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Monitoring and market power in credit markets

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Abstract

Whether or not banks are engaged in monitoring of customers (information acquisition) may have important consequences to the whole economy. Theory suggests an inverse relation between both average loan interest rates and credit losses, and banks' investments in monitoring. In contrast, investments in market power result in a direct relation. These predictions are tested using panel data on Finnish local banks. We find evidence that banks' investments in branch network density and human capital (personnel) contribute more to monitoring than to market power. We also find that managing the money transactions of customers enables banks to better control risks in their lending.

JEL classification: D21; G21; L15

Keywords: Banks; Credit losses; Information acquisition; Human capital; Location; Market power

1. Introduction

A well-established literature shows that banks earn rents. For example, Fama (1985) and Cosimano and McDonald (1998) show that banks exist despite having higher marginal costs than alternative sources of finance. Further, Neven and Röller (1999) find strong evidence of cartel-like behavior using a sample of European countries. We take banks' ability to earn rents as one starting point of our analysis. A second observation on which we build is that a growing but separate strand of literature suggests that banks operate in peculiar ways as a source of financing, and that this has to do with their ability to solve

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information (and agency) problems.[1] The objective of this paper is to empirically study in a unified framework whether certain banks' investments in assets involving fixed costs, such as a branch network (local presence) and human capital (of personnel), are investments in market power, or investments to solve information problems.

A stream of theoretical literature suggests that banks' *raison d'etre* is to collect and analyze information, or monitoring as it is often called.[2] Whether banks are indeed engaged in such activities may have significant consequences outside the industry itself: banks' (in)ability to solve informational problems may for example affect the severity of the effects of macro-level shocks (e.g. Greenwald and Stiglitz, 1993; Holmström and Tirole, 1997). It is therefore of importance to know whether, and through which assets, banks collect and process information.

A central feature of monitoring is that it most likely necessitates fixed investments (but see Petersen and Rajan, 1994, and Section 4). Notwithstanding recent investments in electronic banking, the most obvious such investments of commercial banks are their branch network, and the human capital of their personnel. In this paper, we argue that branch network and human capital are essential prerequisites for a bank to be able to acquire information. Monitoring necessitates personnel who can collect and analyze information, and investments in human capital increase the capability of a bank's personnel to deal with these tasks. Information is often local, and therefore a local presence (in the form of a branch) may facilitate the collection of such information. The obvious alternative explanation that these investments are made to gain market power, either in the deposit and/or the loan markets.[3]

In the next section, we discuss the correlation that monitoring and market power investments generate between different bank level measures of investment, and measures of bank performance. After discussing the relevant theories, and the hypotheses that they generate, we build a reduced form econometric model that allows us to test the predictions using data from Finnish cooperative banks. In addition to suiting well to our needs, our data set also nicely complements previous empirical work that almost exclusively has used US (and sometimes UK) data.

Anticipating, we find evidence that both branch density and personnel costs per branch, our proxies for investment in local presence and human capital, respectively, are negatively and significantly correlated both with credit losses, and average loan interest rates. These results support the hypothesis that these fixed investments of banks contribute more to monitoring than to market power.

The remainder of this paper is organized as follows. In Section 2, we outline (as mentioned above) the predictions that the two theoretical strands of the banking literature yield for the correlation between banks' fixed investments and selected measures of bank

[1] See the excellent survey of Berger and Udell (1998) and the references therein.

[2] For a textbook treatment, see Freixas and Rochet (1997).

[3] In this paper, we abstract from the alternative motivation for fixed investments that arises from the deposit side. By offering deposit customers more conveniently located and/or faster services, a bank may be able to attract deposits at lower interest rates. We control for the deposit side in the empirical model by including deposit interest rate(s) and the deposits' share of total bank funding as (potentially endogenous) explanatory variables. See for example Calem and Nakamura (1998) for an empirical study of branch proliferation and the deposit market.

performance. In Section 3, we describe the environment in which the banks of our sample operate as well as the bank-level data. In Section 4, we present our econometric model and in Sections 5 and 6 we report our econometric results. Brief conclusions are offered in Section 7.

2. Theory

2.1. Monitoring hypotheses

Asymmetric information naturally creates incentives for the less-informed party to acquire information. The acquisition of information can happen in a variety of ways, depending on the nature of the information asymmetry. Freixas and Rochet (1997, p. 29) categorize monitoring into: (i) ex ante (screening of projects to deal with adverse selection), (ii) interim (preventing moral hazard) and (iii) ex post (punishing or auditing a debtor who fails to meet the debt service obligation).[4]

Banks collect a wealth of quantitative information that may be analyzed rather mechanically (e.g. through credit scoring). However, in practice banks often complement such information with qualitative information, which is best processed by humans, not machines. Such information may be more circumstantial, like knowing the state of the local economy, and being on top of news regarding the performance of local small businesses. We therefore hypothesize that the more a bank invests in information acquisition, the better the quality of its lending (see, e.g., Broecker, 1990; Gehrig, 1998; Hauswald and Marquez, 2003). In particular, the more a bank has human capital, the better it is able to monitor borrowers. Likewise, the denser is a bank's branch network, the better it is able to gather local information, and the better it is able to monitor.

To see how improved monitoring affects bank performance, compare a bank that is able to monitor customers to a completely uninformed bank who is forced to make the inference that every customer is identical. Assume, further, that customers are heterogeneous with respect to their default probability. The effect of knowing (better) the type of a credit customer means that the informed bank can attract ("choose") those with lower risks as long as it offers such customers contracts that they prefer over contracts offered by the less well-informed competitor. The simplest way to improve the contract is to lower the interest rate. The uninformed bank cannot match the interest rate offer as it can at most offer the interest rate it would offer to a customer with an average default probability. Actually, its situation is worse. As it rationally anticipates that the informed bank keeps all the low-risk customers, the interest rate that it offers is one that allows it to break even when lending to high-risk customers only. The informed bank will be happy to offer loans to high-risk customers, too, but only at an interest rate that allows it to at least break even.

[4] For theoretical models of each of these, see e.g., Broecker (1990), Holmström and Tirole (1997), and Gale and Hellwig (1985).

Therefore, the informed bank will, on average, charge lower interest rates than an uninformed bank.[5]

If the interest rate effect were the only one, investments in monitoring would not be profitable.[6] The effect that makes them profitable is that the informed bank has a clientele that is of better quality on average than that of the uninformed bank. This quality difference arises either because the informed bank screened out bad applicants and therefore faced fewer defaults (adverse selection), or was more effective at monitoring on-going projects of customers (moral hazard), or was able to recapture more from defaulted customers (costly state verification).

