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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 construct a monthly empirical distribution of credit spread curves by calculating credit spreads of corporate bonds at the firm level in Japan and examine whether it can be used to predict a Japanese business cycle. We find that the credit spread curve information in higher deciles (implying lower credit quality) provides more predictive power for the future economy than the information of government bond yield curve or the credit spread index suggested by the previous studies. Also, the smooth-transition predictive regression analysis demonstrates that the credit spread curves have more predictive power under the low uncertainty regime, and show a significant predictive power for a short horizon for both regimes. Finally, our component-wise analysis shows that the credit spread curve information has robust predictive power for producer-side indicators under the low uncertainty regime and for labor market conditions regardless of the 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

We propose a new method to predict economic activity by constructing an empirical distribution of credit spread curves that is parsimonious, model-independent, and observable in real time. Since at least the work of Fisher (1933), the credit cycle has been thought to affect the business cycle. Recent studies focusing on corporate bond spreads in the U.S., see e.g., Gilchrist et al. (2009), Gilchrist and Zakrajšek (2012), Faust et al. (2013), and Mueller (2009) and European countries, see e.g., Bleaney et al. (2016) and Gilchrist and Mojon (2018) provide strong evidence for their linkage with economic activity. Another strand of literature demonstrates that the credit spread term structure of each credit rating class is associated with economic activity, e.g. Wu and Zhang (2008), Okimoto and Takaoka (2017, 2020). While a growing body of literature on the information content of credit spread fluctuations for economic activity focuses on the *level* of corporate bond spreads, we incorporate the information from the distribution of credit spread curves by focusing the *term structure* of credit spreads for predicting the business cycle.

In this study, we construct a monthly empirical distribution of credit spread curves from April 2004 to March 2019 using Japanese corporate bond spread data. Our methodology exploits the predictive power in an empirical distribution of credit spread curves constructed from the trading prices in the secondary market of individual corporate bonds. In particular, we demonstrate that the credit spread curve information in higher deciles (implying lower credit quality) provides more accurate forecasts for the business cycle than any other deciles. Our results imply that the forecast model with the average credit spread can improve the predictive power by taking into consideration the term structure of cread spreads as well as an empirical distribution of credit spread curve.

The empirical analysis focuses on the behavior of the term structure of credit spread curves. For this purpose, we calculate an empirical distribution of credit spread curves using Japanese corporate bond spread data. The reasons for 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.[1] Then we use information from the level and the slope of

[1] 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. Whereas limiting the sample to noncallable bonds in the U.S. would severely limit the time span of the data, 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.

the term structure for each decile of the credit spread distribution. This information is valuable to control the bond's credit quality. In Gertler and Lown (1999) and Mody and Taylor (2004), below-investment-grade (high-yield) corporate bond spreads are found to be a significant predictor of economic activity, along the lines of the theory of the financial accelerator. While Okimoto and Takaoka (2017) find that the predictive power of the term structure of the credit spreads on the business cycle in Japan improved even with the credit spread index by investmen-grade rating category matrix, this study expands the coverage of credit spreads data to all individual corporate bonds in the secondary market. Moreover, this enables to calculate the cross section corporate bond market uncertainty and specify the regime-switching structure.

We find four 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 the individual bond issue level data. For example, the largest corporate bond issuer in Japan was TEPCO at the time of the nuclear disaster at TEPCO's Fukushima Daiichi Nuclear Power Plant in March 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 (BM) model, which regresses the future economic growth rate on government bond yield curve information. Then, we extend it to the more general predictive regression (PR) model with credit spread information. Specifically, 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)). Moreover we confirm that the information contained in the credit spread curve distribution does have the better predictive performance than the aggregate level index of credit spreads proposed by Gilchrist and Zakrajšek (2012).

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 uncertainty 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, suggesting that the predictive power of credit spread curves heavily depends on uncertainty in the corporate bond market. However, even under the high corporate bond market uncertainty regime, the information from the term structure of credit spreads demonstrates a significant predictive power for the business cycle for a short horizon.

Lastly, we perform our model estimation for the several cyclical components of the business cycle to analyze the extent to which our credit spread curve information has predictive power. Our results confirm that the credit spread information improves the forecasting power for the business cycle regardless of the cyclical components and forecasting horizons. Also, our results suggest that the STPR model outperforms the PR model for all components and horizons except the one-month horizon. More specifically, our results show that the credit spread curve information has robust predictive power for the producer-side indicators only in the low uncertainty regime and for labor market conditions regardless of the regime.

This study contributes to streams of the literature on forecasting economic activity. First, it adds to the literature on the potentially useful predictors of economic activity. Forecasting a business cycle has been of great interest among economists. In addition to forecasting methods, the quest for potentially useful predictors gives us a wide array of indicators to forecast economic activity, see e.g., Estrella and Mishkin (1998), Stock and Watson (2003a), Ang et al. (2006), Gilchrist et al. (2009), Gilchrist and Zakrajšek (2012), and Faust et al. (2013). Particularly, our results reveal the better predictive power of information in the credit spread curve distribution against the common aggregate level index of credit spreads proposed by Gilchrist and Zakrajšek (2012).

Second, this study contributes to literature on the associations between yield curve and economic activities. The term structure information of Treasury yield curves has been shown to convey useful information for economic growth, see, among others Harvey (1989), Stock and Watson (1989), Dotsey (1998), Hamilton and Kim (2002), and Ang et al. (2006). The behavior of the corporate bond yield curve also varies over the business cycle, then we document that the term structure of credit spread curves has predictive power for economic activity even after conditioning on the information of Treasury yield curves.

