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Vladimir Yankov

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In Search of a Risk-free Asset

Search Costs and Sticky Deposit Rates

Vladimir Yankov*

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Abstract

I examine the role of costly consumer search for the pricing of insured deposits, which is characterized by a large dispersion of offer rates, negative spreads over Treasuries, and upward rigid adjustments following increases in the federal funds rate. Estimates of a model of costly search reveal a large fraction of high-search-cost and a small declining fraction of low-search-cost depositors. The large fraction of high-search-cost depositors, composed mostly of elderly and less financially sophisticated households, grants banks monopoly power and allows for the low interest rate pass-through. The predictions of the estimated model are consistent with responses in the Survey of Consumer Finances to questions related to financial sophistication, search for investment return, and deposit allocations across multiple bank accounts. The model also reveals a non-monotone relationship between bank entry, deposit rates, and consumer surplus.

JEL Classification: G21, D83, E43
Keywords: Deposit rates, rate dispersion, rate rigidity, consumer search, monetary policy pass-through

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*The Board of Governors of the Federal Reserve System, 20th Street and Constitution Avenue N.W., Washington, D.C. 20551. Views expressed in this paper do not reflect the official position of the Federal Reserve System. E-mail: `Vladimir.L.Yankov@frb.gov`.

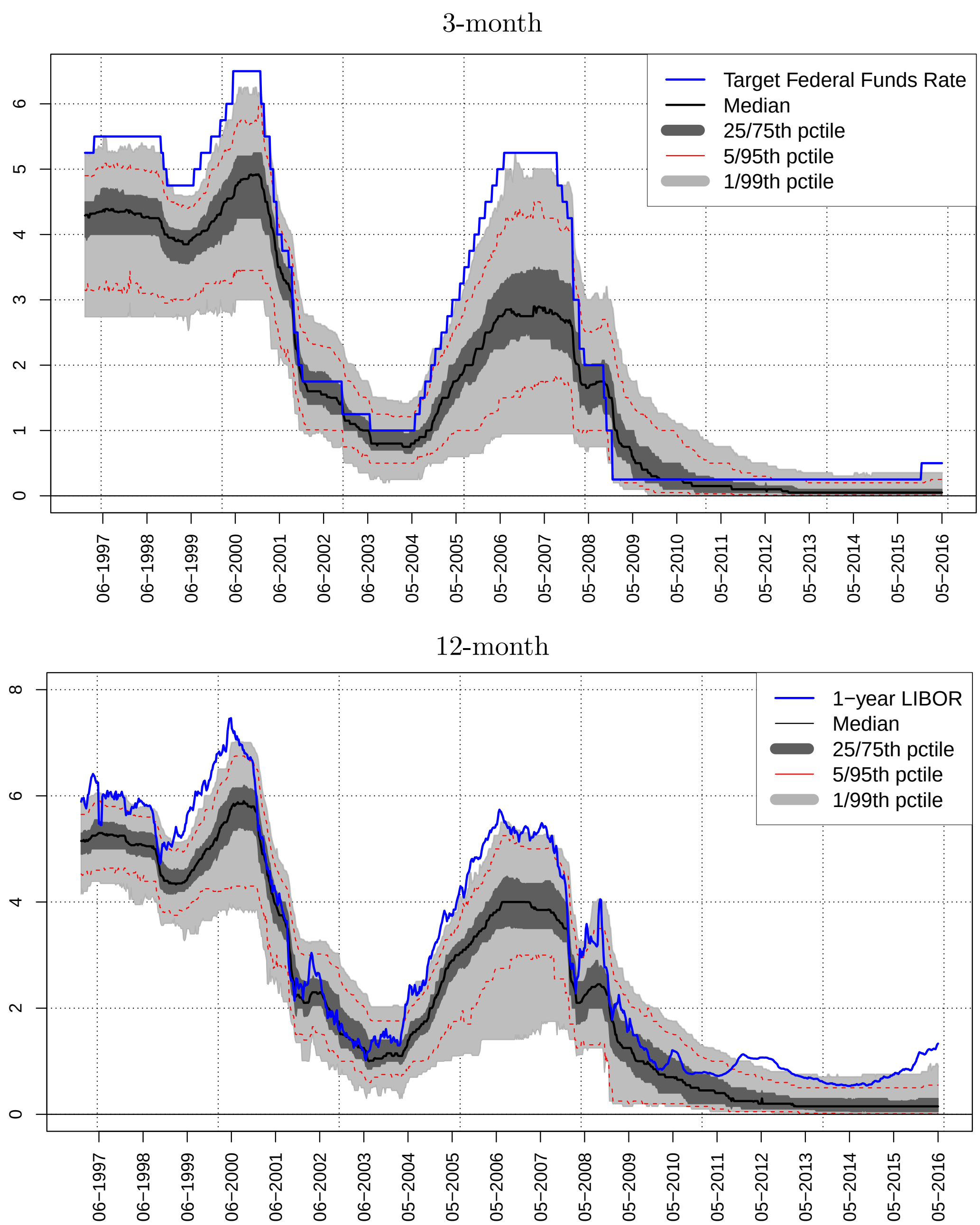
1 Introduction

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 a large number of competitors. I study the systematic violation of the law of one price in the market for retail FDIC-insured certificates of deposit (CD), or time deposits—a component of the M2 monetary aggregate and a close substitute for a Treasury security, a widely used proxy for a nominally risk-free asset. On average, banks pay significantly lower rates on time deposits as compared to matched-maturity Treasury bonds indicating the presence of significant monopoly power. 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 pricing facts, I develop a model of competition for deposits with heterogeneous search cost investors based on the mixed strategies equilibrium of Burdett and Judd (1983). The model and estimation framework builds on earlier work on nonsequential consumer search with heterogeneous search cost by Janssen and Moraga-González (2004), Hong and Shum (2006), Moraga-González and Wildenbeest (2008), Moraga-González, Sándor, and Wildenbeest (2013), and Moraga-González, Sándor, and Wildenbeest (2017), and differs from the original Burdett-Judd model along three dimensions. First, there is a finite number of firms (banks). Second, search costs are heterogeneous, and, third, demand for time deposits is price-elastic and determined by a consumption-savings decision of households. Differences in search costs lead to endogenous market segmentation according to the optimal investors' search intensity. Segments with high search costs remain rationally uninformed about the presence of better returns and inactive in terms of shopping for rates. The relative size of uninformed investors determines the equilibrium price dispersion, monopoly profits, and the degree of pass-through of wholesale interest rates to deposit rates. The elasticity of deposit demand is determined by the intertemporal elasticity of substitution of depositors who solve a consumption-savings decision problem taking into account their optimal search effort and expected return on savings.

The model is estimated with a maximum likelihood proposed by Moraga-González and Wildenbeest (2008). The advantage of this approach is that the estimation of the search cost distribution relies only on the observed deposit rates and does not require information on quantities. Furthermore, the estimation also uncovers the underlying marginal costs of supplying deposits for which there is no readily available empirical proxy. The search

Figure 1: The cross-sectional distribution of CD yield offers



NOTE: The light gray shaded area represents offer rates between the 1st and 99th percentile. The dark gray shaded area represents 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.

cost estimates reveal a bimodal distribution of search costs with two distinct groups of investors—an inactive group with high search costs and an active group with low search costs. More than one third of investors have high enough search cost, so that they do not shop for rates but accept the rate offered from their main bank. The magnitude of search costs for these inactive investors range from 30 basis points to as high as 140 basis points or more. Over the sample period, a significant fraction of high-search-cost investors switches between examining only one offer and comparing the offers of at most two banks.

The active investors have low enough search costs, and are able to identify and act on 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, because over the period, there has been rapid introduction of information technologies such as rate comparison websites or mobile banking that should have eased information gathering and reduced transaction costs of opening and maintaining multiple deposit accounts. I provide two potential explanation for the observed trends in the composition of search costs. First, using data from the Survey of Consumer Finances, I document that households who invest in certificates of deposit are mostly elderly households. Compared to younger households, elderly households have adopted the Internet at a much slower pace and their Internet use remains low. This could explain why the introduction of technologies such as rate comparison websites or mobile banking have not produced a measurable effect on search costs in these markets and, hence, on the pricing of deposits. Regression results at the MSA level confirm that the share of households of age 65 and above is a significant determinant for the presence of high-search-cost depositors and low search intensities across geographic deposit markets.

Second, the exit of low-search-cost investors from the market of time deposits could be explained by the increasing demand for accounts in retail money market funds that offer higher returns. Such an exit of low-search-cost investors complements findings in related study by Hortaçsu and Syverson (2004), who attribute the existence of sizable dispersion in fees charged by retail mutual funds and the proliferation of such funds to the entry of novice investors. These developments in the retail mutual fund industry could be related to the exit of low-search-cost investors from time deposits and their entry into mutual funds, where those novice investors face large information costs. To test this hypothesis, I provide evidence that banks have used their affiliated money market mutual funds to price discriminate between high-search-cost depositors, who continued to invest in time deposits, and the active segment of depositors, who were steered into bank-affiliated money funds.

The documented deposit pricing facts contribute to previous empirical studies of deposit pricing. 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.[1] Hannan and Berger (1991) and Neumark and Sharpe (1992) document the asymmetric rigidity of deposit rates to changes in banks' marginal cost of funds and relate the magnitude of these rigidities to the degree of local market competition. Driscoll and Judson (2013) test theories of price rigidity related to menu costs. Their conclusion is that the existing models based on firm menu costs face a challenge in fitting some of the unique characteristics of banks' rate-setting behavior. Unlike the existing literature, the focus of this work is on the time-varying market-level rate dispersion, which in the context of search costs is intimately related to the degree of interest rate pass-through and monopoly profits. The most closely related work is Honka, Hortaçsu, and Vitorino (2016), which examines the effect of advertisement on shopping for bank deposits and estimates the underlying search cost distribution. However, their survey data are limited to a single point in time in a low-interest-rate environment with compressed rate dispersion and their work does not study pass-through and its determinants.

The stylized facts on the pricing of deposits resemble those of retail consumer goods. For example, Bils and Klenow (2004) document price rigidity for many consumer goods and services that lasts for more than 4 months. Lach (2002) documents that the pricing of homogeneous retail goods in Israel exhibits persistent price dispersion and constant repositioning of shops' price rankings very similar to the one documented here. The asymmetric adjustment of rates is also reminiscent of pricing of retail goods such as gasoline as discussed in Tappata (2009). 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.

Finally, understanding the mechanism behind banks' monopoly power is important beyond deposit markets. Recent work by Duffie and Krishnamurthy (2016), Drechsler, Savov, and Schnabl (2017), Brunnermeier and Koby (2018), and Xiao (2020) shows that incomplete interest pass-through has a first-order effect on monetary policy transmission through banks' and nonbanks' balance sheets. The mechanisms for generating monopoly profits and incomplete pass-through in these studies, however, are based on product differentiation and monopolistic competition. In contrast, I propose a novel mechanism based on endogenous search and document that, conditioning on measures of market concentration, consumer search has an independent and economically significant effect on rate dispersion, monopoly

[1] 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. In addition, in 1990, changes in Regulation D lifted the requirement for banks to hold reserves against time deposits. Finally, in 2011, restrictions on payment of interest on demand deposits were removed.

profits, and interest rate pass-through. I examine those issues in detail through a set of counterfactual exercises in sections 4.7 and 4.8. Unlike a Cournot model of competition assumed in the literature, increases in the number of bank competitors does not always benefit depositors and could lead to increases in deposit rate dispersion and declines in the average deposit rates.

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 over 10,000 FDIC-insured commercial banks in more than 80,000 branch offices covering all major metropolitan statistical areas (MSA). The survey represents more than 90 percent of deposits at FDIC-insured banks.[2] I supplement these data with information on industry concentration from the Summary of Deposits 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 household-level information on financial asset holdings and allocations of deposits across financial institutions. MSA-level demographic and income information is obtained from the Census Bureau. Microlevel data on money market mutual funds are obtained from iMoneyNet.[3]

2.2 Dispersion decomposition

To understand the sources of dispersion documented in Figure (1), let us first 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

[2] See Appendix A.1 for further details on the scope of the data

[3] RateWatch deposit rate data http://www.rate-watch.com/; Summary of Deposit data http://www2.fdic.gov/sod/; Call Reports and bank holding company data https://cdr.ffiec.gov/public/; Survey of Consumer Finances https://www.federalreserve.gov/econres/scfindex.htm; Census Bureau data http://www.census.gov/main/www/access.html; iMoneyNet data https://www.mfanalyzer.com/

$W_t = \sum_{m,j}(R_{j,m,t} - \bar{R}_t)^2$, can be decomposed in two ways

$$W_t = \begin{cases} \underbrace{\sum_{m,j}(R_{j,m,t} - \bar{R}_{j,t})^2}_{within} + M \underbrace{\sum_{j}(\bar{R}_{j,t} - \bar{R}_t)^2}_{across} & \text{Bank decomposition} \\ \underbrace{\sum_{m,j}(R_{j,m,t} - \bar{R}_{m,t})^2}_{within} + N_t \underbrace{\sum_{m}(\bar{R}_{m,t} - \bar{R}_t)^2}_{across} & \text{Market decomposition.} \end{cases} \tag{1}$$

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 (1) shows that more than 90 percent of the overall variation in rates can be attributed to differences in rates across banks, and less than 10 percent 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 percent of the variation in rates is due to differences in median rates across markets.

Table 1: Decomposition of total variation in deposit rates, 2007

Fraction of total variation:	3-mo	6-mo	12-mo	24-mo	36-mo	60 -mo
Across market variation	0.17	0.16	0.17	0.18	0.19	0.17
Within market variation	0.83	0.84	0.83	0.82	0.81	0.83
Across bank variation	0.92	0.92	0.91	0.92	0.92	0.91
Within bank variation	0.08	0.08	0.09	0.08	0.08	0.09

SOURCE: RateWatch

To measure the economic significance of rate dispersion, the first four columns of Table (2) 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, by identifying and depositing 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 2: Dispersion in deposit rates across and within markets, 2006

	Median rate				Rate dispersion $P(0.95) - P(0.05)$			
Maturity	25^{th}	50^{th}	75^{th}	Mean†	25^{th}	50^{th}	75^{th}	Mean†
3-mo	2.50	2.75	3.00	2.69	1.75	2.12	2.57	2.42
6-mo	3.00	3.27	3.53	3.18	1.85	2.20	2.50	2.49
12-mo	3.69	3.84	4.00	3.75	1.60	1.95	2.25	2.22
24-mo	3.75	3.98	4.07	3.83	1.35	1.59	1.98	1.89
60-mo	4.05	4.25	4.42	4.11	1.20	1.35	1.60	1.53

NOTE: † This is the weighted mean across markets with weights equal to the total deposits in the market. SOURCE: RateWatch and Summary of Deposits (FDIC)

2.3 Product differentiation and rate dispersion

Certificates of deposits are interest-paying fixed-term deposit products offered by banks that have an investment purpose rather than the transaction purpose of other deposit products such as checking accounts. If held until maturity, an FDIC insured CD is a nominally riskless investment similar to a Treasury bond.[4] CDs differ from government bonds in terms of their taxation, liquidity, and riskiness.[5] Unlike government bonds, certificates of deposits are taxed both at the state and at the federal level. Without a secondary market and with large early withdrawal penalty fees, retail CDs are significantly less liquid than a Treasury bond. Although CD contracts differ across banks in their early withdrawal penalties or minimum deposit amount, such differences are not priced. Furthermore, banks do not compete or publicly advertise the size of the penalty fees for early withdrawal, making these attributes shrouded add-on costs of this financial product. [6]

Although CDs are fairly homogeneous financial products, depositors may perceive contracts offered by different banks as differentiated products. For example, the convenience of maintaining a single deposit account, the location of a banks' branches or the customer

[4]Even if a bank fails, the FDIC takes over the bank in receivership that allows for continued access to insured deposits by either repaying existing insured depositors or transferring the deposits to another bank in an assisted merger and acquisition.

[5]Certificates of deposits are offered in small denomination with balances below $100,000 and in large (jumbo) denomination with balances above $100,000. The FDIC insurance limit per depositor per bank was set to $100,000 in 1980 and was changed to $250,000 in October 2008.

