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Predicting Recessions and Information about Yield Curves and Stock Markets in Japan

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Abstract

This study examines the predictability of the Japanese recession using data from Japanese government bonds and stock markets. It uses a probit model to estimate Japan's recession probability. The ratio between the expected and current short-term interest rates and the term premium, the two factors comprising the yield spread, with each containing independent information explaining future recessions. This research also demonstrates that stock market information can be used to predict recessions when interest rates are constrained by a lower bound. In particular, this study demonstrates that, in addition to the expected future short-term interest rate and term premium, Japanese stock market capitalization can help predict Japanese economic recessions.

Keywords: recession forecast; term spread; stock market capitalization; trading volume
JEL Classification: E32; E43; E44

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1 Introduction

Many researchers have compiled studies on the predictability of future recessions using financial market information. After the 1980s, several studies have reported the yield spread's usefulness in forecasting future consumption, inflation, output, and recession in the United States. For example, Harvey (1988) reported¹ that the real yield spread is related to real consumption growth at 2 or 3 quarters ahead in the subperiod from January 1972 to January 1987 in U.S. data. Estrella and Hardouvelis (1991) analyzed whether yield spreads have explanatory power for individual private sector components of real economic activity in the United States. According to their findings, yield spreads have explanatory power for the majority of economic activity components: consumption, consumer durables, and investment. Compared to those components, the yield spread's explanatory power for government spending is limited. Meanwhile, Estrella and Mishkin (1997) investigated the relationship between future real economic and inflation rates and yield spreads in European countries² in addition to the United States. Their research employed models that incorporated yield spreads and other financial variables.³ The explanatory power of the other financial variables varies by country, but they found that yield spreads have independent information in predicting real economic growth in most countries.

The pure expectations hypothesis easily explains the background behind the usefulness of yield spreads for predicting future recessions. It posits that long-term interest rates can be considered as the average of the expected value of short-term interest rates from the present to the future. Therefore, the yield spread (i.e., the difference between long- and short-term interest rates) can therefore be viewed as the expected value of future short-term interest rates. Additionally, in accordance with

¹Harvey (1988) demonstrated that the real yield spread has nonsignificant explanatory power for real consumption growth.

²Moneta (2005) analyzed the relationship between yield spreads and recession probabilities for eurozone countries using various definitions of yield spreads.

³Estrella and Mishkin (1997) predicted future changes in real GDP using the central bank rate, the real central bank rate, the short-term government rate, M0, M1, or M2, in addition to the yield spread.

the Taylor rule (Taylor, 1993; Woodford, 2001, Orphanides, 2001), the yield spread can be regarded as containing information about future inflation and the future GDP gap because short-term interest rates can be explained by the inflation rate and the GDP gap. Therefore, the relevance of the yield spread to future economic trends, inflation rates, or business cycles is theoretically valid.

A probit model was used by Estrella and Hardouvelis (1991), Estrella and Mishkin (1997), Estrella and Mishkin (1998), Bernard and Gerlach (1998), Moneta (2005), and Erdogan et al. (2015) to examine the relationship between the yield spread and the probability of a future recession. Their empirical findings indicate that the yield spread can be used to forecast a future recession. Furthermore, Estrella (2005) discussed the theoretical foundations of yield spreads' usefulness in predicting recessions. The estimation of recession probabilities has been applied to various other areas in addition to analyzing business cycle fluctuations.⁴

Thus, many previous studies have focused on forecasting future inflation rates, (real) economic growth, or recession probability in the United States or Europe, whereas only a few studies have investigated forecasting the Japanese recession. Therefore, this study uses data from the financial markets to forecast future Japanese recession. The yield spread has been shown in prior studies to be useful in predicting future recessions in the United States; as this paper will demonstrate later, the yield spread lags in Japan also have explanatory power for business cycle fluctuations when using quarterly data, but the usefulness of the model decreases during periods of low interest rates. Additionally, prior research (Okimoto and Takaoka, 2017) has shown that yield spreads have weak explanatory power⁵ for the business cycle fluctuations. One of the main causes of this is that yields on Japanese government bonds have remained low for a long time and the yields, including long-term maturity, have fluctuated little since the Bank of Japan implemented its zero interest

⁴Ang and Smedema (2011) used the recession probability estimated from the yield spread as a proxy for the recession prospects of firm managers.

⁵Nakaota (2005) showed that the yield spreads have no explanatory power for the industrial production growth in Japan.

rate policy in February 1999.

This study considers using stock market data in addition to government bond yields to forecast recessions in Japan to overcome this issue. According to Erdogan et al. (2015), the market capitalization and trading volume of the U.S. stock markets provide information that can be used to forecast a future recession in the country. Following the research, this study employs the market capitalization and trading volume of the Japanese stock market, as well as information from the Japanese government bond markets, to predict Japan's future recession. Why is stock market data regarded as important in forecasting future recessions? Fama (1990) and Schwert (1990) reported the link between stock market information and economic activity. Meanwhile, Nyberg (2010) showed that apart from yield spreads, stock return lags can be used to predict recessions. Moreover, Farmer (2015) specified that the U.S. stock market contains information explaining the variation in the unemployment rate. In theory, stock prices are determined by a firm's future free cash flow and dividends. Furthermore, stock prices are cyclical, with market capitalization falling during recessions. In other words, market capitalization peaks before a recession. In particular, Japan has had a long period of low interest rate policy, and the independent information that interest rates is thought to be limited due to the bond market's low volatility. Therefore, this study aims to improve the predictions of future recessions in Japan by adding stock market information to the model.

This study analyzes the relationship between the yield spread and recession probability using the following models: a spread-only model as a baseline model, a model that decomposes the yield spread into expected future interest rates and term premiums, and a model that adds information on the Japanese stock market's trading volume and market capitalization to that model. Many studies analyzing U.S. recessions have used the benchmark model (Estrella and Hardouvelis, 1991; Bernard and Gerlach, 1998). Additionally, Hamilton and Kim (2002) showed that the spread can be divided into the expected future short-term interest rate relative to the current

short-term interest rate and the term premium. Based on this concept, this paper predicts a Japanese recession using a model that decomposes the spread. Finally, this paper shows that incorporating stock market information into a model that decomposes the spread, referred to as an extended model in this study, improves recession predictions.

