What Determines Banks' Market Power? Akerlof or Herfindahl*

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Abstract

We derive empirical implications from a stylized theoretical model of bank-borrower relationships. Banks' interest rate markups are predicted to follow a life-cycle pattern over the borrowing firms' age. Due to endogenous bank monitoring by competing banks, borrowing firms initially face a low markup, thereafter an increasing markup until it falls for older firms. By applying a large sample of small unlisted firms and a new measure of asymmetric information, we find that firms with significant asymmetric information problems have a more pronounced life-cycle pattern of interest rate markups. We also examine effects of concentrated banking markets on interest markups. Results indicate that markups are mainly driven by asymmetric information problems (Akerlof). However, we find weak evidence that bank market concentration matters for old firms. (Herfindahl).

1. Introduction

We examine how competition and asymmetric information problems are interlinked in credit markets. During the course of a lending relationship a bank obtains soft information (non-codifiable and non-transferable information) about borrowers.[1] This soft information is a two-edged sword seen from borrowers' point of view. It alleviates frictions in credit markets, but creates lock-in effects and market power for the inside bank (the current lender).

We use a simple theoretical model of bank-borrower relationships to illustrate how asymmetric information problems drive interest rate markups. The model points to three distinct periods in the life cycle of the borrowing firm. Initially, before any bank has obtained soft information, young firms are offered loans with low interest rate markups. By interest rate markup we mean the difference between the observed interest rate and the interest rate consistent with zero expected profit for the bank. As the inside bank obtains soft information about the borrowing firm, the firm becomes informationally locked-in and the bank can extract rents by increasing the interest rate markup. The bank is thereby compensated for the low interest rate offered initially. However, as firms mature, and credit information about some of them becomes more dispersed, the market power of the inside bank may decline and thus a downturn of the markup sets in.[2] We consider this cyclical pattern and the decline of the markup in the third period as the novel prediction of the theoretical model and the empirical application that follows. The rise of the lock-in phenomenon has already been carefully and extensively explored both theoretically (Klemperer (1995), Sharpe (1990), von Thadden (2004)) and empirically (Ongena and Smith (2000), Ongena and Smith (2001), Kim, Kliger, and Vale (2003)) in the existing literature. Furthermore, the model highlights the profile and pattern of the life-cycle of the interest rate markup to show that it is more pronounced when the inside bank obtains a larger information advantage during the relationship.

[1] Soft information can for instance be knowledge about the quality of the firm's management and its employees or the ability of the management to implement its business plans. This information can be acquired by the bank during the course of a bank-borrower relationship.

[2] Bouckaert and Degryse (2006) have recently argued that incumbent lenders release information about a portion of their profitable borrowers for strategic reasons. Thus, the pool of unreleased borrowers becomes characterised by a severe adverse selection problem. This prevents entrants from bidding for all the incumbent's profitable borrowers and reduces their scale of entry.

Our paper is mainly empirical in nature and the theoretical model is introduced to show how the life-cycle pattern of interest rate markups may follow from endogenizing monitoring efforts of competing banks. We test the predictions of our model using a large sample of unlisted small Norwegian non-financial firms during the 2000-2001 period (30,665 firms). To assess the implications of asymmetric information on banks' interest rate markups we construct a novel measure proxying the importance of the information asymmetry. Our measure captures the fact that inside banks obtain information about borrowers *before* outsiders do. This implies that an inside bank's information advantage is positively related to how rapidly firm specific credit information and credit quality changes over time in an industry.[3] In an industry where firms' credit qualities move slowly, the inside bank's information advantage is, according to our asymmetric information proxy, small.

We find empirical support for the following predictions; i) banks' interest rate markup follows the suggested life cycle pattern, ii) the life cycle pattern is more pronounced for firms that are more subject to asymmetric information problems (i.e., the initial markup is lower and the mark up keeps increasing for a longer time span), iii) firms more exposed to asymmetric information problems experience the predicted fall in the interest rate markup at a higher age. Since the theoretical model predicts that asymmetric information problems determine pricing of loans we associate these results with Akerlof. In addition, we also assess whether bank market concentration can contribute to the understanding of the observed interest rate markups. Since the Herfindahl index is a commonly used variable measuring market concentration, we associate the potential link between market concentration and pricing of loans with Herfindahl although we use different measures of market concentration to check the robustness of our results. We do not find any significant effects from market concentration onto interest rate markups for borrowing firms, except for oldest ones. All in all, this leads us to conclude that asymmetric information problems are important for understanding markups facing young and middle-aged firms, while bank market concentration only plays a potential role in understanding interest rate markups facing older firms.

[3] An inside bank's soft information about a borrower will finally become hard information accessible to outside banks.

There is a branch of the banking literature explaining the role of bank-borrower relationships (see Gorton and Winton (2003) and Ongena and Smith (2000) for good overviews of this literature). Our paper is most closely related to Petersen and Rajan (1995) which shows that banks and borrowers intertemporally share surplus in long-term bank relationships. Petersen and Rajan construct a model where lack of competition in the credit markets – represented by high market concentration – allows banks to subsidize young de novo firms and recapture this loss by charging older locked-in borrowers an interest rate above the one yielding zero expected profits. Our study differs from Petersen and Rajan in the sense that we let the competitiveness of the credit market be determined by the inside banks' unique access to soft information about borrowers (Akerlof). In our empirical setup we test to what extent intertemporal surplus sharing through long-term bank relationships is determined by the degree of information asymmetry between the inside bank and outside banks. Our empirical model also facilitates a test of the market concentration hypothesis (Herfindahl) as in Petersen and Rajan (1995).

Some empirical papers build on the ideas first introduced by Petersen and Rajan. All in all these studies give mixed results. Black and Strahan (2002) find that less concentrated banking markets lead to more incorporations of new firms, thus casting doubts on Petersen and Rajan's findings. Similarly Cetorelli (2004) finds that a more concentrated banking industry leads to larger size of the non-financial firms. Cetorelli and Gambera (2001), however, report results indicating that younger firms relying on external finance grow faster the more concentrated is the banking sector. A brief overview of this literature can be found in Berger, Hasan, and Klapper (2003). Our paper suggests that pricing of loans might be better explained by asymmetric information variables than market concentration variables.

In contrast to the existing literature which assumes that borrowers determine the number of monitoring banks, we develop a model where banks decide when to spend resources on monitoring. By endogenizing the number of banks that monitor a particular borrower we endogenize the strength and the time-span of the lock-in effect. Our starting point is that multiple monitoring of newly established firms is unprofitable. We argue that fixed bank monitoring costs associated with loans to young firms cannot be covered by more than one bank. Others have argued that multiple monitoring is infeasible due to free-riding problems (Thakor (1996)).[4] Furthermore, in our theoretical model we assume that credit risks of firms improve as firms mature, and in equilibrium outside banks find it increasingly attractive to start monitoring a borrower in order to make a loan offer. As more banks do monitoring, the informational lock-in effect in the bank-borrower relationship is weakened and the interest rate markup falls.[5]

This latter point adds to the existing literature on relationship lending and informational lock-in which only considers two distinct periods – the initial period when the borrower receives very favorable loan-terms and the second period when he is locked-in (Rajan (1992), Sharpe (1990) and, von Thadden (2004)). In contrast, we also examine a third period where information about borrowing firms is more widely distributed and lock-in effects are weaker.

The paper is organized as follow: In Section 2 we present a theoretical model suggesting that the severity of asymmetric information drives the lock-in effects and the dynamic pricing of bank loans. In Section 3 we present our data set and introduce our empirical model which we use to test predictions from our theory model. We also examine potential relationships between market concentration and markups on bank loans. The empirical results are presented and discussed in Section 4. Section 5 concludes.