Third, it also contributes to the literature on credit quality measure of the firm. The credit rating is the most common measure of credit quality as Wu and Zhang (2008) and Okimoto and Takaoka (2017) use credit spread for each credit rating class, though it has some problems, see e.g. Hilscher and Wilson (2017). For example, the credit rating information depends on a few credit rating agencies. Another problem is that the rating change will be generally made stepwise and sometimes with time delay.[2] This study mitigates such concerns by using deciles of an empirical distribution to capture the credit quality of the firm. This has the important advantages of providing a model-free measure, data-parsimonious, and relying on observable in real time data only. First, alternative methods such as latent model and principal component analysis need to estimate the model each time the data change, but our method does not. Also, by using the decile in an empirical distribution, our credit curve data are robust to outliers. Second, we need observable credit spread data only to capture the credit quality. Our method does not use data on issuer's equity, financial statement, or credit rating. This means that our analysis can include unlisted firms and firms with missing financial data. Third, the credit spreads are data observable in real time. During market turmoil, such as that caused by the unprecedented COVID-19 pandemic, firms facing difficulties in tallying up financial data overseas put off the release of financial statements. Unlike the macro data and corporate financial data, the credit spread is published directly from the market prices and without subsequent revisions.

Finally, this study adds to the literature on the time-varying predictive relationship between the

[2]The arithmetic average of credit spreads for each rating class can be affected by these problems. Serious problems can be caused by a large issuer's credit rating change. The representative example was that Tokyo Electric Power Co.'s (TEPCO's) Fukushima Daiichi Nuclear Power Plant on March 11, 2011, where outstanding corporate bonds issued by TEPCO, which was Japan's largest corporate bond issuer, influenced them decisively. In particular, the yield for the rating class to which TEPCO belongs was affected, as TEPCO's rating was stepwise downgraded from AA+ to BBB.

credit spreads and the economic activity. The implicit assumption of the constant predictive content of many macro time series over time is strong, see e.g. Ng and Wright (2013). Linear models do not explain well the data when business cycles are asymmetric. Regime switching literature documents the parameter values alternate between different states, e.g. Hamilton (1989), Kim et al. (2007), and Hwang (2019). Gilchrist and Zakrajšek (2012) find the instability of the forecasting regression function in the relationship between the credit spreads and economic activity. Our firm level credit spread data from all individual corporate bonds in the market enables this study to specify the source of regime switching and identify two different states, depending on the credit spread market uncertainty.

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 model, while Section 5 summarizes the results based on the STPR model and presents the component-wise analysis results of business cycle. Section 6 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. Possible explanations for this result are that the bond price is less affected by the growth options and 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), Stock and Watson (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.[3] 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

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

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 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,[4] 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

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

where N_{imt} 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. 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

[4] 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.

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-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 consider the BM and PR models, following Ang et al. (2006), Gilchrist and Zakrajšek (2012), and Okimoto and Takaoka (2017). In addition, we extend the PR 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 the BM and PR models and then discuss the STPR model.

3.1 PR model

Our BM model regresses 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.[5]

To investigate whether credit curve distribution information can improve forecasts of economic growth rates in Japan, we extend the BM model (1) to the PR model 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 model is suitable to identify regimes without specifying determinants of regime changes, it is agnostic on 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,

[5] 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.

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.

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 δ 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:

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

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 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 δ. 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 δ 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 δ takes a small value, but it is faster for larger values of δ. Once δ 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 δ.

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 δ using a grid search.[6] Given fixed values of c and δ, 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.[7] 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,

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

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

a first-order Taylor approximation leads to an auxiliary regression of the form

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

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 Results of the PR Model

In this section, we summarize our empirical results based on the linear PR model (2). First, we discuss the results of the in-sample analysis. More specifically, based on the in-sample analysis, we examine 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 investigate the same questions based on the out-of-sample forecast comparison.

4.1 In-sample analysis

Our BM 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 BM 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 section.

[Table 4 around here]

4.2 Out-of-sample forecast comparison

In this subsection, we conduct the out-of-sample forecast comparison to examine the same questions: (i)whether credit curve distribution information can improve forecasts of economic growth rates in Japan and (ii) which deciles of the empirical distribution of credit spread curves that have more predictive power for the business cycle in Japan.

To compare the models based on the out-of-sample, we conduct an out-of-sample forecast evaluation using a 5-year rolling window. We explain the detail of our procedure using 1-month forecasts as an example. First, we estimate the BM model (1) and the PR models (2) with every possible pairing of the first to ninth deciles of the levels and slopes of the credit spreads using data from April 2004 to March 2009. Then we evaluate the terminal 1-month-ahead forecast error based on the estimation results. Next, the data are updated by 1 month, and the terminal 1-month-ahead forecast error is re-calculated from the updated sample (specifically, from May 2004 to April 2009). This procedure is repeated until reaching 1 month before the end of the sample period, namely, February 2019. Finally, we calculate the root-mean-squared forecast error (RMSE) using the time series of 1-month-ahead forecast errors. We also evaluate the RMSE ratios of all PR models to the BM model (1).

The results are summarized in Table 5. The second and third columns show the optimal deciles of the level and slope factors with the smallest RMSE values. As can be seen, the results for the out-of-sample forecast comparisons suggest that the optimal decile is either 8 or 9 for all cases. In other words, the results indicate that higher deciles have more predictive power on the business cycle, regardless of the forecast horizons. This is contrast to the in-sample analysis which demonstrates the similar results only for shorter horizons. The fourth column of Table 5 reports the RMSE ratios of the PR model with the best deciles to the BM model without the credit spread information. As can be seen, the RMSE ratios are smaller than 1 for all horizons, meaning that the RMSE of the

PR model is smaller than that of the BM model. Therefore the results demonstrate that the out-of-sample forecast performance of the PR model is better than the BM model. The results also indicate that the relative performance becomes better as the forecast horizon gets longer.

