What Determines Borrowing Costs at the Firm-Level: Firm-Specific and Aggregate Information*

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Abstract

We analyze the relationship between firm-specific shocks and aggregate fluctuations. In particular, profitability of firms affected by a negative shock worsens. To the extent that the banks cannot distinguish between aggregate and firm-specific profitability shocks, they will adjust interest rates for all borrowers. We test the influence of individual and bank specific data on lending rate using individual data for firm-bank relationships in Germany between 2005 and 2007. We provide the evidence that firm lending conditions depend on both individual and aggregate profitability. This result is consistent with the interpretation that banks use firm-specific as well as aggregate information when setting corporate lending rates.

Key words: Bank lending; spill-over effects; business cycle.

JEL codes: E32; G21; L14.

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1 Introduction

The business cycle at the aggregate level involves synchronized movements in output across firms and sectors. Yet, shocks appear to be only relatively weakly correlated at disaggregated levels. Hence, why do we observe business cycles at the aggregate level? Gabaix (2011) argues that idiosyncratic developments at a small number of firms can result in aggregate business cycles if the distribution of firm size is fat-tailed. Alternatively, aggregate business cycles may arise as some type of interaction turns uncorrelated sector-specific or firm-specific shocks into fluctuations in aggregate activity.[1] Veldkamp and Wolfers (2007) emphasize the role information. Specifically, they show how complementarities in information acquisition between sectors can turn shocks, which are uncorrelated at the industry level, into aggregate fluctuations. In their model, the agents in one sector can learn about their sector-specific productivity only at cost. Since information about the aggregate state of productivity is cheaper to acquire, agents base their production decisions on largely similar information sets and consequently make similar decisions.

In this paper, we empirically study a similar type of interaction resulting from informational externalities. However, instead of focusing on information acquisition by firms, we study the role of the banking sector. One of the main functions of banks, and the financial systems in general, is to screen potential borrowers and determine appropriate financing conditions. To do so, banks gather and process information in various ways. Since borrower-specific information is harder to obtain and perhaps less reliable, lenders may also take general developments into account as these may also help to evaluate prospective borrowers. For instance, suppose that some firms are hit by an adverse shock and these firms are no longer able to repay loans. By aggregation, banks observe higher repayment difficulties of their borrowers. As a result, banks observe an increase in defaults and may infer that default risk has increased for all borrowers as banks may not be able to clearly distinguish between aggregate and firm-specific developments. Put differently, firms face financing conditions that partly mirror firm-specific information, but also information obtained from aggregated data. Consequently, even firms which are not directly affected by the shock may face less favorable financing conditions and the banking sector generates what Manski (2000) refers to as *constraint interaction*.[2]

[1] Long and Plosser (1983), Hornstein and Praschnik (1997), Horvath (1998) and Horvath (2000) emphasize input-output structures and trade as channels through which industry-level productivity shocks are transmitted to other sectors.

[2] See e.g.: 'Even solid firms feel the pinch from banks', The Wall Street Journal Europe, Thursday, March 12,

We study interactions using a unique data set on bank relations of German firms covering the period 2005 - 2007. In particular, we compare the role of firm-specific and aggregate determinants of bank lending rates of individual firms. We use data from the Dafne database, which is merged with data from the Bankscope. Although the Dafne dataset provides the most detailed information on German firms and their bank relations, it is rarely used in academic research.

While a large number of studies emphasizes the role of informational issues for financial arrangements, the novel aspect of our analysis is the focus on interactions between firms via the banking sector. That is, we explore if and to what extent firm-specific financing conditions do not only mirror firm-specific developments, but also reflect developments at a more aggregated level. To our knowledge, the present paper is the first attempt to study this issue.

We provide robust evidence showing that aggregate information about overall profitability developments significantly reduces lending rates for individual firms. Although the effect is less pronounced than for firm-specific information, we conclude that the banking sector generates interaction effects via the use of aggregate information. Thus, our results provide empirical support in favor of the role of information emphasized by Veldkamp and Wolfers (2007).

The remainder of the paper is structured as follows. We present a model of financing conditions and information externalities in the next section. Section 3 describes the dataset discusses the empirical methodology. In Section 4, we present our estimation results and Section 5 concludes the paper.

2 A Simple Model of Financing Conditions and Information Externalities

In this section we present a simple model that describes in a highly stylized way how interaction effects in financing conditions may arise due to informational externalities. It also highlights the role of the financial system in synchronizing output across firms.

Each firm $i = 1, ..., N$ produces output according to a standard Cobb-Douglas production function with capital as the only input.

$$y_i = a_i k_i^{\alpha}, \tag{1}$$

where k_i is firm i's capital stock, which depreciates fully during the production process and $\alpha \in (0, 1)$. Firm i's productivity, a_i is stochastic and contains a component which is common

2009, for anecdotal evidence.

to all firms, $\bar{a} \sim N(\mu_a, \sigma_a)$, and a firm-specific component, $z_i \sim N(0, \sigma_\theta)$: $a_i = \bar{a} + z_i$. z_i are independently distributed across firms. Thus, $\bar{a}$ is the average productivity in the economy.