2. A simple theoretical model of bank-borrower relationships

In this section we introduce a three period model of bank-borrower relationships. The model is stylized and developed for the purpose of exploring the dynamic nature of interest rate markups which we empirically investigate in later sections. The model illustrates that the lifecycle pattern of the interest rate markup is determined by two types of asymmetric information problems: Firstly, there is an asymmetric information problem between banks and borrowers. Secondly, there is a potential

[4] Carletti (2004) endogenizes banks' monitoring intensities and shows how firms by choosing to borrow from more than one bank can induce a preferred monitoring intensity. In contrast to our model, Carletti does not introduce a dynamic model that allows the number of monitoring banks to change as the firms mature.

[5] In a related study Ioannidou and Ongena. (2006) find that interest rate markups fall when borrowers switch banks

asymmetric information problem between inside and outside banks when they compete for borrowers. By endogenizing the number of monitoring banks we show how lock-in effects in a bank-borrower relationship are dynamically resolved through time as firms get older and more than one bank monitors the borrower.

We use the theoretical model to study how the two types of asymmetric information problems influence the length of the lock-in period and how the interest rate markup evolves over time. The theoretical model is not designed to capture pure market concentration effects on markups, i.e., effects on markups that are not driven by asymmetric information problems but by market shares of banks per se. However, as mentioned previously we also include pure market concentration effects when we engage in the empirical analysis.

In what follows we outline the theoretical model in detail.

2.1. The borrowing firm

A firm is modelled as a sequence of projects all requiring an investment of 1 dollar. For simplicity, we assume that the firm does not have own funds and that it needs to borrow 1 dollar from a bank in each period t, $t \geq 0$.

A project in each period is either good or bad independently of the quality of the previous project. At the outset, the quality of the project is private information to the borrowing firm. A *good* project succeeds with probability $\overline{\theta}$ while a *bad* project succeeds with probability $\underline{\theta}$, where $\overline{\theta} > \underline{\theta}$. A successful project is worth R while a failure is worth 0. Both good and bad projects have positive net present value, i.e., $\underline{\theta}R > 1$. The probability that a firm has a good project in period t is common knowledge and denoted $s(t)$. We assume that the average quality of projects improves as the firms mature, i.e., $s'(t) > 0$. This could for instance be due to the fact that the entrepreneur or the management of the firm becomes better at discovering good projects and business opportunities over time (this is often denoted learning by doing). Consequently, we assume that experienced firms are more likely to have good projects than young and inexperienced firms.[6]

[6] This assumption has good empirical support, and is documented in a recent empirical paper by Ioannidou and Ongena. (2006). Furthermore, in the bankruptcy probability model that we apply in the empirical section, the bankruptcy probability is decreasing in firm age. See Appendix B for details.

2.2. Banks

There are two banks that consider monitoring the firm.[7] Let $F > 0$ denote a bank's per-period monitoring costs. Although, monitoring costs incur in each period, we assume that monitoring decisions are long-term commitments; a monitoring bank will continue to perform monitoring even though the rivaling bank starts monitoring as well. Furthermore, it is assumed that F is sufficiently large compared with expected profit to make it unprofitable for *both* banks to start monitoring in period 0. Since a firm's average project is improving over time ($s'(t) > 0$), in equilibrium it is increasingly profitable for the second bank to start monitoring the borrower and thereby reduce the informational lock-in effect in the borrower-bank relationship.

The inside bank will with probability $\lambda > 0$ observe whether the firm's current project is good or bad. With probability $(1 - \lambda)$ monitoring does not reveal private information to the inside bank. In this case the outside and inside banks have the same information about the firm's project. Notice, however, that since the outside bank does not know whether the inside bank has obtained private information or not, the outside bank will always fear winner's curse and offers interest rates accordingly.

The competition between the two banks is considered as an "English auction" where the banks decrease their offered interest rates until only one bank is active and this bank captures the borrower. If the two banks' lowest interest rates are identical and they both monitor the borrower, they capture the borrower with equal probability. If only one bank does monitoring or only one bank has observed the quality of the borrower's project, the borrower will weakly favor this bank if the contract terms are identical. This assumption ensures that, in equilibrium, there will not be change of lenders as long as only one bank does monitoring. However, the rivaling outside bank limits the interest-rate markup the inside bank can charge.[8]

For simplicity, we assume that firms and banks are risk neutral and that the risk-free interest rate is 0. Figure 1 illustrates the timing of events. Note that a bank

[7] We endogenize when the second bank starts monitoring. A generalization of our model would be to allow for more than two competing banks.

[8] In an English auction an auctioneer starts with a high interest rate and gradually decreases it. The current interest rate, r, is observed by all banks (bidders) and the banks choose whether to be in the competition or to exit. Banks may drop out at any time, and if they do they are not allowed to reenter the competition (auction) for the borrower. When the auction ends there is only one active bank. See Krishna (2002) for a discussion of different rules in English auctions.

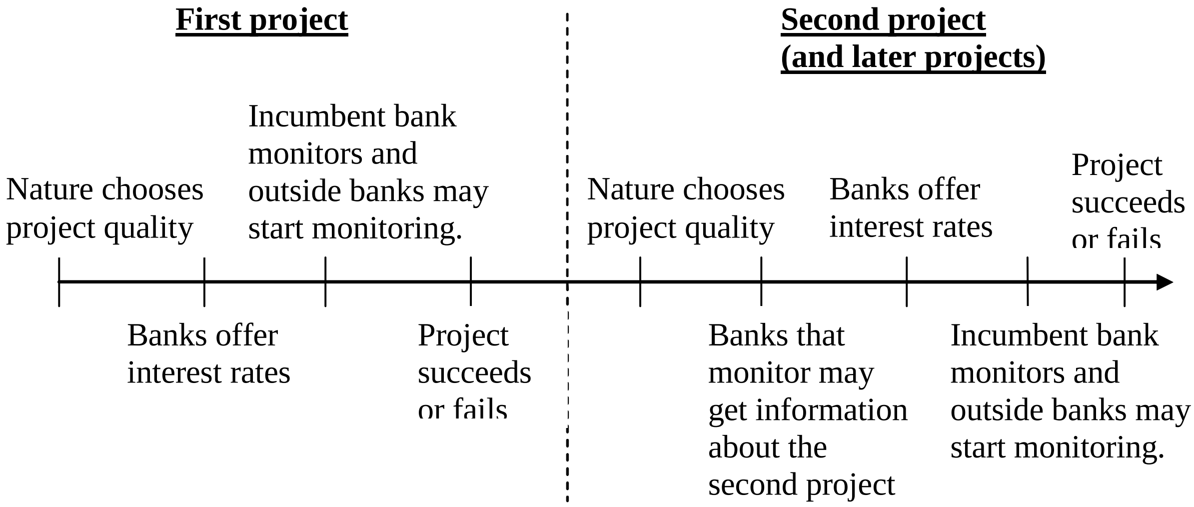

Figure 2.1: The timing of the game

that start monitoring of a current project may get information about the success probability of the next project.

We have assumed that the bank monitoring costs are constant while the average project improves as the entrepreneur or the management becomes better at discovering business opportunities. An alternative approach, would be to assume that the costs associated with monitoring a borrower is decreasing over time (F is decreasing). This approach would also make it increasingly attractive for outside banks to start monitoring a borrower. Consequently, this modelling approach would provide similar empirical predictions regarding the lifecycle pattern of the interest rate markup to those we derive below.[9]

2.3. Equilibrium

In this subsection we show that there exists a pure strategy subgame perfect Nash equilibrium where one bank lends to and monitors a firm from date 0 and the second bank starts monitoring at date $T > 0$. Let π denote the profit obtained by the first bank until the second bank starts monitoring (π will be analyzed subsequently).

[9] A third approach would be to assume that the amount of potential private information is decreasing over time, i.e., $\overline{\theta} - \underline{\theta}$ is decreasing over time. Also this approach would yield similar predictions as derived in the current setup.

