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Credit boom or credit crunch?

– A general-to-specific approach to modeling bank lending

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Abstract

In this thesis factors affecting bank lending in the United States are sought for. For this purpose variables that can be derived from prevailing theories and previous research are used. These include for example the interest rate, the nonperforming loans ratio and the capital to asset ratio. The data series cover the time period 1988Q1-2009Q3. Regression models in a-general-to-specific framework together with other econometric methods are applied to attain the results. The nonperforming loans ratio followed by the interest rate, excess reserves to total reserves and house prices are found to be the most important variables in explaining bank lending. Another finding is that banks allocate more loans to loan categories that are less risky than the average bank loan.

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1 Introduction

> ***"credit crunch**. A period where lenders are unwilling to extend or renew advances to existing or potential borrowers. Such conditions increase the likelihood of default by borrowers since they may find it impossible to obtain new funds"*[1]

In 2008 Wall Street and the American economy experienced the biggest crisis since the Great Depression. In September 2008 the investment bank Lehman Brothers went bankrupt and financial turmoil and worries spread. The Financial crisis resulted in $700 billion bailout of the financial industry in October 2008 and a $787 billion stimulus measure in February 2009 adopted by the federal government.[2] The Federal Reserve, whose chairman Ben Bernanke has published academic research related to the Great Depression, bank lending and the credit view, took extreme measures in defeating the recession. These measures included dropping the interest rate to zero, lending funds to investors and companies, buying up treasury bonds and purchasing unwanted or troubled assets.[3] As Bernanke urged for a swift passage of the $700 billion rescue of the financial sector in order to restore credit to households and businesses it is obvious that the Federal Reserve believes that bank credit plays an important role in the business cycle. The central bank's extreme actions also prove that dropping the interest rate alone was not sufficient to fight the recession and the "credit crunch".[4]

Bernanke (1983) concludes that the depth and the length of the Great Depression cannot be fully explained by a decrease in money or money supply as Monetarists, especially Milton Friedman and Anna Schwartz, accentuated. However, Bernanke has showed that an augmentation of the Monetarists' model with bank loans and proxies of the financial crisis improves the explanatory power of the depth and the length of the depression.[5] A study by Lown and Morgan (2006) indicates that a tightening of bank lending standards leads to lower output and lower supply of bank loans. In the paper it is argued that every recession in the United States between 1967 and 2000 except for one has been preceded by tightening standards. Credit standards are also found

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[1] http://www.oxfordreference.com.ludwig.lub.lu.se/views/ENTRY.html?subview=Main&entry=t181.e1820, Accessed 2010-01-12

[2] http://topics.nytimes.com/top/reference/timestopics/subjects/c/credit_crisis/index.html, Accessed 2009-10-28

[3] http://money.cnn.com/2009/10/08/news/economy/bernanke_fed_balance_sheet/index.htm, Accessed 2009-11-15

[4] http://www.bloomberg.com/apps/news?pid=20601170&sid=anu37z.PbcLA, Accessed 2009-11-12

[5] Bernanke B. (1983), pp. 257-276

to be more informative about future lending than are loan rates.[6] In an IMF working paper Bayoumi and Melander (2008) confirm that credit and credit standards are linked to the macro economy.[7] Kashyap, Lamont, Stein (1994) conclude that financial factors influence inventory movements. They also point out that financial constraints are much more binding during tight money or recessionary periods.[8] Apart from the studies just mentioned, there are many other papers that confirm a linkage between credit and the economy.

If credit or money influence macroeconomic performance, why are these not used to guide monetary policy? Monetary targeting, i.e. targeting the growth rate of money supply measures such as M1 and M2, has been used by many central banks around the world, for example the Federal Reserve in the USA. However, the relationship between money, price level, velocity of money and output stated in the quantity equation broke down which led to a formal abandonment of monetary targeting in 1987. The breakdown of the quantity equation came to be known as the "velocity decline" as it appeared as if the velocity of money declined in the equation. Economists could not explain where the money went. This episode was named "the case of the missing money" by the Princeton economist Stephen Goldfeld. Instead of monetary aggregates more attention has been paid to inflation by central banks since then.[9] Some authors have found the credit-output relationship more stable than money-output. Bernanke and Blinder (1988) report that the credit-demand function is more stable over time than the money-demand function, at least since 1979.[10] B. Friedman (1983) concludes that the information about subsequent movements in nonfinancial activity contained in total net credit is at least comparable to that contained in the M1 money supply measure. In other words, total net credit is at least as good an indicator of economic activity as money supply.[11] The velocity decline could according to some authors, Palley(1995), Pollin and Schaberg (1998), Field (1984) and Furey (1993), have occurred because of an increase of non-GDP transactions in the money supply. Put differently, financial and real estate transactions are not included in GDP so if these non-GDP transactions increase or decrease as a share of money, or credit, the relationship between money and output will not hold. Werner (2005) has estimated net credit used for GDP transactions, which resulted in a stable quantity equation for Japan. He also claims that the long recession in Japan in the

[6] Lown C. and Morgan D. (2006), pp. 1-23
[7] Bayoumi T. and Melander O. (2008), pp. 1-27
[8] Kashyap K., Lamont O. and Stein J. (1994), pp. 565-592
[9] http://www.federalreserve.gov/newsevents/speech/bernanke20061110a.htm, Accessed 2009-11-23
[10] Bernanke B. and Blinder A. (1988), pp. 435-439
[11] Friedman B. (1983), pp. 117-148

1990's was a mistake of the BOJ (bank of Japan), which failed to make Japanese banks extend credit.[12]

There is a growing interest in the treatment of bank assets (credit) in macroeconomic analysis. The proponents of the so called "credit view" criticize Keynesian, Monetarist and Classical approaches for their one-sided attention, if any, to bank deposits or money supply. Money, unlike credit, is by the adherents of the credit view believed to underestimate binding constraints of real activity and thereby also economic fluctuations. Some of the most notable authors of the credit view are Bernanke, Blinder, B. Friedman and Stiglitz. Although this approach is rather new, credit-based economic theories can be traced back to Wicksell and Schumpeter. There are different perspectives of the credit view. One of them is credit rationing. In this view markets do not clear because of asymmetric information about risks and returns. As a result of this banks ration credit.[13]

1.1 Formulation of problem

As we now have seen there are many interesting articles and papers that link credit and output. Credit is therefore an important building block of the business cycle, at least in the credit view. It is therefore interesting to investigate why credit fluctuates or, in other words, what determines bank lending. This is re-formulated into the scientific question of this thesis:

- Which factors determine bank lending?

1.2 Purpose and delimitation

The purpose of this thesis is to investigate which factors determine bank lending. The target group of the study is students of economics, the banking sector, financial regulators or anyone interested in finance and macroeconomics. The thesis is delimited to bank lending in the USA during the period 1988Q1-2009Q3.

[12] Werner R. (2005), pp. 1-341
[13] Trautwein H-M. (2000), pp. 155-183

2 Prior research

One of the most influential papers of the credit view is the work by Bernanke and Blinder (1988) which presents the IS-LM model augmented with bank loans and bonds. The IS-LM model is developed through a model for bank lending constraints when only loans and bonds are considered. Finally money and credit demand are estimated, in which the bank prime rate and the three month Treasury bill rate are significant.[14]

In a report by the RBI (Reserve Bank of India) the determinants of bank credit during the period 1996-2006 are modeled econometrically. As a structural break appears to have occurred in the beginning of 2003, the data is divided into two sub periods which are modeled separately. The empirical results indicate that the interest rate, lendable resources and the level of NPAs (nonperforming assets) have been the major forces behind bank credit in the first sub period. In the second sub period lendable resources, the level of NPAs and asset prices defined as the index of house rentals were significant. The conclusion is that the effect of interest rates on credit demand was overshadowed by increasing wealth during the second sub period. Bank credit also tends to grow pro-cyclically as the output gap (GDP de-trended by the HP-filter) has a significant positive coefficient for both sub periods.[15]

Barajas, Luna and Restrepo (2008) have carried out a study in which they analyze bank behavior and banks' reactions to macroeconomic shocks in Chile 1989-2006. In order to find out whether certain macroeconomic factors and banking variables (de-trended by a HP-filter) lead or lag the business cycle, Granger causality tests are performed. In addition to that, a VAR model (Vector Autoregressive Model) is used to estimate impulse response functions to compute elasticities. The conclusion is that bank loans are pro-cyclical and generally lag the GDP cycle. However, demand deposits and the nonperforming loan ratio of consumer loans from local and retail banks were found to lead the cycle. Nonperforming loans exhibit countercyclical movements whereas demand deposits are pro-cyclical. The CAR (capital adequacy ratio), banks' liquid assets and financial investments are countercyclical. This shows that banks may restrict the supply of loans and maintain financial investments during a recession.[16]

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[14] Bernanke B. and Blinder A. (1988), pp. 435-439
[15] Reserve Bank of India (2007), pp. 148-149
[16] Barajas A., Luna L. and Restrepo J.E. (2008), pp. 21-56

In a paper by Wu, Chang and Selvili (2003) the link between nonperforming loans, real estate prices and the banking sector in Taiwan is examined. To obtain the results Granger causality tests are applied in both a VAR (Vector Autoregressive Model) and a VEC (Vector Autoregressive Error correction Model) framework. Finally, structural and reduced form regressions are estimated. Wu, Chang and Selvili conclude that increasing levels of nonperforming loans can be caused by risky lending behavior of banks. High levels of nonperforming loans can in turn make banks adopt more restrictive real estate lending policies, which cause a slump in the real estate market. Hence, the findings of the paper suggest that reducing the nonperforming loan ratio has a positive influence on the real estate sector and the banking system. [17]

Goodhart, Hofmann and Segoviano (2006) investigate bank regulation and macroeconomic fluctuations. Through simulations of CAR (Capital Adequacy Ratio), by three different approaches (Standardized, IRB and ICRM), they conclude that Basel II is pro-cyclical and could lead to banks reducing credit during recessions and increasing credit in good times. The reason for this is that the CAR (Capital Adequacy Ratio), especially when measured by the IRB approach, is countercyclical and may encourage banks to shift its credit portfolio to higher-quality or higher rated credits during recessions. This could exacerbate capital fluctuations. The authors point out that the Basel I framework reinforced the 1991/1992 recession in the USA. Rolling regressions show that rising property prices significantly increase bank lending for seven out of ten countries in the study after financial liberalizations. It is argued that financial liberalization relaxes the borrowing constraints of the private sector. A positive productivity shock leads to an increase in the value of collateralizable assets such as property. This gives rise to higher lending, which in turn fuels economic activity and lending, which increases borrowing capacity through collateralized asset prices and so on. This boom leads to a bust when eventually all variables converge back to their steady-state levels.[18]

Another study by Kashyap and Stein (2004) confirms the pro-cyclicality of Basel II. The capital requirements are estimated by the KMV credit rating approach and S&P credit ratings. It is shown that KMV is more pro-cyclical than the S&P ratings. A suggestion by the authors is the use of business cycle indicators to determine capital requirements. For example, whenever the GDP growth falls below a chosen threshold one might drop the CAR from 8 to 6 percent.