We argue that larger investments in certain types of assets involving fixed costs—such as branch network and human capital of personnel—lead to more accurate information. One way of approaching the question of how increases in investments affect the equilibrium interest rate and credit losses is to assume that a given level of investments allows a bank to sort out a given number of customers. With respect to the remaining customers, the bank is as (un)informed as its rivals. By investing more, the bank can sort a larger number of customers. This discussion yields the following monitoring hypotheses:

Hypothesis 1a. The higher a bank's investment in human capital (local presence), the lower its credit losses relative to the amount of loans granted.

Hypothesis 2a. The higher a bank's investment in human capital (local presence), the lower its average interest rate.

2.2. Market power hypotheses

An old and plentiful (e.g. Klein, 1971; Degryse, 1996) banking literature argues that banks' source of rents stems from industrial organization-type sources of an oligopolistically small number of firms, product differentiation, and/or price discrimination (that is not based on customer risk characteristics). The predictions from this literature are very different to those derived above: The Industrial Organization literature predicts that the higher the level of investments, the higher the price (here, the loan interest rate). In Hyytinen and Toivanen (in press), we show that in a vertical differentiation model a fixed investment in quality leads to an increase in credit losses even after conditioning on the loan interest rate.[7] The reason for this increase is that customers with a lower success probability put relatively less weight on the loan interest rate (which they only pay in case of success) and relatively more weight on the quality of service (which they receive irrespective of project outcome). In other words, a positive correlation may emerge due to

[5] For sake of brevity, we have omitted formal modeling here. It should be noted, however, that the non-existence of pure strategy equilibrium often characterizes simultaneous move games where bidders have asymmetric information (see Broecker, 1990; Hauswald and Marquez, 2003). Here, we are implicitly assuming a sequential game where the informed bank is a first-mover with some positive probability (for a formal model, see the previous version of this paper (Hyytinen and Toivanen, 2000).

[6] Consistent with this argumentation, there is evidence that relationship lending leads to lower loan rates (see Berlin and Mester, 1998, p. 579 and the references therein).

[7] Were borrowers heterogeneous with respect to the cost of state verification and the probability of default endogenous, similar insights would follow (see the previous version of this paper; Hyytinen and Toivanen, 2000).

the less creditworthy borrowers self-selecting into the bank charging a high interest rate in exchange for the quality of service it offers. As long as customers' tastes for quality are not systematically correlated with the quality of their projects, no correlation between credit losses and fixed investments arises. Such correlation may, however, be induced through the selection of quality.

The foregoing discussion yields the following market power hypotheses:

Hypothesis 1b. A bank's investment in human capital (local presence) has no or a positive effect on credit losses.

Hypothesis 2b. The higher a bank's investment in human capital (local presence), the higher its average interest rate.

It is these market power hypotheses that we contrast with the monitoring hypotheses in the empirical section. It is important to note that because a reconciliation of the theories (or sets of hypotheses) is possible and because we rely on reduced form estimations, we will only be able to estimate the "net" effect of monitoring and market power as motivations for fixed investments.

3. The data

3.1. The cooperative banks

To test our hypotheses, we need data with variation in the environment in which the banks in the sample operate. Such variation leads to variation in the optimal level of investments in monitoring. However, as we have already pointed out, banks may operate in different ways. We would therefore want to have a sample of banks that are likely to use their fixed investments similarly, what ever that use.

The data that we use consist of Finnish cooperative banks.[8] If anything, they are small and local. For several reasons, this data should provide a good test bed for us. Being local means that they operate in small, non-overlapping markets, and therefore do not compete with each other. The latter point implies that their investments should be independent of each other. The markets of cooperative banks, as documented below, differ markedly, and one would therefore expect optimal investment levels in monitoring to differ, too. Banks' observed investments indeed vary both in the cross section and time-series dimensions of the data. Being all cooperative banks, and sharing a common culture, means that they are more likely to use their fixed investments similarly than would be the case in a random sample of banks.[9]

[8] We describe the general environment in which the sample banks operate in the Appendix (available at http://www.mgmt.purdue.edu/centers/ijio/eo/eosup.htm). Here, we describe the banks themselves and the specific markets on which the banks operate in.

[9] A comparison of the nationwide branch networks of different banking groups reveals that as a group, the cooperative banks have by far the largest branch network. The branch network of the largest Finnish bank, called then Merita, is roughly two thirds or less of that of cooperative banks combined. This supports our assumption that these are the banks that have made (larger) fixed investments.

Besides being small and local, cooperative banks share a common organizational form and some institutions. For example, they own a "central bank", have an association that collects and disseminates information, and share other facilities usually found in the headquarters of a bank. Though most decision making power is at the level of individual banks, group coherence and guidelines from the common bodies affect sometimes strongly the behavior of individual banks. During the boom years of the late 1980s, the cooperative banks were among the conservative: as an example, the volume of their lending grew less than that of deposit banks on average. They also experienced a smaller surge in the amount of bad loans during the crisis in the early 1990s (see, e.g., Koskenkylä and Vesala, 1994).

Compared to other banking groups, cooperative banks are clearly more focused on private customers, agriculture, and small business.[10] As a matter of fact, cooperative banks are the biggest source of loans to agriculture and SMEs. Given the special nature of agricultural loans, one could conjecture that banks with a large geographical branch network are those operating on the countryside, and that these banks direct a relatively larger proportion of their loans to agriculture. As these loans are guaranteed by the government, we might observe a spurious correlation between the branch network and credit losses and interest rates, respectively. We address this question in the econometric analysis.

The fact that these banks are cooperatives, not explicitly profit maximizing institutions, suggests that one may have to worry about using theories based on the latter premise in generating hypotheses characterizing the behavior of institutions of the former type. In the Appendix, we discuss in detail why this should not be a problem.

3.2. Descriptive statistics: the banks

There are 250 banks in our data, and the data covers the period 1992–1996. We use a relatively short and recent panel to exclude the 1980s, as the consensus view is that banks then had not yet learned to operate in a liberalized environment. Another reason is to allow time for banks to adjust their branch networks and personnel to levels that are optimal under deregulated conditions; such adjustments necessarily take time.

The descriptive statistics of our sample are given in Table 1.[11] Although these banks share several features, they are a rather diversified group: the smallest bank's loans amount to just over 6 million FIM (FIM ≈ 1/6 EUR) whereas the largest one's are almost 4000 million FIM, with the mean at 257 million.[12] On average, the banks

[10] The cooperative banks were originally established to channel government loans to small farms which had difficulties getting loans from established banks. This was the main line of business until the 1950s (personal correspondence with historian Antti Kuusterä). The prevailing legislation has guaranteed the loans made to farms. These therefore do not expose banks to credit risk. The cooperative banks' joint market share of SME lending is circa 40%.

