Three Essays on
The Transmission of Monetary Policy,
Non-Linearities, and Interbank Markets

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To my parents

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Preface

Every major economic crisis changes certain fundamental beliefs and practices of the economists and policy makers who are involved in explaining them and dealing with their aftermath. The Great Depression, for example, revealed that the economy would not get back on track by itself with numerous *laissez-faire* policies in place. Only after paradigm shifts in monetary policy – the dilution of the gold standard – and fiscal policy – increased government spending to counteract the slump in output – did the economy begin to gradually recover.

The global financial crisis of 2007-2009 is another case in point. Despite the lessons learned from previous crises, most academics and policy makers seemed surprised by the causes of the global financial crisis, the channels by which it got transmitted throughout the economy, and the necessary responses by monetary and fiscal policy makers to stop it from spreading even further. The shortcomings of orthodox models to fully capture such phenomena have sparked interest in many strands of the literature that try to address the limitations of our current understanding. Two such areas have been of particular interest. The first area relates to the limits of monetary policy in the current environment, and how to overcome such limits. The second area focuses on the institutional setting of the economy, and tries to identify the role of important economic agents such as financial institutions in the generation and propagation of shocks.

As for monetary policy, the central banks of many countries have lowered their respective policy rate to values close to zero. The zero lower bound of the interest rate creates an obstacle for monetary policy makers who intend to stimulate the economy even further. In many countries, central banks have relied on quantitative easing measures, i.e. the attempt to reduce longer-term interest rates, in order to deliver the desired additional stimulus. Some questions of interest are whether the purchase of long-term bonds has similar effects as traditional policy instruments, whether fiscal multipliers are different in the presence of a zero lower bound, whether central banks should pay attention to additional targets besides the traditional ones of inflation, and, in some cases, output, or whether inflation targets should be raised under certain circumstances in order for central banks to have more room to respond to shocks. At the heart of many of these questions lie non-linearities in certain economic variables. For example, the zero lower bound embodies such a non-linearity because the interest rate cannot decline below this threshold even if the economic situation might warrant it. Additionally, sudden unpredictable changes in these variables may produce discontinuities that cannot be properly captured if one relies on a smooth representation in one's models. A proper understanding of such supposedly abnormal effects may pay off exactly when it is needed most, i.e. during crisis times or at the limits of traditional policy instruments.

As for the second area, financial intermediation is an essential element of modern economies. At the most basic level, financial intermediaries channel funds from individuals or institutions that have an excess of money – the savers – to those that have an immediate need for such funds – the borrowers. For instance, banks collect savings from depositors who seek to earn interest on the share of their income that they do not need for immediate consumption. Banks in turn grant loans to companies in order for them to undertake worthwhile investment projects that will generate future cash flows that allow them to pay back the loans and make a profit. In an ideal world, perfectly functioning financial intermediation enables an economy to generate a higher level of output by channeling financial resources to the users who can generate the highest benefits from them.

Financial intermediaries include banks, insurance companies, pension funds, and securities firms. They all perform different roles in various segments of the financial market. Historically, banks used to be the most important intermediaries, and they are still the most significant players in many developing, emerging, and even advanced economies. Their main functions are to transform short-term liabilities into long-term assets, manage and transfer risks, and provide liquidity services. The traditional view of banks, sketched in the above example, mainly sees them as intermediaries between individual savers and companies. However, during the last several decades, financial systems have become more complex and differentiated, especially in advanced economies like the United States and the United Kingdom. The reasons for this trend are manifold and include financial deregulation, such as the abolishment of the Glass-Steagall Act in the US in 1999, technological progress, especially in modern information and communications technologies, as well as globalization, mainly in the form of the reduction of trade barriers and international capital controls. These and other trends have enabled and promoted advances in the financial industry, among them innovative financial products, a global reach matching the needs of intermediaries' multinational clients, as well as new funding and investment opportunities that were previously inaccessible.

Financial institutions do not only intermediate between original savers and final borrowers, but they also interact among themselves. These interactions can take a variety of forms. For instance, a securities firm may enter into an interest-rate-swap agreement with a bank, or one bank may give a long-term loan to another bank. One of the most important markets in which financial institutions interact, though, is the money market. According to Stigum & Crescenzi (2007), the "money market is a wholesale market for low-risk, highly liquid, short-term IOUs". Such debt securities mostly have a maturity of less than one year; frequently, they are just overnight. While there are many different players in the money market, banks are very important in two segments of this market: the market for immediately available reserves at the respective central bank (e.g. the federal funds market in the US), and the repo market. In the first market, banks trade unsecured overnight funds to meet their reserve requirements, while in the second market, funds are collateralized. Both markets are instrumental for banks to manage their short-term liquidity needs which can arise from, for example, unexpected depositor withdrawals or sudden fluctuations in the value of a bank's assets. The interest rate that banks pay and receive in the first market is a key rate for the economy, i.e. many other interest rates are based on it. In fact, it is so important that it is, in many countries, the immediate instrument of monetary policy in order to achieve certain targets for economic variables such as inflation, output, and long-term interest rates. Therefore, banks and the markets they act in are an essential part of the economy even if financial markets have become more diversified and differentiated.

Despite the importance of financial intermediaries, standard macroeconomic frameworks rarely incorporate them explicitly, or only take a simplistic approach to modeling certain aspects of their role, such as deposit taking and loan making by banks (Woodford, 2010). But the nature of financial intermediation plays a crucial role for the functioning of the economy and the implementation of monetary policy. For example, a distinction is often made between bank-based and market-based economies. In the former, for example Germany, France, and Italy, firms mainly finance themselves through bank loans. In the latter, for example the United States and the United Kingdom, firms much more often access the capital markets through the issuance of commercial paper or corporate bonds that get sold directly to investors. Such structural differences have consequences for the transmission of monetary policy. According to Worms (2004), the pass-through of changes in the policy rate to other interest rates is faster in securities than in bank loan markets. As a result, the cost of capital for firms is thought to take more time to adjust in a bank-based system, an effect that needs to be taken into consideration by central bankers in their day-to-day decision-making.

The central position of financial intermediaries in the economy also becomes apparent in times of crisis, when the proper functioning of the financial system is impaired. The characteristics of such crisis episodes can be very diverse, as the following three short examples demonstrate. First, during bank runs, savers withdraw their deposits from banks in large numbers. The reason for this phenomenon might be doubts about the solvency or liquidity of a particular institution. In a fractional reserve banking system, banks only need to have a certain amount of funds available to cover their costumers' liquidity needs. If a bank experiences the loss of too many deposits, it will become illiquid. In fact, many countries have deposit insurance schemes in place that are designed to prevent self-fulfilling bank runs in the first place. Second, the failure of one institution can trigger a cascading effect throughout the financial system, since one institution's liabilities are often another one's assets. The extent of such financial contagion is more severe the more interconnected the individual entities are. Measures to prevent contagion are adequate capital requirements that allow for a sufficient buffer against losses or government intervention if the crisis turns out to be too severe. Third, the financial sector can experience a systemic crisis. This can occur if liquidity in the banking system dries up, i.e. if it is not possible for a large number of banks to secure the short-term funds they require. If a large shock or a sudden negative outlook affects a considerable number of financial intermediaries, they may abruptly turn risk-averse, hoarding liquidity instead of distributing it in the market in order to guard against future potential financing needs. This may cause a shortage of liquidity for nearly all institutions, and may not only put them at the risk of insolvency, but also impair the effectiveness of monetary policy to counter the initial shock.

A case in point for these three examples is the global financial crisis of 2007-2009. First, the British bank Northern Rock experienced a classic run on its deposits in September 2007. This came after it approached the Bank of England for liquidity support after it could not secure sufficient funding in the money market any more. Concerned costumers started withdrawing money, further depleting Northern Rock's funds. Second, in the US, the collapse of the investment firm Lehman Brothers in September 2008 spread rapidly through the US and international financial system: As a direct consequence of Lehman's demise, the money market mutual fund Reserve Primary Fund 'broke the buck', i.e. its share price fell below $1. The insurance company AIG was bailed out by the Federal Reserve Bank after it could not come up with sufficient collateral after a ratings downgrade. Further contagion to AIG's creditors was prevented by this and additional bailouts. Third, liquidity disappeared system-wide during the global financial crisis, for example causing the funding problems at Northern Rock to begin with. After the collapse of Lehman Brothers, the interbank market dried up completely as a source of liquidity.

Against this backdrop, my dissertation addresses several questions about monetary policy and the role of financial intermediaries in the economy. What effects do non-linearities in monetary policy have on the economy? How important is interbank lending and borrowing for banks extending loans to the real economy? How does monetary policy influence this relationship? Are there differences in monetary transmission in the interbank markets of different countries?

My dissertation contributes to the literature both from a theoretical and an empirical perspective. First, it extends the impulse matching technique to an economy with a differentiated banking sector, and draws comparison between two countries. Second, it uses a novel method to empirically assess the role of bank size for the lending behavior of financial institutions and approaches the geographical dimension of monetary policy transmission. Third, it applies a recently developed procedure to a New Keynesian model that is subject to different types of non-linearities in the Taylor rule in order to assess the effects of bounds and discontinuities in monetary policy on the economy.

The first chapter of my dissertation seeks to analyze differences in the role of the interbank market with respect to the United States and Germany. This is done by developing a structural model of an economy with a banking sector that includes an interbank market and using parameters that are calibrated by matching the theoretical impulse responses of the model with the empirical responses of a vector autoregression model for the United States and Germany, respectively. This method overcomes the identification problem of changes in total loan volume by distinguishing between supply and demand factors that simultaneously influence aggregate balance sheet data. The chapter finds evidence for a bank lending channel in both countries. However, there does not seem to be a systematic difference between the market-based economy of the United States and the bank-based economy of Germany. Additionally, frictions in the interbank market cause a larger decline in lending by small banks as compared to the case of a frictionless interbank market. The absolute impact of such frictions on bank lending is larger in Germany than in the United States.

The second chapter uses the balance sheet data of US banks to determine the importance of the interbank market for the transmission of monetary policy. It finds evidence that the credit channel does not work through bank size *per se*, but that it has substantial effects on banks' balance sheet positions depending on their size. It is important not to aggregate or net out balance sheet items such as securities, interbank lending and borrowing, since they have distinct effects on real sector lending. Additionally, there is some evidence that the credit channel has changed over time and has a more pronounced effect on banks operating in smaller geographic areas.

The third chapter uses policy function iteration methods to numerically solve and analyze a dynamic stochastic general equilibrium model that incorporates various non-linearities. The model includes firms' marginal cost spread in the Taylor rule to directly take account of their financial situation. First, the effects of the zero lower bound of the interest rate are analyzed. It is shown to produce a kink in the policy functions. Second, the chapter models changes to the parameters in the central bank's Taylor rule. This results in a discontinuity in the policy functions. Different solution techniques are implemented, and the accuracy of the results is compared by means of Euler equation residuals. The chapter highlights some of the advantages of policy function iteration over alternative methods with respect to modeling such non-linearities.

These findings are relevant for policy makers because non-linearities in monetary policy and the structure of financial markets have important effects on the economy in both crisis and normal times. A better understanding of their functioning can help policy makers reach more informed decisions and can mitigate the effects of unforeseen events.

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Chapter 1

The Bank Lending Channel and Interbank Relations in the United States and Germany

1.1 Introduction

Monetary policy affects the real economy through a large number of channels (for an extensive overview, see Worms, 2004). One way to distinguish between different types of transmission channels is the degree to which they rely on the existence of frictions in financial markets (Bernanke & Blinder, 1992). These frictions constitute a violation of the Modigliani-Miller theorem which states that, in an efficient market, the capital structure of a firm is irrelevant to the firm's value (Modigliani & Miller, 1958). Traditional mechanisms do not need to rely on financial frictions to work. In the case of the interest rate channel, an increase in the monetary policy rate leads to a rise in the real interest rate, assuming a certain degree of price stickiness. For firms, this leads to an increase in their cost of capital and reduces the profitability of new investments. For households, a higher lending rate may result in lower borrowing and subsequently lower consumption. Hence, aggregate demand declines as a result of changes in both the firm and the household sectors.

In a modern economy, different types of financial frictions can lead to a break-down of the Modigliani-Miller theorem. One can broadly distinguish between three different sectors where such financial imperfections can play out: banks, the non-bank sector comprising firms and households, and the private capital market. The four types of financial frictions that are most important for the question of how monetary policy gets transmitted to the real economy arise A) between firms/households and banks, B) between different banks, C) between banks and other funding sources, especially the private capital market, and D) between the non-bank sector and the non-bank capital market. A vast literature exists for each of these frictions.

This paper examines the first two types of frictions and their role for the transmission of monetary policy. It presents a model of an economy with two classes of banks which maximize profits by deciding on their supply of loans to the real sector and by interacting in the interbank market, given their expectations about the development of central bank policy. The notion that monetary policy can directly affect loan supply (type A) illustrates the working of the so-called bank lending channel, considered one of the most important non-traditional transmission mechanisms of monetary policy (Bernanke & Gertler, 1995). On the firm side, the prerequisite for this channel to work is a lack of alternative funding sources, such as from the private capital market (type D). On the bank side, loan supply only falls if the bank has no substitutes for reservable deposits at its disposal, for instance by relying on interbank lending (type B) or by issuing bank bonds in the capital market (type C; Romer & Romer, 1990).

Empirically, the bank lending channel is subject to an identification problem. Since bank balance sheet positions are the result of both supply and demand, it is difficult to interpret changes in such positions being driven by a single factor. As a consequence, the literature has developed ways to make use of informational asymmetries as proxied, for example, by size to identify the response of lending to the real sector (Kashyap & Stein, 1995). A common assumption is that informational asymmetries affect smaller firms or banks more strongly than their larger counterparts, so it should be harder for them to find alternative funds and compensate for the loss in bank loans or deposits (Gertler & Gilchrist, 1994).

The two classes of banks in the model can be thought of as representing a small and a large bank sector that face a different degree of financial market frictions caused by these informational asymmetries. The model can distinguish between loan supply and demand, which is necessary for identifying the bank lending channel. It also models the interbank market between the two bank types in order to analyze how a change in frictions between banks can affect lending. It is assumed that the real sector cannot access any other source of funds besides loans, and that small banks do not have access to the private capital markets, but large banks do.

To gain a cross-country perspective, a vector autoregression (VAR) model is estimated for both the United States and Germany. The impulse responses generated by the theoretical model are then matched with the empirical impulse responses for each country individually by means of an impulse matching procedure. This method permits the identification of different loan demand and loan supply components. The comparison of two countries can yield additional insights. Germany is considered to be the archetype of a bank-based economy, while the United States is regarded as a market-based system (Levine, 2002). Systematic differences in loan demand and loan supply between the two countries could lead to distinctive dynamics in economic outcomes. For example, the adjustment of interest rates is usually faster in securities than in bank loan markets, so the interest rate channel should work more slowly in a bank-based system (Worms, 2004).

Additionally, the model sheds light on the importance of the interbank market for lending outcomes. If frictions exist in the way that financial institutions exchange funds, this may affect the relationship between them and the real sector.

The paper is organized as follows. Section 1.2 describes the dynamic general equilibrium model that is used to simulate the economy. Section 1.3 generates the empirical responses of the US and the German economies in response to an exogenous shock in the interest rate and matches these responses with the theoretical model. Section 1.4 examines the evidence for a bank lending channel in each economy and the role of the interbank market for lending. Lessons from comparing both countries are drawn. Section 1.5 concludes.

1.2 Model

The model consists of a banking sector with two different bank types, the central bank, and the real sector. It builds on Cosimano (1988) and Hülsewig, Mayer & Wollmershäuser (2006).

1.2.1 Banks

The model comprises two different types of bank, called S and L. The distinguishing criterion is that one type, S, can only fund itself with deposits and interbank funds and is presumably small, while the other type, L, can additionally access other sources such as the private capital markets. This setup illustrates the existence of frictions in financial markets that contradict the Modigliani-Miller theorem (Modigliani & Miller, 1958). The rationale behind this distinction is the observation that certain banks, especially small institutions such as the savings banks in Germany, rarely fund themselves on capital markets, but rely on the interbank market to raise cash or smooth out fluctuations in deposits. This interaction is mostly limited to their head institutions, in the case of Germany the Landesbanken. On the other hand, banks such as big commercial banks or the Landesbanken regularly tap into both domestic and international capital markets (Upper & Worms, 2004; Koetter, et al., 2004).

One feature of the model is that the small bank type has to pay a larger surcharge on interbank loans the more it borrows (called 'rp' for risk premium). However, this factor can also be interpreted as a cost component that increases more than proportionally with the amount of outstanding debt, such as expenses for monitoring the borrower or evaluating the creditworthiness of the requesting bank. This surcharge is asymmetric, i.e. if a small bank lends to a large bank in the interbank market, it receives the rate set by monetary policy without a risk premium. Hence, this method explicitly takes frictions in credit markets into account, with small banks suffering from larger informational asymmetries that they need to compensate with a higher interest rate.

Banks give loans (L_t) to non-banks, for example households or enterprises. They receive deposits (D_t) which are subject to reserve requirements (R_t). Banks can also access the interbank market and receive interbank loans (B_t). Only banks of type L can access the private capital market (CM^L_t). This variable may be interpreted as equity, which does not enter the firm's profit function. The central bank's policy tool is the nominal short-term interest rate (r^M_t). The model is expressed in real terms, so all interest rates are calculated at real rates (rr_t). Banks charge the (real) loan rate rr^L_t for loans to non-banks. rr^D_t is the rate paid on deposits.

As outlined in Appendix A in detail, the profit for a given bank i of type T at time t + j is

$$\Pi^{Ti}_{t+j} = rr^L_{t+j}*L^{Ti}_{t+j} - rr^D_{t+j}*D^{Ti}_{t+j} - (rr^M_{t+j} + rp^T_t)*B^{Ti}_{t+j} - C^{Ti}_{t+j},\ T = S, L \tag{1}$$

where

$rp^T_t = \max(0, \rho_1^T/2*B^{Ti}_{t+j})$ is the risk premium in the interbank market, and

$C^{Ti}_{t+j} = a^T/2*(L^{Ti}_{t+j} - L^{Ti}_{t+j-1})^2$ is the cost of adjusting the loan portfolio.

Banks maximize profits with respect to L and B. Π^{Ti}_{t+j} are profits of one bank of type T at time t + j. The other variables are defined accordingly.

The risk premium rp depends on the size of interbank borrowing, scaled by the coefficient ρ_1^T. Since large banks do not face a risk premium by definition, $\rho_1^L = 0$ in all cases. In the baseline version of the model, the risk premium is set to zero for small banks as well to simulate a frictionless interbank market. Section 1.4 analyzes the effects that a positive risk premium on small bank interbank borrowing has on lending to the non-bank sector as compared to this benchmark case.

Banks face costs of adjusting their loan portfolio, reflected in the last term of equation (1). The costs are assumed to be quadratic, indicating that a larger adjustment is relatively more expensive than a small correction. a^T represents a scaling factor associated with adjusting the loan portfolio. These costs arise because banks need to monitor their loans and evaluate the borrowers' risk.

The profit maximization function for a single bank over time is characterized by

$$V^{Ti}_t = E_t \sum \beta^j * \Pi^{Ti}_{t+j} \tag{2}$$

with E_t being the rational expectations operator based on the information set available to the bank at time t. β is the discount factor. The above equation shows that the bank maximizes the present value of all future profits.

The balance sheet differs by bank type. For banks of type S, the constraint is

$$L^{Si}_{t+j} + R^{Si}_{t+j} = D^{Si}_{t+j} + B^{Si}_{t+j} \quad (3a)$$

while for banks of type L, it is

$$L^{Li}_{t+j} + R^{Li}_{t+j} = D^{Li}_{t+j} + B^{Li}_{t+j} + CM^{Li}_{t+j} \quad (3b)$$

The difference between the two types of banks is that type L can access additional sources of funding on the capital market, while type S cannot.

Loan demand is given by

$$L^{L}_{t} + L^{S}_{t} = b_1 * y_t - b_2 * rr^{L}_{t} \quad (4)$$

The sum of both banks' loans depends positively on the output gap and negatively on the real lending rate. The parameters b_1 and b_2 reflect the income elasticity and the interest elasticity of aggregate loan demand.

Appendix A derives the optimality conditions for each banking type and calculates the loan volume that maximizes the bank's profits. The loan volume aggregated over n banks for each type individually is

$$\begin{aligned} L^{S}_{t} = {} & 1/\psi_1 * \beta * E_t L^{S}_{t+1} + 1/\psi_1 * L^{S}_{t-1} + b_1/b_2 * na^{S\,(-1)}/\psi_1 * y_t \\ & - rp_t - na^{S\,(-1)}/\psi_1 * rr^{M}_{t} - na^{S\,(-1)}/\psi_1/b_2 * L^{L}_{t} \end{aligned} \quad (5)$$

$$\begin{aligned} L^{L}_{t} = {} & 1/\psi_2 * \beta * E_t L^{L}_{t+1} + 1/\psi_2 * L^{L}_{t-1} + b_1/b_2 * na^{L\,(-1)}/\psi_2 * y_t \\ & - na^{L\,(-1)}/\psi_2 * rr^{M}_{t} - na^{L\,(-1)}/\psi_2/b_2 * L^{S}_{t} \end{aligned} \quad (6)$$

where $\psi_1 = (\beta + 1/(na^{S} * b_2) + 1)$ and $\psi_2 = (\beta + 1/(na^{L} * b_2) + 1)$.

Banks smooth their loans over time. Loans depend negatively on the real interest rate, and they also depend on the other type's loans. The reason for this interaction is that loan demand depends on the loan volume, so a change in loans for one bank type has repercussions through the lending rate on the other bank. An increase in output leads to a rise in the loan volume.

Equations (7) and (8) are the balance sheet constraints of the respective bank type after aggregation, which are derived from the profit maximization problem (see equations A.7a and A.7b in Appendix A):

$$B^S_t = (d - 1)*D^S_t + L^S_t \tag{7}$$

$$B^L_t = (d - 1)*D^L_t + L^L_t - CM^L_t \tag{8}$$

where d is the required reserve ratio. In the simulation, the balance sheet variables are weighted by their average real value over the estimation horizon because the variables in equations (7) and (8) represent percentage deviations from steady state and need to be converted to absolute numbers to be summable.

The interbank market has to clear:

$$B^S_t = - B^L_t \tag{9}$$

Interbank lending from one bank type has to match interbank borrowing from the other type. This assumption is strict in that it does not account for interactions with a third type, such as foreign banks. Nevertheless, interbank lending between the types of banks examined in this paper has a large share of total interbank lending, especially for the savings banks in Germany (see Upper & Worms, 2004).

This model of the banking sector is an extension of the Hülsewig et al. (2006) paper which assumes that the balance sheet constraint for a single bank always holds since a bank will unconditionally get the money it needs from the central bank as the lender of last resort in response to deposit shocks. Here, funds are intermediated by large banks if there is a shock to small bank deposits (or loans). And large banks demand a risk premium, so there is no free lunch for small banks.

Rewriting equation (4) yields the real lending rate:

$$rr^L_t = b_1/b_2*y_t - 1/b_2*(L^L_t + L^S_t) \tag{10}$$

Since we assume a homogenous loan market, the effect of the loan volume of each bank is symmetrical on the real lending rate.

1.2.2 Central bank

The central bank follows an interest-rate smoothing Taylor rule that takes into account the output gap. The weight on the output gap is usually small, but significant in some cases, so that it is included in the model. The central bank is forward-looking in that it takes account of inflation in the next period:

$$r^M_t = \delta_1 * r^M_{t-1} + \delta_2 * E_t\pi_{t+1} + \delta_3 * y + \eta_t \quad (11a)$$

The shock to the policy rate is modeled as an AR(1) process:

$$\eta_t = \delta_4 * \eta_t + u_t \quad (11b)$$

The exogenous shock to monetary policy is reflected in the term u_t. The nominal interest rate r^M_t is used to calculate the real interest rate and the real lending rate, as the two next identities show:

$$rr^M_t = r^M_t - \pi_t \quad (12)$$

$$rr^L_t = r^L_t - \pi_t \quad (13)$$

1.2.3 The real economy

The model incorporates a Phillips curve with forward-looking inflation expectations (see for example Gali, 2008). Inflation depends on tomorrow's inflation as well as today's output gap.

$$\pi_t = \alpha_1 * E_t\pi_{t+1} + \alpha_3 * y_t \quad (14)$$

Aggregate demand follows a dynamic IS equation.

$$y_t = \gamma_1 * E_t y_{t+1} + \gamma_3 * y_{t-1} - \gamma_2 * rr^L_t \quad (15)$$

The fact that the real lending rate affects the output gap demonstrates how the situation in the banking sector influences the real economy.

Equation (16) represents a deposit supply equation. An increase in output raises the supply of bank deposits available to banks. An increase in the spread between the lending rate and the central bank interest rate reduces the supply of deposits. The reason behind this behavior is that households or enterprises face an increase in their borrowing costs when their lending rate goes up, or, alternatively, they receive a lower return on their deposits when the central bank decreases the money market rate. In both cases would their ability or willingness to deposit funds with their banks decline.

$$ds_t = \theta_3 * ds_{t-1} + \theta_1 * y_t - \theta_2 * (r^L_t - r^M_t) \tag{16}$$

The supply of deposits, ds, gets distributed to the two bank types according to the following equation:

$$D^T_t = \sigma^T * ds_t \text{, with } T = L, S \text{ and } \sigma^S + \sigma^L = 1 \tag{17}$$

The interaction of the real sector, as represented by households and enterprises, with the banking sector is modeled with ad hoc equations and is not based on an explicit profit maximizing problem in order to reduce the complexity of the model. The real sector is limited to demanding loans according to equation (4) and supplying deposits based on equation (16).

In the next section, a VAR model is estimated for both the United States and Germany. The impulse responses generated by this model are then matched with the impulses that result from an interest rate shock to the theoretical model outlined in this section.

1.3 VAR models and impulse matching

Similar approaches of estimating VARs including aggregate bank balance sheet variables have been pursued by Garretsen & Swank (1998), Küppers (2001), Morsink & Bayoumi (2001), Kakes & Sturm (2002), Holtemöller (2003), and Papadamou & Siriopoulos (2010), among others. Impulse matching has been performed by, for example, Rotemberg & Woodford (1998), Altig, Christiano, Eichenbaum, & Linde (2005), Christiano, Eichenbaum, & Evans (2005), Hülsewig, Mayer, & Wollmershäuser (2006), Meier & Müller (2006), and Henzel, Hülsewig, Mayer, & Wollmershäuser (2009).

