Credit policies before and during the financial crisis

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Abstract

This paper empirically distinguishes between the two main contending explanations for credit cycles. Namely, the bank lending channel and the balance sheet channel. This is done by using unique Danish survey, register, rating, and bank data. The results indicate that the bank lending channel explains most of the changes in credit policy by Danish banks towards small and medium (SME) sized firms. However, the results show that both channels are operational, but the balance sheet channel is surprisingly weak partly because discouragement during the crisis kept struggling firms from applying for credit. The analysis also reveals that the credit supply was weaker in banks that were struggling during the crisis and indirectly that firms could not off-set this effect by changing banks. Furthermore, the evidence suggests that the financial crisis also affected the liquidity of non-financial firms, as credit demand rose immediately following the crisis.

JEL codes: E32, E44, G21, G32.

Keywords: Business Fluctuations, Financial Markets and the Macroeconomy, Banks, and Credit Policies.

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1 Introduction

Does the availability of credit depend on the financial health of banks and/or the balance sheets of borrowing firms? Stated differently, does the agency cost of borrowing between banks and their depositors, the so-called bank lending channel as in e.g. Kiyotaki and Gertler (2010), make lending significantly less likely during a period of low economic activity? Or do lending contract as the value firms' assets depreciate during a recession, the so-called balance sheet channel as in Kiyotaki and Moore (1997) and Bernanke, Gertler, and Gilchrist (1999) (BGG, henceforth), which increase agency costs between firms and their banks? And, are the bank lending channel and balance sheet channel both operational, and if so, which is better at explaining credit cycles?

The main challenge is to separate the two channels because how do you disentangle credit demand from supply? Most studies focus on either macro data (e.g. Bernanke and Blinder (1992)) or on bank level data as in Kashyap and Stein (2000), and thereby potentially neglect important effects. However, a sparse but growing literature has developed different identification strategies. One strategy is to use credit register data on firms that have multiple lenders to control for demand effects, see e.g. Albertazzi and Marchetti (2010) and Iyer et al. (forthcoming). This strategy is further extended to include loan applications and outcomes on the extensive margin in Jimenez et al. (2012). [1] However, these strategies do not take into account the changing composition of firms that demand bank loans as they do not observe which firms select themselves out of the loan application process. Some firms will not apply for loans as they simply have no need for credit and some firms might be discouraged from applying as the general lending environment is deteriorating. This could potentially lead to an underestimation of the true extent of the bank lending channel. Another strategy is to identify constrained firms from survey data which contains information on loan applications, outcomes, and whether firms were discouraged as in Presbitero et al. (2014), Puri et al. (2011), and Popov and Udell (2012). However, these studies can only to a very limited extent account for declining profits of firms during the business cycle, as they lack good controls. Further, the application outcomes cannot be linked to specific banks and are therefore only linked to banks geographically.

The main contribution to the literature of this paper is to combine the advantages of survey data with

[1] Loan applications are identified from information requests on firms that have applied for a loan in a specific Spanish bank. The applications are on the extensive margin as they only observe applications made to banks in which the firm is not currently a customer.

the advantages of register data. Specifically, this study utilizes a credit survey from Statistics Denmark on the credit availability for small and medium sized firms before and during the financial crisis. This survey is linked using a unique firm identifier to register and credit rating data. Further, the survey can be linked to specific banks using information regarding the primary banking connection of firms provided by the credit rating company Experian. This is, to the best of my knowledge, the first study to combine the advantages of several data types to address the questions raised above.

The study yields the following main results: the bank lending channel explains most of the changes in credit policy by Danish banks towards small and medium (SME) sized firms. However, the results show that both channels are operational, but the balance sheet channel is surprisingly weak as self-selection into the loan application process during the crisis kept struggling firms from applying for credit. The analysis also reveals that the credit supply was weaker in banks that were struggling during the crisis and indirectly that firms could not off-set this effect by changing banks. Furthermore, the evidence suggests that the financial crisis also affected the liquidity of non-financial firms, as credit demand rose immediately following the crisis.

The paper is structured in the following way: section 2 discusses the two main contending explanations for credit cycles. Section 3 explains the data and section 4 includes the empirical analysis. Section 5 discusses whether credit risk can be evaluated from firm specific information and thereby disentangled from macroeconomic conditions, and section 6 concludes.

2 The balance sheet channel vs. the bank lending channel

This section will discuss how financial frictions are thought to affect the real economy. The overall question is how the financial crisis affected firms and/or banks and how this affected lending activities. Further, the section outlines how the theories differ and what implications they will have for the empirical analysis. For a more in-depth discussion of the different credit channels, see e.g. Bernanke (2007) or Hall (2001).

2.1 The balance sheet channel

The balance sheet channel or the firm balance sheet channel describes the connection between the borrowers' financial health and the price of external credit or access to credit. It basically links credit supply to economy-wide fluctuations and generates a so-called financial accelerator effect, i.e. financial markets amplifiy relatively small shocks to productivity.

The BGG model works by linking agency costs and therefore the external finance premium, and the borrowers' financial health. In most other respects, the BGG model is a standard dynamic new Keynesian macroeconomic model. Specifically, BGG assumes that lenders face observation costs with respect to the outcome of borrowers' investments. This is the so-called 'costly state verification' (CSV) setup first analyzed by Townsend (1979) and it implies that the financial structure has a nontrivial role. As observation is costly, lenders charge a premium to cover their expected monitoring costs. The size of this premium is determined by corporate net worth or in other words the firms' financial health. Without asymmetric information, entrepreneurs would acquire capital until the expected return is equal to the cost of funds. In the BGG setup, on the other hand, if a substantial/low portion of an investment project is financed by internal finance it implies a low/high external finance premium which tends to raise/depress investment. The underlying idea is that net worth can be seen as the firms' own stake in a project and therefore increase incentive alignment between borrowers and lenders. Stated differently, lenders would only be willing to lend funds to firms if they get a premium large enough to cover the cost of the greater likelihood of default caused by the borrowers' lower stake in the project. One of the main implications of the model is that the agency cost may vary over time as financial positions fluctuate over the course of the business cycle. In the context of this paper, it is important to note that the external finance premium is therefore counter cyclical, or stated differently, the incentive problem could potentially be very pronounced in times of crisis.

The Kiyotaki and Moore (1997) model differs by looking at collateral constraints as opposed to information asymmetries. They theorize that durable assets perform an important role as collateral for lending. If agents have to put up collateral to get loans, a shock to aggregate demand would not only affect firms directly, but also limit their access to credit as the value of a firm's assets depend on economic activity. The idea is therefore closely related to that of BGG, but focuses instead on collateral constraints rather than information asymmetries. Further, the effects are to a large extent similar, namely, amplified and prolonged shocks. In general these theories are not mutually exclusive, but rather two ways of explaining the same phenomenon and therefore complement each other.

The two frameworks discussed above have been extended and modified in too many ways to be replicated here. However, the underlying logic is basically the same. Namely, that during the course of the business cycle, agency costs are dependent on the economic environment, see Christiano and Ikeda (2012) for a review of the different approaches to modeling financial frictions. To distinguish between the balance sheet channel and the bank lending channel, note that the balance sheet channel approach is related to balance sheet of borrowers. However, it is natural to assume that the same kind of agency problems could apply to banks/lenders that obtain funds from depositors.

2.2 The bank lending channel

The bank lending channel broadly describes how shocks to banks' balance sheets might affect the cost of (or access to) finance for certain borrowers. The channel is believed to be important if the supply of bank loans is dependent on economic conditions and that bank loans are imperfect substitutes for other forms of finance. For instance, if banks face the same agency problems with depositors that firms experience with lenders, this might restrict their ability to grant new loans. For the purpose of this paper, it is important that the substitution between different types of financing could be dependent on firm size. The idea being that large firms - often highly creditworthy - can more easily shift to firm bonds or equity than SMEs as entry barriers could potentially exclude smaller firms from these markets. The empirical analysis is therefore focused on the SME segment. It is possible that the cost of bank loans for these borrowers is much greater, as the actual price is higher or the requirements following the loan (covenants, collateral requirements, etc.) are more restrictive. Further, it is also possible that smaller firms might more often experience being rationed. The tightening in loan supply is often termed as a credit crunch. It could be argued that what matters in a credit crunch is that changes in the official interest rate are no longer the only thing that matters for the cost of finance for certain borrowers. The bank lending channel can therefore be thought of as the additional adjustment to firm activities coming from changes in the degree of quantitative loan rationing (or price changes).