Are these differences in out-of-sample forecasting accuracy statistically significant? West (2006) notes the problems with testing the null hypothesis of no improvement in forecasting accuracy for cases where competing models are nested like our case. Clark and West (2007) propose a simple test appropriate for nested models constructed from the value of

$$s_{t+1} = \hat{e}^2_{1,t+1} - \hat{e}^2_{2,t+1} + (\hat{y}_{1,t+1} - \hat{y}_{2,t+1})^2,$$

where $\hat{y}_{1,t+1}$ is the forecast for date $t+1$ based on the more parsimonious model (in this case, the BM model (1) with no credit spread information) as estimated using observations through date t, $\hat{y}_{2,t+1}$ the forecast from the bigger model (in this case, the PR model (2)), and $\hat{e}_{i,t+1} = y_{t+1} - \hat{y}_{i,t+1}$ denote the respective forecast errors. The test statistic is essentially the usual t-statistic for testing whether s has mean zero over the P out-of-sample observations:

$$CW = \frac{\sqrt{P}\bar{s}}{\sqrt{P^{-1}\sum_{t=R}^{R+P-1}(s_{t+1} - \bar{s})^2}} \tag{6}$$

$$\bar{s} = P^{-1}\sum_{t=Q}^{Q+P-1} s_{t+1}.$$

Here Q is the size of the rolling window. Although the asymptotic distribution of CW is unknown, Clark and West (2007) suggest that the standard normal distribution gives a conservative approximation in the sense that if the null hypothesis is true (that is, if the parsimonious model is the correct one), then CW should exceed 1.645, which is the 5% critical value of the standard normal distribution, a little less than 5% of the time.

The last two columns of Table 5 summarize the results of Clark-West test for the null hypothesis that the PR model offers no improvement in out-of-sample prediction over the BM model. Specifically, each column reports the CW test statistic (6) and an approximate upper bound for the p-value based on the standard Normal approximation, respectively. As can be seen, the P-value is smaller than 1% for all horizons. This means that the RMSE of the PR model is statistically significantly smaller than that of the BM model, suggesting that the out-of-sample forecast performance of the PR model with the credit curve information is better than the BM model with no credit curve information.

In summary, our out-of-sample forecast comparison confirms that the credit curve information has considerable additional predictive power in forecasting the business cycle in Japan even for the out-of-sample. Moreover, in the case of the out-of-sample forecast, higher deciles provide the most accurate prediction of the business cycle in Japan for all horizons. This is a contrast with the in-sample analysis, where higher deciles show the highest predictive power only for the shorter horizons. Again, one possible reason for this result could be the lack of information regarding the regime-switching structure, which we examine in the next section.

4.3 Comparison with the Credit Spread Index

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), empirically confirm that the credit spreads have considerable predictive power for economic activity. For example, Gilchrist and Zakrajšek (2012) construct a new credit spread index (GZ index thereafter) based on prices of individual corporate bonds traded in the secondary market. They show that the predictive ability of the GZ index for future economic activity significantly exceeds that of the widely used default-risk indicators such as the standard Baa-Aaa corporate bond credit spread and the paper-bill spread. Moreover, Bleaney et al. (2016) and Gilchrist and Mojon (2018) employ the same approach using data from European countries and find that their euro area GZ index also had significant predictive power for economic activity for European countries. One natural question arisen from those studies is whether GZ index, that is the *aggregate level* index of credit spreads, has more predictive power than the information from the credit spread *curve* distribution utilized by this paper. In this subsection, we provide results of BM and PR models using Japanese GZ index as an additional predictor to make comprehensive comparisons between the predictive performance of aggregate level index of credit spreads and credit spread curve distribution information.

First, we follow the methodology of Gilchrist and Zakrajšek (2012) and construct a credit spread index using individual corporate bond level data in Japan. This Japanese GZ index is based on the same dataset that we use to calculate the credit spread curve distrubtion. We then compare the predictive power for economic activity of Japanese GZ index and credit spread curve distribution information. To give a broad idea about the performance of models with the Japanese GZ index, Table 6 summarizes the adjusted R^2 of the BM model (1), BM model with the Japanese GZ index as an additional predictor (BMGZ), PR model (2), and PR model with the Japanese GZ index as an additional predictor (PRGZ).[8] As can be seen, if we add the Japanese GZ index to the BM model, the adjusted R^2 increases uniformly regardless of the forecasting horizon. However, the magnitude of the increase is relatively small, ranging from 0.015 to 0.042. These numbers are much smaller than those when we extend the BM model to the PR model by including the best deciles of level and slope of the credit spread curve distribution, ranging from 0.147 to 0.254. In other words, the results suggest that deciles of level and slope of the credit spread curve distribution have much greater additional information about future economic activity over the information from the government bond yield curve than the Japanese GZ index. When we compare the PR and PRGZ model, the PRGZ model has uniformly higher adjusted R^2 but increases are very small, ranging from 0.002 to 0.025. This indicates that the Japanese GZ index, the aggregate level index of credit spreads, has little additional information about future economic activity over the credit spread curve distribution information.