1.3.1 VAR models of the United States and Germany

The VAR model takes the form

$$Z_t = A(L)Z_{t-1} + B(L)X_{t-1} + \mu + \varepsilon_t \tag{18}$$

The vector Z_t comprises the seven endogenous variables

$$Z_t = (GDP_t, CPI_t, r^M{}_t, D^S{}_t, L^L{}_t, L^S{}_t, r^L{}_t)'.$$

GDP stands for real output proxied by industrial production, CPI for the price level, r^M for the central bank rate, D^S, L^L and L^S for deposits of banks of type S, lending of banks of type L, and lending of banks of type S, respectively, as well as the lending rate r^L. The interest rates are expressed in decimals, while the remaining variables are calculated as log levels. The model is estimated in levels which takes account of cointegration relationships between the variables.

The ordering of the VAR implies that the central bank takes current output and prices as given in setting the interest rate, while its decision affects the balance sheet variables and the lending rate in the same period (Hülsewig, Mayer, & Wollmershäuser, 2006).

The exogenous variables in vector X_t comprise a time trend, monthly dummies, dummies for the introduction of the euro and a change in the definition of the lending rate, as well as a forward interest rate. Brissimis & Magginas (2006) have shown that the inclusion of such a forward rate helps to solve or mitigate the price puzzle. This puzzle, a counter-theoretical positive response of the price level to innovations in the interest rate, is a phenomenon that is often found in this strand of literature (Sims, 1992). One plausible explanation for this paradox is that the central bank has superior information about the economy as compared to the informational content of the variables in the VAR, and will react to signs of inflation at an early stage. If the model does not properly account for this information set, it will seem that prices increase in response to monetary tightening.

Additionally, with a forward rate included, the monetary policy shock dies out very quickly, which solves the policy innovation paradox (Brissimis & Magginas, 2006, p. 1231). The rationale for including such a financial market instrument is that it reflects expectations about short-term economic developments that monetary policy takes into account (Brissimis & Magginas, 2006, p. 1228). The data are described in more detail in Appendix B.

Impulse responses are generated for the United States as well as for Germany. The time period is 1991M1 to 2007M12. The decision to start the sample in 1991 is based on the fundamental changes in the German economy and banking sector due to reunification. The end of the sample roughly coincides with the onset of the financial crisis. Since the banking sector was massively supported by governments in the wake of the financial melt-down, the dynamics of borrowing and lending might have changed, so the most recent observations are discarded. The same time period is used for the United States and Germany. The response horizon is 60 months.[1]

The impulse responses are shown in Section 1.3.2, along with the simulated responses based on the impulse matching procedure described in the next section. The thin lines represent the 90% confidence intervals based on a bootstrap procedure with 2000 replications.[2] In the US (Figure 1.1), real output falls and returns to its equilibrium after about four years. The consumer price index increases slightly, which is a sign that the price puzzle has not been solved completely, but it is considerably mitigated in contrast to a model that excludes the forward rate. Another effect of this variable is that both the policy rate and the lending rate decline quickly after the shock. Deposits of small banks spike initially, but then turn negative and return to their equilibrium after about four years. Lending of both large and small banks to non-banks declines and returns to equilibrium after about five to six years.

In Germany (Figure 1.2), output initially spikes and fluctuates during the first year. The price level initially drops, but then bounces back and only declines slowly. The impulse response is never statistically significant, but the price puzzle is nevertheless not completely solved. Deposits drop and are back at their equilibrium after about three years. Lending to non-banks by the Landesbanken and the savings banks follows a roughly U-shaped pattern. This result contradicts Kakes & Sturm (2002) who find a counter-intuitive increase in lending of the savings banks. The response of the policy rate fades quickly, while the lending rate shows a more extended decline and the overall magnitude is much smaller.

In a cross-country comparison, the development of the policy rate, the lending of the large bank type and the price index seem fairly similar. Deposits react a bit more in the United States and are positive initially, while the response is smaller for Germany, and the initial spike is absent. Industrial production seems more reasonable in the US since there are no strong fluctuations. Lending of small banks reacts about twice as much in the US as in Germany, indicating that an interest rate shock has a larger impact on small US banks than on the savings bank sector in Germany. The lending rate seems to be more linked to interest rate policy in the case of the Federal Reserve than in the case of the Bundesbank/European Central Bank (ECB). One possibility is that the German lending rate is disconnected to a certain degree from developments in the money market because the ECB sets the interest rate taking into account the economic situation of the whole Euro Area and not only Germany.

[1] The total number of periods estimated is 120, which is useful for the impulse matching procedure in the next section.
[2] Parts of the Matlab code from James LeSage’s toolbox were used: www.spatial-econometrics.com.

In the next section, an impulse matching procedure is used to find values of the model parameters that are consistent with the empirical impulse responses generated in this section.

1.3.2 Matching impulse responses

The basic idea of the matching impulse response methodology is to approximate the empirical impulse responses generated from the VARs by the theoretical responses predicted by the model outlined in Section 1.2. This is achieved by determining the optimal values for certain model parameters. These optimal parameters are chosen so that they minimize the distance between the theoretical and the empirical impulses, weighted by the inverse of the sample variances of the empirical impulses responses.

Figure 1.1. Empirical and theoretical impulse responses for the United States

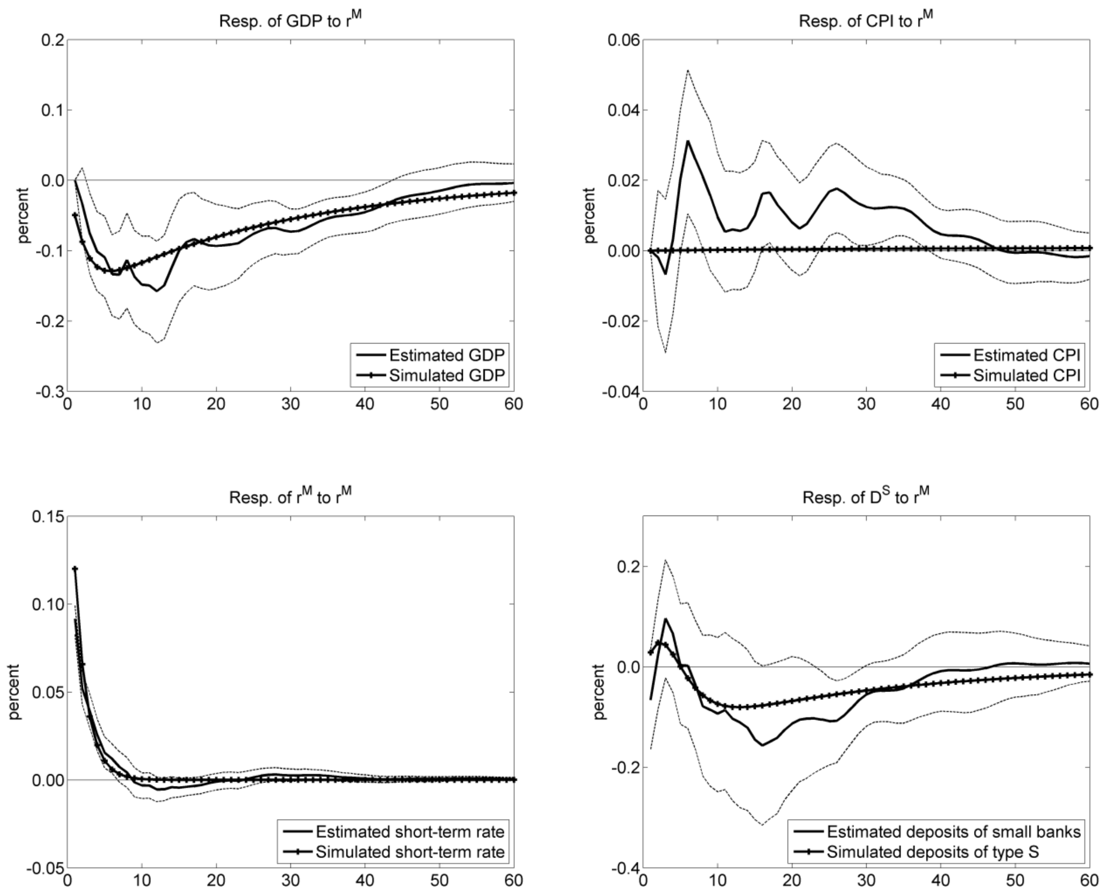
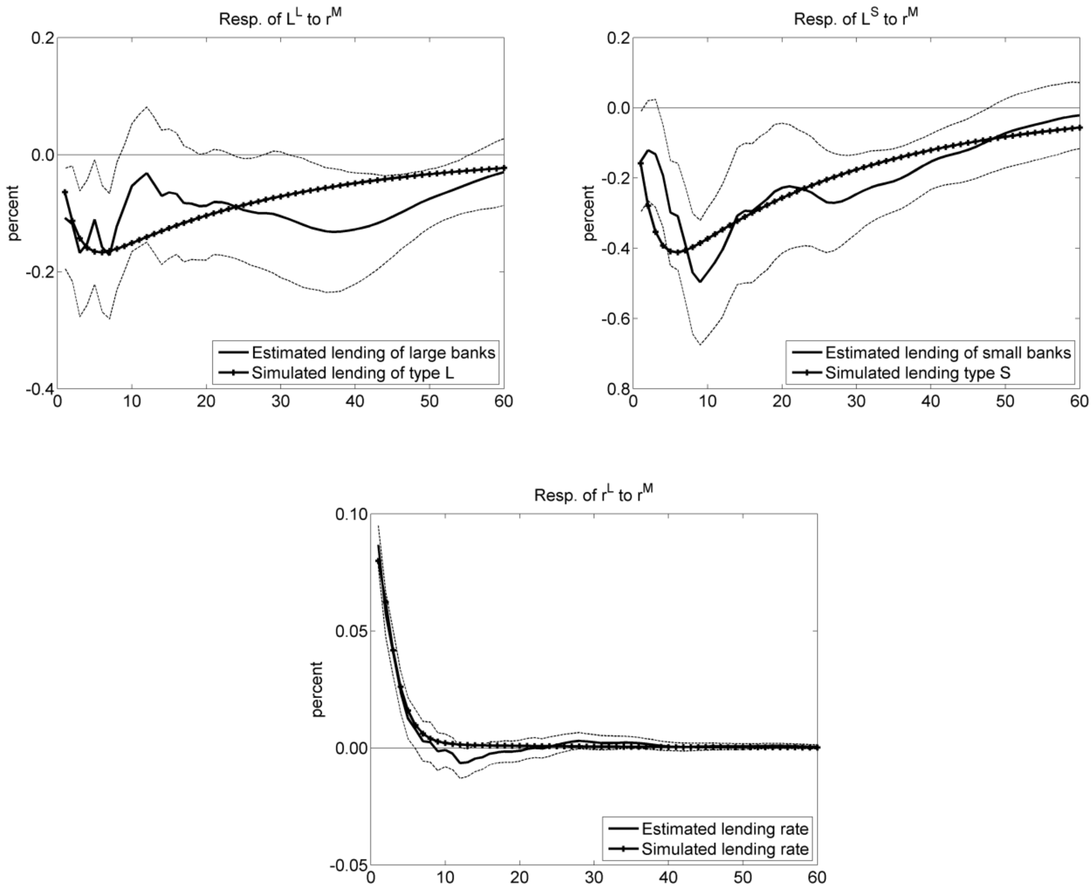


Figure 1.1 continued



Note: The bold lines are empirical impulses. The bold line with symbols depicts theoretical impulses. The thin lines represent the 90% error bounds. The time axis is in months. Note the different scales of the y-axis.

Mathematically,

$$\hat{\Gamma} = (\varrho_1, \varrho_2, \Gamma) \tag{19}$$

where $\hat{\Gamma}$ are the empirical impulse responses, Γ are the theoretical responses, ϱ_1 is a vector of estimated parameters, and ϱ_2 is a vector of calibrated parameters.

Several choices have to be made. The first question is which impulse responses to include in the matching. Hall, Inoue, Nason, & Rossi (2008) suggest several information criteria that help with the decision about which impulse response functions (IRFs) are valid and give efficient estimates. However, their approach starts from the universe of all possible IRFs and selects those that fulfil their criteria. Since this paper is empirically guided as to which IRFs are of interest, i.e. the response of the variables to a shock in the policy rate, these criteria are not implemented in this paper.

The choice of whether parameters are to be calibrated or estimated is somewhat arbitrary. Henzel, Hülsewig, Mayer, & Wollmershäuser (2009) suggest distinguishing calibrated from estimated parameters by their role for the dynamics of the economy. They calibrate the parameters which relate to the evolution of the flexible price equilibrium of their economy, but estimate parameters that reflect inefficiencies resulting from real rigidities, nominal frictions, the cost channel, and the policy response.

In this paper, an ad hoc approach is chosen as to which parameters are estimated. Those parameters are calibrated for which the optimization routine has difficulties finding a stable solution. Table 1.1 lists the parameters that are calibrated and their values. The estimated parameters and their standard errors are shown in Table 1.2.

Table 1.1. Calibrated parameters

Parameter	Symbol	Calibration
Discount factor	β	0.99
Long-run weight on inflation in Taylor rule	δ_2	2.00
Weight on future inflation in Phillips curve	α_1	0.25
Weight on future output in IS equation	γ_1	-0.50
Risk premium coefficient in baseline version	ρ_1	0.00
Share of deposits for bank type S, L	σ^S, σ^L	0.50
Reserve ratio	d	0.10

The estimator of ϱ_1 minimizes the following distance function (Henzel, Hülsewig, Mayer, & Wollmershäuser, 2009; Christiano, Eichenbaum, & Evans, 2005):

$$J = \min_{\varrho_1} \left(\hat{\Gamma} - \Gamma(\varrho_1)\right)' V^{-1} \left(\hat{\Gamma} - \Gamma(\varrho_1)\right) \tag{20}$$

where V is the weighting matrix, calculated as the inverse of the sample variances of the empirical impulse responses. Applying these weights gives point estimates with a smaller variance a higher weight. As Henzel, Hülsewig, Mayer, & Wollmershäuser (2009) note, an efficient estimate of ϱ_1 would require the use of the complete variance-covariance matrix. However, the optimization routine seems to run into convergence problems in this case.

If ϱ_1 is normally distributed, then J is χ^2–distributed with N – m degrees of freedom, where N is the number of observations on the impulse responses and m is the number of coefficients (Hülsewig, Mayer, & Wollmershäuser, 2006).

The figures in this section show the estimated impulse responses from Section 1.3.1 and the matched simulated responses for the United States (Figure 1.1) and Germany (Figure 1.2). In the case of the US, the match between the simulated and estimated impulses for GDP is quite close. Only the first simulation episode lies outside the 90% confidence interval. Unfortunately, the fit is worse for the consumer price index. The reason is that the theoretical model is not well suited to accommodate the price puzzle that is still existent, if abated, in the impulse reponses coming from the VAR model. The simulation results show only a tiny increase in the CPI level, while the empirical reality is more volatile. The fit of large bank lending and deposits is quite good, with all periods inside the confidence band. The simulated results for small bank lending decrease faster than the empirical responses, so three observations lie outside the confidence interval. The confidence bands for the policy and the lending rates are very small, but the simulations lie within the borders in all but one case.

Figure 1.2. Empirical and theoretical impulse responses for Germany

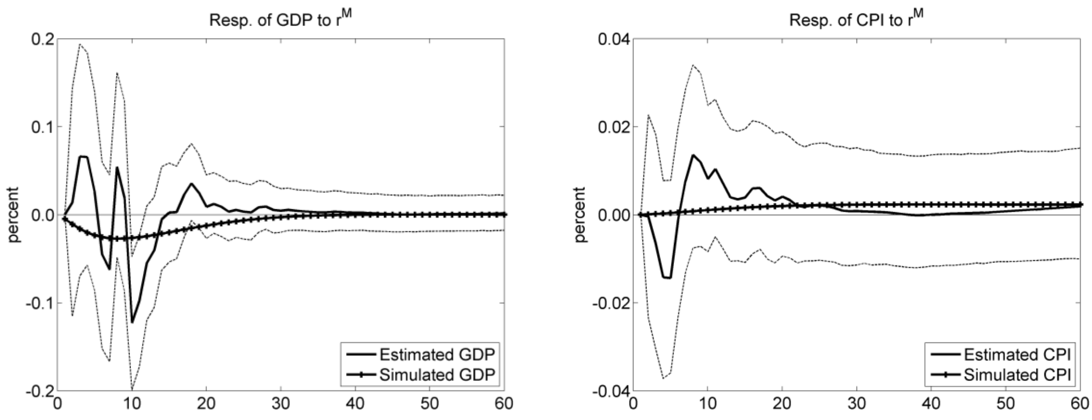
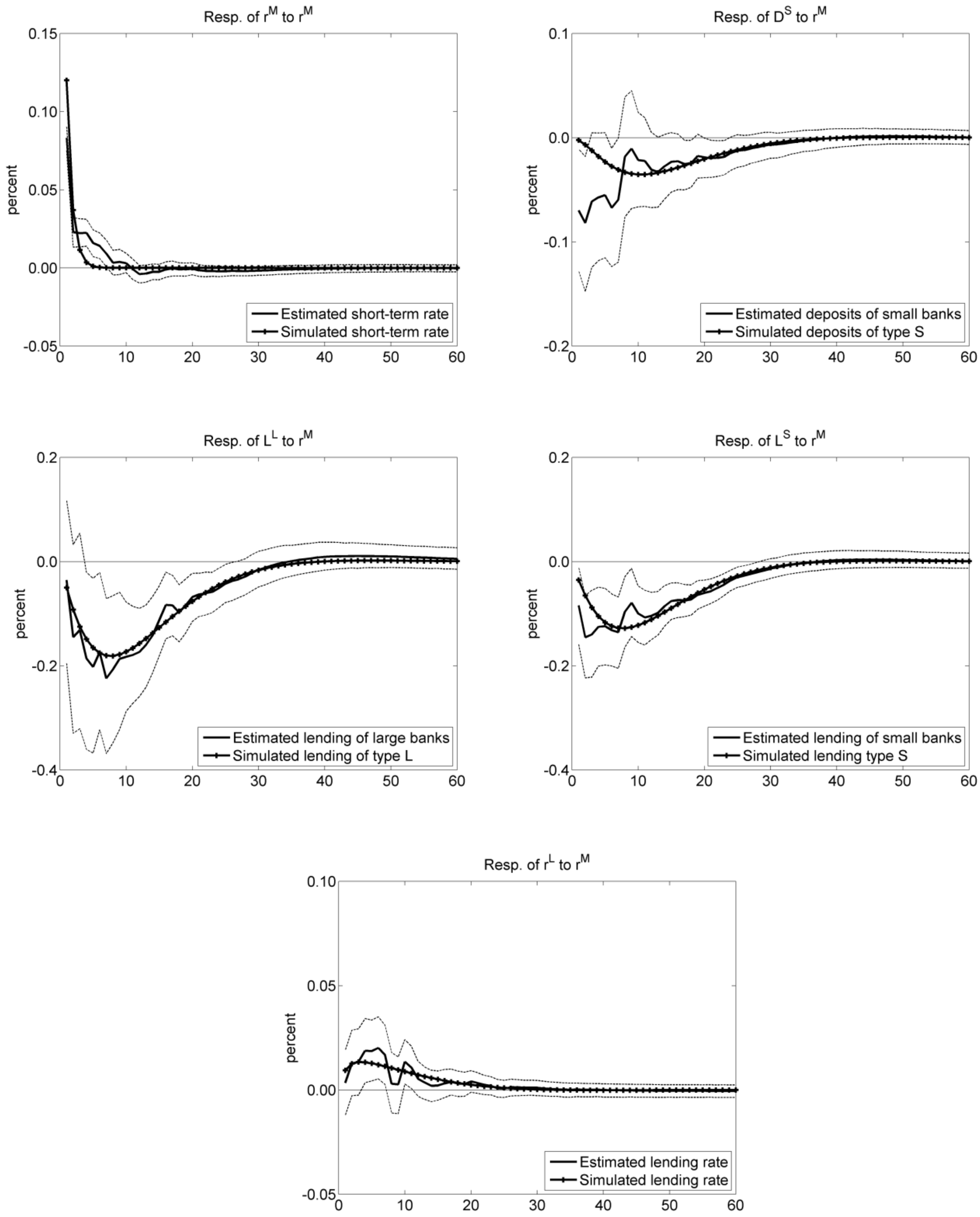


Figure 1.2 continued



Note: The bold lines are empirical impulses. The bold line with symbols depicts theoretical impulses. The thin lines represent the 90% error bounds. The time axis is in months. Note the different scales of the y-axis.

In the case of Germany (Figure 1.2), it is hard for the routine to match the empirical impulse response for industrial production due to its volatile nature. The simulation predicts a slight decline in this variable that lies mostly within the confidence bands. The simulation of the consumer price index ignores the swings in the first year, and predicts a slight overall increase in prices, similar to the case of the United States. Lending matches very well both for small and large banks, while the difference in deposits is only large during the first half year. The lending rate shows a tight fit, while the central bank rate declines a bit too quickly.

The estimated coefficients and standard errors are listed in the following table. The standard errors are calculated using the delta function method. This is necessary since the empirical impulse responses that are used in the matching procedure are associated with uncertainty which needs to be taken into account (Henzel, Hülsewig, Mayer, & Wollmershäuser, 2009).[3]

Table 1.2. Parameter estimates for the United States and Germany

Parameter	Estimate US	Standard error	Estimate Germany	Standard error
b_1	4.4784	1.5430	10.000	4.2430
b_2	0.0010	0.3419	4.2827	0.3032
$na^{S(-1)}$	0.9525	0.4040	0.0542	0.0239
$na^{L(-1)}$	0.3861	0.7833	0.0767	0.1189
δ_1	0.3814	0.0902	0.8677	0.0875
δ_3	0.0000	0.0090	0.2581	0.0821
δ_4	0.5481	0.1562	0.3079	0.0461
α_3	-0.0018	0.0021	-0.0447	0.1080
γ_2	1.1717	1.5423	1.1269	0.0863
γ_3	1.4171	0.0267	1.1512	0.0519
θ_1	0.4821	0.0857	1.0000	0.1544
θ_2	2.0114	1.1412	0.0000	0.1991
θ_3	0.6835	0.1181	0.6384	0.1916

Note: The value of the distance function is 224.9 with a probablity of 0.9999 for the US and 125.3 with a probability of 0.9999 for Germany. The standard errors are calculated based on the delta function method. In the optimization routine, the upper boundaries of the estimated parameters are set to ub = (10; 10; 5; 5; 1; 1; 1; 1; 3; 2; 1; 5; 1), and the lower boundaries are set to lb = (0; 0; 0; 0; 0; 0; 0; -1; 0; 0; 0; 0; 0).

For the US, the low value for b_2, the interest elasticity of aggregate loan demand, is striking. There is zero weight on the coefficient on output in the Taylor rule, δ_3. The fact that the coefficient α_3 is

[3] Parts of Matlab code on Lawrence Christiano's web site were used, based on Altig, et al., 2005.

negative reflects the existence of the price puzzle. However, the coefficient is not statistically significant.

In Germany, some coefficients reach the upper or lower boundaries set in the estimation procedure. The coefficient of the interest elasticity of aggregate loan demand, b_1, is quite large at 10. θ_1 and θ_2 are restricted by their boundaries as well, indicating some potential issues with the deposit supply function. The price puzzle coefficient is not statistically significant.

1.4 Results

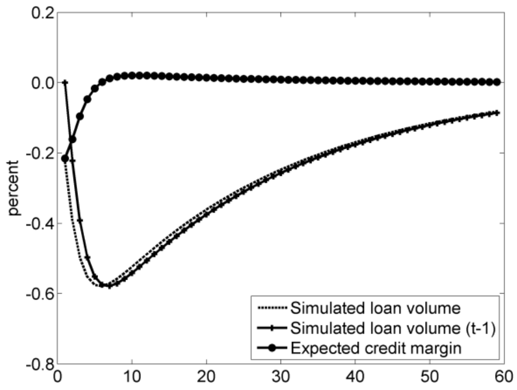
Based on the results of the matching procedure, bank lending can be decomposed into the factors that affect loan supply and those that determine loan demand. Aggregate loan supply is given by equation A.9 in Appendix A. It consists of the previous period's supply and the sums of the net present value of the discounted credit margins for each type. Loan demand depends on output and the real lending rate.

The results correspond qualitatively to the findings of Hülsewig, Mayer & Wollmershäuser (2006). Figure 1.3 shows that, in the US, both supply (a) and demand factors (b) have an important influence on the loan volume. The credit margin plays a substantial initial role but fades quickly, while demand components work with a larger lag. Surprisingly, the lending rate seems to have no effect on loan demand. Hence, the simulated loan volume and the output component coincide. This result is due to the low interest rate elasticity coefficient b_2.

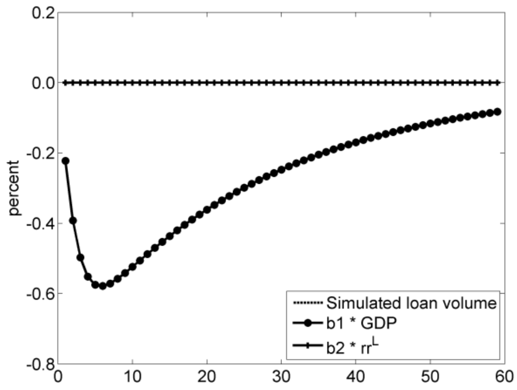
Similar conclusions hold for Germany (c and d). The credit margin has a considerable early effect. The lending rate component of demand is smaller than in the case of Hülsewig, Mayer & Wollmershäuser (2006), but larger than in the United States.

In a cross-country comparison, it seems difficult to establish systematic differences between the two economies. Loan supply has similar effects, and the interest-rate channel in the United States is obscured by the low interest rate elasticity.

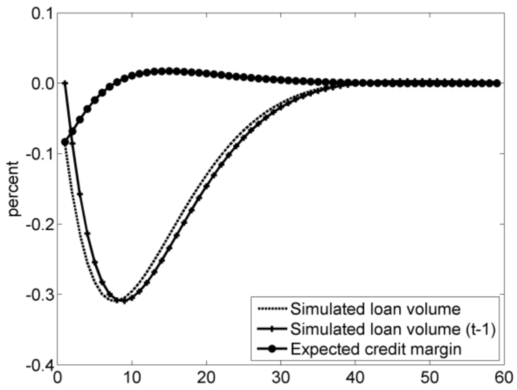
Figure 1.3. Loan volume decomposed in supply and demand factors



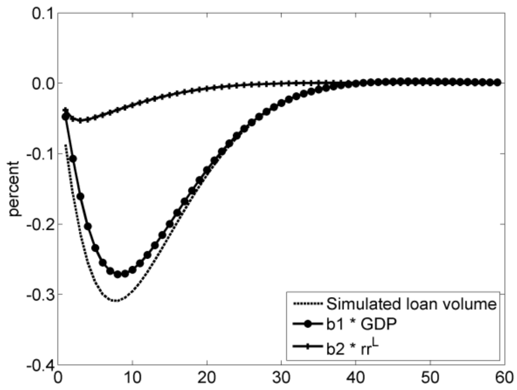
(a) Loan supply components US



(b) Loan demand components US



(c) Loan supply components Germany



(d) Loan demand components Germany

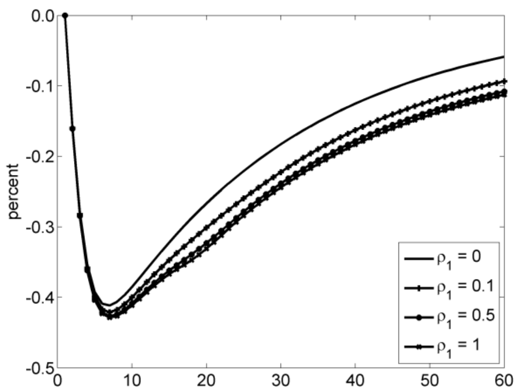
Note: The thin lines show the simulated response of lending to an interest rate shock. The time axis is in months.

