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Is Information Disclosure by Banks Useful for Predicting Their Failure? The Case of Japan's Banking Crisis

By

Mikhail Frolov

Abstract

This study investigates whether bank disclosures are useful in predicting bank failure by focusing on the core quantitative information disclosed by Japanese banks. The informative value of the financial data is tested against the experience of bank failure during the recent banking crisis. The study finds that bank quantitative disclosures convey information which is potentially useful in predicting bank failure. Its empirical results, however, also show that the predictive value of the core disclosures may be significantly reduced in the presence of the perverse investment behavior of insolvent banks.

JEL Classification

G21, G28, G33

Key Words

Public disclosure in banking, Bank failure prediction, Japanese banks.

I. Introduction

In March 2005, Japan's banking regulator drew a line demarcating its position during the public discussion of proposed modifications to the nation's disclosure regime for banks. The changes focused on improving the periodicity and itemization of disclosed information about the structure and loss characteristics of bank assets with the understanding that these loss exposures should be offset by the banks' own capital. The fine schedule of disclosure items is yet to be delivered by the regulator. But it is clear that the modifications closely follow the recommendations of the Basel Committee under the new Capital Accord and focus on the key data inputs of the risk quantification process the banks use to calculate their capital requirements. There is no doubt that these changes will lead to important improvements in the quality of disclosed bank information, making it more forward-looking and up-to-date.

Even before the planned changes, however, Japan's banking industry was already benefiting from a very advanced system of quantitative disclosure requirements. And the major practical challenge has been in making sure that market participants were, in fact, actively accessing and effectively using this information. One problem in this regard involved the decentralized and costly access to the disclosed data (Frolov 2006), which was further complicated by an unclear informative value for many types of disclosures. Unlike the former problem, which is rooted in institutional deficiencies, the latter one is of empirical nature and requires the disclosed information to be tested against practical needs.

Predicting bank failure is among the most common application areas of bank disclosures, for the risk of bank failure is, arguably, a critical concern for both bank creditors and regulators. Furthermore, since the first groundbreaking studies of the 1970s, bank failure prediction has become a very prolific area of economic research. Initially the research focused on the problem of what financial statement information (or financial ratios based on it) gives correct ex-post classification of banking institutions into failure vs. survival groups[1]. Later the literature went to explicitly studying the informative value of available data in prediction (ex-ante classification) of bank failures, while improving its empirical techniques and information scope. The research typically finds that (1) financial statement variables and regulators' internal ratings enable rather accurate ex-post classification in both binominal (failure / survival) and multinominal (regulatory ratings, etc.) setups. At the same time, (2) the addition of market information and local economic variables does not lead to substantial improvements in classification accuracy[2]. Plus, (3) the ex-ante classification value of the information is lower, and the estimated effects seem to be unstable over time and across prediction horizons[3].

The interest in the predictive power of bank disclosures stems from the fact that bank failures inflict significant losses on their stakeholders, as well as society at large. Thus, quantitative assessment of disclosures demands using the occurrence of actual bank failure as the ultimate metric of their usefulness. Open bank failure, however, is rather a rare event, and it requires a nation to experience major banking problems in order to provide researchers enough information for quantitative assessment. For that reason, most studies in the field, both in the U.S. and other countries, have become inevitably tied to the nations' experiences during banking crisis episodes in the past[4]. In Japan, the recent wave of open bank failures was the first such instance since the

[1]Meyer and Pifer (1970), Stuhr and van Wicklen (1974), Martin (1977) were among the first large contributions in the field. For a comprehensive survey of literature on corporate failure prediction, see Altman and Saunders (1998). About bank failure prediction, see also citations in Demirguc-Kunt (1989) and recently in King et al (2006).

[2]See, e.g., Whalen and Thomson 1988, Espahbodi 1991, Whalen 1991, Curry et al 2003, Nuxoll et al 2003, Krainer and Lopez 2004, etc.

[3]For fact finding studies see, e.g., Thomson 1991, Hooks 1995, Helwege 1996, Henebry 1997, Kolari et al 2002. These differences in the ex-post vs. ex-ante classification accuracy have been attributed to several factors: possible differences in business cycle phases (Logan 2001), fundamental changes in financial technology and environment (King et al 2006), and different stages of financial system development (Honohan 1997, Rojas-Suarez 2001). Recently the reduced predictive power of the usual bank disclosures has led some commentators to voice the need of searching for more forward-looking indicators (Rojas-Suarez 2001, King et al 2006).

[4]Among the non-US studies, Rodriguez (1989), Gonzales-Hermosillo et al (1997), Laviola et al (1999), Bongini et al (2001), Logan (2001), Molina (2002), Dabos and Sosa Escudero (2004), Kraft and Galac (2005), Lanine and Vander Vennet (2005) all use data related to nationwide banking crises.

1940s, and it is no surprise that initial studies using Japanese data have appeared just recently[5]. Furthermore, the empirical tests of the studies have utilized only a fraction of the failure episodes, thus, leaving a significant gap in the quantitative assessment of the usefulness of bank disclosures in Japan.

This study addresses the gap and considers all cases of outright bank failure in Japan since 1994. We investigate the question of whether bank disclosures are useful in predicting bank failures by focusing on the quantitative information disclosed by Japanese banks in their financial statements. Our choice reflects the fact that unlike qualitative information or data on the structure of loan portfolios, this information is readily obtainable from public sources at a relatively low cost. Yet, it follows the same reporting format and easily lends itself to comparison across banking organizations. For that reason, this information is arguably at the core of the present disclosure regime for banks, and thus commands the strongest interest from the perspective of ongoing regulatory changes under Basel II.

The study finds that the core quantitative disclosures of banks convey information which is potentially useful in predicting bank failures. But our empirical results also show that the predictive value of the core disclosures may be significantly reduced in the presence of the perverse investment behavior of insolvent banks. The finding leads us to support the view that a wider scope of bank disclosure may be needed to improve the effectiveness of the nation's disclosure regime for banks.

This paper is organized by five sections. After this introductory section, we discuss in Section II factors, which shaped the dynamics of Japan's banking sector during the recent banking crisis, and relate them to the findings of prior research. Section III describes our data set and motivates the choice of empirical setup. Our findings, discussion of these, and concluding remarks are presented in Sections IV and V.

II. Prior Research and the Peculiarities of Japan's Banking Crisis

The banking crisis of 1997-2002 was the second episode of significant problems in the nation's banking system over the last century. Unlike the banking system meltdown in 1927, the recent crisis did not bring about open bank runs and suffering of depositors. But during that period the number of banks dropped to half of the pre-crisis level, and the traditional bank management and regulatory practices were necessarily revamped, ushering in a new set of realities to the banking industry.

At least, three factors were responsible for the great magnitude of this crisis: First, the nation's banking sector faced the large cyclical downturn of the 1990s while being heavily "overcrowded", whereby too many lenders began to compete for a shrinking tort of good-quality lending opportunities. Second, the management practices inherited from the high-growth era led to mispricing of loans in the matured-economy environment (Oyama and Shiratori 2001). As a result, the Japanese banks entered the 1990s with underpriced loan rates and then found themselves without sufficient resources to cover increased credit losses during the economic downturn. Third, the regulatory response to the crisis evolved gradually from denying and concealing the problems to a forceful clean-up of the financial sector, and the course of this regulatory

[5]Their list includes Yamori (2000), Yoshino and Shimabukuro (2002), Aoki et al 2003, DICJ (2005).

evolution influenced the dynamics of bank defaults during the crisis.