In equilibrium the banks set their interest rates, $r^e(t)$, at date t as described by Proposition 1.

Proposition 1.

i) At $t = 0$ both banks offer interest rates that will remove all long term profit

$$r^e\,(t = 0) = s(0)1/\overline{\theta} + (1 - s(0))1/\underline{\theta} - \pi - 1.$$

ii) At $t \in [1, T - 1]$ the outside bank offers interest rates, r^e, reflecting the risk of bad projects

$$r^e\,(1 < t \leq T - 1) = 1/\underline{\theta} - 1.$$

The inside bank keeps the borrower by offering the same interest rate as the outside bank.

iii) At $t \in [T, \infty\rangle$ both banks may acquire private information. Interest rate charged a borrower having a good project depends on whether more than one bank has this information (probability λ^2),

$$r_G^e\,(T \leq t) = \begin{cases} 1/\overline{\theta} - 1 & \text{with probability } \lambda^2 \\ 1/\underline{\theta} - 1 & \text{with probability } 1 - \lambda^2 \end{cases}$$

while the interest rate charged a borrower with a bad project reflects its credit risk

$$r_B^e\,(T \leq t) = 1/\underline{\theta} - 1$$

Proof. Part i): Note that at $t = 0$ there is no asymmetric information between the banks and that the banks are assumed to compete as Bertrand competitors (price competition). Consequently, the banks offer interest rates that imply zero long-term profit taking into account that the banks expect to earn a profit π on locked-in borrowers.

Part ii): If the outside bank decreases it interest rate from $r^e\,(1 < t \leq T - 1)$ it would start a subgame with three potential outcomes. First, if the inside bank has observed that the borrower has a good project, the inside bank will respond by reducing its interest rate until it expects to break-even on lending to the borrower. Second, if the inside bank has observed that the borrower has a bad project, the inside bank will not respond by reducing its offered interest rate and the outside bank will capture the borrower by offering an interest rate which implies negative

bank profit. Third, if the inside bank has not observed the quality of the firm's project, it will respond by lowering its interest rate until it expects zero profit. In the first and third case the outside bank earns zero profit, while in the second case it earns negative profit. Consequently, the outside bank will not find it profitable to offer a lower interest rate than $r^e\,(1 < t \leq T-1) = 1/\underline{\theta} - 1$ which reflects the success probability of a bad project.
Part iii): The same argument as in Part ii) can be applied to Part iii). ■

Proposition 1 describes bank competition taking the second bank's monitoring decision as given (T is taken as given). We will now analyze T and study when the second bank starts monitoring. First, note that the second bank's expected one-period profit is

$$\begin{aligned} G(t) &= \lambda\,(1-\lambda)\,s(t)\left(\overline{\theta}(1/\underline{\theta}) - 1\right) - F \\ &= \lambda\,(1-\lambda)\,s(t)\left(\frac{\overline{\theta}-\underline{\theta}}{\underline{\theta}}\right) - F \end{aligned}$$

if it monitors. In the above expression, $\lambda\,(1-\lambda)$ denotes the probability that one single bank obtains private information, $s(t)$ is the probability that the project is good and succeeds with probability $\overline{\theta}$. Recall that if both banks are informed (happens with probability λ^2) or none of the banks are informed (happens with probability $(1-\lambda)^2$) bank competition will remove all profit. In case of success, the firm is able to pay the face value of debt which is $1/\underline{\theta}$. Recall that the face value of a loan reflects the fact that the other bank fears the borrower has a bad project and therefore offers loan terms reflecting a bad project with low success probability (i.e., $\underline{\theta}$). We have assumed that if the banks' offered loan terms are identical, the borrower chooses the bank with private information about the loan project. Hence, if the outside bank knows the quality of the project while the inside does not, the borrower will switch banks if the offered rates are identical. This simplifies our analysis since we do not need to discuss how the outside bank can attract the borrower without revealing its private information about the current project to the inside bank. Note that $G'(t) > 0$ since $s'(t) > 0$.[10]

[10] We focus on the case where the exists a T such that $G(T)$ is positive. Otherwise, a second bank will never start monitoring. Note that if $\lambda = 1$ (perfect signals) $G(t)$ would have been negative for all values of t.

The second bank finds it profitable to start monitoring when the per-period profit exceeds the monitoring costs. More formally, the following condition (2.1) describes when the second bank starts monitoring (T).

$$G(T) > 0 > G(T-1) \tag{2.1}$$

Condition (2.1) states that it is non-profitable to start monitoring in period $T-1$ but profitable in period T. Since $G'(t) > 0$ it follows that T is uniquely defined by condition (2.1).

We can now calculate the profit from capturing the borrower in period 0 instead of waiting until period T and then start monitoring;

$$\pi = \sum_{t=1}^{t=T-1} G(t) = \frac{\overline{\theta} - \underline{\theta}}{\underline{\theta}} \sum_{t=1}^{t=T-1} s(t) - TF$$

In a competitive bank-loan market (Bertrand competition) where banks expect to profit from long-term bank-borrower relationships, banks price their initial loans at date 0 very aggressively in order to attract new borrowers. Competition at date 0 drives the interest rate down until the winning bank spends the entire anticipated profits (π) to subsidize the initial loan (Proposition 1 i)).[11]

We now compare the equilibrium interest rate with the interest rate yielding zero bank profit given that the two banks only have access to public information. Denote this benchmark interest rate $r^*(t)$,

$$r^*(t) = s(t)1/\overline{\theta} + (1 - s(t))\, 1/\underline{\theta} - 1. \tag{2.2}$$

Note that $r^*(t)$ represents the interest rate in a competitive equilibrium were there is no asymmetric information between inside and outside banks and therefore no informational lock-in effects. Since the average quality of new projects improves as the firms mature (i.e., $s'(t) > 0$) it follows that $r^*(t)$ is decreasing in t. The markup on the benchmark interest rate in period t is $m(t) = r^e(t) - r^*(t)$. From the definition of $r^*(t)$ and Proposition 1 it follows directly that:

[11] Note that the interest rate markup and bank profit depend only on the firm's probability for having a good project and not on the likelihood that the bank obtains private information about the borrower's project.

Proposition 2. *The markup, $m(t)$, follows a life cycle pattern;*

i) in period $t = 0$, the markup is negative, $m(t) < 0$

ii) in the following periods, $t \in [1, T-1]$, the markup is increasing in t, $m'(t) > 0$.

iii) in period T, the second bank starts monitoring and the markup drops, $m(T-1) > m(T)$.

Note that $r^e(T-1)$, the equilibrium interest rate at $T-1$, is $1/\underline{\theta} - 1$, while at T $r^e(T) = \left(1 - \lambda^2 s(t)\right) 1/\underline{\theta} + \lambda^2 s(t) 1/\overline{\theta} - 1$ where $\lambda^2 s(t)$ is the probability that both banks have observed that the firm's project is good.

Proposition 3 shows that the life cycle pattern of the markup depends on the size of the monitoring costs which we associate with the prevalence of asymmetric information problems in the credit market. Firms with more asymmetric information problems that consequently require higher bank monitoring costs have their lock-in resolved at a later stage than firms requiring lower bank monitoring costs.

Proposition 3. *Firms with high monitoring costs (F),*

i) start to be monitored by the second bank at a later point in time (T) than firms with low monitoring costs.

ii) have a higher maximum markup ($m(T)$) than firms with low monitoring costs.

Proof. Part i) follows directly from (2.1) and the assumption that $s'(t) > 0$.