[11] The macroeconomic conditions vary markedly over our observation period. We have therefore checked the year-wise descriptive statistics of our banking variables for any anomalies and/or outliers without finding any (see the Appendix).

[12] It is naturally true that bank-level averages may hide wide variation. For two reasons, this should not be a great concern. First, our sample selection conditions out all but cooperative banks, and as discussed above, they are much more homogenous than banks in general. Second, and more important, our theoretical predictions are concerned with bank-level averages.

Table 1
Descriptive statistics of banks

Variable definition	Mean	S.D.
DEP = The amount of deposits in year *t*, in million FIM	293.56	486.47
LOAN = The amount of credit market loans in year *t*, in million FIM	258.47	474.90
R_D = Deposit interest rate in year *t*, calculated as interest rate expenses/amount of deposits	0.0390	0.0184
R_L = Loan interest rate in year *t*, calculated as interest rate income/amount of outstanding loans	0.0933	0.0166
R_{DM} = Interbank market deposit interest rate in year *t*, calculated as interest rate expenses/amount of interbank market deposits	0.0650	0.0194
RDEP = Ratio of deposits to total funding	0.8551	0.0851
R_{LM} = Interbank market loan interest rate in year *t*, calculated as interest rate income/amount of outstanding interbank market loans	0.0556	0.0216
DEFR = Net charge-offs in year *t*/amount of outstanding loans in year *t*. In the estimations, we use DEF = ln(0.000001 + DEFR)	0.0141	0.0201
BRANCH = # Branches of the bank in year *t*	3.472	9.761
BRA = The number of branches at the beginning of year *t* divided by the size (in square kilometers) of the market area	0.0079	0.0157
PERS = The amount of personnel expenses in year *t*, in million FIM divided by the number of branches at the beginning of year *t*	3.2621	6.2004
INEFF = Ratio of non-interest expenses in year *t* to non-interest revenues	0.7126	0.3012
SBFD = Dummy variable taking value of 1 for 1993–1995 if the bank bought a part of the dismantled SBF-bank in 1993	0.3104	0.4628

Data provided by the Central Bank of Finnish Cooperative Banks; all data on bank level, period 1992–1996. There are 250 banks in the data.

seem to have slightly higher deposits (mean 284 million) than loans. We have calculated four interest rates; two are revenues [loans, and loans made (mainly) to other banks (inter-bank lending)]. The latter also contains revenues from investments in government bonds, etc.), two are costs [deposits, and loans from other banks (inter-bank borrowing)]. The deposit interest rate is lower than that of inter-bank borrowing, although there is bank-level variation. The reverse applies for loans granted. Banks receive a clearly higher interest rate for loans granted to customers, than from inter-bank lending.

One of the variables of most interest in this study is the level of credit losses; they are measured by net charge-offs, i.e., the difference between loans actually written off and recoveries from loans previously categorized as uncollectible. As, e.g. in Angbazo (1997), it will serve as a proxy for asset quality and expected (relative) credit losses and we have calculated it as a percentage of loans given (excluding inter-bank loans).

The percentage of credit losses ($DEFR_{it}$) varies between 0% and 18.5%, with a mean of 1%.[13]

In autumn 1993, the Savings Bank of Finland (SBF) was dismantled through a sale of parts of its balance sheet (loans and deposits) and branches to its rival banks (see, e.g. Vihriälä, 1997, for details).[14] In our sample, 97 banks were involved in this, and we control for this in the estimations through an SBF dummy (SBFD) (see Table 1).

The most direct way of measuring local presence is the number of branches. This varies between 1 and 46. A total of 478 bank-year observations (38% of the sample) have just one branch. Out of 250 banks, 62 (25%) always have one branch, and 27 (11%) have one branch for 4 years out of 5. These 89 banks account thus for 87% of the observations with one branch. Note that the fact that we include a measure of bank human capital into the estimation equation allows us to deal with the fact that some banks only have one branch by controlling for the (average) size of the branch(es). As our main measure of service accessibility/quality and banks' ability to gather local information, we use the number of branches at the beginning of the year per square kilometer (BRA_{it}). It varies between 1.212×10^{-5} and 0.154 (with a mean of 0.008). Following Evanoff (1988) who strongly argues against population based measures of branch density, the idea behind this definition is that geographical proximity matters. If a bank operates in a geographically large market where the customers are disbursed, it is not enough to have a large branch at the center, if one wants to acquire information. The same applies for investments in quality: customers may value a large, geographically disbursed branch network that allows them easier access to services.[15]

To take into account that given geographical proximity, a branch is more effective in providing services and/or monitoring, the more (and better trained) staff it has, we use as another measure of fixed investments personnel expenses per branch ($PERS_{it}$). It varies from 0.018 to 61.014 million FIM per branch.

Hypotheses 1 and 2 propose a relationship between bank level investments (BRA_{it} and $PERS_{it}$) and credit losses and the average loan interest rate. We have looked at their conditional distributions. These suggested that there is some, but no overwhelming evidence, for our Hypothesis 1a, speaking thus against Hypothesis 1b. Further, the conditional distributions provide very little evidence for our Hypotheses 2a or for 2b (see the Appendix).

[13] This variable includes credit losses, both realized and estimated, from various periods, and is therefore most likely a noisy measure of credit losses. We therefore use estimation methods that take measurement error into account. There are a few observations with a negative DEF. These are the result of recoveries and banks making reservations against future profits when customers default: in essence, the banks deduct their estimate of loss from current period's profits. If the loss is overestimated, the difference can be deducted from profits later on.

[14] There has also been some consolidation between the cooperative banks. Whenever two or more banks have merged, our data treats them as if they had merged prior to our observation period. A merger dummy did not come up significant in the estimations.

[15] The most obvious alternative way to measure branch density is to use a population based measure: We test the robustness of our results by using as an alternative to BRA_{it} the variable BRA_p, defined as the number of branches per population.

Table 2
Descriptive statistics of markets

Variable definition	Mean	S.D.
POPULAT = Total population	18.197	36.575
DENS = Ratio of population to the size (in square kilometers) of the area	24.407	62.868
OWNH = Ratio of persons living in their own house to total population	0.298	0.025
FARM = Number of farms	484.445	516.401
WCAP = Taxable wealth per capita	52.248	11.773
UN = Unemployment rate	0.202	0.047
STUDENT = Ratio of students to total population	0.077	0.013
EDUC = Ratio of persons having an MSc/MA or a PhD degree to total population	0.057	0.018
AGRIC = Ratio of workforce working in farming, fishing and other agricultural industries to total workforce	0.275	0.149
SERCON = Ratio of workforce working in services, construction business and manufacturing industry to total workforce	0.322	0.106
OUTSIDE = Number of persons in employment inhabiting the market area but working outside the area	0.155	0.087

Data provided by Statistics Finland; period 1992–1995.