The bank lending channel is formalized in for instance Kiyotaki and Gertler (2010) by modeling intermediation as in Gertler and Karadi (2009) and includes liquidity risk as in Kiyotaki and Moore (2008). The main idea being that if banks are optimizing agents, there exist not only agency problems between banks and borrowers but also between banks and their fund providers. Fund providers, depositors or other banks, might be more reluctant to deposit their funds in banks that are struggling and thereby ultimately affecting the supply of credit.

The two credit channels discussed above are distinct ways where financial market imperfections affect the real economy. However, they are believed to be complementary in the sense that early theoretical studies recognized that both channels could potentially be important (see e.g. BBG), and therefore the distinction is in some ways artificial. The underlying mechanisms are the same, but the policy implications are different. For instance, if governments want to avoid a credit crunch, the source of the problem is obviously important to implement an effective policy.

3 Hypotheses, Data, and Empirical Strategy

The goals of this paper are similar to that of Jiménez et al. (2012) which are to disentangle the supply of credit from the demand and answering whether the bank lending channel is operational, and if so, how pertinent is it compared to the balance sheet channel. Like in Jiménez et al. (2012) individual outcomes of loan applications are used. However, the empirical strategy is different and in some ways resembles those of Presbitero et al. (2014), Puri et al. (2011), and Popov and Udell (2012), but extended along several dimensions. The data consists of a broad range of Danish register, survey, bank, and rating data. The data is also representative of lending to firms more generally compared to Jiménez et al. (2012) who focus on the extensive margin i.e. banks lending to firms that are not currently customers. It seems natural that this is important, as the outcome in Jiménez et al. (2012) to some extend is conditioned on the firm being rejected by their current bank connections.

3.1 Hypotheses

The theory discussed above has some very important testable hypotheses: (H1) Well capitalized and liquid firms have better access to credit (see e.g. BGG), (H2) Firms access to credit is better in solid banks (see e.g. Kiyotaki and Gertler (2010)), (H3) If only the balance sheet channel is operational, there should be no significant effect on the supply of credit to firms with no change in creditworthiness during the business cycle. This hypothesis follows directly from the BGG model where the credit supply is only affected by the net worth of entreprenuers.

3.2 Data

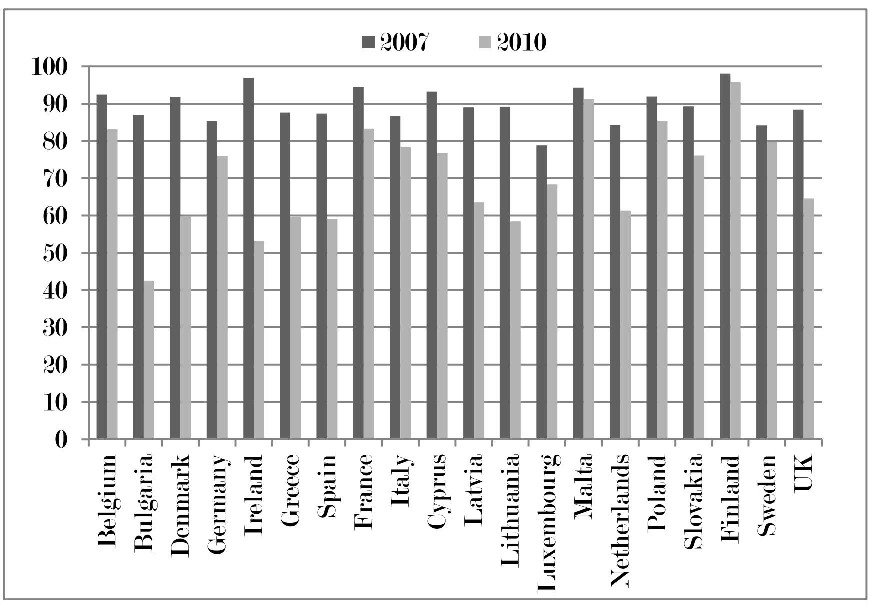
The outcome variable, whether a bank loan is fully granted, partially granted or declined, is taken from a credit survey by Statistics Denmark. The survey was statutory (implying a response rate in excess of 90%) and consists of 2,265 representative responses of a population of 13,990 firms. The goal was to shed light on the access to credit in 2007 and 2009/2010 (April 2009 to March 2010). The survey was restricted to SMEs with 5 to 249 employees in 2005 and at least 5 employees in 2009.[2] Further, the respondents were all in the following sectors: manufacturing, natural resources, and utility, construction,

[2] Note that Danish SMEs accounts for approximately 60 percent of private employment (and revenue) and is therefore a significant part the aggregate economy

trade and transport, or information and communication.[3] The information on the firms' loan applications and outcomes from both 2007 and 2009/2010 was gathered in the same survey in the spring of 2010, which could imply that the information regarding 2007 is more ambiguous than those from 2009/2010. The survey also gathered information on whether firms applied for other types of finance e.g. equity or mortgage loans, and the outcome of these applications. The specific question was: "Did the firms apply for a loan in year x from banks, and with what outcome? (Fully granted, partially granted, or not granted).[4] It is possible to link these answers to all of the register and rating data discussed below by a unique firm identifier (CVR-number).

The Danish credit survey was part of a European collaboration with the European Commission which made it possible to compare the results to other EU countries. It turns out that Danish SME firms were experiencing a high success rate before the crisis but very limited access to credit during the financial crisis, see figure 1. Furthermore, during the crisis Denmark experienced success rates comparable to Greece and Spain, far below our Scandinavian counterparts in Finland and Sweden.

Figure 1: Success rates of bank loan applications by country



Source: Eurostat.

In the group of Danish SMEs there were 439, or approximately 19 percent, that applied for a loan

[3]Based on the NACE code, specifically the DB07 21-groupings C, F, G, H, I, J, L, M, and N.

[4]A corcern regarding this question is that loan contracts can be package deals e.g. consisting of both a share issue, mortgage loans, and bank loans. The respondents might consider package deals as partially granted loans. However, as the ordering of the responses would still be valid, this is not believed to affect the results in any critical way.

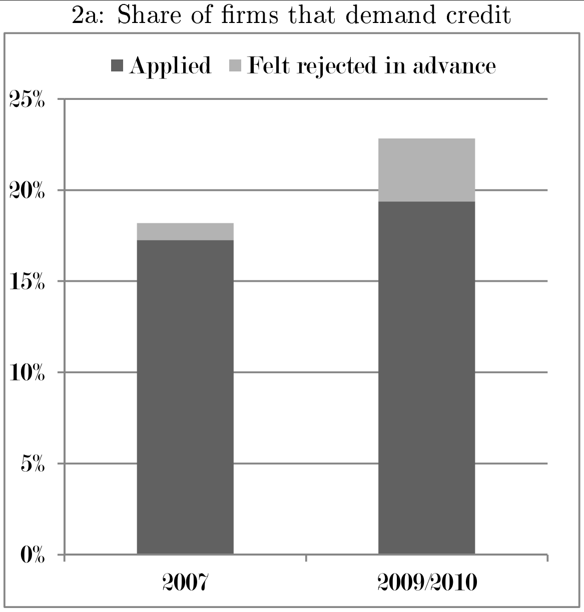
in a bank in 2009/2010, see figure 2a. In 2007 this share was 17 percent. This implies that there is a tendency for more firms to demand credit despite the crisis, i.e. the number of firms that applied for credit rose. The fact that a larger number of firms demanded credit in a period where the economy was significantly weakened is somewhat surprising as it is often conjectured that a declining supply of credit is accompanied by declining demand. Everything else equal we would expect that an economic downturn would lead to lower investment and therefore a lower demand for credit. However, more credit could have been demanded as liquidity vanished, not only for financial institutions but also for non-financial firms. This would point in the opposite direction. By comparing the number of applications, the effect of liquidity vanishing seems to be stronger, at least in the period immediately following the crisis. Further, there was an increasing number of the respondents that did not apply for credit because they expected their applications to be declined or the terms of the loan contract would be unfavorable, see the appendix for the precise definitions. In 2009/2010, this share was 3.4 percent of the survey population compared to 1.0 percent in 2007. This also implies that the underlying demand for credit increased over time, and at the same time that the access to credit was weakened. The result should, however, be read with some caution, as it is not possible to determine how much money firms applied for and because the survey only consists of SMEs that survived until 2010. Further, the data does not contain any information on the interest rate/price of credit and willingness to pay, i.e. the analysis is limited to observing the outcome of loan applications accounting for the fact that firms might be discouraged from applying for credit.