[6]Analysis in section (A.1.3) of the online appendix shows that the correlation between offer rates and nonprice terms are very low. Gabaix and Laibson (2006) introduces a theory of information suppression (shrouding) in competitive markets with consumer myopia and provides examples of shrouding in other markets.

service offered by the bank are valuable for transaction accounts. Depositors may also demand such services for their investment accounts such as CDs. Absent transaction level data, it is hard to test how consumer preferences over these attributes affect time deposit rates. Instead, I do a simple test if bank and bank-market fixed-effects determine a measurable fraction of the variation in rates.[7] In addition, I control for the level of interest rates with the LIBOR rate and the coefficient on LIBOR measures the degree of interest rate pass-through.[8] To proxy for differences in services offered by a bank in a market relative to its competitors in that market, I use two additional variables. The first is the deviation of bank j's number of branches $B_{j,m,t}$ in market m from the average number of branches per bank in the market $\frac{B_{j,m,t}-B_{m,t}}{B_{m,t}}$. The second proxy is the size of the bank relative to the average size of banks in the market $\frac{A_{j,t}-A_{m,t}}{A_{m,t}}$.

Table (3) presents the results from four regressions for the 12-month contract.[9] The first specification regresses bank offer rates on the time series of the 12-month USD denominated LIBOR rate. This regression can explain close to 90 percent of the total variation of rates over the sample period. The remaining 10 percent represent cross-sectional dispersion in rates which remains sizeable. The last two rows of the table present the standard deviation and the difference between the 95th and the 5th percentiles for 2006, a year with high cross-sectional dispersion. The dispersion measure is 2.37 percentage points and is comparable in magnitude to the average dispersion reported in Table (2).

The remaining specifications in Table (3) explore the determinants of the cross-sectional dispersion in rates after controlling for the time-series variation. The second specification adds the two bank controls, which are both statistically significant and, as expected, affect negatively the offer rate. For example, a bank that has two times more branches than the average bank in a given market offers 5 basis points lower rate than the average bank. A bank that is twice as large as the average bank offers 1 basis points lower rates. Although the two bank controls are statistically significant, they only marginally improve the goodness-of-fit of the model or reduce the cross-sectional dispersion of rates. Finally, specifications (3) and (4) add bank fixed-effects and an interaction between bank fixed-effects and market fixed-effects, respectively. The bank fixed-effects should capture any unobserved heterogeneity in service quality offered by banks that is not represented by the branch count and the asset measures. The interaction between the bank and the market fixed-effects allows for those service qualities to vary within a bank across markets. By adding the bank fixed-effects, the cross-sectional dispersion in the residual declines little from 2.37 to 1.92 and

[7] Such approach has been used by Sorensen (2000) and Lach (2002) using prices of prescription drugs and groceries, respectively. Hortaçsu and Syverson (2004) and Wildenbeest (2011) rationalize the approach through the presence of a common utility function that assigns utility $u_j = v_j - p_j$ to store j that is separable in the price of the good p_j and the quality of the store v_j.

[8] Alternatively, adding time fixed-effects leads to similar results.

[9] The results for other maturities are qualitatively similar.

Table 3: Rate dispersion and bank fixed-effects

	Dependent variable:			
	12-month CD rate			
	(1)	(2)	(3)	(4)
LIBOR 12-mo	0.846***	0.846***	0.828***	0.822***
	(0.006)	(0.006)	(0.006)	(0.006)
$\frac{B_{j,m,t}-B_{m,t}}{B_{m,t}}$		−0.047***	−0.002**	−0.039***
		(0.003)	(0.001)	(0.007)
$\frac{A_{j,t}-A_{m,t}}{A_{m,t}}$		−0.013***	0.002***	0.016***
		(0.001)	(0.0003)	(0.002)
Constant	−0.063***	−0.062***		
	(0.021)	(0.021)		
Bank FE			X	X
Bank FE × MSA FE				X
Observations	9,413,628	9,413,628	9,413,628	9,413,628
R^2	0.897	0.900	0.923	0.925
Adjusted R^2	0.897	0.900	0.923	0.925
	Residual dispersion in 2006			
Residual Std. Error	0.73	0.72	0.59	0.58
Residual $P(95) - P(5)$	2.37	2.37	1.92	1.89

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

NOTE: The variable $\frac{B_{j,m,t}-B_{m,t}}{B_{m,t}}$ measures the deviation of the number of branches of bank j in market m at time t from the average number of branches per bank in that market $B_{m,t}$. Similarly, $\frac{A_{j,t}-A_{m,t}}{A_{m,t}}$ measures the deviation of bank j total assets from the average bank's total assets in market m. All four specifications' standard errors are constructed using heteroscedasticity and autocorrelation consistent variance-covariance matrix with clustering at the market level. $P(95) - P(5)$ measures the difference between the 95th and the 5th percentile of the distribution of the residual for 2006. The 12-month U.S. dollar LIBOR rate. The sample period covers January 1997-30 May 2016

1.89, respectively. This represents about 20 percent reduction. All in all, while bank service quality both observable and unobservable appears to play a role in determining relative pricing of CDs, it explains only a relatively small fraction of the overall variation in rates.

2.4 Asymmetric 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: a decreasing, constant, and increasing target federal funds rate.

The median duration of rate adjustments is 6 weeks during periods of an increasing target, slightly lower than the 7 weeks during periods when the target remains unchanged. In

Table 4: Duration between rate adjustments

Fed Fund Target	decreased			constant			increased		
	p25	p50	p75	p25	p50	p75	p25	p50	p75
3-month	0	3	11	1	7	20	1	6	16
6-month	0	2	7	2	6	17	2	5	12
12-month	0	2	6	1	5	15	1	5	11
24-month	0	2	6	1	5	14	1	5	12
60-month	0	1	5	0	3	12	0	3	12

NOTE: Durations are measured in weeks. The sample period is 1-January-1997 - 30-June-2011.
SOURCE: RateWatch

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 that rate adjustments vary considerably among banks. Some banks adjust their rates quite flexibly while others adjust quite 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 its deposit rates with a lag of one week.

Table 5: Synchronization of rate adjustments

Fed Fund Target	decreased			unchanged			increased		
	p25	p50	p75	p25	p50	p75	p25	p50	p75
3-month	0.13	0.20	0.28	0.08	0.11	0.13	0.10	0.12	0.14
6-month	0.16	0.26	0.36	0.09	0.13	0.16	0.12	0.14	0.16
12-month	0.18	0.27	0.36	0.11	0.14	0.17	0.13	0.14	0.17
24-month	0.16	0.25	0.36	0.10	0.13	0.16	0.12	0.13	0.14
60-month	0.15	0.24	0.34	0.09	0.11	0.14	0.09	0.11	0.12

NOTE: The table computes the quartiles of the fraction of synchronized rate changes within a week over three regimes of the target federal funds rate.SOURCE: RateWatch

Although all banks face the same aggregate shocks related to variation in market interest rates, there is little synchronization in deposit rate adjustments as shown in Table (5). During periods of tightening, the median fraction of adjusters is around 12 percent, only slightly higher than 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.

2.5 Rank persistence of bank offers

For consumer search to play a meaningful role, it must be the case that the ranking of banks' offer rates changes over time in a given market. With such repositioning in the distribution, depositors may not rely on past information when choosing a bank to invest in and need to conduct costly search to determine which bank offers the best return. To test if such repositioning occurs and to gauge its magnitude, I examine two measures of the persistence of a bank offer rate relative to its competitors in a market. The first is the duration that a bank rate spends in a given quartile of the distribution of rates in each market. The second measure is based on the transition probabilities of an offer rate from one quartile to another.

Table (6) shows the fraction of time spent in each quartile for the 3-month and the 12-month contracts over six time intervals. Roughly a quarter of the observations remain in a given quartile for only a month and over sixty percent of observations change quartile within 3 months. If a depositor invests in a 3-month CD at a bank and suppose the offer rate is in the fourth quartile, at maturity, there is more than 60 percent chance that this bank's new offer rate will be at a lower quartile. A comparison between the 3-month and the 12-month contract show that the distribution of durations is similar across maturities.

Table 6: Distribution of durations by quartile (percent)

Maturity	3-month				12-month			
Duration	Q_1	Q_2	Q_3	Q_4	Q_1	Q_2	Q_3	Q_4
1 month	0.272	0.233	0.227	0.256	0.275	0.230	0.224	0.245
2 months	0.181	0.189	0.189	0.186	0.193	0.197	0.195	0.192
3 months	0.131	0.155	0.160	0.139	0.137	0.163	0.166	0.149
4 months	0.100	0.127	0.131	0.109	0.107	0.134	0.135	0.117
5 months	0.111	0.130	0.130	0.116	0.107	0.123	0.126	0.117
6+ months	0.204	0.167	0.164	0.195	0.180	0.154	0.153	0.180
Mean	5	3	3	4	4	2	2	3

NOTE: The table computes the average fraction of time spent measured in months in each of the quartiles of market-level rate distributions. Markets with at least 20 banks are considered.

Table (7) shows estimates of the transition probabilities across the quartiles of the offer rate distribution. The diagonal elements of the transition matrices show the probability that a bank rate remains in the same quartile after 1-month and 12-month horizons. For example, the probability that a bank remains in the first quartile is 50 percent over 1-month horizon and 30 percent over a 12-month horizon. The persistence is higher for the middle quartiles than it is for the smallest and the largest. If a rate starts in the first quartile, it is more likely to transition to the third quartile indicating a potentially large increase in the rate. Similarly, if a rate starts in the fourth quartile, it is more likely for this rate to drop to the second quartile. The evidence in this section points to the fact that even with the observed rate rigidity, there is an active repositioning of banks' offer rates within the distribution of rates within markets. This makes it hard for a depositor who observed offer rates of certain banks in the past to infer their position in the distribution of offer rates in the future. This feature of the pricing will determine the modeling choices for the structural model.

Table 7: Quartiles transition matrix: 12-month CD

	1-month horizon				3-month horizon			
	Q_1	Q_2	Q_3	Q_4	Q_1	Q_2	Q_3	Q_4
Q_1	**0.50**	0.13	0.31	0.06	**0.30**	0.25	0.34	0.11
Q_2	0.06	**0.64**	0.13	0.17	0.12	**0.47**	0.23	0.18
Q_3	0.14	0.14	**0.65**	0.07	0.16	0.23	**0.48**	0.14
Q_4	0.05	0.30	0.16	**0.49**	0.09	0.33	0.27	**0.31**

NOTE: Every row in the transition matrices computes the average fraction of observations for a particular transition based on market-level distribution of offer rates. Markets with at least 20 banks are considered.

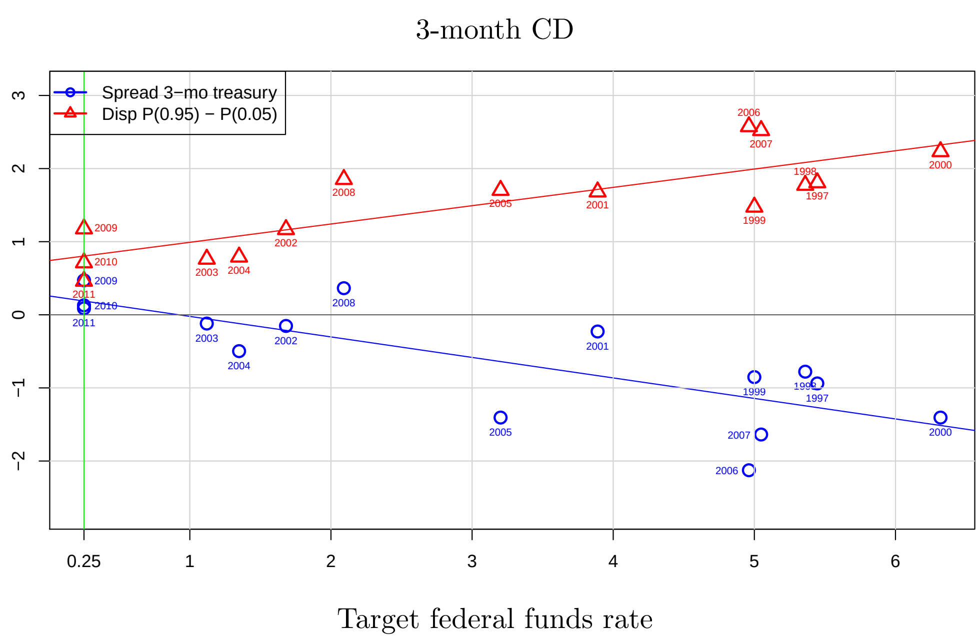
2.6 Interest rate pass-through and rate dispersion

Deposit spreads over Treasuries are large, time-varying, and increasing with higher market rates. This fact is illustrated in Figure (2), which plots the spread over a 3-month Treasury and a measure of dispersion for the 3-month CD against the level of the target federal funds rate. In the high interest rate environments of 1997-2000 and 2006-2007, when the target federal funds rate was 5 percentage points or higher, the average spread on the 3-month CD was negative 100 basis points or lower, and the difference between the 95th and the 5th percentiles exceeded 150 basis points.[10] These negative spreads translate into potentially sizable accounting 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 reduced interest payments from time deposits alone or 11

[10] An incomplete pass-through of 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).

percent of their total net income in 2006.[11]

Figure 2: Target federal funds rate, spreads, and dispersion



NOTE: The spreads and dispersion measures are annual averages of weekly data expressed in percentage points. Dispersion is measured as the difference between the 95th and the 5th percentile of the distribution of offer rates. SOURCE: RateWatch and FRED, Federal Reserve Bank of St. Louis.

2.7 Stylized facts on consumer search in deposit markets from the SCF

Given the high dispersion in rates documented in the previous section, do households search for better return on their savings? Is preference for search for better return on savings distinct from other characteristics of depositors such as risk aversion, degree of intertemporal elasticity of substitution, planning horizon, and overall financial sophistication? Household demand for and investments in time deposits offer a laboratory to disentangle those different aspects of savings behavior.

The market for certificates of deposit is well suited to address these questions. First, a CD is a relatively simple financial instrument that has undergone little financial innovation over the years.[12] Therefore, it requires little financial sophistication to evaluate the desir-

[11] Most time deposits have remaining maturity below one year, which justifies the treatment of outstanding amounts as flows over an annual horizon. Furthermore, for the purposes of this calculation, I treat the cost of maintaining a branch network as a sunk cost in the short-run.

[12] In recent years, some banks have introduced new time deposit products that include the option to adjust

ability 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 the 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 begin, we need to distinguish between financial sophistication and the preference for search for return. To do so, 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 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; and Diversity of financial asset holdings measured by a HHI index. Table (8) 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. In addition, the table shows the preference of risk-taking, the preference for shopping for investment return, and the means of gather information about financial returns.

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.[13] By construction of the score, those households have an 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 a much higher share

rates during the lifetime of the contract. Such contracts are very sparse in the data and I focus on the bulk of the contracts that are plain vanilla certificates of deposit.

[13] Gabaix, 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.

