How Does Monetary Policy Affect Shadow Bank Money Creation? *

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Abstract

This paper studies the impact of monetary policy on money creation of the shadow banking system. Using the U.S. money supply data over the past thirty years, I find that shadow banks behave in the opposite way to commercial banks: shadow banks create more money exactly when the Fed tightens monetary policy to reduce money supply. Using a structural model of bank competition, I show that this phenomenon can be explained by clientele heterogeneity between the shadow and commercial banking sector. Monetary tightening allows commercial banks to charge higher prices on their depository services by driving up the opportunity cost of using cash. However, shadow banks cannot do so because their main clientele are more yield-sensitive. As a result, monetary tightening makes shadow bank money cheaper than commercial bank money, which drives marginal depositors of commercial banks to switch to shadow banks. My finding cautions against using monetary tightening to address financial stability concerns, as it may unintentionally expand the shadow banking sector.

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1 Introduction

Economists have traditionally focused on the role of commercial banks in the transmission of monetary policy. However, over the past thirty years a group of non-bank financial intermediaries, collectively known as the shadow banking system, have become increasingly important in the economy. Similar to commercial banks, shadow banks create short-term, money-like liabilities to finance long-term assets. These money-like liabilities were a major source of systemic risk in the 2008-09 financial crisis, and continue to account for a large fraction of aggregate money supply after the crisis. By the end of 2014, more than 20% of the aggregate money supply is created by shadow banks. Despite the significant size and potential implications for financial stability, little is known about the money creation process of the shadow banking system.

In this paper, I study the impact of monetary policy on money creation of the shadow banking system. Unlike commercial banks which combine money creation and loan origination under one roof, the shadow banking system breaks down the intermediation process into multiple steps. Each step is conducted by one type of specialized shadow banks. Money market funds (MMFs) stand in the first step of shadow banking intermediation process: they create money-like deposits for households and businesses and pass the proceeds to other shadow banks which specialize in loan origination. In this paper, I focus on MMFs because their liabilities consist of the dominant part of shadow bank money in the official money supply statistics, and are widely considered as close substitutes to commercial bank deposits.

Using the U.S. money supply data over the past thirty years, I find that shadow banks increase money supply when the Fed Funds rates are high. This is opposite to the behavior of commercial banks, and is at odds with the conventional wisdom that monetary tightening reduces money creation. Using a structural model of bank competition, I show that clientele heterogeneity can explain the different behaviors of shadow banks and commercial banks. This finding suggests that monetary policy could be less effective in controlling aggregate money supply in presence of a large shadow banking sector. This finding also casts doubts on the policy proposal of using tight monetary policy to address financial stability concerns, as it may unintentionally expand the shadow banking sector.

I first document a set of stylized facts using the U.S. money supply data over the past thirty years[1]. Figure 1 and 2 reveal a striking difference between two types of banks in their responses

[1] In this paper, I focus on "MZM" (money zero maturity), a measure of liquid deposits in the economy. This measure is a modification of M2 after the usefulness of previous measures became comprised in the 1990s. This measure includes currency, Traveler's checks of non-bank issuers, demand deposits, other checkable deposits, saving deposits, retail and institutional MMF shares. Choosing a specific definition of money aggregate, however, is not important, because my question is about each component of the money aggregates, rather than the sum.

to monetary policy: high Fed Funds rates are associated with low growth rates of commercial bank deposits, but high growth rates of shadow bank deposits. Given two types of banks are engaging in similar liquidity transformation business, it is surprising to see such different responses to monetary policy. To understand the underlying mechanism, I develop a structural model of bank competition following the industrial organization literature on oligopoly markets[2]. I show that the different clientele of the two banking sectors is the key institutional feature that affects banks' response to monetary policy.

In the model, commercial and shadow banks provide differentiated depository services to a group of heterogeneous depositors. Commercial banks mainly attract depositors who value transaction convenience, but are insensitive to yields. Shadow banks, however, mainly attract depositors who are less concerned about transaction convenience, but are very sensitive to yields. Monetary tightening makes the transaction-oriented depositors more attached to commercial banks by increasing the opportunity cost of holding cash. This allows commercial banks to charge higher deposit spreads during these periods. However, shadow banks cannot raise the prices as much as commercial banks because their main clientele is more yield-sensitive. As a result, monetary tightening makes shadow bank deposits relatively cheaper than commercial bank deposits, driving marginal depositors of commercial banks to shadow banks.

To access the quantitative importance of this channel, I estimate the model using institutional level data on commercial banks and MMFs. The result first verifies two key assumptions of the channel: there is significant dispersion in the yield sensitivity among depositors, and yield-sensitive depositors are more likely to choose shadow banks. Second, the model successfully generates different responses to monetary policy across banking sectors: as the Fed Funds rates increase, the demand for commercial bank deposits becomes more inelastic, whereas the demand of shadow bank deposits remains relatively elastic. As a result, commercial banks raise deposit spreads and lose deposits, while shadow banks maintain low deposit spreads and gain deposits. Third, I find that heterogeneity in yield sensitivity is the key to explain the different pricing behaviors of two types of banks: if yield sensitivity is the same for all depositors, then monetary policy has no differential impacts on two types of banks. Lastly, I find that yield sensitivity is related to local demographics. Local markets with wealthier or younger population have higher yield sensitivity than markets with poorer or older population.

I use the structural model to quantify the welfare consequence of the entry of shadow banks. Depositors gain on average 50 billion dollar per year due to greater competition and product diversity. However, the welfare gain should be balanced by potential threats to financial stability. The presence

[2]See Berry (1994), Berry, Levinsohn, and Pakes (1995) and Nevo (2001).

of a large shadow banking sector could make monetary policy less effective in controlling money supply. Lastly, this finding casts doubt on the policy proposal of using monetary policy as a financial stability tool, which has gained increasing support after the 2008-09 financial crisis. I show that this policy proposal may unintentionally shifts money creation from the regulated commercial banking sector to the unregulated shadow banking sector, which potentially creates more systemic risk.

This paper contributes to three strands of literature. The first strand of literature studies the inner working of the shadow banking system. Pozsar et al. (2010) and Krishnamurthy and Vissing-Jorgensen (2016) argue that the shadow banking sector grew rapidly before the recent financial crisis precisely because it satisfies the increasing demand for money-like claims from firms and institutional investors. Sunderam (2015) provides empirical evidence that investors treat short-term liabilities of shadow banks as money-like. My paper shed lights on the industrial organization aspect of the shadow banking system. I show that shadow banks mainly compete in the yield-sensitive segment of the deposit market by offering low-cost (high-yield) deposits. The entry of shadow banks significantly reduces market power of commercial banks, and substantially improves welfare for depositors.

The second literature studies monetary transmission mechanisms in the banking system. Traditionally, this literature has been focused on commercial banks. Bernanke and Blinder (1988) first propose the "bank lending channel" which postulates that monetary tightening reduces money creation and credit supply by removing reserves from the commercial banking system. Kashyap and Stein (1995, 2000) provide empirical evidence for this channel. Drechsler, Savov and Schnabl (2015) propose a new “deposit channel” in which monetary policy affects market power of commercial banks. My paper differs from previous literature by focusing on the other important component of the banking system, the shadow banking sector. I show that shadow banks behave in the opposite direction from commercial banks due to their different clientele, so they may partially offset the effect of monetary policy on the commercial banking sector.

The third strand of literature studies objectives of monetary policy. Before the 2008-09 financial crisis, the consensus among policy makers is that monetary authority should focus on a relatively narrow mandate of price stability and employment. However, a new view which gains popularity after recent financial crisis argues that monetary policy should be used to address financial stability concerns. This idea can be dated back to Borio and Lowe (2002), White (2006), and others. Stein (2012) constructs a theoretical model showing that monetary policy can be used to regulate excessive money creation by commercial banks. The potential complication caused by an unregulated shadow banking sector is also mentioned in this paper. Ajello et al. (2015) show that optimal policy should respond to financial stability risks especially when the probability and severity of financial crises are uncertain. My finding suggests that policy makers should be aware of potential heterogeneous responses by different entities in the financial system. A over-generalization of the conventional wisdom to the shadow banking sector may lead to unintended consequences as evident in this paper. My paper supports the view that "monetary policy is too blunt a tool to address possible financial imbalances" as expressed by Bernanke (2011) and Yellen (2014).

The remainder of this paper is organized as follows. Section 2 presents several stylized facts on money creation of the shadow banking system. Section 3 presents a simple model to highlight the main channel. Section 4 presents the full structural model. Section 5 presents the estimation results. Section 6 discusses the policy implications, and Section 7 concludes.

2 Money Creation of the Shadow Banking System

The shadow banking system is a collection of financial intermediaries which conduct maturity, credit and liquidity transformation outside regulatory oversight[3]. Examples of shadow banks include securitization vehicles, asset-backed commercial paper (ABCP) conduits, MMFs, investment banks, and mortgage companies. Like commercial banks, shadow banks transform long-term illiquid assets such as a thirty-year mortgage into short-term money-like claims. Since households and business have a preference for liquidity, issuing money-like claims allows shadow banks to lower their financing costs. Many researchers argue that shadow banks grew rapidly before the recent financial crisis exactly because they satisfy the increasing demand for money-like assets (Pozsar et al., 2010; Krishnamurthy and Vissing-Jorgensen, 2015).

Figure 4 provides a simple representation of the U.S. banking system[4]. The upper branch represents the shadow banking sector, while the lower represents the commercial banking sector. Unlike commercial banks which combine deposit taking and loan origination under one roof, the shadow banking system breaks down the intermediation process into several steps, each of which is conducted by one type of shadow banks. MMFs stand at the first step of the shadow banking intermediation process. MMFs take deposits from households and businesses and then pass the proceeds to other shadow banks which conduct loan origination such as securitization vehicles, mortgage conduits, broker dealers, and mortgage companies.

MMFs are widely (though not necessarily accurately) regarded as safe as bank deposits yet providing a higher yield. Similar to commercial bank deposits, MMFs provide intraday liquidity, and some of them even allow depositors to write checks on their deposits. Unlike other shadow

[3]Former Federal Reserve Chair Ben Bernanke provided a definition of the shadow banking system in April 2012: "Shadow banking, as usually defined, comprises a diverse set of institutions and markets that, collectively, carry out traditional banking functions–but do so outside, or in ways only loosely linked to, the traditional system of regulated depository institutions."

[4]A more detailed description of shadow banking intermediation process can be found in Pozsar et al. (2010).

banking liabilities which are generally held within the shadow banking system, MMF shares are directly held by households and businesses. Due to the similarity to commercial bank deposits, MMF shares are included in the official money supply statistics while other types of shadow banking liabilities are generally not. The amount of MMF shares also provides a good proxy of the amount of funds flowing into the shadow banking sector.

In the asset side, MMFs hold various money market instruments. Figure 6 shows the average of portfolio holding of the MMFs over time. The asset holdings can be grouped into three major categories. The majority 50% are invested in short-term debts of other shadow banks such as repurchase agreement (repos), asset backed commercial papers (ABCPs), commercial papers (CPs) and floating rate notes (FRNs)[5]. 20% are invested in Treasury and agency securities. Lastly, 18% of the shadow bank deposits goes back to the commercial banking sector in the form of large denomination commercial bank obligations.

Over the past thirty years, the shadow banking sector becomes increasingly important in money creation. Figure 5 shows the breakdown of the official money supply over time[6]. The share of shadow bank deposits has increased from around 15% in the 1980s to around 40% in 2007, while the share of commercial bank deposits is in a downward trend. There are also substantial cyclical variations in the share of shadow and commercial bank deposits.

Table 2 examines the potential drivers of money supply of the two banking sectors. I conduct time series regression of the deposit growth rates on a list of macroeconomic variables: monetary policy stands out as a key factor: 1% increase in the Fed Funds rates is associated with 1.4% decrease in the growth rates of commercial bank deposits, but 3.9% increase in the growth rates of shadow bank deposits. Such difference can be easily seen from a time series plot in Figure 1 and 2.

Given shadow banks conduct similar liquidity transformation as commercial banks, it is indeed surprising to observe such different responses to monetary policy. As the first step to understand the underlying mechanisms, I investigate the pricing strategies of the two types of banks. The price of deposit service is measured by the spread between the Fed Funds rates and deposit rates, subtracting

[5]Some of large industrial corporations also issue commercial papers to obtain short term financing. These commercial papers are mainly used to finance their captive finance companies, which are also considered as shadow banks. For example, one of the largest issuers of commercial paper, General Motors Acceptance Corporation (GMAC), is a captive finance company that provides financing for the customers of its parent company, General Motors.

[6]There are several measures of aggregate money supply, classified along a spectrum between narrow and broad monetary aggregates. In this paper, I focus on MZM (money zero maturity), a measure of money that includes balances that can be used for transactions immediately at zero cost. This measure is a modification of M2 (M2 - Small-denomination time deposits + Institutional MMFs) after the usefulness of M2 became comprised in the 1990s (Teles and Zhou, 2005). This measure includes currency, Traveler's checks of non-bank issuers, demand deposits, other checkable deposits, saving deposits, retail and institutional MMF shares. Choosing a specific definition of money aggregate, however, will not change the empirical results since I am interested in the behaviour of each component, rather than the sum.

account fees or expense ratio[7]. Figure 3 plots the average deposit spreads of commercial banks and MMFs over time. I find that commercial banks increase their deposit spreads substantially when the Fed Funds rates are high, while MMFs charge very stable deposit spreads. The changes in relative prices are economically significant. For example, in the 2004 tightening cycle the price difference increased from less than 0.5% to nearly 3%. Since transaction convenience of bank deposits are relatively stable over time, such big change in relative price may significantly affect depositor's choice between two banking sectors. Therefore, to understand the impact of monetary policy on the quantity of deposits, we must understand how monetary policy affects the prices of deposits.

3 A Simple Model of Deposit Pricing With Heterogeneous Depositors

This section develops a simple model of deposit pricing to highlight the key economic mechanism through which monetary policy exerts differential impacts on deposit pricing. These ingredients are then incorporated in a more quantitative setting in the next section which allows structural estimation of the key parameters.

3.1 Banks

Suppose there are three types of liquid assets (or products) can provide monetary service: cash (c), deposits (d), and Treasury bills (b) with different level of transaction convenience, l. Cash is the most liquid, followed by bank deposits, and bonds are least liquid.

$$l_c > l_d > l_b \tag{1}$$

The cost of holding liquid assets is the deposit spread, which is defined as the spread between the Fed Funds rates and the yield of the asset. Since cash bears no interest, the deposit spread is simply the Fed Funds rates, f. The yield of Treasury bills closely track the Fed Funds rates, so the deposit spread of Treasury bills is 0.

In this simple model, I assume that there is only one bank supplying bank deposits. This bank can be a commercial bank or a shadow bank. The only difference is the clientele, which determines the demand function that the bank faces. I will come back to this point in the next subsection.

[7]In the data, MMFs frequently change expense ratios: 62% fund-year observations experience change in the expense ratio. Among them, 80% are associated with change in the incurred cost, while the rest 20% are potentially due to strategic fee setting. It is often reported MMFs waive part of the fee when facing poor demand. For commercial banks, variations in deposit spreads are mainly driven by he difference between the Fed Funds rates and gross deposit rates, while the account fees accounts for a smaller portion of the deposit spreads.

The problem of the bank is to choose a deposit spread, p_d, to maximize its profits

$$\max_{p_d} \pi_d = p_d q(p_d) \tag{2}$$

Where $q(p_d)$ is the demand function of the bank.

Notice that the loan origination decision is not modeled here because I want to focus on the deposit taking decision. The underlying assumption is that there is an efficient inter-bank market to equalize the marginal lending rates of each bank to the inter-bank lending rates, which are the Fed Funds rates.

3.2 Depositors

There are two types of depositors: a fraction of μ is yield-oriented depositors (y) who are more sensitive to deposit spreads while a fraction of $1-\mu$ is transaction-oriented depositors (t) who are less sensitive. The difference between two types of banks is captured by the faction of yield-oriented depositors: a shadow bank has a larger fraction of yield-oriented depositors. The simple model takes the distribution of clientele as given. The full model in next section will endogenize the distribution of clientele as a function of product characteristics and prices of all the competing products in the deposit market.

