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Research on ESG score impacted on credit risk of commercial banks

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Abstract: With transformation in green technology and increasing attention from governments and authority, ESG score and its impact on credit risk have gradually become a significant subject after the financial crisis. By analyzing the data of 42 commercial banks in China from 2012 to 2020, we found that a better performance in ESG score can improve the reduction of credit risk exposures. Through mediating effect analysis, we found investor sentiment index is the mediator and it has a marginal increasing effect on decreasing credit risk. Relevant studies indicate that there is regional heterogeneity and government support heterogeneity in the impact of ESG score and default distance. The theoretical and practical orientation of our paper is to mitigate the negative consequences and strengthen the control of credit risk under the internal and external supervision of banks.

1. Introduction and Background to the Research Topic

With the continuous development of the modern economy, the expansion of various industries has led to destruction of the natural environment. In 2020, for example, the total global carbon dioxide emissions reached 32.284 billion tons, still before companies in various countries consider the environment, society, and corporate governance, the average annual growth rate has increased year by year, with the United States, China, and India bearing the brunt. As a result, China made a global commitment in September 2020 to achieve "carbon peak" by 2030 and "carbon neutral" by 2060. In the face of this profound all-round change in environment, society and corporate governance, many enterprises, especially the banking industry, have taken the lead in carrying out green and low-carbon model transformation and incorporating ESG scores into the management of commercial banks[1-2].

2. Data and Methodology

2.1 Data Sources

In this paper, we select the sample data of domestic listed banks from 2012 to 2020.By the following rules, we selected 378 observations:

(1)Exclude the samples with missing values in the ESG score;

(2)Exclude the samples with numerous and continuous missing data;

(3)Exclude the samples with ST or PT signals in their stocks.

In the meantime, the data containing 27 related types were obtained from Wind.

2.2 Credit Risk Model Selection

Our paper uses the modified KMV model to access the credit risk level. The model was established by KMV Company in San Francisco in 1997. It is used to estimate the default probability of borrowing enterprises. At the same time, the probability that a borrower defaults on a particular loan is the probability that the counterpart (mostly savings institutions, such as commercial banks) faces credit risks. This model holds that the credit risk of a loan is determined by the market value of the debtor's assets given the liability. But assets are not traded on the market, and the market value of assets cannot be directly observed. Therefore, the model reverses the loan problem of the banks and it considers the loan repayment problem from the perspective of the owner of the borrowing enterprise. Thus, it uses BS model to estimate the market value of enterprise assets and the volatility of asset value according to the market value of enterprise equity, its volatility, the maturity time, risk-free lending rate and the book value of liabilities. Secondly, the default distance of the borrower calculates by the default execution point of the company according to the liabilities of the enterprise. Finally, the expected default rate is calculated according to the correspondence between the default distance and the expected default frequency (EDF). Due to the lack of a domestic expected default rate database, we cannot directly compare the default distance withthe default rate quantitatively. This paper adopts the general method in the industry and uses the value of default distance to qualitatively assess the credit risk status.

2.3 Variables Introduction

Default distance (DD).When analyzing credit risk by KMV model, the element distance to default, also means d2,has a negative relationship with the actual credit risk. After the adjustment, the industry established the DD index, which indicates that distance between the expected future market value of a firm's assets and the default point. This indicator represents the ratio of the difference between the value of a commercial bank's assets and floor K to the amount of fluctuation in the value of the bank's assets. In this paper, the index DD calculates using the selected commercial bank data, which uses as the dependent variable of this study. However, in the process of data collating, there are missing values in the total assets of some banks and their related data in some years, so we use the relative model of volatility estimation to simulate the bank value on the time point.To reduce the error, we use daily stock price data from 2012 to 2020 to calculate daily stock returns (σn), and the average annual volatility of equity value of 42 banks is obtained ($\sigma E-$year n).

