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The Credit Spread Curve Distribution and Economic Fluctuations in Japan*

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Abstract

Predicting the future economy is of great interest for practitioners and policymakers. This study challenges this problem by examining the relation between credit spread curves and future economic activity. To this end, we calculate the credit spreads of corporate bonds at the firm level to construct an empirical distribution of credit spread curves covering every month from April 2004 to March 2019. Then we examine which deciles of this empirical distribution have more predictive power for economic growth rates. Our results indicate that the credit spread curve information in higher-ranked deciles (implying lower credit quality) is the most useful and economically important for the business cycle. We also distinguish between two regimes according to credit spread uncertainty by employing a smooth-transition model to determine whether this uncertainty affects the predictive relationship between credit spread curves and the business cycle in Japan. Our results suggest that the predictive power of credit spread curves heavily depends on uncertainty in the corporate bond market. More specifically, our results demonstrate that the credit spread curves have more predictive power for economic growth rates under the low corporate bond market uncertainty regime.

Keywords: Corporate bond spreads, Credit spread curve distribution, Smooth transition regression, Term structure
JEL classification: E32, E43, E44, G12

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1 Introduction

Predicting the future economy is of great interest for practitioners and policymakers. This study considers whether and how the information contained in the credit spread curves can improve the forecast of the future economy. This is meaningful because firms' levels of credit risk vary over the business cycle due to changes in their balance sheets and the supply of external finance, suggesting that the behavior of the corporate bond yield curve also varies over the business cycle.

Often, a prolonged period of low short-term interest rates leads to the yield curve becoming the center of discussion. Economists try to determine the relationship between the economic cycle and the shapes of yield curves, particularly the Treasury yield curve, because signals from yield curves are seen as informative in forecasting the evolution of the real economy. However, the global financial crisis of 2008-2009 and the European debt crisis have lowered the long-term interest rates very low, making the information contained in the yield curves limited and several studies use the credit spreads to forecast the future economic activity. Despite the importance of the credit spreads for economic activity, relatively little research on the relationship between credit spread curves and economic fluctuations has been conducted in the literature, although the credit spread curves should obviously contain more information about the future economy than the credit spreads.

In an effort to shed light on this challenging problem, this study examines the relation between credit spread curves and economic activity by constructing an empirical distribution of the credit spread curves from April 2004 to March 2019. To understand the behavior of credit spread curves across firms and over time, we need to calculate the term structures of corporate bond spreads at the individual firm level. However, the contract terms of corporate bonds differ even if bonds of different maturities are available for the same firm, as Han and Zhou (2015) point out. Gilchrist and Zakrajšek (2012) show that 67.2% of the senior unsecured corporate bonds traded in the U.S. secondary market from 1973 to 2010 are callable, and the share of callable bonds varies over time. Such bonds are not applicable for studying credit spread term structures, however, because the contract terms may be too complicated to study these term structures at the firm level.

We use a dataset of straight corporate bonds in Japanese secondary bond market to calculate credit spread curves at the firm level. Two key advantages of using data on corporate bonds issued publicly in Japan are that their contracts are simple and the maturities of corporate bond contracts are easily comparable across firms and over time. Whereas limiting the sample to noncallable bonds in the U.S. would severely limit the time span of the data (see Gilchrist and Zakrajšek (2012)), our data allow us to study a period that includes most of the unconventional monetary policy regime and the recent financial crisis even if we exclude subordinated and structured bonds, such as callable bonds, from our sample.

A growing body of literature on the information content of credit spreads for economic activity focuses on corporate bond spread fluctuations. Since at least the work of Fisher (1933), the credit cycle has been thought to affect the business cycle. Among asset prices (see Stock and Watson (2003a) for a survey of the predictive contents of asset prices), corporate bond credit spreads could be better predictors of economic activity than equity prices are, as shown by Philippon (2009). Moreover, recent studies focusing on corporate bond spreads in the U.S. (e.g., Gilchrist et al. (2009), Gilchrist and Zakrajšek (2012), Faust et al. (2013), and Mueller (2009)) and European countries (e.g., Bleaney et al. (2016) and Gilchrist and Mojon (2018)) provide strong evidence for their linkage with economic activity.

The rapid growth of the market for credit default swaps (CDS) in the U.S. provides a direct measure of the default component in credit risk, and recent studies, such as those of Longstaff et al. (2005), Jorion and Zhang (2007, 2009), Ericsson et al. (2009), Zhang et al. (2009), and Wang et al. (2013), provide incisive results on credit spread variations in terms of the systematic component, volatility, and jump risk. In particular, studies that make good use of variation in the term structures of CDS across firms, such as those of Lando and Mortensen (2005), Han and Zhou (2015), and Han et al. (2017), help to build an understanding of the term structures of CDS. For example, Han and Zhou (2015) demonstrate that the shape of the term structure of CDS spreads varies over time and across firms.

We focus on the distribution of corporate bond spread curves because the corporate bond market, which has a longer established history and a larger number of issuers than CDS market has, is preferred for analyses of economic fluctuations. We find three important results. First, by calculating credit spreads for each individual corporate bond to construct an empirical distribution of credit spread curves for every month after 2004, we find that credit spread curves vary over time, specifically with economic fluctuations. Our credit spread data are calculated at the individual firm level, which means that our credit curve data are less contaminated by a small number of issuers with large outstanding corporate bonds than data at the individual bond issue level are. For example, the largest corporate bond issuer in Japan was Tokyo Electric Power Co. (TEPCO) by the time the nuclear disaster at TEPCO's Fukushima Daiichi Nuclear Power Plant occurred on March 11, 2011. The credit spreads for outstanding TEPCO corporate bonds jumped from just eight basis points before the disaster to about 400-500 basis points after the earthquake and tsunami. Outstanding TEPCO corporate bonds therefore decisively influence the arithmetic average when considering data at the individual bond issue level. Our data mitigate this effect, and the distribution of the credit spread curves appears to be linked to economic fluctuations.

Second, we examine which deciles of the empirical distribution of credit spread curves have more predictive power for the business cycle in Japan. Our estimations begin with the benchmark model, which is a predictive regression (PR) model of the economic growth rate on government bond yield curve information. Then, the estimations are executed using government bond yield curve information and 81 combinations of credit spread levels and slopes, as we consider every possible pairing of the first to ninth deciles of the levels and slopes. The credit spread curve distribution has more predictive power for economic fluctuations when the estimation model includes credit spread curve information for higher-ranked deciles (implying lower credit quality). This finding is consistent with investors paying attention to the movement of high-yield bond spreads, as is suggested academically by the theory of the financial accelerator (Bernanke and Gertler (1989) and Bernanke et al. (1996)).