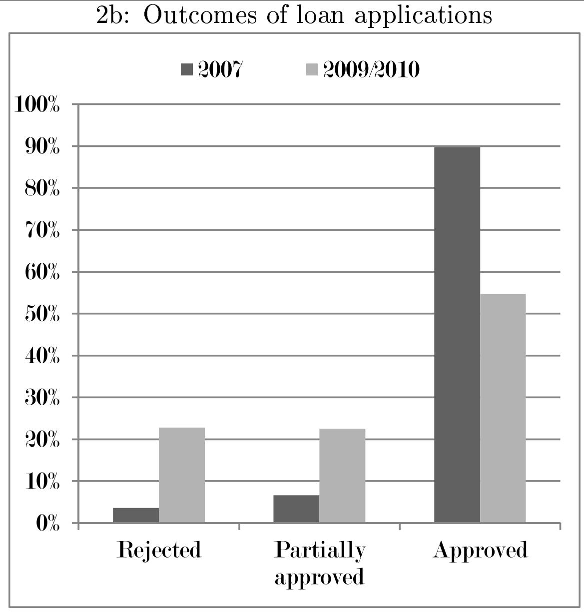
At the same time, as more firms were applying for credit, there was apparently a large difference in how many firms successfully obtained a loan, see figure 2b.[5] In 2007, towards 90 percent of the loan applications were fully granted. In 2009/2010 this fell to 55 percent. This reflects that firms had relatively easy access to credit when the economy was booming in 2007, but also the credit policies of banks were significantly tightened after the financial crisis escalated in 2008.

The central question is whether the tightened credit policies were due to SMEs being less creditworthy (the balance sheet channel) in 2009/2010, i.e. whether the loan applications were rejected because the credit risk was higher due to failing profits and/or plunging asset values, or whether the tightened credit policies were due to banks being affected by the financial crisis (the bank lending channel). To answer this question the analysis includes Danish register data, bank data and Experian credit rating data. The Danish firm register (FIRM) contains information on firm equity, total assets, profits before taxes, sector, number of employees, location code and revenue. Further, the Danish firm survey (FIRE) has information

[5] Be aware that figure 2b only includes outcomes of loan applications where background data was available. This is done to ensure consistency throughout the paper.

Figure 2: Credit demand and outcomes of applications





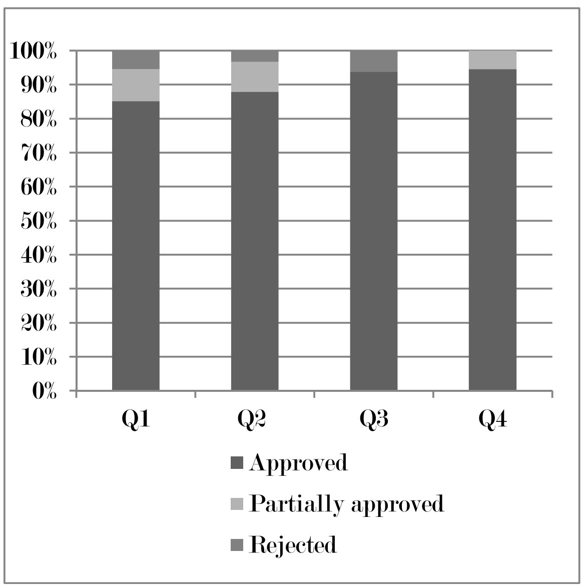
Note: Author's calculations based on Statistics Denmarks credit survey.

on firm liquidity, financial assets, short term debt, and interest rate payments. New to the literature is to include credit ratings in this type of analysis. The credit ratings are obtained from Experian, a private credit agency, and are included in order to have a better estimate of the creditworthiness of the firms. The credit ratings are computed from firm specific information about: legal status, age, number of employees, official written remarks, secured debt obligations, and collected experience on whether firms pay their bills. Further, the ratings are based on accounting numbers. Specifically, profits before taxes, equity, profit over equity and liquid assets over total assets. The official written remarks are gathered from Statstidende and can contain information on bankruptcy, liquidation, and enforced winding up of companies. The collected experience on whether firms pay their bills stems from Experians agreement with larger Danish companies on providing information on whether bills are paid on time. This information is included in the credit rating if Experian has a minimum of 10 data points for a given firm. The credit rating is therefore based on firm specific information and not subjective information from other institutions. Further, the credit rating does not contain information of the firms' ability to offer security, macroeconomic information, sector specific information, or information on outcomes of loan applications. But, the specific algorithm used by Experian is not available. The credit rating should, however, be comparable over time and sector as the same algorithm is used every year independently of sector. Experian also provides information on the firms' primary bank connection.[6] This information is combined with the Danish Financial Supervisory Authority's (FSA) public bank data.

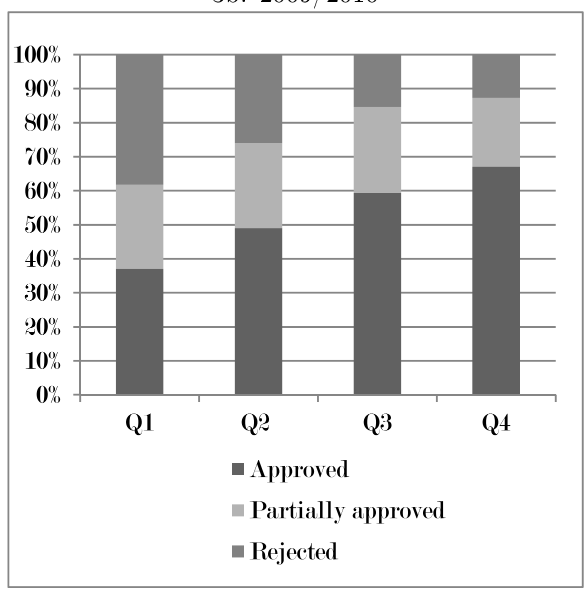
Figure 3 shows the connection between the credit ratings from Experian and the outcomes of the loan applications in 2007 and 2009/2010. Specifically the firms that applied for loans divided into 4 equally sized groups ranked by their ratings such that the lowest ratings are placed on the left side of the figure. To ensure consistency over time the 25-, 50- and 75-percentiles from 2009/2010 are used. In both periods, there is a clear tendency for firms with higher ratings to have a larger probability of attaining a loan. It is also apparent that the probability of attaining a loan was much higher in 2007 than in 2009/2010 regardless of whether the firm had a high or low credit rating. Credit policies in this regard seem lax in 2007 and severely tightened in 2009/2010.

Figure 3: Outcomes of applications allocated by credit ratings

3a: 2007



3b: 2009/2010



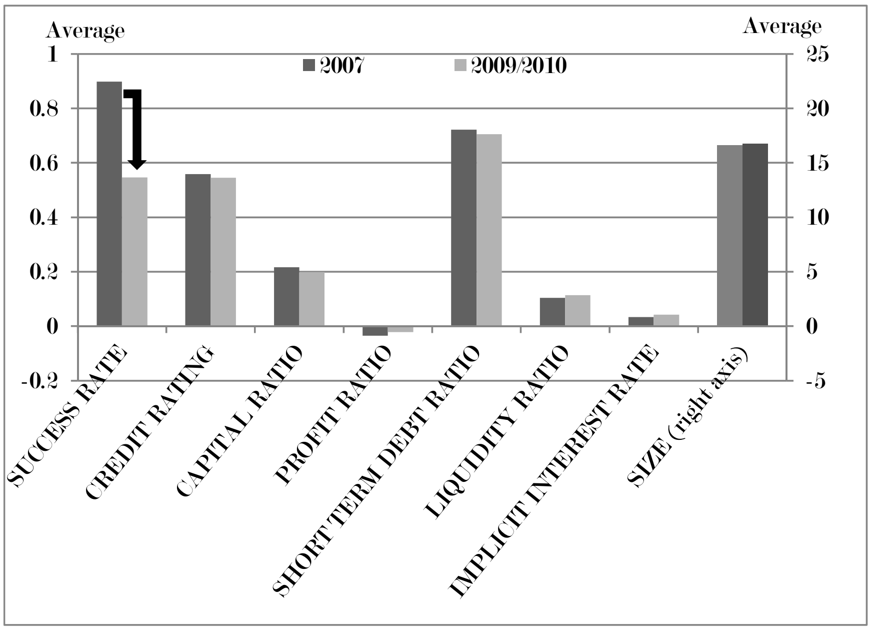
Note: Author's calculations based on Statistics Denmarks credit survey and Experian rating data. Q1, Q2, Q3, and Q4 are devided between the 25%, 50% og 75% quartiles of credit ratings in 2009/2010, respectively. Hence, Q1 is all firms with a rating lower than or equal to 0.43, Q2 a rating between 0.44 and 0.55, Q3 a rating between 0.56 and 0.67, and Q4 a rating of 0.68 or more.