3.3. Descriptive statistics: the markets

As to the operating environment of cooperative banks, they operate in different, non-overlapping markets. These markets are well defined, i.e., in line with what the banks themselves do, a bank's market is identified to consist of those counties in which it has branches. Typically, there are only very few competitors in the market so that competitive conduct is approximately duopolistic. Most often the rival is either a savings bank, or one of the nationwide commercial banks, and only in larger cities is this approximation weaker.

In Table 2, we present descriptive statistics of the markets the banks operate in. This demographic and socio-economic data is available to us only for 1992–1995. As can be seen, the markets vary in terms of population (and its density), average wealth, in the number of farms (or the proportion of workforce employed in agriculture), unemployment rate, and average education level.

4. The econometric model

4.1. The model

A central feature of our identification strategy is that our sample is special in that the banks operate in a similar way, and that they operate in different, non-overlapping markets. Our data supports the assumption that at least as group cooperative banks have made fixed investments. The common ownership form and other shared features suggest that they use their fixed investments for the same purpose(s), be it monitoring, market power, or something else.

We estimate the following dynamic reduced form equations for credit losses (DEF_{it}) and loan interest rates (INTL_{it}):

$$\begin{aligned}\mathrm{DEF}_{it} = {} & \alpha_D \mathrm{DEF}_{i,t-1} + \beta_{D1}\mathrm{LOAN}_{it} + \beta_{D2}\mathrm{INTL}_{it} + \beta_{D3}\mathrm{INEFF}_{it} + \beta_{D4}\mathrm{BRA}_{it} \\ & + \beta_{D5}\mathrm{PERS}_{it} + \mu_{Di} + \gamma_{Dt} + v_{Dit} \end{aligned} \tag{1}$$

$$\begin{aligned}\mathrm{INTL}_{it} = {} & \alpha_I \mathrm{INTL}_{i,t-1} + \beta_{I1}\mathrm{LOAN}_{it} + \beta_{I2}\mathrm{DEF}_{it} + \beta_{I3}\mathrm{INEFF}_{it} + \beta_{I4}\mathrm{BRA}_{it} \\ & + \beta_{I5}\mathrm{PERS}_{it} + \beta_{I6}\mathrm{INTD}_{it} + \mu_{Ii} + \gamma_{It} + v_{Iit} \end{aligned} \tag{2}$$

where t=1992,...,1996 and i=1,..., 250. In these equations, the $\gamma_{jt}(j=D,I)$ are time dummies, and v_{jit} are i.i.d. error terms. The time dummies should capture the effects of any economy-wide shocks on loan pricing and credit losses (especially important in the early years of our sample). The μ_{ji} are firm-specific effects, possibly correlated with explanatory variables, which control for bank and market-specific unobservables. The most important market (bank)-specific unobservables are the (average) riskiness of loan customers and the average expected value of their projects, and (possibly) the scope for managerial rent-seeking. To the extent to which behavioral patterns and competitive pressures of the rival banks are time-invariant, μ_{ji} controls also for the competitive situation of the market. Given that our sample only includes cooperative banks, sample selection is a potential issue. By allowing for fixed effects, this particular persistent feature (and its implications for bank behavior) can under certain conditions be controlled for (see, in particular, Bond and Meghir, 1994, p. 209 and the references therein).

The once lagged endogenous variables are included to capture any adjustment processes in banks' pricing behavior and gradual realization of loan losses. In addition, as relationship banking would mean that customers tend to stay at the same bank, one wants to control for past behavior as this reflects the quality of those customers who have a relationship with the bank. As to other explanatory variables, the variable LOAN_{it} is included to control for the size of a bank (its loan book). The size of a bank is an especially important control for the following reasons: size may allow a bank (i) to gain reductions in costs; (ii) to enjoy economies of scope, for example, by facilitating cross-selling of products; (iii) to better diversify its loan book; (iv) to achieve lower funding costs (this we control also separately: see below); and (v) to increase the likelihood of a government bailout (see the Appendix: in Finland, all banks were guaranteed by the government during the crisis in early 1990s. Therefore, this reason plays no role with our data).

The remaining control variables are as follows: INEFF_{it} (ratio of non-interest expenses to non-interest revenues) is included as a summary variable to control for (i) the (in)efficiency of management, (ii) implicit interest rates (possibly) charged in the form of fees on loans and commissions and (iii) income smoothing. As these (mixed) effects are all represented by INEFF_{it}, and since this summary variable also probably proxies the extent to which banks are engaged in other operations besides traditional loan business, its sign is not predicted. The cost of funding, INTD_{it}, and the proxy for expected credit losses, DEF_{it}, are included in the interest rate equation and they are predicted to have positive coefficients. We do not model deposit-market-related reasons for fixed investments.

$INTD_{it}$ controls for the indirect effects of such investments were they to exist. Theory drives the inclusion of the loan interest rate $INTL_{it}$ in the credit loss equation, and its effect on credit losses should be positive. The credit loss equation also contains the SBF-dummy.[16]

Finally, branch density (BRA_{it}) and personnel costs per branch ($PERS_{it}$) measure the extent to which a bank has invested in local presence and human capital, respectively. It is important to control for both forms of investment, as both are needed for a bank to be able to monitor (or to gain market power). We want to control for human capital investments, as empty branches yield no informational benefits. Conditional on the level of investments in human capital, a denser branch network should lower both average loan interest rates and credit losses if branches are used for monitoring. Similarly, the larger the branch density, the more effective the human capital per branch is in acquiring information. Conditioning on the level of human capital also allows us to deal with the fact that some banks have only one branch, as these variable controls for the size of the (average) branch. Similar reasoning applies were BRA_{it} and $PERS_{it}$ investments in market power.