Third, we extend the PR model by applying a smooth transition model. This approach allows us to relax the implicit assumption that credit curve information has a constant ability to predict the business cycle. We distinguish between two regimes depending on the uncertainty of credit spreads by employing a smooth-transition predictive regression (STPR) model to determine whether corporate bond market uncertainty affects the predictive relationship between credit spread curves and economic fluctuations. The results of estimating the STPR model suggest that when the variance in corporate bond spreads is small, the predictive relationship between credit spread levels and slopes and the business cycle appears to be stronger and more stable. When uncertainty in the corporate bond market increases, this relationship weakens and holds over only a short horizon. Thus, our results show that the predictive power of credit spread curves heavily depends on uncertainty in the corporate bond market.

In summary, the predictive relation between credit spread curves and economic activity differs across the credit spread curve distribution. Our results support the view that the credit spreads of firms with low credit quality signal the business cycle. However, when uncertainty in the corporate bond market is high, including during the 2008 global financial crisis, the European debt crisis, and the Great East Japan earthquake of 2011, this predictive relationship is not stable. From a policy standpoint, the information content of the credit spread curve distribution is useful for predicting future economic activity, but heavy reliance on this financial indicator may not be advisable depending on market conditions.

The remainder of this paper is organized as follows. Section 2 discusses some theoretical predictions regarding the relationship between the term structures of credit spread curves and economic activity and describes our data set. Section 3 explains the empirical methodology, including the econometric models. Section 4 describes the empirical results obtained from the analysis using the distribution of the credit spread curve information based on the PR and STPR models. Section 5 provides our conclusions.

2 Theoretical Prediction and Data

2.1 Theoretical prediction

The corporate bond spread, which is the difference in the yields of defaultable debt instruments and risk-free government securities of comparable maturity, depends inversely on the borrower's financial strength. Stock and Watson (2003a) show that asset prices are useful predictors of output growth because they are forward-looking. Comparing several asset prices, Philippon (2009) finds that corporate bond spreads could be more precise predictors of economic activity than equity prices are by showing that a market-based measure of Tobin's q based on corporate bond prices outperforms the traditional measure that uses equity prices. One possible explanation for this result is that the bond market is less susceptible to bubbles than the equity market is. Moreover, a number of studies explore the information contained in corporate bond spreads that can forecast the business cycle because the credit cycle has been thought to affect the business cycle since at least the work of Fisher (1933).

The emergence of the U.S. high-yield bond market in the mid-1980s has allowed researchers to investigate the credit spreads of corporate bonds, which are highly sensitive to financial conditions and default risk. Gertler and Lown (1999) demonstrate a strong inverse relationship between the high-yield spread and the output gap for the period from 1985 to 1999. Similarly, Mody and Taylor (2004) test the ability of the high yield spread to predict real economic activity and show that this spread significantly predicts economic activity during the 1990s. However, Stock and Watson (2003b) suggest that high-yield bond indexes do not necessarily have superior forecasting ability compared to other economic and financial indicators. In contrast, recent studies using U.S. corporate bond spreads, such as those of Gilchrist et al. (2009), Gilchrist and Zakrajšek (2012), Faust et al. (2013), and Mueller (2009), provide empirically strong evidence that an increase in credit spreads signals a decline in economic activity. Gilchrist et al. (2009), Gilchrist and Zakrajšek (2012), and Faust et al. (2013) construct an original and novel portfolio-based credit-spread index that significantly outperforms the predictive ability of the standard default-risk indicators by taking a bottom-up approach and adjusting individual corporate bond information. Bleaney et al. (2016) and Gilchrist and Mojon (2018) employ the same approach and find predictive power using data from European countries. Thus, based on numerous insightful studies of corporate bond spreads, we predict a negative relationship between credit spreads and future economic activity.

The term structures of credit spreads reflect the shape of the conditional risk-neutral default probability over different time horizons. Investors draw inferences from publicly available information, such as business cycle data, as well as accounting data. The business cycle affects firms' credit quality. The shape of corporate bond yield spreads has been widely investigated from various perspectives by Duffie and Lando (2001), Han and Zhou (2015), Fons (1994), Helwege and Turner (1999), Sarig and Warga (1989), Johnson (1967), Jaffee (1975), and Jones et al. (1984), among others. Theoretical and empirical evidence show that the shapes of credit spreads' term structures depend on credit quality. For example, Fons (1994) notes that lower-rated issuers tend to have wider credit spreads that narrow with maturity, whereas higher-rated firms tend to have narrower credit spreads that widen with maturity.[1] Using CDS data, Lando and Mortensen (2005) find a downward-sloping term structure of credit spreads for high-risk issuers because their default probability conditional on survival is likely to decrease.

Regarding the business cycle, previous studies imply that, given that no default occurs, firms have a higher probability of improving their credit for longer maturities when the economy is recovering or is in a better period. Investors also expect a string of positive earnings reports to appear in the near future in such periods. Hence, the credit spreads are expected to be lower for longer maturities. Conversely, in bad times, firms face higher default probabilities over shorter maturities, particularly for firms with low credit quality. In addition, when the economy is entering

[1] The data used for this estimation are the yields of 2,848 bonds collected as of September 30, 1993.

a downturn, a string of negative earnings reports is expected, preventing investors from taking risks, and the premia on long bonds are therefore higher.

Thus, the credit spread curve provides information about future economic activity. When the economy is recovering, the spreads for longer maturities decrease as the probability of a good earnings report for the firm increases. Conversely, the spreads for shorter maturities remain high until the expansion continues. The smaller this slope is, the greater the expected economic growth is. In contrast, spreads for longer maturities are higher when the economy contracts, leading to a steeper slope. The greater this slope is, the lower the expected economic growth is.

2.2 Data

This subsection describes the definitions and sources of the data used for the estimations. In this study, we focus on credit spread curves and macroeconomic fluctuations. We use data on individual corporate bond issues obtained from the Japan Standard Bond Price (JS Price) database, which includes such information as the interest rates, coupon rates, redemption dates, and issue dates of public and private offerings of domestic bonds, foreign bonds, and Eurobonds. This data source provides the most extensive coverage of secondary market prices of corporate bonds publicly issued in the Japanese market. We use data on straight corporate bonds that are publicly issued in Japan by Japanese corporations, and we exclude subordinated corporate bonds. We also exclude Fiscal Investment and Loan Program (FILP) agency bonds that are guaranteed by the central government. To guarantee that we measure the borrowing costs of firms at the same point in their capital structures, we limit the sample to only senior issues with fixed coupon schedules, following prior studies. Our final dataset contains 8,308 bonds during the period from April 2004 to March 2019. The original yield data have a daily frequency, and we use them to construct a dataset of month-end compound yields for individual corporate bond issues.

We use these data and data on the government bond zero curve to calculate the credit spread. The government bond yield data are obtained from Thomson Reuters Eikon, which collects market data on Japanese government bonds from Tradeweb and calculates the zero curve. Thomson Reuters Eikon offers monthly government bond zero curve data with different maturities, ranging from one month to forty years. If the government bond zero curve is missing for a particular corporate bond maturity, it is filled in using cubic spline interpolation. The government bond yields are used to calculate the credit spreads and to estimate the PR and STPR models.