To further compare the predictive power for economic activity of the Japanese GZ index and credit spread curve distribution, we also conduct the out-of-sample exercise, as in the previous subsection. Table 7 reports the RMSE ratios of the BMGZ, PR, and PRGZ models to the BM model. The results indicate that the RMSEs of the BMGZ model are larger than 1 for all horizons except for 12 months, meaning that the out-of-sample forecasting performance of the BMGZ model is worse than the BM model for the short to middle horizons. This is a great contrast to the PR model, which can provide significantly better out-of-sample forecast than the BM model for all horizons, as we demonstrated in the previous subsection. In addition, even for the 12 month horizon, the RMSE ratio of BMGZ is much larger than that of the PR model. On the other hand, all RMSE ratios of PRGZ are smaller than 1 for all horizons, suggesting that PRGZ model can improve the out-of-sample forecast over the BM model. However, if we compare the PR and PRGZ models, the RMSE ratios of PR models are smaller than those of PRGZ model for all horizons except for 12 months. This indicates that the out-of-sample forecasting performance of PRGZ is worse than the PR model for the short to middle horizons.

In sum, our analyses arguably demonstrate that the Japanese GZ index has little additional information for future economic activity over the information of credit spread curve distribution. Although, the BMGZ (PRGZ) model can provide a better in-sample fit than the BM (PR) model,

[8] In this subsection, all results of PR and PRGZ models are based on those models using best deciles for the PR model reported in the previous subsections.

the degree of improvement is rather limited. Moreover, the Japanese GZ index fails to improve the out-of-sample forecasting performance of the BM or PR model for the short and middle forecast horizons. It is evident from these evaluations that the information contained in the credit spread *curve* distribution does have the advantage of providing a model-free measure as well as the better predictive performance than the *aggregate level* index of credit spreads. Therefore, we will focus on the information of credit spread curve distribution credit to predict future economic activity based on the regime-switching model in the next section.

5 Results of the STPR Model

5.1 Main results

The previous section 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. Also, although the out-of-sample forecast comparison demonstrates that higher deciles provide the most accurate forecast of the business cycle in Japan for all horizons, this is the case only for shorter horizons for in-sample analysis. 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. Although their model is suitable to identify the regimes without assuming possible determinants of this regime change, it is silent about 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 more light 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 8. 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, which is consistent with the results of out-of-sample forecast comparison for the PR model without the smooth-transition. 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.

Next, Table 9 reports the estimates of the parameters c and δ 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 -0.25 and -0.30, meaning that if corporate bond market uncertainty over the last six months is 0.25 to 0.30 standard deviations below average, the regime moves closer to the regime with low corporate bond market uncertainty. In addition, the large estimate of δ indicates that transitions between the low-uncertainty and high-uncertainty regimes are very rapid. This result is also confirmed by Figure 2. It plots the estimated dynamics of the transition function (4), which can be considered as the weight on the regime with high corporate bond market uncertainty, alongside the corporate bond market uncertainty measured by the cross-sectional volatility over the previous six months and 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 10 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 low grade corporate bond spread curves captured by higher deciles of the credit spread curve distribution seem to contain more information about the business cycle in Japan. Although the prolonged monetary easing by the BOJ over the last 15 years or so has been made the slopes of the government bond yield and high-grade credit spread curves less useful for predicting the future economy, our results suggest that the slopes of low-grade corporate bonds still have some useful information to predict 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.

5.2 Credit spread curve and cyclical components

Our results so far demonstrate the predictive power of credit spread curve information for the business cycle in Japan, that is, the growth rate of CI. We now turn to the decomposition of the CI and perform our model estimation for each cyclical component to analyze the extent to which our credit spread curve information has predictive power. More specifically, those components include: IIP = Index of Industrial Production (Mining and Manufacturing), IPSPG = Index of Producer's Shipments (Producer Goods for Mining and Manufacturing), IPSDCG = Index of Producer's Shipment of Durable Consumer Goods, INSWH = Index of Non-Scheduled Worked Hours, IPSIG = Index of Producer's Shipment (Investment Goods Excluding Transport Equipments), RSV = Retail Sales Value (Change from Previous Year), WSV = Wholesale Sales Value (Change from Previous Year), OP = Operating Profits (All Industries), and EJOR = Effective Job Offer Rate.

First, we compare the forecasting power of three models, namely, the BM model (1), the PR model (2), and the STPR model (3) for each component of CI. For this exercise, we use the optimal combination of level and slope deciles of the credit curve for the STPR model in Table 3. Moreover, we assume that the regime classifications for the STPR model are the same as the CI for each component by using the same estimates of transition function parameters in Table 9. Table 11 shows the comparison results for each component of CI and each forecast horizon. The adjusted R^2 values of the PR models reported in Table 11 indicate that the predictive power for each component substantially improves when the model includes the credit spread curve information compared with the BM model that includes only the government bond yield curve information. The increase in the adjusted R^2 is sizable regardless of the variables and forecast horizon. These results clearly demonstrate that the credit spread information improves the forecasting power for the business cycle across its components and forecasting horizons. Particularly, those variables with remarkable improvements include IIP, IPSPG, IPSDCG, INSWH, and IPSIG. In other words, to predict those variables, including the credit spread information is quite beneficial.

