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BANK-FIRM RELATIONSHIPS AND THE SURVIVAL OF NON-FINANCIAL FIRMS DURING THE FINANCIAL CRISIS 2008-2009

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Abstract

Utilising a unique data set with annual accounts from around 37,000 Danish non-financial firms spanning almost one and a half decade, we offer microeconometric evidence on bank-firm relationships and the survival of firms during the financial crisis 2008-9. Within the framework of accounting-based credit-scoring models we find that the probability of default during the crisis was significantly higher for firms with a “weak” bank than for comparable firms with a “sound” bank– even after controlling for differences in the credit quality of firms. We discuss how to interpret these results in relation to the real effects of financial crisis.

Keywords: Financial crisis; bank-firm relationships; probability of default; firm survival

JEL Classification: E44; G21; G33

Non-technical summary

We use unique Danish micro data and multinomial logit models to show that the probability of default during the financial crisis 2008-09 was significantly higher for firms with a "weak" bank than for firms with a "sound" bank – even after controlling for differences in the credit quality of firms. We discuss how to interpret these results in relation to the real effects of financial crises.

For each firm our data contains information about annual accounts during the period 1995-2009 and the firm's operating status (active or exit by default, voluntary liquidation or acquisition by another firm) during the period 1996-2010. A range of non-financial characteristics (age, industry, legal form, geographical location *etc*.) is also available for each firm as well as information on the firm's main Danish bank relationships since 2003. These firm-level data are combined with data about the financial health of each bank prior to the recent crisis. The combination of detailed firm-level data and information about the financial situation for individual banks allows for a microeconometric analysis of causal effects of having a "weak" bank during the recent financial crisis.

The paper relates mainly to the empirical literature on bank-firm relationships. Several microeconometric studies based on firm-level and bank-level data have addressed the issue regarding financial crises, bank-relationships and economic performance. Our paper contributes to this strand of literature by providing empirical evidence about the effect of bank stress on the survival of the banks' corporate customers during the recent financial crisis 2008-09 based on a comprehensive firm-level data set from Denmark. The data covers around 37,000 listed as well as unlisted non-financial firms and contains approximately 550,000 firm-year observations of annual accounts from the period 1995-2009 and a total of almost 15,000 cases of corporate defaults during the period 1996-2010. This unique micro data set is considerably larger than those previously analysed in the literature.

A common potential misspecification problem in empirical studies on bank-firm relationships is the issue of omitted variable biases. It is therefore crucial to control for the credit-quality of the firms in order to isolate the link from the financial health of a firm's bank to the firm's probability of default. The large data set analysed in the paper spans almost two complete business cycles and allows us to control for a large number of firm-specific variables, which are commonly known to be correlated with the credit-quality of the firm according to the accounting-based credit-scoring literature. This reduces the risk of omitted variable bias. Our paper therefore also relates to the literature on accounting-based credit-scoring models.

We expand the framework of traditional accounting-based credit-scoring models with dummy variables for the "health status" of each firm's main bank. The financial health of a firm's main bank relationship might be of crucial importance to the economic performance of the firm during a severe financial crisis. If a bank is in financial stress it might have to reduce its credit exposure. This can have a negative impact on the bank's corporate clients if they are unable to switch bank or get access to alternative sources of finance due to asymmetric information problems between debt issuers and debt holders. The corporate clients of the bank might therefore have to scale down their operations and investments. In the worst case scenario financial problems in a firm's bank might increase the probability of default of the firm relative to similar firms with a "sound" bank relationship. A firm having a "sound" bank might better be able to overcome times of economic crises via less restrictive access to bank credit compared to a firm with a bank in financial stress.

An exploratory analysis of our data shows that firms with "weak" banks had a higher failure rate both in the period leading up to and during the financial crisis. The corporate clients of the "weak" banks are in general smaller measured by total assets, equity capital or the number of employees compared to the clients of the "sound" banks. "Weak" banks apparently also attract slightly younger firms and more firms, who are doing less well financially, measured by the proportion of firms with a recent reduction of the capital base or a critical auditor qualification. This illustrates that it is indeed important to control for systematic differences between firms with "weak" and "sound" banks in order to identify causal effects of having a weak bank during the recent financial crisis.

We use two different measures for the financial health of a firm's main bank relationship in order to check the robustness of the results in our analysis. Our first measure is based on the so-called "Supervisory Diamond" used by the Danish Financial Supervisory Authority as part of its bank supervision. The Supervisory Diamond for banks consists of a number of benchmarks for what must be considered as banking activity subject to enhanced risk. The benchmarks of the Supervisory Diamond concern lending growth, property exposure, large exposures, excess liquidity cover and funding ratio. We classify a bank as "weak" if it based on data from mid-2007 exceeded the limit values fixed by the Danish Financial Supervisory Authority for at least four out of the five benchmarks in the Diamond.

Our second measure of "weak" banks is based on the banks' excess capital in per cent of loan and guarantees relative to the banks' individual capital needs according to the Basel II capital adequacy rules. We classify a bank as "weak" if it based on data from mid-2007 is among the 10 per cent of banks with the lowest excess capital ratio. Our results are robust with respect to the two different definitions of a "weak" bank.

The interpretation of our results is however not straightforward. Since the analysis is carried out within a common-effects framework we cannot distinguish the following two opposing explanations. One in which all firms with a "weak" bank are affected by a marginally higher probability of default during the crisis and one where the majority of firms are not affected by having a "weak" bank but a smaller number of firms are heavily affected by having a "weak" bank during the crisis.

The two explanations may however have very different effects on the overall economy depending on the costs of defaults of different types of firms. If healthy firms are forced into bankruptcy it implies a real cost on the economy. If unhealthy firms are pushed into bankruptcy the effects on the real economy are not so obvious. Further analysis of potential heterogeneous effects across firms would therefore be highly relevant to gain more insight into the link between financial crises and the real economy.