Table 8: Financial sophistication, financial assets, and deposit accounts

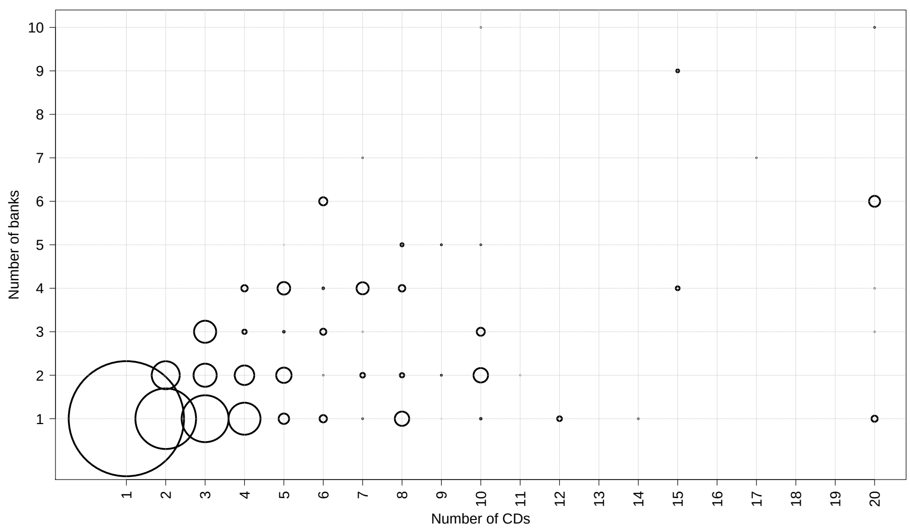
	Financial Sophistication Score				
	Q1 (low)	Q2-Q3	Q4 (high)	Own CD	All
	(1)	(2)	(3)	(4)	(5)
Age	50	50	54	60	50
College education	18	40	72	47	35
Income	38,764	85,777	278,051	121,404	88,162
—Share income from financial assets	1	3	15	8	3
Net worth (Assets–Debt)	124,349	476,309	2,830,072	1,047,925	583,351
Leverage (Debt/Assets)	32	32	17	15	30
Bankruptcy	14	13	3	6	12
Homeowner	52	75	93	85	69
Financial assets/total assets	24	30	44	42	29
—Share deposits/financial assets	72	32	11	45	43
—Share MMMF/financial assets	0	1	2	1	1
—Share equity/financial assets	0	5	16	6	4
—Share risky/financial assets	0	7	39	12	8
—Share retirement and life ins./fin. assets	22	50	39	35	40
Own CD	10	18	26	100	16
—owned jointly [Own CD==1]	43	60	60	57	57
—above FDIC limit [Own CD==1]	8	11	18	12	12
Deposits above FDIC limit	3	7	21	24	7
Own money market mutual fund	0	4	31	8	5
Own mutual fund	0	7	77	20	11
Number of institutions	2	4	6	4	4
—Number of banks	1	2	2	2	2
Take above average financial risks	5	25	50	20	21
Budgeting horizon over 5 years	13	50	72	47	40
Great deal shopping for investment	17	23	22	23	21
Use Internet for investment decisions	21	32	46	25	30
Use professional investment advice	24	46	54	50	40
Excellent understanding of SCF	36	52	71	53	48
Financial Sophistication Index percentile	0.1	0.5	0.9	0.5	0.5

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

of their financial assets in deposits. Only a fifth of these households report a preference for a 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, which is slightly below the average and about half of the share that uses the Internet among the high sophistication group. When comparing the preference for shopping for investment return, there is very little variation across the quartiles of the financial sophistication score. That said, most of the variation occurs within the means of obtaining information—for example, the likelihood that a household uses the Internet or relies on professional advice increases with financial sophistication.

The results from this analysis lead to the conclusion that the preference for search for higher return is distinct from financial sophistication. The notion that search is a distinct activity is consistent with 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 a 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 among their consideration set, 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.

Next, 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 is 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. Some households hold as many as 20 different CD contracts with as many as 6 banks or more.

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, that investor

Table 9: Certificate of deposit accounts with multiple banks

	Dependent variable: Own Certificates of Deposits with Multiple Banks					
	Survey of Consumer Finances:					
	1998	2001	2004	2007	2010	2013
Age 65 plus	0.187***	−0.006	−0.023	0.089**	0.100**	0.168***
	(0.048)	(0.048)	(0.051)	(0.045)	(0.043)	(0.056)
College degree	0.158***	0.088*	0.087	0.116**	0.018	−0.046
	(0.049)	(0.048)	(0.053)	(0.047)	(0.045)	(0.058)
log(Assets)	0.072***	−0.025	0.034**	0.051***	0.082***	0.013
	(0.016)	(0.017)	(0.016)	(0.015)	(0.016)	(0.020)
Deposits exceed FDIC limit	−0.014	0.407***	0.244***	0.223***	0.135**	0.495***
	(0.056)	(0.058)	(0.056)	(0.051)	(0.059)	(0.079)
CD held jointly	−0.159***	−0.074	−0.120**	0.136***	0.087**	0.366***
	(0.047)	(0.047)	(0.048)	(0.042)	(0.040)	(0.053)
Take above average financial risks	0.011	−0.009	−0.221***	0.015	−0.036	0.003
	(0.056)	(0.057)	(0.058)	(0.049)	(0.052)	(0.067)
Great deal shopping for investment	−0.019	0.055	0.215***	0.135***	0.226***	0.235***
	(0.052)	(0.052)	(0.053)	(0.046)	(0.044)	(0.057)
Use Internet for investment decisions		−0.024	0.045	0.025	0.007	0.312***
		(0.064)	(0.059)	(0.047)	(0.043)	(0.056)
Financial Sophistication	0.085***	0.101***	0.098***	0.040*	0.093***	0.010
	(0.022)	(0.023)	(0.025)	(0.022)	(0.023)	(0.030)
Constant	−0.812***	0.205	−0.334	−0.920***	−1.133***	−0.610**
	(0.205)	(0.222)	(0.204)	(0.204)	(0.203)	(0.260)
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: The survey provided weights are used as regression weights. SOURCE: Survey of Consumer Finance

faces the credit risk of that bank for the uninsured portion. Opening additional accounts with different banks allows diversification of 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 full deposit insurance.[14] 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.

[14] 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.

To disentangle the two motives for multiple deposit accounts, Table (9) presents results from a probit regression on whether a household owns CDs with one or several banks 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.[15] 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 to be significant in the 2013 survey. It indicates that more tech-savvy households are more likely to have multiple deposit accounts, perhaps due to both lower search costs and 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

Source: Survey of Consumer Finances

Finally, we would like to relate price dispersion with deposit allocations among different banks. Panel A of Figure (4) shows that low sophistication households with preference for a 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 and 2013. In contrast, Panel B shows that high sophistication households have a 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 in the two surveys following the 2007 survey.

[15]The FDIC allows the insurance coverage to be extended to joint account ownership for a single institution (see http://www.fdic.gov/deposit/).

All in all, the stylized facts on household demand for CDs are consistent with the presence of active search for better returns on deposits by a subset of households who either have higher preference for shopping for higher return or are wealthier and more financially sophisticated. This heterogeneity in underlying search technologies and preferences are captured in a stylized way in the model presented in the next section.

3 Model of heterogeneous search cost investors

3.1 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_τ to fund consumption in some future period $\tau \geq 1$. The optimal consumption-savings problem is

$$\begin{aligned} \nu_\tau(R, A_0) = max_{A_\tau} u(c_0, c_\tau) \\ \text{subject to:} \\ c_0 = A_0 - A_\tau, \\ c_\tau = R_\tau A_\tau, \end{aligned} \tag{2}$$

where utility takes the following constant elasticity of substitution form

$$u(c_0, c_\tau) = \begin{cases} \left\{ c_0^{1-\frac{1}{\sigma}} + \beta^\tau ([E(c_\tau^{1-\gamma})]^{\frac{1}{1-\gamma}})^{(1-\frac{1}{\sigma})} \right\}^{\frac{\sigma}{\sigma-1}} & \text{if } \sigma \neq 1 \\ \ln c_0 + \beta^\tau \ln(E c_\tau^{1-\gamma})^{\frac{1}{1-\gamma}} & \text{if } \sigma = 1. \end{cases} \tag{3}$$

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

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

$$\begin{aligned} c_0 &= h_\tau(R) \times A_0, \\ c_\tau &= R(1 - h_\tau(R)) \times A_0, \\ A_\tau &= (1 - h_\tau(R)) \times A_0. \end{aligned}$$

The marginal propensity to consume $h_\tau(R)$ is

- *for insured deposits:*

$$h^d_\tau(R) = \frac{1}{1 + \beta^{\tau\sigma} R^{\sigma-1}} \tag{4}$$

- *for a risky asset with log-normal returns* $log(R^r) \sim N(\bar{R}^r, \nu_r^2)$*:*

$$h^r_\tau(\bar{R}^r) = \frac{1}{1 + \beta^{\tau\sigma}\left(\bar{R}^r e^{-\frac{\gamma}{2}\nu_r^2}\right)^{\sigma-1}} \tag{5}$$

Indirect utility is linear in financial wealth:

$$\nu_\tau(R, A_0) = \phi^i_\tau(R) A_0, \tag{6}$$

where the marginal utility of wealth $\phi^i_\tau(R) = h^i_\tau(R)^{\frac{1}{1-\sigma}}$ *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.

If σ 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.

3.2 Costly search

Although investors are aware of the offer distribution, they have no prior information about the specific rates of each bank.[16] Information gathering is costly as each depositor faces search cost $\xi \geq 0$ per bank offer and unit of wealth. 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.[17] 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 $R_{max}(n)$. The cumulative probability function of $R_{max}(n)$ is $Pr(R_{max}(n) \leq R) = F_R(R)^n$. It is easy to show that the

[16] 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.

[17] The assumption of a 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 $R_{max}(n)$ 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 per dollar of wealth

$$n^*(\xi) = argmax_{1<n\leq N}\Big\{ \int_{R_{min}}^{R_{max}} \phi(R) n F_R(R)^{n-1} f_R(R) dR - (n-1) \times \xi \Big\}, \tag{7}$$

where search costs enter linearly in the utility. 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.

Next, let us define the marginal value of information from increasing the sample size by an extra offer given that k offers have been sampled,

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

Integration by parts leads to an equivalent representation,

$$\Delta_k = \int_{R_{min}}^{R_{max}} \phi'(R) \Big\{ 1 - F_R(R) \Big\} F_R(R)^k dR, \tag{9}$$

which reveals that the marginal value of information Δ_k is a decreasing sequence in the sample size k.[18] Once incurred search costs are sunk, and investors can always choose to invest in their outside option. 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_1^d is the expected utility from one deposit offer. The indirect utility with optimal search $V_{n^*(\xi)}^d$ for any search cost ξ dominates V_1^d. The condition for participation can be written as $V_{n^*(\xi)}^d \geq V_1^d \geq V^0$. Participation in the deposit market, therefore, does not depend on the individual search cost ξ. $\square$

[18]This follows from the fact that $F_R(R) \leq 1$ and $\phi'(R) > 0$.

It is easy to compute that the reservation rate for a log-normally distributed risky asset with expected return $\bar{R}$ and return variance ν^2 is $\dot{R} = \bar{R} \times e^{-\frac{\gamma}{2} \times \nu^2}$. The more risk-averse depositors are (i.e. higher γ), the lower deposit rates they would be willing to accept.

We can group depositors into segments according to the intensity of their search efforts. Depositors with search costs higher than $\xi > \Delta_1$ optimally choose not to shop for rates and obtain an offer rate from one bank. Depositors with search costs in the range $\Delta_k \leq \xi < \Delta_{k-1}$ examine offers of k banks. Finally, depositors 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 as follows

$$\begin{aligned} q_1 &= 1 - F_\xi(\Delta_1) \\ &\vdots \\ q_k &= F_\xi(\Delta_{k-1}) - F_\xi(\Delta_k) \\ &\vdots \\ q_N &= F_\xi(\Delta_{N-1}) = 1 - \sum_{j=1}^{N-1} q_j. \end{aligned} \tag{10}$$

3.3 Deposit pricing

A bank would always offer a rate R that is at least as high as the reservation rate $\dot{R}$. Depositors who sample k offers choose this bank's offer if the other $k-1$ offers are inferior. The probability of this event is $F_R(R)^{k-1}$. Because each bank is sampled randomly, the 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

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

The deposit demand is composed of an intensive margin, that determines how much is saved, and an extensive margin, that determines the mass of depositors a bank is expected to attract with an offer rate R. The marginal cost of funds $\tilde{R}$ is assumed common to all banks in a given market.[19] Let us define $\psi(R, \tilde{R}) = (\tilde{R} - R)(1 - h^d(R))$ to be the profit per

[19] The Federal Reserve directly controls the interest on the discount window as well as the interest paid on reserves, which effectively determine the marginal cost of funds of banks. In addition, banks incur costs to maintaining branch locations in a market and those costs could be heterogeneous. Although this assumption simplifies the model, it 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. However, due to the lack of a good proxy for those marginal costs, I estimate the model under the assumption of a common marginal cost. The online appendix discusses how well the

captured depositor. The bank profit function

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

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 $\mathcal{S} = [R_{min}, R_{max}]$ of the equilibrium offer rate distribution. Banks expect to earn positive profit and any rate outside the equilibrium support leads to strictly lower profit

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

In order to sustain equal profits, the following trade-off is at work. Higher deposit rates generate lower profits per captured depositor but attract a larger mass of depositors. 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 in obtaining this low rate.

The lower bound of the support of the equilibrium distribution is the largest between the monopoly rate $R^m = argmax_R \psi(R, \tilde{R})$ and the reservation rate, $R_{min} = max\{\dot{R}, R^m\}$. A bank would not post a rate lower than the reservation rate, because it would either attract no depositors or fail to 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*

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

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

The size of banks' monopoly power i.e. the ability to offer deposit rates below marginal cost of funds is determined by the share of high search cost investors q_1. To see this, let us

model estimates capture banks' marginal costs.

examine the ratio of deposit spreads over marginal costs for the two ends of the support

$$\frac{\tilde{R} - R_{max}}{\tilde{R} - R_{min}} = \underbrace{\frac{q_1}{\sum_{k=1}^{N} k q_k}}_{Extensive\ margin} \times \underbrace{\frac{(1 - h^d(R_{min}))}{(1 - h^d(R_{max}))}}_{Intensive\ margin}. \tag{15}$$

If all investors consider only one offer $q_1 = 1$, then the offer rate distribution is degenerate at the monopoly price equilibrium $R_{max} = R_{min} = max\{\dot{R}, R^m\}$. This finding is consistent with the "Diamond paradox" (Diamond (1971)). If all investors observe only one rate, banks can sustain monopoly equilibrium by charging the monopoly rate. As 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 for every depositor with at least one more bank. This results in a Bertrand competition and the equilibrium rate distribution becomes degenerate at the marginal cost $R_{min} = R_{max} = \tilde{R}$. However, this is not an equilibrium outcome that would rationalize the existence of large price dispersion. Therefore, for a dispersed price equilibrium to exist, there must 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 $\left(F_R(R), R_{min}, R_{max}, \pi^*, h(R), \{q_k\}_{k=1}^N\right)$ is a *dispersed equilibrium* if for a given distribution of investor types $F_\xi(\xi)$, reservation rate $\dot{R}$, and marginal cost $\tilde{R}$:

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) $\left(F_R(R), R_{min}, R_{max}, \pi^*\right)$ 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 three dimensions—there is a finite number of competing banks, search costs are heterogeneous, and individual demand is price-elastic.[20] It is easy to show that the equilibrium rate distribution has the same

[20] 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, while consumers are heterogeneous in their search costs.

properties as in 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 $F_R(R)$ that 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 $R \in [R_{\min}, R_{\max}]$ must equal the profit achieved at the minimum rate R_{min}. We can express this condition as follows

$$\sum_{k=1}^{N} kq_k F_R(R)^{k-1} = \frac{(\tilde{R} - R_{\min})(1 - h^d(R_{\min}))q_1}{(\tilde{R} - R)(1 - h^d(R))}. \tag{16}$$

Note that the left-hand side is a monotone increasing function in F_R and the right-hand side is a monotone increasing function in R. Therefore, there exists a monotone increasing function $\Phi(\cdot)$ such that

$$F_R(R) = \Phi\Big(\frac{(\tilde{R} - R_{\min})(1 - h^d(R_{\min}))q_1}{(\tilde{R} - R)(1 - h^d(R))}\Big). \tag{17}$$

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. A change of variables $z = F_R(R)$ and defining $R(z) = F_R^{-1}(z)$ allows us to express the the critical search cost thresholds $\{\Delta_k\}_{k=1}^{N-1}$ (8) as

$$\Delta_k = \int_0^1 \phi(R(z))\Big((k+1)z - k\Big)z^{k-1}dz, \text{ for } k = 1, .., N-1. \tag{18}$$

With some abuse of notation, let us define $\Delta_N = \sup\{\xi : F_\xi(\xi) = 0\}$ and $\Delta_0 = \inf\{\xi : F_\xi(\xi) = 1\}$, then the percentiles of the offer distribution can be expressed as follows

$$R(z) = \psi^{-1}\Big(\psi(R_{min}, \tilde{R})\frac{1 - F_\xi(\Delta_1)}{\sum_{k=1}^N kz^{k-1}(F_\xi(\Delta_{k-1}) - F_\xi(\Delta_k))}\Big). \tag{19}$$

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.[21]

4 Model estimation and implications of search cost estimates

4.1 Intertemporal elasticity of substitution

The coefficient of intertemporal elasticity of substitution σ is estimated independently from the search cost distribution using the consumption savings decision relationship between deposit balances and interest rates. The optimal savings rule is an intertemporal choice of households equivalent to postponement of current consumption to fund future consumption with principal and interest income from investments in time deposits. Taking derivatives of the optimal deposit allocation $A_\tau = (1 - h(R))A_0$ 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 that relates the growth in time deposits to the growth in rates

$$\Delta log(A_{\tau,t+1}) = \alpha_0 + (\sigma - 1)(1 - s_{\tau,t}) \times \Delta log(R_t) + \epsilon_t, \tag{20}$$

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 $\Delta log(R_t)$ is the percent change in the time deposits rate. The empirical framework is similar to the estimation of the intertemporal elasticity of substitution introduced by Hall (1988) and assumes a stable relationship between expected future consumption and investments in time deposits.

