INTERNATIONAL JOURNAL OF BUSINESS, 7(2), 2002 ISSN:1083-4346

Contingent Fuzzy Approach for the Development of Banks' Credit-Granting Evaluation Model: The Case of Taiwan

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ABSTRACT

In the past Taiwanese banks that evaluated customers' credit emphasized collaterals and guarantors, adopting such methods as the rule of thumb, a credit rating system, and numeric credit scoring system that are primarily based upon subjective judgements. However, Taiwanese banks nowadays no longer possess a superior competitive position, owing to the internationalization and liberalization of Taiwan's financial market. Therefore, it is necessary to develop a credit evaluation model to lower banks' credit-granting risk.

This study proposes a contingent fuzzy approach to reduce the type I error or type II error in banks' credit-granting. This approach combines cost-volume-profit analysis with Morkovian dynamic programming and uses fuzzy theory to estimate the break-even point interval for the linguistic variable. In other words, the model addresses an objective credit-granting indicator by cost-volume-profit analysis and assures the safety-first decisions through Markovian dynamic programming. This can provide loan officers a measure of whether a loan applicant would enhance his business performance after being granted a loan.

JEL: *C61, G21, G30, M20*

Keywords: *Contingent fuzzy approach; Credit-granting; Cost-volume-profit analysis; Markovian dynamic programming*

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I. INTRODUCTION

The performance evaluation on banks' credit-granting is in place to make sure whether or not the banks can ensure the loans' safety. It is important for a loan officer to ascertain credit quality prior to granting credit; nonetheless, many apparently qualified borrowers become poor loan risks for reasons that develop subsequent to the granting of credit. In such cases it is important to identify weak loans as early as possible so that an appropriate action can be taken to avoid or minimize losses.

The conceptual framework for judgmental credit decisions has endured for a few decades. In a basic system a number of predictor characteristics is chosen for the ability to discriminate between those who repay their credit (good) and those who do not (bad). Banks typically evaluating customers' credits have emphasized collaterals and guarantors, and have adopted the rule of thumb, credit rating and credit scoring to measure loan quality as being either good or bad based on the bank investigator's judgment. Unfortunately, these methods are mostly based on subjective judgments or trial and error which lack unbiased and objective standards, and may raise misunderstandings. During a bank's credit-granting process, loan officers must adjudicate the riskiness and profitability of debtors. In fact, some research has devoted a lot of attention to the riskiness analysis, and could not enhance the study for the quality of credit-granting.

Corporate failure literature contains a plethora of methodologies used to discriminate between failed and successful firms ever since Beaver's (1966) univariate comparison of financial ratios. The better-known multivariate studies use multiple discriminate analysis (Altman, 1968; Altman, Haldeman, and Narayanan, 1977), logit analysis (Ohlson, 1980), and multiple regression analysis to find out firms' financial/non-financial attributes as bankruptcy indicators, which can separate firms' status into good or bad. Dietrick and Kaplan (1982), Srinivasan and Kim (1987a), Houghton and Woodliff (1987), Platt and Platt (1990), and Laitinen (1991) extended prior studies and used financial ratios to predict a business' status. Using the methods proposed by these aforementioned studies may serve as reliable grounds for credit-granting decisions; however, the validation results testing the predictive ability of these models have been somewhat disappointing.

Mehta (1980) proposed that record of a customer's payment as being good, fair, or poor could be a vital reference for credit-granting decisions. Capon (1982) used measuring variables and past experience to make credit-granting decisions. Stowe (1985) incorporated the concept of net present value into credit-granting decisions, while Srinivasan and Kim (1987b) considered future benefit and loss of collection. These approaches are all valid, but remain subject to loan officers.

Kuo (2001) developed an integrated approach that applied a cost-volume-profit (CVP) analysis based on a Markovian dynamic programming process to manage decisions when granting credit. Markovian dynamic programming is a process of probability, and it is a quantity technique that solves a multistage decision procedure. It also measures whether a customer would enhance his business performance after being granted credit.

Taiwanese banks have gradually been deregulated and internationalized while competition has heated up in providing loans. As a result, banks no longer possess a superior competitive position. For them, to further secure their outstanding loans and minimize the risks, it is important to strengthen the credit-granting system to meet with the changing economic environment. As a result of deregulation, competition among banks has meant granting credit to secondary credit-rating clients in order for the banks to succeed in a competive environment. This in turn has increased the bad debt risks of banks. Thus, it is necessary to develop a credit evaluation model to reduce bad debt losses for banks in Taiwan.