A possible explanation for the large decrease in the success rate of loan applications could be that firms applying for loans experienced a significant decline in their economic performance and ratings from 2007 to 2009/2010. Figure 4 displays several averages of accounting numbers from 2007 and 2009/2010

[6] Using only the primary bank connection suggests that we might underestimate the effects from being a customer in an unhealthy bank. If, for instance, firms with multible banks automatically turn to their secondary or tertiary bank, if their primary bank is struggling, it is implicitly assumed that any fully/partially granted loans were coming from the primary bank. This bias would, however, further support the conclusions of this paper and is therefore not considered critical.

for the firms in the survey, that actually applied for credit during the two years, respectively. At first glance, it seems that firms applying for a loan only had a marginally lower rating on average in 2009/2010, while their profit ratio was a little higher. They were on average a little bit bigger, had a little less short term debt and were more liquid. The indirect interest rate increased a bit. So overall there is not much evidence that the decrease in the success rate was a consequence of significantly lower key performance indicators among those firms that applied for a loan.

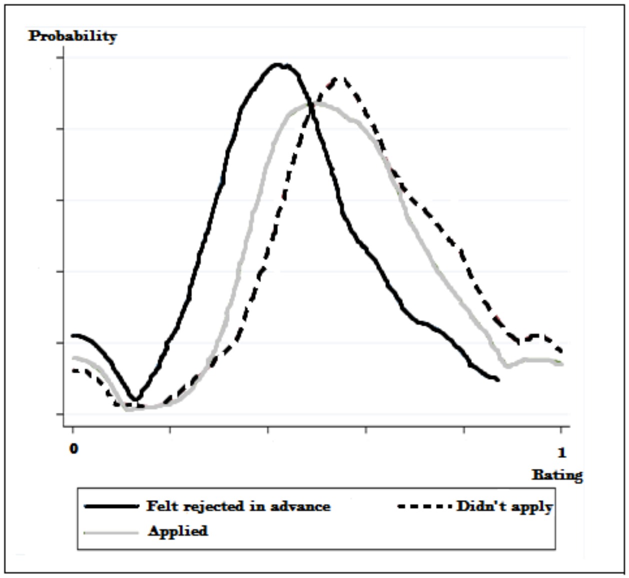
Figure 4: Success rates, key ratios, ratings, ect.



Note: Author's calculations based on Statistics Denmarks credit survey, firm registers, and Experian rating data. The definitions of the variables are discussed in detail in section 3 below.

One reason why firms seem relatively unaffected by the financial crisis is that there is an element of selection in who applies for a loan. Firms, that do not apply for a loan if they expect to be declined or the terms of the loan contract to be unfavorable, have a tendency to have a much lower rating on average than those who do apply, see figure 5. It is also apparent that firms that do not apply for loans have a higher rating than those who apply for loans in their bank. To further and more precisely analyze this, the next subsection will describe the empirical approach used to explain the credit policies of banks.

Figure 5: The distribution of ratings



Note: Author's calculations based on Statistics Denmarks credit survey and Experian rating data. The probability (y-axis) is measured as the reciprocal unit of the rating (x-axis). The distribution is estimated using the Epanechnikocs kernel (kdensity in STATA).

3.3 Empirical strategy

The aim is to model the probability that a given firm with a given primary bank connection attain a loan, partially attain a loan or is declined. The outcome variable, y, is therefore discrete and can take on 3 values. Namely, 1 of the loan application is declined, 2 if it is partially granted, and 3 if it is fully granted. Formally, the outcome equation can be written as

$$y_{jt} = \sum_{h=1}^{3} \nu_h 1\left(\kappa_{h-1} < x_{jt}\beta + u_{jt} < \kappa_h\right)$$

where x_j is the control variables if the outcome is observed, see the subsection below, 1(.) is an indicator function, β is a vector of coefficients, and u_{jt} is an error term. The observed outcomes, ν_1, ν_2, ν_3, are whole numbers $(1, 2, 3)$ and naturally satisfies that $\nu_i < \nu_m$ for $i < m$. κ_1 and $\kappa_1$are real numbers and satisfies $\kappa_i < \kappa_m$ for $i < m$. Further, $\kappa_0$takes the value $-\infty$ and $\kappa_3$takes the value ∞.

It is presumably not random which firms apply for lending. To account for this fact, selection is modelled. The firm applies for a loan if the selection variable, s_j, takes the value 1, and do not if s_j equals 0. Formally,

$$s_{jt} = 1(z_{jt}\gamma + \varepsilon_{jt} > 0)$$

where1(.) is an indicator function, z_j is the variables relevant for selection, γ is a vector of coefficients and a constant α, and ε_j is the error term. The error terms are assumed to be bivariate normal i.e.

$$\begin{pmatrix} u_{jt} \\ \varepsilon_{jt} \end{pmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right)$$

where ρ is the correlation between the error terms. The above specification is the standard ordered probit model accounting for selection and can be estimated using standard ML methods, see De Luca and Perotti (2011).

3.4 Variables in the analysis

Table 1 defines the full list of variables employed in the analysis, see appendix A for a complete data description. As mentioned above, the dependent variable is LOAN APPLICATION OUTCOME that took on the values $(1, 2, 3)$. The dependent variables can be divided into 2 groups: firm characteristics and bank characteristics. Firm characteristics include the following variables: the CREDIT RATING from Experian as discussed above; SIZE, log of total assets; the CAPITAL RATIO, which is the ratio of firm equity over total assets; the PROFIT RATIO, current profits over revenue; the SHORT TERM DEBT RATIO, short term debt over total debt; OTHER TYPES OF FINANCE, dummy variable for whether the firm applied for any other types of finance; the LIQUIDITY RATIO, liquid assets and financial assets over total assets; and the IMPLICIT INTEREST RATE, total interest payments over total debt. The bank characteristics include: LOAN IMPAIRMENT CHARGE RATIO, write offs over total loans; BANK GROUP 1, dummy variable for the largest banks as defined by the Danish FSA; BANK CAPITAL RATIO, equity over total assets; FAILING BANK, customer in a bank that later failed as defined in Østrup (2014); DEPOSIT DEFICIT, total loans over total deposits; and BANK Z-SCORE, the distance to insolvency, see Roy (1952).

Table 1: Variables in the Analysis

Variable	Units	Definition
Dependent variable:		
$LOAN\ APPLICATION\ OUTCOME_{i,b,t}$	1/2/3	= 3 if the loan application by a firm is fully approved, = 2 if the loan application by a firm is partially approved, = 1 if the loan application is denied.
Independent variables:		
Firm characteristics (i)		
$CREDIT\ RATING_{i,t-1}$	%	The Experian credit rating.
$SIZE_{i,t-1}$	-	The log of total assets.
$CAPITAL\ RATIO_{i,t-1}$	%	The ratio of equity over total assets.
$PROFIT\ RATIO_{i,t-1}$	%	The ratio of profits over total revenue.
$SHORT\ TERM\ DEBT\ RATIO_{i,t-1}$	%	The ratio of short term debt over total debt.
$OTHER\ TYPES\ OF\ FINANCE_{i,t}$	0/1	= 1, when the firm applied for other types of finance, = 0 otherwise.
$LIQUIDITY\ RATIO_{i,t-1}$	%	The ratio of liquid assets (including financial assets) over total assets.
$IMPLIED\ INTEREST\ RATE_{i,t-1}$	%	The implied interest rate from total interest payments over total debt.
$CHANGE\ IN\ MARKET\ VALUE_{i,t-1}$	%	The change in market value from $t-3$ to t of commercial buildings owned by firm i at time $t-1$.
Primary bank connection characteristics (b)		
$LOAN\ IMPAIRMENT\ RATIO_{b,t}$	%	The ratio of write offs over total loans.
$BANK\ GROUP\ 1_{b,t}$	0/1	= 1, if the primary bank is large enough to be part of bank group 1, = 0, otherwise.
$BANK\ CAPITAL\ RATIO_{b,t}$	%	The ratio of bank equity over total assets.
$FAILING\ BANK_{b,t}$	0/1	= 1, if the firm was customer at time t in a bank that later failed according to Østrup (2014).
$DEPOSIT\ DEFICIT_{b,t}$	-	The difference between total loans and total deposites over total deposites.
$BANK\ Z-SCORE_{b,t}$	-	The distance to bankruptcy, as in Roy (1952). Can be shown to be inversely proportional to the probability of insolvency - the lower the Z-SCORE the higher the probability of bankrupcy.

4 Results

This section provides the main results of the paper. First, the results are presented and in the final subsection the robustness of the results is discussed.