The remainder of this paper is organized as follows. Section 2 depicts the models used to forecast Japan’s future recession. Section 3 shows the in-sample prediction and out-of-sample forecasting of future recession in Japan for each model. Section 4 discusses the findings. Finally, Section 5 concludes the paper.

2 Material and methods

2.1 Decomposed yield spread model

This section begins to establish the baseline model to predict the future recession in-sample-fit. Like previous studies (Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1997; Estrella and Mishkin, 1998; Bernard and Gerlach, 1998; Moneta, 2005; Erdogan et al., 2015),⁶ the present study also employs a probit model to construct the relationship between the recession and yield spread. This study utilizes the following static probit model to investigate the predictability of recessions:

$$P(X_t = 1) = \Phi(\alpha_{BS,j} + \beta_{SPREAD,j} \times SPREAD_{t-j}), \quad (1)$$

where X_t is a dummy variable representing economic recession and expansion. $X_t = 1$ when the economy is in recession at time t , and $\Phi(\cdot)$ is cumulative standard density function. During the expansion period, $X_t = 0$ is taken. This study employs the recession dates that are published by the Cabinet Office of Japan.⁷ j denotes the time lag. In this paper, the time frequency is an end of a quarter because the GDP information is incorporated into the model constructed in the following section. In this paper, Equation (1) is defined as a baseline model. This study computes the

⁶The dynamic probit models were used by Kauppi and Saikkonen (2008) and Nyberg (2010).

⁷Data are available from the Cabinet Office website (<https://www.esri.cao.go.jp/jp/stat/di/hiduke.html>).

SPREAD⁸ as the difference between the yield to maturity⁹ of Japanese government bonds (JGBs) with 10- and 1-year maturity terms. This model’s sample period is from 1994:Q2 to 2012:Q1. As demonstrated by Hamilton and Kim (2002), the SPREAD can be broken down into the future expected short-term interest rate and the term premium. Let i_t^{10} and i_t^1 denote the 10-year interest rate (i.e., the long-term interest rate) and the 1-year interest rate (i.e., the short-term interest rate), respectively. Figure 1 depicts the recessionary periods and dynamics of short- and long-term interest rates. Short- and long-term interest rates have been declining since Japan’s asset bubble burst in 1990s. Furthermore, with the exception of mid-2000, short-term interest rates have remained at an extremely low level since the Bank of Japan adopted a zero interest rate policy in 1999.

The frequency of the yield data is quarterly, and the sample period¹⁰ extends from 1994:Q2 to 2012:Q1. The three recession periods analyzed are from 1997:Q3 to 1999:Q1, from 2001:Q1 to 2002:Q1, and from 2008:Q2 to 2009:Q1. Here, the long-term interest rate with a time-varying term premium TP_t can be defined as follows:

$$i_t^{10} = \frac{1}{40} \sum_{k=0}^{39} E_t i_{t+k}^1 + TP_t, \quad (2)$$

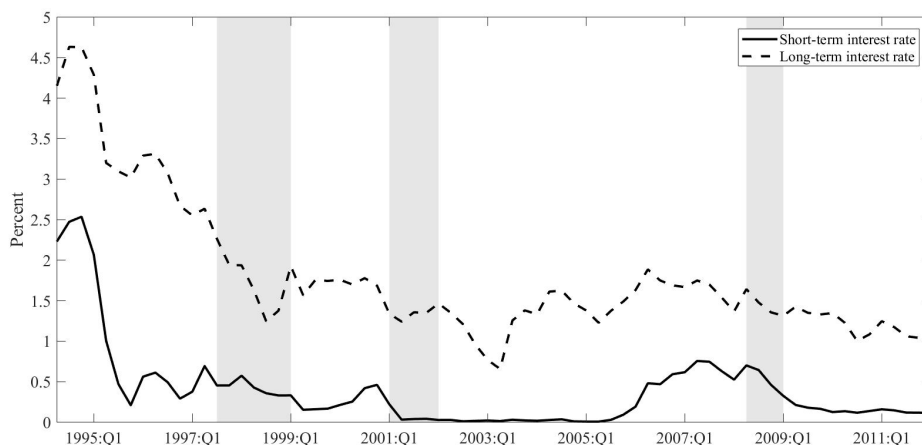
where $\sum_{k=0}^{39} E_t i_{t+k}^1$ denotes the average of the market expectation of the short-term interest rate,¹¹ and TP_t is the term premium, which includes a liquidity premium

⁸Erdogan et al. (2015) employed SPREAD calculated from the difference between 10-year Treasury bonds and 3-month Treasury bills, but because Japan’s Ministry of Finance (MOF) only publishes yield data for 1-year maturities, the 10-year and 1-year yields were used in this study. Furthermore, for the analysis’ reproducibility, this paper relies on data published by MOF rather than fee-based databases like Bloomberg or Refinitiv EIKON. The data can be found on the MOF website ([https://www.mof.go.jp/jgbs/reference/interest rate/index.htm](https://www.mof.go.jp/jgbs/reference/interest%20rate/index.htm)).

⁹Although it is preferable to assess the spot rate, this study instead used the yield to maturity due to convenience. During the preliminary analysis, the results did not change regardless of whether spot rates or the yield to maturity were used for the analysis.

¹⁰We need to use data up to 9 years ahead to calculate the term premium. Following that, the sample period for models estimated using term premiums will be the same.

¹¹The pure expectations hypothesis posits that a long-term spot interest rate is an average of short-term forward rates.



Note: Figure 1 depicts the dynamics of the short- and long-term yields. The short-term (the solid line) and long-term (the dashed line) yields represent the yields on 1-year and 10-year Japanese government bonds, respectively. The shadow areas in the figure represent Japan's recessionary periods.

Figure 1: The time-series of the short-term interest rate and long-term interest rate in JGB markets.