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[17] Wu W-C., Chang C-O. and Selvili Z. (2003), pp. 43-62
[18] Goodhart C., Hofmann B. and Segoviano M. (2006), pp. 3-37

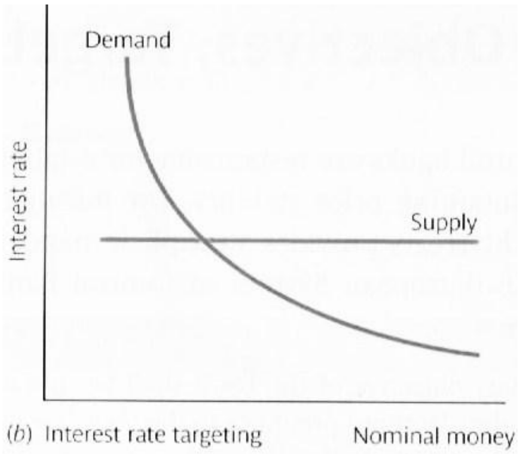
BIS (Bank for International Settlements) has published a study by Mohanty, Schnabel and Garcia-Luna (2006), in which the causes of bank lending fluctuations in emerging economies are sought for. A panel data regression encompassing several countries is used for this purpose. The empirical evidence shows that both demand and supply factor contribute to the growth rate of private sector credit. Bank lending is pro-cyclical as it correlates with the output gap. It is also highly sensitive to the NPL (Nonperforming loans) ratio. Other major findings are that the deposit base has a major impact on lending and that a higher interest rate tends to reduce bank credit.[19]

[19] Mohanty M.S., Schnabel G. and Garcia-Luna P. (2006), pp. 11-39

3 Theory

Money, or money supply, is determined by the interest rate when the central bank uses interest rate targeting, according to many macroeconomic textbooks. This can be derived from the demand for money, which is assumed to be a function of for example the interest rate and income. This is displayed in diagram 3.1 below.

Diagram 3.1 Money demand and supply



Source: Burda and Wyplosz (2005)

Although the model describes money supply there are good reasons to use it for bank credit as well as money expands when new bank loans are created by banks. In many studies, e.g. RBI (2007), Bernanke and Blinder (1988) and Mohanty, Schnabel and Garcia-Luna (2006), it has been demonstrated that bank lending is sensitive to interest rates. The interest rate is perhaps best described as a variable that affects the demand for money or credit.[20] On the other hand, Stiglitz and Weiss (1981) develop a model of credit rationing which shows that bank loans are interest rate inelastic. Monetary policy influences the level of investment through loanable funds rather than through interest rates.[21]

Except from the interest rate, the demand for money is often also defined as a function of income, GDP. Barajas, Luna and Restrepo (2008) found that GDP is slightly more likely to cause bank loans than the other way around although this causation can certainly be disputed. It is also possible that GDP affects the general risk level of bank loans which in turn would make banks

[20] Burda M. och Wyplosz C. (2005), pp. 174-226
[21] Stiglitz J. and Weiss A. (1981), pp. 393-410

more (less) risk averse and thereby less (more) willing to lend. However, in this study GDP will be considered mostly as a demand variable as risks are believed to be captured by other variables described in this chapter.[22]

Another variable that is often argued to influence the level of new bank loans, or money creation, is the reserve ratio requirement. Bank reserves are vault cash and reserves at the central bank and the reserve ratio is the proportion of reserves to deposits. The reserve ratio requirement in the USA for depositary institutions is 10 percent on transaction accounts more than $43,9 million. However, there are no requirements for time deposits.[23] Some countries (eg. Canada, the UK, Sweden and Switzerland) do not have any reserve requirements and it is therefore up to banks to make prudent decisions on this. Banks must have enough currency for to meet everyday withdrawals by customers. This is a good reason to have vault cash or reserves at the central bank, which can be converted into cash immediately. Sometimes bank hold excess reserves, i.e. reserves in excess of the reserve ratio requirements.[24] Although it is often believed that the reserve ratio requirements constrain bank deposits the Federal Reserve claims that requirements place little constraint on the expansion of deposits as the Federal Reserve accommodates such expansions through open market operations.[25] This view is also shared by Goodhart (1989).[26] As the reserve ratio requirement is described as a factor that limits bank loans it has to be viewed as a variable that influences the supply of credit.

Bliss and Kaufman (2002) develop a model for constraints of bank credit expansion. They argue that banks do not only have a reserve requirement constraint but also a capital requirement constraint. Although the Federal Reserve supplies a bank with reserves it may be unable to expand the supply of loans if the capital constraint is reached. The regulatory frameworks Basel I (introduced in 1988 in the USA) and Basel II make banks subject to capital requirements measured as Capital Adequacy Ratio (CAR). CAR is a ratio of capital to risk-weighted assets. Capital consists of for example common stock and retained earnings, whereas risk-weighted assets is a measure of bank assets given different weights for their perceived risk level. Basel II is an augmentation of Basel I where for example operational and market risks have been added to the risk-weighted assets. In addition to that, loans, or assets, of the same classification can now be

[22] Burda M. och Wyplosz C. (2005), pp. 174-226
[23] http://www.federalreserve.gov/pubs/supplement/2008/02/table1_15.htm, Accessed 2009-12-17
[24] Burda M. och Wyplosz C. (2005), pp. 174-226
[25] Feinman J. (1993), pp. 569-589
[26] Goodhart C. (1989), pp. 29-34

individually risk-weighted by different approaches, such as the IRB (internal rating-based) and the standardized method. Basel II has been criticized by several authors, as discussed earlier, for being pro-cyclical and Basel I has been pointed out as a factor that caused the credit crunch in the USA 1990-1991 by for example Bernanke and Lown (1991) and Berger and Udell (1994). Basel I and Basel II are very complex and will therefore not be explained more in detail in this thesis. However, banks are not only constrained by capital requirements by regulators. Often banks have self-imposed minimum levels for capital, typically scaled by their riskiness, for internal risk-management purposes. Bliss and Kaufman point out that capital constraint are more likely to be binding during a recession than an expansion. Monetary policy in recessions, defined by dropping the interest rate and supplying the banking system with more reserves, will therefore be less efficient, making monetary policy asymmetrical. Instead of using the ratio of capital to risk-weighted assets, the capital-asset ratio can be used. This has been examined by e.g. Lown and Morgan (2006) and can be interpreted as ratio set by the bank for internal purposes. Internal or external capital requirements will be regarded as variables that affect the supply of bank loans.[27]

Many authors (e.g. RBI (2007), Barajas, Luna and Restrepo (2008), Wu, Chang and Selvili (2003), Mohanty, Schnabel and Garcia-Luna (2006) etc) have found that bank credit depends negatively on the ratio of nonperforming loans. A nonperforming loan is a loan on which the borrower is not making any interest payment or loan repayments. Local regulation determines at what point a loan is classified as a nonperforming loan. In order to cover potential losses banks normally set aside money. Banks are profit-maximizing units and a rising level of nonperforming loans will reduce earnings. Therefore it may be optimal for banks to decrease the supply of new loans or at least tighten credit standards so that potential losses are minimized. This makes nonperforming loans a supply variable.[28]

Asset prices are found to have a positive influence on bank lending in studies carried out by Goodhart, Hofmann and Segoviano (2006) and RBI (2007). Goodhart et al argue that financial deregulation gives rise to boom-bust cycles. Collateralized lending plays an important part in this. Positive productivity shocks result in higher asset prices whereas higher asset prices lead to more collateralized lending. In turn, more collateralized lending leads to higher asset pricing and so on. Before the financial regulation credit controls were a constraint to private sector lending. Thereby

[27] Bliss R. and Kaufman G. (2002), pp. 1-15 and
Saunders A.and Allen L. (2002), pp. 23-45

[28] http://lexicon.ft.com/term.asp?t=non_performing-loan--NPL, Accessed 2009-12-12

asset prices and financial regulation will be regarded as supply variables. In spite of this, it can certainly be argued that asset prices also determine the demand for new bank loans. [29]

Return on equity (ROE) and Return on Assets (ROA) are variables that are sometimes used to describe the lending behavior of banks. Barajas, Luna and Restrepo (2008) study the cyclical fluctuations of these variables in comparison to bank lending. ROA generally refers to net income divided by total assets and ROE is net income to shareholder's equity. These are both indicators of profitability of companies. ROA and ROE are variables that are used to describe the supply of bank loans in this study.[30]

[29] Goodhart C., Hofmann B. and Segoviano M. (2006), pp. 3-37
[30] Barajas A., Luna L. and Restrepo J.E. (2008), pp. 21-56

4 Data description

The data series used in this study cover the period 1988Q1 – 2009Q3 for which quarterly periodicity has been applied. The reason why this time frame has been chosen is due to the fact that two of the series, NPLTOTLOANS and CAPASSET, are only available since 1988. The variables are denominated in nominal terms and most of them are not seasonally adjusted in order to fully capture seasonality. However, in the case of GDPNOM, only seasonally adjusted data was available from Bureau of Economic Analysis (BEA) and this has therefore been used. The descriptions of the variables below state which fransformations (e.g. differentiation and HP-filtering) that have been applied in accordance with the stationarity analysis in chapter 6.

AVPRICEHOUSES

This variable denotes the quarterly growth rate of the average sales price of new houses sold in the USA. The series is not seasonally adjusted and therefore exhibits strong seasonality. It is provided by the United States Census Bureau that is responsible mainly for census, national demographic and economic data. The variable is meant to capture the effect of asset prices on bank loans.[31]

CAPASSET

CAPASSET is the ratio of total bank equity to total bank assets de-trended by the Hodrick-Prescott filter in order to obtain the cyclical fluctuations as the ratio is not stable over time. This is measured at the end of each period, which is every quarter, and is not seasonally adjusted. The data is taken from the database FRED at the website of the Federal Reserve Bank of St. Louis.[32]

[31] http://www.census.gov/const/www/newressalesindex_excel.html, Accessed 2009-01-06
[32] http://research.stlouisfed.org/fred2/series/EQTA?cid=93, Accessed 2009-01-05

EXCRES_RES

This is the cyclical fluctuations of the ratio of excess reserves of depositary institutions to total reserves. Excess reserves are measured in billions of Dollars on a monthly basis and are not seasonally adjusted. In this study the value of the last month of each quarter is used to represent the quarterly measure. This data is taken from the database FRED.[33] Total reserves are available through the flow of funds accounts of US-chartered commercial banks published by the Federal Reserve. The measure is stated in millions of Dollars and is not seasonally adjusted.[34]

FEDFUNDSRATE

The federal funds rate is the interest rate at which banks lend balances at the Federal Reserve to other banks overnight. This market rate does not normally deviate much from the federal funds rate target. Changes in the federal funds rate are believed to trigger a chain of events that can affect the exchange rate, long-term interest rates and much more. This interest rate certainly influences the interest rates at which banks lend to their customers too. The federal funds rate is transformed from monthly to quarterly periodicity by using the observation of the last month of each quarter. The data is provided by the Federal Reserve.[35]

GDPNOM

Bureau of Economic Analysis (BEA) is an agency that provides important economic statistics such as the gross domestic product used here. GDPNOM is seasonally adjusted nominal GDP in billions of Dollars and is measured quarterly. The variable has been transformed into the quarterly growth rate.[36]

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33 http://research.stlouisfed.org/fred2/series/EXCRESNS?rid=19&soid=1, Accessed 2009-01-05

34 http://www.federalreserve.gov/datadownload/default.htm, Accessed 2009-01-05

35 http://www.federalreserve.gov/datadownload/default.htm, Accessed 2009-01-05

36 http://www.bea.gov/national/index.htm#gdp, Accessed 2009-01-06

LOANSLEASESNSA

LOANSLEASESNSA is the quarterly growth rate of total loans and leases from the consolidated balance sheet of US-chartered commercial banks. This implies that claims on other US-chartered banks are netted so that loans are not counted twice. What about off-balance sheet loans such as mortgage-backed securities then? If a bank sells e.g. mortgage-backed securities to another bank, the security will show up on the balance sheet of the buying bank as a security and not a loan. Thereby securitized loans are not included in total loans and leases. Instead they comprise a large share of total bank credit, in which loans are also included. It can also be worth mentioning that when estimating money supply, deposits at US-chartered commercial banks are measured. Total loans and leases are not seasonally adjusted and stated in millions of Dollars.[37]

NPLTOTLOANS

This variable is the cyclical fluctuations of total nonperforming loans divided by total loans. Nonperforming loans are classified as loans 90-days or more past due or nonaccrual by bank managers. This data can be found in the FRED database described earlier. It is measured quarterly at the end of each period.[38]