Since our focus is on the banking sector, the only source of funds available to firms are bank loans. The gross interest rate on loans is ρ_i. Although firms know average productivity, $\bar{a}$, when making investment decisions, they cannot observe their firm-specific productivity. Instead, they only know the distribution from which z_i is drawn. Thus firms use the unconditional expectation of z_i to forecast their firm-specific productivity.[3] The optimal level of capital is determined by equating expected marginal productivity to the lending rate:

$$\rho_i = \bar{a}\alpha k_i^{\alpha-1}. \tag{2}$$

The market for bank loans is perfectly competitive and lending is costless. Moreover, banks are risk neutral and can refinance loans they extend to firms at an exogenous gross interest rate r. Since all banks have the same information set and therefore behave identically when setting lending rates, we focus on a representative bank.

When setting lending rates, the representative bank takes into account that a firm may default. Default occurs if firm i's output is insufficient to repay its debt. We assume that in the event of default the firm can simply walk away from its debt obligations. Thus, the probability of default on a loan extended to firm i is $p_i = \Pr[y_i < \rho_i k_i|\Omega]$, where Ω is the information set available to the bank when setting lending rates. Since the expected profit $(1 - p_i)\rho_i l_i - r l_i$ on a loan of size l_i extended to firm i has to be equal to zero due to free entry, the rate at which a loan is extended to firm i is

$$\rho_i = \frac{r}{1 - \Pr[y_i < \rho_i k_i|\Omega]}. \tag{3}$$

Thus, the higher the probability of default the higher the lending rate, given a certain level of refinancing costs.

The crucial element for our purposes is the determination of the default probability p_i. Here we distinguish two cases:

Aggregate Information: Suppose that banks have only access to aggregate information. That is, banks, just like firms, observe only average productivity, $\bar{a}$ but have no information

[3] Of course, we could also analyze cases which differ with respect to different information sets of firms. However, this is essentially what has been done in Veldkamp and Wolfers (2007), therefore we do not put a particular emphasis on this issue and focus on different information sets of the lender.

about z_i. In this case the interest rate is

$$\rho_i^A = \frac{r}{1 - \Pr[a_i < \bar{a}(\alpha - 1)]}. \tag{4}$$

Here, the interest rate on loans mirrors only aggregate information and all firms are charged the same interest rate since the default probabilities are perceived to equal across firms. Thus, in this case, an adverse realization of $\bar{a}$ leads to higher interest rates for all firms, even to those that experience favorable realizations of idiosyncratic productivity z_i. Facing higher borrowing costs, all firms will reduce their production levels in a correlated way.

Firm-Specific Information: Now suppose that the bank has also access to firm-specific information, e.g. from balance sheets, in addition to the observation of the aggregate component of the productivity shocks. As firm-specific information may not be fully reliable, we model it as a noisy signal: $s_i = z_i + v_i$, where $v_i \sim N(0, \sigma_v)$ is again *i.i.d.* across all firms and independent of a and z_i. Here the firm i is charged an interest rate of

$$\rho_i^{FS} = \frac{r}{Pr\left[v_i < (1-\alpha)\bar{a} + s_i\right]}, \tag{5}$$

which is conditional on particular realizations of $\bar{a}$ and also on particular realization of the signal, s_i. Thus, we see that the lending rate mirrors firm-specific information to some extent and therefore interaction effects are less pronounced.

3 Data and Estimation Strategy

3.1 Data

The purpose of our analysis is to study interaction or peer group effects that arise through informational externalities in the banking sector. In other words, we ask to what extent borrowing costs of firms mirror aggregate information in addition to firm-specific information. To do so, we construct a measure that captures the cost of obtaining a bank loan at the level of individual firms using the Dafne databank provided by the Bureau van Dijk. This unique dataset provides information on balance sheets, profit and loss accounts and the legal form for about $400,000$ German firms. Although some of the data is available from 1999, the coverage is limited and therefore we use only the three years period before the financial crisis, 2005 to 2007. We can use up to $25,000$ firms for subsequent estimations with approximately $54,000$ observations.[4]

[4] Note that the data set is substantially larger than any other data set available, including the Amadeus database.

To obtain a measure for bank financing costs, we calculate an implicit interest rate associated with interest rate payments on bank loans, using the reported balance sheet data of firms. Note that while we have information on bank relations, the data is not detailed enough to calculate bank or loan specific implicit interest rates. Thus, we can only calculate an average interest rate that firm i pays on its entire bank debt. Specifically, for each firm i we calculate the implicit average corporate interest rate as

$$R_{it} = 100 \frac{I_{it}}{BL_{it}}, \tag{6}$$

where I_{it} denotes the total interest payments of firm $i = 1, ..., N$ and BL_{it} are total bank loans reported by firm i. Note that I_{it} does not only include interest payment but also comprises fees and other costs associated with bank loans.

Since the implicit bank lending rate, I_{it} may be subject to errors, due to e.g. new loans, loan repayment, and received interest payments, we exclude possible outliers. We define outliers as the highest and lowest five percentiles of all financial data.