The volatility estimation models commonly used in the industry include EWMA model, ARCH model and GARCH model. Since GARCH model considers the meanreversion process, and GARCH (1, 1) is very conducive to most practical time series modeling, we use GARCH (1, 1) model to fit stock returns. Using annual average equity value volatility data for 42 banks, we plug the data for adjacent years into the following equation: $\begin{cases} \sigma_n^2 = \alpha r_{n-1}^2 + \beta\sigma_{n-1}^2 + \gamma V \\ \sigma_{n+1}^2 = \alpha r_n^2 + \beta\sigma_n^2 + \gamma V_L \end{cases}$ L, $y + \alpha + \beta = 1$ .Thus, we can solve the sets of (α, β, γ) . Using the OLS method to find the value of the closest vertical distance of the linear regression fitting line as the optimal solution, the GARCH (1, 1) model equation was obtained： $\sigma_n^2 = 0.0548 r_{n-1}^2 + 0.7541\sigma_{n-1}^2 + 0.1911V_L$.

Floor-K is composed of short-term liabilities and long-term liabilities of the enterprise, and its calculation formula is floor − K(D) = ST liability + $\frac{1}{2}$ × LT liability. Since major commercial banks do not disclose the amount and proportion of each bank's liabilities, we use the CICC Financial Annual Report to indirectly obtain the conclusion: The proportion of short-term liabilities of most commercial banks between 2012 and 2020 is about 29.2%,the proportion of long-term liabilities is about 70.8%. Therefore, it can conclude that the floor-K value is 64.6% of the total liabilities.

Based on the equation TA = TL + OE we can get: ∂TA = ∂(TL + OE) = ∂TL + ∂OE.Thus, we conclude that the volatility of bank asset value positively correlates with the volatility of equity value. Therefore, it is feasible to use the GATCH (1, 1) model to estimate the volatility of bank asset value (Siyao & Peilong, 2023). Thus, we can use the product of last year's total bank assets and the volatility fitted by the GATCH (1, 1) model to represent the fluctuation amount of bank asset value.Based on the above steps, we can derive the default distance of each bank for each year.

Bank ESG score (ESG). Based on in-depth research on international Standards and guidelines, including ISO 26000, SDGs, GRI Standards, SASB Standards, TCFD Recommendations, etc., Wind combined with the policy and current situation of Chinese companies' ESG information disclosure, relying on its substantial data collection, analysis and processing capabilities, it has built a unique ESG rating system for Chinese companies. Wind ESG performance measures ESG score in terms of environment(E), society(S) and government(G). But the Wind database is much better than traditional mainstream ratings (e.g., Huazheng ESG rating) because it is more realistic, and the survey indicators covered are subdivided into many indicators in the original three dimensions, such as the proportion of the first shareholder, the degree of shareholder responsibility, the level of corporate ESG financing, environmental responsibility, corporate value recognition, and other secondary indicators. At the same time, the weights of different indicators in forming ESG scores have been improved under the mainstream method. In the ESG score of banks, the bank's investment, financing ability and internal management are mainly considered. Therefore, among the three dimensions, the corporate governance index will receive more consideration in the score. So in this paper, we use Wind ESG measurement to analyze the dependent variable. However, we don’t tend to use three indicators for further research but consider it as a whole.

Based on the relevant studies on ESG score and credit risk in commercial banks, we choose GDP (GDP), M2 money supply (M2), return on equity (ROE), and deposit reserve ratio (DRR) as the main explanatory variables.

We choose asset-liability ratio and investor sentiment index as mediating variables.Asset-liability ratio: ESG scores will not only be considered by investors as the direction of investment, but the impact of this score will have a contagious effect on the bank's deposit and loan position. High ESG ratings improve banks’ creditworthiness, boost demand for deposits and loans, and encourage companies to raise debt and equity. Based on the research of Chengxiao et al. (2021), the leverage level of commercial banks will be affected by national macroeconomic conditions and banks ’ operating conditions. In this paper, we choose GDP, M2 money supply, ROE and deposit reserve rate as macro indicators for research.

Investor sentiment index: As an annual indicator, the investor sentiment index reflects the stability and vitality of China's investment market this year (Prasad et al., 2023). Investor sentiment has a conductive effect, often with concentration, characteristics of high influence and lag. A concentrated, large-scale market anomaly often causes by irrational investor sentiment and driving stock, spot and forward market volatility. At the same time, current market conditions and personal expectations can change investor behavior. In this paper, we choose GDP, money M2 supply and deposit reserve ratio as macro indicators for research.