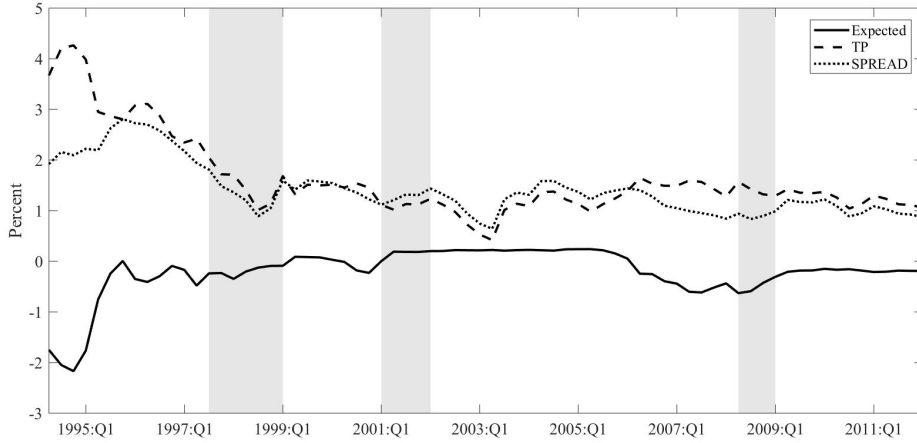
as well as a risk premium. Using Equation (2), we can rewrite SPREAD as follows:

$$SPREAD_t = \left(\frac{1}{40} \sum_{k=0}^{39} E_t i_{t+k}^1 - i_t^1 \right) + \left(i_t^{10} - \frac{1}{40} \sum_{k=0}^{39} E_t i_{t+k}^1 \right), \quad (3)$$

where $SPREAD_t = i_t^{10} - i_t^1$. The first term of the right-hand side in Equation (3) is the difference between the expected short-term interest rate over the next 40-quarter period and the current rate (hereafter, Expected), and the second term is the term premium¹² (hereafter, TP). Fig. 2 shows the recession periods, Expected, and TP from 1994:Q2 to 2012:Q1.

The shadow parts in Fig. 2 depict Japan's economic downturns during those times. The solid, dashed, and dotted lines represent the time-series of the Expected, TP, and SPREAD terms, respectively. Particularly, the declining term premium during recessionary times demonstrates the flight-to-quality (Longstaff, 2004; Bansal et al., 2014; Asgharian et al., 2015). Investors favor government bonds over risky

¹²According to the liquidity premium hypothesis, investors will demand excess returns on long-term bonds because they cannot sell them at favorable prices, and finding buyers is more difficult than selling short-term bonds.



Note: Fig. 2 shows the recession periods and the dynamics of the expected short-term interest rate and the term premium. The shadow parts in the figure indicate the recession periods in Japan. The solid, dashed, and dotted lines indicate the variations of the expected short-term interest rate, term premium, and the yield spread in Japanese government bond markets, respectively.

Figure 2: Recession periods, the expected short-term interest rate, and the term premium.

investments in the economic recession.

This study uses Hamilton and Kim's (2002) framework¹³ to predict a recession. Substituting Equation (3) for Equation (1), we can extend Equation (1) to Equation (4) under the rational expectations hypothesis:

$$P(X_t = 1) = \Phi \left[\alpha_{DP,j} + \beta_{Expected,j} \times \left(\frac{1}{40} \sum_{k=0}^{39} i_{t+k-j}^1 - i_{t-j}^1 \right) + \beta_{TP,j} \times \left(i_{t-j}^{10} - \frac{1}{40} \sum_{k=0}^{39} i_{t+k-j}^1 \right) \right]. \quad (4)$$

In this paper, Equation (4) is defined as a decomposed model. Ordinarily, a decrease in the yield spread indicates a coming recession. Such decrease in yield spread is caused by two possibilities: (1) a decrease in expected future short-term interest rates, or (2) a decrease in the risk premium of holding a long-term bond. The former is caused by market participants' expectation that the central bank will

¹³Nakaoka (2005) applies this framework to explain fluctuations in Japanese economic activity (industrial production index).

raise short-term interest rates. The latter is caused by investor behaviors, such as rebalancing their portfolio to risk-free long-term government bonds from risk assets, particularly equity, if the investor anticipates a future recession. The parameters of Equation (4) are the generalized representation. Strictly speaking, $\beta_{Expected} = \beta_{TP}$ should hold.

2.2 Macro-liquidity and macro-depth model

Thus far, the discussion has centered on the recession and yield spread. Nevertheless, according to Erdogan et al. (2015), it is reasonable to assume that not only interest rate market information but also stock market information is useful for forecasting recessions. Therefore, this study extends Equation (4) to a model that incorporates market liquidity and market depth for the Japanese stock market.

Following (Erdogan et al., 2015), this study extends Equation (4) to models incorporating macro-depth (MD)¹⁴ and macro-liquidity deviation (MLD). However, as analyzed by Hamilton and Kim (2002), the previous study (Erdogan et al., 2015) does not separate the SPREAD term into its two components: Expected and TP. This study defines the MD and the macro-liquidity (ML) as the ratio of Tokyo Stock Exchange’s first section¹⁵ market capitalization to Japan’s nominal GDP¹⁶ and the ratio of Tokyo Stock Exchange first section’s quarterly trading volume¹⁷ to Japan’s nominal GDP.

The recession periods and dynamics of the ML and MD from 1994:Q1 to 2012:Q1 are depicted in Fig. 3. The solid and dashed lines represent the ML and MD, respectively. During recessionary periods, MD decreases as investors shun risky assets, and flight-to-quality ensues. In addition to these results, the MD tends

¹⁴Erdogan et al. (2015) defined the ML and MD as the ratio of NYSE market capitalization to nominal GDP in the United States and the ratio of NYSE quarterly trading volume to the US nominal GDP.

¹⁵After April 2022, Tokyo Stock Exchange reorganized the market classification.

¹⁶The series is the seasonally adjusted nominal GDP in Japanese yen.

¹⁷Japan Exchange Group (JPX) publishes data on the trading volume and market capitalization of the Tokyo Stock Exchange 1st section. Data are available on the JPX website (<https://www.jpx.co.jp/markets/statistics-equities/misc/index.html>).

to peak just prior to a recessionary period. Meanwhile, the ML rises during an economic downturn. Due to a decline in stock market capitalization, the amount of equity available for purchase per unit of GDP rises during a recession. The ML reflects such a situation.

Many previous studies have demonstrated the usefulness of the stock market information in predicting a recession. Estrella and Mishkin (1998) demonstrated the usefulness of the New York Stock Exchange (NYSE) composite index for both in-sample-fit prediction and out-of-sample forecasting of the U.S. recession. They concluded that the stock price provides additional information that does not include the yield spread for recession prediction. In particular, they claimed that the predictability of the recession can be improved by incorporating GDP into the yield spread and the NYSE composite index. Næs et al. (2011) reported that the business cycle and liquidity are related. Along with these studies, Fama (1990) and Schwert (1990)¹⁸ also offered proof of the connection between the stock markets and actual economic activity.