The model permits an insight into the effect of interbank frictions on the lending behavior of banks. For this purpose, the model is simulated using the coefficient values from the matching procedure, but with different values for the risk premium parameter ρ_1. This risk premium may represent higher riskiness of larger loans, or the higher administrative costs associated with such loans. Under the riskiness interpretation, the rationale for having a risk premium coefficient of zero in the benchmark model may come from the observation that during normal times, interbank loans are considered relatively riskless, depending on a variety of characteristics such as their maturity or collateral. Especially in the case of Germany, the Landesbanken as the head institutions of the savings sector have an interest in the smooth functioning of interbank lending. The savings banks rely on the

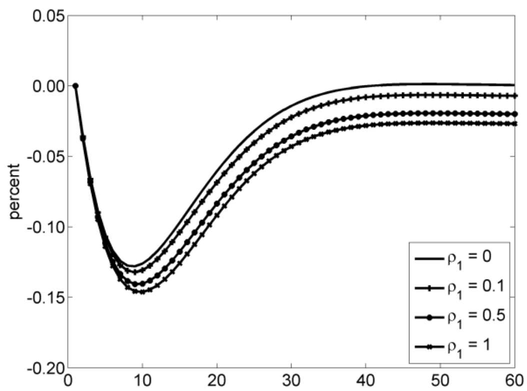
Landesbanken as their nearly sole provider of funds besides deposits, so the incentives of charging a higher interest rate are relatively low. If a savings bank gets into trouble, it tends to be merged with other banks rather than priced out of the market (Koetter, Bos, Heid, Kolari, Kool, & Porath, 2007).

Four different values of the risk premium coefficient are imposed. The effects of this change are not large, but noticeable. Looking at the impact at the trough might be of special interest to policymakers since it reflects the worst outcome of the shock. At the trough, the difference of small bank loans between a value of ρ_1 = 1 and the benchmark case of ρ_1 = 0 is about 4% in the case of the US, and 15% for Germany. Hence, interbank frictions do have a negative influence on the lending behavior of small banks, with German banks being comparatively more affected than US institutions if measured at the nadir. Although this difference of about 2 to 3 basis points is relatively small in economic terms, it still reflects a considerable difference in total lending of small banks, calculated back-of-the-envelope, of about \$54 million in the US and about €194 million in Germany, measured in 2005 dollars and euros, respectively. The two reasons for this disparity are the smaller difference due to interbank frictions in the US, and the larger size of the small bank sector in Germany.

Figure 1.4. Impulse responses of small bank lending in response to a shock to the policy rate under different scenarios for the risk premium parameter



(a) United States



(b) Germany

Note: Different scales on the y-axes

These results are qualitatively in agreement with those of Worms (2003) and Ehrmann & Worms (2001) who find evidence for a credit channel in Germany. However, they show that small banks use interbank funds to shield their costumers from a policy shock, reducing the extent of this transmission channel. A theoretical approach by Freixas & Jorge (2008) that models the relationship between banks in greater detail finds that interbank market imperfections can have an effect on lending behavior.

Consistent with this line of research, this paper has shown that, as it becomes more costly for small banks to obtain interbank deposits, their capacity to counteract the policy-induced fall in loan supply is reduced. This effect is smaller in the case of the United States, which provides some evidence that interbank relations play a more modest role for the bank lending channel as compared to Germany.

1.5 Conclusion

This paper has presented a structural model of the economy with a banking sector that included an interbank market. Banks are profit-maximizing in their decision to lend to the real economy and tap into the interbank market. The parameters of the model were calibrated by matching the theoretical impulse responses of the model with the empirical responses of a VAR model for the United States and Germany, respectively. This method overcomes the identification problem of changes in total loan volume by distinguishing between supply and demand factors that simultaneously influence aggregate balance sheet data.

The paper finds evidence for a bank lending channel in both countries. Loan supply drops quickly after an interest rate shock because of the expected decrease in the credit margin, while the reduction in loan demand is more protracted. However, there does not seem to be a systematic difference between the market-based economy of the United States and the bank-based economy of Germany. Additionally, frictions in the interbank market cause a larger decline in lending by small banks as compared to the case of a frictionless interbank market. The absolute impact of such frictions on bank lending is larger in Germany than in the United States.

Appendix A. A model of the banking sector

The basic model outline follows Hülsewig et al. (2006), but there are a few twists.

The profit maximization problem of a bank of type T is (i stands for an individual bank, t is time):

$$\Pi^{Ti}_{t+j} = rr^{L}_{t+j}*L^{Ti}_{t+j} - rr^{M}_{t+j}*D^{Ti}_{t+j}$$

$$- (rr^{M}_{t+j} + \max(0, \rho_1^{T}/2*B^{Ti}_{t+j}))*B^{Ti}_{t+j} - a^{T}/2*(L^{Ti}_{t+j} - L^{Ti}_{t+j-1})^2 \qquad (A.1)$$

$$\text{s.t. } L^{Si}_{t+j} + R^{Si}_{t+j} = D^{Si}_{t+j} + B^{Si}_{t+j} \text{ if } T = S \text{ or} \qquad (A.2)$$

$$\text{s.t. } L^{Li}_{t+j} + R^{Li}_{t+j} = D^{Li}_{t+j} + B^{Li}_{t+j} + CM^{Li}_{t+j} \text{ if } T = L \qquad (A.3)$$

and $R^{Ti}_{t+j} = d* D^{Ti}_{t+j}$, where R^{T} are reserves and d is the required reserve ratio.

$C^{Ti}_{t+j} = a^{T}/2*(L^{Ti}_{t+j} - L^{Ti}_{t+j-1})^2$ is the cost of adjusting the loan portfolio.

Π^{Ti}_{t+j} is profits of one bank of type T at time t + j.

The deposit rate rr^{D}_{t} is set to rr^{M}_{t} for arbitrage reasons.

A single bank seeks to maximize the expected present value of its profit flow:

$$V^{Ti}_{t} = E_t \sum \beta^{j}* \Pi^{Ti}_{t+j} \qquad (A.4)$$

So, the objective function is max V^{Ti}_{t} with respect to L^{Ti}_{t}, B^{Ti}_{t}. Deriving the optimality conditions yields:

$$\partial V^{Ti}_{t}/\partial L^{Ti}_{t} = rr^{L}_{t+j} - a^{T}*(L^{Ti}_{t+j} - L^{Ti}_{t+j-1})$$

$$+ a^{T}*\beta *E_{t+j} (L^{Ti}_{t+j+1} - L^{Ti}_{t+j}) + \lambda^{Ti}_{t} = 0 \qquad (A.5)$$

$$\partial V^{Ti}_{t}/\partial B^{Ti}_{t} = - rr^{M}_{t+j} - \max(0, \rho_1^{T} * B^{Ti}_{t+j}) - \lambda^{Ti}_{t} = 0 \qquad (A.6)$$

$$\partial V^{Si}_{t}/\partial \lambda^{Si}_{t} = L^{Si}_{t+j} + (d-1)*D^{Si}_{t+j} - B^{Si}_{t+j} = 0 \qquad \text{if } T = S \text{ or} \qquad (A.7a)$$

$$\partial V^{Li}_{t}/\partial \lambda^{Li}_{t} = L^{Li}_{t+j} + (d-1)*D^{Li}_{t+j} - B^{Li}_{t+j} + CM^{Li}_{t+j} = 0 \qquad \text{if } T = L \qquad (A.7b)$$

From A.5 and A.6 follows the optimal loan supply for a bank of type T:

$$rr^{L}_{t+j} - a^{T} * (L^{Ti}_{t+j} - L^{Ti}_{t+j-1}) + a^{T} * \beta * E_{t+j} (L^{Ti}_{t+j+1} - L^{Ti}_{t+j}) - rr^{M}_{t+j}$$

$$- \max(0, \rho_1^{T} * B^{Ti}_{t+j}) = 0 \qquad \text{(A.8)}$$

Optimal loan supply depends on the spread between the lending and the policy rate, the marginal cost of changing the loan portfolio, and a factor related to the risk premium in the interbank market. Aggregate loan supply (evaluated at j = 0) is the sum of loans of n identical banks of each type:

$$L_t = L_{t-1} + na^{L\,(-1)} \sum_{s=0}^{\infty} \beta^S E_t(r^L_{t+s} - r^M_{t+s}) + na^{S\,(-1)} \sum_{s=0}^{\infty} \beta^S E_t(r^L_{t+s} - r^M_{t+s}) \qquad \text{(A.9)}$$

Hülsewig et al. (2006) show how to derive the loan market equilibrium from equation (A.9). There is a small change compared to their paper, since there are two bank types in the model here. Hence, the loan demand equation is given by

$$L^{L}_{t} + L^{S}_{t} = b_1 * y_t - b_2 * rr^{L}_{t} \qquad \text{(A.10)}$$

Following the steps in Hülsewig et al. (2006) yields the final equations:

$$L^{S}_{t} = 1/\psi_1 * \beta * E_t L^{S}_{t+1} + 1/\psi_1 * L^{S}_{t-1} + b_1/b_2 * na^{S\,(-1)}/\psi_1 * y_t$$

$$- rp_t - na^{S\,(-1)}/\psi_1 * rr^{M}_{t} - na^{S\,(-1)}/\psi_1/b_2 * L^{L}_{t} \qquad \text{(A.11)}$$

$$L^{L}_{t} = 1/\psi_2 * \beta * E_t L^{L}_{t+1} + 1/\psi_2 * L^{L}_{t-1} + b_1/b_2 * na^{L\,(-1)}/\psi_2 * y_t$$

$$- na^{L\,(-1)}/\psi_2 * rr^{M}_{t} - na^{L\,(-1)}/\psi_2/b_2 * L^{S}_{t} \qquad \text{(A.12)}$$

Appendix B. Data

For Germany, industrial production, the CPI index, and the money market rate are taken from the IMF IFS. Data on German banks are available from the Bundesbank website. The following series have been used: Lending to non-banks (non-MFIs) by savings banks (OU1083), lending to non-banks (non-MFIs) by Landesbanken (OU1033), deposits and borrowing from domestic non-banks (non-MFIs) of savings banks (OU1842). Ideally, one would want to exploit micro data to calculate aggregate balance sheet positions of the small and large bank sectors for all banks in Germany. Unfortunately, such data are not publicly available. Using data for the Landesbanken and savings banks can nevertheless be considered a valid approximation since decision-making is relatively autonomous and independent in these institutions. However, one should keep possible limitations in mind.

Bank balance sheet data and the industrial production index are all in log-levels. Bank data have been deflated using the CPI index. Interest rates are in decimals. The monetary instrument is the overnight market rate in Frankfurt. Potential breaks due to the introduction of the euro and the switch in lending rates in June 2003 are captured by dummy variables. It is perceivable that only including a dummy variable at the break in the lending series might not sufficiently capture the change in its definition. However, one has to weigh the loss of several years of data against the risk of inappropriately putting the two series together. Since it can be assumed that the new definition of the lending variable is highly correlated with the counterfactual of the old definition, adding more than 50 observations might be worthwhile. The lending rate is calculated as the average of the effective interest rates of German banks / Outstanding amounts / Housing loans to households with maturity of over 1 year and up to 5 years (SUD007), as well as the corresponding rates for consumer credit and other loans to households (SUD010) and loans to non-financial corporations (SUD013).

The two-month forward rate one-month ahead, fr, is calculated based on Gurkaynak, Sack, & Wright (2006, p. 6):

$$fr_t(1, 2) = (3 * r^M_{3m,\,t} - r^M_{1m,\,t}\ ) / 2 \qquad \text{(B.1)}$$

where r^M_{3mt} and r^M_{1mt} are the money market rates in Frankfurt for three-month and one-month contracts, respectively. The data, series ECWGM3M and ECWGM1M, are downloaded from Datastream.

For the US, data on banks are retrieved from the Federal Reserve. The series used are deposits, small domestically chartered commercial banks, not seasonally adjusted (H8/H8/B1058NSMDM), commercial and industrial loans, small domestically chartered commercial banks, not seasonally adjusted (H8/H8/B1023NSMDM), and commercial and industrial loans, large domestically chartered commercial banks, not seasonally adjusted (H8/H8/B1023NLGDM).

Industrial production, the CPI index, the Fed funds rate, and the lending rate are downloaded from the IMF IFS. The one-month forward rate one-month ahead is created similarly as for Germany. The difference is due to data availability, but should not have a large influence on the final results. The data used, obtained from Datastream, are the US interbank offered rate for one-month and two-month funds, respectively (BBUSD1M, BBUSD2M).

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Chapter 2

The US Interbank Market, Bank Size, and the Credit Channel

2.1 Introduction

Monetary policy affects the real economy in a variety of ways. The transmission mechanism which is best understood, and commonly thought to have the strongest effect, is the so-called interest rate channel. This concept holds that, in the presence of price rigidities, an increase in the policy rate will raise the real interest rate, reducing investment by firms and credit-related consumption by households, eventually weakening aggregate demand. Additionally, the rate increase will put upward pressure on the exchange rate which will make exports more, but imports less, expensive. Restrictive monetary policy also tends to depress asset prices, which in turn reduces aggregate demand (Worms, 2004).

The transmission channels described above function independently of frictions in financial markets: they operate even if these markets are perfect. The literature refers to them as traditional transmission channels (Bernanke, 1983; Bernanke & Blinder, 1992). In this view, financial institutions are treated as a black box, seen as merely passing on interest rates and reacting to aggregate demand-induced changes in loan volume, but with no distinct economic significance for macroeconomic variables such as output and inflation. However, the research of Ben Bernanke and others (e.g. Bernanke & Blinder, 1992; Kashyap, Stein, & Wilcox, 1993; Bernanke & Gertler, 1995; Bernanke, Gertler, & Gilchrist, 1999) has highlighted the importance of banks' idiosyncratic supply decisions in providing credit to their clients and has created theories of the credit channel which accord the financial sector a more active role in the transmission of monetary policy.

For the credit channel to operate, financial markets need to be subject to imperfections (commonly considered to be the result of informational asymmetries). For instance, in the balance sheet channel, a sub-mechanism of the credit channel, a potential borrower's ability to obtain funds depends on the amount of his net worth that can be used to finance projects internally or as collateral for loans. However, due to informational asymmetries, external finance is subject to agency costs that lead to a markup of external over internal finance, the so-called external finance premium. Therefore, an increase in interest rates will tend to decrease an individual's net worth because of higher interest payments on debt and a diminished value of collateral, which in turn will raise the amount of external finance that an individual would need and thereby the external finance premium. Hence, the borrower will be able to acquire fewer external funds due to loan supply restrictions, which reduces aggregate demand.

The focus of this paper is the bank lending channel, another sub-channel of the credit channel, in which informational asymmetries also play an essential role. In this channel, monetary policy influences bank lending by manipulating the aggregate amount of required reserves, affecting the credit available through the banking system. Under a restrictive monetary policy, the central bank decreases the amount of required reserves, which results in a reduction of deposits that banks can accept in order to meet their reserve requirements. When deposits decline, banks may be compelled to reduce their supply of loans, negatively affecting aggregate demand. Unlike the traditional transmission channels, for this channel to be operative, two conditions that are related to market frictions are necessary. First, deposits and other funding sources, such as certificates of deposit or commercial paper, must be imperfect substitutes for one another (Fama, 1985; Romer & Romer, 1990). This might be the case when there are high transaction costs for such instruments. Second, bank loans and other bank assets such as securities holdings must also be imperfect substitutes for one another, which is a reasonable assumption given their distinct risk diversification and liquidity characteristics (Worms, 2004). If these instruments were perfect substitutes, a bank could simply draw down its holdings of such alternative assets instead of its loan portfolio. If these two conditions are met, a decline in deposits cannot be fully compensated for by other means and a bank must adjust its lending portfolio by decreasing the availability of loans.

Bank lending channel literature postulates that such market imperfections should affect some types of banks more than others. Most importantly, small banks are thought to be particularly susceptible to market imperfections, as they have fewer financing and investment options at their disposal than large banks. As such, one would expect that, *ceteris paribus*, smaller financial institutions should be less able to shelter their lending portfolio from shocks.

However, small banks may have developed strategies to circumvent such 'shortcomings'. For instance, literature on relationship banking emphasizes the frequently close, even personal, long-term ties most prevalent between small banks and their customers (Elyasiani & Goldberg, 2004). Small banks are at an advantage in this regard because they are located in closer geographic proximity to their clients and may therefore have access to more 'soft' information than large banks that rely on standardized methods and 'hard' facts, such as credit scores, to determine whether to approve a loan (Petersen, 2004). Such a close, long-term relationship brings with it the need for a small bank to shelter its borrowers if shocks put pressure on their balance sheets (Deutsche Bundesbank, 2001; Worms, 2003). It is conceivable that these banks adjust their balance sheets in ways that allow them to respond adequately to such situations (Worms, 2004). One would therefore expect that the bank lending channel does not necessarily manifest itself as a direct size-dependence of lending, but as different adjustments of balance sheet positions for banks of different sizes.

In contrast to this position, studies on the US banking system generally find support for a direct size dependence in the credit channel (e.g. Kashyap & Stein, 1995; Kashyap & Stein, 2000; Peek & Rosengren, 1995), though there are exceptions (Den Haan, Sumner & Yamashiro, 2007). Studies on Europe, however, are more mixed (deBondt, 1999; Favero, Giavazzi & Flabbi, 1999; Gambacorta, 2005).

One underexplored aspect of the financial sector's role in the functioning of the credit channel is the relationship between banks in the interbank market. In the literature, interbank variables are frequently mixed with other balance sheet positions to form measures of bank liquidity (e.g. Kashyap & Stein, 2000; Gambacorta, 2005), if they are included at all (e.g. Kashyap & Stein, 1995). This is surprising since it seems essential to control for changes in the precise composition of banks' balance sheets when identifying the differential effects of various transmission channels. For example, imagine a very simple bank with only loans as assets and both capital and deposits as liabilities. A negative exogenous shock to capital would force the bank to restrict lending if it cannot attract more deposits. In this case, the capital-asset ratio would decline, while the deposit ratio would increase, and lending growth would be negative. If one neglected the capital-asset ratio in a regression, it would appear that lower lending growth was associated with a higher deposit ratio. Therefore, most regressions either include the capital-asset ratio (Gambacorta & Mistrulli, 2004) or divide banks up into groups based on this ratio before running a regression (Kishan & Opiela, 2000). This paper argues that such an omitted variable bias could likewise exist if a regression did not properly account for interbank lending and borrowing.

One reason that interbank positions might get overlooked is that they typically comprise only a small share of total bank assets, especially when compared to other balance sheet items like loans or deposits (see Section 2.3 below). Nevertheless, interbank activities perform valuable functions for banks, both as lenders and borrowers, and should not be treated as rounding errors. First, interbank lending can be a profit center, especially for small banks (Stigum & Crescenzi, 2007). Additionally, it can provide some buffer against shocks, similar to cash or security holdings (Stein, 1998). Further, banks may benefit from a relatively cheap and reliable funding alternative, especially when they are able to develop relationships with other banks (Furfine, 1999; Cocco, Gomes & Martins, 2009).

Hence, it is vital to distinguish different balance sheet positions in order to determine their respective importance for the bank lending channel. Based on the above discussion, one may hypothesize that interbank lending is more important for small than for large banks. Also, interbank borrowing and lending are no substitutes since they may fulfill distinct functions for different banks and therefore cannot be netted out.

These questions are of great relevance since an accurate understanding of the transmission channels of monetary policy is essential for central banks to set an adequate policy rate. Moreover, banks' behavior in the interbank market may give policy makers valuable information about the effects of their measures, so that they can make necessary adjustments. Also, the credit channel may operate differently if it relies directly on bank size as opposed to a scenario in which the balance sheet *composition*, rather than its *magnitude*, matters for the transmission of monetary policy.

There are relatively few papers that pay attention to the specific influence of the interbank market on the credit channel. Freixas & Jorge (2008) develops a theoretical model of how financial imperfections in the interbank market affect the transmission of monetary policy. The authors find support for Kashyap & Stein's (2000) liquidity effect which provides that less liquid banks react more strongly to monetary policy changes, as well as for credit rationing. The latter can occur when banks, after a raise in the monetary policy rate, are unable to secure sufficient funding in the interbank market and therefore decrease lending to the real economy rather than pass on the higher lending rate to their clients. Worms (2001, 2003) and Ehrmann & Worms (2001, 2004) provide evidence for the existence of the credit channel in Germany, taking into account the specific network structure of the German banking sector.

Literature dealing with financial crises has often focused on the interbank market, particularly on how liquidity shortages can spread through the interbank market during such times (Allen & Gale, 2000; Upper & Worms, 2004; Mistrulli, 2011). However, this paper emphasizes that the interbank market should be considered essential for having effects on the real economy even during 'normal' times. Hence, this paper focuses on the last 20 years and encompasses both good and bad times. Additionally, one of the robustness checks in this paper is to exclude observations during the recent financial crisis.

The paper is structured as follows. Section 2.2 outlines the estimation methodology. Section 2.3 describes the data and presents more detailed information on the US interbank market. Section 2.4 reports the results and interprets the findings in light of the hypotheses described above. Section 2.5 concludes.

2.2 Model

The model represents a reduced form of the loan market in the spirit of Kashyap & Stein (1995) and Ehrmann et al. (2003). It includes interaction terms for both the size dependency of the balance sheet variables and their dependency on monetary policy.

$$\frac{(C_{n,t} - C_{n,t-1})}{C_{n,t-1}} = \alpha_n + \beta \cdot size_{n,t-1} + \gamma \cdot (\Delta i_{t-1} \cdot size_{n,t-1}) + \delta \cdot b_{n,t-1} + \theta \cdot (b_{n,t-1} \cdot size_{n,t-1})$$
$$+ \lambda \cdot (b_{n,t-1} \cdot \Delta i_{t-1}) + \mu \cdot (b_{n,t-1} \cdot size_{n,t-1} \cdot \Delta i_{t-1})$$
$$+ \rho \cdot bcon_{n,t-1} + \tau \cdot (bcon_{n,t-1} \cdot size_{n,t-1}) + \varphi \cdot \Delta X_{n,t-1} + d_t + \varepsilon_{n,t}$$

The dependent variable *C* (for credit) is quarter-on-quarter growth in total bank lending, as defined in the next section. The term *b* stands for the bank balance sheet variables of interest. *Size* represents the logarithm of total bank assets. The term *i* reflects the interest rate or an alternative monetary policy indicator. *Bcon* is a term for other bank control variables, such as idiosyncratic risk. *X* stands for non-bank control variables. A full set of time dummies is captured by d_t.

The term $\Delta i_{t-1} * size_{n,t-1}$ is of special interest. It reflects the credit channel, interpreted as a direct size dependence of interest rate changes: as explained earlier, a restrictive monetary policy should have a smaller (less negative) effect on lending growth for a larger than for a smaller bank. Hence, if this form of the credit channel exists, γ should be positive and significant.

All regressions are based on the fixed-effects model. The standard errors are assumed to be cluster-robust, that is, errors are independent across banks, but allow for intra-cluster (within bank) correlation, for $N \rightarrow \infty$. In other words, observations are independent across banks, but they need not be independent within banks. This is a weaker assumption than the errors $\varepsilon_{n,t}$ being i.i.d.

A complete set of time dummies d_t is included in all regressions. The advantage of this method is that it controls for common factors that affect all banks simultaneously, such as the business cycle, inflation, regulatory changes or shifts in risk attitude. Most importantly, it eliminates unobserved time-related shocks that could violate the assumption that the errors are independently distributed across clusters (Worms, 2003; Roodman, 2006).

The disadvantage of time dummies is that variables that are identical for every bank at time *t*, such as the current monetary policy rate, cannot be directly included in the regressions. A set of time dummies completely controls for the variation of such variables. However, a time-variant common variable can be interacted with a variable that varies across both time and clusters. This interaction term can be included in a regression with time dummies. The details are described further below.

All right-hand side bank variables enter the regressions with one lag due to possible endogeneity issues arising from the balance-sheet nature of the data (Worms, 2003). This approach mitigates interpretation problems related to the causality of the estimated effects, though this method might not be completely effective. For example, it is conceivable that a bank (correctly) *anticipates* approving more loans next quarter, and therefore increases its deposit base this quarter. However, one would usually assume that the bank faces external constraints and, in a profit-maximization framework, adapts when these constraints change. Hence, one would presume that a more steady deposit base today would allow banks to increase lending going forward.

The main dependent variable is quarter-on-quarter total loan growth, but some robustness checks make use of quarter-on-quarter commercial and industrial (C&I) loans or loans secured by real estate.

2.3 Data and the US interbank market

Bank data are taken from the Consolidated Reports of Condition and Income (Call Reports) which are filed quarterly by all US commercial banks (for a description of the variables used, see Appendix A). The Call Reports have been available since 1976, though there have been several changes in the definition of many variables and several new variables have been introduced. The time horizon in this paper is 1990Q1 to 2010Q4, though for some comparisons, data going back to 1976Q1 are used. The sample is chosen to comprise several business cycles, ensure a relatively stable monetary policy and regulatory environment, as well as to limit the extent of variable redefinitions.

The Call Report data have been 'cleaned up' by dropping observations for which total assets are negative, presumably typos. The same was done for all balance sheet variables that should be, by definition, non-negative. Due to the special nature of certain bank locations, data for American Samoa, the Federated States of Micronesia, Virgin Islands, Puerto Rico, Guam, and 'not applicable' ("0", "XX") have been removed. Bank balance sheet variables have been calculated as ratios of total assets or total liabilities, except for allowances for loan and lease losses, which is more meaningfully expressed as a ratio of total loans. Some variables, notably interbank lending and borrowing, as well as liquidity, undergo changes in their Call Report definition.[4] Although these changes are relatively minor, it is possible that there may be discontinuities in the variables. The time dummies may be able to take care of such discontinuities to a certain degree, and the screening mechanism for outliers described below should remove the affected observations in severe cases.