Figure 1 shows the primary trend of national GDP and money M2 supply from 2012 to 2020. We can see that in recent years, both macro indicators have maintained an upward trend, especially the total GDP, which has doubled. In addition, one year after the beginning of COVID-19, the national macroeconomic indicators have continued to rise steadily, which indicates that the national macroeconomic situation is healthy and the development stability is vital. Moreover, it proves that the country's economic solid policies promote market activity. In recent years, China's GDP growth rate has been kept within a reasonable range, not only realizing the goal of a moderately prosperous society in all respects, but also making an important contribution to the world economy. The continuous growth of GDP reflects the constant optimization of China's industrial structure, the constant improvement of innovation ability and the gradual expansion of the consumer market. Second, M2 is the core measure of the money supply, and its growth means that there is enough money in the market to stimulate investment, consumption and economic growth. Because China's M2 growth has kept pace with GDP growth, it not only meets the demand for money for economic development, but also effectively suppresses the risk of inflation. In addition, the steady growth of M2 also helps to reduce the volatility of the financial markets and provides an excellent monetary environment for the development of the real economy. Therefore, we predict GDP and M2 will continue to increase in the following years, and the increment will remain stable.

Figure 2 shows the trend of the reserve requirement ratio from 2012 to 2020. We find that since 2015, the deposit reserve ratio has been in a state of negative growth. From 2013 to 2015, the rate of decline gradually increased, and from 2014 into a negative, resulting in a decline in bank interest rates. During the same period, deposits flowed into the market, providing additional funds for economic development. At this stage, more funds are released, making loans and investments fully funded, thereby increasing the overall liquidity of the financial system. At this time, savings funds flowed into the market, helping to ease financing pressure and provide impetus for the development of the real economy. At the same time, this period also contributed to the rise of the stock market and improved investor sentiment[3-5].