Following Erdogan et al. (2015), this study estimates the MLD as the first difference of the model's residuals:

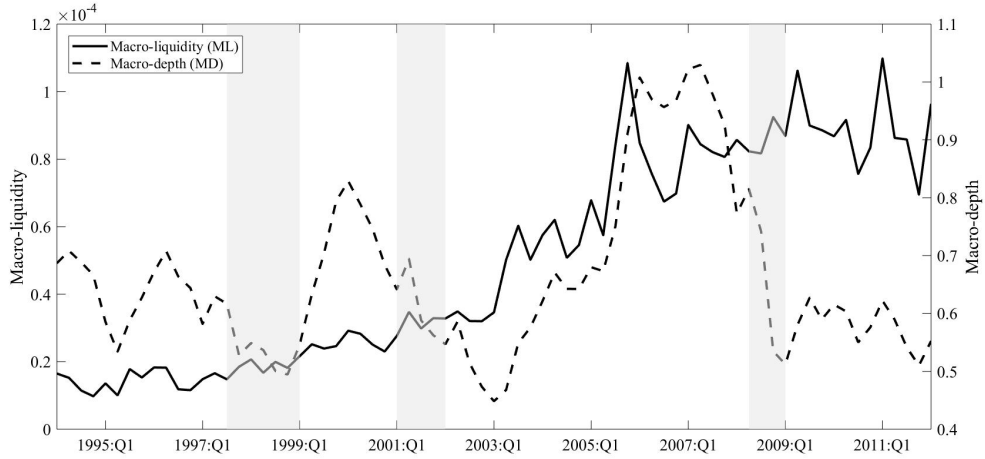
$$ML_t = \gamma_0 + \gamma_1 \times MD_t + u_t. \quad (5)$$

The following is the extended model:

$$P(X_t = 1) = \Phi[\alpha_{EX} + \beta_{Expected,l} + \beta_{TP,l} \times TP_{t-l} + \beta_{DMD,l} \times DMD_{t-l} + \beta_{MLD,l} \times MLD_{t-l}], \quad (6)$$

where $Expected_{t-l} = \frac{1}{40} \sum_{k=0}^{39} E_t i_{t+k}^1 - i_t^1$ and $TP_{t-l} = i_t^{10} - \frac{1}{40} \sum_{k=0}^{39} E_t i_{t+k}^1$. l denotes the time lag. DMD't is the first difference of MD. MLD is a cyclical variable that is closely related to recessions. If the stock market capitalization is high in comparison to the level of trading volume, the stock market capitalization will eventually fall to an appropriate level.

¹⁸Their study employed United States data.



Note: Fig. 3 shows the recession periods and the dynamics of the macro-liquidity and the macro-depth. The shadow parts in the figure indicate the recession periods in Japan. The solid line and the dashed line indicate the variations of the macro-liquidity and the macro-depth in Japanese stock markets.

Figure 3: Recession periods and the dynamics of the macro-liquidity and the macro-depth.

Table 1 shows the descriptive statistics of each variable, the short-term interest rate, long-term interest rate, yield spread (SPREAD), Expected, TP, DMD, and MLD. The sample period spans the periods 1994:Q2–2012:Q1. Table 1 shows that the maximum value of Expected is 0.24, indicating that it has been at a low level for a long time. As shown in Table 1, the variation in the term premium is greater when comparing the standard deviation of the Expected and the TP.

3 Results

3.1 Results of in-sample-fit

This section demonstrates the estimation outcomes of Equations (1), (4), and (6). These probit models are non-linear models, so this paper shows the pseudo- R^2 proposed by Estrella (1998). Pseudo- R^2 is obtained as follows:

$$\text{pseudo-}R^2 = 1 - \frac{\log L_u^{-(2/T)\log(L_c)}}{\log L_c}, \quad (7)$$

Table 1: Descriptive statistics of each variable.

	Mean	Std. Dev.	Min	Max	Obs
One-year	0.394	0.530	0.008	2.536	72
Ten-year	1.801	0.871	0.657	4.632	72
Spread	1.408	0.516	0.640	2.809	72
Expected	-0.216	0.494	-2.169	0.240	72
TP	1.623	0.814	0.418	4.264	72
DMD	-0.002	0.06	-0.207	0.161	72
MLD	1.23×10^{-6}	9.69×10^{-6}	-3.00×10^{-5}	2.42×10^{-5}	72

Note: Table 1 shows the descriptive statistics of each variable. 1-year and 10-year indicates the Japanese government bond yields of 1-year and 10-year maturity. SPREAD indicates the difference between the yields of 10-year maturity and 1-year maturity in Japanese government bonds. Expected and TP indicate the future expected short-term interest rate and the term premium in Equation (3). DMD is the first difference of MD. MLD is Macro-Liquidity-Deviation, which is the first-order difference of the residuals calculated from Equation (5). Obs indicates the number of observations of each variable.

where $\log L_u$ is the log-likelihood of the models and $\log L_c$ is the log-likelihood of the constant only model. T indicates the size of the sample. However, pseudo- R^2 does not consider the number of explanatory variables in the model. Therefore, to compare the goodness of fit of models between models with different numbers of explanatory variables, Equation (7) needs to be modified as follows:

$$\text{Adjusted pseudo-}R^2 = 1 - (1 - ps.R^2) \frac{T - 1}{T - K - 1}, \quad (8)$$

where $ps.R^2$ and K indicate the pseudo- R^2 and the number of estimated parameters in the model.

Table 2 displays the estimation result of Equation (1). In this study, lags from the 1st to the 12th quarter were employed. The estimated parameters of the probit models are not the marginal effects, although the sign is consistent with that of marginal effects. As presented in Table 2, the yield spreads of JGB have explanatory power to the future recession from 7-quarters ahead to 11-quarters ahead at a 1% significance level. For the sample period of this study, the yield spreads have independent information about future business cycle fluctuations.

