Banking Technology in a Markov Switching Economy

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Abstract:

We take the user cost approach to modeling the financial firm that maximizes capitalized variable profit to investigate whether the monetary transmission mechanism differs in low and high interest rate environments. We use the panel of U.S. commercial banks from 1992 to 2014 to construct the user costs of financial goods and propose a two-step procedure to estimate a regime-dependent variable profit function in the normalized quadratic semiflexible functional form. We derive demands for and supplies of financial and non-financial goods and provide evidence consistent with neoclassical microeconomic theory. We find several significant differences in the technology of the financial firm across low and high interest rate regimes.

JEL classification: E5, G2, D2, C3.
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1 Introduction

Conventional dynamic new Keynesian models that are widely used to study business cycle and monetary policy assume no active role for the financial intermediary sector. This assumption implies that banks perfectly channel monetary policy conducted by the central bank to the private sector. However, this simplification is unrealistic in most macroeconomic conditions. For example, changes in banks' willingness to lend significantly affect the monetary transmission mechanism through the bank lending channel as discussed, for example, in Bernanke and Blinder (1988) and Kashyap and Stein (1995). In periods of economic expansion, when the interest rate is relatively high and the opportunity cost of holding excess reserves is positive, banks increase lending and expand deposits until reserves reach the required (or desired) levels. The increase in the money supply stimulates the level of economic activity and puts upward pressure on prices. However, during economic downturns when the interest rate is low and close to the zero lower bound, a low opportunity cost of holding excess reserves removes the incentives for banks to lend out their excess reserves. This may lead to the creation of a large quantity of excess reserves as the global financial crisis of 2008 has revealed. In this case, the monetary transmission mechanism becomes ineffective, because of underinvestment in firms with limited access to external capital other than banks.

There are several economic channels through which low interest rates affect the banking technology. First, periods of low interest rates are usually associated with recessions, high risk premia, and low asset prices. A large fraction of nominal bank liabilities accompanied by declining prices of assets suggests that the leverage of the banking sector rises during a crisis. However, a stricter regulatory environment and stronger precautionary incentives force many financial intermediaries to deleverage during crises. Therefore, the overall effect on bank leverage is ambiguous. He, Khang, and Krishnamurthy (2010) find that while leverage dynamics vary across intermediary sectors, commercial banks increased their leverage during the Great Recession. Second, low interest rates, increased volatility of return on assets, and stricter regulation during recessions change the composition of bank assets. Finally, the presence of government-backed debt financing and government liquidity injections in the form of hybrid debt (preferred stocks) alter bank decisions with respect to the sources of funds in the low interest rate environment. Changes in banks' lending and borrowing policies in periods with relatively high and low interest rates, including the recent period of persistently low interest rates, suggest that the banking technology is different across different interest rate regimes. If these differences are not recognized, they can severely affect estimates and conclusions drawn from the data.

In this paper, we develop and estimate a model of the banking firm where the interest rate switches between low and high regimes. We take the user cost approach to modeling the financial firm that maximizes capitalized variable profit choosing the quantities of financial and non-financial goods — see Barnett (1978) and Hancock (1985). We impose the theoretical regularity conditions to obtain inference consistent with neoclassical economic theory — for discussion, see Barnett and Serletis (2008). To estimate the model, we use a Markov regime switching filter, studied in Hamilton (1989), Krolzig (1997), and Sims *et al.* (2008), and Bayesian estimation methods developed in Albert and Chib (1993) and Kim and Nelson (1999). We propose a two-stage procedure to estimate our model. In the first stage, we estimate a regime switching interest rate process and the filtered probabilities of the regimes at each moment of time. In the second stage, we apply the structural model of a profit maximizing bank and, using the filtered regime probabilities, formulate the posterior distribution of the parameters of the normalized quadratic demand system. Since the number of parameters in demand systems is usually large (70 in our two-regime case) the numerical efficiency of the estimation procedure is important. The two-stage estimation routine allows us to significantly reduce the estimation complexity of the problem.

We conduct the empirical analysis in two stages. At the first stage, we model the interest rate regime using an index built on interest rates with different tenors. In doing so, we make an implicit assumption that the federal funds interest rate is an exogenous variable with respect to an individual bank. Though at the macro level the interest rate can hardly be deemed exogenous, an individual bank has little effect on it and we find the assumption reasonable. We construct factors underlying movements in the term structure of interest rates using the principal component analysis of yields on treasury bonds with different maturities. We use the first principal component as a "level" factor of the yield curve — see Litterman and Scheinkman (1991) — to estimate the Markov switching model and recover filtered probabilities of the interest rate regimes.

In the second stage, we use the panel of the U.S. commercial banks from 1992 to 2014 to estimate a regime-dependent variable profit function with a normalized quadratic approximation. We estimate the price elasticities of demands and supplies of financial and non-financial goods and their substitutability implied by the financial technology under different interest rate regimes. We find several significant differences in the technology under alternative regimes. For example, the own-price elasticity of the supply of loans and leases declines from 6.02 to 4.68 when the economy moves from a high to a low interest rate regime. Also, the supply of loans and leases is very inelastic with respect to the cost of debt capital in both regimes. These changes in elasticities of bank's demands and supplies determine the ability of monetary and regulatory policies to affect markets of financial and non-financial goods through changes in their user costs.

Our two-step approach differs from a "standard" hidden regime (one-step) setup where the coefficients of the profit function are regime dependent and a latent regime follows a Markov chain. In our model the economic regime depends on the macroeconomic interest rate, i.e. based on additional macro-level information, while the bank's profit function relates bank-level prices and quantities of financial goods. As a result we mitigate the risk of overparameterization inherent in the standard hidden regime model. In addition, since we explicitly define economic regimes as the interest rate regimes, our model suggests a clear interpretation of differences in the banking technology in alternative regimes compared to the standard hidden regime model. Finally, our approach de-links the estimation of the interest rate regime from the sample of micro-level data and makes it possible to estimate the regime more efficiently using a much longer sample of macroeconomic time series.

It is to be noted that the user cost approach allows us to classify financial goods into inputs and outputs based on their contribution to the bank profit. In particular, an asset is considered to be an output if the return on investment into this asset exceeds the opportunity cost of funds. Otherwise, the asset is an input. Similarly, a liability is classified as an input if the cost of holding this liability is greater than the opportunity cost of funds. Otherwise, the liability is an output. According to this classification scheme, deposits are likely to be labeled as outputs, especially, if only interest expenses are taken into consideration. We find that an asset or liability can be classified as input for one bank and as output for another bank, because of differences in the opportunity cost of funds. Also, for a particular bank, the type of a financial good can change in different economic regimes.

Our paper contributes to the growing body of literature studying financial disintermediation in crises and financial technology in a low interest rate environment. See, for example, Diamond and Rajan (2005), Farhi and Tirole (2012), He and Krishnamurthy (2013), and Tobian and Liang (2016). We quantify the effect of the low interest rate regime on the elasticity of banking technology and the efficiency of the monetary policy transmission mechanism. We find that the monetary policy transmission mechanism becomes less efficient in the low interest rate environment. This finding is consistent with Karras (1996), Gambacorta and Rossi (2010), and Borio and Gambacorta (2017). In a broader context, we find that the banking technology is relatively inelastic in both regimes. This confirms the conclusion in Hancock (1985).

An alternative to the estimation of the bank's profit function in the user cost approach is the estimation of the bank's cost and revenue functions. This approach is often used in the analysis of the cost-efficiency, profit-productivity and scale economies in the banking sector. See, for example, Berger and Mester (2003) and Wheelock and Wilson (2017). An advantage of this approach is the absence of the assumption that the banks are price takers. One drawback of the cost function estimation is that it requires an ex ante classification of bank financial goods into inputs and outputs. Since there is an inconclusive debate about whether some financial goods (e.g. deposits) are inputs or outputs, the classification often amounts to a researcher's arbitrary choice. Another drawback of the cost function estimation is that it ignores bank's cost of capital in calculating bank's input prices. The user cost approach takes into account banks' cost of capital and does not require an ex ante classification of financial goods into inputs and outputs. We summarize the ex post classification in Table 3. We also discuss the assumption that the banks are price takers below.