I. Introduction

In the wake of the international financial crisis in 2008-9, the real effects of financial crisis have once again been among the top issues on the research agenda. We use unique Danish micro data to show that the probability of default during the financial crisis 2008-9 was significantly higher for firms with a "weak" bank than for firms with a "sound" bank – even after controlling for differences in the credit quality of firms. We discuss how to interpret these results in relation to the real effects of financial crisis.

The financial health of a firm's main bank relationship might be of crucial importance to the economic performance of the firm during a severe financial crisis. If a bank is in financial distress it might have to reduce its credit exposure. This can have a negative impact on the bank's corporate clients if these are not able to switch bank or get access to alternative sources of finance due to asymmetric information problems between debt issuers and debt holders (Bernanke, 1983). The corporate clients of the bank might therefore have to scale down their operations and investments, cf. e.g. Gibson (1993). In the worst case scenario financial problems in a firm's bank might increase the probability of default of the firm relative to similar firms with a "sound" bank relationship. A firm that has a "sound" bank might better be able to overcome times of economic crisis via less restrictive access to bank credit compared to a firm with a bank in financial distress (Petersen and Rajan, 1994; Hall and Weinstein, 2000).

Utilising a unique data set on annual accounts from around 37,000 Danish non-financial firms the paper at hand offers microeconometric evidence on bank-firm relationships and the survival of non-financial firms during the financial crisis 2008-9. For each firm the data set contains information on annual accounts during the period 1995-2009 and the firm's operating status (active or exit by default, voluntary liquidation or acquisition by another firm) during the period 1996-2010. A range of non-financial characteristics (age, industry, legal form, geographical location *etc*.) is also available for each firm as well as information on the firm's main Danish bank relationships since 2003. These firm-level data are combined with data on the financial health of each bank prior to the recent crisis. The combination of detailed firm-level data and information about the financial situation for individual banks allows for a microeconometric analysis of causal effect of having a weak bank during the recent financial crisis.

We find that the probability of default during the financial crisis was significantly higher for firms with a “weak” bank than for comparable firms with a “sound” bank – even after controlling for differences in the credit quality of firms. The interpretation of this result is however not straightforward. Since the analysis is carried out within a common-effects framework we cannot distinguish the following two opposing explanations. One in which all firms with a weak bank are affected by a marginally higher probability of default during the crisis and one where the majority of firms are not affected by having a weak bank but a smaller number of firms are heavily affected by having a weak bank during the crisis. The two explanations may however have very different effects on the overall economy depending on the costs of defaults for different types of firms. If healthy firms are forced into bankruptcy it implies a real cost on the economy. If unhealthy firms are pushed into bankruptcy the effects on the real economy are not so obvious. Further analysis of potential heterogeneous effects across firms would therefore be highly relevant to gain more insight into the link between financial crisis and the real economy.

The remainder of this paper proceeds as follows. After a brief review of the previous micro-based empirical literature on bank-firm relationships and economic performance in section II we offers a comprehensive description of the data set and issues related to our sample selection in section III. Our general identification strategy is explained in details in section IV within the framework of the potential outcome approach to causality. Section IV also contains an evaluation of the plausibility of the assumptions needed to justify our choice of econometric procedures. Section V explains the two measures of bank health we use in order to distinguish between “weak” and “sound” banks with particular attention to the issue of reverse causality. Our main empirical results are presented in section VI followed by an outline of the scope for further research in section VII.

II. A short review of related literature

The paper relates mainly to the empirical literature on bank-firm relationships. Several microeconometric studies based on firm-level and bank-level data have addressed the issue regarding financial crisis, bank-relationships and economic performance.

Gibson (1995, 1997) found that Japanese firms with low-rated banks had lower investment ratios than comparable firms with high-rated banks during the crisis in the 1990s. Using data from Japan in the 1990s and early 2000s Minamihashi (2011) also found that the clients of failed banks reduced their investments significantly.

Polonchek *et al*. (1993) found a negative share price effect on the corporate customers of the US Continental Illinois Bank after the collapse and bailout of the bank in 1984. Similar results have been found following the failure of banks in Japan in the 1990s (Murakami and Yamori, 1999; Brewer III *et al.*, 2003) and in East Asia during the crisis in the second half of the 1990s (Bae *et al*., 2002; Djankov *et al*., 2005). For Norway, Michalsen *et al*. (2003) were not able to trace similar significant share price effects of bank distress on the bank's exchange-listed clients during the systemic crisis 1988-1991 and attributed mainly this finding to the firms' easy access to the equity market.

Klein *et al*. (2002) found that financial difficulties at banks had a negative impact on the number of FDI projects made by Japanese firms into the United States in the 1990s. The study was based on a data set that contained the number of FDI projects by individual Japanese firms and information on the firms' main bank relationships. Klein *et al*., *op. cit*., found that a rating downgrade of a Japanese bank by Moody's resulted in a decline of around one-third in the number of FDI projects into the United States by those firms that used the bank as their main bank. Ushijima (2008) reports similar findings.

A number of papers have focused on the link between bank health and the survival of the banks' clients. Joeveer (2004) studied a sample of 119 firms which were clients of the Land Bank of Estonia that failed in 1998 and found a higher rate of bankruptcies among the failed banks' clients compared to a group of 114 other randomly selected Estonian firms. In a more comprehensive study Akashi *et al*. (2009) found that the financial health of a firm's bank have a significant impact on the firm's probability of default, even after controlling for the credit-quality of the firm. The results in Akashi *et al*., *op. cit*., were based on a multinomial probit model estimated for a sample of 6,266 unlisted Japanese companies 1997-2003 of which around 300 went bankrupt.

