The Global Credit Spread Puzzle*

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Abstract

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JEL Classification: G12, G13

Keywords: Corporate credit spreads, Credit spread puzzle, Structural credit risk models; the Merton model, the Black and Cox model, CDS, Fixed income asset pricing

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Abstract

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1 Introduction

The corporate bond market outside the US has expanded rapidly over the past few decades, and become a more and more important source of financing for corporations. Indeed, the growth rate of debt securities outstanding as a fraction of GDP in six major developed countries (the G7 countries excluding the US) over the past 20 years mostly exceeds the growth rate in the US (Figure 1). Yet, we know little about how these foreign debt securities are priced. In particular, how are they priced relative to the popular benchmark credit risk model such as the Merton (1974) or the Black and Cox (1976) models? We investigate the performance of structural credit risk models in these countries using security-level data.

The bond markets in these six countries–Japan, UK, Germany, France, Italy and Canada– are among the largest ones in terms of the market size outside the US.[1] In this paper, we study bonds issued in domestic currency by domestic issuers so that our results provide out-of-sample evidence for the so-called credit spread puzzle, which is primarily documented in the US (e.g. Huang and Huang 2012 and Chen, Collin-Dufresne, and Goldstein 2009). Otherwise, large global issuers issuing both in US and overseas mechanically generate foreign credit spreads similar to US.

We compare credit spreads for the constituents of ICE Bank of America Merrill Lynch Global Corporate and High Yield Index with structural-model implied credit spreads, calculated based on bond issuers' balance sheet data and stock price information in Compustat Global. The idea of structural models hinges on no arbitrage relationship between bonds and stocks for the same issuer. As both corporate bonds and stocks depend on firm's earnings, absent market frictions, they should be priced consistently with each other. In our baseline analysis, we use the Black-Cox (1976) model as the benchmark because it can generate more realistic term structure of credit spreads by allowing firms to default before maturity of debt. We also consider the Merton (1974) model as a robustness check.

In estimating the Black-Cox model, we need to ensure that physical ($\mathbb{P}$-measure) default probability generated from the model matches the historical default frequency of corporate bonds. To this end, we follow Feldhütter and Schaefer (2018) and back out the firm's unobservable default boundary to match the model-based default probability to historical default frequency since 1920. Specifically, we take firm-level inputs to the model as given (asset volatility, payout ratio, risk-free rate and leverage), and find the optimal value

[1] As of December 2017, these six countries account for 28% of the market values of corporate bonds in the Merrill Lynch Global Corporate Index while US accounts for about 50%. For the Merrill Lynch High Yield Index, these six countries account for 19%, while US accounts for 51%.

of default boundary that minimizes the distance between historical default frequency and model-implied probability of default, separately for each country.

With different values of default boundary for each country, we find that the probability of default implied by the Black-Cox model is statistically insignificantly different from the historical default frequency for most markets, partly reflecting the large uncertainty in historical default frequency.

With the estimated default boundary, we study how close the Black-Cox model-implied credit spreads are to the credit spreads in six countries. Once we average credit spreads in the data and model-based spreads at the credit rating level for each country, the Black-Cox model generates the results similar to those documented by Huang and Huang (2012) for most countries. Namely, the structural model generates reasonably large credit spreads for high-yield (HY) bonds, underscoring the importance of default risk in pricing those bonds. On the other hand, the Black-Cox model underestimates the credit spreads for investment-grade (IG) bonds, leading to the "credit spread puzzle" for these bonds. Since the Black-Cox model relies on diffusion shocks in generating default risk, it does not generate large enough tail risk, leading to lower credit spreads for IG bonds.

Though the totality of evidence points to the credit spread puzzle in six countries, there is considerable heterogeneity across countries. The credit spreads and model performance in UK, Germany, Italy and Canada are similar to those in the US: the model generally underpredicts credit spreads, particularly on short-term bonds with high credit rating. In Japan, credit spreads are quite low though leverage and asset volatility are comparable to other countries. Thus, the gap between the data and model is smaller in magnitude than other countries. Still, the pricing errors as a fraction of credit spreads in Japan are as large as other countries. In France, due to a few firms with high leverage, the average model-implied credit spreads for A and BAA bonds are large. However, the model still underpredicts credit spreads for a median firm. Furthermore, these high credit spreads in some French firms can be explained by relatively large mismatch in $\mathbb{P}$-measure default probability.

To ensure our results are not driven by the specific bond data that we use, we also fit the Black-Cox model to single-name CDS spreads in each country, and test whether the model can match CDS spreads on average. Except for Japan, CDS spreads are on average lower than corporate credit spreads, and thus the gap between spreads and the model predictions are narrower for most countries. In Japan, CDS spreads are higher than corporate credit spreads, leading to more pronounced mispricing in CDS than in corporate bonds. For all countries, the Black-Cox model consistently underestimates the CDS spreads for IG issuers, while matching the spreads for HY issuers better. Furthermore, the term structure of model-based IG credit spreads is steeper than that in the CDS data. As a result, for highly-rated firms, the model underpredicts short-term CDS spreads more than long-term spreads. Therefore, the analysis on CDS spreads confirms that the credit spread puzzle exists in the debt markets outside the US.