Figure 1 reports the dynamics of Japanese bank failures during the 1990s. As can be observed, a significant buildup of the number failure cases has occurred only since FY 1997. Due to regulatory forbearance, bank failures before that point were few and far between, but with exceptionally high loss rates. In absolute terms, the bank failure history of the past decade was dominated by the defaults of credit cooperatives (134 of 180 cases) – both in the number of defaults and average loss rates. On the other hand, credit associations, representing another equally numerous group of small banking organizations, gave 27 cases, and commercial banks 19 cases only. By FY 2002, the cleanup operation of the national banking regulator coincided with the first positive signs of an end to the economic downturn, as outright bank failures stopped[6] with remaining weak institutions being actively absorbed by stronger banks.

The nation's experience with bank failures over the last decade has recently become the focus of economic research. To date, three large studies have empirically investigated causes of the bank failures[7]. The research unit of the Deposit Insurance Corporation of Japan (DICJ), a public body responsible for bank failure resolution, leveraged the DICJ's internal documentation to conduct a thorough investigation of all the 180 resolution cases (DICJ 2005). Table 1 summarizes the case study results. In particular, DICJ (2005) finds credit quality deterioration to be the leading failure factor in more than 90% of all cases (coupled with deficient management in 65% cases). Failures due to excessive credit concentration on the "risky" sectors (real estate, construction, nonbank finance, and insurance) are especially prominent among urban banks. This factor had reached its peak in FY 1996–8, that is, 3 to 4 years after the sharp decline of land prices (and corresponding collateral value deterioration). But in FY 1999–2001 the factor of risk concentration loses its importance giving place to the factor of general economic downturn. Furthermore, case-by-case comparison with sound peer institutions reveals that the failed banks exhibited relative decline in loan and deposit growth rates starting 3 to 4 years prior to their failure. DICJ (2005) also investigates bank failures by the rate of asset losses shouldered by the Corporation during their resolution and finds that failures due to excessive credit concentration are associated with increased loss rates and that deficient management contributes with a loss rate increase.

Aoki et al (2003) approached bank failure episodes from a different perspective. The study used pairs of "failed bank–sound peer-bank" to investigate what financial ratios are good in explaining the failures of credit associations and cooperatives over FY 1998–2001. In particular, Aoki et al (2003) focused on financial ratios related to the hypothesis that the observed small bank failures result from the banks' inability to cover credit losses by available financial resources and from subsequent evergreening of the troubled credit exposures. The study finds that the ratio of the realized credit cost (recorded accounting loss from disposing delinquent credit exposures) to loan portfolio actually works best in discriminating sound banks from failed ones. Furthermore, when combined with the non-performing loan (NPL) ratio and an indicator of

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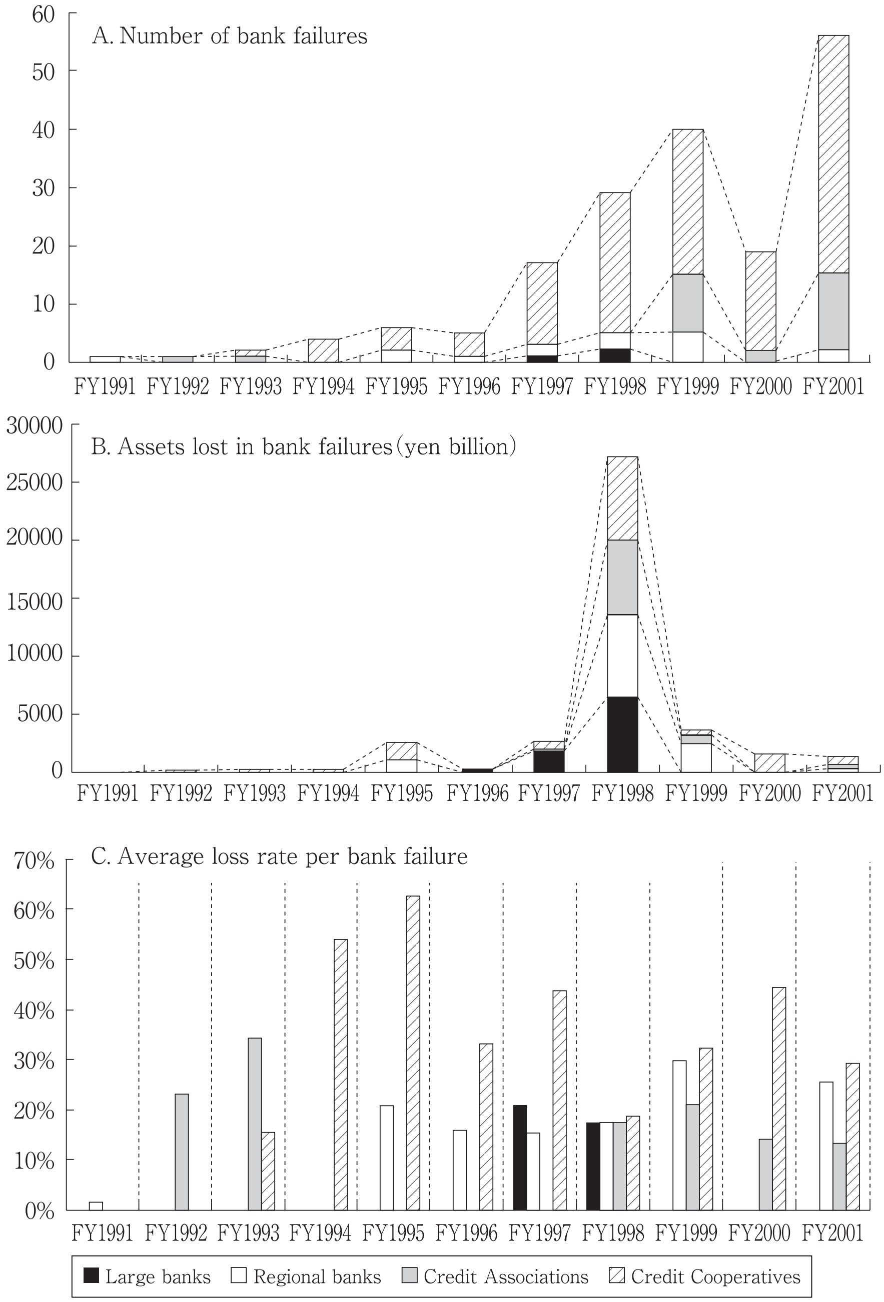
[6]The two noticeable exceptions are the temporal nationalization of *Ashikaga* Bank and the public fund injection to *Resona* Bank. In both cases, however, the troubled institutions did not cross the line of absolute capital deficiency and their cases were resolved without outright liquidation / reorganization.

[7]Yamori (2002) was first to empirically analyze the financial characteristics of banks failed during the early stage of the crisis. Although being based on a limited number of failures, his study reports several findings consistent with results of DICJ (2005).

Figure 1. Japanese Bank Failures in FY 1991-2001



Data of individual failure cases are aggregated by the date of the first official action (failure recognition). Asset losses are estimated as the combined amount of outright monetary grants and indirect financial assistance received from both public and private sources during the failure resolution process.
Source: the author' calculations based on DICJ (2005), pp. 23-46, 168-277.