As explained earlier, following Hamilton and Wu (2002), the spread can be de-

composed into two terms. The question of which factor is more important in explaining future business cycle fluctuations in Japan is critical. Table 3 shows the estimation result of Equation (4). The model that decomposes the yield spread is based on Expected and TP terms. Table 3 shows that Expected has explanatory power for future recessions with a 7- to 11-quarter lag. Similarly, TP has explanatory power for future recessions. At a lag of 6 to 12 quarters, the term premium parameter is statistically significant. These findings suggest that Expected and TP contain information that can be used to explain future business cycle fluctuations. The chi-squared value in Table 3 shows the Wald test of the null hypothesis, $\beta_{Expected} = \beta_{TP}$. Except for the models of 8- and 9-quarter lags, we cannot reject the null hypothesis. The largest value is the pseudo- R^2 of the 8-quarter lags. Based on the results of pseudo- R^2 , we will use an 8-quarter lag for Expected and TP in the following analysis.

Next, the model is extended by incorporating DMD and MLD as stock market information. This paper follows Erdogan et al. (2015) in defining MLD as the difference of residuals in the regression model of Equation (5). Equation (9) is the estimated result.

$$ML_t = \underbrace{6.82 \times 10^{-6}}_{\substack{\text{standard error} \\ (1.66 \times 10^{-5})}} + \underbrace{6.50 \times 10^{-5}}_{\substack{\text{standard error} \\ (2.46 \times 10^{-5})^{***}}} \times MD_t + u_t, \quad (9)$$

The explanatory power of MD in Equation (5) is statistically significant at 1% significant level. The result shows that increasing MD by one unit increases ML by 6.50×10^{-5} times. Table 4 shows the results of Equation (6). The model employs Expected and TP of an 8-quarter lag.

Table 2: Predicting recession probability using yield spread-only model.

Lags	α_{BS}	β_{SPREAD}	Pseudo- R^2	Adjusted pseudo- R^2	Number of observations
1	0.256 (0.506)	-0.755** (0.362)	0.05	0.02	71
2	-0.130** (0.488)	-0.445 (0.336)	0.02	-0.01	70
3	-0.596 (0.478)	0.096 (0.316)	0.00	-0.03	69
4	-1.020** (0.492)	0.205 (0.317)	0.01	-0.02	68
5	-1.496*** (0.509)	0.529* (0.321)	0.04	0.01	67
6	-1.945*** (0.540)	0.824** (0.333)	0.09	0.06	66
7	-2.350*** (0.555)	1.087*** (0.332)	0.14	0.11	65
8	-2.813*** (0.555)	1.385*** (0.322)	0.19	0.17	64
9	-2.745*** (0.552)	1.348*** (0.318)	0.19	0.16	63
10	-2.470*** (0.573)	1.181*** (0.331)	0.16	0.13	62
11	-2.159*** (0.560)	0.989*** (0.332)	0.13	0.10	61
12	-1.884*** (0.553)	0.820** (0.334)	0.09	0.06	60

Note: Table 2 shows the estimation results of Equation

(1), $P(X_t = 1) = \Phi(\alpha + \beta \times SPREAD_{t-j})$. Using as instruments a constant and $SPREAD_{t-j}$, where $SPREAD$ is the difference between 10-year Japanese government bond interest rate, i_t^{10} and one-year Japanese government bond, i_t^1 . j denotes a lag, and the time frequency is a quarterly in the model. Pseudo- R^2 proposed by Estrella (1998) is defined by

$\text{pseudo-}R^2 = 1 - \left(\frac{\log L_u}{\log L_c} \right)^{-(2/T) \log L_c}$, where $\log L_u$ is the log-likelihood of Equation (1) and $\log L_c$ is the log-likelihood of the constant only model. Adjusted pseudo- R^2 is calculated as $1 - (1 - ps.R^2) \frac{T-1}{T-K-1}$, where $ps.R^2$ and K are the pseudo- R^2 and the number of estimated parameters, respectively. The values in the parenthesis are robust standard error. The asterisk, ***, **, * indicate the statistical significance level at 1%, 5%, and 10%, respectively.

Table 3: Predicting recession probability using yield expected interest rate and term premium model.

Lags	α_{DP}	$\beta_{Expected}$	β_{TP}	$H_0 : \beta_{Expected} = \beta_{TP}$	χ^2	Pseudo- R^2	Adjusted pseudo- R^2	Number of observations
1	0.300 (0.518)	-1.060* (0.576)	-0.825** (0.391)	0.67	0.06	0.01	71	
2	-0.085 (0.506)	-0.784 (0.564)	-0.521 (0.373)	0.85	0.03	-0.02	70	
3	-0.570 (0.492)	-0.331 (0.549)	-0.145 (0.349)	0.41	0.01	-0.04	69	
4	-1.003** (0.503)	0.034 (0.550)	0.171 (0.346)	0.21	0.01	-0.04	68	
5	-1.492*** (0.523)	0.487 (0.568)	0.520 (0.351)	0.01	0.04	-0.01	67	
6	-1.967*** (0.570)	0.988 (0.610)	0.859** (0.376)	0.16	0.09	0.05	66	
7	-2.472*** (0.631)	1.667*** (0.643)	1.234*** (0.400)	1.85	0.16	0.11	65	
8	-3.165*** (0.705)	2.464*** (0.692)	1.726*** (0.425)	5.03**	0.23	0.19	64	
9	-3.091*** (0.665)	2.375*** (0.614)	1.675*** (0.400)	5.78**	0.22	0.18	63	
10	-2.602*** (0.613)	1.628*** (0.554)	1.314*** (0.371)	1.08	0.17	0.13	62	
11	-2.129*** (0.557)	0.869* (0.525)	0.955*** (0.340)	0.07	0.13	0.08	61	
12	-1.760** (0.543)	0.222 (0.508)	0.668** (0.335)	2.11	0.12	0.07	60	

Note: Table 3 shows the estimation results of Equation (4), $P(X_t = 1) = \Phi \left[\alpha + \beta_{Expected} \times \left(\frac{1}{40} \sum_{k=0}^{39} i_{t+k}^1 - i_t^1 \right) + \beta_{TP} \times \left(i_t^{10} - \frac{1}{40} \sum_{k=0}^{39} i_{t+k}^1 \right) \right]$.

