Life-Cycle Patterns of Interest Rate Markups in Small Firm Finance*

Moshe Kim
University of Haifa and Universitat Pompeu Fabra

Eirik Gaard Kristiansen
Norwegian School of Economics and Business Administration

Bent Vale†
Norges Bank (The central bank of Norway)

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Abstract

We derive empirical implications from a 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 due to informatonal lock-in until it falls for older firms when lock-in is resolved. By applying a large sample of predominantly 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. Additionally, we examine the effects of concentrated banking markets on interest rate markups. Results indicate that the life cycle of markups is mainly driven by asymmetric information problems and not by concentration. However, we find evidence that bank market concentration matters for older firms.

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† Corresponding author address: Norges Bank, C51, Box 1179, Sentrum, N-0107 Oslo Norway. Fax: +47 22 42 40 62, e-mail: bent.vale@norges-bank.no

1. Introduction

We examine how competition and asymmetric information problems are interlinked in credit markets. Bank monitoring provides banks with reliable private information about borrowers. This information alleviates frictions in credit markets, but also creates lock-in effects and market power for the inside bank.

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 private information, young firms are offered loans with low interest rate markups. By interest rate markup we refer to the difference between the observed interest rate and the break-even interest rate for the bank (i.e., the interest rate that gives the bank zero expected profits). As the monitoring bank obtains private 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 initial bank may decline and thus a downturn of the markup sets in.[1] We consider this cyclical pattern and the decline of the markup in the third period as the novel prediction of the theoretical model. The empirical application that follows explores this prediction.[2] 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 initial bank obtains a larger information advantage from monitoring the borrower.

We test the predictions of our model using a large sample of unlisted small Norwegian non-financial firms during the 2000-2001 period (30,173 firms). To assess the implications of asymmetric information on banks' interest rate markups, we apply a measure

[1]Bouckaert and Degryse (2006) have 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 incumbents' profitable borrowers and reduces their scale of entry.

[2]The existence of the lock-in phenomenon has been explored both theoretically (Klemperer (1995), Sharpe (1990), von Thadden (2004)) and empirically (Ongena and Smith (2000a), Ongena and Smith (2001), Kim, Kliger, and Vale (2003)) in the banking literature.

of asymmetric information that captures the fact that inside banks obtain information about borrowers *before* outsiders do. A bank which does not monitor a borrower cannot observe a firm's assets directly and must instead rely on delayed accounting reports and other publicly available information, for example industry-wide changes in demand. This implies that an inside bank's information advantage is positively related to how rapidly publicly available firm-specific credit quality changes over time in that particular industry. In an industry where firms' credit qualities change slowly, the inside bank's information advantage is, according to our asymmetric information proxy, small.[3]

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 markup reaches a higher maximum value), iii) firms more exposed to asymmetric information problems experience the predicted fall in the interest rate markup at an older age. Additionally, we assess whether bank market concentration contributes to the formation of the observed interest rate markups in addition to information asymmetry. We do not find significant effects from market concentration on interest rate markups for borrowing firms, except for the 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 may play a role in determining interest rate markups facing older firms with smaller asymmetric information problems.

There is a large branch of the banking literature explaining the role of bank-borrower relationships (see Gorton and Winton (2003) and Ongena and Smith (2000a) for good overviews of this literature). Our paper is 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

[3]We do not originate this measure of asymmetric information, but as far as we know it has not been applied in the bank-relationship literature. Duffie and Lando (2001) apply a similar measure of asymmetric information where non-monitoring outsiders obtain delayed accounting reports to explain term structure of credit spreads.

interest rate above the break-even interest rate. Our study complements that of Petersen and Rajan in the sense that we let the competitiveness of the credit market be determined by the monitoring banks' unique access to private information about borrowers. 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 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 non-financial firms. Cetorelli and Gambera (2001), however, report results indicating that younger firms relying on external finance grow faster the more concentrated the banking sector is. A brief overview of this literature can be found in Berger, Hasan, and Klapper (2003). In this paper, we suggest that interest rates charged to young firms are merely determined by asymmetric information problems, while market concentration is more important for interest rates charged to older firms.

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. Since we do not assume that all banks collecting information or monitoring a borrower start lending to the borrower, we do not have any predictions regarding how many banks a firm borrows from or to what extent borrowers switch banks. Our starting point is that, due to fixed monitoring costs, it is unprofitable to have multiple monitoring of a newly established firm. Others have argued that multiple monitoring is made difficult by free-riding problems as in (Thakor (1996)). Carletti (2004) endogenizes banks' monitoring intensities and shows how borrowers, by choosing to borrow from more than one bank, can induce a favourable monitoring intensity. In contrast to Carletti, we introduce a dynamic model that allows the number of monitoring banks to change as firms mature. Furthermore, in our theoretical model, we assume that firms' credit risks decrease 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.[4]

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 when information about borrowing firms is more widely distributed and lock-in effects are weaker.

The paper is organized as follows: 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 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 life-cycle 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 asymmetric information problem between monitoring and non-monitoring banks when they compete for borrowers. By endogenizing the number of monitoring banks, we show how lock-in effects in a bank-borrower relation-

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

ship 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. Although the theoretical model does not capture pure market concentration effects on markups (i.e., market power driven by firms' market shares), we allow for pure market concentration effects 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. For simplicity, we assume that the firm does not have own funds and that it needs to borrow 1 from a bank in each period t, $t \geq 0$.

A project 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.[5]

[5] This assumption has empirical support. See e.g. Ioannidou and Ongena (2006).

