Monetary Transmission through Shadow Banks[*]

Kairong Xiao[†]

Columbia University

Abstract

This paper documents a new transmission channel of monetary policy: the shadow money channel. Analyzing U.S. money supply data from 1987 to 2012, I find that shadow money, namely liquid deposits created by shadow banks, expands significantly when the Federal Reserve tightens monetary policy. Using a structural model of bank competition, I show that this new channel is a result of imperfect competition between commercial and shadow banks in the deposit market with heterogeneous depositors. Due to a lack of a bank charter, shadow banks offer lower transaction convenience and hence must compete on yields. During periods of monetary tightening, shadow banks pass through more rate hikes to depositors, thereby poaching yield-sensitive deposits from commercial banks. Fitting my model to institution-level data from commercial banks and money market funds, I show that shadow money creation offsets 35 cents of each dollar in commercial bank deposit reductions, significantly dampening the impact of monetary tightening. My results suggest that monetary tightening may unintentionally drive more deposits into the uninsured shadow banking sector, thereby amplifying the risk of bank runs.

JEL Classification codes: G23

1. Introduction

The U.S. banking system has experienced significant structural changes over the past thirty years. A group of non-bank financial intermediaries, collectively known as the *shadow banking system*, has grown outside of the traditional commercial banking sector. Important components of the shadow banking system include money market funds (MMFs), securitization vehicles, broker-dealers, and mortgage companies. Shadow banks compete with commercial banks in many traditional banking businesses. For example, MMFs compete in the deposit market by creating liquid claims which, in many ways, are similar to commercial bank deposits, yet provide higher yields. In recent years, more than 30% of deposits have been created by shadow banks.

The rapid growth of shadow banks has raised concerns for policy makers on the effectiveness of monetary policy.[1] Traditionally, commercial banks play an important role in transmitting monetary policy to the real economy. Over the years, however, an increasing share of deposits is now created outside of the commercial banking sector. Despite the importance of shadow banks in current economy, we do not know how deposit competition from shadow banks affects the transmission of monetary policy.

Unlike commercial banks, which combine deposit creation and loan origination under one roof, the shadow banking system separates the intermediation process into different entities. This paper focuses on shadow banks in the deposit market, MMFs. MMFs provide depository services for households and businesses and then pass the proceeds to other shadow banks that specialize in loan origination. The liquid claims created by MMFs constitute the main component of aggregate money supply from the shadow banking system.[2]

I first document a new transmission channel of monetary policy in the shadow banking system—the shadow money channel. Standard theories of monetary transmission predict that high interest rates are associated with low deposit creation (Bernanke and Blinder 1988; Drechsler, Savov, and Schnabl 2017).[3] This prediction has been verified empirically by previous literature in the commercial banking sector (Kashyap and Stein 1995, 2000; Drechsler et al. 2017). However, using aggregate U.S. money supply data from 1987 to 2012, I find the *opposite* of what happens in commercial banks happens in shadow banks.[4]

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[1] For instance Federal Reserve Board Chair, Janet Yellen, in response to a question by IMF Managing Director Christine Lagarde on Shadow Banking in July 2014, said, "We won't be able to detect them (shadow banks), and if we can, we won't have adequate regulatory tools. That is a huge challenge to which I don't have a great answer."

[2] Other types of shadow banking liabilities, such as repos and asset-backed commercial paper, are generally not included in the aggregate money supply because first, they are less liquid than MMF shares, and second, they are generally held within the shadow banking system rather than being held by households and businesses. Including these short-term shadow banking liabilities in money supply would double count the amount of funds that go into the shadow banking system.

[3] The shared idea of these two theories is that a high interest rate policy increases the opportunity cost of holding liquid deposits, which reduces the amount of bank deposits in the economy. The difference between these two theories is how a high interest rate policy increases the opportunity cost of holding liquid deposits. Bernanke and Blinder (1988) suggest reserve requirements of commercial banks as an important channel, while Drechsler et al. (2017) show that market power of commercial banks can also play a role.

[4] In this paper, I use "MZM" (money zero maturity) as the measure of money supply in the economy.

When the Federal Reserve wants to reduce deposits by raising interest rates, shadow bank deposits expand dramatically, and as a result, dampen the impact of monetary policy. The contrast between shadow and commercial banks can easily be seen in a time-series plot of the deposit growth rates as shown in Figure 1. This finding contradicts conventional wisdom that high interest rates are contractionary for deposit creation. It suggests that the monetary transmission channel in the shadow banking sector is different from the traditional channels in the commercial banking sector. Moreover, my results show that monetary policy not only affects the *total amount* of bank deposits but also the *relative shares* between the shadow and commercial banking sectors. Because shadow bank deposits are outside of government safety nets such as deposit insurance and the discount window, shifts in the relative shares of deposits have important implications for financial stability. To the best of my knowledge, the present study is one of the first to document this counterintuitive result of shadow bank deposit creation.

In order to understand the underlying mechanism, I develop a structural model of bank competition. The prior literature on monetary transmission often assumes homogeneous banks and depositors. I introduce product differentiation for bank deposits and heterogeneous preference for depositors following the industrial organization literature (Berry 1994, Berry, Levinsohn, and Pakes 1995, and Nevo 2001). Because of product differentiation, competition is imperfect and banks make a tradeoff between deposit volumes and rates. Such trade-off differs for shadow and commercial banks because of their different depositor clientele. In equilibrium of deposit rate competition, monetary policy drives the spreads between shadow and commercial deposit rates, which results in deposit flows between the two banking sectors.

In my model, banks are differentiated by their respective degrees of transaction convenience and yields. Shadow banks offer lower transaction convenience compared to commercial banks because the lack of bank charters prohibits them from operating branch networks and payment systems. Instead, they try to differentiate themselves by competing on yields. Product differentiation between shadow and commercial banks results in different clientele for each banking sector. Commercial banks attract a group of transaction-oriented depositors who value transaction services but are insensitive to yields. Typical examples of transaction-oriented depositors include small and unsophisticated depositors who choose banks mainly based on geographical proximity rather than yields. In contrast, shadow banks attract a group of yield-oriented depositors such as wealthy individuals and corporate treasurers. These yield-oriented depositors are not primarily concerned with transaction convenience, but instead, are very sensitive to yields.

Depending on their depositor clientele, commercial and shadow banks strategically set their deposit rates to maximize profits. When the Fed Funds rates are high, commercial banks are able to keep deposit rates low because their main clientele, the transaction-oriented depositors, are attached to their transaction services. In contrast, shadow banks have to pay high deposit rates to compensate for the low transaction convenience so that yield-

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This measure is a modification of M2 after the usefulness of previous measures became compromised in the 1990s. This measure includes currency, traveler's checks of non-bank issuers, demand deposits, other checkable deposits, savings deposits, retail MMF shares, 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.

sensitive depositors will not leave. Therefore, the spreads between shadow and commercial bank deposit rates are usually high when the Fed Funds rates are high. When the Fed Funds rates fall, commercial banks cannot reduce deposit rates much lower than zero as they face increasing competition from cash, while shadow banks cannot afford to offer rates much higher than zero as lending rates are low. Therefore, the spreads between shadow and commercial bank deposit rates are compressed. Since the difference in transaction convenience between two banking sectors are relatively stable over monetary cycles, changes in the relative deposit rates drive the marginal depositors to switch between the two banking sectors.[5] This gives rise to the shadow money channel in which shadow banks expand their deposit creation when the Federal Reserve tightens monetary policy and shrink when the policy reverses.

The key institutional features that generate the shadow money channel are the differences in transaction convenience and depositor clientele. However, there are many other institutional differences that may generate predictions in the same direction. It is challenging to quantify their relative contribution using a reduced-form method. This challenge lends itself to a structural estimation approach, in which competing channels are evaluated by altering the corresponding structural parameters. Specifically, I incorporate a bank reserve channel in which reserve requirements lead to a contraction of commercial bank deposits and a substitution to shadow bank deposits in periods of monetary tightening. I also consider a risk channel in which default probabilities of the two banking sectors vary over time. I estimate my model using institution-level data on U.S. commercial banks and MMFs. The estimation shows that commercial bank deposits provide significantly higher convenience than shadow bank deposits. Depositors exhibit significant heterogeneity in their preference over convenience and yields. Compared to other alternative channels, the shadow money channel is the dominant channel in explaining both deposit rates and volumes.

The structural model also allows a set of counterfactual analysis. I simulate a counterfactual economy without shadow banks using the estimated parameters. Comparing the real data with the counterfactual economy, I find that shadow money creation offsets 35 cents of each dollar in commercial bank deposit reductions, significantly dampening the impact of monetary tightening. This result suggests a new explanation for the diminished monetary impact which has occurred since the 1990s as documented in the macroeconomic literature (see Boivin, Kiley, and Mishkin 2011 for a summary of existing explanations). Finally, my results suggest a cautious stance towards a recent policy proposal that suggests using monetary tightening as a tool for promoting financial stability (Borio and Zhu 2012; Stein 2012; Ajello, Laubach, López-Salido, and Nakata 2015). I show that this policy proposal may unintentionally drive deposits from the insured commercial banking sector into the uninsured shadow banking sector, and in doing so, heighten the risk of bank runs.

This paper contributes to three strands of literature. The first strand studies monetary transmission mechanisms in the banking system. Traditionally, this literature has focused on commercial banks (Bernanke and Blinder 1988; Kashyap and Stein 1995, Kashyap and

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[5]Even though commercial banks lose some deposits to shadow banks, commercial banks would not replicate the shadow banks' strategy because passing through more rates would reduce their profitability margin. On the other hand, shadow banks cannot copy the commercial banks' strategy as shadow banks cannot offer the same transaction services to keep depositors attached.

Stein 2000; Drechsler et al. 2017). This paper brings shadow banks into the forefront of the theoretical and empirical analysis of monetary policy. Theoretically, traditional monetary transmission channels in banks usually rely on regulatory constraints while abstracting away from imperfect competition. Tobin and Brainard (1963) and Bernanke and Blinder (1988) study the role of deposit rate ceilings and reserve requirements in monetary transmission. While these regulatory constraints were important historically, they have become less relevant since 1990s because of technological innovation and regulatory reform.[6] In search of alternatives, recent papers such as Scharfstein and Sunderam (2016) and Drechsler et al. (2017) point out that imperfect competition of the banking sector may play a role in transmitting monetary policy. Following this line of research, I introduce product differentiation and depositor heterogeneity into the existing framework of Drechsler et al. (2017) and find that monetary tightening may have expansionary effects on certain types of banks depending on their transaction convenience and depositor clientele. This paper also adds to a new and growing body of literature that applies a structural IO approach to financial intermediation topics such as bank runs (Egan, Hortaçsu, and Matvos 2017a), bank value creation (Egan, Lewellen, and Sunderam 2017b), insurance (Koijen and Yogo 2016), and mortgages (Buchak, Matvos, Piskorski, and Seru 2017). This paper is the first attempt to use a structural IO model to study transmission channels of monetary policy.

Empirically, I document a new transmission channel of monetary policy in the shadow banking system—the shadow money channel. I show that this new channel partially offsets the traditional channels in commercial banks and dampens the impact of monetary policy. I further use a structural estimation to quantify the magnitude of this channel. The structural approach complements the previous literature such as Kashyap and Stein (1995, 2000), Scharfstein and Sunderam (2016), and Drechsler et al. (2017), which use reduced-form methods. My finding also relates to the literature on the shift between bank loans and commercial paper over monetary cycles (Kashyap, Stein, and Wilcox 1992; Calomiris, Himmelberg, and Wachtel 1995). Prior literature relies on the difference in reserve requirements between commercial banks and commercial paper lenders to explain such shift.[7] In contrast, my paper identifies a different transmission channel through the imperfect competition in the deposit market between commercial banks and MMFs. I show that the increase in commercial paper issuance during monetary tightening is likely the result of deposit inflows into MMFs, which are major lenders in the commercial paper market (Hanson, Scharfstein, and Sunderam 2015). I also find similar results for other types of non-bank credits held by MMFs such as repos and floating rate notes.

The second strand of literature to which this paper contributes concerns the interaction between monetary policy and macro-prudential policies. Prior to the 2008–09 financial crisis, the consensus among policy makers was that monetary authority should focus on price stability and employment (Smets 2013). However, this consensus has been challenged by an alternative view that took shape after the financial crisis, which argues that monetary

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[6]The Depository Institutions Deregulation and Monetary Control Act of 1980 abolished most of the interest rate ceilings that had been imposed on deposit accounts since the Banking Act of 1933. The sweep technology developed in the early 1990s allows banks to automatically move funds from checking accounts to saving accounts, which reduces required reserves.

[7]For instance, Kashyap et al. (1992) use a model similar to Bernanke and Blinder (1988) in which monetary tightening leads to a reduction in commercial bank deposits and loans through reserve requirements.

policy should also be used to promote financial stability (Borio and Zhu 2012; Stein 2012; Ajello et al. 2015). Proponents of this view contend that by tightening monetary policy, the central bank can curb, among other things, the creation of money-like liabilities by the banking system. On the other hand, the potential complication caused by the shadow banking sector is also mentioned (Stein 2012; Yellen 2014). My findings contribute to this debate by showing empirical evidence that monetary tightening may lead to an unintended consequence of driving deposits to the shadow banking system. Since shadow banks are not protected by deposit insurance, such a policy may actually increase systemic risk. My paper supports the view that "monetary policy is too blunt a tool to address possible financial imbalances" as argued by Bernanke (2011) and Yellen (2014).

The third strand of literature studies the fragility of the shadow banking system. Previous research finds that the lack of deposit insurance (Gorton and Metrick 2012), leverage (Adrian and Shin 2010), and information opacity (Dang, Gorton, and Holmström 2016) create fragility in the shadow banking system. My paper contributes to this literature by studying the industrial organization aspect of the shadow banking sector. I show that shadow banks face much more elastic demand than commercial banks as a result of product differentiation. With highly elastic demand, a small shock to the underlying asset value may trigger a large withdrawal of deposits, forcing shadow banks to liquidate assets at fire-sale prices and resulting in self-reinforcing bank runs (Egan et al. 2017a). Therefore, the yield-sensitive clientele could be an additional source of financial fragility for the shadow banking sector.

The remainder of this paper is organized as follows. Section 2 presents several new stylized facts on deposit creation in the shadow banking system. Section 3 presents a structural model of bank competition to rationalize the empirical findings. Section 4 presents the estimation procedure and results. Section 5 discusses policy implications and Section 6 concludes.

2. Deposit Creation by Shadow Banks

In this section, I provide a brief description of the institutional background of the shadow banking system. I then present several new stylized facts about the shadow money channel.

2.1 Institutional Background

The shadow banking system is a collection of financial intermediaries that conduct maturity, credit, and liquidity transformation outside the traditional commercial banking system.[8] 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 into short-term money-like claims. Since households and businesses have a preference for liquidity, issuing money-like claims allows shadow banks to lower their financing costs.

Figure 2 provides a simplified representation of the U.S. banking system.[9] The upper

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[8]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."

[9]A more detailed description of the shadow banking intermediation process can be found in Pozsar,

branch represents the commercial banking sector, while the lower branch represents the shadow banking sector. Unlike commercial banks, which combine deposit creation and loan origination under one roof, the shadow banking system separates the intermediation process into different entities. MMFs constitute the first stage of the shadow banking intermediation process. MMFs take deposits from households and businesses and then pass the proceeds to other shadow banks such as securitization vehicles, mortgage conduits, broker dealers, and mortgage companies, which specialize in loan origination. In this process, MMFs create money-like liabilities—MMF shares—which resemble commercial bank deposits.

MMF shares are widely (though not necessarily accurately) regarded as being 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. Due to their similarity with commercial bank deposits, MMF shares are included in the official money supply statistics. The amount of MMF shares also provides a good proxy of the quantity of funds flowing into the shadow banking sector.