Pseudo- R^2 proposed by Estrella (1998) is defined by pseudo- $R^2 = 1 - \left(\frac{\log L_u}{\log L_c} \right)^{-2(T) \log L_c}$, where $\log L_u$ is the log-likelihood of Equation (4) and $\log L_c$ is the log-likelihood of the constant only model. Adjusted pseudo- R^2 is calculated as $1 - (1 - ps.R^2) \frac{T-1}{T-K-1}$, where $ps.R^2$ and K are the pseudo- R^2 and the number of estimated parameters, respectively. The values in the parenthesis are robust standard error. The asterisk, ***, **, * indicate the statistical significance level at 1%, 5%, and 10%, respectively. This study tests the null hypothesis, $\beta_{Expected} = \beta_{TP}$ by using Wald test. Table 3 shows the chi-square statistics.

Table 4: Predicting recession probability using macro-depth and macro-liquidity-deviation.

Lags	α_{EX}	$\beta_{Expected}$	β_{TP}	β_{DMD}	β_{MLD}	Pseudo- R^2	Adjusted pseudo- R^2	Number of observations
1	-4.012*** (0.966)	3.329*** (0.909)	2.187*** (0.563)	-11.610*** (3.823)	3.106×10^4 (2.157×10^4)	0.32	0.26	64
2	-3.588*** (0.944)	2.897*** (0.967)	1.948*** (0.559)	-10.315*** (3.733)	0.621×10^4 (1.747×10^4)	0.29	0.23	64
3	-3.442*** (0.883)	2.674*** (0.858)	1.867*** (0.533)	-8.367** (3.527)	0.169×10^4 (1.563×10^4)	0.27	0.21	64
4	-4.040*** (0.826)	3.170*** (0.791)	2.216*** (0.504)	-12.315*** (3.428)	-0.181×10^4 (2.100×10^4)	0.30	0.24	64
5	-3.251*** (0.682)	2.590*** (0.657)	1.780*** (0.404)	-3.797 (3.083)	0.473×10^4 (2.273×10^4)	0.24	0.17	64
6	-3.179*** (0.732)	2.411*** (0.707)	1.724*** (0.438)	2.046 (3.321)	-0.171×10^4 (2.205×10^4)	0.23	0.16	64
7	-3.285*** (0.743)	2.292*** (0.729)	1.740*** (0.449)	6.093* (3.551)	-0.505×10^4 (-2.465×10^4)	0.25	0.18	64
8	-3.241*** (0.742)	2.274*** (0.713)	1.709*** (0.446)	5.426 (3.449)	-0.169×10^4 * (2.412×10^4)	0.24	0.18	64
9	-3.439*** (0.886)	2.487*** (0.826)	1.820*** (0.516)	4.769 (3.391)	-8.105×10^4 * ** (2.959×10^4)	0.30	0.24	63
10	-3.448*** (0.806)	2.465*** (0.806)	1.856*** (0.474)	5.767 (4.214)	-4.447×10^4 * (2.277×10^4)	0.28	0.21	62
11	-3.430*** (0.800)	2.250** (0.947)	1.823*** (0.457)	8.139* (4.368)	-1.630×10^4 (2.716×10^4)	0.27	0.21	61
12	-3.696*** (0.554)	1.900** (0.866)	1.982*** (0.345)	8.354** (3.738)	0.978×10^4 (2.912×10^4)	0.29	0.22	60

Note: Table 4 shows the estimation results of Equation (4),

$P(X_t = 1) = \Phi[\alpha + \beta_{Expected} \times Expected_{t-s} + \beta_{TP} \times TP_{t-s} + \beta_{DMD} \times DMD_{t-l} + \beta_{MLD} \times MLD_{t-l}]$. Pseudo- R^2 proposed by Mishkin (1998) is defined by pseudo- $R^2 = 1 - \left(\frac{\log L_u}{\log L_c}\right)^{-2/T \log L_c}$, where $\log L_u$ is the log-likelihood of Equation (4) and $\log L_c$ is the log-likelihood of the constant only model.

Adjusted pseudo- R^2 is calculated as $1 - (1 - ps.R^2)^{\frac{T-1}{T-K-1}}$, where $ps.R^2$ and K are the pseudo- R^2 and the number of estimated parameters, respectively. The values in the parenthesis are robust standard error. The asterisk, ***, **, * indicate the statistical significance level at 1%, 5%, and 10%, respectively.

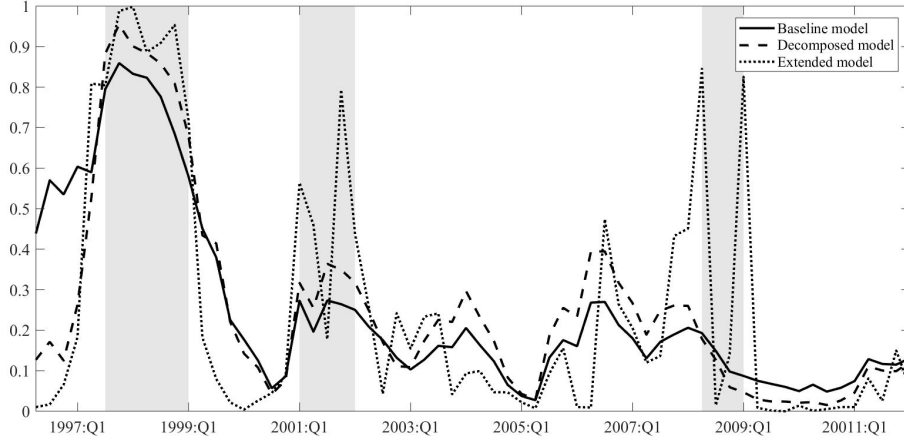
Table 4 shows that an increase in Expected and TP terms with an 8-quarter lag predicts a future recession.¹⁹ Furthermore, DMD of a 1-quarter lag is statistically significant in each model. Meanwhile, MLD is statistically significant only at an 8- to 10-quarter lag. When the DMD has a 1-quarter lag, the pseudo- R^2 is the greatest in this model.

Fig. 4 depicts the in-sample-fit predictions of the baseline, decomposed, and extended models. The baseline model is only an 8-quarter lag spread model. The decomposed model is based on the Expected and the TP of an 8-quarter lag. Meanwhile, the extended model is built on the Expected and TP of an 8-quarter lag, the DMD and MLD of a 1-quarter lag. This extended model has the largest adjusted pseudo- R^2 in Tables 2, 3, and 4. The solid, dashed, and dotted lines represent the in-sample-fit prediction of these models, respectively. As illustrated in Fig. 4, the extended model predicts a higher recession probability in the three recession periods from 1997:Q3 to 1999:Q1, 2001:Q1 to 2002:Q1, and 2008:Q2 to 2009:Q1. Moreover, Fig. 4 shows that by incorporating information from both the stock and bond markets, we can build models that are more useful in predicting future economic recessions in Japan.