Each depositor has exactly one dollar to allocate, and he can only choose one type of product. The problem of depositors is to choose the product which gives rise to the highest utility. Define the utility of product j for type i depositor as $u_{i,j}$. The optimization problem of depositor i is given by

$$\max_{j\in\{c,d,b\}} u_{i,j} = -\alpha_i p_j + l_j \text{ for } i = t, y \tag{3}$$

Where α_i is the sensitivity to deposit spread of type i depositor. Assume the Fed Funds rates are in a range that neither cash nor bond becomes the dominant choice for both types of depositors. This requires:

$$f \in \left(\frac{l_c}{\alpha_y}, \frac{l_c}{\alpha_t}\right) \tag{4}$$

In this range, transaction-oriented depositors prefer cash over bonds, and yield-oriented depositors prefer bonds over cash.

3.3 Prediction

This simple model generates predictions on how monetary policy affects the pricing decision of the banks, and the resulting adjustment in deposit supply.

Proposition 1: *If the Fed Funds rates are higher than a cutoff value f^*, banks will increase their price from $\underline{p} = \frac{l_b}{\alpha_y}$ to $\bar{p} = f - \frac{l_c - l_b}{\alpha_t}$, and the equilibrium quantity of deposits will drop from 1 to μ.*

Proof: There are only two potential prices that banks may choose: A high price which extracts higher rent from transaction-oriented depositors, but prices out yield-oriented depositors

$$\bar{p} = f - \frac{l_c - l_b}{\alpha_t} \tag{5}$$

Or a low price which attracts both types of depositors

$$\underline{p} = \frac{l_b}{\alpha_y} \tag{6}$$

f^* is the cutoff value of Fed Funds rates at which the profits from charging the low price, $\underline{p}$, equals the profit from charging the high price, $\bar{p}$.

$$\bar{p}(1 - \mu) = \underline{p} \tag{7}$$

I can solve the cutoff Fed Funds rates

$$f^* = \frac{l_c - l_b}{\alpha_t} + \frac{l_b}{(1 - \mu)\alpha_y} \tag{8}$$

When $f < f^*$, the bank charges $\underline{p}$. Both types of depositors choose to hold deposits, and the equilibrium quantity of deposits is 1.

When $f > f^*$, the bank will charge $\bar{p}$. Only transaction oriented depositors choose to hold deposits, and the equilibrium quantity is $1 - \mu$.

Proposition 2: *a bank with a larger fraction of yield-oriented depositors is less likely to increase the deposit spreads for a given level of Fed Funds rates.*

Proof: as shown above, the cutoff value of the Fed Funds rates f^* at which banks switch to the high price, $\bar{p}$, is positively related to the fraction of yield-oriented depositors, μ. Therefore, if a bank has a larger fraction of yield-oriented depositors, the set of the Fed Fund rates at which it charges the high price, $\bar{p}$, will be smaller.

Figure 7 shows the intuition graphically. I plot the demand curve and iso-profit curve of a bank. The top panel shows a bank with a small faction of yield-oriented depositors (a commercial bank) and the bottom panel shows a bank with a large faction of yield-oriented depositors (a shadow bank). When the Fed Funds rates increase, the reservation price of transaction-oriented depositors increases because their second best alternative, cash, becomes more costly to hold. However, the yield-oriented depositors are not affect since their second best alternative, bonds, still have the same deposit spreads. If a bank has a small fraction of yield-oriented depositors, it will find it profitable to increase the deposit spreads to $\bar{p}'$, because by doing so it will lose a small fraction of depositors but earn a high profit margin from a large fraction of transaction-oriented depositors. In contrast, if a bank has a large fraction of yield-oriented depositors, it will find it profitable to maintain low deposit spreads to keep the yield-sensitive depositors.

In practice, commercial banks attract more transaction-oriented depositors because their branch networks, ATMs and payment system provide more transaction convenience. Shadow banks, however, attract more yield-oriented depositors with low prices. As predicted by the above model, shadow banks should be more hesitated to increase deposit spreads when the Fed Funds rates are high because it may lose a larger fraction of their depositors to bonds. This can explain the different pricing behaviors shown in Figure 3. What the simple model does not capture is the competition between commercial and shadow banks: as the deposit spreads of the two sectors diverge, shadow banks steal some yield-sensitive depositors from commercial banks. In the next section, I will build a full model with multiple banks and endogenous clientele for each bank. The full model allows me to verify the key assumptions and assess the magnitude of the channel.

4 A Structural Model of Bank Competition

In this section, I propose a structural model of bank competition. The model uses the oligopoly competition framework developed by Berry, Levinsohn, and Pakes (1995). Early applications of this framework to the commercial banking industry includes Adams, Brevoors, and Kiser (2007) and Ho and Ishii (2010). My paper is first to consider the competition between commercial and shadow banks.

4.1 Banks

A deposit market is defined as a MSA-year combination (m, t). There are $J_{m,t}$ products in a market, which include commercial banks, MMFs, cash and Treasury bonds. $x_{j,m,t}$ is the vector of product characteristics for product j in market (m, t). Examples of characteristics include the branch density for a commercial bank, and the check-writing privilege for a MMF.

The decision of bank j is to choose a deposit spread $p_{j,m,t}$ to maximize the present value of profits:

$$\max_{\{p_{j,m,t+k}\}} \sum_{k=1}^{\infty} \beta^k \left(p_{j,m,t+k} - mc_{j,m,t+k}\right) M_{m,t+k} \hat{s}_{j,m,t+k} \left(p_{j,m,t+k}\right) \tag{9}$$

where $mc_{j,m,t}$ is the marginal cost of providing depository services, $\hat{s}_{j,m,t}(p_{j,m,t})$ is the market share of bank j[8], $M_{m,t}$ is the size of the market, and β is the discount rates.

4.2 Depositors

Following Adams, Brevoors, and Kiser (2007) and Ho and Ishii (2010), I model the depositor's problem as a discrete choice decision among different banks. A depositor is assumed to have only one dollar, and it can only choose one product which gives the highest utility. The assumption is not restrictive as we can think as if the depositor makes multiple discrete choices for each dollar that he has.

Suppose there are I depositors that can change their portfolio at time t in MSA m. For simplicity, I assume depositors are myopic. The utility of depositor i from product j at market (m, t) is

$$u_{i,j,m,t} = -\alpha_i p_{j,m,t} + \beta' x_{j,m,t} + \xi_{j,m,t} + e_{i,j,m,t} \tag{10}$$

where $x_{j,m,t}$ is a K dimensional vector of product characteristics of bank j, $p_{j,m,t}$ is the deposit spreads, $\xi_{j,m,t}$ is the unobservable demand shocks, and $e_{i,j,m,t}$ is a mean-zero i.i.d stochastic shocks to utility, which follows the extreme value distribution. Finally, (α_i, β) are $K+1$ individual-specific taste parameters. A key assumption is that depositors are heterogeneous in their sensitivity to deposit spreads. This is modeled by assuming α_i follows a normal distribution with a mean of $\bar{\alpha}$ and a standard deviation of σ_α. This model is intuitively referred as "random coefficient" model in the literature.

In addition to bank deposits, depositors can also hold cash. The return of cash is zero. Therefore, the opportunity cost of holding cash equals to the Fed Funds rates.

$$p_{cash,t} = f_t \tag{11}$$

The opportunity cost of holding Treasury bills is zero. I normalize the utility from Treasury bills to a mean-zero random noise.

$$u_{i,0,m,t} = e_{i,0,m,t} \tag{12}$$

The depositor's problem is to choose a product j from $J_{m,t}$ possible choices to maximize its utility

$$\max_{j \in \{0,1,\dots J_{m,t}\}} u_{i,j,m,t} = \max_{j \in \{0,1,\dots J_{m,t}\}} \left\{ -\alpha_i p_{j,m,t} + \beta' x_{j,m,t} + \xi_{j,m,t} + e_{i,j,m,t} \right\} \tag{13}$$

Take expectation with respect to the logit error term, the probability for depositor i to choose

[8] $\hat{s}$ is the market share measured by the stock of deposits. Later I will introduce s, which is the market share measured by the inflow of deposits.

bank j can be written as

$$s_{i,j,m,t} = \frac{exp\left(-\alpha_i p_{j,m,t} + \beta' x_{j,m,t} + \xi_{j,m,t}\right)}{\sum_{k=1,\ldots,J_{m,t}} exp\left(-\alpha_i p_{k,m,t} + \beta' x_{k,m,t} + \xi_{k,m,t}\right)} \tag{14}$$

The numerator of the above expression is the exponential mean utility of bank j for depositor i. The denominator is the sum of the exponential utility of all possible choices. Notice that the exponential mean utility of the outside good is one.

The market share of bank j can be calculated by summing up across all the individuals,

$$s_{j,m,t}\left(x_{m,t}, p_{m,t}, \xi_{m,t}, \theta\right) = \sum_{i=1}^{I} \mu_i s_{i,j,m,t} \tag{15}$$

where θ is the preference parameters, $\theta = (\bar{\alpha}, \sigma_\alpha, \beta)$. μ_i is the frequency type i depositors. α_i and μ_i are constructed as a discrete approximation to the normal distribution $N(\bar{\alpha}, \sigma_\alpha)$[9].

Lastly, I discuss the deposit adjustment process. Previous papers such as Adams, Brevoors, and Kiser (2007) and Ho and Ishii (2010) assume all the depositors optimize their choice of banks every year. This implies market shares of banks should be measured by the stock of deposits. However, the data shows considerable stickiness in deposit adjustment. To account for the slow adjustment speed, I introduce partial adjustment in depositor's choices in the spirit of Calvo (1983). Define $\hat{s}_t$ as the market share of a bank at time t measured by the deposit stock. Each period only a fraction $1-\rho$ of depositors can adjust their deposits, so a fraction $\rho\hat{s}_t$ of the deposits will stay in the same institution in next period, and $(1-\rho)\,\hat{s}_t$ will re-allocate their wealth. In next period, an inflow of $(1-\rho)\,s_t$ new deposits will enter the institution, where s_t is defined as the market share measured by deposit inflows. This assumption implies is a simple linear relation between the stock-based market share, $\hat{s}_t$, and the inflow-based market share, s_t.

$$\hat{s}_t = \rho\hat{s}_{t-1} + (1-\rho)\, s_t \tag{16}$$

4.3 Equilibrium

The pure-strategy Bertrand-Nash equilibrium is a set of prices p^* chosen by banks and a set of product j^* chosen by depositors such that each bank maximizes its profits, each depositor maximizes their utility, and the deposit market clears.

Assuming the existence of the equilibrium, the markup can be approximated by the following expression[10]:

$$p_{j,m,t} - mc_{j,m,t} = b_{j,m,t} = \left(-\frac{\partial s_{j,m,t}/s_{j,m,t}}{\partial p_{j,m,t}}\right)^{-1} \tag{17}$$

[9] In the estimation, I use sparse grid quadrature with 7 nodes to approximate the normal distribution.
[10] The derivation can be found in the appendix.

Basically, this formula decomposes deposit spreads into two components: marginal cost and markup. Markup is determined by the semi-elasticity of the demand: the lower of the elasticity, the higher of the markup that a bank can charge.

4.4 Estimation

4.4.1 Demand equation

Now I describe how to estimate the model using institutional-level data of commercial banks and MMFs. In the estimation, it is convenient to express the depositor's utility as the sum of a mean utility across all depositors, δ_j, and a depositor specific term, $\lambda_{i,j}$

$$u_{i,j} = \delta_j + \lambda_{i,j} = \left(-\bar{\alpha} p_j + \beta' x_{m,t} + \xi_j\right) + \left(\left(\alpha_i - \bar{\alpha}\right) p_j + e_{i,j}\right) \tag{18}$$

Following Nevo (2001), model parameters can be separated into two groups, linear parameters $\theta_1 = (\bar{\alpha}, \beta, \gamma)$ and non-linear parameters, $\theta_2 = \sigma_\alpha$.

I first numerically invert the market share equation 15 to solve the vector of mean utility $\delta_{m,t}$ as a function of product characteristics, deposit spreads, market shares, and non-linear preference parameters.

$$\delta_{m,t} = s^{-1}\left(x_{m,t}, p_{m,t}, s_{m,t}, \theta_2\right) \tag{19}$$

This involves a contraction mapping method used in Berry, Levinsohn, and Pakes (1995).

$$\delta^N_{j,m,t} = \delta^{N-1}_{j,m,t} + lns_{j,m,t} - lns_{j,m,t}\left(x_{m,t}, p_{mt,}, \delta^{N-1}_{m,t}, \theta_2\right) \tag{20}$$

where N denotes the $N-$th iteration, $s_{j,m,t}$ is the observed market share, and $s_{j,m,t}\left(x_{m,t}, p_{m,t}, \delta^{N-1}_{m,t}, \theta_2\right)$ is the simulated market share defined as equation 15. I start with an initial guess of $\delta^0_{m,t}$. For each iteration, a new vector $\delta^N_{m,t}$ is computed. The iteration continues until $\|\delta^N_{m,t} - \delta^{N-1}_{m,t}\|$ is smaller than some tolerance level.

Once the inversion has been computed, the demand equation can be written as

$$\delta_{j,m,t} = x'_{j,m,t}\bar{\beta} + \bar{\alpha} p_{j,m,t} + \xi_{j,m,t} \tag{21}$$

As is typical in demand estimation, the deposit spreads are potentially endogenous to unobservable demand shocks. A positive demand shock increases both the quantity of deposits and the deposit spreads, which could bias the coefficient of deposit spreads. To address this endogeneity, I need to find exogenous shock to the deposit spreads which are orthogonal to demand shocks. Common instruments in the literature includes cost shifters and rival product attributes. These variables affect the pricing of the products but are orthogonal to demand shocks. The choice of instruments will be covered later in the data section.

4.4.2 Supply equation

I assume that the marginal cost of providing depository services is linear in vector of cost characteristics, which can be decomposed into a subset which are observed by the econometrician, t w_j, and an unobserved component, ω_j.

$$mc_{j,m,t} = w'_{j,m,t}\gamma + \omega_{j,m,t} \tag{22}$$

where γ is a vector of cost parameters to be estimated.

In the equilibrium, the price of any depository service must satisfy the first order conditions. Using the equation 17, marginal costs can be solved as the difference between price and markup. The markup depends only on the parameters of the demand system and the equilibrium price. The supply equation can be written as

$$p_{j,m,t} = b_{j,m,t} + w'_{j,m,t}\gamma + \omega_{j,m,t} \tag{23}$$

4.4.3 The Estimation Algorithm

I use a multiple equation GMM to jointly estimate the demand and supply parameters. The moment conditions are given by the expectation of the unobservable demand shocks $\xi_{j,m,t}$ and unobservable cost shocks $\omega_{j,m,t}$ interacted with exogenous instruments $z_{m,t}$.

$$E\left[\left(\xi_{j,m,t}, \omega_{j,m,t}\right) z_{m,t}\right] = 0 \tag{24}$$

The GMM estimator is given by

$$\hat{\theta} = \arg\min\left(\xi\left(\theta\right), \omega\left(\theta\right)\right)' ZA^{-1}Z\left(\xi\left(\theta\right), \omega\left(\theta\right)\right) \tag{25}$$

where A is a consistent estimate of $E\left[Z'\left(\xi,\omega\right)\left(\xi,\omega\right)' Z\right]$.

To summarize, the estimation proceeds in the following steps:

1. For a given non-linear preference parameters θ_2, I calculate the corresponding mean utility δ_j for each product using the fixed point algorithm of equation 20.

