Abstract

TERMOS, ALI AHMAD. Banking Structure and the Effect of Monetary Policy on Bank Lending. (Under the supervision of Douglas K. Pearce)

This dissertation examines the role of bank structure on the effectiveness of monetary policy. Using time series data for U.S. banks, I examine the varying effect of monetary policy on bank lending for the period 1976-2003. It is found that as the banking industry gets more concentrated (through mergers and acquisitions), the effect of monetary policy transmission (through open market operations) is being mitigated. That was the result of the deregulation of the banking sector that took place in the first half of the 1990s which led to an unprecedented wave of consolidation in the banking sector.

Then I investigate the lending channel evidence at the bank level. That is, how important is the cross-sectional differences in the way that banks with varying characteristics respond to policy shocks. Three bank characteristics are highlighted: bank size, liquidity and capitalization. It is found that large, more liquid, and well capitalized banks are more impervious to changes in monetary policy than other banks. Real estate loans, agriculture, commercial and industrial (C&I), and consumer loans are analyzed. The size of the bank is found to be most crucial for real estate lending, where small banks are much more sensitive to changes in the federal funds rate compared to large banks. The effect is comparatively less pronounced for C&I and consumer lending and largely disappears when it comes to agriculture lending. Finally, the question of monetary policy asymmetry is examined. As expected, monetary policy has more effect on bank lending when it tightens than when it eases interest rates. This is found to be the case for all types of loans except for real estate loans, where a decline of FFR entices more real estate lending than a rise.

BANKING STRUCTURE AND THE EFFECT OF MONETARY POLICY ON BANK LENDING

by

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a dissertation submitted to the graduate faculty of

north carolina state university

in partial fulfillment of the

requirements for the degree of

doctor of philosophy

economics

raleigh

August 2005

approved by:

chair of advisory committee

Biography

I was born and raised in Beirut, Lebanon, in one of the most difficult periods in this country's modern history: a civil war that lasted 15 years (1975-1990). I finished my high school at College St. Joseph and went on to college when the war ended in 1990-1991. I graduated with a bachelor degree in Business Administration from Beirut Arab University in 1993. During college, I was mostly fascinated by the lectures on public finance, public administration, and economics. I started my first job as a banker before I came to the U.S. to pursue my postgraduate studies, a goal that I had dreamed about since the early days in college. I went to Oklahoma City University where I got my MBA degree in finance in 1997. After working a year for a consulting firm in Beirut while I was applying for doctorate programs, I came back to the U.S. to North Carolina State University in the fall of 1999 to pursue Ph.D. in economics. I passed my final oral exam on July 20, 2005.
Fifteen years after the war is over, my country is still struggling to stand on its feet.

Acknowledgments

I would like to acknowledge all my professors who inspired my economic thinking. I am especially grateful to my advisor Professor Douglas Pearce. I am also grateful to my committee members, professors Matt Holt, John Lapp, and John Seater. The discussions with other professors were highly insightful; I would like to thank Professor David Dickey for his advice on chapter 3. Professors Alastair Hall and Denis Pelletier enlightened my ideas on chapter 4. Also on that chapter I am very grateful to Professor Henry Schaffer of the High Performance Computing Center (HPC) at North Carolina State University for generously making available his time and expertise which enabled me to estimate the model on a super computer. All remaining errors are mine.

Lastly, I would like to thank my loving wife for patiently putting up with me while I was working on this dissertation.

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Chapter 1

Introduction

The literature on monetary policy transmission is immense. The two main mechanisms through which monetary policy is transmitted to the economy are: the traditional *money view* and more recently, the *credit view*.

According to the money view, an expansionary monetary policy would lead to a fall in real interest rates, which in turn lowers the cost of capital and causes a rise in investment spending. This leads to an increase in aggregate demand and a rise in output.[1] There are only two assets in this world, money and bonds. Therefore, the financial intermediaries play no special role; that is in a world of perfect information borrowers can finance their projects directly through lenders with no need for banks' intermediation and, hence, monitoring. The role of banks is merely to create money by issuing deposits.

This is based on the Modigliani-Miller (1958) model which asserts that economic decisions do not depend on financial structure in a setting of perfect capital markets. Therefore, a financial intermediary in this environment has no consequence for real activity. This interest rate channel relies on three key assumptions. First, the central bank must control the supply of money, for which there are no perfect substitutes. Second, the central bank is able to affect real as well as nominal short-term interest rate so prices do not adjust instantaneously. Third, changes in real short-term interest rates affect longer-term interest rates influencing household and business spending decisions.

[1]Friedman and Schwartz (1963) classic book *'A Monetary History of The United States'* provides strong evidence in favor of the money view.

The revolutionary emergence of the informational imperfections literature in financial intermediation and credit markets that emphasizes the problems of asymmetric information between borrowers and lenders, led to the recognition of a gap between the cost of external finance and internal finance or what is known as the *external finance premium*. Therefore banks proved to play a vital role in the policy transmission mechanism. As a result, a number of authors have questioned the Modigliani-Miller proposition and asserted that financial intermediation provides important real services to the economy through specializing in gathering information about investment projects. Thus, banks help to reduce market imperfections and thus facilitate lending and borrowing.

That paved the way to the emergence of a new theory of the monetary transmission mechanism known as the *credit view*. According to the credit view there are three assets: money, publicly issued bonds, and intermediated loans. The banking sector now can specialize in two relevant ways: in addition to creating money, it issues loans. Therefore the effect of monetary policy on interest rates is amplified by changes in the external finance premium. A change in monetary policy that raises or lowers open-market interest rates tends to change the external finance premium in the same direction.

Two mechanisms have been suggested to explain the link between monetary policy actions and the external finance premium. *The balance sheet channel* and *the bank lending channel*. The balance sheet channel stresses the potential impact of changes in monetary policy on borrowers' balance sheets and income statements. For instance, in response to a monetary contraction, an increase in interest rates raises borrowers' debt service and reduces the present value of their net worth, thereby increasing the marginal cost of external finance and reducing firms' ability to carry out new investments.

The bank lending channel focuses more narrowly on the effect of monetary policy actions on the supply of loans by banks. It is amplified when banks are subject to reserve requirement on liabilities; a monetary contraction drains reserves, hence decreasing banks' ability to lend. As a result, credit allocated to bank-dependent borrowers may fall, causing these borrowers to reduce their spending.

1.1 The dynamics of the banking sector in the U.S.

The banking sector in the U.S. has changed dramatically over the past fifteen years; thousands of banking institutions have disappeared. This change was a product of a spectrum of policy regulations and deregulations ranging from capital requirements, reductions in reserve requirements, deregulation of deposits accounts, to liberalization of geographic restrictions on interstate and intrastate banking. In addition, a huge wave of technical innovations and automation of information processing brought about significant competition among U.S. banks, augmented by external competition from foreign banks and from non-bank financial intermediaries.

The scope of this study covers the period 1976-2004, a period that experienced all the changes cited above. The main deregulation acts of the banking industry were enacted in early 1980s (the deregulation of bank deposit accounts). Between the mid 1980s and early 1990s, the U.S. banking market saw a large spate of bank failures which drove thousands of banks out of the market. That prompted the implementation of risk-based capital standards, leading to what was called the bank credit crunch of the early 1990s. This period has been described as "undoubtedly the most turbulent period in U.S. banking history since the Great Depression."[2] Then the next era in banking, the mid 1990s to the present, is known as *nationwide banking*.

These dynamics have altered the way banks of different sizes lend to their borrowers and changed the composition of their balance sheets. For example, researchers have analyzed the so-called " consolidation hypothesis", that is, the lifting of geographic restrictions leads to mergers, which reduce small business lending. A study by Peek and Rosengren (1994), combined a single cross-section of Call Report data on bank lending to small businesses in the New England states for the third quarter of 1994 and found that, after larger banks merge with smaller banks, the consolidated bank typically reduces the amount of small business lending from that made earlier by the acquired bank.

A number of authors argued that if the consolidation hypothesis is correct economic efficiency is likely to be improved by the new allocation of funds (Berger and Hannan (1989)).

[2] A. Berger, A. Kashyap, and J. Scalise; The Transformation of the U.S. Banking Industry: What a Long Strange Trip It's Been, *Brookings Papers on Economic Activity* (1995), 55-201.

The argument is parallel to a presumption in economics that the relaxation of artificial constraints on trade (i.e. the lifting of geographical restrictions on the bank's expansion) will improve the efficiency of allocating resources and allow them to flow freely toward activities that yield higher returns. It has been found that bank consolidation in some communities have allowed banks to exercise market power and buy deposit funds at below competitive rates by about 50 basis points. [3] This ability of large banks to raise funds at cheaper rates may have allowed these banks to invest profitably in loans that would have had negative net present values if funded at competitive rates.

These observations raise two important questions about bank consolidation in the future. First, what is the effect of this movement on the dynamics of the transmission of monetary policy? And second, what will be the effect of bank consolidation on lending?

These questions are tackled empirically in the following chapters. After giving a brief history and description of the major deregulation acts of the banking sector in the U.S. the rest of the dissertation is organized as follows. Chapter 2 reviews the literature of the bank lending channel theory of monetary policy transmission. Chapter 3 examines bank lending in light of the consolidation in the banking industry that followed the deregulation acts between the mid 1980s and the early 1990s. Using a vector error-correction model, it is found that as bank assets consolidate by mergers and acquisitions, the effect of monetary policy on bank lending is mitigated. Chapter 4 examines the effect of policy transmission using bank-level data. Banks loan portfolios' responsiveness to monetary policy is studied in light of three bank characteristics: size, liquidity, and capitalization. It is shown that while bank size proves to be decisive in the bank's immunity to policy changes, the liquidity effect is ambiguous. It is also shown that the response gap between moderately and well capitalized banks is not significant. A conclusion and final thoughts are laid out in the last chapter, chapter 5.

[3] Berger and Hannan (1989)

1.2 Banking history in the U.S. at a glance

The banking sector in the U.S. has undergone several legal challenges. At the inception of the Federal Reserve System in 1913, all national banks were required to become members of the Fed. However, state banks could choose to become members but were not required to. Most of these banks chose not to become members of the Fed because of the high costs of membership associated with the Fed's regulations. During the Great Depression years of 1930-1933, around 9000 commercial banks failed in the U.S. This financial distress prompted banking legislators to establish the Federal Deposit Insurance Corporation (FDIC), in 1933, which provides federal insurance on bank deposits. All member banks of the Fed were required to purchase FDIC insurance for their depositors. Another major legislation in that year was the passing of the Glass-Steagall Act. Perhaps one of the major regulations that shaped the structure of the banking industry in the U.S. was the branching regulations (Douglas Amendment of 1956 which amends the McFadden Act of 1927) under which banks were prohibited from opening branches across some states. For decades, due to these branching regulations, the number of banks in the U.S. grew far more than in any other country, reaching 14482 banks in 1984. One way banks could overcome branching regulations is through organizing as holding companies. A bank holding company can own several local banks across states. These holding companies own today over 90% of all commercial banks. All these regulations have brought remarkable stability to the banking sector between the period 1934 and mid 1984. Post 1984, the number of banks starts to decline dramatically (to about 7000 banks in 2003). This decline was in part due to a number of bank failures but largely was a result of banking deregulation, in particular, the tremendous amount of banks' consolidation across the states after the repealing of the branching regulations act in 1994. Since then, banks in one state are allowed to own banks in other states.

The two major deregulations that have changed the path of the banking industry in the U.S. in the last decade allow for both *horizontal* and *vertical integration* in banking:

- Riegle-Neal Interstate Banking and Branching Efficiency Act (Sep., 1994). This act allows banks and bank-holding companies to freely establish branches across state lines. This opened the possibility of substantial geographical consolidation in the banking industry (horizontal integration).

- Gramm-Leach-Bliley Financial Services Modernization Act (Nov., 1999). This act allows integration between banks, securities firms, and insurance companies (vertical integration). This act also allows the creation of the financial holding company which provides a wide range of financial services under one corporate roof. A quick response emerged from the industry: by 2001, 558 financial holding companies were formed, and the largest 20 banks in the U.S. now belong to financial holding companies.

Chapter 2

The Bank Lending Channel of Monetary Policy: A Review of the Literature

The early work on the lending channel focused on various dimensions of the microeconomic foundations of informational imperfections. For example, on the effects of adverse selection problems on market allocation, the literature was pioneered by the seminal work of Akerlof (1970) and Rothschild and Stiglitz (1976), and has been applied to loan markets by Stiglitz and Weiss (1981), and to equity markets by Myers and Majluf (1984).

Research on principal-agent problems in financial economics was initiated by Jensen and Meckling (1976) and followed by Diamond (1984), Gertler (1988), and Bernanke (1983).[1]

Bernanke and Blinder (1988) have pointed out that there are three necessary conditions that must hold if there is a distinct credit channel of monetary policy transmission. First, intermediated loans and open-market bonds must not be perfect substitutes, at least for some firms. That is, the Modigliani-Miller theory of the irrelevance of capital structure must break down, so that these firms are unable to offset a decline in the supply of loans simply by borrowing more directly from the household sector in public markets. Second, the Federal Reserve must be able to affect the supply of intermediated loans, by changing the quantity of reserves available to the banking system. That is the banking sector must not be able to switch from deposits to commercial paper or equity issuance in order to insulate its lending activities from shocks to reserves. Third, there must be some sort of imperfect

[1] Some authors trace the early work on the lending view of monetary transmission back to Roosa (1951), Tobin and Brainard (1963), Brunner and Meltzer (1963), and Brainard (1964). A detailed survey is found in Kashyap and Stein (1993).

price adjustment that prevents any monetary policy shock from being neutral in the short term.

If prices adjust perfectly, a change in nominal reserves will be met with a proportionate change in prices and both bank and corporate balance sheets will remain unaltered in real terms. If this is the case then there can be no real effects of monetary policy through either the lending channel or the classical money channel.

This theory has gained enormous attention from both theorists and empiricists. One issue that went under thorough examination is the ability of banks to raise funds from non-deposit sources when the Fed tightens reserves, which implies that the bank lending channel is weakened. That is, if banks see deposits (as they are subject to reserve requirements) and CDs as perfect substitutes, then the link between open market operations and the supply of credit to bank-dependent borrowers is broken. Since large denomination CDs are not insured by federal deposit insurance, prospective lenders (i.e. buyers of CDs) must ascertain the quality of the issuing bank's portfolio.

Given banks' private information about their portfolio composition, adverse problems may arise and cause an increase in the cost of external finance. This again will increase the external finance premium and the bank-lending channel will become active. Another issue that had also gained parallel attention from researchers is the ability of the firms to raise their own financing. In other words, the question was: to what extent are firms bank-dependent? This in turn raises the question of the availability of non-bank intermediation in supplying loans and the relative size of this market compared to the banking market.

2.1 A theoretical perspective

In this line of research, there has been a growing branch of literature that applies micro-foundation theoretic models. As mentioned earlier, issues such as monitoring, moral hazard, adverse selection, contracts, and agency problems have gained great attention and been applied extensively to bank lending or the lender-borrower relationship, but these models seldom study the implications for monetary policy. Perhaps the most notable paper in this context is the one by Diamond (1991). Diamond shows that in periods of high present or anticipated future real interest rates or low economy-wide profitability, a higher credit rating is required to borrow without monitoring, implying that the demand for bank loan monitoring is then high and that the average new bank loan goes to a safer, higher-rated customer, *a flight to quality* in lending practices.

This fact seems to be in accordance with Holmstrom and Tirole (1997) where they show how all forms of capital tightening (credit crunch, collateral squeeze, or saving squeeze) hit poorly capitalized firms the hardest. In another setting, Repullo and Suarez (2000) analyze how moral hazard problems affect the choice between market lending and bank lending within the framework of monetary policy transmission. They show theoretically that firms with high net worth ratios prefer market lending, those with intermediate net worth get bank lending, and those with little net worth are unable to borrow. Therefore, small, bank-dependent, less liquid and less capitalized firms suffer the most from a tightening of monetary policy. Parallel analysis for banks is carried out in chapter 4.

2.2 An empirical perspective.

On the existence of the lending channel, Bernanke's (1983) work provides empirical support. Bernanke examines the extent to which the money view of monetary policy transmission can account for the decline in U.S. output between 1930 and 1933. He finds that a significant amount of the decline cannot be solely explained by the monetary mechanism. The disruptive effects of bank panics seemed capable of explaining the persistence of the depression. This opens the possibility of a shift in loan supply along with a shift in loan demand. An extended work by Bernanke and Harold (1991) that included a sample of 24 countries finds the same results; during periods of large panics, the decline in output cannot be exclusively explained by standard factors such as exchange rates, interest rates, or fiscal policy. Additional evidence is provided by Bernanke (1986) using VAR models. The resulting instrumental variable estimates suggest that lending shocks do seem to have a significant effect on aggregate demand.

Another study by Bernanke and Blinder (1992) shows that increases in the Federal Funds Rate (FFR) lead banks to slowly downsize by cutting off loans. Thus, as loans decline, the economy slows. As this result can be interpreted through the conventional interest rate channel, that is a tight monetary policy would depress economic activity and bank lending even if there is no sign of a lending channel so an identification problem arises: is it a decline in loan demand or loan supply that drives the results?. To correct for this identification problem, Kashyap, Stein, and Wilcox (1993) analyzed the relative fluctuations in bank loans and commercial paper issuance by firms as a substitute for loans. They show that at the same time a monetary contraction is reducing bank lending, it is increasing commercial paper volume.

This provides evidence that what has taken place is an inward shift in loan supply, as suggested by the lending view, rather than just an inward shift in loan demand. In this strand of the literature it has been shown that small banks are hit more severely compared to large banks when monetary policy tightens. Several studies have provided various explanations as why this is the case. Kashyap and Stein (1994) disaggregated banks' portfolios, particularly the asset side, and found that within the category of loans, larger banks tend to concentrate more heavily on Commercial and Industrial (C&I) loans, while smaller banks tend to concentrate on agriculture, real estate, and consumer lending.

Since there is some evidence that C&I lending responds more sluggishly to monetary shocks than other forms of lending (Gertler and Gilchrist (1994)) this provides some explanation for why loan demand at small banks is more procyclical than loan demand at large banks. In addition, large banks usually lend to large firms whose loan demand is less cyclical than that of smaller firms.

In another attempt by Kashyap and Stein (1993), they surveyed the period between 1977 and 1991 and observed that despite the rapid growth of non-bank financing loans and commercial paper, traditional commercial banks still are the most important source of finance, representing over 68% of the combined total in 1991. Using the Quarterly Financial Report (a survey of over 7000 manufacturing firms), Kashyap and Stein break down manufacturing firms into three categories: small, medium, and large. They looked how the balance sheets of firms in each category have changed between 1973 and 1991. The interesting result was that bank debt represents 34.4% of total debt in 1973 and 33% in 1991. Although this reinforces the conclusion that financing practices have not diminished the role of banks, this result does not reveal much about the change in the size distribution of these firms over that period. For example, banks have lost some ground in the area of short-term lending. This had seen an overall fall from 78.8% to 44.9% of short term lending by banks, and the largest chunk among the manufacturing firms was that of large corporations, which are more capable of issuing commercial paper. Short-term bank loans as a fraction of all short-term debt of large corporations fell from 64.9% in 1973 to 22.8% in 1991. However, banks' share of short-term debt for small and medium firms was still substantial, at 82.9% and 77% respectively. Oliner and Rudebusch (1996) challenged the credibility of this conclusion by arguing that it may be that during recessions, small firms are hurt badly, and hence have sharply reduced demand for credit, while large firms increase their demand for credit. Given that the majority of commercial paper volume comes from the largest firms, this is indeed what Bernanke and Gertler (1995) called the balance sheet channel. So one may conclude that the effect is compositional. All these studies provide strong evidence for the existence of the lending channel.

2.2.1 Two opposite views on the existence of the bank lending channel

This section reviews two seminal papers in the literature of monetary policy transmission that have made opposite cases against and for the importance of the bank lending channel. The first is the work by Romer and Romer (1989 &1990), and the other is the one by Kashyap and Stein (2000).

Romer and Romer (1989), R&R (1989) hereafter, addressed the question of whether monetary policy affects real economic activities through a qualitative non-statistical approach by detecting the major policy shifts as declared in the Federal Reserve records and their impact on the real economy.[2] They identified six times since World World II when the Federal Reserve appears to have in effect decided to create a recession in order to reduce the inflation rate. These anti-inflationary episodes (the focal episodes) or the so-called Romers' dates, are October 1947, September 1955, December 1968, April 1974, August 1978, and October 1979. Because these policy decisions were motivated mainly by concerns about

[2]These records are the Federal System's Record of Policy Actions and the Minutes of the Federal Open Market Committee.

inflation, they were relatively independent of contemporaneous real activities. That very fact would enable the authors to quantify how real activities are affected by monetary policy transmission, following the period of these decisions, through isolating the response of real economic developments.

They found that after a Federal Reserve shift to a tighter policy, these shifts are consistently followed by sharp declines in real economic activities. The authors specify that 33 months after a tightening shift, industrial production was typically 12% lower than would have been predicted on the basis of real economic developments up to the time of the shock.

Although R&R (1989) answers an important question of the significance of monetary policy transmission, they did not address the issue of how those real effects come about, a task they tackle in R&R (1990). Building on the same concept of the six policy episodes mentioned above, R&R (1990) compared the behavior of three main activities in the focal episodes with the usual cyclical behavior through the following specifications:

$$\Delta lnM_t = a + bt + \sum_{i=1}^{24} c_i \Delta lnM_{t-i} + \sum_{i=-12}^{12} d_i \Delta lnY_{t-i} + \sum_{i=1}^{11} k_i D_{it} \tag{2.1}$$

$$\Delta lnL_t = a + bt + \sum_{i=1}^{24} c_i \Delta lnL_{t-i} + \sum_{i=-12}^{12} d_i \Delta lnY_{t-i} + \sum_{i=1}^{11} k_i D_{it} \tag{2.2}$$

where M is money measured by $M1$ money stock, Y is industrial production, L is bank lending, and $D's$ are monthly dummies.

The sample periods are Feb.1946 - May1989 for the money regression and Feb.1950 - Dec.1986 for the lending regression. So the first policy shift episode was excluded from the lending regression. R&R then constructed dynamic forecasts of the paths of money and lending, using, in addition to the own behavior of these variables, the behavior of industrial production before and after the shocks. Then they constructed the resulting forecast errors derived from equations (2.1) and (2.2) above. Interestingly, the authors found that considerable parts of the movement in both money and bank lending in the focal episodes appear to reflect just the usual cyclical behavior. Moreover, the movements in lending reflect the usual cyclical behavior to a greater extent than do the movements in money; about three-quarters of the average forecast errors for lending reflect usual cyclical patterns. However, for money this figure is about half. This finding led to the conclusion that bank lending plays no significant role in the monetary policy transmission mechanism and the response of bank lending to policy is merely an endogenous response to declines in output. R&R (1990) concluded that " the evidence appears to favor the traditional money view over recent theories that emphasize banks' lending activities. Two types of evidence particularly support the traditional money view. The first concerns the structure of financial markets and banks' ability to raise funds. Because reserve requirements on certificates of deposit (CD) are low, banks can obtain funds with little cost in terms of reserve holdings. [3] It follows that even if bank loans are special, restrictive monetary policy will have only a small direct impact on banks' ability to lend. By contrast, because reserve requirements on transactions balances are much higher, monetary policy has a much stronger effect on the stock of transactions balances. Thus the impact of monetary policy on interest rates is likely to operate largely through bank liabilities (transactions balances) rather than bank assets (bank lending)."

Furthermore, R&R (1990) studied the spread between CD and commercial paper interest rates in the last 3 episodes of tight monetary policy to test whether banks are willing to pay a premium to obtain funds to maintain their lending activities in times of restrictive policy; that is, if bank loans were special, banks might be willing to pay such a premium. They calculated that the spread increases about 10 basis points in the four months after the shock and then falls to roughly its pre-shock level over the next several months. As the spread rises, this suggests that as the reduced quantity of reserves shrinks the funds available to banks from transactions deposits, banks are willing to pay premium to maintain their lending by shifting to alternative sources of funds with lower costs. Since CDs and commercial paper are not exact substitutes, this process leads to a modest temporary widening of the CD-commercial paper yield differential. Therefore, as R&R argue, the impact of monetary policy on bank lending is mostly not direct but takes place through an increase in the general level of interest rates.

As the data used by R&R (1990) run between 1950 and 1986 for the bank lending regression, the missing factor that may change dramatically the conclusion of the R&R study–that is, bank lending did not respond differently to monetary policy shifts– is the tremendous change that happened to the banking industry since 1986. As mentioned in chapter 1, the change had various dimensions: legal, technological, and organizational.

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[3] In fact the reserve requirements on CD were completely lifted in late 1990, the same year Romer and Romer (1990) study was published.

Supporting the finding of Bernanke and Blinder (1992) –that changes in the stance of monetary policy are followed by significant movements in aggregate bank lending volume– the work by Kashyap and Stein (2000) –K&S (2000)–on U.S. commercial banks over the period 1976-1993 came to the opposite conclusion to R &R (1990) and claimed strong evidence for the existence of the bank lending channel. [4] [5] Using the data of the Consolidated Report of Condition and Income, known as Call Reports, K&S found that the impact of monetary policy on lending behavior is significantly more pronounced for banks with less liquid balance sheets, i.e. banks with lower ratios of cash and securities to assets. In this paper, banks are broken into three size categories, the smallest one encompasses all banks with total assets below the 95th percentile; the middle one includes banks from the 95th to 99th percentiles, and the largest one has those banks above the 99th percentile. The main idea of K&S was to measure the quantity $\frac{\partial^2 L_{it}}{\partial B_{it} \partial M_t}$ where L_{it} is the bank-level measure of lending activity, B_{it} is a measure of balance sheet strength, i.e. high ratios of liquid assets to total assets, and M_t is a monetary policy indicator. [6]

K&S hypothesize that for banks without perfect access to uninsured sources of finance, $\frac{\partial^2 L_{it}}{\partial B_{it} \partial M_t} < 0$.