4.1 Results

A central challenge regarding this analysis is that the inclusion of additional variables reduces the number of observations due to lack of overlap in the datasets. Therefore the estimation strategy is to estimate the probability of attaining a loan, ignoring the selection effects, parsimoniously. The results are shown in table 2. The results are compared to a model with only the firm CAPITAL RATIO and PROFIT RATIO, see regression (1) in table 2. The variables that can potentially identify firm creditworthiness are CREDIT RATING, SIZE, CAPITAL RATIO, PROFIT RATIO, SHORT TERM DEBT RATIO, LIQUIDITY RATIO, and IMPLICIT INTEREST RATE, respectively. When the Experian CREDIT RATING, that contains further information than accounting numbers e.g. payment history, and SIZE are included, the other variables do not seem to significantly (even at a 10% significance level) affect the outcome of the loan application. The CREDIT RATING is however very significant in both periods, even in 2007 where CAPITAL RATIO and PROFIT RATIO are not significant at a 5% significance level. The CREDIT RATING therefore in general seems to be a more precise measure of the banks' assessment of the firms' creditworthiness. Specifically, to only include relevant information and minimize the loss of data points, the CREDIT RATING and SIZE are included to in the estimation with only firm CAPITAL RATIO and PROFIT RATIO, see regression (2) in table 2. The firm size - measured as total assets - is included because size could have an independent effect and is part of the Experian CREDIT RATING (SIZE turns out that to be insignificant when the analysis accounts for selection, see below). In the next step the significant variables (at a 5% significance level) from regression (1) are supplemented with SHORT TERM DEBT RATIO, LIQUIDITY RATIO, and IMPLICIT INTEREST RATE, see regression (3) in table 2. The stepwise procedure reflects that the number of observations decline when new variables are added. None of the added variables are significant (even at a 10% significance level) either in 2007 or 2009/2010. In the next step, information on the firms' primary bank connection is included, specifically, LOAN IMPAIRMENT CHARGE RATIO, BANK GROUP 1 and BANK CAPITAL RATIO, see regression (4). There is a weak tendency for bigger banks (group 1 banks) to decline more loan applications during the crisis. The IMPAIRMENT CHARGE RATIO is however significant during the crisis at a 5% significance level. The regression including only significant variables (at a 5% significance level) is seen in table 2, regression (5).[7]

With the chosen modelling strategy, firm accounting numbers become redundant when CREDIT RATING and SIZE are included. Further, information about the primary bank connection also seems to matter as the LOAN IMPAIRMENT CHARGE RATIO is significant at a 5 percent significance level in 2009/2010. Stated differently, if the primary banks had large provisions during the crisis, it was ceteris paribus harder to attain a loan. The LOAN IMPAIRMENT CHARGE RATIO is probably a reasonable proxy for how healthy a bank is, and therefore implies that firms that were customers in banks that were hit hard by the crisis had a harder time obtaining a loan. This also implicitly implies that firms can not just apply for a loan in a secondary bank if their primary bank connection is struggling. If this was the case we would not be able to observe any effects from the primary bank. Anecdotal evidence also suggests that changing bank is not cost free, as the new bank does not have the credit history and therefore tends to be more cautious when dealing with new customers. This behavior can also be rationalized by banks dealing with a lemon problem, i.e. shifting bank might reveal latent information on the creditworthiness of the firm. The IMPAIRMENT CHARGE RATIO is insignificant in 2007, which is probably due to the fact that loan losses were very small before the crisis, and that internal bank characteristics back then were not particularly limiting to lending activities. The CREDIT RATING was also significant in 2007, but computing the marginal effect (evaluated at the mean) of a loan application being fully successful reveals that the marginal effect is smaller in 2007 than 2009/2010. This could indicate that banks, during the boom in 2007, put less emphasis on the economic performance of firms when forming their credit policy.

The regressions above estimate the probability of obtaining a loan for those firms that actually applied for a loan. By ignoring the selection effect, the fact that loan applications are not random is not accounted for. On one hand, economically strong firms are expected to finance their projects and operations using internal capital. This group of firms has a tendency to not apply for external funds. On the other hand, some struggling firms, in need of funds, do not apply as they expect to be declined or the terms to be unfavorable. This heterogeneity can affect the estimates above. Further, it is likely that the selection is different before and during the crisis. As mentioned above, it is possible to identify the group of firms that did not apply for a loan because they expected to be declined. This group of firms will for now be excluded from the selection analysis but they will be included below in the robustness analysis.

[7] The model selection could also have been done using Akaike's Information Criterion (AIC) with the added difficulty of varying sample sizes. A stepwise AIC criterion procedure (from the largest sample to the smallest) favors the same model, however, including the PROFIT RATIO. Including this variable does not seem to affect the results below.

Table 2: Regression results (without selection).

Model	(1)	(2)	(3)	(4)	(5)
			.... 2009/2010		
Firm characteristics (i)					
$CREDIT\ RATING_{i,t-1}$	-	2.29*** (0.453)	1.92*** (0.512)	2.12*** (0.451)	2.11*** (0.442)
$SIZE_{i,t-1}$	-	−0.18*** (0.054)	−0.13* (0.071)	−0.14** (0.064)	−0.144** (0.064)
$CAPITAL\ RATIO_{i,t-1}$	0.47*** (0.189)	−0.28 (0.315)	-	-	-
$PROFIT\ RATIO_{i,t-1}$	0.63** (0.320)	0.24 (0.325)	-	-	-
$SHORT\ TERM\ DEBT\ RATIO_{i,t-1}$	-	-	−0.30 (0.376)	-	-
$LIQUIDITY\ RATIO_{i,t-1}$	-	-	−0.09 (0.793)	-	-
$IMPLIED\ INTEREST\ RATE_{i,t-1}$	-	-	−2.22 (3.013)	-	-
Primary bank characteristics (b)					
$LOAN\ IMPAIRMENT\ RATIO_{b,t}$	-	-	-	−5.05** (2.187)	−3.33** (1.568)
$BANK\ CAPITAL\ RATIO_{b,t}$	-	-	-	−3.02 (2.787)	-
$BANK\ GROUP\ 1_{b,t}$	-	-	-	−0.45* (0.256)	-
κ_1	−0.62* (0.080)	−2.62*** (0.818)	−2.24* (1.200)	−2.67** (1.043)	−2.20** (0.986)
κ_2	0.04* (0.075)	−1.91** (0.814)	−1.48 (1.197)	−1.92* (1.039)	−1.46 (0.982)
Number of observations	386	335	193	236	236
			.... 2007		
Firm characteristics (i)					
$CREDIT\ RATING_{i,t-1}$	-	2.42*** (0.811)	2.33*** (0.888)	2.70*** (0.774)	2.67*** (0.759)
$SIZE_{i,t-1}$	-	−0.23** (0.099)	−0.23 (0.141)	−0.26** (0.121)	−0.27** (0.121)
$CAPITAL\ RATIO_{i,t-1}$	0.79* (0.423)	0.43 (0.864)	-	-	-
$PROFIT\ RATIO_{i,t-1}$	−0.01 (0.083)	−0.01 (0.087)	-	-	-
$SHORT\ TERM\ DEBT\ RATIO_{i,t-1}$	-	-	−1.02 (0.766)	-	-
$LIQUIDITY\ RATIO_{i,t-1}$	-	-	6.82 (4.325)	-	-
$IMPLIED\ INTEREST\ RATE_{i,t-1}$	-	-	−6.70 (9.573)	-	-
Primary bank characteristics (b)					
$LOAN\ IMPAIRMENT\ RATIO_{b,t}$	-	-	-	49.84 (48.050)	49.55 (46.590)
$BANK\ CAPITAL\ RATIO_{b,t}$	-	-	-	1.40 (5.679)	-
$BANK\ GROUP\ 1_{b,t}$	-	-	-	0.01 (0.431)	-
κ_1	−1.66*** (0.149)	−4.38*** (1.495)	−5.14** (2.488)	−4.76** (1.922)	−4.89*** (1.824)
κ_2	−1.12*** (0.121)	−3.79** (1.487)	−4.51* (2.479)	−4.23** (1.914)	−4.36** (1.816)
Number of observations	337	288	152	202	202

Note: Standard errors in parentheses.***Significant at a 1 percent level, **Significant at a 5 percent level, and *Significant at a 10 percent level.

Table 3: Regression results with selection.