Outliers are removed by discarding observations below the first and above the 99th percentile of all variables but size and the interest rate, unless the first percentile is zero. Additionally, the change of all ratios between two periods is computed, and observations for which the change in ratio falls below the first or above the 99th percentile are dropped. This process ensures that sudden large changes in the balance sheet composition of a bank, possibly due to mergers or acquisitions (M&As), do not bias the results.[5] The choice of the percentiles is arbitrary, but for every variable a visual inspection was undertaken to ensure an adequate distribution of observations.

Size interaction variables are created by multiplying the respective balance-sheet or interest rate variable by the bank size variable. In a panel framework, one potential bias can arise in interaction variables when a coefficient of interest varies with the panel identifier, such as banks in this paper (Balli & Sørensen, 2012). In this case, the coefficients of the interaction terms may incorrectly pick up differences in the bank-specific slopes of the variables. Balli & Sørensen (2012) show that the subtraction of bank-specific means from each variable in the interaction term can eliminate this potential bias, a suggestion that is implemented in this paper. The variable 'bank size' was additionally modified by subtracting the time-varying mean across all banks from the log of assets of bank *n*. This process results in a more meaningful interpretation of the coefficients of the interaction terms because they measure the effect for a bank of average size (Worms, 2003). It also removes unwanted trends in bank size (Ehrmann, Gambacorta, Martinez-Pages, Sevestre & Worms, 2003).

To measure the interaction effects for banks of different sizes, the mean is replaced by the respective size percentile of interest. This process is crucial to the understanding of the methodology

[4] In the case of interbank lending, for observations before 2001Q4, series rcfd1350 was used. After 2003Q1, the Call Reports have individual series for federal funds purchased (rcfdb987) and securities sold (rcfdb989), so these two series are added together. In 2002, only the rcon series for domestic offices are available. Interbank borrowing is handled accordingly (series rcfd2800, rcfdb993, rcfdb995). Liquidity consists of series rcfd0390 until 1993Q4 and the sum of series rcfd1754 and rcfd1773 afterwards as indicated on the Federal Reserve Data Dictionary website.

[5] It is not clear whether alternative methods of dealing with M&As would be better. Some options include discarding all banks that have merged or gotten acquired (e.g. Favero, Giavazzi, & Flabbi, 1999), combining banks involved in an M&A before the period in which it took place (e.g. Peek & Rosengren, 1995; Worms, 2003; Gambacorta & Mistrulli, 2004) or dropping the bank observations for the quarter in which a merger took place (e.g. Kashyap & Stein, 1995). The method chosen here does not lead to a large loss of observations and is purely data-driven. It basically assumes that, at a given point in time, two banks with similar characteristics such as size, but with one bank having been affected by an M&A, will behave similarly after a sufficiently short period of time. To the extent this period increases, this method will be less accurate.

used in this paper. To see why, assume that the size variable would not be re-centered at all. In this case, the coefficient δ in the model equation above would measure the effect of a change in *b* for an average bank with no assets (size 0). This does not make sense in the first place, since banks do have positive assets. Additionally, it may not be in the researcher's interest to measure the effect of *b* at this size level. Therefore, by centering the *size* variable on different points of the size spectrum so that it is zero at the size level of interest, one can measure the remaining coefficients as well as their significance and analyze their changes as size varies.

Data on not seasonally-adjusted county- or state-level employment come from the Bureau of Labor Statistics' *Local Area Unemployment Statistics* (LAUS) program. The monthly employment figures are averaged by quarter, converted to logs and first-differenced. If data on county-level employment are unavailable, missing data are replaced with state-level employment. The federal funds rate is taken from the IMF *International Financial Statistics* (IFS) database.

Table 2.1 summarizes some of the key statistics for the first and final quarter of the sample, as well as for the adjusted dataset as described above.

Table 2.1. Key US bank statistics

	1990Q1	2010Q4	1990Q1 – 2010Q4
Number of banks	13,733	7,284	17,291
Total number of observations	-	-	832,224
Aggregate asset size (US$ trillion)	4.2	15.5	8.5
Aggregate asset size (2005 US$ trillion)	6.3	13.8	9.1
Aggregate asset size as share of US GDP	72.7%	105.2%	79.1%
Total lending-to-asset ratio	54.0%	61.5%	58.9%
Interbank lending-to-asset ratio	6.9%	2.3%	4.0%
Interbank borrowing-to-asset ratio	1.6%	1.4%	1.4%
Liquidity-to-asset ratio	28.5%	21.0%	26.1%
Cash-to-asset ratio	7.6%	9.6%	5.4%
Capital-asset ratio	9.3%	11.8%	10.2%
Deposit-to-liability ratio	96.6%	92.8%	94.8%
Goodwill-to-asset ratio	0.0%	0.4%	0.1%

Note: Numbers do not sum to 100% on either the asset or liability side since not all balance sheet items are included.

Source: Author's calculation based on US Call Report data, IMF *International Financial Statistics*

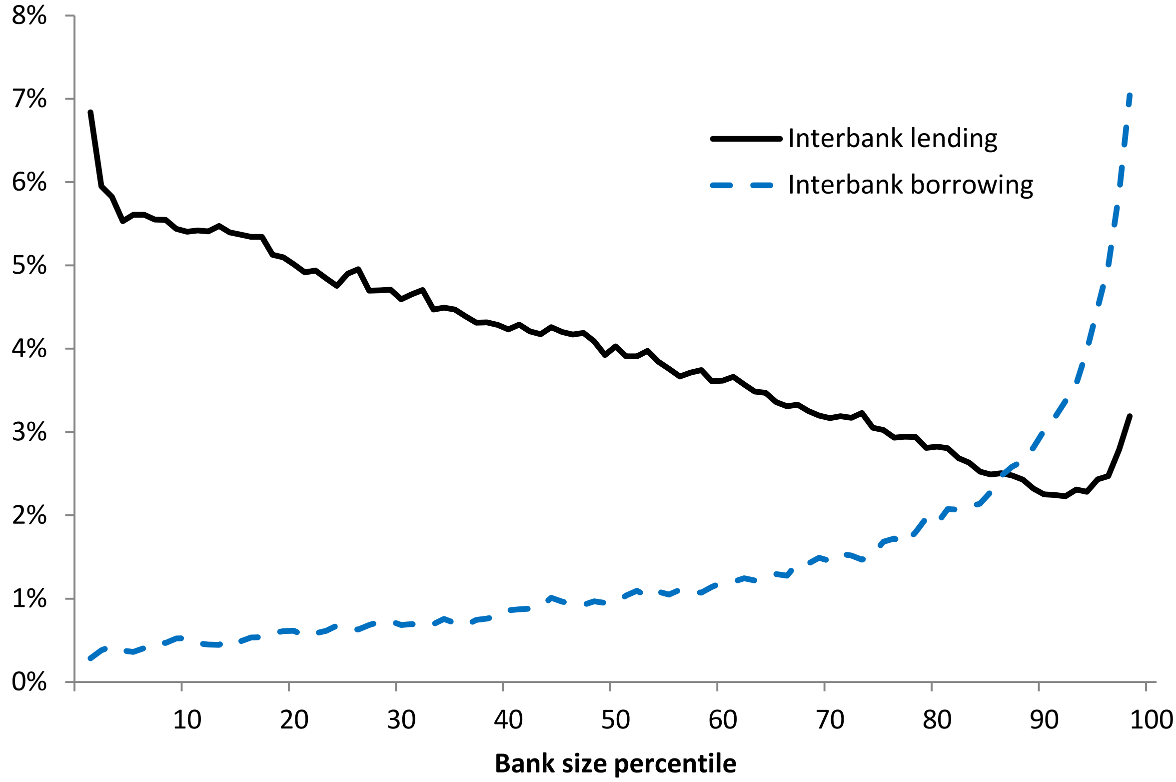
Although the numbers are neither seasonally nor cyclically adjusted, and hence have to be taken with a grain of salt, some broad trends emerge. The number of banks has decreased by almost half during the sample period. At the same time, new banks have been created as demonstrated by the total number of more than 17,000 individual banks over the whole sample period. This consolidation and evolution of the US banking industry has been documented elsewhere (Wheelock & Wilson, 2004; Jones & Critchfield, 2005). The aggregate size of this sector has almost doubled in real terms, and increased by 45% as a share of GDP.

The largest asset position, total lending to the real economy, is used as the dependent variable *C* is the baseline regression. It comprises, among others, loans secured by real estate, commercial and industrial loans, and loans to individuals for personal expenditure. It has on average increased by 7.5 percentage points as a share of total assets. Interbank lending has decreased by two-thirds as a share of assets, while interbank borrowing has remained relatively stable. Liquidity in the form of securities has lost somewhat of its importance, but comprises on average more than 25% of bank assets over the whole sample. The cash ratio has declined throughout most of the sample period up to the financial crisis, when banks started holding large amounts of cash. The capital-asset ratio has continuously increased by about 2.5 percentage points. Although the goodwill ratio is very small on average, one should keep in mind that it may play a larger role for certain banks. For example, in 2010Q4, goodwill amounts to 6.4% of total assets for banks at the 99th percentile.

It is important to consider a comprehensive selection of balance sheet variables, since they may have their own individual characteristics and fulfill different roles for different banks. Therefore, interbank lending and borrowing are reported individually here, while many papers only focus on one of these positions, such as lending (Worms 2003), or net out interbank activities (Ehrmann & Worms, 2001). Similarly to goodwill, although the average numbers for interbank activities are relatively low, their distribution can be quite dispersed. For example, the interbank lending ratio for institutions at the 99th percentile is about 23%.

It is a common finding in the literature that especially small banks tend to be net providers of liquidity to large banks (Ho & Saunders, 1985; Allen & Saunders, 1986; Furfine, 1999; Stigum & Crescenzi, 2007). The reason is that small banks, in the short term, often take in more deposits than they can hand out in loans to potential customers, since their geographical range is usually limited. The banks can earn interest on this surplus by selling it to a regional bank overnight which in turn would collect funds from many small banks and re-sell them to a money center institution. The following figure illustrates this result by calculating the average of interbank lending and interbank borrowing as a share of a bank's total assets by bank size percentile for the sample period of 1990Q1 – 2010Q4.

Figure 2.1. Average of interbank lending and interbank borrowing as a share of a bank's total assets by bank size percentile, 1990Q1 – 2010Q4



Source: Author's calculation based on Call Report data

The interbank lending ratio decreases from about 7% to almost 2% as banks get larger, but ticks up for very large banks above the 97th percentile. However, this behavior of the interbank lending ratio for large institutions is not consistent over time: it is only present in the first half of the sample period, but goes away in the second half, when there is a continuous decline. The interbank borrowing ratio is below 1% for banks up to the 53rd size percentile, and rises up to 7% for the largest banks.

Most banks are regular providers or buyers of federal funds and it is not the norm for them to switch their status, as shown in Table 2.2. For instance, 89% of all banks that were lending in the interbank market in a given quarter did so in the next quarter as well, while 8.5% of banks that did not borrow in the interbank market in one quarter did so in the next. This is important since it suggests that banks' participation in the interbank market does not happen by accident, driven by random factors, but is a strategic business decision that banks make about the management of their balance sheets.

Table 2.2. Transition probabilities of participating in interbank lending and borrowing in quarter *q+1*, given participation in quarter *q*, percent

Interbank lending	No participation in *q+1*	Participation in *q+1*	Total
No participation in *q*	66.1	33.9	100.0
Participation in *q*	11.0	89.0	100.0
Total	24.1	75.9	100.0
Interbank borrowing	**No participation in *q+1***	**Participation in *q+1***	**Total**
No participation in *q*	91.5	8.5	100.0
Participation in *q*	14.9	85.1	100.0
Total	64.5	35.5	100.0

Source: Author's calculation based on US Call Report data (1990Q1 – 2010Q4)

2.4 Results

2.4.1 Baseline regressions

Table 2.3 shows several baseline regression results with and without interaction terms. Regressions 1 and 2 represent the time period from 1990Q1 to 2010Q4, while Regressions 3 and 4 use data from the period covered by the seminal Kashyap & Stein paper (1995, henceforth KS), 1976Q1 to 1992Q2.

Regression 1 specifies a parsimonious model with no interaction variables except for the 'credit channel' term, while Regression 2 uses the full set of control variables. A comparison of the coefficients between both regressions does not reveal substantial differences. Most notably, the capital-asset ratio coefficient is larger and the deposit ratio is not significant in Regression 1. The similarity is not surprising given that all bank balance sheet variables as well as bank size are measured at their mean as described above. This means that the coefficients for every variable are estimated for a bank of average size. Section 2.4.2 analyses the sensitivity of the results when the size variable is allowed to differ from its mean.

Most bank balance sheet variables have the expected sign. The size variable is negative and significant in Regressions 1 and 2. One explanation is that larger banks have more diversified asset portfolios than smaller banks and hence lower overall loan growth. In other words, a larger institution has more options to invest its funds, while a smaller one tends to increase its investments in loans if possible.

The next variable, *Δi*size*, is central to the analysis of the credit channel. The change in the federal funds rate is interacted with size, modified as described in Section 2.3. Note that monetary policy cannot be included directly in a regression with time dummies because they are perfect controls for variables with no bank-variation. If the credit channel view is correct, the interaction term should be positive: A restrictive monetary policy should have a less negative effect on lending growth for a larger than for a smaller bank. The credit channel term is insignificant in the first two regressions, so there is no evidence for a credit channel in the US banking sector. This difference with other papers in this literature could arise because a larger set of control variables is included in this paper, accounting more precisely for the composition of bank balance sheets.

In Regression 2, the ratios of interbank lending, interbank borrowing, liquidity, cash, capital, deposits, and goodwill are all significantly positive, while allowances for lease and loan losses are significantly negative. The magnitude of the coefficients differs considerably for these variables. For example, a one percentage increase in the average bank's liquidity ratio is associated with an increase in the lending growth rate of about 9 basis points. Cash holdings have a similar coefficient. This finding supports the hypothesis that banks with sound balance sheets that can absorb shocks by reducing their cash holdings or selling off securities are able to shelter their loan portfolio (Kashyap & Stein, 2000; Gambacorta, 2005). The effects are larger for interbank lending (14 basis points) and goodwill (23 basis points), but smaller in the case of interbank borrowing (1.3 basis points) and deposits (0.9 basis points).

Likewise, a higher capital-asset ratio is related to higher lending growth. An increase of one percentage point is associated with about 12 basis points of stronger lending growth. Deposits are only positively correlated with lending growth in the full-set Regression 2. Since it is usually assumed that deposits are a very stable and reliable source of funding because a bank with a higher share of such funds can enter, *ceteris paribus*, into more customer relationships or pay out higher loans than a bank with a weaker deposit base, the inclusion of the interaction terms seems preferable to the alternative specification in Regression 1. Alternatively, banks with a stable deposit base might not be required to reduce their lending by as much in bad times (Berlin & Mester, 1999; Shin, 2009; Cornett, McNutt, Strahan, & Tehranian, 2011). The effect is rather small, with a 1 percentage point increase in the deposit ratio indicating an increase of around one basis point in lending growth.

Allowances for loan and lease losses (ALLL) are considered to be a proxy for bank-idiosyncratic risk. Since they are calculated not as a ratio of total assets but of total loans, they are not interacted with the interest rate in order to make sure the results are comparable. A bank with a higher ALLL ratio may either have a more risky loan portfolio, suggesting a negative relationship with lending, or it may be more careful and therefore have more precautionary provisions, possibly implying a positive correlation. It is not possible to disentangle these two effects with the data provided, but the large negative coefficient of -1.2 for this variable indicates that the first effect should prevail.

Changes in (the log of) county-level employment are associated with a higher lending growth rate. One reason might be that an increase in employment is a proxy for increased business activity, so firms would hire workers and demand bank loans to match their full order books. Additionally, a higher employment number usually indicates stronger household balance sheets, so more individuals should qualify for loans, such as for cars and consumption goods, or mortgages.

County-level employment numbers are an imperfect proxy for demand factors influencing bank balance sheets. First, a bank does not necessarily lend only in the county in which it is located, or it might just approve loans in a subsection of its county. Second, employment numbers do not directly factor in the particularities of an individual bank's balance sheet. For example, the exposure of banks' loan portfolios to various industrial sectors might differ, with overall employment not reflecting the different compositions. Third, there might be the issue of reverse causality. A supply-side induced increase in bank lending to firms or in mortgages might allow companies to hire more workers. This could result in higher construction activity, leading to a positive correlation between lending growth and employment. However, the hiring decision of firms is more likely to be directly based on the demand for their products than on the availability of credit, and the demand for mortgages should depend, over a long time horizon, on the strength of household balance sheets. Ideally, one would want to use data on the specific structure of banks' loan portfolios to control for demand effects, but such data are not publically available. To help make up for this lack of availability, the robustness analysis discussed in Section 2.4.4 uses commercial & industrial loans, as well as loans secured by real estate, as the dependent variable to distinguish between differential effects of various loan types, and the results of this analysis mostly hold up qualitatively. This shows that while county-level employment is not a perfect proxy for demand factors, it should perform reasonably well.

As for the interest rate interaction terms in Regression 2, $b_{n,t-1} \cdot \Delta i_{t-1}$, the coefficients are positive in the case of interbank lending, negative for interbank borrowing and insignificant for all other variables. These results show that interest rate changes get transmitted through certain banks' balance sheet positions since the interest rate coefficient depends on the structure of banks' assets and liabilities. For example, in Regression 2, the direct effect of a change in the interest rate would be, *ceteris paribus*, 1.77 basis points higher (less negative) for a bank with a one percentage point higher interbank lending rate. For liquidity, this effect is 0.3 basis points, but is insignificant. Note that all these coefficients are estimated for a bank of average size. Section 2.4.2 shows that the results may change for banks of different sizes.

Table 2.3. Regression results

Variable	Regression 1 Parsimonious model, baseline period	Regression 2 Full model, baseline period	Regression 3 Parsimonious model, KS period	Regression 4 Full model, KS period
Size	-0.0140***	-0.0135***	-0.0075***	-0.0012
	(0.0007)	(0.0006)	(0.0007)	(0.0009)
Δi * size	0.0011	0.0011	0.0019***	0.0007
	(0.0007)	(0.0008)	(0.0003)	(0.0004)
Interbank lending	0.1493***	0.1418***	0.1793***	0.1790***
	(0.0041)	(0.0043)	(0.0030)	(0.0030)
Size interaction		-0.1473***		-0.1384***
		(0.0155)		(0.0117)
i interaction		0.0177***		-0.0031***
		(0.0061)		(0.0011)
joint interaction		-0.0466**		-0.0025
		(0.0215)		(0.0056)
Interbank borrowing	0.0143**	0.0137**	-0.0168	-0.0352***
	(0.0068)	(0.0070)	(0.0118)	(0.0118)
Size interaction		-0.0759***		0.1110***
		(0.0216)		(0.0184)
i interaction		-0.0326***		-0.0137***
		(0.0112)		(0.0021)
joint interaction		-0.0115		0.0309***
		(0.0334)		(0.0094)
Liquidity ratio	0.0909***	0.0907***	0.1114***	0.1145***
	(0.0020)	(0.0020)	(0.0017)	(0.0017)
Size interaction		-0.0168*		0.0091
		(0.0091)		(0.0092)

i interaction		0.0030		-0.0028***
		(0.0027)		(0.0010)
joint interaction		0.0121		0.0036
		(0.0084)		(0.0049)
Cash ratio	0.0929***	0.0869***	0.1709***	0.1697***
	(0.0046)	(0.0048)	(0.0033)	(0.0033)
Size interaction		-0.0628***		-0.0514***
		(0.0173)		(0.0152)
i interaction		-0.0054		-0.0114***
		(0.0075)		(0.0018)
joint interaction		-0.0280		-0.0001
		(0.0255)		(0.0088)
Capital-asset ratio	0.1890***	0.1160***	0.2870***	0.1864***
	(0.0108)	(0.0145)	(0.0097)	(0.0097)
Size interaction		-0.3362***		-0.6206***
		(0.1069)		(0.0294)
i interaction		-0.0212		-0.0291***
		(0.0156)		(0.0049)
joint interaction		-0.0932		0.0046
		(0.0701)		(0.0148)
Deposit ratio	0.0040	0.0090**	0.0098	0.0070
	(0.0037)	(0.0037)	(0.0106)	(0.0105)
Size interaction		-0.0111		0.1242***
		(0.0116)		(0.0240)
i interaction		0.0068		0.0048
		(0.0053)		(0.0030)
joint interaction		-0.0293*		0.0358***
		(0.0158)		(0.0123)
Goodwill ratio	0.1974***	0.2302***		
	(0.0323)	(0.0345)		
Size interaction		0.0269		
		(0.1499)		
i interaction		-0.0728		
		(0.0528)		
joint interaction		0.0937		
		(0.1534)		
ALLL ratio	-1.2159***	-1.1839***	-1.1838***	-1.1925***
	(0.0271)	(0.0276)	(0.0221)	(0.0220)

Size interaction		0.2878***		-0.4347***
		(0.1112)		(0.0964)
Δ ln(employment)	0.1277***	0.1275***	0.4193***	0.4169***
	(0.0067)	(0.0067)	(0.0128)	(0.0128)
Constant	0.0078***	0.0066***	0.0157***	0.0127***
	(0.0007)	(0.0008)	(0.0007)	(0.0008)
# observations	636,915	636,915	762,518	762,518
# banks	15,194	15,194	18,176	18,176
Time period	1990Q1-2010Q4	1990Q1-2010Q4	1976Q1-1992Q2	1976Q1-1992Q2
Average T	42.0	42.0	42.0	42.0

Cluster-robust standard errors in parentheses. *, **, *** denote significance at the 10%, 5%, 1% level, respectively. The size variable is centered at its mean for each quarter. Time dummies not shown. Full regression equation:

$$\frac{(C_{n,t}-C_{n,t-1})}{C_{n,t-1}} = \alpha_n + \beta \cdot size_{n,t-1} + \gamma \cdot (\Delta i_{t-1} \cdot size_{n,t-1}) + \delta \cdot b_{n,t-1} + \theta \cdot (b_{n,t-1} \cdot size_{n,t-1}) + \lambda \cdot (b_{n,t-1} \cdot \Delta i_{t-1}) + \mu \cdot (b_{n,t-1} \cdot size_{n,t-1} \cdot \Delta i_{t-1}) + \rho \cdot bcon_{n,t-1} + \tau \cdot (bcon_{n,t-1} \cdot size_{n,t-1}) + \varphi \cdot \Delta X_{n,t-1} + d_t + \varepsilon_{n,t}$$

Table 2.3 also lists results for the KS period of 1976Q1 to 1992Q2 in Regressions 3 and 4. While the average time horizon is identical at 42 quarters, this sample has a larger number of banks, indicative of the continuous consolidation in the industry, so the number of total observations available is larger. Note that data for the variable goodwill is only available since 1985Q2, so it is dropped from the estimation. Otherwise, the same Call Report variables are used as in KS, though they are not necessarily added together the same way in order to show the differences, while employment and the interest rate are defined as described above.

One notable difference between the baseline sample and the KS sample is that the credit channel term is significant in the parsimonious regression (#3), while it is insignificant in the full-scale model (#4). This indicates that the interaction variables are important to correctly capture the effect of a change in the interest rate. If the interaction terms are omitted, the regression will incorrectly attribute variation to the credit channel term, while in the true model, changes in the interest rate work through the balance sheet variables, and not through size *per se*. This is an important difference to the results of Kashyap & Stein (1995).

There are additional differences to the baseline sample. Several coefficients have the opposite sign, most notably interbank borrowing. Similarly, size and interest rate interaction terms for several variables have different signs. The coefficient on employment is much larger.

While these differences seem substantial, they only measure the coefficients for a bank of average size. One can get a much more detailed understanding of the relationships by comparing banks across all sizes, as outlined in the next section.

2.4.2 Size dependence

So far, the coefficients discussed have been determined for banks of average size. But the structure of the model also allows for the estimation of the effects on banks of any desired size by centering the size variable not at its average, but at whichever size one would like to examine. Based on this analysis, the relationships between different balance sheet positions, as well as the monetary transmission channel, can be examined more precisely because it allows distinguishing the effects for banks of different size.

Figure 2.1 shows the results based on the model used in Regression 2 (baseline sample) for seven bank balance sheet variables and interest rate interaction terms in dependence of each size centile. For example, the coefficients at the 50th percentile show the effects for a bank of median size.

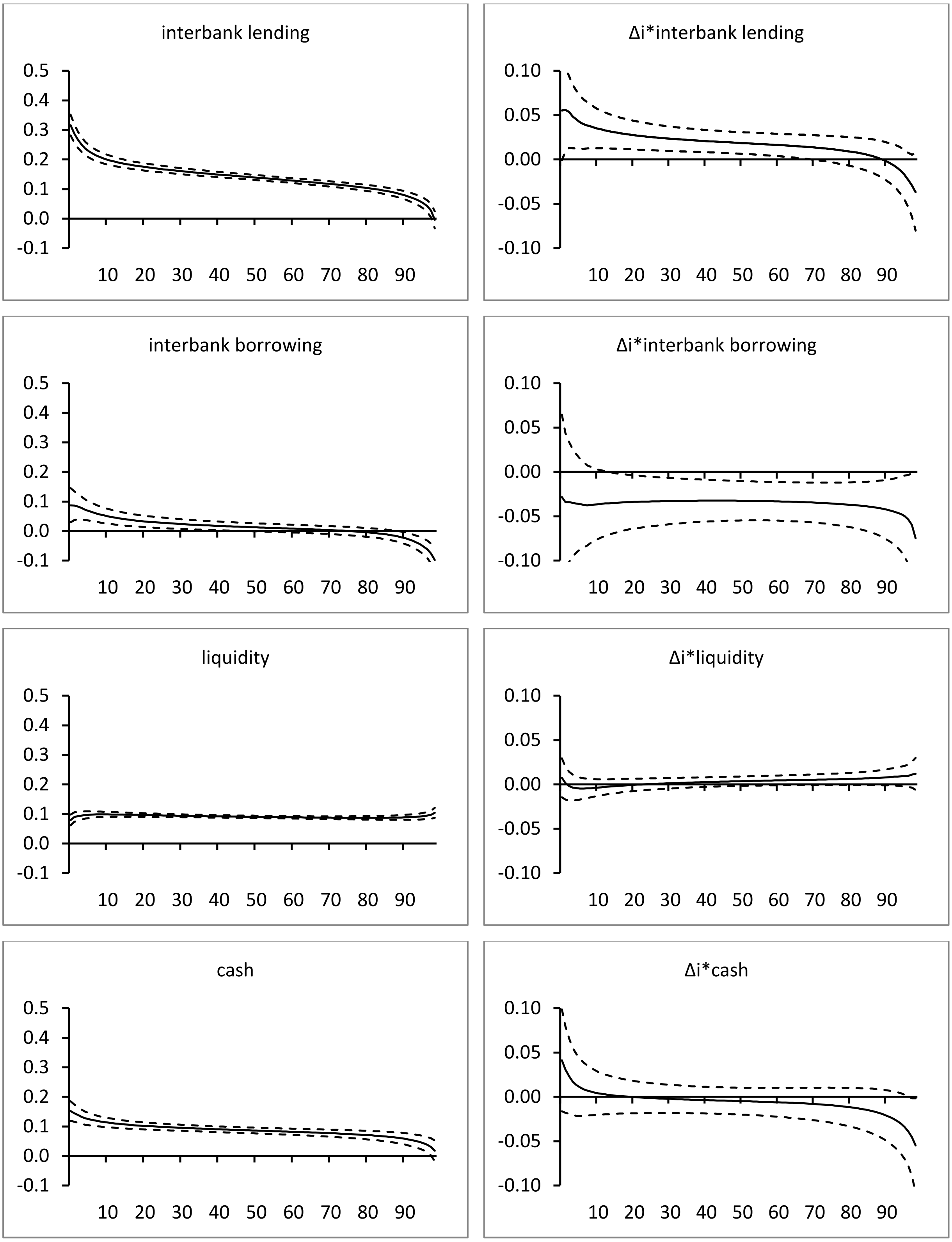
For the non-interacted variables on the left, the coefficients usually decrease with bank size. For example, interbank lending has a coefficient of more than .2 for a bank at the 10th percentile, but it is indistinguishable from zero for a bank at the 99th percentile of the size distribution. Interbank borrowing coefficients are much smaller for a large part of the size spectrum. They turn from significantly positive for small banks to significantly negative for large institutions. Liquidity, however, shows a different pattern, with the coefficients remaining remarkably stable around .1. This pattern is strikingly different from interbank lending, so it does not seem appropriate to aggregate the two variables, as is often the case (e.g. Gambacorta, 2005). Cash holdings show a similar behavior as interbank lending. Although the capital coefficient is much larger than the one for deposits, both variables exhibit a similar pattern in that they are significantly positive for small and medium banks, but they turn significantly negative for very large banks. One explanation could be that for large banks with sophisticated balance-sheet management techniques, a higher capital ratio is not a sign of a strong balance sheet, but of a less efficiently managed one. In this case, one would expect a large bank to have a lower lending growth rate. Similarly, large banks rely on deposits to a lesser degree than small institutions. For a large bank, a higher deposit ratio could be a sign of a less well diversified entity, implying a lower lending rate. Goodwill is significantly and positively related to lending growth, except for very small banks.