2. Then I use a GMM estimator of equation 25 to solve the linear preference parameters and cost parameters θ_1.

3. Then I search for a new non-linear preference parameters θ_2, and repeat step 1 and 2.

4. The estimation stops when the GMM objective function is minimized.

I refer to this model as the random coefficient model. In addition to the baseline model, I estimate two alternative models with different assumptions. One is the Logit IV model which assumes that depositors are homogeneous $\sigma_\alpha = 0$ so that the utility of the depositor is the following

$$u_{i,j,m,t} = -\alpha p_{j,m,t} + \beta' x_{j,m,t} + \xi_{j,m,t} + e_{i,j,m,t} \tag{26}$$

In this case, there is a closed form relation between observed market share and the mean utility of the representative depositor

$$lns_{j,m,t} - lns_{0,m,t} = \delta_{j,m,t} = -\alpha p_{j,m,t} + \beta' x_{j,m,t} + \xi_{j,m,t} \tag{27}$$

where $s_{0,m,t}$ is the market share of the outside good. The Logit IV model allows deposit spreads to be endogenous to unobservable demand shocks, $\xi_{j,m,t}$, so the instruments are needed to estimate the model.

The other alternative model is the Logit OLS model. This model assumes that deposit spreads are orthogonal to unobservable demand shocks, $\xi_{j,m,t}$. Therefore, the preference parameters, α, β, are estimated by a simple OLS regression of $lns_{j,m,t} - lns_{0,m,t}$ on deposit spreads and product characteristics.

4.5 Data source

The first main data used for this paper is iMoneyNet. This data provides monthly share-class-level data for the U.S. MMFs dating back to 1985. After cross-check with the aggregate money supply statistics from the Federal Reserve Board, I find that this database covers essentially all the MMFs which are included in the official statistics after 1987. The data contains rich information on fund characteristics such as deposit amounts, charged expense ratio, yields, check-writing privilege, bank affliction and fund sponsors. The data also provides information on fund operating cost such as incurred management fee, share service fee, 12b1 fee and other fees. Portfolio holding information becomes available since 1998, which includes the average portfolio maturity, and portfolio weight of each asset class. As data on shadow banks are generally very scarce, this data set provides a rare opportunity to look into the inner working of the shadow banking system.

The second main data is the Consolidated Report of Condition and Income, generally referred to as the Call report. This data provides quarterly bank-level data for every U.S. insured commercial bank, including detailed accounting information such as deposit amounts, interest income, salary expense, and fixed asset expenses. I complement the Call report with FDIC Summary of Deposits, which provides branch-level information of the deposit amounts in annual frequency since 1994. Following the literature, deposit rates are imputed from bank financial statements by dividing the deposit interest expense over the total amount of deposits (Dick, 2008; Hannan and Prager, 2004). In the following analysis, I focus on "liquid deposits" which is defined as the sum of checking and savings deposits. This definition is consistent with the money supply statistics in the previous section[11].

[11] Previous literature has shown that the pricing and quantities of "liquid deposits" are quite different from "illiquid deposits" such as small time saving deposits (Driscoll and Judson, 2002; Drechsler et al., 2009).

4.6 Data for structural estimation

Two measures are central to the empirical framework: price and market share. For deposit market, neither concept is as straightforward as it often is for other products. First, a large portion of the price of commercial bank depository service is charged implicitly by setting deposit rates below the short-term market interest rates. To have a consistent measure of prices across different product groups, I use deposit spread, i.e. the spread between Fed Funds rates and deposit rates, to measure the price of the depository service. For commercial banks and MMFs, I net out account fees and expense ratio from the before-fee return to compute the net deposit rates[12]. Since cash does not bear any interest, the deposit spread of cash is simply the Fed Funds rates. The yield of short-term Treasury bills closely tracks the Fed Funds rates. I assume the price of Treasury is zero.

The measurement of market share is also not a clear-cut. On one hand, banks earn profits from both new and existing depositors. So the pricing decision of banks should consider stock-based market shares, rather than flow-based market shares. On the other hand, the flow-based market shares are more appropriate to capture the behavior of depositors because not all depositors change their portfolio every year[13]. These two problems are addressed by explicitly modeling the adjustment process of deposits as shown in equation 16. Under this assumption, the unobservable inflow-based market share can be written as a function of the stock-based market share[14].

A drawback of this approach is that the fraction of non-adjustable depositors, ρ, is unobservable. In the baseline estimation, I calibrate the value as 0.7. In robustness check I show that market shares calculated based on different value of ρ are highly correlated and the main estimation result is robust for a reasonable range of values.

For commercial banks, I combine the branch-level deposits in a MSA to compute the MSA-bank-level deposit amounts. For MMF shares, cash, and Treasury bonds, there is no MSA-level information. I calculate the MSA-level deposits assuming that the ratio of local deposits over national deposits is the same as the ratio of local personal income over the national total personal

[12] Previous literature such as Dick (2008) and Ho and Ishii (2010) use deposit rates rather than deposit spreads when in the demand estimation. However, this approach is less than ideal in my setting since the deposit rates are driven by both pricing decisions of banks as well as monetary policy over the long sample period.

[13] Market shares in standard markets such as automobile and airline are typically measured by the purchase volume, which is a flow concept. However, information on gross inflows are not available for commercial banks or MMFs. Using net inflows as a proxy of gross inflow will result in many negative values and it is not clear how market share should be defined in this case. Hortacsu and Syverson (2004) partially circumvent this issue in the mutual fund setting by summing up only the positive monthly net flows. However, this approach is not feasible for commercial banks because monthly net flows are not observed.

[14] The advantage of this approach is that for a reasonable value of ρ, there will be very rare negative value for this inflow-based market share, which means relatively less loss of information comparing to the approach used by Hortacsu and Syverson (2004). There are less than 1% negative observations when $\rho = 0.7$.

income[15].

The market size is defined as the total liquidity assets in a MSA, which equals to the sum of cash, commercial bank deposits, MMF shares and Treasury bonds in this MSA[16]. The stock-based market share of a product j is given by the following:

$$\hat{s}_{j,m,t} = \frac{Deposit_{j,m,t}}{Total\ Liquid\ Assets_{m,t}} \tag{28}$$

Following the literature, I combine tiny banks or MMFs (market share less than 0.2%) with Treasury bonds as the outside option[17].

The demand equation includes the deposit spread, a set of product characteristics, MSA fixed effects, time fixed effects and product fixed effects. Product characteristics are chosen based on the belief that they are important and recognizable to depositors' choice. [18]. Product characteristics of commercial banks include branch density in the local market, average number of employees in a branch, bank age, and single-market dummy. Product characteristics of MMFs include rating dummy (whether the MMF is rated by three major rating agencies), bank fund dummy (whether the fund is affiliated with a commercial bank), check-writing dummy (whether the fund allows depositors to write a check), and fund age. I include product fixed effects to absorb all the unobservable time-invariant product characteristics. Notice that bank fixed effects also absorb observable time-invariant product characteristics. To retrieve the taste coefficients on these product characteristics, I follow the minimum-distance procedure proposed by Chamberlain (1982) to estimate coefficients of time-invariant product characteristics. Lastly, I include time fixed effects to absorb aggregate demand shocks for liquid assets, and MSA-fixed effect to absorb cross-market differences in demand.

The supply equation includes product characteristics, cost shifters, MSA fixed effects, time fixed effects and product fixed effects. The set of product characteristics is the same as the demand function. The cost shifters of MMFs include incurred management fee, incurred share service fee and incurred other fee. The cost shifters of commercial banks include salary expenses and expenses of fixed assets[19]. In addition, the deposit spread of cash is instrumented by the Fed Funds rates.

[15] Instead of imputing the local level of deposits, I estimate the model using all national-level data. The alternative approach generate qualitatively similar result, but may bias the magnitude because it inflates the number of commercial banks in the choice set of local depositors.

[16] Treasury bills are more appropriate for the model setting. However, the information of the aggregate Treasury bills outstanding is not always available in the sample period.

[17] Without the outside goods a homogeneous increases in the deposit spreads of all kinds of deposits (including cash) does not change the quantities held.

[18] For commercial banks which operate in multiple markets, I only have bank-level rather than branch-level information on deposit rates, so there is no cross-market variation for these multi-market banks. Nevertheless, this may not be a major issue since previous empirical studies have shown multi-market banks usually use uniform pricing across local markets within a state (Radecki, 1998, Heitfield, 1999).

[19] This set of cost shifters of commercial banks are also used in previous literature such as Dick (2008) and Ho and

Lastly, I include bank fixed effects to absorb time-invariant bank-specific cost shocks, time fixed effects to absorb aggregate shocks to marginal costs, and MSA-fixed effects to absorb cross-market differences in the cost of providing depository services.

To identify the demand coefficient to endogenous deposit spreads, I need a set of instruments. Following the previous literature, I use a second-order polynomial of a set of cost shifters as instruments for demand function, i.e., $w_{j,m,t}$ and their squares and interactions. I use Chamberlain's (1987) optimal instruments in the second stage of estimation to increase the estimator's efficiency and stability (Reynaert and Verboven, 2014). The optimal instruments are defined as the conditional expectation of the derivatives of the residuals with respect to the parameter vector.

Table 1 provide the summary statistics of the sample. Each MSA-year has on average 12 large commercial banks and 23 large MMFs. The commercial banking sector is more concentrated than MMF sector: the HHI is 0.23 for the commercial banking sector, but is 0.08 for MMFs. A commercial bank typically has a larger market share than a MMF: the average market share is 2.6% for a commercial bank and is 0.36% for a MMF. A commercial bank also tends to charge higher deposit spreads: the average deposit spreads are 1.41% for commercial banks and 0.17% for MMFs. A commercial bank on average has 7.89 branches in a MSA, and each branch has 18.17 employees. 52% of MMFs are rated, 49% are affiliated with commercial banks, 36% allow depositors to write checks.

5 Estimation Results

I begin by accessing how well the model fits the data. Then I present parameter estimates. Next, I examine model-implied demand elasticities and markups. I further investigate cross-MSA variations in depositor preferences. Finally, I discuss alternative explanations.

5.1 Model Fit

Figure 8 compares model predicted market shares and deposit spreads with the data. The random coefficient model successfully generates similar patterns in the data: when the Fed Funds rates increase, commercial banks charge higher deposits spreads while MMFs keep relative stable prices[20]. Correspondingly, market shares of cash and commercial banks drop while market shares of MMFs increase.

Ishii (2011).

[20]The deposit spreads of MMF dipped briefly by around 1% in 2007 and 2008 as the risk premium in the money market spiked. However, this is not driven by monetary policy.

The ability of the model to generate different behaviors across banking sectors is remarkable given commercial and shadow banks are modeled in a similar way. In the following subsection, I will show that the different behaviors arises endogenously as heterogeneous depositors self-select into different banking sector.

5.2 Parameter Estimates

Table 3 reports the estimates of demand parameters for three different models. Column 1 reports the random coefficient model in which depositors are heterogeneous in their sensitivity to deposit spreads and deposits spreads are instrumented. Column 2 shows the Logit IV model where depositors are homogeneous and deposits spreads are instrumented. Column 3 shows the Logit OLS model where depositors are homogeneous and deposit spreads are not instrumented.

The estimated yield sensitivity are negative and significant across all three models, but the magnitude of the random coefficient model is much larger than the other two. For the characteristics of commercial banks, all three models show that depositors value higher branch density, more employees per branch, single market banks, and younger banks. For the characteristics of MMFs, depositors prefer funds sponsored by independent asset management firms (non-bank), funds with check-writing privilege but no credit rating, and older funds. These results make intuitive sense.

The key departure of the random coefficient model from the logit IV and OLS model is to allow yield sensitivity to be different across depositors. The estimation shows the dispersion is statistically significant. Later I will explore the economic implications of such dispersion.

Table 4 presents the estimation of the cost function. For commercial banks, greater branch density is associated with lower marginal costs, implying there is increasing return to scale; high expense of fixed assets and salary increase the marginal cost. For MMFs, higher incurred management fee, share service fee, and other fees are associated with higher marginal cost, which is also intuitive.

5.3 Transaction Convenience and Depositor Choice Probability

Given the demand parameters, I can calculate transaction convenience of each bank. The transaction convenience is defined as inner product between the vector of product characteristics and the demand coefficients, $x_j'\beta$. Figure 10 shows the scatter plot of transaction convenience estimated by the random coefficient model against deposit spreads. There is a significant positive correlation between the two: products with higher transaction convenience charge higher deposit spreads. Consistent with the assumption, cash has the highest transaction convenience, MMFs have the least, and commercial banks are in the middle.

With banks offering differentiated products, I expect different types of depositors to self select into different types of banks. Figure 9 shows the probability of choosing commercial banks or MMFs for different types of depositors over time. Yield-oriented depositors are defined as depositors with above-median yield sensitivity, while transaction-oriented depositors are defined as depositors with below-median yield sensitivity. The first lesson is that transaction-oriented depositors are much more likely to choose commercial banks, while yield-sensitivity depositors are equally likely to choose MMFs and commercial banks. This result verifies the assumption of the simple model presented in Section 3. The second observation is that the choice probability of yield-oriented depositors varies significantly over monetary cycles, while the choice probability of transaction-oriented depositors is very stable. This is consistent with the intuition that yield-oriented depositors are constantly looking for cheaper options for liquidity, while transaction-oriented depositors care more about transaction convenience which does not change over monetary cycles.

5.4 Demand Elasticity

Using the estimated demand parameters, I can also compute own-price demand elasticities of each bank and MMF at each point of time using the following equation.

$$\frac{\partial s_{j,m,t}/s_{j,m,t}}{\partial p_{j,m,t}} = \frac{1}{s_{j,m,t}} \sum_{i=1}^{I} \mu_i \alpha_i s_{i,j,m,t} \left(1 - s_{i,j,m,t}\right) \tag{29}$$

The own-price demand elasticity measures the percent change of market share to one percent change in deposit spreads of the same product. I first examine demand elasticity in the cross-section of banks. Figure 11 shows the scatter plot of average deposit spreads against the demand elasticity of each bank. A key prediction of the random coefficient model is that a bank with an inelastic demand turns to charge a higher deposit spreads. Specifically, commercial banks as a group have more inelastic demand than MMFs. In contrast, IV and OLS models demand elasticity and deposit spread are not significantly as shown in the online appendix.

Table 5 reports the summary statistics of the own-price elasticity. The result make intuitive sense: the demand for cash is most inelastic while the demand for MMFs is the most elastic. The demand for commercial bank deposits lies in the middle. There is large standard deviation in the demand elasticity of commercial bank deposits comparing to MMFs. In the later discussion, I will show that a large proportion of variation is related to monetary policy.

Next, I discuss the cross-price demand elasticity. Cross-price elasticity measures the percent change of market share due to changes in deposit spreads of a competitor. The cross-price demand elasticity of product j with one percent change in deposit spreads of product k is calculated according to the following formula:

$$\frac{\partial s_{j,m,t}/s_{j,m,t}}{\partial p_{k,m,t}} = \frac{1}{s_{j,m,t}} \sum_{i=1}^{I} \mu_i \alpha_i s_{i,j,m,t} s_{i,k,m,t} \tag{30}$$

Table 6 presents the median cross-price elasticity. The result suggests that price changes of a high quality product tend to have greater effects on other products. In addition, MMFs in general have the highest cross-price elasticity to the price of other products. This is consistent with the evidence that MMF depositors are more sensitive to yields.

5.5 What Drives Deposit Spreads?

After confirming that the model generates a list of sensible results, now I examine the central mechanism through which monetary policy affects the prices and quantities of deposits. I decompose deposit spreads into two components, marginal costs and markups. I then examine which component drives the deposit spreads. If monetary policy mainly works through marginal costs, then the key mechanism should lie in the supply side. If monetary policy works through markups instead, then the key mechanism should be from the demand side.

Figure 12 and 13 plot the median markups and marginal costs of the each banking sector over time. The random coefficient model reveals that the deposit spreads are mainly driven by the markups: as the Fed Funds rates go up, the markups of commercial banks increase while the markup of MMFs remain stable. The marginal costs, however, do not exhibit cross-sector variations. Quantitatively, the differential response of the markups to the Fed Funds rates almost drive all the variations in deposit spreads[21].