Part ii): Note that the markup for period $t \in [1, T-1]$ is given by

$$\begin{aligned} m(t) &= \left(\frac{1}{\underline{\theta}} - 1\right) - \left(s(t-1)\frac{1}{\overline{\theta}} + (1 - s(t-1))\,\frac{1}{\underline{\theta}} - 1\right) \\ &= \frac{2\beta}{\left(\overline{\theta}\right)\left(\underline{\theta}\right)} s\,(t-1) \end{aligned}$$

and that $s'(t) > 0$. Part ii) follows from observing that $m(t)$ reaches its maximum at $t = T-1$ and that T is increasing in F (follows from part i). ■

In the following sections, we examine the life-cycle pattern of interest rate markups for a large sample of Norwegian firms and compare the empirical results with the predictions of our theoretical model.

3. Empirical investigation

3.1. Hypotheses and modelling

In this section we specify an empirical model in order to assess the hypotheses derived in the theoretical model:

I The interest rate markup follows a life cycle pattern over the firm's age: young firms pay a low or negative markup, thereafter the markup increases until it falls for old firms (see Proposition 2).

II The life cycle pattern described in I is more pronounced for more opaque firms, i.e., more opaque firms pay a lower interest rate markup when young but a higher interest rate markup when they are locked in (see Proposition 3 part ii).

III For the more opaque firms the lock-in is resolved and the mark up drops at a higher firm age (see Proposition 3 part i).

Unlike the existing literature, our empirical model allows us to distinguish effects originating from asymmetric information from those originating from market concentration. In their much cited paper, Petersen and Rajan (1995) examine loan terms associated with the degree of competition in credit markets, measured as market concentration. They introduce a theoretical model that shows how intertemporal pricing of loans may depend on market concentration. Consistent with their theoretical model they find that concentrated credit markets allow banks to take a loss initially in order to benefit from a long-term relationship with a borrower. Petersen and Rajan argue that market concentration determines to what extent firms can establish long-term relationships. However, we examine directly whether lock-in effects due to the information advantage of an inside bank is crucial for establishing long-term bank relationships. In our theoretical model it is the informational advantage of the inside bank that reduces competition and allows the bank to intertemporally share its surplus in a long-term bank relationship. In order to compare our study with that of Petersen and Rajan (1995) we introduce market concentration variables in addition to the asymmetric information variables in our empirical model. Thereby we can assess whether market concentration has a separate effect on the intertemporal pricing of loans according to the following hypothesis derived from Petersen and Rajan:

IV Increased market concentration leads to lower markups for *de novo* firms and higher interest rate markups for mature firms (i.e., less bank competition due to higher market concentration implies more intertemporal cross-subsidization).

To test hypotheses I to IV, we present an econometric model with the actual interest rate markup (i.e., the actual interest rate minus the interest rate implying zero expected profit) paid by firms as the LHS variable. As RHS variables we use the age of the firm (represented by dummies for different age groups, like in Petersen and Rajan (1995)), a variable representing the degree of asymmetric information, a variable measuring market concentration in the different credit markets covered by the data, and some control variables.

We specify the zero-expected profits interest rate as the interest rate a borrowing firm would pay in a world with a risk neutral competitive banking industry in the following way:

$$
\begin{aligned}
1 + r_{f,t} &= p_{i,t-1}(1 - LGB) + (1 - p_{i,t-1}) \cdot (1 + r^*_{i,t}) \\
r^*_{i,t} &= \frac{r_{f,t} + p_{i,t-1} LGB}{1 - p_{i,t-1}}
\end{aligned}
$$

where $r_{f,t}$ is the risk-free money market interest rate, $p_{i,t-1}$ is the probability at time $t-1$ that firm i will go bankrupt, Our motivation for using the lagged value of the bankruptcy probability is the fact that during year t only the information from balance sheet and income statements for year $t-1$ are publicly available. LGB is the loss given bankruptcy, i.e., the fraction of the principal of the loan that the bank will have to write off in case of bankruptcy.[12] $r^*_{i,t}$ is then defined as the risk-adjusted interest rate.

[12] In the actual empirical model LGB is set at 0.6. The Basel Committee suggests in its Third Consultative Paper, Basel Committee on Banking Supervision (2003), that loss given default (LGD) is set to 45% for senior unsecured debt and 75 % for subordinated claims without specific collateral (the IRB Foundation approach). Note however that we look at bankruptcy which is more 'severe' than default. To check for robustness we have also estimated the model using LGB of 0.3 and 0.9. Our main results are not affected by these changes.

Our LHS variable, the interest rate markup is thus

$$m_{i,t} = r_{i,t} - r^*_{i,t} \quad , \tag{3.1}$$

where $r_{i,t}$ is the actual interest rate firm i pays in year t.

The general form of our empirical model is

$$m_{i,t} = (AINFO, \mathbf{d}_{AGE;i,t}, concentration, \epsilon_{i,t}) \quad , \tag{3.2}$$

$AINFO$ is a variable representing the severity of asymmetric information. $\mathbf{d}_{AGE;i,t}$ is a vector of the dummies representing the age group for firm i in year t. It will enable us to test how the interest rate markup differs between firms of various ages. $concentration$ captures the degree of concentration in the credit market from which the firm demands credit. $\epsilon_{i,t}$ is the stochastic residual.

3.2. Data

Our data are collected from the SEBRA database covering all limited liability firms in Norway. All limited liability firms in Norway have to file their annual financial statements with a public registry, The Register of Public Accounts at The Brønnøysund Register Centre. The information in this register is public.[13] The database includes annual financial statements (balance sheets and income statements) from 1988 to 2004 as well as firms' characteristics such as the industrial sector code, the geographical location of the firms' head offices, and the firms' age. Data from the SEBRA database is used to predict bankruptcy probability for each firm for the years 1990 to 2001 (see Appendix A for a detailed description of this estimation). In this empirical model, bankruptcy is defined as the event in which a firm is declared bankrupt within the next three years, hence the truncation of bankruptcy probabilities after 2001. Henceforth, the bankruptcy probability model will be referred to as the SEBRA model.[14] In our empirical model (3.2) we use the predicted bankruptcy probabilities from the SEBRA model.

From year 2000 the SEBRA-database allows us to separate bank loans from other debt. Hence, we use data from year 2000 and 2001. The database includes

[13] The data in the SEBRA database is bought from Dun and Bradstreet which has collected them electronically from The Brønnøysund Register Centre.

[14] This model is equivalent to the one in Eklund, Larsen, and Bernhardsen (2001). A more comprehensive description is given in Bernhardsen (2001).

information on approximately 135,000 to 140,000 firms each year. Of those, however, we only consider non-financial firms. Since we are particularly interested in the asymmetric information aspect in relationship lending we have removed firms that have issued bonds and thus often have a bond rating. Furthermore we drop firms that either lend to, borrow from, have financial transactions with or receive or pay group contribution from or to other companies in the same conglomerate. Lending inside a conglomerate is not associated with significant asymmetric information problems. We also exclude large firms, those with an annual operating income above 100 NOK million (appr. EUR 12.5 million), leaving us with a sample of rather small and unlisted firms, firms about which there is little public information. At the other end, we exclude firms with total assets less than NOK 0.5 million. In several cases such small firms borrow against collateral posed by their owners, for instance their house.[15]

Actual paid interest rates are calculated from firms' income statements and balance sheets by dividing each firm's interest cost by the unweighted average of bank loans outstanding at the end of year $t-1$ and t.[16] Since most loans extended by Norwegian banks have a floating interest rate, we believe our approach of calculating interest rate is more accurate than interest rates from annual loan contracts, had they been available. In 2000 and 2001 the central bank changed its deposit rate five times and one time, respectively. Contractual interest rates observed once a year would not capture intra-year changes in interest rates caused by the central bank. By calculating the interest rates using the interest cost for the whole year, we implicitly include these intra-year changes of interest rates.

Our panel then consists of 47,993 observations of 30,665 firms over two years. We have 23,392 observations in 2000 and 24,601 observations in 2001. Table 3.1 gives a summary of the variables used in the empirical model as well as some other firm characteristics.