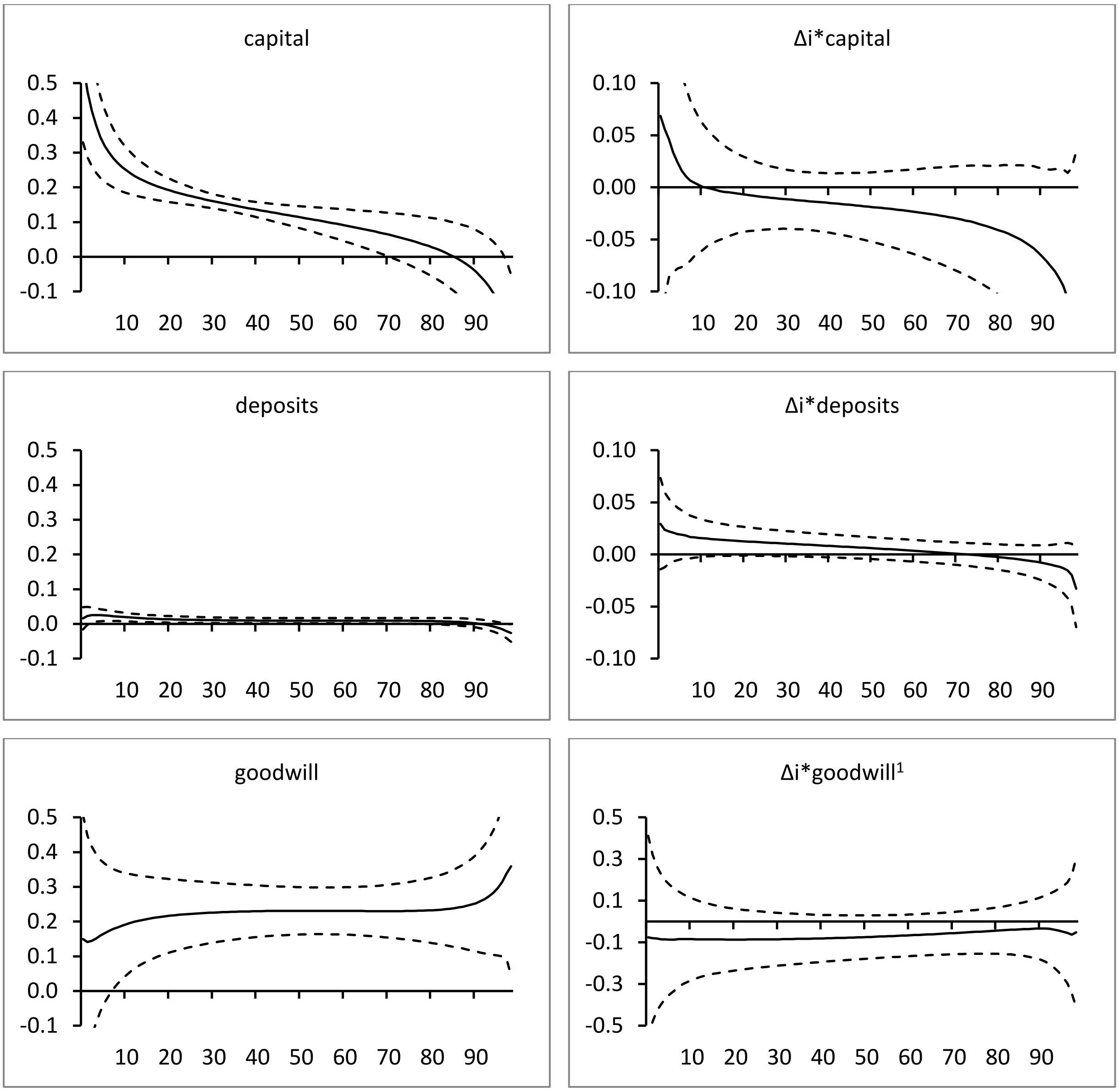
As for the interaction terms on the right side of Figure 2.1, the two terms that have significant portions are interbank lending (positive up to the 70th percentile) and interbank borrowing (negative except for banks below the 14th percentile). This means that, in response to an increase in the interest rate, the lending growth rate of small banks is significantly higher (less negative) than that of large banks the higher interbank lending becomes. The opposite is true for interbank borrowing: After an increase in the interest rate, the lending growth rate for all but very small banks is significantly more negative the higher interbank borrowing gets. Intuitively, these opposite results make sense because banks with a higher interbank lending buffer are in a better position to weather increases in the interest rate, while banks that rely to a larger extent on interbank borrowing for funding are more vulnerable when the interest rate goes up. The positive effect for interbank lending goes away for large banks, indicating that this variable is not important for the transmission of interest rate changes for this group. One possible explanation is that large banks have more means at their disposal to mitigate the effects of policy changes, so they depend less on interbank lending as a buffer to shelter their loan portfolio.

All other interest rate interaction variables are insignificant for banks of all sizes (only the cash interaction term is significant for banks above the 97th percentile). This indicates that the relationship between the respective bank balance sheet variables and lending growth is independent of the stance of monetary policy.

In conclusion, for the baseline sample, changes in the policy rate affect the relationship between a bank’s balance sheet position and lending growth only in the case of interbank lending and borrowing. Especially small and medium sized banks benefit from a higher interbank lending ratio to mitigate the effect of interest rate changes.

Figure 2.2. Size dependence of balance sheet coefficients, baseline sample (1990Q1 – 2010Q4)





Note the different scales on the right and left side of the figure. Dashed lines represent the 95% confidence interval.

[1] The scale is different for this variable.

Figure 2.2 shows the same variables except for goodwill, but for the Kashyap & Stein sample period of 1976Q1 to 1992Q2, as a way to assess changes in the relationships between the variables over time. As for the non-interacted variables on the left side of the figure, many of them resemble the results from Figure 2.1. Interbank lending and cash holdings are now significantly positive for the whole size spectrum, while they were insignificant for large banks in Figure 2.1. The liquidity coefficients are nearly identical. The capital-asset ratio curve has a very similar shape, but is more precisely estimated.

However, interbank borrowing and deposits are now upward-sloping, resulting in a significantly negative correlation with lending growth for small banks and, in the case of deposits, resulting in a significantly positive correlation for large banks. One explanation for this change in the effects of interbank borrowing could be that this funding source used to be seen as a sign of trouble, i.e. banks were not able to attract enough deposits, so they had to rely on the interbank market the fill the funding gap. However, more recently, banks have developed more sophisticated methods to manage their balance sheet and access to short-term funds in the interbank market has been one of the strategies employed to boost returns (FDIC, 2005)[6], though there are considerable risks of this strategy (Shin, 2009; Demirgüç-Kunt & Huizinga, 2010). However, this supposition would fail to explain the negative correlation for large banks in the baseline sample.

The right column of the figure shows the interest rate interaction coefficients. One notable difference to the results found in Figure 2.1 is that the coefficients are usually smaller, but more often significant: Except for the deposit term, an increase in the interest rate is associated with a more negative effect of the respective balance sheet variable on lending growth. This makes sense in the case of interbank borrowing if one assumes that this sort of funding is less reliable, but it is somewhat puzzling in the other cases. In contrast to the results in Figure 2.1, the deposits interaction term is significantly positive for banks above the 53rd percentile. One interpretation could be that a higher deposit ratio helped banks to shelter their loan portfolio from interest rate changes during the KS sample period, but the roles have changed in the more recent period when interbank lending seems to fulfill a similar function.

Several reasons may be responsible for the changes between Figures 2.1 and 2.2, though it is beyond the scope of this paper to pinpoint the exact causes or elaborate the precise mechanisms. One potentially important factor might be changes to the regulatory environment such as the introduction of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 or the Financial Services Modernization Act of 1999. Similarly, changes in the implementation of monetary policy, e.g. the Fed’s monetarist experiment which occurred from 1979-1982, the borrowed-reserves operating procedure, or today’s interest-targeting regime, may also have influenced the transmission channel. Another reason could be technological advances in information and communications technologies, such as computers and the internet. Based on all of these factors, banks’ business models and the structure of the banking industry may have changed, for example contributing to the process of rapid consolidation described in Section 2.3.

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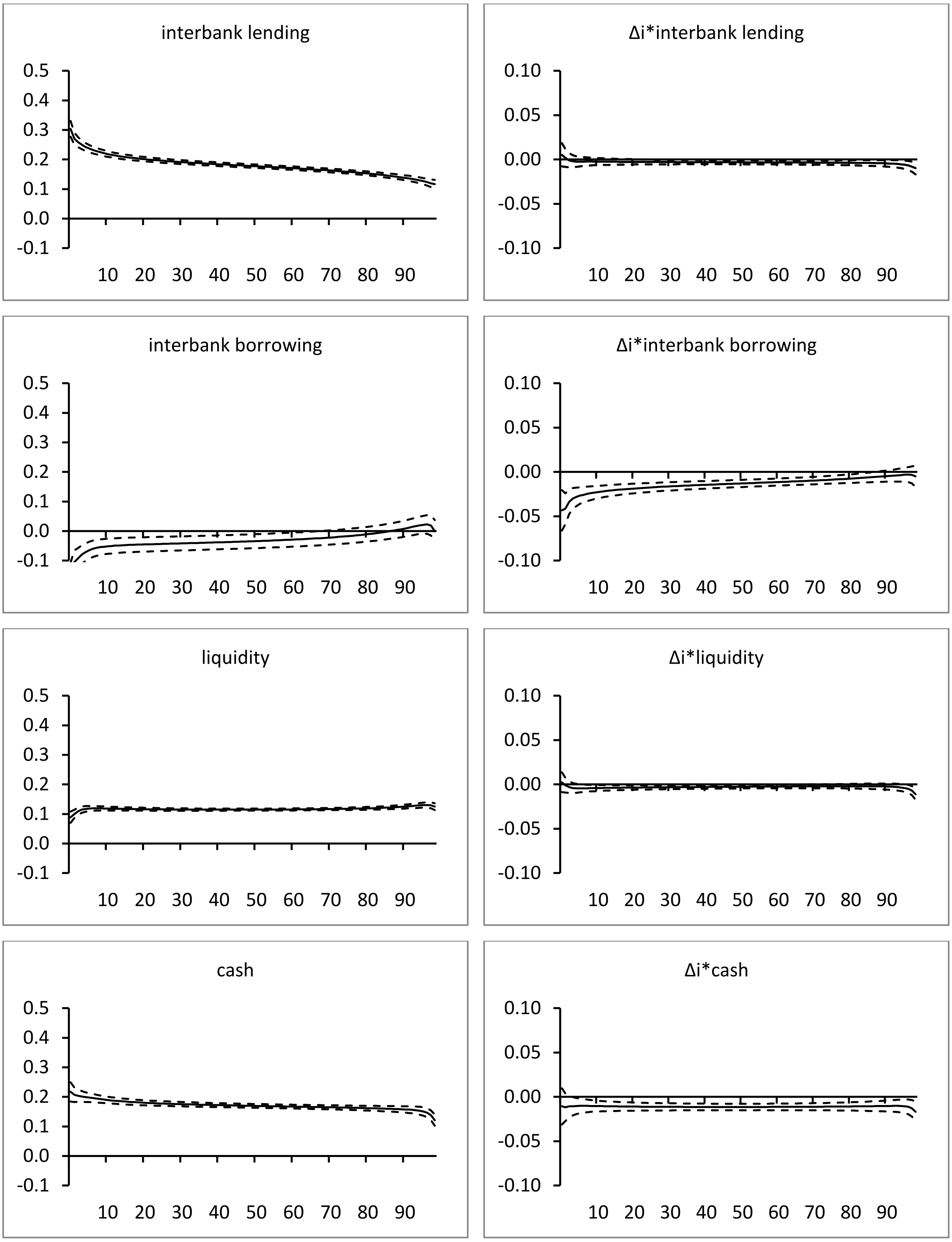
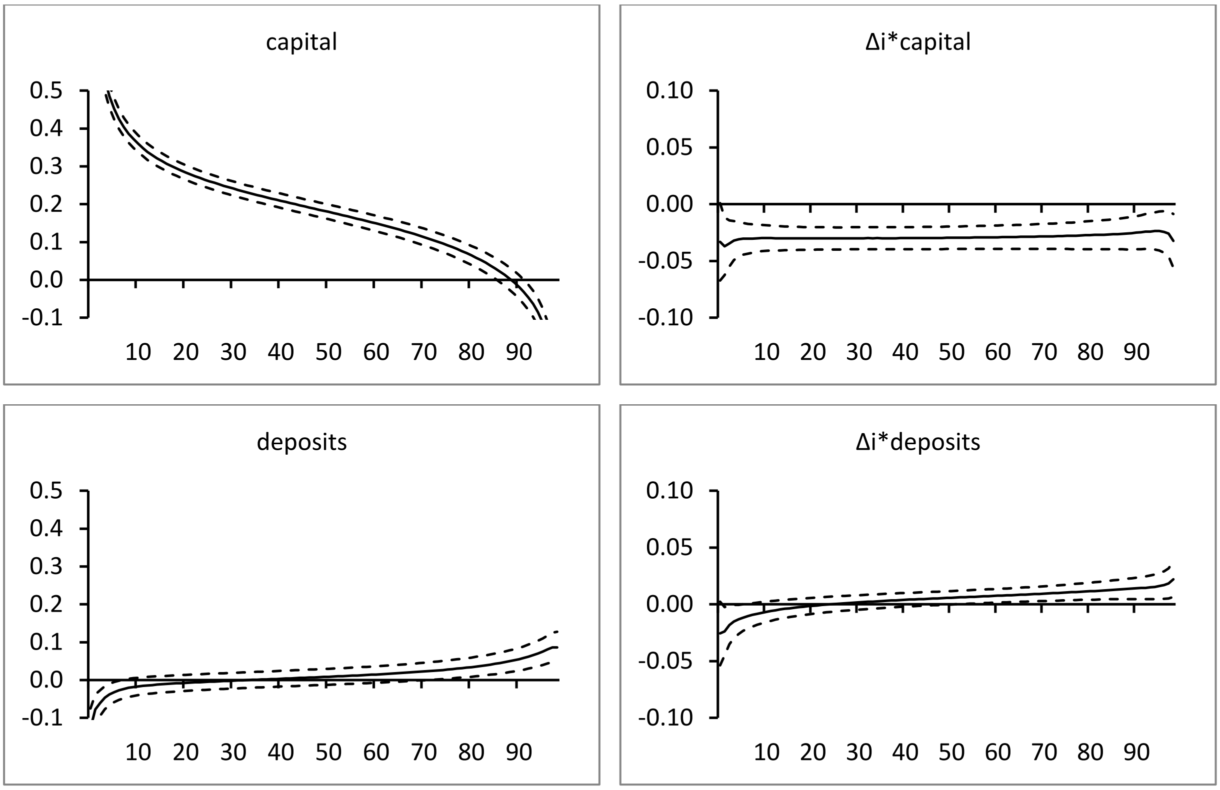
[6] Section 6.1: Liquidity and Funds Management, p.11: “Some institutions may access Federal funds routinely, perhaps as a liability management technique whereby the buyer (borrower) attempts to utilize the acquired funds to support a rapid expansion of its loan-investment posture as a means of enhancing profits.”

Figure 2.3. Size dependence of balance sheet coefficients, KS sample (1976Q1 – 1992Q2)





Note the different scales on the right and left side of the figure. Dashed lines represent the 95% confidence interval.

2.4.3 Comparison with the analysis in Kashyap & Stein (1995)

Kashyap & Stein (1995) employ a different strategy to identify the credit channel in the US. First, they aggregate all bank balance sheets and therefore do not use a panel framework. Second, they sort banks into different size categories and run regressions only for the respective groups. Nevertheless, it is instructive to qualitatively compare their results with the methodology used in this paper for the same sample period of 1976Q1 to 1992Q2. Note that KS use economic variables such as GDP which are identical for all banks, so these variables will drop out in a panel framework with time dummies.

KS find that lending of the largest 1% of banks does not have any significant reaction to a change in the interest rate, while the effect is significantly negative for banks below the 98th percentile and increasingly so the smaller they become. At first glance, these findings are supported by the results of Regression 3 in Table 2.3 which applies the same regression model as in the baseline scenario, but for the KS period. The credit channel term, *Δi*size*, is significantly positive, corroborating the view that the smaller a bank, the more negative the effect of a contraction in monetary policy on lending. However, Regression 4 casts some doubts on this conclusion because the credit channel term becomes insignificant when accounting for a larger set of bank control variables. Running regressions for every size percentile yields a U-shaped dependency of the credit channel term on size (graph not shown), with only very small and very large banks having a significantly positive credit channel coefficient. This result contradicts KS because they find a gradually more negative effect the smaller banks become.

Several causes could be attributed to this discrepancy. First, KS use the growth rate of lending, aggregated by the respective bank size group, as the dependent variable, while this paper utilizes a panel framework with individual bank data. Second, KS use only macro control variables such as changes in the CPI or nominal GDP, but no bank-specific controls. This may be problematic if other bank characteristics are systematically correlated with bank size. For example, if smaller banks are more exposed to credit risk than larger banks, it is perceivable that small institutions will react more strongly to restrictive monetary policy than large ones, even if size *per se* is uncorrelated with lending behavior. As such, the regression used by KS might then wrongly attribute the variation in riskiness to differences in size. Third, KS use seasonal dummies and a different lag structure.

In conclusion, the model described and developed in this paper enables a more differentiated picture than in KS. The role of individual balance sheet positions can be examined in greater detail. Their main result, a direct size dependence of interest rate changes, can only be partly confirmed.

2.4.4 Robustness analysis

The results of this paper hold up for a wide range of robustness checks, though there are some exceptions. First, the dependent variable, total loan growth, is replaced in turn by two important sub-categories, commercial and industrial (C&I) loans (Table 2.4[7], Regression 5) and loans secured by real estate (Regression 6). In both cases, for banks of average size, the credit channel term is insignificant, emphasizing the importance of accurately accounting for all the balance sheet channels through which monetary policy may work. While the real estate loan regression is very similar to the baseline scenario, one noteworthy difference in the C&I loan regression is the fact that the interest rate-interbank interaction terms are insignificant. This would indicate that the effects of interbank lending and borrowing on the monetary transmission channel would be more relevant for real estate lending. Also, the deposit ratio coefficient has the opposite sign in Regression 5.

[7] Regression 2 is reproduced from Table 2.3 for convenience.

In a second check (Regression 7), a different definition of size is used. Instead of calculating the log of total assets, a bank's asset share of the aggregated assets of the whole banking system is computed for every quarter. This method takes care of potential issues that could arise because bank assets are increasing over time. In the original size definition, this issue is addressed by re-centering bank size in every quarter. But if banks grow larger over time, the dispersion around the zero mean will increase. This alternative definition normalizes the aggregate size of the banking sector to one, and therefore only relative shifts in the size of banks matter, but not overall growth. Nevertheless, the regression shows that the results are very similar to the benchmark, and also the behavior across banks of different size is very close to the baseline scenario. Not unexpectedly, the size interaction terms are affected most, with several of them changing their sign or significance. However, the main results, especially with respect to the interest rate-interbank interaction terms, hold for this specification as well.

In Regression 8, the interest rate is replaced by the residuals of a vector autoregression (VAR) model that are thought to represent the exogenous component of monetary policy. This model is comprised of a GDP volume index, inflation, an oil price index, a real effective exchange rate index, and the federal funds rate as endogenous variables. These variables all come from the IMF's *International Financial Statistics* database. A time trend and quarterly dummy variables are included as exogenous variables. The VAR model is estimated with three lags. The coefficients are used to calculate the residuals in response to a shock to the federal funds rate. These residuals can be interpreted as the exogenous component of monetary policy that is independent of the business cycle to which the central bank responds endogenously. Since the objective is to measure the effects of the interest rate, and not of the business cycle, these residuals should, in theory, be a better method to identify the impact of changes in monetary policy than the federal funds rate (Bernanke & Mihov, 1998; Uhlig, 1998). However, as Worms (2003) points out, the validity of both the federal funds rate and the VAR residuals rests on their own specific assumptions. First, to be able to correctly assess the impact of monetary policy, one needs to assume that the VAR residuals have a comparable effect to the federal funds rate. Additionally, the VAR residuals depend on the specification of the VAR model, while the federal funds rate is directly observable. Indeed, the results were sensitive to the specification of the VAR model, so the residuals of the most plausible specification were chosen.

The federal funds rate, as mentioned above, suffers from an endogeneity problem because the central bank reacts to other economic variables, confounding the proper measurement of the effects of changes in the interest rate. Worms (2003) concludes that any potential endogeneity issue of the federal funds rate is likely to be less severe in regressions such as those undertaken in this paper, because monetary policy is unlikely to react to individual bank information and it enters the regressions with a lag. Hence, in this paper, the focus has been on regressions with the federal funds rate, but the VAR residual results may nevertheless provide a useful robustness check. As can be seen from Regression 8, the credit channel term is again insignificant. The two major differences with respect to the baseline regression are that the interest rate interaction term with interbank borrowing is insignificant, while it has become highly significant for cash holdings. Moreover, one can examine the marginally significant interest rate-interbank lending term for banks of average size in Regression 8 in greater detail by estimating the model for every size centile as in Figures 2.1 and 2.2. This reveals that this term is significant at the 5% level for banks between the 58th and 90th percentile. This is a higher and smaller range than in the baseline scenario, in which it is significant from the first up to the 70th percentile.

Additionally, different time horizons besides the one described in Section 2.4.1 have been chosen. Results are similar when excluding the financial crisis episode starting in 2007Q3. Results also do not change qualitatively in most cases when choosing the much shorter time period of 2004Q3 to 2006Q4. Results during the financial crisis episode (2007Q3 to 2009Q4) differ by more, but this is not unexpected given the unique circumstances. Also, it is generally questionable whether choosing short time periods of only 10 quarters is sensible given that they do not comprise a full business cycle or represent episodes during which the monetary policy rate is exclusively falling and/or close to the zero bound.

Another robustness check undertaken is to split the sample based on episodes of restrictive vs. accommodative monetary policy. The results are surprisingly similar for most variables, but the interest rate interaction terms are more often significant in times of increasing rates. One caveat of this procedure is the possibility that variables related to the business cycle may not be sufficiently accounted for in the regression. Since the sample is split based on the stance of monetary policy, this might introduce a bias in the estimation. However, the time dummies and macro-control variable should mitigate or potentially even do away with this issue.

The errors $\varepsilon_{n,t}$ have also been clustered not at the bank, but the county and state levels, respectively. Note that some observations get lost in these cases since banks whose physical locations change from one county or state to another need to be excluded. This change in the assumption of the error structure does not, however, lead to qualitatively different results.