Table 1. Japanese Bank Failures by Failure Cause

Primary failure cause	All cases: Cases	share (%)	Av. loss rate (%)	including faulty management: Cases	share (%)	Av. loss rate (%)
1. Credit quality deterioration	165	91.7	25.9	109	93.2	29.4
a. Credit concentration on real estate, etc.	83	46.1	27.7	54	46.2	30.6
b. Credit concentration on other sectors	47	26.1	28.8	40	34.2	31.0
(both a. and b.)	14	7.8	33.0	13	11.1	34.5
c. Local economic downturn, etc.	49	27.2	21.9	28	23.9	27.1
2. Losses from securities investment	50	27.8	17.2	23	19.7	19.1
(incl. high-yield papers/loss-hiding schemes)	8	4.4	17.5	5	4.3	19.3
3. Scandals and irregularities	9	5.0	24.8	4	3.4	31.4
Total	180	100.0	25.1	117	100.0	28.6
(both 1. and 2.)	37	20.6	—	16	13.7	—
(both 1. and 3.)	5	2.8	—	3	2.6	—
(both 2. and 3.)	4	2.2	—	1	0.9	—
(1. and 2. and 3.)	2	1.1	—	1	0.9	—

Notes:
1. "Credit concentration on real estate, etc." includes cases of 30 percent and more credit concentration on lending to the combined real estate, construction, nonblank finance and insurance sectors.
2. "Credit concentration on other sectors" includes cases of 25 percent and more credit concentration on lending to a single economic sector (other than in 1. a.).
3. "Local economic downturn, etc." encompasses all other cases of credit quality deterioration (including all the failure cases of profession-type and industry-type credit cooperatives).
4. Average loss rates are simple averages of the DICJ monetary grant to total assets ratios calculated across 178 individual cases; two cases (*Fukutoku* Bank and *Naniwa* Bank) are excluded due to no DICJ grants.
5. The "faulty management" cases encompass failure episodes in which either the DICJ filed criminal (or civil) charges against bank managers, or the management was unconstrained in its actions, or DICJ grant applications contained references to management mistakes.

Source: DICJ (2005), Tables 1, 2, and 24 with minor alterations by the author.

available resources for NPL disposal, the credit cost ratio correctly classifies more than 93% of all observations.

A study by Yoshino and Shimabukuro (2002) focused on regional characteristics of failed credit cooperatives. First, using a long panel of balance sheet data they found that urban credit cooperatives, which failed in the late 1990s, had exhibited significant differences in pricing their loans over the period since 1985. Second, they performed the cluster analysis in search of regional characteristics closely associated with the presence of cooperative failures in a region. Yoshino and Shimabukuro (2002) have suggested that cooperative failures were likely to occur in urban regions with relatively volatile land prices and higher credit concentration of (cooperative) lending on the real estate sector. Finally, the finding is further confirmed by the principal component analysis indicating strong association of the presence of cooperative failures with urban region characteristics.

In sum, the three studies draw a very specific view of the primary factors behind the recent wave of bank failures. They suggest that besides the "usual" factor of economic downturn, the majority of failure episodes result from the past expansion of urban cooperative banks to the real estate related lending. The expansion was a rational choice because these banks faced a reduction of traditional lending opportunities while being exposed to a stronger competition from commercial banking. But the cooperative banks mispriced the credit risk they took and thus undermined their ability to withstand the credit loss buildup during an economic downturn later experienced in the 1990s.

By advancing this view, however, the prior research also effectively suggests the recent bank failure experience is shaped by a transitory factor, which is likely to decline in importance in the future as the nation's banking sector overcomes its overcapacity and pricing mismatch. From the viewpoint of this study, the feature may undermine the applicability of the failure data to the task of predicting bank problems in the future – when the importance of the specific factor diminishes. At the same time, we also see the timing of individual failure episodes is far from being random but strongly influenced by the transition process in the national system of banking regulation. This feature constitutes another empirical challenge of carefully controlling for changes in the regulator's behavior.

III. Data and Empirical Setup

The great belief in bank failure prediction rests on the view that bank defaults result primarily from gradual deterioration of the economic value of bank assets. But it is also well known that, in practice, the occurrence of bank failures is actually more a function of regulatory and accounting procedures than a pure indicator of the banks' market value dynamics. In some circumstances, the very first sign of problems can trigger an over-reaction by the market (and by the authorities) and lead to a bank's formal failure, whereas there is also the possibility that an insolvent bank is "zombied" and kept running over a significant period of time. It implies that a researcher would ideally use the market value of a bank's assets as the dependent variable when testing the usefulness (informativeness) of the bank's disclosures. In the case of going concern banks, however, such indicators of the market value are normally not available, and the parameter is, at most, inferred indirectly from the market pricing of the banks' equity and debt. Furthermore, only in the case of failed banks can their asset values (upon failure) be reliably assessed. Specifically, disbursements by failure resolution bodies reflect their assessment of the market (disposal) value of assets found at failure. And, given the knowledge of a failure resolution procedure applied in each case, one can recover the assessed asset value from disclosed data on the disbursements.

The lack of reliable asset-value indicators in the case of going concern banks, and especially those small, privately-held institutions, rules out the use of such indicators as the main dependent variable in our study. Nevertheless, we believe that given the transitory state of the Japanese banking supervision during the crisis, testing disposal asset values of failed banks can prove to be of paramount importance in our case. As argued by Kane (1987) and many other studies, the investment behavior of the "zombie" (*de facto* insolvent) banks may be quite different from that of (truly) solvent banks. The loss rate dynamics on Figure 1 suggests the presence of such institutions before the Japanese regulator moved to clean up the cooperative bank mess. Furthermore, since the limited number of bank failure observations forces us to use all available cases, the feature can mislead inferences about the informative value of bank disclosures for predicting bank failures after the cleanup operation. In this view, testing disposal asset values of failed banks can help to highlight robust explanatory variables and discard those which exhibit inconsistency vis-a-vis the main regression results (for failure occurrence), because of being arguably distorted by the feature.

The transitory nature of the nation's banking supervision during the past crisis also limits our choice of utilizable empirical techniques to that of discrete variable regression. Modeling the time to a bank's default (the duration approach) has become another standard technique of the empirical research on failure prediction. The method, however, is questionable in our case because it is excessively dependent on the timing of bank failure recognition. As argued above, the nation's regulatory policy in dealing with bank failure was considerably upgraded over the sample period. Furthermore, if the duration approach were employed, one would then face difficulty in distinguishing the effect of banks' financial condition on their time to failure from that of regulatory policy change on the timing of failure recognition.

Accordingly, the occurrence of bank failures, *DEF*, is the main dependent variable that we intend to test the informative value of bank disclosures upon. The timing of failure in each case is decided as the earliest date of either bankruptcy recognition (intervention by authorities or voluntary filing for bankruptcy) or posting negative wealth in annual statements. In Japan, the DICJ has made public its disbursements and resolution procedures for all the 180 failure cases it handled in the past. This is the most reliable and complete source of information about failed banks, especially when identifying failure dates.

The information is also utilized in the construction of an auxiliary dependent variable, *VAL*. Specifically, we use data in DICJ (2005, pp.167-277) to calculate the disposal value of assets upon resolution expressed as a percentage of their nominal book value. Here, we consider the fact that before the resolution of *Teishin* Credit Cooperative in March 1998, monetary grants by the DICJ were legally confined to the limits of maximum payout amount on protected deposits. And all resolution costs in excess of this limit were effectively covered from private sources, when, for example, the assuming institutions shouldered the costs in exchange of acquiring branches and other valuable assets of failed banks. Accordingly, we adjust the public resolution disbursements over this period upward by the amount of private source assistance, as reported in DICJ (2005, Tables 1, 3, 5, and 6, pp. 27-41). After removing several observations because of data constraints, etc[8]., we arrive at a sample of 163 failure

[8]11 cases (of *Toho Sogo* B., Toyo Credit Assn., *Kamaishi* Credit Assn., *Osaka Fumin* Credit Coop., *Gifu Shogin* Credit Coop., *Kenmin Daiwa* Credit Coop., *Kita-Kyushu* Credit Coop., *Tokai* Credit Coop., Tokyo Teachers' Credit Coop., *Harue* Credit Coop., and *Iwate* Credit Coop.) were excluded because of unavailable or ambiguous balance sheet data, 2 cases (*Fukutoku* B. and *Naniwa* B.) because of no public grants, 2 cases (*Midori* B. and *Namihaya* B.) because of the recent experience of public rescues, and 2 cases (LTCB and NCB) because of double-counting.

cases. In total, the failure observations are scattered over 8 years.