In order to test this hypothesis they implement a two-step procedure by looking first at the cross-sectional derivative $\frac{\partial L_{it}}{\partial B_{it}}$, which captures the degree to which lending is liquidity constrained at time t. They run the following cross-section regression separately for each bank size class at each time period t:

$$\Delta L_{it} = \sum_{j=1}^{4} \alpha_{tj} \Delta L_{it-j} + \beta_t B_{it-1} + \sum_{k=1}^{12} \theta_{kt} R_{ik} + \epsilon_{it} \tag{2.3}$$

L_{it}, as before, is the log of total lending at the bank-level, but also was confined to Commercial and Industrial loans at some other stage for robustness. R is a dummy variable for Federal Reserve district.

[4] As mentioned earlier, Bernanke and Blinder also admit another interpretation of their results, that is activity is being depressed via standard interest-rate effects, and it is a decline in loan demand, rather than loan supply, that drives the results.

[5] A. Kashyap and J. Stein, "What Do a Million Observations on Banks Say About the Transmission of Monetary Policy?" *The American Economic Review*, (Jun. 2000), 407-428

[6] Kashyap and Stein entertained three measures of monetary policy: Boschen-Mills, the Federal Funds rate, and Bernanke-Mihov. They concluded that "FFR clearly has the most explanatory power of our three measures." These measures are discussed below in chapter 3.

In the second step of their procedure, K&S take the coefficients β_t's from equation (2.3) and use them as the dependent variable in a purely time-series regression. They consider two specifications as follows:

$$\beta_t = \eta + \sum_{j=0}^{4} \phi_j \Delta M_{t-j} + \delta T_t + u_t \tag{2.4}$$

$$\beta_t = \eta + \sum_{j=0}^{4} \phi_j \Delta M_{t-j} + \sum_{j=0}^{4} \gamma_j G_{t-j} + \delta T_t + u_t \tag{2.5}$$

where T is a time variable and G is for real GDP growth.

The hypothesis here was that $\frac{\partial \beta}{\partial M}$ is negative for the smallest class of banks. That is, the sum of the ϕ's should be negative for these banks. Adding GDP to the equation helps to capture the workings of the lending channel rather than the capital-shock effect. In the latter case, tight money simply raises interest rates and suppresses economic activity, causing banks to experience loan losses and reductions in capital. This in turn leads weaker banks to cut back on lending. If this is the case then γ coefficients on GDP growth should be negative.

K&S reported that the sum of the ϕ coefficients on FFR for equation (2.4) is -0.0088 for small banks, -0.0126 for medium size bank, and 0.0258 for large banks. For equation (2.5) these figures are -0.0046, -0.0040, and 0.0460 respectively. The surprising aspect of their result is the positive sign of the coefficient of monetary policy indicator, FFR, for large banks. That is a tightening in monetary policy, i.e. an increase in FFR, leads to a rise in bank lending at large banks. K&S attributed this positive relationship to what they call *the rational buffer-stocking* story. According to this story, all banks have the same risk aversion, but some have more opportunities to lend to cyclically sensitive customers than others. In this case, those banks with more cyclically sensitive customers will rationally choose to insulate themselves against the greater risk by having higher values of B_{it} i.e. high liquid assets. This would create a positive influence (upward bias) on key coefficients of the model. That is translated into positive γ's, the coefficient of real GDP growth.

The other source of bias is *the heterogenous risk aversion* story, which is a counter argument to the rational buffer-stocking. According to this story, certain banks are inherently more conservative than others and tend to protect themselves both by having larger values of

B_{it} and by cutting on cyclically sensitive borrowers. Here there is a negative correlation between B_{it} and the cyclical sensitivity of loan demand. This can lead to a bias in which the estimated effect of M_t on β_t is too negative.

Constrained by their "semi-panel data model", K& S implicitly assumed that the size of the rational buffer-stocking bias is the same for small and big banks which may lead to overstate the quantitative effect of monetary policy. In chapter 4, I will employ a "full" panel data model for the same data set and allow for a bank-level-effect variable that captures banks heterogeneity. But first, an elaborate examination of the aggregate time series data on bank lending and monetary policy is discussed in the next chapter.

Chapter 3

Is Monetary Policy Weakened by Banking Consolidation?

3.1 Introduction and background

As discussed above, two mechanisms have been suggested to explain the credit channel of monetary policy transmission: *The Balance Sheet Channel* and *The Bank Lending Channel*. The balance sheet channel stresses the potential impact of changes in monetary policy on borrowers' balance sheets and income statements. For instance, in response to a monetary contraction, the increase in interest rates raises borrowers' debt service and reduces the present value of their net worth, thereby increasing the marginal cost of external finance and reducing firms' ability to carry out new investments (Bernanke and Gertler, 1995). The bank lending channel, however, focuses more narrowly on the effect of monetary policy actions on the supply of loans by banks. It is amplified when banks are subject to reserve requirements on liabilities, whereby a monetary contraction drains reserves, causing a decline in banks' ability to lend. As a result, credit allocated to bank-dependent borrowers may fall (Bernanke and Blinder, 1992).

Bernanke and Blinder (1992) find that a contraction in monetary policy is followed by a decline in the volume of aggregate bank lending. Though this finding supports the notion of the lending channel, it also implies another interpretation; an increase in interest rates would depress economic activity, which in turn may result in a decline in loan demand rather than loan supply. In an attempt to solve this identification problem, Kashyap, Stein, and Wilcox (1993) show that at the same time a monetary contraction is reducing bank lending, it is increasing commercial paper volume. This suggests a decline in loan supply rather than loan demand.

Some research highlights the importance of bank size in absorbing the transmission mechanism. Kashyap and Stein (1994) disaggregated bank's portfolios, particulary the assets side, and found that while large banks tend to concentrate relatively more heavily on Commercial and Industrial (C&I) loans, small banks tend to concentrate relatively more on agriculture, real estate and consumer lending. Therefore, since C&I lending responds more sluggishly to monetary shocks than other forms of lending (Gertler and Gilchrist, 1994) this provides some evidence as why loan demand at small banks is more procyclical than loan demand at large banks. Another piece of evidence regarding the impact of bank size is provided by Romer and Romer (1990). They pointed out that if banks see deposits and Certificates of Deposits (CDs) as perfect substitutes, then the link between open market operations and the supply of credit to bank-dependent borrowers is broken. Given that larger banks are relatively more capable at issuing large CDs, that raises the question of how capable large banks are at insulating the effect of the monetary policy actions. That is the subject of this paper.

In another study by Kashyap and Stein (2000), the authors test the cross-sectional differences in the way that banks with varying characteristics respond to policy shocks. More specifically, the authors linked banks financial constraints to the liquidity of the banks's balance sheets. They provided evidence that the impact of monetary policy on banks' lending behavior is significantly more pronounced for banks with less liquid balance sheets. Kishan and Opiela (2000) studied banks' capital:asset ratios as a proxy for the bank's size. They show that the lending of well-capitalized banks is less sensitive to a monetary policy tightening than the lending of poorly capitalized banks in the same size category. Other studies focused on the affiliation of a bank with a bank holding company as a proxy for the bank is to have access to non-reservable funds. Campello (2002), for example, found that the lending of small banks that are affiliated with a bank holding company is less sensitive to monetary policy tightening than the lending of small stand-alone banks with similar characteristics. In a recent study by Holod and Peek (2004), the authors conclude that lending by publicly traded banks is less affected by a monetary policy tightening than non-publicly traded banks.

Another branch of studies focused on the effect of banking consolidation on lending but ignored the stance of monetary policy. For example, in a study by Berger, Klapper, and Udell (2001), the authors looked at the circumstances under which firms borrow from large versus small banks, foreign-owned versus domestically-owned banks, and distressed versus healthy banks. They also analyzed the circumstances under which a firm borrows from a single bank versus multiple banks. One main finding was that larger banks tend to have difficulty extending relationship loans to informationally opaque small businesses. This may occur because large banks may be disadvantaged in relationship lending as this type of lending often requires soft information that may be difficult to transmit through the communication channels of large organizations (Stein, 2001). Most studies on Mergers and Acquisitions (M&A) in the banking industry have conflicting conclusions about the extent to which bank lending is affected. There is, however, some consensus that M&A between small banks increase, rather than decrease, small business lending.

Strahan and Weston (1998) studied the change in lending behavior of banks as they grow, and found that small business lending increases rapidly at first, thereby increasing the ratio of small business loans to assets, but later, as banks get larger, lending to large businesses takes off, therefore lowering the ratio of small business loans to assets but not the overall level of small business lending. This result conforms to the evidence that small business lending increases following small bank mergers but falls following large bank mergers (Berger et al., 1998). Consequently, the complexity of large banks may lead to organizational diseconomies that make relationship loans more costly for them. Hence, a large bank's ability to diversify risks across borrowers reduces the cost associated with delegated monitoring (agency cost), because bank managers' efforts are more easily inferred from a bank's portfolio return when risks are better diversified (Diamond, 1994). This conclusion has opposing effects: on the one hand, diversification reduces monitoring costs and improves internal capital markets; these effects should lower the costs of risky lending as a bank's size increases. On the other hand, organizational diseconomies associated with bank size and complexity may increase the relative costs of small business lending. Strahan and Weston (1998) report that the ratio of small business loans to assets rises by about 0.95 percentage points when small banks (with assets under$100 million) merge, and by 0.55 percentage points when medium sized banks (with assets between \$100 million and \$billion) acquire small banks, and by 0.31 to 0.35 percentage points when large banks (with assets over \$1 billion) acquire small banks.

Most of these studies that focused on the institutional effect on lending have ignored to a large extent the role of monetary policy transmission. In this paper I test the hypothesis that as banks get larger and the size distribution of total assets in the banking sector skews toward the largest few banks in the tail of the distribution, these banks become more efficient in raising funds other than non-borrowed reserves. Hence, this increases the ability of these banks to insulate or mitigate any policy procedure taken by the central bank to keep the economy in control, whether this was conducted through open market operations or through bank reserves. I analyze the aggregate effect of banking concentration on total lending in the U.S. market and examine the hypothesis that these institutional and organizational developments have weakened the impact of the monetary policy actions on the macroeconomy.

3.2 Empirical analysis

The question to be examined is whether the effect of monetary policy decreases as the banking industry becomes more and more concentrated. If this is true, one implication is that the lending channel is weakened as banks get larger. The proposed reduced form function is given by:

$$L = f(F, FC, B, G) \tag{3.1}$$

where L is total lending measured as total loans made by the banking sector, F is the federal funds rate (FFR), FC is the interaction between F and C where C is the concentration ratio of the largest 100 banks in the U.S. measured as total assets of the largest 100 banks to total assets of the banking sector as a whole. B is borrowing made by banks and measured as total liabilities minus transaction deposits and borrowing from other banks in the U.S. This last variable reflects the borrowing activity of the banking system when monetary authority tightens money supply. The main component of the variable B is large time deposits which reflects the ability of bank to raise funds other than insured deposits. G is nominal GDP (the other variables,L and B are in nominal terms too). All variables are expressed in logarithms. The data run quarterly from 1976:1 to 2003:3. Data on banks balance sheets are obtained from the Consolidated Report of Condition and Income (the Call report) which includes all insured commercial banks in the United States.[1] All series are originally quarterly except for FFR which has been aggregated from a monthly frequency.

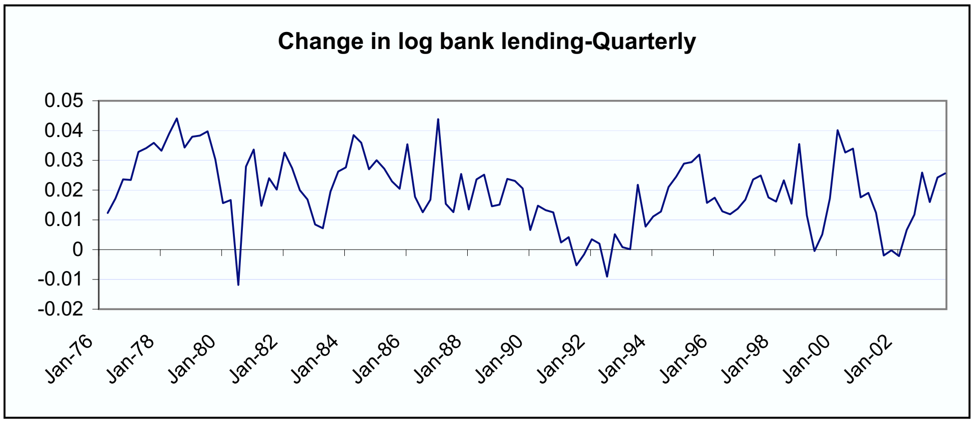

Figure 3.1: Change in Log Banks lending- Quarterly

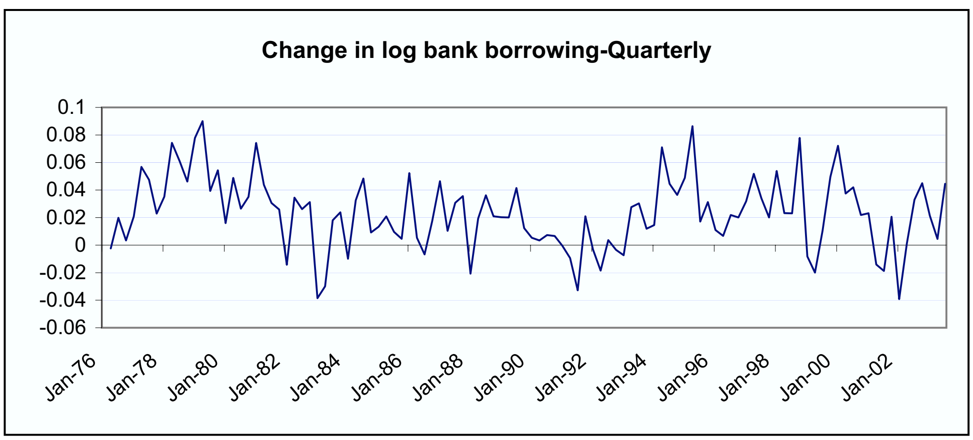

Figure 3.2: Change in Log Banks Borrowing- Quarterly

[1] Lease Financing Receivables had been reported as a component of Total Loans and Leases only post 1984. Following Kashyap and Stein (2000), I added this item to total Loans and Leases prior to 1984.

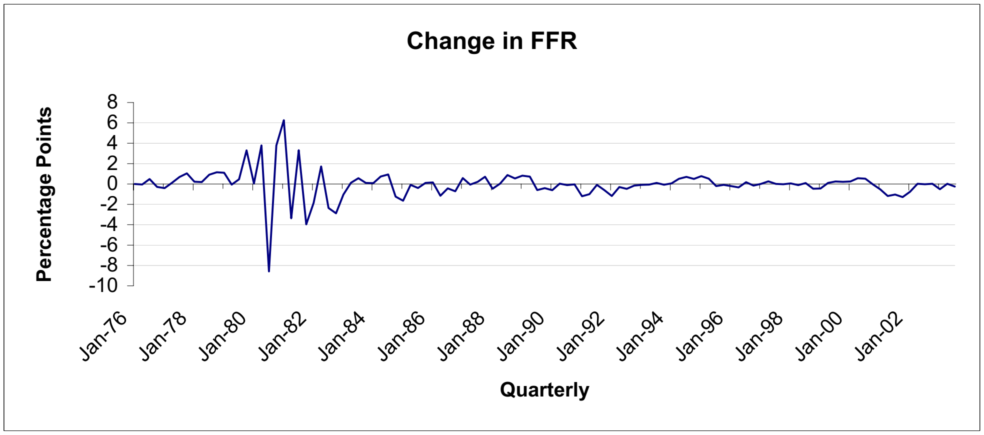

Figure 3.3: Change in Federal Funds Rate- Quarterly

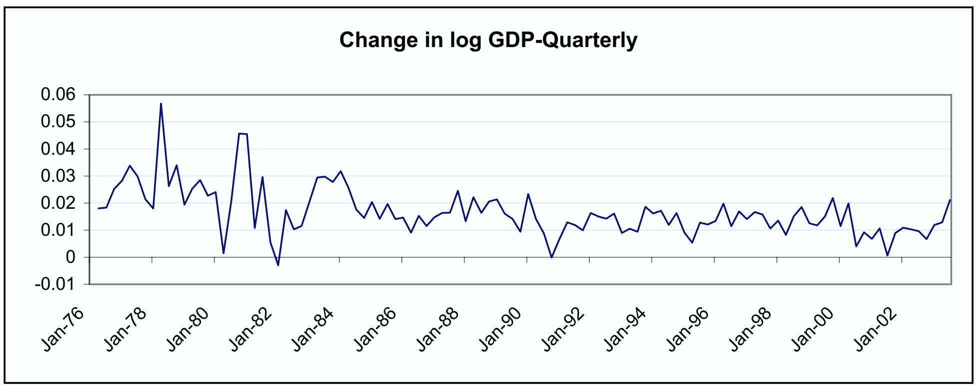

Figure 3.4: Change in Log GDP- Quarterly

3.2.1 Measuring the stance of monetary policy

The question of how to measure the stance of monetary policy is very controversial in the macroeconomic literature. Two broad methods have been used in that direction; the *narrative approach* and VAR analysis. The narrative approach is based on the readings of the minutes of the Federal Open Market Committee (FOMC) of the Federal Reserve System. Romer and Romer (1989&1990) were among the first to introduce this method. They identify six dates since World War II when the Fed appears to have opted for a clear shift to a tighter policy. These 'Romer dates' are Oct. 1947, Sep. 1955, Dec. 1968, Apr. 1974, Aug. 1978, and Oct. 1979. The disadvantage of this method is that it does not clearly distinguish between the endogenous and exogenous components of policy changes in order to identify the effect of monetary policy on the economy. For example, Romer dates were only assigned to contractionary changes in policy, not expansionary shifts,in addition, this method provides no indication of the severity or duration of each episode.[2]

Another narrative approach is that of Boschen and Mills (1995). The Boschen-Mills index identifies five measurements of the FOMC minutes and assigns weights to various policy actions: strongly expansionary, mildly expansionary, neutral, mildly contractionary, and strong contractionary. Another contribution parallel to the Boschen-Mills index is that of Lapp, Pearce and Laksanasut (2003), LPL index hereafter. LPL index assigns weights to policy actions adopted by FOMC in the same manner as in Boschen-Mills. However, the former identifies only three policy directions instead of five, to avoid some subjectivity borne by the latter.

The more quantitative approach to monetary policy measurement is carried out by a number of VAR studies. These studies differ in settling on what is the best indicator of monetary policy. For example, Christiano and Eichenbaum (1992) used the quantity of non-borrowed reserves as a measure of monetary policy. Cosimano and Sheehan (1994) used borrowed reserves instead. Strongin (1995) suggested orthogonalized non-borrowed reserves, which is the ratio of non-borrowed reserves to total reserves. The most widely accepted measure is the one by Bernanke and Mihov (1998). They pool all the common measures used in previous attempts into a vector of policy measurement. The authors employed a semi-structural VAR model that leaves the relationship among macroeconomic variables in the system unrestricted but imposes contemporaneous identification restrictions on a set of variables relevant to the market for commercial bank reserves. This analysis leads to estimates of a new policy indicator that is optimal in the sense of being consistent with the estimated parameters describing the Fed's operating procedure and the market for bank reserves. Based on a sample period of 1965-1996, Bernanke and Mihov concluded that the FFR measure is found to do well for the pre-1979 period, and it does exceptionally well for the Greenspan era, post-1988. Therefore, FFR is in general a reasonable representative for monetary policy except for the period between October 1979 and October 1982 (the

[2] In a recent study, Romer and Romer (AER, 2004) provide a new measure of the stance of monetary policy based on the residuals of a regression of the intended funds rate as disclosed by the Greenbook, and the actual funds rate. The authors discussed the duration and severity of policy shocks in quantitative terms.

Volcker Experiment). During that period, the Fed indicated publicly that it was using a non-borrowed reserves targeting procedure.[3] Despite the fact that between 1979-1982 the declared target was non-borrowed reserves, some authors argue that a majority of the policy actions during that period were conducted in order to adjust the level of the FFR. Thus, that period could be simply characterized as indirect interest rate targeting but with looser daily control and less smoothing than other periods (Poole, 1982; Cook, 1989).

3.2.2 Augmented Dickey-Fuller test(ADF)and lag length selection

In this section, the series are tested for first and second unit roots to detect nonstationarity. To test for unit roots each of the series of equation (3.1), is examined using the augmented Dickey-Fuller test, given the following autoregressive specification,

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + a_3 y_{t-3} + ... + a_{k-2} y_{t-k+2} + a_{k-1} y_{t-k+1} + a_k y_{t-k} + \varepsilon_t$$

adding and subtracting $a_p y_{t-p+1}$ to the right hand side we obtain

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + a_3 y_{t-3} + ... + a_{k-2} y_{t-k+2} + (a_{k-1} + a_k) y_{t-k+1} - a_k \Delta y_{t-k+1} + \varepsilon_t$$

Next, adding and subtracting $(a_{k-1} + a_k) y_{t-k+2}$ to obtain

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + a_3 y_{t-3} + ... - (a_{k-1} + a_k) \Delta y_{t-k+2} - a_k \Delta y_{t-k+1} + \varepsilon_t$$

Continuing in this fashion, then the ADF equation is given by:

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t \tag{3.2}$$

where

$$\gamma = -(1 - \sum_{i=1}^{k} a_i)$$

$$\beta_i = -\sum_{j=i}^{k} a_j$$

The equation for testing for a second unit root is given by the second order of equation (3.2)

$$\Delta^2 y_t = a_0 + \gamma \Delta y_{t-1} + \sum_{i=1}^{8} \Delta^2 y_{t-i} \tag{3.3}$$

The results of testing equation (3.3) are given in tables(3.1)-(3.5).

[3]This conclusion asserts the finding of an earlier study by Bernanke and Blinder (1992) that the funds rate is the best predicting variable, among other interest rates, of monetary policy

Table 3.1: Testing for second unit root for Bank Lending

k	γ	t_γ	AIC	SBC
1	-0.3524	-4.01	-693.2418	-685.1677
2	-0.3292	-3.47	-684.6348	-673.9062
3	-0.3559	-3.52	-675.9916	-662.6274
4	-0.3277	-3.05	-668.4654	-652.4847
5	-0.3358	-2.96	-659.6713	-641.0936
6	-0.3216	-2.69	-651.3129	-630.1577
7	-0.3460	-2.74	-642.4237	-618.7111
8	-0.2860	-2.19	-638.0871	-611.8374

Table 3.2: Testing for second unit root for Federal Funds Rate

k	γ	t_γ	AIC	SBC
1	-0.7843	-6.04	-106.4234	-98.3770
2	-0.6631	-4.34	-104.7398	-94.0485
3	-0.6979	-4.13	-101.2736	-87.9564
4	-0.5283	-2.92	-103.0342	-87.1105
5	-0.5760	-3.04	-101.1174	-82.6066
6	-0.6686	-3.32	-99.8538	-78.7760
7	-0.7044	-3.16	-95.9206	-72.2959
8	-0.5539	-2.24	-94.2129	-68.0617

The critical t-values as tabulated by Dickey and Fuller (1981) are -3.17, -2.89, and -2.58 for significance levels of 2.5, 5 and 10% respectively. Investigating tables (3.1)-(3.5) reveals that at the lag levels chosen by either AIC or SBC criterion, the null hypothesis of second unit root is rejected. That is at these lag levels the values of the calculated t statistic exceeds-in absolute terms- the values of critical τ at all conventional significance levels. Therefore we reject the null that the series are $I(2)$ processes. Next, the series are examined for whether they are $I(1)$ processes against the alternative hypothesis of $I(0)$. Since the stock series are expressed in nominal terms $(L, B, and\, G)$, a time trend term is added to the ADF equation (3.2) when testing these series against first unit root. The equation to be tested for the stock series is as follows:

$$\Delta y_t = a_0 + \gamma y_{t-1} + \eta t + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t \tag{3.4}$$

If $\gamma = 0$ the process is in first differences and so has a unit root. However, if it is possible to reject the null hypothesis $\gamma = 0$, then the process is trend stationary. One advantage

Table 3.3: Testing for second unit root for Interaction of FFR and banking consolidation

k	γ	t_γ	AIC	SBC
1	-0.8052	-6.22	-101.7301	-93.6837
2	-0.6865	-4.47	-100.3380	-89.6467
3	-0.7044	-4.17	-99.0369	-85.7197
4	-0.5247	-2.91	-101.3579	-85.4342
5	-0.5987	-3.20	-101.1834	-82.6726
6	-0.6214	-3.08	-98.1177	-77.0398
7	-0.7086	-3.22	-95.1638	-71.5390
8	-0.4953	-2.05	-95.7223	-69.5711

Table 3.4: Testing for second unit root for Bank Borrowing

k	γ	t_γ	AIC	SBC
1	-0.5576	-5.69	-551.5297	-543.1424
2	-0.4405	-4.07	-551.9755	-540.8256
3	-0.4269	-3.66	-544.5131	-530.6175
4	-0.4795	-3.88	-538.6780	-522.0538
5	-0.5272	-4.00	-532.6866	-513.3514
6	-0.5023	-3.53	-525.4944	-503.4657
7	-0.5034	-3.38	-523.0642	-498.3598
8	-0.5178	-3.26	-515.4583	-488.0964

of employing the ADF equation is that it helps determine the appropriate lag length, the value of k, that eliminates serial correlation of the residuals. The technique to be used in that direction is to start with $k = 8$ (2 years) and pare down the model by the usual t test or F test. If the t statistic on lag k^* for example is insignificant at some critical value I re-estimate the regression using a lag of $k^* - 1$, and repeat the process until t is significantly different from zero. Other selection criteria like AIC and SBC are also reported.