With individual corporate bond data and government bond data, credit spreads are calculated as differences between corporate bond yields and government bond yields of the same maturity. Thus, we calculate credit spreads using corporate bond yields and government bond yields with exactly the same maturity. Then, for the estimation, we obtain the month-end credit spreads of outstanding corporate bonds traded in the secondary market between April 2004 and March 2019. Our estimation sample of credit spreads is limited to corporate bonds with fixed coupon schedules and bullet bonds with no embedded options. These criteria guarantee that the corporate bond contract terms are comparable so that bonds of different maturities from the same firm can be used to study credit spread curves.

Specifically, the credit spread for corporate bond k with maturity m issued by firm i at time t is given by

$$S_{imt}[k] = y_{imt}[k] - y^f_{mt}[k],$$

where m is $12, 15, \ldots$, 84 months,[2] and $y_{imt}[k]$ is the yield of corporate bond k with maturity m at time t and $y^f_{mt}[k]$ is the corresponding government bond yield of the same maturity at time t. Given this credit spread, we calculate the credit spreads for bonds of different maturities from the same firm as

$$cs_{imt} = \frac{1}{N_{mt}} \sum_k S_{imt}[k],$$

where N_{mt} is the number of observations in month t of corporate bonds with maturity m issued by firm i. That is, an individual firm i's credit spread in a given month is the arithmetic average of the firm's credit spreads of each maturity m.

Following previous studies, such as that of Gilchrist and Zakrajšek (2012), we eliminate extreme observations such that bond and month observations with credit spreads greater than 2,000 basis points are excluded. As a lower bound, we eliminate observations with credit spreads below zero basis points to avoid including negative credit spreads, which are economically nonsensical. These selection criteria leave us with credit spread curve data for 729 firms.

[Table 1 around here]

Table 1 reports descriptive statistics for each decile of the credit spread distribution and the slope of the credit spread term structure, defined as the difference between the seven-year and one-

[2]To mitigate the data scarcity problem of particular maturity months, we calculate the credit spread for every 3 maturity month by pooling the data every 3 maturity month.

year credit spreads. As the table shows, the standard deviations vary widely across the deciles and increase as the decile ranking rises. A high decile ranking implies low credit quality, meaning that the median values of the one- and seven-year credit spreads are higher for high decile rankings than for low decile rankings. The median credit slope is slightly negative in deciles 2 and 3, suggesting a downward-sloping credit spread term structure, but the average slope is positive for all other deciles and increases as the decile ranking rises.

With these credit spread curve data, we explore the credit spread curve's ability to predict future economic performance. Previous studies exploring the ability to predict economic activity typically use the GDP growth rate to measure output growth; however, GDP is not available at a monthly frequency. Thus, we measure economic performance using the growth rate of the coincident index (CI), which is an index of business conditions published monthly by the Cabinet Office of the government of Japan. The values of this index are obtained directly from its website. The index is constructed from the following coincident indicators: the production index, the shipments index for mining and manufacturing, the shipments index for durable consumer goods, the index for non-scheduled hours worked, the shipments index for investment goods (excluding transportation equipment), retail sales, wholesale sales, operating profits (all industries), the shipments index for small and medium-sized enterprises (manufacturing), and the ratio of active job openings.

In the top panel of Figure 1, we plot the time series of the one- and seven-year credit spreads at the 20th percentile, median, and 80th percentile and the CI. The one- and seven-year credit spreads at the 80th percentile vary widely. The movement of credit spreads caused by the 2008-2010 global financial crisis is notable. At the beginning of the crisis, the Japanese economy was hit by a sudden drop in stock prices due to the sizable outflow of capital from the stock markets and the rapid appreciation of the yen. Although Japanese banks did not suffer a direct financial impact of the financial crisis and no major Japanese bank collapsed, the sagging global demand and the decline in stock prices caused Japanese banks to curb loans as the financial crisis progressed. Because of the credit crunch caused by the global financial crisis, the Japanese corporate bond market experienced defaults for the first time in seven years in 2008, and a series of defaults followed over the next few years. We observe the peak of the one- and seven-year credit spreads at the 80th percentile when these defaults had completely deteriorated market confidence.

[Figure 1 around here]

The bottom panel of Figure 1 displays the time series of the one- and seven-year credit spread slope at the 20th percentile, median, and 80th percentile along with the CI. The variation in the credit spread slope at the 20th percentile is small. In contrast, the credit spread slope at the 80th percentile exhibits wide variation. On average, the credit spread slope is higher for the 80th percentile than for the 20th percentile. During our sample period, the Japanese economy experienced two recessions and several significant events, including the global financial crisis, the European debt crisis, and the Great East Japan Earthquake of 2011. Consequently, corporate bond market uncertainty fluctuated considerably over the sample period. We examine the link between credit spread curves and macroeconomic fluctuations carefully by taking corporate bond market uncertainty into account using the STPR model.

3 Methodology

The main objectives of this study are to examine whether the information contained in credit spread curve distributions can improve forecasts of economic growth rates in Japan and to identify the deciles of the empirical distribution of credit spread curves that have more predictive power for business cycles in Japan. To this end, we employ a predictive regression (PR) model, following Ang et al. (2006), Gilchrist and Zakrajšek (2012), and Okimoto and Takaoka (2017). In addition, we extend the model by incorporating a smooth-transition model to check whether credit spread uncertainty affects the predictive relationship between credit spread curves and the business cycle in Japan. In this section, we briefly discuss our PR model and then discuss the STPR model.

3.1 PR models

Our benchmark model is based on the PR model. We regress the CI growth rate on government bond yield curve information, namely, the short-term yield (level) and the slope of the yield curve. Specifically, the regression is given as follows:

$$\Delta^h ci_{t+h} = \alpha + \beta_1 gst_t + \beta_2 gslo_t + \phi \Delta ci_t + \varepsilon_t, \tag{1}$$

where ci is the CI; $\Delta^h ci_{t+h} = \frac{100}{h} \ln(ci_{t+h}/ci_t)$, $h = 1, 3, 6$, or 12 is the forecast horizon; gst is the government short-term rate, defined as the one-year government bond yield; and $gslo$ is the slope of the government yield curve, or term spread, defined as the difference between the seven-year and one-year government bond yields.[3]

To investigate whether credit curve distribution information can improve forecasts of economic growth rates in Japan, we extend the benchmark model (1) by adding the short-term level and slope of the credit spread curve, as follows:

$$\Delta^h ci_{t+h} = \alpha + \beta_1 gsr_t + \beta_2 gslo_t + \delta_1 scs_t^i + \delta_2 cslo_t^j + \phi \Delta ci_t + \varepsilon_{t+h}, \tag{2}$$

where scs^i is the ith-decile of the credit spread distribution of one-year corporate bonds and $cslo^j$ is the slope of the credit spread, defined as the difference between the jth deciles of seven-year and one-year credit spread distributions. To examine which deciles of the credit spread curve distribution have more predictive power for the business cycle in Japan, we compare every possible pair of the first through ninth level and slope deciles.