Moreover, if we compare the adjusted R^2 values between the PR and STPR models, the results suggest that the STPR model has the higher predictive power than the PR model with very few exceptions, as at the one-month forecast horizon, and the increase in the forecasting power tends to be obvious at longer forecast horizons. More specifically, at the one-month forecast horizon, the PR model has slightly better predictive power than the STPR model for IIP, IPSDCG, and RSV and almost the same predictive power for other variables except OP, which seems to be better predicted by the STPR model. At longer horizons, the STPR model outperforms the PR model for all components and horizons, confirming our previous results of the importance of capturing the different regimes depending on the corporate bond market uncertainties for the longer horizon forecasts. Among cyclical components of CI, the results confirm that our STPR model contains substantial predictive power for cyclically volatile components such as WSV and EJOR, with adjusted R^2 values ranging from 0.561 to 0.861 and from 0.785 to 0.871, respectively. On the other hand, our results show that the STPR model has relatively limited predictive power for IPSDCG and RSV with less than 0.3 R^2 for most of the cases.

We then estimate the STPR model (3) for each component of CI. Table 12 reports the estimated coefficients on the credit spread (δ_1) and the term spread of credit spreads (δ_2) only to conserve space, but for all forecast horizons. Overall, the credit spread curve information contains significant forecasting power for cyclical components in regime 1 with low corporate bond market uncertainty. With the exception of RSV and WSV, the estimated coefficients on cyclical components in regime 1 indicate that the credit spread curve information is a robust predictor for all forecast horizons. For producer-side indicators, the absolute magnitude of the estimated coefficients on credit spreads suggests that an increase in credit spreads has greater impacts on components associated with producer's shipments. The estimated coefficients also imply the credit spread curve information signals a deterioration in labor market conditions. For two components of labor market conditions, INSWH and EJOR, the estimated coefficients are statistically significant over all forecast horizons in regime 1. In particular, the estimated coefficients on credit spread curve information for EJOR are significantly negative even in regime 2 with high corporate bond market uncertainty, except the one-year forecast horizon. The analysis of decomposing the CI reveals that in regime 1 the credit spread curve information has robust predictive power for producer-side indicators and labor market conditions, and has modest predictive power for labor market conditions even in regime 2.

6 Conclusions

The use of credit spread curve distribution is motivated by its observable real-time information content, which may be a good indicator of the business cycle. Our main result demonstrates the usefulness of the information content of credit spread curve distribution after conditioning on government bond yield curve information, and what is more important, the information contained in the credit spread curve distribution has a better predictive power against the aggregate level index of credit spreads proposed by Gilchrist and Zakrajšek (2012). Specifically, 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. This finding is particularly important when 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. It also contributes to the literature on the quest for useful predictors given that the curve the movement of long-term interest rates is limited under the monetary authorities' control (Engstrom and Sharpe (2018)).

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 in the literature 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 spread curves to capture the credit quality. Our results complement and extend previous studies by suggesting that the credit spread curve information in higher deciles 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 distribution of credit spread curves 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. Nonetheless, it has significant predictive power for the business cycle over a short horizon.

Our cyclical component-wise analysis provides fairly consistent results and additional evidence of the predictive power of the distribution of credit spread curves regardless of the cyclical components. Moreover, our results suggest that distinguishing between the high and low corporate market uncertainty regimes is reasonable for all cyclical components and forecast horizons except the one-month horizon. More specifically, our results show that the distribution of credit spread curves has robust predictive power for producer-side indicators under the low uncertainty regime and for labor market conditions regardless of the regime.

In summary, our findings indicate that the predictive relation between credit spread curves and economic activity differs across the credit spread curve distribution. Our results support the view in the literature that the credit spreads of firms with low credit quality signal the business cycle. Although this predictive relationship is not stable 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, the information from the distribution of credit spread curves has predictive power for labor market conditions regardless of the corporate bond market uncertainty over a short horizon. From a policy standpoint, our results provide important implications, since the policymaker could better predict future economic activity by employing the information content of the credit spread curve distribution.

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 U.S. 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 that an empirical distribution of the credit spread curve, which is observable real-time data, can be used as a potentially good indicator of the business cycle given its overall informativeness.