Estimates of the IES are presented in Table (10). The first two columns present the OLS estimates of the IES for the 6-month and 12-month CD contracts, whereas the last two columns use an instrumental variables (IV) approach. The IV regressions use exogenous variation in deposit rates coming from unexpected movements in the target federal funds rate due to monetary policy shocks identified from the federal funds futures following Kuttner (2001). A second instrument is the second lag of the growth in time deposits.

The estimates of IES from all specifications are statistically greater than one and smaller than two. These estimates imply that the substitution effect dominates the income effect. This implies that the marginal propensity to save is increasing in the deposit rate and the marginal utility of wealth is increasing and concave in rates.

[21] Solving this system of non-linear equations using global numerical methods leads to unique solutions in most feasible parametrizations. 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.

Table 10: Estimates of the coefficient of intertemporal elasticity of substitution

	Dependent variable: Growth in time deposits			
	OLS		*IV*	
	6-month	12-month	6-month	12-month
	(1)	(2)	(3)	(4)
σ	1.190***	1.202***	1.311***	1.276***
	(0.033)	(0.035)	(0.101)	(0.092)
Constant	0.012***	0.011***	0.017***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	73	73	72	72
R^2	0.319	0.315	0.188	0.271
Adjusted R^2	0.309	0.306	0.176	0.261
Residual Std. Error	0.028 (df = 71)	0.028 (df = 71)	0.031 (df = 70)	0.029 (df = 70)
			p-value	p-value
Weak instruments			0.007***	0.007***
Wu-Hausman			0.163	0.325
Sargan			0.010**	0.003***

*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 the Newey and West (1987) heteroskedasticity and autocorrelation consistent estimator.

4.2 Maximum likelihood

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

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

$$f_R(R|\Theta) = \begin{cases} \frac{-\psi'(R,\tilde{R})}{\psi(R,\tilde{R})} \times \frac{\sum_{k=1}^{N} k q_k F_R(R)^{k-1}}{\sum_{k=1}^{N} k(k-1) q_k F_R(R)^{k-2}}, & \text{for } R \in [R_{\min}, R_{\max}] \\ 0, & \text{otherwise,} \end{cases} \tag{21}$$

where the equilibrium offer rate distribution $F_R(R)$ is implicitly defined in (31), and $\Theta = \left(F_\xi(\cdot), \sigma, \tilde{R}, \dot{R}\right)$ are primitives of the model.

Proof The probability density function is derived by applying the implicit function theorem to equation (31). For $\sigma < 2$, the derivative of the profit function is negative, $\psi'(R) < 0$, which guarantees that the likelihood is non-negative.

The maximum likelihood estimates of the market segments $\{q_k\}_{k=1}^N$ are obtain from the maximization of the log-likelihood function

$$max_{\{q_k\}_{k=1}^N}\Big\{\frac{1}{N}\sum_{j=1}^{N}\log(f_R(R_j|\sigma,\{q_k\}_{k=1}^N))\Big\}, \tag{22}$$

where $F_R(R_j)$ solves

$$\sum_{k=1}^{N} kq_k F_R(R_j)^{k-1} = \frac{(\tilde{R}-R_{\min})(1-h^d(R_{\min}))}{(\tilde{R}-R_j)(1-h^d(R_j))}q_1,\ \text{for } j=1,..,N. \tag{23}$$

The marginal cost of funds is derived from the equilibrium indifference condition $\pi(R_{min}) = \pi(R_{max})$ and plugged into the likelihood function

$$\tilde{R} = \frac{R_{\max}(1-h(R_{\max}))\sum_{k=1}^{N} kq_K - R_{\min}(1-h(R_{\min}))q_1}{(1-h(R_{\max}))\sum_{k=1}^{N} kq_K - (1-h(R_{\min}))q_1}. \tag{24}$$

The estimation starts with the support of the equilibrium offer distribution. The minimum and maximum offer rates are estimated with their sample equivalents $\widehat{R_{min}} = min\{R_{j,m,t}\}_{j=1}^N$ and $\widehat{R_{max}} = max\{R_{j,m,t}\}_{j=1}^N$. Given a set of estimates $\{\widehat{q_k}\}_{k=1}^N$, 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)

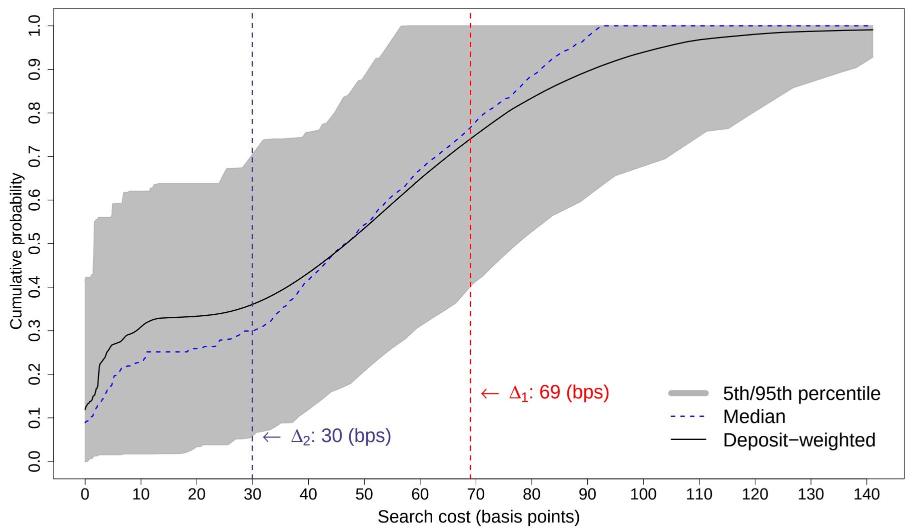
$$\widehat{F_\xi(\Delta_k)} = 1 - \sum_{j=1}^{k}\widehat{q}_k \text{ for } k=1,2,..,N-1. \tag{25}$$

The upper percentiles of the search cost distribution are identified up to Δ_1. Higher percentiles are extrapolated using non-decreasing Hermite polynomials fitted to the set of points $\{\Delta_k, \widehat{F_\xi(\Delta_k)}\}_{k=1}^{N-1}$.

4.3 Estimates of the search cost distributions

The search costs distributions are estimated for 234 MSAs in which at least 20 banks operate at any given time. This selection guarantees meaningful price dispersion and good coverage of banks' branch networks. Because the average outstanding maturity of time deposits on banks' balance sheets is 10 months, the model is estimated using offer rates for the 12-month CD and the estimate of the IES in column (4) of Table (10). The estimates of the distributions of search costs for different markets in 2006 are plotted in Figure (5). For each search cost level the range of cumulative probabilities between 5th and 95th percentile markets is presented as the shaded area. The median and deposit-weighted cumulative densities are presented in dashed blue and solid black lines, respectively. The median search cost is about 50 basis points in the aggregate and exhibits a wide range across markets. The range of search costs also varies between zero and as high as 140 basis points or more, with some markets exhibiting less dispersed search costs, while other markets exhibiting more dispersed search costs.[22]

Figure 5: Estimated search cost distribution



NOTE: The figure is based on estimates of the search cost distribution for June 2006. Values outside the estimates of the critical search costs values are extrapolated using monotone Hermite polynomials. The 5th and 95th percentiles of the search cost distributions across markets 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 search cost cumulative density function.

The shape of the search cost distribution in most markets as well as in the aggregate is bimodal with three distinct groups of investors. The first group are investors with relatively low search costs of less than 15 basis points. This group is about a third of all investors with about 12 percent of investors with search costs that are close to zero. Those are the active low-search-cost depositors that examine the offer rates of most banks in their market. The cumulative search cost distribution remains relatively flat between 15 and 30 basis points, indicating few investors with search costs in this range.

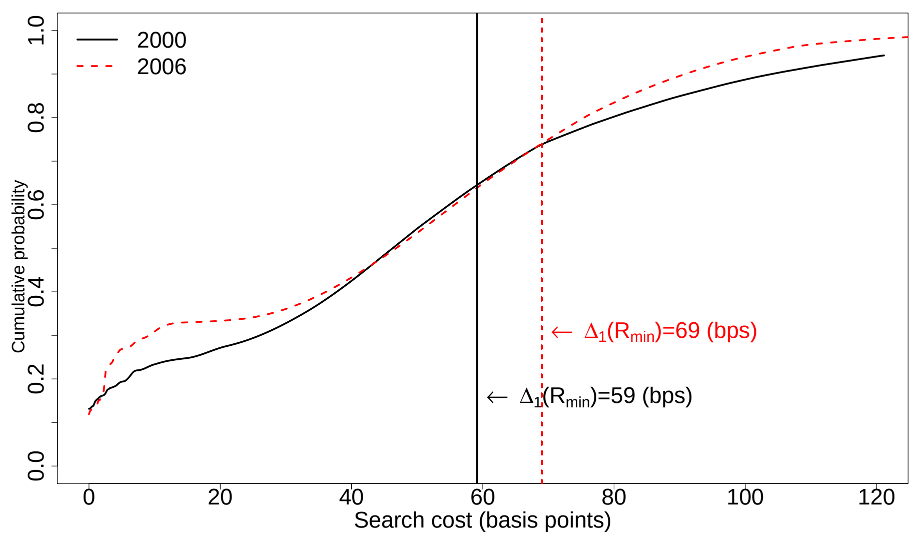
The second group are investors with high search costs exceeding 69 basis points. Those are high-search-cost investors, who do not shop for rates and their share in 2006 was about 30 percent of the population of depositors. The third group of investors lies between the

[22] Note that in the model search costs and the marginal values of information are expressed in utils. To make the estimates easier to interpret, I convert search costs into interest rate equivalents. An interest rate equivalent expresses the marginal value of information as the expected increase in the best offer rate starting. In particular, the interest rate equivalent $\Delta(R_{min})_k$ for sample size k and R_{min} as reference rate 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 $k = 1, 2, .., N-1$.

red vertical line (Δ_1) in Figure (5) and the blue vertical line (Δ_2). In this range of search costs, depositors compare two bank offers and this segment contains about 40 percent of the population of depositors (q_2). The size of this segment of depositors is very sensitive to changes in rate dispersion and increases with higher dispersion.

The estimated segments of depositors and search behavior are close to the observed deposit allocations of households across multiple banks documented in the SCF shown in Figure (3). This is an encouraging validation of the methodology of estimating the search cost distribution, which relies on the deposit offer rates and does not involve quantities.

Figure 6: Search cost distribution



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

The estimated search costs vary across markets and over time. The evidence from the SCF reveals that search for better return on savings is related to an underlying set of preferences and technologies for gathering information. These preferences and technologies change slowly over long periods of time and across different generations of investors. For example, the Internet, 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. The results from the SCF surveys indicate that households that use the Internet for investment decisions became increasingly more likely to own time deposit accounts with multiple banks and the effect becomes statistically significant only in the

2013 survey indicating a relatively slow adoption of such technologies.

To examine the potential effects of the introduction of the Internet on search costs, I examine how the aggregate search cost distribution changes over time. 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 periods when examining search cost estimates. Figure (6) compares the aggregate search cost distribution in the high-dispersion environment of 2000 with that of 2006. Although the median search cost is identical in the two periods at 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. However, despite those changes, there still remains a large fraction of inactive depositors in the later part of the sample. This is consistent with the slow adoption hypothesis and evidence presented in Section (2.7), which reveals that many households do not actively use the Internet as a means to search for better return on their savings.

To understand how the search cost distributions vary over time and across markets, I relate the first and second moments of the search cost distribution to market characteristics and a time trend. Table (11) summarizes the results of this analysis based on two econometric approaches. The first approach, is a two-step estimation that first constructs the mean and standard deviation of the search costs for each market and each period based on a Hermite polynomial fit to the critical points of search cost distribution. I then estimate a panel regression of the moments of the search cost distribution on market characteristics. The second approach is a single-step non-linear least squares estimation that fits a parametric distribution function, the log-normal, to the estimated critical points of the search cost distribution.

The results of the two-step non-parametric analysis shows that a higher share of elderly households, those with age above 65, is associated with higher and less dispersed search costs. In particular, MSA areas with 10 percentage points higher share of elderly households have on average 1 basis points higher search costs and 1.3 basis points less dispersed search-cost distribution. Those results are consistent with the average characteristics of investors in CDs documented in Section (2.7). Markets with larger population have more dispersed search costs reflecting a more diverse groups of households. A larger population per bank is related to higher and less dispersed search costs. Markets with higher share of deposits in total income are also high search cost markets. Finally, the time trend shows a reduction over time in the average search costs and their dispersion. These time trends are consistent with the introduction and adoption of Internet banking and the changing shape of the search cost distribution illustrated in Figure (6). The overall reduction in search costs, however, is relatively small. Over the 15 years of data, the average search cost has declined by about 2 basis points and the standard deviation of search costs has also declined by about 5 basis points.

Table 11: Search cost distribution and market characteristics

	Hermite polynomial fit		*Log-normal fit*	
	Mean	Std.	Mean	Std.
	(1)	(2)	(3)	(4)
Share population age 65+	0.109***	−0.137**	0.098***	0.295***
	(0.033)	(0.066)	(0.002)	(0.009)
log(Population)	0.218	9.068***	0.019***	0.099***
	(0.313)	(0.544)	(0.0001)	(0.002)
log(Population per bank)	0.619*	−2.423***	−0.019***	−0.102***
	(0.372)	(0.659)	(0.001)	(0.002)
log(Income per capita)	0.535	−1.126	−0.008***	−0.054***
	(0.816)	(1.690)	(0.001)	(0.001)
Deposits/Income	0.007***	−0.001	−0.005***	−0.018***
	(0.002)	(0.003)	(0.001)	(0.001)
Time trend	−0.147***	−0.364***	−0.002***	−0.01***
	(0.036)	(0.059)	(0.001)	(0.0002)
Observations	2,472	2,472	81, 727	81, 727
R^2	0.040	0.032		
F Statistic	16.843***	12.355***		
MSE			0.026	0.026

NOTE: Columns (1) and (2) present results from a two-step estimation. In the first step, the critical points of the search cost cumulative density functions for each market and each period are fit to a Hermite polynomial function. The mean and standard deviation are computed as the appropriate integrals of those fitted polynomials. In a second step, the two moments of the search cost distribution are fit to a panel regression with MSA and year fixed effects. Inference is based on a robust variance-covariance matrix estimator with MSA-level clustering (See Arellano (1987)). Columns (3) and (4) summarize results from a one -step estimation that fits a log-normal distribution through the critical search cost points using non-linear least squares. The mean and standard deviation of search costs are assumed to be a linear function of the market characteristics $\mu_\xi(X) = X'_{i,t}\beta^\mu$ and $\sigma_\xi(X) = X'_{i,t}\beta^\sigma$ and the parameters of the log-normal are chosen so that they match the mean and the standard deviation $\mu = ln\Big(\frac{\mu_\xi^2}{\sqrt{\mu_\xi^2+\sigma_\xi^2}}\Big)$ and $\sigma = ln(1 + \frac{\sigma_\xi^2}{\mu_\xi^2})$. Significant at *p<0.1; **p<0.05; ***p<0.01.

The parametric approach are summarized in columns (3) and (4). There are notable differences across the estimates based on the two approaches. For example, the log-normal fit reveals similar sensitivity of the mean search costs to the population of elderly households but it also shows that the dispersion in search costs is incfeases with a higher share of elderly households. Both models predict reductions in the mean and dispersion of search costs over the sample period. However, the log-normal fit shows a much smaller decreases than the non-parametric approach. Those discrepancies are explained by the fact that, even though the non-parametric approach is less efficient than the parametric approach, it allows for more flexibility in fitting the underlying search cost distribution and, in particular, the distinct feature of a bimodal distribution of search costs.[23]

The analysis so far indicates a reduction in search costs since 2000. However, this reduction is not as dramatic as one would have anticipated given the potential cost saving potential related to the adoption of Internet and online banking. 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.[24] This result also confirms the stylized facts in Table (8), 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 CDs, the low adoption rate of the Internet contributed to the relatively unchanged search cost distributions. Finally, the bimodal nature of the underlying search cost distribution captures such differences in search technologies among depositors.