We estimate the models (1) and (2) using ordinary least squares (OLS). For forecasting horizons $h > 1$, the overlapping observations imply that the error term, ε_{t+h}, has an MA($h-1$) structure, which affects the calculation of the standard errors of OLS estimates. We compute the p-values of the coefficients based on Hodrick (1992) standard errors to correct for this moving average error term.

3.2 STPR model

Okimoto and Takaoka (2017) extend the PR model (2) by incorporating Markov switching and identify two distinct regimes to show that the relationship between credit spread curves and the business cycle was quite different around the global financial crisis. Although their results seem to be reasonable, their model cannot identify the possible determinants of this regime change. Consequently, it is unclear whether the relationship between the credit spread and real economy was different only for the crisis period or if it differs for turbulent periods in general. To shed light more on this question, we adopt a smooth-transition model to identify two regimes according to credit spread market uncertainty to determine whether this uncertainty affects the predictive relationship between credit spread curves and the business cycle in Japan.

[3] We use seven-year yields to calculate the slope of the government bond yield curve to ensure consistency with the slopes of the corporate bond spreads.

The STPR model is given by

$$\begin{aligned}\Delta^h ci_{t+h} \;=\; & (1-F(s_{t-1};c,\gamma))(\alpha^{(1)}+\beta_1^{(1)}gsr_t+\beta_2^{(1)}gslo_t+\delta_1^{(1)}scs_t^i+\delta_2^{(1)}cslo_t^j+\phi^{(1)}\Delta ci_t)\\ & +F(s_{t-1};c,\gamma)(\alpha^{(2)}+\beta_1^{(2)}gsr_t+\beta_2^{(2)}gslo_t+\delta_1^{(2)}scs_t^i+\delta_2^{(2)}cslo_t^j+\phi^{(2)}\Delta ci_t)+\varepsilon_t,\end{aligned} \tag{3}$$

where $F(\cdot;c,\gamma)$ is a transition function taking values between zero and one with a transition variable s_{t-1} and c and γ are parameters determining the threshold between the two regimes and the smoothness of the regime transition, respectively. When $F(s_{t-1})=0$, the STPR model reduces to the PR model with parameters indexed by one (e.g., $\alpha^{(1)}$). We refer to this regime as regime 1. Similarly, the other regime is characterized by $F(s_{t-1})=1$, and we call it regime 2.

The transition function and the transition variable are determined according to the purpose of the analysis. For example, to analyze the role of oil price uncertainty in the effects of oil prices on the real economy, Nguyen et al. (2019) use a logistic transition function with oil price uncertainty as the transition variable. In a similar fashion, we use the following logistic transition function:

$$F(s_{t-1};c,\gamma)=\frac{1}{1+\exp\big(-\gamma(s_{t-1}-c)\big)},\;\;\gamma>0. \tag{4}$$

We use corporate bond market uncertainty, measured by the cross-sectional volatility of credit spreads over the previous six months, as the transition variable s_{t-1}. As is convention, we date the variable s at time $t-1$ to avoid contemporaneous feedback. With this transition function and transition variable, we can interpret regime 1 as the regime with low corporate bond market uncertainty and regime 2 as the regime with high corporate bond market uncertainty. This assignment is because if corporate bond market uncertainty is low, s_{t-1} takes smaller values, and $F(s_{t-1})$ is close to zero. Conversely, if corporate bond market uncertainty is relatively high, s_{t-1} becomes large, and $F(s_{t-1})$ is close to one.

One advantage of using the logistic transition function (4) is that it can express various forms of the transition between regimes 1 and 2 depending on the values of c and γ. The location parameter c determines the threshold between regimes 1 and 2, that is, the low- and high-uncertainty regimes, respectively. More specifically, if s_{t-1} is less (greater) than c, the weight on the low- (high-) uncertainty regime is greater than 1/2, implying that the model moves closer to the low- (high-) uncertainty regime at time t. The smoothness parameter γ determines the speed of the transition from regime 1 to regime 2 as the uncertainty in the corporate bond market over the past six months increases. More specifically, the transition is relatively smooth when γ takes a small value, but it is faster for larger values of γ. Once γ exceeds a certain value, the transition function behaves like a step function with a very rapid transition. For this reason, we set an upper bound of 300 for γ.

In principle, we can estimate the parameters of the STPR model (3) simultaneously by using, for example, non-linear least squares estimation. However, it is challenging to minimize the sum of squared residuals with respect to all parameters because of the nonlinear structure of the STPR model. Thus, following the suggestion of Granger and Teräsvirta (1993), we estimate c and γ using a grid search.[4] Given fixed values of c and γ, the STPR model becomes a standard linear regression model, and we can estimate the remaining parameters using OLS. For forecasting horizons $h > 1$, we also compute the p-value of each coefficient based on Hodrick (1992) standard errors to correct for the moving average error terms.

3.3 Test of the linear PR model against the STPR model

As discussed in the previous subsection, we estimate the STPR model to distinguish between two regimes depending on the uncertainty of the credit spread to investigate a possible non-linear predictive relationship between credit spread curves and the real economy in Japan. As shown by Okimoto and Takaoka (2017), it is not unreasonable to assume that this relationship may differ under different market conditions. However, it is still instructive to check for evidence of a smooth-transition model before performing the estimation. To this end, we conduct a test of the linear PR model (2) against the STPR model (3), which we discuss in this subsection.

The null hypothesis of the linear PR model (2) and the alternative hypothesis of the STPR model (3) can be expressed as $H_0 : \gamma = 0$ and $H_1 : \gamma > 0$, respectively, in the STPR model. However, this test is not standard because the parameters for each regime cannot be identified under H_0.[5] To address this identification problem, Luukkonen et al. (1988) suggest approximating the logistic function with a first- or third-order Taylor approximation around $\gamma = 0$. For example, a first-order Taylor approximation leads to an auxiliary regression of the form

$$\begin{aligned} \Delta^h ci_{t+h} &= b_0 + b_1 gsr_t + b_2 gslo_t + b_3 scs_t^i + b_4 cslo_t^j + b_5 \Delta ci_t + b_6 s_{t-1} + b_7 gsr_t s_{t-1} \\ &\quad + b_8 gslo_t s_{t-1} + b_9 scs_t^i s_{t-1} + b_{10} cslo_t^j s_{t-1} + b_{11} \Delta ci_t s_{t-1} + e_t. \end{aligned} \tag{5}$$

[4] One cost of estimating c and γ with a grid search is that the standard errors of c and γ cannot be evaluated. Thus, the standard errors in the following regression do not take into account the effects of estimating c and γ.