To understand the comovement in spreads at the global level including US, we compute US credit spreads and pricing errors against the Black-Cox model. We then extract principal components of country-level credit spreads and pricing errors of the Black-Cox model. Specifically, we compute the covariance matrix of credit spreads and pricing errors, and extract principal components that capture the comovement across seven countries including US. We find that the first principal component explains 81% of total variation in credit spreads and 73% of total variation in pricing errors. Comparing the principal component in credit spreads and pricing errors, we find that the Black-Cox model captures little systematic movements in credit spreads among these countries, as the majority of global comovement in credit spreads is missed by the model. Furthermore, since the pricing errors in US and other countries strongly comove with each other, the credit spread puzzle is not unique to US. Instead, the mispricing against the Black-Cox model is a widespread phenomenon which has a common component across the seven developed markets.

We further evaluate the economic significance of the pricing errors by running predictive regressions of economic growth in each country on the pricing errors and the credit spreads predicted by the Black-Cox model. In US, Gilchrist and Zakrajšek (2012) show that pricing errors against the Merton model carry a strong predictive power for the business cycle variation in US real economy. Their findings suggest that the pricing errors against the Merton model in US are not simple white noise. Rather, the model misses an important information in US corporate bond prices that are tied to expectations for future real economic activities. We follow Gilchrist and Zakrajšek (2012) and predict GDP growth rate, industrial production and unemployment rate changes in the six countries. We find that pricing errors from the Black-Cox model strongly negatively predict economic growth over the 3- and 12-month horizon. The strong association with business cycle and the pricing errors confirms the importance of the information missed by the Black-Cox model.

Furthermore, the 'global credit mispricing factor', or the first principal component of the mispricing in the seven countries, predicts negative growth in each country, and the predictive performance is just as good as the pricing errors of *that* country. This finding understates that the systematic risk in global credit market provides useful signals for business cycle in developed countries.

Having established the evidence that the Black-Cox model generates significant pricing errors, we analyse what drives the corporate bond pricing errors in the seven countries. To this end, we run a panel regression of country-level pricing errors on financial conditions in each country. We find that option-based uncertainty, liquidity proxies such as fitting errors of corporate bond yield curve and TED spreads, the level and slope of yield curves are positively related with the gap between the credit spreads in the data and the model-implied spreads. We also find heterogeneous reactions to commodity price indices. In Canada, credit spreads are negatively related with the commodity index, while the relationship is positive for the rest of the economies.

Taken these evidence together, the pricing errors against the Black-Cox model are unlikely to be a simple reflection of measurement errors in the data. Rather, they reflect the systematic factors that are tied to economic and financial conditions.

This paper relates to a strand of literature which explains the corporate credit spread using structural models of risky debt in the US. See, e.g., Bai, Goldstein, and Yang (2018), Bao and Pan (2013), Bhamra, Kuehn, and Strebulaev (2010), Chen, Collin-Dufresne, and Goldstein (2009), Chen (2010), Chen et al. (2018), Collin-Dufresne and Goldstein (2001), Collin-Dufresne, Goldstein, and Martin (2001), Culp, Nozawa, and Veronesi (2018), Du, Elkamhi, and Ericsson (2018), Eom, Helwege, and Huang (2004), Feldhütter and Schaefer (2018), Gourio (2012), He and Xiong (2012), Huang and Huang (2012), Kelly, Manzo, and Palhares (2016), Leland (1994), and Schaefer and Strebulaev (2008) among others.

Most notably, recent work by Feldhütter and Schaefer (2018) shows surprising results that the Black-Cox model can explain a significant fraction of US corporate credit spreads. In contrast, Bai, Goldstein, and Yang (2018) study CDS spreads in the US, and argue that Feldhütter and Schaefer (2018)'s results are not robust to perturbations to the calibration method. We contribute to this discussion by empirically examining the corporate bond and CDS markets outside the US. To focus on our contribution, we do not try to improve existing structural models or calibration methods. Instead, we closely follow Feldhütter and Schaefer (2018) in fitting the Black-Cox model to our sample of non-US corporate bonds, because their methodology is presumably the most promising one to match the observed credit spreads. Furthermore, we analyse the commonality in pricing errors, and their relation with business cycle to shed light on the nature of mispricing of the model.

There are fewer papers that examine corporate bond markets outside the US. Liu (2016) uses international corporate bond data to study the diversification benefit across countries. Valenzuela (2016) studies the rollover risk in international bonds, while Liao (2017) studies the relationship in corporate bond yields of the same issuer in different currencies. Kang and Pflueger (2015) show the link between inflation risk and corporate bond prices using international bond index data. None of these papers, however, test structural credit risk models for domestic issuers outside the US, which is the focus of this paper.

The rest of the paper is as follows. In Section 2, we describe the data sets for the empirical analysis. In Section 3, we introduce the Black-Cox model and describe our procedure to calibrate the model by selecting the optimal values of default boundary to match the $\mathbb{P}$-measure default probability to the historical default frequency. We then compare the credit spreads in the data with the model's prediction, and evaluate the model's performance. In Section 4, we examine the source of the pricing errors and study the factor structure of errors. We also show that the pricing errors against the Black-Cox model predict economic growth negatively. Section 5 concludes.