Tables (3.6)-(3.10) show the results of equation(3.4). ϕ_2 is the F statistic for the joint test for the hypothesis $a_0 = \gamma = \eta = 0$ and ϕ_3 is the F statistic for the hypothesis $\gamma = \eta = 0$. AIC and SBC refer to Akaike Information Criterion and the Schwartz Bayesian Criterion. The critical values of ϕ_2 and ϕ_3 as tabulated by Dickey and Fuller (1981) are 4.88 and 6.49, respectively, for 100 observations at the 5% significance level (these values are 6.50 and 8.73 at the 1% significance level). The critical τ values for the null hypothesis that $\gamma = 0$ when the equation contains a constant and a time trend are -4.04, -3.45, and -3.15

Table 3.5: Testing for second unit root for GDP

k	γ	t_γ	AIC	SBC
1	-0.4500	-4.46	-729.1177	-721.0713
2	-0.4281	-3.87	-720.5380	-709.8467
3	-0.3973	-3.35	-712.6137	-699.2965
4	-0.3992	-3.19	-705.2117	-689.2880
5	-0.3871	-2.93	-696.4033	-677.8925
6	-0.3770	-2.70	-686.6770	-665.5992
7	-0.4080	-2.80	-678.2148	-654.5900
8	-0.5659	-2.84	-705.4089	-679.2577

for 1%, 5%, and 10% significance levels. These values are -3.51, -2.89, and -2.58 when the equation has a constant but no time trend. For the series Banks Borrowing (B) and Banks Lending (L), the calculated ϕ_2 are larger than the critical values of F. Therefore the null hypotheses are rejected but when the constant term (a_0) is eliminated, the ϕ_3 statistics become insignificant and the null hypothesis that $\gamma = \eta = 0$ is not rejected. For GDP series, however, both null hypotheses ϕ_2 and ϕ_3 are rejected. Given that $\gamma = 0$ is not rejected, the GDP series is a unit root process. Adding a time trend to the test has changed this result which indicates, as expected, that nominal GDP has a time trend. As for the series FFR (F) and FFR multiplied by the proxy for Banks Concentration (FC), The critical values of ϕ_1 are 6.70, 4.71, and 3.86 at 1%, 5%, and 10% respectively, where ϕ_1 is the F test for the null hypothesis that $a_0 = \gamma = 0$. Inspecting the tables (3.7) and (3.8, the reported ϕ_1 values are all smaller than their critical counterpart. Thus, we do not reject the null that $a_0 = \gamma = 0$ for these series.

Having assured the presence of unit roots, an Error Correction Model (ECM) is specified. To assure the robustness of the results, an ECM is modelled with different lag lengths and residuals diagnostic checks along with other information criteria are examined in order to select the appropriate fit for the model.

3.2.3 Testing for Cointegration

For an n-dimensional system of $I(1)$ processes, it can occur that a linear combination $\nu'\mathbf{x}$ is stationary. If this is the case, the variables are called cointegrated, the stationary relation is a cointegration relation, and ν is the cointegrating vector. Therefore, the common trends

Table 3.6: Augmented Dickey-Fuller test for Bank Lending (L)

k	γ	t_γ	ϕ_2	ϕ_3	AIC	SBC
1	-0.0247	-2.36	10.27	5.96	-709.2256	-698.4237
2	-0.0275	-2.54	8.24	6.00	-701.1457	-687.6890
3	-0.0293	-2.59	6.99	5.70	-692.0867	-675.9939
4	-0.0307	-2.60	7.43	6.08	-684.2676	-665.5578
5	-0.0313	-2.53	5.94	5.20	-675.1530	-653.8455
6	-0.0317	-2.44	5.54	4.85	-665.7756	-641.8899
7	-0.0324	-2.38	4.74	4.34	-656.4899	-630.0460
8	-0.0334	-2.36	4.87	4.36	-647.7575	-618.7755

Table 3.7: Augmented Dickey-Fuller test for FFR (F)

k	γ	t_γ	ϕ_1	AIC	SBC
1	-0.0063	0.23	0.43	-106.4756	-98.4015
2	-0.0025	-0.09	0.40	-104.4318	-93.7033
3	-0.0146	-0.50	0.43	-102.9966	-89.6324
4	-0.0122	-0.39	0.35	-99.4360	-83.4553
5	-0.0358	-1.13	0.86	-102.3866	-83.8089
6	-0.0276	-0.81	0.65	-99.8202	-78.6651
7	-0.0153	-0.43	0.53	-98.0567	-74.3441
8	-0.0127	-0.53	0.51	-94.0533	-67.8036

can be eliminated by considering the linear combination $\nu'\mathbf{x}$. As noted by Johansen (1992), a very basic consequence of cointegration as a statistical concept is that the cointegrating properties of a multivariate time series can be analyzed from the reduced form of the model, even if they gain their importance only when interpreted in a suitable structure model. Johansen (1988) and Johansen and Juselius (1990), (J&J) set out a maximum likelihood (ML)method to test for cointegration. The advantage of this method is that it allows one to detect the number of cointegrating vector(s), if any, and to pin these vectors down. This method is implemented here. The starting point is the single vector autoregression (VAR) representation of the form given by

$$y_t = a_1 y_{t-1} + \varepsilon_t$$

or

$$\Delta y_t = (a_1 - 1) y_{t-1} + \varepsilon_t$$

Table 3.8: Augmented Dickey-Fuller test for $FFR \times Banking\ Concentration$ (FC)

k	γ	t_γ	ϕ_1	AIC	SBC
1	-0.0158	-0.51	0.37	-102.4985	-94.4245
2	-0.0230	-0.72	0.51	-100.2611	-89.5326
3	-0.0352	-1.07	0.84	-99.5294	-86.1653
4	-0.0367	-1.07	0.74	-98.2516	-82.2710
5	-0.0650	-1.88	1.91	-103.0858	-84.5080
6	-0.0514	-1.39	1.20	-101.2471	-80.0920
7	-0.0506	-1.30	1.15	-97.9633	-74.2508
8	-0.0437	-1.09	0.89	-94.4636	-68.2139

Table 3.9: Augmented Dickey-Fuller for Bank Borrowing (B)

k	γ	t_γ	ϕ_2	ϕ_3	AIC	SBC
1	-0.0331	-1.99	8.70	2.53	-559.5307	-548.3146
2	-0.0342	-2.01	6.82	2.43	-552.4905	-538.5115
3	-0.0381	-2.26	4.56	2.70	-553.5217	-536.7967
4	-0.0414	-2.39	4.43	3.02	-546.7670	-527.3131
5	-0.0382	-2.14	4.46	2.47	-539.8583	-517.6928
6	-0.0352	-1.91	4.37	1.98	-532.8944	-508.0348
7	-0.0377	-2.01	3.87	2.12	-526.0357	-498.4998
8	-0.0411	-2.18	4.39	2.69	-524.8679	-494.6736

For a VAR process of n variables and lag order of $k = 1$,

$$\mathbf{x}_t = \mathbf{A}_1\mathbf{x}_{t-1} + \varepsilon_t$$

$$\Delta\mathbf{x}_t = \mathbf{A}_1\mathbf{x}_{t-1} - \mathbf{x}_{t-1} + \varepsilon_t$$

$$\Delta\mathbf{x}_t = (\mathbf{A}_1 - \mathbf{I})\mathbf{x}_{t-1} + \varepsilon_t$$

$$\Delta\mathbf{x}_t = \mathbf{\Pi}\mathbf{x}_{t-1} + \varepsilon_t \tag{3.5}$$

where $\mathbf{x}_t$ and ε_t are $(n \cdot 1)$ vectors, $\mathbf{x}_t = (x_{1t}, x_{2t}, \cdots, x_{nt})'$ and ε_t is an n-dimensional vector of independent and identically distributed errors with zero mean and variance matrix $\sum_\varepsilon$, $\varepsilon_t \sim NID(0, \sum_\varepsilon)$. $\mathbf{A}_1$ is a $(n \cdot n)$ matrix of parameters, $\mathbf{I}$ is a $(n \cdot n)$ identity matrix, and $\mathbf{\Pi} = (\mathbf{A}_1 - \mathbf{I})$.

Expanding the VAR process to a higher order,

$$\mathbf{x}_t = \mathbf{A}_1\mathbf{x}_{t-1} + \mathbf{A}_2\mathbf{x}_{t-2} + \mathbf{A}_3\mathbf{x}_{t-3} + \cdots + \mathbf{A}_p\mathbf{x}_{t-k} + \varepsilon_t \tag{3.6}$$

Table 3.10: Augmented Dickey-Fuller test for GDP

k	γ	t_γ	ϕ_2	ϕ_3	AIC	SBC
1	-0.0294	-2.79	21.58	13.00	-755.1246	-744.3592
2	-0.0339	-3.08	14.54	11.94	-747.6427	-734.2320
3	-0.0368	-3.17	12.81	11.72	-738.8710	-722.8340
4	-0.0393	-3.18	10.79	10.72	-729.3865	-710.7425
5	-0.0398	-3.02	9.62	9.66	-720.2920	-699.0603
6	-0.0427	-3.06	8.83	9.30	-710.9978	-687.1983
7	-0.0520	-3.56	10.12	11.62	-705.6574	-679.3102
8	-0.0701	-4.79	16.58	20.28	-711.8141	-682.9394

$$\mathbf{x}_t = \sum_{i=1}^{k} \mathbf{\Pi}_i \mathbf{x}_{t-i} + \varepsilon_t \tag{3.7}$$

Following the same procedure that led to equation (3.2), equation(3.7)can be generalized and expressed with an intercept as

$$\Delta \mathbf{x}_t = \mathbf{\Pi} \mathbf{x}_{t-1} + \sum_{i=1}^{k-1} \mathbf{\Gamma}_i \Delta \mathbf{x}_{t-i} + \delta + \varepsilon_t \tag{3.8}$$

where

$$\mathbf{\Pi} = -(\mathbf{I} - \sum_{i=1}^{k} \mathbf{A}_i)$$

and

$$\mathbf{\Gamma}_i = -\sum_{j=i+1}^{k} \mathbf{A}_j$$

The rank of $\mathbf{\Pi}$ is equal to the number of cointegrating vectors. If the rank (r) of $\mathbf{\Pi}$ is zero, then all $\{x_t\}$ sequences are unit root processes, and the variables are not cointegrated or there is no long-run relationship between the variables and the system can be properly estimated as a VAR in first differences. However, if $\mathbf{\Pi}$ has full rank, $r = n$, all variables are stationary and there are n independent linear combinations between the variables and they span all dimensions in n space. This indicates that all the variables are individually $I(0)$ and the system can be properly estimated as a VAR in levels. The intermediate case is when the matrix $\mathbf{\Pi}$ is of reduced rank. If $0 < r < n$, then there are r cointegrating vectors. The linear combinations of the rows (or columns) of $\mathbf{\Pi}$ span r dimensions in n space. If this is the case, J&J (1990) decomposed $\mathbf{\Pi}$ as $\mathbf{\Pi} = \alpha\beta'$, where α and β are $(n \cdot r)$ matrices with rank r. The columns of β define the r cointegrating vectors and the rows of α define the speed of adjustment to the long-run equilibrium, analogous to the coefficient on the error-correction variable in the ECM of Engle and Granger (1987). Then equation (3.8) is rewritten as

$$\Delta \mathbf{x}_t = \alpha\beta' \mathbf{x}_{t-1} + \sum_{i=1}^{k-1} \mathbf{\Gamma}_i \Delta \mathbf{x}_{t-i} + \delta + \varepsilon_t \tag{3.9}$$

J&J (1990)develop a maximum likelihood estimation procedure for $\mathbf{\Gamma}_i$, α,β, and $\sum_\varepsilon$ and a vector of constants δ. The lagged values of $\Delta \mathbf{x}_{t-i}$ are stacked in a vector $\mathbf{Z}_t$ with the parameter coefficients arranged in the matrix $\mathbf{\Gamma}$. Then the model is rewritten as

$$\Delta \mathbf{x}_t - \alpha\beta' \mathbf{x}_{t-i} = \mathbf{\Gamma} \mathbf{Z}_t + \delta + \varepsilon_t \tag{3.10}$$

The variables $\Delta \mathbf{x}_t$ and $\mathbf{x}_{t-1}$ are regressed on the lagged values $\Delta \mathbf{x}_{t-1}, \cdots, \Delta \mathbf{x}_{t-k}$ and 1 (the vector $\mathbf{Z}$) to form residuals $\hat{\mathbf{R}}_{0t}$ and $\hat{\mathbf{R}}_{kt}$,

$$\Delta \mathbf{x}_t = \sum_{i=1}^{k-1} \hat{\mathbf{\Gamma}}_\mathbf{i} \Delta \mathbf{x}_{t-i} + \hat{\mathbf{R}}_{0t}$$

$$\mathbf{x}_{t-k} = \sum_{i=1}^{k-1} \hat{\mathbf{\Gamma}}_\mathbf{i} \Delta \mathbf{x}_{t-i} + \hat{\mathbf{R}}_{kt}$$

These residuals represent the variables $\Delta \mathbf{x}_t$ and $\mathbf{x}_{t-k}$ after the removal of short-run dynamics. Using these residuals, the likelihood function can be concentrated and estimates of $\mathbf{\Gamma}$, α, and $\sum_\varepsilon$ can be found as functions of β. The product moment matrices of these residuals, $\mathbf{S}_{ij}$ are calculated as

$$\mathbf{S}_{ij} = T^{-1} \sum_{t=1}^{T} \hat{\mathbf{R}}_{it} \hat{\mathbf{R}}'_{jt}$$

for $i, j = 0, k$. J&J show that the likelihood-maximizing solution for $\hat{\beta}$ is found by solving the eigenvalue problem

$$|\lambda \mathbf{S}_{kk} - \mathbf{S}_{k0} \mathbf{S}_{00}^{-1} \mathbf{S}_{0k}| = 0$$

This results in the eigenvalues $\hat{\lambda}_1 > \cdots > \hat{\lambda}_n$ which represent the eigenvalues that correspond to the squared canonical correlations between $\mathbf{x}_{t-1}$ and $\Delta \mathbf{x}_t$, corrected for the lagged differences based on the likelihood ratio (LR) test. Two test statistics are derived to distinguish between non-zero and zero eigenvalues. First, let $H(r)$ be the model with rank($\mathbf{\Pi}$) $= r$, for $r = 0, \cdots, n$. The trace test is a test of the hypothesis $H(r)$ against the unrestricted model $H(n)$. The trace statistic is given by

$$\lambda_{trace}(r) = -2ln(Q; H(r)|H(n)) = -T \sum_{i=r+1}^{n} ln(1 - \hat{\lambda}_i) \tag{3.11}$$

where $Q(\cdot)$ is the LR test statistic,$\hat{\lambda}_{r+1}, \cdots, \hat{\lambda}_n$ are the $(n-r)$ smallest eigenvalues obtained from $\mathbf{\Pi}$ matrix, T is the number of observations, and n is the number of variables. Equation (3.11) tests the null hypothesis that the number of distinct cointegrating vectors is less than or equal to r, so that $\lambda_{trace} = 0$ when all $\lambda_i = 0$. The further the eigenvalues are from zero, the larger is the λ_{trace} statistic. The second test is the maximum eigenvalue procedure that tests the hypothesis $H(r)$ against $H(r+1)$. The max statistic is given by

$$\lambda_{max}(r, r+1) = -2ln(Q; H(r)|H(r+1)) = -Tln(1 - \hat{\lambda}_{r+1}) \tag{3.12}$$

Equation (3.12) tests the null that the number of cointegrating vectors $= r$ against the alternative of $r+1$ cointegrating vectors. If the eigenvalue is close to zero, λ_{max} will be small.

In a Monte Carlo study, Cheung and Lai (1993) find that Johansen's LR tests are sensitive to the lag length (k) specification in the VAR model. In higher order VAR, these tests are biased towards finding cointegration more often than in lower order VAR models. This observation is also confirmed by Ahlgren and Antell (2002). To check the robustness of the results to the lag length specification, the *trace* and *max* test statistics are computed with different lag lengths as reported in tables (3.11). Critical values are adopted from the tabulation of Osterwald-Lenum (1992).

Table (3.11) reports the results of the eigenvalues, λ_{trace} and λ_{trace} for lag length 1-8 for the model

$$L = f(F, FC, B, G)$$

Starting with testing the null hypothesis $r = 0$ against the alternative hypothesis $r \geq 1 \cdots, 3$ for λ_{trace} or $r = 1$ for λ_{max}. All λ_{trace} andλ_{max} are statistically significants (significantly greater than the critical values at both significance levels 5% and 1%). Thus, the restriction that $r = 0$ is binding, therefore the null hypothesis $r = 0$ is rejected and there is at least one cointegrating vector. Now testing the null of the trace statistic that $r = 1$ against the alternative $r = 2, 3$, λ_{trace} is statistically significant at most k with the exception of $k = 2$ for λ_{trace} and $k = 2, 6, 7, 8$ for λ_{max} . This mixing result signals a likelihood to reject the null that $r = 1$ versus the alternative $r = 2$. The results, however, are more consistent for the test $r = 2$ where both the trace and the max statistic values are smaller than the critical value at 5% and 1% significance levels for most k. The tests do not reject the null that $r = 2$. Therefore, there are 2 cointegrating vectors in the system, implying that these vectors have a long run equilibrium and they move altogether in tandem. The next step is to determine the optimal lag length for the system as whole. This lag length must guarantee that the residuals are white noise. Various tests are conducted to check for residuals normality, autocorrelation, and homoscedasticity. The results are shown in table (3.12).

Table 3.11: The estimated eigenvalues, the *trace* and the *max* eigenvalue test statistics, and the critical values for VECM(1)-VECM(8).

r		1	2	3	4	5	6	7	8	95%	99%
0	$\hat{\lambda}_{r+1}$	0.9129	0.4340	0.3551	0.4444	0.3550	0.3407	0.4024	0.2840		
	λ_{trace}	332.16	111.78	103.90	127.20	109.09	101.34	117.22	114.28	75.74	71.86
	λ_{max}	268.42	62.05	47.38	62.88	46.48	43.74	53.54	49.91	34.40	31.66
1	$\hat{\lambda}_{r+1}$	0.2622	0.2117	0.2477	0.2968	0.2645	0.2047	0.2112	0.2318		
	λ_{trace}	63.74	49.73	56.52	64.32	62.61	57.60	63.68	64.37	53.42	49.65
	λ_{max}	33.45	25.93	30.74	37.68	32.56	24.05	24.67	27.16	28.14	25.56
2	$\hat{\lambda}_{r+1}$	0.1542	0.1209	0.1177	0.1151	0.1322	0.1746	0.1768	0.1887		
	λ_{trace}	30.29	23.80	25.78	26.64	30.05	33.55	39.01	37.21	34.80	32.00
	λ_{max}	18.42	14.05	13.52	13.07	15.04	20.15	20.24	21.54	22.00	19.77
3	$\hat{\lambda}_{r+1}$	0.0680	0.0649	0.0737	0.0744	0.0800	0.0651	0.1124	0.0950		
	λ_{trace}	11.87	9.75	12.26	13.57	15.01	13.40	18.77	15.67	19.99	17.85
	λ_{max}	7.75	7.31	8.27	8.28	8.83	7.06	12.41	10.29	15.67	13.75
4	$\hat{\lambda}_{r+1}$	0.0367	0.0221	0.0362	0.0482	0.0566	0.0586	0.0593	0.0509		
	λ_{trace}	4.12	2.44	3.99	5.29	6.18	6.34	6.36	5.38	9.13	7.52
	λ_{max}	4.12	2.44	3.99	5.29	6.18	6.34	6.36	5.38	9.13	7.52

Table 3.12: Residuals diagnostic checks and information criteria for different lag orders.

k	1	2	3	4	5	6	7	8
J-B	3.17	3.68	5.20	14.45	7.86	68.14	70.19	42.51
	(0.2054)	(0.1591)	(0.0741)	(0.0007)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)
B-P	12.6525	15.01196	11.37728	10.04259	9.7125	13.2785	12.4571	10.7950
	(0.2438)	(0.1316)	(0.3289)	(0.4368)	(0.4661)	(0.2085)	(0.2556)	(0.3737)
ARCH(1)	0.00	0.61	1.79	0.49	1.26	0.01	0.00	1.00
	(0.9439)	(0.4383)	(0.1836)	(0.4841)	(0.2635)	(0.9258)	(0.9438)	(0.3202)
AR(1)	36.12	0.00	0.11	0.00	0.03	0.25	0.01	0.00
	(< 0.0001)	(0.9576)	(0.7418)	(0.9468)	(0.8701)	(0.6215)	(0.9345)	(0.9573)
AR(2)	17.12	0.01	0.09	0.06	0.22	0.12	0.01	0.31
	(< 0.0001)	(0.9943)	(0.9174)	(0.9413)	(0.8011)	(0.8880)	(0.9886)	(0.7316)
AR(3)	10.96	0.12	0.06	0.33	0.21	0.10	0.02	0.21
	(< 0.0001)	(0.9502)	(0.9823)	(0.8042)	(0.8873)	(0.9626)	(0.9958)	(0.8921)
AR(4)	8.16	0.20	0.19	0.31	0.19	0.09	0.02	0.25
	(< 0.0001)	(0.9402)	(0.9418)	(0.8729)	(0.9411)	(0.9865)	(0.9994)	(0.9114)
AIC	-38.1184	-38.7528	-38.6473	-39.1972	-39.2490	-39.5781	-39.9060	-39.7530
SBC	-37.7502	-37.7651	-37.0331	-36.9490	-36.3595	-36.0395	-35.7105	-34.8928

3.2.4 Residuals diagnostic checks

Table (3.12) reports the results for various tests on residuals. J-B is the Jarque-Bera test statistic for normality. B-P is the Breusch-Pagan (1979) test for heteroscedasticity in the error distribution. The tests' distributions are χ^2 for both J-B and B-P tests under the null hypothesis of normality and homoscedasticity respectively. However, the test distributions for the remaining diagnosing tests are F. ARCH(1) is the first order auto-regression conditional heteroscedasticity test. The values reported in the table are the Lagrange Multiplier (LM) measures and the values in the parentheses are the p-values for the test significance (i.e if $p > 0.05$ we do not reject the null hypothesis at 5% significance level). Starting with lag $k = 1$, the null hypothesis that the residuals are normal based on J-B test is not rejected. The null hypothesis that the residuals distribution is homoscedastic is not rejected too based on the Breusch-Pagan test. The null that the coefficient of ARCH(1) is zero is not rejected either. So at this lag order there is no ARCH effect and therefore, the residuals are homoscedastic. The test for autocorrelation is based on the null that the coefficients of AR(1)-AR(4) are zero. for $k = 1$ there is autocorrelation of orders 1,2,3, and 4. Examining the analysis for the other orders reveals that, for $k = 2$ and 3 residuals are normally distributed, homoscedastic, and not autocorrelated at given orders. Investigating the information criteria, AIC and SBC, lag order 2 is the best fit model chosen by SBC, which tends to choose more parsimonious models compared to AIC. Given the fact that the data set consists of 111 observations, preserving more degrees of freedom is key to avoid depleting the power of estimates from its significance. Therefore, the feasible lag order to work with is 2.

3.2.5 Error-Correction representation for the model

Table (3.2.5) reports the estimation of the unrestricted VECM estimations. Again, equation (3.8) is reproduced here and given by

$$\Delta \mathbf{x}_t = \mathbf{\Pi} \mathbf{x}_{t-1} + \sum_{i=1}^{k-1} \mathbf{\Gamma}_i \Delta \mathbf{x}_{t-i} + \delta + \varepsilon_t$$

Table 3.13: Unrestricted estimations of $\mathbf{\Pi}$ and $\mathbf{\Gamma}$ elements.

$Variable$	δ	L_{t-1}	F_{t-1}	$(FC)_{t-1}$	B_{t-1}	G_{t-1}	ΔL_{t-1}	ΔF_{t-1}	$\Delta(FC)_{t-1}$	ΔB_{t-1}	ΔG_{t-1}
ΔL_t	-0.03786	-0.00867	-0.02159	0.02287	-0.01680	0.02713	0.48270	-0.00514	-0.01077	0.0615	0.32155
se	(0.05300)	(0.00518)	(0.01043)	(0.01136)	(0.01004)	(0.01860)	(0.10359)	(0.03083)	(0.03053)	(0.04223)	(0.11240)
t ratio	-0.71	-1.67	-2.07	2.01	-1.67	1.46	4.66	-0.17	-0.35	1.59	2.86
ΔF_t	-1.42053	-0.12017	-0.19873	0.22767	-0.23281	0.44724	1.11940	-0.51099	0.37930	-0.16735	7.70736
	(0.79917)	(0.07814)	(0.15735)	(0.17137)	(0.15138)	(0.28043)	(1.56208)	(0.46497)	(0.46041)	(0.63680)	(1.69485)
	-1.78	-1.54	-1.26	1.33	-1.54	1.59	0.72	-1.10	0.82	-0.26	4.55
ΔB_t	-0.34363	-0.05115	-0.11031	0.11977	-0.09910	0.17215	0.13492	0.09488	-0.05100	0.10884	0.25876
	(0.12907)	(0.01262)	(0.02541)	(0.02768)	(0.02445)	(0.04529)	(0.25228)	(0.07509)	(0.07436)	(0.10284)	(0.27372)
	-2.66	-4.05	-4.34	4.33	-4.05	3.80	0.53	1.26	-0.69	1.06	0.95
ΔG_t	0.14738	0.00325	-0.00918	0.00678	0.00630	-0.02241	-0.06408	-0.01589	0.01178	0.01820	0.24680
	(0.04526)	(0.00443)	(0.00891)	(0.00971)	(0.00857)	(0.01588)	(0.08847)	(0.02633)	(0.02608)	(0.03607)	(0.09599)
	3.26	0.74	-1.03	0.70	0.73	-1.41	-0.72	-0.60	0.45	0.50	2.57

Table 3.14: The effect of banking consolidation on monetary policy

Concentration ratio	Effect on lending	Effect on borrowing	Effect on GDP
0.40	-0.02189	0.01209	-0.01765
0.45	-0.02129	0.01553	-0.01672
0.50	-0.02068	0.01897	-0.01579
0.55	-0.02008	0.02240	-0.01486
0.60	-0.01947	0.02584	-0.01393
0.65	-0.01887	0.02928	-0.01301
0.70	-0.01826	0.03272	-0.01208
0.75	-0.01766	0.03616	-0.01115
0.80	-0.01705	0.03960	-0.01022
0.85	-0.01645	0.04303	-0.00929

Reading the results reported in table (3.2.5) indicates that lending's own lagged effect is 1.47403.[4] The effect of FFR is given by

$$\frac{\partial L_t}{\partial F_{t-1}} = -0.02159 + 0.02287(0.507) - 0.00514 - 0.01077(0.507) = -0.02059$$

where 0.507 is the average concentration ratio of banks assets over the period of study. That is, a one percentage point increase in FFR depresses loans by 2.06% given that the concentration ratio of banking industry is around 50%. To put this figure in the context of Kashyap and Stein (2000) result, they obtained -0.0046 on the coefficient of FFR when they considered small banks only (banks below the 95th percentile by asset size), and -0.0040 for middle size banks (banks between the 95th and 99th percentile). That figure was 0.0460 for large banks (banks above the 99th percentiles).