[5] We can also express the null hypothesis as all parameters being equivalent across the two regimes. In this case, γ and c cannot be identified, and the identification problem still remains.

Luukkonen et al. (1988) show that testing $H_0 : \gamma = 0$ in the STPR model (3) is equivalent to testing $H_0' : b_6 = b_7 = \cdots = b_{11} = 0$ using the auxiliary regression (5). Because this auxiliary regression does not have an identification problem, we can relatively easily test H_0'. Specifically, Luukkonen et al. (1988) show that the Lagrange-multiplier (LM) test statistic to test H_0' asymptotically follows a Chi-squared distribution with six degrees of freedom. Based on this result, we can test the PR model (2) against the STPR model (3).

4 Empirical Results

In this section, we summarize our empirical results. First, we discuss the results of estimating the PR models to determine whether credit curve distribution information can improve forecasts of economic growth rates in Japan and to identify the deciles of the empirical distribution of credit spread curves that have more predictive power for the business cycle in Japan. Then, we document the additional results using the STPR model to show that corporate bond market uncertainty affects the predictive relationship between credit spread curves and the business cycle in Japan.

4.1 Results of the PR model

Our benchmark model (1) involves a predictive regression of the CI growth rate on the level and slope of the government bond yield curve. The level is defined as the one-year yield, and the slope is calculated as the difference between the seven-year and one-year yields. The estimated coefficients and their p-values based on Hodrick (1992) standard errors to correct for the moving average error terms are reported in Table 2. The results suggest that the coefficients on the levels are significantly negative at the 10% level or better for all horizons. Specifically, the results suggest that if the short-term rate increases by one basis point, the CI growth rate would decrease by 0.014% over the next month, which equates to 0.17% on an annual basis. This negative relationship strengthens with the forecasting horizon. For a twelve-month horizon, a one-basis-point increase in the short-term rate induces a 0.26% decrease in the CI on an annual basis. Thus, the level of the government bond yield curve seems to have a rather large impact, but this result is reasonable given the extremely low short-term rates and the relatively low growth rates over the last 15 years in Japan. The effect of the slope of the government bond yield curve is also highly significant at the 10% level or better for all horizons. In addition, the adjusted R^2 ranges from 0.20 for the one-month horizon to 0.33 for the one-year horizon, showing the sizable predictive power of the government yield curve. These results are fairly consistent with the many previous studies that find a strong relationship between the government bond yield curve and the business cycle.

[Table 2 around here]

To examine whether credit spread curve information can provide more predictive power beyond that of the government bond yield curve, we extend the benchmark model (1) to the PR model (2) by adding the level and slope of the credit spread curve. We consider the 1st through the 9th deciles for the level and slope and compare every possible decile combination to investigate which deciles have more predictive power.

The estimation results of the PR model (2) indicate that even the least powerful combination of deciles can increase the adjusted R^2, except over the one-month horizon. On average, the adjusted R^2 value increases to 0.23, 0.34, 0.39, and 0.49 for the one-, three-, six-, and twelve-month horizons, respectively. Thus, our results demonstrate that we can gain considerable additional predictive power by incorporating credit curve information. Table 3 allows us to identify the deciles with the most predictive power, as it shows the optimal deciles of the level and slope factors with the highest adjusted R^2 values. The results for the PR model suggest that for shorter horizons, higher deciles provide more information on the business cycle, whereas for longer horizons, the evidence is rather mixed.

[Table 3 around here]

We provide more details of the role of credit curve information in Table 4, which reports the estimation results of the PR model (2) with the optimal combination of level and slope deciles of the credit curve. As the table shows, although the coefficient of the level of government bond yield curve is significantly negative, the coefficient of its slope is insignificant for shorter horizons. In contrast, the coefficients of the credit curve slope are significantly negative and have economically significant magnitudes for all horizons. For example, a one basis point increase in the credit curve slope decreases the CI by 0.43% on an annual basis over a one-month horizon. Our results for the level of the credit curve provide some mixed evidence; for shorter horizons, the coefficients on the credit spread level are significantly negative, whereas, for longer horizons, the credit spread level is positively related to the CI. One possible reason for this result could be the lack of information regarding the regime-switching structure, which we examine in the next subsection.

[Table 4 around here]

4.2 Results of the STPR model

The previous subsection clearly indicates the usefulness of credit curve information to predict economic conditions in Japan. However, the signs of the coefficients on the credit spread level are mixed, making it rather difficult to interpret the results. One possible reason for this outcome could be some change in the predictive relationship between credit spread curves and the business cycle in Japan. Indeed, using a Markov-switching model, Okimoto and Takaoka (2017) identify two distinct regimes and show that this relationship was quite different around the global financial crisis. However, their results fail to provide possible determinants of this regime change, making it unclear whether the relationship between the credit spread and the real economy differed only for the crisis period or if it differs for turbulent periods in general. To shed light more on this question, this subsection reports the estimation results of a STPR model (3) using the transition function (4) and using corporate bond market uncertainty, measured by the cross-sectional volatility over the previous six months, as a transition variable.

Although it is quite interesting to estimate the STPR model (3) to investigate whether credit spread uncertainty affects the predictive relationship between credit spread curves and the business cycle in Japan, it is instructive to check for evidence of a smooth transition before estimating the model. To this end, we test the linear PR model (2) against the STPR (3) model using the LM test proposed by Luukkonen et al. (1988). We summarize the results in Table 5. As the table shows, this test strongly rejects the linear PR model (2), with P-values of almost zero for all horizons except the one-month horizon. This result indicates that for one-month-ahead forecasts, corporate bond market uncertainty does not affect the predictive relationship between the credit spread curve and the business cycle in Japan, but this uncertainty does matter for other horizons. Thus, it seems reasonable to estimate the STPR model (3) using the transition function (4) and using corporate bond market uncertainty as a transition variable.

Having determined that the STPR model provides a better description of the long-run predictive relationship between credit spread curves and the business cycle, we now discuss the estimation results of the STPR model (3). First, Table 3 shows the optimal deciles of the level and slope factor with the highest adjusted R^2 values to determine which deciles provide the most predictive power. As the table shows, the STPR model suggests that higher deciles provide more information on business cycle for all horizons. Next, Table 6 reports the estimates of the parameters c and γ for the transition function (4) using the optimal decile combination. We observe that both parameters are very closely estimated regardless of the forecasting horizon. Specifically, c is estimated to be between -0.21 and -0.26, meaning that if corporate bond market uncertainty over the last six months is 0.21 to 0.26 standard deviations below average, the regime moves closer to the regime with low corporate bond market uncertainty. In addition, the large estimate of γ indicates that transitions between the low-uncertainty and high-uncertainty regimes are very rapid. This result is also confirmed by Figure 2, which plots the estimated dynamics of the transition function (4) and the weight on the regime with high corporate bond market uncertainty alongside the recession periods defined by the Cabinet Office of the government of Japan. The estimated regime dynamics indicate that the corporate bond market tends to be in a high uncertainty regime around periods of recessions.