2 Data

We use month-end corporate bond prices for bonds in ICE Bank of America Merrill Lynch Global Corporate Index and ICE Bank of America Merrill Lynch Global High Yield Index ("Merrill Lynch data") from January 1997 to December 2017 obtained via Mercury, the client portal of Bank of America Merrill Lynch. In this study, we focus on six advanced economies: Japan, UK, Germany, France, Italy and Canada. For each country, we choose bonds offered domestically in a domestic currency which have at least 24 monthly observations. The database imposes the minimum maturity of one year and minimum face value which varies across currencies.[2]

We merge the bond data with the firm and stock data from Compustat, which provides balance sheet information and stock return volatility. We link the bond-level observations and firm-level observations based on issuer's names. We use Compustat name history data to track the history of names for each identifier (gvkey), then use the Levenshtein Algorithm to find a candidate match, and manually verify each match. For firms with multiple stock issues, we remove duplicate observations for shares listed in multiple stock exchanges. If a firm has multiple share classes, then we add them up to compute the market value of firm equity, while we take value-weighted average across shares in computing stock returns (which we use in computing volatility). To reduce the effect of outliers, we drop an observation if book-to-market ratio of the stock is more than 8 (the 99 percentile of the distribution) or

[2]For the investment-grade index, the minimum face values are CAD 100 million, EUR 250 million, JPY 20 billion, GBP 100 million, and USD 250 million. For the high-yield index, the minimum are USD 250 million, EUR 250 million, GBP 100 million, or CAD 100 million. The high-yield index does not include Japan given the lack of the market activity.

less than 0.05 (the 1 percentile).

For bond characteristics, Merrill Lynch data provides credit rating, maturity date, coupon of each issue. Furthermore, we use Bloomberg to identify callability, seniority and security of the bonds. After merging Bloomberg data, we choose senior, unsecured, noncallable bonds issued by nonfinancial issuers.

We also use Bloomberg to check the large shareholders of the bond issuers. We drop state-owned firms if the government ownership is more than 50%. We decrease credit rating of a firm by one notch (e.g. change from AA to AA-) if the ownership ratio is between 20% and 50%, following Moody's (2014).[3]

Table 1 presents the sample selection process. In the original data, there are 8,275 bonds that are offered in six countries of our interest, and have at least 24 monthly observations. Among those, 4,091 bonds are issued by public firms appearing in Compustat. Within those bonds, we focus on noncallable, senior unsecured bonds in nonfinancial sector, which gives our final sample of 2,022 bonds issued by 332 firms with 130,069 bond-month observations.

We use government bond yields (0.25, 1, 5, 10 20 years to maturity) as risk-free rates[4] and stock market index[5] data in each country obtained from Global Financial Data. We obtain macroeconomic data for six countries from OECD website and FRED, and month-end single-name CDS spreads from Markit. Finally, we obtain historical probability of default and recovery rates for non-US issuers from Moody's Default and Recovery Database.

Table 2 presents the summary statistics for our sample of corporate bonds. We take (simple) average across bonds for each portfolio formed on credit ratings and maturity. For credit ratings, we form four portfolios: AA+, A, BAA and HY. For maturity, we use *short* (less than 5 years to maturity), *long* (between 5 and 12 years to maturity) and *slong* (more than 12 years to maturity).

Among European countries, the credit spreads are reasonably close to each other, with AA+ bonds ranging from 46bps (Germany) to 86bps (Italy) and HY bonds ranging from 271bps (Germany) to 419bps (UK). The credit spreads in Japan are notably lower than other countries, with 18bps, 29bps, 42bps for AA+, A and BAA-rated bonds. In contrast, Canada has relatively high credit spreads, with 161bps, 161bps, 225bps and 403bps for AA+, A, BAA, and HY bonds, respectively.

[3] This adjustment leads to removal of one firm (Areva S.A.) and downgrading for five firms (Engie S.A., ENBW Energie Baden, Deutsche Telekom, Thales, Deutsche Post A.G.).

[4] We use German Bund yields for risk-free rates in all Euro-area countries.

[5] We use TOPIX for Japan, FTSE100 Index for UK, DAX for Germany, Paris CAC40 Index for France, FTSE MIB Index for Italy and Toronto Stock Exchange Composite Index for Canada.

Years to maturity vary across countries as well. The UK and Canada have long maturity bonds, ranging from 7.2 years (UK AA+ bonds) to 16.6 years (Canada A bonds) for IG bonds. In contrast, Germany has the shortest maturity on average, with 3.8 years for AA+ bonds and 4.7 years for BAA bonds.

Regarding the issue size (face value of bonds), Canada has the smallest average issue size, ranging from 93 to 215 million US dollars, while European countries have large average issue size.

Table 2 shows the average number of bond issues per month as well as the average number of bonds per issuer. Regarding the number of bonds, Japan is the largest country in our sample, though we only observe IG bonds. France has the second largest number of issues per month, followed by Canada and UK.

Regarding the concentration of issuers, IG bonds in Japan and Canada are dominated by large issuers: the average number of bonds per issuer ranges from 5.4 to 13.5 in Japan, and from 4.4 to 12.9 issues in Canada. The average number of bonds per issuer is lower in other countries, with Germany being the lowest (1.8, 4.2 and 3.0 bonds per issuer for AA+, A, BAA firms, respectively).

In order to ensure that our sample selection process and data quality are sound, in Appendix A, we follow Collin-Dufresne, Goldstein and Martin (2001) and run regressions of monthly changes in credit spreads on issuers' stock returns, changes in volatility, the level and slope in risk free rates, stock market indices and skewness. In summary, we find the estimation results similar to the one in the US; for example, monthly stock returns both at the security and index level are significantly negatively related to credit spread changes, while stock volatility is positively related to credit spreads. However, the regression R-squared is generally low, ranging from 0.06 in Japan to 0.31 in Italy. This regression exercise underscores the reliability of our bond-stock matched sample.