2.2. Banks

There are two banks that consider monitoring the firm.[6] 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 improves over time ($s'(t) > 0$), we show in Section 2.3 that it is increasingly profitable for the second bank to start monitoring the borrower.

The monitoring 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 bank. In the last case, the non-monitoring and monitoring banks have the same information about the project. Notice, however, that since the non-monitoring bank does not know that the monitoring bank in this case has no private information, the outside bank fears winner's curse and offers interest rates accordingly.

Competition for borrowers occurs in two stages. First, both banks compete for a borrower by offering their respective interest rates. Second, after observing the interest rates offered by the rivaling bank, the bank with private information about the borrower may make an improved offer to a borrower it wants to retain. If it is a new firm without a monitoring bank, none of the banks make an improved offer at the second stage. This timing assumption captures the idea that borrowers are able to use offers by outside banks to bargain for better conditions from the bank they have a relationship with. Our two-stage model of competition between asymmetrically informed banks is similar to Dell'Ariccia and Marquez (2004).

For simplicity, we assume that firms and banks are risk-neutral and that the risk-free interest rate is 0. Figure 2.1 illustrates the timing of events. Note that a bank that starts monitoring a current project gets information about the next project. All results continue

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

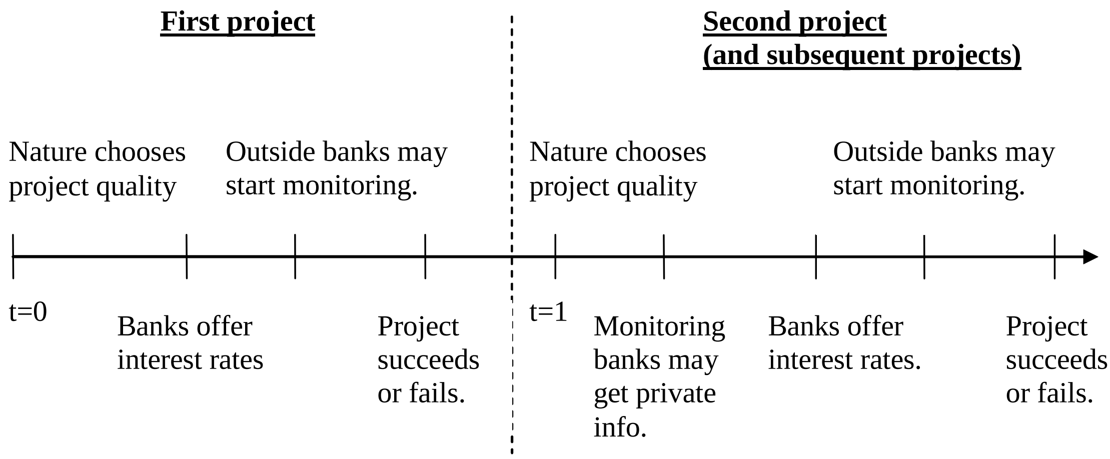

Figure 2.1: The timing of the game

to hold if monitoring starts between projects instead.

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 decrease over time (F decreases). This approach would also make it increasingly attractive for outside banks to start monitoring a borrower. Consequently, this modelling approach would provide empirical predictions regarding the life-cycle pattern of the interest rate markup similar to those we derive below.

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).

In equilibrium, the banks set their interest rates, $r^e(t)$, at date t as described by Proposition 1. The equilibrium outcome is similar to the one obtained in Dell'Ariccia and Marquez (2004)[7]. The main difference is that we consider the case where banks take into

[7]Dell'Ariccia and Marquez (2004) consider a more general setting where banks may have different costs of funds. Our equilibrium is similar to their equilibrium given that banks have the same funding costs.

account future profits (π) when they choose interest rates.

Proposition 1.

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

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

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. The interest rate charged to a borrower with a good project depends on whether more than one bank has this information (probability λ^2),

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

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

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

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. 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 reduced its interest rate below $r^e\,(1 < t \leq T - 1)$, it would start a subgame with three potential outcomes. Consider the first case where 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. Note that $\lambda\,(1-\lambda)$ is 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. The borrower does not need to switch bank or borrow from more than one bank in order to take advantage of increased bank competition. 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 $s'(t) > 0$.[8]

The second bank finds it profitable to start monitoring when the per-period profit exceeds the monitoring costs; $G(T) > 0 > G(T-1)$. Since the per-period profit from monitoring increases over time, $G'(t) > 0$, it follows that T is unique.

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

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

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) on subsidizing the initial loan (Proposition 1 i)).[9]

We now compare the equilibrium interest rate with the break-even interest rate given that the two banks only have access to public information. Denote this break-even interest rate $r^*(t)$,

$$r^*(t) = s(t) \cdot 1/\overline{\theta} + (1 - s(t)) \cdot 1/\underline{\theta} - 1. \tag{2.1}$$

Note that $r^*(t)$ represents the interest rate in a competitive equilibrium were there is no asymmetric information between 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 $r^*(t)$ decreases 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:

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

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

[8] We assume that F is sufficiently small such that there exists a finite T.

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

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

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

Note that the equilibrium interest rate falls from $r^e(T-1) = 1/\underline{\theta} - 1$ to $r^e(T) = \left(1 - \lambda^2 s(t)\right) 1/\underline{\theta} + \lambda^2 s(t) 1/\overline{\theta} - 1$ when the second bank starts monitoring. Recall that $\lambda^2 s(t)$ is the probability that both banks have observed that the project is good and therefore charge an interest rate reflecting a high probability of success.

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 $G(T) > 0 > G(T-1)$ and the assumption that $s'(t) > 0$.