3.2 Results of out-of-sample

In the preceding section, this study demonstrated the explanatory power to the future recession in-sample-fit. Nonetheless, one of the concerns in economics and financial economics is the out-of-sample forecasting of future recessions. This subsection shows the out-of-sample projections of the future recession for the baseline, decomposed, and extended models. Using recursive rolling probit regression, this study estimates a 1-quarter-ahead forecast. It first predicts the probability of a recession in 2006:Q4 using data from 1994:Q2 to 2006:Q3. Subsequently, this

¹⁹Owing to space limitations, we did not present estimation results for the baseline model in addition to DMD and MLD in the in-sample-fit analysis, although the estimation results were consistent with the findings of this study. A later, out-of-sample analysis revealed the predicted results of that model as an extended SPREAD model.



Note: Fig. 4 shows in-sample-fit prediction of the three models from 1996:Q2 to 2012:Q1. The solid, dashed, and dotted lines indicate the prediction of the baseline, decomposed, and extended models, respectively. The shadow parts in the figure indicate the recession periods in Japan.

Figure 4: In-sample-fit forecast of the recession probability.

study predicts the probability of a recession in 2007:Q1 using data from 1994:Q2 to 2006:Q4. The recursive probit regression estimates a one-period out-of-sample forecast based on the sample period preceding the forecast. The baseline model is the only yield spread model with an 8-quarter lag:

$$P(X_{t+1}) = \Phi[\alpha_{SPREAD} + \beta_{SPREAD} \times SPREAD_{t-7}]. \quad (10)$$

The decomposed model is as follows:

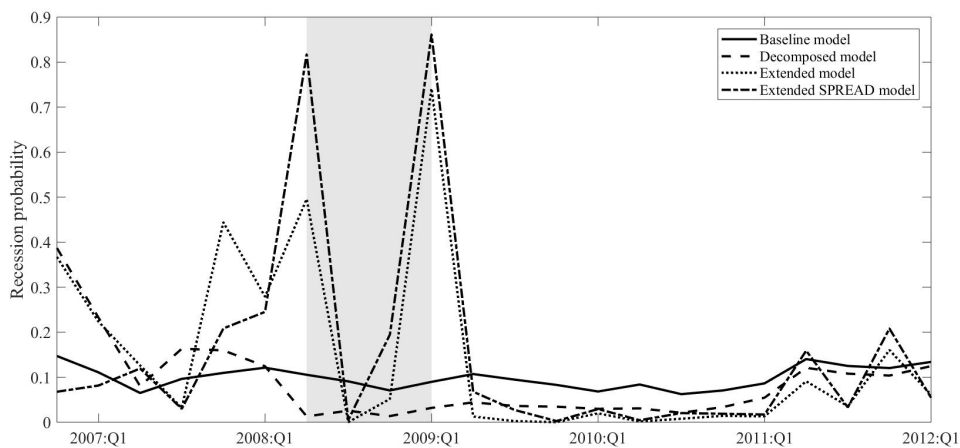
$$P(X_{t+1}) = \Phi[\alpha_{DP} + \beta_{Expected} \times Expected_{t-7} + \beta_{TP} \times TP_{t-7}]. \quad (11)$$

Meanwhile, the extended model is as follows:

$$P(X_{t+1}) = \Phi[\alpha_{MLD} + \beta_{Expected} \times Expected_{t-7} + \beta_{TP} \times TP_{t-7} + \beta_{DMD} \times DMD_t + \beta_{MLD} \times MLD_t]. \quad (12)$$

In the out-of-sample forecast, this study employs the 8-quarter lag of the Expected and the TP, and the 1-quarter lag of DMD and MLD from the previous estimation results.

However, these models are not strictly out-of-sample analysis because the Expected and TP are calculated based on the future realized interest rates. Therefore,



Note: Fig. 5 shows the out-of-sample forecast of the recession probability in the models of Equation (10), (11), (12), and (13). The forecast sample period is from 2006:Q4 to 2012:Q1. The solid line indicates the forecast of the baseline model, and the dashed and the dotted lines indicate the forecast of the decomposed, extended, and extended SPREAD models. The shadow parts in Fig. 5 indicate the recession period.

Figure 5: Out-of-sample forecast of the recession probability.

to confirm the usefulness of the Japanese stock market information for recessions in out-of-sample analysis, we also present the forecasting result for the following model:

$$P(X_{t+1}) = \Phi [\alpha_{EXS} + \beta_{Expected} \times Expected_{t-7} + \beta_{TP} \times TP_{t-7} + \beta_{DMD} \times DMD_t + \beta_{MLD} \times MLD_t]. \quad (13)$$

This model is defined as the extended SPREAD (EXS) model. The setting of this model is similar to that of the model developed by Erdogan et al. (2015).

Figure 5 shows the results of out-of-sample recession forecasts for the baseline, decomposed, extended, and extended SPREAD models. The solid, dashed, dotted, and the dashed and dotted lines represent the forecasted line of the baseline, decomposed, extended, and the extended SPREAD models, respectively. The periods of forecast are from 2006:Q4 to 2012:Q1. The shadow part in Fig. 5 represents the recession.

As shown in Fig. 5, the forecasted value of the extended and the extended SPREAD models has more variation than both the baseline and the decomposed

Table 5: Forecast errors and the forecast accuracy test

	MSE	RMSE	<i>p</i> -value
Baseline model	0.160	0.400	
Decomposed model	0.190	0.436	0.0996
Extended model	0.124	0.353	0.0292
Extended SPREAD	0.086	0.294	0.0097

Note: Table 5 shows the mean squared error and root mean squared error of the baseline, decomposed, extended, and extended SPREAD models, as well as the *p*-value of Diebold and Mariano’s (1995) test. The forecast period is 22 periods from 2006:Q4 to 2012:Q1. The extended SPREAD (decomposed, extended) model’s forecast accuracy is assumed to be the same as the baseline model, which is the null hypothesis.

models. In particular, the extended and the extended SPREAD models accurately depict the recession during the global financial crisis (2007–2008). Subsequently, the study employs Diebold and Mariano’s (1995) test to assess the forecasting accuracy of the recession probability. The null hypothesis for the statistical test is that the forecasting accuracy of the two models is equivalent.