4.4 Search intensity

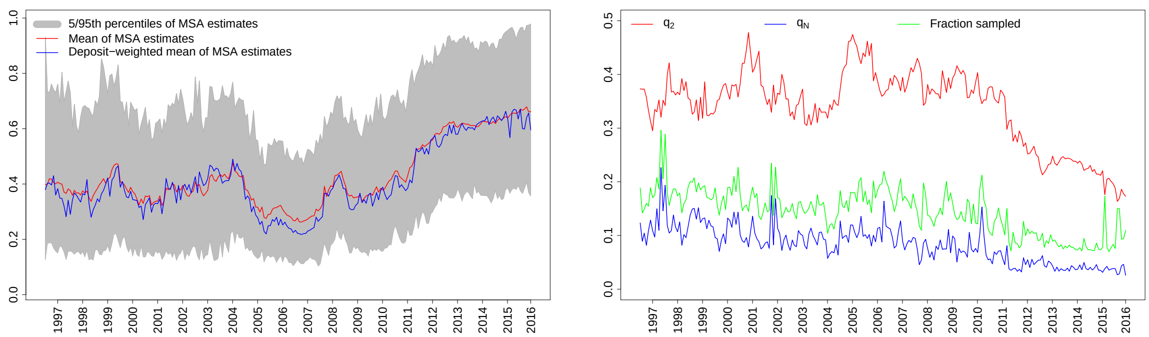
The estimates of the segments of investors based on their search intensities $\{q_k\}_{k=1}^N$ vary across markets and over time. Of particular importance is the the share of uninformed or inactive investors q_1, whose estimates are plotted in Panel A of Figure (7). The weighted average share of inactive investors is large and hovers around 40 percent over the period from 1997 to 2004. The range of estimates of inactive investors across markets varies between less than 20 percent and more than 60 percent. The aggregate share increases in the low interest rate environment of 2001-04 to close to 50 percent. It then drops to less than 30 percent in the increasing and high interest rate environment of 2005-07. However, as the level and dispersion in rates decreases starting in 2008 with market interest rates hitting the zero lower bound, the incentives to search diminish and the share of inactive investors increases across all markets to reach 60 percent for the average market by the end of the sample.

[23]I am thankful to an anonymous referee for suggesting this approach. This non-linear regression approach has been applied in other empirical papers such as Wildenbeest (2011) and Nishida and Remer (2018). The most efficient way to conduct the market-level analysis is to estimate a fully parametric model that combines the market characteristics in a single-step estimation. However, such a model would still not be able to fully characterize the shape of the search cost distribution.

[24]See "Computer and Internet Use in the United States" (2010), U.S. Census Bureau.

Figure 7: Estimates of search intensity

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 distribution of q_1 estimates in the the cross-sectional of MSA markets. 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 calculated as $\frac{1}{N}\sum_{k=1}^{N} kq_k$. Comparing panel A and B, the two segments q_1 and q_2 combined comprise close to 80 percent of investors in most markets. The two segments are also strongly negatively correlated. For example, in contrast to q_1, q_2 increases in the high dispersion environment of 2005-07 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 Δ_1 as can be seen in Figure (5). As Δ_1 increases, a mass of inactive investors find it worthwhile to search for rates and compare the rates of two banks.[25]

The most active investors, those that examine offers of more than two banks, comprise on average 20 percent of the population. Of those, the largest segment is the lowest search cost segment q_N, which observes and acts upon information on all bank offers in the market. 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. The reason for that is that the marginal value of information Δ_{N-1} is insensitive to rate dispersion and constant over time. Therefore, the decline q_N can be attributed to changes in the shape of the search cost distribution and the fraction of low-search cost depositors as illustrated in Figure (6).

Table (12) examines how market characteristics such as demographic composition, size

[25] See the appendix for descriptive analysis on the variation in the marginal value of information over the sample.

Table 12: Search intensity and market characteristics

	Dependent variable: Search intensity share q_k					
	q_1		q_2		q_N	
	(1)	(2)	(3)	(4)	(5)	(6)
Share population age 65+	4.799***	1.451*	−2.263***	−0.145	−1.643***	−0.717**
	(0.537)	(0.874)	(0.727)	(0.638)	(0.590)	(0.350)
log(Population)	−0.402***	−0.404***	0.171*	0.172**	−0.0005	0.0002
	(0.065)	(0.095)	(0.089)	(0.088)	(0.086)	(0.038)
HHI	0.090	0.097	−0.002	−0.006	−0.004	−0.006
	(0.080)	(0.090)	(0.085)	(0.079)	(0.074)	(0.058)
log(Population per bank)	0.186***	0.068	−0.126***	−0.051	0.024	0.057**
	(0.036)	(0.049)	(0.043)	(0.042)	(0.040)	(0.026)
log(Income per capita)	−0.118***	0.042	0.105***	0.004	−0.041	−0.085***
	(0.024)	(0.030)	(0.033)	(0.028)	(0.029)	(0.017)
Deposits/Income	0.001	−0.007	−0.001	0.004	−0.008	−0.006
	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.009)
Range ($R_{max} - R_{min}$)		−7.439***		4.707***		2.059***
		(0.389)		(0.381)		(0.228)
Observations	2,441	2,441	2,441	2,441	2,441	2,441
R^2	0.071	0.238	0.038	0.142	0.032	0.076

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. All panel regressions include MSA market and year fixed effects. Standard errors are based on a robust variance-covariance matrix estimator with MSA level clustering (See Arellano (1987)). Significant at *p<0.1; **p<0.05; ***p<0.01.

of markets, incomes, deposit wealth, and measures of market concentration relate to search intensities. Two sets of regressions with market fixed-effects are estimated separately for the three market segments q_1, q_2, and q_N. The first set of regressions does not condition on rate dispersion, a proxy for incentives to search, whereas the second set includes rate dispersion. As expected, higher rate dispersion measured by the range of rates in a market leads to higher search intensities i.e. lower share of q_1 and higher shares of q_2 and q_N. The share of elderly households of age 65 and remains economically and statistically significant determinant of search intensities across markets even after conditioning on rate dispersion. A higher share of elderly households contributes to a 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 particular, a percentage point increase in the share of elderly households increases the share of inactive investors by about 1.5 percentage points and decreases the share of active depositors by about 0.7 percentage points. A larger population is associated with lower q_1 and higher share of q_2 investors, whereas a higher population per bank increases the share of active investors. Markets with higher incomes have higher shares of q_2 investors, but lower shares of q_N investors. The deposit-to-income ratios do not relate to search intensities. Finally, measures of market concentration such as the Herfindahl-Hirschman Index (HHI) are not statistically significant in explaining search intensities.

4.5 Exit of low-search-cost depositors

The downward trend of the share of q_N investors in Figure (7) indicates a compositional change in depositor types and a potential exit of low search cost depositors. 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, the Internet did not have a significant impact on deposit markets. Younger, wealthier, and more sophisticated households have likely exited the CD market for higher-yielding alternatives such as money market mutual accounts.

The hypothesis of exit of low-search-cost depositors is consistent with the stylized facts in Table (8), which shows that high financial sophistication households, who are also twice as likely to use the Internet and professional advise when making investment decisions, are significantly more likely to own shares in money market, equity, and bond mutual funds. The exit hypothesis is also consistent with findings in Hortaçsu and Syverson (2004) who document a proliferation of S&P 500 index funds over the period 1995-2000 with significant fee dispersion. They attribute these trends to the entry of novice investors with high search costs. Although their focus is on S&P 500 index funds, they also document similar patterns of high fee dispersion in the retail money market mutual funds (MMF).

The MMF industry developed as a response to binding interest-rate ceilings on deposits under Regulation Q during the high-inflation period of the late 1970s. Even after the repeal of most of Regulation Q ceilings, MMFs continue to compete with banks by providing access to a relatively safe and high-interest-earning alternative to bank deposits. The low-search-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 heterogeneity in investor types in the MMF market is not without empirical support. 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 investors who remain inactive. To the extent that the heterogeneity in price elasticities is related to the heterogeneity in 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, which are money funds that

Table 13: Distribution channels, expense ratios, and bank-affiliation of MMFs

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

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

are advised, managed, and sponsored by major bank holding companies.[26] Table (13) shows that in 2006 more than $300 billion of the $950 billion retail MMFs were 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. This allows banks to steer the active depositors into their affiliated money market funds. In contrast, non-bank affiliated MMFs attract investors either directly or through non-bank affiliated brokers and advisers.

The composition of distributional channels allows banks to retain the monopoly pricing of their deposit deposit products and extend their monopoly pricing to MMF product offerings. Indeed, bank-affiliated funds charge, on average, 10 basis point higher fees as compared to unaffiliated funds. The difference is even larger for direct investments with bank-affiliated funds charging on average 25 basis points higher fees than unaffiliated funds. The dispersion in fees is also much larger for bank-affiliated as compared to unaffiliated funds across most distributional channels. For example, the dispersion in fees measured by the difference in the 95th and 5th percentiles for direct distribution channels is 137 basis points for bank-affiliated funds and only 62 for unaffiliated funds. The large dispersion in fees is consistent with the presence of search costs and monopoly mark-ups exploited by retail bank-affiliated MMFs.

In contrast to retail investors, the average asset-weighted fees charged to institutional

[26] Kacperczyk and Schnabl (2013) document that many bank-affiliated funds received support from their 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.

investors are identical for bank-affiliated and unaffiliated funds, and significantly below retail fund fees. The asset-weighted average fee is 27 basis points or more than half the average fee charged by retail funds. The magnitude of fee dispersion is similar between the bank-affiliated and unaffiliated funds indicated less heterogeneity in search costs among institutional investors.[27]

4.6 Asymmetric and incomplete pass-through

Let us next examine how well the model matches the incomplete pass-through of changes in market rates into deposit rates. We can use equation (14) for the case of $\sigma = 1$ to obtain a closed-form expression for interest rate pass-through across the percentiles of the equilibrium offer rate distribution

$$\begin{aligned} \frac{\partial R_{max}}{\partial \tilde{R}} &\approx 1 - \frac{q_1}{\sum_{k=1}^{N} k q_k} \\ \frac{\partial R(z)}{\partial \tilde{R}} &\approx 1 - \frac{q_1}{\sum_{k=1}^{N} k q_k z^{k-1}}, \text{ for } z \in [0,1]. \end{aligned} \tag{26}$$

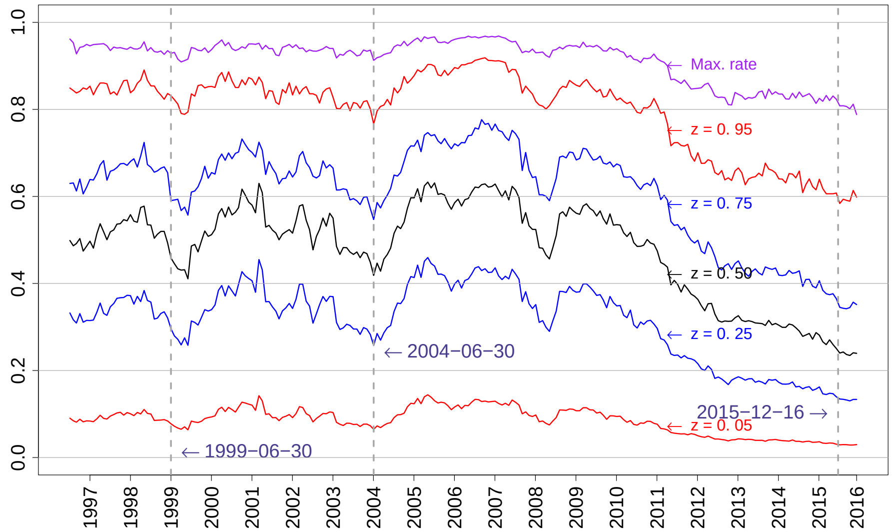
Interest rate pass-through in the model is determined by the intensity with which depositors shop for rates. Pass-through decreases with the share of inactive depositors and declines monotonically for lower percentiles of the distribution, keeping search intensity fixed. This is consistent with the stylized facts observed in Figure (1) in which the lower percentiles of the rate distribution are relatively less sensitive to changes in market rates, whereas the upper percentiles are significantly more responsive. Furthermore, because incentives to search respond to price dispersion, pass-through in a low dispersion environment is much lower than in a high dispersion environment.

To visualise the variation in pass-through, Figure (8) plots the time series variation of the model-implied interest rate pass-through. Pass-through increases with higher percentiles of the distribution. The average pass-through over the sample period for the median rate is about 50 percent, and the upper and lower quartiles are at 36 percent and 67 percent, respectively. Those estimates are in the ballpark of estimates in the literature. For example, Driscoll and Judson (2013) and Drechsler, Savov, and Schnabl (2017) document a pass-through of 54 percent for small time deposits.

The three vertical lines indicate the beginning periods of monetary policy tightening. In June 1999 and June 2004, the start of the tightening of monetary policy coincided with roughly similar pass-through across all the percentiles of the deposit rate distribution. Pass-

[27] These findings are not surprising given that institutional funds are comprised of large investors with minimum investments exceeding $1 million and investment decisions are often made by sophisticated corporate treasury departments.

Figure 8: Model-implied pass-through



NOTE: The pass-through of marginal costs to percentiles of the deposit rate distribution ($z \in \{0.05, 0.25, 0.5, 0.75, 0.95, 1\}$) are based on the monthly estimates of the structural model. The three vertical lines indicate the dates of increases in the target federal funds rate following a period of constant target.

through is usually low at the start of monetary policy tightening and it was significantly lower in December 2015. The reason for this difference is that the prolonged period of very low interest rates with the federal funds rate close to its zero lower bound compressed the dispersion in deposit rates and, hence, the incentives for search as already documented in Figure (7). The reductions in pass-through is also notable for the maximum rate, which normally hovers around 90 percent, but, by December 2015, declined to about 80 percent. The model can rationalize the incomplete and asymmetric pass-through of interest rate increases and decreases documented in Section (2).

4.7 Market concentration and deposit pricing

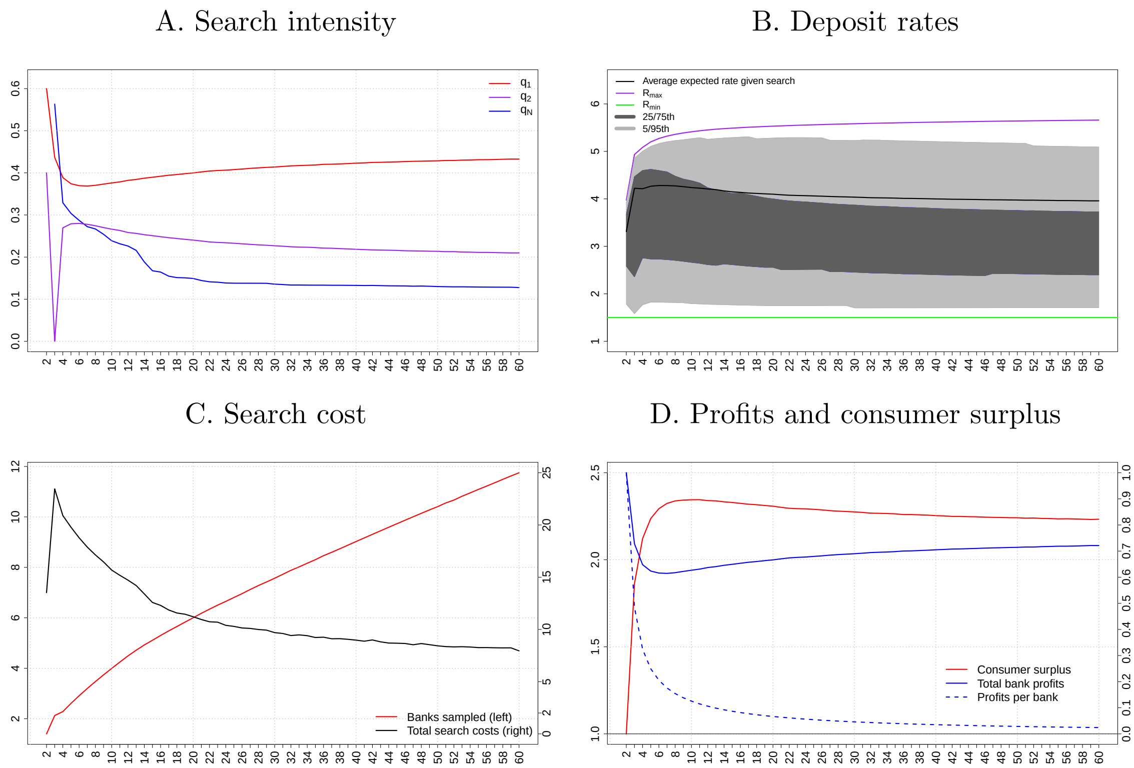
A change in the number of competitors would affect deposit pricing only if it leads to changes in the equilibrium search behavior. Because search costs are invariant to changes in the number of competitors, search behavior would change if there are significant changes in the equilibrium offer rate distribution that would alter the incentives to search. Let us examine how changes in the number of banks affects market outcomes. For this analysis, I use the estimate of the aggregate search costs based on data from 2006 reported in Figure (5), which reveals dispersed search costs with a distinct mass of depositors with low search costs and a distinct mass of depositors with high search costs. I also use the estimated marginal cost for 2006, which averages at 581 basis points. I compute the resulting equilibrium numerically by gradually increasing number of banks starting from a duopoly setting to a market with 60 competing banks.