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

$$\begin{aligned} m(t) &= \left(\frac{1}{\underline{\theta}} - 1\right) - \left(s(t)\frac{1}{\overline{\theta}} + (1 - s(t))\frac{1}{\underline{\theta}} - 1\right) \\ &= s(t)\left(\frac{1}{\underline{\theta}} - \frac{1}{\overline{\theta}}\right) \qquad\qquad t \in [1, T-1] \end{aligned}$$

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). ■

The costs associated with monitoring of a particular borrower may vary across banks due to, for instance, geographic distance between the borrower and the bank or different knowledge about the market served by the borrower. So far we have not taken this possibility into account. However, an extension of our analysis would allow for the fact that banks often have different monitoring costs. Let $F_1 < F < F_2$, where F is the average monitoring costs and F_1 and F_1 are the monitoring cost of bank 1 and bank 2. In a competitive market, the bank with the lowest monitoring costs (bank 1) will capture the borrower at date 0 and the bank with the highest monitoring costs will start monitoring as soon as it becomes profitable. Consequently, if the difference in monitoring costs grows while the average monitoring cost is kept constant, the second bank, which has highest monitoring costs, will delay its monitoring decision, which in turn will imply that the lock-in period is extended and the maximum markup is increased.

Another extension would be to let banks become more efficient monitors over time. Both investments in improved information technology as well as bank mergers may reduce banks' monitoring costs. In fact, one of the driving forces behind mergers might be to reduce the costs of monitoring borrowers. In this regard, bank mergers may increase traditional market power measured as market shares as well as market power due to information advantages. This example suggests that banks' information advantages due to monitoring and traditional market concentration might be intertwined in different ways not captured in our simple model.

In our empirical analysis of interest mark ups in different borrower segments, we control for market power due to market concentration and relate differences in mark-ups to differences in monitoring costs and opaqueness of borrowers. We are, however, not able to examine whether access to different costly monitoring technologies can be the driving force behind both different levels of market concentration (economies of scale in monitoring) as well as banks' information advantages.

In the following sections, we examine the life-cycle pattern of interest rate markups for a large sample of small Norwegian firms and compare the empirical results with the predictions of our theoretical model. In the empirical section, we assume that firms with more volatile credit ratings are more costly to monitor in order to get updated credit quality information.

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).

Hypothesis II claims that very opaque firms have low interest markups initially and higher interest rate markups later than less opaque firms. This requires that competing banks have general knowledge about the prevalence of lock-in effects in different industries (level of F) before they make loans. The banks' knowledge about prevalence of lock-in effects in particular industries can be based on previous lending to other borrowers in the same industry or general information about industry characteristics.[10]

In addition to the existing literature on competition in credit markets, 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

[10] Although we claim that more opaque firms will face a lower markup when young than less opaque firms will do, there is one exception to this predicted outcome. If $s\prime(T)$ is sufficiently high, the expected profit of the inside bank will fall as F increases. This is because the increase in monitoring costs are not compensated by a sufficiently large increase in the lock-in period to make the firm's expected profit increase. Hence, in this case, an increase in F will cause higher markups for young firms.

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. In the present paper, we examine directly whether lock-in effects due to the information advantage of an inside bank are 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 also 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 break-even interest rate) paid by firms as the LHS variable. As RHS variables we use the age of the firm (represented by dummies for different age groups, as in Petersen and Rajan (1995))[11], a variable representing the degree of asymmetric information, a variable measuring market concentration in the different geographical credit markets covered by the data, and control variables.

We specify the break-even 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:

[11] See also Zarutskie (2006) for similar practice. In samples where the distribution on the RHS variable is skewed to the left (cf. Table 3.1), representing the variable by groups or splines yields better results than forcing a specific poynomial, e.g., a quadratic form, on the data. This is demonstrated for instance by McAllister and McManus (1993) and Humphrey and Vale (2004) in studies of scale economies in banking.

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

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 break-even interest rate.

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

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

$AINFO$ 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.

[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.

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 firms' head offices, and firms' ages.[14] Data from the SEBRA database is used to predict bankruptcy probability for each firm for the years 1990 to 2001. Here, 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.[15] 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 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 contributions from or to other companies in the same conglomerate. Lending inside a conglomerate is not associated with significant asymmetric information problems. This leaves us with a sample of unlisted, predominantly small firms, firms about which there is little public information, except that available from the Register of Public Accounts. We exclude firms with total assets

[13]The data in the SEBRA database is bought from Dun and Bradstreet, who collect them electronically from the Brønnøysund Register Centre.

[14]Firm's age is the real age of the firm, not just the time since it was transformed into a limited liability company.

[15]This model is equivalent to the one in Eklund, Larsen, and Bernhardsen (2001). A more comprehensive description is given in Bernhardsen (2001). A detailed description of the version of the SEBRA model used in this paper is available as Appendix 1 in the following document at the corresponding authors' website: `http://www.norges-bank.no/templates/article____12492.aspx`

of less than NOK 0.5 million. In several cases such small firms borrow against collateral posted by their owners, for instance their house.[16] We also exclude observations where firms report a debt ratio equal to or larger than 1.

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.[17] Since most loans extended by Norwegian banks have a floating interest rate, we believe our approach to calculating interest rates is more accurate than interest rates from annual loan contracts, had they been available. In 2000 and 2001, the central bank changed its key interest rate five times and once, 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 in interest rates. In some cases, however, calculated interest rates can be misleading due to large changes in loan sizes early or late in the year. To deal with this problem, we trim the data at the 10 and 90 percentiles of the calculated interest rates. It is unlikely that the occurrence of large changes in loan size at the beginning or end of a calendar year should be connected to the nature of bank relationships investigated in this paper. Hence the exclusion of these observations should not bias our results.[18]

Our dataset then consists of 30,173 observations of 19,753 firms over two years. We have 15,247 observations in 2000 and 14,926 observations in 2001. Table 3.1 gives a summary of the main variables used in the empirical model as well as some additional firm characteristics.