[15] In a previous version of the paper we did not exclude small firms but received similar results as in the current version.

[16] In some cases the calculated interest rates are misleading due to changes in loan sizes in the beginning or at the end of the year. Consequently, we exclude firms with calculated interest rates under 0.06 and above 0.25 and this leaves out 23 per cent of the observations. Note also that Bernhardsen and Larsen (2003) use a similar procedure for calculating interest rate on bank loans. They find strong evidence that this a reasonably accurate measure of the interest rate borrowing firms face.

Table 3.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max
Operating income	6,260	10,301	$-4,607$	99,826
Total assets	5,983	14,077	500	677,873
Bank debt	2,638	11,746	0	1,365,769
Collateralizable assets to total debt	0.6259	0.5482	0	2
Interest rate	0.1214	0.0441	0.06	0.25
Interest rate markup	0.0351	0.0513	-0.515	0.181
Probability of bankruptcy	.0206	.0413	.00008	.4665
Volatility of bankruptcy probability	0.0128	0.0141	0.00002	0.3136
Firm age	11.0	13.0	1	148
Herfindahl index	1664	406	1111	2895

Number of observations is 47,993. Operating income, total assets, and bankdebt are measured in NOK thousands. Interest rate and interest rate markup are measured as ratios. Probability of bankruptcy, measured as a ratio, is predicted from the SEBRA model. Firm age is measured in years. For the precise definition of collateralizable assets to total debt, volatility of bankruptcy probability, and the Herfindahl index, see section 3.3

Table 3.1 illustrates that there is a considerable firm heterogeneity in the sample. 2,879 of the firms have zero bank debt by the end of one of the years. The variation in the probability of bankruptcy is also reflected in the interest rate markup. There are a few firms in the sample with large negative markups. These are firms with high bankruptcy probabilities for which the zero-bank profit interest rates are correspondingly high. Large negative markups can be due to banks aggressive pricing of loans to new borrowers as suggested by our model.[17]

There is also considerable variation in the age of firms. The average firm in the sample is 11 years old, and the oldest firm is 148 years. The peak age of firms in our sample is 3 years. The median age is 7 years. This skewed distribution is typical for the age of firms in large samples. Many of the relatively young firms will not survive because they go bankrupt, are closed before bankruptcy, or are acquired by other firms. Nevertheless 5,505, or 11.5 pct. of the observations in the sample relate to firms older than 20 years.

[17] Alternatively, a large negative markup can also be due to firms' moral hazard problems which prevent banks from increasing the interest rate (see Stiglitz and Weiss (1981) and Williamson (1987)).

3.3. The empirical model

Our theoretical model predicts that the interest rate markup follows a life-cycle pattern where young firms face a low and increasing markup, middle-aged firms face a high markup, while old firms face a lower markup. Furthermore, the lifecycle pattern is more pronounced for borrowers in industries where the lock-in effects is stronger due to a larger informational advantage of the inside bank. In order to test these hypotheses we assign firms into different age groups. However, the age at which firms are 'middle aged' in terms of being informationally locked in and having the highest interest markup during their life cycle, may vary according to the severity of asymmetric information (see Hypothesis III). To allow for this, we divide the sample into 5 age groups. Age groups are represented by dummies. Furthermore, we allow the age dummies to interact with our measurement of the severity of asymmetric information.

We suggest a novel measure of the severity of information asymmetry between inside and outside banks. In line with our theoretical model, we assume that an inside bank obtains soft information relevant to a firm's credit quality before outside banks do. This informational advantage of inside banks is particularly valuable in industries where firms' credit qualities change quickly. Hence we propose the volatility of bankruptcy probability in the industry to which the firm belongs, as a measure of the inside banks' informational advantage over outside banks. Consider a firm belonging to an industry where firms' bankruptcy probabilities and hence credit ratings based on publicly available information vary considerably over time. In such an industry soft information about firms' prospects acquired through a bank relationship is particularly valuable because the publicly available information about credit quality quickly becomes outdated. This informational advantage of the inside bank may expose firms in this industry to considerable informational lock-in effects.[18]

As alluded to earlier, we also want to test the predictions set out by Petersen

[18] An alternative measure of the inside bank's information advantage, could be the errors in the predictions of the bankruptcy probability model SEBRA. However, use of such a measure would implicitly assume that the inside bank has perfect information about the true bankruptcy probability of a borrower from the start of the lending relationship. We believe this to be too strong an assumption, and therefore we choose not to use this measure.

and Rajan (1995). In their paper the potential lock-in phenomenon of borrowers in relationship banking stem from the exogenous competitiveness of the credit market, represented by a market concentration variable. Thus we include a measure of credit market concentration and allow it to interact with the firm age dummies in the same way as our measure of asymmetric information. Consequently, our empirical model can be used to test whether asymmetric information, credit market concentration, or both determine how the interest rate markup evolves over a firm's age.

We apply the following empirical model:

$$\begin{aligned} m_{i,t} &= \beta_0 + \sum_{j=1}^{4} \beta_j d_{j;i,t} + \gamma_0 VL_{c,k} + \sum_{j=1}^{4} \gamma_j VL_{c,k} \cdot d_{j;i,t} + \delta_0 HI_{c,t} \\ &\quad + \sum_{j=1}^{4} \delta_j HI_{c,t} \cdot d_{j;i,t} + \theta coll_{i,t-1} + \lambda bankdebt_{i,t-1} + \xi p_{i,t} + \epsilon_{i,t} \quad , \end{aligned} \tag{3.3}$$

where:

$d_{j;i,t}$ $j = 1 \ldots 4$ are dummies for the four firm age groups, 11 to 20 years, 21 to 30 years, 31 to 40 years, and above 40 years, respectively. I.e., 1 to 10 years is the benchmark group represented by the subscript $_0$ on the coefficients.

$p_{i,t}$ is the bankruptcy probability of firm i in year t, calculated from SEBRA.

$\Delta p_{i,t}$ is the change in bankruptcy probability of firm i from year $t-1$ to year t.

$\sigma(\Delta p_i)$ is the standard deviation across time of $\Delta p_{i,t}$, i.e., a measure of the volatility in the bankruptcy probability of firm i. As discussed above, we use this volatility measure as a proxy for the asymmetric information problems related to lending to firm i. Higher volatility implies more severe asymmetric information problems.

$VL_{c,k}$ is the mean of $\sigma(\Delta p_i)$ for all firms in industry sector k in county c. Essentially it captures the *volatility* of the bankruptcy probability of firms in the specific industry and county. We regard it as a proxy for the severity of the *ex ante* asymmetric information problem in lending to a firm within this particular group of firms.[19]

[19]To calculate $VL_{c,k}$ we use observations spanning the whole period of the SEBRA-database, 1988 to 2001.

$HI_{c,t}$ is the Herfindahl index for county c in year t, measuring the market concentration of bank loans to all domestic non-financial business borrowers. Data for this variable is collected from the Norwegian banks statistics produced by Norges Bank.[20] [21]

$coll_{i,t-1}$ is the ratio of the firm's collateralizable assets to its total debts lagged one year.[22]

$bankdebt_{i,t-1}$ is the size of the firm's bank debt lagged one year.

$coll_{i,t}$ is included to reduce the inaccuracies implied by assuming all loans having the same loss given bankruptcy when calculating the risk-adjusted interest rate. The expected sign of its coefficient is negative. The inclusion of $bankdebt_{i,t}$ controls for the possibility that firms with large bank debt are considered more important customers to their bank. Since small firms commonly borrow from small banks, firms with large debt may have more market power vis-à-vis the bank. The expected value of this coefficient is either negative or zero. $p_{i,t}$ is also included as a control variable. This is done in order to take care of a possible bias when calculating the actual paid interest rate $r_{i,t}$: Firms that have defaulted on servicing their debt may have entered into debt renegotiations and achieved lower interest rates. This will most likely be firms with high bankruptcy probability. Since we do not have information on debt renegotiations in the data we control for this potential bias by including the bankruptcy probability $p_{i,t}$ as a RHS. The expected sign of the coefficient for $p_{i,t}$ is negative.