3 Structural Credit Risk Models

In this study, we consider two well-known structural models of corporate debt pricing, those of Merton (1974) and Black and Cox (1976). We focus on the latter in this section given the recent literature on the credit spread puzzle (see, e.g., Bao 2009; Huang and Huang 2012; Feldhütter and Schaefer 2018). In particular, while Bao (2009) finds that the Black-Cox model underestimates the US corporate credit spreads, Feldhütter and Schaefer (2018) report that the model performs well in matching the US spreads. Therefore, it is an interesting out-of-sample test to use the same model against the corporate credit spreads in non-US debt markets. We present the analysis of the Merton (1974) model in Appendix D.

Below we review the Black and Cox (1976) model and describe the procedure to estimate the model parameters. We then evaluate the model-implied credit spreads by comparing them with the data.

3.1 The Black-Cox Model

The Black-Cox (1976) model provides a framework to price a corporate bond that can default before maturity due to covenant violation. The idea is, if the firm value falls enough relative to the face value of debt, firms may default even before the maturity of the debt. The firm value threshold at which firms choose to default is called default boundary.

Let us fix the loss given default (face value lost upon default) to be R, then the credit spread is given by

$$s = -\frac{1}{T-t}\log[1-(1-R)\pi^Q(T-t)] \tag{1}$$

where $T-t$ is time to maturity and $\pi^Q(T-t)$ is risk-neutral default probability.

We follow Bao (2009) in computing the Black-Cox model-implied risk-neutral probability of default as:

$$\begin{aligned}\pi^Q(T-t) &= N\left[-\left(\frac{-\log(dK/A_t)+(r-\delta-0.5(\sigma^A)^2)(T-t)}{\sigma^A\sqrt{T-t}}\right)\right] \\ &+ \exp\left(\frac{2\log(dK/A_t)(r-\delta-0.5(\sigma^A)^2)}{(\sigma^A)^2}\right) N\left[\left(\frac{\log(dK/A_t)+(r-\delta-0.5(\sigma^A)^2)(T-t)}{\sigma^A\sqrt{T-t}}\right)\right]\end{aligned} \tag{2}$$

where $N[\cdot]$ is the cumulative standard normal density function, d is default boundary, K/A is leverage, r is risk-free rate, δ is payout rate, and σ^A is asset volatility.

We obtain all parameters except d from the data, and then set d to match the model-implied probability of default under the $\mathbb{P}$-measure to historical default frequency.

3.2 Parameters and Inputs

In this section, we describe our methodology to estimate the parameters of the model. We estimate asset volatility (σ^A), leverage (K/A_t) and the payout rate (δ) at the firm level. For the Sharpe ratio, recovery rate and probability of default, we use the fixed values across firms.

3.2.1 Firm-Level Inputs

Following Schaefer and Strebulaev (2007), we estimate asset volatility as

$$\sigma^A_{i,t} = \sqrt{(1 - L_{i,t})^2 \sigma^E_{i,t} + L^2_{i,t}\sigma^D_{i,t} + (1 - L_{i,t})L_{i,t}\sigma^E_{i,t}\sigma^D_{i,t}\rho^{ED}} \tag{3}$$

where $L_{i,t}$ is leverage, $\sigma^E_{i,t}$ is equity volatility, $\sigma^D_{i,t}$ is debt volatility and ρ^{ED} is correlation across debt and stock returns.

We estimate $\sigma^E_{i,t}$ using daily stock returns with 1-year rolling window. Estimating debt volatility and correlation is more challenging. To strike a balance between accuracy and transparency, we take the following steps: First, we compute constant volatility for each bond using monthly returns. Second, we take simple average across bonds within each rating category for each country to compute the average debt volatility. Third, we assign the same debt volatility for bonds in each rating/country bin. For correlation, we repeat the similar steps by computing correlation using monthly stock and bond returns for each bond, then take average for each rating and in each country.

After computing asset volatility for all firms every month, we take average over time to obtain the constant asset volatility.

We compute leverage as the ratio of book value of debt to the value of asset, defined as the sum of book value of debt and market value of equity. Payout ratio is the ratio of payment to outside stakeholders (dividend payment, share repurchases and net interest payment) over the past one year divided by the asset value. For firms with extremely high payout ratio (more than three times the median payout ratio in each country), we set the payout ratio to be three times the median payout ratio.

Table 3 presents the summary statistics of the firm-level inputs to the model. Leverage varies substantially across countries for highly-rated firms. For the higher end of the distribution, AA+ firms in Japan have average leverage of 0.44, and AA+ firms in Canada have average leverage of 0.40. The leverage of these firms is considerably higher than the one in the UK (0.19) or Italy (0.26). For comparison, Feldhütter and Schaefer (2018) report that the average AA firm in the US has leverage of 0.14, even lower than the value in the UK.

For speculative-grade firms, the average leverage ranges from 0.39 (Canada) to 0.61 (Italy), which is somewhat closer to the ones in the US (0.46 for BB and 0.52 for B).

The high leverage of highly-rated firms, especially in Japan and Germany can be explained by lower level of business risk for those firms. For example, asset volatility in Japan is 15% (per year) for AA+ firms, and 17% for A firms, which are lower than those for US firms (23% for AA firms, 24% for A firms). In Canada, asset volatility is 13% for AA+ firms and 20% for A firms.

The payout ratio in these six countries are generally lower than the ones in the US, with Japan being the lowest (ranging from 0.5% to 0.9% depending on credit rating) and Italy being the highest (ranging from 4.7% to 6.7%). All else equal, a higher value of payout ratio pushes down the growth of asset value, and thus increases the probability of default of the issuer both under the $\mathbb{P}$- and risk-neutral ($\mathbb{Q}$-) measures.