Table 5 displays the MSE and the RMSE for the baseline, decomposed, extended, and extended SPREAD models and Diebold and Mariano’s test statistics. Table 5 shows that the RMSE of the extended SPREAD model is lower than that of the other models. Additionally, Diebold and Mariano’s (1995) test supports better forecasting accuracy of the extended SPREAD model at the 1% statistical significance level. Additionally, the test supports better forecasting accuracy of the extended model at the 5% statistical significance level. Therefore, compared to the traditional spread-only baseline model, these models incorporating stock market information is more reliable for forecasting recessions.

4 Discussion

This section discusses the estimation results and interprets them in light of previous research findings. Previous research (Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1997; Estrella and Mishkin, 1998; Bernard and Gerlach, 1998; Mon-

eta, 2005; Erdogan et al., 2015) found spreads to be useful in predicting recessions probability. The major difference in the results from the previous study is that the spread coefficient is positive in Table 2. In Japan, a larger yield spread, rather than an inverse yield, is a predictor of an impending recession. This result suggests that in Japan, the long-term interest rate plays a more important role than the short-term interest rate in stimulating an economic recession. The work of Okimoto and Takaoka (2017) is among the studies that forecast the Japanese business cycle. The coincident index is used as a measure of the business cycle in their study. Their findings reveal that term spreads²⁰ are only useful for forecasting the business cycle 1 month ahead.²¹ Nakaoka (2005) also reports that yield spreads have no explanatory power for economic activity. However, this study, using quarterly data, reveals that yield spread has explanatory power to recessions in the medium term.

By decomposing the spreads into their Expected and TP terms, this study investigates which factor is more useful in explaining a future recession. Fig. 3 illustrates this trend. Hamilton and Kim (2002) used the Expected and TP obtained by decomposing the spread to predict GDP growth; they discovered that these variables exhibit explanatory power within an 8-quarter lag. These two variables are applied to the recession probability model in this study. Table 3 shows that they have explanatory power in predicting recessions with a lag between 7 and 11 quarters. A positive coefficient of Expected indicates that a situation in which we expect relatively more monetary accommodation than at present will reduce the probability of a future recession. Furthermore, the results indicate that the recession probability increases as the term premium increases and that increased risk in the government bond market predicts a future recession.

Adding the Japanese stock market's market capitalization and trading volume per national income to the expected future short-term interest rate and term pre-

²⁰The study defines the spread as the interest rate at 5-year maturity minus the interest rate at 1-year maturity.

²¹Ahrens (2002) demonstrated that yield spreads can be used to forecast recessions in Japan for data up to December 1996.

mium improves the explanatory power for future recessions. As DMD has explanatory power for future recessions, market capitalization contains more independent information about future economic trends than trading volume. The results of this study are theoretically valid because equity prices are determined from future corporate free cash flow or dividends. As shown in Fig. 3, market capitalization per GDP tends to rise during boom periods, but it falls a few quarters before recessions. This interpretation is supported by the estimation results in Table 4, which show that an increase in DMD decreases the probability of a recession in the short run, but it predicts a recession (increases the recession probability) in the long run. In this study, MLD represents the change in the amount by which MD deviates from ML. In other words, it measures the deviation of market capitalization relative to trading volume. While MLD has explanatory power for recessions at 8- and 9-quarter lags, Erdogan et al. (2015) found that MLD has explanatory power in the short run, which contradicts our findings.

As shown in Table 4, the DMD parameters are negative, particularly for short-term lags, which is consistent with Erdogan et al. (2015). The results of this study are valid because increasing market capitalization is associated with a booming economy, at least in the short-term. In addition, the recession probability falls significantly in the middle of the recessionary period, which is due to a temporary rebound occurring during the downturn in the stock market. This is due to the DMD of the 1-period lag in the model, which affected the predicted values.

Using data from Tables 2, 3, and 4 and Fig. 4, we show that in the in sample-fit predictions, the extended model, which incorporates stock market data, demonstrates greater predictive power than the model based solely on information about government bond interest rates. Similar to the findings for the United States, this suggests that market capitalization and trading volume in the Japanese stock market have independent information about future recessions. Even with only government bond interest rate data, the extended model predicts a high probability of recession

in the period preceding the introduction of the zero interest rate policy. Despite the fact that models that rely solely on government bond rates have become ineffective during the period of low interest rates since the early 2000s, it is evident that models that incorporate stock market information are useful for predicting recessions. Specifically, the model with DMD and MLD predicts a high probability of recession during the recessionary period corresponding to the global financial crisis. The results indicate that stock market information is important in predicting future recessions when government bond interest rates remain at low levels.

Meanwhile, the out-of-sample forecasting results show that the extended and the extended SPREAD models' forecast accuracy is statistically and significantly higher than that of the baseline and the decomposed models. For the United States, Binswanger (2000) examined the relationship between stock returns and economic trends and reported findings that suggested the relationship might vary over time. Fig. 5 suggests that out-of-sample forecasts were sufficient to predict recessions during the global financial crisis but may not be sufficient to forecast other recessions.

5 Conclusions

This paper provides empirical evidence that information about Japanese government bond markets and stock markets predicts Japan's future recession. The evidence suggests that yield curves and Japanese stock markets contain substantial information. To forecast future recession, this study used expected future short-term interest rates and the term premium in Japanese bond markets, and the liquidity and depth in Japanese stock markets, as independent variables. The term premium and expected future short-term interest rates have a greater predictive power for future recessions than the yield spread alone. In addition to the results, incorporating stock market information improves the predictive power for the recession.

The paper provides evidence that, apart from bond market information, stock market information is effective in predicting future recessions, particularly in Japan,

where interest rates are low. Given that stock prices are theoretically explained by a firm's future free cashflow and dividends, it is reasonable to expect that stock market data predict future recessions. The method becomes more useful in predicting recessions in countries like Japan, where low interest rate policies make interest rates less volatile.

However, the following points should be noted. The market capitalization and trading volume of firms listed in the First Section of the Tokyo Stock Exchange are used in this study. Therefore, this study does not analyze the relationship between market capitalization (or market trading volume) and the likelihood of a recession by industrial sector. Furthermore, due to the limited sample period, additional analysis is required in the future.

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