For 2005 and 2006, we have up to $100,000$ firms reporting the basic financial indicators. Excluding outliers leaves us with about $70,000$ firms. The data coverage is slightly lower for the last available year. Moreover, we can see that the interest rates and productivity indicators were relatively stable between 2005 and 2007. Surprisingly, the leverage ratio shows that the average debt level was reduced from 6.6 percent to 4.7 percent of equity during the same period.

Figure 5 shows the distribution of R_{it}. The first line of Table 1 shows selected descriptive statistics. Note that on average, the implicit interest rate is 9.168 percent, which may seem to be high at first glance. However, it needs to be kept in mind that, as discussed above, interest expenses include additional cost items associated with loans and not only the interest rate.

Having discussed our measure of borrowing costs, we turn to the variables which we use as proxies for the information about borrower quality. While banks presumably analyze the balance sheets of prospective borrower in great detail, we focus on earnings before interest and taxes (EBIT) in percent of sales, as broad indicator of the quality of firm i as a borrower and therefore as a determinant of borrowing costs. We do so for mainly two reasons: first EBIT indicates profitability in a broad sense and it seems conceivable that profitability is a main determinant for the future repayment probability. Second, EBIT excludes interest payment, which helps us in avoiding endogeneity problems in our regressions.[5]

[5]The focus on EBIT may still seem a bit narrow. It also appears conceivable that bank base their decisions on other indicators available from firm balance sheets, for instance leverage. However, since leverage is closely related to debt and especially for smaller firms, bank debt, this variable, and variables related to capital structure

We also control for sectoral (one digit industries according to the NACE classification) and regional (defined for the federal states in Germany) effects and firm size, which is defined according to employment.

We merge firm data with bank data according to the Bankscope, which is provided also the Bureau van Dijk. Thus we can control also also for the capitalization of banks (ratio of bank equity to liabilities) in the robustness analysis. Table 1 shows descriptive statistics for the analyzed variables and selected additional variables (employment and leverage ratio).

3.2 Regression Model with Individual and Median Profitability

To study the effects of firm-specific and aggregate information on borrowing costs, we estimate regressions of the type

$$R_{it} = \beta_0 + \beta_1 EBIT_{it} + \beta_2 \overline{EBIT}_{it} + \boldsymbol{Z}_{ibt}\boldsymbol{\gamma} + \theta_t + u_{ibt}, \tag{7}$$

where R_{ibt} is our measure of borrowing costs, $EBIT_{ibt}$, captures the profitability of firm i, as a proxy for firm-specific information. Form the point of view of a bank that decides on granting a loan, this information is available from the balance sheet of firm i, to which the bank has access. Moreover, profitability is also likely to be mirrored in firm revenues and therefore also in the firms' banking account, which can be easily observed by the bank. $\boldsymbol{Z}_{ibt}$ is a vector of control variables which are either specific to firm i or bank b. Finally, θ stands for time fixed effects and u denotes the residual, which will be described in Section 3.4.

What we are ultimately interested in, is the possibility that banks do not only use firm-specific information, but also information about profitability developments more generally. Although this type of more aggregate information is perhaps less informative about individual firms, it may the easier and cheaper to obtain and it may also be subject to less measurement error to a lesser extent. Once source of aggregate information that can be used is information obtained from other customers of the bank. As long as profitability developments are not fully uncorrelated across firms, it contains information. We incorporate aggregate information effects through the inclusion of $\overline{EBIT}_{ibt}$ which is the median EBIT over firms which report a connection with bank b.

Note that we assume in equation (7) a contemporaneous relationship between the profitability variables and financing costs, although banks may obtain balance sheet information only with

of firms, are already used to the construction of our dependent variable. Hence, including those variable would result in endogeneity issues.

a lag. However, since the data are only available at an annual frequency, and since banks may get updates about current profitability developments, it still appears plausible that a large part of the information about current profitability becomes available during the course of a year.

It is well known that the estimation of spill-over effects based on a specification such as equation (7) is complicated by a number of identification problems.[6] The so-called reflection problem refers to the fact that $\overline{EBIT}_{ibt}$ in equation (7) also includes the information contained in the firm-specific variable $EBIT_{it}$. Therefore identifying the effect of $\overline{EBIT}_{it}$ in addition to $EBIT_{it}$ is complicated. We deal with this problem in two ways: first, we calculate $\overline{EBIT}_{ibt}$ as the median EBIT over subsets of firms which report a connection with bank b.[7] And second, we concentrate only on larger banks with a large number of customers. Therefore firm-specific developments should be less relevant for the construction of $\overline{EBIT}_{ibt}$. Specifically, we include only banks with at least 100 reporting customers. While this restriction reduces the sample size, we still have information for more than 200 banks and their lenders.