Table 3.1 illustrates that there is considerable firm heterogeneity in the sample. The variation in the probability of bankruptcy is reflected in the interest rate markup. There are a few firms in the sample with large negative markups, 4 of which have markups below -10 percentage points. These are firms with high bankruptcy probabilities for which the

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

[17]Bernhardsen and Larsen (2003) use a similar procedure for calculating interest rates on bank loans. They find strong evidence that this a reasonably accurate measure of the interest rate borrowing firms face.

[18]The remaining random measurement errors will be captured by the residuals of the estimated models.

Table 3.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max
Operating income	9,770	54,395	0	6,517,853
Total assets	6,995	69,270	500	$10.8{\cdot}10^6$
Bank debt	2,185	12,728	0	1,526,000
Collateralizable assets to total debt	.5596	.5216	0	2
Total debt to total assets	.7601	.1600	.0023	.9999
Sales growth	18.11	556.04	−.9999	50632
Interest rate	14.13	6.45	7.23	37.50
Interest rate markup	6.33	6.40	−12.62	30.55
Probability of bankruptcy	.013	.0264	.00008	.3623
Volatility of bankruptcy probability	.0160	0.0120	0.0001	0.1826
Firm age	12.6	13.3	1	148
Herfindahl index banks	1663	405	1111	2895
Sum market share of 3 largest banks	62.77	6.79	48.81	78.33

This table refers to the sample used for estimating Model 1 (see Section 4). Number of observations is 30,173. Operating income, total assets, and bankdebt are measured in NOK thousands. Interest rate and interest rate markup are measured as percentage points. Market shares and the corresponding Herfindahl index are also measured as percenatge points. Probability of bankruptcy, measured as a ratio, is predicted from the SEBRA model. Firm age is measured in years. Collateralizable assets to total debt, total debt to total assets, and sales growth are also measured as ratios. For the precise definition of collateralizable assets to total debt, volatility of bankruptcy probability, and the Herfindahl index, see sections 3.3 and 3.4. table of descriptive statistics broken down on different age groups can be obtained from teh authors.

break-even 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.[19] Also note that in view of the way we define the markup as the difference between the actual interest rate charged and the break-even interest rate (cf. (3.1)), it cannot be interpreted as pure profits to the bank. A positive markup will cover the bank's lending costs, other than funding and expected loan lossses, including borrower screening and monitoring costs.

There is also considerable variation in the age of firms. The average firm in the sample is almost 13 years old, and the oldest firm is 148 years. The peak age of firms in our sample is 3 years. The median age is 9 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 4142, or 13.7 per cent of the observations in the sample relate to firms older than 20 years.[20]

[19] Alternatively, a large negative markup can also be due to firms' moral hazard or adverse selection problems which prevent banks from increasing the interest rate.

[20] We do not have information on the individual firm's number of bank relationships. However, empirical

3.3. A measure of asymmetric information

We suggest a novel measure of the severity of information asymmetry between monitoring and non-monitoring banks. In line with our theoretical model, we assume that a monitoring bank obtains private information relevant to a firm's credit quality before non-monitoring banks do. This informational advantage of monitoring banks is particularly valuable in industries where firms' publicly available credit qualities change quickly, and therefore we propose the volatility of the estimated bankruptcy probability in the industry to which the firm belongs as a measure of the monitoring banks' informational advantage over non-monitoring banks. The estimated bankruptcy probability relies solely on publicly available firm information.

Let $p_{i,t}$ be the estimated bankruptcy probability measure of firm i in year t, i.e., the probability that the firm will be bankrupt, say during the next three years. $p_{i,t}$ is estimated from firm-specific data up to and including year t. We regard $p_{i,t}$ as publicly available information, as it is solely based on current and past accounting and balance sheet data that are publicly available through the Register of Public Accounts. To firm i's lender, however, what matters is how the probability of going bankrupt will develop in the coming years. To what extent can the lender rely on the publicly available information about the firm in order to assess that development? If the bankruptcy probability estimated from the publicly available accounting data has shown a steady pattern in the past, it indicates that this information may be quite useful in assessing the future development of firm i's bankruptcy probability. If, on the other hand, the estimated bankruptcy probability has shown a more erratic or volatile pattern, the current publicly available accounting information is less useful for assessing the future bankruptcy probability of the firm. To the extent such volatility merely reflects the overall economy or industry wide business cycles, publicly available macroeconomic or industry wide forecasts may be used. However,

evidence on the number of bank relationships of listed Norwegian firms, as documented by Ongena and Smith (2001), shows that these firms, which are among the largest in Norway, on average have 1.4 bank relationships, whereas the median number is 1. Firms in our sample are significantly smaller than listed firms. Since empirical evidence shows that smaller firms have fewer bank relationships than larger firms (see Ongena and Smith (2000b)), we can safely assume that almost all firms in our sample only have one bank relationship. Furthermore, Farinha and Santos (2002) document that nearly all young firms borrow from only one bank.

if the volatility in the estimated bankruptcy probability is more firm-specific, neither these forecasts nor the publicly available accounting information will be that useful in assessing the future bankruptcy probability of the firm. The larger such firm-specific volatility is, the more important private information about the firm will be in assessing how its bankruptcy probability will develop in the future. This reasoning motivates the measure of the importance of private information we use in this paper. Below, we describe in detail how we calculate the volatility of firm-specific bankruptcy probability for different industries.