One cannot interpret the interest rate equation as a supply equation as we are lacking the usual (see, e.g. Neven and Röller, 1999) cross-equation parameter restrictions to a demand function, and because we do not have measures of input prices (or even proxies thereof) at our disposal, apart from the deposit interest rate. Therefore, our quantity variable (amount of loans) may capture both demand effects and possible (dis)economies of scale.[17] Even though Eq. (2) cannot be interpreted as a supply function it is still instructive to think whether other effects than information acquisition could lead to negative or positive coefficients on the branch and personnel variables. It is easy to see that standard marginal cost arguments would imply positive coefficients for both variables. Therefore, a positive coefficient is not necessarily due to market power. Whilst it is hard to come up with an alternative story for a negative branch variable coefficient, a negative personnel (recall that our personnel variable is the total wage bill, i.e., labor cost per worker times number of employees, divided by the number of branches) coefficient could imply that in response to a wage increase, banks substitute away from labor on a large scale. This is the interpretation that Neven and Röller (1999, p. 1070) give on a (insignificant) negative wage coefficient in their supply function. For this interpretation to apply to our model, banks should have operated so deep in the region of diminishing marginal productivity that a small increase in wages prompts them to substitute away from labor on a large scale. Although possible, we find this implausible especially in the light of the information that mean personnel costs (as measured in million FIM) decreased only from 5.65 in 1992 to 5.45 in 1995.

As is clear from the above equations, we impose the assumption that all parameters are constant over all banks. This means that, apart from differences captured by fixed bank and period effects, we assume that banks use their inputs equally efficiently, and also for

[16] The SBF-dummy was never significant in the interest rate equation and was therefore dropped. The results are robust to including it into the specification.

[17] Comparison of our equations to, e.g., Neven and Röller (1999, Eqs. (8–10), p. 1067) shows a difference in the treatment of branches: Neven and Röller allow branch networks to affect marginal costs only, and do not estimate a separate equation for credit losses.

example that the level of competition does not change at a different pace for different banks. Finally, all variables are in logs, and since there are observations with zero values for $DEFR_{it}$, we use $DEF_{it} = \ln(0.000001+DEFR_{it})$. We did experiment with different definitions of DEF_{it} (linear, $\ln(1+DEFR_{it})$), and our results are robust in this sense. The nominal values of variables are used.[18]

4.2. Econometric methods and exogeneity assumptions

Including dynamics into the model is decisive for our choice of estimation method. It is well known (e.g., Nickell, 1981) that OLS and standard Within (“fixed effects”) estimators are biased with panel data if dynamics are important. We have therefore chosen to estimate the model using Generalized Method of Moments (GMM) estimators designed for dynamic panel data (Arellano and Bond, 1991; Blundell and Bond, 1998, 1999).[19] These estimators allow us to test the importance of dynamics. We report two different GMM estimates: GMM-DIF is the Arellano and Bond (1991) estimator, and GMM-SYS the Blundell and Bond (1998) (see also Arellano and Bover, 1995) estimator, where the latter is more efficient, but requires that some additional assumptions are satisfied. Both utilize first-differenced data. For comparison, we also report the OLS and Within results.

Our main explanatory variables are bank and period specific. It is likely that some of them are endogenous, i.e., affected by the same unobservables as our dependent variables. It is also possible that some of them are measured with error. For these reasons, we adopt a conservative strategy and treat all bank level variables either as endogenous, or at most, as predetermined (see the Appendix for more details). These assumptions are tested.

The estimators we use employ suitably lagged levels and possibly differences of explanatory variables as instruments. For these to be valid instruments, the error term may not be serially correlated. We therefore test that this is not the case. In addition, we test with a Sargan over-identification test that our instruments are valid.

5. Empirical evidence I: the credit loss equation

5.1. Main results

The results for the credit loss equation are presented in Table 3. We find that the coefficients of the lagged dependent variable generated by different estimation methods

[18] The reason for using nominal values is that (i) it is not clear what deflator to use, (ii) inflation was very low during the (short) observation period. We have however estimated the base specification using variables deflated by the consumer price index, and the cost of living index, respectively. The results did not change.

[19] In the Appendix, we describe these estimators, and our choice of moment conditions and instruments in detail. Estimating a static model with Error Component 2SLS (Baltagi, 1981) produced similar results, but autocorrelation tests for the estimated residual suggested mixed conclusions. It should be noted, however, that these estimations were based on a set of covariance restrictions that were somewhat stronger than the ones adopted in this paper. These (exogeneity) restrictions were made to obtain valid instruments, and we did not test for their validity in that framework.

Table 3
Credit loss estimation

Variable	(1) OLS (levels)	(2) Within groups	(3) GMM-DIF	(4) GMM-SYS	(5) GMM-SYS	(6) GMM-SYS	(7) GMM-SYS	(8) GMM-SYS
DEF_{t-1}	0.3597	− 0.0676	0.2062	0.1874	0.1864	0.1691	0.1805	0.1744
	(0.0432)	(0.0415)	(0.0645)	(0.0586)	(0.0590)	(0.0759)	(0.0777)	(0.0766)
LOAN	0.8075	0.9424	1.7024	3.7453	2.6333	2.7800	3.2025	2.7991
	(0.1505)	(1.4133)	(3.7771)	(0.7300)	(0.6069)	(0.6899)	(0.8311)	(0.8369)
INTL	4.8798	3.8350	8.7792	6.6033	4.3394	5.3234	5.4560	5.3366
	(1.8183)	(2.5887)	(3.0866)	(2.8105)	(2.7927)	(2.8791)	(2.9362)	(3.0813)
INEFF	1.7917	− 1.2155	0.1381	− 0.0133	− 1.0459	− 0.6972	− 0.2317	− 0.1519
	(0.3763)	(0.8235)	(1.1478)	(1.1657)	(1.1714)	(1.3052)	(1.2875)	(1.3086)
BRA	− 0.0816	− 0.4618	− 8.3117	− 1.7526	− 0.9105	− 0.9589	− 1.5315	− 0.5968
	(0.0871)	(1.6473)	(4.3744)	(0.6883)	(0.4830)	(0.5282)	(0.9922)	(0.6700)
PERS	− 0.3318	− 0.9108	− 10.1814	− 3.3185	− 2.3859	− 2.4946	− 3.1466	− 2.0503
	(0.1117)	(1.6092)	(4.4300)	(0.9000)	(0.7332)	(0.8032)	(1.2863)	(0.9521)
SBFD	–	–	–	− 1.2651	− 1.1486	− 1.1676	− 1.2964	− 1.0320
				(0.5088)	(0.4733)	(0.5202)	(0.5965)	(0.4988)
RDEP	–	–	–	–	− 8.3351	− 8.6013	− 7.4997	− 7.3036
					(3.2574)	(4.1885)	(3.8598)	(4.4642)
DENS	–	–	–	–	–	–	− 2.8371	–
							(1.6670)	
EDUC	–	–	–	–	–	–	0.9744	–
							(0.9063)	
OWNH	–	–	–	–	–	–	7.0733	–
							(3.3794)	
UE	–	–	–	–	–	–	–	0.1693
								(1.3596)
WCAP	–	–	–	–	–	–	–	1.5145
								(0.8060)
AGRIC	–	–	–	–	–	–	–	0.4435
								(0.3559)
Nobs.	1000	1000	750	1000	1000	750	750	750
Sargan	–	–	0.281	0.195	0.278	0.556	0.479	0.430
m1	0.467	− 5.016	− 5.302	− 5.053	− 4.963	− 3.877	− 3.903	− 3.897
	(0.640)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
m2	0.801	− 1.539	− 0.393	0.270	0.418	–	–	–
	(0.423)	(0.124)	(0.695)	(0.788)	(0.676)			
Wald1	342.643	12.826	21.206	54.881	84.384	77.291	75.018	98.562
	(0.000)	(0.046)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wald2	10.488	8.433	9.850	7.144	9.987	13.164	18.475	4.558
	(0.015)	(0.038)	(0.020)	(0.067)	(0.019)	(0.001)	(0.000)	(0.102)
Wald3	–	–	9.463	13.968	10.827	9.872	7.760	6.850
			(0.009)	(0.001)	(0.004)	(0.007)	(0.021)	(0.033)