3.2.2 Country-Level Inputs

In order to match model's prediction for the $\mathbb{P}$-measure default probability to historical default frequency, we estimate the Sharpe ratio of asset for each country. As we work on bond-level data to evaluate the structural model, we need the Sharpe ratio of individual firms rather than that of the aggregate market. Chen, Collin-Dufresne and Goldstein (2009) and Feldhütter and Schaefer (2018) use a constant value of the Sharpe ratio for the US firms. Thus, we also use constant value of the Sharpe ratio estimated separately for each country. Specifically, using all Compustat firms from 1987 to 2017, we compute average annual returns and average volatility for each stock. We then compute the Sharpe ratio for each stock, and take median value in each country for the country-level Sharpe ratio.

Panel A of Table 4 presents the estimated Sharpe ratios for each country. The median values using all firms shown in Panal A1 are 0.19 for Japan, 0.28 for UK, 0.22 for Germany, 0.28 for France, 0.17 for Italy and 0.23 for Canada. The estimates using a smaller sample of firms that are matched to our bond data sets are presented in Panel A2. The median values are generally similar to the estimates using all firms, and thus we use the Sharpe ratio for all firms in this paper.

With the estimated Sharpe ratio θ, we compute the drift of firm's asset value by

$$\mu_{i,t} = r_t + \theta \sigma_i^A.$$

By replacing risk-free rate in (2) with $\mu_{i,t}$, we compute the model-implied probability of default under the $\mathbb{P}$-measure.

The recovery rate, the fraction of firm's asset which investors recover upon default, is often assumed to be constant across countries, and the previous literature (e.g. Huang and Huang (2012) and Feldhütter and Schaefer (2018)) relies on Moody's estiamte for recovery rate at the global level (including both US and non-US bonds) in analysing US corporate bond prices. Such assumption is justified as long as bankruptcy laws and the definition of seniority and collateral security are common across countries.

In practice, bankruptcy laws and covenants may differ across countries, leading to a potential difference in recovery rates across countries. We investigate this possibility using the recovery data for each default case since 1983 when Moody's recovery data starts. However, we find that, though Moody's data covers default events across countries, recovery rate is mostly missing in countries outside the US, Canada and the UK, possibly reflecting the lack of active distress debt market outside these three countries. Thus, we aggregate all six countries (Japan, the UK, Germany, France, Italy and Canada) in computing average international recovery rate, and compare them against the values in the US.

The average recovery rate for senior unsecured debt is estimated at 37.3% for the six countries, which is very close to the US average of 38.0% in the sample period. The difference across countries is negligible compared with the relatively large countercyclical variation in recovery over time (Chen (2010)). Thus, we use the five-year moving average recovery rate (shown in Figure 2) at the global level to price corporate bonds in non-US markets.

In estimating the structural model of debt, we match the probability of default under the $\mathbb{P}$-measure to historical default frequency. The previous research in the literature (e.g. Huang and Huang (2012) and Feldhütter and Schaefer (2018)) uses Moody's probability of default estimated at the global level. If Moody's credit rating standard is consistent across countries, this choice is justified as we measure the probability of default *given* credit rating.

To verify the consistency, we compute the cumulative default probabilities using Moody's event-level default data separately for US firms and non-US firms in the six countries that we study. Table 5 shows that the cumulative default frequency given credit ratings are similar between US and other six countries. Thus, we use the historical default probability at the global level. Since credit spreads in Japan are lower than other countries, we also compute the default probabilities only for Japanese firms. For Aaa and Aa-rated Japanese firms, there is no default in the data, reflecting the smaller sample. For A- and Baa-rated firms, the 10-year cumulative default probability in Japan is 0.89% and 2.75%, not statistically significantly different from the estimates in other countries (2.66% and 2.38%, respectively).

Regarding the sample period, Feldhütter and Schaefer (2018) emphasize the importance of using the longer history of default data. We follow their approach and use the global default frequency from 1920 to 2017.[6]

3.2.3 Default Boundary

Following Feldhütter and Schaefer (2018), we back out the values for default boundary by minimizing the distance between Moody's default probability and the Black-Cox model prediction at the rating and maturity bin level.

$$d = \text{argmin} \sum_{T=1}^{20} \sum_{R=Aa+}^{HY} |\pi_{T,R}^{Model}(d) - \pi_{T,R}^{Moody's}(d)| \tag{4}$$

where $\pi_{T,R}(d)$ is the probability of default for T-year bonds with rating R under the $\mathbb{P}$-measure.

To maximize the sample size, we use all nonfinancial bond issuers, regardless of whether these bonds are senior, unsecured non-callable bonds or not. We also assume that all firms have debt maturing from 1 to 20 years regardless of actual maturity of the bond issued by these firms.

Table A3 in Appendix B presents the summary statistics of inputs of all nonfinancial firms in the bond data that we use to evaluate the $\mathbb{P}$-measure default probability. The tables show that firms' characteristics are similar to the smaller sample of noncallable bond issuers in Table 3.

As Bai, Goldstein, and Yang (2018) argue, even with 100 years of data, precisely estimating default probability is difficult since default occurs infrequently. To strike balance between robustness and flexibility, for our main results, we hold default boundary constant at the country level. Given the finding of Feldhütter and Schaefer (2018), this procedure presumably gives the best chance for the model to match credit spreads in the data.

In order to quantify the estimation errors in historical default boundary, in principle we need a micro-level data of default dating back to 1920. Since Moody's Default and Recovery Database covers the default since 1970, the micro-level data is not available to us. Thus, we follow Feldhütter and Schaefer (2018) and use simulation-based methods to compute confidence intervals for historical default frequency.[7]

[6] The micro-level data is available after 1970, but Moody's publishes the historical default frequencies at the aggregate global level averaged since 1920.