RELGR_DELRT

RELGR_DELRT is the relative quarterly growth rate of the delinquency rate of real estate loans to the delinquency rate of total loans and leases. The relative growth rate can be expressed as:

$$RELGR\_DELRT = \ln\frac{DELRT\_REALEST_t}{DELRT\_LOANSLEASESNSA_t} - \ln\frac{DELRT\_REALEST_{t-1}}{DELRT\_LOANSLEASESNSA_{t-1}} \quad \textbf{Equation 4.1}$$

where $DELRT\_REALEST_t$ and $DELRT\_LOANSLEASESNSA_t$ are the delinquency rates of real estate loans and total loans and leases respectively at time t. Delinquent loans are defined as loans past due thirty days or more and still accruing interest as well those in nonaccrual status. The

[37] http://www.federalreserve.gov/datadownload/default.htm, Accessed 2010-01-05
[38] http://research.stlouisfed.org/fred2/series/NPTLTL?cid=93, Accessed 2010-01-07

delinquency rate refers to the percentage of delinquent loans to total loans of a specified category, for example real estate loans. The delinquency rate is measured at the end of each quarter.[39]

RELGR_LOANS

This denotes the relative growth rate of real estate loans to total loans and leases Real estate loans at US-chartered commercial banks. It can be written as follows:

$$RELGR\_LOANS = \ln\frac{REALEST_t}{LOANSLEASESNSA_t} - \ln\frac{REALEST_{t-1}}{LOANSLEASESNSA_{t-1}}$$ **Equation 4.2**

$REALEST_t$ and $LOANSLEASESNSA_t$ are real estate loans and total loans and leases respectively at time t. Real estate loans include both residential and commercial loans and are not seasonally adjusted.[40]

ROE

ROE is return on equity for US banks and is provided by the Federal Reserve Bank of St. Louis. The data is measured at the end of each quarter and is designated in annualized percent. It is not seasonally adjusted and has been de-trended by the Hodrick-Prescott filter.[41]

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[39] http://www.federalreserve.gov/releases/chargeoff/delallnsa.htm#fn1, Accessed 2010-01-07
[40] http://www.federalreserve.gov/datadownload/default.htm, Accessed 2010-01-07
[41] http://research.stlouisfed.org/fred2/series/USROE?cid=93, Accessed 2010-01-05

5 Econometric method

5.1 Unit root test

In order for regression models containing time series data to be estimated correctly it is required that the time series are stationary. Regressions with non-stationary variables generally give high R^2 and insignificant p-values. However, non-stationary series can be used in a meaningful regression if they are co-integrated but for now on we focus on stationarity. For a time series to be strictly stationary the joint distribution of y_t and $y_{t-\mathrm{k}}$ must not depend on time (t). This is very rare and therefore often only weak stationarity is tested for. $E[y_t]$, $Var[y_t]$ and $Covar[y_t, y_{t-1}]$ are constant for weakly stationary series. This can be tested by ensuring that ρ in the equations below is less than 1.

$$y_t = \rho y_{t-1} + \varepsilon_t$$ **Equation 5.1**

$$y_t = \alpha_0 + \rho y_{t-1} + \varepsilon_t$$ **Equation 5.2**

$$y_t = \alpha_0 + \rho y_{t-1} + \gamma t + \varepsilon_t$$ **Equation 5.3**

Equation 5.1 does not contain an intercept which equations 5.2 and 5.3 do whereas equation 5.3 contains a time trend that the other two equations lack. If ρ is equal to 1, y_t contains a unit root. To see why ρ has to be less than 1 we can derive $Var[y_t]$ from equation 5.2 which gives us:

$$Var[y_t] = \frac{\sigma_{\varepsilon_t}^2}{1-\rho^2}$$ **Equation 5.4**

where $\rho = 1$ is impossible and $\rho > 1$ implies a negative variance. A stationary series is mean reverting as it moves towards its mean α_0 (0 in the case without an intercept). To test whether ρ is less than 1, equations 5.1 - 5.3 are normally re-written as:

$$\Delta y_t = (1-\rho) y_{t-1} + \varepsilon_t$$ **Equation 5.5**

$$\Delta y_t = \alpha_0 + (1-\rho) y_{t-1} + \varepsilon_t$$ **Equation 5.6**

$$\Delta y_t = \alpha_0 + (1-\rho)y_{t-1} + \gamma t + \varepsilon_t$$ **Equation 5.7**

The advantage of this is that most econometric programs automatically give the t-values and corresponding p-values for the coefficients $(1-\rho)$. We now test if $(1-\rho)$ is equal to 0. Unfortunately the t-value for $(1-\rho)$ is biased as it is not asymptotically normally distributed due to the presence of the regressor y_{t-1}. Instead t has a so called Dickey-Fuller distribution, named after its founders Dickey and Fuller (1979), which critical values have been estimated by for instance MacKinnon (1991). The unit root tests (Dickey-Fuller tests) in equations 5.5 – 5.7 can be augmented with more than one lag of y_t in order to fit AR (Autoregressive) models with a higher order than 1. In this case the tests are simply called Augmented Dickey-Fuller (ADF) tests. The ADF version of equation 5.6 will then take the form:

$$\Delta y_t = \alpha_0 + (1-\rho)y_{t-1} + \alpha_1 \Delta y_{t-1} + \alpha_{p-1}\Delta y_{t-p+1} + \varepsilon_t$$ **Equation 5.8**

When a time series is tested for a unit root and it turns out not be stationary the series may be stationary after differentiation. In this case we say that it is integrated of order one, I(1). Likewise, a series that becomes stationary after a second differentiation is integrated of order two, I(2). If co-integration is present the variables, for example y and x, have a common trend. This can be tested by estimating the regression in equation 5.9 and testing whether its residual contains a unit root in equation 5.10. In other words, we now test if $(1-\rho)$ is equal to 0.

$$y_t = \alpha + \beta x_t + \varepsilon_t$$ **Equation 5.9**

$$\Delta \varepsilon_t = (1-\rho)\varepsilon_{t-1} + u_t$$ **Equation 5.10**

When the ADF test is used for testing co-integration between y and x critical values for two variables are required. [42]

[42] Harris R. och Sollis R. (2003), pp. 25-108

5.2 Hodrick-Prescott filter

Many macroeconomic and financial time series fluctuate around a growing time trend. GDP, for example, fluctuates around a growing time trend that is generally denoted potential GDP. The cyclical components of GDP, i.e. when GDP is above or below potential GDP, are of great interest when studying business cycles. The cyclical component c_t is normally written

$$c_t = y_t - g_t \qquad \textbf{Equation 5.11}$$

where y_t is GDP and g_t is potential GDP. All variables in equation 5.11 are in logarithmic form. Naturally, cyclical fluctuations can be of interest for many time series other than GDP. A method that is widely used in macroeconomics to estimate cyclical fluctuations is the Hodrick-Prescott filter (HP-filter). This method is named after the American economists Robert Hodrick and Edward Prescott. The filter can also be described as a device to de-trend time series making them stationary. Put differently, time series become mean-reverting as they fluctuate around the long run growth path (potential GDP for GDP) with the mean 0. The HP-filter is obtained by minimizing the expression in equation 5.12 below with respect to all of the g_t.

$$\text{HP} = \sum_{t=1}^{T} \underbrace{(y_t - g_t)}_{C_t}^2 + \lambda \sum_{t=2}^{T-1} \left[\underbrace{(g_{t+1} - g_t)(g_t - g_{t-1})}_{Change\ in\ the\ growth\ rate} \right]^2 \qquad \textbf{Equation 5.12}$$

The parameter λ is the weight of changes in the trend growth rate and determines the smoothness of the trend. Since this parameter is chosen by the observer, the cyclical fluctuations can have different appearances. λ is often set to 1600 for quarterly time series.[43]

5.3 Dynamic regression models

A dynamic regression model can be written as:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + \varepsilon_t \qquad \textbf{Equation 5.13}$$

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[43] Sörensen P.B. and Whitta-Jacobsen H. J. (2005), pp. 397-430

This model is referred to as an autoregressive distributed lag model (ARDL) and it can be consistently estimated with OLS (Ordinary Least Squares). Naturally more lags can be added if required. Equation 5.14 is called the impact multiplier whereas 5.15 is the long-run multiplier.

$$\frac{\partial y_t}{\partial x_t} = \beta_0$$ **Equation 5.14**

$$\frac{\beta_0 + \beta_1}{1 - \alpha_1}$$ **Equation 5.15**

Another dynamic model used for multivariate regressions is the vector autoregressive (VAR) model. It only includes lagged values of the explanatory variables and is displayed in equation 5.16.

$$y_t = \delta_1 + \alpha_{11} y_{t-1} + \beta_{12} x_{t-1} + \varepsilon_{1t}$$ **Equation 5.16**

$$x_t = \delta_2 + \alpha_{21} y_{t-1} + \beta_{22} x_{t-1} + \varepsilon_{2t}$$

The dynamic evolution of a number of variables is described from their common history in the VAR model. The use of the model was advocated by the economist Christopher Sims as it does not require any a priori distinction between endogenous and exogenous variables. This entails a theory-free method for estimation of economic relationships if desired.[44]

5.4 Granger causality

"Correlation does not imply causation" is a phrase commonly used in statistics. It means that correlation between, for example, two variables does not automatically imply that one causes the other. In other words, the causation might be the opposite. In order to investigate causation the economist and Nobel laureate[45] Clive Granger developed a test in 1969 that has been called "Granger Causality". The Grange causality test is a significance test to see if lagged values of the explanatory variable, or variables in the multivariate case, have any predictive power for the dependent variable. The regression in the test is a VAR model and variables can thereby be tested

[44] Verbeek M. (2008), pp. 269-354

[45] http://nobelprize.org/nobel_prizes/economics/laureates/2003/index.html, Accessed 2009-12-03

either pair wise or all together in a multivariate regression.[46] A Granger test with two variables, y and x, and with lag length l will look like equation 5.17 and 5.18 below.

$$y_t = a_0 + a_1 y_{t-1} + \cdots + a_l y_{t-l} + b_1 x_{t-1} + \cdots + b x_{t-l} + \varepsilon_t$$ **Equation 5.17**

$$x_t = a_0 + a_1 x_{t-1} + \cdots + a_l x_{t-l} + b_1 y_{t-1} + \cdots + b y_{t-l} + \varepsilon_t$$ **Equation 5.18**

When the regressions are estimated a joint significance test for the coefficients b_1 to b_l is performed (in the case of equation 5.17), which is done by testing if $b_1 = b_2 = \cdots = b_l = 0$.[47] If we denote the regression $y_t = a_0 + a_1 y_{t-1} + \cdots + a_l y_{t-l}$ the restricted model (r) and $y_t = a_0 + a_1 y_{t-1} + \cdots + a_l y_{t-l} + b_1 x_{t-1} + \cdots + b x_{t-l}$ the unrestricted model (ur) the joint significance can be determined with an F-test as described below.

$$F = \frac{(R_{ur}^2 - R_r^2)/j}{(1 - R_{ur}^2)/(t-k)} \sim F_{j,t-k}$$ **Equation 5.19**

j is the number of restrictions, t the number of observations and k the number of regressors including the intercept. Assymptotically the F-distribution approximates the x^2-distribution which implies that a significance test based on the x^2-distribution can be applied instead. The lag length can be chosen by the maximum time period the variables are believed to affect each other, which might be quite an arbitrary choice. Alternatively, the choice of lag length could be determined by an information criterion such as BIC (Bayesian Information Criterion). Under the assumption of normally distributed residuals BIC is written as:

$$BIC = \ln \frac{1}{t} \sum_{i=1}^{t} e_i^2 + \frac{k}{t} \ln t$$ **Equation 5.20**