The GMM-estimates are all one-step. Numbers reported are coefficient and asymptotic standard errors (S.E.). Reported standard errors are robust to general cross-section and time-series heteroskedasticity. Nobs. is the number of useable observations. All estimations include time dummies.

Sargan is a test of the over-identifying restrictions for the GMM estimators. Reported numbers are p-values.

m1 and m2 are tests for first- and second-order autocorrelation in the first differenced residuals (except for OLS and Within estimations, in which the tests are for levels residuals); they are asymptotically distributed $N(0,1)$; Reported numbers are p-values.

Wald1 = a Wald test of joint significance of explanatory variables (p-value).

Wald2 = a Wald test of joint significance of time dummies (p-value).

Wald3 = a Wald test of joint significance of BRA and PERS terms (p-value).

follow the expected pattern,[20] with the GMM-SYS estimate being 0.19. Notice that the lagged dependent is highly significant in the GMM estimations, suggesting that controlling for dynamics is important, and that OLS and Within produce biased estimates. Furthermore, we have tested the exogeneity of branch density and personnel costs per branch and had to reject the null hypothesis of exogeneity. The GMM-DIF and GMM-SYS estimates are reasonably close to each other, but the latter seem to be more efficient as expected. Concentrating on the GMM-SYS estimates [base specification in Column (4)] we find first of all that an increase in the loan interest rate (INTL_{it}) increases the credit losses significantly (the long-run interest rate elasticity of credit losses is 8.126). This finding is in line with the received theory. Even after controlling for this effect, banks with larger loan books have larger relative credit losses. This could reflect the specificity of our sample period. However, it is also possible that the result is not period specific. It implies that conditional on the level of fixed investments, a larger loan book (implying a higher number of granted loans) leads to larger credit losses. Decreasing returns to scale in monitoring would lead to the result.

The summary variable INEFF_{it} has no effect on credit losses, but we find that banks to which former savings banks' branches have been merged have lower credit losses. A possible explanation for this is that only healthier (the dismantling of SBF took place during 1992–1993, in the midst of the banking crisis) cooperative banks were willing (alternatively, were allowed to by the government) to take over former savings banks' branches. In addition, as a part of the dismantling of SBF, its worst loans were transferred into a government run 'bad' bank, and the banks buying parts of SBF only took on their books loans deemed healthy. Most significantly, however, we find that both variables capturing fixed investments have significant negative effects on credit losses, supporting the monitoring hypothesis. The estimated long-run elasticities are −2.15 for branch density and −4.08 for personnel costs. Specifically, these results suggest that monitoring dominates the alternative market power explanation for fixed investments.

Turning to the test statistics, the first-differenced residuals display first order autocorrelation as expected,[21] and no second-order autocorrelation. The Sargan tests do not reject the over-identifying restrictions in GMM-DIF or GMM-SYS estimations, validating our choice of instruments. A Wald statistic testing the joint significance of BRA_{it} and PERS_{it} rejects the null hypothesis of them not being jointly different from zero.

5.2. Robustness tests

We conducted a number of robustness tests. First, we allowed the coefficients to vary over time by dividing the observation in an early (1992–1994, the recession years) and a

[20] The GMM results to be reported are based on the one-step GMM estimators. The asymptotic variance matrix for them is more reliable than that for the two-step GMM (see, e.g. Blundell and Bond, 1998). The estimates have been produced using Arellano–Bond DPD98, kindly provided by Steve Bond. For reference, we also report OLS and Within Groups estimates. The consistency of these two estimators requires that all explanatory variables are strictly exogenous w.r.t. ν_{jit}. Blundell and Bond (1998) show that the OLS estimate of the lagged dependent variable's coefficient should be the largest, the Within estimate the smallest, and the (consistent) GMM estimates between these two.

[21] The econometric model assumes no autocorrelation in levels. Taking first differences induces (negative) first-order autocorrelation.

late period (the growth years). We could not reject the null hypothesis that coefficients are stable over time. Second, we allowed large banks to have different coefficients (by splitting the sample at either the mean or the median bank).[22] Again, we could not reject the null hypothesis that coefficients are identical in the two groups.[23] Third, inspired by Fama (1985) and Vale (1993), we introduced the extent to which the bank is funded by deposits. The ratio of deposits to total funding ($RDEP_{it}$) variable (see Column (5)) obtained a negative and significant coefficient (−8.34) when added to the specification and treated as being endogenous and correlated in levels with the bank-specific effects. This provides evidence that banks can indeed use information obtained from monitoring their customers' cash flows to decrease their credit losses. Concurrently and independently, Mester et al. (2002) have obtained a similar result using data on U.S. checking accounts. Adding $RDEP_{it}$ reduces the absolute size of the branch density and personnel costs per branch coefficients to −0.91 and −2.38, respectively. They do remain statistically significant, however.

Fourth, we checked whether our results are robust to including exogenous regressors that control for differences in the characteristics of the (local) markets that our sample banks operate in. We only have such data for 1992–1995. Excluding the 1996 data does not materially affect the results (Column (6)). Adding exogenous control variables to the specification changes somewhat the branch density (BRA_{it}) and personnel costs per branch ($PERS_{it}$) coefficients; however, only one of the six exogenous regressors (house ownership, $OWNH_{it}$) obtains a statistically significant coefficient. Adding population density ($DENS_{it}$), the proportion of population with a university degree ($EDUC_{it}$) and house ownership ($OWNH_{it}$) renders the coefficient of branch density (BRA_{it}) significant at only the 12% level; BRA_{it} and $PERS_{it}$ are still jointly significant at the 5% level. Adding unemployment (UE_{it}), taxable per capita wealth ($WCAP_{it}$) and $AGRIC_{it}$ results in an insignificant branch density coefficient, but BRA_{it} and $PERS_{it}$ are still jointly significant at the 5% level.