In addition to the reflection problem, we may also face a selection problem since firms which borrow from a specific bank share observed as well as unobserved characteristics. Suppose for instance that banks specialize in lending to certain groups of borrowers, e.g. firms belonging to the same industry or firms which are located in the same geographical region. Then it appears conceivable that firms are exposed to the same shocks which may result in correlated lending rates across firms even in the absence of spill-over effects. In this case, the coefficient on aggregate profitability may simply pick up this correlation and may therefore be misleading as a indicator for spill-over effects occurring through the banking sector. As in the case of the reflection problem, this selection effect does not appear to be too severe in our case as we include only large banks with a large number of customers and presumably well-diversified loan portfolios. Moreover, we include bank effects and bank-specific data in selected specifications.

3.3 Subsamples Identifying Different Types of Bank Relationships

A crucial point for our analysis is the construction of $\overline{EBIT}_{ibt}$ which is a proxy for the extent to which banks use information from their customers in general. We calculate $\overline{EBIT}_{ibt}$ as the median EBIT over firms which report relations with bank b since the bank has access to this information and may use it to set lending rates. However, if a firm reports relations with multiple

[6]See Manski (2000) for a general discussion.

[7]This is standard in the literature, since the median is less influenced by single observations and therefore the median is less prone to the self-reflection problem than the mean (Manski, 2000).

banks, then the same firm i is used to calculate $\overline{EBIT}_{ibt}$ for different banks. Thus, although using all firms i which report a connection to bank b to calculate $\overline{EBIT}_{ibt}$ gives the largest number of observations, and uses all the available information, it also creates dependencies between the observations.[8]

Therefore, we calculate $\overline{EBIT}_{ibt}$ using different subsamples of firms. Overall, firms in our sample have reported bank relations with more than $3,000$ German banks. Although this number may appear to be surprisingly high, Germany has a large number of small, independent cooperative banks and saving banks (Brunner et al., 2004; Krahnen and Schmidt, 2004). Moreover, we base our analysis on the so called bank routing number (the so-called BLZ), which differs also for large commercial banks in different regions (federal states). This ensures a larger degree of comparability of commercial and regional banks. Figure 5 illustrates the distribution of the number of bank relationships for the firms in our sample. The average number of bank relations is 1.5 in our data sample. Thus, the majority of firms reports relations to only one bank. Nevertheless, nearly 40 percent of the firms have business relations to two or more banks and it is also quite common that a firm has business relations with up to three or four banks. And there are a few instances when firms have five or more (up to seven) reported bank relationships. The number of banks remains large also if we consider only banks which are reported by 100 or more firms, as used later in our analysis. Still, we can identify more than 200 banks. Firms have 1.4 bank relations in average, and some firms report up to six relatively large banks.

To avoid problems with multiple bank relations, we use firms which report only a single bank relation. While financing conditions are determined by a single bank in this subsample, the subsample is likely to predominantly include small and medium sized firms. In fact, firms reporting only one bank connection turn out to have 265 employees on average, while the firms in the whole sample have 354 employees on average. Firms with only one bank connection also tend to have their bank accounts in smaller banks, lower leverage ratio and slightly higher profitability indicators. Interestingly, the average implied interest rate for these firms is nearly 0.3 percentage points lower than in average.

Since banks which have close and long-lasting relationships with their customers are more likely to have detailed firm-specific information on which they can base their decisions, we try to identify the main or the so-called 'house bank', to capture the role of relationship lending. We

[8]Another complication arises due to possible changes of bank relations. While we cannot fully avoid this issue, bank relations are generally very stable in Germany. Moreover, as the time dimension of our data set is rather short, we only have between 1.7 and 2.3 observations per firm in average (depending on exact specification).

expect a relatively small effect of aggregate information in this case. Although our data set does not explicitly include any information on relationships banking, we identify the 'house bank' by assuming that the first bank on the list of reported bank relations is the house bank. While this assumption may seem rather ad hoc at first glance, it is actually supported by descriptive statistics, as the banks which are listed first by firms with multiple bank relations less frequently reported by the other firms than the remaining banks.

And finally, for each individual firm we select the bank relationship to a bank with the highest number of observations in our sample (e.i., which are most frequently reported by the firms).[9] The largest banks are more likely to put more weight on aggregate information. Thus, firm-specific information may be less important for these banks, in contrast to the 'house bank'. Consequently, we expect the largest effect of aggregate profitability in this case. Therefore, this subsample represents our preferred data set, which will be used for sensitivity analysis.

Finally, we exclude the main German banks (Hypovereinsbank, Commerzbank, Deutsche Bank and Postbank) from our data sample, while we identify again the bank which is most frequently reported by firms in our data sample. Fidrmuc and Hainz (2013) argue that the main banks can behave differently, for example they provide less loans to small and medium enterprises and they use more sophisticated models of borrower evaluation. Indeed, the descriptive statistics show that the average employment is only 261 employees in this subsample. The firms in this subsample are also slightly more profitable. Nevertheless, the lending rate and the leverage ratio are nearly unchanged.