The rest of the paper is organized as follows. Section 2 provides a brief review of the user-cost approach to modeling the financial firm. In Section 3, we discuss data and measurement matters. Section 4 deals with econometric setup. Section 5 presents and discusses the empirical results. The final section concludes the paper.

2 The Bank Variable Profit Function

A representative bank operates with a set of assets A, a set of liabilities L, and a set of non-financial goods (such as labor) M. The total number of goods is N. The bank chooses the quantities of these goods to maximize its capitalized value of variable profit π. We assume that there are no adjustment costs and, therefore, the bank finds the optimal quantities of the goods in each period independently. We let P^t denote the general price index, R^t – the discount rate, y_k^t and h_k^t – the real balance and the holding cost or revenue (per unit) of the financial good $k \in A \cup L$, w_k^t and q_k^t – the real balance and the cost (per unit) of non-financial good $k \in M$, and y_F^t – the quantity of a fixed in the short run good in period t. Then the capitalized value of variable profit over T periods is

$$\pi = \sum_{t=2}^{T} \prod_{s=1}^{t} \frac{1}{(1+R^s)} \Bigg(\sum_{k \in A} \left[\left(1+h_k^{t-1}\right) y_k^{t-1} P^{t-1} - y_k^t P^t \right] \\ + \sum_{k \in L} \left[y_k^t P^t - \left(1+h_k^{t-1}\right) y_k^{t-1} P^{t-1} \right] - \sum_{k \in M} q_k^t w^t P^t \Bigg). \tag{1}$$

In the righthand side of equation (1), the first line represents the total net revenue from holding bank assets and the second line the total net expenses of servicing bank liabilities. The total net revenue for an asset k (such as a loan) in period t is the initial nominal value $y_k^{t-1}P^{t-1}$ plus the revenue from holding the asset $h_k^{t-1}y_k^{t-1}P^{t-1}$ minus the nominal asset value at the end of the period $y_k^t P^t$. Similarly, the total net expense for a liability k (such as a deposit) in period t is the nominal value at the end of the period $y_k^t P^t$ minus the initial nominal value $y_k^{t-1}P^{t-1}$ minus holding cost $h_k^{t-1}y_k^{t-1}P^{t-1}$. The negative of the coefficients of real balances y_k^t in equation (1) are beginning of the period nominal user costs. Thus the beginning of period t nominal user cost of assets is

$$u_k^t = \frac{R^t - h_k^t}{1 + R^t} P^t, \; k \in A \tag{2}$$

and the beginning of period t nominal user cost of liabilities is

$$u_k^t = \frac{h_k^t - R^t}{1 + R^t} P^t, \; k \in L. \tag{3}$$

Equations (2) and (3) imply that the user costs may be positive or negative. The signs of the user costs permit financial goods to be classified as inputs or outputs. Those items with a positive user cost are classified as inputs (because the variable profit decreases when the quantity increases) and those with a negative user cost are classified as outputs (because the variable profit increases when the quantity increases). With this classification of goods, we can also perform a change of variables, transferring the sign from the user costs to the quantities, as follows

$$\bar{u}_k^t = \left|u_k^t\right|, \tag{4}$$

$$\bar{y}_k^t = -\text{sign}(u_k^t)\, y_k^t, \; k \in A \cup L. \tag{5}$$

Since the absence of adjustment costs effectively makes the bank profit maximization a repeated one-period problem, for the rest of the section we omit the time index for simpler exposition. We let $\boldsymbol{v} = (\{\bar{u}_k\}_{k \in A \cup L}, \{q_k\}_{k \in M})$ be the vector of the absolute values of the user costs and prices of non-financial goods and $\boldsymbol{x}_t = (\{\bar{y}_k\}_{k \in A \cup L}, \{w_k\}_{k \in M})$ be the vector of quantities where $x_t^k < 0$ for inputs and $x_t^k \geq 0$ for outputs. With these notations the variable profit of the bank, i.e. total revenue less variable cost, is $\boldsymbol{v}_t \boldsymbol{x}_t$ and the bank's profit maximization problem is

$$\pi\left(\boldsymbol{v}, y_F\right) = \max_{\boldsymbol{x} \in S} \boldsymbol{v}\boldsymbol{x} \tag{6}$$

where $\pi\left(\boldsymbol{v}, y_F\right)$ denotes the variable profit function and S is the production possibility set. The variable profit function is: (i) nondecreasing in output prices and nonincreasing in input prices; (ii) homogeneous of degree one in $\boldsymbol{v}$; (iii) continuous in $\boldsymbol{v}$; and (iv) convex in $\boldsymbol{v}$.

In principle, assuming an explicit functional form for the variable profit function and having data on prices and observed profit, one could estimate equation (6) directly. However, we can substantially improve the accuracy of the estimation if we simultaneously estimate the system of supply and demand functions induced by the variable profit function. We obtain the system of supplies of outputs and demands for inputs using Hotelling's lemma, differentiating (6) with respect to prices

$$x_k = \frac{\partial \pi\left(\boldsymbol{v}, y_F\right)}{\partial v_k}, \; k = 1, ..., N. \tag{7}$$

In using Hotelling's lemma, we implicitly assume that the bank is a price taker. While the degree of competition could vary across different segments of commercial banking and over time, the level of concentration in the U.S. commercial banking industry is relatively low. For example, Bolt and Humphrey (2015) estimate that in 2010 the average HHI for banks with total assets in excess of $1 billion is 1364. For the banks with total assets between $100 million and $1 billion, the HHI is 1132. According to the U.S. Justice Department's 2010 horizontal merger guideline, markets with an HHI below 1500 can be considered to be unconcentrated. Section 3 discusses the classification of financial goods for the purpose of this study.

Estimation of (7) allows us to calculate own- and cross-price elasticities of supply of and demand for the financial goods. In particular, the elasticity of transformation can be calculated from the Hessian matrix $\boldsymbol{H}$ as follows

$$\sigma_{ij} = \pi \frac{\partial^2 \pi}{\partial v_i \partial v_j} \left[\frac{\partial \pi}{\partial v_i} \frac{\partial \pi}{\partial v_j} \right]^{-1} = \frac{\pi \boldsymbol{H}_{ij}}{x_i x_j},\ i,j = 1, ..., N \tag{8}$$

and the compensated price elasticities of supply and demand as[1]

$$\eta_{ij} = \sigma_{ij} \frac{x_i}{\pi},\ i,j = 1, ..., N. \tag{9}$$

We approximate the period t variable profit function $\pi\left(\boldsymbol{v}, y^F\right)$ with the normalized quadratic locally flexible functional form of Diewert and Wales (1987) as

$$\begin{aligned}
\pi\left(\boldsymbol{v}, y_F\right) &= \left(\boldsymbol{b}'\boldsymbol{v} + \frac{\boldsymbol{v}'\boldsymbol{C}\boldsymbol{v}}{2\boldsymbol{\alpha}'\boldsymbol{v}} + \boldsymbol{d}'\boldsymbol{v}t \right) y_F \\
&= \left(\sum_{i=1}^{N} b_i v_i + \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} c_{ij} v_i v_j}{2\sum_{i=1}^{N} \alpha_i v_i} + t \sum_{i=1}^{N} d_i v_i \right) y_F,
\end{aligned} \tag{10}$$

where elements of $\boldsymbol{b}' = [b_1, ..., b_N]$, $\boldsymbol{d}' = [d_1, ..., d_N]$ and the $n \times n$ matrix $\boldsymbol{C} = [c_{ij}]$ are the unknown parameters to be estimated. The vector of parameters $\boldsymbol{\alpha}' = [\alpha_1, ..., \alpha_N]$ is predetermined and satisfies $\boldsymbol{\alpha} > \boldsymbol{0}_N$; in the empirical section we assume that it is a vector of ones. As can be seen, $\pi\left(\boldsymbol{v}, y^F\right)$ in (10) is linearly homogeneous in $\boldsymbol{v}$. The quadratic form matrix $\boldsymbol{C}$ is symmetric, i.e. $c_{kl} = c_{lk}$ for $k, l = 1, ..., N$. Further, we impose the following condition on matrix $\boldsymbol{C}$

$$\boldsymbol{C}\boldsymbol{v}^* = \boldsymbol{0},\ \text{for some } \boldsymbol{v}^* > \boldsymbol{0}.$$

A natural choice of $\boldsymbol{v}^* = \boldsymbol{1}$ allows us to express the main diagonal elements of $\boldsymbol{C}$ in terms of its off-diagonal elements as follows

$$c_{ii} = -\sum_{j \neq i} c_{ij},\ i = 1, ..., N. \tag{11}$$

[1]The formula is adjusted for user costs measured in percentage points.