[20]In calculating the Herfindahl index we also include lending from mortgage companies to non-financial business borrowers. If a mortgage company is owned by a bank its loans are considered as part of the banks' loans. However, we do not include lending from finance companies, that mainly do factoring and leasing. Debts to these companies normally will not be included in the debt numbers we use to calculate the interest rates paid by borrowing firms.

[21]Dell'Ariccia, Friedman, and Marquez (1999) show in a theoretical model how the accumulation of private information by incumbent banks in a credit market can serve as an entry barrier for outside banks. Thus, the more important private information is in a credit market the more likely that market will be concentrated. In our model, however, we do not take this effect into consideration. We measure the importance of private information across industries and geography, whereas market concentration is just measured across geography. Hence, theory does not predict any specific effect from our variable $VL_{c,k}$ onto $HI_{c,t}$.

[22]As collateralizable assets we have included land, buildings, moveable machinery like ships, rigs and planes, cash, shares and bonds. The variable $coll_{i,t-1}$ is truncated in the sense that whenever its calculated value is larger than 2 it is replaced by 2.

The model (3.3) is estimated using OLS and White robust standard errors also robust to clustering of the Herfindahl index $HI_{c,t}$.[23] Results are presented in Table 3.2.

The results reported in Table 3.2 show that all terms including our measure of the severeness of asymmetric information, $VL_{c,k}$, are statistically significant. Among the terms just including the age dummies, two are statistically significant. The control variables are all significant and have the expected signs. Hypotheses I to III concerning the relation between the life-cycle pattern of the interest rate markup and the opaqueness of a firm, however, cannot be tested by only considering the individual estimated coefficients and their statistical significance. When specifying the model (3.3) we explicitly allowed firms with different measures of the importance of asymmetric information ($VL_{c,k}$) to face their maximum interest rate markup at different ages. In line with this we apply the following strategy to test Hypotheses I to III:

Using the estimated coefficients and variance-covariance matrix from model (3.3) we predict the expected interest rate markup and its standard error for firms in all the five age groups using different values of $VL_{c,k}$. $HI_{c,t}$ and the three control variables are all set at their sample median value for all the firms. For $VL_{c,k}$ we use the 5 pct. fractile, the 25 pct. fractile, the 50 pct. fractile, the 75 pct. fractile, and finally the 95 pct. fractile. The predictions are shown in Table 3.3. By comparing cells in Table 3.3 horizontally one detects the *partial* effect of age for a borrowing firm. Similarly, a vertical comparison between the cells gives the *partial* effect of the importance of asymmetric information, $VL_{c,k}$

Table 3.3 shows that all firms pay a significantly lower interest rate markup when they are young (1–10 years) than when they belong to the next age group (11–20 years) irrespective of the degree of opaqueness. These differences are both statistically and economically significant. For firms with a value of the opaqueness

[23] We note that the Herfindahl index $HI_{c,t}$ has constant values over all observations pertaining to one particular county in one particular year which implies that it is clustered. Clustering of RHS-variables tend to bias the estimated parameter standard errors downwards, (Bertrand, Duflo, and Mullainathan (2004)). To obtain White robust standard errors also robust to clustering we use the *cluster* command in STATA.

Table 3.2: Results, dependent variable $m_{i,t}$

Independent variable	Coefficient	Robust t-values
β_0	0.05581	17.62**
$d_{1;i,t}$	0.00604	2.39**
$d_{2;i,t}$	0.00613	1.46
$d_{3;i,t}$	0.00591	1.00
$d_{4;i,t}$	−0.01303	−2.08**
$VL_{c,k}$	−0.28807	−7.35**
$VL_{c,k} \cdot d_{1;i,t}$	0.38169	6.59**
$VL_{c,k} \cdot d_{2;i,t}$	0.56255	4.55**
$VL_{c,k} \cdot d_{3;i,t}$	0.57427	3.86**
$VL_{c,k} \cdot d_{4;i,t}$	0.72027	5.12**
$HI_{c,t}$	$-2.76 \cdot 10^{-7}$	−0.16
$HI_{c,t} \cdot d_{1;i,t}$	$-1.15 \cdot 10^{-6}$	−0.83
$HI_{c,t} \cdot d_{2;i,t}$	$-1.40 \cdot 10^{-6}$	−0.61
$HI_{c,t} \cdot d_{3;i,t}$	$-7.83 \cdot 10^{-7}$	−0.23
$HI_{c,t} \cdot d_{4;i,t}$	$7.32 \cdot 10^{-6}$	1.78*
$coll_{i,t-1}$	−0.01697	−26.13**
$bankdebt_t$	$-3.74 \cdot 10^{-7}$	−2.95**
$p_{i,t}$	−0.38949	−26.10**
F-test for $HI_{c,t}$ terms	1.10	0.38
corr($age_{i,t}, \widehat{\epsilon}_{i,t}$)	0.0167	
# clusters	36	
# observations	47993	
R^2adj.	0.1338	

The t-values reported are White-robust and adjusted for clustering of $HI_{c,t}$. * represents a 10 pct. statistical significance and ** 5 pct. significance. For the F-test we report the F-statistic and the p-value respectively

Table 3.3: Predicted markups

Volatility fractiles	Age groups, years: 1–10		11–20		21–30		31–40		Above 40
5 pct.	0.0440 (0.0010)	$\nearrow^{**}$	0.0492 (0.0014)	$\longrightarrow$	0.0493 (0.0013)	$\longrightarrow$	0.0500 (0.0014)	$\searrow_{**}$	0.0433 (0.0012)
25 pct.	0.0437 (0.0010)	$\nearrow^{**}$	0.0493 (0.0014)	$\longrightarrow$	0.0496 (0.0013)	$\longrightarrow$	0.0503 (0.0013)	$\searrow_{**}$	0.0438 (0.0012)
50 pct.	0.0420 (0.0010)	$\nearrow^{**}$	0.0498 (0.0015)	$\longrightarrow$	0.0511 (0.0011)	$\longrightarrow$	0.0519 (0.0013)	$\searrow_{**}$	0.0463 (0.0012)
75 pct.	0.0399 (0.0011)	$\nearrow^{**}$	0.0505 (0.0016)	$\nearrow^{**}$	0.0532 (0.0014)	$\longrightarrow$	0.0541 (0.0018)	$\searrow_{*}$	0.0495 (0.0020)
95 pct.	0.0337 (0.0016)	$\nearrow^{**}$	0.0525 (0.0023)	$\nearrow^{*}$	0.0591 (0.0033)	$\longrightarrow$	0.0602 (0.0043)	$\longrightarrow$	0.0588 (0.0050)

Predicted interest rates reported as ratios. Predicted standard errors in parantheses below. The Herfindahl index and the control variables are all set at their median values when the predictions are calculated. Increasing or decreasing arrows with one and two stars at the end indicate a 10 pct. and 5 pct. difference between two neighbouring predictions. A horizontal arrow indicates no significant difference between the predictions. The differences and their standard errors are calcualted using the estimated model and covariance matrix.

measure, $VL_{c,k}$, up to and including the 75 pct. fractile, the interest rate markup stays high until it significantly falls between the age groups 31–40 years and above 40. For the 75 pct. fractile, though, the fall is only significant at a 10 pct. level. These findings indicate that the interest rate markup follows a life cycle pattern over firms' age as described in Hypothesis I. Young firms pay a low or negative markup,[24] thereafter it increases and finally falls for the older firms.