To see the effect of monetary policy on lending when concentration ratio is higher, various scenarios are simulated with a range of concentration ratio running between 40% and 85%. The results are reported in table(3.14).

It is obvious that as consolidation in the banking industry increases the lending channel effect is being mitigated, falling about 3 basis points, from 2% to 1.7% when the concentration ratio is around 75% as it currently is. In other words, a tightening in monetary

[4]The equation is written as: $\Delta L_t = -0.03786 - 0.00867L_{t-1} - 0.02159F_{t-1} - 0.01680B_{t-1} + 0.02287(FC)_{t-1} + 0.02713G_{t-1} + 0.48270\Delta L_{t-1} - 0.00514\Delta F_{t-1} + 0.06715\Delta B_{t-1} - 0.01077\Delta(FC)_{t-1} + 0.32155\Delta G_{t-1}$. Thus, $L_t = -0.03786 + 1.47403L_{t-1} - 0.02159F_{t-1} - 0.01680B_{t-1} + 0.02287(FC)_{t-1} + 0.02713G_{t-1} - 0.00514\Delta F_{t-1} + 0.06715\Delta B_{t-1} - 0.01077\Delta(FC)_{t-1} + 0.32155\Delta G_{t-1}$

policy through rising FFR by one percentage point would lead to a decline in bank lending by 1.7% today compared to 2% 15 years ago. Could this declining effect of FFR be due to the supply side or the demand side of the credit market? To put it differently, is this merely a reluctance from the market to ask for more loans when FFR is high? To be able to correctly identify this effect, we need to investigate the borrowing behavior of banks as they react to monetary tightening. Any increase in bank borrowing would reflect an attempt to offset a tightening action in order to maintain an ongoing level of lending. This can be seen by inspecting the effect of FFR on borrowing as reported in table (3.2.5) and given by the following function:

$$\frac{\partial B_t}{\partial F_{t-1}} = -0.1103 + 0.11977(0.507) + 0.09488 - 0.05100(0.507) = 0.01943$$

Given a level of concentration of 50%, a one percentage point increase in FFR would entice banks borrowing by 1.94%. This figure rises as banks consolidation increases (as examined in table (3.14)) and reaches 3.6% when concentration is 75%. That reflects the ability of banks to raise funds as they become larger.

In order to quantify the demand side reaction to monetary policy we need to look at the effect of FFR on GDP. As reported in table (3.14), this effect is diminishing as banks consolidation rises.

3.2.6 Testing for weak exogeneity

In general, the weak exogeneity test suggests that the errors in the VAR equations are not serially correlated. This elimination of serial correlation in ε_t is caused by including lagged changes of the endogenous variable and the regressors in the system. In a cointegrated system, weak exogeneity implies that a variable does not respond to the discrepancy from the long-run equilibrium relationship. Therefore, if the speed of adjustment is zero, the variable is said to be weakly exogenous. A formal elaboration on weak exogeneity based on Johansen (1992) is provided in appendix 3.A.

Following the methodology of J&J (1990), in order to detect weak exogeneity in the system, $\mathbf{\Pi}$ is decomposed into $\alpha\beta'$, both α and β have $(n \cdot r)$ dimension. $\mathbf{\Pi}$ represents the full error correction model or the vector error correction model (VECM). β is the matrix of cointegrating parameters, where its rows defined as the r distinct cointegrating vectors. α

Table 3.15: β' matrix with L being normalized

	L	F	FC	B	G
coint 1	1.0000	0.55822	-0.92095	1.93665	-4.49640
coint 2	1.0000	2.25433	-2.42837	1.93762	-3.29676

Table 3.16: α' matrix

	L	F	FC	B	G
coint 1	0.00121	-0.04256	-0.06039	-0.00294	0.00974
coint 2	-0.00988	-0.07762	-0.08179	-0.04820	-0.00649

is the matrix of weights with which each cointegrating vector enters the n equations of the VAR system. In other words, the rows of α show how the cointegrating vectors of β are loaded into each equation in the system. Hence, a valid cointegrating vector will produce a significant non-zero eigenvalue and the estimate of the cointegrating vector will be given by the corresponding eigenvector. Tables (3.15), (3.16), and (3.17) show, respectively, β, α, and $\mathbf{\Pi}$ for the model.

The elements of matrix α represent the speed of adjustment of these variables to the long run equilibrium. The coefficients of L,F, B, and G are tested against weak exogeneity. A variable that has a slow return to the long run equilibrium in case of a shock to the system will be weakly exogenous. The test hypotheses are $\alpha_{ij} = 0$, for $i = L,F$, B, and G and $j = 1, 2$. The test statistic is distributed as χ^2_{rs}, where $s =$ the number of restrictions on the α matrix, and is calculated as

$$-2ln(D_2|D_1) = -T \sum_{i=r+1}^{n} [ln(1-\hat{\lambda}_i^*) - ln(1-\hat{\lambda}_i)] \tag{3.13}$$

where D_1 is the unrestricted model, D_2 is the restricted model, $\hat{\lambda}_i$ is the i^{th} eigenvalue

Table 3.17: Full VECM $\mathbf{\Pi}$ matrix

$Variable$	L	F	FC	B	G
L	-0.00867	-0.02159	0.02287	-0.01680	0.02713
F	-0.12017	-0.19873	0.22767	-0.23281	0.44724
FC	-0.05115	-0.11031	0.11977	-0.09910	0.17215
B	-0.14217	-0.21808	0.25422	-0.27542	0.54115
G	0.00325	-0.00918	0.00678	0.00630	-0.02241

Table 3.18: Testing weak exogeneity of the variables

Variable	L	F	B	G
	3.47	1.70	9.22	16.59

from the unrestricted model, and $\hat{\lambda}_i^*$ is the i^{th} eigenvalue after imposing the restriction associated with D_2. The results of the test are shown in table (3.18). As $\chi^2_{0.05}(2) = 5.99147$, the variables L and F seem to be weakly exogeneous, hence, B and G enter the lending equation with high speeds of adjustment.

3.3 Splitting the sample into pre and post 1990

As a result of banking deregulation in the 1990s, bank mergers and consolidations exhibit a sharp take off since that time (figure(3.5)). Therefore, it would be a revealing experiment to split the sample into two subsamples representing pre- and post-deregulation. Although deregulation of interstate branching took place in 1994, the two samples are split in 1990 to allow for a reasonable number of observations. That leads to 60 observations in the pre-1990 period (1976:1-1990:4) and 55 observations in the post-1990 period (1990:1-2003:3). The same procedure is applied here as in the previous section. The results are consistent with the ones obtained earlier, as shown in tables (3.3) and (3.3).
Another point raised by examining bank assets concentration in figure (3.5) is the two large spikes in the beginning of the period of study (1976-1979). These sudden jumps and declines in bank concentration are difficult to explain other than assuming the possibility of data inconsistency or mishandling for these specific quarters, problems that are not uncommon when handling such huge data set. To avoid any bias in the results that may be propelled by these anomalies, the model was re-estimated for the period 1979-2003. The results are conformable with the results obtained above for the entire period. The re-estimated results are reported in appendix C.

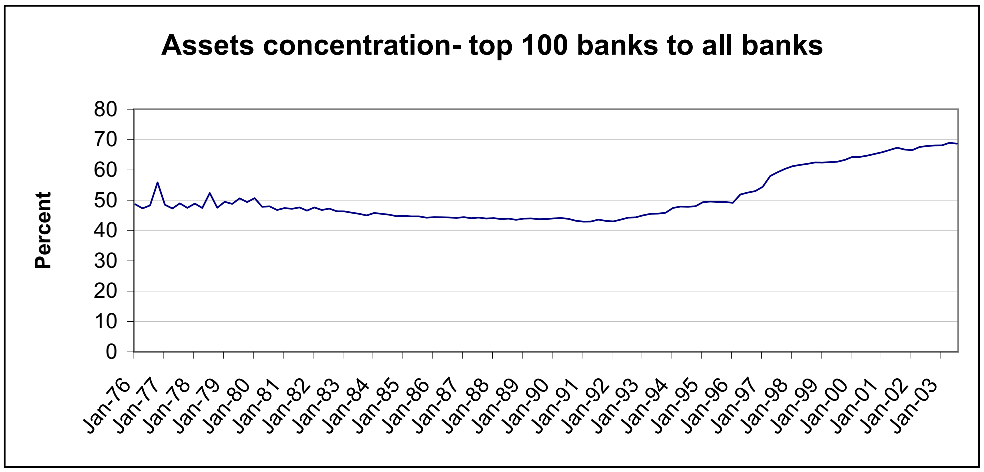

Figure 3.5: Concentration ratio of bank assets.

Table 3.19: Unrestricted estimations of $\mathbf{\Pi}$ and $\mathbf{\Gamma}$ elements for pre-1990 sample.

$Variable$	δ	L_{t-1}	F_{t-1}	$(FC)_{t-1}$	B_{t-1}	G_{t-1}	ΔL_{t-1}	ΔF_{t-1}	$\Delta (FC)_{t-1}$	ΔB_{t-1}	ΔG_{t-1}
ΔL_t	-0.22970	-0.12106	0.02716	-0.03608	0.00937	0.12490	0.48916	-0.04327	0.01790	0.03786	0.28382
se	(0.12270)	(0.06068)	(0.06898)	(0.06459)	(0.00825)	(0.06682)	(0.13700)	(0.04321)	(0.04044)	(0.05735)	(0.13748)
t ratio	-1.87	-1.99	0.39	-0.56	1.14	1.87	3.57	-1.00	0.44	0.66	2.06
ΔF_t	1.80222	0.98466	0.66055	-0.56869	-0.12328	-1.07947	2.32077	-1.12860	0.65074	-1.35845	10.21521
	(2.21222)	(1.09408)	(1.24373)	(1.16448)	(0.14869)	(1.20472)	(2.47006)	(0.77910)	(0.72910)	(1.03398)	(2.47876)
	0.81	0.90	0.53	-0.49	-0.83	-0.90	0.94	-1.45	0.89	-1.31	4.12
ΔB_t	0.39206	0.20186	0.03908	-0.02236	-0.02013	-0.21435	0.56914	0.01637	-0.02872	0.07184	1.00764
	(0.36504)	(0.18054)	(0.20523)	(0.19215)	(0.02454)	(0.19879)	(0.40759)	(0.12856)	(0.12031)	(0.17062)	(0.40903)
	1.07	1.12	0.19	-0.12	-0.82	-1.08	1.40	0.13	-0.24	0.42	2.46

Table 3.20: Unrestricted estimations of $\mathbf{\Pi}$ and $\mathbf{\Gamma}$ elements for post-1990 sample.

$Variable$	δ	L_{t-1}	F_{t-1}	$(FC)_{t-1}$	B_{t-1}	G_{t-1}	ΔL_{t-1}	ΔF_{t-1}	$\Delta(FC)_{t-1}$	ΔB_{t-1}	ΔG_{t-1}
ΔL_t	1.12740	-0.19345	0.01103	-0.02469	0.18623	-0.10386	0.03660	-0.04912	0.08762	0.13433	0.42438
se	(0.49641)	(0.10947)	(0.01004)	(0.01078)	(0.08117)	(0.03914)	(0.14342)	(0.07721)	(0.07735)	(0.06580)	(0.24478)
t ratio	2.27	-1.77	1.10	-2.29	2.29	-2.65	0.26	-0.64	1.13	2.04	1.73
ΔF_t	13.58848	-4.21370	-0.47770	0.30965	2.17746	0.48897	1.97922	0.14947	0.21505	-1.91933	5.87072
	(5.80733)	(1.28067)	(0.11750)	(0.12612)	(0.94965)	(0.45792)	(1.67787)	(0.90331)	(0.90493)	(0.76977)	(2.86360)
	2.34	-3.29	-4.07	2.46	2.29	1.07	1.18	0.17	0.24	-2.49	2.05
ΔB_t	0.56933	-0.16948	-0.01920	0.01244	0.08762	0.01961	0.09481	-0.37612	0.49891	-0.05139	0.10902
	(1.39449)	(0.30752)	(0.02821)	(0.03029)	(0.22803)	(0.10996)	(0.40290)	(0.21691)	(0.21730)	(0.18484)	(0.68763)
	0.41	-0.55	-0.68	0.41	0.38	0.18	0.24	-1.73	2.30	-0.28	0.16

The pre-1990 regression reveals that

$$\frac{\partial L_t}{\partial F_{t-1}} = 0.02716 - 0.03608(0.463) - 0.04327 + 0.01790(0.463) = -0.024527$$

The FFR elasticity of lending for post-1990 period is expressed by

$$\frac{\partial L_t}{\partial F_{t-1}} = 0.01103 - 0.02469(0.551) - 0.04912 + 0.08762(0.551) = -0.0034156$$

where 0.463 and 0.551 are bank concentration ratios for the pre-1990 and post-1990 periods respectively. Again the effect of policy on lending is diminished for the period when banking consolidation had increased compared to the pre-deregulation period. This conforms with the conclusion drawn in the previous section for the whole period of study. This poses a policy dilemma for monetary authority; promoting deregulation to foster the banking industry and to make it healthier would weaken the role of policy transmission which aims at controlling the macroeconomic variables.

Since the data set is split in that time manner, the model was estimated for both periods again but this time the interaction term between the policy variable and concentration ratio (FC) is omitted from the model. This will allow for a robustness check whether the results obtained above are sustainable.

Tables (3.21) and (3.22) show the results of the VEC model. The effect of FFR on bank lending once again assures the previous analysis and is given by the following equations:

For the pre-1990 period:

$$\frac{\partial L_t}{\partial F_{t-1}} = 0.00609 - 0.03809 = -0.0320$$

For the post-1990 period: [5]

$$\frac{\partial L_t}{\partial F_{t-1}} = -0.00598$$

The results are similar to the ones obtained above with a slight increase of the effect of monetary policy change in both periods.

[5]The matrix for a lag order of 2 (or higher) for this model was not positive definite. Thus the model was estimated with lag order 1.

Table 3.21: Pre-1990 estimation (no interaction term)

	δ	L_{t-1}	F_{t-1}	π_{t-1}	B_{t-1}	G_{t-1}
ΔL_t	0.01076	0.01929	0.00609	-0.21697	-0.01462	-0.00791
	(0.01224)	(0.02147)	(0.00677)	(0.24151)	(0.01628)	(0.00880)
		ΔL_{t-1}	ΔF_{t-1}	$\Delta \pi_{t-1}$	ΔB_{t-1}	ΔG_{t-1}
		0.56305	-0.03809	0.13605	-0.00595	0.49630
		(0.14669)	(0.00866)	(0.16825)	(0.05906)	(0.11290)

Table 3.22: Post-1990 estimation (no interaction term)

	δ	L_{t-1}	F_{t-1}	π_{t-1}	B_{t-1}	G_{t-1}
ΔL_t	0.35580	-0.20934	-0.00598	1.23541	0.10104	0.06530
	(0.08299)	(0.05086)	(0.00145)	(0.30016)	(0.02455)	(0.01587)

3.3.1 Impulse response functions (IRF)

Lutkepohl and Reimers(1992) show that impulse response analysis can be used to obtain information concerning the interactions among the variables and check whether the dynamic responses of these variables conform to the theory. Figures (3.6) to (3.23) show the response functions; figure (3.6) shows the effect of a FFR shock on bank lending. Bank lending declines sharply after an standard deviation innovation to FFR by about 0.2% and continues to decline slowly to 1% of its initial level.

Bank borrowing, however, responds conversely to a FFR shock. Figure (3.8) shows that bank borrowing increases by 0.4% over the first two quarters after a positive shock to FFR before it starts to return to its long-run equilibrium. Figure (3.9) Bank lending respond positively to a standard deviation shock in bank borrowing, whereby lending increases up to 1% over the next 24 quarters following the shock. The response of bank lending to a shock to GDP is presented in figure (3.10). Bank lending jumps by 0.4% in the next few quarters following the shock before restoring its long-run equilibrium after 13 quarters. One remark should be made about constructing impulse response functions in VECM context; as noted by Lutkepohl (1993), impulse response functions from a cointegrating VECM, unlike those from a stationary VAR, do not always die out. By "die out" here we mean convergence to zero. In a stationary VAR each variable has a time-invariant mean and time-invariant finite variance, therefore, the effect of a shock to any of these variables must die out so that the variable can revert to its mean. However, the I(1) variables modelled in a cointegrating

VECM are not mean reverting. The unit modulus in the companion matrix implies that the effects of some shocks will not die out over time. In other words, by construction, the shocks in VECM are permanent rather than transitory. To detect the comparative effect of monetary policy on bank lending and the other variables for the pre-deregulation period as well as for post-deregulation, IRFs are constructed for the pre-1990 and for the post-1990 periods. The results are depicted in figures (3.12)-(3.17) and (3.18)-(3.23) for both periods respectively.

For the pre-1990 period, lending drops immediately by 0.3% after a FFR shock and continues to drop, after a small correction, to 0.5% (figure(3.12)).

The response for the post-1990 period (figure(3.18)) indicates a positive, though negligible (0.5%), reaction of bank lending to a FFR shock, then dropping by 0.1% over a period of 13 quarters before picking up again to its long run equilibrium. The IRF analysis confirms the conclusion of the VECM results that the oscillations in bank lending due to monetary policy changes are noticeably wider in scope in the pre-1990 period compared to the post-1990 one. It is 0.5% for the former and 0.1% for the latter.

As for bank borrowing, a shock to FFR would boost borrowing in general, as depicted in figures (3.13) and (3.19). However, the response function of bank borrowing behaves differently in both periods. For the 1976-1990 period bank borrowing has increased by about 1.7% after a one standard deviation shock of FFR. This figure is less for the post-1990 period where bank borrowing rises only by 1.2% over a period of four quarters after the shock, then reaches its equilibrium after eight quarters. One anomaly in the response function of bank borrowing for the period 1990-2003 is the sharp decline after the 4th quarter of a FFR shock then turns negative before it starts to pick up again. However, the variations in bank borrowing in that period is within 0.2% compared to 1.7% for the pre-1990 era. That figure, again explains how banking activities responds more sluggishly in the post-1990 period.
The effect of other FFR shocks to GDP (figures (3.14) and (3.20)) and that of bank borrowing shocks to bank lending (figures (3.15) and (3.21)) have similar functional reactions in both periods but with a slight difference in scale. Lastly, the effect of a GDP shock on lending is more pronounced in the pre-1990 period than in the post-1990 one as shown

in figures (3.16) and (3.22) respectively. The response in the former spans a 1.2% change compared to 0.8% in the latter.

One question that remains to be answered is whether there is an asymmetric response of lending to monetary policy, i.e. could it be that banks are more responsive to monetary tightening than they are to an easing policy? This question will be answered in the next chapter in a panel data framework.

3.4 Conclusion

Using time series data for U.S. banks, This chapter examined the varying effect of monetary policy on bank lending for the period 1976-2003. It is found that as the banking industry gets more concentrated (through mergers and acquisitions), the effect of monetary policy transmission (through open market operations) is being mitigated. That was the result of deregulation of the banking sector that took place in the first half of the 1990s which led to an unprecedented wave of consolidation in the banking industry.

To check the robustness of this finding, the data were split into two periods; 1976-1990 and 1990-2003. As it was proposed by the initial finding of this paper, the effect of monetary policy on bank lending was found to be more pronounced for the period prior to the deregulation era (1976-1990).

Appendix 3.A :Weak exogeneity and partial models

This brief review of weak exogeneity and partial models is based on Johansen (1992). Given the autoregressive model

$$\Delta \mathbf{x}_t = \mathbf{\Pi x}_{t-1} + \sum_{i=1}^{k-1} \mathbf{\Gamma}_i \Delta \mathbf{x}_{t-i} + \delta + \varepsilon_t \tag{3.14}$$

under the hypothesis of cointegration where $\mathbf{\Pi} = \alpha\beta'$. Let the process $\mathbf{x}_t$ be decomposed into the variables $\mathbf{Y}_t$ and $\mathbf{Z}_t$ of dimensions p_y and p_z, respectively, where $p = p_y + p_z$, and let α, $\mathbf{\Gamma_1} \cdots, \Gamma_{k-1}$, ε_t, and Σ be decomposed correspondingly. Model (3.14) can be decomposed into the conditional model for $\mathbf{Y}_t$ and $\mathbf{Z}_t$:

$$\Delta \mathbf{Y}_t = \omega \Delta \mathbf{Z}_t + (\alpha_y - \omega\alpha_z)\beta' x_{t-1} + \sum_{1}^{k-1} (\mathbf{\Gamma}_{yt} - \omega \mathbf{\Gamma}_{zt}) \Delta \mathbf{x}_{t-1} + \delta_y - \omega\delta_z + \varepsilon_{yt} - \omega\varepsilon_{zt} \tag{3.15}$$

and the marginal model of $\mathbf{Z_t}$:

$$\Delta \mathbf{Z_t} = \alpha_z \beta' \mathbf{x}_{t-1} + \sum_{1}^{k-1} \mathbf{\Gamma}_{zt} \Delta \mathbf{x}_{t-1} + \delta_z + \varepsilon_{zt} \tag{3.16}$$

where $\omega = \Sigma_{yz}\Sigma_{zz}^{-1}$ where again, Σ is the covariance matrix of ε_t.

Note that all the cointegrating relations $\beta' \mathbf{x}_{t-1}$ enter into the marginal as well as the conditional model, and that the coditional model has new adjustment coefficients $\alpha_y - \omega\alpha_z$ depending on the covariance matrix of the errors and all the adjustment coefficients. In general, the parameters of the marginal and the conditional system are interrelated, which means that a full system analysis is needed to draw efficient inference about the parameters. There is a very special case where the partial model (3.15) contains as much information as the full system about the cointegrating relations and the adjustment coefficients, and where the analysis of the partial model is efficient. This is when $\mathbf{Z}_t$ is weakly exogeneous for α and β. [6] The variable $\mathbf{Z}_t$ is said to be weakly exogenous for the parameters of interest if first, the parameters of interest are functions of the parameters in the conditional model. Second, The parameters in the conditional model and the parameters in the marginal model are variation-free; that is, they do not have any joint restrictions.

It can be shown that if we define the parameters of interest in model (3.14) to be all the

[6] for a detailed discussion see Engle, Hendry, and Richard (1983).

parameters of β, then weak exogeneity of $\mathbf{Z}_t$ with respect to β is equivalent to the condition that $\alpha_z = 0$. That is, the rows of α corresponding to the Z equations are zero and the models (3.15) and (3.16) are reduced to

$$\Delta\mathbf{Y}_t = \omega\Delta\mathbf{Z}_t + \alpha_y\beta'\mathbf{x}_{t-1} + \sum_1^{k-1}(\mathbf{\Gamma}_{yt} - \omega\mathbf{\Gamma}_{zt})\Delta\mathbf{x}_{t-1} + \delta_y - \omega\delta_z + \varepsilon_{yt} - \omega\varepsilon_{zt} \tag{3.17}$$

and

$$\Delta\mathbf{Z_t} = \sum_1^{k-1}\mathbf{\Gamma}_{zt}\Delta\mathbf{x}_{t-1} + \delta_z + \varepsilon_{zt} \tag{3.18}$$

In this case β and the remaining adjustment coefficients α_y enter only in the partial model (3.17), and the properties of the Gaussian distribution show that the parameters in the models (3.17) and (3.18) are variation free.[7] Thus weak exogeneity means that $\Delta\mathbf{Z}_t$ does not react to disequilibrium errors but may still react to lagged changes of $\mathbf{Y}_t$, and strong exogeneity implies that $\Delta\mathbf{Z}_t$ does not react to the lagged values of $\mathbf{Y}_t$, whether $\mathbf{Y}$ is in changes or levels.

[7]For proof, see Johansen (1995) pp.122-23

Appendix 3.B

Re-estimating the model for the period 1979-2003

The following tables report the rank selection procedure and lag selection for the model re-estimated for the period 1979-2003. Since the optimal lag order was 2 for the entire period- model, the reported results here are confined to lag 4.

Table (3.23) shows that the rank of the Π matrix is one. Therefore, only one cointegrating vector exists in this model. Lag selection is given in table (3.24) where lag order 2 is shown to be optimal.

The results of bank lending and bank borrowing sensitivity to changes in monetary policy are given in table (3.4) and are summarized by the following derivations:

$$\frac{\partial L_t}{\partial F_{t-1}} = 0.00027902 - 0.00102(0.51) - 0.01393 + 0.02465(0.51) = -0.00160$$

$$\frac{\partial B_t}{\partial F_{t-1}} = -0.00003241 + 0.00011897(0.51) - 0.04274 + 0.09679(0.51) = 0.00665$$

where 0.51 is the average asset concentration ratio for the period 1979-2003. The counterparts figures for the entire period were -0.02059 for bank lending and 0.01943 for bank borrowing. Removing early quarters from the data set because of unexplained spikes in bank concentration between 1976 and 1979, yields slightly different results in magnitude. Particularly, the effect of FFR on bank lending is less pronounced here as expected, given a slightly higher bank concentration in this period of study.