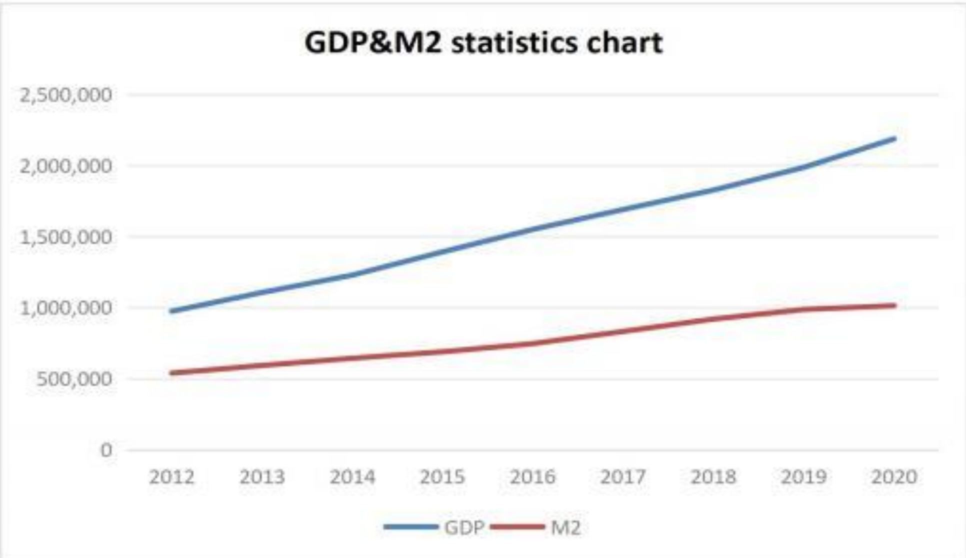

Figure 1: GDP&M2 statistics chart

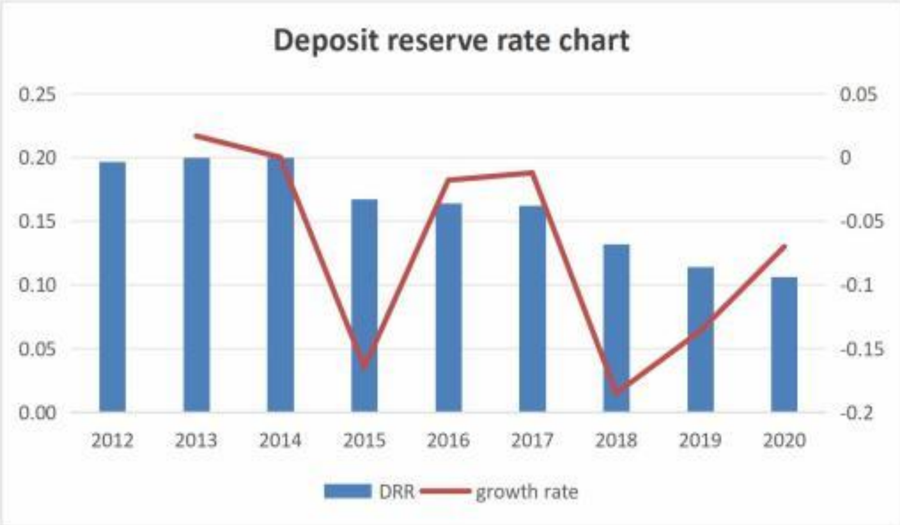

Figure 2: Deposit reserve rate chart

2.4 Descriptive Analysis

Table 1 shows the data for different variables. As for default distance, the mean value is 14.095, standard deviation is 2.052, with minimum and maximum values are 10.397 and 3.108 respectively, which reflects the slight difference among different banks. The mean, standard deviation, minimum and maximum values of ESG score are 0.795, 0.036, 0.653 and 0.879. It indicates that the gap between the difference is small but the average level in the samples is in the middle or upper location. Apart from macro indicators, the standard deviation of the investor sentiment index is very small, which is at 0.005, which indicates economy and market condition always keep stable. The mean, standard deviation, minimum and maximum values of asset-liability ratio are 0.929, 0.012, 0.884 and 0.977, which shows banks are under pressure from deteriorating balance sheets, but it is controllable.

Table 1: Descriptive statistics

Variable	Obs	Mean	SD	Min	Max
year	378	2016.01	2.61	2012	2022
region	378	1.21	0.41	1	2
ESG	378	0.80	0.04	0.65	0.88
ROE	378	0.15	0.043	0.068	0.294
GDP	378	1551599.70	393327.41	974148.80	2664320.80
M2	378	774569.19	165740.98	538579.95	1210207.20
α	378	45.63	4.36	39.25	58.15
DRR	378	0.16	0.04	0.06	0.20
AR	378	0.93	0.01	0.88	0.98
DD	378	14.10	2.05	10.40	19.42
BEY	378	8.90	0.69	5.90	10.63
Stru	378	0.21	0.15	0.04	0.68

2.5 Methodology

In the face of the multicollinearity problem encountered by the regression models, we use principal component analysis to solve it. It converts a set of highly correlated variables into linearly uncorrelated variables by orthogonal transformation to solve the error caused by a strong correlation between variables in regression analysis. At the same time, this method makes it difficult to explain the concrete meaning of principal components. Therefore, we conduct relevant analyses on the obtained principal components to determine their explanatory power to the original variables.

On the basis of hypothesis testing, this paper analyzes the mechanism of intermediate variables. We study the influence of the mediating variable on the dependent variable and the degree of its effect. According to assumptions H2 and H3, it can be seen that the influence path of the independent variable on the two intermediary variables is independent, and the influence of the intermediary variable on the dependent variable is also independent. Therefore, this model belongs to the parallel mediation model. At the same time, due to multiple independent variables in the model, we analyzed the structural equation model in AMOS Graphics and verified it using a series of test methods.

3. Models

3.1 Model Setup

To test the aggregate effect of ESG score on credit risk in commercial banks, we first set the benchmark regression model:

$$DDi,t = \beta0 + \beta1\ EsGi,t + \beta2\ ROEi,t + \beta3ARi,t + \beta4\ \alpha i,t + \beta5\ BEyi,t + \beta6strui,t + Ei,t \quad (1)$$

Where i,t denote bank and year, BEyi , strui,t are the set of control variables and μi, δt are used for controlling bank and year. Ei, ttis the random error term, β0 is the intercept and β 1−6 are coefficients for different variables in the equation.