On the asset side, MMFs hold various money market instruments. The asset holdings of MMFs can be grouped into three major categories. According to iMoneyNet data, the majority 50 percent are invested in short-term debts of other shadow banks such as repurchase agreement (repos), asset-backed commercial paper (ABCP), commercial paper (CP) and floating rate notes (FRNs).[10] 20 percent are invested in Treasury and agency securities. Lastly, 18 percent of shadow bank deposits go back to the commercial banking sector in the form of large denomination commercial bank obligations.

Over the past thirty years, the shadow banking sector has become increasingly important in the economy. Based on the aggregate money supply statistics from the Federal Reserve, the share of shadow bank deposits has increased from around 15 percent in the 1980s to around 40 percent in 2007, while the share of commercial bank deposits is on a downward trend.

2.2 Data Source

The first main database used in this paper is iMoneyNet. This data set provides monthly share class level data for U.S. MMFs dating back to 1985. After a cross-check with the aggregate money supply statistics from the Federal Reserve Board, I find that this database covers essentially all the MMFs after 1987. The data contain detailed information on fund characteristics such as deposit amounts, charged expense ratios, yields, management costs, and other costs. Portfolio holding information became available since 1998 and includes average portfolio maturity and portfolio weights by asset class. As data on shadow banks are generally very scarce, this data set provides a rare glimpse of the inner workings of the shadow banking system.

The second main data set is the Consolidated Report of Condition and Income, generally

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Adrian, Ashcraft, and Boesky (2010).

[10]Some large industrial corporations also issue commercial paper to obtain short term financing. This commercial paper is mainly used to finance their captive finance companies, which are also considered 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.

referred to as the Call Report. This data set provides quarterly bank-level data for every U.S. insured commercial bank, including detailed accounting information such as deposit amounts, interest income, salary expenses, and fixed asset expenses. I complement the Call Report with the FDIC Summary of Deposits, which provides branch-level information on deposit amounts in annual frequency since 1994. Following the literature, deposit rates are imputed from bank financial statements by dividing deposit interest expenses over total amount of deposits (Dick 2008). In the following analysis, I focus on "liquid deposits", which are defined as the sum of checking and savings deposits.[11] Table 1 provides the summary statistics of the final sample used for the structural estimation.

In addition to the two main data sources above, I also use the Survey of Consumer Finance (SCF) 2013 to obtain depositor-level deposit holdings and demographic information. Lastly, I retrieve aggregate time series of the amount of cash held by households and the Fed Funds rates from Federal Reserve Economic Data (FRED). I retrieve aggregate time series of the amount of Treasury bills held by households from the Financial Accounts of the United States. I obtain Metropolitan Statistical Area (MSA) level demographic information from the 2010 Census.

2.3 Shadow Money Channel

In what follows, I document a new transmission channel of monetary policy using aggregate money supply data from 1987 to 2012 from the Federal Reserve. I break down the aggregate money supply into cash, commercial bank deposits, and shadow bank deposits. Commercial bank deposits include demand and savings deposits. Shadow banking deposits include retail MMF shares and institutional MMF shares. Figure 1 plots the Fed Funds rates and the annual deposit growth rates of each banking sector over time. Conventional monetary transmission channels predict that high Fed Funds rates have tightening effects on the money supply (Bernanke and Blinder 1988; Kashyap and Stein 1995, 2000; and Drechsler et al. 2017). Indeed, as shown in the top panel of Figure 1, high Fed Funds rates are associated with low growth rates of commercial bank deposits. However, the opposite happens in the shadow banking system. As shown in the bottom panel of Figure 1, high Fed Funds rates are associated with high growth rates of shadow bank deposits. This finding implies that monetary policy may have a different transmission channel in the shadow banking system. A high interest rate policy, which is intended to reduce money supply in the economy, surprisingly increases deposit creation by shadow banks.

Formally, I regress deposit growth rates of each banking sector on the Fed Funds rates, controlling for a list of macroeconomic variables such as GDP growth rates, inflation, TED spread, and a time trend:

$$Deposit\ Growth\ Rates_t = \alpha + \beta Fed\ Funds\ Rates_t + \gamma X_t + \epsilon_t \tag{1}$$

Table 2 presents the results. Consistent with the graphical observation, monetary policy has opposite effects on these two sectors: a 1 percent increase in the Fed Funds rates is associated with a 2.29 percent decrease in the growth rates of commercial bank deposits, but a 4.11 percent increase in the growth rates of shadow bank deposits. The estimates are

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[11]Previous literature has shown that the pricing and quantities of "liquid deposits" are quite different from "illiquid deposits" such as small time savings deposits (Driscoll and Judson 2009; Drechsler et al. 2017).

both statistically and economically significant.

Column 4 of Table 2 shows the results for the total money supply. The coefficients of the Fed Funds rates are insignificantly different from zero. This result shows that deposit creation by shadow banks partially offsets the reduction of commercial bank deposits and attenuates the impact of monetary tightening on aggregate money supply. As shadow banks create more deposits, they obtain more loanable funds for lending. In Section 5.2, I further show that shadow bank lending also increases as the Fed tightens monetary policy.

This paper focuses on conventional monetary policy, namely, the intervention on short-term interest rates. However, this sample period witnessed some major monetary policy changes during the 2008-09 financial crisis. After 2008, a set of unconventional monetary policy tools were adopted: the effective lower bound (ELB) was in place; target Fed Funds rate became a range; the Fed's asset holdings became an additional monetary policy tool; the Fed Funds rates were managed through Interest on Excess Reserves (IOER). One may worry that the unconventional monetary policy in the post-2008 period may affect the result. To address this concern, I use the pre-2008 sample to conduct the regression. As shown in column 5-8 of Table 2, the result is very similar to the full sample analysis. One may also wonder whether the result may differ across retail MMFs and institutional MMFs. In Figure 1 of the online appendix, I plot the deposit growth rates of retail and institutional MMFs separately. The cyclical pattern is quite similar for both retail and institutional MMFs while the magnitude is slightly greater for institutional ones.

The above result shows that shadow banks may dampen the impact of monetary policy by creating more money-like liabilities when the Fed wants to reduce money supply. Furthermore, this channel implies that monetary policy not only affects the total amount of money supply but also the relative shares between the shadow and commercial banking sector. Since shadow banks do not have access to government safety nets such as the deposit insurance and the discount window, such shifts in the composition of money supply have important implications for financial stability.

To summarize, by decomposing the aggregate money supply into a commercial and shadow banking component, I find that monetary tightening leads to a surprising expansion of shadow bank money supply, a phenomenon that contradicts the conventional wisdom in the commercial banking sector. This implies that monetary policy has a different transmission channel in the shadow banking system. In the next section, I will examine the underlying mechanism of this channel.

3. A Structural Model of Bank Competition

3.1 Intuition

The previous section documents that monetary policy has very different impacts on the amount of deposits created by the commercial and shadow banking sectors. In this section, I develop a structural IO model to rationalize the above empirical findings.

There are two key ingredients of the model. First, commercial and shadow bank deposits offer different degrees of transaction convenience. Specifically, commercial bank deposits

offer a lot of transaction services such as branch networks, ATMs, and payment systems.[12] In contrast, shadow banks cannot offer these transaction services because they do not bank charters allowing them to do so.[13] In practice, obtaining a bank charter is a costly process that usually takes a year or more and involves permissions from at least two regulatory authorities among the Federal Reserve, the FDIC, and the OCC. Therefore, a shadow bank cannot easily convert to a commercial bank. To compensate for the lack of transaction convenience, shadow banks usually compete on yields.

In addition to differentiated banks, the second key ingredient of the model is that depositors exhibit heterogeneous preference over convenience and yields. There is a group of "transaction-oriented" depositors who care a lot about transaction convenience, but are not sensitive to yields. For example, "mom and pop" depositors choose banks mainly based on geographical proximity rather than deposit rates paid by banks. There is also a group of "yield-oriented depositors" who are very sensitive to yields but are relatively insensitive to convenience. For example, large corporations and wealthy individuals usually have large deposits. A small difference in yields can make a big difference in the dollar value of income. Moreover, these depositors are often more sophisticated than "mom and pop" depositors. Therefore, they are better-equipped to find the highest-yielding options in the market.

These two groups of depositors are likely to self-select into different types of banks. Commercial banks are likely to attract more transaction-oriented depositors because of the superior transaction services offered by them, while shadow banks attract more yield-oriented depositors because of the high deposit rates. Consistent with this idea, using the Survey of Consumer Finances (SCF) 2013, I find that depositors who are rich or more sophisticated (proxied by college education) are more likely to choose shadow banks. The result is reported in Table 3.

The monetary authority determines the level of the Fed Funds rates, which pins down the marginal return that banks can earn from their assets. For a given level of the Fed Funds rates, banks optimally choose their deposit rates to pass on to depositors. Shadow and commercial bank deposit rates exhibit different sensitivities to monetary policy. When the Federal Reserve increases interest rates commercial banks are not pressured to increase their deposit rates, because their main depositor clientele—transaction-oriented depositors—are attached to transaction services offered commercial banks. This allows commercial banks to keep deposit rates relatively low and earn higher spreads between the rising lending rates and the depressed deposit rates. In contrast, shadow banks have to raise their deposit rates with the market interest rates. Otherwise, their yield-oriented clientele will switch to other higher-yielding liquid assets such as short-term bonds. As a result, when the Fed raises interest rates, the gap between shadow and commercial banks' deposit rates widens. In equilibrium, as the gap becomes larger, some of the marginal depositors will switch over from commercial banks to shadow banks. In aggregate, we will observe that shadow bank deposits expand while commercial bank deposits shrink.

One may ask why commercial banks do not replicate the strategy of shadow banks to

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[12]In addition, the deposit insurance on commercial bank deposits also increases their convenience relative to shadow banks. The deposit insurance of the commercial bank deposits is less relevant for very large depositors because the FDIC only insures commercial bank deposits up to a certain amount.

[13]In practice, some MMFs provide check-writing services by working with commercial banks. However, there are restrictions on the minimum dollar amount for each check and the numbers of checks per month.

avoid losing deposits in periods of high interest rates. The answer is that passing through more rates depresses the net interest margin. Since the demand function for commercial bank deposits is inelastic, the loss in the margin outweighs the gain in the quantity. Therefore, it is not optimal for commercial banks to have high pass-through. On the other hand, shadow banks are unable to replicate commercial banks' strategy because shadow banks cannot offer the same transaction services to keep depositors attached. With an elastic demand, not passing through the rate hikes will result in a large loss in the deposit quantity which dominates the gain from the margin.

This explanation seems to be consistent with the data. Figure 3 plots the average deposit rates of commercial banks and MMFs over time. I find that when the Fed raises interest rates, shadow banks pass through more rate hikes to depositors than commercial banks do. The changes in relative deposit rates are economically significant. For example, in the 2004–2006 tightening cycle, the difference in deposit rates increased from less than 0.5 percent to nearly 3 percent. Since transaction convenience of bank deposits is relatively stable over time, such big changes in relative yields may significantly affect depositors' choice between these two banking sectors.

3.2 Model Setting

Having shown the basic intuition of the shadow money channel, I now proceed with offering a full structural model to formalize the idea. The model uses the discrete choice framework of oligopoly competition developed by Lancaster (1966), McFadden et al. (1973), and Berry et al. (1995) (BLP). This framework models competition between differentiated products in a tractable way that can be easily estimated using data.[14] The discrete choice framework has been successfully applied to many industries such as the automobile, cereal, and airline industries. It has been a workhorse model in the quantitative IO literature over the past 20 years.

The deposit market seems to be a natural application of the BLP framework.[15] Similar to the automobile, cereal, and airline industries, commercial banks and MMFs are differentiated along the dimensions such as deposit rates and transaction convenience. The framework not only captures competition between shadow and commercial banks, but also allows for

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[14]There is a long history of estimating demand for a set of differentiated products in the IO literature. Before the discrete choice framework was introduced, the demand was defined over actual products. However, this approach runs into the "curse of dimensionality" as the number of products grows, since a demand system with J products has J^2 parameters (each demand equation has 1 sensitivity to its own price and $J - 1$ sensitivities to competitors' prices). A key insight of the discrete choice framework is that consumer preference should be defined over product characteristics as oppose to actual products so the number of parameters is fixed by the number of product characteristics instead of growing with the number of products. For example, instead of defining a demand system on each brand of cars, we can define the preference on the horse power, size, and price. The degree of substitutability is captured by how close two products are in terms of these characteristics. Berry et al. (1995) further shows that how to estimate such models with heterogeneous customers and how to address the endogeneity of prices.

[15]Early applications of the BLP framework to banking industry includes Adams, Brevoors, and Kiser (2007) and Ho and Ishii (2011). My paper contributes to this line of literature by introducing competition from shadow banks, a sector which has become increasingly important in the modern banking system. In addition, I use this framework to study the impact of monetary policy on the banking system, an aspect which has not yet been explored in this literature.

competition among commercial banks and among shadow banks. Using this model, I am able to estimate the demand function for each commercial and shadow bank using observable deposit rates and quantities. This will shed light on how banks set deposit rates in response to changes of monetary policy. More importantly, the structural model can quantify the magnitude of the proposed channel. This is crucial given that there are alternative explanations that give rise to the same qualitative results. Lastly, the structural approach allows counterfactual simulations that are useful for examining policy implications.

I first introduce the basic setup of the framework where depositors are homogeneous. The basic setup is useful to show how the model is estimated with the data. I then introduce depositor heterogeneity—a key feature for the proposed channel. Lastly, I estimate the model with the data.

3.3 Banks

There are J banks in the market. Among them, J_1 are commercial banks, and J_2 are shadow banks. A bank j is characterized by its transaction convenience and deposit rate, (ℓ_j, r_j). The fundamental difference between a commercial bank and a shadow bank lies in their transaction convenience, which is determined exogenously by charter restrictions on the range of transaction services that non-bank firms can engage. Due to these restrictions, shadow banks offer lower transaction convenience than commercial banks.

$$\ell_{sb} < \ell_{cb} \tag{2}$$

The demand for deposits depends on a bank's own deposit rates and transaction convenience as well as its competitors' rates and convenience. In addition, outside options such as cash and Treasury bills also affect the demand for deposits. I will explicitly derive the demand system from the depositor's optimal choices in the next section. For now, assume each bank faces a demand function $s_j(r_j)$. Facing the demand, the decision of bank j is to choose a deposit rate r_j to maximize profits

$$\max_{r_j} (f - r_j - c_j) s_j(r_j) \tag{3}$$

where f is the Fed Funds rates, r_j is the deposit rate of bank j, c_j is the marginal cost of providing depository services. $s_j(r_j)$ is the market share of bank j.[16]

Banks' optimal pricing decision is given by the following FOC:

$$\text{FOC: } f - r_j = \left(\frac{\partial \log(s_j)}{\partial r_j} \right)^{-1} + c_j \tag{4}$$

On the left-hand side, the spread between the Fed Funds rates and deposit rates, commonly referred to as deposit spread, represents the price that banks charge for their depository services. On the right hand side, the first term $\left(\frac{\partial \log(s_j)}{\partial r_j} \right)^{-1}$ is the markup that a bank

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[16]The underlying assumption of this formulation is that there is an efficient interbank market so that marginal lending rates of all the banks are equal to the Fed Funds rates. This is also consistent with prior literature such as Hannan and Berger (1991) and Drechsler et al. (2017). In the post-2008 period, the Fed introduced Interest Rate on Excess Reserves (IOER). Therefore, a more accurate measure of the marginal lending rates for commercial banks could be the IOER in the post-2008 period. However, since IOER and the effective Fed Funds rates are very close (around 10 basis points), the results will not change much using either of these two rates. For the simplicity of exposition, I use the Fed Funds rates for the rest of the discussion.

can charge on its depository service over the cost of providing it. It is inversely related to the demand elasticity. If the demand is inelastic, then the bank can charge a higher markup. In contrast, if the demand is elastic, then the markup is likely to be low.

I specify the marginal cost as a linear function of cost shifters

$$c_j = \gamma' w_j + \omega_j \tag{5}$$

where w_j is a vector of observable supply shifters. Examples of supply shifters of a commercial bank include salary paid to employees and fixed asset expenses. Examples of supply shifters of an MMF include management costs and other operating costs. γ is the sensitivity of marginal cost to these cost shifters. ω_j is an idiosyncratic supply shock.