BIC penalizes the number of the regressors unlike R^2 and to a greater extent than for instance AIC (Akaike Information Criterion), which is not discussed in this thesis.[48]

[46] Granger C.W.J. (1969), pp. 424-438
[47] Eviews 6 User's Guide (2007)
[48] Verbeek M. (2008), pp. 7-62

5.5 General-to-specific modeling

When estimating regression models with many explanatory variables there is a small chance that we reject the null hypothesis that the coefficient is 0 although this is wrong (type I error). This kind of error is very likely to occur if a long sequence of tests is performed to select variables to include in our model. This is often called data snooping or data mining. The likelihood of including wrong variables is particularly high when the specification search is from simple to general, i.e. when you start with few variables and add more as they turn out to be significant. Another common approach is general-to-specific modeling advocated by Professor David Hendry among others. This approach is typically referred to as the LSE (London School of Economics) Methodology. Adherents of this methodology start with an unrestricted model that includes many explanatory variables, on which restrictions are imposed. Eventually, they end up with a model that contains only significant variables. General-to-specific modeling is relatively insensitive to data-mining problems as only the true specification will survive the specification tests when sample size grows to infinity White (1990) concludes.[49]

In this thesis an automated step-wise regression will be used for the downward reduction of the unrestricted model to the parsimonious model. First forward and backward significance levels are set to for example 0,05 (5 %). The stepwise regression procedure starts by estimating a regression with all selected variables (unrestricted model). Thereafter it removes the least significant variable (the variable with the highest p-value), as long as it its p-value is higher than our chosen backward significance level, and estimates a new regression without the removed variable. Once again the variable with the highest p-value is removed and the regression is re-estimated without it. Now the two removed variables are tested to see if any of them can be significantly added back into the model given the forward significance value. Every time a variable has been removed all removed variables are re-tested for inclusion in the regression model. The procedure continues until we end up with only significant variables according to our chosen significance levels.[50]

[49] Verbeek M. (2008), pp. 58-61
[50] Eviews 6 User's Guide (2007)

5.6 Tests for structural breaks

It is interesting to see if regression coefficients are stable over time. If coefficients have changed at any point in time we say that a structural break has occurred. In order to test whether a coefficient in one period is significantly different from a coefficient in another period we can specify following test:

$$y_t = \alpha + \beta x_t + \gamma g_t x_t + \varepsilon_t \qquad \textbf{Equation 5.21}$$

where g_t is a dummy variable equal to 0 and 1 for period 1 and 2 respectively. If the coefficient γ is significant, a structural break has occurred. This test can be performed as a mass significance test in a multivariate regression with several explanatory variables including the intercept. In that case an F-test similar to that explained in section 5.4 is used. This is generally referred to as the Chow test for structural change or simply Chow's breakpoint test.[51]

When we do not have any a priori assumptions of when a structural break might have occurred, or instead of making an arbitrary in choosing a potential structural break date, a structural break can be searched for. The idea behind this method, that is called Quandt-Andrews breakpoint test, is that a Chow breakpoint test is performed at every observation between two specified dates and then the date with the most significant structural break is chosen. As the distribution of all the individual breakpoint tests becomes less credible at the beginning and the end of all observations the first and the last observations are normally excluded. A standard level for this "trimming" is 15 percent, which means that the first and the last 7,5 percent of the observations are excluded.[52]

5.7 Variance Inflation Factor

If the correlation between two explanatory variables in a regression model is too high, it may lead to problems. This phenomenon is called multicollinearity and may result in unreliable estimates such as high standard errors and wrong signs of coefficients. In order to detect multicollinearity the Variance Inflation Factor (VIF) is often used and is defined as follows:

[51] Verbeek M. (2008), pp. 66-67
[52] Eviews 6 User's Guide (2007)

$$VIF(b_k) = \frac{1}{1 - R_k^2}$$ **Equation 5.22**

$VIF(b_k)$ is the VIF of coefficient b_k and R_k^2 denotes the R^2 obtained from regressing x_k on the other explanatory variables. If the Variance Inflation Factor is higher than 20[53], multicollinearity can cause problems. This value can therefore be used as critical value.[54]

5.8 Contribution to R²

A regression model does not explicitly tell which variable that is the most important in explaining the variation of the dependent variable. To estimate the importance of the explanatory variables R^2 can be decomposed into contributions of the explanatory variables. One way of doing this is to run a regression with standardized variables for which standardized regression coefficients are obtained. A standardized variable is a variable with a standard error equal to one and a mean that is zero. The standardized regression coefficients are then multiplied with the correlation between each corresponding explanatory variable and the dependent variable. This gives us contribution to R^2 which is more easily illustrated as:

$$Contribution\ to\ R^2\ of\ x_j = b_j \rho_{yx_j}$$ **Equation 5.23**

$$and \qquad R^2 = \sum_{j=1}^{k} b_j\ \rho_{yx_j}$$ **Equation 5.24**

where b_j is the standardized regression coefficient and ρ_{yx_j} is the correlation coefficient between y and x_j.[55]

[53] http://www.nek.lu.se/nekded/Teaching/MasterEcon/Lect4.pdf, Accessed 2010-01-21
[54] Verbeek M. (2008), pp. 43-45
[55] http://biol09.biol.umontreal.ca/borcardd/partialr2.pdf, Accessed 2010-01-21

6 Results and analysis

6.1 Stationarity analysis

In order to find out which variables that are stationary, so that they can be used in a regression, Augmented Dickey-Fuller (ADF) tests are performed. Some of the variables used are ratios, e.g. CAPASSET, and if these are found not to be stationary they will be de-trended by the Hodrick-Prescott filter instead of being differentiated. The reason for this is that the level, rather than the increase or decrease, is of interest according to the chosen theories. Assume that a reasonable level for CAPASSET, that is not stable over time, has been set individually by banks. In that case it would be the cyclical fluctuations of the ratio that are of interest. For those variables de-trended by the HP-filter, λ has been set to 1600 as this value is recommended for quarterly time series, as discussed earlier. Variables that are not denominated as ratios, or in percent, are first tested in logarithmic level form. If they are not found to be stationary, they will be differentiated. A differentiation of a variable in logarithmic form gives the growth rate, in this case the quarterly growth rate. The lag lengths of the ADF tests have been chosen by the minimum BIC value of a maximum lag length of 12 quarters. The results are displayed below.

Table 6.1 ADF test with an intercept, BIC maximum 12 lags

	Level			HP-filter		
	t-Statistic	p-value	lags	t-Statistic	p-value	lags
CAPASSET	-0,586	0,867	0	-4,092	0,002	1
EXCRES_RES	1,027	0,997	0	-4,859	0,000	0
FEDFUNDSRATE	-2,858	0,055	3			
NPLTOTLOANS	-1,600	0,478	5	-5,518	0,000	4
ROE	-0,442	0,896	4	-5,352	0,000	4

Table 6.2 ADF test with an intercept, BIC maximum 12 lags

	LN(Level)			DLN(Level)		
	t-Statistic	p-value	lags	t-Statistic	p-value	lags
AVPRICEHOUSES	-1,161	0,688	5	-12,723	0,000	0
GDPNOM	-1,771	0,392	1	-3,544	0,009	1
LOANSLEASESNSA	0,613	0,989	1	-5,897	0,000	0

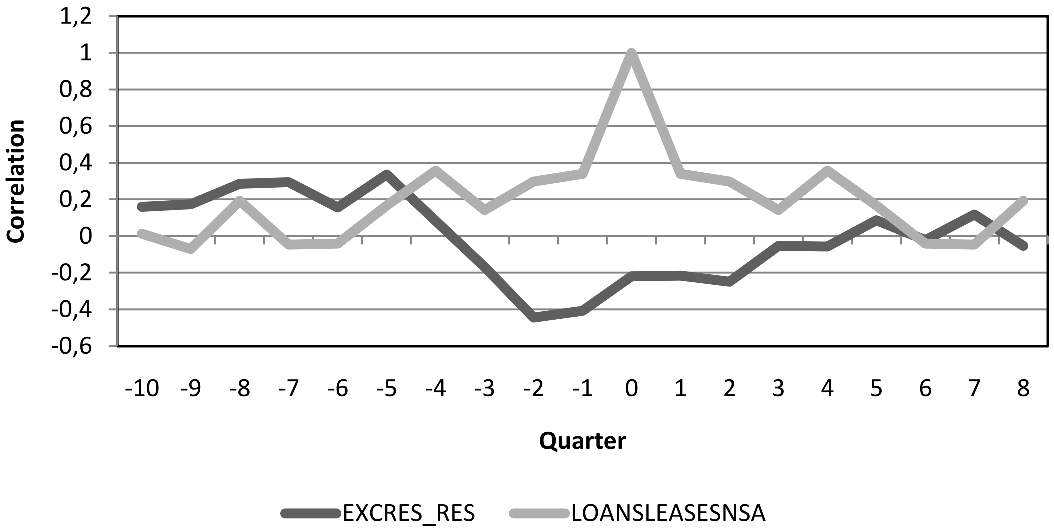
The tables above show that the variables CAPASSET, EXCRES_RES, NPLTOTLOANS and ROE are not stationary in level form and have therefore been transformed by the HP-filter to describe cyclical fluctuations. When extracting cyclical fluctuations the logarithmic level form of the variable is normally used in order to get deviations from the trend in percent. This procedure has not been possible to apply to ROE as it contains negative numbers. Therefore this variable has been kept in level form when extracting the cyclical fluctuations. FEDFUNDSRATE is significant on the 0,10 level and almost significant on the 0,05 level. This variable has therefore been kept in level. AVPRICEHOUSES, GDPNOM and LOANSLEASESNSA will be used as quarterly growth rates.

6.2 Analysis of correlation and bivariate causation

Before moving on to the general-to-specific regression it can be valuable to unravel correlations between the explanatory variables and LOANSLEASESNSA at different lag lengths. This is not merely a way to investigate whether the correlation is negative or positive but also a way to describe the lag structure. If we assume that there is a strong correlation between two variables at a lag length of 5 quarters, a lag length of 3 quarters in the general-to-specific model will most likely be too narrow to express the full relationship.

Let us start by examining the correlation between EXCRES_RES and LOANSLEASESNSA. In the diagram below correlations between -10 to +8 quarters can be seen.

Diagram 6.1 Correlogram



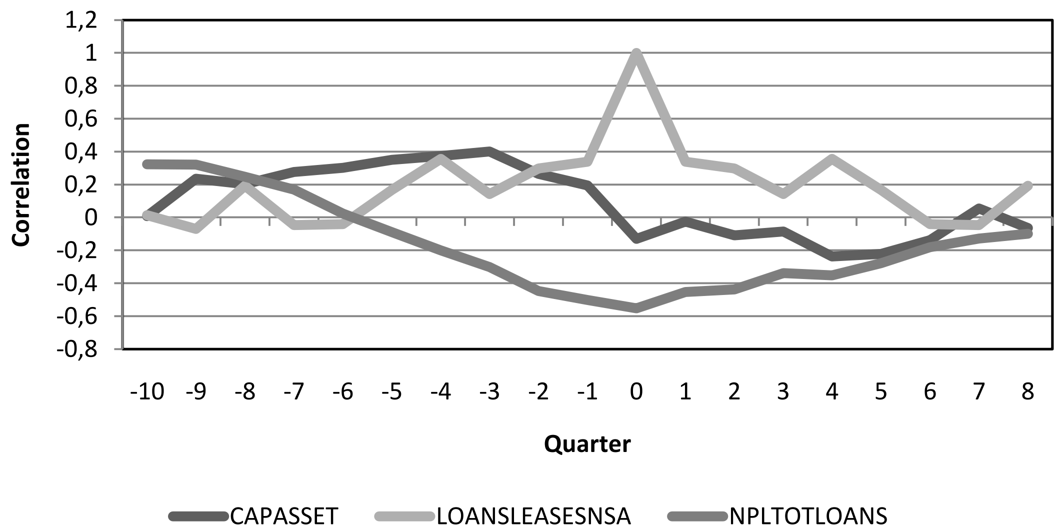
LOANSLEASESNSA, like many other economic variables, exhibits persistence as the correlation stays positive a couple of quarters both backwards and forwards. A seasonal pattern is also visible as the correlation at quarters one and two years in both directions is stronger than others. The highest correlation between LOANSLEASESNSA and EXCRES_RES is present at -2 quarters suggesting that EXCRES_RES leads LOANSLEASESNSA by two quarters, which is somewhat confusing. On theoretical grounds one was expecting to find that more excess reserves lead to higher bank lending instead of less bank lending. A Granger causality test in table 6.3 also confirms the negative causation from EXCRES_RES to LOANSLEASESNSA. The lag length has been chosen by the minimum BIC value of maximum 4 lags.