At the same time, in order to explore whether the investor sentiment index and leverage ratio or related components play an intermediary effect on the credit risk of commercial banks, we established the following model, conducted correlation analysis and test on this basis, and tried to modify the model:

$$ARi,t = y0 + y1\ EsGi,t + y2\ GDpt + y3\ M2t + y4\ DRRt + y5\ BEyi,t + y6strui,t + \delta t + Ei,t \quad (2)$$

$$\alpha i,\ t = \mu0 + \mu1\ EsGi,t + \mu2\ GDpt + \mu3\ M2t + \mu4\ DRRt + \mu5\ BEyi,t + \mu6strui,t + \delta t + Ei,t \quad (3)$$

3.2 Multicollinearity Test

In this paper, the above three models were tested by VIF respectively, and Table 2 reflects the three groups oftest results. It’s easy to detect that the VIF values of M2, GDP and DRR are larger than 10. Therefore, we decided to use factor analysis (FA) and principalcomponent analysis (PCA) to reduce the collinearity of variables.

Table 3 is the summary of principal components, and due to the eigenvalue is above 1, component 1 is the key factor extracted from the three groups of variables. Therefore, after replacing the original variable with the principal component index, the regression model formed is shown as follows:

$$ARi,t = y0 + y1\ ESGi,t + y2f1\ t + y3\ BEyi,t + y4Strui,t + \delta t + Ei,t \quad (4)$$

$$\alpha i,t = \mu0 + \mu1\ ESGi,t + \mu2f1\ t + \mu3\ BEyi,t + \mu4Strui,t + \delta t + Ei,t \quad (5)$$

By principal component regression, we can solve the multicollinearity problem of the original model, and the Table 4 shows VIF test results of the revised model.

Table 2: VIF test of the original model

model	Model 1		Model 2&3	
	VIF	1/VIF	VIF	1/VIF
ESG	1.20	0.832	1.14	0.879
α	3.90	0.256		
AR	1.55	0.644		
ROE	1.51	0.664		
M2			73.11	0.014
GDP			72.87	0.014
DRR			17.60	0.057
BEY	3.30	0.303	1.75	0.572
Stru	1.87	0.535	1.67	0.598
Mean VIF	2.22	0.45	28.02	0.036

Table 3: PCA results

	Principal	component	Eigenvalue	Cumulative
M2&GDP&DRR		f1	2.95337	0.985

Table 4: VIF test of the revised model model Model 4&5

	VIF	1/VIF
ESG	1.09	0.912
f1	1.15	0.868
BEY	1.74	0.574
Stru	1.67	0.60
Mean VIF	1.41	0.709

3.3 Basic Regression Analysis

Table 5: Benchmark regression results of three models

	DD (model 1)	AR (model 4)	α (model 5)
ESG	2.247***	0.607***	1.472***
	(0.575)	(0.017)	(0.459)
ROE	-9.095*** (0.728)		
α	0.405***		
	(0.039)		
AR	11.308*** (1.892)		
f1		-0.004***	4.359***
		(0.001)	(0.017)
Control variables	YES	YES	YES
Control year	YES	YES	YES
Control region	YES	YES	YES

*, **, *** denote that the variables are significant at the 10%, 5%, 1% level, respectively.

Our paper uses OLS regression in this part. Table 5 reflects the influence degree of independent variables corresponding to the regression model. According to the results, the p-values are all <1% in the three models. The ESG regression coefficient is 2.247, indicating that the ESG score has a significant positive impact on the default distance of commercial banks, that is to say, the higher the

ESG score, the lower the default risk of commercial banks. At the same time, AR and α are both significant, and the regression coefficients of variables are 11.308 and 0.405, indicating that the asset-liability ratio has a significant impact on default distance, that is to say, the higher the asset-liability ratio, the lower the default risk. After that, the investor sentiment index positively correlates with default distance. Therefore, hypothesis 1 is verified and asset-liability ratio has the most significant positive effect on credit risk levels of commercial banks. We also found that ROE has a strong negative impact on default distance[6].

3.4 Intermediary Effect Analysis

When considering the influence of independent variable X on dependent variable Y, if X influences Y by influencing variable M, M is called mediator or mediating variable, similarly, the influence of X on Y through the mediating variable M is called the mediation effect. The standard mediation model has one independent variable and several mediating and control variables. But if there is more than one independent variable and they do not simultaneously appear in both the primary model and mediating test model, some traditional methods like Stepwise Regression cannot work.

Given that our master model contains more than one independent variables, we attempt to use structural equation model (SEM) to quantify the intermediary process.