In comparison, the markup estimated by the Logit IV and OLS model shows essentially no time-series variation for neither types of banks. Furthermore, the level of markup is much higher than the deposit spreads, which implies the marginal cost is counter-intuitively negative[22]. This result

[21] In the random coefficient model, the markup of commercial banks are occasionally higher than the deposit spreads. This is likely due to the measure error of using the imputed deposit rates. Recall that I use the total interest expense divided by the total deposits to compute the implied deposit rates. The problem is that both of them includes a small amount of term deposits. When the Fed lowers the Fed Funds rates: the deposit rates for demand deposits have changed but the existing term deposits still pay the old deposit rates. This makes the imputed deposit rates artificially higher, and the imputed deposit spreads artificially lower than the actual rates. Therefore, the imputed deposit spreads may be temporarily lower than the markup. The average markup of MMFs seems to be more concerning, since it is constantly higher than deposit spreads. This could be caused by using the measurement error of using the long-run steady state markup to approximate current markup. Nevertheless, the level of markup is much closer to deposit spreads in the random coefficient model than logit IV and OLS model.

[22] In the random coefficient model, the markup of commercial banks are occasionally higher than the deposit spreads. This is likely due to the measure error of using the imputed deposit rates. Recall that I use the total interest expense divided by the total deposits to compute the implied deposit rates. The problem is that both of them includes a small amount of term deposits. When the Fed lowers the Fed Funds rates: the deposit rates for demand deposits have

shows that depositor heterogeneity is essential for the model fit.

5.6 Local Demography

The above discussion remains agnostic on why depositors have such dispersion in yield sensitivity. In this subsection, I explore cross-market variations in demographics to examine the determinants of the yield sensitivity. I re-estimate the random coefficient model for each MSA which gives me MSA-specific preference parameters. Then I regress the estimated preference parameters on local demographic information such as mean household income, average age, proportion of population with college degree, total payroll, number of establishments, and number of employees scaled by population in a cross-section of 325 MSAs where all the above demographic information are available. Table 7 reports the result. MSAs with high household income have higher yield sensitivity. This is consistent with the idea that there are fixed costs to manage wealth: wealthy people are more likely to actively manage their wealth because potential benefits of doing so are sufficient large to overcome the fixed cost. The result also shows that MSAs with younger population have higher yield sensitivity. This is consistent with the idea that seniors use deposit accounts for “storage" purposes while non-seniors use deposit accounts for investment purpose (Choi and Choi, 2016). MSAs with more business activities as measured by higher total payroll, more establishments and employees are not associated with higher yield sensitivity, which is somewhat surprisingly. The result of yield sensitivity dispersion is similar to mean yield sensitivity, as a MSA with high yield sensitivity also tends to have a large dispersion. Last but not least, MSAs with fewer college graduates and larger population value branch density more; MSAs with more business establishments value number of employees per branch more.

5.7 Alternative Explanations

One may argue that there are many other institutional differences across banking sectors could also possibly explain these results. One intuitive candidate is the reserve requirement. When commercial banks take deposits, they are required to keep a fraction of the deposits as reserves instead of lending them out. Before October 2008, bank reserves do not bear interests. Therefore, holding reserves imposes a cost for commercial banks which is increasing to the Fed Funds rates. In contrast, shadow

changed but the existing term deposits still pay the old deposit rates. This makes the imputed deposit rates artificially higher, and the imputed deposit spreads artificially lower than the actual rates. Therefore, the imputed deposit spreads may be temporarily lower than the markup. The average markup of MMFs seems to be more concerning, since it is constantly higher than deposit spreads. This could be caused by using the measurement error of using the long-run steady state markup to approximate current markup. Nevertheless, the level of markup is much closer to deposit spreads in the random coefficient model than logit IV and OLS model.

banks are not subject to reserve requirement. As a result, monetary policy may have differential impacts across banking sectors through the cost of providing depository services. This reserve channel features underlying mechanisms of several papers such as Kashyap and Stein (1995), Stein (2012), and Sunderam (2015).

Although intuitive, the reserve based explanation is hard to quantitatively explain the magnitude of pricing difference documented in this paper. To do a back-of-envelope calculation, I assume that 10% reserve requirement applies to all commercial bank deposits[23]. In the 2004 tightening cycle, the Fed Funds rates increase by 4.25%, which increase the marginal cost by 0.425% through the reserve channel. However, this number is still far from explaining 2.5% increase in deposit spreads. This is not surprising since extensive research has suggested that reserve requirement has become less relevant for the decision of banks due to technological innovations and regulatory reforms[24].

The second potential explanation is based on asset-side differences between commercial banks and MMFs. The asset duration of MMFs are much shorter than commercial banks due to both economic and regulatory reasons[25]. Therefore, a change in interest rates may lead to different impacts on the value of the assets due to different asset duration. However, this channel is only relevant for the periods shortly after interest rate changes. It cannot explain the persistent differences in deposit spreads between commercial banks and MMFs long after the change of the Fed Funds rates.

6 Policy Implications

What is the welfare implication of the arise of shadow banks? How do shadow banks change the transmission of monetary policy? In this section, I analyze these questions using the structural model.

[23]In practice, saving deposits face much less reserve requirement (1%), which further reduce the magnitude of this channel.

[24]One example of technological innovations is the sweep technology, which allows banks to easily transfer funds from transaction accounts to saving accounts to avoid the reserve requirement (Teles and Zhu, 2005). As a result, the amount of bank reserve in the economy has become very small before the recent unconventional monetary policy: as of December 31, 2007, the aggregate reserve balance is only 48 billion, which accounts for less than 0.4% of 6,720 billion commercial bank deposits. It is hard to imagine such a small opportunity cost could quantitatively explain the substantial deposit spreads observed in the data. After the start of unconventional monetary policy in 2008, the reserve balance grow dramatically. However, in this period, the Fed started to pay interest on reserves, which essentially eliminate this reserve channel.

[25]Economically, the shadow banking system breaks down the intermediation process in several steps. MMFs only conduct a small amount of maturity transformation: MMFs assets have an average maturity of around 40 days. In terms of regulation, Rule 2a-7 of the Investment Company Act of 1940 restrict the highest maturity of any debt held by MMFs to be under 13 months, and the portfolio must maintain a weighted average maturity (WAM) of 60 days or less.

6.1 Depositor Welfare

Commercial banks used to have considerable market power in local depository market. The entrance of shadow banks may potentially increase price competition and improve depositor welfare by providing a low-cost alternative. To access the welfare consequence of the entrance of shadow banks, I use the estimated structural model to simulate the counterfactual economy with no MMFs. I solve deposit spreads and market shares of commercial banks in this counterfactual economy and calculate depositor welfare according to the new set of choices and prices.

Figure 14 shows the average counterfactual deposit spreads and market share over time. In absence of MMFs, commercial banks charge slightly higher deposit spreads and gain much larger market share. The price increase is more prominent when the Fed Funds rates are high.

I follow McFadden (1981) and Nevo (2001) to estimate the welfare gain for depositors from the entrance of MMFs. I first compute the change of expected utility for each type of depositors. The expectation is taken with respect to the idiosyncratic taste shocks.

$$\Delta EU_i = EU_i' - EU_i \tag{31}$$

Where EU_i is the expected utility of type-i depositors in the real economy with MMFs, and EU_i' is the expected utility of type-i depositors in the counterfactual economy without MMFs.

$$EU_i = E_e \max_{j\in\{0,1,\ldots J\}} u_{i,j} = \ln\left(\sum_{j=0}^{J} \exp\left(\delta_{ij}\left(p_j, x_j; \theta_D\right)\right)\right) \tag{32}$$

Then, I divide expected utility by the yield sensitivity to calculate the equivalent variation (EV) for each type i depositors. The equivalent variation measures the change in welfare by the unit of deposit spreads.

$$EV_i = \frac{1}{\alpha_i}\left(EU_i - EU_i'\right) \tag{33}$$

Lastly, I sum up the equivalent variation across all the depositors to obtain the aggregate welfare gain.

$$EV = \sum_i \mu_i EV_i \tag{34}$$

Figure 15 shows the time series of the welfare gain. The entrance of shadow banks on average generates 0.36 cents of a dollar per year in the sample period. This amounts to 50 billions welfare improvement with an aggregate money supply of 14 trillions at the end of 2015. The welfare gain has the same magnitude as national branching deregulation in the 1980s estimated by Dick (2008).

I further examine the time-series variation of the welfare gain. The welfare gain is larger when the Fed Funds rates are high, which is consistent with the previous result that commercial banks enjoy greater market power during these periods.

Lastly, I decompose the welfare gain to two sources: change in product diversity and change in price. To calculate the welfare gain due to the change in product diversity, I use the original deposit spreads of commercial banks, but drop all the MMFs from the choice set of depositors. To calculate the welfare gain due to the change in product diversity, I use the counterfactual deposit spreads of commercial banks when there are no MMFs competing, but keep the MMFs in the choice set. Figure 15 shows the decomposition. The welfare gain mainly comes from the increase in price competition.

To summarize, the entrance of MMFs increases price competition and enhances product diversity. The caveat of the above analysis is that the risks brought by the shadow banks is abstracted away. The next subsection will focus on the implication of shadow banks to financial stability.

6.2 Shadow Banks and Monetary Policy Transmission

There is a long-lasting concern that financial innovations may undermine monetary control of the central bank. Such concern is elevated in recent years as the unregulated shadow banking sector grows outside the traditional commercial banking sector. Has the rise of shadow banking system affected the effectiveness of monetary policy? To answer this question, I calculate aggregate money supply in the counterfactual economy without MMFs. Figure 16 shows the amount of aggregate money supply divided by the sum of money and Treasury bonds. In absence of MMFs, aggregate money supply becomes more responsive to monetary policy. This suggests that the existence of shadow banking system indeed reduces the effectiveness of monetary policy.

The counterfactual analysis offers new insights on the the monetary transmission in an economy with both commercial banks and MMFs. MMFs provide a low-cost buffer for the yield-sensitive depositors. Depositors do not have to switch between money and bonds over monetary cycles. Instead, they switch between commercial bank money and shadow bank money. This reduces the impact of monetary policy on aggregate money growth.

6.3 Shadow Banks and Financial Stability

My finding also speaks to the current debate on objectives of monetary policy. After the 2008-2009 financial crisis, there is increasing support for incorporating financial stability as the third mandate of monetary policy, along with price stability and full employment (Smets, 2016). The possibility of using monetary tightening to reduce excessive money creation is often raised.

The finding of the structural model directly speaks to this debate. It suggests that using monetary tightening to reduce money creation may be ineffective as the effects on different types of banks tend to cancel each other. Moreover, such policy may be counter productive as it shifts money creation from commercial banks to shadow banks which are not insured by the deposit insurance.

I further examine the impact of monetary policy on the credit supply of MMFs which is abstracted away in the structural estimation. There are five categories of assets that MMFs holds: commercial papers, repurchase agreements, floating rates notes (FRNs), large denomination commercial bank obligations (CB), and Treasury bills. Commercial papers, repurchase agreements and floating rates notes (FRNs) are often used by other types of shadow banks to obtain financing, while large denomination bank certificates of deposit (CDs) are an important source of financing for commercial banks. In the following I conduct panel regressions of MMFs on Fed Funds rates for each type of loans that MMFs make:

$$\Delta MMF\ Lending_{i,t} = \alpha + \beta Fed\ Funds\ Rates_t + \gamma X_{i,t} + \epsilon_{i,t} \tag{35}$$

The dependent variable is the annual change of MMF lending normalized by the lagged total lending[26]. The control variables include the Fed Funds rates, various macro economic variables, fund characteristics and fund fixed effects.

Table 8 reports the results. Column 1 to 3 show that as MMFs get more deposits, MMFs significantly increase their lending to other shadow banks. The economic magnitude is big, too: 1% increase in the Fed Fund rates are associated with 0.17%-0.45% increase in lending.

With an increase in the supply of funding from MMFs, assets of other shadow banks should grow bigger. I examine five types of shadow banks which rely on MMFs to obtain funding: funding corporations, finance companies, ABCP issuers, captive financial institution and broker-dealers[27].

I regress aggregate asset growth rates of different types of shadow banks on the Fed Funds rates and various macro economic variables:

$$Shadow\ Bank\ Asset\ Growth_t = \alpha + \beta Fed\ Funds\ Rates_t + \gamma X_t + \epsilon_t \tag{36}$$

[26] The denominator is the lagged total lending because the a specific loan type can be zero for an individual MMF.

[27] Finance companies are financial entities that sell commercial paper and use the proceeds to extend credit to borrowers which usually tend to be riskier than that of commercial banks (Carey, Post, and Sharpe, 1998). In the mortgage market, these shadow lenders such as Quicken Loans, PHH and loanDepot.com accounted for 53 per cent of government-backed mortgages originated in April, 2015. Funding corporations are subsidiaries of foreign banks and non-bank financial firms that raise funds from the commercial paper market and pass the proceeds to foreign parent companies abroad or to foreign banking offices in the U.S.. ABCP issuers are structured investment vehicles which purchase and hold financial assets from a variety of asset sellers and finance their portfolio by selling asset-backed commercial paper to MMFs or other "safe asset" investors like retirement funds. Captive finance company is a subsidiary whose purpose is to provide financing to customers buying the parent company's product through issuing commercial papers. Examples include the captive finance of the Big Three car manufacturers: General Motors Acceptance Corporation (GMAC), Chrysler Financial and Ford Motor Credit Company. Broker-dealers include both non-bank firms and subsidiaries of commercial banks that engages in the business of trading securities for its own account or on behalf of its customers. Broker-dealers heavily rely on repo to obtain funds from MMFs and then lend to their customers through reverse repo. A prominent example of broker-dealers is Lehman Brothers which went bankrupted during the 2008-09 financial crisis.

Table 9 presents the results. Consistent with the increase in MMF lending, the assets of these shadow banks also grow faster when the Fund Funds rates are high. The composition shift in the aggregate credit supply may also increase the systemic risk, because shadow banks usually lend to the riskier segment of borrower (Carey, Post, and Sharpe, 1998). The positive relation between shadow bank asset growth rates and the Fed Funds rates is also documented by a contemporaneous paper by Nelson, Pinter and Theodoridis (2015).

The second lesson of Table 8 is that MMFs also increase their lending to commercial banks through large denomination bank obligations in periods of monetary tightening as shown in Column 5. This result reveals an interesting interaction between the shadow and commercial banking system. As commercial banks lose their retail deposits to shadow banks, they borrow from the money market to finance their long term assets. Such arrangement is profitable for both types of banks as it effectively conducts price discrimination on the transaction-oriented depositors. Table 10 provides concordant evidence from the balance sheets of commercial banks. I regress the change of commercial bank liability on the Fed Funds rates:

$$\Delta CB\ Liability_{i,t} = \alpha + \beta Fed\ Funds\ Rates_t + \gamma X_{i,t} + \epsilon_{i,t} \tag{37}$$

The dependent variable is the annual change of commercial bank liabilities normalized by the lagged total borrowing[28]. The control variables include the Fed Funds rates, various macro economic variables, bank characteristics and bank fixed effects. High Fed Funds rates are associated with less checking and saving deposits from retail depositors, but more large time deposits which are mainly sold to MMFs (Hanson, Scharfstein, and Sunderam, 2015). In column 3-8, I split the sample into three size groups: small (below 95 percentile), medium (95-99 percentile) and large (above 99 percentile) following Kashyap and Stein (2000). Large banks usually have better access to money market. Therefore, I expect large banks will substitute more from retail checking and saving deposits to large time deposits. The result is consistent with the conjecture. This result has implications for financial stability: monetary tightening may make commercial banks increasingly rely on the run-prone whole-sale funding market, and potentially introduce more risk of contagion between the shadow and commercial banking system.

To summarize, using monetary policy to reduce excessive money creation may be ineffective as depositors may simply switch to shadow banks. Even worse, it can cause unintended consequences of expanding the shadow bank lending and destabilizing the funding structure of commercial banks.

[28]The denominator is the lagged total lending because the a specific loan type can be zero for an individual MMF.

7 Conclusion

This paper studies how monetary policy affects the shadow banking system, which has become increasingly important in the U.S. economy but remains poorly understood. I find that shadow bank money supply expands when the Fed increases the Fed Funds rates. This is at odds with the conventional wisdom in the commercial banking sector that monetary tightening reduces money creation. Using a structural model of bank competition, I show that clientele difference across banking sectors can explain their different responses to monetary policy.