Fifth, we made sure that our results are robust to cooperative banks being a large lender to agriculture. As agricultural activity is largely time-invariant, it is to a great extent already controlled through the bank specific effects. To the extent that it is not, we separately included two measures of agricultural activity (in unreported regressions): the number of farms in the market, and the average size of farms. These were never significant.

Sixth, we checked whether the relationship between credit losses and fixed investments is nonlinear by including the squares of BRA_{it} and $PERS_{it}$. Our results

[22] Strictly speaking, one should allow the data to determine the break point. Hansen (1999) has developed a threshold regression method for such analysis. Unfortunately, the method only applies to non-dynamic panels and relies on the assumption that the explanatory variables are strictly exogenous. These assumptions are rejected by our data. For this reason, we experimented with two break points and also by including nonlinear terms for the fixed investments (see the main text).

[23] When using the median of ($LOAN_{it}$+interbank loans) as the size criterion (instead of the mean of ($LOAN_{it}$+interbank loans) criterion), we could not reject the Null that large banks have different BRA_{it}, $PERS_{it}$, $Def_{i,t-1}$ and $INTL_{it}$ coefficients than small banks. This was however entirely driven by the coefficient of the interaction variable obtained by $DEF_{i,t-1}$ times the dummy (the other interactions carried insignificant coefficients), and we therefore do not report these results.

remained unchanged. Seventh, notwithstanding our arguments for a geography-based definition of BRA_{it}, we re-estimated the model using the number of branches per population as our measure of branch density. Again, our reported results were confirmed.

6. Empirical evidence II: the interest rate equation

6.1. Main results

The interest rate estimation results are presented in Table 4. Comparing first the coefficients of the lagged dependent variable, we observe that these follow closely the expected pattern. Again, the lagged dependent is highly significant in the GMM estimations.

Turning to the other parameters, the OLS and Within estimates differ sometimes substantially from the GMM estimates. Concentrating then on the GMM-SYS estimates of our base specification (Column (4)), we find that expected credit losses (DEF_{it}) do not affect interest rates, but that interest rate costs (INTD_{it}) do have a positive effect. The long-run cost-of-financing elasticity of loan interest rates is 0.148. The coefficient of loan book size (LOAN_{it}) is positive and has a *p*-value of 0.09. The summary variable INEFF_{it} obtains a negative and significant coefficient. Our variables of most interest, branch density (BRA_{it}) and personnel costs per branch (PERS_{it}), both carry negative and significant coefficients, implying that banks with a larger branch network and more human capital at branch level charge lower interest rates. These results are in line with monitoring, and again suggest that monitoring dominates market power as a motivation for fixed investments.[24] The estimated elasticities for BRA_{it} and PERS_{it} are small. This indicates that the costs of monitoring in terms of having to offer lower interest rates to attract those customers the bank has identified as 'good' are low.

An important question is whether there is some other interpretation for the negative coefficients. Whilst it is hard to come by one for the branch variable, the negative personnel variable might indicate that banks merely substitute away from labor if wages are increased. However, and importantly for us (see below), Neven and Röller (1999) find that marginal costs of lending are increasing in the number of branches, and decreasing in wages. The latter results may suggest that as a response to increases in wages, banks substitute capital for labor on a large scale. If, as they assume, branches (personnel) affected the marginal costs, one should obtain positive coefficients.

[24] At the very minimum, it is the case that information acquisition strongly dominates any market power use of fixed investments. It is worth noticing that the Within estimate produces positive and significant coefficients for BRA and PERS (OLS for PERS), which would support the market power hypothesis and reject the information acquisition hypothesis. We have however tested the null hypothesis of BRA and PERS being predetermined against the alternative of them being endogenous. Using a difference Sargan test, we rejected the null hypothesis at the 5% level (*p*-value was 0.034). Based on this test, the consistency of OLS and Within Groups estimators can be questioned.

Table 4
Interest rate estimation

Variable	(1) OLS (levels)	(2) Within groups	(3) GMM-DIF	(4) GMM-SYS	(5) GMM-SYS	(6) GMM-SYS	(7) GMM-SYS	(8) GMM-SYS
$INTL_{t-1}$	0.4042	− 0.0857	0.2838	0.2620	0.2503	0.2685	0.2662	0.2639
	(0.0542)	(0.0464)	(0.0635)	(0.0567)	(0.0544)	(0.0748)	(0.0699)	(0.0748)
LOAN	− 0.0033	− 0.1292	0.0763	0.0323	0.0215	0.0263	0.0261	0.0171
	(0.0037)	(0.0650)	(0.0745)	(0.0194)	(0.0143)	(0.0217)	(0.0246)	(0.0272)
DEF	0.0030	− 0.0013	0.0014	0.0018	0.0039	0.0031	0.0031	0.0030
	(0.0008)	(0.0010)	(0.0030)	(0.0027)	(0.0025)	(0.0031)	(0.0032)	(0.0031)
INTD	0.0821	0.1388	0.1836	0.1091	0.1202	0.1308	0.1794	0.1448
	(0.0219)	(0.0431)	(0.0775)	(0.0420)	(0.0670)	(0.0604)	(0.0588)	(0.0633)
INEFF	− 0.0805	− 0.1662	− 0.1598	− 0.0893	− 0.0851	− 0.1185	− 0.1220	− 0.1146
	(0.0111)	(0.0215)	(0.0382)	(0.0304)	(0.0331)	(0.0324)	(0.0332)	(0.0310)
BRA	− 0.0008	− 0.1117	− 0.1135	− 0.0343	− 0.0307	− 0.0280	− 0.0557	− 0.0286
	(0.0016)	(0.0599)	(0.0736)	(0.0120)	(0.0094)	(0.0110)	(0.0236)	(0.0162)
PERS	0.0052	− 0.1300	− 0.1233	− 0.0426	− 0.0335	− 0.036	− 0.0595	− 0.0329
	(0.0020)	(0.0626)	(0.0745)	(0.0185)	(0.0145)	(0.0196)	(0.0299)	(0.0254)
RDEP	–	–	–	–	0.0427	–	–	–
					(0.1049)			
DENS	–	–	–	–	–	–	− 0.0844	–
							(0.0384)	
EDUC	–	–	–	–	–	–	0.0483	–
							(0.0199)	
OWNH	–	–	–	–	–	–	0.0998	–
							(0.0790)	
UE	–	–	–	–	–	–	–	− 0.0342
								(0.0330)
WCAP	–	–	–	–	–	–	–	− 0.0011
								(0.0173)
AGRIC	–	–	–	–	–	–	–	− 0.0123
								(0.0082)
Nobs.	1000	1000	750	1000	1000	750	750	750
Sargan	–	–	0.605	0.448	0.251	0.128	0.130	0.138
m1	− 0.669	− 1.929	− 5.309	− 5.420	− 5.918	− 5.136	− 5.167	− 5.011
	(0.503)	(0.054)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
m2	1.605	− 0.340	0.641	0.500	0.393	–	–	–
	(0.108)	(0.734)	(0.521)	(0.617)	(0.695)			
Wald1	360.227	76.242	52.771	38.080	43.598	49.195	51.680	54.679
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wald2	589.97	198.505	182.918	410.077	435.767	27.103	27.607	22.580
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wald3	–	–	–	8.141	10.590	6.620	5.716	3.496
				(0.017)	(0.005)	(0.037)	(0.057)	(0.174)

See Table 3.