Our paper contributes to this strand of literature by providing empirical evidence on the effect of bank distress on the survival of the banks' corporate customers during the recent financial crisis 2008-9 based on a comprehensive firm-level data set from Denmark. The data covers around 37,000 listed as well as unlisted non-financial firms and contains approximately 550,000 firm-year observations of annual accounts from the period 1995-2009 and a total of almost 15,000 cases of corporate defaults during the period 1996-2010. This unique micro data set is therefore considerably larger than those previously analysed in the literature.

A common potential misspecification problem in empirical studies on bank-firm relationships is the issue of omitted variable biases, cf. section IV. It is therefore crucial to control for the credit-quality of the firms in order to isolate the link from the financial health of a firm's bank to the firm's probability of default. The large data set analysed in the paper spans almost two complete business cycles and allows us to control for a large number of firm-specific variables, which are commonly known to be correlated with the credit-quality of the firm according to the accounting-based credit-scoring literature. This reduces the risk of omitted variable bias. Our paper therefore also relates to the literature on accounting-based credit-scoring models, cf. e.g. the seminal survey by Altman and Saunders (1998) and the update in Alam *et al*. (2010).

III. Data and sample selection

The paper is based on a sample selected from a data set supplied by a private data vendor (Experian A/S). The database contains firm-level annual accounts from Danish limited liability companies. Experian A/S mainly collects the information from the Danish Commerce and Companies Agency but enriches the database via information from other sources, including information obtained via telephone interviews.

The total database contains annual accounts from around 73,000 firms in the period 1995-2009. This gives a total of more than 1,100,000 firm-year observations of annual accounts. For each year the data set contains information on all active Danish public and private limited liability companies.

The panel data set consists of time-series data for each firm. Changes in the population of firms from one year to another consist of new firms and firms ceasing to exist due to default, voluntary liquidation or merger. These modes of exit from the population of firms are registered in the database.

From the total database the following firms were excluded:

(i) All holding companies. A holding company is characterised by partial or full ownership of other companies and has typically no other activities. Danish companies owned by holding companies are, however, included in the selected sample.

(ii) All financial firms, firms within agriculture and a range of firms owned or guaranteed by the government, i.e. the analysis in the paper focuses on the non-financial non-farm private sector. Firms within agriculture are excluded since most Danish farms are sole proprietorship and not limited liabilities companies. The number of non-bank financial firms is also relatively sparse.

(iii) All companies with a balance sheet below DKK 150,000 (approximately EUR 20,000). This exclusion ensures that only active firms are included in the analysis.

(iv) All firms without information on their main bank relationship.

After these exclusions and adjustments, the data sample contains around 550,000 firm-year observations from around 37,000 firms. Compared to the full sample we thus removed around half of the observations and the main reason was missing information on bank relationships. However, it is mostly small firms that have no information on their bank relationships. On average for the period 1995-2009, the final sample therefore covers around 90 per cent of the total turnover and around 80 per cent of the total assets of all the firms in the original database.

In order to ensure consistency and comparability, accounting figures from firms with an accounting period shorter or longer than one year are annualised.

Besides accounting information the data set also contains information on a range of non-financial characteristics for each firm (age, industry, legal form, geographical location *etc*.). Furthermore, information on each firm's operating status (active or exit by default, voluntary liquidation or acquisition by another firm) in the period 1996-2010 is available. A firm is regarded as having exited by default if one of the following situations have occurred: (a) The firm has been declared bankrupt or has entered into a bankruptcy procedure; (b) the firm has been compulsory dissolved by the court or is in a process towards compulsory dissolution; (c) the firm has experienced a write down of its debt obligations or is subject to a compulsory scheme of arrangements with the creditors; or (d) the firm has experienced a forced sale. The number of active and failed firms in the data set used for the analysis in the paper is shown in Table 1.

Table 1

Finally, a few remarks should be given regarding the registration of defaults in the data set. All defaults are attributed to the year following immediately after the last year with an account reported from a failed company. However, due to time-consuming legal proceedings *etc*. related to bankruptcy, there can be a considerable time lag between the publication of the last annual account of a failed company and until the date for the official registration of the failure. On average it takes around 19 months from the year of the last account until a failure is registered, and the 90th percentile is 34 months, cf. Lykke *et al*. (2004). Parts of the number of bankruptcies attributed to year t in the database are therefore officially related to subsequent years. However, the timing convention applied in our data analysis makes sense from an economic point of view: We are more interested in the point in time where a firm has been driven by economic factors to file for bankruptcy than in the point in time where the formal bankruptcy procedures are finalised.

IV. Identification strategy

To identify the causal effect of having a "weak" bank on the probability of default for a firm during the financial crisis, we rely on the basic assumption that we are able to control for all variables that simultaneously influences the firm's choice of bank and the outcome variable. Formally the conditional independence assumption[1] has to hold, which can be written as:

$$Y_{weak,i}, Y_{sound,i} \perp D_i \mid X_i \ , \qquad (1)$$

where the stochastic variable $Y_{weak,i}$ is the potential outcome (default or survival) for firm i if it has a "weak" bank and $Y_{sound,i}$ is the potential outcome for firm i if it has a "sound" bank. D_i is a dummy variable for the health status of the bank (equal to 1 if the bank is "weak" and 0 if the bank is "sound") and X_i is the observed characteristics of the firm. By definition, we can only observe one of the potential outcomes. The identification strategy provides a way to estimate the counterfactual outcome. The assumption claims that conditional on X_i there is no dependence (denoted by $\perp$) between the potential outcomes and the indicator dummy for bank health. It is therefore only reasonable to employ this assumption when we have access to quite detailed data on the most important variables determining the selection into different banks. Alternatively, we would have to come up with some sort of instrument that could generate the necessary exogenous variation in the choice of bank without being related to the outcome of interest. We have no information about any such instrument and have therefore found it more fruitful to include a broad range of control variables. We argue that this is a reasonable strategy for attaining unbiased estimates of the effects of having a "weak" bank. To assess the robustness for this identification strategy we test for spurious effects in the years immediately prior to the financial crisis. Given the definition of the treatment dummy, we would not expect to find any effects on firm's probability of default from the health status of the firm's bank prior to the crisis.