This paper highlights the complexity of the current banking system and its implication for monetary policy. The rise of the shadow banking sector may have fundamentally changed the structure of the U.S. banking system and the transmission mechanisms of monetary policy. The shadow banking sector may weaken the influence of monetary policy on the aggregate money supply. Therefore, using monetary tightening to reduce excessive money creation and promote financial stability may lead to unintentional consequences.

This paper also sheds lights on the welfare consequence of the entrance of shadow banking system. Shadow banks intensify the competition in the deposit market by providing a low cost alternative. Potential welfare loss from increased systemic risk should be balanced with substantial welfare gain from increased competition and product diversity.

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Figure 1: Shadow Bank Deposit Growth Rates and the Fed Funds Rates

This figure shows the annual growth rates of the U.S. shadow bank deposits and the Fed Funds rates from 1987 to 2012. The data is in quarterly frequency. Shadow bank deposits include all the U.S. retail and institutional MMF shares. The data is obtained from FRED.

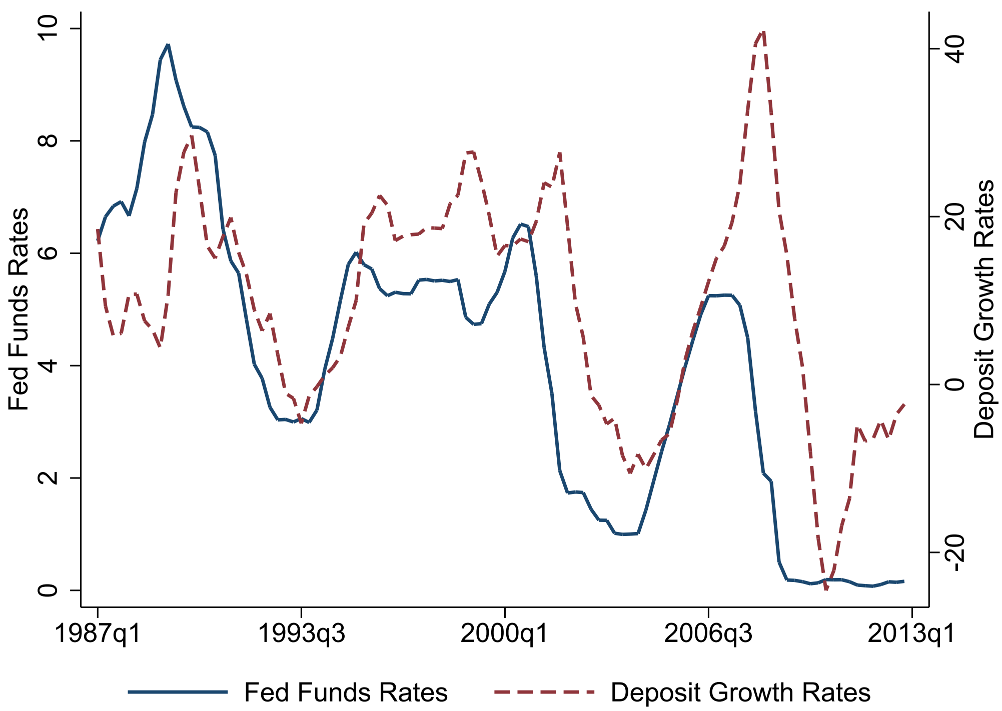


Figure 2: Commercial Bank Deposit Growth Rates and the Fed Funds Rates

This figure shows the annual deposit growth rates of the U.S. commercial banks and the Fed Funds rates from 1987 to 2012. The data is in quarterly frequency. Commercial bank deposits are the sum of checking and saving deposits. The data is in quarterly frequency. The data is obtained from FRED.

Figure 3: Deposit Spreads and the Fed Funds Rates

This figure shows the average deposit spreads of the U.S. commercial banks and MMFs from 1987 to 2012. The deposit spreads are defined as the difference between the Fed Funds rates and the deposit rates subtracting account fees for commercial banks or charged expense for shadow banks. Commercial bank deposit rates are obtained from the Call report. MMF yields are obtained from iMoneyNet.

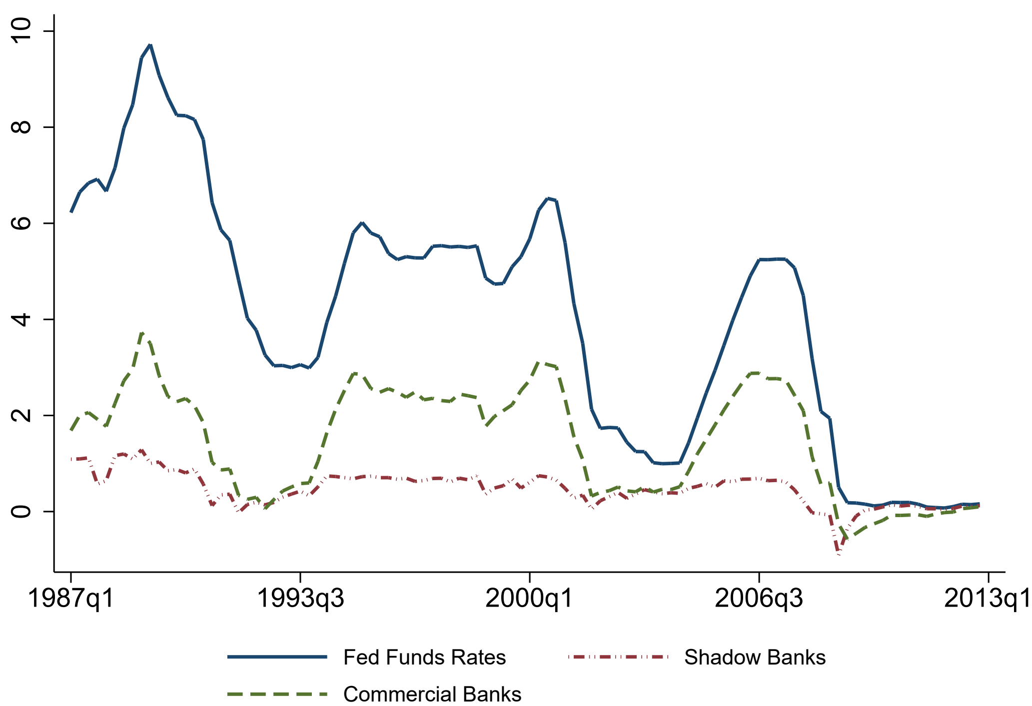


Figure 4: The U.S. Banking System

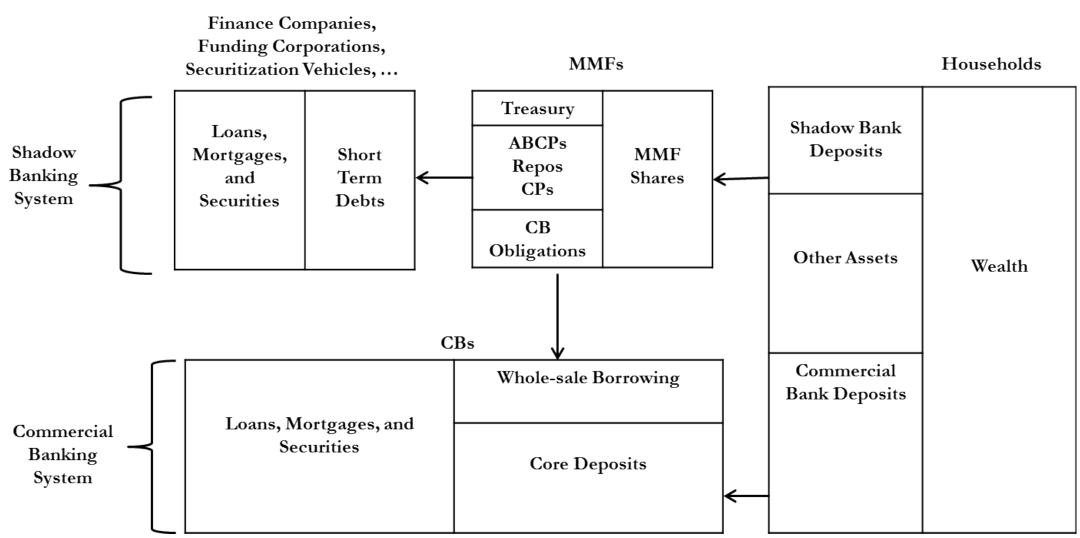


Figure 5: Composition of the U.S. Money Supply

This figure shows the composition of the U.S. money supply from 1987 to 2012. The data is in quarterly frequency. The shadow bank money supply includes all the U.S. retail and institutional MMF shares. The commercial bank money supply includes the checking and saving deposits from all the U.S. commercial banks. The data is obtained from FRED.

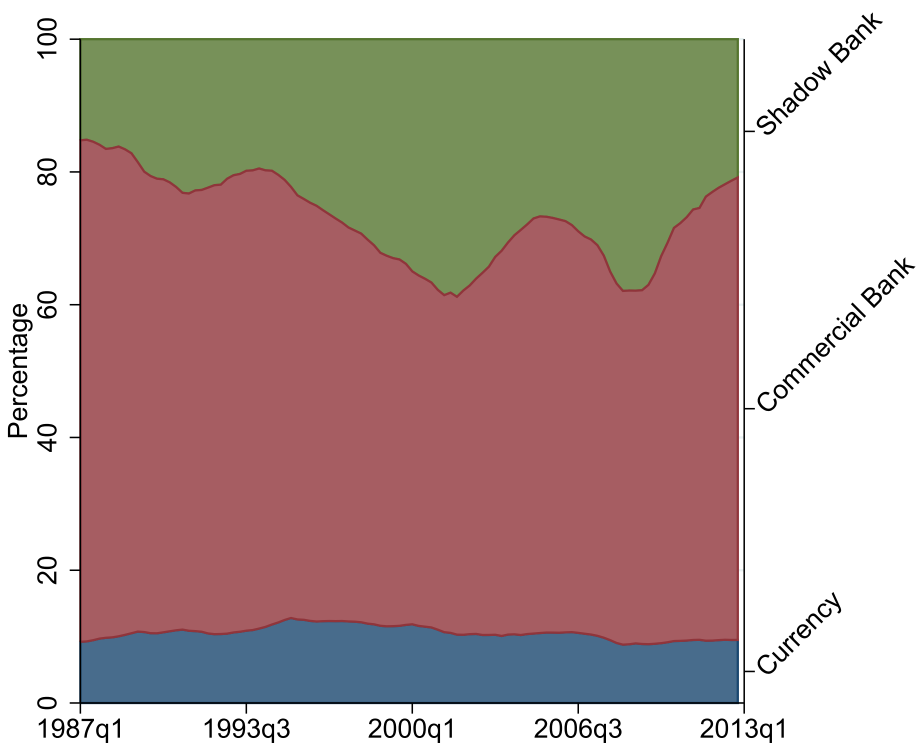


Figure 6: Aggregate MMF Portfolio

This figure shows the aggregate portfolio of the U.S. MMFs from 1998 to 2012. The data is obtained from iMoneyNet.

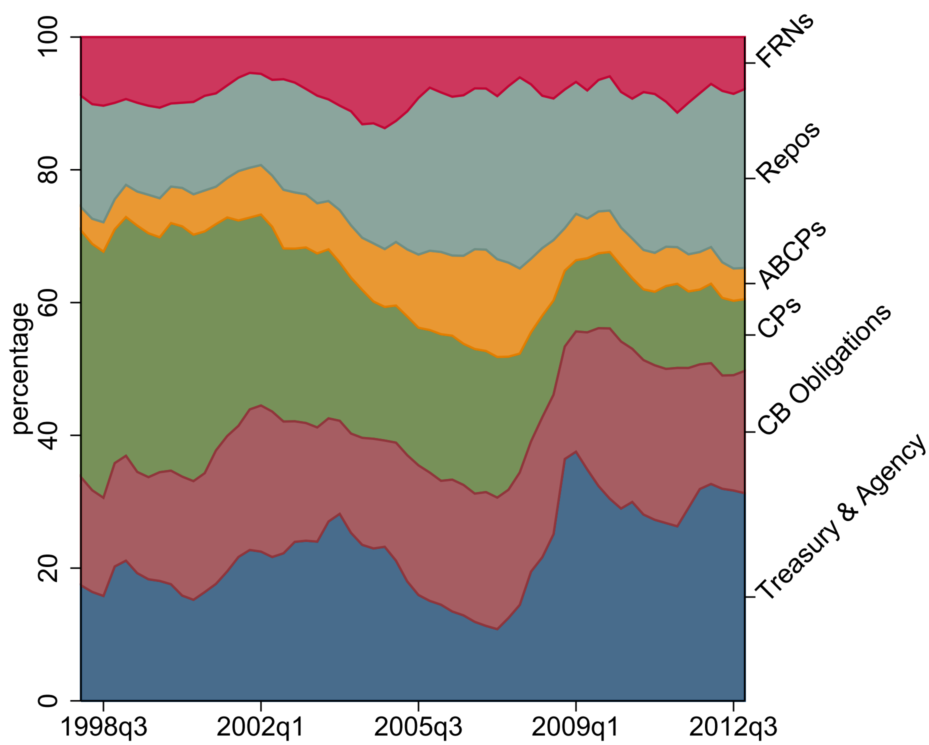
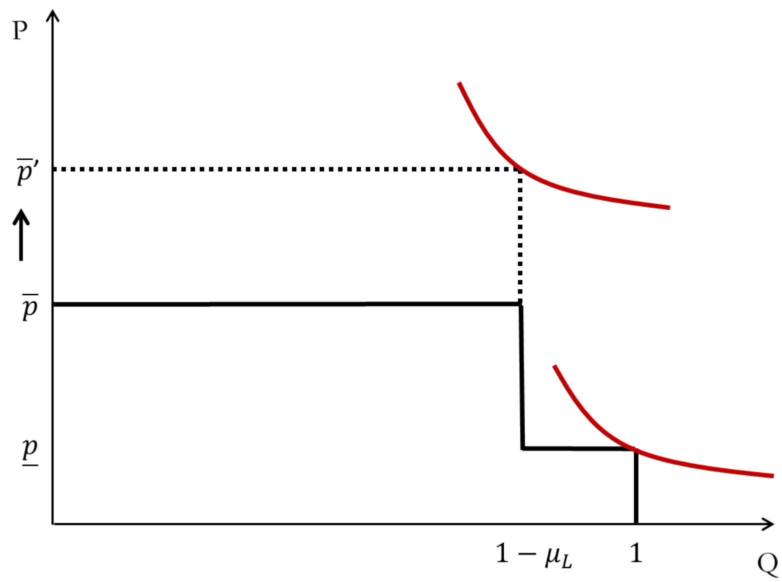


Figure 7: Deposit Demand and Isoprofit Curve of Banks

Commercial Bank



Shadow Bank

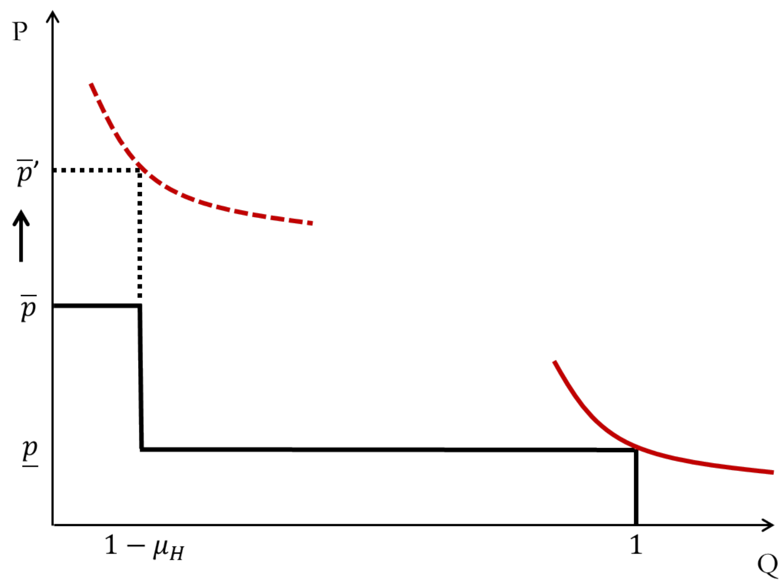


Figure 8: Estimated Market Share and Deposit Spreads

This figure shows the observed and estimated median market share and deposit spreads by the random coefficient model over time. The top, middle and bottom panel shows the result for cash, commercial banks, and MMFs respectively. The sample contains 6,444 MSA-year markets (358 MSAs-18 years).