3.4 Multilevel Models

A specific feature of our data set is that the observations are nested according to several criteria. In particular, interest rates may differ between regions, sectors, or even for the individual borrowers (firms). Moreover, lenders can also offer specific credit conditions, meaning that interest rates may differ by different banks. Given the nested structure of our data set, we apply a so-called multilevel model, which takes allows observations at different levels (e.g. sectors or regions) to be interrelated, generating within-cluster correlation.[10] In particular, we use two

[9] These are not necessarily the largest banks in Germany, because we use the routing number for the identification of bank units. Thus, the firms may have more relations to relatively small banks than to separate units of the main banks.

[10] The multilevel models are increasingly used in economics. For similar questions, Engelen and van Essen (2010) and Kayo and Kimura (2011) apply nested (multilevel) or hierarchical models in finance. Moreover, Pieroni and d'Agostino (2013) use this approach for an analysis of corruption, Havranek and Irsova (2011) for FDI spill-overs,

dimensions in the basic specification: regions (federal states), indexed by r, and sectors (according to the one-digit NACE classification), indexed by a subscript s. As far as these dimensions are not further related in a hierarchical structure (that is, firms may be equally influenced by regional and sectoral effects), both dimensions receive the same weight in the estimation.

Thus, the simple regression model (7) can by estimated as a multilevel random effects model if the residual in the standard regression model is defined as

$$u_{ibt} = u_{ibsrt} = \lambda_{00r00} + \mu_{000s0} + \varepsilon_{ibsrt}. \tag{8}$$

Thus, the residual u in (7) is decomposed into the random effects for regions, λ_{0r00}, sectors, μ_{00s0}, and an error term, ε_{ibsrt}. In this notation, zeros as a subscript indicate the particular dimensions which are hold constant in the definition of particular parameters.

Moreover, we include also random effects for the banks, ω_{0b000}, and firms, ϕ_{i0000}, in the robustness analysis, which extends the previous specification (8) to

$$u_{ibsrt} = \omega_{0b000} + \phi_{i0000} + \lambda_{00r00} + \mu_{000s0} + \varepsilon_{ibsrt}. \tag{9}$$

We estimate the multilevel models by restricted maximum likelihood method, which allows for non-zero covariances of the random effects for different levels. The likelihood ratio test shows that multilevel models provide a better fit than the standard regression model for all analyzed specifications.

4 Estimation Results

We start with a standard pool specification with $EBIT_{it}$ as the dependent variable (see Table 2). From column (I), which shows the results based on a specification excluding aggregate information effects, we can see that more profitable firms tend to face more favorable financing conditions. Although the effect is significant at the one percent level, it appears to be quantitatively small, since an increase in $EBIT_{bit}$ by one standard deviation reduces the implicit lending rate by around 0.51 percentage points. Compared to the average, implicit lending rate of 9 percent in our sample, this decrease appears to be modest.

In column (II) we add $\overline{EBIT}_{ibt}$, calculated using all firms reporting a relation to a specific bank, as a regressor. We see that profitability at the more aggregated level exerts a negative

and Doucouliagos and Stanley (2011) in the meta-analysis. Albright and Marinova (2010) present an introduction to estimation of multilevel models. We refer the readers to these papers for the discussion of the properties and estimation of multilevel models.

and highly significant effect. Thus, firm-specific lending rates mirror aggregate developments to some extent.

Note however, that despite the higher estimated coefficient on aggregate profitability, an increase in aggregate profitability by one standard deviation reduces the implicit interest by approximately 0.26 percentage points. This effect is smaller than in the case of firm-specific profitability since the standard deviation of $\overline{EBIT}_{ibt}$ is lower than the standard deviation of $EBIT_{it}$. In short, while both, firm-specific as well as aggregate profitability, significantly influence lending rates, the effect of firm-specific developments is more pronounced.

In column (III), we consider firms reporting only one single banks relation. The effect of $EBIT_{it}$ remains highly significant and of a similar magnitude. $\overline{EBIT}_{ibt}$ also keeps the negative sign, but its size decreases in comparison to the specification including all firms and bank relations.

Turning to column (IV), we see that firm-specific and especially aggregate profitability exert somewhat smaller, albeit still highly significant, effects, when we try to isolate the house bank. The lower influence of aggregate profitability in this case is consistent with the interpretation that a house bank can use soft information on their customers (Stein, 2002; Hauswald and Marquez, 2006) and need not rely on aggregate information and signals.[11]

For the subsample including only bank relations with the largest, reported bank, we find that $\overline{EBIT}_{ibt}$ exerts a relatively strong effect, although the influence of $EBIT_{it}$ still dominates. Thus, larger banks, which presumably engage in relationship banking to a lesser extent and have easy access to aggregate information, appear to base lending rates to a greater extent on aggregate information.

Finally, the last column (VI), which uses the same subsample as the specification (V), shows the results for specifications including only aggregate profitability. Although this specification does not allow us to distinguish between firm-specific and aggregate information effects, it avoids a possible misleading effect due to reflection problem (Manski, 2000). If there are no information effects, the role of aggregated variable should diminish. However, also this specification indicates important aggregate information effects.

Turning to the control variables, we see that larger firms (with 500 to 999 employees) face slightly lower interest rates than the medium sized firms. Firms with less than 50 employees also show lower financing costs , but the size of this effects depends on the selected subsample.