[7] For each country, we select a cohort of identical firms which start their history with values of leverage, payout, and asset volatility in Table A3. For this simulation, we choose d so that simulation mean probability of default matches the historical default frequency for each rating and maturity. Here, the goal is to quantify the uncertainty around historical default frequency, not to evaluate the Black-Cox model. The size of the

Panel B of Table 4 presents the estimated default boundary for each country. The boundary ranges from 0.74 (Italy) to 1.13 (UK). The fact that some countries have the optimal boundary above 1 implies that our measure of market leverage is only a proxy for true leverage. If we use true leverage, there is no reason for a firm to default when firms' asset value is above the face value of debt. However, since we add market value of equity and book value of debt to measure the market value of asset, our measure of leverage is an approximation to true leverage. As a result, optimal default boundary can be above 1.

We also acknowledge that firms in each country may choose to default under different conditions. For example, firms with higher operating leverage are more likely to default than low operating leverage firms, even if the financial leverage is the same.[8] As firms in each country has different types of non-debt liability, we account for such heterogeneity arising from different legal and business environment by letting d vary across countries. Ultimately, what matters for our test of structural models is that we match the model-based $\mathbb{P}$-measure default probability to the historical data.

Figure 3 compares the Moody's historical default frequency with the Black-Cox implied default probability under the $\mathbb{P}$-measure with the optimal default boundary for each country. Though the resulting match between the model and the Black-Cox varies across countries, we make following observations: The confidence band at the long horizon is large even with 98 years of data, especially for IG bonds. Thus, except for HY bonds in Germany, the model-implied probability of default in 20 years is within the confidence band. For short to medium horizon, the Black-Cox model often overstates the probability of default, which is particularly pronounced in A-rated bonds in UK and France.

Later on, we explore alternative specifications for default boundary. First, we explore heterogeneous default boundaries between IG and HY firms. Table 4 presents the optimal

cohort is the same as the number of firms in each rating category.

We then simulate shocks to firms asset value for 20 years at the weekly frequency by

$$\frac{dA_{i,t}}{A_{i,t}} = (\mu_i - \delta_{i,t})dt + \sigma_i^A dW_{i,t} \tag{5}$$

$$dW_{i,t} = \sqrt{\rho}dW_{s,t} + \sqrt{1-\rho}dW_{i,t} \tag{6}$$

and record firms which touch the default threshold (d times leverage) for the first time. Following Feldhütter and Schaefer (2018), we use correlation coefficient of $\rho = 0.20$. The number of firms that default in year y as a fraction of remaining firms in the cohort gives an estimate for a hazard rate for the cohort in y-th year.

We repeat the exercise for cohort 1 to 78 (98 years of historical default data minus 20 years of estimation horizon), allowing one time-series of systematic shocks to affect multiple (adjacent) cohorts. Finally, we compute average hazard rate across cohorts, and use it to compute the cumulative probability of default for maturity 1 to 20 years. We repeat this process 1,000 times to create the 95 percent confidence interval.

[8] We thank Bob Goldstein for pointing it out.

default boundary for IG and HY separately, and compare them against the homogeneous d. For most countries, the optimal boundary is higher for HY firms than IG firms. For IG firms, the default boundary ranges from 0.66 (Italy) to 1.12 (UK), while for HY firms, d is from 0.76 (Italy) for 1.22 (Germany). The fit of the $\mathbb{P}$-measure default probabilities with heterogeneous default boundary are shown in Figure 4. Our findings are consistent with Bai, Goldstein, and Yang (2018), who find that holding default boundary constant across ratings leads to the probability of default on IG firms that is too high (and too low for HY firms).

Second, we let the default boundary change every year by solving (4) every year (but held constant across credit ratings). We confirm that the performance to match the $\mathbb{P}$-measure default probability is similar to the main results with fixed d.

Third, we let the default boundary change across credit ratings as well as maturities, but hold it constant across countries. In Appendix C, we provide the details of this exercise, and confirm that our main results are largely unchanged with more heterogeneous values of d.

3.3 Empirical Results

3.3.1 Constant Default Boundary

In this section, we present the Black-Cox model-based credit spreads in (1) and compare them with the data.

To start with, we evaluate whether the model can generate credit spreads *on average* close to the average credit spreads, aggregated at the rating/maturity category-level and averaged over time. To this end, every month, we form portfolio of bonds based on credit rating and maturity in each country, and compute equal-weighted average credit spreads using data and the model outputs separately. Then we take average over time, and compare the average spreads in the data to the model. By computing the model-implied credit spreads first at the security level, we address the concern about the convexity bias pointed out by David (2008) and Bhamra et al. (2010).

Table 6 presents the average credit spreads from the data and the model. Though we look at six different countries, there is an important similarity in the performance of the Black-Cox model across countries. First, the Black-Cox model does a reasonable job in pricing high-yield bonds. In fact, for the sample of bonds with all maturities, the Black-Cox model sometimes overpredicts credit spreads – for example, in France, the model predicts 596 bps against the data in 295 bps. For other countries, the model explains more than half of the credit spreads in the data; in the UK, the model predicts 280 bps against 419 bps in the data, in Germany, the model predicts 143 bps against 271 bps in the data. In Japan, relatively high-yield bonds (BAA-rated) have 42 bps in the data, and the model explains a respectable share of 36 bps.