3.4 Depositors

There are I depositors. Each of them is endowed with one dollar. Depositors make a discrete choice among options including Treasury bills, cash, commercial bank deposits, or shadow bank deposits. The choice set is $\{0, 1, ..., J, J+1\}$ where 0 represents cash and $J+1$ represents Treasury bills. Each depositor can choose one option which gives him or her the highest utility. The assumption that each depositor has only one dollar and can choose only one option is not as restrictive as it may appear. We can imagine that depositors make multiple discrete choices for each dollar that they have, and the probability of choosing each of the options can be interpreted as the portfolio weight. The utility for depositor i to choose product j is given by

$$\max_{j \in \{0,1,...,J,J+1\}} u_{i,j} = \alpha r_j + \ell_j + \xi_j + \epsilon_{i,j} \tag{6}$$

r_j is the deposit rate, ℓ_j is the transaction convenience. ξ_j is an unobservable common demand shock to all depositors for product j. $\epsilon_{i,j}$ is a mean-zero idiosyncratic utility shock for depositor i if choosing product j, which follows the extreme value distribution with a probability density function $f(\epsilon) = exp\{-exp(-\epsilon)\}$. This distribution assumption is standard in structural IO literature. It allows closed-form solution of the choice probabilities. Finally, α is sensitivity to deposit rate.

In the data, we cannot directly observe transaction convenience. Therefore, I specify transaction convenience as a function of observable product characteristics. Examples include industry dummy, branch density, number of employees per branch, and the age of the bank.[17] Formally, define x_j as a vector of product characteristics of bank j, and β as a vector of sensitivities to these product characteristics. shocks to convenience.[18]

$$\ell_j = \beta' x_j \tag{7}$$

As will be illustrated later, β will be estimated from the data. Therefore, we will be able to verify empirically whether the convenience of shadow banks is lower than commercial banks. Note that the linear form of utility does not mean that depositors do not care about risk. In fact, aversion to risk can be easily incorporated by introducing a measure of risk

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[17]Branch density and number of employees per branch are zero for a shadow bank.

[18]The model also allows transaction convenience to vary within each banking sector. For example, different commercial banks may have different sizes of branch networks. Therefore, we should view the transaction convenience as a continuous variable.

in the vector of product characteristics and negative loading coefficient to this measure.[19] In the sense ℓ_j can be broadly interpreted as a combination of transaction convenience and safety convenience.

I define δ_j as the mean utility of product j across all depositors.

$$\delta_j = E\left[u_{i,j}\right] = \alpha r_j + \beta' x_j + \xi_j \tag{8}$$

Under the assumption that the idiosyncratic utility shock follows the extreme value distribution, the expected probability that product j is the best choice is given by the following formula:

$$s_j = E\left[\mathbb{1}_{\{u_{i,j} \geq u_{i,k} \forall l\}}\right] = \frac{\exp\left(\delta_j\right)}{\sum_{k=1}^{J} \exp\left(\delta_k\right)} \tag{9}$$

Notice that the above expected probability that product j is the best choice is also the market share of the product. The above formula shows that the higher the mean utility a product generates, the greater the market share it has. In this basic setup, the market share is a simple logit function of the mean utility. Therefore, this model is often referred to as "the logit model of demand" in the literature. Later, I will introduce features that are important to fit the deposit market.

3.5 Equilibrium

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

To fully characterize the equilibrium, I need to know a set of primitive parameters, α, β, γ, which govern how depositors value different products and how much it costs to produce them. Ideally, if I observe mean utility, δ_j, and marginal costs, c_j, I can pin down these parameters by estimating the following two equations.

$$\delta_j = \alpha r_j + \beta' x_j + \xi_j \tag{10}$$

$$c_j = \gamma' w_j + \omega_j \tag{11}$$

The first equation is the "mean utility equation" which describes how deposit rates and product characteristics are valued by depositors; the second is the "marginal cost equation", which describes how observable cost shifters affect the marginal cost of providing depository services. The challenge here, however, is that neither mean utility, δ_j, nor marginal costs, c_j, are observable. Here is how the structural model can help. From the optimal decisions of depositors, I can link unobservable utility to observable market shares. Using equation 9, I can solve unobservable mean utility as a closed-form function of observable market shares.

$$\underbrace{\delta_j}_{\text{Unobservable}} = \underbrace{\log\left(s_j\right) - \log\left(s_0\right)}_{\text{Observable}} = \alpha r_j + \beta' x_j + \xi_j \tag{12}$$

From the optimal decisions of the bank (equation 4), I can solve unobservable marginal costs as the difference between deposit spreads and markups. Markups can be further derived from the market share equation 9 as a function of observable market shares and yield sensitivity,

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[19]This is similar to the mean-variance utility function where aversion to risk is modeled as a disutility to volatility.

α, which can be estimated from the mean utility equation.

$$\underbrace{c_j}_{\text{Unobservable}} = f - r_j - \underbrace{\left(\frac{\partial \log(s_j)}{\partial r_j}\right)^{-1}}_{\text{Unobservable}} = f - r_j - \left(\underbrace{\alpha}_{\text{Estimated}} \underbrace{s_j(1 - s_j)}_{\text{Observable}}\right)^{-1} = \gamma' w_j + \omega_j$$

(13)

The real strength of the structural model is manifested in equations 12 and 13, where the optimality conditions of depositors and banks allow me to link unobserved primitives (preference and technology parameters) to observable quantities (such as market shares, deposit rates, etc.). I can conduct counterfactual analysis using these primitive parameters, rather than relying on reduced form correlations between observable quantities that may be unstable according to Lucas (1976)'s critique.

3.6 Depositor Heterogeneity

What I have shown above is a basic setup of the discrete choice framework. In this basic setup, depositors have homogeneous tastes over yields and convenience. In reality, depositors may exhibit strong heterogeneity, as is evident in Table 3. As argued in Section 3.1, different clientele can lead to different exposure to monetary policy for the banks. As a result, it is important to incorporate this empirical feature into the model.

Formally, define v_i as the taste of individual i. v_i follows a demeaned standard lognormal distribution. In what follows, I will use a discrete approximation of this distribution in which each type has a frequency of μ_i. Define σ as the magnitude of taste dispersion. The depositors' problem is modeled as the following maximization problem

$$\max_{j \in \{0,1,\dots,J+1\}} u_{i,j} = (\alpha + \sigma v_i) r_j + \ell_j + \xi_j + \epsilon_{i,j}$$

(14)

Comparing equation 14 with equation 6, the depositor heterogeneity is represented by the new term, σv_i. When $\sigma = 0$, we go back to the logit model.[20]

Define $s_{i,j}$ as the expected choice probability for depositor type i to choose product j. Again, use the property of the extreme value distribution, the expected probability that product j is the best choice is given by the following formula:

$$s_{i,j} = \frac{\exp(\delta_j + \sigma v_i r_j)}{\sum_{l=1}^{J} \exp(\delta_l + \sigma v_i r_l)}$$

(15)

The aggregate market share of product j is obtained by summing over different depositor types

$$s_j = \sum_i \mu_i s_{i,j} = \sum_i \mu_i \frac{\exp(\delta_j + \sigma v_i r_j)}{\sum_{l=1}^{J} \exp(\delta_l + \sigma v_i r_l)}$$

(16)

where μ_i is the frequency of type i depositors.[21]

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[20]Later, in Section 4.8, I will allow the yield sensitivity to be dependent on demographic variables.

[21]An implicit assumption here is that banks cannot conduct perfect price discrimination—offering a different deposit rate to each type of depositor. In reality, banks do try to conduct price discrimination. However, such practice is far from perfect because of informational and legal constraints. As long as price discrimination is not perfect, banks face a tradeoff between deposit volumes and rates. The existence of shadow banks is also an evidence that price discrimination is imperfect. Otherwise, commercial banks can maintain low rates to transaction-oriented depositors while offering higher rates to yield-oriented depositors,

Note that after introducing depositor heterogeneity, we can no longer solve the mean utility δ_j as a closed form solution of market shares. Instead, we need to numerically solve the system of $J + 1$ implicit equations for each market using the fixed-point algorithm introduced by Berry et al. (1995) for a given value of σ

$$s(\delta; \sigma) = S \tag{17}$$

where $s(.)$ is a vector of $J + 1$ market share function defined in equation 16, and S is the vector of $J + 1$ observable market shares. Solving δ from the implicit equation system, we have the mean utility equation

$$\underbrace{\delta_j(\sigma)}_{\text{Unobservable}} = s^{-1}\left(\underbrace{S}_{\text{Observable}} ; \underbrace{\sigma}_{\text{Unobservable}}\right)_j = \alpha r_j + \beta' x_j + \xi_j \tag{18}$$

where $s^{-1}(.)$ is the inverse function of the market share equation 16.

On the supply side, I can again express the unobservable marginal costs as the difference between deposit spreads and markups, where the markups are also a function of the yield sensitivity dispersion, σ.

$$\underbrace{c_j}_{\text{Unobservable}} = f - r_j - \underbrace{\left(\frac{\partial \log(s_j)}{\partial r_j}\right)^{-1}}_{\text{Unobservable}} = f - r_j - \left(\sum_i \mu_i \underbrace{(\alpha + \sigma v_i) s_{i,j}(1 - s_{i,j})}_{\text{Estimated}}\right)^{-1} \tag{19}$$

3.7 Numerical Example

Before I take the model to the data, it is useful to use a set of numerical examples to illustrate how the model captures the proposed channel. The shadow money channel relies on two conditions: 1) shadow banks offer lower transaction convenience and 2) depositors have heterogeneous yield sensitivity. This section will show that in the absence of either of these two conditions, the shadow money channel will disappear. Specifically, I solve the model under four sets of parameters. The first set features heterogeneous bank convenience and depositors. In the second and third sets, I switch off the depositor and convenience heterogeneity respectively. In the last set in which I consider a case where bank convenience and depositors are homogeneous, but costs are heterogeneous. In particular, the marginal cost of commercial banks is increasing to the Fed Funds rates. The set of parameters are presented in Table 4.

Figure 4 presents the equilibrium under different parameters. The left panel reports deposit spreads, i.e. the difference between the Fed Funds rates and deposit rates, as a function of the Fed Funds rates, and the right panel reports market shares. The first row shows the case in which depositors are heterogeneous and banks are differentiated. The patterns are very similar to the data: when the Fed Funds rates go up, the commercial bank does not increase its deposit rate as much, so the deposit spread goes up. In contrast, the shadow bank passes most of the rate hikes to depositors, so the deposit spread remains tight. At the same time, the commercial bank loses market share, while the shadow bank gains

which will drive shadow banks out of business. In this paper, I assume one bank can only offer one rate to all the depositors.

market share.

In the second row, I shut down the depositor heterogeneity. In this case, both types of banks have very similar spreads. The market shares, although quite different in terms of levels, have a similar increasing pattern to the Fed Funds rates. The result shows that depositor heterogeneity is crucial to generating different responses to monetary policy. Without depositor heterogeneity, the difference in convenience only affects the level of market share but not the sensitivity to monetary policy.

In the third row, I shut down the heterogeneity in bank convenience. In this case, the shadow bank becomes exactly the same as a commercial bank by definition.

The last row considers a case in which the costs are heterogeneous, but both bank convenience and depositors are homogeneous. This case features the classical bank reserve channel of monetary policy. To elaborate, commercial banks are required by regulation to keep a fraction of deposits as reserves. Holding reserves imposes a cost for commercial banks as reserves used to bear no interest.[22] Formally, when a bank faces reserve requirements, the problem becomes the following

$$\max_{r_j} \left((1 - \tau) f - r_j - c_j \right) s_j \left(r_j \right) \tag{20}$$

where τ is the fraction of assets that have to be held as non-interest bearing reserves. Note that this problem can be reformulated as if reserve requirements increases the marginal cost of taking deposits.

$$\max_{r_j} \left(f - r_j - (c_j + \tau f) \right) s_j \left(r_j \right) \tag{21}$$

Therefore, the cost of holding reserves is increasing with the Fed Funds rates. I assume 10 percent reserve requirement for all the commercial bank deposits and the reserves bear no interest. In this case, the marginal cost increases by 0.1 percent with a 1 percent increase in the Fed Funds rates. We see that the spread of the commercial bank increases with the Fed Funds rates, while the spread of the shadow bank remains stable. After a certain threshold, the market share of the commercial bank becomes decreasing to the Fed Funds rates.

Comparing the fourth and the first rows, it is notable that the reserve channel generates qualitatively similar results as the shadow money channel in some regions of the parameter space. How do we differentiate these two models? To answer this question, we can look into the optimal rate setting decision of banks. From the first order condition of the banks, Equation 4, we know that deposit spreads are driven by marginal costs and markups. It turns out that the shadow money channel works in a very different way from the bank reserve channel. The shadow money channel suggests that the effect of monetary policy should go through markups; the traditional bank reserve channel would suggest the effect of monetary policy should go through marginal costs.

In Figure 5, I decompose deposit spreads into markups and marginal costs. The first row shows the shadow money channel and the second shows the bank reserve channel. In the shadow money channel, monetary policy works through markups: higher Fed Funds rates allow the commercial bank to earn a higher spread from the transaction-oriented depositors while the shadow bank has to maintain a tight spread to keep the yield-oriented depositors. In contrast, in the bank reserve channel, monetary policy works through marginal costs because the commercial bank is subject to reserve requirements while the shadow bank is

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[22]In October 2008, the Federal Reserve started to pay interest on reserves.

not. This decomposition will be very helpful later to differentiate these channels.

To summarize, this simple numerical example shows that the shadow money channel depends crucially on whether transaction convenience is significantly different between shadow and commercial banks, and whether depositors exhibit heterogeneous sensitivity to yields. These two assumptions will be tested against the data in the next section. Furthermore, the shadow money channel implies that monetary policy has differential impacts on the markups of commercial and shadow banks.

4. Structural Estimation

In this section, I take the model to the data. The goal here is to pin down the primitive structural parameters and evaluation how they affect banks' response to monetary policy. This will set the stage for the counterfactual analysis that ensues.

4.1 Identification

The set of primitive parameters are $\alpha, \beta, \sigma, \gamma$. Some of the parameters enter linearly (α, β, γ) in the two structural equations below, while the heterogeneity of yield sensitivity σ enters non-linearly.

$$\delta_j\left(\sigma\right) = \alpha r_j + \beta' x_j + \xi_j \tag{22}$$

$$c_j = \gamma' w_j + \omega_j \tag{23}$$

Two alternative procedures can be implemented to estimate the above structural equations. I can estimate them simultaneously using a joint-equation GMM, or I can estimate them sequentially. I choose the sequential approach since in a joint estimation the misspecification of the marginal cost equation may contaminate the estimation of preference parameters. More concretely, I first estimate the mean utility equation (22). Given the estimated demand side parameters, I calculate the marginal costs and estimate the cost coefficients of equation (23).

A key challenge in identifying the demand parameters is that deposit rates are correlated with unobservable demand shocks, ξ_j. As a result, yield sensitivity α will be biased in an OLS regression of mean utility, δ_j, on deposit rates, r_j. I follow the literature to use a set of cost shocks, z_j, as instrument variables. Examples of instrument variables include salary, expense of fixed assets, and other operating costs. These instruments are standard in the literature (Adams et al. 2007; Ho and Ishii 2011). The rationale is that these supply shifters affect depositors' demand only through deposit rates or product characteristics, instead of directly entering depositors' utility. In other words, these shocks shift the supply curve without moving the demand curve. This allows me to trace out the slope of the demand curve.