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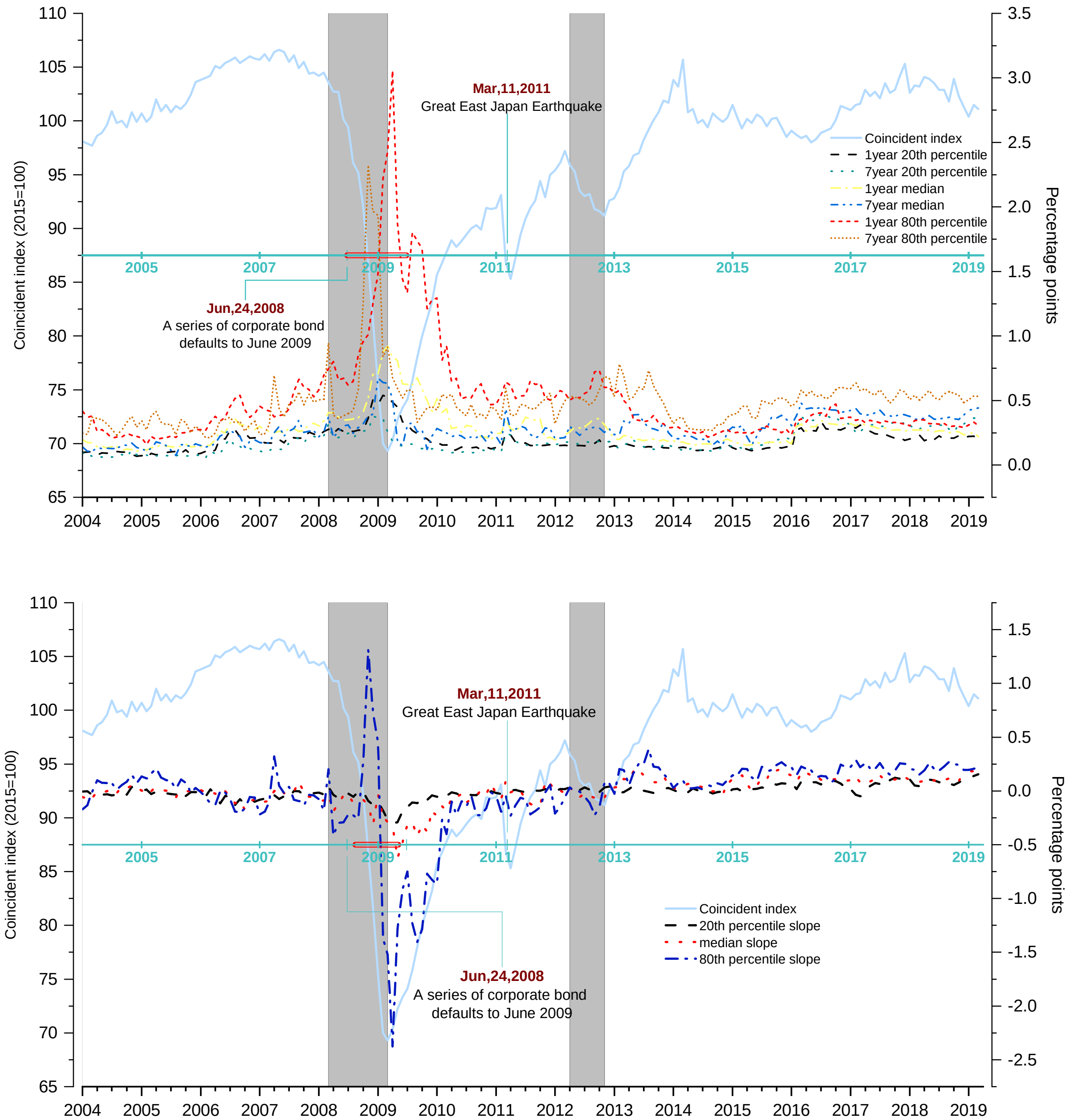
Figure 1: Credit spread curve and the coincident index (CI)



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.