In contrast to the better results for HY bonds, the Black-Cox model does not seem to produce credit spreads large enough for IG bonds. For highly-rated (AA+) bonds, the model prediction is way lower than the data except for France. The Black-Cox model-implied spreads for AA+ bonds are 9 bps, 7 bps, 3 bps, 3 bps and 53 bps for Japan, the UK, Germany, Italy and Canada, respectively. The AA+ credit spreads in data are much higher than the model prediction: 18 bps in Japan, 80 bps in the UK, 46 bps in Germany, 86 bps in Italy and 161 bps in Canada. These results are in line with the finding of Huang and Huang (2012), in that structural models of debt have more trouble pricing highly-rated bonds than those with a low credit rating.

The only exception seems to be France, where the model overpredicts A and BAA credit spreads. Why are France IG bonds different from other countries? Figure 3 provides an answer to this question. The optimal value for default boundary, which is held constant across rating, is as high as 1.13 in France. As a result, the Black-Cox model produces the $\mathbb{P}$-measure default probability higher than the data, especially for A and BAA firms with short- and medium-term bonds. A part of the overestimation comes from the default boundary fixed constant across ratings. As we show later, with default boundary estimated separately for IG and HY firms, the model-implied credit spreads for French IG bonds become lower. Therefore, the high level of credit spreads in France does not reflect the good performance of the model. Rather, it reflects the model's inability to fit the probability of default under the $\mathbb{P}$-measure.

Feldhütter and Schaefer (2018) report that the Black-Cox model works well for the US corporate credit spreads. We follow closely Feldhütter and Schaefer (2018)'s methodology to estimate the model for our sample of international bonds. We also use the same data source (Merrill Lynch data for bonds and Compustat for balance sheet) as they use. Thus, it is important to understand where the apparent difference in the performance of the model comes from.

To better understand the different performance for *average* credit spreads, we compute the distribution of credit spreads using the panel data, separately for the model and the data. For this exercise, we follow Feldhütter and Schaefer (2018) and fit the Black-Cox model to US data as well. Table 7 shows the distribution of BAA bonds for the six countries and the US. The pattern in distribution for other ratings are similar to BAA, and is available upon request.

Table 7 shows that the distribution of the Black-Cox model-implied spreads is severely skewed to the right for all countries, while the credit spreads in data are less skewed. As a result, the average over the panel data depends heavily on the extreme observation in the right tail. For example, in France, the 99-percentile model prediction is 1,692 bps, much higher than 581 bps in the data. The table also reports the model inputs that correspond to the model-implied credit spread in each percentile. The French firm in the 99-percentile has leverage of 0.75, much higher than the mean of 0.39. This extreme observation increases the mean, leading to the average model-based spreads of 174 bps, which is higher than the data (146 bps). On the other hand, the median model-based credit spreads is only 41 bps, less than half of the the median spreads in the data (116 bps).

We observe the same pattern in the mean and median spreads in US. For the US, the average model and empirical spreads are close to each other, but the gap is wider for median. The smaller mispricing for average spreads come from large model-based spreads at the 95- and 99-percentiles. Though the impact of the right tail of the distribution varies somewhat across countries, the underprediction of the model is more pronounced for median values than averages for all seven countries. Thus, our findings in the six countries are consistent with the evidence in the US.

To examine the security-level performance of the Black-Cox model directly, we compute absolute pricing errors at the security level,

$$\begin{aligned} \epsilon_{k,t} &= |s_{k,t} - s_{k,t}^{BC}| \\ \epsilon_{k,t}^{p} &= \frac{|s_{k,t} - s_{k,t}^{BC}|}{s_{k,t}} \end{aligned} \tag{7}$$

and then average over bonds and time to obtain the security-level errors.

Table 8 presents the average security-level pricing errors for each country and each rating/maturity category. The Black-Cox model performs poorly at the security level. For IG bonds, the pricing errors are as large as around 100% for most countries. It is notable that Japan and France, in which the average pricing errors are relatively small at the portfolio level, have as large security-level pricing errors as other countries. In France, the pricing errors for A and BAA bonds are more than 100%, implying that the Black-Cox model severely overpredicts credit spreads for some bonds, while it underpredicts for other bonds such that average errors look small despite large security-level errors. For high-yield bonds, the percentage pricing errors are smaller, ranging from 55% of the credit spreads in the data in the UK to 167% in France.

3.3.2 Heterogeneous Default Boundary

Table 6 also presents the model performance when d is different between IG and HY. Except for Japan, we see changes in model performance. For HY bonds, the model *overpredicts* credit spreads in France and Canada, while for IG bonds, the model produces credit spreads that are significantly lower than the data. This is because with heterogeneous d, the model assigns higher level of default boundary for HY firms than IG firms, and thus the model-implied credit spreads for IG bonds become even lower. For the credit spreads in France, with heterogeneous d, the model generates 79 bps for A-rated bonds and 109 bps for BAA bonds, which are slightly lower than the data (84 bps for A bonds and 133 bps for BAA bonds).

Table 8 presents the security-level pricing errors using heterogeneous d. The security-level pricing errors are as large as the results with homogeneous default boundary. Therefore, our main results with constant d in each country is robust to a change in the model calibration method.

3.3.3 Time-Varying Default Boundary

To allow the possibility of default boundary changing over time, we use five-year moving average default boundary to generate model-based credit spreads as an additional robustness check. Table 8 confirms that allowing d to vary over time does not significantly affect the security-level pricing errors.

3.4 CDS Spreads

Bai and Collin-Dufresne (2013) show that CDS-Bond basis can be negative, implying that CDS spreads can be lower than corporate bond credit spreads depending on the market condition. Therefore, even though the Black-Cox model underpredicts corporate credit spreads, it may fit CDS spreads well. If CDS spreads are less affected by liquidity premiums (Longstaff et al. (2005)) and reflect the issuer's credit risk more accurately, the structural model of debt may perform better in pricing CDS than corporate bonds.