Table 2.4. Robustness checks

Variable	Regression 2 Full model, base period	Regression 5 Dep. var.: C&I lending	Regression 6 Dep. var.: Real estate lending	Regression 7 Alternative size definition	Regression 8 Alt. interest rate definition
Size	-0.0135***	-0.0202***	-0.0145***	-0.0106***	-0.0128***
	(0.0006)	(0.0010)	(0.0007)	(0.0035)	(0.0007)
Δi * size	0.0011	-0.0003	0.0013	-0.0000	0.0002
	(0.0008)	(0.0014)	(0.0009)	(0.0044)	(0.0004)
Interbank lending	0.1418***	0.1463***	0.0865***	0.1617***	0.1392***
	(0.0043)	(0.0076)	(0.0044)	(0.0043)	(0.0044)
Size interaction	-0.1473***	-0.1467***	-0.1491***	0.0762	-0.1380***
	(0.0155)	(0.0237)	(0.0168)	(0.0537)	(0.0170)
i interaction	0.0177***	0.0198	0.0187**	0.0190***	0.0074*
	(0.0061)	(0.0135)	(0.0073)	(0.0063)	(0.0041)
joint interaction	-0.0466**	-0.0147	-0.0301	-0.1855	0.0114
	(0.0215)	(0.0398)	(0.0265)	(0.1157)	(0.0123)
Interbank borrowing	0.0137**	-0.0341**	0.0533***	0.0207***	0.0133*
	(0.0070)	(0.0133)	(0.0079)	(0.0068)	(0.0071)
Size interaction	-0.0759***	-0.0511	-0.0694***	-0.0015	-0.0716***
	(0.0216)	(0.0400)	(0.0242)	(0.0541)	(0.0227)
i interaction	-0.0326***	0.0255	-0.0232*	-0.0322***	-0.0042
	(0.0112)	(0.0246)	(0.0135)	(0.0112)	(0.0077)
joint interaction	-0.0115	-0.1080	0.0341	0.0372	0.0161
	(0.0334)	(0.0679)	(0.0393)	(0.1149)	(0.0189)
Liquidity ratio	0.0907***	0.1014***	0.0722***	0.0912***	0.0926***
	(0.0020)	(0.0036)	(0.0022)	(0.0020)	(0.0020)
Size interaction	-0.0168*	-0.0262**	-0.0153	0.0952**	-0.0179*
	(0.0091)	(0.0132)	(0.0093)	(0.0448)	(0.0105)
i interaction	0.0030	0.0106*	0.0029	0.0034	-0.0009
	(0.0027)	(0.0061)	(0.0033)	(0.0027)	(0.0016)
joint interaction	0.0121	-0.0019	0.0015	0.1478*	0.0079*
	(0.0084)	(0.0161)	(0.0099)	(0.0836)	(0.0045)
Cash ratio	0.0869***	0.1127***	0.0649***	0.1114***	0.0908***
	(0.0048)	(0.0096)	(0.0053)	(0.0048)	(0.0051)
Size interaction	-0.0628***	-0.0398	-0.0441**	-0.0924	-0.0535***
	(0.0173)	(0.0297)	(0.0189)	(0.0800)	(0.0185)
i interaction	-0.0054	0.0101	-0.0156*	-0.0048	0.0155***
	(0.0075)	(0.0185)	(0.0093)	(0.0075)	(0.0053)

joint interaction	-0.0280	0.0372	-0.0708**	0.0141	0.0109
	(0.0255)	(0.0530)	(0.0307)	(0.2531)	(0.0174)
Capital-asset ratio	0.1160***	0.1765***	0.0998***	0.2472***	0.1139***
	(0.0145)	(0.0222)	(0.0153)	(0.0109)	(0.0170)
Size interaction	-0.3362***	-0.2730**	-0.3509***	-0.2643	-0.3087**
	(0.1069)	(0.1359)	(0.1101)	(0.3023)	(0.1328)
i interaction	-0.0212	-0.0106	-0.0172	-0.0285*	-0.0008
	(0.0156)	(0.0330)	(0.0172)	(0.0151)	(0.0078)
joint interaction	-0.0932	-0.1723	-0.0941	0.5478	-0.0098
	(0.0701)	(0.1055)	(0.0705)	(0.5257)	(0.0155)
Deposit ratio	0.0090**	-0.0291***	0.0169***	0.0243***	0.0082**
	(0.0037)	(0.0073)	(0.0040)	(0.0037)	(0.0038)
Size interaction	-0.0111	0.0061	-0.0125	0.0584	-0.0080
	(0.0116)	(0.0265)	(0.0123)	(0.0466)	(0.0129)
i interaction	0.0068	0.0189	-0.0042	-0.0029	-0.0002
	(0.0053)	(0.0129)	(0.0064)	(0.0051)	(0.0036)
joint interaction	-0.0293*	-0.0643	-0.0397**	-0.1068*	0.0116
	(0.0158)	(0.0425)	(0.0174)	(0.0642)	(0.0076)
Goodwill ratio	0.2302***	0.3405***	0.2434***	-0.0040	0.2371***
	(0.0345)	(0.0628)	(0.0382)	(0.0320)	(0.0353)
Size interaction	0.0269	-0.0701	-0.0505	0.2098	-0.0601
	(0.1499)	(0.2097)	(0.1554)	(0.3124)	(0.1787)
i interaction	-0.0728	-0.1787	0.0082	-0.0168	-0.0226
	(0.0528)	(0.1127)	(0.0651)	(0.0485)	(0.0348)
joint interaction	0.0937	0.4438*	-0.0347	0.2055	0.0339
	(0.1534)	(0.2447)	(0.1702)	(0.7271)	(0.0681)
ALLL ratio	-1.1839***	-1.4471***	-1.2336***	-1.2254***	-1.1243***
	(0.0276)	(0.0505)	(0.0318)	(0.0269)	(0.0288)
Size interaction	0.2878***	0.2227	0.2936**	0.1916	0.3837***
	(0.1112)	(0.1792)	(0.1200)	(0.3845)	(0.1336)
Δ ln(employment)	0.1275***	0.0428***	0.0429***	0.1291***	0.1267***
	(0.0067)	(0.0127)	(0.0051)	(0.0067)	(0.0067)
Constant	0.0066***	0.0010	0.0029***	0.0061***	0.0050***
	(0.0008)	(0.0020)	(0.0006)	(0.0007)	(0.0007)
# observations	636,915	620,417	633,655	636,915	614,306
# banks	15,194	15,004	15,153	15,194	15,122

Time period	1990Q1-2010Q4	1990Q1-2010Q4	1990Q1-2010Q4	1990Q1-2010Q4	1990Q1-2010Q4
Average T	42.0	41.0	42.0	42.0	41.0

Cluster-robust standard errors in parentheses. *, **, *** denote significance at the 10%, 5%, 1% level, respectively. The size variable is centered at its mean for each quarter. Time dummies not shown. Regression 2 is reproduced from Table 2.3. Regressions 5 and 6 use C&I loan growth and growth of loans secured by real estate as the dependent variable, respectively. Regression 7 uses a different definition of size, while Regression 8 employs VAR residuals instead of the federal funds rate. See text for details. Full regression equation:

$$\frac{(C_{n,t}-C_{n,t-1})}{C_{n,t-1}} = \alpha_n + \beta \cdot size_{n,t-1} + \gamma \cdot (\Delta i_{t-1} \cdot size_{n,t-1}) + \delta \cdot b_{n,t-1} + \theta \cdot (b_{n,t-1} \cdot size_{n,t-1}) + \lambda \cdot (b_{n,t-1} \cdot \Delta i_{t-1}) + \mu \cdot (b_{n,t-1} \cdot size_{n,t-1} \cdot \Delta i_{t-1}) + \rho \cdot bcon_{n,t-1} + \tau \cdot (bcon_{n,t-1} \cdot size_{n,t-1}) + \varphi \cdot \Delta X_{n,t-1} + d_t + \varepsilon_{n,t}$$

Another dimension that can be exploited as a robustness check is the geographic reach of banks. While there are many possible ways to use such geographic information (e.g. Berger, Miller, Petersen, Rajan & Stein, 2005; Aubuchon & Wheelock, 2010), a simple test is to see whether there are differences between banks that exist only within one county or state as opposed to banks that operate in several such units. The Call Reports do not have sufficient data to analyze this question, but such information can be extracted from the FDIC Summary of Deposits (SOD) and merged with the Call Reports. One limitation is that the SOD data are only available annually as of June 30. Additionally, they are not electronically accessible before 1994.[8] The SOD database has information on branch office deposits for all FDIC-insured institutions. To infer whether banks operate on an interstate or intercounty level, this paper identifies the locations of all branches for each institution. Banks with branches in only one state / county are considered to operate only within the borders of the respective geographical unit.

In order to combine the quarterly Call Report and annual SOD data, the assumption is made that the geographic information does not change during the four quarters of a given year. This is not unreasonable, given that most banks do not change their geographic scope in a given year. Only 4.5% of banks go from doing business in one county to more than one county between two years, and the reverse is true for only 0.9% of banks. The numbers are 0.6% and 1.5% on the state level, respectively. As a matter of fact, only 844 banks accounting for 3.5% of all bank observations have done business in several states during any time between 1990 and 2010, vs. 6,829 banks and 39% of

[8] Source: FDIC website, accessed on 8/24/2012 at www2.fdic.gov/sod/index.asp

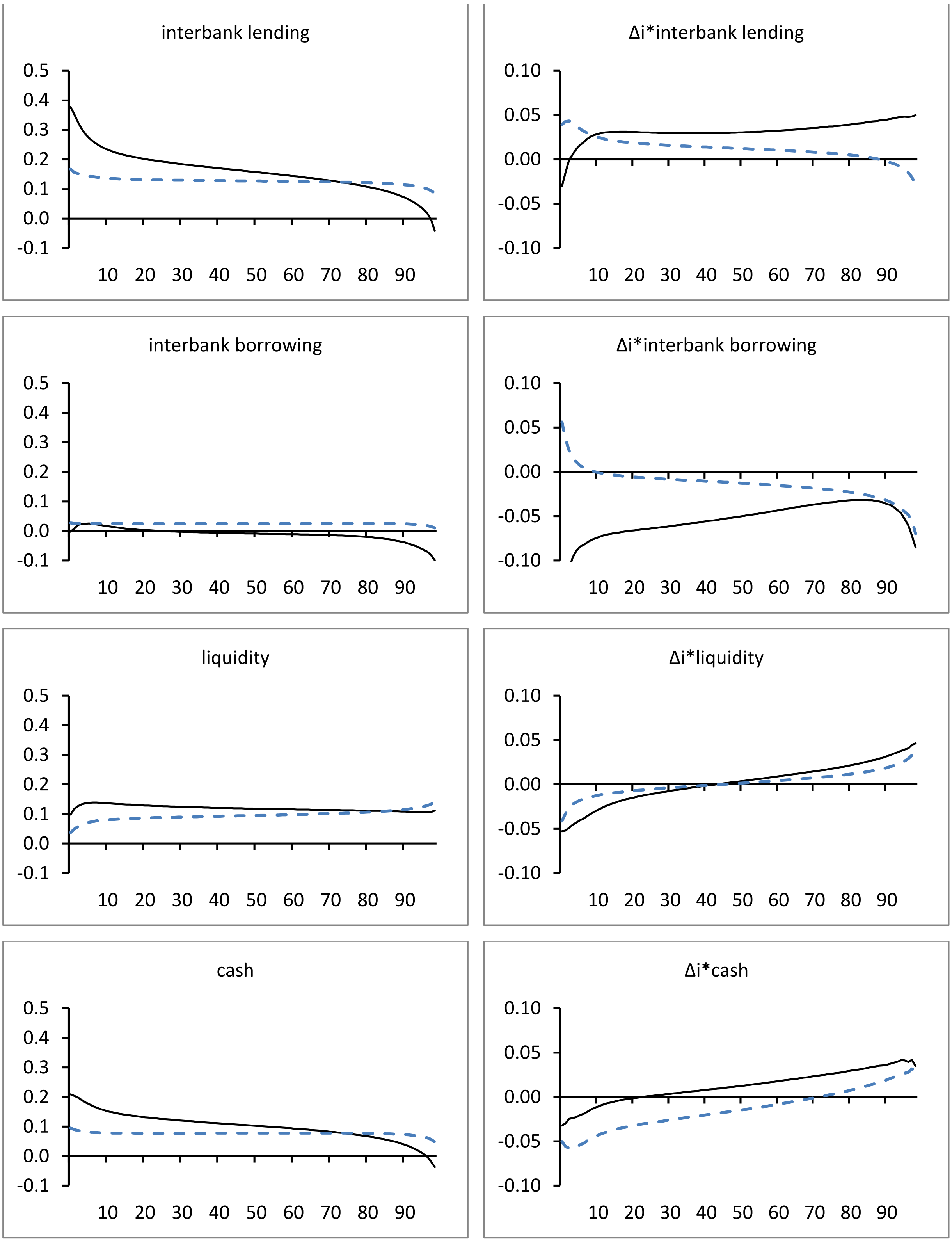
observations on the county level. Since the size of the two bank groups on a state level is very disproportionate, the focus here will be a county-level comparison.

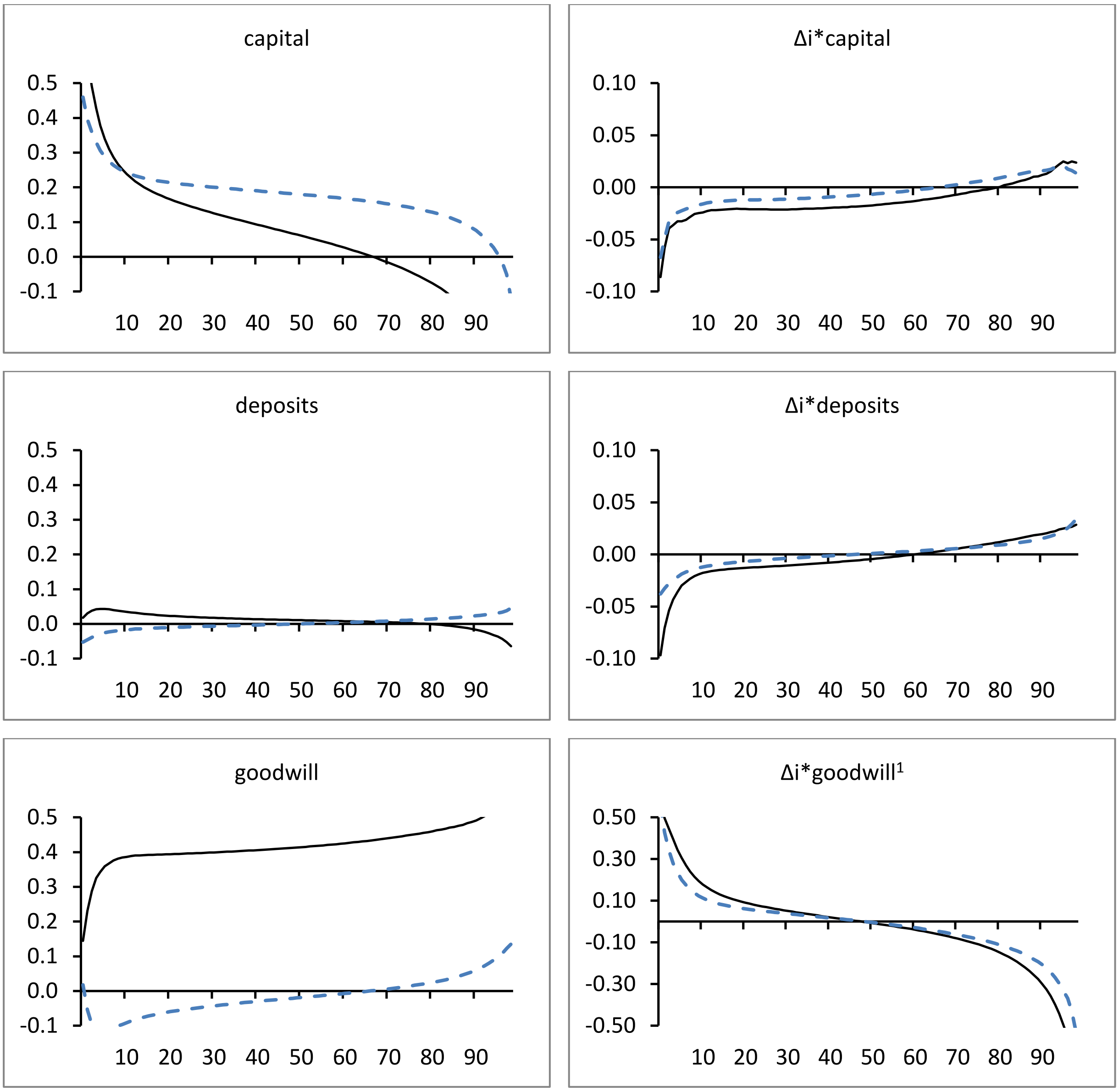
Figure 2.3 combines the size-dependent coefficients for banks operating only within one county (solid line) and in several counties (dashed line). No confidence intervals are shown in order to avoid cluttering the graphs. With the exception of goodwill, the non-interacted variables are reasonably similar. In general, the multi-county estimates are more stable across banks of different size. One explanation could be that banks operating in several counties can better diversify their loan portfolio, which may render size differences less important.

As for the interaction terms, interbank lending and borrowing are the variables that differ the most between the two bank types. The differences are not statistically significant though, i.e. the confidence intervals of the two bank types overlap. All other variables are very similar or nearly identical. The only other variables for which one could potentially expect a similar geographic asymmetry is deposits, though this does not seem to be the case here. The interbank interaction terms are significant for a wide size range only for single-county but not at all for multi-county banks. A higher interbank lending ratio is more important for single-county banks to mitigate a negative impact of restrictive monetary policy on lending than for multi-county banks. This is because banks operating in a narrowly circumscribed area find it more difficult to diversify their portfolio against shocks that hit on a local level than banks in a larger geographic region. Interbank lending is the natural choice to buffer such shocks because it is the most flexible and inexpensive solution (e.g. it does not involve high transaction costs incurred by the sale of securities). Similarly, interbank borrowing by single-county banks is most likely a sign of trouble or bad liabilities management, associated with lower lending growth. On the other hand, multi-county banks that are better geographically diversified are more likely to use it as a deliberate strategy to optimize their balance sheets and act as both lenders and borrowers in the interbank market. However, it is impossible to disentangle the two different motives here. As such, the evidence in this analysis is only circumstantial, but it is perfectly in line with the observation in Stigum & Crescenzi (2007) that federal funds flow from local banks toward the regional and money center banks.

The evidence is also consistent with the relationship banking literature that holds that banks located closer to their clients, such as the ones operating in only a single county, attempt to shelter them from negative shocks to a larger degree than geographically diversified banks (Elyasiani & Goldberg, 2004). Except for very small sizes, single-county banks seem to have higher (less negative) loan growth after a policy rate increase the higher their interbank lending buffer gets, while this is less the case for multi-county institutions.

Figure 2.4. Size dependence of balance sheet coefficients, single- vs. multi-county operations, 1994Q1 – 2010Q4





Solid line: single-county regressions. Dashed line: multi-county regressions. Note the different scales on the right and left side of the figure.

[1] The scale is different for this variable.

2.5 Conclusion

This paper has discussed and discovered several interesting aspects of banks' behavior. First, lending growth depends strongly on banks' balance sheet composition. This relationship varies for banks of different sizes, with small banks usually showing more pronounced reactions than large banks, especially with respect to the share of interbank lending and capital as a part of the balance sheet.

Second, the paper has uncovered in great detail how changes in monetary policy affect banks' lending behavior. For the bank lending channel to operate, monetary policy must be able to alter the supply of bank loans. Controlling for demand factors and unobserved common factors, the paper finds that there is no evidence that the size of a bank *per se* is significantly related to lending growth when monetary policy changes. However, there is a distinct size effect in the reaction of individual balance sheet items. Most importantly, a higher interbank lending ratio may help small banks to better counter monetary policy shocks, while there is no significant effect for large banks. Hence, from a technical perspective, it is essential to control for a broad set of bank characteristics when analyzing the credit channel. Given that balance sheet positions have unique responses to changes in monetary policy, depending on a bank's size, these positions should not be lumped together or netted out. This seems especially relevant for interbank lending and borrowing, which are so often overlooked and lumped in with other variables in papers covering this subject area.

Furthermore, the precise transmission mechanism seems to change over time as innovations in monetary policy or technology take hold. It is essential to understand how banks manage their balance sheets in order to be able to adequately assess the effect that interest rates have on bank lending at any given point in time. Additionally, there is circumstantial evidence that interbank market activities play a more important role for banks operating in a narrowly defined region, such as a single county, as opposed to banks that are more geographically diversified.

Further research should focus in greater detail on whether these results hold for different types of lending at a more disaggregated level, such as different types of mortgages or consumer loans. Also, one could further analyze interbank relations if counterparty data were used. This could shed more light on how interest rate changes work their way through the interbank market. Last, a more detailed analysis of the location of banks and their reach, combined with balance sheet information, could lead to a better understanding of the geographical dimension of monetary policy transmission.

Appendix A. Description of variables from US Call Reports

Variable name	Series and item number	Description
Cash	rcfd0010	Cash and balances due from depository institutions
Interbank lending	rcfd1350	Federal funds sold and securities purchased under agreement to resell

Loans	rcfd1400	Total loans and leases, gross
Loans secured by real estate	rcfd1410	Loans secured by real estate
Securities	rcfd1754	Held-to-maturity securities
Securities	rcfd1773	Available-for-sale securities
Commercial and industrial (C&I) loans	rcfd1766	Commercial and industrial (C&I) loans
Total assets	rcfd2170	Sum of all assets
Deposits	rcfd2200	Total deposits
Interbank borrowing	rcfd2800	Federal funds purchased and securities sold under agreement to repurchase
Total liabilities	rcfd2950	Total liabilities
ALLL	rcfd3123	Allowance for loan and lease losses
Capital	rcfd3210	Total bank equity capital
Federal funds sold	rcfdb987	Federal funds sold in domestic offices
Securities purchased	rcfdb989	Securities purchased under agreement to resell
Federal funds purchased	rcfdb993	Federal funds purchased in domestic offices
Securities sold	rcfdb995	Securities sold under agreement to repurchase

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Chapter 3

Computing Non-Linearities in Monetary Policy with Policy Function Iteration Methods

3.1 Introduction

The global financial crisis of 2007-2009 and its aftermath have pushed both academics and policy makers into uncharted territories. Many observers and forecasters initially underestimated the impact of the subprime mortgage crisis on the banking sector as well as the subsequent decline in output, the rise in unemployment, and the increase in government debt, and were surprised by the speed at which the process occurred. Central bankers in many countries felt impelled to not only decrease the policy rate to levels close to zero, but also engage in quantitative easing to an unprecedented degree to stimulate their respective economies.

From an academic perspective, the financial crisis has boosted interest in models that can take account of so-called non-linearities, such as sudden discontinuities in economic variables, bounds on policy instruments, or different regimes. This interest is mainly due to the usefulness of non-linearities in two broad strands of the literature: financial market frictions and the zero lower bound of the interest rate.

In the first area, the financial crisis has sparked a large interest in modeling such phenomena that tie macroeconomics to frictions in financial markets, especially with respect to financial intermediaries (for an excellent overview, see Brunnermeier, Eisenbach, & Sannikov, 2012). Cúrdia & Woodford (2009) analyze a New Keynesian model with credit frictions that incorporates an interest rate spread between savers and borrowers. Christiano, Motto, & Rostagno (2010; 2013) augment a standard DSGE model with a financial accelerator and find that systemic fluctuations in risk drive the business cycle. Gertler & Karadi (2011) draw lessons for unconventional monetary policy from a quantitative monetary DSGE model with financial intermediaries that face endogenously determined balance sheet constraints. Brunnermeier & Sannikov (Forthcoming) study a macroeconomic model with a financial sector that causes economic volatility and crisis episodes.

The second main area of research that the financial crisis and central bank reactions have stimulated is monetary policy in the presence of a zero lower bound on the policy interest rate. This lower bound represents an occasionally binding constraint that can be analyzed with similar tools as in the first area. Some recent examples of such research on the zero lower bound are Adam & Billi (2007), Fernández-Villaverde, Gordon, Guerrón-Quintana, & Rubio-Ramírez (2012), and Gavin, Keen, Richter, & Throckmorton (2013). However, the zero lower bound may not be the only non-linearity that central banks may be faced with. Changes in the Taylor rule in response to macroeconomic or political circumstances may produce a different type of non-linearity as described later in this paper.

Such examples reveal the benefits of having a technique at hand that can take account of non-linearities and does not discard them as rare exceptions to an otherwise smoothly working economy.

The financial crisis has demonstrated that output and inflation alone may not be the only relevant variables that central banks should take into consideration when assessing the state of the economy: Risks in the financial sector undermined the health of the economy and led to a sudden and sharp collapse in output. This paper goes one step in this direction by including additional economic information in the central bank's reaction function, in this case the marginal cost spread of firms. As shown below, this variable contains information that can help monetary policy makers react more appropriately to shocks compared to a scenario in which they only pay attention to one single target.

This paper is structured as follows. Section 3.2 gives an overview of methods to numerically solve DSGE models that are subject to non-linearities and details the solution method used in this paper. Section 3.3 outlines the baseline model. Section 3.4 introduces two different types of non-linearities in order to demonstrate the strengths of discrete space models: the zero lower bound on the interest rate and a sudden change in the Taylor rule coefficients. Section 3.5 concludes.

3.2 Solution techniques for DSGE models with non-linearities

3.2.1 Overview

Only a few DSGE models have an analytic solution. Therefore, the solutions for most models need to be approximated using numerical methods. Heer & Maußner (2009, Table 1.3) characterize different numerical techniques based on two dimensions. First, they classify methods based on whether they approximate solutions to the model's Euler equations or the policy functions. Second, they distinguish local methods that incorporate information about the true model, for example the deterministic steady state, at a specific location of the state space, from global methods that use information from the entire state space.

The most common approach to solving DSGE models are so-called perturbation methods which belong to the local approximation category. The true function is approximated around the steady state by (log-) linearizing the system of difference equations, or using a Taylor-series approximation of order 2 (or in some cases of higher order). An approximate solution can then be computed analytically. These techniques can be easily implemented, for example by using the software package Dynare[9]. Perturbation methods are relatively simple to set up, can be quickly computed, and are scalable in the sense that additional shocks, state and policy variables can be added without complicating the solution technique (Gaspar & Judd, 1997; Richter, Throckmorton, & Walker, 2013). These attractive characteristics mainly explain their popularity in DSGE modeling. However, perturbation methods require the system of equations governing the model's dynamics to be sufficiently differentiable at a certain point (Heer & Maußner, 2009). Many real-world phenomena fail this condition. For instance, occasionally binding constraints such as non-negative investment (Heer & Maußner, 2009), collateral requirements (Krishnamurthy, 2003), the zero lower bound of the interest rate set by the central bank (Gavin et al., 2013), or liquidity constraints in banks (Freixas & Jorge, 2008) may all cause the approximation procedure to miss the true shape of the policy functions as one moves away from the steady state. Additional examples are models with endogenous regime change, recursive preferences, or heterogeneous agents (Richter et al., 2013).

One technique to address such complications in a perturbation setup is penalty functions methods, pioneered by Luenberger (1973) and Judd (1998). Their essence is that they convert a constraint, such as a binding credit constraint, into a continuous penalty function that punishes choices that violate the constraint. The model can then be solved using perturbation methods. Rotemberg & Woodford (1999) use a penalty function approach to model the zero lower bound of the interest rate in an estimated sticky price model. Preston & Roca (2007) analyze a real business cycle model with heterogeneous agents that are subject to a borrowing limit. Kim, Kim, & Kollmann (2005) apply a penalty function to an incomplete market model with infinite number of agents and exogenous borrowing constraints. Den Haan & De Wind (2012) incorporate a penalty function in a simple model of agents who face idiosyncratic income risk but can smooth their consumption with a non-negative amount of one-period bonds. However, Brandimarte (2006) warns that severe numerical difficulties may arise in penalty functions under certain conditions, and Brzoza-Brzezina, Kolasa, & Makarski (2012) report serious stability issues for higher-order stochastic models.

Two approaches that are characterized in the Heer & Maußner (2009) framework as global and related to the policy functions are parameterized expectations and projection methods. Christiano & Fisher (2000) provide an excellent overview of these methods in the context of occasionally binding constraints. They show that the parameterized expectations approach (PEA) is a special case of projection methods. The PEA makes use of the fact that agents' conditional expectations are time invariant with respect to the state space in the type of DSGE model used here and can be solved with the help of function approximation (Heer & Maußner, 2009). PEA was developed by Wright &

[9] Dynare is a software package used to calculate dynamic general equilibrium models using perturbation methods. For more information on Dynare, see www.dynare.org.