Outcome equation	2007	M.E.	2009/2010	M.E.
$CREDIT\ RATING_{i,t-1}$	1.28***	0.45	1.24***	0.44
	(0.41)		(0.40)	
$LOAN\ IMPAIRMENT\ RATIO_{b,t}$	51.85	18.24	−3.32**	−1.18
	(42.38)		(1.58)	
Selection equation (the probability that a firm applies for a loan)				
Firm characteristics (i)				
$OTHER\ TYPES\ OF\ FINANCE_{i,t}$	1.05***	-	1.34***	-
	(0.12)		(0.10)	
$CAPITAL\ RATIO_{i,t-1}$	−0.80***	-	−0.50**	-
	(0.27)		(0.24)	
$CREDIT\ RATING_{i,t-1}$	−0.14	-	−0.39	-
	(0.33)		(0.30)	
$SIZE_{i,t-1}$	0.09**	-	0.11***	-
	(0.04)		(0.04)	
Primary bank characteristics (b)				
$LOAN\ IMPAIRMENT\ RATIO_{b,t}$	16.08	-	2.15**	-
	(16.00)		(0.98)	
α	−2.25***	-	−2.83***	-
	(0.62)		(0.57)	
κ_1	−0.23	-	0.48*	-
	(0.39)		(0.25)	
κ_2	0.23	-	1.16***	-
	(0.35)		(0.24)	
ρ	0.55***	-	0.53***	-
	(0.17)		(0.10)	
Number of observations	1203		1253	

Note: M.E. is the marginal effect on $P(y_{j,t} = 3|s_{j,t} = 1)$ (the probability that the loan application is successful) evaluated at the mean. Standard errors in parentheses.***Significant at a 1 percent level, **Significant at a 5 percent level, and *Significant at a 10 percent level.

The selection mechanism can be interpreted as a model for the probability of applying for a loan. To successfully address the selection problem all variables described in the data section were included. The results are shown in table 3 and only includes those variables that were significant at a 5 percent significance level in the total regression. It appears that the CREDIT RATING is still significant in the outcome equation, but that the coefficient is smaller when accounting for selection. The coefficient on the IMPAIRMENT CHARGE RATIO is, however, to a large extent unchanged. It is also apparent from table 3 that correcting for selection is relevant as the correlation between the error terms, given by the parameter, ρ, is significant. The results also indicate that SIZE in both 2007 and 2009/2010 no longer has any independent significant effect on the outcome of loan applications. Firm size do however indirectly have a positive effect of the outcome through the positive effect on the CREDIT RATING. The estimated coefficients in the selection equation reveal that larger firms (in the SME segment) ceteris paribus are more prone to apply for loans than smaller firms. Further, firms with a high CAPITAL RATIO (and to some extent CREDIT RATING) are less inclined to apply for a loan, while those firms that apply for other types of finance on the other hand often also apply for loans at their banks. As a last point, primary bank characteristics also seem to affect the probability of applying for a loan. The higher the IMPAIRMENT CHARGE RATIO, the more likely the firms are to apply for a loan. This could reflect that firms in struggling banks are forced to find new bank connections and therefore have to renegotiate/apply for new loans. The negative sign on the CAPITAL RATIO supports the observation that credit demand is counter cyclical as accounting numbers typically decline during a recession. This could reflect special conditions during the financial crisis, e.g. that non-financial firms are also concerned about their liquidity and that the SME segment was under pressure by supplier credit drying up. It could also reflect that some firms needed liquidity to cover temporary deficits during the crisis. The counter cyclical tendency of credit demand in the SME segment is, however, an interesting insight into the otherwise reasonable argument that credit demand is normally assumed to be procyclical due to a lower propensity to invest during a recession.

Returning to the hypotheses above, hypotheses 1 and 2 are both confirmed. (H1) As firms' CREDIT RATINGS significantly affect the outcome of loan applications and (H2) As the health of primary bank connections, as proxied by IMPAIRMENT CHARGE RATIO, also seems to affect the outcome. This indicates that both the bank lending channel and the balance sheet channel are operational. However, their relative magnitude and relevance are hard to evaluate from the results so far. To evaluate (H3) and to grasp the relative magnitude of the two channels, it is possible to compare how much of the change in credit policy from 2007 to 2009/2010 can be explained by changes in applicants' characteristics. (H3) States that if only the balance sheet channel is operational, there should be no significant effect on the supply of credit to firms without any change in creditworthiness during the business cycle. This would be equivalent to the change in outcomes being fully explained by declining profit and liquidity, i.e. increasing credit risk. To answer the question, the identifying assumption is that the credit policy is given as estimated in 2009/2010, and then use the characteristics of the firms that applied for credit in 2007. Stated differently, had the banks had the same credit policy before the crisis as in 2009/2010, how many firms would have been granted a loan back in 2007. The results are shown in table 4. The success rate in 2007 was approximately 90 percent. With the estimated credit policy from 2009/2010, the success rate would have only amounted to approximately 64 percent. Stated differently, 27 percentage points more firms would have had their application declined fully or partially. At the same time, this implies that the decline in the success rate is mainly (approximately 3/4) due to a tightened credit policy. The counter factual success rate in 2007 (with the credit policy from 2009/2010) is only 9.4 percentage points higher than the success rate in 2009/2010. This implies that firm and bank characteristics - the

Table 4: Application outcomes in 2007 given the estimated credit policy in 2009/2010.

Outcome	Rejected	Partially approved	Approved
Actual outcome in 2007	4,0%	5,9%	90,1%
Actual outcome in 2009/2010	22,0%	24,6%	53,4%
Difference	18,1%	18,6%	-36,7%
In 2007 with credit policy from 2009/2010	15,1%	22,0%	62,9%
Change from tighter credit policy	11,2%	16,1%	-27,2%
Change from ratings, impairment charge ratio, and selection	6,9%	2,6%	-9,5%

Note: Formally computed as:

$$P(y = \nu_h | x_{2007}, \beta_{2010}, \kappa_{1,2010}, \kappa_{2,2010}, \gamma_{2010}, s_{2010} | z_{2007} = 1) = \frac{1}{n}\sum_{j=1}^{n} P(y_j = \nu_h | s_j = 1)$$

Using the results from table 3 above.

development in the firms' economy and bank losses - only explains approximately 1/4 of the fall in the success rate. Further, of the 9.4 percentage points decline in the success rate, 4.5 percentage points of the decline result from a higher IMPAIRMENT CHARGE RATIO in the banks compared to if the banks' credit policy had been independent of individual bank characteristics. This implies that we reject H3 and further illustrates that the magnitude of the bank lending channel seems bigger than the effects of the balance sheet channel. Some of the main concerns about this result are addressed in the robustness section below.

As argued in the balance sheet channel literature, a larger incentive for firms to hold internal capital could minimize credit cycles. Policymakers could adjust the tax system to incentivize SMEs to hold capital or postpone tax claims so that SMEs would have more liquidity. To evaluate such policies, CREDIT RATING has been regressed on CAPITAL RATIO and CAPITAL RATIO squared. From this regression we get an approximate relationship between CREDIT RATING and CAPITAL RATIO.[8] This suggests that a 10 percentage points increase in the CAPITAL RATIO is equivalent to a 5.2 percent points increase in the CREDIT RATING. Firms that applied for a loan in 2009/2010 had a CAPITAL RATIO of approximately 20 percent on average. If all firms' CREDIT RATINGs were 5.2 percentage points higher in 2009/2010, then 56.6 percent would have successfully obtained a loan using the estimated model in table 3. That is equivalent to 3.2 percentage points more than the actual amount. The results, therefore,

[8] Approximated by:

$$\triangle CREDIT\ RATING = \beta_1 \triangle CAPITAL\ RATIO + \beta_2 \left(\left(\overline{CAPITAL\ RATIO} + 10\%\right)^2 - \left(\overline{CAPITAL\ RATIO}\right)^2 \right)$$

where $\overline{CAPITAL\ RATIO}$ is the average capital ratio in the sample.

imply that increasing SME capital will minimize the credit cycles, but the effects appear relatively small compared to the effects from bank losses and especially the general tendency of banks to tighten their credit policy.

4.2 Robustness

This section discusses different aspects of the results' robustness. First, which measures are better at measuring bank health. Second, the effects of including firms that did not apply for credit because they expected to be declined or the terms of the contract to be unfavorable are analysed. Third, the distinction between market and accounting values is discussed. Fourth, the problem of timing and the use of lagged and non-lagged values.

4.2.1 Measures of bank health

Jiménez et al. (2012) find that the bank capital ratio and bank liquidity ratio significantly affects the outcome of loan applications. This study indicates that the LOAN IMPAIRMENT CHARGE RATIO better captures the effect of bank health. However, different measures have been analyzed with the central challenge that measures are very correlated. This, combined with the fact that the sample size is relatively small, implies that the variables describing bank health are added one at a time to regression (2) in table 3, excluding LOAN IMPAIRMENT CHARGE RATIO. Table 5 shows the estimated coefficients for credit policy (the banks probability of granting loans) and the coefficient in the selection mechanism (the probability of applying for loans) in 2009/2010.

The coefficients in the selection equation indicate that customers in struggling banks are more prone to apply for loans. As argued above, this could be due to the fact that firms in struggling banks might be forced to apply for loans in a different bank. However, in the outcome equation, it is only the IMPAIRMENT CHARGE RATIO that significantly affects the probability of obtaining a loan (at a 5 percent significance level). The Z-score of the primary bank in 2010 is only significant at a 10 percent significance level. The Z-score can be interpreted as the distance to bankruptcy (it can be shown that it is inversely proportional to the probability of insolvency - the lower the Z-score the higher the probability of bankruptcy). So if the firm's primary bank is far from insolvency then the probability ceteris paribus of obtaining a loan is higher.