Panel A of Figure (9) reports the effects of the changes in the number of competitors on search intensity. In the case of two banks (duopoly), the equilibrium search is characterized by a large segment of inactive depositors q_1 representing 60 percent of all depositors. As the number of banks increases, this segment first decreases, after which it gradually increases to reach 45 percent for a market with 60 banks. At the same time, the segment of the most active investors q_N, who sample all bank offers, gradually declines from around 57 percent for markets with 3 banks to less than 12 percent for a market with 60 banks. The segment of investors q_2, who sample 2 bank offers, gradually declines with increases in the number of banks.

Panel B shows how changes in the number of banks affects deposit pricing. The minimum deposit rate is a proxy for the reservation rate of depositors and is set to 150 basis points based on the average minimum rate observed in 2006. The equilibrium maximum rate is computed from equation (14). The maximum rate increases with the number of banks gradually approaching the marginal cost. The the 75th and 95th percentiles also increase rapidly and peak at about 6 banks. The 75th percentile peaks at about 4.5 percent and then declines to about 3.5 percent at 60 banks. In contrast, the 90th percentile remains stable at around 500 basis points. The difference between the 95th and the 5th percentile, a measure of price dispersion, also remains relatively stable at about 349 basis points. The equilibrium search and the equilibrium rate distribution imply that that the average expected rate increases initially with the number of banks and peaks at around 428 basis points for a market with 6 banks. It then gradually declines to about 396 basis points.

An increase in the number of banks leads to an increasing equilibrium dispersion in rates creating incentives to search, which are counterbalanced with the increasing cost of sampling multiple bank offers. In panel C, we can see that as the number of banks increases, so does the average number of banks sampled reaching 12 banks for a market with 60 banks. The total search costs are at around 13 basis points for a duopoly market. At three banks, total search costs jump to 23 basis points because all active depositors examine all three bank offers and active depositors represent more than 55 percent of the share of depositors. As the number of banks increases, the total search cost declines because of the decline of the share of depositors who sample all bank offers. Total search cost reach about 8 basis points for a market with 60 banks. As shown in panel D, after a rapid decline of profits following a transition from a duopoly to a market with 6 banks, bank profits gradually

Figure 9: Effect of changes in the number of banks on market outcomes



NOTE: The figure is based on a counterfactual simulation of the effects of changes in the number of banks on market equilibrium. The analysis uses the estimate of the aggregate search cost distribution for 2006 shown in Figure (5).

increase with additional entry of competitors. This is due to the fact that the segment of inactive depositors increases and this increases banks' monopoly power and ability to sustain an offer rate distribution tilted toward lower rates. The expected profits per banks, however, decline monotonically with the number of banks. The increase in the number of banks initially raises rapidly consumer surplus, which peaks at 7 banks, before gradually declining to a level still significantly above the duopoly case. The decline in surplus is due to the lower expected rate.

The estimated model reveals a nonlinear effect of the number of competing banks on deposit pricing and consumer welfare. Unlike the standard models assumed in the literature, increases in the number of competitors does not always benefit consumers especially if search costs are dispersed and feature a large segment of high-search cost consumers. The findings in this section are consistent with findings in Moraga-González, Sándor, and Wildenbeest

(2017) who show that when search costs are dispersed, entry of more competitors could lead to higher prices and lower consumer welfare, which is opposite to what a Cournot model of competition would predict.

4.8 Search costs and deposit pricing

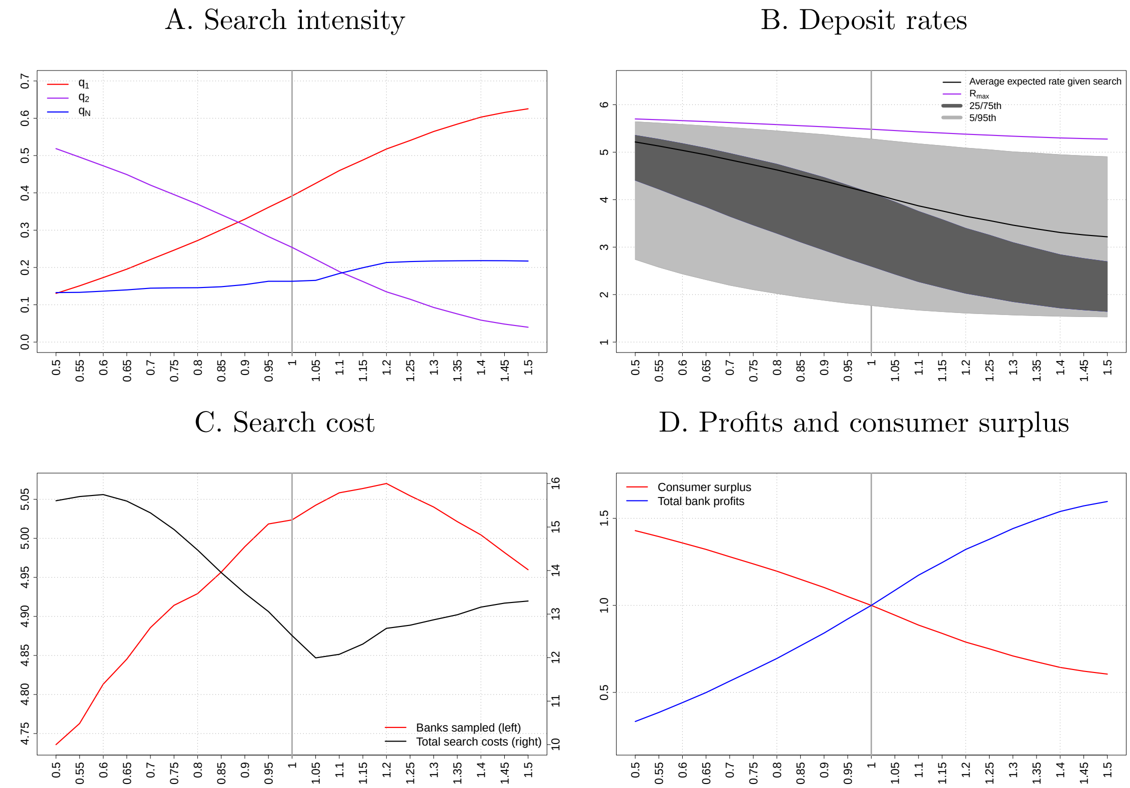
In this section, let us take the number of banks as given and examine how changes in search costs affect market outcomes. In particular, let us pick a market with 15 competing banks, which is the median number of banks per market in 2006, and let us assign the aggregate search cost distribution estimated for 2006 as our baseline. Next, let us assume that a technological shock scales the search costs of all depositors by a factor that is allowed to vary from 0.5 to 1.5. This transformation preserves the shape of the original search cost distribution but changes the mean and dispersion of search costs. A factor below 1 decreases the magnitude and standard deviation of search costs, whereas a factor above one increases search costs and their standard deviation.

The results of this analysis are presented in Figure (10). As expected, in panel A, increases in search costs decrease the incentives to search and increase the share of inactive depositors q_1 mostly because depositors who examine at most two offers q_2 find it too costly to search and become inactive. Somewhat counter-intuitively, however, the share of investors who sample all banks increases slightly as search costs increase. This is due to the effects of search costs on the pricing of deposits. As the share of inactive depositors increases, banks' charge on average lower rates reducing the offer rate distribution. The maximum rate also decreases but by a smaller factor. As a result, some of the low search cost depositors, who sample more than two banks but less than all banks in a market, find it optimal to search all banks to be guaranteed to obtain the maximum rate and the share of q_N increases. Overall, increases in search costs pushes the interquartile range of offer rates well below the maximum rate. The average expected rate given search also declines with higher search costs as the share of inactive depositors increases.

Despite the significant effect of changes in search costs on search intensity, on balance, the average number of banks sampled remains relatively stable at around 5 banks as shown in panel C. Somewhat counter-intuitively, the total search costs are the highest when search costs are scaled down the most. This is due to compositional effects. When search costs are low, there is a larger fraction of active depositors with relatively high individual search costs. For example, more than half of depositors examine at least two bank offers when search costs are reduced by 40 percent or more. This leads to a total search cost of about 16 basis points aggregating across all depositors who examine at least two offers. In contrast, when search costs are scaled above one, the increase in aggregate search costs are moderated by the switch of the relatively high-search cost depositors from searching to not searching.

As a result, the scaling of search costs by 50 percent leads to a smaller increase in the total incurred search costs.

Figure 10: Effect of changes in the search cost distribution



NOTE: The figure is based on a counterfactual simulation of the effects of changes in search costs starting from the baseline of the aggregate search cost distribution shown in Figure (5). Search costs are scaled by a factor ranging from 0.5 to 1.5 with the extremes reducing search cost by 50 percent or increasing search cost by 50 percent, respectively.

Finally, examining panel D, an increase in search costs has a expected negative effect on consumer surplus and positive effect on bank profits. Bank profits are more sensitive to changes in search costs. Profits increase by more than 50 percent when search costs increase by 50 percent and decrease by more than 50 percent when search costs are decreased by 50 percent. Consumer surplus declines with the increases in search costs. However, the sensitivity of consumer surplus to changes is search costs is lower than that of profits in part reflecting the endogenous search intensity and incurred total search costs.

5 Conclusion

Interest rate ceilings on most deposits were repealed by 1986, allowing banks to offer higher deposit rates to compete both with other banks as well as with close deposit substitutes such as money market mutual funds. As a result, the post 1986 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 for a homogeneous financial product with a large number of competitors and available close substitutes such as shares in 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 the asymmetric incomplete pass-through of changes in market interest rates into deposit rates. Furthermore, I have provided evidence that banks have expanded their market power in both deposit markets and through their affiliated money market mutual funds to close substitutes of deposits. The results of this paper are important for understanding how recent financial innovations such as stablecoins and the introduction of a central bank digital currency would affect the banking system and its ability to retain deposits and market power in the face of emerging new deposit substitutes.

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Appendix not for publication
"In Search of a Risk-free Asset"
Vladimir Yankov[28]

This appendix is not intended for publication but to supplement the analysis in the main text and provide the reader with a means to replicate the results of the paper or gain more insight into the data construction and technical analysis. Wherever possible, the author has available code and data for replication purposes that he can share upon request.

A Data construction

A.1 Deposit pricing and market concentration

The main dataset on deposit rates is a novel proprietary database constructed by Rate-Watch which contains the yields on the certificates of deposit (CDs) at weekly frequency over the period of 1997-2016 offered over 6,000 FDIC insured commercial banks in over 80,000 local branch offices in over 10,000 cities across the US covering all 366 Metropolitan Statistical Areas (MSA). The survey represents more than 90 percent of deposits in commercial banking. [29] The dataset contains offer rates on the full range of deposit products such as interest checking accounts, savings accounts, money market deposit accounts, and certificates of deposits.

For the purpose of this study I focus on the small denomination CDs as these were consistently covered by the FDIC insurance. The yield information on deposits of denomination less than $\$100,000$ is almost consistently covered by all banks in the sample. I define the geographic boundaries of a deposit market to coincide with the boundaries of an MSA area. As a result the sample of banks is reduced to 3,796 as I exclude a number of small community banks that operate in small towns not included in a MSA area.

One major obstacle to constructing a consistent panel dataset is that RateWatch only maintains the most recent ownership relationships between branches, banks, and their parent holding company. To properly assign a branch to its bank owner, I use the available unique identification number (ID RSSD) and match that number to a database of historical bank-branch ownership maintained by the National Information Center (NIC).[30] Such correction is important as many branches change ownership due to mergers and acquisitions

[28]The Board of Governors of the Federal Reserve System, 20th Street and Constitution Avenue N.W., Washington, D.C. 20551. Views expressed in this paper do not reflect the official position of the Federal Reserve System. E-mail: `Vladimir.L.Yankov@frb.gov`.

[29]http://www.rate-watch.com/

[30]See https://www.ffiec.gov/nicpubweb/nicweb/SearchForm.aspx

and the NIC database allows to pinpoint the exact date of ownership change and the identities (ID RSSDs) of the acquiring banks. I verify the goodness of the match by using the FDIC Summary of Deposit database, which provides annual snapshots of the bank-branch ownership relationships.

A.1.1 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 (14) 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) and 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 an MSA. For the rest of the analysis, I define a geographic market to correspond to an MSA area.[31]

Table 14: Rate-setting branches in 2007

Institution (BHC)	Rate-setting branches (1)	Coverage of rate-setting branches: Locations (2)	MSA (3)	States (4)	Distance (km) (5)
Bank of America	33	159.1	9	1.1	138.4
JPMorgan	43	58.5	3.8	1.1	69.8
Wachovia	50	46.4	3.5	1	57.6
Wells Fargo	36	86.8	5.7	1.1	127.3
Citigroup	14	37.6	3.4	1.3	73.4
USB	113	18.8	2.3	1.2	52.4
Suntrust	27	67.1	4.9	1.3	70.9
National city	65	36.1	3.4	1.2	38.1
Regions	40	77.0	8.6	2.0	130.8
BB&T	14	99.9	9.1	1.1	149.1

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 SOD.

[31] See also Becker (2007) for a discussion on the degree to which deposit markets are geographically segmented and the appropriateness of an MSA as a well-defined geographic deposit market.

A.1.2 Deposit funding and market penetration of large bank conglomerates

At $1.25 trillion outstanding in 2007, the market for small time deposits is large with a significant number of competitors and several close substitutes offered by non-bank financial institutions.[32] As documented in Table (15), time deposits are an important source of funding for banks. For most banks, more than one third of total deposit funding was in the form of time deposits, and close to half of time deposits were small fully insured retail deposits. For example, in 2007, Bank of America, the largest deposit-taking bank at the time, had over 40 million fully insured deposit accounts with an average balance of $6,000. As a comparison, uninsured accounts were 771,000 with an average balance close to four times the deposit insurance limit. More than 20 percent of deposits were time deposits and close to 50 percent of time deposits were insured.

[32] The market for close substitutes within the M2 aggregate, net of M1, totaled $6 trillion, of which $900 billion was invested in retail money market funds. As a comparison, the publicly traded government debt was around $4 billion in 2007.