6.2. Robustness tests

We have conducted the same robustness tests as with the credit loss equation, with similar results bar one clear exception. The ratio of deposits to total funding plays no role in determining loan interest rates.

7. Conclusions

The main objective of this paper was to shed light on whether banks use their fixed investments for monitoring. The theoretical prediction is that monitoring leads to lower credit losses and to a lower interest rate margin. The alternative hypothesis is that these investments are made to gain market power. We tested the net effect of these theories on panel data covering 250 Finnish local banks and 5 years.

We found persistence in both loan interest rates and credit losses. Unsurprisingly, loan interest rates are an increasing function of deposit interest rates and higher loan interest rates increase credit losses. Our main finding is that banks' investments in both branch network density and human capital (personnel) contribute to the monitoring ability of banks as both loan interest rates and credit losses are decreasing in these variables. In addition, we find evidence supporting the hypothesis (Fama, 1985) that banks use deposits to monitor the cash flow of customers, and are thereby able to decrease the amount of credit losses. These results were robust to a number of experiments.

Our results provide new direct evidence on the relationship between banks' fixed investments and ability to monitor. As discussed in Introduction, the effects of this finding are not limited to the industry itself, but may be of importance at the macro level of the economy as well. The finding may also offer a partial explanation to the earlier findings of market power in the industry (Neven and Röller, 1999). What in a traditional Industrial Organization-model appear to be high mark-ups may be rents to information acquisition. Being based on data on small banks from a small non-U.S. country, the results complement the existing empirical evidence suggesting that banks behave in ways that are in line with them being able to monitor their customers. Our results demonstrate that the quality of a bank's monitoring is endogenously chosen and affected by its locational choices and human capital investments.

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References

Angbazo, L., 1997. Commercial bank net interest margins, default risk, interest-rate risk, and off-balance sheet banking. Journal of Banking and Finance 21, 55–87.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58, 277–297.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-component models. Journal of Econometrics 68, 29–51.

Baltagi, B., 1981. Simultaneous equations with error components. Journal of Econometrics 17, 21–49.

Berger, A., Udell, G., 1998. The economics of small business finance: the roles of private equity and debt markets in the financial growth cycle. Journal of Banking and Finance 22, 613–673.

Berlin, M., Mester, L.J., 1998. On the profitability and cost of relationship lending. Journal of Banking and Finance 22, 873–897.

Broecker, T., 1990. Credit-worthiness tests and interbank competition. Econometrica 58, 429–452.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics 87, 115–143.

Blundell, R., Bond, S., 1999. GMM estimation with persistent panel data: an application to production functions. The Institute for Fiscal Studies Working Paper, W99/4.

Bond, S., Meghir, C., 1994. Dynamic investment models and the firm's financial policy. Review of Economic Studies 61, 197–222.

Calem, P., Nakamura, L., 1998. Branch banking and the geography of bank pricing. Review of Economics and Statistics 80, 600–610.

Cosimano, T.F., McDonald, B., 1998. What's different among banks? Journal of Monetary Economics 41, 57–70.

Degryse, H., 1996. On the interaction between vertical and horizontal product differentiation: an application to banking. Journal of Industrial Economics 44, 169–186.

Evanoff, D.D., 1988. Branch banking and service accessibility. Journal of Money, Credit and Banking 20, 191–202.

Fama, E., 1985. What's different about banks? Journal of Monetary Economics 15, 29–39.

Freixas, X., Rochet, J.-C., 1997. The Microeconomics of Banking MIT Press, Cambridge, MA.

Gale, D., Hellwig, M., 1985. Incentive compatible debt contracts: the one-period problem. Review of Economic Studies 52, 647–663.

Gehrig, T., 1998. Screening, cross-border banking, and the allocation of credit. Research in Economics 52, 387–407.

Greenwald, T., Stiglitz, J., 1993. Financial market imperfections and business cycles. Quarterly Journal of Economics 108, 77–114.

Hansen, B.E., 1999. Threshold effects in non-dynamic panels: estimation, testing, and inference. Journal of Econometrics 93, 345–368.

Hauswald, R., Marquez, R., 2003. Information technology and financial services competition. Review of Financial Studies 16, 921–948.

Holmström, B., Tirole, J., 1997. Financial intermediation, loanable funds, and the real sector. Quarterly Journal of Economics 112, 663–691.

Hyytinen, A., Toivanen, O., 2000. Monitoring and market power in loan markets. Bank of Finland Discussion Paper, No. 9/2000.

Hyytinen, A., Toivanen, O., 2002. Vertical differentiation, asymmetric information and endogenous bank screening. Topics in Theoretical Economics (of The B.E. Journals in Theoretical Economics, in press).

Klein, M.A., 1971. A theory of the banking firm. Journal of Money, Credit and Banking 3, 205–218.

Koskenkylä, H., Vesala, J., 1994. Finnish deposit banks 1980–1993: years of rapid growth and crisis. Bank of Finland. Discussion Papers, No. 16/94.

Mester, L.J., Nakamura, L.I., Renault, M., 2002. Checking accounts and bank monitoring. Federal Reserve Bank of Philadelphia Working Paper, No. 01-3/R.

Neven, D., Röller, L.-H., 1999. An aggregate structural model of competition in the European banking industry. International Journal of Industrial Organization 17, 1059–1074.

Nickell, S., 1981. Biases in dynamic models with fixed effects. Econometrica 49, 1417–1426.
Petersen, M., Rajan, R., 1994. The benefits of lending relationships: evidence from small business data. Journal of Finance 49, 3–37.
Vale, B., 1993. The dual role of demand deposits under asymmetric information. Scandinavian Journal of Economics 95, 77–95.
Vihriälä, V., 1997. Banks and the Finnish credit cycle 1986–1995. Bank of Finland Studies, E:7.