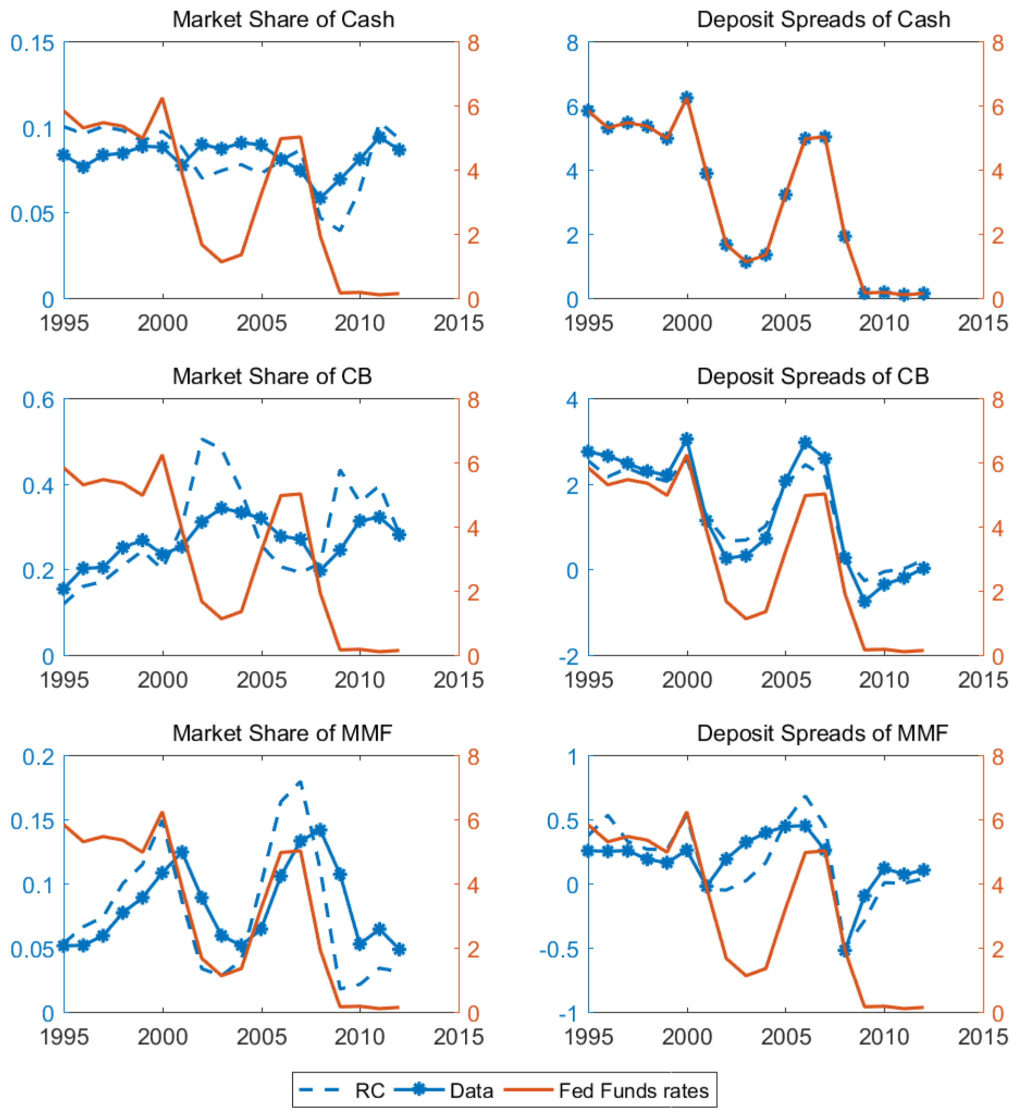


Figure 9: Choice Probability of Depositors by Type

This figure shows the probability for yield-oriented and transaction-oriented depositors to choose commercial banks or MMFs over time. The probability is estimated using the random coefficient model.

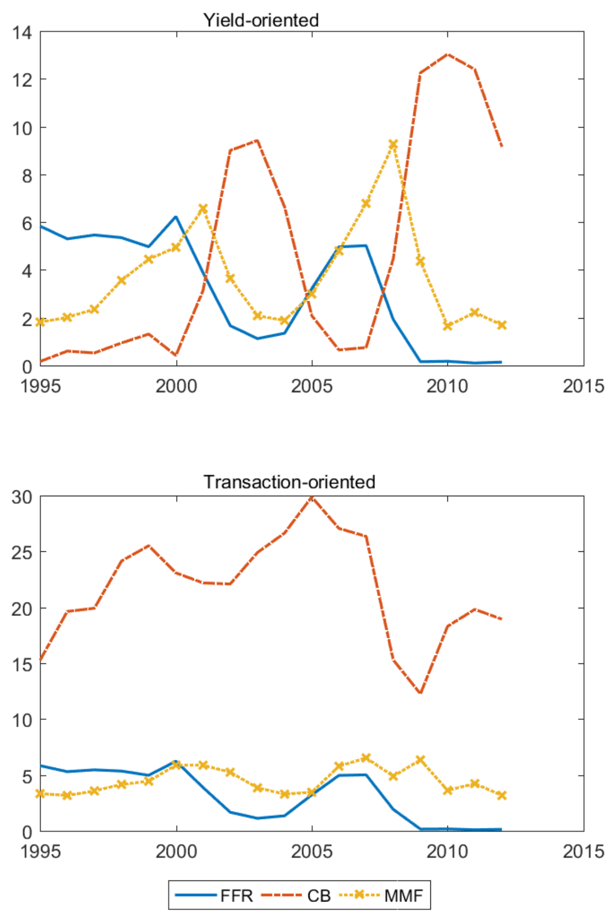


Figure 10: Transaction Convenience and Deposit Spreads

This figure shows the scatter plot of deposit spreads against convenience yields for cash, commercial bank deposits and MMFs. Each dot in the graph represents a MSA-year-product median. The sample includes 6,444 MSA-year markets (358 MSAs-18 years). The top left panel and the bottom right panel show the marginal distribution of deposit spreads and convenience yield respectively.

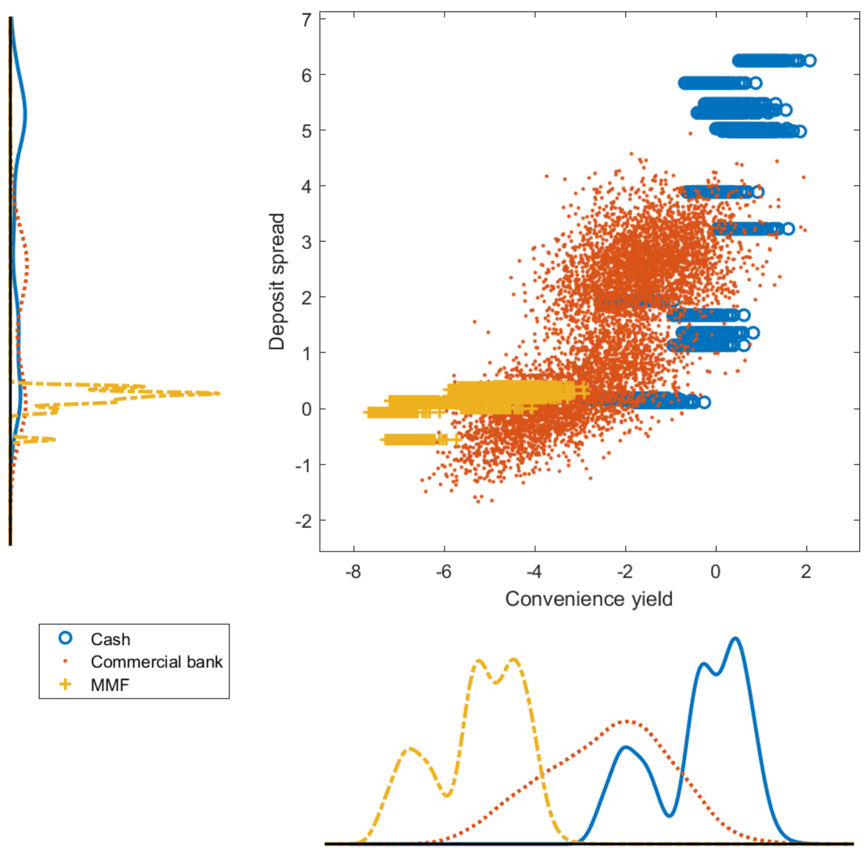


Figure 11: Demand Elasticity and Deposit Spreads

This figure shows the scatter plot of the demand elasticity against deposit spreads for cash, commercial bank deposits and MMFs. Each dot in the graph represents a MSA-year-group median. The sample contains 6,444 MSA-year markets (358 MSAs-18 years). The top left panel and the bottom right panel show the marginal distribution of deposit spreads and demand elasticity respectively.

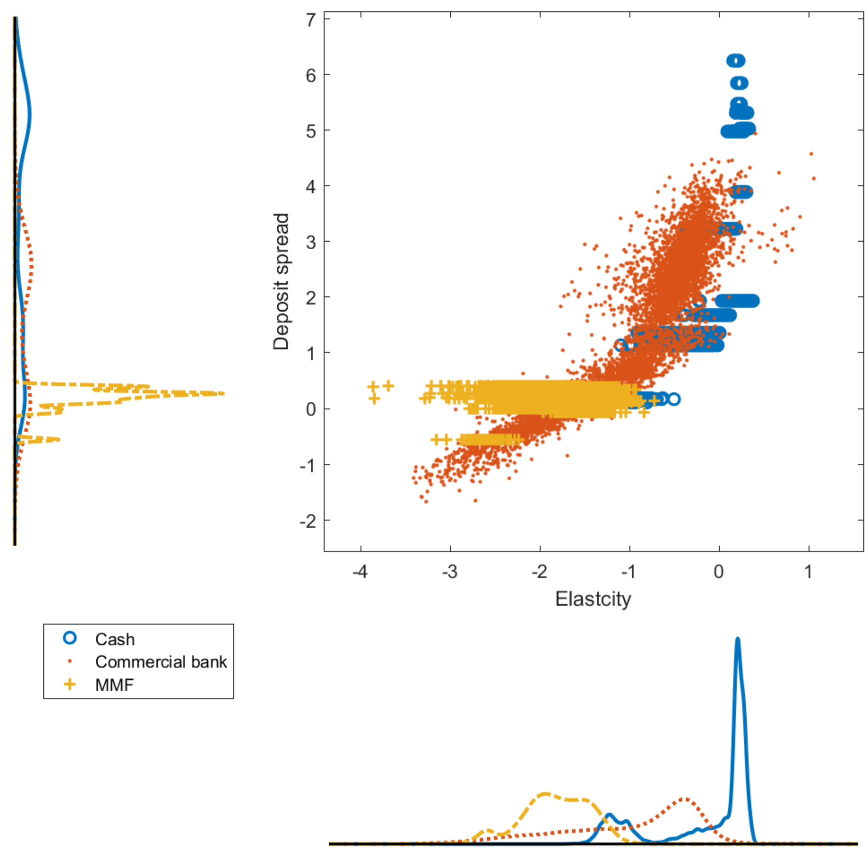


Figure 12: Fed Funds Rates and Predicted Markup

This figure shows the median markup estimated by three different models over time. The top panel shows the result for commercial banks, and the bottom for MMFs. The sample contains 6,444 MSA-year markets (358 MSAs-18 years).

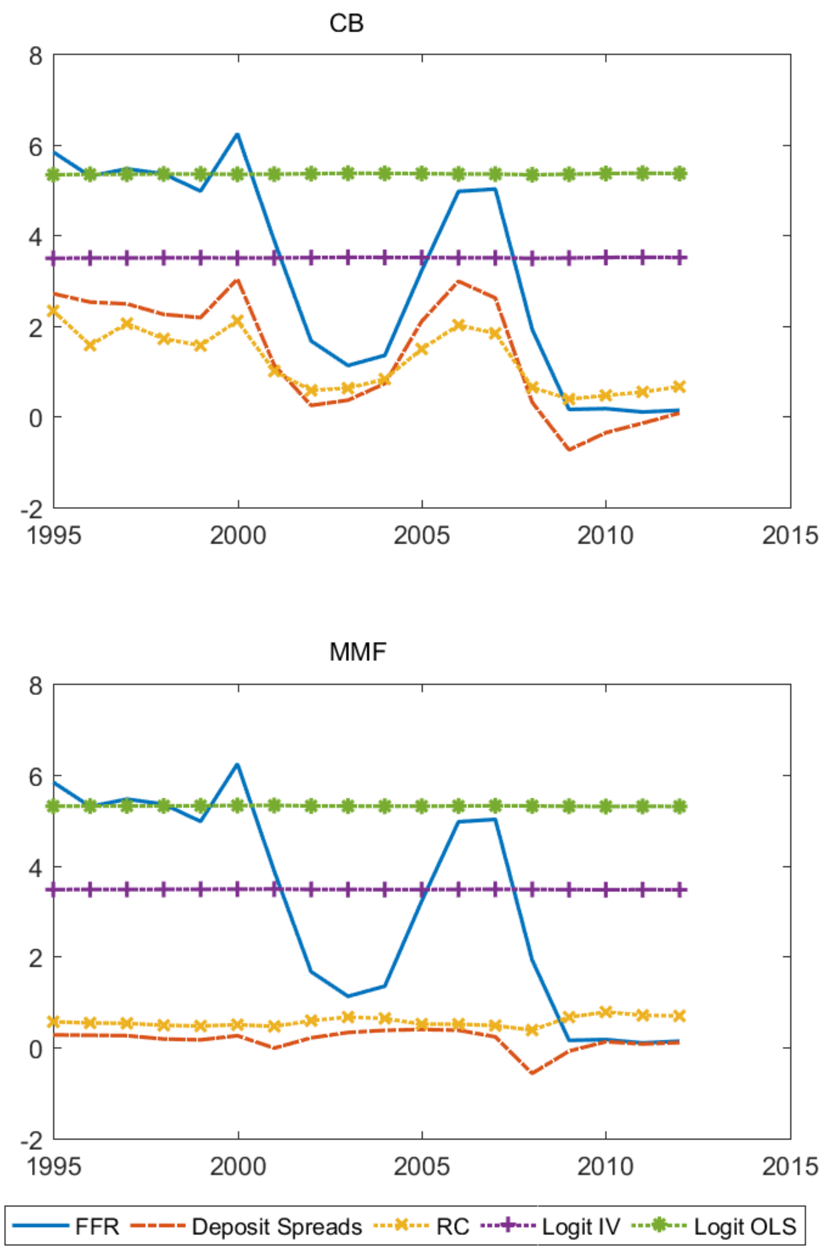


Figure 13: Fed Funds Rates and Predicted Marginal Cost

This figure shows the median marginal cost estimated by three different models over time. The top panel shows the result for commercial banks, and the bottom for MMFs. The sample contains 6,444 MSA-year markets (358 MSAs-18 years).