Williams (1982a; 1982b; 1984). An overview can be found in Marcet & Lorenzoni (1999). Projection methods, also called weighted residual solution methods, do not need to approximate agents' conditional expectations, but can focus on the policy or value functions instead. They can be characterized along three dimensions: the approximation function, the weighting function, and the method for integration (Christiano & Fisher, 2000). Different solution techniques can be applied to each of these dimensions. As for the the approximation functions, spectral methods such as monomials or Chebychev polynomials (e.g. Judd, 1992; Judd, 1998) or finite element methods can be used (e.g. Reddy, 1993; McGrattan, 1996). The second dimension comprises least squares (e.g. Heer & Maußner, 2009), the Galerkin method (e.g. McGrattan, 1996), or collocation methods (e.g. Coleman, 1997; Anderson, Kim, & Yun, 2010). Integrals can be computed with quadrature methods or Monte Carlo integration. There are a number of methods to increase the numerical efficiency of the calculation, such as the Smolyak algorithm, but they are usually subject to certain issues, e.g. their inability to handle non-linearities (Krueger & Kubler, 2004; Brumm & Grill, 2010; Malin, Krueger, & Kubler, 2011). Projection methods can be used on discretized state spaces, though they are not limited to it (Judd, 1992).

One alternative approach to solving DSGE models in this same category are discrete state space methods. Each of the model's state variables *s* is discretized by a number of points p_s, so that the model's entire *n*-dimensional state space (with *n* being the number of state variables) consists of $\mathrm{g} = \prod_{s=1}^{n} p_s$ grid-points, or nodes. One can then compute the value and policy functions on this grid. Value function iteration simply works by iteratively solving the maximization problem described by the Bellman equation, given an initial guess and a fixed state space grid (Heer & Maußner, 2009). This method has been employed, for example, by Christiano (1990). However, the convergence of this procedure is only linear and therefore time-consuming. Policy function iteration improves on value function iteration by updating the value function as if the newly calculated iteration of the policy function were followed forever. With this change, one can achieve a quadratic convergence (Heer & Maußner, 2009).

Discrete state models, such as value or policy function iteration methods, are well suited to address non-linearities. However, the main drawback of these techniques is that they are not easily scalable, i.e. they run into computational limits as the number of state variables and shocks increases. For instance, a two-dimensional state space discretized with 20 points along each dimension will require the evaluation of 20^2 = 400 nodes. Adding two state variables will increase the number of nodes to 20^4 = 160,000, and a model with ten state variables would encompass more than ten trillion nodes. This phenomenon is known as the 'curse of dimensionality'. However, recent advances in both computer hardware and software have made it possible to solve larger models than was possible just a few years ago. Some of the techniques used to speed up computing times will be described in the following section. These developments have brought forth studies on fiscal policy and fiscal limits (Bi, 2011; Bi, Leeper, & Leith, 2012; Davig, Leeper, & Walker, 2010; Davig, Leeper, & Walker, 2011), regime switching in monetary and/or fiscal policy (Chung, Davig, & Leeper, 2007; Davig & Leeper, 2008), and the effects of inequality on the incidence of economic crises (Kumhof & Rancière, 2010).

One procedure to mitigate the computational burden of discrete state models is the endogenous grid method (EGM) developed by Carroll (2006). In contrast to the above mentioned variants, EGM does not start from a fixed grid over the state space, but over the control variables. Hence, the grid over the state space becomes endogenous. The advantage of this procedure is that it avoids rootfinding operations and thereby reduces computational demands. Additionally, EMG can take account of non-linearities such as occasionally binding collateral constraints very efficiently (Hintermaier & Koeniger, 2010). However, EGM has not been generalized to apply to models with more than two policy or state dimensions. Barillas & Fernández-Villaverde (2007) as well as Krueger & Ludwig (2007) extend the basic EGM to two control variables but only one endogenous state variable. Fella (2011) extends EGM to non-concave problems. Hintermaier & Koeniger (2010) use a special case of two endogenous state variables. This variant is generalized by Ludwig & Schön (2013), using Delaunay interpolation. Brumm & Grill (2010) develop a related endogenous grid method, but it cannot deal with discontinuities in the policy functions. Despite the attractive qualities of EGMs, these limitations make this method unsuitable for the purpose of this paper.

Several studies compare different solutions methods. For example, Aruoba, Fernandez-Villaverde, & Rubio-Ramirez (2006) contrast the results of perturbation methods of different order, projection methods, and value function iteration. They find that there is a trade-off between speed and accuracy, with perturbation methods showing some instabilities, while projection methods are computationally intense. Jude (1996) also assesses perturbation and projection methods, and states that a combination of various methods could represent an effective approach. Kollmann, Maliar, Malin, & Pichler (2011) compare perturbation, projection, and so-called stochastic simulation methods and conclude that future research should develop hybrid methods that combine the strengths of different solution techniques. They put special emphasis on the fact that the solution method should depend on the specific problem at hand. Den Haan (2010) compares different methods for an incomplete markets model with an inequality constraint. Similar to Kollmann et al. (2011), he stresses that it is important to choose an algorithm that performs well in terms of accuracy and speed given the particular model of interest. As decribed in the next section, the method used to simulate the model in this paper was carefully selected to strike the right balance between speed, accuracy, and flexibility, given the respective advantages and disadvantages of different solution techniques.

3.2.2 Solution method for modeling non-linearities in monetary policy

Based on policy function iteration, the solution technique used in this paper to solve dynamic stochastic general equilibrium models with substantial non-linearities was implemented in a recent paper and appertaining computer code by Richter et al. (2013). The authors reduce the significant startup costs in terms of programming and software expertise required to design such models by providing a user-friendly package of MATLAB functions. Their code allows for multi-core processing and the use of Fortran[10] via MATLAB's executable function. In contrast to Dynare, however, their code is not model-independent, meaning that most functions need to be manually adapted to the specific model that is to be simulated. For the purpose of this paper, their code is changed to fit the baseline model and its variations described in Sections 3.3 and 3.4, but the general structure and characteristics remain.

Before running the code with the correct model equations, one needs to set the parameters, discretize the state space, and calculate the steady state values of the variables. This paper follows Richter et al. (2013) in using the log-linear solution of the model to initialize the policy functions.

On every node, the program calculates the optimal policy function given the initial or updated policy functions and the state grid. The optimization routine identifies the policy functions that satisfy the equilibrium conditions of the model, up to a specific convergence criterion. Note that there is a choice of the iteration technique. Time iteration uses future values of the policy function and employs a non-linear solver to find the roots of the system of equations. The advantage of this method is, under some circumstances, a relatively quick quadratic convergence. Alternatively, fixed-point projection uses both current and future values of the policy functions. It does not necessarily satisfy the equilibrium system of equations for each iteration, but it can handle occasionally binding constraints since it does not rely on a non-linear solver. However, this comes at the cost of less reliability compared to time iteration (Den Haan, 2010). In most model versions, this paper uses the time iteration method, but fixed-point iteration is used as a robustness check and serves an important purpose in Sections 4.2 and 4.3.

[10] Fortran is a high-level programming language that is particularly applicable to numeric computation.

Policy function values also need to be calculated if they do not coincide with values that are consistent with the nodes of the discretized state space. For this purpose, the values need to be interpolated or, if the policy function is off the grid, extrapolated. There are several options available. First, the main method used in this paper is to simply linearly interpolate/extrapolate the functions. The advantage of this approach is its small computational burden and its stability. However, it can be imprecise if there is curvature in the policy functions. Nevertheless, in most cases analyzed in this paper, it has proven to be the most reliable and precise method. Second, Richter et al. (2013) make use of Chebyshev polynomials of third or fourth order to inter- and extrapolate the policy functions. While these polynomials can theoretically better approximate the functions off the nodes, this method proved unstable in this paper and is therefore not applied. Third, the approximation method can be based on monomials. The advantage of monomials is the fact that their domain is the entire real line, simplifying the algorithm, while for Chebyshev polynomials, it is an interval of the real line. Their disadvantage is the issue of multi-collinearity that can arise for higher degree monomials that may almost be identical (Heer & Maußner, 2009). Other alternatives include cubic splines or neural networks, but these options are not pursued here.

Following the interpolation of the policy variables, the program calculates the $t+1$ values of the forward-looking variables. These values are needed to determine expectations at time t. Since they depend on all discretized realizations of the shock ε_{t+1}, one needs to numerically integrate over all of them to find the correct value. Two options for this integration are Gauss-Hermite quadrature and the Trapezoid rule. In the model at hand, the two methods yield very similar results, so the Gauss-Hermite quadrature is applied in the benchmark model. In order to achieve a close approximation, different runs revealed that the number of nodes for the shock should not be less than 10.

All models used in this paper were solved on an off-the shelf laptop with a two-core processor (2.40GHz) running on Windows 7 64-bit. The MATLAB version used was R2012a, 32-bit. Where possible, the Parallel Computing Toolbox was employed. This tool enables the user to operate several computer cores simultaneously when calculating for-loops instead of running them sequentially, greatly reducing computing times.

3.3 Baseline model

The framework is based on a New Keynesian model taken from Richter, Throckmorton, & Walker (2013) who adopt a standard textbook version from Walsh (2010). It is adapted by including firms' marginal cost spread in the central bank's Taylor rule. This change reflects the insight that the financial situation and cost structure of companies may have indirect consequences for the conduct of monetary policy, and central banks may improve the outcomes of their targets by including additional information available in the economy (Castro, 2011). An additional change is the type of shock, which is assumed to be a shock to firms' marginal cost instead of a tax shock. The model comprises a household sector, firms, and the government consisting of a monetary as well as fiscal authority.

A representative household derives utility from consumption *c*, real money balances *M/P*, and leisure *1 - n*, where *n* is labor hours. Lower case letters stand for real variables. Households maximize expected lifetime utilility by choosing sequences $\{c_{t+i}, n_{t+i}, M_{t+i}, k_{t+i}\}_{i=0}^{\infty}$:

$$E_t \sum_{i=0}^{\infty} \beta^i \left\{ \frac{c_{t+i}^{1-\sigma}}{1-\sigma} - \chi \frac{n_{t+i}^{1+\eta}}{1+\eta} + \nu \frac{(M_{t+i}/P_{t+i})^{1-\kappa}}{1-\kappa} \right\}, \qquad \chi, \nu > 0 \tag{1}$$

where *β* is the subjective discount factor, *1/σ* is the intertemporal elasticity of substitution, *1/η* is the Frisch elasticity of labor supply, and *1/κ* is the semi elasticity of money demand. The household's balance sheet constraint is

$$c_t + m_t + i_t + b_t = (1 - \tau_t)\left(w_t n_t + r_t^k k_{t-1}\right) + \frac{(m_{t-1} + r_{t-1} b_{t-1})}{\pi_t} + \Pi_t \tag{2}$$

i stands for investment, *b* represents the stock of real government bonds, *τ* is a tax imposed on capital and labor income, *w* is the real wage, r^k the rental price of capital, *k* the capital stock, *r* the interest rate, *π* is the gross inflation rate, and *Π* are real profits that households receive from firms.

The law of motion for capital accumulation is

$$k_t = (1 - \delta) k_{t-1} + i_t \tag{3}$$

with *δ* the rate of depreciation.

Solving the household's constrained optimization problem gives four first order conditions. The first order condition for labor is

$$\chi n_t^{\eta} c_t^{\sigma} = (1 - \tau_t) w_t \tag{4}$$

The first order condition for money is[11]

$$\nu m_t^{-\kappa} = (1 - 1/r_t) c_t^{-\sigma} \tag{5}$$

[11] See Walsh (2010) for a derivation of this result.

The bond and consumption Euler equations are

$$1 = \beta r_t E_t\{(c_t/c_{t+1})^\sigma/\pi_{t+1}\} \tag{6}$$

$$1 = \beta E_t\left\{(c_t/c_{t+1})^\sigma\left((1-\tau_{t+1})r_{t+1}^k + 1 - \delta\right)\right\} \tag{7}$$

The model introduces price stickiness through an intermediate goods producing sector. Based on Dixit & Stiglitz (1977), intermediate goods *y(i)* are produced by a continuum *i* ∈ [0 ,1] of monopolistically competitive firms with identical production technology

$$y_t(i) = k_{t-1}(i)^\alpha n_t(i)^{1-\alpha} \tag{8}$$

and firms minimize their operating costs, shown in the following equation, based on the technology

$$t_t(i) = r_t^k k_{t-1}(i) + w_t n_t(i) \tag{9}$$

Following Ireland (1997), a representative final goods producing firm uses $y_t(i)$ units of intermediate goods in order to produce final composite good y according to

$$y_t = \left[\int_0^1 y_t(i)^{(\theta-1)/\theta} di\right]^{\theta/(\theta-1)} \tag{10}$$

The nominal price for an intermediate good is $p_t(i)$; the nominal price for the final good is P_t. The final good firm maximizes profits by choosing y_t and $y_t(i)$ for all *i*

$$P_t y_t - \int_0^1 p_t(i) y_t(i)\, di \tag{11}$$

subject to the production technology in equation (10). The resulting first order condition is

$$y_t(i) = [p_t(i)/P_t]^{-\theta} y_t \tag{12}$$

This is the demand equation of the final good firms for the intermediate good as a function of its final good and the relative price. Final good firms earn zero profits in equilibrium because of competition in the market for the final good. Real profits for intermediate firm *i* depend on the cost of adjusting its nominal price level, $p(i)$ (Rotemberg, 1982). Following Ireland's (1997) representation, real profits for intermediate firm *i* can be modeled as

$$\Pi_t(i) = \left[\left(\frac{p_t(i)}{P_t}\right)^{1-\theta} - \Psi_t\left(\frac{p_t(i)}{P_t}\right)^{-\theta} - \frac{\varphi}{2}\left(\frac{p_t(i)}{\bar{\pi} p_{t-1}(i)} - 1\right)^2\right] y_t,\ \varphi \geq 0 \tag{13}$$

where φ is an adjustment cost parameter, Ψ is real marginal cost, and $\bar{\pi}$ is the steady state gross inflation rate.

Marginal cost can be calculated from the firm's optimization problem, and is

$$\Psi_t = \frac{w_t^{(1-\alpha)} r k_t^{\alpha}}{(1-\alpha)^{1-\alpha}\alpha^{\alpha}} e^{\varepsilon_{\Psi,t}} \tag{14}$$

where the shock is

$$\varepsilon_{\Psi,t} \sim N(0, \sigma_{\Psi}^2) \tag{15}$$

Intermediate firms maximize the expected discounted present value of their profits with respect to their price level $p(i)$: $E_t \sum_{k=t}^{\infty} q_{t,k} \Pi_k(i)$, where $q_{t,k} \equiv \prod_{j=t+1}^{k} q_{j-1,j}$ is the stochastic discount factor with $q_{t,t} \equiv 1$ and $q_{t,t+1} = \beta_{t+1}(c_t/c_{t+1})^{\sigma}$. In equilibrium, the first order condition derived from the profit maximization problem for the intermediate firms is

$$\varphi\left(\frac{\pi_t}{\bar{\pi}} - 1\right)\frac{\pi_t}{\bar{\pi}} = (1-\theta) + \theta\Psi_t + \varphi E_t\left[q_{t,t+1}\left(\frac{\pi_{t+1}}{\bar{\pi}} - 1\right)\frac{\pi_{t+1}}{\bar{\pi}}\frac{Y_{t+1}}{Y_t}\right] \tag{16}$$

The government's flow budget constraint is given by

$$m_t + b_t + \tau_t\left(r_t^k k_{t-1} + w_t n_t\right) = \bar{g} + \frac{m_{t-1} + r_{t-1} b_{t-1}}{\pi_t} \tag{17}$$

with $\bar{g}$ a constant level of discretionary spending. The monetary and fiscal authorities follow these policy rules

$$r_t = \bar{r}\left(\frac{\pi_t}{\pi^*}\right)^{\phi}\left(\frac{\Psi_t}{\bar{\Psi}}\right)^{\omega} \tag{18}$$

$$\tau_t = \bar{\tau}\left(\frac{b_{t-1}}{b^*}\right)^{\gamma} \tag{19}$$

with π* and b* the target levels of inflation and debt. $\bar{r}$, $\bar{\Psi}$, and $\bar{\tau}$ are the steady state interest rate, marginal cost, and tax rate, and ϕ, ω, and γ are parameters. The inclusion of firm's marginal cost in the Taylor rule is a deviation from the Richter et al. (2013) model, and signifies the choices central banks have in including additional economic information in their decision process. In the current setup, it is assumed that marginal cost can be fully observed by policy makers. Marginal cost enters positively in the Taylor rule because increases in firms' costs are inflationary. That is, the setup is akin to a cost-push situation in which firms pass through cost increases they incur to the prices they charge their customers, given the intermediate and final goods producing structure in this model.

The aggregate resource constraint is

$$c_t + i_t + \bar{g} = \left[1 - \varphi\left(\frac{\pi_t}{\bar{\pi}} - 1\right)^2/2\right] y_t \tag{20}$$

The simulated model comprises equations (3) to (7), the production function (8) aggregated across firms, equation (14) and equations (16) to (20). There are five state variables (the four lagged variables – real debt, the interest rate, money, capital – as well as the shock). The choice of policy variables is not unique. Here, marginal cost, inflation, and the rental price of capital, are taken as policies. The model is calibrated as described in Table 3.1. Identical or similar parameter values as in Richer et al. (2013) have been chosen.

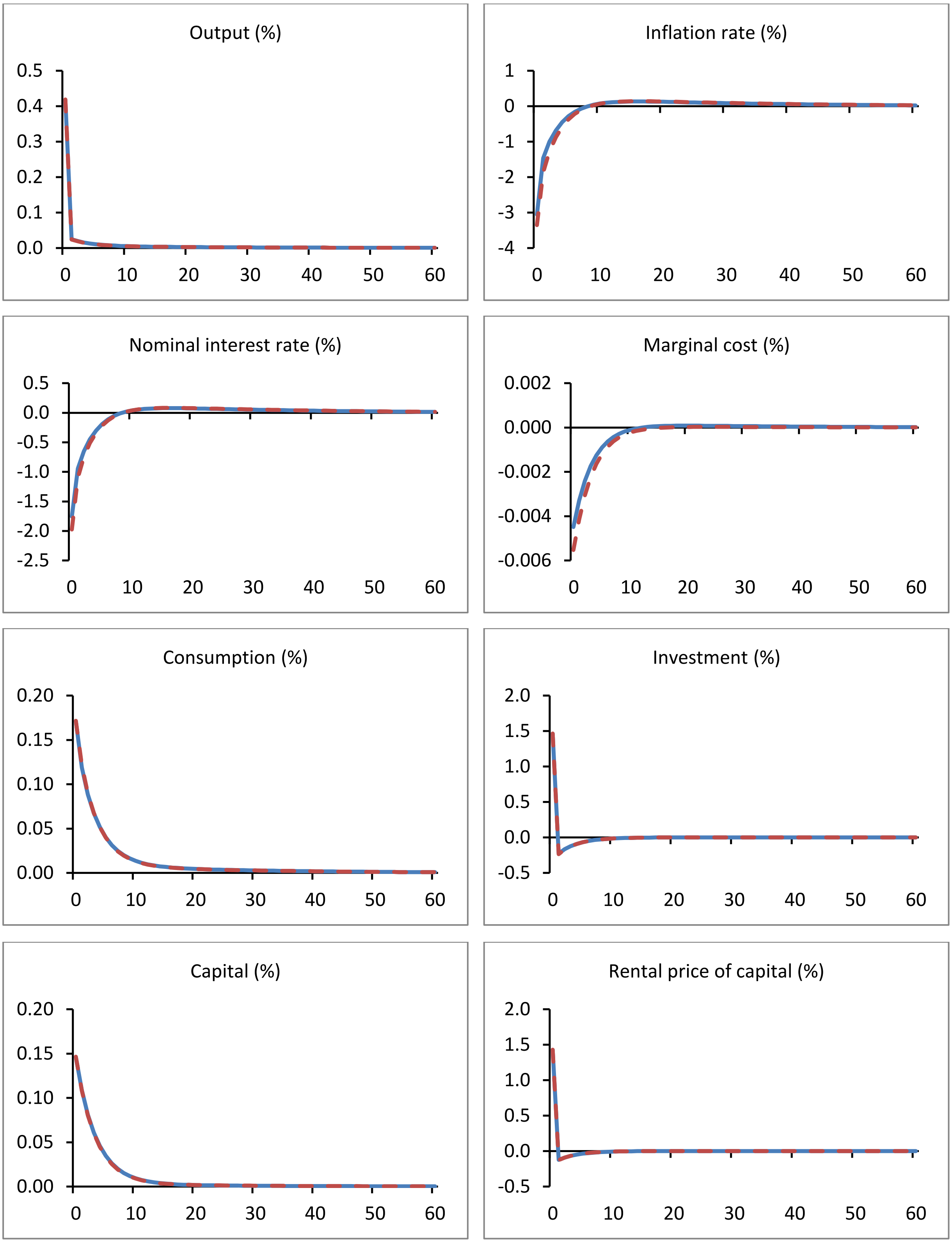
Table 3.1. Calibration of the baseline model

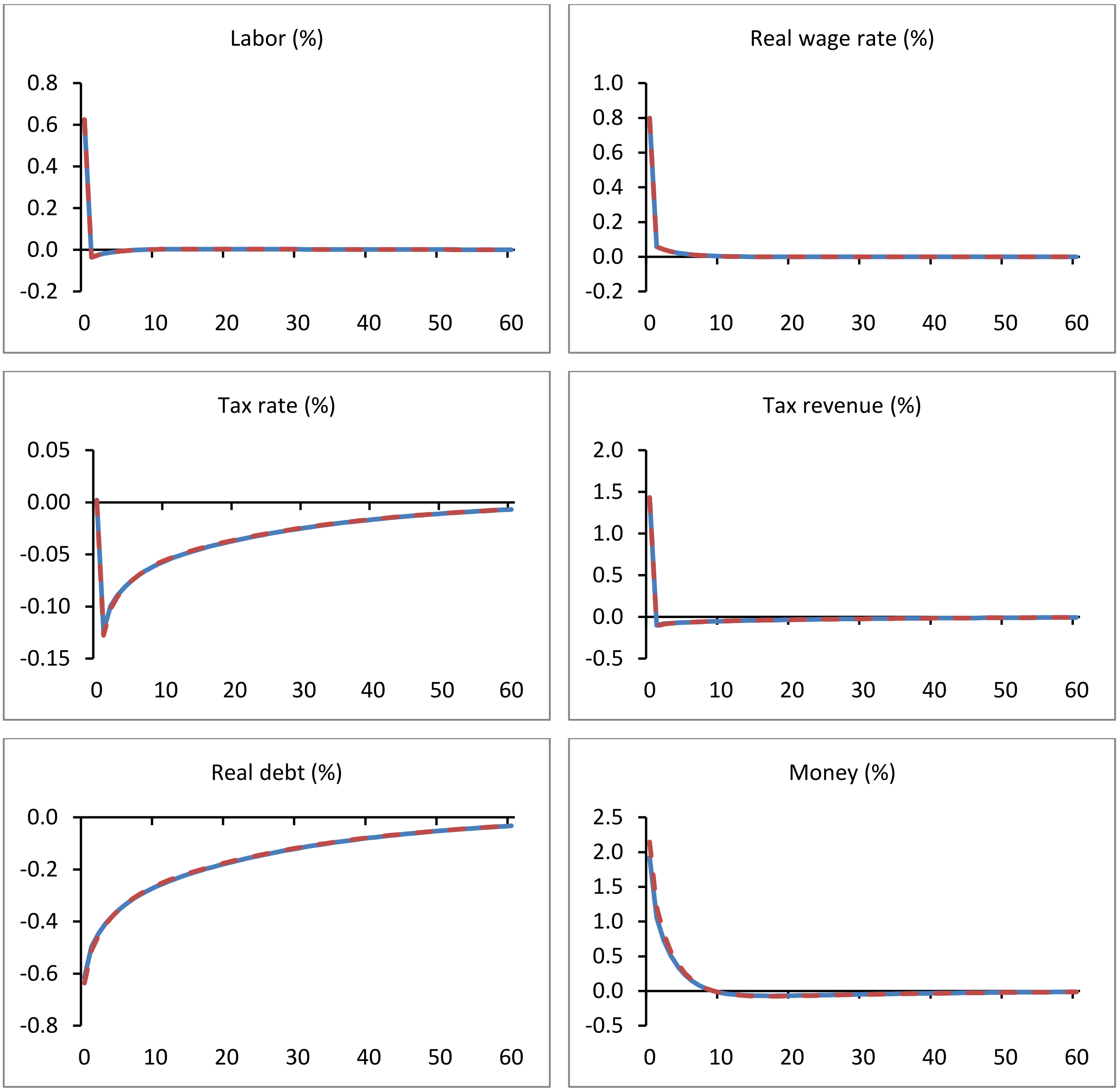
Parameter	Value	Description	Parameter	Value	Description
α	0.33	Cost share of capital	$\overline{\pi}$	1.002	Inflation target
β	0.99	Discount factor	ϕ	1.50	Inflation coefficient
δ	0.10	Depreciation rate	ω	0.50	Marginal cost coefficient
η	1.00	Inverse Frisch elasticity	$\overline{g}$	0.16	Government spending share
κ	1.00	Inverse interest rate elasticity	τ	0.21	Steady state tax rate
ϑ	7.67	Price elasticity of demand	γ	0.20	Debt coefficient
vel	3.80	Money velocity	$\sigma\psi$	0.01	Standard deviation of shock
$\overline{n}$	0.33	Steady state labor	tol	10^{-7}	Algorithm convergence criterion
φ	10.0	Rotemberg adjustment cost	λ	0.50	Algorithm update coefficient

The baseline model is estimated using time iteration, linear interpolation, and the Gauss-Hermite quadrature to integrate over the shock realizations. Further below, the robustness of some of these specifications is assessed by comparing the Euler equation errors of alternative methods.

The impulse responses (Figure 3.1, solid lines) show the behavior of the variables in the baseline model for a shock with a standard deviation of 0.01, with a negative shock imposed. The state variables are discretized with 11 points each, yielding a total number of 11^5 = 161,051 nodes over which to calculate the optimal policy functions. The tolerance level used is 10^{-7}. In addition, the impulse responses with no marginal cost term in the Taylor rule (i.e. ω = 0) are included for comparison (dashed lines).

Figure 3.1. Impulse responses to a negative marginal cost shock in the baseline model





Note: Solid lines reflect Taylor rule with ω = 0.5. Dashed lines reflect Taylor rule with ω = 0.