[11] Unfortunately, a high share of these banks has less than 100 identified customers, which leaves a relatively small number of observations for these estimations.

According to column (I) without aggregate profitability effects, the interest rate level was generally higher in 2005 than in 2006 and 2007. Somewhat surprisingly, this difference disappears if we include aggregate profitability. This underlines the importance of information aggregation for the determination of interest rates.

In Table 3, we include bank and firm random effects in our preferred specification in which we calculate $\overline{EBIT}_{ibt}$ using only bank relations to the largest bank (that is, banks with the largest number of reporting firms in our dataset). Column (I) corresponds to column (V) in Table 2 and is reported for easy reference. In column (II) we add random effects at the level of individual banks and in column (III) at the level of individual firms. In column (IV) we add both, bank as well as firm random effects. Although effects of of $EBIT_{it}$ and $\overline{EBIT}_{ibt}$ decline somewhat in magnitude, they remain relatively stable and highly significant.

As local banks are more likely to have detailed knowledge about their customers, they can use easier soft information (Fidrmuc and Hainz, 2013) than large banks, we now exclude the largest German banks (Hypovereinsbank, Commerzbank, Deutsche Bank and Postbank), for which we expect aggregate information effects to be particularly pronounced.[12] Results are reported in Table 4. The coefficients for $EBIT_{it}$ and $\overline{EBIT}_{ibt}$ remain relatively stable. Overall, it seems that medium-sized banks[13] use the aggregate information even more intensively than large banks.

As an additional robustness check, we augment equation (7) with bank equity relative to bank liabilities. This variable proxies the capital strength of the analyzed banks as well capitalized banks are expected to create higher provisions for future loan losses. Table 5 shows that capitalization is highly significant and exerts a negative effect on lending rates in all specifications. Moreover, individual and aggregate profitability remain negatively signed and significant.

5 Conclusions

A defining feature of the business cycle is that movements in output are synchronized across sectors, while firm-specific shocks are uncorrelated. We argue that the general financing condition act as a synchronization channel which affects also firms not affected directly by adverse profitability shocks. In particular, banks observe only the financial situation of their customers. The increase of arrears is interpreted as general downturn of the economy and generally higher

[12]Dropping these four banks reduces the data sample by about a half.

[13]Note that we exclude small banks from the estimation in order to avoid endogeneity bias.

default risks of borrowers. Correspondingly, the banks adjust the lending conditions, which impact all borrowers.

We test this hypothesis using a detailed data set on firm-bank relationships in Germany between 2005 and 2007. We show that the lending conditions are influenced by the firm-specific profitability indicators, which corresponds to the standard balance-sheet channel. The aggregate profitability computed for all borrowers of a particular bank is also significant. Moreover, the size of the aggregate profitability is significantly higher than that of the firm-specific characteristics.

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Table 1: Data Description and Descriptive Statistics, 2005-2007

			all observ.		firms with only one bank		'house' bank		largest bank		main banks excluded	
variable	description	source	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
R	implicit interest rate (%)	comp.	9.168	5.703	8.839	5.867	8.887	5.654	8.858	5.603	8.461	5.322
EBIT	earnings before interest and taxes (%)	Dafne	6.355	11.676	7.636	15.185	5.738	10.673	5.593	10.252	6.045	10.440
$\overline{\text{EBIT}}$	aggregate (median) EBIT margin (%)	comp.	3.921	1.375	3.832	1.482	3.873	1.220	4.010	1.255	4.090	1.467
lev	leverage ratio(%)	Dafne	6.419	9.067	6.854	9.683	5.435	8.003	5.322	7.847	5.405	7.968
emp	employment (persons)	Dafne	353.7	1643.0	265.3	1108.6	326.4	1643.0	325.4	1571.2	260.8	979.2
equity	ratio of bank equity to liabilities (%)	Bankscope	4.455	1.851	4.650	1.787	4.373	1.831	4.634	2.244	5.642	2.209

Note: sd - standard deviation, comp. - computed.