Table 15: Deposit funding composition at the largest 20 bank holding companies as of June 30, 2007

Institution	Assets	Deposits	Time	Insured deposits			Uninsured deposits		Branches	Markets	States
(BHC)		(total)	deposits	Share	Accounts	Balance	Accounts	Balance		(MSA)	
	($bln)	($bln)	(% total)	(%)	(1,000)	($1,000)	(1,000)	($1,000)			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bank of America	1,536	594	29.9	49.5	47,485	6	771	378	5,370	212	36
JPMorgan Chase	1,458	463	28.7	26.6	17,071	6.3	400	746	3,047	136	31
Wachovia	720	391	33.3	46.5	22,495	5.9	370	414	3,241	170	30
Wells Fargo	540	286	15.2	46	33,833	3.6	313	450.5	2,873	151	32
Citigroup	2,221	238	22.4	45.7	13,142	5.1	114	698.7	990	59	20
Suntrust	180	114	39.4	61.5	5,923	11	134	304.7	1,652	70	12
USB	223	112	23.8	43.9	8,959	5.8	126	522.5	2,208	139	27
Regions	138	88	33.5	58.8	4,535	7.3	77	301.5	1,778	100	16
National City	141	82	34.7	53.4	5,647	7.2	90	394.3	1,377	61	8
BB&T	128	82	42.9	45.7	5,283	6	94	397.4	1,347	85	15
Capital One	146	82	35.1	20.9	3,052	0.9	45	219	675	30	8
PNC	126	73	26	49.5	4,257	6.6	68	420.6	1,106	60	29
Fifth Third	101	66	25.1	47.3	4,445	6.5	72	442.9	1,170	55	12
Keycorp	93	57	31.4	52.9	3,409	8.1	67	370.3	864	69	14
Commerce	48	45	12.6	40.8	2,982	4.2	33	544	438	15	10
Comerica	59	42	31.2	28.4	1,261	9.7	47	654.1	392	29	6
Zions	49	34	22.2	36.7	1,242	7.3	43	367.4	450	43	11
Marshall & Isley	58	32	39.3	42.1	1,115	8.8	28	485	317	32	12
BNY	126	28	69.1	21.9	1,388	6.1	33	925.7	12	5	6
Popular	47	25	43.1	57	4,871	2.7	31	320.7	147	12	7
Other (asset-weighted)	12.8	6.7	42.9	47.5	331	9.3	7	496.5	92	11	5

NOTE: Columns 2-4 present the total assets and deposits in billions of dollars consolidated at the bank holding company level, as well as the share of time deposits in total deposits, respectively. Columns 5-7 show the percent of total deposit balances in accounts below the deposit insurance limit ($ 100,000), the total number of such accounts in thousands, and the average balance in such accounts in thousands of dollars. Columns 8 and 9 show the number of accounts with balances above the deposit insurance limit. Finally, columns 10-12 present the total number of branches as well as the number of MSA markets and states in which the bank has branches. The last row "All other banks" gives the deposit weighted average for all banks other than the largest 20. SOURCE: FR Y-9C, Call Reports, Summary of Deposits

A.1.3 Price and nonprice terms of certificates of deposit

Table 16: Price and non-price characteristics of CDs

		3-month	6-month	1-year	3-year	5-year
Min. deposit amount	median	1000	1000	1000	1000	1000
	mean	1642.35	1444.53	1325.50	1361.67	1795.41
	std	1959.57	1721.50	1490.28	1556.77	2430.28
Early withdrawal penalty (days)	median	90	90	180	180	180
	mean	70.32	96.35	151.62	201.18	246.67
	std	27.91	37.87	58.14	76.75	157.86
Yield	median	2.86	3.75	4.00	3.90	4.07
	mean	2.88	3.59	3.81	3.80	4.06
	std	1.22	1.20	1.07	0.88	0.83
		Spearman rank correlation				
Min.amount - yield	Rank corr.	-0.10	-0.01	0.02	-0.01	0.05
	p-value	0.35	0.93	0.85	0.94	0.63
Penalty (days) - yield	Rank corr.	-0.31	-0.15	-0.10	0.09	0.17
	p-value	0.00	0.15	0.31	0.41	0.11
Min.amount - penalty (days)	Rank corr.	0.03	0.00	-0.19	-0.21	-0.13
	p-value	0.77	0.99	0.07	0.06	0.22

NOTE: The table gives summary statistics for the minimum deposit to open a CD account, the penalty fees for early withdrawal, and the the yield. The data are based on a survey of CD contracts offered by the 10 largest banks in the 10 largest deposit markets in the U.S. conducted by BankRate Monitor in 2006. The penalty fee is stated in days of accrued interest. The lower panel of the table contains the pair-wise Spearman rank correlations and the corresponding p-values using the Sidak correction. SOURCE: BankRate Monitor

Time deposits or certificates of deposit (CD) are arguably the most homogeneous interest-paying deposit product offered by banks. Similar to a Treasury bond, and unlike an interest checking or savings account, a certificate of deposit is a fixed-income instrument with a pre-determined maturity. The standard maturities that banks offer are 3-months, 6-months, 1-year, 2-year, 3-year and 5-year. Terms rarely exceed 5 years. Certificates of deposits are offered in small denomination with balances below \$100,000 and in large (jumbo) denomination with balances above \$100,000.[33] CDs differ from government bonds in terms of their taxation, liquidity, and riskiness. Unlike government bonds, certificates of deposits are taxed both at the state and at the Federal level. Without a secondary market and large early withdrawal penalty fees, retail CDs are significantly less liquid than a Treasury bonds.

Table (16) provides summary statistics on the price and nonprice terms for a set of contracts offered by the ten largest banks in the ten largest deposit markets. The data are based on a survey conducted by BankRate Monitor in 2006. While there is some variation in the two nonprice terms, minimum amount to open an account and the penalty for early withdrawal, such nonprice terms are not reflected in the offer rates. In particular, the

[33]Until October 3, 2008 the FDIC insurance limit per depositor per bank was \$100,000. Since then it was set to \$250,000.

last three rows show the Spearman correlation coefficient between the yield and the two nonprice terms of CD contracts— the minimum amount to open an account and the penalty fee for early withdrawal. The correlation between the yield and the nonprice terms is very small and statistically insignificant. The correlation between the penalty fee and the yield is statistically significant only for the 3-month CD contract. However, the negative correlation of -0.31 goes against the intuition that high penalty fee contracts should compensate for the reduced liquidity with a higher yield. The early withdrawal penalty fees are usually not explicitly advertised and remain a shrouded attribute of the contract.

A.2 Deposit market concentration

Despite the considerable consolidation of the banking industry since the 1994 Riegle-Neal Act, the number of commercial and savings banks exceeded 7,000 institutions in 2007. Moreover, as a result of the consolidation the number of multi-state banks competing in the same states or metropolitan statistical area (MSA) increased as many banks expanded their operations. As shown in the last three columns of Table (15), by 2007, the 20 largest bank holding companies had expanded their operations in multiple states and major Metropolitan Statistical Areas (MSA). By measures of concentration, most MSA markets remain with relatively low market concentration. For example, the median MSA market has HHI of about 11 percent in 2007 and the interquartile range varies between 8 and 14.

Table 17: Summary statistics of MSA markets, 2007

	min	p25	p50	p75	max
Population	55,288	144,712	252,442	560,032	18,572,325
Share population age 65 plus	5.69	10.87	12.59	14.16	31.77
Income per capita	18.82	30.95	34.00	38.07	80.14
Deposits per capita	6.56	15.60	19.80	28.00	244.80
Number of banks	5	20	27	42	252
Number of branches	15	88	123	228	4,190
HHI index	3.21	7.95	10.91	14.24	68.19

NOTE: Summary statistics are constructed for 2007. The first three rows are variables constructed from the Census Bureau data. The last four rows are variables constructed from the Summary of Deposit Database. The Herfindahl-Hirschman Index (HHI) index is constructed as the sum of squared deposit market shares and takes values from 0 (the least concentrated) to 100 (the most concentrated).
SOURCE: Census Bureau and the Summary of Deposits, 2007

The existing literature has emphasized market concentration measures such as the HHI index as a sufficient statistic to capture monopoly power and the degree of interest rate pass-through.[34] The use of the HHI index can be rationalized in a model of Cournot competition with differentiated products. All else equal, in those models increases in the number of competitors decreases market concentration, decreases banks' monopoly power, and increases interest rate pass-through.

Let us establish a few facts about deposit market concentration over the sample period. Figure (11) presents information on two measures of market concentration—number of competing banks in panel A and the HHI index in panel B. The baking industry has undergone significant consolidation over the past three decades spurred in large part by deregulation following the passing of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994. As a result of consolidation, the total number of bank holding companies in my sample declines from around 5200 at the beginning of the sample to less than 4200 by the end of 2016. However, the total number of banks in the median market increases over the sample period from 12 banks in 1997 to 16 banks in 2016. Similarly, the number of banks in the largest markets by total deposits increases from 51 to 61 banks over the same period. These opposing trends are consistent with the fact that the consolidation in the banking industry was driven by the expansion of the geographic scope of large banks.[35]

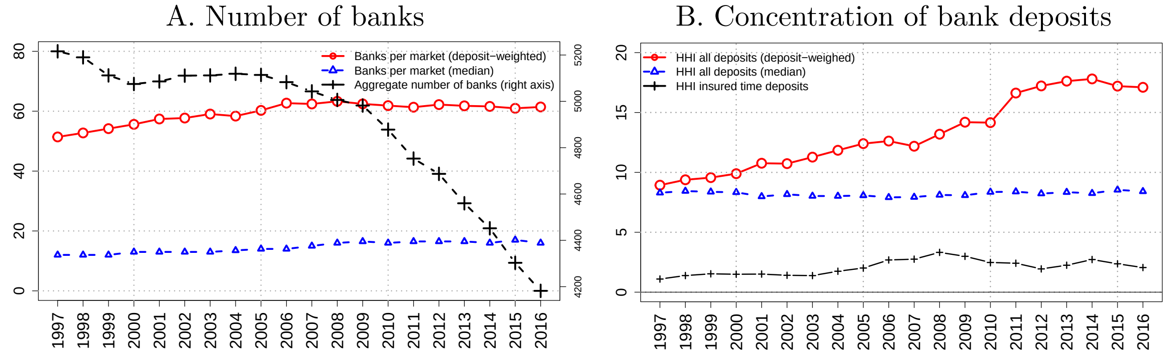
Panel B shows the time series of the deposit-weighted and the median HHI index for total deposits. The aggregate HHI based on the a deposit-weighted HHIs of individual markets shows that the index has doubled over the sample period from around 8 to more than 16. At the same time, the median MSA market HHI experienced little change over the sample period and hovered around 8. There are also notable differences in the average HHI for insured time deposits relative to total deposits.[36] Although the HHI of time deposits increases over the sample period along with the deposit-weighted average of individual markets, its level remains substantially below the HHI indices for total deposits. This could reflect both the fact that HHI for time deposits can only be computed at the bank level as well as the fact that unlike transaction deposits, households are more likely to hold time deposits in multiple banks as documented in section 2.7 and consistent with search for better return.

[34] See Berger and Hannan (1989),Hannan and Berger (1991), Neumark and Sharpe (1992), and Drechsler, Savov, and Schnabl (2017) for analysis of the relationship between market concentration and deposit pricing.

[35] The divergent trend in aggregate and market-level concentration is a phenomenon observed not only in the banking industry, but also across multiple industries as documented by Rossi-Hansberg, Sarte, and Trachter (2021). See Table (15) in the Appendix for summary statistics of the geographic scope of the largest bank holding companies.

[36] Unfortunately, the FDIC Summary of Deposits dataset contains bank-branch-level information only for total deposits. Therefore, I can only compute the HHI index for time deposits at the bank level.

Figure 11: Measures of market concentration



NOTE: Panel A computes the number of competing banks at the MSA market level based on deposit-weighted mean and the median market. The black line shows the total number of competing banks across all markets. Individual commercial bank subsidiaries are consolidated at the top holder holding company. Panel B shows the median and deposit-weighted HHI index based on total deposits across MSA markets. The black line shows the HHI index for insured time deposits, defined as total time deposits with deposit balances below the relevant deposit insurance limit at the time of reporting.
SOURCE: FDIC Summary of Deposits, FR Y-9C, and Call Report data.

A.3 Survey of Consumer Finances

A.3.1 Deposit allocations

To conduct the analysis in Section (2.7), I use the publicly available version of the Survey of Consumer Finances (SCF). The Federal Reserve provides a "Summary Extract Public Data", which contain a set of derived items such as total assets, total debt, net worth, total financial assets, and financial assets breakdowns by asset class. To construct deposit allocations across different bank accounts, I use the reported allocations of deposits across different deposit account types—interest checking, savings, and certificates of deposit, and across different institutions and institution types reported in the raw data. For example, to construct the distribution of investments in CDs across contracts and bank accounts in Figure (3), I use the following items from the raw data

1. X3720: Altogether, how many such CDs do you (and your family living here) have?

2. X3721: What is the total dollar value of (this CD/these CDs)?

3. X3726: How many different institutions do you use for all these CDs?

4. (X3722 X3723 X3724 X3725 X7618 X6654 X6655): Please look at the list of institutions you wrote down. (Is this/Are these) CD(s) with any of the institutions on the list, or from someplace else?

5. (X9134 X9135 X9136 X9137 X9214 X9217 X9218): Type of institution,

where in items 4 and 5 respondents record which institution they hold the CD from a masterlist of institutions and the type of institution (i.e. commercial bank, credit union, mutual fund etc). To identify whether a CD contract is held with a main checking-account bank, I check if the institution matches the bank where the household holds the largest checking account balance.

A.3.2 Financial sophistication index

To construct the financial sophistication index, I use a set of categorical and quantitative characteristics of households related to their financial wealth management. The set of quantitative characteristics are

- Share of interest and dividend income in total income
- Share of risky assets in total financial assets, where risky assets are defined as direct holdings of equity, corporate bonds, and shares in equity and bond mutual funds.
- Diversity of financial asset holdings measured as the Herfindahl index of different asset category holdings.

The set of categorical (qualitative) characteristics take a true or false value

- Use of professional advise (lawyer, accountant, banker, broker, or financial planner) on decisions related to borrowing and saving
- Direct holdings of equity
- Excellent understanding of the SCF questionnaire
- Ownership of a brokerage, MMF, or other mutual fund accounts
- Willingness to take above average financial risks
- Time period for planning or budgeting of saving and spending that exceeds 5 years.

The financial sophistication index is then computed as the first principal component of those two sets of variables. The table below presents summary statistics of the index.

Table 18: Summary statistics for the financial sophistication index

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
−2.34	−1.66	−0.66	0.00	1.60	6.17

Table (19) reports the R-squares and factor loadings of the financial sophistication score on its underlying variables. It is interesting to note that most of the variation in the financial sophistication score is related to the share of risky assets and its different components. The second principal component, not shown, has high correlation with variables related to the use of professional advice.

Table 19: Factor loadings on financial sophistication score

Variable	R-sq	Loading	Std.error
Share interest and dividend income	0.154	0.019	0.0003
Share risky assets	0.490	0.093	0.001
Financial assets HHI	0.047	−0.063	0.002
Use of professional advice (borrowing)	0.073	0.092	0.002
Use of professional advice (investment)	0.047	0.074	0.002
Own equity	0.623	0.234	0.001
Own brokerage account	0.468	0.169	0.001
Own MMF	0.190	0.066	0.001
Own Mutual fund	0.480	0.153	0.001
Excellent understanding of SCF	0.057	0.084	0.002
Above average risk-taking	0.119	0.097	0.002
Long planning horizon (greater than 5 years)	0.121	0.118	0.002

Source: Survey of Consumer Finances, 2007 and author's calculations.

B Maximum likelihood construction and estimation

B.1 Construction

The indifference condition implied by the symmetric mixed strategies equilibrium allows us to construct a likelihood function of observing a particular offer rate. To do so, we equate profit function at the lowest bound of the support with any rate in the support must be the same $\pi(R) = \pi(R_{min})$ for all $R \in S$. Using this equilibrium condition, we can construct a function which relates an offer rate with the observed percentiles of the equilibrium distribution $F = F(R)$.

$$G(R,F) = \psi(R)\Big[\sum_{k=1}^{N} kq_k F^{k-1}\Big] - (\tilde{R} - R_{min})(1 - h^d(R_{min}))q_1 = 0$$

Applying the implicit function theorem to the equation above gives us an expression for the likelihood function

$$f_R(R|\sigma, \{q_k\}_{k=1}^N) = \frac{-\psi'(R)}{\psi(R)} \times \frac{\sum_{k=1}^N kq_k F_R(R)^{k-1}}{\sum_{k=1}^N k(k-1)q_k F_R(R)^{k-2}}. \tag{27}$$

To guarantee that the likelihood function is a proper probability density function (i.e. $f_R(\cdot) \geq 0$), the derivative of the profit function needs to be negative $\psi'(R) < 0$. The derivative of the profit function is

$$\psi'(R) = -(1 - h^d(R))\Big(1 + (1-\sigma)\frac{\tilde{R} - R}{R} h^d(R)\Big). \tag{28}$$

The derivative is always negative for $\sigma < 1$. For $\sigma > 1$, one has to check the following condition $1 + (1-\sigma)\frac{\tilde{R}-R}{R}h^d(R) > 0$ which imposes an upper bound on σ

$$\sigma < 1 + \frac{R_{min}}{\tilde{R} - R_{min}} \frac{1}{h(R_{min})}. \tag{29}$$

For all plausible values of $(\tilde{R}, R_{min})$, the right-hand side of the expression exceeds 2.