The variable profit function (10) is convex if and only if $\boldsymbol{C}$ is positive semidefinite.

Differentiating (10) with respect to prices yields the following system of supplies of outputs and demands for inputs normalized by the quasi-fixed input

$$\frac{x_k}{y_F} = b_k + \frac{\sum_{i=1}^{N} c_{ki} v_i}{\sum_{i=1}^{N} \alpha_i v_i} + \frac{\alpha_k \sum_{i=1}^{N} \sum_{j=1}^{N} c_{ij} v_i v_j}{2\left(\sum_{i=1}^{N} \alpha_i v_i\right)^2} + c_k t, \; k = 1, ..., N \tag{12}$$

or, equivalently

$$\frac{x^k}{y_F} = b_k + \sum_{i=1}^{N} c_{ki} \bar{v}_i + \frac{1}{2} \alpha_k \sum_{i=1}^{N} \sum_{j=1}^{N} c_{ij} \bar{v}_i \bar{v}_j + c_k t, \; k = 1, ..., N \tag{13}$$

where $\bar{v}^k = v^k / \sum_{i=1}^{N} \alpha_i v^i$ for $k = 1, ..., N$ denotes normalized prices. After imposing (11) equation (13) can be written as

$$\frac{x^k}{y_F} = b_k + \sum_{i=1}^{k-1} c_{ki} w_{ki} - \sum_{i=k+1}^{N} c_{ki} w_{ki} + \frac{1}{2} \alpha_k \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} c_{ij} \left(w_{ij}\right)^2 + c_k t, \; k = 1, ..., N \tag{14}$$

where $w_{ij} = \bar{v}_i - \bar{v}_j$, denoting differences in normalized prices.

The elasticities of transformation and compensated price elasticities for the NQ model can be obtained using (8) and (9) with the Hessian $\boldsymbol{H} = [h_{ij}]$ of the normalized quadratic variable profit function given by

$$h_{ij} = \left(\sum_{i=1}^{N} \alpha_i v_i \right)^{-1} \left(c_{ij} - \sum_{k=1}^{N} c_{ik} \bar{v}_k - \sum_{k=1}^{N} c_{kj} \bar{v}_k - \sum_{k=1}^{N} \sum_{l=1}^{N} c_{kl} \bar{v}_k \bar{v}_l \right) y_F.$$

We follow Willey *et al.* (1973) to ensure convexity of $\pi\left(\boldsymbol{v}, y_F\right)$ with respect to prices $\boldsymbol{v}$. In particular, we impose $\boldsymbol{C} = \boldsymbol{G}\boldsymbol{G}'$, where $\boldsymbol{G} = [g_{ij}]$ is an $N \times N$ lower triangular matrix which also satisfies $\boldsymbol{G}'\boldsymbol{v}^* = \boldsymbol{0}$. With $\boldsymbol{v}^* = \boldsymbol{1}$ the diagonal elements of $\boldsymbol{G}$ are

$$g_{ii} = - \sum_{j=i+1}^{N} g_{ji}, \; i = 1, ..., N-1.$$

With this convexity constraint, the NQ variable profit function of seven goods has 35 independent parameters.

3 The Data

We estimate the bank variable profit function using a quarterly panel of the U.S. commercial banks from 1992 to 2014. The data is obtained from the bank Call

Reports provided by the Federal Deposit Insurance Corporation (FDIC). We exclude from the sample savings associations and thrifts which account on average for 10.6% of total assets. During the 1992 to 2014 period the number of banks has declined from 11,725 to 6,262 as a result of the consolidation in the U.S. banking industry. Over time the assets have become more concentrated in the largest financial institutions, as can be seen in Table 1, which shows the distribution of assets over four groups of banks in 1992, 2002 and 2012.

The resulting panel which contains 736,729 observations is unbalanced: only 32.4 percent of the participation patterns cover the entire twenty-three year period. We proceed with the unbalanced panel to reduce the survival bias in parameter estimates. Olley and Pakes (1996) show that using an artificially balanced sample can lead to significant bias in parameter estimates due to the survival effect. They also demonstrate that an explicit selection correction has insignificant effect if the estimation is based on the unbalanced sample. We abstract from the interaction between commercial and investment banking and focus only on commercial banking activity to investigate how changes in the user costs of certain financial goods affect the supplies of outputs and demands for inputs.

We define seven variable financial goods: balances due from depository institutions (y^1), debt securities and trading accounts (y^2), loans and leases (y^3), deposits (y^4), debt other than deposits (y^5), employees (y^6). We follow Berger and Mester (2003) and include bank premises and fixed assets (y_F^1), off-balance-sheet items such as commitments, letters of credit, and derivatives (y_F^2), and equity capital (y_F^3) as quasi-fixed goods. We use the non-interest income as a proxy for the amount of off-balance sheet activities. The quasi-fixed goods multiplicatively enter the scaling factor y_F in equation (10), i.e. $y_F = (y_F^1)^{\delta_1}(y_F^2)^{\delta_2}(y_F^3)^{\delta_3}$, where δ_1, δ_2 and δ_3 are parameters to be estimated. It is to be noted that the user costs of off-balance sheet items cannot be directly calculated because there are no explicit holding costs or revenues associated with off-balance sheet financial goods. For this reason, we cannot classify off-balance sheet items as inputs or outputs. In addition, it is difficult to obtain accurate price information on off-balance sheet items.

The level of aggregation for the financial goods is mainly due to data limitations. Aggregation bias may be present, for example, because we combine demand deposits and term deposits with different maturities. In Table 2 we list the values of the variable goods for each of the 23 years in the sample. The loans and leases on average account for over 60 percent of banks' assets and debt securities and trading accounts account for about 26 percent of assets. Together with bank premises and fixed assets, these two assets on average account for about 88 percent of all assets. Deposits on average account for about 84 percent, equity capital for close to 11 percent, and debt other than deposits for about 5 percent of total liabilities.

We let r_{it}^k denote the realized interest income on the kth asset or the realized interest expense on the kth liability of bank i in quarter t. Then using the values of interest income and expenses we calculate the realized holding costs and revenues $h_{it}^k = r_{it}^k / y_{it}^k$ of the assets and liabilities. We assume that the discount rate R_{it} is specific for each bank and could vary over time. The literature shows no consensus on how to determine the discount rate for a bank. For example, a contentious issue in calculating a bank's weighted average cost of capital (WACC) is accounting for the cost of deposits which on average account for more than 80% of the total liabilities of a commercial bank. The interest rates paid by banks on deposit balances are usually quite low and do not account for non-interest expenses associated with attracting and servicing deposits.

In this regard, Diewert *et al.* (2012) discuss three options for the choice of the discount rate: (i) the average cost of raising financial capital via debt other than deposits; (ii) the weighted average cost of raising capital via deposits and debt; and (iii) the weighted average cost of raising capital via deposits, debt, and equity. While each of these methods can provide a reasonable proxy for the discount rate, the choice depends on the composition of bank liabilities. The first method might result in a biased estimate of the discount rate if the share of debt other than deposits in all liabilities is small or if, for example, a bank has a large credit at special and non-market conditions. In our sample the average share of debt other than deposits is about five percent of total liabilities and equity capital. The second method can produce a significant downward bias, because (1) the interest rate on deposits underestimates the cost of this source of funds [see Basu and Wang (2013) for a discussion] and (2) the method excludes equity capital which is, typically, the most expensive source of bank capital. In what follows, we choose the third method and calculate the weighted average cost of deposits, debt, and equity.