Table 5: Coefficient estimates for different measures of banking health

Outcome equation	Outcome equation	Selection equation
$LOAN\ IMPAIRMENT\ RATIO_{b,2010}$	-3.32^{**}	2.15^{**}
	(1.58)	(0.98)
$FAILING\ BANK_{b,2007}$	0.007	0.372^{***}
	(0.193)	(0.131)
$FAILING\ BANK_{b,2010}$	-0.081	0.481^{***}
	(0.191)	(0.133)
$BANK\ GROUP\ 1_{b,2010}$	-0.118	-0.208^{**}
	(0.141)	(0.090)
$BANK\ Z-SCORE_{b,2007}$	0.108	-0.036
	(0.102)	(0.060)
$BANK\ Z-SCORE_{b,2010}$	$0.188*$	-0.065
	(0.102)	(0.0630)
$DEPOSIT\ DEFICIT_{b,2010}$	-0.283	0.199
	(0.366)	(0.228)
$BANK\ CAPITAL\ RATIO_{b,2010}$	-1.324	-0.493
	(1.523)	(1.095)

Note: Standard errors in parentheses.***Significant at a 1 percent level, **Significant at a 5 percent level, and *Significant at a 10 percent level. The variables with the time subscript, 2007, indicates that the variable is measured in 2010, but with the primary banking connection from 2007.

4.2.2 The effects of including firms that did not apply for credit because they expected to be declined or the terms of the contract were expected to Be Unfavorable

As mentioned above, some firms did not apply for credit because they expected to be declined or the terms of the contract (duration, interest rate, or general conditions) would be unfavorable. This group of firms grew from 2007 to 2009/2010. It is relevant to investigate, which effects it would have to include these firms in the group of firms of declined firms.

In 2009/2010, 78 out of the 2265 respondents answered that they did not apply for this reason. This group is therefore relatively large in 2009/2010. To compare, there were 100 declines in 2009/2010. In 2007, there were only 21 that did not apply because they expected to be declined. This kind of selection could be one of the reasons that the average accounting numbers of the firms that applied for a loan did not fall significantly enough to explain the rapid decrease in the acceptance rate from 2007 to 2009/2010. The estimation results are shown in table 6 with the extended population.

Table 6: Regression results with selection including individuals that did not apply because they believed they would be declined.

Outcome equation	2007	M.E.	2009/2010	M.E.
$CREDIT\ RATING_{i,t-1}$	2.05^{***} (0.52)	0.47	1.75^{***} (0.35)	0.69
$LOAN\ IMPAIRMENT\ RATIO_{b,t}$	41.57 (40.80)	18.24	-3.07^{**} (1.50)	-1.21
Selection equation (the probability that a firm demands credit)				
Firm characteristics (i)				
$OTHER\ TYPES\ OF\ FINANCE_{i,t}$	1.00^{***} (0.12)	-	1.18^{***} (0.10)	-
$CAPITAL\ RATIO_{i,t-1}$	-0.80^{***} (0.27)	-	-0.53^{**} (0.24)	-
$CREDIT\ RATING_{i,t-1}$	-0.32 (0.32)	-	-0.78^{***} (0.29)	-
$SIZE_{i,t-1}$	0.089^{**} (0.04)	-	0.13^{***} (0.92)	-
Primary bank characteristics (b)				
$LOAN\ IMPAIRMENT\ RATIO_{b,t}$	15.05 (15.64)	-	-1.87^{**} (0.55)	-
α	2.16^{***} (0.62)	-	-2.71^{***} (0.55)	-
κ_1	-0.16 (0.43)	-	0.57^{**} (0.24)	-
κ_2	0.14 (0.42)	-	1.15^{***} (0.24)	-
ρ	0.06 (0.28)	-	0.13 (0.15)	-
Number of observations	1217		1293	

Note: M.E. is the marginal effect on $P(y_{j,t} = 3|s_{j,t} = 1)$ (the probability that the loan application is successful) evaluated at the mean. Standard errors in parentheses.***Significant at a 1 percent level, **Significant at a 5 percent level, and *Significant at a 10 percent level.

It turns out that this does not affect the results above in any critical ways. The effect of the CREDIT RATING increases a little bit, while the effect of the IMPAIRMENT CHARGE RATIO decreases a little. The most interesting thing is that accounting for selection no longer seems to be necessary, as the coefficient, ρ, is no longer significantly different from 0. Generally, as the results do not seem to be sensitive to including the observations, these results seem to support the conclusions above.

4.2.3 Market vs. accounting values

The Experian credit rating is a measure of a firm's creditworthiness based on, among others things, accounting numbers, but do not account for market and macro information. However, it might be plausible that the market value of, for instance, real estate is different from the accounting value. This could imply that we underestimate the decline in the actual value of the firm's assets. However, banks might not be able to access this information either and therefore base their credit policy on accounting values. And, accounting values might be relevant when assessing credit risk as they focus on liquidation value.

One way of evaluating the importance of market values is to look at real estate owned by firms. The Danish register data contains detailed information on every building in Denmark such as: who owns it, where it is placed, and the public valuation for taxation purposes. From this, it is possible to estimate how exposed the SMEs are to the real estate market. Next, note that Denmark is devided into 5 regions. In each region, the average changes in prices of commercial buildings from 2005 to 2007, and 2008 to 2010 were collected. The idea is if the market value of assets is not captured by the firms' books, then firms with large capital gains/losses from their real estate would find it easier/more difficult to obtain a loan relative to other firms. However, doing this excise does not seem to significantly (even at a 10 percent significance level) explain the outcome of loan applications in either 2007 or 2009/2010. This could imply that market values are not relevant for the outcome of loan applications or that banks to some extent disregard this information. However, it is also possible that the proxy is too noisy and therefore does not capture the actual difference between market and accounting values.

4.2.4 Lagged and non-lagged variables

The whole analysis of this paper is based on lagged information about firm specific characteristics. Specifically, information from the beginning of 2007 for the 2007 sample and information from the beginning of 2009 for the 2009/2010 sample. For most parts, this is the relevant information for the periods in question and would also be the information available to banks. But, especially in 2009/2010, banks might have had updated accounting numbers for parts of the period. The advantage of using lagged variables to avoid endogeneity[9] might lead us to underestimate the effects of the balance sheet channel. However, inconsistently using data from the beginning of 2008 and 2010, when estimating the model, does not seem to affect the results in any crucial way. Further, above we saw that successrates were relatively insensitive to changes in CREDIT RATINGs. Therefore the balance sheet effects would still be limited relative to the bank lending effects even if the actual accounting numbers, available to banks at the time of the application, were lower.

The analysis is based on non-lagged bank specific information. The main reason is that using lagged information would imply using pre-crisis data for the 2009/2010 sample and thereby make it disproportionately difficult to evaluate which banks were struggling during the crisis. Further, this is generally believed to be reasonable as outcomes of loan application to specific SMEs during the crisis are unlikely to

[9]Specifically, the outcome of the loan application could affect the explanatory variables if these are not lagged.

affect the overall health of the bank. Stated differently, a high impairment charge ratio during the crisis is beleived to be the consequence of decisions made before the crisis, not a consequence of a conservation lending policy during the crisis. However, this could potentially imply that I am underestimating the effect of bank health as banks health was actually worse than what is observed as a conservative lending strategy implies very few write offs on new activities. Again, this would actually support the conclusions of this paper as this bias point towards underestimating the size of the bank lending channel.

5 Discussion

A major concern is whether ignoring macro economic information when evaluating credit risk significantly affects the conclusions. According to Experian, their ratings are objective and comparable over time, thus implying, that including sector or macro evidence is not useful when evaluating credit risk. Jiménez et al. (2012) find that negative changes in the interest rate increase the chance of obtaining a loan, and that it is generally easier to obtain a loan when the economy is booming, i.e. when GDP is rising. However, the main concern is whether this feeds through the balance sheet or the bank lending channel. Further, if firm specific characteristics measure the current state of a firm's financial health, does evidence about the state of the whole economy have implications for the future health of firms as aggregate demand is expected to decline? Unfortunately, the structure of the data does not allow for a formal analysis of this. However, Jiménez et al. (2012) conclude that the negative effect of higher short-term interest rates or lower GDP growth on credit availability is stronger for banks with low capital or liquidity. Hence, the monetary policy and the business cycle effect work through a bank lending channel. This generally favors the results above and leaves the bank lending channel as the main contributor to the credit cycles generated in our sample.