The moment condition of the mean utility equation is given by the orthogonality condition between the unobservable demand shocks, ξ_j, the product characteristics, x_j, and cost shifters, z_j:

$$E\left[\xi_j\left[x_j, z_j\right]\right] = 0 \tag{24}$$

Formally, define θ as a vector of demand parameters, $\theta = [\sigma, \alpha, \beta]$, $Z = [x, z]$, W as a

consistent estimate of $E\left[Z'\xi\xi'Z\right]$. The GMM estimator of the demand parameters is

$$\hat{\theta} = \arg\min_{\theta} \xi\left(\theta\right)' ZW^{-1}Z\xi\left(\theta\right) \qquad (25)$$

An important distinction of the above estimation from standard GMM is that the dependent variable, δ, is not directly observable. I use the Nested Fixed Point (NFP) algorithm as detailed in Nevo (2000). The algorithm first searches over the non-linear parameter space of σ. Second, for a given σ, it solves $\delta_j\left(\sigma\right)$ through fixed-point algorithm using the market share equation. Third, I find a set of linear parameters α, β, which minimize the GMM objective function. The above three steps are repeated until the optimal set of parameters α, β, σ is found. In addition, to increase the estimator's efficiency and stability, I conduct a two-step estimation for the demand. In the first step, I use the supply shifters and their polynomials as instruments. In the second step, I use the set of optimal instruments suggested by 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. The details of constructing the optimal instruments can be found in Reynaert and Verboven (2014).

Estimating the supply-side equation is more straightforward. The moment condition of the cost equation is given by the orthogonality condition between the idiosyncratic supply shock, ω_j, and observable cost shifters, w_j:

$$E\left[\omega_j w_j\right] = 0 \qquad (26)$$

The supply parameters γ can be estimated by an OLS regression of the marginal cost on the supply shifters. Note that since the preference parameters used to compute the marginal cost are estimated from the first stage, the standard errors of the second stage are corrected using the approach in Newey and McFadden (1994).

While it is relatively easy to see how α, β, and γ are identified, the identification of σ is worth further elaboration. What variations of the data will identify the value of σ? Intuitively, σ measures the dispersion of depositors' yield sensitivity. A greater dispersion means that different banks have very different demand elasticity. Therefore, if we observe that the same change in deposit rates leads to quite different changes in market share, that implies that depositors have a quite dispersed yield-sensitivity.[23]

4.2 Data for Structural Estimation

The data used for the structural estimation are a panel of commercial banks and MMFs from 1994 to 2012. Following the literature, a market is defined as an MSA-year combination. Since commercial banks attract deposits mainly through local branches, the choice set of depositors of an MSA includes commercial banks that have local branches in the MSA. In contrast, MMFs generally compete in a national market through telephones and the internet. Therefore, local depositors can access all the MMFs in the market. In addition, depositors can also choose cash or Treasury bonds.

I first construct a measure of market shares for each product. Market shares are typically measured in terms of purchase flows in the IO literature, but unfortunately gross deposit inflows are not observable in the data. It may be tempting to use the stock of deposits to

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[23]In Table 1 in the online appendix, I show that market shares of shadow banks are much more sensitive to rate changes compared to commercial banks in a simple reduced form regression. It implies a large σ.

measure market shares. However, the adjustment of stock-based market shares is very slow and it may take a few years for the stock-based market shares to reach a new equilibrium. Therefore, it could be problematic to use stock-based market shares to capture time-series variations. To address this challenge, I construct a flow-based market share measure in a similar spirit to the partial adjustment model of the money demand literature (see Goldfeld and Sichel 1990, and the reference therein). Specifically, I assume only a fraction of $1-\rho$ of depositors can adjust their choices in each year. The flow-based market share, $s_{j,t}$, is defined as the share of depositors among those who can adjust their portfolios in year t that chooses bank j. Then there is a relation between the stock-based market, $\bar{s}_{j,t}$ and the flow-based market share, $s_{j,t}$: $\bar{s}_{j,t} = \rho \bar{s}_{j,t-1} + (1-\rho)s_{j,t}$. Using this relation, I can solve the flow-based market share as $s_{j,t} = (\bar{s}_{j,t} - \rho \bar{s}_{j,t-1})/(1-\rho)$. In the baseline estimation, I use a value of 0.7 for ρ.[24]

I calculate stock-based market shares of a commercial bank by summing up deposits of local branches of the bank in the MSA. For MMFs, no MSA-level information on quantities is available. I impute MSA-level deposit amounts assuming that they are proportional to local personal income levels.[25] I apply the same procedure to cash and Treasury bills. The total market size is the sum of cash, commercial bank deposits, MMF shares, and Treasury bills in an MSA. Following the literature, I combine tiny banks and MMFs (market share less than 0.2 percent) with Treasury bills as the outside option.

Product characteristics are chosen based on the belief that they are important and recognizable to depositors' choice. Product characteristics include whether deposits are issued by a commercial bank or a shadow bank, branch density, number of employees per branch, the age of the bank, and bank fixed effects. I use the TED spread to measure default risk of the banking system. Since commercial bank deposits are generally insured while shadow bank deposits are not, depositors face different amounts of default risk depending on the banking sector. To capture the difference in risk exposure, I further interact the TED spreads with the sector dummies.[26] Lastly, I include time fixed effects to absorb aggregate demand shocks and MSA fixed effects to absorb cross-market differences in demand.

The marginal cost equation includes a set of cost shifters. The cost shifters of MMFs include management costs and other operating costs. The cost shifters of commercial banks include salary expenses and expenses of fixed assets.[27] Lastly, I include bank fixed effects to

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[24]In the online appendix Table 2, I use different values of ρ, and the results are robust. The partial adjustment process is a simple way to capture the stickiness in deposits. An alternative approach is to add an adjustment cost to depositors' utility when they switch banks. However, this alternative approach will greatly complicate the model since it makes the model dynamic. It is notoriously hard to solve a dynamic industrial equilibrium with high dimensional state space, where every bank's past clientele composition becomes part of the state variable.

[25]More specifically, I first compute the percentage contribution of an MSA total personal income to the national aggregate personal income. Then I calculate the average over the whole sample period. Lastly, I impute the MSA-level deposits according to the average contribution. Alternatively, I use contribution of GDP as the imputation weight as reported in Table 2 in the online appendix. The results are very similar.

[26]Egan et al. (2017a) use CDS spreads of banks as a proxy of risk in the discrete choice framework. However, since single-name CDS spreads are not widely available for small commercial banks and all the MMFs, I choose the above approach, which is sufficient to capture the between-sector variations in default risk.

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

absorb time-invariant bank-specific cost shocks. These cost-shifters and their second-order polynomials also serve as instruments for the demand-side estimation.

Table 1 provides summary statistics of the sample used for the structural estimation. A commercial bank typically has a larger market share than an MMF: the average market share is 2.12 percent for a commercial bank and is 0.37 percent for an MMF. A commercial bank also tends to offer lower deposit rates than shadow banks: the average deposit rates are 1.72 percent for commercial banks and 3.05 percent for MMFs. A commercial bank on average has 8.14 branches per million population in an MSA, and each branch has 16 employees.

4.3 Model Fit

This section presents the results of the structural estimation. The first row of Figure 6 shows the scatter plot of the deposit rates and market shares predicted by the model and in the data. The second and third rows plot the average deposit rates and market shares for commercial and shadow banks separately. The model generates different deposit-rate sensitivities between commercial and shadow banks to monetary policy. The model also successfully generates counter-cyclical market shares for commercial banks, and pro-cyclical market shares for shadow banks. The magnitude matches the data closely. Given that the parameters are identified primarily off the cross-section variations, it is remarkable that the model is able to match the different time series variations for shadow and commercial banks.

4.4 Demand Parameter Estimates

The underlying assumption of the proposed channel is that: 1) the transaction convenience of shadow bank deposits is lower than commercial bank deposits, and 2) depositors have heterogeneous sensitivities to yield. I verify these two conditions with the demand estimates. Column 2 of Table 5 reports the estimates of the baseline model. The estimated yield sensitivity is positive and significant. Most importantly, there is statistically significant dispersion in depositors' sensitivity to yields. Later, I will explore the economic implications of such dispersion. Depositors prefer banks with higher branch density and more employees per branch. Depositors also exhibit aversion to default risks of the banking sector, as higher TED spreads are associated with lower convenience levels. The effect is stronger for the shadow banking sector, consistent with the fact that shadow bank deposits are not insured. Column 1 of Table 5 shows the logit model in which depositors are homogeneous. The sign and magnitude of the estimates are quite similar, except σ is assumed as 0 in this case. Later I will show that this single parameter can generate quite different predictions for the equilibrium deposit rates and market shares.

I have shown that depositors indeed exhibit heterogeneous yield sensitivity. The next question is: Are shadow banks differentiated from commercial banks? I plot the histogram of the estimate convenience, $\hat{\ell}_j = x_j'\hat{\beta}$, in Figure 7. Consistent with the intuition, shadow banks have lower estimated convenience than commercial banks. I further zoom in a random MSA market to examine the relation between deposit rates and convenience. Figure 8 provides a scatter plot of deposit rates against convenience. Each dot represents one commercial

Ho and Ishii (2011).

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bank or MMF. The distance between two dots can be interpreted as a measure of product differentiation. The red horizontal line represents the Fed Funds rates. The left panel shows 2004 when the Fed Funds rates were low, while the right panel shows 2006 when the Fed Funds rates were high. There is a clear trade-off between transaction convenience and deposit rates: products with lower convenience levels usually pay higher deposit rates. More importantly, banks with different conveniences pass through different amounts of rates when monetary policy changes: comparing the rates in 2004 (left panel) and 2006 (right panel), banks with lower convenience levels pass through more rate hikes to depositors. When the Fed Funds rates go up, the distance between shadow and commercial banks increases. Effectively, high Fed Funds rates allow shadow banks to differentiate themselves from commercial banks in the dimension of yields.

With commercial and shadow banks offering differentiated products, I expect different types of depositors to self-select into different types of banks. The estimates show that this is indeed the case. Table 6 shows the summary statistics of the estimated demand elasticity. The median own-rate elasticity of commercial banks is 0.358, which has the same magnitude as previous literature. The median own-rate elasticity of MMFs is 0.904, which is almost three times as large as that of commercial banks. This is consistent with the idea that the clientele of MMFs is more yield-sensitive than that of commercial banks.

Next, I examine the cross-rate demand elasticity. The cross-rate elasticity measures the percent change of market share due to changes in deposit rates of a competitor. Table 7 presents the median and standard deviations of cross-rate elasticity. A 1 percent increase in the deposit rates of a commercial bank lowers a rival commercial bank's market share by 0.003 percent, and a rival shadow bank's market share by 0.006 percent. A 1 percent increase in the deposit rates of a shadow bank lowers a rival commercial bank's market share by 0.001 percent, and a rival shadow bank's market share by 0.003 percent. The takeaway is that the demand of an MMF is quite sensitive to its competitors' rates, while the demand of a commercial bank is relatively insensitive to its competitors' rates.

4.5 Supply Parameter Estimates

Regarding the supply-side parameters, column 2 of Table 8 presents the estimated cost coefficients of the logit and the baseline models. For commercial banks, higher reserve costs, salary expenses, and expenses of fixed assets are associated with higher marginal costs. For MMFs, higher management costs and other costs are associated with higher marginal costs.

Column 1 of Table 8 presents the estimated cost coefficients of the logit model. In this regression, the cost function has exactly the same specification as column 2. The only difference is that the dependent variable—marginal cost—is calculated from a logit model of demand. Comparing with the baseline model, the logit model provides estimates with similar signs but a larger magnitude for commercial banks, but a smaller magnitude for MMFs.

4.6 The Transmission Mechanism

So far I have verified that the two conditions of the shadow money channel hold in the data: 1) shadow banks offer lower transaction convenience, and 2) depositors have heterogeneous yield sensitivity. Now the question is that, quantitatively, how much does the shadow money channel explain the variations in the data? To answer this question, I decompose deposit spreads into markups and marginal costs. The top panel of Figure 9 shows the average difference in markups and marginal costs between commercial and shadow banks over time. It is clear that markups fully drive variations in deposit spreads, while the difference in marginal costs is almost flat over monetary cycles. This is consistent with the prediction of the shadow money channel: in periods of monetary tightening, commercial banks are able to exercise their market power on transaction-oriented depositors, while shadow banks cannot increase their margins because a lack of transaction convenience forces them to pass through the rate increase. To show clientele heterogeneity is essential for monetary policy to have differential impact on market power, in the bottom panels of Figure 9, I shut down the depositor heterogeneity and find that the difference in markups becomes flat as well.

This result highlights the importance of industrial organization in transmission of monetary policy. Traditionally, the banking system is usually modeled as a perfectly competitive industry. It was not until recently that several papers such as Scharfstein and Sunderam (2016) and Drechsler et al. (2017) started to point out that the market power of the banking sector may play a role in transmitting monetary policy. Following this line of research, I make two additional contributions. First, Drechsler et al. (2017) shows that monetary policy affects the market power of commercial banks. My paper shows that the effect of monetary policy on market power is different for shadow banks. Such differential impacts lead to a surprising expansion of shadow bank deposits in periods of high interest rates, which gives rise to the shadow money channel. Furthermore, I derive the theoretical conditions under which monetary policy has differential impacts on the market power of shadow banks. Specifically, Drechsler et al. (2017) assumes symmetric banks and a representative depositor. I introduce product differentiation and depositor heterogeneity into the model. I show that product differentiation results in different depositor clientele for shadow banks, which generates a different exposure of market power to monetary policy.

My second contribution is empirical. Since the aforementioned papers rely on reduced-form models, they cannot quantify the importance of the IO-based channels relative to traditional transmission channels such as the bank reserve channel. This paper complements the above studies by providing a structural framework that allows quantification of different channels. As shown in the top panel of Figure 9, markups are the main sources of variations in the deposit spreads of commercial banks.

4.7 Choice of Depositors

Lastly, I examine the choices of different types of depositors over monetary cycles. I classify depositors with above-median yield sensitivity as yield-oriented depositors, and depositors with below-median yield sensitivity as transaction-oriented depositors. Figure 10 plots their probability to choose commercial or shadow banks over time.

The first observation is that yield-sensitive depositors are on average more likely to choose

shadow banks, while transaction-oriented depositors are more likely to choose commercial banks. The second observation is that the choice probability of yield-oriented depositors varies significantly over monetary cycles: They are more likely to choose commercial banks when the Fed Funds rates are low and switch to shadow banks when the Fed Funds rates go up. In contrast, transaction-oriented depositors are more likely to choose commercial banks all the time. This is consistent with the intuition that yield-oriented depositors are constantly looking for higher yields, while transaction-oriented depositors stay in commercial banks because of the transaction convenience of commercial bank deposits.

4.8 Depositor Demographics

So far, the heterogeneity in yield sensitivity is captured by σv_i. I can further allow the yield sensitivity of depositors to be a function of observable depositor attributes such as income and education. Formally, define $d_i = [d_{i,1}, d_{i,2}, ...d_{i,K}]$ as a vector of depositor demographics, $\pi = [\pi_1, \pi_2, ...\pi_K]$ as a vector of loading coefficients of the yield sensitivity to these demographics. Then, the depositors' problem is given by

$$\max_{j \in \{0,1,...,J+1\}} u_{i,j} = (\alpha + \sigma v_i + \pi'd_i)\, r_j + \ell_j + \xi_j + \epsilon_{i,j} \tag{27}$$

Solving the model with depositor demographics is very similar to solving the baseline model. The only difference is that instead of solving δ for a given value of σ, now I need to solve δ for a given combination of σ and π.

$$s(\delta; \sigma, \pi) = S \tag{28}$$

Note that the logit model and the baseline model are nested in this model: if we set $\pi = \mathbf{0}$, we get our baseline model; if we further set $\sigma = 0$, we get the logit model.

I retrieve demographic information such as average age and average family income for each MSA from the 2010 Census. Note that these variables capture the variations across MSAs, while σv_i captures the within-MSA variations in yield sensitivity. The results are reported in the third column of Table 5 and the the third column of Table 8. I find that MSAs with older population and higher income have higher yield sensitivity.

4.9 Alternative Explanations

Thus far, I have shown that a combination of low transaction convenience and yield-sensitive clientele can quantitatively explain the different responses to monetary policy by shadow banks. One may argue that there are many other institutional differences across banking sectors that could also explain these different responses. In this section, I will go through each alternative explanation.