Another way to think about the identification strategy applied in this paper is to apply the framework of a difference-in-differences estimator. One could first estimate the difference on

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[1] Cf. e.g. Lechner (1999). Other strands of the literature may recognize this assumption as "selection on observable variables" (Heckman and Robb, 1985), "ignorable treatment assignment" or "unconfoundedness" (Rosenbaum and Rubin, 1983).

the probability of default between firms with “weak” and “sound” banks but acknowledge that this comparison has to be adjusted for systematic differences between firms. One could therefore subsequently compare the differences between firms in different periods, i.e. in the period before and during the financial crisis. The estimators we use are not formally difference-in-differences estimators since we restrict the true difference in the years leading up to the crisis to be zero. However, this restriction is not rejected in the data.

Two potential problems regarding endogeneity of the “weak” bank indicators merit an upfront discussion. The first is the question of reversed causality, i.e. that the default of a large firm results in the bank becoming "weak" and not the other way around. In order to avoid this problem with reversed causality we base our bank health indicators on data from just before the outbreak of the financial crisis and do not change the health status of any banks during the years of crisis, cf. section V. This ensures that defaults among the banks’ corporate clients during the financial crisis have no effect on our classification of banks into “weak” and “sound” banks.

The second potential problem is related to firms’ switching between “weak” and “sound” banks. Firms are allowed to switch between “weak” and “sound” banks without violating our identification strategy as long as firms switch bank based on variables observed and used as controls in the model or unobserved variables that are unrelated to the potential outcome. It would be problematic if firms switch banks based on unobserved characteristics that are related to the outcome variable, i.e. the omitted variable bias. This again points to the importance of making sure to include a broad range of control variables in the model. Firms switching banks based on exogenous variation actually helps the identification strategy since this means that we can observe the potential outcome with both “weak” and “sound” bank for these firms, although not in the same year.

The general picture in the data is that firms were switching to the “weak” banks in the period leading up to the financial crisis and then started to switch away towards “sound” banks in 2008 and 2009. However, the patterns are not dramatic and it is much more common in the data that firms have the same bank both before and during the crisis.

V. Defining the financial health status of a bank

We use two different measures for the financial health of a firm's main bank relationship. Our first measure is based on the so-called "Supervisory Diamond" used by the Danish Financial Supervisory Authority as part of its bank supervision, cf. The Danish Financial Supervisory Authority (2010). The Supervisory Diamond for banks consists of a number of benchmarks for what must be considered as banking activity subject to enhanced risk. The benchmarks of the Supervisory Diamond concern lending growth, property exposure, large exposures, excess liquidity cover and funding ratio. We classify a bank as "weak" if it based on data from mid-2007 exceed the limit values fixed by the Danish Financial Supervisory Authority for at least four out of the five benchmarks in the Diamond. Fourteen of the roughly one hundred banks that the companies report as their main bank are classified as "weak" according this definition. Three of the fourteen banks are medium-sized banks whereas eleven are minor banks.

Our second measure of weak bank is based on the banks' excess capital in per cent of loan and guarantees relative to the banks' individual capital needs according to the Basel II capital adequacy rules. We classify a bank as "weak" if it based on data from mid-2007 is among the 10 per cent of banks with the lowest excess capital ratio. Eleven of the roughly one hundred banks that the companies report as their main bank relationship are classified as "weak" according to this definition. Only two of the eleven banks are identical to those banks classified as "weak" according to the Supervisory Diamond. This illustrates the importance of using several different measures of "weak" bank in order to check the robustness of the results in our analysis.

Naturally, the number of banks classified as "weak" depend on the exact cut-off values applied in each of the two definitions and constitutes a classic trade-off between bias and variance. We can either set the cut-offs at a level that result in a low number of very "weak" banks which may result in imprecise parameter estimators due to a low number of observations of firms with a "weak" bank. Or we can use a cut-off that results in a broader group of banks being classified as "weak" banks, thereby exploiting more observations with "weak" bank with the risk of diluting potential effects of having a "weak" bank.

Table 2 shows the number of firms classified as firms with respectively a "weak" and a "sound" bank relationship according to the two different measures. Regardless of the definition of the financial health of a bank we have a relatively large number of firms with a "weak" bank (around 800-3,000 firms) and therefore a good empirical basis for the identification strategy outlined in section IV.

Table 2

Table 3 illustrates the reason why it is important to control for systematic differences between firms with "weak" and "sound" bank relationships. Firms with "weak" banks had a higher failure rate both in the period leading up to and during the financial crisis. The corporate clients of the "weak" banks are in general smaller measured by total assets, equity capital or the number of employees compared to the clients of the "sound" banks. "Weak" banks apparently also attract slightly younger firms and more firms, who are doing less well financially, measured by the proportion of firms with a recent reduction of the capital base or a critical auditor qualification, cf. the definition of these concepts in Table 4.

Table 3

The main point to take away from Table 3 is that it is indeed important to control for systematic differences between firms but also that the groups of firms with "weak" and "sound" banks are not two completely disjoint groups. Combined with the large number of observations it therefore seems reasonable to assume that we can construct appropriate counterfactual outcomes. This assumption of overlapping distributions of potential outcomes across the two groups is in fact also a part of the conditional identification assumption described previously in section IV. Simply stated, we should for each firm with a "weak" bank be able to find at least one comparable firm with a "sound" bank.