Table 7 summarizes the estimation results of the STPR model (3) and shows that the relationships between the two curves and the business cycle differ somewhat over short and long horizons. For short horizons, regardless of the regime, the Japanese economy is negatively affected by the level of government bond yields and the level and slope of the credit spread curve. In addition, these negative relationships between the business cycle and the level and slope of the credit spread curve seem to be weaker when corporate bond market uncertainty is higher, making the level of the government bond yield curve a dominant predictor in regime 2. This tendency becomes more noticeable over longer horizons. More specifically, we observe a solid negative predictive relationship between credit spread curve information and the business cycle only when corporate bond market uncertainty is relatively low. In regime 2, our results suggest a positive relationship between the level of the credit spread curve and the business cycle, but this finding is most likely an artifact of the global financial crisis, as documented by Okimoto and Takaoka (2017). Regarding the government bond yield curve, our results show a clear negative predictive relationship between the level of this curve and the business cycle regardless of the regime but little relationship between its slope and Japan's economy. These results are fairly consistent with those of Ang et al. (2006), who show that the level of the government bond yield curve has more predictive power than the slope does for the U.S. economy.

In sum, our analysis of the STPR model arguably demonstrates the further usefulness of credit curve information to predict the business cycle in Japan, providing several new insights beyond those of previous studies. First, our results indicate that higher deciles of the credit spread curve distribution for low grade corporate bonds seem to contain more information about the business cycle in Japan. One possible reason for this result is the Bank of Japan's (BOJ) aggressive monetary policy. Over the last 15 years or so, the BOJ has set aggressive monetary policies, particularly after introducing a 2% inflation target and conducting quantitative and qualitative monetary easing in 2013. These aggressive monetary policies have noticeably lowered long-term government and high-grade corporate bond yields, making the slopes of the government bond yield and high-grade credit spread curves less useful for predicting the future economy. Nonetheless, our results suggest that we can still use the slopes of low-grade corporate bonds to extract some information regarding the future economy even in these circumstances. Second, we confirm that when corporate bond market uncertainty is low, both the level and the slope of the credit spread curve strongly and negatively affect the economy over the next year. When uncertainty is large, this relationship weakens and holds only for short horizons. Thus, our results show that the predictive power of the credit spread curve heavily depends on corporate bond market uncertainty. When this uncertainty is low, the relationship between the level and slope of the credit spread curve and the business cycle is more stable and more strongly negative in Japan even over long horizons. However, market uncertainty can weaken or eliminate this relationship. This finding is reasonable because corporate bond market uncertainty adds some noise to credit curve information, reducing its predictive power, particularly for long horizons.

5 Conclusions

The use of credit spread curves is motivated by their information content, which may be a good measure of the business cycle. Prolonged expansionary monetary policies, as have been in place in many markets, reduce or eliminate the predictive power of the slope of the government bond yield curve beyond that of the level of the curve because the movement of long-term interest rates is limited under the monetary authorities' control. We confirm the usefulness of the information content of credit spread curves after conditioning on government bond yield curve information. Specifically, our results indicate that credit spread curve information in higher deciles (implying low credit quality) is statistically significant and economically important for predicting the business cycle.

Interestingly, although our dataset consists of corporate bonds that are offered publicly and traded in the Japanese secondary market, which has no so-called high-yield market, the results are consistent with those using information on the high-yield bond spread to predict the business cycle in the U.S. Corporate bonds with below-investment-grade ratings are highly sensitive to default risk and can serve as good proxies for the external finance premium, in line with the theory of the financial accelerator. Market participants also use such bonds as a canary in the coal mine. However, credit ratings are sometimes controversial; in particular, credit rating agencies faced severe criticism over the recent financial crisis. Thus, we instead use the distribution of credit spreads. Our results complement and extend previous studies by suggesting that the credit spread slope for bonds of low credit quality also contains economically important information, as does the high-yield bond spread level.

Our sample period includes recessions, the global financial crisis of 2008-2009, the European debt crisis, and the Great East Japan earthquake of 2011. The recent financial crisis stunned the global financial market and placed the credit market in turmoil. Japan was no exception. Thus, we also examine whether credit spread curve information may be a good measure regardless of financial market conditions. Another key finding of this study is that we distinguish two regimes during our sample period depending on the uncertainty in the corporate bond market by employing a STPR model. Although the information content of the credit spread curve is important for predicting the business cycle, when corporate bond market uncertainty is high, its predictive power is not as stable as in a normal period.

Researchers have considerable interest in exploring the information content of economic and financial indicators from a forecasting perspective. However, heavy reliance on any single indicator can lead to skepticism, particularly when a crisis or shock sends the financial market into turmoil. In this respect, credit ratings, which are a major measure of credit quality, were found by Hilscher and Wilson (2017) to be relatively inaccurate measures of raw default probabilities. As a result of the credit rating controversy, the Justice Department sued Standard & Poor's Ratings Services over its ratings of mortgage bonds in the wake of the recent financial crisis (filed on February 5, 2013). These facts and our results suggest not only that heavy reliance on any single measure for forecasting is dubious but also that we should evaluate financial indicators according to financial market conditions. Nevertheless, the credit spread curve, which is publicly observable to markets, can be used as a potentially good measure of the business cycle given its overall informativeness.