The informative value of bank disclosures is tested using financial statement data. The information on both failed and surviving banks is drawn from data files available in the Keio Banking Database and Nikkei NEEDS Database. We, in particular, pick up the latest available data spanning five years, prior to the date of failure. For the failed banks we use their financial statement data directly. And, for surviving peer banks, we construct balance sheet / income statement numbers averaged across institutions of the same type and located in the same region[9]. The procedure helps to avoid the author' subjective judgment in selecting surviving peer institutions[10]. Yet it does not lead to an extremely unbalanced dataset, which is important, given the need to control for changes in the regulatory environment over the sample period. In all the cases, before being aggregated, the financial statement data went through a thorough check-up and cleaning process to remove asset size variability due to mergers and asset assumptions. Bank failure cases belonging to the same year are considered as a separate sub-sample, and their corresponding peer bank observations are also constructed for each sub-sample independently. As Table 2 reports, the number of the peer bank observations in a year-sample depends on the recorded types of failed institutions and varies between 44 and 97. The combined number of the peer bank observations in our dataset amounts to 571.

Prior studies are strongly concerned with selection of a financial indicator (or an optimal combination of financial variables) best explaining or predicting bank failures. Unlike the prior research, our objective in this study is more modest and limited to testing what information from a bank's disclosures might be useful for predicting problems in its financial position. Given this limited scope, our preferred explanatory variables are not financial ratios, but, instead, the basic balance sheet and income statement items used as inputs in ratio construction. The approach is motivated by the view that one would need to use multiple indicators to assess a bank's financial position. But since they are often constructed from the same (or similar) inputs, the feature may prevent one from measuring the usefulness of the indicators within a single test. For that reason, the financial statement data is the primary type of explanatory variables, and the financial ratios[11] are employed in this study for the sake of preserving comparability with the prior research.

Specifically, the balance sheet (stock) data are used in two forms – in relative levels at the earliest data point (T-5) and in growth rates between the latest (T-1) and earliest (T-5) data points; the income statement (flow) data – as cumulative income

[9]For credit associations and cooperatives, the financial statement information is averaged by prefecture, for regional commercial banks (belonging to the Second Association of Regional Banks) – by major geographic region (Hokkaido-Tohoku, Kanto, Chubu, Kinki, Chugoku-Shikoku, and Kyushu-Okinawa), and for large banks – across all banks of the same type nationwide. In this regard, an anonymous referee expressed concern that such an averaging procedure might induce a bias in the empirical results due to the overlap of the bank level data across the sub-samples. While admitting this possibility, we do not see it as a major issue because, by data construction, each pair of the sub-samples shares no more than 36% of its combined bank-level information.

[10]As suggested by the prior research (e.g. see Meyer and Pifer 1970) to be comparable the control group peer institutions should come from the same local market as failed banks, be approximately of the same size, and subject to the same regulatory treatment. By constructing region-average type-specific data we meet all these requirements. Yet, by employing the approach we strive to properly handle situations with an ambiguous local market size and multiple banks failures coming from the same region. Further controls of the regional characteristics suggested by the prior research make observations in our data set mutually comparable.

[11]In particular, we limit our tests to the representative financial ratios only, as suggested, for example, in Grier (2001, p. 6).

Table 2. Bank Disclosures Recorded in the Dataset

Sub-sample	Period of financial statement data	Number of observations									
		Large banks		Regional banks		Credit associations		Credit cooperatives		All types	
		failed	peer	failed	peer	failed	peer	failed	peer	failed	peer
1	FY 89–93	0	0	0	0	0	0	3	44	3	44
2	FY 90–94	0	0	2	6	0	0	5	44	7	50
3	FY 91–95	0	0	1	6	0	0	7	44	8	50
4	FY 92–96	1	1	2	6	0	0	33	44	36	51
5	FY 93–97	2	1	3	6	4	47	20	43	29	97
6	FY 94–98	0	0	1	6	8	47	9	43	18	96
7	FY 95–99	0	0	0	0	1	47	18	42	19	89
8	FY 96–00	0	0	2	6	12	47	29	41	43	94
Total		3	2	11	36	25	188	124	345	163	571

Notes: The peer bank information is constructed from the individual bank data averaged by region as follows: for credit associations and cooperatives – by prefecture, for regional commercial banks – by major geographic region (Hokkaido-Tohoku, Kanto, Chubu, Kinki, Chugoku-Shikoku, and Kyushu-Okinawa), and for large banks – across all banks of the same type nation-wide. Before being aggregated, the financial statement data went through a thorough check-up and cleaning process to remove asset size variability due to mergers and asset assumptions.

(loss) flows over the 5–year period. The balance-sheet variables mirror the major division of bank books: liquid assets (*LIQU, LIQU-G*), portfolio securities (*SEC, SEC-G*), credit portfolio (*LOAN, LOAN-G*), doubtful loan reserves (*RESV, RESV-G*), deposits (*DEP, DEP-G*), owners' equity (*CAP, CAP-G*), as well as changes in the asset size (*ASS-G*). The income-statement variables reflect the burden of funding (*FNDC*), overhead (*OHC*), and other (*OTC*) costs and the core profitability of a bank's operations (*PROF*)[12].

Similarly, we calculate levels and changes over time for the reference financial ratios based on the stock data and cumulative numbers for those based on the flow data. In particular, our analysis covers the following "representative" indicators: the equity-to-deposits ratio (*EDR, EDR-D*), loans-to-deposits ratio (*LDR, LDR-D*), liquidity-reserves-to-deposits ratio (*QDR, QDR-D*), loan-reserves-to-loans ratio (*RLR, RLR-D*), loans-to-assets ratio (*LOAN, LAR-D*), gross loan-profitability ratio (*ILR-D*), and loan-provisioning ratio (*PLR-D*).

The choice of control variables is motivated by the findings of the prior research and by the structure of our dataset. In particular, we employ indicators of land prices (*LND, LND-G*), urbanization (*DENS*), and bank competition by region (*COMP*) and of economic conditions nation-wide (*STCK*). Other variables control for possible heterogeneity across bank types (*CITY, REGB, LTCB, SHINK*), changes in the nation's

[12]Due to limited availability, we do not test bank disclosures of the regulatory capital ratios and non-performing loan (NPL) ratios. Still, the information conveyed by the two indicators seems to be not unique because (over available data points) the regulatory capital ratio exhibits 89.7% correlation with *CAP*, and the NPL ratio 74.4% correlation with *RESV*. The observation is well in line with the finding of, e.g., Estrella et al (2000) who suggested that the simple leverage ratio (*CAP* in our case) predicts bank failure about as well as the more complex risk-weighted (regulatory) ratio.

regulatory environment (*S1* ~ *S7*), and differences in the timing of failure recognition (*LAG*)[13].