Finally, it could be noted from Table 3 that the geographical distribution of firms with a "weak" bank depends heavily on the definition of a "weak" bank. When "weak" banks are defined in accordance with the Supervisory Diamond a relatively large proportion of the corporate clients of the "weak" banks are located in Copenhagen and Frederiksberg. When "weak" banks are based on the excess capital ratio, a large proportion of the firms with "weak" banks are located in rural districts. This again highlights the importance of making use of several different definitions of a "weak" bank in order to assess the robustness of the results.

VI. The effect of bank health on firms' probability of default

Our baseline model in the analysis of firms' probability of default is a modified version of Danmarks Nationalbank's failure-rate model used in relation to the Nationalbank's assessment of the financial stability outlook, cf. Danmarks Nationalbank (2003, 2007), Lykke *et al*. (2004) and Dyrberg (2004).

The Nationalbank's failure-rate model is also estimated on the basis of the Experian A/S database described in section III. There are, however, two main differences between our model and the failure-rate model of Danmarks Nationalbank. First, our model is only estimated on the subsample where information on the main bank relationship of the firms is available. The Nationalbank's failure-rate model does not make use of this information and is therefore estimated on a larger sample. Second, our baseline model includes a richer set of dummy variables (i.e. time dummies by industry aimed at capturing the business cycle and trends facing the various industries) than the Nationalbank's model. These additional variables are included to control for differences in the credit-quality of the firms (unobserved heterogeneity) and thereby address the issue of endogeneity mentioned in section IV.[2]

The underlying economic model is a hazard model with grouped duration data. Observations are measured on an annual frequency. This type of model is chosen since firms may exit the dataset in multiple ways. The competing-risks hazard model allows for simultaneous modelling of multiple outcomes. This is important even though we are mainly interested in one of the exit types, namely "default". If we did not model the alternative exits we would either have to assume that all other exits can be treated as independently right-censored or alternatively pool all types of exits into one type. The competing-risk hazard model allows us to avoid the unnecessary assumption about random right-censoring and explore the available data more efficiently, when we are able to focus on the specific event of interest.

Assume that a firm can exit from one year to another in one of the following three different ways: (1) the firm exits by "default"; (2) the firm exits by "voluntary liquidation"; or (3) the firm exit via "acquisition by another firm". If none of these events happens, the firm stays "active". Furthermore, assume that a firm's state (i.e. "active", "exit by default", "exit by

[2] Instead of time dummies by industry the Nationalbank's model makes use of only one single variable (real GDP growth) to capture business cycle effects since the Nationalbank's model is used for forecasting.

voluntary liquidation" or "exit by merger") in two subsequent years are independent of each other conditional on the observed firm variables. The assumption of independent exits might be seen as a strong assumption. Note however, that the probability of exit in any given period is allowed to depend on the fact that the firm has been able to survive during a specific number of years. This is possible to estimate without any left-censoring since the data contains information about the start-up year for each firm. This strengthens the identification of the part of the hazard model that is known as the baseline-hazard, i.e. the general time profile for the hazard rate, where time is measured as the number of years since the start-up for each firm. For estimations purposes, it turns out that this hazard model can be estimated as an unordered multinomial logit model with alternative-invariant regressors and "active firms" as the base category, cf. Allison (1982) and Dyrberg (2004).[3]

In the following analysis we will for presentational purposes only focus on exit by default and hence not show the equations and results for the alternative exit types even though these are simultaneously modelled in the estimation.

The baseline failure-rate model for the probability that firm j will exit by default in year t ($PD_{j,t}$) can be written as:

$$PD_{j,t} = F\left(b_0 + \sum_{i=1}^{k} b_i X_{i,j,t-1} + \sum_{i=1}^{m} a_i Z_{i,j,t} \right), \qquad (2)$$

where b_0 is a constant term and $b_1, \ldots, b_k, a_1, \ldots, a_m$ are parameters. The explanatory variables consists of information on firm j's return on assets, debt ratio *etc*. in year t-1 ($X_{1,j,t-1}, \ldots, X_{k,j,t-1}$) and a range of other firm-specific variables such as age, geographical location *etc*. in year t as well as annual time dummies by industry aimed at capturing the business cycle and trends facing the various industries ($Z_{1,j,t}, \ldots, Z_{m,j,t}$).[4] The explanatory variables are described in details in Table 4. The probabilities of the other types of exit can be written in a parallel way.

Table 4

[3] The econometrics of duration data and the multinomial logit model is e.g. covered by Wooldridge (2002) or Cameron et al. (2005). All econometric results presented in the paper at hand have been obtained via SAS.

[4] Since all the firm-specific variables are "hard" indicators from either the firms' annual accounts or structural information about the firms (e.g. age or industry) the potential effect on the failure rate originating from "soft" firm-specific characteristic such as the quality of the firms' management will be part of the error terms in the estimated model.

The baseline model is estimated via maximum likelihood and the results related to the probability of default are shown in Table 5. Due to the large number of observations a significance level of 1 per cent is practically feasible and more appropriate than the conventional 5 per cent level. Employing 5 per cent significance levels would increase the risk of false positive test statistics that would lead us to see too many significant parameters. All the variables are significantly different from zero at a 1 per cent significance level and the estimated coefficients all have the expected signs, cf. also Table 4.

Table 5

For interpretation purposes, table 5 also shows the change in the odds-ratios by a unit change in each of the explanatory variables. The odds-ratio is the probability of exit by "default" relative to the probability that the firm is "active" (i.e. the “relative probability of default”, in the following just denoted as the “probability of default”). Table 5 shows that the probability of default of a firm with a critical auditor qualification is approximately 3 times higher than the probability of default of an identical firm without a critical auditor qualification.