Table 2: Individual and Median Profitability, Basic Specification, 2005-2007

	(I)	(II)	(III)	(IV)	(V)	(VI)
rand. eff.	sect, reg	sect, reg	sect, reg	sect, reg	sect, reg	sect, reg
EBIT	-0.046***	-0.044***	-0.028***	-0.035***	-0.033***	
	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	
$\overline{\text{EBIT}}$		-0.192***	-0.136***	-0.114***	-0.152***	-0.161***
		(0.018)	(0.038)	(0.024)	(0.022)	(0.020)
size: 1-49	-0.831***	-0.792***	-0.707	-0.691***	-0.760***	-0.916***
	(0.187)	(0.187)	(0.514)	(0.239)	(0.201)	(0.192)
size: 50-99	-0.648***	-0.617***	-0.958*	-0.578**	-0.712***	-0.802***
	(0.195)	(0.195)	(0.551)	(0.251)	(0.209)	(0.192)
size: 100-499	-0.371**	-0.347*	-0.901*	-0.431*	-0.571***	-0.617***
	(0.184)	(0.184)	(0.529)	(0.239)	(0.198)	(0.189)
size: 500-999	-0.567**	-0.561**	-1.387**	-0.429	-0.480*	-0.454*
	(0.236)	(0.236)	(0.641)	(0.302)	(0.251)	(0.243)
size: NA	-0.116	-0.096	-0.331	-0.106	-0.184	-0.476***
	(0.176)	(0.175)	(0.496)	(0.226)	(0.190)	(0.184)
year 2006	-0.081	-0.121*	-0.215	-0.113	-0.062	-0.065
	(0.065)	(0.065)	(0.154)	(0.091)	(0.072)	(0.060)
year 2005	-0.097	-0.163**	-0.169	-0.126	-0.045	0.006
	(0.082)	(0.082)	(0.156)	(0.092)	(0.079)	(0.069)
Constant	9.582***	10.333***	10.271***	9.915***	10.047***	10.020***
	(0.296)	(0.301)	(0.593)	(0.354)	(0.337)	(0.328)
No of sectors	11	11	11	11	11	11
No of regions	17	17	17	17	17	17
No of groups	185	183	175	183	185	186
No of obs	53,477	53,477	10,960	30,531	39,475	52,220
LRL	-168214.47	-168161.77	-34738.10	-96227.03	-123985.05	-163987.63

Note: *LRL* - Log restricted-likelihood.
Robust standard errors in parentheses.
***, ** and * denote significance at the 1%, 5% and 10% level.

Table 3: Individual and Median Profitability, Largest Bank , Panel Specifications, 2005-2007

random effects	(I) sect, reg	(II) sect, reg, bank	(III) sect, reg, firm	(IV) sect, reg, bank, firm
EBIT	-0.033***	-0.033***	-0.018***	-0.020***
	(0.002)	(0.003)	(0.003)	(0.003)
$\overline{\text{EBIT}}$	-0.152***	-0.138***	-0.113***	-0.129***
	(0.022)	(0.027)	(0.021)	(0.024)
size: 1-49	-0.760***	-0.727***	-0.796***	-0.829***
	(0.201)	(0.202)	(0.232)	(0.226)
size: 50-99	-0.712***	-0.695***	-0.789***	-0.798***
	(0.209)	(0.209)	(0.240)	(0.234)
size: 100-499	-0.571***	-0.566***	-0.618***	-0.641***
	(0.198)	(0.199)	(0.232)	(0.224)
size: 500-999	-0.480*	-0.433*	-0.423	-0.428
	(0.251)	(0.251)	(0.284)	(0.278)
size: NA	-0.184	-0.195	-0.483**	-0.463**
	(0.190)	(0.191)	(0.221)	(0.215)
year 2006	-0.062	-0.072	-0.301***	-0.314***
	(0.072)	(0.072)	(0.051)	(0.052)
year 2005	-0.045	-0.070	-0.498***	-0.492***
	(0.079)	(0.081)	(0.061)	(0.065)
Constant	10.047***	10.054***	10.410***	10.465***
	(0.337)	(0.336)	(0.367)	(0.359)
No of sectors	11	11	11	11
No of regions	17	17	17	17
No of banks		229		229
No of firms			23455	23455
No of groups	185	3775	23455	26177
No of obs	39,475	39,475	39,475	39,475
LRL	-123985.05	-123862.35	-120874.75	-121479.43

Note: *LRL* - Log restricted-likelihood.
Robust standard errors in parentheses.
***, ** and * denote significance at the 1%, 5% and 10% level.

Table 4: Individual and Median Profitability, Largest Bank (Main Banks Excluded), Panel Specifications, 2005-2007

random effects	(I) sect, reg	(II) sect, reg, bank	(III) sect, reg, firm	(IV) sect, reg, bank, firm
EBIT	-0.036***	-0.035***	-0.020***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.003)
$\overline{\text{EBIT}}$	-0.148***	-0.140***	-0.119***	-0.131***
	(0.023)	(0.028)	(0.022)	(0.025)
size: 1-49	0.387	0.401	-0.003	0.059
	(0.264)	(0.265)	(0.304)	(0.297)
size: 50-99	0.389	0.386	-0.096	0.021
	(0.273)	(0.274)	(0.314)	(0.307)
size: 100-499	0.429	0.430	0.024	0.098
	(0.263)	(0.263)	(0.305)	(0.298)
size: 500-999	0.406	0.458	0.105	0.211
	(0.325)	(0.325)	(0.365)	(0.358)
size: NA	0.979***	0.956***	0.304	0.456
	(0.252)	(0.254)	(0.293)	(0.285)
year 2006	-0.007	-0.013	-0.222***	-0.235***
	(0.086)	(0.085)	(0.060)	(0.061)
year 2005	0.078	0.035	-0.350***	-0.357***
	(0.094)	(0.096)	(0.072)	(0.077)
Constant	8.698***	8.724***	9.432***	9.355***
	(0.384)	(0.382)	(0.424)	(0.415)
No of sectors	11	11	11	11
No of regions	17	17	17	17
No of banks		221		221
No of firms			15990	15990
No of groups	183	2861	15990	17740
No of obs	26,648	26,648	26,648	26,648
LRL	-82900.86	-82805.51	-80745.85	-81136.22

Note: *LRL* - Log restricted-likelihood.
Robust standard errors in parentheses.
***, ** and * denote significance at the 1%, 5% and 10% level.