Results in Table 3.3 also demonstrate that this life cycle pattern is more pronounced for more opaque firms. The interest rate markup for the firms in the youngest age group *decreases* with the opaqueness of the firm. This decrease is statistically significant since the estimated coefficient for $VL_{c,k}$ is significant. A young firm with an opaqueness measure at the 5 pct. fractile is charged an interest rate markup more than 1 percentage point above that of a young firm with an opaqueness measure at the 95 pct. fractile. For all the other age groups, i.e., the age groups where the lock-in is effective, as well as the age groups where the lock-in has been

[24] Note that our definition of markup covers more than pure rent. The markup also covers banks' operating costs. Hence the fact that our empirical model yields positive interest rate markups even for young firms facing a large asymmetric information problems, can be consistent with the prediction of our theoretical model (the bank loses money on a borrower early on).

resolved, the markup *increases* with firm opaqueness. All these increases are also statistically significant.[25] Within the age groups of 21 to 40 years, a firm at the 95 pct. fractile of the opaqueness measure pays about 1 percentage point higher interest rate markup than a firm at the 5 pct. fractile. These results yield support to Hypothesis II.

For firms with an opaqueness measure at the 95 pct. fractile we do not detect any significant fall in the markup for firms older than age group 31–40, as we do with the less opaque firms. This indicates that the lock-in for the most opaque firms is resolved at an older age than it is for the less opaque, giving support to Hypothesis III.

Furthermore, note that Table 3.3 shows that there is a significant increase in the interest rate markup between age groups 11–20 and 21–30 for the most opaque firms. This indicates that inside banks spend more time on collecting information about particularly opaque firms. Consequently, the inside bank's informational advantage and the associated lock-in effect are increasing over a rather long time span before the markup reaches a maximum.

The terms in Table 3.2 which include the Herfindahl index ($HI_{c,t}$) capture effects from market concentration on markups. To check whether this concentration measure is statistically significant for any of the age groups, we consider the significance of δ_0 and $\delta_0 + \delta_j$ for $j = 1 \ldots 4$. For none of the age groups do we find a significant effect of the Herfindahl index. Thus, we do not get any support for Hypothesis IV.

As a robustness check of our results we rerun model (3.3) replacing the Herfindahl index with an alternative measure of market concentration in the credit markets; the sum of the market shares of the three largest banks in each county.[26] The results regarding the estimated coefficients and the predictions are shown in Appendix A. As it appears, results regarding our measure of asymmetric information as well as the control variables remain more or less the same. The only difference is that now we do not get a statistically significant fall in the interest rate markup for firms at the 75 per cent fractile of $VL_{c,k}$ between the age groups 31–40 and above 40.

[25] The statistical significance of these increases is checked by calculating $\widehat{\gamma}_0 + \widehat{\gamma}_j$, and the standard errors for $j = 1 \ldots 4$ using the covariance matrix of the estimated coefficients. The sum of these coefficients is significant at a 5 pct. level for all $j = 1 \ldots 4$.

[26] The correlation between the new and the old measure is as high as 0.9.

As regards the market concentration measure, the coefficients related to it are now jointly significant at a 10 per cent level. Nevertheless, only for firms above 40 years of age do we find that this market concentration measure has a significant positive effect on the markup for the firms. This result can be interpreted in the following way: at this age the informational lock-in is resolved for most of the firms, and a more traditional source of market power – market concentration – starts to have effect. We still do not, however, get support for Hypothesis IV, predicting that the life cycle pattern of the interest rate markup is more pronounced the higher is the market concentration.

Our results demonstrate that the informational advantage of the inside bank, and not market concentration, creates lock-in effects. Thus, to what extent banks subsidize very young firms in order to capture lock-in rents when firms are older, is determined by the informational advantage of the inside bank. Traditional measures of market concentration, like the Herfindahl index or the sum of the markets shares of the three largest banks, cannot explain the life-cycle pattern of the interest rate markup. Nevertheless, for firms old enough such that asymmetric information problems have been resolved, higher market concentration may cause a higher interest rate markup. These results corroborate the general finding in the literature. A recent document by the OECD (2006) surveying this literature reports very mixed results regarding the effect of the Herfindahl index (or some related form of it) on loan rates.[27]

4. Concluding remarks

We develop a simple theoretical model explaining the life cycle pattern of banks' interest rate mark up. Our model predicts that, in order to attract new borrowers, banks offer loans with low or even negative interest rate markups to young firms. The inside bank – the initial lender – obtains an information advantage which later on leads to lock-in effects and positive interest markups. As firms mature they become more attractive borrowers for outside banks and, consequently, one or more outside banks start making their own credit assessments of the borrowers in order to make

[27] See also Gilbert and Zaretsky (2003) for a recent review for the impact of bank market concentration on bank loan rate.

competing loan offers. As more than one bank monitors a borrower, information about the borrower becomes more widely dispersed, lock-in effects weaken, and interest rate markups decrease. Our theoretical model predicts that a stronger information advantage of the inside bank leads to a more pronounced life-cycle pattern of interest rate markups and longer lock-in periods. Using a large sample of Norwegian unlisted small firms and a novel measure to capture the degree of asymmetric information between inside and outside banks, we find empirical support for these hypotheses.

It is common in much of the existing literature to use market concentration in the loan market to explain interest rate markups. Our approach allows us to distinguish market-concentration effects from informational lock-in effects. Unlike Petersen and Rajan (1995) which focuses on market concentration variables, we find that asymmetric information variables better explain how a bank sets its interest rate markup over the lifecycle of a borrower. Our study illustrates that banks' market power is more closely related to the banks' informational advantage – an Akerlof effect, than to their market share per se – a Herfindahl effect. We find, though, weak evidence that higher market concentration in credit markets may cause higher markups for older firms. The specific methods by which a bank obtains soft information about a borrower during a relationship remains, however, to be further explored.

Appendix

A. Robustness check of the market concentration measure

In the model presented and estimated in Section 3 we used the Herfindahl index as a measure of market concentration. In the appendix we reestimate equation (3.3) using the sum of the market shares for the three largest banks in each county for each year ($MS_{3;c,t}$) rather than the Herfindahl index to measure market concentration. Table A.1 presents the estimated coefficients and Table A.2 the predicted interest rate markups for firms in the five age groups at the four percentile values of $VL_{c,k}$.

Table A.1: Results, dependent variable $m_{i,t}$

Independent variable	Coefficient	Robust t-values
β_0	0.05079	8.46^{**}
$d_{1;i,t}$	0.00124	0.23
$d_{2;i,t}$	0.00426	0.44
$d_{3;i,t}$	-0.00488	-0.36
$d_{4;i,t}$	-0.04373	-3.35^{**}
$VL_{c,k}$	-0.28795	-7.35^{**}
$VL_{c,k} \cdot d_{1;i,t}$	0.38151	6.56^{**}
$VL_{c,k} \cdot d_{2;i,t}$	0.56469	4.57^{**}
$VL_{c,k} \cdot d_{3;i,t}$	0.57923	3.90^{**}
$VL_{c,k} \cdot d_{4;i,t}$	0.74313	4.58^{**}
$MS_{3;c,t}$	0.00007	0.78
$MS_{3;c,t} \cdot d_{1;i,t}$	0.00005	0.57
$MS_{3;c,t} \cdot d_{2;i,t}$	$-7.15 \cdot 10^{-6}$	-0.05
$MS_{3;c,t} \cdot d_{3;i,t}$	0.00015	0.72
$MS_{3;c,t} \cdot d_{4;i,t}$	0.00068	3.16^{**}
$coll_{i,t-1}$	-0.01695	-26.03^{**}
$bankdebt_t$	$-3.72 \cdot 10^{-7}$	-2.95^{**}
$p_{i,t}$	-0.38924	-25.95^{**}
F-test for $HI_{c,t}$ terms	2.21^{*}	0.08
corr$(age_{i,t}, \widehat{\epsilon}_{i,t})$	0.0164	
# clusters	36	
# observations	47993	
R^2adj.	0.1341	