As a robustness test of our sample selection we also estimated the baseline failure-rate model (2) on the basis of the full sample in the original database with around 1,100,000 firm-year observations of annual accounts. The full sample includes firms with and without information on their main bank relationship, cf. Table 6. The estimated model based on our sample consisting only of firms with information on bank relationship in Table 5 comes very close to the estimated model in Table 6 based on the full sample from the original database.

Table 6

In order to assess whether dependence on a “weak” bank during the financial crisis increases the probability of default for a firm, we expand the baseline model (2) with a series of weak-bank-dummy variables as follows:

$$PD_{j,t} = F\left(b_0 + \sum_{i=1}^{k} b_i X_{i,j,t-1} + \sum_{i=1}^{m} a_i Z_{i,j,t} + d_{04} D04_{j,t} + ... + d_{10} D10_{j,t} \right). \quad (3)$$

In (3) $D10_{j,t}$ is a dummy variable equal to 1 in 2010 if firm j at the beginning of 2010 has a "weak" bank as its main bank relationship. For other years, the variable is equal to 0. Note that the categorization of banks as weak or sound is fixed over the entire period. The dummy variable for individual firms can therefore only change if firms shifts between weak and sound banks. The other weak-bank-dummy variables in (3) are defined similarly. A positive and significant value of the parameters to the weak-bank-dummy variables during the years of the financial crisis indicate that firms with "weak" banks were more likely to default during the crisis than similar firms with "sound" banks.

To address the risk of omitted variable bias, equation (3) in addition to weak-bank-dummy variables also includes all the explanatory variables which according to the baseline failure-rate model (2) are of relevance for the failure rate of firms. As a further robustness check (3) also contains a number of additional weak-bank-dummy variables, which relate to the period prior to the financial crisis. *A priori* one should not expect the parameters associated with the pre-crisis weak-bank-dummies to be significantly different from zero. It might seem somewhat counterfactual to use weak-bank dummies prior to 2007 defined on the basis of the banks' financial strength in mid-2007. However, the weak-bank dummies prior to 2007 are only included as a robustness check and should not be given any deeper economic interpretation. The estimated parameters for the other variables in the model do not differ significantly from the results reported in the paper if one omits the weak-bank dummies prior to 2007.

Table 7 shows the results of the estimation of model (3) with the two different definitions of a "weak" bank described in section V. Using the Supervisory Diamond to define "weak" banks the parameters d_{08} and d_{09} are clearly different from zero at a 1 per cent significance level. The signs of the estimated parameters are also as expected - dependence on a "weak" bank increased the probability of default of a firm during the financial crisis. The changes in the odds-ratios by a unit change in each of the explanatory variables indicate that firms with a "weak" bank had a failure rate in the years 2008-09, which was around 40 per cent higher than the failure rate of similar companies with a "sound" bank. The parameters related to the weak-bank dummies from before the financial crisis are not significantly different from zero, which are also in line with the *a priori* expectations.

Table 7

The results when “weak” bank are defined on the basis of the excess capital ratio gives roughly the same picture, although with a somewhat larger effect on the probability of default of having a “weak” bank. It can, however, be noted that the parameter d_{07} in this case also is different from zero at a 1 per cent significance level. This might at first seem surprising since the financial crises only began in the second half of 2007 and was rather mild in the beginning. However, as mentioned in section III parts of the failures attributed to the year 2007 in the data set actually relates to subsequent years due to the considerable time lag between the publication of the last annual account of a failed company and the date for the official registration of the failure.

VII. Concluding remarks and scope for further research

Using unique Danish micro data we have shown that the probability of default during the financial crisis 2008-9 was significantly higher for firms with a “weak” bank than for firms with a “sound” bank – even after controlling for differences in the credit quality of firms. However, a few words of caution are in order regarding the interpretation of the estimated effects on the probability of default of having a “weak” bank.

First, to the extent that the explanatory variables in the failure-rate model are not sufficient to control for the credit quality of the firms, the estimated effect on the probability of default of having a “weak” bank might be upward biased. This is due to the fact that “weak” banks in general have a larger share of financially unhealthy firms in their corporate-customer portfolio, cf. section V. The estimated effects on the probability of default of having a “weak” bank might therefore to some degree reflect that “weak” banks have financially unhealthy firms as customers.

Second, model (3) is based on the assumption that there in a given year is a constant effect for all firms on the probability of default of having a “weak” bank. In our interpretation of the results we are therefore not able to distinguish between the following two opposing explanations. One in which all firms with a weak bank are affected by a marginally higher probability of default during the crisis and one where the majority of firms are not affected by having a weak bank but a smaller number of firms are heavily affected by having a weak bank during the crisis. The two explanations may however have very different effects on the overall economy depending on the costs of defaults for different types of firms. If healthy firms are forced into bankruptcy it implies a real cost on the economy. If unhealthy firms are pushed into bankruptcy the effects on the real economy are not so obvious.

Further analysis of potential heterogeneous effects across firms would therefore be highly relevant to gain more insight into the link between financial crisis and the real economy.

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Tables

TABLE 1

Companies included in the analysis in this paper

Year	Number of active firms, beginning of year	Number of exits by		
		Failure	Voluntarily liquidation	Merger
1996................................	29,033	670	255	216
1997................................	30,013	725	257	243
1998................................	31,941	812	233	237
1999	34,956	839	254	294
2000	37,921	1.049	238	316
2001	40,097	1.417	318	340
2002	41,890	1.419	342	356
2003	42,675	1.322	354	526
2004................................	42,936	1.393	424	620
2005................................	39,512	944	390	444
2006................................	34,614	676	278	339
2007................................	33,028	744	257	348
2008................................	31,524	1.151	304	348
2009................................	30,273	1.207	252	274
2010................................	29,684	527	180	196
Average	35,340	993	289	340
Total................................	530,097	14,895	4,336	5,097

Source: Calculated by the authors based on data from Experian A/S.