The dependent variable of the main regression, *DEF*, is a dichotomous indicator of bank failures. Its relationship with bank disclosures is estimated within the probit model that assumes the normal probability link between a linear combination of the explanatory variables and realizations of the dependent variable[14]. In the case of the auxiliary regression, we note that, by their nature, our data on bank asset values (*VAL*) are distributionally truncated from the right and thus may suffer from a sample selection bias. To account for this feature, we follow Heckman (1979) and include probability estimates (inversed Mills' ratios) of the main (probit) model as an additional explanatory variable of the usual least squares estimator. Statistically, the procedure makes the least squares estimates consistent, and economically it makes

Table 3. Variable Definitions

Variable	Definition
Dependent variables:	
DEF	A dummy variable taking on 1 for failed bank observations and on 0 otherwise.
VAL	The disposal value of a failed bank's assets as a percentage of the assets' book value; defined over the failed bank observations only.
Balance sheet / income statement variables:	
LIQU	The ratio of "liquid assets" to "total assets" at T-5. The "liquid assets" category includes cash and reserve items, short-term lending to financial institutions, trading securities, and money trusts.
LIQU-G	The ratio of "liquid assets" at T-1 to those at T-5
SEC	The ratio of "portfolio securities" to "total assets" at T-5.
SEC-G	The ratio of "portfolio securities" at T-1 to those at T-5.
LOAN	The ratio of "loans and bills discounted" to "total assets" at T-5.
LOAN-G	The ratio of "loans and bills discounted" at T-1 to those at T-5.
RESV	The ratio of "doubtful loan reserve" to "total assets" at T-5.
RESV-G	The ratio of "doubtful loan reserve" at T-1 to that at T-5.
ASS-G	The ratio of "total assets" at T-1 to those at T-5.
DEP	The ratio of "deposits" to "total assets" at T-5.
DEP-G	The ratio of "deposits" at T-1 to those at T-5.
CAP	The ratio of "owners' equity account" to "total assets" at T-5.
CAP-G	The ratio of "owners' equity account" at T-1 to that at T-5.
FNDC	The sum of ratios of "funding cost" to "total assets" over T-5 through T-1.
OHC	The sum of ratios of "overhead cost" to "total assets" over T-5 through T-1.
OTC	The sum of ratios of "other operating cost" to "total assets" over T-5 through T-1. The "other operating cost" category includes loan loss provisions, loan and other asset write-offs, losses from portfolio securities sales, etc.
PROF	The sum of ratios of "operating profit" to "total assets" over T-5 through T-1.

[13] Table 3 provides exact variable definitions and further details about information sources.

[14] Although the prior research on bank failure prediction uses mostly the logit model, it is the conventional wisdom that the choice between logit vs. probit is largely a matter of taste (see, e.g., Green (1997, p. 875), Gill (2001, p. 33). As established by Chambers and Cox (1967) the two models may have differences in fit when sample sizes are large and explanatory variables tend to take on extreme values. Our sample, albeit being moderately large, does not exhibit the extreme value property, so that the longer tails of the logistic function do not seem to be important. Yet, the choice of the probit model adds more consistency, as its results become a natural input to the auxiliary regression.

Table 3. (continued)

Variable	Definition
Financial ratios:	
EDR	The ratio of "owners' equity account" to "deposits" at T-5.
EDR-D	The difference between the ratio of "owners' equity account" to "deposits" at T-1 and that at T-5.
LDR	The ratio of "loans and bills discounted" to "deposits" at T-5.
LDR-D	The difference between the ratio of "loans and bills discounted" to "deposits" at T-1 and that at T-5.
QDR	The ratio of {"liquid assets" + "portfolio securities"} to "deposits" at T-5.
QDR-D	The difference between the ratio of {"liquid assets" + "portfolio securities"} to"deposits" at T-1 and that at T-5.
RLR	The ratio of "doubtful loan reserve" to "loans and bills discounted" at T-5.
RLR-D	The difference between the ratio of "doubtful loan reserve" to "loans and bills discounted" at T-1 and that at T-5.
LAR-D	The difference between the ratio of "loans and bills discounted" to "total assets" at T-1 and that at T-5.
ILR-D	The sum of ratios of "interest income from loans" to "loans and bills discounted" over T-5 through T-1.
PLR-D	The sum of ratios of "loan loss provisions" to "loans and bills discounted" over T-5 through T-1.
Control variables:	
LND	The value of a commercial land index for a bank's region at T-5 (in point thousand).
LND-G	The ratio of the value of a commercial land index for a bank's region at T-1 to that at T-5.
STKP	The ratio of the year-average value of the Nikkei 225 stock index in T-1 to that in FY2003.
DENS	The population density for a bank's region at T-1 (in 10,000 per sq. km).
COMP	The average population per bank branch-office in a bank's region at T-1 (in 100, 000 per office).
LAG	A time lag between T-1 and the date of a bank's failure (in years); defined over the failed bank observations only.
CITY	A dummy variable for city bank observations.
REGB	A dummy variable for regional bank observations.
LTCB	A dummy variable for long-term credit bank observations.
SHINK	A dummy variable for credit association observations.
S1	A dummy variable for sub-sample 1 observations.
S2	A dummy variable for sub-sample 2 observations.
S3	A dummy variable for sub-sample 3 observations.
S4	A dummy variable for sub-sample 4 observations.
S5	A dummy variable for sub-sample 5 observations.
S6	A dummy variable for sub-sample 6 observations.
S7	A dummy variable for sub-sample 7 observations.

Notes: T-1 denotes the latest year of available balance sheet information prior to a bank's failure. T-2, T-3, T-4, and T-5 denote the second latest year through the fifth latest year correspondingly.

Sources: financial statement information – the author' calculations by the Keio Banking Database and Nikkei NEEDS Database; *DEF* and *VAL* – based on DICJ (2005); *LND* (*LND-G*), *STKP*, *DENS*, and *COMP* – based on Asahi Shinbunsha (2001).

test results potentially applicable not only to the failed banks, but also to the surviving banks.

IV. Estimation Results and Discussion

Before turning to regression analysis, it is worth confirming whether our data exhibit features consistent with the findings of the prior studies. Table 4 reports some descriptive statistics and results of a test for mean difference significance. We see that many financial statement variables show significant differences between the failed bank and peer bank samples. In particular, 5 years prior to their failure, the troubled banks have less liquid assets and portfolio securities, but more loans and loss reserves in the structure of their balance sheets. They rely less on deposits as a funding source, and yet have less capital. Over the 5-year period prior to their failure, the banks experience less growth / more decline (than peer banks) in their liquid assets, loans, deposits, and capital, and face a significantly larger increase in loss provisioning (and hence a buildup in loss reserves). But they are indistinguishable from the peer banks in the dynamics of their securities portfolio, investment income earned, and overhead expenses paid.

Overall, the largest differences are observed for the growth-rate ("-G" suffix) variables as compared to the structural variables, and they are especially pronounced for cumulative changes in capital, deposits, loans, and operating profit. The observed tendencies are consistent with the findings of DICJ (2005), as well as with the hypothesis of Aoki et al (2003): The failed banks had exhibited a relative decline in the growth rates of their major balance sheet items, and suffered from the inability to cover a credit cost buildup by their operating income.

In the case of control variables, the test results suggest that there are (1) significant differences between the two samples with respect to urban vs. rural location (*DENS*), land price levels (*LND*) and growth rates (*LND-G*), and (2) no differences with respect to securities prices (*STKP*) and retail market competition (*COMP*). The observed effects are consistent with the main finding of Yoshino and Shimabukuro (2002) indicating that failed credit cooperatives were located in urbanized areas and suffered from collateral value deterioration due to falling land prices.