We follow Diewert *et al.* (2012) and calculate realized returns on deposits and other debt as proxies for the cost of deposits and other debt, respectively. These two variables are bank specific and change over time. As for the cost of equity, we use the CAPM to calculate expected returns for publicly traded commercial banks and then for each quarter calculate average expected returns in commercial banking (NAICS industry code 522110) over the period from 1992 through 2014. In particular, we assume a constant equity risk premium and calculate the cost of equity using the CAPM as

$$E_t[R_{i,t+1}] = R_{f,t} + \beta_{i,t}\, RP, \tag{15}$$

where $R_{f,t}$ is the risk-free rate, $\beta_{i,t}$ is a time-varying CAPM beta of bank i and RP is the equity risk premium. We use the three-month Treasury bill rate as the risk-free rate and set the equity risk premium equal to 8%, the average CRSP value-weighted return minus average risk-free return from 1925 to 2014. We obtain banks' betas from CRSP. Our estimates of the cost of equity vary from 7.8 to 14.2 percent.

Following Diewert *et al.* (2011) we calculate the ex post average user costs and revenues of the financial goods based on discount rates and realized holding costs and revenues according to (2) and (3). Given the available data, the ex post average realized user costs and revenues provide a reasonable approximation for the ex ante marginal user costs which drive banks' decision making. The quality of this approximation depends on the amount of risk in the returns on the financial goods. Since the estimation uses bank-level realized user costs of financial goods, our analysis takes into account regional and other differences in the interest rates that banks face. For a discussion on regional differences in interest rates see Landon-Lane and Rockoff (2004).

According to the user cost approach, the sign of a user cost determines whether the financial good is an input or an output for the bank. In our model the sign of the user cost of a particular financial good could change, because both holding costs and discount rates vary over time. In particular, the sign of the user cost depends on the sign of the numerator in (2) and (3). Table 3 reports the percentage of observations when each financial good is an output, i.e. the user cost is negative, in each year of the sample period.

On average, the most stable output is deposits, with negative user costs in 99.8 percent of the observations. Loans and leases are an output in 98.8 percent of the observations. Debt securities and trading accounts have negative user costs in 89.0 percent of the observations. Debt other than deposits is an output in 70.3 percent of the cases. Finally, balances due from depository institutions is an output only in 3.2 percent of the observations. In Table 4 we report the (across banks) average nominal user costs of the financial goods for each year from 1992 to 2014. In order to obtain real quantities of the goods, we use the GDP deflator. This variable and the time series of yields on treasury bonds which we use at the first stage of the empirical analysis are from the FRB database.

4 Empirical Analysis

In this section we estimate the model in two stages. At the first stage we conduct factor analysis of yields on treasury bonds with various maturities and estimate the filtered probabilities of the interest rate regimes using the Markov switching model of Hamilton (1989). At the second stage we estimate the bank variable profit function with regime-dependent parameters.

4.1 Markov Switching Interest Rate Regimes

We assume that the economy has two regimes: low interest rate (ℓ) and high interest rate (h). The regime s_t follows a Markov chain with transition probability matrix

$$\Lambda = \begin{pmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{pmatrix}. \tag{16}$$

While the regime is latent, the econometrician observes an interest rate r_t which stochastically depends on regime s_t. In particular, we assume that the interest rate evolves according to the following equation

$$r_t = \gamma_{s_t} + \varepsilon_t \tag{17}$$

where $\gamma_{s_t} \in \{\gamma^\ell, \gamma^h\}$ is a regime-dependent coefficient and ε_t is a normally distributed error term with zero mean and regime-dependent variance $\sigma_{s_t} \in \{\sigma^\ell, \sigma^h\}$. In order to estimate this model we will define the interest rate index r_t using the principal components analysis (PCA).

Since banks demand and supply financial goods with different maturities, we construct an aggregate interest rate index using PCA. Consistent with previous literature, we find that there is a single factor that explains a significant share of variance in the data and represents the level of the yield curve.[2] We calculate the principal components on the changes in yields on 3-month, 1-year, 3-year, 5-year, and 10-year treasury constant maturity series from the Federal Reserve Bank of St. Louis FRED database. Table 5 reports the loadings of these five bond yields for each of the principal components. All variable loadings of the first principal component are positive and account for 81% of the variance of innovations in the yields. Following previous literature we interpret this component as a *parallel shift* or *level* factor of changes in yields.

We define index r_t as the score of the first principal component and use it to recover the interest rate regime. This index is defined up to a linear transformation because the variable loadings are defined up to a scale factor and the integration is up to an additive term. We normalize the score such that it is equal to the 5-year treasury yield in the middle of the sample and has the same variance. Figure 1 shows the index and the 3-month and 10-year treasury yields. Note that compared to the treasury yields the first principal component score reveals no trend and, in particular, it stays mostly below the 10-year yield in the first half of the sample and mostly above it in the second half.

It is to be noted that our setup does not require stationarity of the interest rates. Instead, we assume that the level factor represented by the first principal component

[2]See, for example, Litterman and Scheinkman (1997) for the PCA of the U.S. Treasury bond series.

is covariance stationary conditional on regime. In general, the stationarity of interest rates is a contentious question. Traditional unit root tests such as the Augmented Dickey-Fuller test have low power and tend to fail to reject the null of a unit root. Casalin (2013) shows that most unit root and stationarity tests provide evidence on the nonstationarity of the yields on 3-, 6- and 12-month U.S. Treasury bills. However, using the ex ante real interest rate, Lai (2004) demonstrates that structural breaks, if not properly accounted for, can induce tests to spuriously find unit-root nonstationarity. Ang and Bekaert (2002) investigate the performance of regime switching models for interest rate data.

The Markov-switching model (16)-(17) has six parameters to be estimated: the regime-dependent interest rate coefficients, γ^ℓ and γ^h, the error term variances, σ^ℓ and σ^h, and the transition probabilities, λ_{11} and λ_{22}. Since the sum of each column in Λ is equal to one, the probabilities λ_{12} and λ_{21} are determined by λ_{11} and λ_{22}.[3] We estimate (16)-(17) and filtered probabilities of the regimes using Hamilton's (1989) filter. Table 6 reports the maximum likelihood parameter estimates. The average interest rate in the low interest rate regime is 3.689 percent and it rises to 6.393 percent in the high interest rate regime. Note that both low and high interest rate regimes are very persistent: the probability of a regime switch is less than 5 percent and the durations of the regimes are 26.43197 and 20.40953 quarters for low and high interest rate regimes, respectively. In our sample, we identify three periods of predominantly low interest rates: from 1992:Q1 to 1994:Q2, from 2001:Q4 to 2005:Q2, and from 2008:Q4 to 2014:Q2. Figure 2 displays the filtered probabilities π_t^1 and π_t^2 of the regimes.

4.2 Estimation of the Bank Variable Profit Function

We assume that the parameters of the bank variable profit function depend on the regime. Then the stochastic specification of the NQ system of input demands and output supplies for bank i in period t has the following form

$$\boldsymbol{x}_{it} = \boldsymbol{x}_{it}(\boldsymbol{v}_{it},\, \boldsymbol{\theta}_{s_t}) + \boldsymbol{\varepsilon}_{it} \tag{18}$$

where $\boldsymbol{\theta}_{s_t}$ is the regime-dependent vector of parameters and $\boldsymbol{\varepsilon}_{it}$ is the vector of stochastic errors which has multivariate normal distribution with zero mean and regime-independent covariance matrix $\boldsymbol{\Omega}$. The vector-valued function $\boldsymbol{x}(\cdot)$ is given by the NQ representation (14). We make the assumption that the covariance matrix $\boldsymbol{\Omega}$ is

[3]We have also tried to add AR terms in equation (17) and obtained similar probabilities of the regimes. Thus, we stick to the simplest specification given by (17) as it accords with our interpretation of the regimes.

identical across the regimes to keep the problem computationally feasible.[4] For the same reason, we constrain our empirical analysis to the case with two regimes. Due to the large number of banks, we do not use bank dummy variables as bank fixed effects. Moreover, the nonlinearity of the demand and supply system precludes us from using the within or the first difference transformations.