The first intuitive candidate is reserve requirements. When commercial banks take deposits, they are required to keep a fraction of the deposits as reserves instead of lending them out. Historically, bank reserves did not bear interest. Therefore, holding reserves imposed a cost for commercial banks, and the cost of holding reserves increases with the Fed Funds rates. In contrast, shadow banks are not subject to reserve requirements. As a result, monetary policy may have differential impacts across banking sectors through the cost of holding reserves. The bank reserve channel features the underlying mechanism of several

papers such as Bernanke and Blinder (1988), Kashyap and Stein (1995), Kashyap and Stein (2000), and Stein (2012).

The reserve-based explanation is unlikely to quantitatively explain the variations in the relative deposit rates between shadow and commercial banks. Technological innovations and regulatory reforms in the past three decades have rendered the bank reserve channel less important. For example, sweep technology allows banks to easily transfer funds from transaction accounts to savings accounts to avoid reserve requirements (Teles and Zhou 2005). As a result, the amount of bank reserves in the economy has become very small. As of December 31, 2007, the aggregate reserve balance was only 48 billion, which accounted for less than 0.4 percent 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 the unconventional monetary policy in 2008, the reserve balance grew dramatically. However, in this period, the Fed started to pay interest on reserves, which essentially eliminated this reserve channel.

The structural model provides more concrete evidence. I solve counterfactual deposit rates assuming that the cost of holding bank reserves is zero. In panels 1 and 2 of Figure 11, I plot the difference between shadow and commercial bank deposit rates. We can see the pro-cyclical pattern of this difference hardly changes without reserve costs. In comparison, panel 4 shows the case when I shut down the shadow money channel by assuming homogeneous clientele. We can see the difference becomes completely flat. This result is consistent with the result in Figure 9, which shows the the variations in the difference of deposit rates mainly come from markups rather than marginal costs.

The second potential explanation for the different response to monetary policy by shadow banks is default risk. Shadow bank deposits are not insured by FDIC. Therefore, in periods of crisis, depositors may withdraw their money from shadow banking sector and put into commercial banks. Since the Fed usually cuts the Fed Funds rates during crisis, we may find a positive correlation between the Fed Funds rates and deposit flows through their correlations with changes of banks' risks.

Although the risk-based explanation seems to be consistent with the pattern of deposit flows, it cannot explain the pattern of deposit rates. This explanation predicts that shadow banks should pay relatively higher deposit rates to compensate for their risks during periods of low Fed Funds rates. However, we usually observe the opposite in the data. Quantitatively, the default risk is too small to explain the data. To see this, I shut down the risk channel by assuming depositors do not care about risk.[28] Comparing panels 1 and 3 of Figure 11, the relative deposit rates hardly change.

The third potential explanation is based on asset-side differences between commercial banks and MMFs. The asset duration of commercial banks is much shorter than MMFs for both economic and regulatory reasons.[29] Therefore, the average asset returns of commercial

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[28]This is achieved by setting the loading coefficients on TED spreads to zero.

[29]Economically, the shadow banking system breaks down the intermediation process in several steps. MMFs only conduct a small amount of maturity transformation: the average maturity of MMF assets is around 40 days based on the iMoneyNet data, while commercial banks usually have much longer asset maturity. In terms of regulation, Rule 2a-7 of the Investment Company Act of 1940 restricts 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.

banks are less sensitive to changes in the short-term interest rates than MMFs, which may explain why their deposit rates are also less sensitive.

This explanation is problematic because conceptually, what matters for deposit rate setting are the marginal asset returns, rather than the average asset returns. On the margin, both a commercial bank or an MMF can easily invest an additional dollar of deposits in Treasury bills so the marginal asset return should be close to the Fed Funds rates or other short-term market interest rates (see also Hannan and Berger 1991; Drechsler et al. 2017). Even if there is some discrepancy between the Fed Funds rates and the actual asset returns, the discrepancy will be absorbed in the marginal cost term in my model.[30] Again, as shown in Figure 9, marginal costs do not seem to explain the variations in deposit rates.

Another possibility is that the difference in asset duration leads to different exposure of asset value to monetary policy changes. Specifically, an increase in the Fed Funds rates decreases the asset value of commercial banks more than that of shadow banks because the former has longer duration, which triggers outflows from commercial banks to shadow banks. This channel implies that the impact should be most pronounced right after the policy rate change. However, as illustrated in Figure 1 and Figure 3, the difference in deposit rates and flows between MMFs and commercial banks persists over the whole monetary cycle with no sign of decline long after the change in the Fed Funds rates. Therefore, it is unlikely that asset-side differences drive the results.

5. Policy Implications

Using the structural model, I conduct a set of counterfactual exercises to study the policy implications of shadow banking. How does shadow banking change the effectiveness of monetary policy? What are the implications of shadow banks for financial stability? Do depositors benefit from shadow banking?

5.1 Shadow Banks and Effectiveness of Monetary Policy

There is a long-standing concern that financial innovation may undermine monetary control of the central bank. Such concern has intensified in recent years as the shadow banking sector has grown outside the traditional commercial banking sector. Has the rise of the shadow banking system affected the effectiveness of monetary policy?

To answer this question, I simulate a counterfactual economy without shadow banks and compare it with the actual data. Columns 5 and 6 of Table 9 report a simple regression of the aggregate money supply as a share of total liquid assets (cash + deposits + Treasury bills) on the Fed Funds rates. The absolute value of the coefficient is 0.897 in the actual economy while is 1.380 in the counterfactual economy. This implies that shadow bank money creation offsets 35 cents of each dollar of the change in commercial bank deposits.

The counterfactual analysis offers insights on how shadow banks affect the transmission of monetary policy. In an economy without shadow banks, when yield-sensitive depositors

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[30]Suppose f' is the actual marginal lending rates. $(f' - r_j - c_j) s_j (r_j) \iff (f - r_j - c'_j) s_j (r_j)$ where $c'_j = c_j - f' + f$.

become unsatisfied with the low rates offered by commercial banks, they flow out of the banking system in periods of monetary tightening, leading to a reduction in money supply and credit supply. In contrast, in an economy with shadow banks, yield-sensitive depositors can switch within the banking system from commercial banks to shadow banks. With more deposit inflow, shadow banks are able to increase their lending, which buffers the decline in commercial bank lending and dampens the impact of monetary tightening. This result relates to the macroeconomic literature which documents that the effect of monetary policy on aggregate real activity seems to have become smaller in the post-1990s compared to the earlier period (Boivin et al. 2011). Prior literature has provided several explanations such as the change of policymakers' focus to inflation stabilization and the changes of housing market credit condition, my result suggests that the rise of the shadow banking sector could also be one contributing factor.

The presence of the shadow banking sector also affects the response of commercial banks to monetary policy. Columns 1-4 of Table 9 compare the response of commercial bank deposit rates and market shares to the Fed Funds rates in the counterfactual economy and in the actual data. I find that in the absence of shadow banks, commercial banks pass through less rate hikes to depositors, and at same time suffer less outflows in periods of high interest rates. This is consistent with the idea that shadow banks exert competitive pressure on commercial banks. Without the competition from shadow banks, commercial banks can better insulate themselves from monetary policy changes.

5.2 Monetary Policy and Credit Supply of Shadow Banks

So far, my empirical analysis has focused on the money supply. This section examines the credit supply of shadow banks. As discussed in Section 2, while shadow bank deposit creation is conducted by MMFs, loan origination is conducted by different shadow banking entities such as funding corporations, finance companies, ABCP issuers, captive financial institution, and broker-dealers.[31] These loan-origination shadow banks do not issue deposits directly. Instead, they obtain funding from MMFs through issuing money market instruments. There are four major categories of money market instruments issued by these loan-origination shadow banks: commercial paper (CP), asset-backed commercial paper (ABCP), repurchase

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[31]Finance companies are financial entities that sell commercial paper and use the proceeds to extend credit to borrowers, which tends 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 that purchase and hold financial assets from a variety of asset sellers and finance their portfolios by selling asset-backed commercial paper to MMFs or other "safe asset" investors like retirement funds. A captive finance company is a subsidiary whose purpose is to provide financing to customers buying the parent company's product through issuing commercial paper. 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 engage 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 bankrupt during the 2008–09 financial crisis.

agreements (repo), and floating rates notes (FRNs). I regress annual changes of MMF lending through these four money market instruments on the Fed Funds rates, controlling for macroeconomic variables, fund characteristics, and fund fixed effects:

$$\Delta MMF\ Lending_{i,t} = \alpha + \beta Fed\ Funds\ Rates_t + \gamma X_{i,t} + \epsilon_{i,t} \tag{29}$$

Columns 1 to 4 of Table 10 show that MMFs significantly increase their lending to the loan-origination shadow banks as the Fed Fund rates increase. The economic magnitude is significant: a 1 percent increase in the Fed Fund rates is associated with a 0.17–0.78 percent increase in lending from MMFs to other shadow banks.

In addition to the four types of money market instruments discussed above, MMFs also hold large denomination commercial bank obligations, which are issued by commercial banks to obtain short-term funding. Column 6 of Table 10 shows that MMFs also increase the holding of large denomination bank obligations when the Fed raises interest rates. This result reveals an interesting interaction between the shadow and commercial banking system. As the Fed tightens monetary policy, commercial banks borrow more from MMFs to compensate for their loss of the core deposits.[32] Such arrangement is profitable for both types of banks: it effectively conducts price discrimination on transaction-oriented depositors. However, it has a downside: through this lending relationship, bank runs on the MMF industry may spread to commercial banks. This result is another unintended consequence of monetary tightening on financial stability.

With an increase in funding supply from MMFs, the loan-origination shadow banks should be able to expand their credit supply. I examine five types of shadow banks that rely on MMFs to obtain financing: funding corporations, finance companies, ABCP issuers, captive financial institutions, and broker-dealers. I regress aggregate asset growth rates of these five types of shadow banks on the Fed Funds rates and various macroeconomic controls:

$$Shadow\ Bank\ Asset\ Growth_t = \alpha + \beta Fed\ Funds\ Rates_t + \gamma X_t + \epsilon_t \tag{30}$$

Table 11 presents the results. When the Fed Funds rates are high, the assets of these shadow banks also grow faster. 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 main difference between the present study and their work is that they attribute the expansion of shadow bank assets to negative shocks of high interest rate policy on equity values of commercial banks, while my paper argues that the expansion of shadow bank assets is driven by the increase in shadow bank deposit creation. This finding also relates to the literature which shows that tighter monetary policy leads to a shift in firms' mix of external financing from bank loans to commercial paper (Kashyap et al. 1992; Calomiris et al. 1995). I find that such shift also occurs for other types of non-bank credits held by MMFs such as repos and floating rate notes. More importantly, the underlying mechanism in my paper is different. Prior literature relies on the difference in reserve requirements between commercial banks and non-bank lenders to explain such shift.[33] In contrast, my paper argues that such shift could be a result of imperfect competition in

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[32]Choi and Choi (2016) examine commercial bank liability data and reach similar conclusion.

[33]Kashyap et al. (1992) use the Bernanke and Blinder (1988) model in which monetary tightening leads to a reduction in commercial bank deposits and loans through reserve requirements.

the deposit market between commercial banks and MMFs. Deposit inflows into the MMFs during monetary tightening drives up the demand for money market instruments. As major lenders in the commercial paper market (Hanson et al. 2015), an increase in demand from MMFs naturally drives up the issuance of commercial paper.

5.3 Shadow Banking and Financial Stability

The shadow banking system played a central role in the 2008–09 financial crisis. Why is the shadow banking system so fragile? Previous literature finds that the lack of deposit insurance (Gorton and Metrick 2012), leverage (Adrian and Shin 2010), and information opacity (Dang et al. 2016) can create fragility in the shadow banking system. The findings in this paper show that the yield-sensitive clientele could also be a source of fragility. As the yield-sensitive clientele is unattached to shadow banks, shadow banks face a highly elastic demand. This means that a small shock to the underlying asset value may lead to large withdrawals by depositors. Large withdrawals may force shadow banks to liquidate assets at a fire-sale price, which may further depress the asset value, resulting in self-reinforcing runs (Egan et al. 2017a). The risk of bank runs is further aggravated by the fact that shadow bank deposits are not insured. According to my estimates in Table 6, the demand for shadow bank deposits is almost three times as elastic as commercial bank deposits. This means that runs on the shadow banking sector may be more severe than that on commercial banks. This seems to be consistent with the experience in the 2008–09 financial crisis.[34] After the crisis, many of the regulatory efforts have been focusing on commercial banks, while progress on shadow banks has been very slow.[35] A policy implication of the above finding is that more stringent liquidity regulations should be installed in the shadow banking sector given the heightened run risk.

My findings also contribute to a debate on the costs and benefits of using monetary policy as a macro-prudential tool. Prior to the 2008–09 financial crisis, the consensus among policy makers was that monetary authority should focus on price stability and employment (Smets 2013). However, this consensus has been challenged by an alternative view that took shape after the financial crisis, which argues that monetary policy should also be used to promote financial stability (Borio and Zhu 2012; Stein 2012; Ajello et al. 2015). Proponents of this view contend that by tightening monetary policy, the central bank can curb, among other things, the creation of money-like liabilities by the banking system. The unique advantage of monetary policy over financial regulations is that monetary policy can "get into all the cracks" outside the authority of regulators (Stein 2013). On the other hand, the potential complication caused by the shadow banking sector is also discussed (Stein 2012; Yellen 2014). My findings contribute to this debate by showing empirical evidence that monetary tightening may lead to the unintended consequence of driving deposits to the shadow banking

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[34]Figure 3 of the online appendix offers some suggestive evidence that MMFs with more elastic demand (estimated by the structural model) before the crisis suffered more severe run during the breaking-the-buck episode in September, 2008.

[35]The Federal Reserve Chair, Janet Yellen, said in a speech that "Measures are being undertaken to address some of the potential sources of instability in short-term wholesale funding markets, including reforms to the triparty repo market and money market mutual funds—although progress in these areas has, at times, been frustratingly slow" (Yellen 2014).

system. Since shadow banks are not protected by deposit insurance, such a policy may actually increase systemic risk. My paper supports the view that "monetary policy is too blunt a tool to address possible financial imbalances" as argued by Bernanke (2011) and Yellen (2014).

5.4 Implication of Shadow Banking for Depositor Surplus

Commercial banks have considerable market power in local depository markets. The entry of shadow banks may increase rate competition in the deposit market and potentially bring significant gains in depositor surplus. To assess the impact of shadow banking on depositor surplus, I compare the real data with the counterfactual economy without shadow banks. Specifically, I follow Nevo (2001) to compute the expected utility for each type of depositor i from its optimal choice.

$$E\left[\max_{j\in\{0,1,\dots J\}} u_{i,j}\right] = \ln\left(\sum_{j=0}^{J}\exp\left(\delta_j + \sigma v_i r_j\right)\right) \tag{31}$$

Then, I divide expected utility by the yield sensitivity to calculate the equivalent utility in the unit of deposit rates. Lastly, I sum past choices and depositor types to calculate the aggregate surplus.

$$\text{Depositor Surplus}_t = \sum_i \mu_i \frac{1}{\alpha + \sigma v_i} E\left[\max_{j\in\{0,1,\dots J\}} u_{i,j}\right] \tag{32}$$

I compare the surplus in the counterfactual economy with the actual economy. The entry of shadow banks on average generates 0.31 cents on a dollar per year in the sample period. This amounts to a \$43 billion increase in depositor surplus with an aggregate money supply of \$14 trillion at the end of 2015. The change in depositor surplus has the same magnitude as national branching deregulation in the 1990s as estimated by Dick (2008), which is estimated to be 0.50 cents on a dollar. I further examine the time-series variation of the change in depositor surplus, which is plotted in online appendix Figure 2. The change in depositor surplus 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.