This study addresses the fact that banks make a credit-granting decision based on the firm's break-even point (BEP), which may easily revolve into wrong decisions. We then employ the fuzzy set theory to calculate the BEP interval of a loan applicant. Moreover, if the banks' loanable funds are limited, then they may make loans according to the customers' credit quality ranking. A contingent model is thus modified within the CVP framework, which combines the fuzzy set theory and Markovian dynamic programming to provide for a credit-granting evaluation and allow loan officers to make safety-first credit-granting decisions.

The rest of the article is organized as follows. We briefly discuss the methodology in the next section. An empirical study is presented in Section 3. Finally, the conclusion is given in the last section.

II. METHODOLOGY

Management requires realistic and accurate information to aid in making decisions. The CVP analysis is a widely accepted generator of information useful in decision-making processes, but decisions are always accompanied by uncertainty. A limitation of the traditional CVP analysis, as pointed out by Jaedicke and Robichek (1964), is its inability to deal with uncertainty and risk. All CVP models were initially deterministic, assuming demand and cost structures to be known with certainty. However, economic decision making is mostly conducted under uncertainty, and thus Hilliard and Leitch (1975), Adar, Barnea and Lev (1977) and Dickinson (1974) took the form of treating various variables, such as sales volume, product prices and cost, as random.

Zadeh (1965) argued that conventional quantitative techniques are inadequate in studying a humanistic system, because they are not equipped to handle the impreciseness of so many such systems and they implicitly assume that precise numerical inputs for the decision analysis are obtainable. He addressed that fuzziness can be employed in situations where "precise" numerical assessments of input variables are not possible. Chan and Yuan (1990) stated that decision-makers prefer to describe their uncertainties by using the English language, rather than reducing everything to numbers. Since the decision-maker's "impreciseness" in describing uncertainties using the language is ignored in the elicitation process, the CVP results can be erroneous. Consequently, the decision outcome can be misleading, if a subjective assessment on certain variables is reguired in the decision analysis, or when "impreciseness" or "fuzziness" is involved. If such fuzziness is not incorporated into the decision model, then the real situations are not being represented correctly and the decision thus made can be erroneous.

Because the credit-granting decision depends on different points from loan officers, we employ a contingent fuzzy approach to quantify the uncertain or unprecise statements. This approach combines cost-volume-profit analysis with Morkovian dynamic programming and uses fuzzy theory to estimate the break-even point interval for the linguistic variable, it is able to measure as the basis of credit evaluation whether a customer enhances his business performance after being granted credit.

A. The contingent fuzzy model

This study applies fuzzy set theory to characterize the linguistic variables and combines CVP analysis and Markovian dynamic programming which is contingent on bank type, industry classification and product line to examine whether a loan applicant is creditworthy enough for banks. This could minimize the bad debt loss based on analyzing the firm's operation status of whether it improves after credit-granting.

In this study, total variable cost (VC) includes purchasing cost (VC_1), variable overhead cost (VC_2) and variable selling and administrative cost (VC_3). The total fixed cost (FC) includes direct labor cost (FC_1), fixed overhead cost (FC_2) and fixed selling and administrative cost (FC_3). To facilitate the presentation, let A represent a domestic/ foreign bank (A=1 represents a domestic bank, and A=2 represents a foreign bank), let B represent the industry (B=1 is "electronics industry", B=2 is "textile industry", and B=0 is "other industry"), and let C represent the single/multiple product (C=1 is "single product", C=2 is "major product of multiproducts", and C=3 is "other product of multiproducts").

The procedures for determining the fuzzy BEP of a loan applicant are as follows.