Let subscript K denote industry and $n_{K,t}$ the number of firms in industry K in year t. Then

$$p_{K,t} = \frac{1}{n_{K,t}} \sum_{i \in K} p_{i,t}$$

is the average (unweighted) bankruptcy probability of all firms in industry sector K in year t. Define

$$\Delta p_{i,t} = p_{i,t} - p_{i,t-1} \text{ and } \Delta p_{K,t} = p_{K,t} - p_{K,t-1}$$

where $\Delta p_{i,t}$ and $\Delta p_{K,t}$ are firm i's and industry K's change in credit quality from $t-1$ to t, respectively. To capture how an individual firms' change in credit quality deviate from industry wide changes in credit quality we compute $\Delta p_{i,t} - \Delta p_{K,t}$, which we denote by $D\Delta p_{i,t}$. $D\Delta p_{i,t}$ captures the firm i specific change in bankruptcy probability compared with the industry average. Hence, if the development of both $\Delta p_{i,t}$ and $\Delta p_{K,t}$ are quite volatile but the bankruptcy probability of individual firms follows the industry average, then $D\Delta p_{i,t} \approx 0$. Hence, to measure firm-specific volatility in bankruptcy probability we look at the standard deviation of $D\Delta p_{i,t}$ across all the years for which there is publicly available accounting information on firm i, i.e., $\sigma(D\Delta p_i)$.

In implementing this measure empirically, we define each K as the subsection over the two-digit industry code according to SIC(94).[21] Furthermore, since several firms in

[21] We also calculated the volatility measure defining each K as the subsection over one-digit and three-digit SIC(94) industry codes. It turned out that these three volatility measures are highly correlated (0.99). This clearly demonstrates that the larger part of volatility in small firms' publicly known credit worthiness is idiosyncratic. See Campbell, Lettau, Malkiell, and Xu (2001) for similar results regarding daily stock market returns for listed firms.

the data set have only existed for one or two years, instead of using $\sigma(D\Delta p_i)$ for each firm, we calculate the average standard deviation across all firms within the subclass of the five-digit SIC code for each of 19 counties, using annual firm data as far back as 1988. We denote this average standard deviation by $VL_{c,k}$, where c denotes the county and k the five-digit SIC code. If a potential lender observes that a borrower within a certain county belongs to an industry subclass with a high value of the volatility measure $VL_{c,k}$, this is an indication that neither the publicly available accounting information nor macroeconomic forecasts relating to the much larger industry subsection are particularly reliable information in order to asses the future bankruptcy probability of this firm. Hence, private or soft information is more important the higher $VL_{c,k}$ is.[22]

3.4. 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 life-cycle pattern is more pronounced for borrowers in industries where the lock-in effects are stronger due to a larger informational advantage of the inside bank. In order to test these hypotheses we assign firms to 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 8 age groups.[23] Age groups are represented by dummies. Furthermore, we allow the age dummies to interact with our measurement of the severity of asymmetric information.

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

[22] 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 implies that we have to guess to what extent these prediction errors can be foreseen by the inside bank.

[23] Tables containing descriptive data for each age group are available as Appendix 3 in the following document at the corresponding authors' website: `http://www.norges-bank.no/template`

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 to what extent 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:

$$\begin{aligned} m_{i,t} &= \beta_0 + \sum_{j=1}^{7} \beta_j d_{j;i,t} + \gamma_0 VL_{c,k} + \sum_{j=1}^{7} \gamma_j VL_{c,k} \cdot d_{j;i,t} + \delta_0 HI_{c,t} \\ &\quad + \sum_{j=1}^{7} \delta_j HI_{c,t} \cdot d_{j;i,t} + \theta_c controls + \epsilon_{i,t} \quad , \end{aligned} \tag{3.3}$$

where:

$d_{j;i,t}$ $j = 1 \ldots 7$ are dummies for the four firm age groups, 4–6 years, 7–9 years, 10–14 years, 15–19 years, 20–29 years, 30–40 years, and above 40 years, respectively. I.e., 1–3 years is the benchmark group represented by the subscript $_0$ on the coefficients.

$VL_{c,k}$ is our proxy for the severity of the *ex ante* asymmetric information problem in lending to a firm within this particular group of firms, see Section 3.3.

$HI_{c,t}$ 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 are collected from the Norwegian bank statistics produced by Norges Bank.[24] [25]

In addition we include some control variables: $coll_{i,t-1}$ is the ratio of the firm's col-

[24] 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 part of the bank's loans. However, we do not include lending from finance companies, that mainly do factoring and leasing. Debts to these companies will normally not be included in the debt numbers we use to calculate the interest rates paid by borrowing firms.

[25] 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 $HI_{c,t}$.

lateralizable assets to its total debts lagged one year.[26] It is included in order to reduce the inaccuracies implied by assuming all loans to have the same loss given bankruptcy when calculating the risk-adjusted interest rate. The expected sign of its coefficient is negative. We also add firms' debt ratio, $dbtr_{t-1}$, size (total assets), $tass_{t\_1}$, and sales growth, $sgrw_{t-1}$ as control variables.

4. Empirical results

The model (3.3) is estimated using OLS and White robust standard errors also robust to clustering of the Herfindahl index $HI_{c,t}$.[27]

To check robustness of our results, we estimate four versions of the model:

Model 1: The "base" model as described in relation to (3.3).

Model 2: As Model 1, but we drop the control variable $sgrw_{i,t-1}$ which takes some extreme values.