6. Conclusion

This paper documents a new monetary transmission mechanism: the shadow money channel. I find that money supply from shadow banks expands when the Fed raises interest rates. This is at odds with the conventional wisdom in the commercial banking sector that monetary tightening reduces money creation. I show that this new channel is a result of deposit competition between commercial and shadow banks in a market with heterogeneous depositors. Due to a lack of a bank charter, shadow banks provide lower transaction convenience and hence are compelled to compete on yields. During periods of monetary tightening, shadow banks pass through more rate hikes, thereby poaching the yield-sensitive depositors from commercial banks. Fitting my model to institution-level commercial bank and MMF data shows that this channel dampens the impact of monetary policy on money supply. I also

explore the macro-prudential implications of shadow banking. I show that monetary tightening could unintentionally drive deposits from the insured commercial banking sector to the uninsured shadow banking sector, which may increase the fragility of the banking system.

This paper highlights the importance of industrial organization of the banking system. Shadow banks provide a valuable alternative to commercial bank deposits which pay too little to depositors due to their market power. In this sense, shadow banks are not merely a way of regulatory arbitrage in the deposit market. They create economic value. Most likely, the shadow banking sector will keep growing and, as a result, the shadow money channel may become more important in years to come. Facing the ever-growing shadow banking sector, what is the right regulatory approach? Should we forbid shadow bank money creation all together? Or should we extend government safety nets such as deposit insurance and the discount window to shadow banks? I will relegate these questions for future research.

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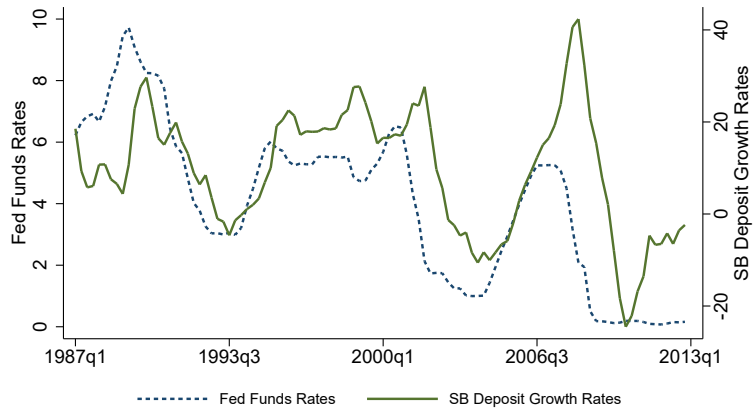
Commercial Banks
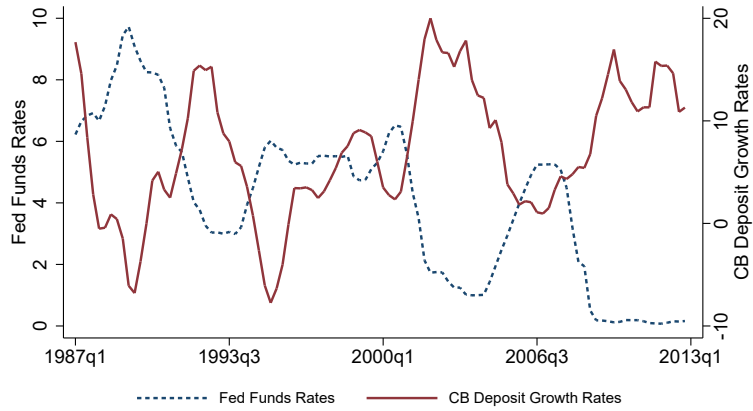
Shadow Banks

Figure 1: **Deposit Growth Rates and the Fed Funds Rates**
This figure shows the annual growth rates of the U.S. commercial and shadow bank deposits from 1987 to 2012. The data are quarterly. Commercial bank deposits are the sum of checking and savings deposits. Shadow bank deposits include all the U.S. retail and institutional MMF shares. The data are obtained from FRED.
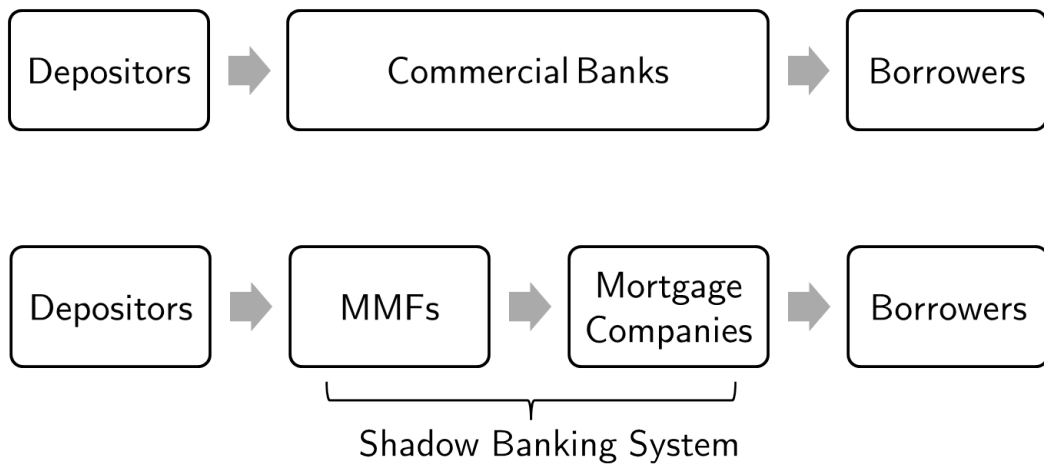
Figure 2: **The U.S. Banking System**
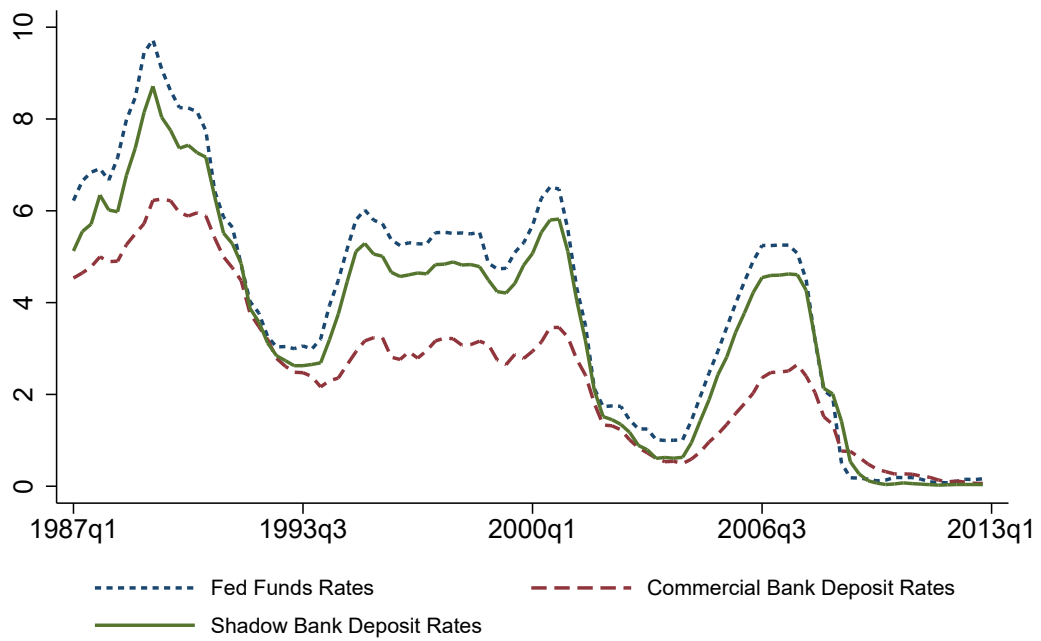
Figure 3: **Deposit Rates and the Fed Funds Rates**

This figure shows the average deposit rates of the U.S. commercial banks and MMFs from 1987 to 2012. The data are quarterly. Commercial bank deposit rates are obtained from the Call Report. MMF yields are obtained from iMoneyNet.
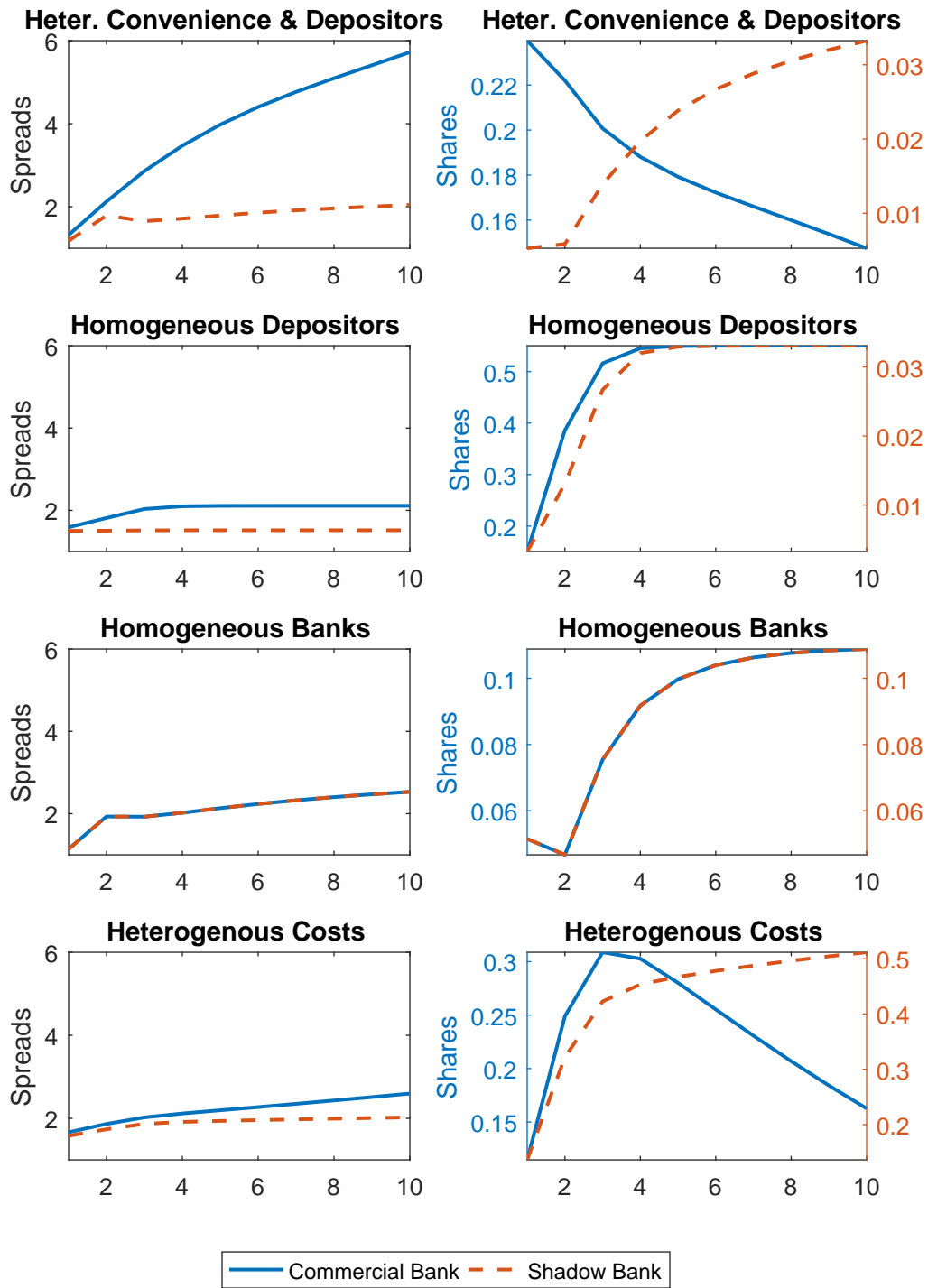
Figure 4: **Numerical Example: Deposit Spreads and Market Shares**
This figure shows the deposit spreads and market shares of commercial and shadow banks in the numerical examples. Each row is simulated using a different set of parameters in Table 4.
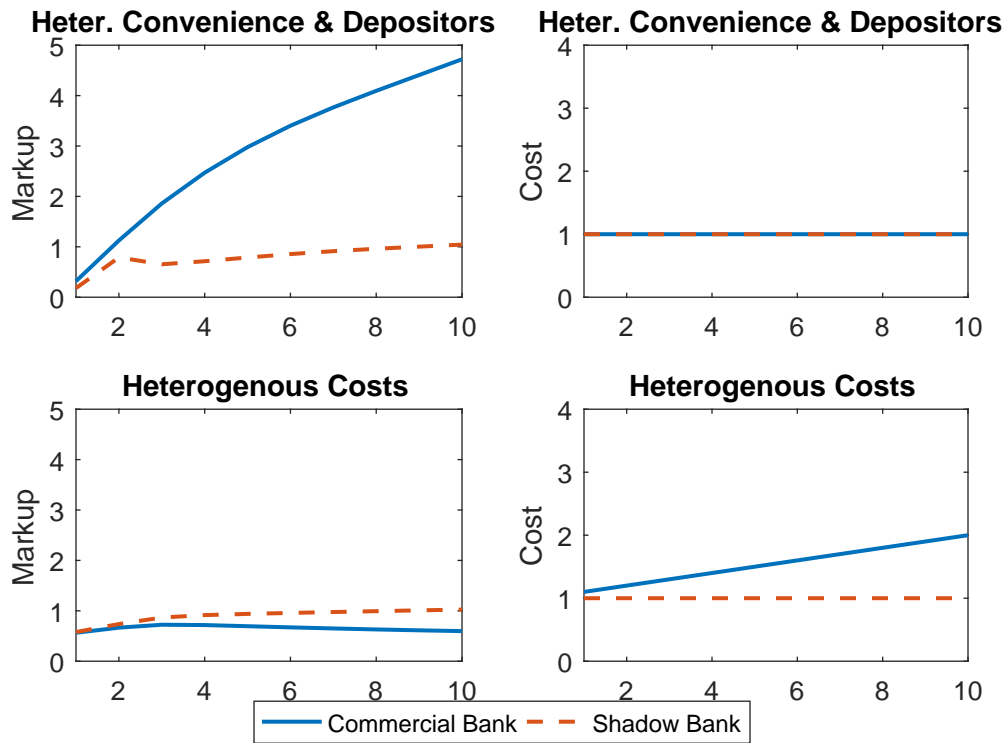
Figure 5: **Numerical Example: Markup and Marginal Cost**
This figure shows the markup and marginal cost of commercial and shadow banks in the numerical examples. Each row is simulated using a different set of parameters in Table 4.
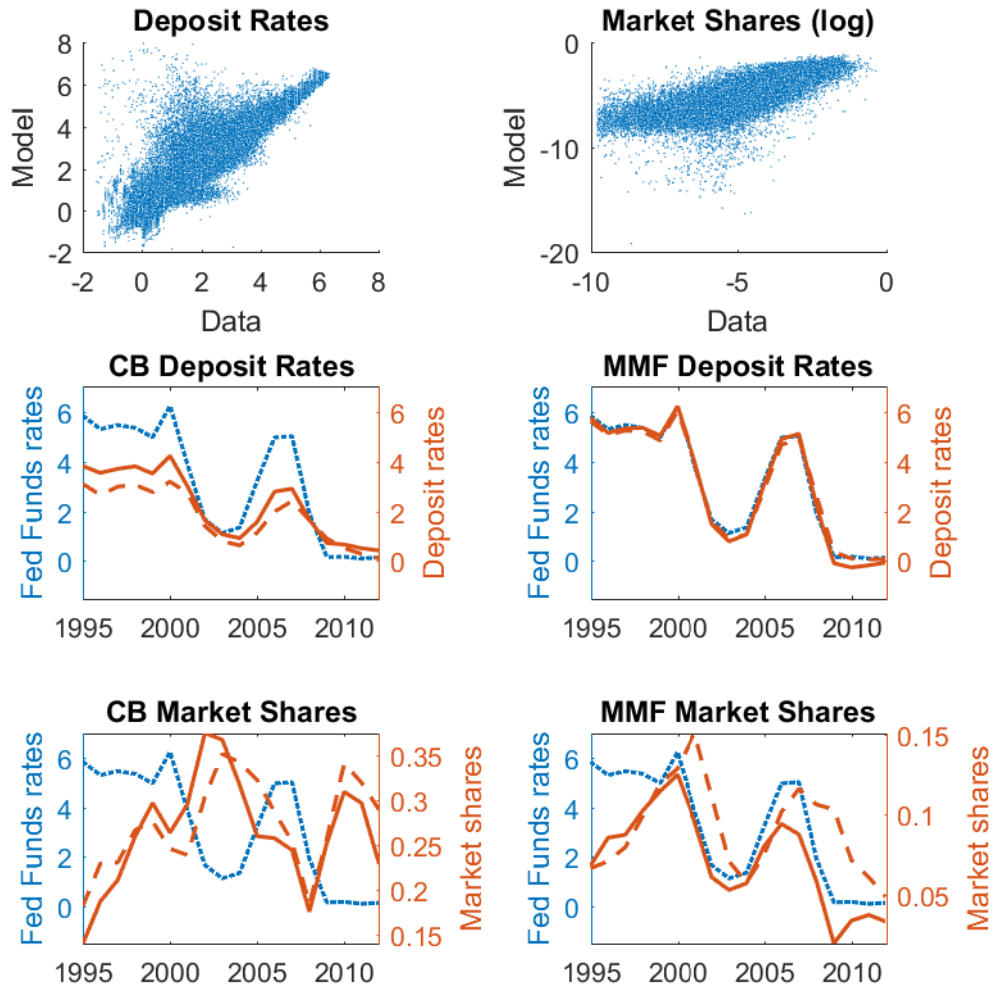
Figure 6: **Model Fit**
This figure shows deposit rates and market shares of commercial and MMFs predicted by the structural model and in the data. The model is estimated using institution-level data on U.S. commercial banks and MMFs from 1994 to 2012.