TABLE 2

Number of firm-observations (end of year) for each definition of “weak” bank

	“Weak” bank defined on the basis of the Supervisory Diamond in mid-2007		“Weak” bank defined on the basis of excess capital ratio in mid-2007	
	Sound bank	Weak bank	Sound bank	Weak bank
2003	42,386	2,987	44,114	1,259
2004	38,455	2,835	40,163	1,127
2005	33,368	2,539	34,898	1,009
2006	31,880	2,497	33,367	1,010
2007	30,938	2,389	32,366	961
2008	29,818	2,188	31,113	893
2009	28,679	1,908	29,814	773
Memo: Number of banks ...	90	14	93	11

Source: See the main text.

TABLE 3

Comparison of key figures for firms with "weak" and "sound" bank

	Average over 1995-2006				Average over 2007-2009			
	"Weak" bank defined on the basis of the Supervisory Diamond in mid-2007		"Weak" bank defined on the basis of excess capital ratio in mid-2007		"Weak" bank defined on the basis of the Supervisory Diamond in mid-2007		"Weak" bank defined on the basis of excess capital ratio in mid-2007	
	"Sound" bank	"Weak" bank	"Sound" bank	"Weak" bank	"Sound" bank	"Weak" bank	"Sound" bank	"Weak" bank
Failure rate (%)	2.5	3.8	2.6	2.8	2.9	4.5	2.9	5.3
Return on assets (%).............	5.6	3.8	5.4	6.2	4.8	3.6	4.7	4.8
Primary operating result (DKK million)	2.1	0.5	2.1	0.8	3.1	0.5	2.9	1.0
Total assets (DKK million)	36.2	12.0	35.3	11.9	67.0	19.4	65.1	16.6
Equity capital (DKK million) ...	15.4	3.6	15.0	4.1	27.5	6.4	26.7	6.2
Debt ratio (short) (% of total assets)	54.0	60.2	54.4	52.9	59.8	65.4	60.1	60.1
Debt ratio (long) (% of total assets)	12.2	12.5	12.2	15.2	10.5	10.7	10.4	13.5
Number of employees	25.6	11.2	25.0	12.6	34.0	14.5	33.1	15.8
Age (years)	17.5	15.3	17.4	16.1	21.2	18.3	21.0	19.5
Reduction of the capital base (% of firms)	14.3	18.8	14.5	15.0	16.3	21.3	16.5	18.2
Critical auditor qualification (% of firms)	7.8	10.1	7.9	9.6	11.0	14.8	11.1	13.5
Geographical location of firms (%)								
Copenhagen and Frederiksberg....................	13.4	28.3	14.5	5.2	12.2	28.4	13.5	4.6
The county of Copenhagen	11.6	23.1	12.5	2.8	10.5	23.0	11.7	1.7
Frederiksborg and Roskilde	12.7	24.4	13.7	2.7	11.8	23.2	12.9	3.1
Other municipalities	19.8	5.3	18.8	21.7	20.8	7.1	19.8	19.6
Rural district........................	42.6	18.9	40.5	67.7	44.7	18.2	42.1	71.1
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Classification of firms by industry (%)								
Trade, etc.	32.3	31.0	32.3	29.8	34.9	32.0	34.9	30.5
Construction........................	12.4	14.4	12.5	15.3	14.0	15.7	14.1	16.9
Letting and sale of real estate	23.0	25.8	23.2	21.1	20.5	25.5	20.9	19.0
Manufacturing	18.1	14.7	17.9	19.9	17.6	13.6	17.3	20.3
Transport, etc......................	5.3	4.2	5.2	4.9	8.9	8.5	8.9	8.0
Other	8.9	9.9	8.9	9.0	4.1	4.5	4.0	5.4
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Number of firm-year-observations	430.843	27.662	446.627	11.878	89.435	6.485	93.293	2.627

Note: For more details on the definitions of the key figures, cf. Table 4.
Source: See the main text.

TABLE 4

Explanatory variables in the baseline failure-rate model (2)

Explanatory variables	Expected effect on failure rate of a change in the variable	Comments
Entering with a time lag:		
Return on assets	-	The company's return on assets relative to the median return for the relevant industry. The return on assets is calculated as the company's profit before interest (primary operating result) in % of the total assets end of year. The expected sign (-) reflects the hypothesis that - all else being equal (including the attitude towards risks) - a high earning reduces the probability of default. Other variables (legal form of ownership and geographical location) aim at controlling for the firms' willingness to take risk.
Debt ratio (short)..........	+	Short-term debt as a ratio of total assets end of year. The expected sign (+) reflects the hypothesis that a high short-term debt ratio increases the risk of default.
Debt ratio (long)...........	+	Long-term debt as a ratio of total assets end of year. The expected sign (+) reflects the hypothesis that a high long-term debt ratio increases the risk of default.
Size.............................	-	Logarithm of total assets end of year deflated by the GDP-deflator (with 1995=1). The expected sign (-) reflects the hypothesis that large firms are less likely to default than small firms.
Reduction of the capital base	+	The dummy variable is set at 1 if the company has had a deficit in the most recent year and if another deficit of the same magnitude will reduce the company's equity capital to a level below the statutory capital requirement for new firms. Otherwise, it is set at 0. The expected sign (+) reflects the hypothesis is that firms with a thin capital base have a higher probability of default.
Critical auditor qualification	+	The dummy variable is set at 1 if the annual account have one or more critical auditor qualifications. Companies without any auditor qualifications are the reference group, for which the dummy variable is set at 0. The expected sign (+) reflects the hypothesis is that firms with critical comments from the auditors have a higher probability of default.
Entering without a time lag:		
Legal form of ownership	+	The dummy variable is set at 1 if the company is a private limited liability company in the beginning of the year. Public limited liability companies, for which the statutory capital requirement for new firms is higher, are the reference group (with the value 0).
Age	-	Dummy variables for the specific age of a firm at the beginning of the year. The reference group (with the value 0) comprises newly established companies with an age below 1 year. The expected sign (-) reflects the hypothesis that the most efficient firms tend to survive and stay in business.
Geographical location	-	Dummy variables ranking the companies' domiciles at the beginning of the year by municipality group, with Greater Copenhagen as the reference group (with the value 0). The Greater Copenhagen is more sensitive to cyclical fluctuations than the provinces. The expected sign (-) reflects the hypothesis that more cyclical volatility increases the risk of default.
Year dummies by industry	+/-	Annual time dummies by industry (7 industries) aimed at capturing the business cycle and trends facing the various industries. Manufacturing is the reference industry (with the value 0).