Step 1: Calculate the average unit price (P) of a loan applicant t (t = 1,…, k).

$$\overline{P}^{ABC} = \frac{1}{k}\left(\sum_{t=1}^{k} P_t^{ABC}\right) = \frac{1}{k} \otimes \left(P_1^{ABC} \oplus P_2^{ABC} \oplus \cdots \oplus P_k^{ABC}\right) \tag{1}$$

Step 2: Calculate the average direct labor cost (FC_1), fixed overhead cost (FC_2) , and fixed selling and administrative cost (FC_3) of a loan applicant t.

$$\overline{FC}_{\alpha}^{ABC} = \frac{1}{k}\left(\sum_{t=1}^{k} FC_{\alpha t}^{ABC}\right) = \frac{1}{k} \otimes \left(FC_{\alpha 1}^{ABC} \oplus FC_{\alpha 2}^{ABC} \oplus \cdots \oplus FC_{\alpha k}^{ABC}\right) \quad \alpha = 1,2,3 \tag{2}$$

Step 3: Calculate the average total fixed cost (FC) of a loan applicant t.

$$\overline{FC}^{ABC} = \frac{1}{3} \otimes \left(\overline{FC}_1^{ABC} \oplus \overline{FC}_2^{ABC} \oplus \overline{FC}_3^{ABC}\right) \tag{3}$$

Step 4: Calculate the average purchasing cost (VC_1), variable overhead cost (VC_2), and variable selling and administrative cost (VC_3) of a loan applicant t.

$$\overline{VC}_{\beta}^{ABC} = \frac{1}{k}\left(\sum_{t=1}^{k} VC_{\beta t}^{ABC}\right) = \frac{1}{k} \otimes \left(VC_{\beta 1}^{ABC} \oplus VC_{\beta 2}^{ABC} \oplus \cdots \oplus VC_{\beta k}^{ABC}\right) \quad \beta = 1,2,3 \tag{4}$$

Step 5: Calculate the average unit total variable cost (AVC) of a loan applicant t.

$$\overline{AVC}^{ABC} = \frac{1}{Q} \otimes \frac{1}{3} \otimes \left(\overline{VC}_1^{ABC} \oplus \overline{VC}_2^{ABC} \oplus \overline{VC}_3^{ABC}\right) \tag{5}$$

Step 6: Calculate the average BEP (number of sale units Q) of a loan applicant t.

$$\overline{Q}^{ABC} = \frac{\overline{FC}^{ABC}}{1 - \dfrac{\overline{AVC}^{ABC}}{\overline{P}^{ABC}}} \tag{6}$$

B. Fuzzy CVP analysis

This study's Markovian dynamic programming is employed by utilizing transition probability and a return function to obtain an optimal solution. For banks, the transition probability could be estimated by group decision making, and the return function could be considered as expected income exceeding BEP of a loan applicant. A bank's loan officers make credit-granting decisions based on whether a loan applicant's expected income after granting credit will better than before granting credit. If u_i^w refers to the expected income resulting from a single transition from state i when w is selected, then u_i^w could be written as follows:

$$u_i^w = \sum_{j=1}^{s} P_{ij}^w Z_{ij}^w \tag{7}$$

Let w represent the credit decisions, and s is the state value at each stage. We define that $f_n(i)$ is the system's initial state I in the n^{th} stage, and is the optimal expected income at stages n, n+1,…, N. For the inverse recursive equation of f_n and f_{n+1}, it can be written as follows:

$$f_N(i) = \max_w \left\{u_i^w\right\} \tag{8}$$

$$f_n(i) = \max_w \left\{ u_i^w + \sum_{j=1}^{s} P_{ij}^w \left[z_{ij}^w f_{n+1}(j) \right] \right\} \tag{9}$$

where w: credit-granting decisions, w=1, 2, represent with and without granting credit, respectively; P_{ij}^{w} : transition probability matrix; P_{ij}^{1} : the probability of BEP from i state (this year) to j state (next year) before credit-granting; P_{ij}^{2} : the probability of BEP from i state (this year) to j state(next year) after credit-granting; Z_{ij}^{w} : exceeding BEP's income matrix; Z_{ij}^{1} : the return of excess BEP from i state (this year) to j state (next year) before credit-granting; Z_{ij}^{2} : the return of excess BEP from i state (this year) to j state (next year) after credit-granting. Also, i=j=1: the BEP has a good status; i=j=2: the BEP has a fair status; i=j=3: the BEP has a bad status.

Assuming a bank makes a 3-year loan to firm H, the recursive Markovian dynamic programming is as the following:

Step 1: Calculate firm H's BEP before credit-granting S_b.