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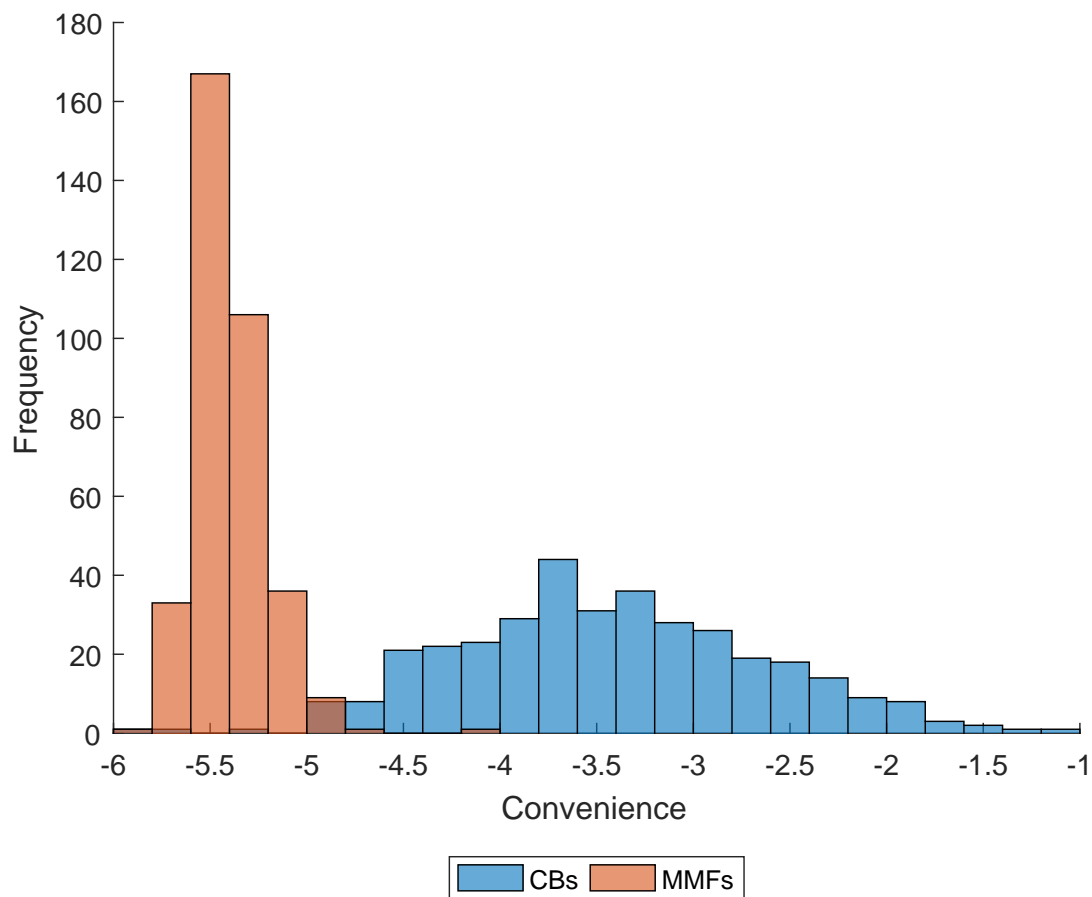
Figure 7: **Distribution of Estimated Convenience**

This figure shows the histogram of the estimated convenience for commercial banks and MMFs. The convenience is defined as the inner product between the vector of characteristics, x, and corresponding sensitivities, β. Each observation is an MSA-sector median. The model is estimated using institution-level data on U.S. commercial banks and MMFs from 1994 to 2012.
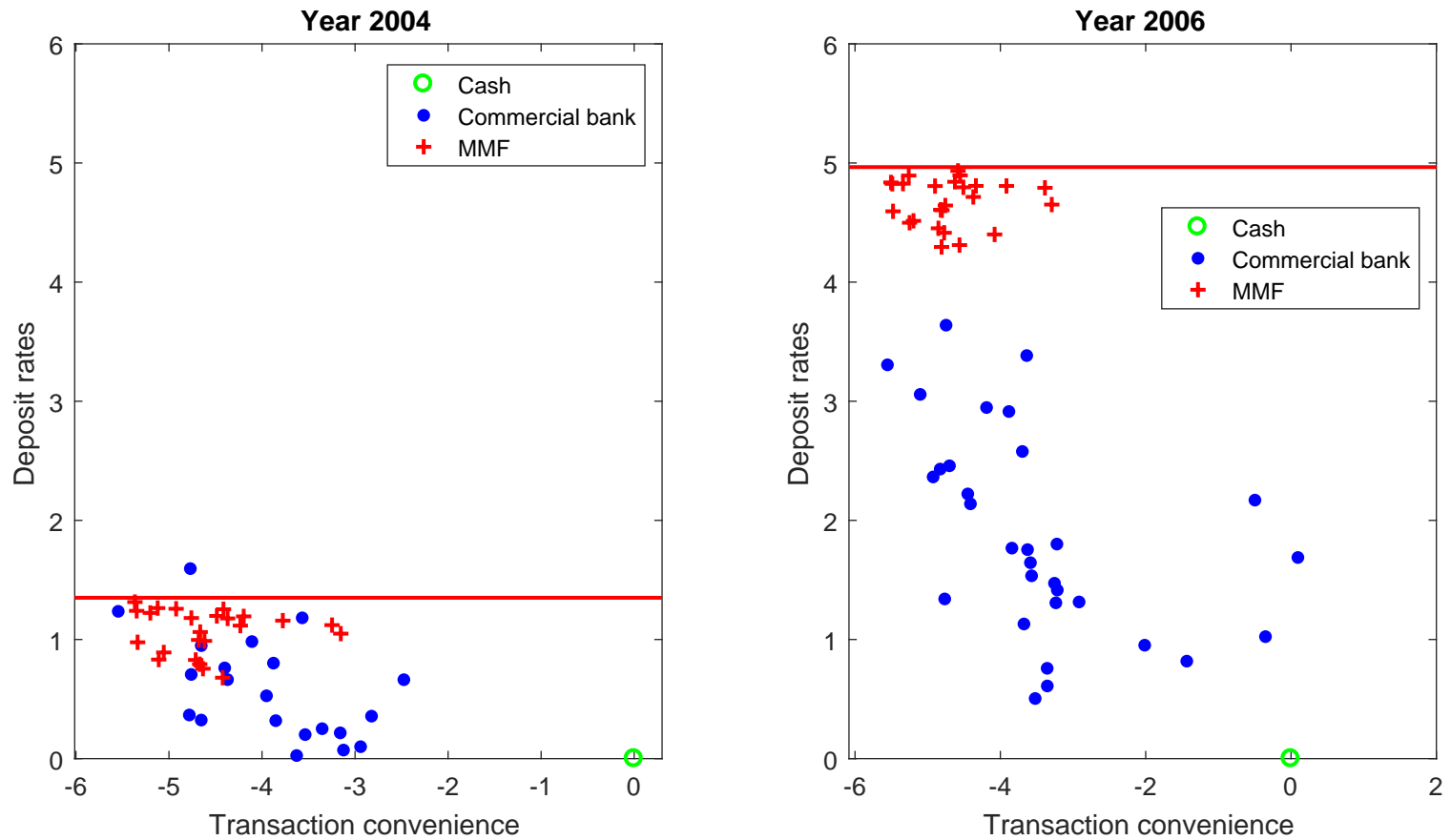
Figure 8: **Scatter Plot of Deposit Rates against Convenience in an MSA**

This figure shows the scatter plot of deposit rates against estimated convenience in a random MSA. Transaction convenience is defined as the inner product between the vector of characteristics, x, and corresponding sensitivities, β. Each observation is a bank. The model is estimated using institution-level data on U.S. commercial banks and MMFs from 1994 to 2012.
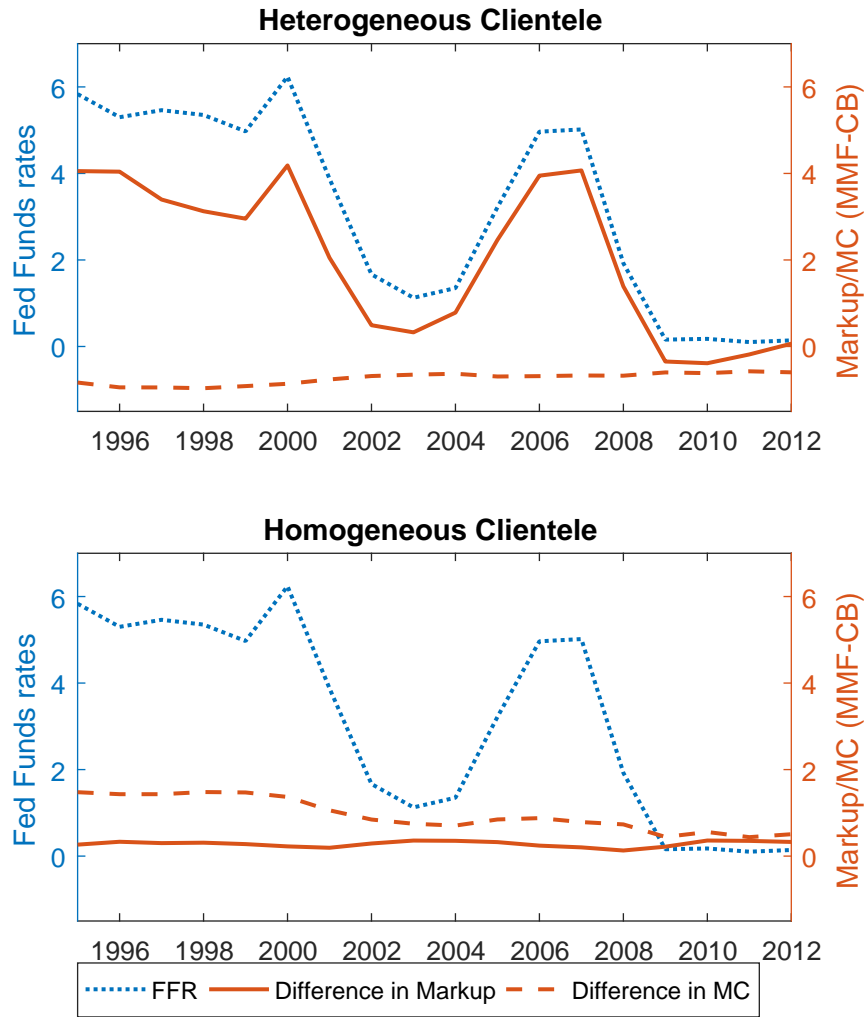
Figure 9: **Difference in Markups and Marginal Costs (CB-MMF)**
This figure shows the difference in average markups and marginal costs between commercial and shadow banks estimated by the structural model. The model is estimated using institution-level data on U.S. commercial banks and MMFs from 1994 to 2012.
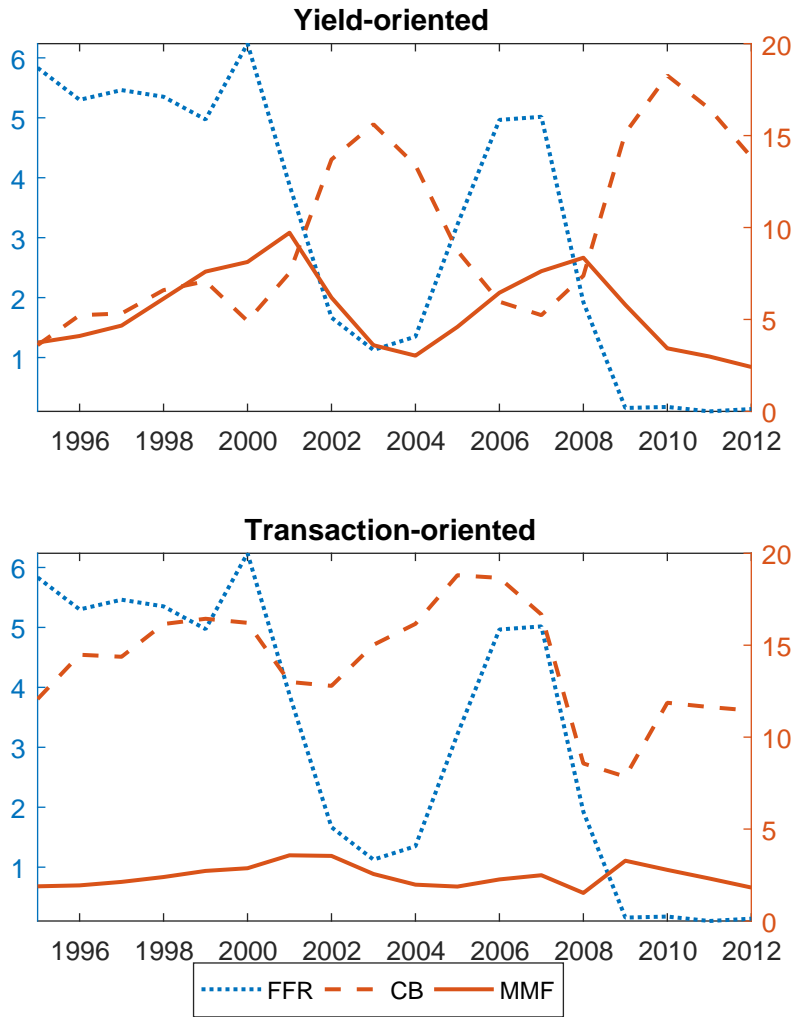
Figure 10: **Choice Probability of Depositors by Type**