We estimate the parameters of the model using Markov chain Monte Carlo (MCMC) methods. In particular, we adopt the Metropolis-Hastings (M-H) algorithm to construct a Markov chain with continuous state space in order to sample from a target distribution of parameters. The method allows us to obtain the statistical inference of the parameters. The M-H algorithm is described in, for example, Chen *et al.* (2000, p. 23–24). In the demand systems literature, the Bayesian approach is often taken to impose theoretical regularity conditions via appropriate choice of prior parameters' distributions. O'Donnell *et al.* (1999) and Griffiths *et al.* (2000) impose curvature constraints using sampling from constrained posteriors. In this paper, we take an alternative approach proposed in Wiley *et al.* (1973) and ensure the convexity of the profit function via the change of the NQ representation parameters as discussed in Section 2.

We use a multivariate normal proposal density with zero mean and covariance matrix $\boldsymbol{\Xi}$ to generate candidates in the random-walk M-H algorithm. We follow O'Donnell and Coelli (2005) and set $\boldsymbol{\Xi}$ equal to the maximum likelihood estimate of the covariance matrix of the parameters of the proposal density adjusted by a tuning scalar. In our estimation, we choose the tuning scalar to target the M-H acceptance ratio of approximately 1/4. Roberts *et al.* (1997) show that the asymptotically optimal acceptance rate is 0.23 under quite general conditions.

For Bayesian inference we adopt the multivariate normal prior with independent components for the vectors of parameters $\boldsymbol{\theta}_s$, $s \in \{1, 2\}$ and the inverse Wishart prior with parameters ν and $\boldsymbol{\Psi}$ for the covariance matrix $\boldsymbol{\Omega}$. The likelihood function has the following form

$$p(x\,|\boldsymbol{\theta}_1, \boldsymbol{\theta}_2) \propto \prod_{t=1}^{T}\prod_{i=1}^{N_t}\sum_{s=1}^{2} \pi_t^s\,|\boldsymbol{\Omega}|^{-1/2} \exp\left((\boldsymbol{x}_{it} - \hat{\boldsymbol{x}}_{it}^s)'\,\boldsymbol{\Omega}^{-1}\,(\boldsymbol{x}_{it} - \hat{\boldsymbol{x}}_{it}^s)\right)$$

where N_t is the number of banks in quarter t, $\hat{\boldsymbol{x}}_{it}^s$ is the vector of fitted quantities of bank i in quarter t corresponding to system (18) in interest rate regime s, and π_t^s is the filtered probability of regime s in quarter t. We perform 10,000 draws in the MCMC simulation after discarding the first 5,000 draws as the burn-in period. Table 7 reports the means and p-values of the parameter estimates. We approximate

[4] The covariance matrix contains 28 independent parameters and the NQ variable profit function has 35 parameters in each regime.

the p-values using the normal distribution and posterior standard deviations of the parameters.

We implement the following procedure to simplify inference in the second stage.[5] Since there is almost no ambiguity about which regime prevails at each moment of time (see Figure 2), we assume that the periods of the different regimes are known: we set the probability equal to unity if the filtered probability of the regime is greater than 0.5. Then we maximize the likelihood functions of the two sets of parameters separately and use the parameters estimates as initial points for the parameters in two regimes in our second stage estimation. Since we assume identical covariance matrix across the regimes, we set the initial covariance matrix to the average of the covariance matrices from the separate estimations. We find that the estimates of price elasticities based on the estimates of the second stage are close to those based on separate estimations in each regime.

5 Empirical Results

In the aftermath of the global financial crisis, the Federal Reserve and many central banks around the world departed from the traditional interest-rate targeting approach to monetary policy and started using nonconventional monetary policy tools such as quantitative easing and credit easing. For example, during the Great Recession the Fed directly intervened in the asset markets to purchase distressed assets. The Federal Reserve and government-sponsored enterprises purchased nearly \$1.8 trillion of mortgage-backed securities over the period from August 2007 to August 2009. There has also been a move towards tougher standards in prudential regulation for banks, mostly in the form of higher regulatory capital requirements. These policy changes affect the banking technology and the monetary policy transmission mechanism even when the policy rate is at the zero lower bound. Our model allows us to analyze these effects through the differences in the elasticities of bank financial goods.

Our main finding is that bank behavior significantly differs across low and high interest rate environments. While we observe that the estimates of the coefficients $\boldsymbol{\theta}_s$ are significantly different in the two regimes, we focus our analysis on the estimates of the price elasticities because the interpretation of the coefficients of the NQ variable profit function is cumbersome. The compensated own- and cross-price elasticities of demands and supplies in low and high interest rate regimes are reported in Tables 8 and 9, respectively. Note that the elasticities of financial goods determine the percentage change in quantity demanded or supplied in response to a one percent change in user costs. Since the user costs are measured in percentage points, the formula for the compensated price elasticities is $\epsilon_{ij} = (x_i)^{-1}\partial x_i/\partial v_j$. As Tables 8 and

[5] We thank an anonymous referee for this suggestion.

9 show, in both interest rate regimes most of the elasticities are statistically significant. The magnitudes of the values significantly vary between the two regimes.[6]

The size of bank assets varies significantly in our main sample. To control for bank heterogeneity, we estimate the model in two subsamples of banks: banks with assets below 100 million and over 1 billion in 2009 U.S. dollars. Tables 10 and 11 show the estimates of the price elasticities in the low and high interest rate regimes, respectively, for the small banks. Tables 12 and 13 report the elasticity estimates in alternative regimes for large banks. We find that most of the price elasticities change significantly and several cross-price elasticity estimates (for example, the elasticity of deposits with respect to the debt other than deposits) change their signs. However, as we show below, certain qualitative inferences on the monetary transmission mechanism remain unchanged.

With the recent recovery of the U.S. economy, the Federal Reserve has moved its focus back to conventional monetary policy instruments. We focus on the traditional interest rate channel by analyzing the changes in the user costs and the elasticities of financial goods with respect to their user costs. It follows from equation (3) that, in general, a change in the interest rate on a liability has two effects on its user cost: through the change of the holding cost and the discount rate, e.g. as a component of weighted average cost of capital. A change in the interest rate on an asset has no direct effect on the discount rate and affects the user cost only through the holding cost as equation (2) shows. If the discount rate is small, a change in the interest rate on an asset such as loans and leases is approximately equal to the change in its user cost.

The supply of loans and leases, the primary interest of the Fed, is elastic in both regimes but less elastic in the low interest rate regime. In the high interest rate regime, the own-price elasticity of loans and leases is 6.02 and the average return on loans and leases is 7.6 percent. It means that if the return increases by one percent to 8.6 percent, banks increase the supply of loans and leases by 6.02 percent. In the low interest rate regime, the own-price elasticity of loans and leases drops to 4.68. This elasticity consistently decreases before the financial crisis of 2007-2008. In the subsample of banks with assets below \$100 million, the own-price elasticities of loans and leases are 7.10 and 5.05 in the high and low interest rate regimes, respectively. In the subsample of banks with assets over \$1 billion, these elasticities are 2.93 and

[6] As we discuss in Section 2, the model assumes that the banks are price takers. If the price taking assumption is violated, the parameter estimates can be biased. The direction and the magnitude of the bias in bank demand and supply elasticities depends on the functional form of the demand and supply facing the bank. For example, Hancock (1986) considers independent log-linear downward sloping demand and upward sloping supply functions facing a bank. In this case, it is possible that if the price-taking behavior is imposed in estimation, elasticity estimates in absolute value understate the elasticities under imperfect competition.

4.82 in the high and low interest rate regimes, respectively.

The efficiency of monetary stimuli depends on the elasticity of loans and leases with respect to the costs of bank funds. We assume that the primary channel through which the federal funds rate affects the production of financial goods by banks is the interest rate on debt other than deposits (consistent with the discount window policy, interbank loans and money markets). If R is the bank's cost of capital, a one percent increase in the user cost corresponds to a $(1 + R)$ percent increase in the holding rate on a financial good. The cross-price elasticity of loans and leases with respect to the user cost of debt other than deposits determines how the bank would increase the output of loans and leases if it faces a lower interest rate on debt other than deposits. In both interest rate regimes this elasticity is statistically significant but very small. It is estimated to be -0.45 in the high interest rate regime and -0.22 in the low interest rate regime. In the subsample of small banks, these elasticities are -0.17 and -0.06 in the high and low regimes, respectively. For large banks, this elasticity estimate is -3.66 in the high interest rate regime and statistically insignificant in the low regime. Consistent with Hancock (1985), these findings emphasize the limitation of the monetary policy effect on bank behavior, especially in the low interest rate environment.