Step 2: Assume that firm H's fuzzy BEP interval after credit-granting is (a_1, b_1, c_1). Use equations (1)～(6) to calculate firm H's BEP after credit-granting S_a.

$$S_a = \begin{Bmatrix} S_b \otimes (1+a_1) - [S_b \otimes (1+a_1) - S_b] \\ S_b \otimes (1+b_1) - [S_b \otimes (1+b_1) - S_b] \\ S_b \otimes (1+c_1) - [S_b \otimes (1+c_1) - S_b] \end{Bmatrix} \tag{10}$$

Step 3: Adopt expected net sales (r_{ij}) to calculate firm H's income matrix before credit-granting Z_{ij}^{1} and after credit-granting Z_{ij}^{2}.

$$\begin{aligned} Z_{ij}^{1} &= \begin{bmatrix} Z_{11}^{1} & Z_{12}^{1} & Z_{13}^{1} \\ Z_{21}^{1} & Z_{22}^{1} & Z_{23}^{1} \\ Z_{31}^{1} & Z_{32}^{1} & Z_{33}^{1} \end{bmatrix} \\ &= \begin{bmatrix} \dfrac{r_{11}}{S_a/S_b} - S_b & \dfrac{r_{12}}{S_a/S_b} - S_b & \dfrac{r_{13}}{S_a/S_b} - S_b \\ \dfrac{r_{21}}{S_a/S_b} - S_b & \dfrac{r_{22}}{S_a/S_b} - S_b & \dfrac{r_{23}}{S_a/S_b} - S_b \\ \dfrac{r_{31}}{S_a/S_b} - S_b & \dfrac{r_{32}}{S_a/S_b} - S_b & \dfrac{r_{33}}{S_a/S_b} - S_b \end{bmatrix} \end{aligned} \tag{11-1}$$

$$Z_{ij}^{2}=\begin{bmatrix} Z_{11}^{2} & Z_{12}^{2} & Z_{13}^{2} \\ Z_{21}^{2} & Z_{22}^{2} & Z_{23}^{2} \\ Z_{31}^{2} & Z_{32}^{2} & Z_{33}^{2} \end{bmatrix}=\begin{bmatrix} r_{11}-S_a & r_{12}-S_a & r_{13}-S_a \\ r_{21}-S_a & r_{22}-S_a & r_{23}-S_a \\ r_{31}-S_a & r_{32}-S_a & r_{33}-S_a \end{bmatrix} \tag{11-2}$$

Step 4: Calculate the before and after credit-granting u_i^w in the good, fair and bad status, respectively. At w=1 (before credit-granting):

$$\begin{aligned} u_1^1 &= P_{11}^1 Z_{11}^1 + P_{12}^1 Z_{12}^1 + P_{13}^1 Z_{13}^1 \Rightarrow f_1(1) \\ u_2^1 &= P_{21}^1 Z_{21}^1 + P_{22}^1 Z_{22}^1 + P_{23}^1 Z_{23}^1 \Rightarrow f_1(2) \\ u_3^1 &= P_{31}^1 Z_{31}^1 + P_{32}^1 Z_{32}^1 + P_{33}^1 Z_{33}^1 \Rightarrow f_1(3) \end{aligned} \tag{12-1}$$

At w=2 (after credit-granting):

$$\begin{aligned} u_1^2 &= P_{11}^2 Z_{11}^2 + P_{12}^2 Z_{12}^2 + P_{13}^2 Z_{13}^2 \Rightarrow f_2(1) \\ u_2^2 &= P_{21}^2 Z_{21}^2 + P_{22}^2 Z_{22}^2 + P_{23}^2 Z_{23}^2 \Rightarrow f_2(2) \\ u_3^2 &= P_{31}^2 Z_{31}^2 + P_{32}^2 Z_{32}^2 + P_{33}^2 Z_{33}^2 \Rightarrow f_2(3) \end{aligned} \tag{12-2}$$

C. Credit-granting decision rules

Assume a loan applicant's expected income exceeding BEP interval before and after credit-granting are (d_1, e_1, f_1) and (d_2, e_2, f_2), respectively. The credit-granting decision rules for banks are as follows.

(1) If $d_2-d_1+f_2-f_1>0$, implying a 'good' business performance, then banks *will accept* the firm's loan application.