Model 3: As Model 2, but here, rather than using the Herfindahl index as a measure of market concentration in the market for bank loans to all domestic non-financial business borrowers in the county, we use the sum of the corresponding market shares for the three largest banks.

Model 4 As Model 2, but in this model – unlike in the others – we exclude observations where firms have an annual operating income above NOK 100 million (appr. € 12.5 million).[28]

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

[27] 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.

[28] To the extent $coll_{i,t-1}$ is correlated with $p_{i,t-1}$, which is used to calculate our dependent variable, it may bias the results. To check the robustness of our results to this problem, we have also estimated Model 2 without $coll_{i,t-1}$ among the RHS variables. Our main results continue to hold. Due to space limitations, this result is not reported in the paper. However it is available, referred to as Model 5, in Appendix 2 in the following document at the corresponding authors' website: `http://www.norges-bank.no/template`

Table 4.1: Results, dependent variable $m_{i,t}$

Independent variable	Model 1	Model 2	Model 3	Model 4
β_0	13.609*** (17.67)	13.489*** (18.34)	12.670*** (8.76)	13.608*** (18.70)
$d_{1;i,t}$	−.2769 (−0.53)	−.1582 (−0.32)	−.2544 (−0.24)	−.1400 (−0.29)
$d_{2;i,t}$	−.0630 (−0.11)	−.0881 (−0.15)	−.2512 (−0.20)	.0734 (0.12)
$d_{3;i,t}$	.0959 (0.21)	.2184 (0.49)	−.2352 (−0.23)	.1843 (0.42)
$d_{4;i,t}$	1.3048** (2.33)	1.4303*** (2.74)	1.4200 (1.25)	1.4681*** (2.81)
$d_{5;j,t}$	.4116 (0.64)	.5367 (0.87)	.4999 (0.40)	.5277 (0.86)
$d_{6;j,t}$	−.3649 (−0.29)	−.2396 (−0.20)	−.2244 (−0.09)	−.3309 (−0.29)
$d_{7;j,t}$	−2.6090*** (−3.86)	−2.4816*** (−3.96)	−4.8685*** (−3.38)	−2.5252*** (−3.94)
$VL_{c,k}$	−4.1028 (−0.60)	−3.4267 (−0.52)	−2.9750 (−0.45)	−5.1607 (−0.79)
$HI_{c,t}$	−0.0005 (−1.24)	−0.0004 (−1.20)	0.0008 (0.04)	−0.0005 (−1.30)
$coll_{i,t-1}$	−3.3338*** (−32.35)	−3.3378*** (−32.81)	−3.3291*** (−32.51)	−3.2392*** (−29.20)
$dbtr_{t-1}$	−6.7943*** (−28.16)	−6.7962*** (−28.19)	−6.7549*** (−27.99)	−6.7308*** (−28.60)
$tass_{t\_1}$	0.0000 (0.21)	0.0000 (0.22)	0.0000 (0.26)	−0.00003*** (−5.49)
$sgrw_{t-1}$	0.00005 (1.17)	−−	−−	−−
F-test for $HI_{c,t}$ terms	0.0000	0.0000	0.0041	0.0000
F-test for $VL_{c,k}$ terms	0.0000	0.0000	0.0000	0.0000
# clusters	36	36	36	36
# observations	30173	30482	30482	30259
R^2	0.0698	0.0725	0.0720	0.0765

For the sake of brevity we do not report the estimated coefficients of the interaction terms; by themselves these coefficients do not have any interesting economic interpretations. In Model 3, $HI_{c,t}$ represents the sum of the three largest banks' market shares. t-values are reported in the parantehses below the coefficients. The t-values are White-robust and adjusted for clustering of $HI_{c,t}$. * represents a 10 per cent statistical significance, ** 5 per cent significance and *** 1 per cent significance. For the F-test, we report the p-values.

The results reported in Table 4.1 show that all terms that contain our measure of the severeness of asymmetric information, $VL_{c,k}$, are statistically significant for all four versions of our model. Furthermore, the control variables are 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 cannot, however, 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 $VL_{c,k}$. The market concentration measures and the control variables are all set at their sample median value for all the observations. For $VL_{c,k}$ we use the 5 per cent fractile, the 25 per cent fractile, the 50 per cent fractile, the 75 per cent fractile, and finally the 95 per cent fractile. The predictions are shown in Tables 4.2 to 4.5. By comparing cells in these tables horizontally, the *partial* effect of age for a borrowing firm can be detected. Similarly, a vertical comparison between the cells gives the *partial* effect of the importance of asymmetric information, $VL_{c,k}$.