Table 5: Profitability and Bank Equity, Largest Bank, Panel Specifications, 2005-2007

random effects	(I) sect, reg	(II) sect, reg, bank	(III) sect, reg, firm	(IV) sect, reg, bank, firm
EBIT	-0.032***	-0.032***	-0.017***	-0.019***
	(0.003)	(0.003)	(0.003)	(0.003)
$\overline{\text{EBIT}}$	-0.189***	-0.190***	-0.172***	-0.202***
	(0.027)	(0.036)	(0.028)	(0.033)
equity[a]	-0.066***	-0.071***	-0.045**	-0.053***
	(0.015)	(0.016)	(0.018)	(0.018)
size: 1-49	-0.662***	-0.639***	-0.677***	-0.685***
	(0.218)	(0.219)	(0.249)	(0.244)
size: 50-99	-0.632***	-0.616***	-0.640**	-0.644**
	(0.226)	(0.227)	(0.258)	(0.252)
size: 100-499	-0.494**	-0.489**	-0.518**	-0.524**
	(0.214)	(0.215)	(0.249)	(0.242)
size: 500-999	-0.315	-0.270	-0.221	-0.210
	(0.272)	(0.273)	(0.307)	(0.302)
size: NA	-0.061	-0.065	-0.310	-0.277
	(0.206)	(0.207)	(0.238)	(0.232)
year 2006	-0.115	-0.126*	-0.344***	-0.360***
	(0.076)	(0.076)	(0.055)	(0.055)
year 2005	-0.173**	-0.206**	-0.580***	-0.593***
	(0.088)	(0.092)	(0.070)	(0.075)
Constant	10.445***	10.523***	10.702***	10.840***
	(0.358)	(0.366)	(0.391)	(0.388)
No of sectors	11	11	11	11
No of regions	17	17	17	17
No of banks		225		225
No of firms			20259	20259
No of groups	183	3435	20259	22320
No of obs	33,171	33,171	33,171	33,171
LRL	-78823.471	-103955.41	-101640.95	-102071.34

Note: *LRL* - Log restricted-likelihood. [a] - equity to liability ratio.
Robust standard errors in parentheses.
***, ** and * denote significance at the 1%, 5% and 10% level.

Figure 1: Implicit Interest Rate

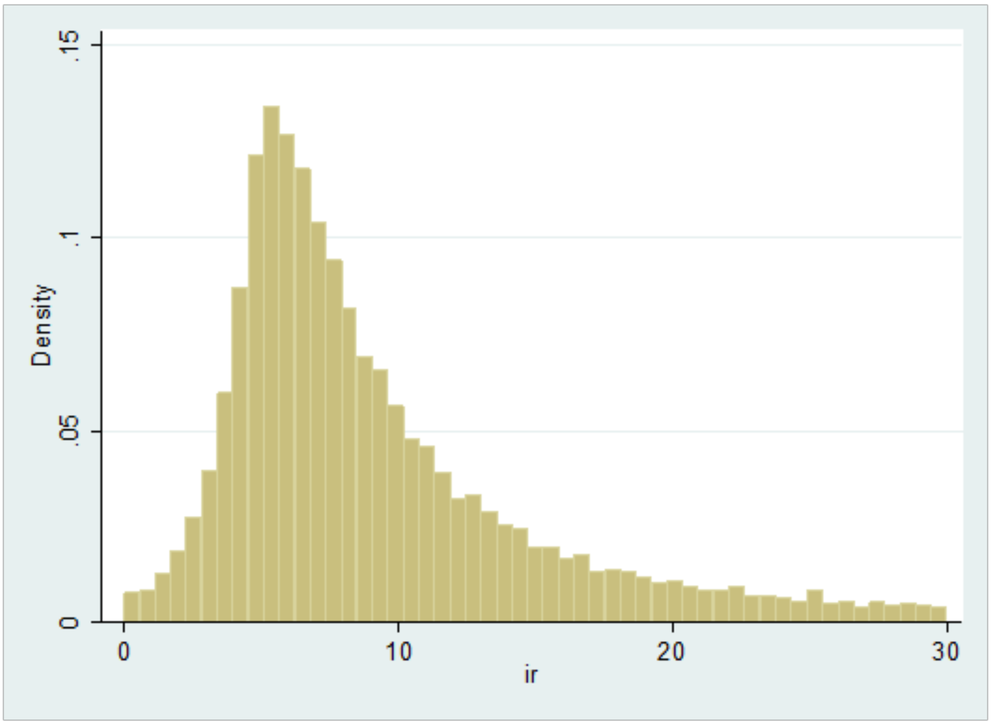

Figure 2: Bank Relationships