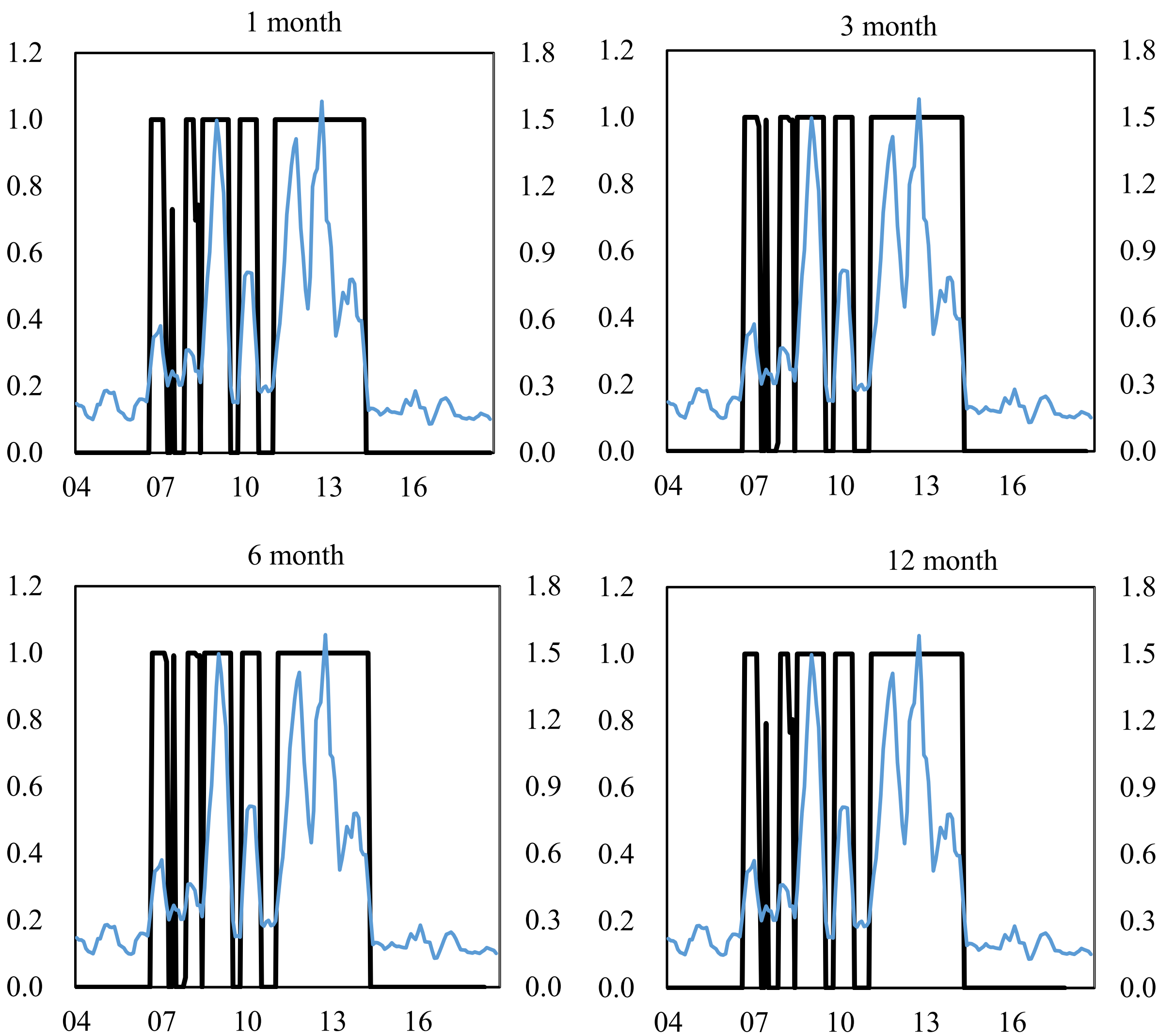


Figure 2: Transition function

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

$Notes$: 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 (1). "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.	1.044	-1.640	0.143	-1.201	-3.589	0.046	0.442
	P-val.	0.000	0.000	0.509	0.000	0.000	0.564	
3	Est.	0.633	-2.059	0.387	-0.775	-2.796	0.045	0.527
	P-val.	0.000	0.012	0.183	0.000	0.000	0.532	
6	Est.	-0.635	-2.785	0.859	1.795	-4.609	0.160	0.437
	P-val.	0.029	0.034	0.020	0.000	0.078	0.010	
12	Est.	-0.346	-2.769	0.626	1.088	-4.552	-0.007	0.541
	P-val.	0.020	0.000	0.004	0.005	0.001	0.706	

$Notes$: 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: Out-of-sample forecast comparison

	Best decile		RMSE ratio	CW test	
Horizon	level	slope		CW stat.	P-val.
1	9	8	0.947	2.848	0.002
3	8	8	0.913	2.851	0.002
6	9	8	0.853	3.209	0.001
12	8	9	0.704	3.226	0.001

$Notes$: The table reports the results of out-of-sample forecast comparison. The second and the third columns report the decile ranks of the credit spread level and slope for which the model provides the smallest RMSE using the PR model (2). The out-of-sample forecast evaluation is conducted for each forecast horizon h using 81 combinations of first through ninth decile ranks of the credit spread level and slope. The fourth column reports the RMSE ratios of the PR model with the best deciles to the BM model (1). The last two columns of Table 5 summarize the results of Clark-West test for the null hypothesis that the PR model offers no improvement in out-of-sample RMSE over the BM model. Specifically, each column reports the CW test statistic (6) and the an approximate upper bound for the p-value based on the Normal approximation, respectively.

Table 6: Comparisons of adj. R^2 across models with and without the GZ index

Horizon	BM	BMGZ	PR	PRGZ
1	0.202	0.244	0.442	0.467
3	0.273	0.298	0.527	0.536
6	0.290	0.305	0.437	0.439
12	0.327	0.358	0.541	0.563

$Notes$: This table reports the adjusted R^2 values of the BM model (1), BM model with the GZ index as an additional predictor (BMGZ), PR model (2), and PR model with the GZ index as an additional predictor (PRGZ). "Horizon" refers to the forecast horizon h.

Table 7: Comparisons of RMSE across models with and without the GZ index

Horizon	BMGZ	PR	PRGZ
1	1.019	0.947	0.959
3	1.032	0.913	0.957
6	1.026	0.853	0.893
12	0.943	0.704	0.666

$Notes$: This table reports the RMSE of the BM model with the GZ index as an additional predictor (BMGZ), PR model (2), and PR model with the GZ index as an additional predictor (PRGZ). "Horizon" refers to the forecast horizon h.

Table 8: Results of testing the linear PR model against the STPR model

Horizon	1	3	6	12
LM stat.	6.43	25.81	29.48	42.19
P-val.	0.266	0.000	0.000	0.000

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

Table 9: Estimates transition function parameters

Horizon	1	3	6	12
c	-0.250	-0.271	-0.284	-0.302
δ	300	300	300	300

$Notes$: This table reports the estimated c and δ 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 10: 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.	1.305	-1.377	-0.057	-1.514	-4.435	-0.169	0.456
		P-val.	0.000	0.000	0.792	0.000	0.000	0.000	
	Regime 2	Est.	0.791	-3.230	1.512	-1.103	-3.051	0.121	
		P-val.	0.057	0.004	0.232	0.000	0.000	0.365	
3	Regime 1	Est.	1.336	-1.514	-0.110	-1.537	-4.567	-0.187	0.610
		P-val.	0.000	0.000	0.506	0.000	0.000	0.002	
	Regime 2	Est.	0.028	-4.237	2.696	-0.608	-1.963	0.098	
		P-val.	0.959	0.015	0.099	0.019	0.001	0.341	
6	Regime 1	Est.	0.815	-1.466	0.146	-0.990	-2.995	-0.135	0.576
		P-val.	0.000	0.000	0.183	0.000	0.000	0.082	
	Regime 2	Est.	-0.852	-5.404	3.773	0.098	-0.199	0.093	
		P-val.	0.132	0.028	0.035	0.223	0.533	0.284	
12	Regime 1	Est.	0.603	-1.444	0.277	-1.080	-1.694	-0.032	0.660
		P-val.	0.000	0.000	0.001	0.000	0.000	0.190	
	Regime 2	Est.	-0.462	-3.499	1.451	0.556	0.316	0.018	
		P-val.	0.220	0.007	0.218	0.000	0.031	0.585	

$Notes$: 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.