Table 4.2: Predicted markups, Model 1

Volatility fractiles	Age groups, years														
	1–3		4–6		7–9		10–14		15–19		20–29		30–40		Above 40
5 pct.	6.18	$\rightarrow$	6.27	$\rightarrow$	6.60	$\rightarrow$	6.71	$\rightarrow$	6.81	$\rightarrow$	6.91	$\searrow^{**}$	6.19	$\rightarrow$	6.01
	(0.22)		(0.16)		(0.24)		(0.22)		(0.32)		(0.22)		(0.38)		(0.19)
25 pct.	6.16	$\rightarrow$	6.31	$\nearrow^{**}$	6.69	$\rightarrow$	6.81	$\rightarrow$	6.93	$\rightarrow$	7.00	$\searrow^{*}$	6.51	$\rightarrow$	6.22
	(0.22)		(0.16)		(0.24)		(0.23)		(0.30)		(0.19)		(0.34)		(0.17)
50 pct.	6.14	$\rightarrow$	6.35	$\nearrow^{**}$	6.80	$\rightarrow$	6.91	$\rightarrow$	7.06	$\rightarrow$	7.09	$\rightarrow$	6.85	$\rightarrow$	6.44
	(0.21)		(0.17)		(0.25)		(0.24)		(0.29)		(0.19)		(0.31)		(0.18)
75 pct.	6.11	$\nearrow^{*}$	6.41	$\nearrow^{***}$	6.93	$\rightarrow$	7.05	$\rightarrow$	7.23	$\rightarrow$	7.23	$\rightarrow$	7.30	$\rightarrow$	6.75
	(0.22)		(0.18)		(0.26)		(0.26)		(0.29)		(0.21)		(0.32)		(0.24)
95 pct.	6.04	$\nearrow^{*}$	6.54	$\nearrow^{***}$	7.25	$\rightarrow$	7.36	$\rightarrow$	7.62	$\rightarrow$	7.52	$\rightarrow$	8.33	$\rightarrow$	7.43
	(0.28)		(0.24)		(0.32)		(0.32)		(0.33)		(0.37)		(0.47)		(0.44)

Table 4.3: Predicted markups, Model 2

Volatility fractiles	Age groups, years														
	1–3		4–6		7–9		10–14		15–19		20–29		30–40		Above 40
5 pct.	6.10	$\rightarrow$	6.24	$\nearrow^{*}$	6.59	$\rightarrow$	6.69	$\rightarrow$	6.79	$\rightarrow$	6.89	$\searrow^{**}$	6.17	$\rightarrow$	5.99
	(0.21)		(0.16)		(0.25)		(0.25)		(0.31)		(0.22)		(0.38)		(0.19)
25 pct.	6.08	$\nearrow^{*}$	6.28	$\nearrow^{**}$	6.69	$\rightarrow$	6.79	$\rightarrow$	6.91	$\rightarrow$	6.98	$\searrow^{*}$	6.48	$\rightarrow$	6.20
	(0.21)		(0.16)		(0.24)		(0.23)		(0.30)		(0.19)		(0.34)		(0.17)
50 pct.	6.06	$\nearrow^{**}$	6.33	$\nearrow^{***}$	6.79	$\rightarrow$	6.89	$\rightarrow$	7.04	$\rightarrow$	7.08	$\rightarrow$	6.83	$\rightarrow$	6.43
	(0.21)		(0.17)		(0.25)		(0.24)		(0.29)		(0.18)		(0.31)		(0.18)
75 pct.	6.04	$\nearrow^{***}$	6.38	$\nearrow^{***}$	6.92	$\rightarrow$	7.03	$\rightarrow$	7.21	$\rightarrow$	7.20	$\rightarrow$	7.28	$\rightarrow$	6.72
	(0.22)		(0.18)		(0.26)		(0.26)		(0.29)		(0.21)		(0.32)		(0.26)
95 pct.	5.98	$\nearrow^{**}$	6.51	$\nearrow^{***}$	7.22	$\rightarrow$	7.34	$\rightarrow$	7.60	$\rightarrow$	7.50	$\rightarrow$	8.31	$\rightarrow$	7.41
	(0.27)		(0.24)		(0.32)		(0.32)		(0.33)		(0.37)		(0.47)		(0.44)

Predicted interest rate markups reported as percentage points. 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, two or three stars at the end indicate a 10, 5 or 1 per cent statistical significance in the difference between two neigbouring predictions. A horizontal arrow indicates no statistically significant difference between the predictions. The differences and their standard errors are calculated using the estimated model and covariance matrix.

Table 4.4: Predicted markups, Model 3

Volatility fractiles	Age groups, years														
	1–3		4–6		7–9		10–14		15–19		20–29		30–40		Above 40
5 pct.	6.00	$\rightarrow$	6.18	$\rightarrow$	6.54	$\rightarrow$	6.63	$\rightarrow$	6.63	$\rightarrow$	6.83	$\searrow^{**}$	6.13	$\rightarrow$	6.07
	(0.19)		(0.14)		(0.22)		(0.19)		(0.29)		(0.21)		(0.37)		(0.19)
25 pct.	5.98	$\rightarrow$	6.22	$\nearrow^{**}$	6.63	$\rightarrow$	6.72	$\rightarrow$	6.76	$\rightarrow$	6.92	$\searrow^{*}$	6.43	$\rightarrow$	6.28
	(0.18)		(0.14)		(0.21)		(0.19)		(0.28)		(0.18)		(0.32)		(0.15)
50 pct.	5.96	$\nearrow^{*}$	6.26	$\nearrow^{**}$	6.73	$\rightarrow$	6.83	$\rightarrow$	6.89	$\rightarrow$	7.02	$\rightarrow$	6.77	$\rightarrow$	6.51
	(0.18)		(0.15)		(0.21)		(0.20)		(0.27)		(0.17)		(0.29)		(0.14)
75 pct.	5.94	$\nearrow^{**}$	6.32	$\nearrow^{***}$	6.86	$\rightarrow$	6.97	$\rightarrow$	7.06	$\rightarrow$	7.16	$\rightarrow$	7.22	$\rightarrow$	6.82
	(0.20)		(0.16)		(0.23)		(0.22)		(0.26)		(0.20)		(0.30)		(0.19)
95 pct.	5.89	$\nearrow^{**}$	6.45	$\nearrow^{***}$	7.17	$\rightarrow$	7.28	$\rightarrow$	7.47	$\rightarrow$	7.46	$\rightarrow$	8.24	$\rightarrow$	7.51
	(0.26)		(0.22)		(0.28)		(0.28)		(0.32)		(0.37)		(0.46)		(0.40)