This figure shows the estimated probability for yield-oriented and transaction-oriented depositors to choose commercial banks or MMFs over time. The model is estimated using institution-level data on U.S. commercial banks and MMFs from 1994 to 2012.
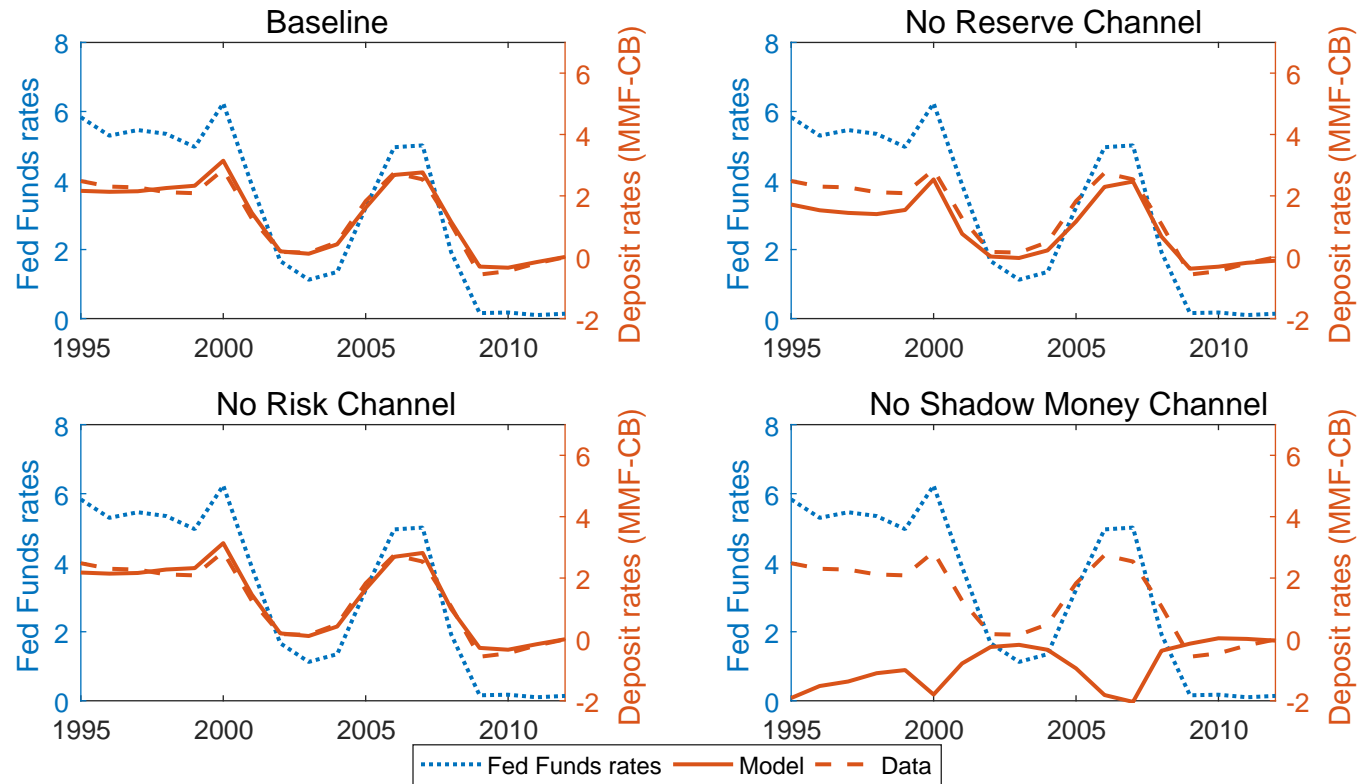
Figure 11: **Decomposition of Monetary Transmission Channels**

This figure shows the difference in deposit rates between commercial and shadow banks in the data and predicted by the structural model under different assumptions. The first panel is the baseline case where the bank reserve channel, the risk channel, and shadow money channel are all present. The second, third, and forth panel show the cases where the bank reserve, default risk, or shadow money channel is switched off respectively.

Table 1: Summary Statistics

	mean	sd	p25	p50	p75
Cash					
Amount	1265.944	3041.716	228.954	397.011	943.684
Market share	8.537	1.084	8.393	8.950	9.211
Commercial banks					
Amount	332.101	1533.831	25.593	69.897	191.991
Market share	2.122	3.309	0.308	0.850	2.543
Deposit rates	1.721	1.298	0.648	1.638	2.731
Branch density	8.139	17.975	2.000	4.000	8.000
Employees per branch	16.012	6.126	11.167	14.875	20.450
Age	90.564	44.987	51.000	94.000	125.000
Expenses of fixed assets	0.103	0.031	0.080	0.101	0.129
Salaries	0.487	0.110	0.415	0.489	0.577
Reserves	0.570	0.760	0.000	0.171	0.895
Money market funds					
Amount	53.427	172.836	6.262	13.993	36.391
Market share	0.376	0.352	0.134	0.270	0.519
Deposit rates	3.050	2.157	0.832	3.108	5.054
Age	28.177	7.872	23.000	26.000	34.000
Management costs	0.195	0.121	0.117	0.183	0.270
Other costs	0.136	0.130	0.041	0.094	0.181

Note: This table presents summary statistics of a sample of commercial banks and MMFs in 375 MSAs from 1994 to 2012 in the U.S. Expenses of fixed assets, salaries, and reserves are normalized by total assets. Deposit amount is in millions of dollars. Deposit rates, market shares, expenses of fixed assets, salaries, reserves, management costs, and other costs are given as percentages.

Table 2: Monetary Policy and Money Growth

	(1) CB	(2) MMF	(3) Cash	(4) Total	(5) CB	(6) MMF	(7) Cash	(8) Total
FFR	−2.291***	4.108***	−0.476**	−0.368	−2.917***	4.581***	−0.576***	−0.623
	(0.316)	(0.672)	(0.181)	(0.344)	(0.443)	(0.650)	(0.213)	(0.422)
GDP growth	−0.135	−1.441***	−0.254*	−0.436	−0.855**	−2.969***	−0.222	−1.335***
	(0.252)	(0.536)	(0.144)	(0.274)	(0.400)	(0.586)	(0.192)	(0.381)
Inflation	−0.097	−1.353	−0.569**	−0.453	−0.730	−6.062***	−0.577*	−2.309***
	(0.400)	(0.852)	(0.229)	(0.435)	(0.661)	(0.969)	(0.318)	(0.630)
TED Spread	−2.146	15.869***	−0.290	4.250***	3.469	13.745***	2.257*	7.147***
	(1.375)	(2.929)	(0.788)	(1.497)	(2.668)	(3.913)	(1.283)	(2.543)
Observations	92	92	92	92	72	72	72	72
Adj. R^2	0.569	0.634	0.332	0.109	0.546	0.704	0.450	0.216

Note: This table presents time series regressions of aggregate annual money growth rates on the Fed Funds rates. A time trend is also included in the regressions. The data frequency is quarterly. The sample period is from 1990 to 2012 for column 1-4 and 1990 to 2007 for column 5-8. Standard errors in brackets are computed with Newey-West standard errors with 4 lags. ***, **, * represent 1%, 5%, and 10% significance, respectively.

Table 3: Demographic Determinants of Shadow Bank Deposit Holding

	(1) Shadow Deposit Dummy	(2) Shadow Deposit Share
Income	0.036***	0.020***
	(0.000)	(0.000)
College	0.040***	0.014***
	(0.000)	(0.000)
Unemployed	0.005	0.002
	(0.530)	(0.755)
Age	-0.011***	-0.006***
	(0.000)	(0.000)
Age2	0.001	0.004***
	(0.456)	(0.000)
Home owner	-0.010**	-0.007**
	(0.018)	(0.017)
Car owner	-0.010**	-0.007***
	(0.017)	(0.008)
Female	0.023***	0.018***
	(0.000)	(0.000)
Married	0.018***	0.009***
	(0.000)	(0.009)
Observations	27764	27764
Adj. R^2	0.047	0.025

Note: This table presents cross-sectional regressions of shadow bank deposit holding on demographic variables for a cross section of 27,764 households in the Survey of Consumer Finance (2013). Shadow bank deposits are defined as deposits that are not insured by the government. Shadow dummy equals 1 if a household has shadow bank deposits, 0 otherwise. Shadow share is the share of shadow bank deposits in the total deposits of a household. The independent variables are the demographics of the head of the household. Robust standard errors are in brackets. ***, **, * represent 1%, 5%, and 10% significance, respectively.

Table 4: Parameters for the Numerical Examples

	σ	α	ℓ_{bond}	ℓ_{cb}	ℓ_{sb}	γ_1	γ_2	w_1	w_2
Heter. convenience & depositors	3.5	2.0	-5.0	-0.5	-4.5	0.0	1.0	f	1.0
Homogeneous depositors	0.0	2.0	-5.0	-0.5	-4.5	0.0	1.0	f	1.0
Homogeneous convenience	3.5	2.0	-5.0	-0.5	-4.5	0.0	1.0	f	1.0
Heterogeneous costs	0.0	2.0	-5.0	-0.5	-4.5	0.1	1.0	f	1.0

Note: This table presents the parameter values of the numerical examples in Figure 4 and 5. Each row presents the set of parameters for a different model.

Table 5: Demand Parameter Estimation

	(1) Logit	(2) Baseline	(3) Demographics
Yield Sensitivity(α)	0.250*** [0.076]	0.898*** [0.066]	0.741*** [0.104]
Yield Sensitivity Dispersion(σ)		0.688*** [0.056]	0.331*** [0.109]
Age(π_1)			2.640*** [0.618]
Income(π_2)			1.048*** [0.261]
Branch Density(β_1)	0.103*** [0.001]	0.104*** [0.001]	0.103*** [0.002]
No. of Employees(β_2)	0.030*** [0.002]	0.048*** [0.003]	0.030*** [0.010]
TED*CB(β_3)	-0.664*** [0.099]	-0.288*** [0.036]	-3.514*** [0.670]
TED*MMF(β_4)	-0.146 [0.144]	-0.613*** [0.059]	-5.621*** [1.044]
Bank F.E.	Y	Y	Y
City F.E.	Y	Y	Y
Time F.E.	Y	Y	Y
Adj. R^2	0.573	0.455	0.140
Observations	242472	242472	242472

Note: This table presents the estimates of demand parameters of the structural model. The sample is a panel of U.S. commercial banks and MMFs from 1994 to 2012. Robust standard errors are in brackets. ***, **, * represent 1%, 5%, and 10% significance, respectively.

Table 6: Own-rate Elasticity

	$\Delta log\left(s_{cb}\right)$	$\Delta log\left(s_{sb}\right)$
Δr_{cb}	0.385	
	(1.415)	
Δr_{sb}		0.904
		(0.538)

Note: This table presents the median and standard deviation (in brackets) of own-rates elasticity of commercial and shadow banks estimated from the baseline model. Each entry gives the percent change of the market share of a bank with a one percent change of its own deposit rates.

Table 7: Cross-rate Elasticity

	$\Delta log\left(s_{cb}\right)$	$\Delta log\left(s_{sb}\right)$
Δr_{cb}	-0.003	-0.006
	(0.022)	(0.009)
Δr_{sb}	-0.001	-0.003
	(0.005)	(0.007)

Note: This table presents the median and standard deviation (in brackets) of cross-rate elasticity of commercial and shadow banks estimated from the full model. The entry of the i-th row and j-th column shows the percent change of the market share of a product j with a one percent change of the deposit rates of a rival product in category i (CB, SB).

Table 8: Supply Parameter Estimation

	(1) Logit	(2) Baseline	(3) Demographics
		CB	
Reserve cost (γ_1)	0.552***	0.085***	0.437***
	[0.097]	[0.027]	[0.077]
Expense of fixed assets (γ_2)	6.550*	0.096	4.949*
	[3.506]	[0.831]	[2.814]
Salaries(γ_3)	2.690**	0.409*	2.074**
	[1.124]	[0.244]	[0.855]
		MMF	
Management costs(γ_4)	0.259	0.667	0.496
	[0.405]	[0.472]	[0.439]
Other costs(γ_5)	0.277	0.448*	0.392*
	[0.203]	[0.259]	[0.233]
Share service costs(γ_6)	-0.186	-0.068	-0.153
	[0.294]	[0.378]	[0.333]
Bank F.E.	Y	Y	Y
Adj. R^2	0.632	0.411	0.614
Observations	242472	242472	242472

Note: This table presents the estimates of supply parameters of the structural model. The sample is a panel of U.S. commercial banks and MMFs from 1994 to 2012. Robust standard errors reported in brackets are clustered by time. Note that since the preference parameters used to compute marginal costs are estimated from the demand estimation, the standard errors here are corrected using the approach in Newey and McFadden (1994). ***, **, * represent 1%, 5%, and 10% significance, respectively.

Table 9: Monetary Policy and Money Supply in the Counterfactual Economy

	(1) CB Deposit rates	(2)	(3) CB Market Shares	(4)	(5) Money Aggregates	(6)
	Data	Count.	Data	Count.	Data	Count.
FFR	0.503***	0.471***	-1.801***	-1.114	-0.897	-1.380
	[0.042]	[0.041]	[0.435]	[0.964]	[0.744]	[0.994]
GDP Growth	-0.101*	-0.093*	1.774***	1.088	1.245*	1.881*
	[0.058]	[0.054]	[0.374]	[0.965]	[0.704]	[1.011]
Inflation	-0.090	-0.105	-1.304**	-1.522	-1.459	-1.833
	[0.095]	[0.092]	[0.565]	[1.335]	[1.019]	[1.458]
TED Spread	0.145	0.103	-3.312*	-5.220	-4.445	-6.414
	[0.291]	[0.279]	[1.888]	[4.768]	[3.481]	[4.985]
City F.E.	Y	Y	Y	Y	Y	Y
Observations	6372	6372	6372	6372	6372	6372
Adj. R^2	0.915	0.894	0.487	0.619	0.398	0.531

Note: This table presents regressions of commercial bank deposit rates, commercial bank market shares, and aggregate money supply on the Fed Funds rates in the data and in the counterfactual economy without shadow banks. The sample includes a panel of U.S. commercial banks and MMFs from 1994 to 2012. The data frequency is annual. Standard errors in brackets. ***, **, * represent 1%, 5%, and 10% significance, respectively.

Table 10: Monetary Policy and MMF Lending

	(1) Commercial Paper	(2) ABCP	(3) Repo	(4) FRNs	(5) Treasury & Agency	(6) Bank Obligations
Fed Funds Rates	0.781***	0.170***	0.565***	0.323***	0.504***	0.330***
	(0.036)	(0.014)	(0.044)	(0.030)	(0.061)	(0.022)
GDP Growth	−0.209***	0.030**	−0.007	0.033	−0.879***	−0.187***
	(0.036)	(0.014)	(0.045)	(0.030)	(0.069)	(0.023)
Inflation Rates	−0.006	−0.059**	0.456***	−0.086	0.415***	0.244***
	(0.060)	(0.026)	(0.082)	(0.054)	(0.120)	(0.039)
TED Spread	0.079	−0.107	−0.180	0.300**	5.024***	0.110
	(0.168)	(0.069)	(0.214)	(0.145)	(0.335)	(0.106)
Observations	15060	15060	15060	15060	15060	15060
Adj. R^2	0.076	0.051	0.107	0.049	0.146	0.093

Note: This table presents regressions of MMF Lending on Fed Funds rates. The dependent variable is the annual change in a specific type of lending normalized by the lagged total lending (lagged one year). Fund characteristics include fund size (log), fund age, management costs, and other costs. The sample includes 1,148 MMFs in the period of 1998 to 2012. The data frequency is quarterly. Standard errors in brackets are clustered by time. ***, **, * represent 1%, 5%, and 10% significance, respectively.

Table 11: Monetary Policy and Asset Growth of Shadow Banks

	(1) Funding Corporations	(2) Finance Companies	(3) ABCP Issuers	(4) Captive Financials	(5) Broker Dealers	(6) Shadow Bank Total
FFR	2.768***	1.438***	4.526***	0.975***	0.744	1.773***
	(0.500)	(0.359)	(0.677)	(0.347)	(0.554)	(0.316)
GDP growth	3.067***	1.813***	0.850	0.840**	1.792***	1.645***
	(0.542)	(0.389)	(0.734)	(0.376)	(0.601)	(0.342)
Inflation	−2.851***	0.647	−0.138	−4.273***	1.667*	−1.002*
	(0.864)	(0.621)	(1.171)	(0.600)	(0.958)	(0.546)
VIX	0.206	0.417***	−0.203	−0.0541	−0.528***	−0.137
	(0.163)	(0.117)	(0.221)	(0.113)	(0.181)	(0.103)
TED Spread	16.98***	−5.198**	−4.000	11.61***	−5.212	2.275
	(3.349)	(2.407)	(4.536)	(2.324)	(3.711)	(2.116)
Observations	92	92	92	92	92	92
Adj. R^2	0.640	0.386	0.495	0.484	0.449	0.561

Note: This table presents time series regressions of the aggregate asset growth rates of shadow banks on the Fed Funds rates. The dependent variable is the annual growth rates of the shadow bank assets. 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.