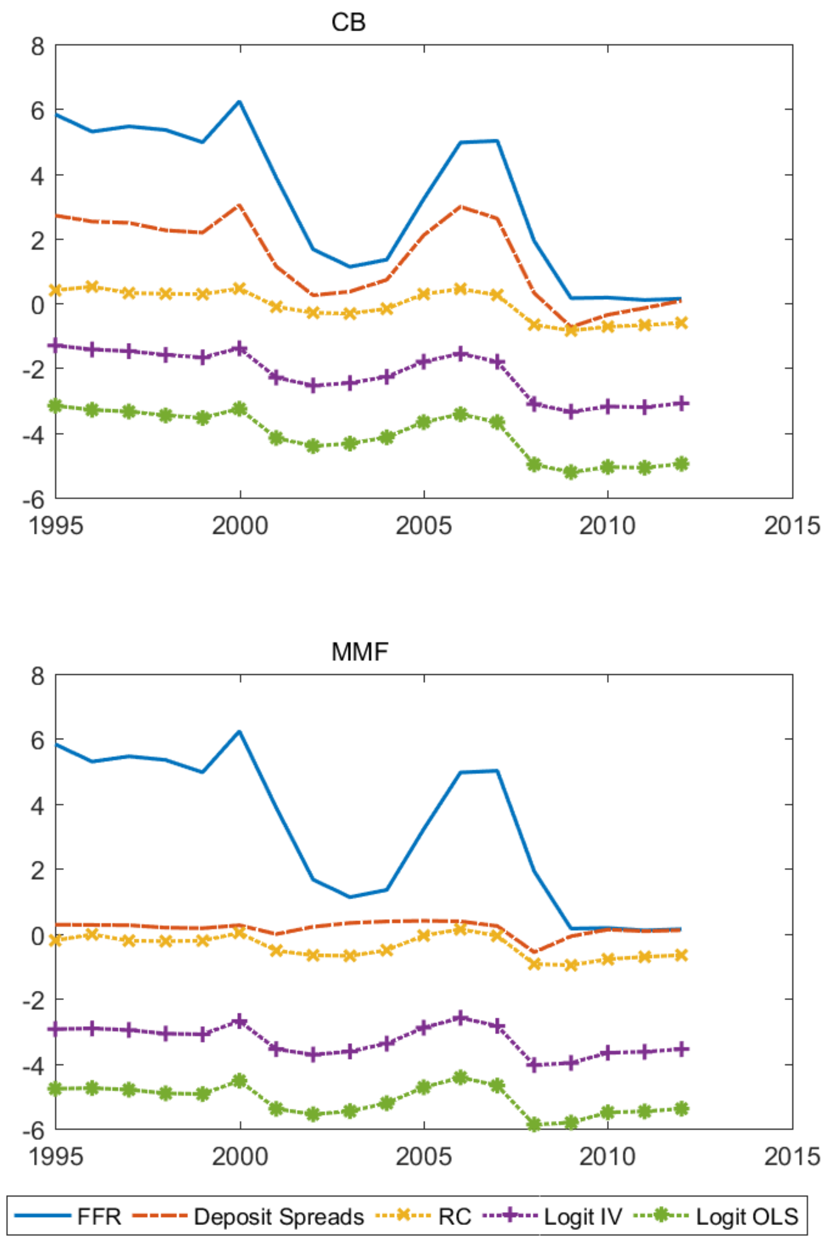
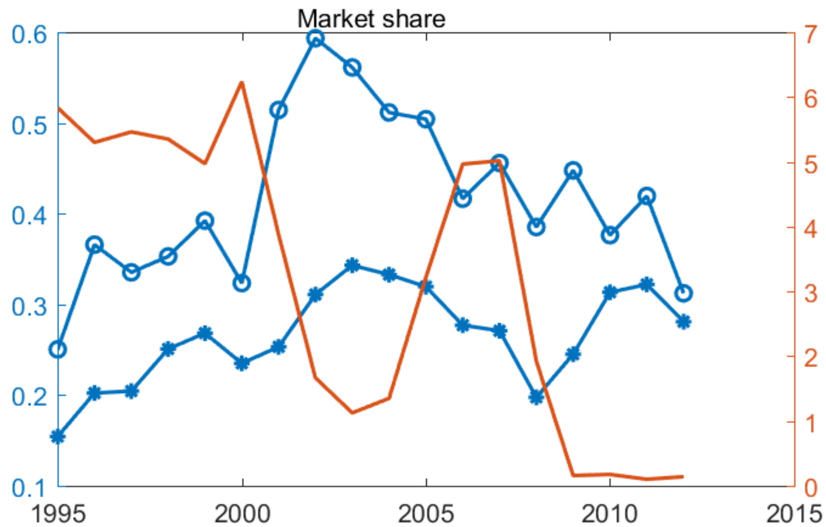


Figure 14: Counterfactual Market Share and Deposit Spreads of Commercial Banks

This figure shows the observed and counterfactual market share and deposit spreads of commercial banks in a counterfactual economy with no MMFs. The top and bottom panel show the result of market share and deposit spreads respectively. The sample contains 6,444 MSA-year markets (358 MSAs-18 years).



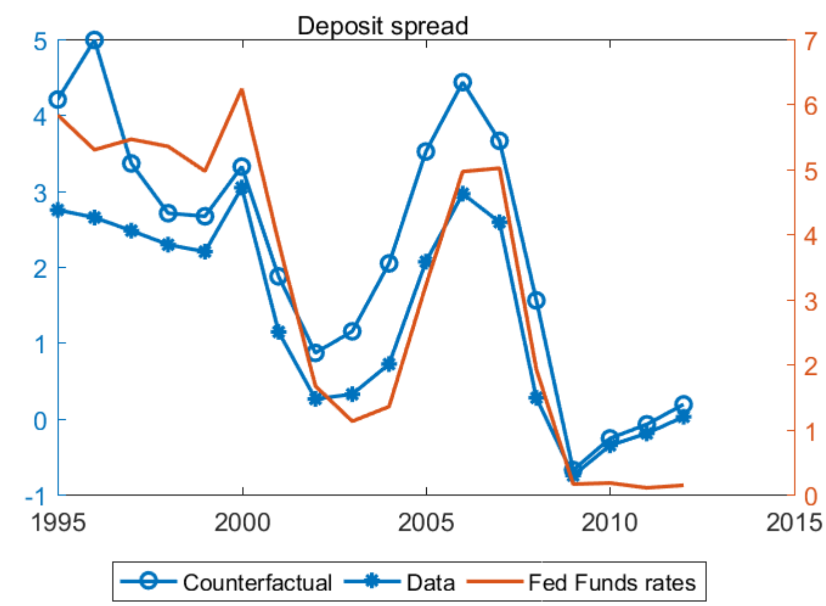


Figure 15: Welfare Gain Due to MMFs

This figure shows depositor welfare gain due to MMFs over time. The sample contains 6,444 MSA-year markets (358 MSAs-18 years).

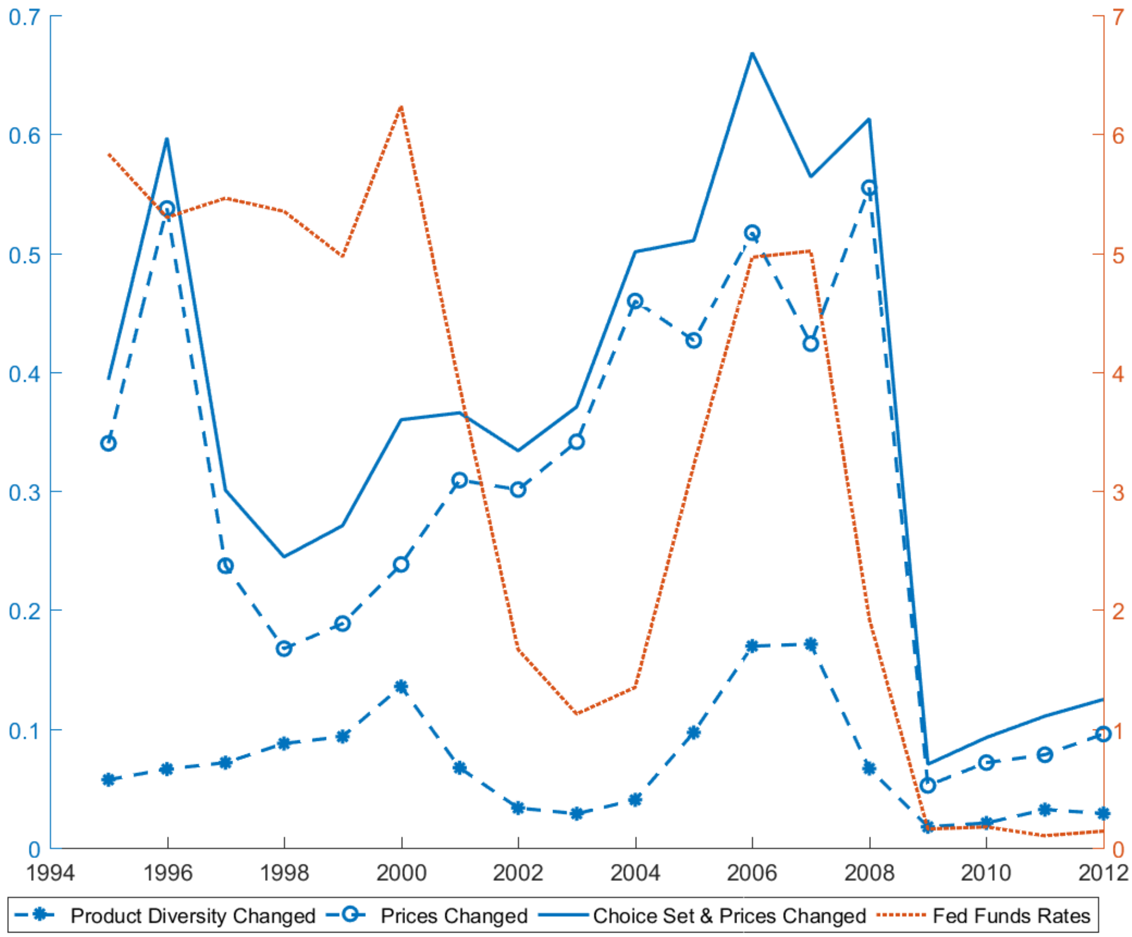
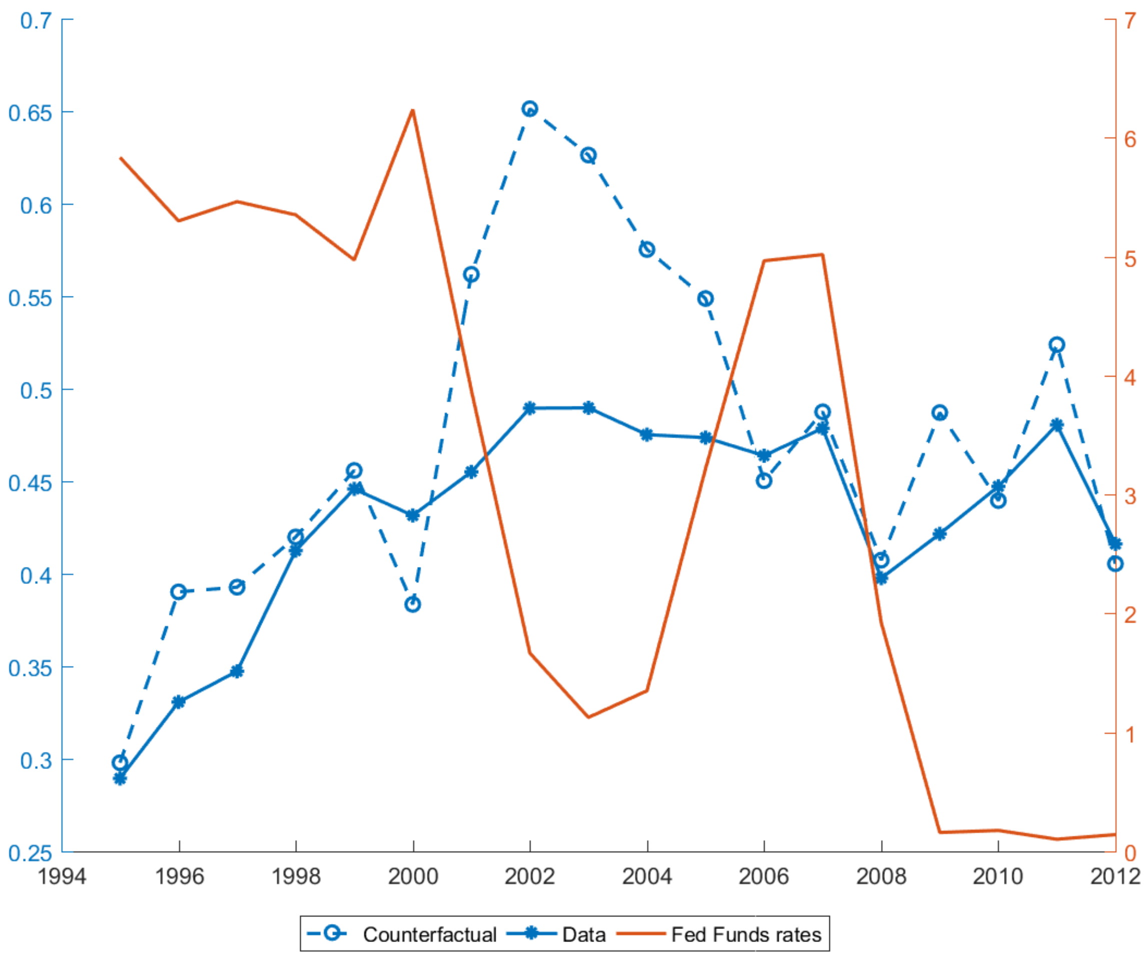


Figure 16: Counterfactual Aggregate Money Supply as the Share of Total Liquid Assets

This figure shows the observed and counterfactual aggregate money supply as share of total liquidity assets. The counterfactual analysis is conducted assuming there is no MMF in the market. The sample contains 6,444 MSA-year markets (358 MSAs-18 years).



Appendix

Markup Equation

The first order condition of the bank's problem is

$$\hat{s}_t + (p_t - mc_t)\frac{\partial \hat{s}_t}{\partial p_t} + \sum_{k=1}^{+\infty} \beta^k (p_{t+k} - mc_{t+k})\frac{\partial \hat{s}_{t+k}}{\partial p_t} = 0 \tag{38}$$

According to the partial adjustment assumption of equation 16

$$\frac{\partial \hat{s}_{t+k}}{\partial \hat{s}_{t+k-1}} = \rho \tag{39}$$

Therefore, I can write the effect of current deposit spreads on future market share as following

$$\frac{\partial \hat{s}_{t+k}}{\partial p_t} = \frac{\partial \hat{s}_{t+k}}{\partial \hat{s}_{t+k-1}}\frac{\partial \hat{s}_{t+k-1}}{\partial \hat{s}_{t+k-2}}\cdots\frac{\partial \hat{s}_t}{\partial p_t} = \rho^k \frac{\partial \hat{s}_t}{\partial p_t} \tag{40}$$

Moreover, the partial derivatives of stock-based market share to deposit spreads is proportional to the same partial derivatives of flow-based market share

$$\frac{\partial \hat{s}_t}{\partial p_t} = (1-\rho)\frac{\partial s_t}{\partial p_t} \tag{41}$$

In long-run steady state, the market share and deposit spreads are constant, and the stock-based market share equals to the flow-based market share. The first order condition can be written as

$$s + (p - mc)(1-\rho)\frac{\partial s}{\partial p} + \sum_{k=1}^{+\infty} \beta^k \rho^k (p - mc)\frac{\partial s}{\partial p} = 0 \tag{42}$$

I can solve the markup in long-run steady state as

$$p - mc = \left(-\frac{\partial s/s}{\partial p}\right)^{-1}\frac{1-\beta\rho}{1-\rho} \tag{43}$$

When the discount factor β is close to 1, the markup in long-run steady state can be approximated by

$$p - mc = \left(-\frac{\partial s/s}{\partial p}\right)^{-1} \tag{44}$$

This expression is exactly the same as the static case despite the definition of market share is based on deposit inflows rather than deposit stock. In the empirical exercise, I will use the steady state markup to approximate the real-time markup for the sake of simplicity.