6 Conclusion

Over the past decade, major central banks have brought policy interest rates down close to the zero bound. Although periods with relatively low interest rates happened before, the behavior of financial institutions in low interest rate environments has been studied insufficiently. In this paper, we model a profit maximizing bank and analyze the flexibility of financial production. In particular, we estimate the elasticities of the demand for and supply of financial and non-financial goods with respect to their user costs.

We find that the price elasticities of most financial goods differ significantly in alternative interest rate regimes. The supply of loans and leases is inelastic in both regimes and it is more inelastic in the low interest rate regime. This finding suggests that the efficiency of the monetary policy declines as the interest rate approaches zero —an important policy implication.

While in this paper we estimate the normalized quadratic demand system under two interest rate regimes, our analysis can be extended in several directions. For instance, future research could estimate the model with other empirically attractive demand systems — see Barnett and Serletis (2008) for discussion. Subsequent research might also generalize the model of stochastic volatility demand systems of Serletis and Isakin (2017) for a regime switching economy.

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Table 1. Size distribution of U.S. banks

Assets	1992 Number of banks	1992 Assets held	1992 Share of assets held (%)	2002 Number of banks	2002 Assets held	2002 Share of assets held (%)	2012 Number of banks	2012 Assets held	2012 Share of assets held (%)
Less than \$100 million	8,282	350	9.6	4,125	213	2.9	1,886	112	0.8
\$100 million – \$1 billion	3,024	749	20.5	3,583	963	13.1	3,804	1,152	8.5
\$1 billion – 10 billion	368	1,117	30.5	359	1,022	13.9	484	1,275	9.4
More than \$10 billion	51	1,445	39.5	87	5,175	70.2	88	11,042	81.3
Total	11,725	3,662	100	8,154	7,374	100	6,262	13,580	100

Note: Bank assets are in billions of dollars.

Table 2. Assets and liabilities of U.S. banks (in billions)

Year	Balances due	Debt securities	Loans & leases	Deposits	Other debt	Equity
1992	0.0364	0.1080	0.2779	0.3450	0.0646	0.0331
1993	0.0340	0.1224	0.2986	0.3566	0.0792	0.0379
1994	0.0384	0.1330	0.3324	0.3793	0.1006	0.0406
1995	0.0400	0.1388	0.3789	0.4123	0.1184	0.0468
1996	0.0445	0.1428	0.4181	0.4426	0.1271	0.0504
1997	0.0486	0.1629	0.4532	0.4862	0.1596	0.0585
1998	0.0506	0.1815	0.5050	0.5377	0.1808	0.0661
1999	0.0521	0.1878	0.5475	0.5632	0.2057	0.0700
2000	0.0525	0.2000	0.5987	0.6187	0.2212	0.0776
2001	0.0562	0.2197	0.6140	0.6566	0.2301	0.0876
2002	0.0561	0.2604	0.6593	0.7099	0.2566	0.0971
2003	0.0562	0.2859	0.7020	0.7597	0.2758	0.1035
2004	0.0560	0.3040	0.7668	0.8291	0.2848	0.1253
2005	0.0571	0.3012	0.8250	0.8856	0.2915	0.1319
2006	0.0609	0.3279	0.9139	0.9688	0.3285	0.1473
2007	0.0673	0.3482	0.9995	1.0414	0.3731	0.1615
2008	0.1395	0.3660	0.9368	1.0796	0.3995	0.1533
2009	0.1422	0.4236	0.9656	1.2211	0.3092	0.1902
2010	0.1377	0.4614	1.0116	1.2772	0.3096	0.2007
2011	0.1800	0.4942	1.0645	1.4006	0.2873	0.2120
2012	0.2037	0.5344	1.1573	1.5432	0.2875	0.2315
2013	0.2519	0.5271	1.2168	1.6366	0.2697	0.2381
2014	0.2927	0.5806	1.3107	1.7715	0.3032	0.2581

Note: The data are aggregated by year.

Table 3. Percentage of Observations When Financial Goods are Outputs

Year	Balances due	Debt securities	Loans & leases	Deposits	Other debt
1992	4.89	95.75	99.33	99.61	89.68
1993	3.61	95.12	99.48	99.84	88.56
1994	4.39	96.63	99.39	99.86	78.13
1995	2.00	92.05	98.86	99.85	73.91
1996	2.62	94.98	98.77	99.81	80.56
1997	2.00	94.88	98.41	99.83	78.59
1998	2.53	87.28	98.09	99.87	80.70
1999	4.57	94.01	98.14	99.61	76.27
2000	3.39	94.19	98.26	99.80	58.38
2001	3.45	88.40	98.73	99.29	68.38
2002	2.70	93.95	99.26	99.88	62.40
2003	2.96	88.94	99.04	99.81	59.94
2004	3.55	91.33	98.70	99.92	58.20
2005	4.24	87.39	98.30	100.00	51.12
2006	4.34	76.28	97.70	99.96	51.38
2007	4.58	68.48	96.98	99.86	72.71
2008	3.72	86.67	97.83	99.92	71.90
2009	2.76	81.17	98.91	99.91	64.13
2010	2.32	82.19	99.40	99.94	55.67
2011	1.47	84.82	99.75	99.98	58.89
2012	0.78	79.15	99.71	100.00	63.92
2013	1.68	83.15	99.83	100.00	67.42
2014	2.29	89.59	99.76	99.98	71.80

Note: The observations are averaged across banks in each year.

Table 4. User costs averaged across banks

Year	Balances due	Debt securities	Loans & leases	Deposits	Other debt
1992	0.0219	-0.0163	-0.0341	-0.0047	-0.0170
1993	0.0201	-0.0146	-0.0332	-0.0057	-0.0141
1994	0.0203	-0.0141	-0.0326	-0.0058	-0.0079
1995	0.0271	-0.0110	-0.0314	-0.0077	-0.0081
1996	0.0261	-0.0130	-0.0321	-0.0060	-0.0127
1997	0.0276	-0.0135	-0.0312	-0.0068	-0.0115
1998	0.0276	-0.0103	-0.0312	-0.0077	-0.0133
1999	0.0240	-0.0137	-0.0314	-0.0054	-0.0101
2000	0.0286	-0.0140	-0.0305	-0.0070	-0.0004
2001	0.0251	-0.0134	-0.0334	-0.0051	-0.0074
2002	0.0192	-0.0164	-0.0356	-0.0054	-0.0041
2003	0.0159	-0.0112	-0.0359	-0.0059	-0.0015
2004	0.0154	-0.0119	-0.0338	-0.0074	-0.0008
2005	0.0186	-0.0091	-0.0335	-0.0087	0.0026
2006	0.0251	-0.0058	-0.0319	-0.0103	0.0044
2007	0.0276	-0.0049	-0.0296	-0.0110	-0.0073
2008	0.0248	-0.0124	-0.0307	-0.0095	-0.0069
2009	0.0230	-0.0111	-0.0314	-0.0121	-0.0054
2010	0.0171	-0.0101	-0.0386	-0.0094	0.0004
2011	0.0149	-0.0098	-0.0412	-0.0092	-0.0003
2012	0.0144	-0.0075	-0.0403	-0.0106	-0.0012
2013	0.0108	-0.0076	-0.0407	-0.0089	-0.0010
2014	0.0104	-0.0099	-0.0396	-0.0092	-0.0023

Note: The observations are averaged across banks in each year.

Table 5. Variable Loadings of the Principal Components

	PC1	PC2	PC3	PC4	PC5
10-year Treasury yield	0.415	0.391	0.372	-0.642	0.352
7-year Treasury yield	0.467	0.343	0.155	0.171	-0.782
5-year Treasury yield	0.511	0.253	-0.272	0.598	0.493
1-year Treasury yield	0.468	-0.437	-0.641	-0.403	-0.127
3-month Treasury yield	0.358	-0.689	0.594	0.196	0.072

Note: The principal components are based on the first differences of the interest rates. The rotation matrix is calculated using the covariance matrix of the variables.