Table 6.3 Granger causality, BIC maximum 4 lags

	BIC	lags/df	Chi-sq	Prob.
LOANSLEASESNSA → EXCRES_RES	1,4275	1	3,4461	0,0634
EXCRES_RES → LOANSLEASESNSA	-5,9439	1	20,9390	0,0000

Perhaps the negative correlation tells us something about banks' willingness to hold excess reserves. A possible explanation to this is that banks may prefer to hold excess reserves in periods considered as risky as an arrangement to protect themselves against potential bank runs or future losses. The risk level then translates into lower bank lending. In that case lower bank lending is not a direct result of more excess reserves. The negative correlation also strengthens the view of the Federal Reserve and Goodhart (1989) that reserve requirements are no constraints to bank lending as the Federal Reserve accommodates such lending expansions through open market operations. On the other hand, the correlation is positive at -10 to -4 quarters, which could be interpreted as that the relationship between excess reserves and bank lending works with a long delay.

Diagram 6.2 Correlogram



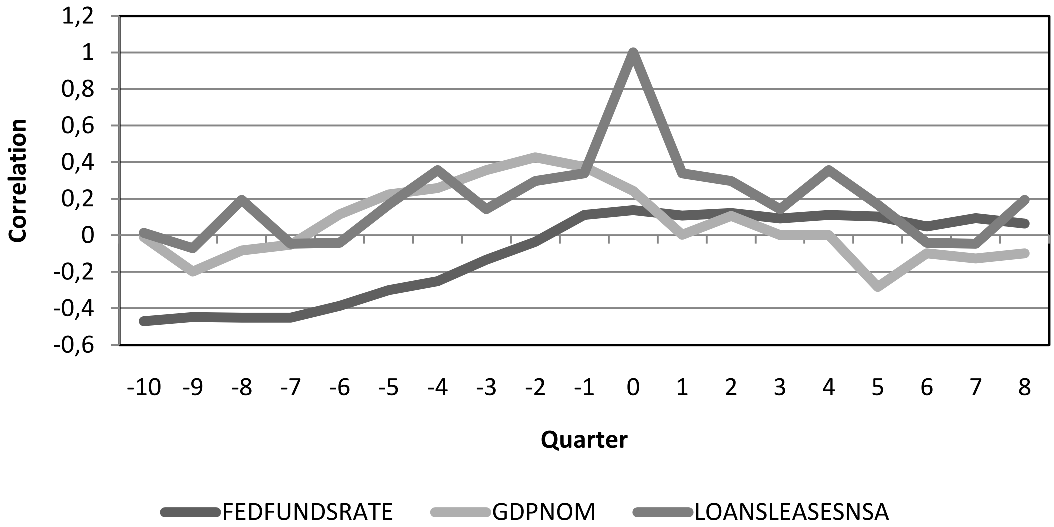
CAPASSET seems to lead LOANSLEASESNSA by a few quarters and has a positive correlation, as can be seen in diagram 6.2. This is in line with the theory. Also NPLTOT behaves as expected and shows a negative correlation with bank lending. The Granger test below suggests that there is bidirectional causation between bank lending and the capital to asset ratio. The fact that the causation from LOANSLEASENSA to CAPASSET is negative is not surprising and implies that more bank lending leads to a lower capital to asset-ratio as bank loans are bank assets. The two-way relationship is therefore not considered to be peculiar.

Table 6.4 Granger causality, BIC maximum 4 lags

	BIC	lags/df	Chi-sq	Prob.
LOANSLEASESNSA → CAPASSET	-5,2001	2	11,0268	0,0040
CAPASSET → LOANSLEASESNSA	-5,7442	2	8,3717	0,0152
LOANSLEASESNSA → NPLTOTLOANS	-3,1944	3	7,8168	0,0500
NPLTOTLOANS → LOANSLEASESNSA	-5,8790	1	14,5997	0,0001

There is also bidirectional causation in the case of NPLTOTLOANS and LOANSLEASENSA at the 0,05 level. Theory points out that nonperforming loans lead bank lending with a negative correlation but what about the opposite causation? It could be that less bank lending amplifies the nonperforming loans ratio as less lending creates a severe economic climate for households and companies which in turn makes it more difficult for them to amortize loans. However, the causation from NPLTOTLOANS to LOANSLEASESNSA is strongest and can therefore not be overlooked. Next we consider FEDFUNDSRATE and GDPNOM displayed below.

Diagram 6.3 Correlogram



FEDFUNDSATE behaves as expected with a negative correlation at -10 to -2 quarters. The correlations of GDPNOM seem to be consistent with money demand theories since GDPNOM leads bank lending by a few quarters and exhibits a positive correlation. The Granger causality test in table 6.5 indicates that the causations just discussed cannot be rejected.

Table 6.5 Granger causality, BIC maximum 4 lags

	BIC	lags/df	Chi-sq	Prob.
LOANSLEASESNSA → GDPNOM	-7,2516	1	0,3631	0,5468
GDPNOM → LOANSLEASESNSA	-5,8270	1	9,7986	0,0017
LOANSLEASESNSA → FEDFUNDSRATE	1,9624	3	2,9913	0,3930
FEDFUNDSRATE → LOANSLEASESNSA	-5,8027	2	13,5122	0,0012

In the diagram 6.4 we compare AVPRICEHOUSES and ROE with LOANSLEASESNSA. Both AVPRICEHOUSES and ROE lead bank lending and have a positive correlation. The Granger test in table 6.6 supports this observation and thereby the causations are as expected. Hence, there is evidence that increasing prices of collateral, such as real estate, may make banks more willing to lend in a manner that is described by Goodhart, Hofmann and Segoviano (2006).

Diagram 6.4 Correlogram

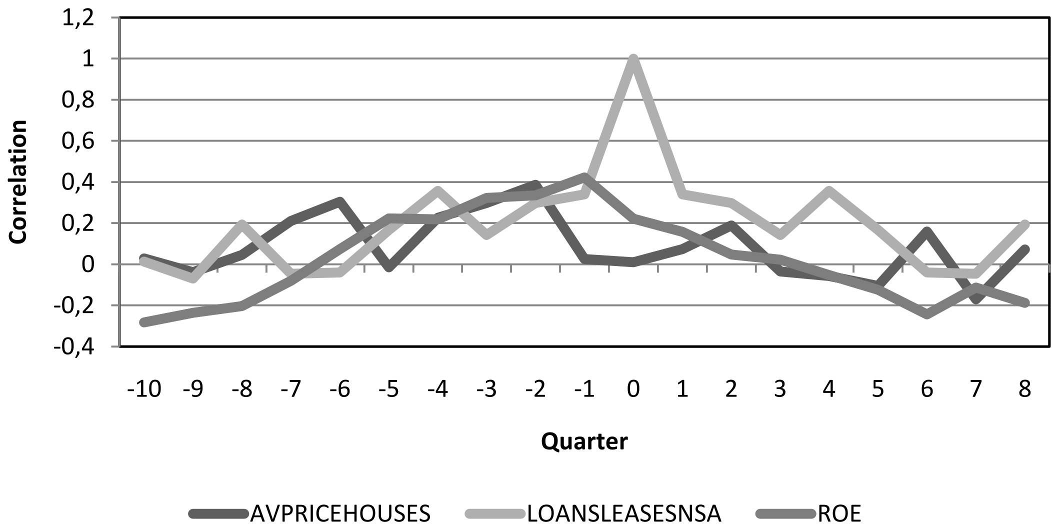


Table 6.6 Granger causality, BIC maximum 4 lags

	BIC	lags/df	Chi-sq	Prob.
LOANSLEASESNSA → ROE	3,3457	1	0,0721	0,7882
ROE → LOANSLEASESNSA	-5,8175	1	8,9544	0,0028
LOANSLEASESNSA → AVPRICEHOUSES	-4,1415	1	0,6592	0,4168
AVPRICEHOUSES → LOANSLEASESNSA	-5,8172	3	24,1217	0,0000

6.3 General-to-specific analysis of bank lending

The seven potential explanatory variables of bank lending discussed in the previous section are now used in a general-to-specific regression model. They are added to the regression with lags from 1 to 6 quarters as this seems to be appropriate based on the correlations in the correlograms in section 6.2. Lags (1 to 6 quarters) of the dependent variable, LOANSLEASESNSA, have also been added. Therefore the unrestricted regression is a VAR model. The intercept, C, and the seasonal dummies, S2, S3 and S4, will always be included in the regression in order to capture seasonalities. The downward reduction of the regression uses the significance level 0,01. The result of this regression (regression 1) is displayed in table 6.7 below.

Table 6.7 Regression 1

General-to-specific, 0,01 significance level, lags of explanatory variables: 1-6

Dependent Variable: LOANSLEASESNSA
Sample (adjusted): 1989Q2 2009Q3
Included observations: 82 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.	Contribution R^2
S2	0,0137	0,0028	4,8248	0,0000	
S3	0,0080	0,0027	2,9973	0,0038	
S4	0,0154	0,0028	5,5576	0,0000	
C	0,0136	0,0029	4,6811	0,0000	
AVPRICEHOUSES(-2)	0,1774	0,0387	4,5844	0,0000	0,1310
AVPRICEHOUSES(-3)	0,1477	0,0399	3,7011	0,0004	0,0749
EXCRES_RES(-1)	-0,0099	0,0021	-4,8111	0,0000	0,1367
FEDFUNDSRATE(-1)	0,0057	0,0011	5,2845	0,0000	0,0915
FEDFUNDSRATE(-4)	-0,0076	0,0011	-7,1838	0,0000	0,2657
NPLTOTLOANS(-4)	0,0894	0,0269	3,3245	0,0014	-0,2090
NPLTOTLOANS(-5)	-0,1044	0,0263	-3,9716	0,0002	0,1082

R-squared	0,7482	Mean dependent var	0,0156
Adjusted R-squared	0,7128	S.D. dependent var	0,0155
S.E. of regression	0,0083	Akaike info criterion	-6,6157
Sum squared resid	0,0049	Schwarz criterion	-6,2928
Log likelihood	282,2426	Hannan-Quinn criter.	-6,4861
F-statistic	21,0996	Durbin-Watson stat	2,0398
Prob(F-statistic)	0,0000		

The parsimonious regression model shows that four explanatory variables survived the downward reduction from general to specific model. Two lags of the variables AVPRICEHOUSES, FEDFUNDSRATE and NPLTOTLOANS are significant whereas only one lag of EXCRES_RES is significant. The result of a similar regression but with a significance level of 0,05 gives the same explanatory variables. This regression can be found in the appendix and is denoted regression 2. Regression 1 shows very high explanatory power, R^2 0,7482, and does not exhibit any sign of violating e.g. the OLS assumptions in table 6.8. However, the contribution to R^2 seen in table 6.7 is negative for the variable NPLTOTLOANS(-4) which makes the total contribution of NPLTOTLOANS to R^2 negative. It sounds very odd that a variable with negative contribution to R^2 has survived the downward reduction of the model. Therefore one might expect multicollinearity in the regression.