Table 3.23: The estimated eigenvalues, the *trace* and the *max* eigenvalue test statistics, and the critical values for VECM(1)-VECM(4) for the period 1979-2003.

r		1	2	3	4	95%	99%
0	$\hat{\lambda}_{r+1}$	0.9300	0.4517	0.3984	0.4351		
	λ_{trace}	328.54	109.28	108.07	118.02	75.74	71.86
	λ_{max}	260.59	58.30	48.78	54.26	34.40	31.66
1	$\hat{\lambda}_{r+1}$	0.2651	0.1897	0.2769	0.2547		
	λ_{trace}	67.95	50.98	59.29	63.76	53.42	49.65
	λ_{max}	30.18	20.41	31.13	27.93	28.14	25.56
2	$\hat{\lambda}_{r+1}$	0.2258	0.1322	0.1532	0.1857		
	λ_{trace}	37.77	30.57	28.16	35.83	34.80	32.00
	λ_{max}	25.08	13.75	15.97	19.51	22.00	19.77
3	$\hat{\lambda}_{r+1}$	0.0820	0.1135	0.0745	0.0978		
	λ_{trace}	12.69	16.82	12.19	16.32	19.99	17.85
	λ_{max}	8.38	11.69	7.43	9.78	15.67	13.75
4	$\hat{\lambda}_{r+1}$	0.043	0.0515	0.0484	0.0665		
	λ_{trace}	4.31	5.13	4.76	6.54	9.13	7.52
	λ_{max}	4.31	5.13	4.76	6.54	9.13	7.52

Table 3.24: Residuals diagnostic checks and lag selection for the period 1979-2003.

	k			
	1	2	3	4
J-B	0.94	3.07	3.04	3.32
	(0.6254)	(0.2152)	(0.2183)	(0.1898)
ARCH(1)	1.20	1.57	0.57	0.33
	(0.2761)	(0.2134)	(0.4534)	(0.5685)
AR(1)	41.82	0.03	0.03	0.04
	($<$ 0.0001)	(0.8640)	(0.8691)	(0.8409)
AR(2)	19.95	0.03	0.06	0.05
	($<$ 0.0001)	(0.9714)	(0.9394)	(0.9554)
AR(3)	13.08	0.03	0.04	0.06
	($<$ 0.0001)	(0.9937)	(0.9897)	(0.9791)
AR(4)	10.24	0.12	0.09	0.08
	($<$ 0.0001)	(0.9753)	(0.9859)	(0.9887)
AICC	-26.2153	-27.0062	-26.9844	-26.7879
SBC	-26.0077	-26.4018	-26.0128	-25.4862
HQC	-26.1333	-26.7813	-26.6494	-26.3834

Table 3.25: Unrestricted estimations of $\mathbf{\Pi}$ and $\mathbf{\Gamma}$ elements for the period 1979-2003.

$Variable$	δ	L_{t-1}	F_{t-1}	$(FC)_{t-1}$	B_{t-1}	G_{t-1}	ΔL_{t-1}	ΔF_{t-1}	$\Delta(FC)_{t-1}$	ΔB_{t-1}	ΔG_{t-1}
ΔL_t	0.05105	-0.0353	0.00027902	-0.00102	0.00809	-0.00880	0.41194	-0.01393	+0.02465	0.09545	0.39088
	(0.06463)	(0.00453)	(0.00035790)	(0.00131)	(0.01038)	(0.01128)	(0.10821)	(0.00532)	(0.01166)	(0.04200)	(0.13602)
ΔB_t	0.00763	0.00041012	-0.00003241	0.00011897	-0.00093993	0.00102	-0.05620	-0.04274	0.09679	0.22784	0.24822
	(0.16955)	(0.01188)	(0.00093901)	(0.00345)	(0.02723)	(0.02960)	(0.28390)	(0.01396)	(0.03059)	(0.11019)	(0.35688)

Appendix 3.C: Impulse Response Functions (IRF)

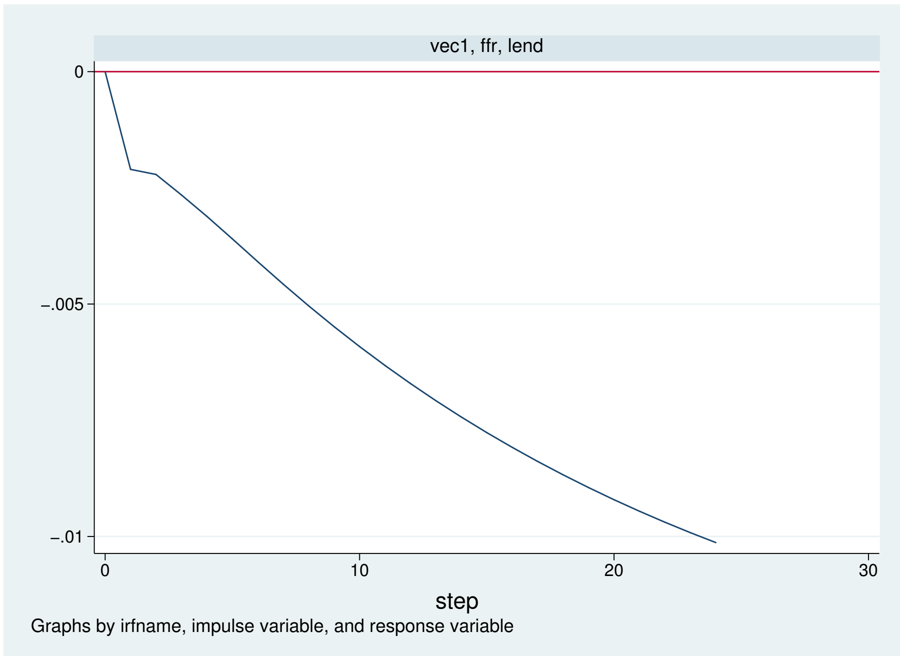

Figure 3.6: IRF of bank lending to FFR shock for the period 1976-2003.

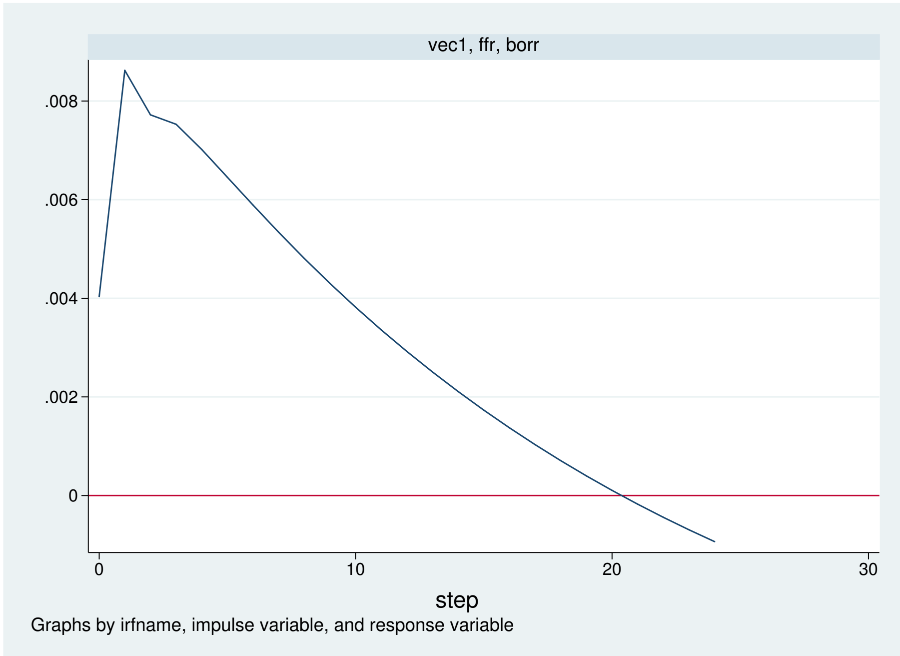

Figure 3.7: IRF of bank borrowing to FFR shock for the period 1976-2003.

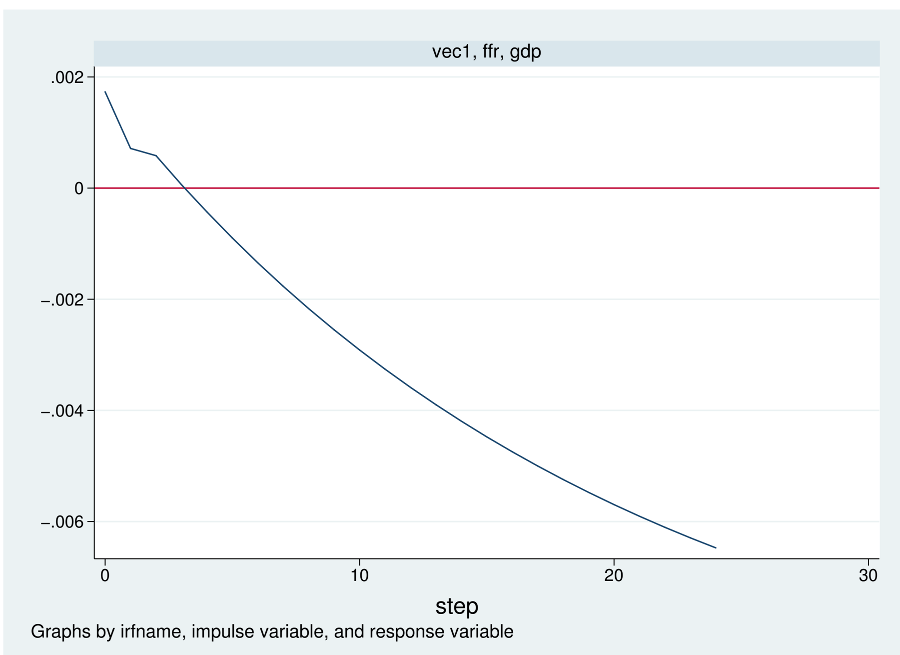

Figure 3.8: IRF of GDP to FFR shock for the entire period 1976-2003.

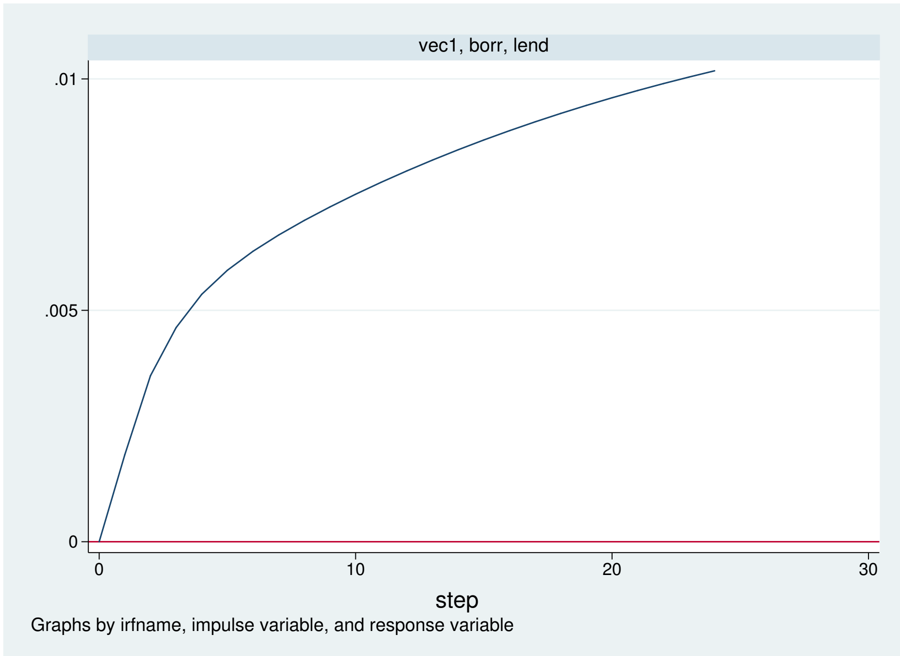

Figure 3.9: IRF of bank lending to bank borrowing shock for the period 1976-2003.

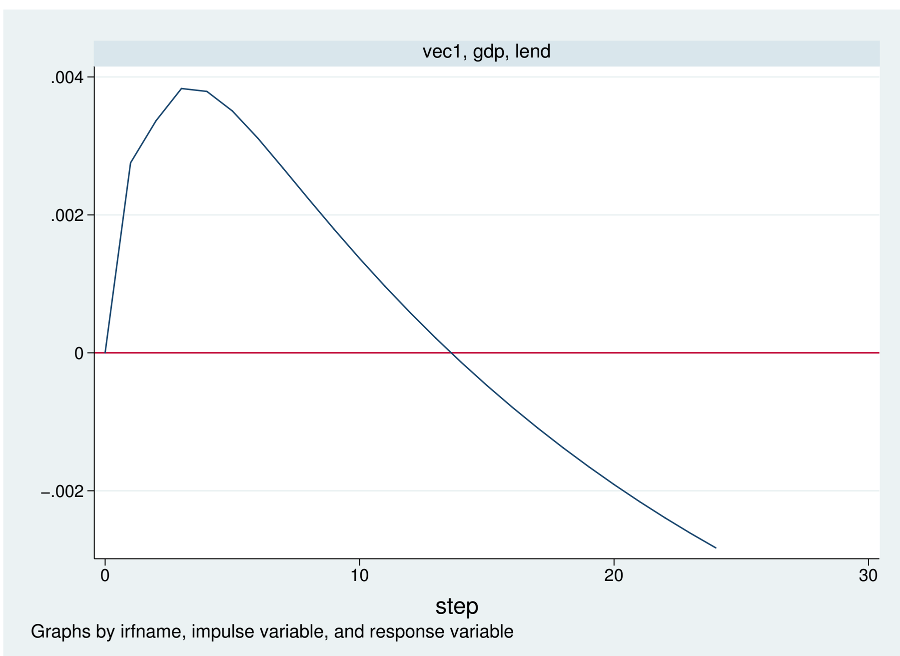

Figure 3.10: IRF of bank lending to GDP shock for the period 1976-2003.

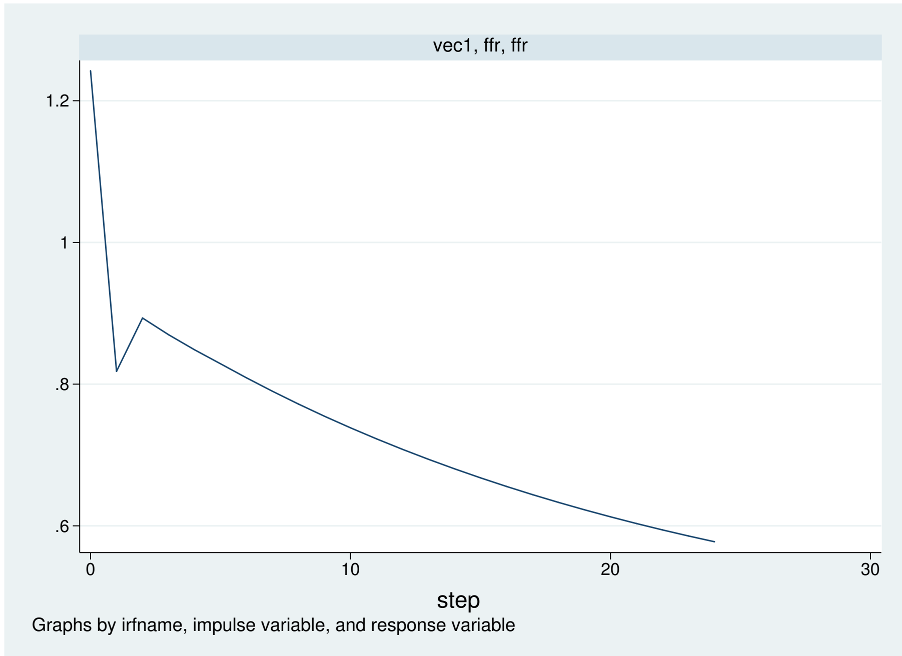

Figure 3.11: IRF of FFR to FFR shock for the entire period 1976-2003.

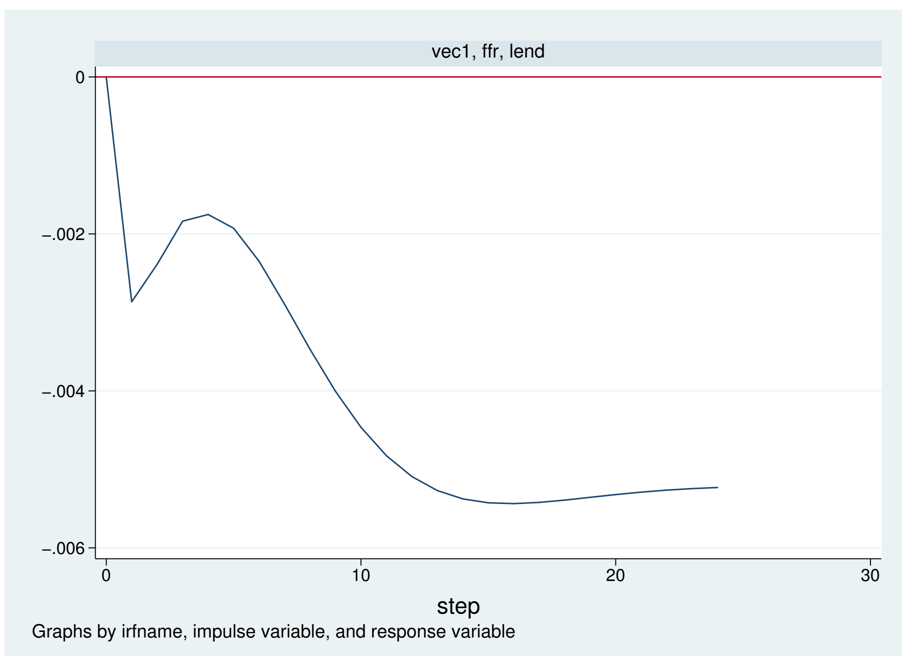

Figure 3.12: IRF of bank lending to FFR shock for the pre-1990 period: 1976-1990.

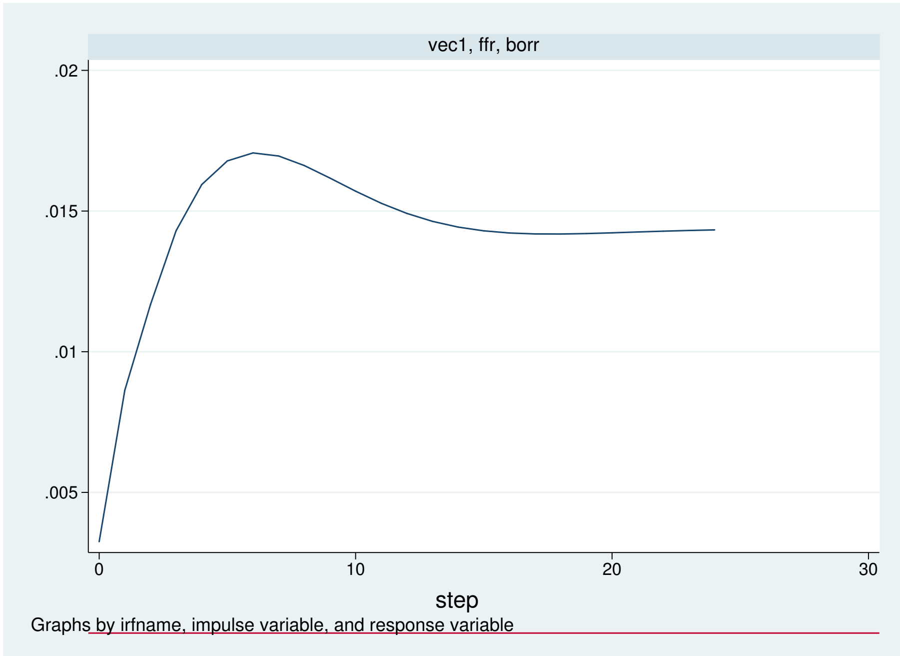

Figure 3.13: IRF of bank borrowing to FFR shock for the pre-1990: period 1976-1990.

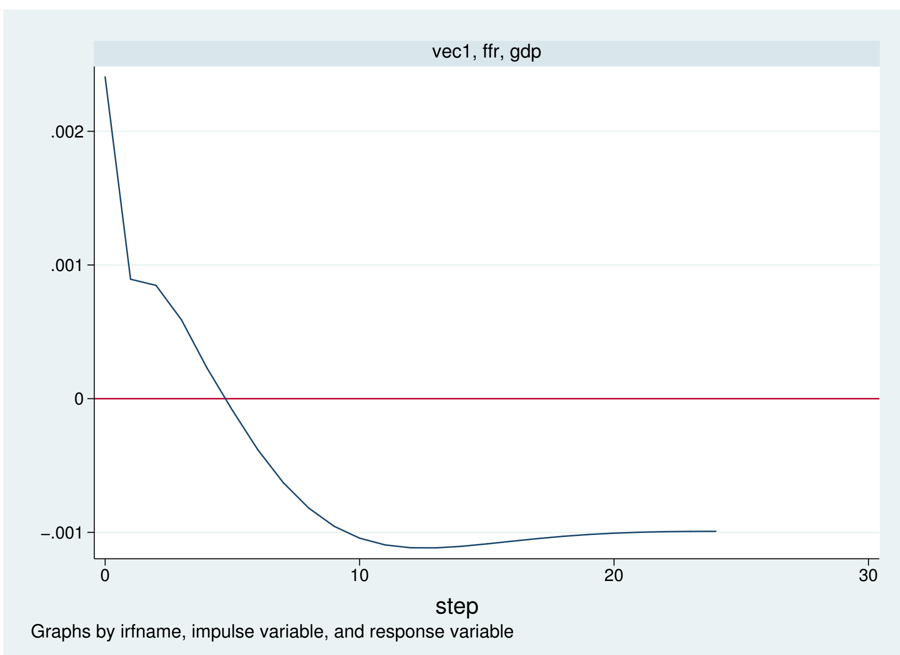

Figure 3.14: IRF of GDP to FFR shock for the pre-1990 period: 1976-1990.

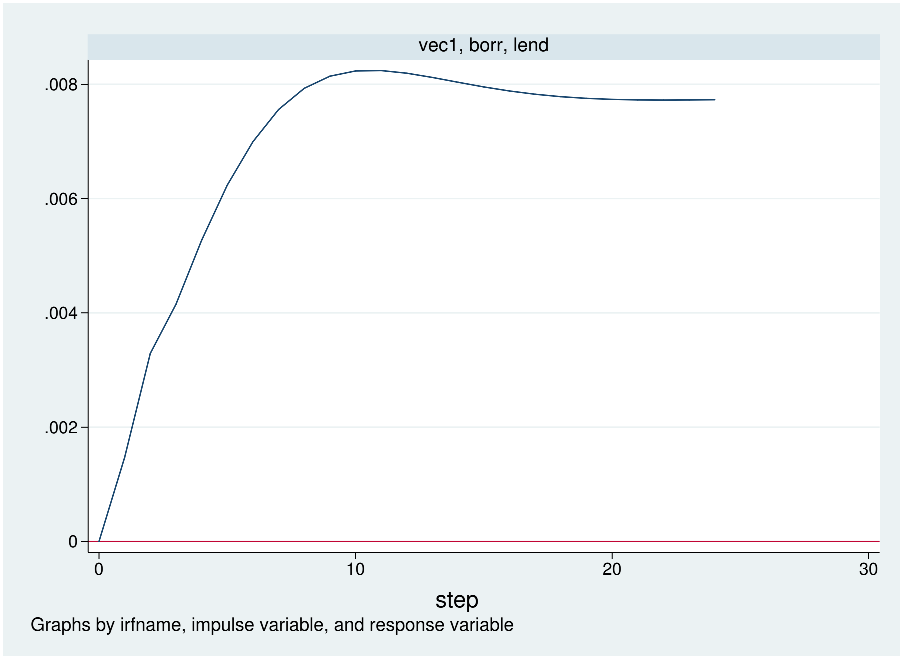

Figure 3.15: IRF of bank lending to bank borrowing shock for the period 1976-1990.

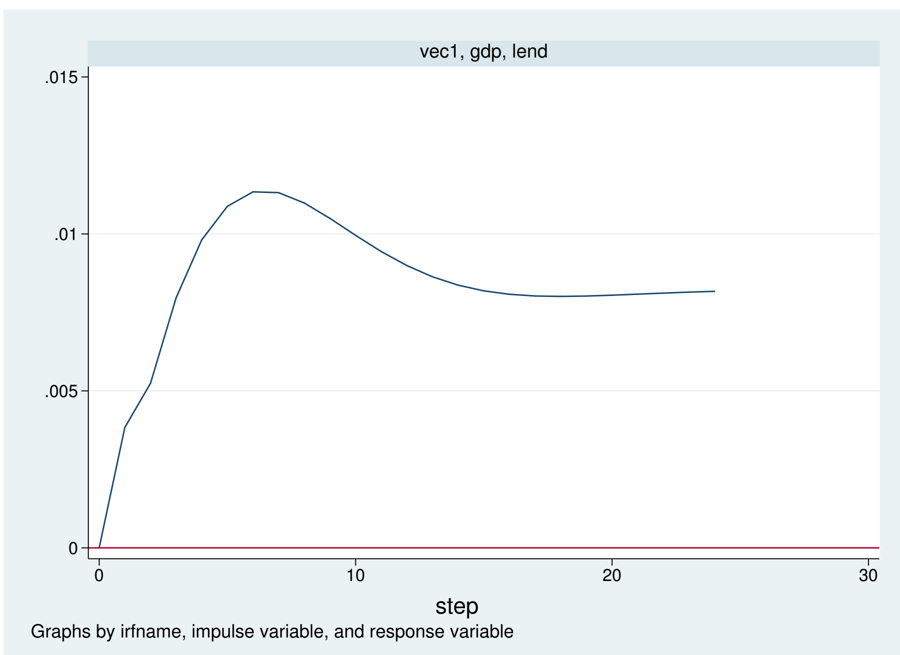

Figure 3.16: IRF of bank lending to GDP shock for the period 1976-1990.