Table 11: Comparisons of adj. R^2 across three models for each component of CI

Horizon	Model	IIP	IPSPG	IPSDCG	INSWH	IPSIG	RSV	WSV	OP	EJOR
1	BM	0.031	0.125	0.013	0.078	0.072	0.163	0.841	0.303	0.715
	PR	0.272	0.393	0.090	0.345	0.211	0.191	0.860	0.402	0.767
	STPR	0.261	0.401	0.066	0.352	0.236	0.185	0.861	0.465	0.785
3	BM	0.072	0.103	0.027	0.141	0.108	0.171	0.786	0.199	0.704
	PR	0.391	0.370	0.165	0.536	0.364	0.238	0.843	0.554	0.823
	STPR	0.422	0.471	0.193	0.594	0.499	0.274	0.854	0.655	0.871
6	BM	0.161	0.134	0.095	0.176	0.250	0.136	0.617	0.148	0.650
	PR	0.255	0.245	0.145	0.326	0.478	0.205	0.739	0.337	0.762
	STPR	0.404	0.416	0.273	0.504	0.590	0.289	0.763	0.534	0.844
12	BM	0.244	0.192	0.164	0.241	0.418	0.116	0.348	0.193	0.584
	PR	0.371	0.370	0.263	0.363	0.459	0.144	0.485	0.471	0.627
	STPR	0.535	0.556	0.423	0.598	0.570	0.280	0.561	0.699	0.785

$Notes$: The table reports adjusted R^2 values for three models: the BM model (1), the PR model (2), and the STPR model (3). Dependent variable is $\Delta^h y_{t+h}$, where y_t denotes a component of CI in month t and h is the forecast horizon: IIP = Index of Industrial Production (Mining and Manufacturing); IPSPG = Index of Producer's Shipments (Producer Goods for Mining and Manufacturing); IPSDCG = Index of Producer's Shipment of Durable Consumer Goods; INSWH = Index of Non-Scheduled Worked Hours; IPSIG = Index of Producer's Shipment (Investment Goods Excluding Transport Equipments); RSV = Retail Sales Value (Change from Previous Year); WSV = Wholesale Sales Value (Change from Previous Year); OP = Operating Profits (All Industries); and EJOR = Effective Job Offer Rate.

Table 12: Credit spread curve and the components of CI

Horizon			IIP	IPSPG	IPSDCG	INSWH	IPSIG	RSV	WSV	OP	EJOR
1	δ_1	Regime 1	-1.833***	-2.930***	-2.904**	-1.121***	-1.307***	-0.150	-1.597	-1.984***	-0.658**
		Regime 2	-1.469***	-1.339***	-1.833***	-0.910***	-1.794***	-0.917***	-1.937***	-3.974***	-1.118***
	δ_2	Regime 1	-4.045***	-6.380***	-6.968**	-3.253***	-6.015***	-0.411	-3.895	-1.561**	-1.853***
		Regime 2	-4.646***	-5.177***	-5.994***	-2.637***	-2.113***	-0.933***	-2.277***	-10.834***	-1.908***
3	δ_1	Regime 1	-1.837***	-2.854***	-2.880***	-1.152***	-1.050***	-0.032	-2.330*	-4.427***	-1.233***
		Regime 2	-0.828**	-0.388	-0.664	-0.653***	-1.182***	-1.096***	-3.108***	-3.935***	-1.437***
	δ_2	Regime 1	-4.441***	-6.208***	-7.126***	-3.184***	-4.767***	-1.530	-9.208***	-7.153***	-3.951***
		Regime 2	-2.849***	-2.547**	-3.143***	-1.994***	-1.499***	-1.002***	-4.416***	-14.756***	-2.309***
6	δ_1	Regime 1	-1.013***	-1.313***	-1.527***	-0.805***	-1.064***	-0.253	-3.852**	-3.388***	-1.399***
		Regime 2	0.130**	0.563***	0.490***	-0.062	-0.710***	-0.989***	-4.686***	0.681	-0.979***
	δ_2	Regime 1	-2.459***	-2.625***	-2.900***	-2.021***	-3.094***	-2.318	-12.678***	-8.062***	-4.307***
		Regime 2	-0.082	0.482	0.422	-0.478***	-1.222***	-0.566**	-5.319***	-2.034	-1.717***
12	δ_1	Regime 1	-1.315***	-1.512***	-1.964***	-0.947***	-0.924***	-0.323	-5.539**	-4.384***	-1.945***
		Regime 2	0.531***	0.872***	0.970***	0.371***	0.090	-0.801***	-6.030***	3.080***	-0.130**
	δ_2	Regime 1	-1.812***	-2.100***	-2.731***	-1.260***	-1.299***	-0.698	-3.917**	-6.730***	-2.832***
		Regime 2	0.275	0.514***	0.382	0.224***	0.035	-0.335	-2.917*	1.958***	-0.016

$Notes$: The table reports the coefficients of credit spread (δ_1) and the term spread of credit spreads (δ_2) for the equation (3) using the decile ranking of Table 2, and the dependent variable is $\Delta^h y_{t+h}$, where y_t denotes a component of CI in month t and h is the forecast horizon: IIP = Index of Industrial Production (Mining and Manufacturing); IPSPG = Index of Producer's Shipments (Producer Goods for Mining and Manufacturing); IPSDCG = Index of Producer's Shipment of Durable Consumer Goods; INSWH = Index of Non-Scheduled Worked Hours; IPSIG = Index of Producer's Shipment (Investment Goods Excluding Transport Equipments); RSV = Retail Sales Value (Change from Previous Year); WSV = Wholesale Sales Value (Change from Previous Year); OP = Operating Profits (All Industries); and EJOR = Effective Job Offer Rate. 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. *** significant at 1%, ** significant at 5%, * significant at 10%