Table 6.8 Diagnostic tests of regression 1

RESET test - 2 fitted items	F-statistic	0,6254	Prob.	0,5380
Normality test	Jarque-Bera	1,3937	Prob.	0,4982
Breusch-Godfrey - 4 lags	F-statistic	0,2792	Prob.	0,8905
Breusch-Pagan	F-statistic	0,6161	Prob.	0,7952
Ljung-Box/ARCH test - 4 lags	Q-stat	1,3559	Prob.	0,8520

Multicollinearity is tested for by measuring the Variance Inflation Factor (VIF) in table 6.9 below.

Table 6.9 Variance Inflation Factor (VIF) – regression 1

	R^2	VIF
AVPRICEHOUSES(-2)	0,2723	1,3742
AVPRICEHOUSES(-3)	0,2572	1,3462
EXCRES_RES(-1)	0,2636	1,3579
FEDFUNDSRATE(-1)	0,8493	6,6351
FEDFUNDSRATE(-4)	0,8388	6,2033
NPLTOTLOANS(-4)	0,9637	27,5391
NPLTOTLOANS(-5)	0,9616	26,0675

The VIF indicates that multicollinearity is present in the regression as the two lags of NPLTOTLOANS have values of VIF above 20. The correlation matrix reveals a high correlation between NPLTOTLOANS(-4) and NPLTOTLOANS(-5). Hence it is likely that the inclusion of two lags of NPLTOTLOANS caused the problem of multicollinearity. Regression 1 is therefore re-estimated but this time with only one lag of NPLTOTLOANS, NPLTOTLOANS(-5). This regression is called regression 3 and is found in the appendix. In regression 3 FEDFUNDSRATE exhibits multicollinearity. Therefore it may be more appropriate to run a new regression with only one lag of each explanatory variable in order to estimate the relative importance of the explanatory variables defined by their contributions to R^2.

Regression 4 in table 6.10 is the downward reduction of an unrestricted model with only one lag of each explanatory variable chosen by the maximum correlation with LOANSLEASENSA between -1 and -6 quarters. The significance level is 0,01. This specification gives the same explanatory variables as before with the exception of AVPRICEHOUSES. However, AVPRICEHOUSES is significant on the 0,05 significance level as seen in regression 5 in the appendix.

Table 6.10 Regression 4

General-to-specific, 0,01 significance level, lags of explanatory variables: only preselected

Dependent Variable: LOANSLEASESNSA					
Sample (adjusted): 1989Q3 2009Q3					
Included observations: 81 after adjustments					

	Coefficient	Std. Error	t-Statistic	Prob.*	Contribution R^2
S2	0,0109	0,0034	3,1999	0,0020	
S3	0,0113	0,0034	3,3700	0,0012	
S4	0,0158	0,0034	4,6079	0,0000	
C	0,0167	0,0037	4,5248	0,0000	
EXCRES_RES(-2)	-0,0080	0,0026	-3,0112	0,0036	0,1143
FEDFUNDSRATE(-6)	-0,0023	0,0006	-4,0791	0,0001	0,1242
NPLTOTLOANS(-1)	-0,0275	0,0069	-4,0089	0,0001	0,1755

R-squared	0,5672	Mean dependent var	0,0155
Adjusted R-squared	0,5321	S.D. dependent var	0,0156
S.E. of regression	0,0107	Akaike info criterion	-6,1589
Sum squared resid	0,0084	Schwarz criterion	-5,9520
Log likelihood	256,4373	Hannan-Quinn criter.	-6,0759
F-statistic	16,1607	Durbin-Watson stat	1,7921
Prob(F-statistic)	0,0000		

Table 6.11 Diagnostic tests of regression 4

RESET test - 2 fitted items	F-statistic	2,9970	Prob.	0,0562
Normality test	Jarque-Bera	3,5574	Prob.	0,1689
Breusch-Godfrey - 4 lags	F-statistic	1,5147	Prob.	0,2073
Breusch-Pagan	F-statistic	1,1012	Prob.	0,3699
Ljung-Box/ARCH test - 4 lags	Q-stat	3,6722	Prob.	0,4520

Regression 4 does not violate any of the assumptions of OLS tested for in table 6.11 at the 0,05 significance level but the RESET test is almost significant. This could be a sign that the correct specification of the model consists of more lags. The problem of multicollinearity seems to have been avoided to judge by the Variance Inflation Factor in table 6.12.

Table 6.12 Variance Inflation Factor (VIF) – regression 4

	R^2	VIF
EXCRES_RES(-2)	0,1972	1,2457
FEDFUNDSRATE(-6)	0,0563	1,0597
NPLTOTLOANS(-1)	0,2116	1,2683

As no multicollinearity is present, regression 4 will most likely give us more credible contributions to R^2. Table 6.10 indicates that NPLTOTLOANS is the most important variable in explaining bank lending followed by FEDFUNDSRATE and EXCRES_RES respectively.

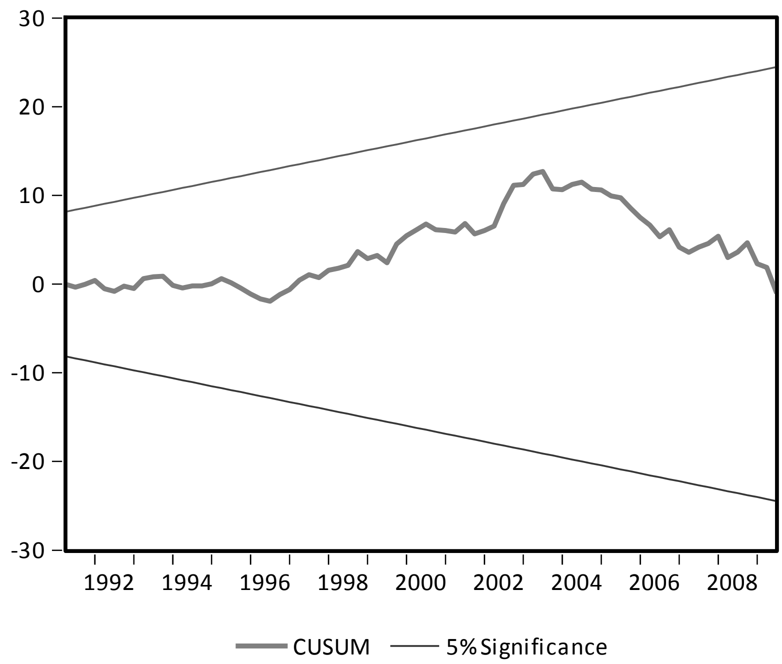
It is valuable to see if the coefficients are stable over time. For this purpose a Quandt-Andrews breakpoint test with a trimming of 10 percent has been carried out in table 6.13. This test cannot reject the null hypothesis of no structural break. The conclusion is therefore that the variables are stable over the time period covered in this study.

Table 6.13 Quandt-Andrews breakpoint test – regression 4

	Maximum F-statistic	Probability
(2006Q3)	3,6405	1,0000

The CUSUM test does not either detect any instability of the equation as the cumulative sum of the recursive residuals never crosses the two lines representing the 0,05 significance level in the chart below.

Diagram 6.5 CUSUM test



Multivariate Granger causality tests are also performed for the variables in regression 4 to see if the bivariate causations in section 6.2 hold. The results in table 6.14 indicate that FEDFUNDSRATE and EXCRES_RES cause LOANSLEASESNSA at the 0,05 level. NPLTOTLOANS is only significant on the 0,10 signifiance level. It is likely that this is a result of multicollinearity as discussed earlier. LOANSLEASESNSA does not significantly cause EXCRES_RES, FEDFUNDSRATE or NPLTOTLOANS at the 0,05 or 0,10 level. Therefore, this suggests that none of the explanatory variables in regression 4 is inaccurately used as an explanatory variable in the regression.

Table 6.14 Multivariate (VAR) Granger causality tests – regression 4, BIC max 4 lags

Dependent variable: **LOANSLEASESNSA,** BIC -5,9549 (2 lags)			
	Chi-sq	lags/df	Prob.
FEDFUNDSRATE → LOANSLEASESNSA	11,9632	2	0,0025
EXCRES_RES → LOANSLEASESNSA	17,9848	2	0,0001
NPLTOTLOANS → LOANSLEASESNSA	4,9221	2	0,0853
Dependent variable: **FEDFUNDSRATE,** BIC 1,9028 (2 lags)			
	Chi-sq	lags/df	Prob.
LOANSLEASESNSA → FEDFUNDSRATE	1,8295	2	0,4006
EXCRES_RES → FEDFUNDSRATE	7,7928	2	0,0203
NPLTOTLOANS → FEDFUNDSRATE	25,8299	2	0,0000
Dependent variable: **EXCRES_RES,** BIC 1,4517 (1 lag)			
	Chi-sq	lags/df	Prob.
LOANSLEASESNSA → EXCRES_RES	0,0573	1	0,8108
FEDFUNDSRATE → EXCRES_RES	0,0029	1	0,9571
NPLTOTLOANS → EXCRES_RES	4,7990	1	0,0285
Dependent variable: **NPLTOTLOANS,** BIC -3,0610 (2 lags)			
	Chi-sq	lags/df	Prob.
LOANSLEASESNSA → NPLTOTLOANS	3,5527	2	0,1693
FEDFUNDSRATE → NPLTOTLOANS	6,1037	2	0,0473
EXCRES_RES → NPLTOTLOANS	1,2556	2	0,5338

At last, the results of the five regressions performed are summarized in table 6.15. As can be seen, AVPRICEHOUSES, EXCRES_RES, FEDFUNDSRATE and NPLTOTLOANS are significant in all of them except regression 4 where AVPRICEHOUSES was insignificant at the 0,01 level. The sums of the coefficients of each variable (long-run multipliers) are rather similar in all regressions and have the same sign. The contributions to R^2 of all lags (if any) of each explanatory variable are somewhat spurious in regression 1 and 2 as NPLTOTLOANS contributes negatively to the R^2 value. This is regarded as a product of multicollinearity, which makes the contributions to R^2 more reliable in regression 4 and 5. Therefore NPLTOLOANS seems to be the most important variable in explaining bank lending. This result was also obtained in regression 3, but in that case the lags of FEDFUNDSRATE exhibited high correlation that resulted in multicollinearity.

Table 6.15 Regression summary

Regression	1	2	3	4	5
Significance level	0,01	0,05	0,01	0,01	0,05
R^2	0,7482	0,7858	0,6780	0,5672	0,5953
Adjusted R^2	0,7128	0,7449	0,6388	0,5321	0,5565
BIC	-6,2928	-6,2934	-6,1317	-5,9520	-5,9650
Observations	82	82	84	81	81
Sum of coefficients:					
AVPRICEHOUSES	0,3251	0,3735	0,2813	-	0,1015
EXCRES_RES	-0,0099	-0,0130	-0,0081	-0,0080	-0,0072
FEDFUNDSRATE	-0,0019	-0,0018	-0,0015	-0,0023	-0,0022
NPLTOTLOANS	-0,0150	-0,0187	-0,0252	-0,0275	-0,0255
Contribution R^2:					
AVPRICEHOUSES	0,2059	0,1926	0,1724	-	0,0756
EXCRES_RES	0,1367	0,1358	0,1159	0,1143	0,1039
FEDFUNDSRATE	0,3572	0,2861	0,1206	0,1242	0,1156
NPLTOTLOANS	-0,1008	-0,0079	0,1606	0,1755	0,1629

The negative sign of EXCRES_RES is somewhat complex as mentioned before. Perhaps this is a consequence of banks' willingness to hold excess reserves at different stages of the lending cycle. In other words, it may be that banks prefer to hold excess reserves when losses are expected, i.e. when the risk level rises and banks apply more cautious lending standards. In turn, this leads to less bank lending. The multivariate Granger causality test in table 6.14 supports this theory since NPLTOTLOANS significantly causes EXCRES_RES. Stauffert (2000) claims that banks can circumvent reserve requirements by moving money in and out of different types of deposit accounts. In that way the reserve requirements on transaction accounts are met.[56] Therefore it can be disputed how important reserve requirements really are. EXCRES_RES also significantly causes the FEDFUNDSRATE. As the Federal Reserve supplies the banking system with more/less liquidity in order to decrease/increase the interest rate this sounds reasonable. A bivariate causation between FEDFUNDSRATE and NPLTOTLOANS also seems to exist. It

[56] Stauffert R. (2000), pp. 565-571

may not be surprising that higher interest rates make some borrowers unable to amortize their loans resulting in a higher nonperforming loans ratio, but what about the opposite causation? Does the Federal Reserve really monitor the nonperforming loans ratio when making interest rate decisions? This is of course possible but perhaps it is more likely that the NPLTOTLOANS is a good indicator of future economic growth, as Wu, Chang and Selvili (2003) have found, which in turn may be targeted by the Federal Reserve.[57]

The results are much in line with prior research in this field with the exception of excess reserves. Therefore, this negative correlation may need further detailed studies in order to fully understand the banking system. In this study it has been assumed that some of the variables affect the demand of bank loans whereas others affect the supply. This assumption could be challenged. As an example, the interest rate is very often described as a demand variable. In spite of this, banks carefully look at the interest rate when deciding if a household is capable of repaying a loan in order to either grant or deny a loan application.[58] Therefore the interest rate could also be a supply variable.