An exogenous negative shock to firms' marginal cost is good news for the economy. Output increases since there is more demand for firms' products as inflation is lower. This reflects the fact that marginal cost and inflation are positively correlated in this model. If marginal cost declines, firms pass it on to consumers. The central bank is aware of this relationship, and therefore marginal cost is included in the Taylor rule in this model to begin with. As expected, the interest rate drops since inflationary pressures are subdued. Consumption is up, reflecting the fact that consumers can spend more money in this benign environment. Investment is up initially, though there is some undershooting in subsequent periods. The capital stock increases and returns slowly back to its steady state level since investment does not keep up with depreciation. Labor, the real wage rate, and the rental price of capital are all up. The tax rate declines, even though tax revenues go up initially because the government receives higher payments from labor and capital. The higher tax revenue allows the government to decrease its debt burden, and real debt slowly converges back to its steady state level. The increase in money is the flipside of the lower interest rate.

The impulse responses with and without the marginal cost term in the Taylor rule are fairly similar for most variables. However, including the term helps the central bank to achieve better outcomes for its main policy target, the inflation rate, which deviates by 30 basis points less from the steady state in the first period compared to the set of impulse responses that does not include the marginal cost term. Additionally, the central bank needs to cut the interest rate by 22 basis points less in the first period to achieve this outcome. Similarly, money increases by 22 basis points less in the marginal-cost-augmented Taylor rule scenario. These results show that including additional information available in the economy, such as the cost structure of firms, can support central banks to stick to their targets more closely after economic shocks compared to a case in which they focus on a more narrow set of variables.

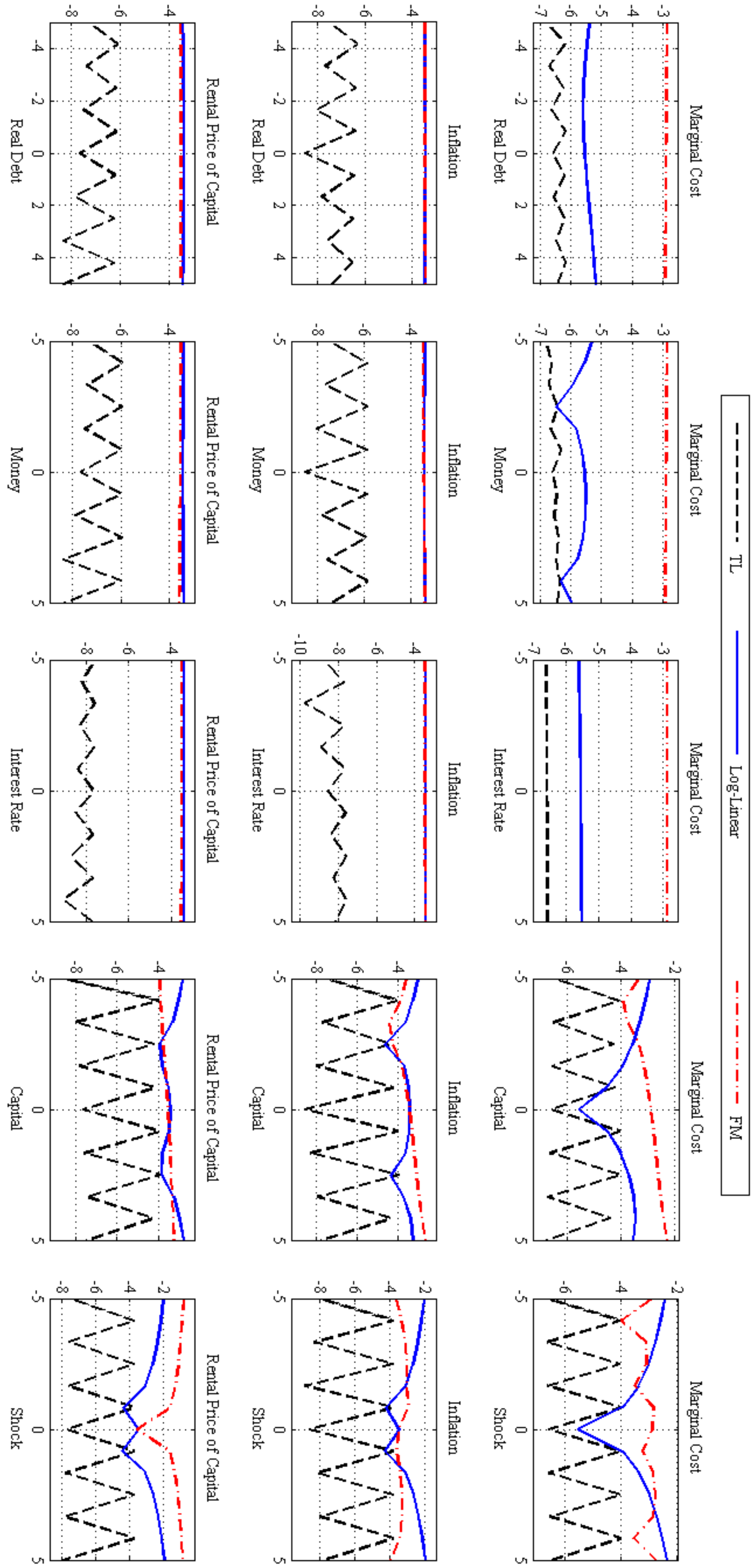
The model can be estimated using different techniques. Euler equation errors (EEE) are one way to compare the goodness of fit of different methods (Heer & Maußner, 2009; Richter et al., 2013). Figure 3.2 compares the EEE of three different techniques:

- the residuals of a log-linear representation of the model. This method could also be implemented using Dynare with a first order approximation ("log-linear").
- the residuals of a model using fixed-point iteration with a monomial basis ("FM")
- the residuals of a model using time iteration with linear interpolation ("TL"). This method was also used to compute the impulse responses in Figure 3.1.

The scale is logarithmic with a base of 10. The number of nodes to simulate the EEE is increased to 13 in order to see the performance of the different methods off the original grid on which the approximations were performed. The first row shows the EEE for the interest rate policy, while the second row displays the EEE for the price level policy function. The columns correspond to the state variables.

In general, the TL method has the smallest EEE. This is especially the case for values that are further away from the steady state. The zigzag movement of the TL methods stems from the fact that the linear interpolation is imprecise if the functions experience curvature. Nevertheless, in the majority of cases, the off-grid errors are smaller compared with the other techniques.

Figure 3.2. Euler equation errors for different estimation methods of the baseline model



Note: x-axis in percent deviation from steady state, y-axis logarithmic with base 10

3.4 Non-linearities in monetary policy

This section introduces two different types of non-linearities in the model. In contrast to perturbation methods, the method used in this paper can take care of non-linearities or discontinuities in a sense that there can be abrupt changes in regions further away from the steady state.

3.4.1 Zero lower bound on the interest rate

In response to the financial crisis, several central banks around the world reduced their respective policy rates. Following a conventional Taylor rule, the severity of the shock, however, might have required short-term rates that were substantially below zero (Asso, Kahn, & Leeson, 2010). Policy rates are believed, though, to be subject to the zero lower bound, since economic agents can always hold cash instead of suffering from a negative nominal interest rate, should it be implemented. This bound has implications for other economic variables. In order to simulate the zero lower bound, the minimum value that the interest variable can assume is set to 1.005. This number reflects the fact that central banks cannot typically push down the interest rate completely to zero, but it is usually slightly positive. For example, as of writing, the Federal Reserve in the US has set a range for the Federal funds rate of 0 to 0.25%, and the respective numbers for Japan are 0 to 0.1%, instead of the traditional point target. This is due to the fact that it is difficult for central banks to bring the short-term policy rate completely to zero.

The simulation procedure is similar to the one implemented in Richter et al. (2013). In a first step, the model is simulated using the time iteration method without imposing the binding constraint. The result is an updated policy function for the inflation rate on every node although the interest rate might actually be below zero. In a second step, the nodes for which this is the case are determined, and these nodes are re-calculated with the fixed-point method and the zero lower bound in place. Note that the nodes that are calculated with the fixed-point method do not necessarily satisfy the equilibrium conditions for all future values. However, using this initial two-step procedure allows calculating a relatively precise guess for the initial values of the policy functions. In a third step, these initial guesses are used to compute the optimal policy functions with the time iteration method and the zero lower bound in place. Hence, in the third step, the equilibrium conditions are fulfilled for all periods on all nodes.

Each respective step is repeated for every iteration until the convergence criterion is met. To improve the stability of the algorithm, the updated values are calculated as a linear combination of the old and updated policy function values, using an update weight of $\lambda = 0.5$.

The advantage of this three-step method is that it ensures both the stability of the algorithm and can handle an occasionally binding constraint by using fixed-point iteration. Time iteration alone would not ensure the stability of the algorithm, since relatively precise initial guesses for the policy functions are necessary, and time iteration has difficulties to incorporate non-linear constraints since it relies on a non-linear solver for the current policies, while fixed-point iteration does not (Richter et al., 2013).

Whether there are any noticeable differences between the impulse responses with and without binding constraints depends both on the number of binding nodes as well as on the location of the nodes where the lower elasticity is in effect. In general, the larger the shock the lower is the weight on the outcome. Hence, if all the nodes where the borrowing constraint binds are located far from the steady state, their small weight will not make any discernible expectational difference on the future development of the forward-looking variables, and therefore the impulse responses will look identical. As the number of nodes on which the constraints binds increases and as they are located closer to the steady state where they receive more weight, the differences in the impulse responses with and without a zero lower bound will increase.

Another way to illustrate the differences for a specific variable is by directly comparing the values calculated on each node. Since every variable is a five-dimensional object (one dimension for every state variable), the values of some state variables have to be fixed to produce meaningful graphs. Figures 3.3a-c show the effect of a zero lower bound on the policy variables, holding the state variables m_{t-1}, k_{t-1} and the shock constant at 5% below, 5% above, and 5% below their steady state values, respectively. This produces a three-dimensional chart in the state variables b_{t-1} (x-axis), r_{t-1} (y-axis), and the policy variable of interest – marginal cost (psi_t), inflation (pi_t) or the rental price of capital (r^k_t) – on the z-axis. The angle is chosen to best reveal the interesting properties of the surface. One can clearly see a kink in the surface, which represents the lower bound on the interest rate. Taking inflation policy as an example, the figure shows that inflation is lower where the zero lower bound is in effect (in the south-east section of the surface) compared to what it would otherwise be. The reason is that since the interest rate is higher than appropriate due to the zero lower bound, inflation is more subdued than it would optimally be.

Figure 3.3a. Marginal cost with a zero lower bound

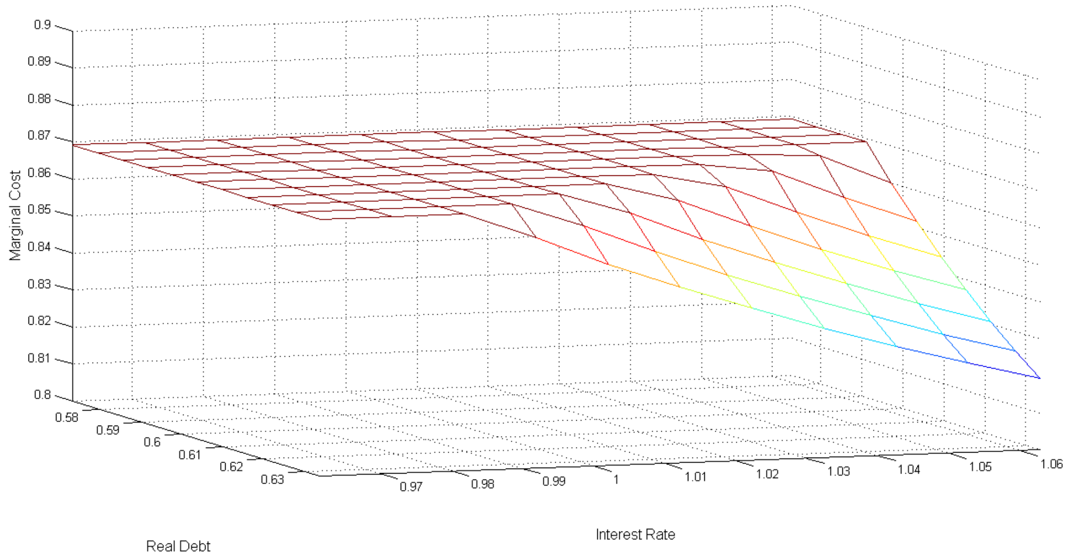


Figure 3.3b. Inflation with a zero lower bound

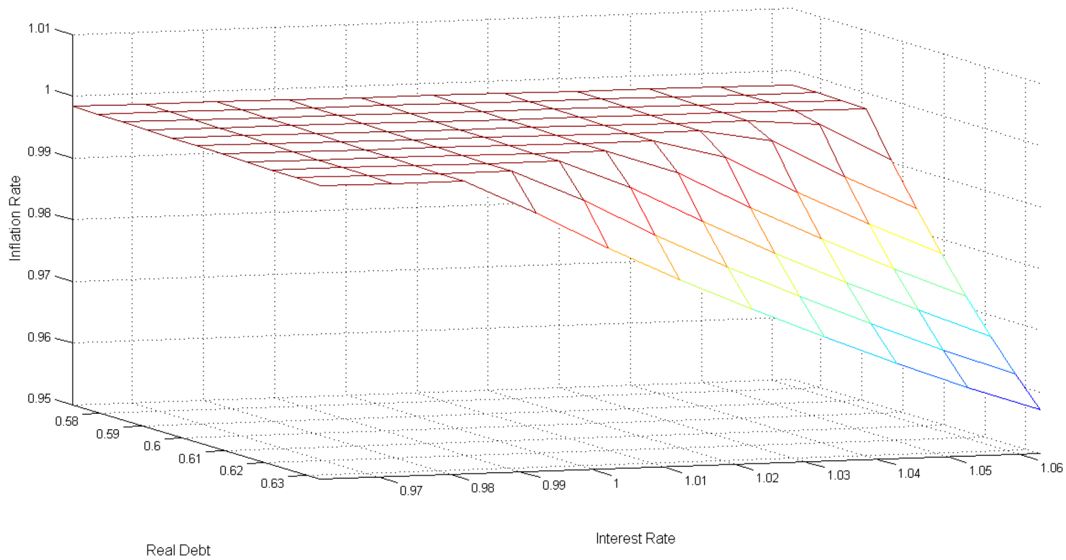
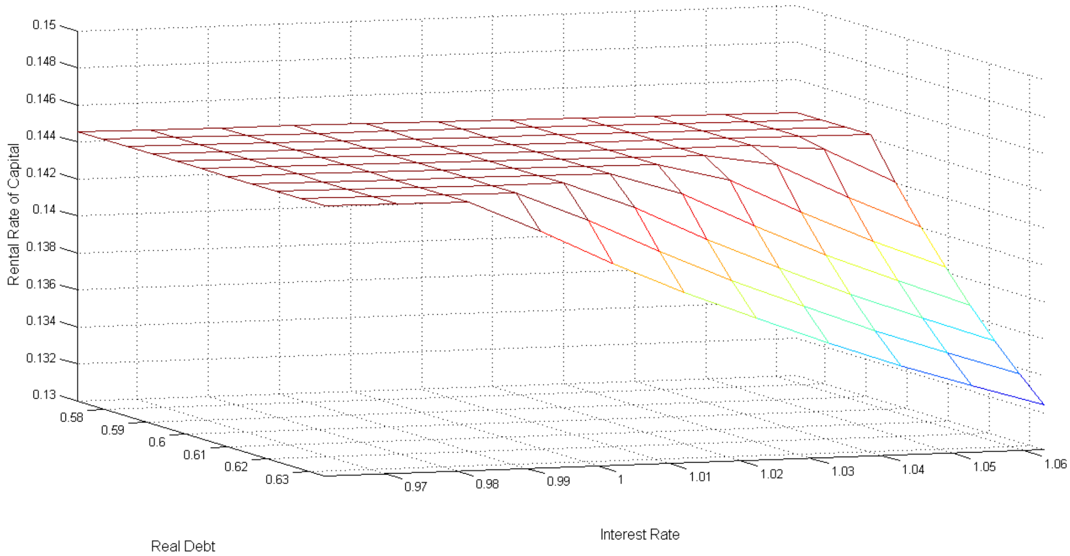


Figure 3.3c. Rental price of capital with a zero lower bound



3.4.2 Changes in the Taylor rule

Central banks are embedded in a certain political context. Even if their independence is guaranteed by law, pressure might arise under specific circumstances that tend to push monetary policy making into a particular direction. The global financial crisis and the crisis in Europe can illustrate this notion. For example, the United Kingdom has fallen back into recession several times since the start of the crisis, despite unprecedented quantitative easing by the Bank of England. The UK government was dissatisfied to some degree with the Bank of England's record, and changed its remit in 2013 to give it more leeway in choosing its policies in order to respond appropriately to the economic circumstances. Another example is the European Central Bank, which only has to adhere to an inflation target, with no statutory role for output stabilization. In the wake of the European crisis, several observers and politicians asked whether a dual mandate with respect to both inflation and output would lead to better outcomes for many euro area countries that faced large slumps in economic activity. However, no explicit changes to the ECB's remit have been made so far, even if it is conceivable that the ECB may respond differently *de facto* to output and inflation than before the crisis.

Such situations of changes in central banks' behavior may be captured by modifications in the central bank's Taylor rule if certain economic circumstances prevail. Setting up a very simple example, one may presume that, in the current setup, central banks may react less to inflationary pressures if output is far below its steady state. This may occur, as described above, if politicians increase the pressure on a central bank to be more accommodative after the economy has suffered a large negative shock. This abrupt change in central banks' reaction may be modeled as a reduction of the Taylor rule coefficients. Hence, given a state of the economy with very low output, a central bank reacts less restrictive to inflation and marginal cost than it otherwise would. Martin & Milas (2004) find a related non-linear response of monetary policy in the UK when inflation is far from the target. In their example, the central bank reacts more aggressively to inflation, not less, but the difference is due to the fact that the shock in this paper is assumed to be of a cost-push nature. The underlying idea of a non-linear change in the Taylor rule remains, though.

One additional realistic feature of this setup is that the change may occur suddenly, for example mimicking politicians who become aware of the issue and demand changes at one specific time. The consequence is that there is no comparatively smooth kink in the policy functions as in the previous section, but a sudden discontinuity or break. It is possible to ensure a smooth transition or kink by adjusting the Taylor rule so as to avoid the break, but this may actually be a less realistic setup in a real world context.

The coefficients of the Taylor rule are adjusted from 1.5 to 1.3 for inflation, and from 0.5 to 0.3 for marginal cost to reflect such changes. The same simulation strategy as in Section 3.4.2 is chosen. First, the model is simulated with time-iteration without imposing a change in the Taylor rule. Then, the nodes are identified for which output falls below a level of 0.455. This value reflects a large negative output gap with respect to the steady state value of 0.471. In a second step, the policy functions for these nodes are re-calculated with the changed Taylor rule coefficients in place using fixed-point iteration. Third, the results are taken as initial guesses for the policy functions, and the model is simulated with the time-iteration method and the coefficient changes for certain output values in place.

Figures 3.4a-c show the effect on the policy functions for an interesting subset of the grid when the output restriction is in place on some nodes. The state variables m_{t-1}, k_{t-1} and the shock are held constant at its steady state value, 5% below, and 5% above its steady state, and the variables b_{t-1} (x-axis), r_{t-1} (y-axis), and policy variable (z-axis) are shown in the graph, respectively. One can clearly see a discontinuity that reflects the change in the Taylor rule coefficients. For example, inflation is higher on the nodes where the change is in place, signifying the more accommodative response of monetary policy. As in the zero lower bound case above, perturbation methods would be unable to properly take account of this discontinuity because they rely on a smooth function that gets approximated around the steady state.

Figure 3.4a. Marginal cost with a change in the Taylor rule

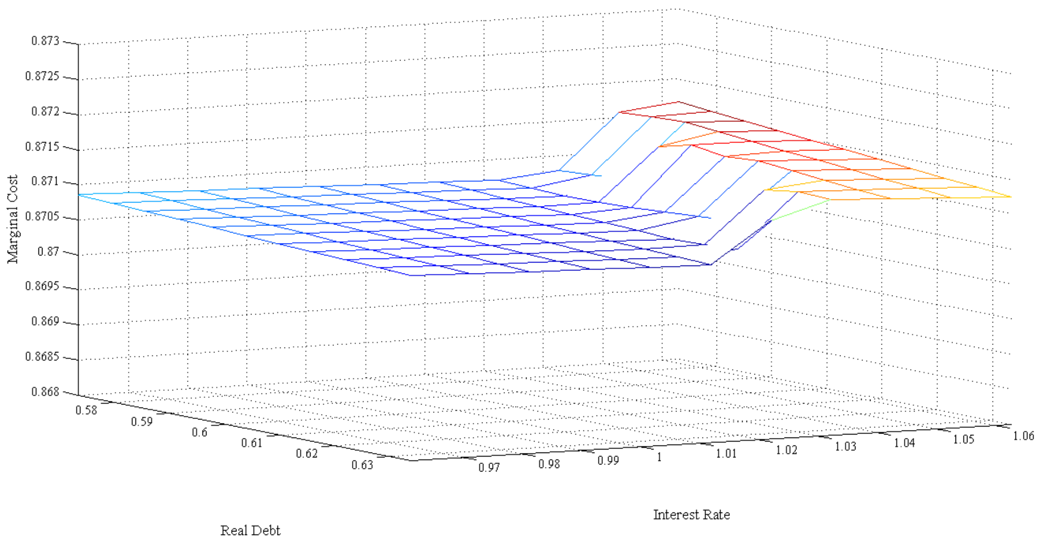


Figure 3.4b. Inflation with a change in the Taylor rule

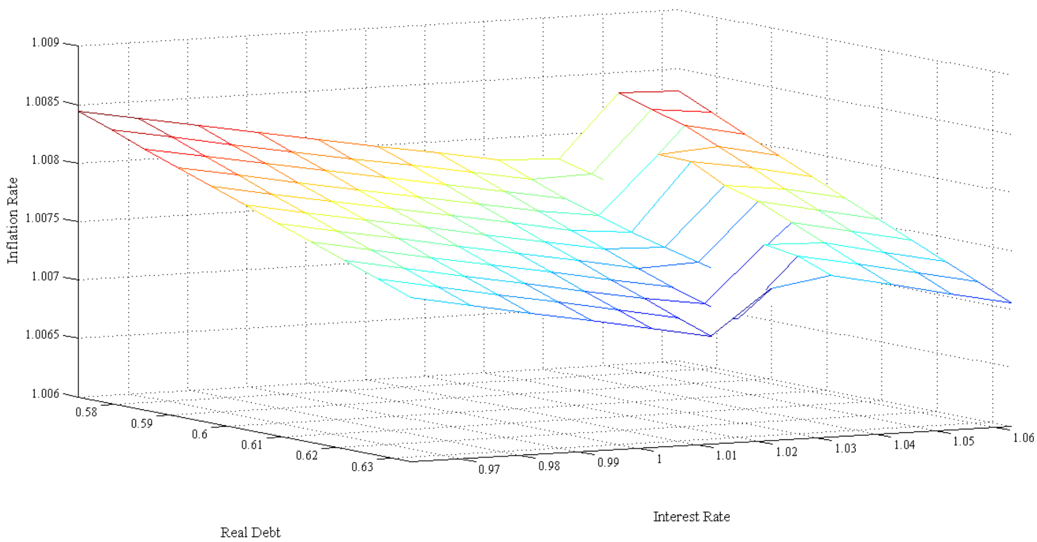
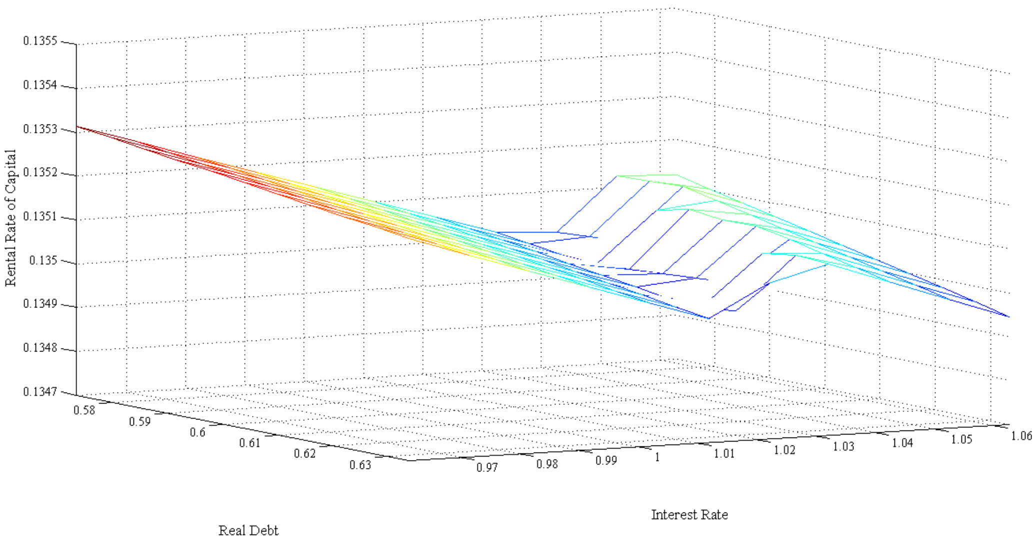


Figure 3.4c. Rental price of capital with a change in the Taylor rule



3.5 Conclusion

This paper has demonstrated the strengths of policy function iteration as a method to model non-linearities in dynamic stochastic general equilibrium models. Two non-linearities and their effects on macroeconomic variables have been analyzed. First, a zero lower bound on the interest rate has been shown to produce a kink in the policy functions that would be missed in a simulation using perturbation methods. Second, changes in the Taylor rule in response to certain macroeconomic conditions result in a discontinuity in the policy functions. The accuracy of different simulation methods has been compared using Euler equation errors, and in general, time iteration using linear approximation has proven to produce the most accurate and stable results.

The global financial crisis has demonstrated that monetary policy can be subject to a variety of non-linearities with potentially substantial consequences for the broader economy. This paper is a step toward modeling such non-linearities as they may arise in central banking. Further research may concentrate on introducing heterogeneous agents and financial intermediaries. This will necessitate the introduction of more state and policy variables as well as additional shocks, which will exponentially increase the computational burdens. Several steps could be taken to keep such demands manageable. First, researchers could make it easier to use Fortran, which is a powerful language when it comes to numeric computation. Second, MATLAB allows users to employ parallel computing not only with respect to computer processors, but also with respect to graphics processing units (GPUs), using the right hardware. This is much more cost-effective than the computer cores alternative. Third, MATLAB also allows running models on computer clusters, grids, and clouds by means of its Distributed Computing Server (MDCS). This seems especially suitable for large-scale models. Future research could establish best practices for computationally intensive programs using one or several of these potential avenues.

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Ich versichere hiermit eidesstattlich, dass ich die vorliegende Arbeit selbständig und ohne fremde Hilfe verfasst habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sowie mir gegebene Anregungen sind als solche kenntlich gemacht.

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