The last two columns of Table 4 report the Pearson correlation coefficients for the two dependent variables used in the regression analysis. Their pairwise comparison gives a preliminary insight into whether the specific investment behavior of "zombie" (*de facto* insolvent) banks is a factor of concern in our case. Indeed, if there are no differences in the investment behavior between the failed-bank and peer-bank samples, then *DEF* and *VAL* should have close levels of correlation but be opposite in sign. If a significant part of observations in the failed bank sample is represented by banks which had been "zombied" during the 5 year sampling period (i.e., prior to their *de jure* failure), then the correlation coefficients for *DEF* and *VAL* will either both have high levels and the same sign, or exhibit a large difference in levels. The reported numbers of Table 4 clearly indicate the presence of differences in the investment behavior of banks between the two samples. The numbers, thus, suggest that estimation results for some explanatory variables may be misleading as measures of the data's usefulness for predicting bank failures.

Table 4. Descriptive Statistics and Test Results

	Failure cases		Peer cases		Mean difference test	Correlation	
	Mean	St.dev	Mean	St.dev		v.*DEF*	v.*VAL*
VAL	0.683	0.136	—	—		—	—
LIQU-G	0.977	0.409	1.131	0.269	-4.54***	-0.21	0.11
LIQU	0.180	0.099	0.197	0.070	-2.08**	-0.09	0.16
SEC-G	2.124	6.815	1.538	3.129	1.07	0.06	0.04
SEC	0.079	0.092	0.122	0.072	-5.60***	-0.23	0.41
LOAN-G	0.955	0.208	1.079	0.141	-7.16***	-0.31	-0.40
LOAN	0.643	0.104	0.609	0.099	3.65***	0.14	-0.32
RESV-G	5.587	6.518	3.063	2.412	4.85***	0.27	0.03
RESV	0.008	0.008	0.006	0.004	3.16***	0.16	0.18
DEP-G	0.956	0.184	1.109	0.108	-10.11***	-0.44	-0.31
DEP	0.827	0.099	0.863	0.046	-4.51***	-0.24	0.15
CAP-G	0.741	0.403	1.141	0.239	-12.09***	-0.51	-0.20
CAP	0.038	0.013	0.048	0.013	-8.72***	-0.31	0.09
ASS-G	0.949	0.283	1.093	0.109	-6.40***	-0.34	-0.21
FNDC	0.079	0.056	0.081	0.054	-0.40	-0.02	-0.39
OHC	0.082	0.023	0.080	0.014	1.13	0.05	0.33
OTC	0.046	0.032	0.026	0.014	8.07***	0.40	0.15
PROF	-0.014	0.031	0.016	0.015	-12.01***	-0.53	-0.08
EDR-D	-0.012	0.020	0.001	0.009	-8.56***	-0.42	-0.07
EDR	0.048	0.023	0.056	0.016	-4.35***	-0.19	0.06
LDR-D	0.001	0.094	-0.019	0.054	2.60**	0.13	-0.16
LDR	0.811	0.358	0.710	0.148	3.52***	0.19	-0.11
QDR-D	-0.005	0.090	0.016	0.059	-2.89***	-0.13	0.20
QDR	0.325	0.210	0.372	0.129	-2.75***	-0.13	0.32
LAR-D	0.012	0.083	-0.009	0.044	3.07***	0.15	-0.17
RLR-D	0.140	0.132	0.080	0.058	5.61***	0.30	0.27
RLR	0.012	0.014	0.009	0.007	2.65***	0.14	0.22
PLR-D	0.034	0.036	0.016	0.018	6.32***	0.31	0.20
ILR-D	0.230	0.056	0.239	0.063	-1.75*	-0.06	-0.36
LND-G	0.529	0.193	0.601	0.215	-4.13***	-0.14	0.05
LND	12.208	10.608	5.492	5.899	7.75***	0.36	-0.39
STKP	2.233	0.254	2.219	0.233	0.60	0.02	-0.30
DENS	0.230	0.227	0.066	0.109	8.99***	0.43	-0.33
COMP	0.045	0.012	0.044	0.010	0.65	0.03	0.12
LAG	0.927	0.318					-0.17
Num. observ.	163		571			734	163

Notes: The column under "Mean difference test" heading reports t-statistics for a two-tail test of the hypothesis that the difference between the means of the failure sample and peer sample is nonzero. ***, **, and * denote 1%, 5%, and 10% significance levels correspondingly.

Table 5. Estimation Results for Financial Statement Variables

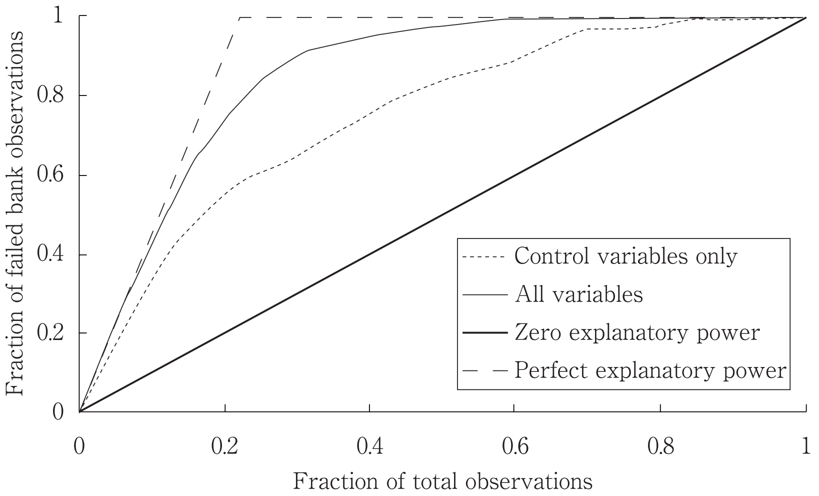
	Probit estimation (dependent variable=*DEF*)				Least Squares estimation (dependent variable= *VAL*)	
	Estimate	dP/dX	Estimate	dP/dX	Estimate	Estimate
Constant	0.136 (0.29)	0.030	12.477 (4.40)***	1.479	0.757 (5.35)***	0.240 (1.10)
LIQU-G			0.335 (0.99)	0.040		0.023 (0.78)
LIQU			-5.926 (-1.54)	-0.702		0.535 (1.92)*
SEC-G			0.037 (1.80)*	0.004		-0.0004 (-0.58)
SEC			-4.936 (-1.2)	-0.585		0.501 (1.67)*
LOAN-G			2.979 (2.35)**	0.353		-0.242 (-2.19)**
LOAN			-8.085 (-1.84)*	-0.958		0.168 (0.56)
RESV-G			0.056 (1.91)*	0.007		-0.0002 (-0.15)
RESV			14.005 (0.68)	1.660		-1.238 (-1.14)
DEP-G			-5.592 (-3.60)***	-0.663		0.059 (0.48)
DEP			-4.623 (-1.48)	-0.548		0.086 (0.34)
CAP-G			-1.409 (-3.36)***	-0.167		-0.002 (-0.06)
CAP			-40.668 (-4.66)***	-4.820		-0.925 (-0.95)
ASS-G			0.206 (0.37)	0.024		0.006 (0.24)
FNDC			35.413 (4.09)***	4.197		-0.586 (-1.42)
OHC			20.830 (3.31)***	2.469		1.420 (2.95)***
OTC			12.555 (1.78)*	1.488		0.329 (0.61)
PROF			-8.681 (-1.04)	-1.029		0.779 (1.29)
LND-G	-1.026 (-1.88)*	-0.227	-1.410 (-1.78)*	-0.167	0.025 (0.29)	0.073 (1.03)
LND	0.031 (1.67)*	0.007	0.017 (0.68)	0.002	-0.003 (-0.96)	0.001 (0.6)
STKP					-0.025 (-0.44)	0.095 (1.47)
DENS	2.377 (3.22)***	0.527	1.605 (1.58)	0.190	-0.090 (-0.85)	-0.166 (-1.98)**
COMP	-2.597 (-0.47)	-0.576	-0.513 (-0.06)	-0.061	0.257 (0.34)	0.774 (1.27)
LAG					-0.005 (-0.13)	-0.037 (-1.17)
CITY	-0.203 (-0.22)	-0.045	-2.792 (-2.72)***	-0.331	0.177 (4.48)***	0.199 (3.12)***
REGB	-0.108 (-0.45)	-0.024	-0.432 (-0.93)	-0.051	0.079 (2.53)**	0.107 (3.29)***
LTCB	0.510 (0.66)	0.113	-9.363 (-3.56)***	-1.110	0.112 (1.76)*	0.282 (1.46)
SHINK	-0.672 (-4.49)***	-0.149	0.257 (0.92)	0.030	0.108 (4.85)***	0.116 (4.79)***
S1	-1.828 (-3.53)***	-0.405	-5.739 (-3.81)***	-0.680		
S2	-1.470 (-3.93)***	-0.326	-5.687 (-4.04)***	-0.674		
S3	-1.392 (-4.46)***	-0.309	-4.848 (-4.39)***	-0.575		
S4	-0.491 (-2.25)**	-0.109	-2.617 (-3.38)***	-0.310		
S5	-0.548 (-2.87)***	-0.121	-2.332 (-4.31)***	-0.276		
S6	-0.598 (-3.10)***	-0.133	-1.545 (-3.91)***	-0.183		
S7	-0.558 (-2.84)***	-0.124	-1.060 (-3.26)***	-0.126		
MILLS					-0.018 (-0.79)	-0.023 (-0.89)
Number of observations	734		734		163	163
Correct predictions	0.83		0.90			
Adjusted R-squared					0.22	0.53
Scaled R-squared	0.26		0.62			
Log Likelihood	-292.34		-157.63		120.88	171.95
F zero slopes					5.18***	7.55***