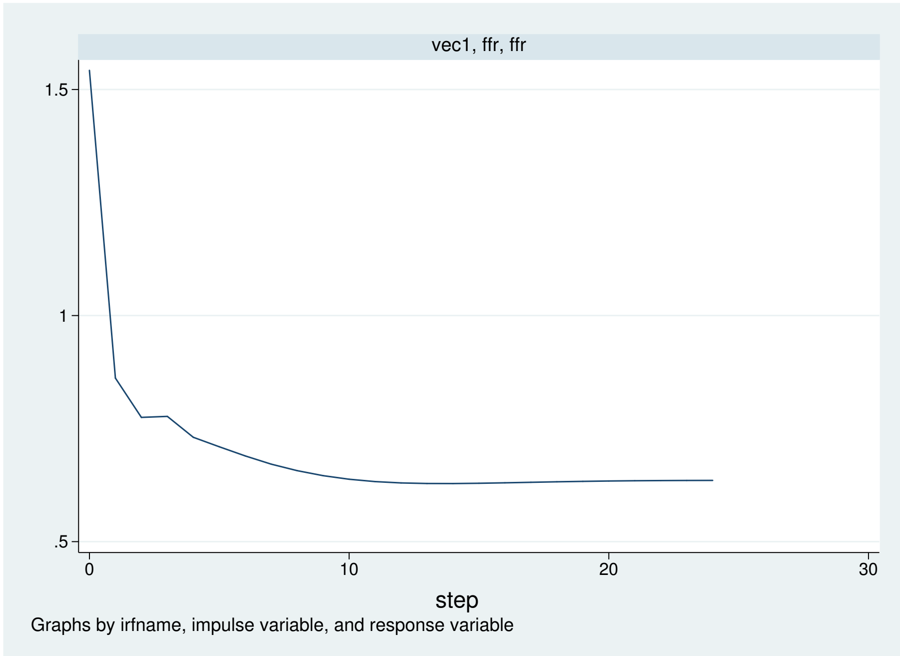

Figure 3.17: IRF of FFR to FFR shock for the pre-1990 period: 1976-1990.

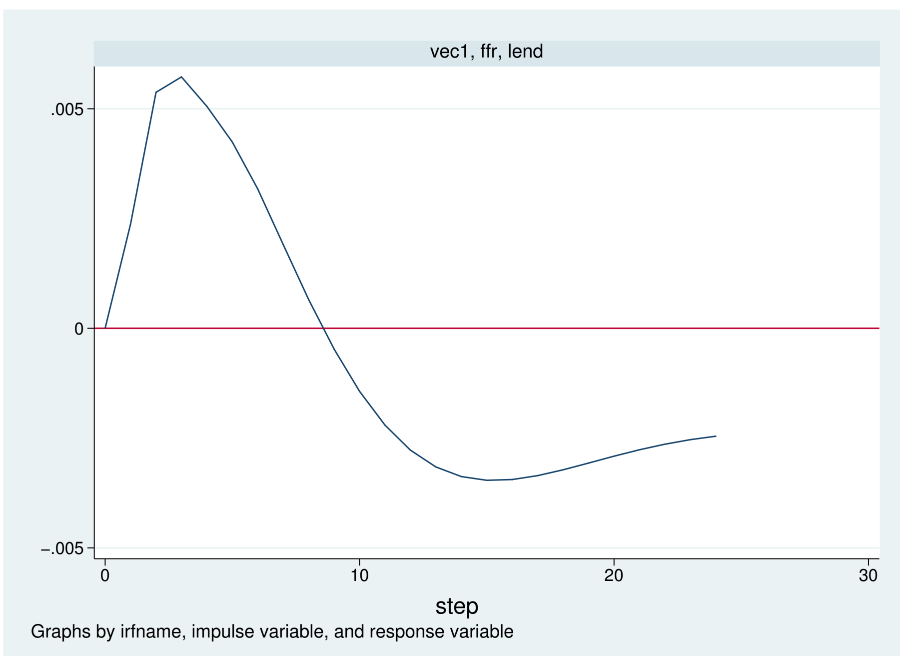

Figure 3.18: IRF of bank lending to FFR shock for the period 1990-2003.

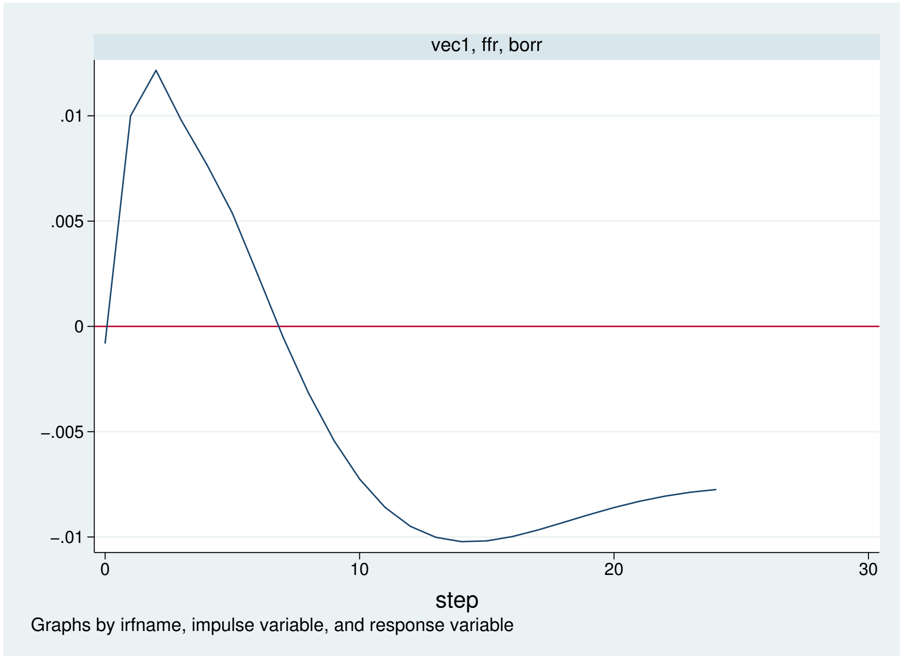

Figure 3.19: IRF of bank borrowing to FFR shock for the period 1990-2003.

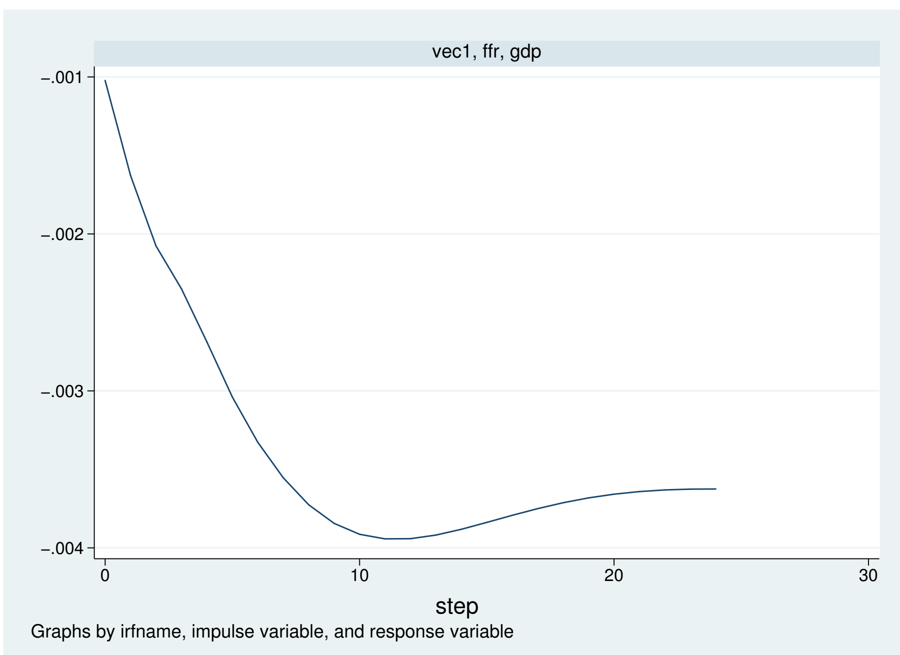

Figure 3.20: IRF of GDP to FFR shock for the post-1990 period: 1990-2003.

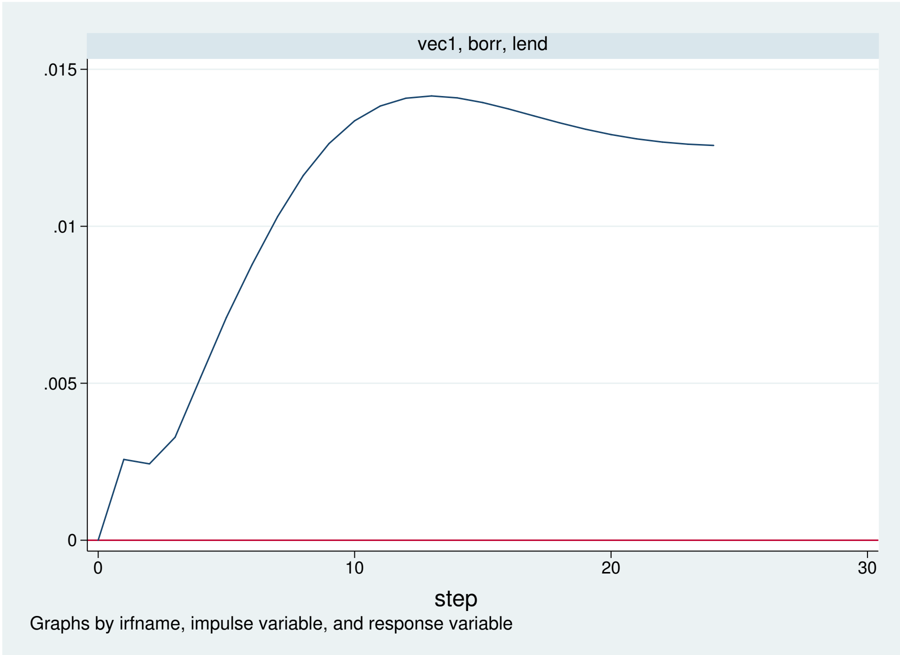

Figure 3.21: IRF of bank lending to bank borrowing shock for the period 1990-2003.

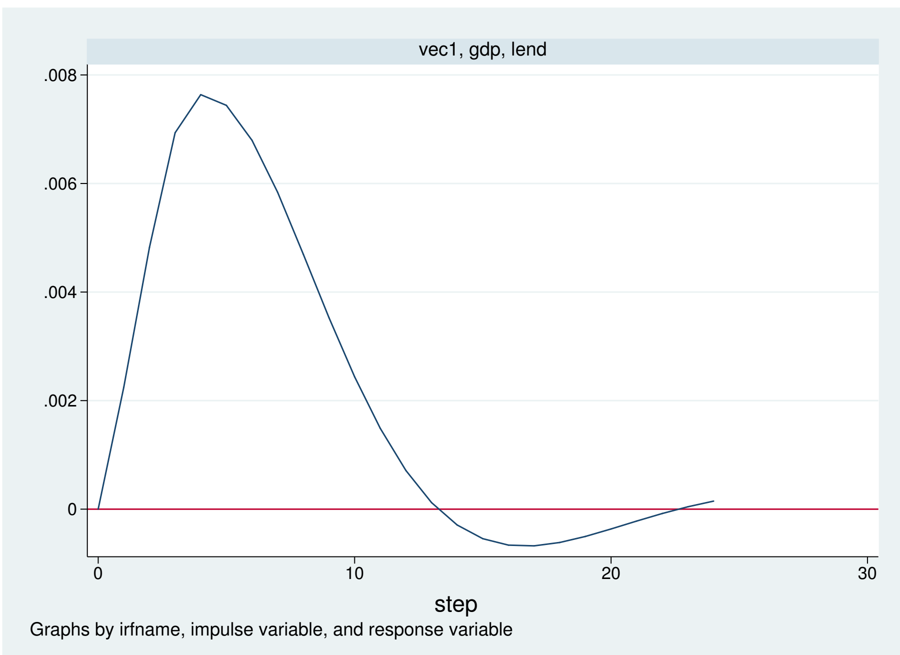

Figure 3.22: IRF of bank lending to GDP shock for the period 1990-2003.

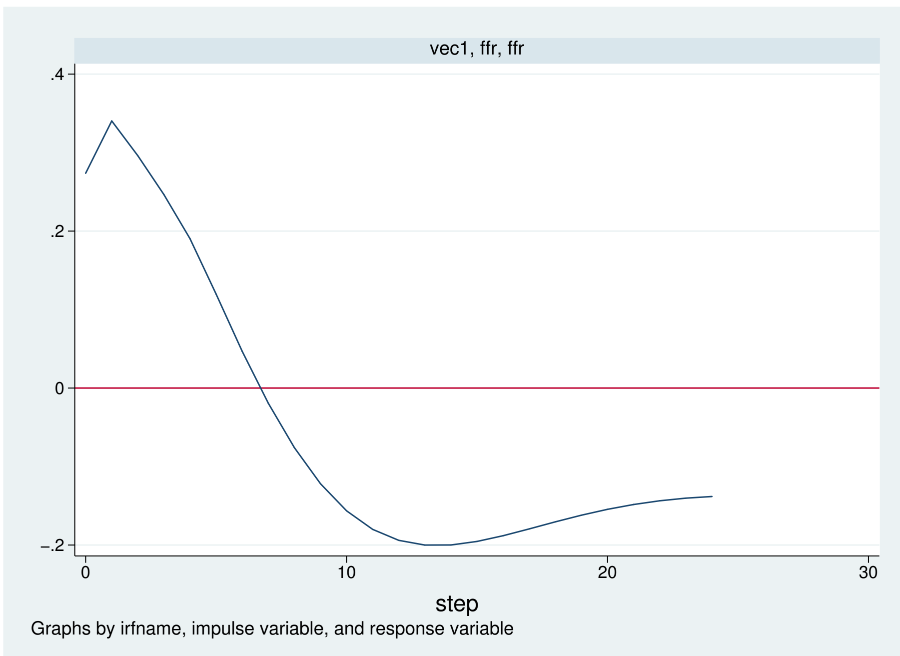

Figure 3.23: IRF of FFR to FFR shock for the post-1990 period: 1990-2003.

Chapter 4

The Differential Response of Bank Portfolios to Monetary Policy

4.1 Research outline

4.1.1 Background

Several studies on the bank lending channel have been conducted at the bank level as opposed to a previous wave of studies using only aggregate data. The aim is to gain more insights into how the differential responses of monetary policy transmission are being propagated through the lending channel when bank-specific characteristics are controlled for. These characteristics vary across the array of studies in this line of research. For instance, Kashyap and Stein (1995) argue that the size of the bank matters in the way monetary policy is transmitted; small banks face more asymmetric information problems on the capital market than large banks do, and consequently find it more difficult to raise non-reservable funds when the Fed tightens interest rates. In another study, Kashyap and Stein (2000) focused on the liquidity of the bank's balance sheet. Within the class of small banks, they find that changes in monetary policy matter more for the lending of those banks with the least liquid balance sheets. Other studies (Peek and Rosengren (1995) and Kishan and Opiela (2000)) suggest that well capitalized banks are more able to raise funds when monetary policy tightens compared to less capitalized banks, using the capital:asset ratio as a proxy. Therefore monetary policy actions are more pronounced through poorly capitalized banks that are forced to cut their loan supply by more than well-capitalized banks. More recently, studies by Campello (2002) and Peek and Holod (mimeo, 2004) provide evidence that banks that are affiliated with publicly traded bank holding companies are more impervious to changes in monetary policy than stand-alone banks of the same size. This paper studies in more detail banks' balance sheets and particularly the different types of loans to detect how monetary policy is transmitted through the asset side of bank balance sheets while controlling for the characteristics that have been previously examined in the literature mentioned above. These loans, as categorized in the Call Reports, are: Real Estate loans, Agriculture loans, Commercial and Industrial (C&I) loans, and Loans to Individuals. It has been noted in the literature, for instance, that large banks do relatively more C&I lending, which is procyclical in nature, and that this makes demand for C&I respond less to a monetary contraction than other loan demands Kashyap and Stein (1994). Another item on the asset side of the balance sheet worth analyzing, along with the response of loans, is investment in securities. Despite the consensus that banks draw on their securities to offset the decrease in the money supply when the Fed tightens, there is no clear cut agreement on the differential response of selling securities by banks of different sizes (or other characteristics).

In Kashyap and Stein (1994), the results are not totally decisive in favor of the proposition that small bank securities holdings are more sensitive to monetary policy; there is also no real evidence to support the converse proposition– that is small bank securities holdings are less sensitive to monetary policy. On the liabilities side, one needs to make a parallel analysis of the response of bank deposits to monetary shocks. The conventional hypothesis is that a tightening in monetary policy does in fact lead to a contraction in the deposits available to both small and large banks (Bernanke and Blinder (1992) and Kashyap and Stein (1994)). In these studies, the authors use the growth rate of nominal "core deposits" as a dependent variable, where core deposits are defined as total deposits less any deposits in denominations greater than $100,000. The reason to exclude these large deposits is because they had been subjected to low reserve requirements and may be used by banks to offset Fed-induced shocks to core deposits (Romer and Romer 1990). Moreover, during the first half of the 1990s the Federal Reserve twice relaxed reserve requirements. In December 1990, the reserve requirements on non-transaction accounts (e.g. large deposits) were completely removed and in April 1993, the reserve requirement for transaction deposits was reduced from 12% to 10%.

4.1.2 Data and econometric strategy

Data are available quarterly in the Call Reports from the Federal Reserve Bank of Chicago since 1976:1. Two difficulties emerge when dealing with this data set. First, the number of banks has gone down dramatically since 1976, declining from around 14000 banks to around 7500 in 2004. A number of these banks were either merged into or acquired by other banks. Others had simply exited the market. To maintain a consistent and balanced panel data set for the same banks, a backward tracking of the existing banks in the last quarter of 2004 was conducted. Each bank is identified by the Federal Reserve Board by an identification number. This tracking process eliminates the banks that have disappeared along the way. Since the number of banks is large, that gives a margin to retain only the banks that have existed for the whole period. The final sample consists of 6188 banks. The second difficulty to be resolved is the fact that reporting formalities have undergone some occasional changes over time, which creates inconsistency in the time series of this data set. Particularly, some of the data definitions were changed in 1984:1. In order to circumvent this problem the sample was cut off at this date, starting 1985:1. Now the data set runs from 1985:1 to 2004:4, a total of 76 quarters. Therefore, the total number of observations sums up to 470,288.

Table (4.1.2) presents brief descriptive statistics for the balance sheets of banks in this sample. Banks are categorized by their assets as small, medium, and large. Banks with assets up to $100 million are classified as small banks and they constitute the big bulk of the sample, 4,370 banks. Banks with assets ranging between 100 and 400 million are classified as medium banks. These are 1,341 such banks in the sample. And lastly, large banks are banks with assets greater than 400 million and there are 477 large banks in the sample. What is remarkable about these statistics is the huge size gap of banks across the three categories. For instance, an average medium bank has 183.51 million in assets whereas an average large bank has 5689.76 million. Reading the rest of the comparative statistics one can notice the following differences in the composition of the balance sheets. Large banks have less securities investment and less transaction deposits than small or medium banks. That explains the larger percentage of C&I lending at large banks compared to other banks.

Table 4.1: Summary Statistics of the Bank Balance sheet

Bank's Assets	Below 100million	101-399	above 400
	All ratios are percentages of total assets		
Number of Banks	4370	1341	477
Total Assets (millions)	41.27	183.51	5680.76
Securities	32.41	28.43	23.01
Total Loans	52.82	59.21	58.81
Real Estate loans	25.18	36.29	30.33
C&I loans	8.63	10.43	13.17
Loans to Individuals	9.18	8.35	9.48
Total Deposits	87.32	85.44	78.02
Transaction Deposits	24.79	23.51	16.84
Large Time Deposits	9.13	10.88	13.19
Other Borrowing	2.18	4.01	5.51
Equity	4.67	9.66	8.92

In addition, the larger proportion of Large Time Deposits at large banks reflects the ability of these banks to raise uninsured funds, what makes them more impervious to monetary policy transmission than other banks. This fact is also supported by a larger proportion of Other Borrowing at large banks.

The main proposed specification to be examined is given by the following equation: [1]

$$\Delta logL_{it} = \alpha_i + \sum_{j=1}^{k} \beta_j \Delta logL_{it-j} + \sum_{j=1}^{k} \mu_j \Delta F_{t-j} + \sum_{j=1}^{k} \gamma_j X_{it-j} \Delta F_{t-j} + \sum_{j=1}^{k} \lambda_j X_{it-j} \quad (4.1)$$
$$+ \sum_{j=1}^{k} \rho_j \Delta logY_{t-j} + \sum_{j=1}^{k} \eta_j \Delta log\pi_{t-j} + \sum_{j=1}^{3} Q_j + \upsilon_i + \varepsilon_{it}$$

where Δ is a difference operator.

L represents various types of loans as mentioned above; real estate, agriculture, $C\&I$, and loans to individuals.

F is the measure of monetary policy proxied by the Federal Funds Rate (FFR).

X represents bank characteristic variable; size, liquidity, and capitalization.

Y is real GDP.

π is inflation as measured by the rate of change of the CPI.

Q_j for quarter dummies to correct for any remaining seasonal trend.

[1] This specification is inspired by a model proposed by a group of researchers at the European Central Bank and later published in 'Monetary Policy Transmission in the Euro-Area' edited by Kashyap A., Angeloni I., and Mojon, B., Cambridge University press, 2003

υ_i is the individual bank effect.
ε_{it} is the error term.
Size, liquidity, and capitalization are given by:

$$Size_{it} = lnA_{it} - \frac{\sum_i lnA_{it}}{N}$$

$$Liquidity_{it} = \frac{l_{it}}{A_{it}} - (\sum_t \frac{\sum_i l_{it}/A_{it}}{N})/T$$

$$Capitalization_{it} = \frac{c_{it}}{A_{it}} - (\sum_t \frac{\sum_i c_{it}/A_{it}}{N})/T$$

A_{it} is total assets as a measure for the bank's size. l_{it} is the liquid assets of the bank measured as the sum of cash and government securities. c_{it} is the capital of the bank. l_{it} and c_{it} are divided by total assets of the bank to obtain liquidity and capitalization ratios. The three criteria above are then normalized with respect to their averages across banks so that they sum to zero over all observations. In the case of size, the normalization is not just over the sample mean over the whole period, but over the means per quarter as well, so the trends in bank size are removed.

Past research emphasized the parameters μ_j and γ_j when examining the existence of the lending channel. Monetary tightening, in most research[2], depresses bank lending more for small, less liquid, poorly capitalized banks. Therefore μ_j is expected to be negative for all banks but less pronounced for large, liquid, and well-capitalized banks. Thus, γ_j is expected to be positive since an increase in X means that the bank is bigger, more liquid, or better capitalized.

GDP growth and CPI are introduced as control variables for macroeconomic activities. CPI had been included as a regressor by some authors when all variables are in nominal terms, as is the case for banks balance sheets (Kashyap and Stein, 1994).

In an alternative specification, bank deposits will be introduced as a dependent variable to determine the differential elasticity of deposits (or 'core deposits') to monetary policy. As mentioned above, there is no decisive conclusion as whether deposits react differently depending on bank characteristics.

[2]An exception perhaps is the case of Spain where the coefficient of monetary policy measure was found to be negligible, Hernando and Martinez-Pages (2001)

Another unresolved issue is whether the effect of monetary policy on bank securities holding depends on bank characteristics. Previous studies show that the response of banks drawing on their securities when the central bank tightens is ambiguous and no conclusive evidence has been reached as how banks of different sizes react differently to changes in monetary policy stance. Lastly, quarterly dummy variables are introduced to control for any remaining seasonal effects.

The aim of this paper is to disaggregate banks' loan portfolios as opposed to pooling all loans in one regression. By analyzing the differential response of various types of loans while controlling for bank size and other characteristics, one can unveil some of the unresolved issues in the lending channel theory. Most important is to determine the elasticities of different types of loans to monetary policy.

4.1.3 Difference GMM versus system GMM estimatation technique

The presence of a lagged dependent variable term in equation(4.1) necessitates the differencing of the variables since otherwise the least-squares dummy variable (LSDV) estimator is inconsistent under the fixed effects formulation for the case of small T and large N (Anderson and Hsiao, 1982). Then if the ε_{it} are not serially correlated, either L_{it-k} or ΔL_{it-k} are valid instruments for the regressor ΔL_{it-k+1}. Arellano (1989) finds that for simple dynamic error components models the estimator that uses the levels, L_{it}, is preferred to the one that uses the differences, ΔL_{it}. For example, for $t = 3$, L_{i1} is a valid instrument for ΔL_{it-1} and for $t = 4$, both L_{i2} and L_{i1} are valid instruments. Therefore, for period T the set of valid instruments becomes $(L_{i1}, L_{i2}, \cdots, L_{iT-2})$.

Using these instruments, one can obtain the Arellano-Bond (1991) preliminary one-step consistent estimates and two-step GMM estimates. The one-step and two-step estimators are asymptotically equivalent if ε_{it} are independent and homoscedastic across units and over time. The consistency of the Arellano-Bond GMM estimator is critically based on the assumption that $E(\Delta\varepsilon_{it}\Delta\varepsilon_{it-2}) = 0$, that is on the lack of second-order serial correlation in the first-differenced residuals. In addition, this estimation is based on the assumption that there are unobservable individual effects in the data. One can test for the presence of these individual effects in dynamic panel data models using the test of Holtz-Eakin (1988) which utilizes the additional restrictions on sample moments implied by the absence of individual effects.

The first-difference GMM estimation technique is discussed in Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998). The following is a brief description of the model.