(2) If $d_2-d_1+f_2-f_1=0$, meaning a 'fair' business performance, then banks *may accept* the firm's loan application.

(3) If $d_2-d_1+f_2-f_1<0$, representing a 'poor' business performance, then banks *will reject* the firm's loan application.

III. AN EMPIRICAL STUDY

To illustrate our method, we apply the above model to an empirical study of banks in Taiwan.

A. Data

The credit-granting data were collected through personal interviews and self-administered, mailed questionnaires. After successful pre-tests were completed, the questionnaires along with a cover letter describing the study's general purpose were sent to 300 domestic bank branches (29 domestic banks) and 144 foreign bank branches (13 foreign banks). In order to avoid bias from banks' loan policies, rules, and regional allocation, the subjects were randomly drawn from 1 to 3 branches out of each domestic and foreign bank in the Taipei, Taichung and Kaohsiung areas. A 54% response rate from 138 domestic banks and a 44.44% response rate from 80 foreign banks were received, while there were 27% efficient questionnaires from the responding domestic banks and 26.69% efficient questionnaires from the responding foreign banks.

The reliability of "the actual operations of a firm" and "the future operations and perspective of a firm" are defined as Cornbach α. A Cornbach α between 0.7 and 0.98 implies reliability, otherwise, unreliability. The maximum validity is defined as the square root of Cornbach α. The results show that the Cornbach α of "the actual operations of a firm" and "the future operations and perspective of a firm" are 0.8866 and 0.7010, and the maximum validity are 0.9416 and 0.8373, respectively. This appears to show that the variables are consistent and stable.

B. Empirical results

On the average of contingent fuzzy BEP interval of loan applications for domestic and foreign banks by industries are summarized in Table 1. The results show that the average fuzzy BEP intervals of loan applications for domestic banks are all greater than foreign banks no matter if it is single product or other product of multiproducts. However, the average fuzzy BEP interval for loan applications of domestic banks is smaller than foreign banks for major product of multiproducts. In general, domestic banks' credit-granting requirements are looser than foreign banks.

For a bank's evaluation process, the first step is to calculate the fuzzy BEP interval of a loan applicant. In order to reduce its bad debt loss, a bank must ensure the loan applicant's payment, which is based on whether a loan applicant's operating performance could be improved after credit-granting. We now will randomly select two banks from the survey samples, one a domestic bank and the other one a foreign bank, to illustrate the credit-granting evaluation by fuzzy-Markovian-CVP.

Assume four applicants I, II III, and IV make a 1-year loan application. Table 2 and Table 3 are summaries of the contingency for expected income exceeding BEP interval before and after credit-granting for applicants I, II III, and IV.

In Table 2 the business performance of applicants II and IV becomes better after credit-granting, while not for applicants I and III. The domestic bank should thus make a loan to applicants II and IV, and reject applicants I and III.

In Table 3 the business performance of applicant II improves under a good business status after credit-granting, while applicant III's business performance becomes better for three status after credit-granting. The foreign bank should accept the loan applicantion of III and re-evaluate applicant II.

Table 1
The contingent fuzzy BEP interval of loan applications for domestic and foreign banks by industry

Panel 1: Electronics industry

Banks	Single product	Multiple products	
		Main products	Other products
Domestic banks	(0.0300,0.0863,0.8837)	(0.0569,0.1203,0.8228)	(0.0447,0.0986,0.8567)
Foreign banks	(0.0560,0.1475,0.7965)	(0.0523,0.1205,0.8273)	(0.0525,0.1233,0.8242)

Panel 2: Textile industry

Banks	Single product	Multiple products	
		Main products	Other products
Domestic banks	(0.0364,0.0965,0.8671)	(0.0457,0.1032,0.8671)	(0.0457,0.1032,0.8511)
Foreign banks	(0.0347,0.0932,0.8721)	(0.0347,0.0932,0.8721)	(0.0199,0.6560,0.9145)

Panel 3: Other industries

Banks	Single product	Multiple products	
		Main products	Other products
Domestic banks	(0.0459,0.1044,0.8497)	(0.0473,0.1258,0.8269)	(0.0577,0.1659,0.7765)
Foreign banks	(0.0618,0.1509,0.7792)	(0.0432,0.1265,0.8303)	(0.0569,0.1463,0.7967)