1. Notes: t-statistics are in parentheses (based on heteroskedastic-consistent errors in the case of the least squares estimates). ***, **, and * denote 1%, 5%, and 10% significance levels correspondingly. Columns under "P/dX" heading report the slopes (derivatives) of the probability of *DEF*=1 evaluated at sample means. *MILLS* denotes inverse Mills ratios based on the normal CDF and PDF estimates of the probit regression.

Table 5 reports estimation results for the financial statement variables. For each model, we use two specifications: One is a benchmark case and includes only the control variables. Another is the full model encompassing both control and information (financial statement) variables.

In the main (probit) regression we estimate normal probabilities of each observation being classified into the failed bank group. Since the parameter estimates reflect slopes of the fitted (latent) argument of the probability function, the table also reports the slopes of corresponding (fitted) probabilities evaluated at sample means[15]. The explanatory power of the estimated models is reflected by their cumulative accuracy (CAP) profiles, or accuracy ratios (AR). From Figure 2 we see that both benchmark and full models exhibit high accuracy with ARs equal to 64% and 92%, correspondingly. The surprisingly good fit of the benchmark model suggests that the factors of geographic location, customer base, and regulatory treatment were indeed among the leading drivers of bank failures over the last decade. In particular, the year-sample dummies (*S1* ~ *S7*) indicate that there was a regulatory shift from forbearance at early

Figure 2. Cumulative Accuracy of the Probit Regression



The figure presents the cumulative accuracy profile (CAP) of the failure probabilities estimated at the first stage of regression analysis (see Table 5). The horizontal axis shows a fraction of total observations classified into the upper precentile of the estimated failure probabilities, and the vertical axis shows a fraction of actual failures classified into this percentile. The closer the CAP curve of an estimated model is to that of the perfect explanatory power case, the better is the classification accuracy of the model. The relation is measured by the accuracy ratio (AR), which is defined as the ratio of the area between the model's curve and the diagonal line (of zero explanatory power) to the area between the perfect explanatory power curve and the diagonal line. In the case of Table 5 estimates, the accuracy ratio is approximately 64% for the benchmark (control variable) model and 92% for the full model.

[15]These probability slopes are reported under "dP/dX" heading and show the effect of change in one of the explanatory variables on the probability of belonging to the failed bank group. Hence, their scale lends itself to the direct comparison across explanatory variables in terms of their association with failure occurrence.

stages towards stricter enforcement of regulation in last crisis years, whereas *DENS* shows that the failures concentrated more on banks positioned in urbanized areas.

The inclusion of the information (financial statement) variables improves the accuracy ratio further by 28%. This suggests that the data does successfully convey information, which is potentially useful for bank failure prediction and yet different from that conveyed by the location and status characteristics of banks. Specifically, we see that the level of own funds (*CAP*), cumulative funding cost (*FNDC*), and cumulative overhead cost (*OHC*) exhibit significant and strong association with high probability of bank failure. The effects of the loan growth rate (*LOAN-G*), deposit growth rate (*DEP-G*), and capital growth rate (*CAP-G*) are also significant, but their "contribution" to (their degree of statistical association with) bank failures is relatively small.

In the auxiliary model, we regress its dependent variable *VAL* on the same factors. To get consistent estimates, the list of regressors also includes the inversed Mills ratios (*MILLS*) calculated from the fitted probabilities of the full model. Similar to the main estimation, the inclusion of the information variables yields a significant increase in the explanatory power of the model, thus again suggesting that these variables are potentially useful. Some estimates, however, deliver conflicting signs with the main model results. Notably, the effects of the level of their own funds (5 years prior to failure) *CAP*, the cumulative overhead cost *OHC*, and other (provisioning, etc.) cost *OTC* have the same sign as at the main regression. As argued above, the feature suggests that the information conveyed by these variables is significantly distorted by the presence of the "zombie" banks. Among other variables, only three of them – the loan growth rate *LOAN-G*, cumulative funding cost *FNDC*, and level of liquid assets *LIQU* – remain robust with respect to the distortion and have some explanatory power in either regression.

Overall, the regression analysis suggests that the financial statement variables do convey useful information but they would require additional controls to become reliable leading indicators of bank failure probability. Arguably, the major weakness of the financial statement data is that they fail to adequately reflect the quality of bank management. The distortion in the informativeness of the quantitative data occurs not only because the authorities may be prone to regulatory forbearance and let *de facto* insolvent banks exist over a period of time, but also because the banks have weak internal governance, which neither prevents nor exposes their imprudent investment behavior. At the same time, one cannot simply omit the distorted quantitative information, because the remaining (not distorted) variables would lead to too imprecise inferences[16]. Hence, a wider scope of bank information, beyond the core quantitative information we have analyzed so far, may be needed to improve the overall usefulness of bank disclosure.

Table 6 reports the second round of estimation using the financial ratio variables. The probit estimation pinpoints several ratios which exhibit significant and strong statistical association with the probability of failure. They are the changes and levels of the equity-deposit ratio (*EDR-D, EDR*), loan-deposit ratio (*LDR-D, LDR*), loan-asset ratio (*LAR-D, LOAN*), and the (5-year cumulative) funding cost to asset ratio

[16]Performing an additional round of regression analysis in which we employ only *LOAN-G*, *FNDC*, *LIQU*, and the control variables, shows that they can explain only 41% of *VAL* variability and accuracy ratio of the probit estimation does not reach 70%. The additional estimation results are available from the author upon request.