The t-values reported are White-robust and adjusted for clustering of $MS_{3;c,t}$. * represents a 10 pct. statistical significance and ** 5 pct. significance. For the F-test we report the F-statistic and the p-value respectively

Table A.2: Predicted markups

Volatility fractiles	Age groups, years: 1–10		11–20		21–30		31–40		Above 40
5 pct.	0.0439	$\nearrow^{**}$	0.0488	$\longrightarrow$	0.0489	$\longrightarrow$	0.0495	$\searrow_{**}$	0.0436
	(0.0009)		(0.0012)		(0.0013)		(0.0013)		(0.0011)
25 pct.	0.0435	$\nearrow^{**}$	0.0489	$\longrightarrow$	0.0492	$\longrightarrow$	0.0499	$\searrow_{**}$	0.0441
	(0.0009)		(0.0012)		(0.0012)		(0.0012)		(0.0010)
50 pct.	0.0419	$\nearrow^{**}$	0.0494	$\longrightarrow$	0.0508	$\longrightarrow$	0.0516	$\searrow_{**}$	0.0466
	(0.0009)		(0.0013)		(0.0010)		(0.0012)		(0.0009)
75 pct.	0.0397	$\nearrow^{**}$	0.0501	$\nearrow^{**}$	0.0528	$\longrightarrow$	0.0537	$\longrightarrow$	0.0499
	(0.0010)		(0.0014)		(0.0013)		(0.0017)		(0.0016)
95 pct.	0.0335	$\nearrow^{**}$	0.0521	$\nearrow^{**}$	0.0588	$\longrightarrow$	0.0600	$\longrightarrow$	0.0593
	(0.0016)		(0.0021)		(0.0032)		(0.0042)		(0.0046)

Predicted interest rates reported as ratios. Predicted standard errors in parantheses below. The market concentration measure and the control variables are all set at their median values when the predictions are calculated. Increasing or decreasing arrows with one and two stars at the end indicate a 10 pct. and 5 pct. difference between two neighbouring predictions. A horizontal arrow indicates no significant difference between the predictions. The differences and their standard errors are calcualted using the estimated model and covariance matrix.

B. The bankruptcy probability model SEBRA[28]

This appendix contains a brief description of the bankruptcy probability model SEBRA. More detailed presentations are given in Eklund, Larsen, and Bernhardsen (2001) and in Bernhardsen (2001).

The SEBRA model is estimated based on annual firm level accounting data covering most Norwegian limited liability firms. Estimating firm level bankruptcy or default probabilities from firms' financial statements has been common in the credit risk literature.[29] Moody's KMV RiskCalc™ (see Dwyer, Kocagil, and Stein (2006)) is also in the same tradition. The SEBRA model predicts the probability that a firm has its last year with a submitted account and within the next three years the firm is registered as bankrupt. All RHS variables, which are either firm or industry specific, are collected from the The Register of Public Accounts at The Brønnøysund Register Centre.[30] In the above-mentioned papers the SEBRA model is estimated using data

[28] We are grateful to Eivind Bernhardsen for providing us with the program used to estimate the SEBRA model.

[29] An early example is Ohlson (1980). A review of the literature can be found in Morris (1997).

[30] Electronic versions of these acoounts have been supplied by Dun & Bradstreet.

from 1990 to 1996. For this paper, however, the data used to estimate SEBRA covers the years 1990 – 2001. Nevertheless, we apply the same model specification as in Bernhardsen (2001) and in Eklund, Larsen, and Bernhardsen (2001). Firms with total assets less than NOK 500,000 ($\approx$ 65,000 euros) are excluded. The total data set used consists of about 836,640 firm observations. The estimated model is a logit model in the predicted bankruptcy probability $\widehat{p}$ with the following RHS variables x_i:

- Earnings
  - earnings in per cent of total assets (tkr)
- Liquidity
  - liquid assets less short-term debt in per cent of operating revenues (lik)
  - unpaid indirect taxes in per cent of total assets (ube)
  - trade accounts payable in per cent of total assets (lev)
- Financial strength
  - equity in per cent of total assets (eka)
  - dummy for the event of book equity less than paid-in capital ($taptek$)
  - dummy for dividend payments the last accounting year (div)
- Industry variables
  - industry average for eka ($meaneka$)
  - industry average for lev ($meanlev$)
  - industry standard deviation for tkr ($stdtkr$)
- Age
  - dummy variable for each of the first 8 years of the firm's age (a_1 to a_8)
- Size

Table B.1: Estimated coefficients

Variable	β	α/δ	$1/\delta$
eka	-1.2283	-0.6970	0.0749
tkr	-1.0750	0.1092	0.2291
lik	-1.1847	3.7600	0.1894
lev	1.2627	0.2518	0.1929
ube	7.6555	1.3233	0.0256
a_1	0.5179	$\cdots$	$\cdots$
a_2	0.5595	$\cdots$	$\cdots$
a_3	0.5222	$\cdots$	$\cdots$
a_4	0.4326	$\cdots$	$\cdots$
a_5	0.3225	$\cdots$	$\cdots$
a_6	0.1914	$\cdots$	$\cdots$
a_7	0.1248	$\cdots$	$\cdots$
a_8	0.1116	$\cdots$	$\cdots$
div	-1.1595	$\cdots$	$\cdots$
taptek	0.5183	$\cdots$	$\cdots$
size	-0.0270	$\cdots$	$\cdots$
meanlev	2.5761	$\cdots$	$\cdots$
meaneka	-4.3491	$\cdots$	$\cdots$
stdtkr	4.2219	$\cdots$	$\cdots$
constant	-10.230	$\cdots$	$\cdots$

– total assets (*size*)

The structure of the model is as follow:

$$\begin{aligned}
\widehat{p} &= \frac{1}{1+e^{-\widehat{y}}} \quad \text{where} \\
\widehat{y} &= \widehat{\beta}_0 + \widehat{\beta}_1 T_1(x_1) + \widehat{\beta}_2 T_2(x_2) + \ldots + \widehat{\beta}_k T_k(x_k) \quad \text{and} \\
T_i(x_i) &= \begin{cases} \dfrac{1}{1+e^{-\left(\frac{x_i-\widehat{\alpha}_i}{\widehat{\delta}_i}\right)}} & \text{if } x_i \in \{eka, tkr, lik, lev, ube\} \\ x_i \quad \text{if } x_i \notin \{eka, tkr, lik, lev, ube\} \end{cases}
\end{aligned}$$

The values of the estimated coefficients are reported in Table B.1 .

All coefficients are significantly different from 0 at significance level of 1 pct., except the coefficient for a_8 which has a p-value of 0.012 and α/δ for tkr with a p-value of 0.235.

As expected $\widehat{p}$ is decreasing in tkr, eka, and lik, and it is increasing in lev and ube. For the first 8 years of a firm's life the model predicts lower bankruptcy probability by each year, except going from the first to the second year. After 8 years, age has by construction no effect on the bankruptcy probability. For the 5 non-linearly transformed variables the marginal effect on $\widehat{p}$ is non-linear in the sense that the absolute value of the marginal effect has a peak around a certain value of x_i.

Syversten (2004) compares the predictive power of the SEBRA model estimated on data from 1990 to 1996, with that of Moody's KMV Private Firm model for Norway.[31] Syversten applies "power curves" and their corresponding "accuracy ratios" to compare the bankruptcy predictions of SEBRA and the default probability predictions of KMV Private to actual bankruptcies for the four years 1998 – 2001 and concludes that SEBRA's accuracy is at least as good as the accuracy of KMV Private.

[31] As KMV Private for Norway only covers about 3,500 firms and the SEBRA model covers more than 100,000 firms the comparison is based on a relatively small sample of the firms in the SEBRA model.

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