Consider the auto-regressive model $AR(1)$ with unobserved individual-specific effects

$$y_{it} = \alpha y_{it-1} + \eta_i + \nu_{it} \qquad |\alpha| < 1 \tag{4.2}$$

$$for \qquad i = 1, \cdots, N \qquad and \qquad t = 2, \cdots, T$$

where

$$\eta_i + \nu_{it} = u_{it}$$

has the standard error components structure:

$$E[\eta_i] = 0, \qquad E[\nu_{it}] = 0, \qquad E[\eta_i \nu_{it}] = 0$$

$$for \qquad i = 1, \cdots, N \qquad and \qquad t = 2, \cdots, T$$

assuming that the transient errors are serially uncorrelated

$$E[\nu_{it}\nu_{is}] = 0 \qquad for \qquad i = 1, \cdots, N \qquad and \qquad s \neq t$$

These assumptions imply that the moment restrictions are

$$E[y_{it-s}\Delta\nu_{it}] = 0 \tag{4.3}$$

$$for \qquad t = 3, \cdots, T \qquad and \qquad s \geq 2$$

where the number of these moments is

$$m = 0.5(T-2)(T-1)$$

This can be written as

$$E[Z_i^{'}\Delta\nu_i] = 0$$

where Z_i is the $m \times (T-2)$ matrix given by

$$Z_i = \begin{bmatrix} y_{i1} & 0 & 0 & \cdots & 0 & \cdots & 0 \\ 0 & y_{i1} & y_{i2} & \cdots & 0 & \cdots & 0 \\ . & . & . & \cdots & . & . & . \\ 0 & 0 & 0 & \cdots & y_{i1} & \cdots & y_{iT-2} \end{bmatrix} \tag{4.4}$$

and $\Delta\nu_i$ is the $(T-2)$ vector $(\Delta\nu_{i3}, \Delta\nu_{i4}, \cdots, \Delta\nu_{iT})'$. The moment restrictions imply the use of lagged levels dated $t-2$ and earlier as instruments for the equations in first-differences. That yields a consistent estimation of α as $N \to \infty$ and T fixed.

The Generalized Method of Moments estimator based on these moment conditions minimizes the quadratic distance $\Delta\nu' Z W_N Z' \Delta\nu$ for the weight matrix W_N. This gives the GMM estimator for α as

$$\hat{\alpha} = (\Delta y_{-1}' Z W_N Z' \Delta y_{-1})^{-1} \Delta y_{-1}' Z W_N Z' \Delta y \tag{4.5}$$

where $\Delta y_i'$ is the $(T-2)$ vector $(\Delta y_{i3}, \Delta y_{i4}, \cdots, \Delta y_{iT})$.

$\Delta y_{i,-1}'$ is the $(T-2)$ vector $(\Delta y_{i2}, \Delta y_{i3}, \cdots, \Delta y_{iT-1})$, and Δy and Δy_{-1} are stacked across individuals in the same way as $\Delta\nu$.

In general the optimal weights are given by

$$W_N = \left(\frac{1}{N}\sum_{i=1}^{N} Z_i' \widehat{\Delta\nu_i} \widehat{\Delta\nu_i'} Z_i\right)^{-1} \tag{4.6}$$

where $\widehat{\Delta\nu_i}$ are the residuals from an initial consistent estimator. This was refered to by Arellano-Bond(1991) as the *two-step* GMM estimator. This estimator is asymtotically efficient in the class of estimators based on the linear moment conditions (4.3) (Hansen (1982) and Chamberlain(1987)).

However, Blundell and Bond (1998) found this first-difference GMM estimator to have poor finite sample properties especially when the lagged levels of the series are only weakly correlated with first-differences and their lags, so the instruments available for the first-differenced equation are weak. Simulation results show that this estimator may be subject to a large downward finite-sample bias. This suggests that some caution may be warranted before relying on this method particularly when the lagged dependent variable is included as a regressor. Blundell and Bond proposed that the inclusion of current or lagged values of the regressors in the instrument set will improve the behavior of the first-difference GMM estimator. The following subsection will lay out this model as suggested by Blundell and Bond (1998).

System GMM

Consider the following additional condition

$$E(\eta_i \Delta y_{i2}) = 0 \qquad for \quad i = 1, \cdots, N \tag{4.7}$$

Condition (4.7), combined with the assumptions of the first-differenced model, yields $T-2$ additional linear moment conditions

$$E(u_{it} \Delta y_{it-1}) = 0 \tag{4.8}$$

$$for \quad i = 1, \cdots, N \qquad and \quad t = 3, 4, \cdots, T$$

These moments allow the use of the lagged first-differences of the series as instruments for equations in levels. Then a GMM estimator is constructed based on both sets of moment restrictions (4.3) and (4.8). Now the system GMM model uses $(T-2)$ equations in first-differences and $(T-2)$ equations in levels, corresponding to periods $3, \cdots, T$ for which instruments are observed. The matrix of instruments for this system is given by

$$Z_i^* = \begin{bmatrix} Z_i & 0 & 0 & \cdots & 0 \\ 0 & \Delta y_{i2} & 0 & \cdots & 0 \\ 0 & 0 & \Delta y_{i3} & \cdots & 0 \\ . & . & . & \cdots & . \\ 0 & 0 & 0 & \cdots & \Delta y_{iT-1} \end{bmatrix} \tag{4.9}$$

Given condition (4.7), The complete set of second-order moment conditions available can be expressed as

$$E(Z_i^* u_i^*) = 0 \tag{4.10}$$

where $u_i^* = (\Delta\nu_{i3}, \cdots, \Delta\nu_{iT}, u_{i3}, \cdots, u_{iT})'$

In addition, condition (4.7) requires that the first-differences Δy_{it} are not correlated with the individual-specific effects η_i, allowing lagged first-differences to be used as instruments in the levels equations.

The derivation of this system GMM estimator is discussed in full detail in Blundell and Bond (1998). Their simulations that compare the finite sample performance of the first-differenced and system GMM estimators, show that there is a dramatic reductions in finite sample bias and gains in precision from exploiting these additional moment conditions. Before discussing the estimations results, here is a look at the correlations among the variables of the model (4.1.3).

Table 4.2: Correlation Coefficients

	Correlations among the variables of the model												
	Total Loans	Real Estate	Agriculture	C&I	Individ.	T. Deposits	Equity	CPI	GDP	FFR	Liquidity	Capital	Size
Total Loans	1.0000												
Real Estate	0.9388	1.0000											
Agriculture	0.1701	0.0341	1.0000										
C&I	0.8957	0.7975	0.1642	1.0000									
Individuals	0.8851	0.8286	0.0219	0.7875	1.0000								
Total Deposits	0.9678	0.9009	0.1534	0.8729	0.8736	1.0000							
Equity	0.9178	0.8478	0.1704	0.8122	0.8163	0.9575	1.0000						
CPI	0.2749	0.3333	0.1098	0.1700	0.1571	0.2316	0.2846	1.0000					
GDP	0.2827	0.3362	0.1097	0.18442	0.1644	0.2349	0.2877	0.9705	1.0000				
FFR	-0.1299	-0.1700	-0.0591	-0.0575	-0.0636	-0.1208	-0.1495	-0.5649	-0.4472	1.0000			
Liquidity	-0.0044	-0.0197	0.0338	-0.0054	0.0343	0.1301	0.1926	-0.0022	-0.0020	0.0023	1.0000		
Capital	0.4086	0.3957	0.1505	0.3125	0.3103	0.4292	0.5746	0.5285	0.5337	-0.2764	0.2679	1.0000	
Size	0.9238	0.8375	0.1341	0.8505	0.8539	0.9680	0.9209	-0.0102	-0.0090	0.0049	0.1397	0.3191	1.0000

The correlation between inflation and loans is positive, which reflects the fact that loans are expressed in nominal terms. To investigate the data more carefully, I plot the change in CPI versus the change in total loans. Graph (4.1) shows how these two variables move in tandem contemporaneously. However, allowing 3 or 4 lags of inflation the effect on lending has dramatically changed, graph (4.2). This simple example reflects the validity of the dynamic nature of the model and particularly for modeling lending which has a contractual dimension such that the changing of the macroeconomic environment will have a lag effect on loans.

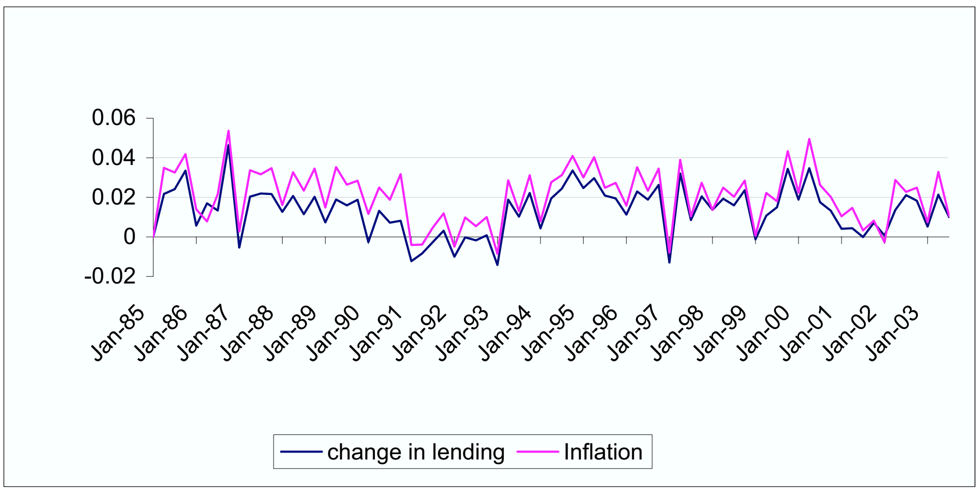

Figure 4.1: Change in lending versus inflation.

4.2 Estimation results

The estimation results are shown in tables (4.8) - (4.14) of appendix 4.B.[3] All estimates are significant at the 1% level of significance except for the figures where a superscript is placed

[3] In these tables standard errors for the sum of the coefficients of the four quarters are computed based on the square root of the following equation:

$$Var(x_1 + x_2 + x_3 + x_4) = var(x_1) + var(x_2) + var(x_3) + var(x_4) + 2cov(x_1x_2) + 2cov(x_1x_3)$$
$$+2cov(x_1x_4) + 2cov(x_2x_3) + 2cov(x_2x_4) + 2cov(x_3x_4).$$

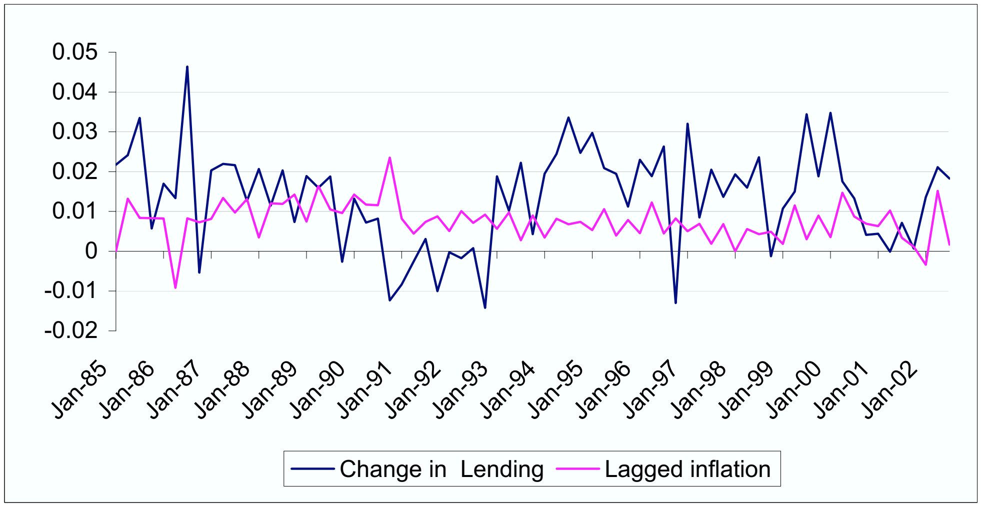

Figure 4.2: Change in lending versus lagged inflation.

to indicate that the significance level is either at 5% or 10% level.[4] The general equation for lending, where no bank charactersitic is taken into consideration, reveals that the sum of coefficients on the monetary policy proxy for four quarters is -0.0066351. This figure is close to the one obtained by Kashyap and Stein (2000) as mentioned in the previuos chapter (-0.0046 for small banks, or -0.0040 for middle size banks). It is negative as expected and in fact it is more significant than this mere coefficient if we realize that FFR in this equation is not expressed in logs unlike the other variables. The true interpretation of this coefficient stems from the following derivation.

$$\Delta(ln(y_t)) = \alpha + \beta(\Delta x_t) + error$$

$$ln(y_t) - ln(y_{t-1}) = \alpha + \beta(\Delta x_t)$$

$$ln(\frac{y_t}{y_{t-1}}) = \alpha + \beta(\Delta x_t)$$

$$\frac{y_t}{y_{t-1}} = e^{\alpha+\beta(\Delta x_t)}$$

$$y_t = y_{t-1} \cdot e^{\alpha+\beta(\Delta x_t)}$$

$$\frac{\partial y_t}{\partial x_t} = \beta y_t$$

[4]The estimation of the system GMM model is largely based on the algorithm developed by David Roodman, Center for Global Development, Washington, DC.

the elasticity term is given by:

$$\frac{\partial y_t}{\partial x_t} \cdot \frac{x_t}{y_t} = \beta x_t$$

given the average value of FFR as 5.427, the elasticity of bank lending to a change in monetary policy is approximately 0.036% decline for every 1 % increase in FFR. Or to put another way, a rise of 10% in FFR leads to a 0.36% fall in lending. That is , if FFR rises from 4% to 4.4%, lending would fall by about 0.36%. [5]

The effect of inflation on lending seems more pronounced but not always as expected. Since all loans are expressed in nominal terms, one would expect a positive correlation of growth in loans with inflation. However, this is not the case for total loans. A rise of 1% in inflation causes nominal loans to drop by 0.06% on average. Examining the various types of loans reaction to inflation, real estate loans and agriculture loans respond significantly positively as expected. Nominal C&I and consumer lending respond negatively, however. The effect of GDP is highly significant. A 1% rise in real GDP leads to a 2.62% increase in lending.

Now breaking total loans into subcategories sheds light on some details about lending practices by banks. For example, real estate loans responsiveness to FFR is given by $-0.0088(5.427) = -0.04775$. The real estate loan response to inflation is as expected, the coefficient of inflation is significantly positive. The effect of inflation is given by 1.29047. Thus, for a 1% rise in inflation, nominal real estate loans rise by 1.3%. As for GDP, the figure is 2.26%.

For agriculture loans, the reaction to FFR is almost negligible. This may be due to the fact that most of the agriculture loans are subsidized by the government in addition to the seasonal borrowing from the Fed to agriculture banks. The response to inflation is given by 0.624% for a 1% increase in inflation. These loans are highly seasonal as explained by significant quarterly dummy variables. The effect of GDP is relatively less pronounced for this type of lending compared to the other categories. A 1% rise in GDP would lead to a

[5] To put this figure in light of other work, recently two similar panel data studies have been conducted, one by David Peek and Dmytro Holod (university of Kentucky, memo 2004) where the effect of policy (as a change in FFR) on lending was found to be -0.57% for publicly traded banks and -0.82% for non-publicly traded banks (Peek and Holod p.39). The other study, by David Vera (UCSD, dissertation 2004), using IV estimation, the effect was -0.10% for all banks and -0.07% for small banks (Vera, p.48).

0.48% rise in agriculture lending.

Commercial and Industrial loans' elasticity to change in FFR is given by $-0.0132196(5.427) = -0.0717$. Their reaction to inflation is significantly negative, -1.26, and that for real GDP is 3.33. The fact that C&I nominal loans are negatively correlated with inflation may reflect the fact that these loans are not highly procyclical, they respond sluggishly to changes in monetary policy.

Consumer loans or loans to individuals have a FFR elasticity of $-0.0156(5.427) = -0.0845$. The response to inflation is -0.0817 and that for real GDP is 1.567.

That was the general view of the different types of bank lending and their reactions to policy. In the following subsections bank characteristics like size, liquidity, and capital will be examined in line with the macro economic variables, FFR , CPI, and GDP.

4.2.1 The size effect

Not surprisingly, there is a positive correlation between a bank's size and its lending volume. The aim of this analysis here is to dismantle the size effect across the various types of loans. First, the macro effect of bank size is given by $0.96 + 0.00871(5.427) = 1.007$, where again, 5.427 is the average rate of FFR. That is a 1% growth in bank's assets would be translated into an equal 1% growth in its lending. Now what is the differential response of various types of loans to the change in monetary policy?

For real estate and for C&I loans the effect of FFR is almost the same as for total loans, again it is about 1%. However, for agriculture and consumer loans the figure is less significant and about 0.789. So as the bank grows by 1% its agriculture lending grows by only 0.78%. That is, this type of loan grows less then proportionally with assets compared to C&I or real estate loans as the bank grows larger. The same story applies to consumer lending, the growth rate of loans to individuals grows by a similar figure of 0.77% as bank assets grow by 1%. To put it differently, banks mobilize their loans portfolio in favor of C&I and real estate loans as they become larger. On the liabilities side of the bank balance sheet, the relationship between total deposits growth and assets growth is again one (1.0049%) and that of equity is 0.836%. As the bank raises equity by 1% its lending is expected to rise by 0.83%.

Now to infer the answer about the effect of bank's size on the responsiveness to monetary policy we need to assume different values for bank size. The average of bank's size the way calculated here is zero because it is the deviation of a bank's average assets from the average of total assets of all banks. For this sample, banks have the following size percentile distribution. For large banks, those in the 75th percentile the average size is 0.576. The effect

Table 4.3: Percentile distribution for banks assets

Percentiles				
10%	25%	50%	75%	90%
-1.36223	-0.818488	-0.155376	0.57621	1.4378

of FFR on lending for these banks is calculated as $-0.00613+0.008714(0.576) = -0.00111$ and for small banks or average banks in the 50th percentile, the effect is $-0.00613 + 0.008714(-0.155376) = -0.00748$. Again for these figures to be conformable with log lending, they have to be multiplied by the average value of FFR. Therefore, the effect of monetary policy on large banks is given by $-0.00111(5.427) = -0.006$ and for small banks is $-0.00748(5.427) = -0.0406$. This obviously supports earlier findings that the effect of monetary policy is more pronounced for small banks than for large ones.
Repeating this derivation for other types of loans yields the following results (table (4.4)).

Table 4.4: Effect of monetary policy on small and large banks

Sum of coefficients of $\sum_{j=1}^{4} \mu_j \Delta F_{t-j}$ and $\sum_{j=1}^{4} \gamma_j Size_{it-j} \Delta F_{t-j}$		
	Small Banks	Large Banks
Real Estate loans	-0.05145	-0.0011375
Agriculture loans	-0.0093328	-0.0088976
C&I loans	-0.09356	-0.0363638
Loans to Individuals	-0.11610	-0.034802

The gap between the responses of small and large banks are mostly pronounced for real estate loans where small banks' real estate lending seem to be highly elastic to a tightening in monetary policy compared to the response of large banks. This may reflect the ability of large banks to raise funds that small banks have no access to. Looking at other loans, the gap appears to be mild between the two types of banks. For instance, the reaction of agriculture loans to policy is almost the same for both types. That for C&I and loans to individuals is 2 to 3 times larger for small banks compared to large banks.

4.2.2 The liquidity effect

The effect of liquidity on the lending ability of banks varies with the definition of liquidity. It is common to proxy liquidity by the ratio of cash plus securities over total assets. Following this conventional wisdom produces a negative effect, in most cases, of liquidity on lending which sounds counter-intuitive. However, given the fact that securities dominate cash in the liquidity ratio, the whole effect is dominated by securities, therefore as the bank diversifies its portfolio, the more it invests in securities the less funds will be available for loans and vice versa, hence the negative relationship particularly if a large part of securities is invested in long-term maturity bonds. In order to isolate the dominating effect of securities, the cash to assets ratio was taken as the sole measure for liquidity. In this case the effect is positive and varies in significance.

The cumulative effect of liquidity on bank lending seems not to be a decisive factor on the ability of banks to extend additional loans. The effect on total lending is 0.023% for 1% increase in liquidity.[6] The liquidity effect is especially least pronounced for real estate loans where the long-run coefficient is 0.000946, is almost negligible. This may be well explained by the duration gap analysis of banks through matching long-term loan contracts (i.e. mortgage contracts) with long-term liabilities (i.e. saving deposits) which are not considered as liquid assets. Liquidity, however, seems relatively more pronounced for agriculture loans with a long-run coefficient of 0.042%. Also bank liquidity is important to consumer loans, the impact is 0.0257% and less important to C&I loans where the effect is 0.0078%.

It ia useful to compare our results to the Kashyap and Stein (2000) study discussed in chapter 2, where they obtained the following results when they ran equation (2.5) for C&I loans: for small banks the sum of the coefficient ϕ is -0.0151, 0.0097 for middle size banks, and 0.1175 for large banks. These are the effects of FFR on the liquidity of the bank.[7]

The analysis of liquidity requires a more detailed scrutiny over the composition of banks

[6] This figure is obtained by adding the coefficient on liquidity to the interaction term: $0.4638 - 0.0817(5.427) = 0.023$.

[7] Kashyap and Stein (2000), p.417, table 3, panel A.

investment in securities. Using 3-month or 6-month Treasury bills for securities, in addition to cash, will surely yield a better proxy for liquidity than pooling all securities together. One difficulty with this issue is the inconsistency of the time series data of the Call Reports. As mentioned earlier in this chapter, this data set was subject to occasional transformations on reporting. It is not impossible to correct these misalignments though and it will be examined in future research.[8]

4.2.3 The capital effect

Bank capital is measured by equity. We expect highly capitalized banks to be less sensitive to a change in FFR and therefore have less volatile lending. The results shown in the appendix confirm this proposition. For all types of loans the effect of capital on lending is positive and significant. The long-run effect on total loans is given by a coefficient of 3.26. For a 1 % rise in equity, lending in general soars 3.26%. As the percentage changes in both sides of the bank's balance sheet increase or decrease proportionally, this 1% rise in equity may enhance the bank's ability to attract more deposits or to raise more borrowing, so the liabilities side will have a multiplication effect by this increase in equity. Therefore, total lending will increase by more than the increase in equity while both sides of the bank's balance sheet stay in balance.

For real estate loans this figure is 3.24%. For agriculture loans it is 2.52%. For consumer loans the figure is 2.43% and 2.64% for C&I loans. As was shown in the bank balance sheet statistics, table(4.1.2), real estate loans make up about 40% of bank total assets, which explains why equity is significantly correlated with real estate loans as compared to other loans.

A closer look at moderately versus well capitalized banks gives an even clearer picture. Similar to the analysis in the previous section on the size effect, the percentile distribution for bank's capital is given below. (table(4.5))

[8] For the period 1976-1983, Total Securities was the sum of U.S. Treasury Securities(RCFD0400)+ U.S. Government Agency and Corporation Obligations(RCFD0600)+ Obligations of State and Political Subdivisions(RCFD0900)+All Other Bonds, Stocks, and Securities (RCFD0380). For the period 1984-1993, Total Securities was the sum of Total Investment Securities(RCFD0390)+Assets Held in Trading Accounts(RCFD2146). For the period 1993-present it is the sum of Securities Held to Maturity (RCFD1754) and Securities available for sale(RCFD1773). As it is noted, for the period 1993 and after one can build a more accurate measure for bank's liquidity by considering only RCFD1773 account but before that period the data is more involved.

The effect of monetary policy on moderately versus well capitalized banks is given in table

Table 4.5: Percentile distribution for banks capital

Percentiles				
10%	25%	50%	75%	90%
0.008219	0.017844	0.031814	0.052619	0.080619

(4.6). For moderately capitalized banks the 50th percentile was used, whereas for the well

Table 4.6: Effect of monetary policy on average vs. well capitalized banks

Sum of coefficients of $\sum_{j=1}^{4} \mu_j \Delta F_{t-j}$ and $\sum_{j=1}^{4} \gamma_j capital_{it-j} \Delta F_{t-j}$		
	Moderately capitalized	Well capitalized
Total loans	-0.3840	-0.3590
Real Estate loans	-0.24818	-0.23097
Agriculture loans	-0.0810	-0.07737
C&I loans	-0.6570	-0.607713
Loans to Individuals	-0.2534	-0.23079

capitalized banks the 90th percentile was used. It is obvious that well capitalized banks are more impervious to monetary policy change than other banks but the gap between the two categories is not as wide as in the case of bank size. Bank capital does not seem to play a pivotal role in the bank's responsiveness to change in monetary policy as bank size does.

In conclusion, bank size and capital proved to be significant to bank lending. Bank liquidity is of less importance to lending but again that may be due to the way the liquidity proxy is measured, as mentioned above.

4.3 The question of monetary policy asymmetry.

It has been argued that business cycles are characterized by 'sharp' troughs and 'round' peaks (McQueen and Thorley (1993); Acemoglu and Scott (1997)). In addition, monetary policy has a more pronounced effect on the economy when it raises the interest rate than when it pushes it down. This proposition is re-examined here in light of various types of lending. To test for this policy asymmetry, a policy dummy variable is incorporated in equation (4.1) as follows

$$\Delta logL_{it} = \alpha_i + \sum_{j=1}^{4}\beta_j \Delta logL_{it-j} + \sum_{j=1}^{4}\mu_{1j}\Delta F_{t-j} \times D + \sum_{j=1}^{4}\mu_{2j}\Delta F_{t-j} \times (1-D)$$
$$+ \sum_{j=1}^{4}\rho_j \Delta logY_{t-j} + \sum_{j=1}^{4}\eta_j \Delta log\pi_{t-j} + \sum_{j=1}^{3} Q_j + \upsilon_i + \varepsilon_{it} \qquad (4.11)$$

where D is the dummy variable for change in FFR. $D = 1$ when the change in FFR is positive. This equation was applied to the four types of loans considered so far in addition to total loans.

The results of specification (4.11) are shown in appendix 4.B in table (4.15).

If asymmetry is indeed the case, one would predict the coefficients of μ_1 and μ_2 to be different and, moreover, μ_1 to be larger in absolute term than μ_2 in general. Formal hypothesis tests results, shown in table (4.7), indicate that the null hypothesis $\mu_1 = \mu_2$ is always rejected. The magnitude of this asymmetry as it varies depending on the types of loans is discussed below.

For total loans $\mu_1 = -0.0462$ and $\mu_2 = -0.0222$. Again for these figures to be translated into elasticity terms, they are multiplied by the average value of FFR (5.427), so they become $\mu_1 = -0.2507$ and $\mu_2 = -0.1204$. That is while an increase in the Federal Funds Rate of 1% leads to depressing lending by 0.25%, an equal percentage fall in FFR would actually raise lending by only 0.12%, half the effect.

This asymmetric effect varies in magnitude when we further look at lending details. In all other types of loans the asymmetric effect is, as suggested in the literature, more upward sensitive than downward. One exception is real estate loans. First, all other loans are discussed.