Figure 3 is a diagram of the influence mechanism of variables drawn by AMOS. We will examine the effects of the five paths a, a’, c, c’ and d. According to the test results in Table 6, the indirect effect value is negative, indicating that the impact of ESG on the default distance cannot be realized through the asset-liability ratio. Meanwhile, both the value of the indirect effect and the value of the indirect effect are positive, indicating that the investor sentiment index acts as an intermediary of the impact of ESG score on default distance. And the direct effect is not equal to zero, which proves that investor sentiment index is a partial intermediary.

Table 7 reflects the effect significance of the two paths. ind_ 1 represents the influence path of ESG → AR → DD, and ind_2 represents the influence path of ESG → AR → DD.We can obtain that P-value of ind_ 1 is larger than 10%, indicating that the ESG score can’t influence indirectly through the asset-liability ratio. That is to say, the asset-liability ratio can’t serve as the mediator. On the other side, P-value of ind_2 is larger than 5% but below 10%, which means that the investor sentiment index does not totally mediate between ESG score and default distance, but it plays a partial intermediary role.

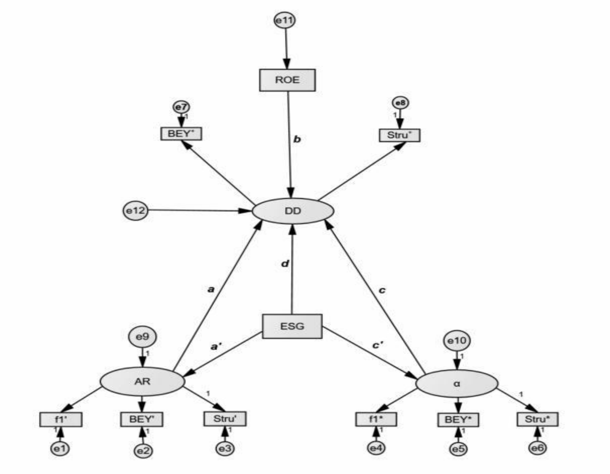

Figure 3: The variable impact mechanism diagram drawn by AMOS.

Table 6: Mediating effects path analysis

	Total Effects	Direct Effects	Indirect Effects	Signal
ESG → AR	0.196	0.151	0.045	' a
ESG → α	2.909	1.593	1.316	' c
ESG → DD	3.107	1.989	1.118	d
AR → DD	0.451	10.004	-9.553	a
α → DD	0.668	0.507	0.161	c

Table 7: Path regression (significance) analysis

Parameter	Estimate	Lower	Upper	P value
ind_1	0.001	-0.250	0.353	0.991
ind_2	1.839	0.133	0.938	0.006***
R1	0.000	-0.242	0.095	
R2	0.226	0.124	0.255	
diff	-1.838	-0.585	-0.383	
ind_1 = pa · pa' ind_2 = pc · pc'				
R1 = ind_1/total effect R2 = ind_2/total effect				
diff = ind_1 − ind_2				

*, **, *** denote that the variables are significant at the 10%, 5%, 1% level, respectively.

Based on the sample data, we explain the relationship between ESG score, asset-liability ratio and investor sentiment index through empirical analysis and relevant tests. Our paper finds that: (1) Generally, the score of ESG has a significant influence to default distance, that is, ESG score can cause a manifest impact on the credit risk of commercial banks. In addition, asset-liability ratio and investor sentiment index have a great impact on credit risk. (2) Investor sentiment index has a mediating effect but asset-liability ratio has not. The series of research proved that the influence path from ESG score to default distance relying on investor sentiment index exists and its mediating variable served as the role of indirect intermediary. (3) By studying the regional fixed model and the government financial support fixed model, it can be seen that critical explanatory variables (ESG score, asset-liability ratio and investor sentiment index) all have a significant impact on the default distance. It also proves that under the control of different conditions, models are characterized by heterogeneity. For the regional fixed model, the less developed region (region 2) has a more significant impact on the default distance regarding ESG score and asset-liability ratio. In contrast, the difference between different regions in the investor sentiment index is not apparent. For the fixed model of government support, the regression coefficients of key explanatory variables are more significant in regions with more financial support. (4) ESG score has a marginal decreasing effect on the default distance of commercial banks. However, ESG score has a marginal increasing effect on investor sentiment and investor sentiment on default distance.

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