Table 1: Summary Statistics

This table presents summary statistics of 6,444 MSA-year markets (358 MSAs-18 years) used for structural estimation. Deposit amount is in millions of dollars, deposit spreads, market share, expense of fixed asset, salary/asset, reserve/asset, incurred management fee, incurred other fee, and incurred share service fee are in percent.

variable	N	mean	sd	p10	p25	p50	p75	p90
				Market				
HHI (whole market)	6444	0.13	0.05	0.08	0.10	0.12	0.15	0.19
Weight (personal income)	6444	0.19	0.44	0.03	0.04	0.06	0.15	0.40
Cash (level)	6444	1271.87	3030.41	157.57	228.98	399.23	953.35	2643.71
Cash (share)	6444	8.25	0.85	6.94	7.73	8.40	8.86	9.07
Fed Funds rates	6444	3.16	2.23	0.14	1.13	3.55	5.30	5.83
outside	6444	56.97	11.37	43.06	50.81	57.78	64.42	70.34
				Commercial Banks				
HHI (CB)	6444	0.23	0.11	0.13	0.16	0.21	0.27	0.36
Number of banks	6444	11.82	5.52	6.00	8.00	11.00	15.00	20.00
Deposits (level)	6444	308.96	709.89	49.58	71.35	116.02	237.57	562.86
Deposits (share)	6444	2.60	1.43	1.17	1.63	2.30	3.23	4.32
Deposit Spreads	6444	1.41	1.35	-0.32	0.13	1.62	2.59	3.07
Number of branches	6444	7.89	9.83	2.55	3.33	4.90	8.00	15.17
Number of employees per branch	6444	18.17	4.56	13.33	15.02	17.33	20.25	24.57
Single Market	6444	0.19	0.17	0.00	0.00	0.17	0.30	0.43
Age	6444	90.94	20.86	65.45	75.67	90.20	104.17	118.71
Expense of fixed assets/asset	6444	0.11	0.02	0.09	0.10	0.11	0.12	0.14
Salary/asset	6444	0.51	0.07	0.43	0.47	0.51	0.55	0.60
Reserve/asset	6444	1.12	1.54	0.13	0.24	0.46	1.10	3.41
				MMFs				
HHI (MMF)	6444	0.08	0.02	0.06	0.06	0.08	0.09	0.11
Number of funds	6444	23.22	5.12	16.00	18.00	22.50	28.00	29.00
Deposits (level)	6444	51.50	124.22	5.91	9.36	15.88	39.05	105.11
Deposits (share)	6444	0.36	0.12	0.19	0.24	0.37	0.46	0.54
Deposit Spreads	6444	0.17	0.22	-0.10	0.10	0.22	0.26	0.45
Rating Dummy	6444	0.52	0.05	0.45	0.50	0.50	0.57	0.61
Bank Fund Dummy	6444	0.49	0.08	0.38	0.39	0.49	0.57	0.61
Check-writing Dummy	6444	0.36	0.06	0.29	0.31	0.38	0.39	0.45
Age	6444	27.84	3.16	24.29	24.52	28.31	30.83	32.31
Incurred Management Fee	6444	0.20	0.03	0.17	0.19	0.20	0.23	0.24
Incurred Other Fee	6444	0.14	0.04	0.10	0.12	0.13	0.16	0.22
Incurred Share Service Fee	6444	0.08	0.05	0.00	0.07	0.08	0.12	0.13

Table 2: Effect of Monetary Policy on Aggregate Deposit Growth Rates

This table presents time series regression of the aggregate deposit growth rates on the Fed Funds rates. The data frequency is quarterly. The sample period is from 1990 to 2012. Standard errors in brackets are computed with Newey-West standard error with 4 lags. ***, **, * represent 1%, 5%, and 10% significance, respectively.

	(1) CB	(2) MMF	(3) Cash	(4) Total
Fed Funds rates	-1.407***	3.929***	0.340	0.177
	[0.263]	[0.875]	[0.256]	[0.369]
GDP growth	0.253	-1.289*	-0.156	-0.171
	[0.265]	[0.691]	[0.285]	[0.333]
Inflation rates	0.609	-1.124	-0.337	0.0252
	[0.412]	[1.520]	[0.419]	[0.548]
VIX	0.412***	0.161	0.106	0.282**
	[0.101]	[0.263]	[0.0866]	[0.128]
TED	-8.175***	14.47**	-2.914*	0.231
	[1.735]	[6.503]	[1.607]	[2.725]
N	92	92	92	92
adj. R-sq	0.662	0.636	0.072	0.194

Table 3: Demand Parameter Estimation

This table presents the demand parameter estimation results. Each column presents a different estimation model. The sample includes 6,444 MSA-year markets (358 MSAs-18 years). The data frequency is annual. Standard errors are in brackets. ***, **, * represent 1%, 5%, and 10% significance, respectively.

	BLP	Logit IV	Logit OLS
Yield Sensitivity	-1.5***	-0.19***	-0.29***
	[0.034]	[0.006]	[0.0032]
Branch Density	0.045***	0.045***	0.045***
	[0.00046]	[0.0003]	[0.0003]
No. of Employees	0.016***	-0.00094	0.00027
	[0.0014]	[0.00072]	[0.00073]
Single Market	0.026***	0.063***	0.052***
	[0.008]	[0.0091]	[0.0092]
Age (CB)	-0.0013***	-0.002***	-0.0012***
	[8.9e-05]	[8.5e-05]	[8.5e-05]
Age (MMF)	0.0042***	0.0066***	0.0051***
	[0.00033]	[0.00031]	[0.00031]
Rating	-0.032***	0.042***	0.027***
	[0.0062]	[0.0059]	[0.006]
Bank Fund	-0.19***	-0.11***	-0.062***
	[0.0063]	[0.0062]	[0.0062]
Check Writing	0.069***	0.0068	-0.0078
	[0.0064]	[0.0068]	[0.0068]
Yield Sensitivity Dispersion	1.5***	NA	NA
	[0.032]	NA	NA
Bank F.E.	Y	Y	Y
City F.E.	Y	Y	Y
Time F.E.	Y	Y	Y
N	232242	232242	232242
adj. R-sq	0.443	0.624	0.626

Table 4: Supply Parameter Estimation

This table presents the supply parameter estimation results. Each column presents a different estimation model. The sample includes 6,444 MSA-year markets (358 MSAs-18 years). The data frequency is annual. Standard errors are in brackets. ***, **, * represent 1%, 5%, and 10% significance, respectively.

	BLP	Logit IV	Logit OLS
Share of Branches	-0.0046***	-0.0045***	-0.006***
	[0.00017]	[0.00016]	[0.00016]
Number of Employees per Branch	-0.0035***	0.0039***	0.0035***
	[0.00043]	[0.00043]	[0.00043]
Incurred Management Fee	3.4***	5.9***	6***
	[0.094]	[0.093]	[0.093]
Incurred Other Fee	0.27***	0.26***	0.27***
	[0.026]	[0.026]	[0.026]
Incurred Share Service Fee	0.28***	0.64***	0.63***
	[0.035]	[0.035]	[0.035]
Expense of Fixed Assets	0.37***	0.71***	0.72***
	[0.025]	[0.025]	[0.025]
Salary	0.9***	1.9***	1.9***
	[0.03]	[0.03]	[0.03]
FFR*Cash Dummy	1.1***	0.81***	0.81***
	[0.0031]	[0.0031]	[0.0031]
Bank F.E.	Y	Y	Y
City F.E.	Y	Y	Y
Time F.E.	Y	Y	Y
N	232242	232242	232242
adj. R-sq	0.690	0.779	0.772

Table 5: Own-price Semi-elasticity

This table presents the median and standard deviation (in bracket) of own-price semi-elasticity of cash, commercial banks, and MMFs estimated from RC model. Each entry gives the percent change of the market share of product *i* with one percent change in its own deposit spreads.

	Cash	CB	MMF
Cash	-0.1486		
	(0.571)		
CB		-1.0668	
		(1.0208)	
MMF			-1.8112
			(0.4647)

Table 6: Cross-price Semi-elasticity

This table presents the median and standard deviation (in bracket) of cross-price semi-elasticity of cash, commercial banks, and MMFs estimated from RC model. The entry of the *i*-th row and *j*-th column gives the percent change of the market share of product *i* with one percent change in the deposit spreads of product *j*.

	Cash	CB	MMF
Cash		-0.0018	0.0002
		(0.0204)	(0.0007)
CB	-0.0073	0.0087	0.0021
	(0.1264)	(0.0247)	(0.0032)
MMF	0.0062	0.0119	0.0048
	(0.0456)	(0.0156)	(0.0052)

Table 7: Demand Parameters and Local Demography

This table presents the cross-section regression of estimated MSA-level demand parameters on demographic information. The demand parameters are estimated MSA by MSA using RC model. Standard errors are in brackets. ***, **, * represent 1%, 5%, and 10% significance, respectively.

Dependent Variable	(1) Yield Sensitivity	(2) Yield Sensitivity Dispersion	(3) Branch Density	(4) # of Employees per Branch
Income	-0.550**	0.474*	0.0207	0.0313
	[0.232]	[0.241]	[0.0163]	[0.0192]
Age	0.0250***	-0.0270***	-0.000568	-0.000592
	[0.00644]	[0.00660]	[0.000394]	[0.000608]
College Degree	0.00337	-0.00431	-0.000528*	-0.000282
	[0.00497]	[0.00487]	[0.000290]	[0.000377]
Population	0.00773	-0.00507	0.0237***	-0.00380
	[0.0275]	[0.0286]	[0.00225]	[0.00232]
Payroll/Population	0.00402	-0.000399	0.000172	-0.000720
	[0.0119]	[0.0125]	[0.00119]	[0.00105]
Establishment/Population	7.255	-5.166	0.0354	1.201*
	[6.286]	[6.770]	[0.467]	[0.645]
Employees/Population	0.775	-0.903	-0.0497	-0.00564
	[0.680]	[0.713]	[0.0584]	[0.0657]
Cons	3.567	-2.765	-0.428**	-0.265
	[2.512]	[2.595]	[0.179]	[0.209]
N	325	325	325	325
adj. R-sq	0.105	0.097	0.433	0.015

Table 8: Monetary Policy and MMF Asset Holding

This table presents the panel regressions of various types of MMF asset holding on Fed Funds rates. The dependent variable is the annual change in a specific type of asset normalized by the lagged total assets (lagged one year). Fund characteristics include fund size (log), fund age, incurred management fee, incurred other fee, incurred share service fee, and incurred 12b-1 fee. The sample includes 1,148 MMFs in the period of 1998 to 2012. The data frequency is quarterly. Standard errors in brackets are clustered in time. ***, **, * represent 1%, 5%, and 10% significance, respectively.

	Dependent Variable: Asset Change/Total Assets					
	(1)	(2)	(3)	(4)	(5)	(6)
	Treasury	CB	CP	ABCP	Repos	FRNS
Fed Funds rates	0.171***	0.217***	0.670***	0.0848***	0.457***	0.270***
	[0.0243]	[0.00887]	[0.0176]	[0.00468]	[0.0184]	[0.0128]
GDP growth	-0.534***	-0.0968***	-0.102***	0.00534	-0.144***	0.111***
	[0.0361]	[0.0122]	[0.0246]	[0.00648]	[0.0256]	[0.0178]
Inflation rates	-0.0337	0.195***	0.139***	-0.000660	0.355***	-0.0913***
	[0.0606]	[0.0209]	[0.0411]	[0.0113]	[0.0448]	[0.0307]
VIX	0.126***	0.00990***	0.0315***	-0.00506***	-0.0117*	0.0186***
	[0.00949]	[0.00337]	[0.00670]	[0.00180]	[0.00706]	[0.00487]
TED	1.568***	-0.0861	-0.268**	-0.145***	-0.0882	-0.0463
	[0.180]	[0.0619]	[0.126]	[0.0332]	[0.132]	[0.0915]
Fund Characteristics	Y	Y	Y	Y	Y	Y
Fund F.E.	Y	Y	Y	Y	Y	Y
N	41006	41006	41006	41006	41006	41006
adj. R-sq	0.094	0.076	0.102	0.093	0.098	0.069

Table 9: Monetary Policy and Asset Growth of Commercial and Shadow Banks

This table presents time series regression of the aggregate asset growth rates of commercial and shadow banks on the Fed Funds rates. The dependent variable is the annual asset growth rate. The data frequency is quarterly. The sample period is from 1990 to 2012. Standard errors in brackets are computed with Newey-West standard error with 4 lags. ***, **, * represent 1%, 5%, and 10% significance, respectively.

	(1) Funding Corporations	(2) Finance Companies	(3) ABCP Issuers	(4) Captive Financial Institutions	(5) Broker-dealers	(6) Shadow Banks	(7) Commercial Banks
Fed Funds rates	2.765***	1.439**	4.528***	0.972*	0.747	1.773***	0.270
	[0.617]	[0.649]	[1.184]	[0.500]	[0.839]	[0.555]	[0.273]
GDP growth	3.068***	1.813***	0.849	0.841	1.791	1.645***	0.143
	[0.693]	[0.574]	[0.851]	[0.638]	[1.089]	[0.369]	[0.266]
Inflation rates	-2.853***	0.647	-0.138	-4.271***	1.667	-1.001*	-0.464
	[0.951]	[0.720]	[1.078]	[0.784]	[1.608]	[0.583]	[0.339]
VIX	0.206	0.418***	-0.203	-0.0540	-0.528*	-0.137	-0.00978
	[0.147]	[0.151]	[0.336]	[0.109]	[0.267]	[0.144]	[0.0728]
TED	16.98***	-5.206*	-4.021	11.61***	-5.235	2.261	4.249***
	[2.861]	[2.625]	[6.480]	[2.036]	[4.939]	[2.984]	[1.389]
N	92	92	92	92	92	92	92
adj. R-sq	0.641	0.386	0.495	0.484	0.449	0.561	0.214

Table 10: Monetary Policy and Funding Structure of Commercial Banks

This table presents panel regressions of commercial bank deposits on the Fed Funds rates for all U.S. commercial banks in the period of 1990 to 2012. The dependent variable is the annual change in the dollar amount of deposits normalized by the lagged total deposits (one-year lag). The odd column considers checking and saving deposits, and the even columns consider large time deposits. Column 1 and 2 include all the banks, and column 3-8 separate the sample by bank size group, small, medium and large. Bank characteristics include HHI, log(Assets), salary/assets, expense of fixed asset, number of employees per branch, loan to asset ratio, real estate loan to asset ratio, commercial and industry loan to asset ratio. The data frequency is quarterly. The standard errors in brackets are clustered in time. ***, **, * represent 1%, 5%, and 10% significance, respectively.

	All		Small		Medium		Large	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Checking and Saving	Large Time	Checking and Saving	Large Time	Checking and Saving	Large Time	Checking and Saving	Large Time
Fed Funds rates	-0.963***	0.355***	-0.993***	0.369***	-1.271**	0.334***	-1.294**	0.431***
	[0.304]	[0.0384]	[0.306]	[0.0382]	[0.507]	[0.0652]	[0.556]	[0.0674]
GDP growth	0.940***	-0.203***	0.927***	-0.214***	1.031**	0.0357	0.781*	0.174**
	[0.317]	[0.0405]	[0.309]	[0.0393]	[0.408]	[0.0677]	[0.467]	[0.0670]
Inflation rates	-1.209**	-0.00471	-1.172**	-0.0147	-1.554**	0.0209	-1.096*	0.373***
	[0.517]	[0.0803]	[0.500]	[0.0783]	[0.588]	[0.124]	[0.633]	[0.114]
VIX	-0.119	-0.00610	-0.118	-0.00763	-0.157	0.0278	-0.162	0.0394*
	[0.126]	[0.0116]	[0.123]	[0.0113]	[0.160]	[0.0183]	[0.166]	[0.0217]
TED	1.439	-0.253	1.511	-0.264	1.168	-0.510	1.256	-0.282
	[1.729]	[0.195]	[1.708]	[0.194]	[2.264]	[0.387]	[2.417]	[0.506]
Bank Characteristics	Y	Y	Y	Y	Y	Y	Y	Y
Bank Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
N	633568	633568	601897	601897	25332	25332	6339	6339
adj. R-sq	0.064	0.041	0.064	0.044	0.066	0.038	0.060	0.063