6.4 Analysis of banks' portfolio choice

Bliss and Kaufman (2002) suggest that banks often have self-imposed minimum levels for capital, typically scaled by their riskiness.[59] This could mean that banks prefer to lend more to sectors that are perceived to be less risky than others as they require less capital. This may also be optimal in order to minimize losses and thereby maximize profit.

In diagram 6.6 the relative year-on-year growth rate of real estate loans to total loans and leases is displayed together with the ratio of the delinquency rate of real estate loans to the delinquency rate of total loans and leases. The delinquency rate is used as a proxy for the nonperforming loans ratio, which is not released sector wise, and describes the risk level of a certain type of loans. In the diagram it can be seen that relative growth rate is higher when the ratio of delinquency rates is lower and vice versa.

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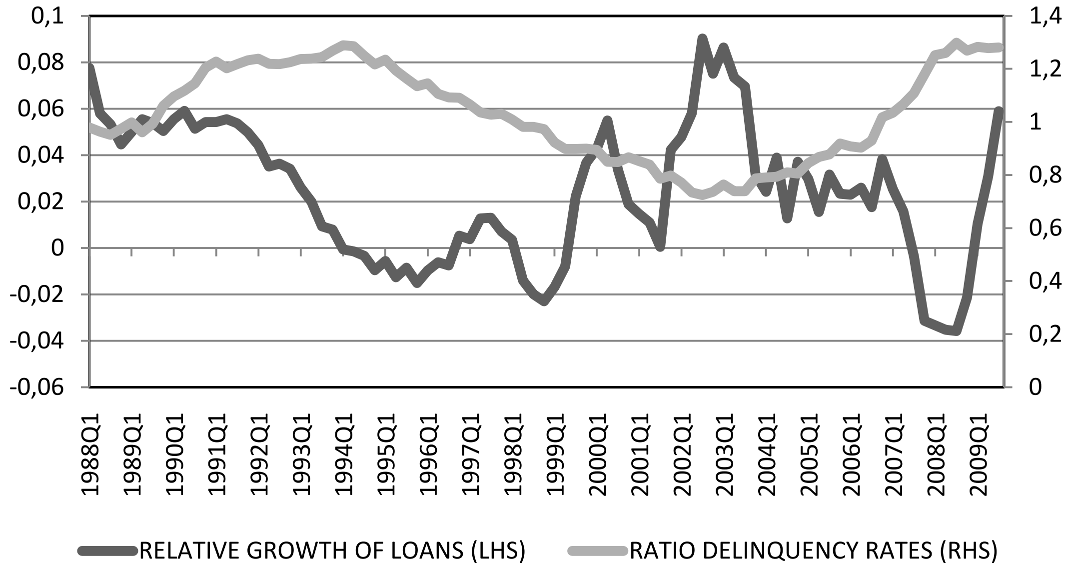
[57] Wu W-C., Chang C-O. and Selvili Z. (2003), pp. 43-62
[58] Meeting with Lars-Gunnar Hermansson, Credit Manager at Nordea, 2010-01-19
[59] Bliss R. and Kaufman G. (2002), pp. 1-15

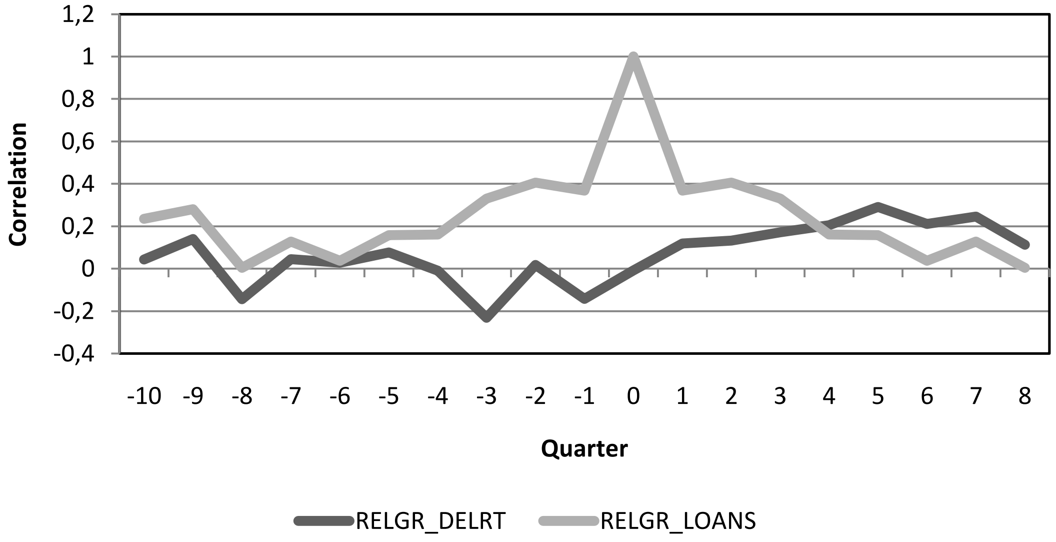
Diagram 6.6 Relative growth rate of loans and the ratio of delinquency rates



Source: http://www.federalreserve.gov/

For the analysis of this relationship the two variables RELGR_DELRT and RELGR_LOANS described in the data chapter have been used The correlogram below (diagram 6.7) tells us that there is a negative correlation that is highest at -3 quarters. A positive correlation is also visible and is strongest at +5 quarters possibly suggesting that a higher relative growth rate after a few quarters also leads to a higher ratio of delinquency rate. However, both correlations are quite low.

Diagram 6.7 Correlogram



The Granger causality test in table 6.16 strengthens the theory of a causation from RELGR_DELRT and RELGR_LOANS as it is significant on the 0,05 level. The sum of both coefficients of RELGR_DELRT in the Granger test is negative which supports the negative correlation in the correlogram. Consequently it seems like banks allocate bank loans to different sectors depending negatively on their corresponding risk level.

Table 6.16 Granger causality, BIC maximum 4 lags

	BIC	lags/df	Chi-sq	Prob.
RELGR_LOANS → RELGR_DELRT	-4,3441	1	2,1964	0,1383
RELGR_DELRT → RELGR_LOANS	-6,2654	2	7,9856	0,0184

7 Conclusion

The purpose of this thesis is to examine which factors that affect bank lending in the United States. The choice of variables was made in conformity with theories and previous studies related to the field of bank lending. Variables such as the interest rate, the nonperforming loans ratio and the capital to asset ratio were used. The data series span over the time period 1988Q1-2009Q3.

The methods applied to attain the results consist of general-to-specific regression models, Granger causality tests, correlograms and Augmented Dickey-Fuller tests. Also the relative importance of the explanatory variables was calculated as contribution to R^2.

The results of the study provide empirical evidence that the most important variable in explaining the variation in bank lending is the nonperforming loans ratio followed by the interest rate, excess reserves to total reserves and house prices respectively. However, the negative correlation between bank lending and excess reserves to total reserves appears somewhat puzzling. Judging by the dummy variables, there is also a seasonal pattern in bank lending. The explanatory variables used in this thesis explain between 57 and 79 percent of the variation in bank lending depending on which regression model one prefers. Moreover, it is shown that banks allocate loans to loan categories that are less risky than the average bank loan.

7.1 Reflections and policy implications

It could be of great interest to ensure that the banking system is well-functioning and that bank lending works frictionless. Just imagine what would happen if no entrepreneur received credit in order to fund his/her new capital investments. Certainly much less investment would be made resulting in slower economic growth. Economic growth theories generally accentuate the importance of capital accumulation for economic growth. It is therefore vital that entrepreneurs get access to credit. Of course capital investments can be funded by issuing corporate bonds that are sold to e.g. the private sector. However, in that case purchasing power is transferred from the private sector to capital investments. In the case of bank lending, or banks purchasing corporate bonds, banks can create purchasing power that did not exist before, i.e. banks can create new money.

The empirical results of this study indicate that the most important factor behind bank lending is the nonperforming loans ratio followed by the interest rate (federal funds rate), excess reserves and house prices. Central banks can stimulate the economy by lowering interest rates, which is their primary weapon. The nonperforming loans ratio, on the other hand, is more rarely discussed. Should central banks or governments give this factor more attention as dropping the interest rate alone may not be sufficient to stimulate lending? At present the nonperforming loans ratio is very high by a historical comparison.[60] This is a strong reason for banks to remain risk-averse. A government could of course buy troubled or nonperforming assets but in the long run this may be very costly for the tax payers. A solution to this is to let the central bank create credit, by extending its balance sheet, and purchase troubled assets. In this way tax payers would not have to pay for the purchases. This solution has been suggested by Werner (2005). [61] On the other hand, if reducing the nonperforming loans ratio becomes a regularly used policy tool it could create a moral hazard problem. Why would banks apply cautious lending policies if they know that a central bank or government will take care of "bad loans" as they arise? Therefore this tool may be effective only in extreme situations.

Another implication of the results in this thesis is that lower interest rates may stimulate lending only to some sectors. If we assume that the perceived risk level of real estate loans is lower than for example the risk level of loans to corporations for capital investment purposes, lending to real estate may grow at the expense of less lending to capital investments. A possible objection to this is that higher risk levels of some sectors could reflect that they are in economic trouble and thereby also be less willing to borrow from banks. In that case the problem is not a supply problem but a demand problem which banks are not responsible for. More research is therefore needed to separate the demand and the supply forces of bank loans.

Reserve requirements may not be a very efficient way to control bank lending, at least not in the prevailing system. Firstly, the ratio of excess reserves to total reserves had a negative correlation with bank lending in this study perhaps indicating that banks prefer to hold excess reserves when losses are expected. Secondly, the Federal Reserve itself and some authors, e.g. Goodhart (1989), claim that reserves are supplied to accommodate demand in the banking sector. In this view reserve requirements do not constrain bank lending.[62] Lastly, Stauffert (2000) points out that

[60] http://research.stlouisfed.org/fred2/series/NPTLTL?cid=93, Accessed 2010-01-24
[61] Werner R. (2005), pp. 1-341
[62] Goodhart C. (1989), pp. 29-34

banks can circumvent reserve requirements by moving money in and out of different types of deposit accounts so that the reserve requirements on transaction accounts are met.[63] In addition, Bennett and Peristiani (2002) conclude that banks use inventory optimization methods to manage reserves instead of complying with a quantitative regulatory minimum. Thereby reserve requirements are losing relevance.[64] However, many countries do not have any reserve requirements at present.