Table 2
Contingent fuzzy BEP interval of a loan applicant before and after credit-granting for a domestic bank

Panel 1: Loan applicant I

Business status	Before credit-granting	After credit-granting	Business performance
Good	(-118,290,368)	(-211,290,339)	Bad
Fair	(-56,402,488)	(-99,402,451)	Bad
Bad	(-4.69,493,587)	(-8.35,493,542)	Bad

Panel 2: Loan applicant II

Business status	Before credit-granting	After credit-granting	Business performance
Good	(1237,2877,3211)	(2222,2877,2946)	Good
Fair	(1432,3227,3593)	(2572,3227,3296)	Good
Bad	(1515,3377,3757)	(2722,3377,3446)	Good

Panel 3: Loan applicant III

Business status	Before credit-granting	After credit-granting	Business performance
Good	(-1326,2693,2693)	(-2652,2693,2693)	Bad
Fair	(-1028,3290,3290)	(-2055,3290,3290)	Bad
Bad	(-1198,2949,2949)	(-2396,2949,2949)	Bad

Panel 4: Loan applicant IV

Business status	Before credit-granting	After credit-granting	Business performance
Good	(283,1983,1983)	(566,1983,1983)	Good
Fair	(458,2333,2333)	(916,2333,2333)	Good
Bad	(341,1816,1816)	(682,1816,1816)	Good

Table 3
Contingent fuzzy BEP interval of a loan applicant before and after credit-granting for a foreign bank

Panel 1: Loan applicant I

Business status	Before credit-granting	After credit-granting	Business performance
Good	(102727, 880540, 1123892)	(153875, 880540, 1018021)	Bad
Fair	(102727, 880540, 1123892)	(153875, 880540, 1018021)	Bad
Bad	(116079, 900540, 1145972)	(173875, 900540, 1038021)	Bad

Panel 2: Loan applicant II

Business status	Before credit-granting	After credit-granting	Business performance
Good	(4048, 27855, 31508)	(7233, 27855, 29532)	Good
Fair	(1995, 24155, 27560)	(3533, 24155, 25832)	Bad
Bad	(583, 21655, 24893)	(1033, 21655, 23332)	Bad

Panel 3: Loan applicant III

Business status	Before credit-granting	After credit-granting	Business performance
Good	(23061, 62653, 74373)	(34933, 62653, 67575)	Good
Fair	(14644, 49903, 60340)	(22183, 49903, 54825)	Good
Bad	(22731, 62513, 73822)	(34433, 62153, 67075)	Good

Panel 4: Loan applicant IV

Business status	Before credit-granting	After credit-granting	Business performance
Good	(333, 9158, 10512)	(566, 9158, 9888)	Bad
Fair	(412, 9292, 10653)	(700, 9292, 10022)	Bad
Bad	(-97, 8452, 9732)	(-166, 8425, 9155)	Bad

IV. CONCLUSION

In a basic system, a number of predictor characteristics are chosen for their ability to discriminate between those who repay their credit (good) and those who do not (bad). A bank in Taiwan evaluating customers' credits has typically emphasized collaterals and guarantors, and has adopted the rule of thumb, credit rating and credit scoring to measure loan quality as being either good or bad, based on the judgment of its investigator. However, the validation results testing the predictive ability of these methods have unfortunately been somewhat disappointing. This study proposes a contingent fuzzy approach which combines CVP analysis, fuzzy set theory, and Markovian dynamic programming to assure a safety-first credit-granting quality decision before granting credit. This research also develops a quantitative credit-granting decision rule for a loan officer, which is able to reduce banks' bad debt loss.

Banks can thus use a BEP interval as a preliminary decision indicator, and then employ Markovian dynamic programming to calculate and compare the contingent fuzzy BEP before and after granting credit for loan applicants. If the firms' operating performance is good or fair after credit-granting, banks will or may grant the credit, otherwise the banks will reject the loan application. This approach not only can reduce the type I error or type II error for banks' credit-granting, but also might enhance the quality of the loan.

ACKNOWLEDGMENT

We greatly appreciate the helpful comments provided by Professor Ming-Shu Hwa and Professor K.C. Chen. This study is fully supported by National Science Council of Taiwan, R.O.C. under contract: NSC-86-2416-H-260-001.

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