TABLE 5

The estimated baseline failure-rate model (2)

	Coefficient estimate		Standard error	Change in the odds-ratio by a unit change in the explanatory variable
Constant term	-2.816	***	0.0857	...
Return on assets	-0.00125	***	0.000205	0.999
Debt ratio (short)....................................	0.359	***	0.0132	1.431
Debt ratio (long).....................................	0.322	***	0.0297	1.380
Size	-0.217	***	0.00753	0.805
Critical auditor qualification....................	1.168	***	0.0218	3.214
Legal form of ownership	0.354	***	0.0228	1.425
Reduction of the capital base	1.281	***	0.0218	3.599

Notes: The response variable is the natural logarithm to the odds-ratio, i.e. the probability of exit by "default" relative to the probability that the firm is "active". The figures in the column "Change in the odds-ratio by a unit change in the explanatory variable" are the antilogarithm to the corresponding coefficient estimates. Besides the variables listed in the table, the estimated model contains dummy variables for geographical location and age. Furthermore time dummies by industry are included. The model is estimated on the basis of 554,425 firm-year-observations.

* indicates that the coefficient is significant different from zero at a 10 % level of significance.

** indicates that the coefficient is significant different from zero at a 5 % level of significance.

*** indicates that the coefficient is significant different from zero at a 1 % level of significance.

TABLE 6

The estimated failure-rate model (2) based on the full sample in the original database

	Coefficient estimate		Standard error	Change in the odds-ratio by a unit change in the explanatory variable
Constant term	-2.181	***	0.0482	...
Return on assets	-0.00158	***	0.000121	0.998
Debt ratio (short)....................................	0.286	***	0.0081	1.331
Debt ratio (long).....................................	0.216	***	0.0173	1.241
Size	-0.273	***	0.00444	0.761
Critical auditor qualification....................	1.063	***	0.0129	2.894
Legal form of ownership	0.300	***	0.0160	1.350
Reduction of the capital base	1.006	***	0.0130	2.736

Notes: The response variable is the natural logarithm to the odds-ratio, i.e. the probability of exit by "default" relative to the probability that the firm is "active". The figures in the column "Change in the odds-ratio by a unit change in the explanatory variable" are the antilogarithm to the corresponding coefficient estimates. Besides the variables listed in the table, the estimated model contains dummy variables for geographical location and age. Furthermore time dummies by industry are included. The model is estimated on the basis of 1,091,482 firm-year-observations.

* indicates that the coefficient is significant different from zero at a 10 % level of significance.

** indicates that the coefficient is significant different from zero at a 5 % level of significance.

*** indicates that the coefficient is significant different from zero at a 1 % level of significance.

TABLE 7

The estimated failure-rate model (3) with weak-bank-dummies

	Coefficient estimate		Standard error		Change in the odds-ratio by a unit change in the explanatory variable	
	"weak" bank defined on the basis of					
	Supervisory Diamond	Excess capital ratio	Supervisory Diamond	Excess capital ratio	Supervisory Diamond	Excess capital ratio
Constant term	-2.825 ***	-2.821 ***	0.0857	0.0857	...	...
Return on assets	-0.00126 ***	-0.00126 ***	0.000205	0.000205	0.999	0.999
Debt ratio (short)........	0.358 ***	0.358 ***	0.0132	0.0132	1.431	1.431
Debt ratio (long).........	0.322 ***	0.321 ***	0.0297	0.0297	1.379	1.379
Size	-0.217 ***	-0.217 ***	0.00753	0.00753	0.805	0.805
Critical auditor qualification................	1.167 ***	1.167 ***	0.0218	0.0218	3.211	3.214
Legal form of ownership	0.354 ***	0.353 ***	0.0228	0.0228	1.424	1.424
Reduction of the capital base	1.280 ***	1.282 ***	0.0218	0.0218	3.596	3.602
D10	-0.00842	0.195	0.170	0.241	0.992	1.216
D09	0.337 ***	0.763 ***	0.106	0.147	1.400	2.144
D08	0.323 ***	0.711 ***	0.105	0.152	1.382	2.035
D07	0.302 **	0.752 ***	0.128	0.174	1.352	2.122
D06	-0.121	0.268	0.160	0.233	0.886	1.307
D05	0.124	0.219	0.133	0.212	1.132	1.245
D04	0.108	0.011	0.122	0.195	1.114	1.011

Notes: The response variable is the natural logarithm to the odds-ratio, i.e. the probability of exit by "default" relative to the probability that the firm is "active". The figures in the column "Change in the odds-ratio by a unit change in the explanatory variable" are the antilogarithm to the corresponding coefficient estimates. Besides the variables listed in the table, the estimated model contains dummy variables for geographical location and age. Furthermore, time dummies by industry are included. The model is estimated on the basis of 554,425 firm-year-observations.

* indicates that the coefficient is significant different from zero at a 10 % level of significance.

** indicates that the coefficient is significant different from zero at a 5 % level of significance.

*** indicates that the coefficient is significant different from zero at a 1 % level of significance.