Figure 1. First Principal Component and the 3-Month and 10-Years Treasury Yields

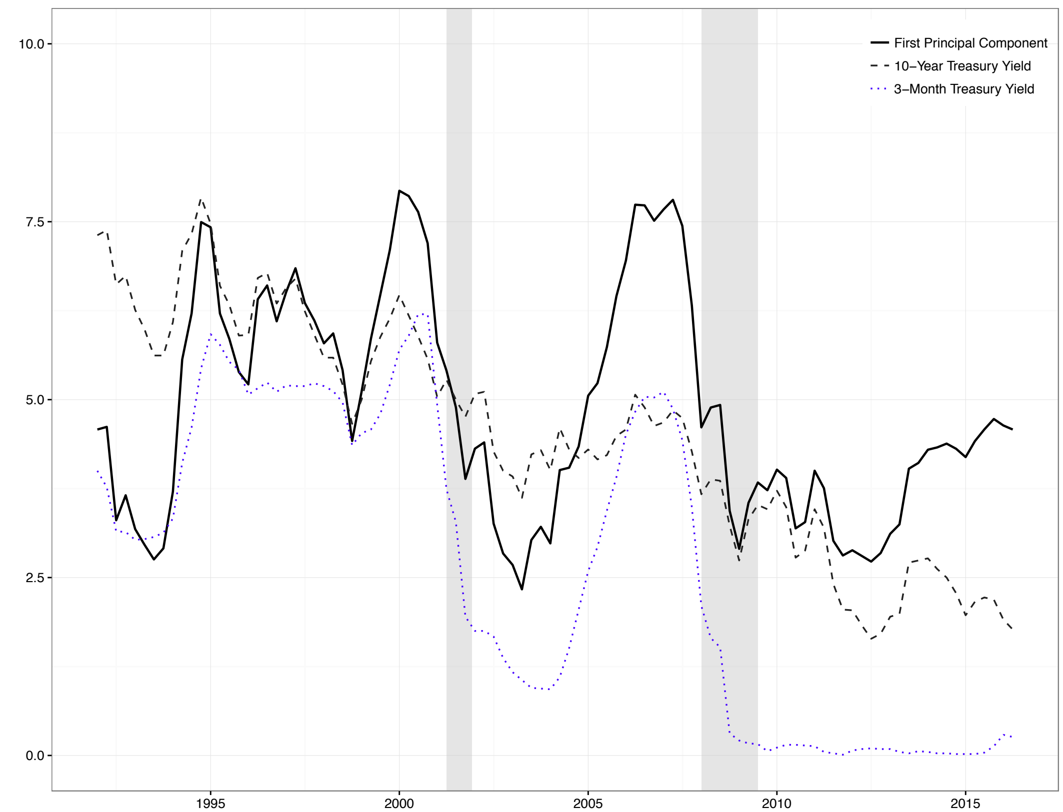

Table 6. Parameter Estimates of the Markov-switching Model

Coefficients and variances				Transition probability matrix		
γ^L	γ^H	σ^L	σ^H		L	H
3.689	6.393	0.701	0.962	L	0.962	0.038
(0.105)	(0.167)	(0.073)	(0.113)	H	0.049	0.951

Note: Standard errors are in parentheses.

FIGURE 2. FILTERED PROBABILITIES OF THE ECONOMIC REGIMES

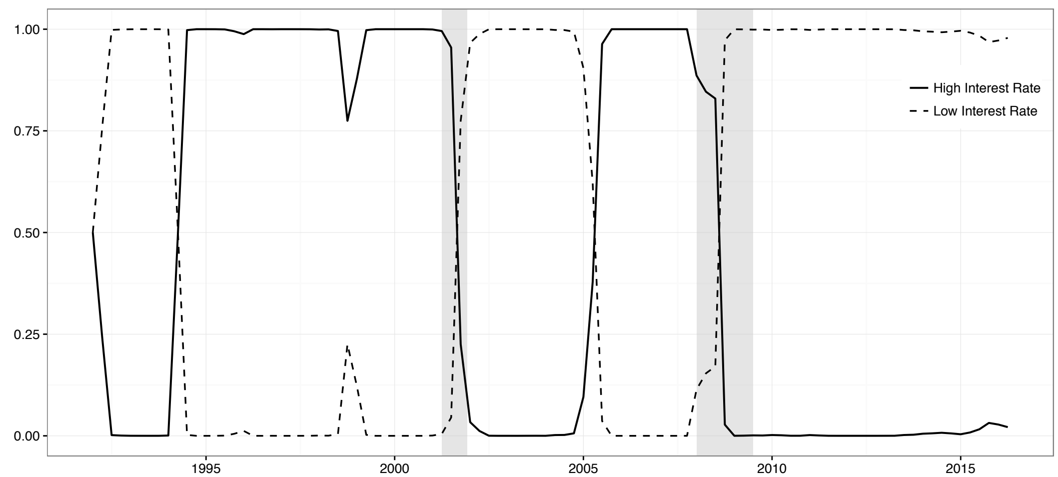

Table 7. Parameter Estimates of the Variable Profit Function

Coefficient	Estimate	p-value	Estimate	p-value
	Low interest rate regime		High interest rate regime	
b_1	-0.0536	0.0000	-0.0498	0.0000
b_2	0.1771	0.0000	0.1596	0.0000
b_3	0.3574	0.0000	0.3277	0.0000
b_4	0.5728	0.0000	0.5198	0.0000
b_5	-0.0105	0.0000	-0.0115	0.0000
b_6	-0.2585	0.0000	-0.2442	0.0000
c_1	-0.0569	0.0000	0.0248	0.0000
c_2	-0.1231	0.0000	-0.2887	0.0000
c_3	0.3828	0.0000	0.4100	0.0000
c_4	0.2504	0.0000	0.1253	0.0000
c_5	-0.0453	0.0000	-0.0220	0.0000
c_6	0.0729	0.0000	0.0667	0.0000
g_{11}	0.3466	0.0000	0.2962	0.0000
g_{21}	-0.0693	0.0000	-0.1053	0.0000
g_{22}	-0.1821	0.0000	-0.2447	0.0000
g_{31}	-0.6304	0.0000	-0.6035	0.0000
g_{32}	0.1052	0.0000	0.1669	0.0000
g_{33}	0.2964	0.0000	-0.1924	0.0000
g_{41}	0.0841	0.0000	-0.1823	0.0000
g_{42}	-0.0124	0.1500	0.0921	0.0000
g_{43}	-0.1414	0.0000	0.1257	0.0000
g_{44}	-0.2181	0.0000	-0.1683	0.0000
g_{51}	-0.3329	0.0000	-0.2716	0.0000
g_{52}	0.1311	0.0000	0.0724	0.0000
g_{53}	0.0035	0.9210	-0.1378	0.0000
g_{54}	-0.0005	0.8345	0.0012	0.7533
g_{55}	0.0004	0.8028	-0.0004	0.8110

Note: The sample contains quarterly series over the period from 1992:I to 2014:IV.

Table 8. Compensated Price Elasticities in the Low Interest Rate State

	v_1	v_2	v_3	v_4	v_5	v_6
Balances Due, x_1	-13.845	2.901	5.992	26.807	3.356	-4.531
	(0.404)	(0.367)	(0.268)	(0.763)	(0.237)	(0.212)
Debt Securities, x_2	-0.695	10.120	8.469	12.455	-1.490	-8.716
	(0.088)	(0.284)	(0.161)	(0.347)	(0.079)	(0.160)
Loans, x_3	-0.525	3.096	4.682	8.136	-0.219	-4.554
	(0.023)	(0.059)	(0.074)	(0.105)	(0.024)	(0.058)
Deposits, x_4	-1.673	3.246	5.801	11.573	0.126	-5.490
	(0.048)	(0.090)	(0.074)	(0.175)	(0.038)	(0.067)
Other Debt, x_5	-23.264	-43.128	-17.348	14.046	14.511	22.341
	(1.701)	(2.484)	(1.969)	(4.239)	(1.225)	(1.867)
Labor, x_6	-0.866	6.958	9.946	16.819	-0.616	-0.545
	(0.040)	(0.128)	(0.126)	(0.207)	(0.049)	(0.006)

Notes: Variables x_i and v_i are the quantity and user cost of the ith good respectively. The indexing is as follows: 1 = Balances due from depository institutions, 2 = Debt securities and trading accounts, 3 = Loans and leases, 4 = Deposits, 5 = Debt other than deposits, 6 = Labor. Posterior standard errors are specified in parentheses.