7.2 Suggestions for further research

As a negative correlation between bank lending and excess reserves to total reserves was found further research may be needed. In this study it was suggested that banks prefer to hold excess reserves at some stages in the lending cycle when for example future losses are expected. This feature could possibly explain the negative correlation.

The question of whether the availability of credit to entrepreneurs affects the long-run growth rate of GDP is another area of research that needs to be illuminated. For example, does a low risk level of real estate loans relative to the average risk level of loans result in less availability of loans to entrepreneurs, as they may be perceived as riskier? In other words, do some loans grow at the expense of others when banks make their portfolio choices? In many countries, e.g. Sweden, credit controls were used prior to financial deregulation. These were argued to ensure that credit was allocated for purposes considered important for society such as capital investment.[65] Was this a more effective way to stimulate high long-run economic growth? Perhaps these questions can be answered if more research is carried out in the future.

[63] Stauffert R. (2000), pp. 565-571
[64] Bennett P. and Peristiani S. (2002), pp. 1-16
[65] Schön L. (2007), pp. 402-407

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9 Appendix

Table 9.1 Regression 2

General-to-specific, 0,05 significance level, lags of explanatory variables: 1-6

Dependent Variable: LOANSLEASESNSA

Sample (adjusted): 1989Q2 2009Q3

Included observations: 82 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.	Contribution R^2
S2	0,0159	0,0028	5,7690	0,0000	
S3	0,0102	0,0026	3,8960	0,0002	
S4	0,0185	0,0028	6,5945	0,0000	
C	0,0105	0,0029	3,6078	0,0006	
AVPRICEHOUSES(-1)	0,0811	0,0402	2,0181	0,0475	0,0012
AVPRICEHOUSES(-2)	0,1865	0,0401	4,6472	0,0000	0,1377
AVPRICEHOUSES(-3)	0,1059	0,0396	2,6743	0,0094	0,0537
EXCRES_RES(-1)	-0,0079	0,0020	-3,8908	0,0002	0,1093
EXCRES_RES(-3)	-0,0051	0,0023	-2,1776	0,0329	0,0265
FEDFUNDSRATE(-1)	0,0044	0,0013	3,4727	0,0009	0,0702
FEDFUNDSRATE(-4)	-0,0062	0,0012	-5,0761	0,0000	0,2159
NPLTOTLOANS(-2)	-0,0339	0,0162	-2,0881	0,0405	0,1848
NPLTOTLOANS(-4)	0,1361	0,0313	4,3444	0,0000	-0,3180
NPLTOTLOANS(-5)	-0,1209	0,0255	-4,7361	0,0000	0,1253

R-squared	0,7858	Mean dependent var	0,0156
Adjusted R-squared	0,7449	S.D. dependent var	0,0155
S.E. of regression	0,0078	Akaike info criterion	-6,7043
Sum squared resid	0,0042	Schwarz criterion	-6,2934
Log likelihood	288,8744	Hannan-Quinn criter.	-6,5393
F-statistic	19,1921	Durbin-Watson stat	2,0960
Prob(F-statistic)	0,0000		

Table 9.2 Diagnostic tests of regression 2

RESET test - 2 fitted items	F-statistic	0,8818	Prob.	0,4189
Normality test	Jarque-Bera	3,2295	Prob.	0,1989
Breusch-Godfrey - 4 lags	F-statistic	0,2348	Prob.	0,9178
Breusch-Pagan	F-statistic	0,5227	Prob.	0,9028
Ljung-Box/ARCH test - 4 lags	Q-stat	2,0826	Prob.	0,7210

Table 9.3 Regression 3

General-to-specific, 0,05 significance level, lags of explanatory variables: 1-6, NPLTOTLOANS preselected

Dependent Variable: LOANSLEASESNSA
Sample (adjusted): 1988Q4 2009Q3
Included observations: 84 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.*	Contribution R^2
S2	0,0075	0,0031	2,4013	0,0188	
S3	0,0058	0,0031	1,8878	0,0630	
S4	0,0115	0,0030	3,7792	0,0003	
C	0,0138	0,0031	4,4290	0,0000	
AVPRICEHOUSES(-2)	0,1322	0,0409	3,2334	0,0018	0,0948
AVPRICEHOUSES(-3)	0,1491	0,0423	3,5228	0,0007	0,0776
EXCRES_RES(-2)	-0,0081	0,0024	-3,4357	0,0010	0,1159
FEDFUNDSRATE(-1)	0,0054	0,0020	2,7105	0,0083	0,0860
FEDFUNDSRATE(-2)	-0,0069	0,0019	-3,5792	0,0006	0,0346
NPLTOTLOANS(-1)	-0,0252	0,0073	-3,4650	0,0009	0,1606

R-squared	0,6780	Mean dependent var	0,0156
Adjusted R-squared	0,6388	S.D. dependent var	0,0154
S.E. of regression	0,0092	Akaike info criterion	-6,4211
Sum squared resid	0,0063	Schwarz criterion	-6,1317
Log likelihood	279,6852	Hannan-Quinn criter.	-6,3047
F-statistic	17,3115	Durbin-Watson stat	2,2773
Prob(F-statistic)	0,0000		

Table 9.4 Diagnostic tests of regression 3

RESET test - 2 fitted items	F-statistic	0,8481	Prob.	0,4325
Normality test	Jarque-Bera	1,2401	Prob.	0,5379
Breusch-Godfrey - 4 lags	F-statistic	0,8314	Prob.	0,5097
Breusch-Pagan	F-statistic	0,6587	Prob.	0,7432
Ljung-Box/ARCH test - 4 lags	Q-stat	1,8892	Prob.	0,7560

Table 9.5 Variance Inflation Factor (VIF) – regression 3

	R^2	VIF
AVPRICEHOUSES(-2)	0,2292	1,2974
AVPRICEHOUSES(-3)	0,2084	1,2633
EXCRES_RES(-2)	0,2434	1,3218
FEDFUNDSRATE(-1)	0,9505	20,2139
FEDFUNDSRATE(-2)	0,9453	18,2702
NPLTOTLOANS(-1)	0,4845	1,9398

Table 9.6 Regression 5

General-to-specific, 0,05 significance level, lags of explanatory variables: only preselected

Dependent Variable: LOANSLEASESNSA

Sample (adjusted): 1989Q3 2009Q3

Included observations: 81 after adjustments

	Coefficient	Std. Error	t-Statistic	Prob.*	Contribution R^2
S2	0,0086	0,0035	2,4856	0,0152	
S3	0,0100	0,0033	3,0276	0,0034	
S4	0,0144	0,0034	4,2624	0,0001	
C	0,0164	0,0036	4,5719	0,0000	
AVPRICEHOUSES(-2)	0,1015	0,0450	2,2536	0,0272	0,0756
EXCRES_RES(-2)	-0,0072	0,0026	-2,7900	0,0067	0,1039
FEDFUNDSRATE(-6)	-0,0022	0,0006	-3,8698	0,0002	0,1156
NPLTOTLOANS(-1)	-0,0255	0,0067	-3,7906	0,0003	0,1629

R-squared	0,5953	Mean dependent var	0,0155
Adjusted R-squared	0,5565	S.D. dependent var	0,0156
S.E. of regression	0,0104	Akaike info criterion	-6,2015
Sum squared resid	0,0079	Schwarz criterion	-5,9650
Log likelihood	259,1614	Hannan-Quinn criter.	-6,1066
F-statistic	15,3411	Durbin-Watson stat	2,0720
Prob(F-statistic)	0,0000		

Table 9.7 Diagnostic tests of regression 5

RESET test - 2 fitted items	F-statistic	2,0504	Prob.	0,1362
Normality test	Jarque-Bera	1,5580	Prob.	0,4589
Breusch-Godfrey - 4 lags	F-statistic	1,2265	Prob.	0,3077
Breusch-Pagan	F-statistic	0,6220	Prob.	0,7361
Ljung-Box/ARCH test - 4 lags	Q-stat	2,0606	Prob.	0,7250

Diagram 9.1 Variables used in the study

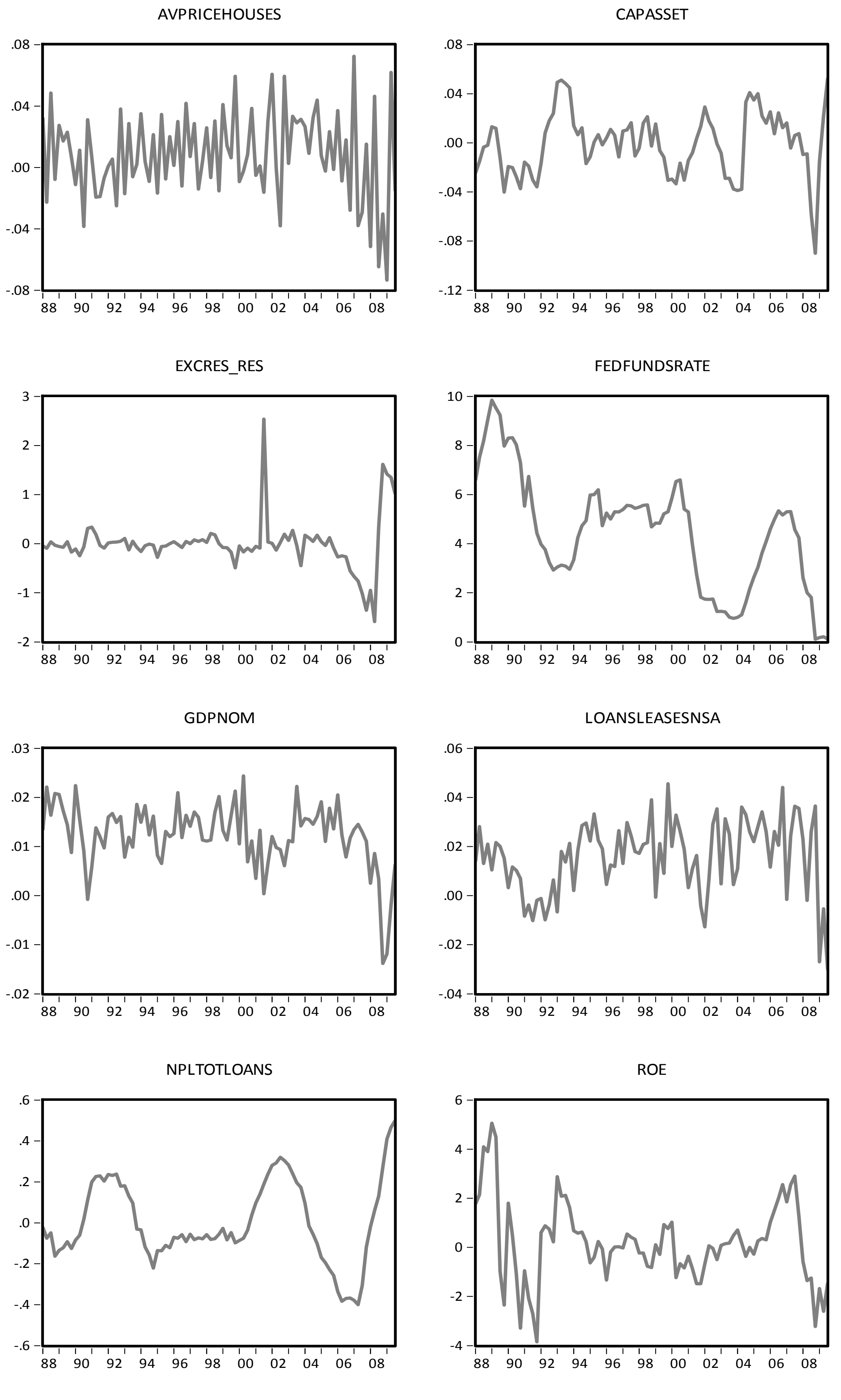

Diagram 9.2 Variables used in the study