As for agriculture loans the asymmetric effect is more pronounced on the upward side, where a 1% rise in FFR decreases this type of lending by 0.345% compared to 0.124% increase in lending if FFR falls. Here this upward asymmetry is about 2.5 times.

C&I loans react in the same direction but with a higher magnitude. The asymmetry here is -0.3808 upward compared to -0.052039 downward . More precisely, the response of commercial and industrial loans to a rise in FFR is 7 times larger in scale than to a fall. Loans to individuals have a similar reaction to total loans, $\mu_1 = -0.0423$ versus $\mu_2 = -0.0226$. It is almost double the pressure for consumer loans triggered by FFR rise.

Table 4.7: Hypothesis testing for policy asymmetry

Equation for:	Testing the hypothesis $\mu_1 = \mu_2$ in eqaution (4.11)	
Total Loans	$F(1, 456349) = 41.10$	$Prob. > F = 0.000$
Real Estate loans	$F(1, 450608) = 30.44$	$Prob. > F = 0.000$
Agriculture loans	$F(1, 369656) = 134.26$	$Prob. > F = 0.000$
C&I loans	$F(1, 367840) = 100.18$	$Prob. > F = 0.000$
Loans to Individuals	$F(1, 441241) = 18.08$	$Prob. > F = 0.000$
Total Deposits	$F(1, 445163) = 45.71$	$Prob. > F = 0.000$
Total Equity	$F(1, 445190) = 511.15$	$Prob. > F = 0.000$

4.3.1 Investigating why real estate loans respond differently

Back to real estate loans, the actual upward effect is -0.015846 whereas the actual downward effect is -0.11923. This asymmetric effect goes against the reaction of all other lending. That is a decline in FFR sparks more real estate lending than a rise does depress it by about 7 times. To further investigate this issue, time series data on real estate lending was examined in a VAR context along with the other macroeconomic variables used in the main model in this paper for the panel data. Time series data are available since 1955. Then quarterly data of all variables are employed for the period 1955-2004, a total of 200 observations. The following basic VAR equation was tested:

$$V_t = \theta_0 + \sum_{i=1}^{4} \Phi_i V_{t-i} + \epsilon_t \tag{4.12}$$

where V is a vector of the following variables: real estate lending, $FFR \times D$, $FFR \times (1-D)$, CPI, and real GDP. D again is one when the change in FFR is positive. All variables are first-differenced and in logs. Only the results of the real estate equation are shown to examine the asymmetry effect as discussed above. The results are shown in table (4.16) of appendix 4.B.

The long-run coefficient on $FFR \times D$ is -0.0165545 compared to -0.02692 for $FFR \times (1 - D)$. This finding supports the conclusion, reached by panel data analysis above, that the asymmetric effect of monetary policy on real estate loans is in the opposite direction to that of other loans. Here for this long time series data, a 1% increase in FFR leads to 0.0165 % decline in real estate loan compared to 0.027% increase in these loans when the Fed eases. To further investigate the reversed response of real estate loans to monetary policy, and apart from VAR specification as suggested above, a simple multivariate regression was conducted using the same variables as described above and given by:

$$\Delta S_t = \alpha_0 + \sum_{i=1}^{4} \Delta \mathbf{X}_{t-i} + \epsilon_t \tag{4.13}$$

where S is for real estate loans and $\mathbf{X}$ contains the same variables described in equation (4.12). The results of this estimation are shown in table (4.17). The aggregate effect of a monetary policy tightening is given by -0.0037028 and that of a monetary policy ease is given by -0.0062116. Here again real estate loans are less responsive to an increase in FFR than to a decline.

4.4 Conclusion

A system-GMM technique is employed to analyze the effect of monetary policy on various types of lending at the bank level. The panel data run quarterly from 1985 to 2004 for 6188 American banks. Three bank characteristics are highlighted: bank size, liquidity and capitalization. Similar to the usual findings in the literature that large, more liquid, and well capitalized banks are more impervious to changes in monetary policy than other banks, this study provides a cross section analysis of bank characteristics and various types of loans. Real estate loans, agriculture, commercial and industrial, and consumer loans are analyzed. The size of the bank is found to be most crucial for real estate lending, where small banks are much more sensitive to changes in the federal funds rate compared to large banks. The effect is comparatively less pronounced for C&I and consumer lending and it is almost the same for both types of banks when it comes to agriculture lending. The effect of the capitalization of the bank on the response to changes in monetary policy is found to be equally significant for well capitalized versus adequately capitalized banks. However, the effect of bank's liquidity is found to be ambiguous, where more liquid banks are more impervious to policy changes only for agriculture and consumer lending.

Finally, the question of monetary policy asymmetry is examined. As expected, monetary policy has more effect on bank lending when it tightens than when it eases interest rates. This is found to be the case for all types of loans except for real estate loans, where a decline of FFR entices more real estate lending than a rise.

Appendix 4.A

Note on overidentifying restrictions in GMM: the Sargan test.

An instrumental variable must satisfy two requirements; first, it must be correlated with the endogenous variable, and, second, it must be orthogonal to the error process. Since the instrumental variable in both difference and system GMM are merely the lag of the differenced endogenous variable or the lag of the level, the correlation requirement is warranted. If the number of instruments excluded from the equation exceeds the number of included endogenous variables, then the question of the instruments independence from an unobservable error process will arise. The standard test for testing the validity of the moment conditions used in GMM estimation is the Sargan test of overidentification restrictions (Sargan, 1958). Sargan statistic is given by [9]

$$Sargan\ \ statistic = \frac{1}{N}\widehat{\Delta u}' Z W_N Z' \widehat{\Delta u}$$

Sargan statistic is χ^2 distributed. However, the distribution of Sargan statistic is no longer χ^2 in the presence of heteroscedasticity. Before checking for heteroscedasticity in the current panel data, Sargan test was always rejected. That is the probability that Sargan statistic is larger than χ^2 was always zero. The the model was ran with the same instrumental variables but with smaller sample (i.e. a number of samples was examined ranged from 600 to 4000 banks instead of 6188) every time the sample is smaller Sargan statistic gets closer to the no-rejection area until the sample is 1000 or smaller, the p value was approaching one. This realization asserts that the instruments are valid and orthogonal to the errors process, and conform with the proposition that in the presence of heteroscedasticity Sargan statistic will take a distribution other than χ^2 and in a model containing a very large set of instruments, such a test may have very little power (Baum, Schaffer, and Stillman (2002)) . A test for panel heteroscedasticity test was conducted and proved to be true that the error process is indeed heteroscedastic. Then a two-step estimation procedure was applied to correct for heteroscedasticity.[10]

Another finding in the GMM literature that supports this proposition suggests that Sargan

[9] Another test wich is commonly used in the context of GMM is J statistic of Hansen (1982).

[10] The advantage of GMM over IV lies in the fact that if heteroscedasticity is present, the GMM estimator is more efficient than the simple IV estimator. In case of no heteroscedasticity the two estimators are asymptotically identical.

test, in many cases, leads the econometrician to accept misspecified models with sometimes severely biased parameter estimates as a result. Dahlberg, Johansson, and Tovmo (2002) re-estimated Arellano and Bond (1991) employment equations while deliberately imposed additive and multicative measurement errors in the employment and wage variables. They found that Sargan test always accepted the misspecified models while they ended up with biased parameter estimates. They concluded that "in case of measurement errors in either the dependent or any of the independent variables, Sargan test will quite likely accept a misspecified model and end up with biased results".

Appendix 4.B

Table 4.8: Total Loans

	Bank Characteristics (X_{it})			
	None	Size	Liquidity	Capitalization
	S-GMM	S-GMM	S-GMM	S-GMM
$\sum_{j=1}^{4} \mu_j \Delta F_{t-j}$	-0.0066351	-0.0061307	0.052794	-0.0738106
	(0.0003871)	(0.0002429)	(0.0031409)	(0.0029957)
$\sum_{j=1}^{4} \eta_j \Delta log\pi_{t-j}$	-0.062315	-0.026581[11]	-0.055477	-0.0197805[12]
	(0.0182649)	(0.0114598)	(0.0181986)	(0.0162597)
$\sum_{j=1}^{4} \rho_j \Delta logY_{t-j}$	2.623118	2.569209	2.61848	1.917231
	(0.0172783)	(0.0108409)	(0.0172154)	(0.0154231)
$\sum_{j=1}^{4} \gamma_j X_{it-j} \Delta F_{t-j}$		0.0087147	-0.081716	0.09488
		(0.0001342)	(0.0042864)	(0.0037041)
$\sum_{j=1}^{4} \lambda_j X_{it-j}$		0.9604902	0.463818	3.78144
		(0.0012808)	(0.0269818)	(0.0225465)
$AR(1) : Pr > z$	0.0000	0.0000	0.0000	0.0000
$AR(2) : Pr > z$	0.7667	0.5924	0.8101	0.9959
$AR(3) : Pr > z$	0.8369	0.7878	0.9018	0.7683
$AR(4) : Pr > z$	0.4435	0.5446	0.6990	0.3925

Table 4.9: Real Estate Loans

	Bank Characteristics (X_{it})			
	None	Size	Liquidity	Capitalization
	S-GMM	S-GMM	S-GMM	S-GMM
$\sum_{j=1}^{4} \mu_j \Delta F_{t-j}$	-0.0088068	-0.0075058	0.047633	-0.047758
	(0.000467)	(0.0003691)	(0.0039524)	(0.0038561)
$\sum_{j=1}^{4} \eta_j \Delta log\pi_{t-j}$	1.290474	1.337389	1.29702	1.14654
	(0.0220544)	(0.01743)	(0.0220738)	(0.0206417)
$\sum_{j=1}^{4} \rho_j \Delta logY_{t-j}$	2.26305	2.203298	2.2629	1.75728
	(0.0208523)	(0.0164801)	(0.0208706)	(0.0195653)
$\sum_{j=1}^{4} \gamma_j X_{it-j} \Delta F_{t-j}$		0.012666	-0.07752	0.064932
		(0.0002083)	(0.0053998)	(0.0047711)
$\sum_{j=1}^{4} \lambda_j X_{it-j}$		0.930942	0.421539	3.591448
		(0.0020205)	(0.033866)	(0.0288594)
$AR(1) : Pr > z$	0.0000	0.0000	0.0000	0.0000
$AR(2) : Pr > z$	0.3812	0.3391	0.3663	0.3344
$AR(3) : Pr > z$	0.3582	0.5193	0.3378	0.6205
$AR(4) : Pr > z$	0.0424	0.0428	0.0561	0.0558

Table 4.10: Agriculture Loans

	Bank Characteristics (X_{it})			
	None	Size	Liquidity	Capitalization
	S-GMM	S-GMM	S-GMM	S-GMM
$\sum_{j=1}^{4} \mu_j \Delta F_{t-j}$	-0.000589[13]	-0.0017027[14]	-0.13787	-0.0153655[15]
	(0.0007715)	(0.0007431)	(0.0068023)	(0.0074165)
$\sum_{j=1}^{4} \eta_j \Delta log\pi_{t-j}$	0.624435	0.722855	0.626913	0.5843679
	(0.0364781)	(0.0348945)	(0.036453)	(0.0386566)
$\sum_{j=1}^{4} \rho_j \Delta logY_{t-j}$	0.4802088	0.467211	0.478354	0.0042696[16]
	(0.034519)	(0.0330163)	(0.0344956)	(0.0366395)
$\sum_{j=1}^{4} \gamma_j X_{it-j} \Delta F_{t-j}$		0.0001097[17]	-0.190211	0.0137465
		(0.0004528)	(0.0093636)	(0.0091977)
$\sum_{j=1}^{4} \lambda_j X_{it-j}$		0.789634	1.072458	2.601007
		(0.0044767)	(0.0583708)	(0.0557706)
$AR(1) : Pr > z$	0.0000	0.0000	0.0000	0.0000
$AR(2) : Pr > z$	0.3743	0.0884	0.5116	0.2841
$AR(3) : Pr > z$	0.0000	0.0008	0.000	0.000
$AR(4) : Pr > z$	0.0000	0.3253	0.000	0.000

Table 4.11: Commercial and Industrial Loans

	Bank Characteristics (X_{it})			
	None	Size	Liquidity	Capitalization
	S-GMM	S-GMM	S-GMM	S-GMM
$\sum_{j=1}^{4} \mu_j \Delta F_{t-j}$	-0.0132196	-0.0149999	-0.0152518[18]	-0.1269794
	(0.0007208)	(0.0006385)	(0.0064087)	(0.0077471)
$\sum_{j=1}^{4} \eta_j \Delta log\pi_{t-j}$	-1.261121	-1.17692	-1.25125	-1.421888
	(0.0306381)	(0.0271241)	(0.0305447)	(0.030064)
$\sum_{j=1}^{4} \rho_j \Delta logY_{t-j}$	3.336698	3.254835	3.325854	2.910911
	(0.0298834)	(0.0264558)	(0.0297989)	(0.0295203)
$\sum_{j=1}^{4} \gamma_j X_{it-j} \Delta F_{t-j}$		0.0144088	0.0392557	0.1860649
		(0.0004028)	(0.0087645)	(0.0100659)
$\sum_{j=1}^{4} \lambda_j X_{it-j}$		0.938586	-0.204952	1.63727
		(0.0038389)	(0.057138)	(0.0652721)
$AR(1) : Pr > z$	0.0000	0.0000	0.0000	0.0000
$AR(2) : Pr > z$	0.2520	0.3379	0.3127	0.2571
$AR(3) : Pr > z$	0.9140	0.9533	0.9163	0.9851
$AR(4) : Pr > z$	0.0157	0.0448	0.0224	0.0257

Table 4.12: Loans to Individuals

	Bank Characteristics (X_{it})			
	None	Size	Liquidity	Capitalization
	S-GMM	S-GMM	S-GMM	S-GMM
$\sum_{j=1}^{4} \mu_j \Delta F_{t-j}$	-0.0156089	-0.0181215	-0.0383918	-0.0494171
	(0.0004771)	(0.0004258)	(0.0041906)	(0.004393)
$\sum_{j=1}^{4} \eta_j \Delta log\pi_{t-j}$	-0.0817114	-0.0082727[19]	-0.0786881	-0.2691918
	(0.0225659)	(0.0201303)	(0.0225527)	(0.0236454)
$\sum_{j=1}^{4} \rho_j \Delta logY_{t-j}$	1.567173	1.486071	1.565848	1.224608
	(0.0213123)	(0.0190122)	(0.021305)	(0.022374)
$\sum_{j=1}^{4} \gamma_j X_{it-j} \Delta F_{t-j}$		0.0204878	0.0742859	0.0854625
		(0.0002502)	(0.0057348)	(0.0054335)
$\sum_{j=1}^{4} \lambda_j X_{it-j}$		0.6676191	-0.3774943	1.965479
		(0.0024072)	(0.0358998)	(0.0328396)
$AR(1) : Pr > z$	0.0000	0.0000	0.0000	0.0000
$AR(2) : Pr > z$	0.2696	0.2941	0.2476	0.2742
$AR(3) : Pr > z$	0.7357	0.8824	0.7773	0.6963
$AR(4) : Pr > z$	0.0029	0.0334	0.0056	0.0025

Table 4.13: Total Deposits

	Bank Characteristics (X_{it})			
	None	Size	Liquidity	Capitalization
	S-GMM	S-GMM	S-GMM	S-GMM
$\sum_{j=1}^{4} \mu_j \Delta F_{t-j}$	-0.014970	-0.0131676	-0.1110022	0.047108
	(0.0003158)	(0.0001184)	(0.002717)	(0.002612)
$\sum_{j=1}^{4} \eta_j \Delta log\pi_{t-j}$	0.1205046	0.2359319	0.1257334	0.1684232
	(0.0149038)	(0.0055835)	(0.014831)	(0.0142537)
$\sum_{j=1}^{4} \rho_j \Delta logY_{t-j}$	1.795569	1.674736	1.791361	1.075547
	(0.0140972)	(0.0052814)	(0.01404)	(0.0135181)
$\sum_{j=1}^{4} \gamma_j X_{it-j} \Delta F_{t-j}$		0.0029068	-0.1734241	-0.0710743
		(0.000069)	(0.003716)	(0.0032289)
$\sum_{j=1}^{4} \lambda_j X_{it-j}$		0.98927	0.9478415	3.587565
		(0.000652)	(0.0232945)	(0.0196205)
$AR(1) : Pr > z$	0.0000	0.0000	0.0000	0.0000
$AR(2) : Pr > z$	0.9831	0.8423	0.9491	0.9829
$AR(3) : Pr > z$	0.4711	0.9724	0.5049	0.4709
$AR(4) : Pr > z$	0.2516	0.9279	0.1526	0.2487

Table 4.14: Equity

	Bank Characteristics(X_{it})			
	None	Size	Liquidity	Capitalization
	S-GMM	S-GMM	S-GMM	S-GMM
$\sum_{j=1}^{4} \mu_j \Delta F_{t-j}$	-0.016326	-0.0155647	0.1517406	0.0478996
	(0.0003074)	(0.0001772)	(0.0026437)	(0.0022251)
$\sum_{j=1}^{4} \eta_j \Delta log\pi_{t-j}$	0.26865	0.352054	0.2724863	0.2856264
	(0.0145084)	(0.0083595)	(0.0144484)	(0.0121831)
$\sum_{j=1}^{4} \rho_j \Delta logY_{t-j}$	2.101357	2.007463	2.094416	1.154675
	(0.0137229)	(0.0079071)	(0.0136664)	(0.0115532)
$\sum_{j=1}^{4} \gamma_j X_{it-j} \Delta F_{t-j}$		-0.0082793	-0.2315298	-0.0715
		(0.0001033)	(0.0036158)	(0.0027503)
$\sum_{j=1}^{4} \lambda_j X_{it-j}$		0.881246	1.277733	4.787357
		(0.0009733)	(0.0226217)	(0.0167068)
$AR(1) : Pr > z$	0.0000	0.0000	0.0000	0.0000
$AR(2) : Pr > z$	0.7356	0.5726	0.6871	0.5419
$AR(3) : Pr > z$	0.6930	0.7250	0.6694	0.1407
$AR(4) : Pr > z$	0.0773	0.0172	0.0880	0.9912

Table 4.15: Testing Monetary Policy Asymmetry for Bank Lending

	Variables			
Equation for:	$\sum_{j=1}^{4} \mu_{1j} \Delta F_{t-j} \cdot D$	$\sum_{j=1}^{4} \mu_{2j} \Delta F_{t-j} \cdot (1-D)$	$\sum_{j=1}^{4} \eta_j \Delta log \pi_{t-j}$	$\sum_{j=1}^{4} \rho_j \Delta log Y_{t-j}$
Total Loans	-0.0462104	-0.0222528	0.0324134[20]	2.590171
	(0.0026442)	(0.0017868)	(0.0168498)	(0.0168118)
Real Estate Loans	-0.0029256[21]	-0.0219711	1.441801	2.183787
	(0.0031933)	(0.0021576)	(0.0203569)	(0.020302)
Agriculture Loans	-0.0635408	-0.0228938	0.6263133	0.4930556
	(0.0052777)	(0.0035681)	(0.0337804)	(0.0337157)
C&I Loans	-0.0701762	-0.0095891	-1.688072	3.741094
	(0.0038729)	(0.003335)	(0.0249577)	(0.0265005)
Loans to Individuals	-0.0423201	-0.0226576	-0.4178334	1.770531
	(0.0032741)	(0.0022089)	(0.0208611)	(0.0207857)

Table 4.16: VAR Representation for Real Estate Loans

	Lags			
Equation for	$L1$	$L2$	$L3$	$L4$
Real Estate loans	0.5735194	0.0723534	0.1334758	-0.0525714
	(0.0721471)	(0.0819861)	(0.083627)	(0.0718644)
$FFR \times D$	-0.0009581	-0.000829	-0.0004582	-0.0008051
	(0.001162)	(0.0012464)	(0.0012645)	(0.0012324)
$FFR \times (1 - D)$	-0.0014317	-0.0016418	-0.0017437	-0.0001433
	(0.00116088)	(0.0011188)	(0.0012527)	(0.000987)
CPI	0.2511299	0.0856045	-0.2022586	-0.1326513
	(0.1447027)	(0.1424569)	(0.1432996)	(0.1504604)
GDP	0.1967715	0.1127449	0.11771	0.079852
	(0.0741557)	(0.08031)	(0.080730)	(0.0833038)

Table 4.17: A multivariate regression for Real Estate Loans

	Lags			
Variable	$L1$	$L2$	$L3$	$L4$
Real Estate loans	0.401712	0.16559	0.0768753	-0.118634
	(0.087006)	(0.101469)	(0.108898)	(0.091419)
$FFR \times D$	-0.0003861	-0.0010833	-0.0016451	-0.0005884
	(0.001409)	(0.0015245)	(0.0015418)	(0.0014962)
$FFR \times (1 - D)$	-0.0006072	-0.0026844	-0.001843	-0.001077
	(0.0013429)	(0.001361)	(0.0015217)	(0.0011912)
CPI	0.408429	0.1880334	-0.235982	-0.300934
	(0.175708)	(0.1728138)	(0.1746453)	(0.180785)
GDP	0.2222865	0.1918926	0.1679166	0.1348709
	(0.0911932)	(0.0969934)	(0.0977422)	(0.100796)
α_0	0.0043934			
	(0.0027585)			
R^2	0.4465			

Chapter 5

Conclusion and Thoughts on Future Research

This dissertation examines the role of bank structure on the effectiveness of monetary policy. First, I review the literature and conclude that the question of monetary policy and its conduits to the economy is undoubtedly an open and dynamic question to which yet there is no quantified absolute answer. That was the subject of chapter 2.

Second, I test the aggregate effect of monetary policy on bank lending given the unprecedented evolution in the structure of the banking industry that started in the 1990s. Using time series data for U.S. banks, chapter 3 examined the varying effect of monetary policy on bank lending for the period 1976-2003. It is found that as the banking industry gets more concentrated (through mergers and acquisitions), the effect of monetary policy transmission (through open market operations) is being mitigated. That was the result of the deregulation of the banking sector that took place in the first half of the 1990s which led to a substantial amount of consolidation in the banking assets.

To check the robustness of this finding, the data were split into two periods; 1976-1990 and 1990-2003. Consistent with the initial finding of this paper, the effect of monetary policy on bank lending was found to be more pronounced for the period prior to the deregulation era (1976-1990).
Third, I investigate the lending evidence at the bank level. That is, how important is the cross-sectional differences in the way that banks with varying characteristics respond to policy shocks. That was the subject of chapter 4. A system-GMM technique is employed

to analyze the effect of monetary policy on various types of lending at the bank level. The panel data run quarterly from 1985 to 2004 for 6188 U.S. banks. Three bank characteristics are highlighted: bank size, liquidity and capitalization. Similar to the usual findings in the literature that large, more liquid, and well capitalized banks are more impervious to changes in monetary policy than other banks, this study provides a cross section analysis of bank characteristics and various types of loans. Real estate loans, agriculture, commercial and industrial, and consumer loans are analyzed. The size of the bank is found to be most crucial for real estate lending, where small banks are much more sensitive to changes in the federal funds rate compared to large banks. The effect is comparatively less pronounced for C&I and consumer lending and largely disappears when it comes to agriculture lending. The effect of the capitalization of the bank on the response to changes in monetary policy is found to be equally significant for well capitalized versus adequately capitalized banks. However, the effect of bank liquidity is found to be ambiguous, where more liquid banks are more impervious to policy changes only for agriculture and consumer lending.
Finally, the question of monetary policy asymmetry is examined. As expected, monetary policy has more effect on bank lending when it tightens than when it eases interest rates. This is found to be the case for all types of loans except for real estate loans, where a decline of FFR entices more real estate lending than a rise in FFR.

Where to go from here

Perhaps the most puzzling question about the response of bank lending to the stance of monetary policy is the so-called the identification problem of loan supply versus loan demand, as discussed in an earlier chapter. This certainly will be a target of research for monetary economists in the years to come. As it was proven to be difficult to be resolved empirically, tackling this question theoretically will be a challenging and promising exercise for future work.
In addition, two more subjects deserve special attention from monetary and financial researchers: firstly, what is know as " global money", and secondly, the implications of the Basel accords on the way banks conduct their business.

- The globalization of money. One of the underlying themes of this dissertation was that banks, particularly large ones, are becoming more capable of raising funds beyond their conventional sources. That makes them more impervious to monetary policy shocks. Analyzing the impact of monetary policy in any open economy without controlling for the global aspect of capital movement is incomplete. For example, in today's world, massive amounts of money flow into the U.S. markets from overseas, exerting downward pressure on long-term interest rates. Banks have wider access to international money in times when the Federal Reserve bank is exerting pressure to slow down borrowing. Therefore, formulating monetary policy in the age of globalized money is becoming a very difficult task. That indeed was one of the conclusions drawn from this work, although the attribution was not directly linked to global money.

  In fact, Alan Greenspan, the chairman of the Fed admitted in the International Monetary Conference in Beijing, on June 6, 2005, that "the economic and financial world is changing in ways that we still do not fully comprehend."[1] Ben Bernanke explained recently that "the glut arose as emerging-market nations shifted from net borrowers to net lenders in the capital markets while industrialized nations such as Germany and Japan continued to accumulate savings. One result was a downward push on global rates."

  These observations highlight the importance of the global movement of capital on the performance of monetary authorities around the world and their attempts to exercise power over their economies. This is the direction in which I would like to expand and build my research on.

- The Basel accords and their implications. This is an obvious response from the international banking communities, represented by the Bank for International Settlements, to the challenges mentioned above. While trying to enhance the standards of banking operations in Europe and abroad, the Basel accord imposes a set of measures on banks balance sheet that banks have to meet. These measures expand over a spectrum of rules regarding capital adequacy, liquidity, risk exposure and risk mitigation. All these rules, which will be enacted in the

[1] Businessweek, June 27, 2005 p.29.

summer of 2006, will impact the way monetary policy intervenes in the economy. What are the costs of compliance? How are small or poorly capitalized banks going to survive? Are we going to see a new and additional wave of bank mergers and acquisitions? Are monetary authorities going to gain or lose power over the variables they wish to control? These are merely a few questions that are yet to be answered.

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