Table 9. Compensated Price Elasticities in the High Interest Rate State

	v_1	v_2	v_3	v_4	v_5	v_6
Balances Due, x_1	-11.005	8.559	10.434	25.823	-0.894	-5.872
	(0.209)	(0.266)	(0.224)	(0.625)	(0.140)	(0.178)
Debt Securities, x_2	-1.698	9.088	12.713	16.412	-1.653	-10.720
	(0.053)	(0.222)	(0.157)	(0.350)	(0.069)	(0.165)
Loans, x_3	-0.626	3.847	6.015	8.705	-0.454	-5.312
	(0.013)	(0.047)	(0.074)	(0.102)	(0.024)	(0.056)
Deposits, x_4	-1.174	3.762	6.595	12.597	0.199	-6.138
	(0.028)	(0.080)	(0.078)	(0.170)	(0.033)	(0.066)
Other Debt, x_5	4.021	-37.488	-33.998	19.665	21.884	16.826
	(0.637)	(1.811)	(1.958)	(3.243)	(1.104)	(1.599)
Labor, x_6	-0.773	7.113	11.648	17.767	-0.492	-0.554
	(0.023)	(0.110)	(0.123)	(0.191)	(0.044)	(0.005)

Notes: Variables x_i and v_i are the quantity and user cost of the ith good respectively. The indexing is as follows: 1 = Balances due from depository institutions, 2 = Debt securities and trading accounts, 3 = Loans and leases, 4 = Deposits, 5 = Debt other than deposits, 6 = Labor. Posterior standard errors are specified in parentheses.

Table 10. Compensated Price Elasticities in the Low Interest Rate State: Banks with Assets under \$100 Million

	v_1	v_2	v_3	v_4	v_5	v_6
Balances Due, x_1	-13.363	2.334	2.861	18.973	2.167	-1.126
	(0.534)	(0.489)	(0.384)	(1.229)	(0.192)	(0.335)
Debt Securities, x_2	-0.571	7.146	5.759	7.797	-0.152	-6.655
	(0.120)	(0.370)	(0.226)	(0.447)	(0.052)	(0.219)
Loans, x_3	-0.309	2.540	5.048	7.451	-0.057	-5.076
	(0.041)	(0.099)	(0.110)	(0.160)	(0.018)	(0.090)
Deposits, x_4	-1.303	2.190	4.746	8.815	0.167	-4.677
	(0.084)	(0.125)	(0.102)	(0.296)	(0.028)	(0.099)
Other Debt, x_5	-16.919	-4.866	-4.112	18.926	3.406	6.480
	(1.537)	(1.672)	(1.316)	(3.252)	(0.560)	(1.229)
Labor, x_6	-0.218	5.260	9.096	13.157	-0.160	-0.489
	(0.065)	(0.172)	(0.162)	(0.281)	(0.030)	(0.008)

Notes: Variables x_i and v_i are the quantity and user cost of the ith good respectively. The indexing is as follows: 1 = Balances due from depository institutions, 2 = Debt securities and trading accounts, 3 = Loans and leases, 4 = Deposits, 5 = Debt other than deposits, 6 = Labor. Posterior standard errors are specified in parentheses.

Table 11. Compensated Price Elasticities in the High Interest Rate State: Banks with Assets under $100 Million

	v_1	v_2	v_3	v_4	v_5	v_6
Balances Due, x_1	-14.601	8.315	9.866	23.592	0.129	-4.032
	(0.314)	(0.382)	(0.313)	(0.942)	(0.163)	(0.254)
Debt Securities, x_2	-1.671	8.309	11.907	14.424	-0.360	-10.709
	(0.078)	(0.287)	(0.208)	(0.473)	(0.048)	(0.224)
Loans, x_3	-0.703	4.221	7.101	9.018	-0.174	-6.449
	(0.022)	(0.072)	(0.101)	(0.144)	(0.018)	(0.079)
Deposits, x_4	-1.159	3.526	6.218	12.487	0.117	-6.081
	(0.046)	(0.115)	(0.099)	(0.265)	(0.031)	(0.087)
Other Debt, x_5	-0.622	-8.650	-11.835	11.540	1.889	7.650
	(0.788)	(1.166)	(1.261)	(3.020)	(0.337)	(1.147)
Labor, x_6	-0.534	7.059	11.991	16.399	-0.210	-0.577
	(0.034)	(0.145)	(0.147)	(0.237)	(0.031)	(0.006)

Notes: Variables x_i and v_i are the quantity and user cost of the ith good respectively. The indexing is as follows: 1 = Balances due from depository institutions, 2 = Debt securities and trading accounts, 3 = Loans and leases, 4 = Deposits, 5 = Debt other than deposits, 6 = Labor. Posterior standard errors are specified in parentheses.

Table 12. Compensated Price Elasticities in the Low Interest Rate State: Banks with Assets over $1 Billion

	v_1	v_2	v_3	v_4	v_5	v_6
Balances Due, x_1	-15.135	6.097	4.897	14.339	3.395	-1.931
	(1.961)	(1.408)	(1.045)	(2.704)	(1.735)	(0.569)
Debt Securities, x_2	-1.534	6.041	5.273	6.576	-2.785	-3.615
	(0.352)	(0.918)	(0.606)	(0.997)	(0.692)	(0.410)
Loans, x_3	-0.408	1.748	4.819	5.928	0.278	-3.172
	(0.087)	(0.200)	(0.287)	(0.346)	(0.210)	(0.161)
Deposits, x_4	-0.980	1.787	4.858	6.317	0.524	-3.139
	(0.186)	(0.270)	(0.284)	(0.513)	(0.254)	(0.189)
Other Debt, x_5	-3.793	-12.373	3.720	8.571	13.798	-1.215
	(1.938)	(3.042)	(2.834)	(4.189)	(4.268)	(1.804)
Labor, x_6	-0.468	3.487	9.227	11.142	0.264	-0.432
	(0.137)	(0.393)	(0.471)	(0.675)	(0.391)	(0.021)

Notes: Variables x_i and v_i are the quantity and user cost of the ith good respectively. The indexing is as follows: 1 = Balances due from depository institutions, 2 = Debt securities and trading accounts, 3 = Loans and leases, 4 = Deposits, 5 = Debt other than deposits, 6 = Labor. Posterior standard errors are specified in parentheses.

Table 13. Compensated Price Elasticities in the High Interest Rate State: Banks with Assets over $1 Billion

	v_1	v_2	v_3	v_4	v_5	v_6
Balances Due, x_1	-6.055	10.472	-6.208	-2.646	-7.566	4.429
	(5.519)	(4.846)	(0.908)	(1.215)	(1.503)	(1.607)
Debt Securities, x_2	-2.052	15.932	-3.628	2.516	-2.092	-1.061
	(0.980)	(3.288)	(4.165)	(2.444)	(3.128)	(0.789)
Loans, x_3	0.375	-1.119	2.928	0.677	-3.661	-0.912
	(0.056)	(1.295)	(1.159)	(0.385)	(0.463)	(0.239)
Deposits, x_4	0.141	0.686	0.599	0.557	-0.994	-0.444
	(0.065)	(0.661)	(0.340)	(0.260)	(0.286)	(0.077)
Other Debt, x_5	18.152	-25.615	-45.404	-44.624	33.068	30.461
	(4.447)	(39.634)	(28.309)	(15.815)	(63.116)	(8.896)
Labor, x_6	0.794	0.971	2.704	1.487	-2.275	-0.108
	(0.293)	(0.714)	(0.707)	(0.258)	(0.460)	(0.010)

Notes: Variables x_i and v_i are the quantity and user cost of the ith good respectively. The indexing is as follows: 1 = Balances due from depository institutions, 2 = Debt securities and trading accounts, 3 = Loans and leases, 4 = Deposits, 5 = Debt other than deposits, 6 = Labor. Posterior standard errors are specified in parentheses.