The log-likelihood optimization problem can be written as

$$L(R|\theta) = \frac{1}{N}\sum_{j=1}^{N} \log(f_R(R_j|\theta)) \longrightarrow max_\theta \tag{30}$$

where θ is the parameter vector to be estimated $\theta = \{\sigma, \{q_k\}_{k=1}^N\}$. The equilibrium offer distribution $F_R(R)$ is implicitly defined from the equilibrium condition

$$\psi(R)\sum_{k=1}^{N} kq_k F_R(R)^{k-1} = \psi(R_{min})q_1. \tag{31}$$

To derive the score of the likelihood function requires straightforward but tedious algebra. Let us express analytically the following derivatives with respect to the underlying parameters

$$h_\sigma(R) \equiv \frac{\partial h(R)}{\partial \sigma} = -h(R)(1-h(R)) \times \ln(\beta^\tau R) \tag{32}$$

$$\psi_\sigma(R) \equiv \frac{\partial \psi(R)}{\partial \sigma} = -(\tilde{R} - R) \times h_\sigma(R) + \tilde{R}_\sigma(1-h(R)) \tag{33}$$

$$\psi'_\sigma(R) \equiv \frac{\partial \psi'(R)}{\partial \sigma} = \Big(1 + (1-\sigma)\frac{\tilde{R}-R}{R}h^d(R)\Big)h_\sigma(R) + \tag{34}$$

$$(1-h(R))\Big(\frac{\tilde{R}-R}{R}h(R) - (1-\sigma)\frac{\tilde{R}-R}{R}h_\sigma(R) + (1-\sigma)\frac{\tilde{R}_\sigma}{R}h(R)\Big) \tag{35}$$

where $\tilde{R}_\sigma$ is the derivative of the expression for the marginal cost of funds (24) with respect to IES. To simplify notation further, let us define the following sums

$$s_1 = \sum_{k=1}^{N} k q_k F_R(R)^{k-1} \tag{36}$$

$$s_2 = \sum_{k=2}^{N} k(k-1) q_k F_R(R)^{k-2} \tag{37}$$

$$s_3 = \sum_{k=3}^{N} k(k-1)(k-2) q_k F_R(R)^{k-3}. \tag{38}$$

Applying the implicit function theorem to (31), we can analytically express the derivative of the equilibrium offer distribution with respect to the coefficient of intertemporal substitution

$$F_\sigma(R) = -\frac{1}{s_2\psi(R)}\Big(s_1\psi_\sigma(R) - \psi_\sigma(R_{min})q_1\Big). \tag{39}$$

Similarly, we can calculate the derivatives with respect to the market segments

$$F_{q_1}(R) = -\frac{1}{s_2\psi(R)}\Big(\psi(R) + \psi_{\tilde{R}}(R)\tilde{R}_{q_1}s_1 - \psi(R_{min}) - \psi_{\tilde{R}}(R_{min})\tilde{R}_{q_1}q_1\Big) \tag{40}$$

$$\text{for k = 2,..,N} \tag{41}$$

$$F_{q_k} = -\frac{1}{s_2\psi(R)}\Big(\psi(R)kF^{k-1} + \psi_{\tilde{R}}(R)\tilde{R}_{q_1}s_1 - \psi_{\tilde{R}}(R_{min})\tilde{R}_{q_k}q_1\Big). \tag{42}$$

Using the notation introduced above, the derivative of the likelihood function with respect to σ can be expressed as

$$f_\sigma = -\frac{\psi'_\sigma(R)\psi(R) - \psi_\sigma(R)\psi'(R)}{\psi(R)^2}\frac{s_1}{s_2} - \frac{\psi'(R)}{\psi(R)}\Big(1 - \frac{s_1 s_3}{s_2^2}\Big)F_\sigma. \tag{43}$$

The derivatives of the likelihood function with respect to $\{q_k\}_{k=1}^N$ are

$$f_{q_k} = -\frac{\psi'_{\tilde{R}}(R)\psi(R) - \psi_{\tilde{R}}(R)\psi'(R)}{\psi(R)^2}\frac{s_1}{s_2}\tilde{R}_{q_k} - \tag{44}$$
$$-\frac{\psi'(R)}{\psi(R)}\Big(\frac{1}{s_2}kF^{k-1} - \frac{s_1}{s_2^2}k(k-1)F^{k-2} + (1 - \frac{s_1 s_3}{s_2^2})F_{q_1}\Big)$$

The gradient of the log-likelihood function is

$$S(\theta) = \sum_{j=1}^{N} S_j(\theta) \tag{45}$$

where

$$S_j(\theta) = \frac{\partial L(R_j|\theta)}{\partial\theta} = \frac{1}{f_R(R_j|\theta)} \times \begin{pmatrix} f_\sigma(R_j|\theta) \\ f_{q_1}(R_j|\theta) \\ \vdots \\ f_{q_k}(R_j|\theta) \\ \vdots \\ f_{q_N}(R_j|\theta) \end{pmatrix}', \text{ for } j = 1, .., N.$$

The variance-covariance matrix of the parameter estimates is estimated with the inverse of the outer product of the gradients $COV(\widehat{\theta}) = (S(\widehat{\theta})^T S(\widehat{\theta}))^{-1}$.

B.2 Maximum likelihood estimation

The optimization of the log-likelihood function is computationally demanding. To find the global optimum, I use the global optimization toolbox of Matlab and parallelize computations in a cluster of 32 CPU cores. I use a trust region reflective algorithm and the analytical scores and the Hessian derived in (45). This set-up significantly speeds up the computation of the optimum. For almost all estimates, the optimization algorithm arrives at a global optimum that satisfies the optimality conditions for the specified tolerance levels. I discard markets and periods for which the optimization does not achieve convergence.

B.2.1 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. The 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 distribution for most of the MSA markets throughout the sample period. One fails to reject the null hypothesis of equality at the 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, which excludes at most 8 mostly small markets.

Table 20: Kolmogorov-Smirnov two-sample statistic p-value (percent)

year	5th	25th	Median	75th	95th	Weighted mean	p-value $< 5\%$ Markets	Share	Markets number
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1997	0	7.1	35.9	63.7	90.8	26.3	7	8	101
1998	0	11.3	39.9	69.6	94.5	29.2	3	6	118
1999	0	11.6	43.8	74.5	94.4	26.1	4	7	124
2000	0.1	26.8	63.1	86.6	98.2	44.1	5	7	137
2001	1.5	38.4	71.7	90.1	98.9	49.6	0	0	138
2002	2.1	36.7	63.3	84.8	98.1	45.1	1	5	147
2003	0.8	29.4	61.2	83	97.4	37.9	1	4	149
2004	0.5	21	50.1	79.2	96.4	35.3	0	0	159
2005	0.5	21.7	54.9	83.8	97.9	32.5	2	3	173
2006	2.8	20.8	59.7	86.3	98	35.4	4	4	179
2007	4.6	33.1	69.3	90.7	99.1	45.1	3	2	192
2008	4.5	41.5	72.9	90.8	99.1	51.4	2	5	212
2009	5.5	35.2	65.1	86.3	98.3	43.1	1	4	217
2010	5.2	36.9	66.8	87.2	98	37.8	1	4	222
2011	3.2	36.4	61.9	82.3	96.6	34.3	2	14	215
2012	2	30.8	56.4	77.4	94.7	43	2	5	214
2013	4.4	24.1	51	74.9	92.9	41.4	5	2	201
2014	3	22.3	47.6	73.2	94	45.7	5	2	193
2015	1.6	18.4	44.7	70.8	93.6	44.3	8	7	191
2016	2.1	20.5	46.6	74.3	95.5	42.8	7	8	174

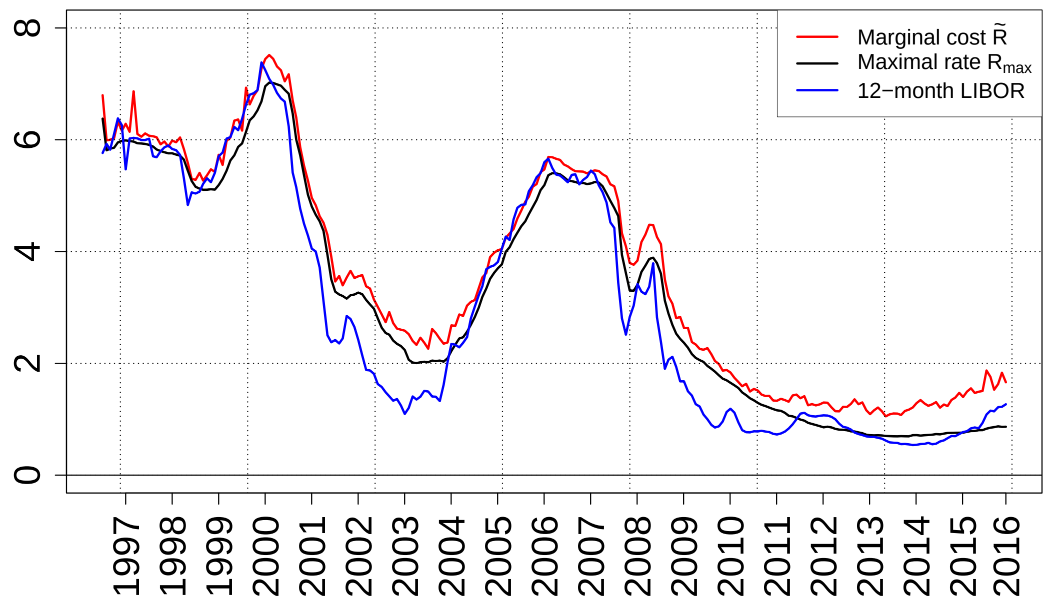
Note: The Kolmogorov-Smirnov test statistic is calculated using the empirical and the model generated CDF of offer rates on the 12-month CD under null hypothesis that the two distributions are the same. P-values are calculated for each MSA market and for each period. The weighted-mean is weighed by the total MSA-level deposits reported in the FDIC's SOD for that year.

Table (20) shows the p-values of the goodness-of-fit measure based on the Kolmogorov-Smirnov two-sample statistic. Columns two through five show select percentiles of the distribution of the p-values across different markets. Column 7 gives the deposit-weighted average of the p-values to summarize the statistic for the largest markets. Columns (8) and (9) show the number of markets for which the p-value is below 5 percent. Overall, the test statistic fails to reject the null hypothesis that the the model generated and the empirical distribution of rates are the same.

B.3 Marginal cost of funds

Figure (12) plots the deposit-weighted average of the market-level estimates of the marginal cost of funds and compares them with the 12-month LIBOR and the maximal deposit rate. The marginal cost of funds tracks closely the LIBOR rate in the increasing interest rate environments of 1999-2000 and 2004-2006. However, outside those periods, the average marginal cost of funds is much higher than the LIBOR rate likely reflecting other costs to supplying deposits including maintaining a branch network in a particular market or the loan demand conditions in the market.

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

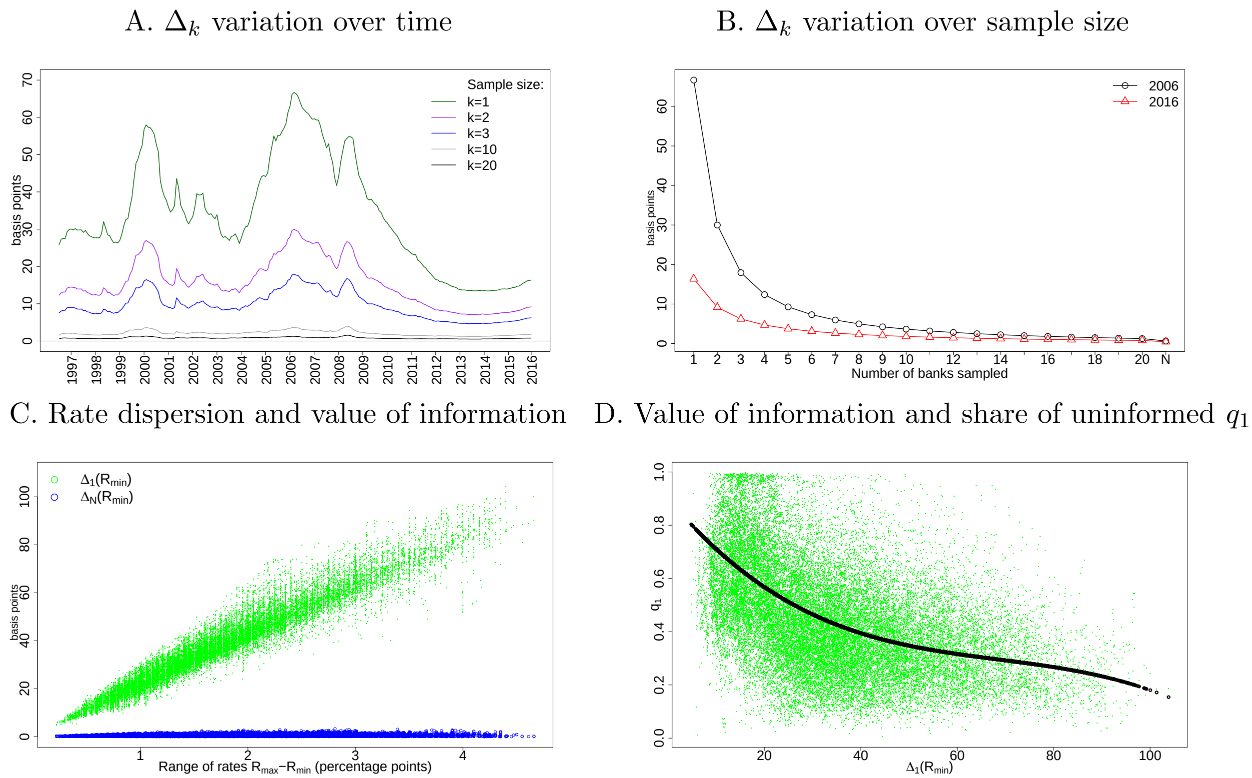


NOTE: The figure plots the deposit-weighted average estimate of the model-implied marginal cost of funds computed from equation (24) as well asthe deposit-weighted estimate of the maximum rate for the 12-month CD.These estimates are contrasted with the 12-month USD LIBOR rate.

B.4 Marginal value of information

To gain intuition into how variation in marginal values of information determines search intensities, panel A of Figure (13) plots the time-series variation of Δ_k for a number of sample sizes. In the high dispersion period of 2006, the marginal values of information Δ_1 is high at about 70 basis points. In contrast, Δ_1 is about 16 basis points in the low dispersion period of 2013. Furthermore, as the sample size of bank offers increases, the marginal value of information decreases. This relationship can be seen more 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. Furthermore, for sample sizes above 10 banks, the marginal value of information drops below 5 basis points and remains flat and independent of the magnitude of rate dispersion.

Figure 13: Marginal value of information, rate dispersion, and search intensity



NOTE: Panels A plots the time series variation of the deposit-weighted averages of market-level estimates of the marginal values of information for search intensities. Panel B compares the marginal value of information in 2006 with that in 2016 across different sample sizes. Panel C compares the market-level marginal values of information for different rate dispersion as measured by the observed ranges of rates. Panel D, is a scatter plot of the marginal value of information of sampling two bank offers and the share of inactive depositors. The the black line is a polynomial fit based on a weighted regression using the total deposits of an MSA market as weights.

To see this, panel C shows scatter plots of Δ_1 and Δ_{N-1} against the range of rates. For some markets and time periods, the range is as large as 5 percentage points and Δ_1 is as high as 100 basis points. The relationship between rate dispersion and Δ_1 is strongly positive. As predicted, Δ_{N-1} has little sensitivity to rate dispersion. This low sensitivity explains the relatively stable fraction of the most active investors q_N. As we will see in the next section, most time series variation in q_N is attributed to changes in the search cost distribution. Finally, panel D shows that the share of high-search-cost inactive investors q_1 is a decreasing nonlinear function of the marginal value of information Δ_1.