusion

By 1986 interest rate ceilings on most deposits had been repealed, and banks were allowed to offer competitive rates. Subject to deposit insurance, time deposits are nominally riskless, homogeneous fixed-income financial product that is comparable to Treasuries. As a result, the post interest-rate-ceiling period should have brought convergence of retail deposit rates to market rates. Yet this paper documents persistent rate dispersion and sizable negative spreads over matched maturity Treasuries, indicating significant monopoly power in a market with large number of competitors and available substitutes such as retail money market mutual funds.

Banks achieved the surprising feat of retaining and expanding their monopoly power in the face of competition from money market funds and the advent of information technologies that should have reduced information gathering and other transaction costs. This paper has shown that a model with heterogeneous search cost investors can provide a coherent framework to rationalize the observed monopoly power, the resulting rate dispersion, and asymmetric pass-through of changes in the target Federal funds rate into deposits rates. Understanding the mechanism behind banks’ monopoly power is important beyond deposit markets. Contemporaneous work by Duffie and Krishnamurthy [2016] and Drechsler, Savov, and Schnabl [2017] shows that incomplete interest pass-through has a first-order effect on monetary policy transmission through banks’ balance sheets and on the efficiency of other money markets.

This paper shows that through affiliation with money market mutual funds the largest banks have expended their span-of-control in the market for money-like instruments to capture sophisticated and active investors whom banks steer into their affiliated funds. This allowed banks to segment the demand for riskless assets into a segment of inactive high search cost depositors who invest predominantly in deposits and a segment of active investors who choose other more complex and higher yielding financial instruments. The segment of high search cost depositors was predominantly elderly households who are more
risk-averse and have been slow to adopt the new information technologies to improve the
return on their savings.

Given the sizable estimated search costs, coupled with estimates of relatively high in-
tertemporal elasticity of substitution, the increase in monopoly power reveals potentially
sizable welfare losses and distortions in saving behavior of U.S. households that exacerbate
wealth inequality. Analysis of the effects of those distortions on aggregate savings behavior
is of high policy importance. For example, McKay [2013] finds that privatization of social
security can lead to sizable welfare losses in a market where households face search costs.

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