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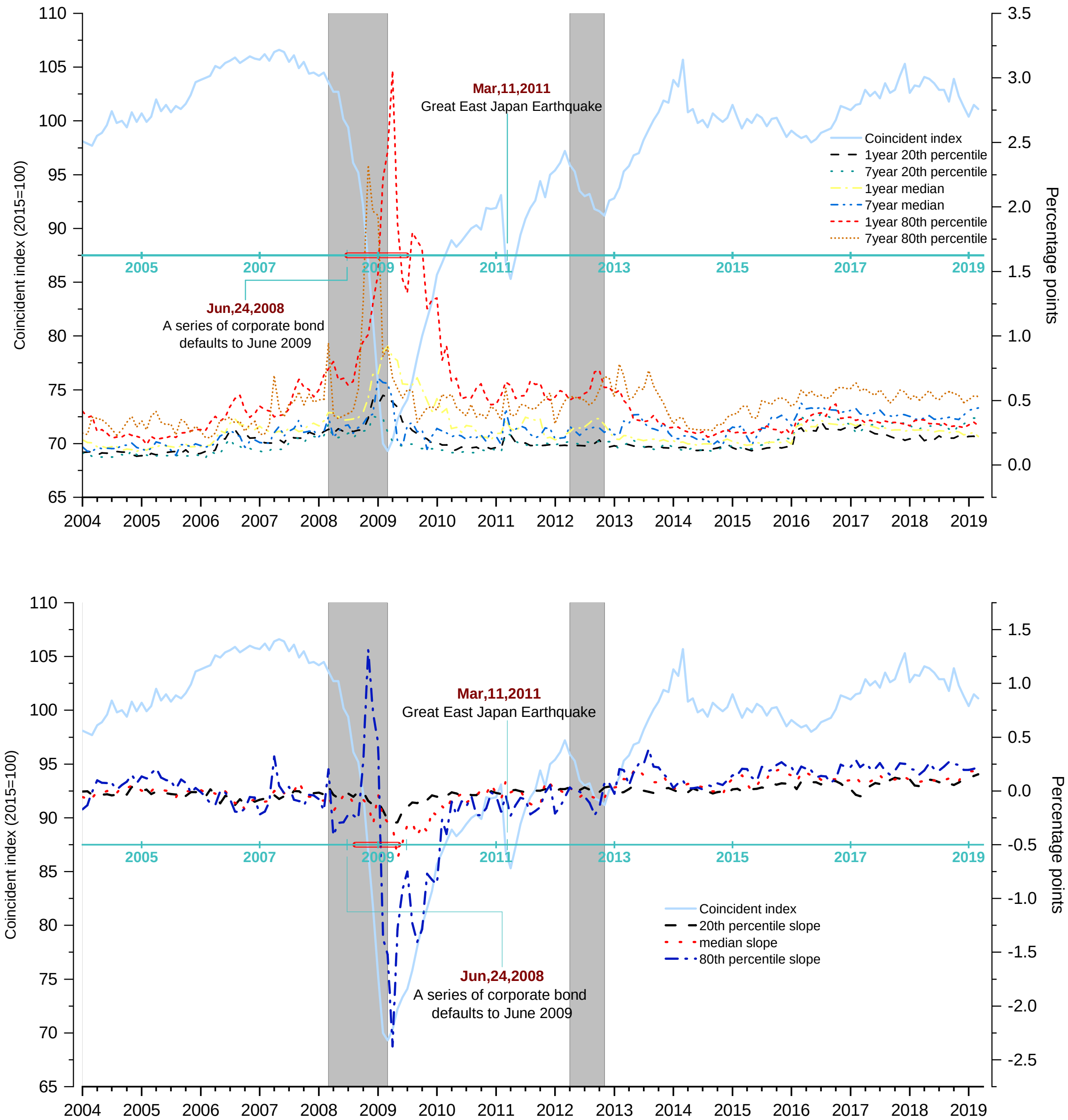
Figure 1: Credit spread curve and the coincident index (CI)



Notes: Sample period: 2004:4-2019:3. Figure 1 plots the monthly CI together with the one- and seven-year credit spreads (slopes) at the 20th percentile, median, and 80th percentile in the top (bottom) panel. Extreme observations with credit spreads greater than 2,000 basis points or less than zero basis points are eliminated. The shaded vertical bars represent recession periods, as defined by the Cabinet Office of the government of Japan.

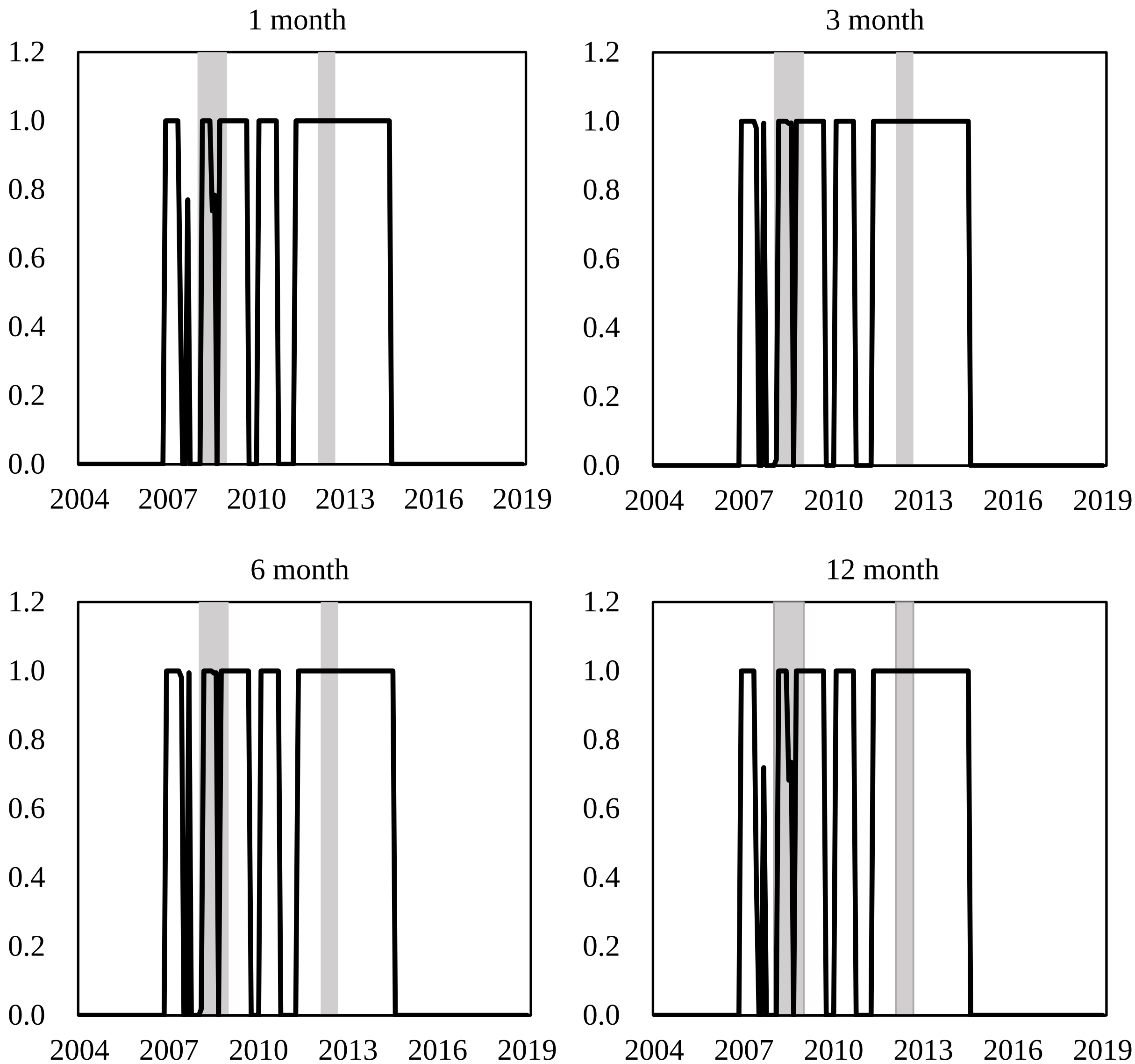


Figure 2: Transition function

Notes: Sample period: 2004:4-2019:3. The figures plot the probability of being in Regime 1 over each horizon (i.e., one, three, six, and twelve months). Regime 1 refers to the period in which the variance in credit spreads is smaller, and regime 2 refers to the period in which the variance in credit spreads is larger. The shaded vertical bars represent recession periods, as defined by the Cabinet Office of the government of Japan.