Table 4.5: Predicted markups, Model 4

Volatility fractiles	Age groups, years														
	1–3		4–6		7–9		10–14		15–19		20–29		30–40		Above 40
5 pct.	6.16	$\rightarrow$	6.33	$\rightarrow$	6.66	$\rightarrow$	6.75	$\rightarrow$	6.91	$\rightarrow$	7.00	$\searrow^{*}$	6.40	$\rightarrow$	6.16
	(0.21)		(0.16)		(0.25)		(0.21)		(0.30)		(0.22)		(0.37)		(0.20)
25 pct.	6.13	$\rightarrow$	6.36	$\nearrow^{**}$	6.75	$\rightarrow$	6.84	$\rightarrow$	7.02	$\rightarrow$	7.09	$\rightarrow$	6.69	$\rightarrow$	6.36
	(0.20)		(0.16)		(0.24)		(0.22)		(0.29)		(0.18)		(0.33)		(0.18)
50 pct.	6.11	$\rightarrow$	6.40	$\nearrow^{**}$	6.85	$\rightarrow$	6.95	$\nearrow^{**}$	7.15	$\rightarrow$	7.18	$\rightarrow$	7.02	$\rightarrow$	6.58
	(0.21)		(0.17)		(0.24)		(0.23)		(0.28)		(0.17)		(0.31)		(0.19)
75 pct.	6.07	$\nearrow^{**}$	6.44	$\nearrow^{***}$	6.99	$\rightarrow$	7.08	$\nearrow^{**}$	7.31	$\rightarrow$	7.30	$\rightarrow$	7.45	$\rightarrow$	6.87
	(0.22)		(0.18)		(0.25)		(0.24)		(0.28)		(0.20)		(0.31)		(0.26)
95 pct.	5.98	$\nearrow^{**}$	6.55	$\nearrow^{***}$	7.30	$\rightarrow$	7.39	$\rightarrow$	7.68	$\rightarrow$	7.59	$\rightarrow$	8.44	$\rightarrow$	7.54
	(0.27)		(0.24)		(0.31)		(0.30)		(0.34)		(0.37)		(0.46)		(0.49)

Predicted interest rate markups reported as percentage points. 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, two or three stars at the end indicate a 10, 5 or 1 per cent statistical significance in the difference between two neigbouring predictions. A horizontal arrow indicates no statistically significant difference between the predictions. The differences and their standard errors are calculated using the estimated model and covariance matrix.

Results for all our four models show that all firms pay a lower interest rate markup when they are young (1–3 and 4–6 years) than when they belong to the next age group (7–9 years), irrespective of the degree of opaqueness. These differences are both statistically and economically significant for Models 1–3.[29] For firms with a value of the opaqueness measure, $VL_{c,k}$, up to and including the 25 per cent fractile, the interest rate markup stays high until it falls significantly between the age groups 20–29 years and 30–40 years. In Model 4, this is only the case for the 5 per cent fractile. 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 markup,[30] thereafter it increases and finally falls for the older firms.

Results in Tables 4.2 to 4.5 also demonstrate that this life-cycle pattern is more pronounced for more opaque firms, to the extent that firms in the age group 7–9 years and older have higher markups the larger their degree of opaqueness is. This difference is economically and statistically significant, except for the age group 20–29 years where it lacks statistical significance.[31] However, the differences in markups across the degree of opaqueness within the two youngest age groups (1–3 and 4–6 years) are not statistically significant. These results yield some support to Hypothesis II.

For firms with an opaqueness measure at the 50, 75, and 95 per cent fractiles, we do not detect any statistically significant fall in the markup for firms older than age group 20-29, as we do with the less opaque firms. These observations indicate 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.

The terms in Table 4.1 which include the market Herfindahl index ($HI_{c,t}$) or the market shares, capture effects on markups from market concentration in credit markets. To check

[29] In Model 3, the p-value for this significance test for the 5 per cent fractile is 0.109 between age groups 4–6 and 7–9 years.

[30] 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 problem, can be consistent with the prediction of our theoretical model (the bank loses money on a borrower early on).

[31] The statistical significance of the effect of increased opaqueness inside an age group is checked by calculating $\widehat{\gamma}_0 + \widehat{\gamma}_j$, and the standard errors for $j = 1....7$ using the covariance matrix of the estimated coefficients.

whether these concentration measures are statistically significant for any of the age groups, we consider the significance of δ_0 and $\delta_0 + \delta_j$ for $j = 1 \ldots 7$. In all the Models 1–4, we do find a positive and significant effect of market concentration on the markups for firms older than 40 years. 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 an effect. In Models 1, 2, and 4, where we use the Herfindahl index, we get a negative and statistically significant effect of higher market concentration for the age group 15–19 years. Nevertheless, this result is not robust to use of another market concentration measure, the sum of the three largest banks' markets shares, applied in Model 3. For all the other age groups the effect of market concentration on the markup is statistically insignificant in all the four models. Thus, we do not get support for Hypothesis IV, predicting that the life-cycle pattern of the interest rate markup is more pronounced the higher the market concentration is.

Our results demonstrate that the informational advantage of the inside bank, and not market concentration, creates lock-in effects. These results are robust across our four model versions. Traditional measures of market concentration, like the Herfindahl index or the sum of the three largest banks' market shares, 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 document by the OECD (2006) surveying this literature reports mixed results regarding the effect of the Herfindahl index (or related indices) on loan rates.[32]

5. 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 interest rate markups to young firms. The monitoring inside bank – the

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

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 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, than to their market share per se. We find, though, some 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.

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