The above points reveal valid limitations of the analysis. However, it seems unlikely that these would significantly change the main conclusion. Namely, that the bank lending channel seems to be the main reason for the decline in credit access for Danish SMEs during the crisis.

6 Concluding remarks

Whivh channel is better at explaining credit cycles during the recent financial crisis? This analysis indicates that the bank lending channel explains most of the differences between credit policies before and during the crisis.

This paper adds to the literature by including a very rich set of variables to explain on one side firm characteristics and on the other side bank characteristics. To the best of my knowledge, the analysis is also the first to utilize both register, survey, rating and bank connection data to analyze these questions. This has obvious advantages and generally validates the emerging evidence that bank lending channel plays a significant role during the business cycle.

The best policy to limit credit cycles should therefore focus on the bank lending channel. Ensuring that banks are robust and therefore do not have to limit their credit supply seems obvious. Further, and also suggested by Jiménez et al. (2012), lowering the interest rate in times of crisis could be an effective tool to limit the likelihood of a credit crunch. However, the analysis also indicates that other policies might be useful as the low interest rate during the financial crisis did not seem to effectively prevent the cyclical credit supply. However, focusing policy solely on the balance sheet channel seems fruitless in minimizing credit cycles due to the very modest effects estimated in this paper.

7 Literature

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A Appendix

This appendix gives a full description of the data used in the analysis. Table A.1 summerizes the underlying variables used to compute the controls used in the analysis. Table A.2 defines the variables used in the analysis in terms of the underlying variables.

The following changes were made to underlying variables. If rating_(time) was in ('810' (Undergoing liquidation), '830' (Cannot be computed as the share of equity does not satisfy the minimum requirements set by law), '834' (Cannot be computed as equity is negative), '836' (Cannot be computed as equity (including subordinated loan capital) is negative), and '840' (Cannot be computed as the firms annual accounts have not been submitted and the deadline has not been met)) then the rating was set to 0. All ratings in this group are classified as 'very high risk'. As argued above, it is natural to devide the Danish real estate market into 5 regions. This is done by using a stardard mapping from the KOMNR to the regions.[10] The regional price changes $\triangle P_{r,t}$ is the regional price change for commerical buildings (excluding farms) indexed using the Statistics Denmarks regional sales price data[11] from 2005 to 2007, and 2008 to 2010.

[10] Specifically: if KOMNR in ('101','147','151','155','157','159','161','163','165','167','169','173','175','183','185','187','189','207','201','208','227','217','219','231','233','223','181','205','171' ,'235','237','209','225','229','233','211','221','213','215','400') then Region = Hovedstaden; if KOMNR in ('253','259','267','255','263','265','269','305','327','343','315','321','339','341','345','313','351','385','301','309','317','319','323','329','311','325','331','333','271','389','303','335','337','251','257','261','355','359','363','367','379','381','383','307','353','357','373','393','369','371','375','387','391','395','361','365','377','397') then Region = Sjælland; if KOMNR in ('429','445','451','421','433','437','485','491','499','425','431','473','477','497','439','441','447','449','489','495','461','427','435','479','423','471','483','475' ,'481','487','443','493','509','511','515','525','543','551','565','661','501','507','513','523','533','535','537','505','517','521','525','531','541','557','561','567','571','563','553','555','567','573','577','527','559','569','575','503','519','529','539','545','607','509','605','621','623','629','627','617','603','605','611','631') then Region = Syddanmark; if KOMNR in ('601','609','615','651','657','677','685','661','679','683','665','673','671','675','701','721','733','739','707','725','735','747','709','711','713','717','767','727','717','719','723','729','731' ,'747', '705','743','749','771','741','601','703','715','737','745','751','625','653' ,'663','655','659','667','669','681','613','619','627','777','779','781','783','761','763','769','775','789','791','793') then Region = Midtjylland; if KOMNR in ('773','765','785','787','805','807','813','841','847','793','809','827' ,'861','825','833','843','845','719','793','801','815','823','833','803','811','835' ,'849','817','831','837','851','819','821','829','839') then Region = Nordjylland.

[11] See: http://www.statistikbanken.dk/statbank5a/default.asp?w=1440.

Table A.1: Underlying variables in the analysis

Variables from the FIRM register	
Total assets	GF_AT
Equity	GF_EGUL
Profits (before taxes)	GF_RFEP
Revenue	GF_OMS
Variables from the FIRE survey	
Other short term debt	AKG
Short term debt to suppliers	KGL
Total assets (end of year)	PAST
Liquid assets	LIBE
Total liquid and financial assets	VKT
Long term debt to suppliers	LGL
Total interest cost	RUDG
Other long term debt	ALG
Variables from the Statistics Denmarks credit survey	
Outcome of loan application (in banks)	lfkil_(time)_banker
Applied for equity from owners	lfkil_(time)_ejer
Applied for equity from employees	lfkil_(time)_ansatte
Applied for equity from family	lfkil_(time)_familie
Applied for equity from other firms	lfkil_(time)_andrevirk
Applied for mortgage loan	lfkil_(time)_realkredit
Applied for equity from other sources	lfkil_(time)_andre
Didn't apply: Expected to be declined	lfnej_(time)_ikkemuligt
Didn't apply: The interest rate was expected to be too high	lfnej_(time)_kunmuligt
Didn't apply: Terms of the contract unfavorable e.g. loan period	lfnej_(time)_betingelser
Variables from the Experian dataset	
Experian credit rating	rating_(time)
Primary bank	Bank1_(time)
Secondary bank	Bank2_(time)
Tertiary bank	Bank3_(time)
Variables from the Danish FSA dataset	
Total loans	AS02051
Profits (before taxes)	AS0116
Total deposits	AS02251
Impairment of loans and receivables (et cetera)	AS0113
Total equity	AS0255
Total assets	AS0256
Variables from BBR, EJER, and EJVK registers (Real estate registers)	
Building ID	ejendomnummer
Owner ID	ejdnr
Public value (for taxation purposes)	EJDVBLB
Location (Municipality)	KOMNR
Ownership of building (in percentages)	EJERPCT

Table A.2: Variables in the analysis in terms of the underlying variables

Variable	Definition
Dependent variable:	
$LOAN\ APPLICATION\ OUTCOME_{i,b,t}$	= 3 if lfkil_(time)_banker = 1, = 2 if lfkil_(time)_banker = 2, = 1 if lfkil_(time)_banker = 3.
Independent variables:	
Firm characteristics (i)	
$CREDIT\ RATING_{i,t-1}$	= rating_(time)
$SIZE_{i,t-1}$	= ln(GF_AT)
$CAPITAL\ RATIO_{i,t-1}$	= GF_EGUL / GF_AT
$PROFIT\ RATIO_{i,t-1}$	= GF_RFEP / GF_OMS
$SHORT\ TERM\ DEBT\ RATIO_{i,t-1}$	= (AKG + KGL) / PAST
$OTHER\ TYPES\ OF\ FINANCE_{i,t}$	= 1, if lfkil_(time)_ejer > 0, lfkil_(time)_ansatte >0, lfkil_(time)_familie > 0, lfkil_(time)_andrevirk > 0, lfkil_(time)_realkredit > 0, or lfkil_(time)_andre > 0. = 0, otherwise.
$LIQUIDITY\ RATIO_{i,t-1}$	= VKT / PAST
$IMPLIED\ INTEREST\ RATE_{i,t-1}$	= RUDG / (LGL + ALG + KGL + AKG)
$CHANGE\ IN\ MARKET\ VALUE_{i,t-1}$	= $\sum_{k=1}^{h} EJDVBLB_{k,i,t-1} EJERPCT_{k.i,t-1} \triangle P_{r,t}$ (The sum of all h commercial building owned by firm i times the price change in region r. The regional price change is defined in the text above.)
Primary bank connection characteristics (b)	
$LOAN\ IMPAIRMENT\ RATIO_{b,t}$	= AS0113 / AS02051
$BANK\ GROUP\ 1_{b,t}$	= 1, if firms primary bank was: Danske Bank, Jyske Bank, Nordea Bank, Nykredit Bank, Sydbank. = 0, otherwise.
$BANK\ CAPITAL\ RATIO_{b,t}$	= AS0255 / AS0256.
$FAILING\ BANK_{b,t}$	= 1, if the firm was customer at time t in a bank that later failed according to Østrup (2014).
$DEPOSIT\ DEFICIT_{b,t}$	= (AS02051 - AS02251) / AS02251
$BANK\ Z-SCORE_{b,t}$	= (AS0116 / AS0256 + AS0255 / AS0256) / σ(AS0116 / AS0256), where σ(.) is the standard deviation on the return on assets estimated from a sample from 2000 to 2012.

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