Table 1: Descriptive statistics: Distribution by credit spread curve decile

	one-year credit spread		seven-year credit spread		credit spread slope	
decile	Std. Dev.	median	Std. Dev.	median	Std. Dev.	median
1(low)	0.0722	0.1439	0.0840	0.1390	0.0525	0.0023
2	0.0868	0.1658	0.0906	0.1578	0.0714	-0.0063
3	0.0936	0.2049	0.0964	0.1827	0.0859	-0.0033
4	0.1185	0.2363	0.1024	0.2251	0.1036	0.0060
5	0.1455	0.2620	0.1063	0.2660	0.1338	0.0073
6	0.1812	0.2973	0.1149	0.3183	0.1606	0.0188
7	0.2743	0.3274	0.1638	0.3827	0.2535	0.0417
8	0.4509	0.3702	0.2527	0.4792	0.4256	0.0557
9	0.9783	0.4946	0.4650	0.6050	0.7857	0.0382
10(high)	4.8003	2.7577	2.5296	1.2143	4.8653	-1.2026

Notes: This table reports the standard deviations and medians of the one- and seven-year credit spreads and credit spread slopes during the sample period of 2004:04-2019:03 by credit spread decile (in percentage points).

Table 2: Results of predictive regressions using the government bond yield curve

Horizon		α	β_1	β_2	ϕ	Adj. R^2
1	Est.	-0.298	-1.405	0.591	0.373	0.202
	P-val.	0.000	0.000	0.000	0.041	
3	Est.	-0.353	-1.742	0.709	0.285	0.273
	P-val.	0.051	0.026	0.008	0.023	
6	Est.	-0.397	-2.113	0.824	0.152	0.290
	P-val.	0.142	0.079	0.060	0.001	
12	Est.	-0.339	-2.144	0.769	-0.019	0.327
	P-val.	0.172	0.014	0.071	0.465	

$Notes$: This table reports the estimated coefficients, p-values, and adjusted R^2 values for the equation (2). "Horizon" refers to the forecast horizon h, and the p-value of each coefficient is calculated using Hodrick (1992) standard errors.

Table 3: Optimal decile ranks of the level and slope factors

	Linear		Smooth transition	
Horizon	level	slope	level	slope
1	9	8	9	8
3	9	8	9	8
6	6	1	9	8
12	8	2	9	9

$Notes$: The table reports the decile ranks of the credit spread level and slope for which the model provides the highest R^2 values using a linear model and a smooth-transition model, respectively. The model is estimated for each forecast horizon h using 81 combinations of first through ninth decile ranks of the credit spread level and slope.

Table 4: Results of the predictive regression with government bond and credit spread curves

Horizon		α	β_1	β_2	δ_1	δ_2	ϕ	Adj. R^2
1	Est.	1.037	-1.728	0.169	-1.214	-3.620	0.010	0.436
	P-val.	0.000	0.000	0.442	0.000	0.000	0.890	
3	Est.	0.562	-2.141	0.427	-0.700	-2.712	0.037	0.508
	P-val.	0.000	0.013	0.123	0.000	0.000	0.657	
6	Est.	-0.645	-2.763	0.835	1.860	-4.640	0.163	0.434
	P-val.	0.032	0.034	0.020	0.001	0.081	0.009	
12	Est.	-0.210	-2.720	0.548	0.492	-4.479	-0.010	0.539
	P-val.	0.196	0.001	0.015	0.043	0.024	0.594	

$Notes$: This table reports the estimated coefficients, p-values, and adjusted R^2 values for the equation (2) using government bond yield curve and credit spread curve information. The credit spread curve information relates to the variables in Table 2: sct_t and cts_t. "Horizon" refers to the forecast horizon h, and the p-value of each coefficient is calculated using Hodrick (1992) standard errors.

Table 5: Table: Results of testing the linear PR model against the STPR model

Horizon	1	3	6	12
LM stat	4.38	21.98	20.44	26.68
P-val	0.496	0.001	0.001	0.000

$Notes$: This table reports LM statistics and their p-values to test the linear PR model (2) against the STPR (3) model using the LM test proposed by Luukkonen et al. (1988).

Table 6: Estimates transition function parameters

Horizon	1	3	6	12
c	-0.2114	-0.2339	-0.2471	-0.2625
γ	300	300	300	300

$Notes$: This table reports the estimated c and γ for the transition function (4) using corporate bond market uncertainty, measured by the cross-sectional volatility over the previous six months, as the transition variable and using the optimal combination of deciles.

Table 7: Results of the STPR model with government bond yield and credit spread curves

Horizon			α	β_1	β_2	δ_1	δ_2	ϕ	Adj. R^2
1	Regime 1	Est.	1.345	-1.425	-0.049	-1.579	-4.567	-0.162	0.444
		P-val.	0.000	0.000	0.820	0.000	0.000	0.000	
	Regime 2	Est.	0.781	-3.418	1.612	-1.130	-3.058	0.063	
		P-val.	0.101	0.004	0.251	0.000	0.000	0.639	
3	Regime 1	Est.	1.351	-1.617	-0.068	-1.571	-4.689	-0.176	0.585
		P-val.	0.000	0.000	0.704	0.000	0.000	0.006	
	Regime 2	Est.	-0.029	-4.283	2.696	-0.544	-1.842	0.089	
		P-val.	0.958	0.016	0.100	0.030	0.011	0.460	
6	Regime 1	Est.	0.841	-1.511	0.136	-1.017	-3.116	-0.132	0.576
		P-val.	0.001	0.000	0.227	0.001	0.000	0.096	
	Regime 2	Est.	-0.911	-5.250	3.594	0.236	-0.023	0.135	
		P-val.	0.104	0.027	0.034	0.041	0.948	0.152	
12	Regime 1	Est.	0.499	-1.540	0.343	-0.927	-1.599	-0.039	0.661
		P-val.	0.000	0.000	0.000	0.000	0.000	0.043	
	Regime 2	Est.	-0.385	-3.427	1.278	0.539	0.203	0.029	
		P-val.	0.364	0.010	0.311	0.000	0.444	0.410	

$Notes$: The table reports the coefficients, p-values, and adjusted R^2 values for the equation (3) using the credit spread as sct_t, the term spread of credit spreads as cts_t, and the decile ranking of Table 2. Regime 1 refers to the period in which the variance in credit spreads is larger, and regime 2 refers to the period in which the variance in credit spreads is smaller.