Table 6. Estimation Results for Financial Ratios

	Probit estimation (dependent variable=*DEF*)		Least Squares estimation (dependent variable=*VAL*)
	Estimate	dP/dX	Estimate
Constant	11.307 (3.50)***	1.434	0.418 (1.61)
EDR-D	-54.280 (-6.59)***	-6.882	0.704 (0.82)
EDR	-46.286 (-6.54)***	-5.868	-0.325 (-0.31)
LDR-D	7.182 (3.18)***	0.911	0.102 (0.62)
LDR	7.365 (4.28)***	0.934	-0.348 (-2.96)***
QDR-D	-6.013 (-2.39)***	-0.762	0.371 (1.41)
QDR	-6.424 (-2.63)***	-0.814	0.509 (2.76)***
LAR-D	-10.479 (-3.91)***	-1.329	-0.315 (-0.85)
LOAN	-17.651 (-4.86)***	-2.238	0.579 (1.94)*
RLR-D	2.777 (1.15)	0.352	-0.052 (-0.53)
RLR	-8.658 (-0.68)	-1.098	-0.428 (-0.66)
PLR-D	5.953 (1.06)	0.755	-0.293 (-0.90)
ILR-D	5.568 (1.81)*	0.706	0.092 (0.23)
ASS-G	-2.369 (-4.16)***	-0.300	-0.114 (-1.58)
FNDC	13.434 (2.22)***	1.703	-1.040 (-1.69)*
LND-G	-1.370 (-1.81)*	-0.174	0.063 (1.03)
LND	0.002 (0.08)	0.0003	0.001 (0.56)
STKP			0.089 (1.36)
DENS	1.952 (1.98)**	0.247	-0.138 (-1.72)*
COMP	-8.239 (-1.04)	-1.045	0.642 (0.93)
LAG			-0.030 (-0.93)
CITY	-1.823 (-1.82)*	-0.231	0.183 (4.46)***
REGB	-0.315 (-0.80)	-0.040	0.112 (3.66)***
LTCB	-6.659 (-1.00)	-0.84	0.489 (1.38)
SHINK	-0.061 (-0.22)	-0.008	0.119 (4.98)***
S1	-3.611 (-2.94)***	-0.458	
S2	-3.671 (-3.24)***	-0.465	
S3	-3.138 (-3.43)***	-0.398	
S4	-1.563 (-2.33)***	-0.198	
S5	-1.639 (-3.37)***	-0.208	
S6	-1.202 (-3.16)***	-0.152	
S7	-0.834 (-2.69)***	-0.106	
MILLS			-0.036 (-1.30)
N. observations	734		163
Correct predictions	0.91		
Adjusted R-squared			0.51
Scaled R-squared	0.59		
Log Likelihood	-166.17		166.39
F zero slopes			7.71***

Notes: See Table 5.

(*FNDC*). But the least squares estimation shows that the usefulness of some variables is compromised and only few of them (*LDR, QDR, LOAN, FNDC*) seem to be not distorted. In sum, these estimation results deliver the same message that the core quantitative disclosures (be they in “raw” financial data, or in analytical ratios) convey information potentially useful for predicting bank failures. But in order to yield reliable results, the information needs to be further complemented by other indicators of bank management.

As discussed above, the literature on bank failure prediction draws a clear distinction between the value of bank information for ex-post classification and that for prediction (ex-ante classification) purposes, while making a pronounced emphasis on the latter type of information use[17]. The emphasis rests on the view that if the interpretation of bank disclosures refers to a past period with a different structure of failure determinants, then signals conveyed by present disclosures may be misread by information users. This aspect of the usefulness of bank information is vividly present in our estimation results as well. On the one hand, we observe that an increase in the default probability (a decline in the value of bank assets) is associated with a more-than-average growth in lending assets and funding costs in previous years. And the finding is well in line with the view that the majority of the recent failure episodes are a result of the expansion of small urban banks into new lending areas amidst their unpreparedness to handle new credit risks. On the other hand, this seems to be a transitory factor, and hence, using this interpretation to predict bank failures may be inappropriate for the post-crisis financial environment.

Certainly, it is inevitable that the interpretation of bank disclosures is conditioned on past experiences. And the question is in the length of the time lag between major changes in the banking industry dynamics and corresponding updates to prevailing interpretations. The feature highlights another important dimension of needed bank disclosures: Too much time elapses before information users learn the correct interpretation of factors driving banks' financial numbers, unless the banks themselves provide an accurate explanation of their financial results. Hence, the institutionalization of such managerial disclosures in the nation's disclosure regime for banks promises to improve the usefulness of their disclosed quantitative information[18].

V. Concluding Remarks

This study has investigated the question of whether bank disclosures are useful in predicting bank failures. We approached the task focusing on the quantitative information disclosed by Japanese banks in their financial statements. This information is at the core of the present disclosure regime for banks, and thus commands the strongest interest from the perspective of ongoing regulatory changes under Basel II. The informative value of the financial data was tested against the experience of bank failures during the recent banking crisis. In particular we focused on determining the degree to which the financial statement disclosures by banks are useful in predicting the occurrence of bank failures, as well as assessing the dynamics of their asset values.

The study finds that the traditional quantitative disclosures of banks convey information which is potentially useful in predicting bank failures. Estimated relationships give high accuracy of ex-post classification and explain a significant part of asset value variability. Yet, our tests of individual effects between the failed bank and peer bank samples yield results consistent with the findings of the prior research.

[17]This study does not test this aspect of bank disclosures explicitly because the strong differences in the regulatory environment over the crisis years would prevent one from meaningful interpretation of estimates for a holdout sample.

[18]For further discussion of information needs in a disclosure regime for banks, see, e.g., Frolov (2004).

Further investigation also shows that some individual effects may be strongly distorted by the perverse investment behavior of insolvent banks, and, thus, the question of whether bank disclosures are useful should be viewed as if the disclosures are sufficient to allow correct interpretation of bank dynamics. But in this regard, the traditional quantitative disclosures the study has focused upon seem to be inadequate. And they should be necessarily complemented by other managerial information, both to control for differences in bank behavior and to overcome the excessive reliance on the past dynamics of the banking industry.

The view that a wider scope of bank disclosure may be needed to improve its overall usefulness in predicting bank failures is, certainly, not new, for the use of managerial information beyond the core quantitative disclosures has become a commonplace in the analysis of banking risks. The novelty of our result is that the insufficiency of the core disclosures alone has been shown empirically. The importance of the result also stems from the fact that it comes just before the Japanese banking regulator unveils its new detailed rules of bank disclosure under the Basel II Accord. The existing regulatory rules focus on the core quantitative disclosures and largely neglect other managerial information. But our results suggest that this feature undermines the usefulness of the published information and, thus, the effectiveness of the entire disclosure regime.

The result also poses questions about the nature of needed disclosure. First, the comparability of information across banking organizations is among the core features of an effective disclosure regime, and, hence, types of disclosures should be uniformly prescribed by the system. But there is general ambiguity over exactly what pieces of the other managerial information need actually be disclosed. Second, the determinants of banking dynamics tend to evolve over time. And an effective disclosure regime should have built-in incentives for banks to improve their disclosure, while supplying new information the market needs. But yet, there is no clear understanding of how to optimally incorporate such incentives into an effective regulatory system. The two questions are obviously important for the successful implementation of the nation's disclosure regime for banks, and, thus, they constitute tasks for further research.

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