Furthermore, by studying CDS spreads, we can largely circumvent the issue of the choice of risk-free rate. In the previous section, we compute corporate credit spreads by taking the difference between corporate bond yield and government bond yield in each economy. Using government bond yield as a benchmark risk-free asset may raise a concern due to the convenience yield associated with these bonds. However, using swap rate as a benchmark is at least as equally problematic since interbank rates contain significant default risk premiums. (In Appendix E, we show our main results are qualitatively similar when using swap rates as proxies for risk-free rates.) In contrast to corporate credit spreads, CDS spreads are directly observable measures for insurance premiums for default events, and thus the results are less sensitive to the choice of risk-free rates.

We fit the Black-Cox model to month-end single-name CDS spreads in each country. Following Bai et al. (2018), we compute the model-based CDS spreads as follows:

$$CDS(T) = \frac{4(1-R)\sum_{i=1}^{4T} DF(\frac{t_{i-1}+t_i}{2})[\pi^Q(t_i) - \pi^Q(t_{i-1})]}{\sum_{i=1}^{4T} DF(t_i)(1-\pi^Q(t_i)) + \frac{1}{2}\sum_{i=1}^{4T} DF(\frac{t_{i-1}+t_i}{2})[\pi^Q(t_i) - \pi^Q(t_{i-1})]}$$

where $\pi^Q(\cdot)$ is Black-Cox model-based $\mathbb{Q}$-measure default probability in (2) and $DF(t) = e^{-rt}$.

In computing model prediction, we use the same values of default boundary as the corporate bonds, as default boundary is calibrated to the $\mathbb{P}$-measure default probability which does not depend on asset prices.

Table 9 presents the average CDS spreads in the data for each country, rating and maturity bin. The table shows the CDS spreads are on average lower than corporate credit spreads for all countries except Japan.

Table 9 also shows the prediction of the Black-Cox model averaged across firms for each country and each rating/maturity bin. For IG issuers, CDS spreads are notably higher than the prediction of the Black-Cox model for all markets other than A and BAA firms in France. In Japan, CDS spreads are on average higher than corporate credit spreads, leading to the wider gap between the data and the model prediction than between the corporate credit spreads and the model.

For HY issuers, the Black-Cox model performs quite well in matching CDS spreads. The model overpredicts HY CDS spreads for the UK and France, while it matches the data well in Italy and Canada. The Black-Cox model underpredicts HY spreads for Japan and Germany, but still generates a non-trivial fraction of the observed credit spreads.

CDS spreads also present a clear pattern in the term structure of credit spreads. For all countries and rating, CDS spreads are on average increasing in maturity. The Black-Cox model also generates upward sloping term structures of credit spreads for IG firms. However, the Black-Cox implied CDS curve tends to be steeper than the data. As a result, the Black-Cox model underestimates CDS spreads for short-term IG debt than long-term IG debt. For HY firms, the Black-Cox model generates downward sloping term structures for the UK, France and Canada, which contradicts the upward sloping curve in the data. The underprediction of the short-term IG credit spreads is not surprising. Since the Black-Cox model does not include a jump in firm's asset value process, the magnitude of risk scales with bond's maturity, and thus the model will have more trouble matching short-term credit spreads than long-term spreads.

The analysis on CDS spreads confirms the findings in the corporate bond market that the Black-Cox model underestimates credit spreads for issuers with low default risk, especially for short-term debt.

4 Liquidity, Factor Analysis and the Link with Macroeconomy

The previous section shows that the Black-Cox model does not match the observed credit spreads in the six countries well. But does this fitting error reflect pure white noise/measurement errors in the data, or is there a systematic pattern in errors which the model fails to capture? We address these questions in this section.

4.1 Principal Component Analysis

To better understand the nature of the pricing errors of the Black-Cox model, we conduct a principal component analysis on the credit spreads and pricing errors. If the Black-Cox model captures the systematic factors driving credit spreads, the pricing errors will be closer to independent white noise with a weaker factor structure than credit spreads themselves. To understand the global comovement in credit spreads and pricing errors, we include US sample in the analysis as well.[9]

To conduct factor analysis, we compute median credit spreads and pricing errors for each country, including US. We use subscript c to denote the country-level variable.

Figure 5 plots the median credit spreads and the Black-Cox model-implied credit spreads for each country. The four European countries share common variation in credit spreads, which peaks during the financial crisis in 2008 and the sovereign debt crisis in 2012. On the other hand, the credit spreads in Japan are lower and relatively stable after the Asian

[9] To this end, we follow Feldhütter and Schaefer (2018) and fit the Black-Cox model to US bonds from 1997 to 2017, and compute fitting errors for each bond.

financial crisis in 1998. In Canada, the credit spreads increase shortly after the economy recovers from the financial crisis, in line with the fall in commodity prices during the period.

Figure 5 also shows the median model-implied credit spreads. Consistent with the skewed distribution in Table 7, model-implied spreads tend to be volatile, and spike up and down more quickly than credit spreads do.

We extract the first principal component from the standardized credit spreads and pricing errors, and compute its variance as well as the share of total variance explained by the first principal component. We use standardized series to avoid overweighting the country with high credit spread volatility.

Table 10 presents the variance of the first principal components of credit spreads in the seven countries, $s_{c,t}$, and pricing errors of the Black-Cox model, $s_{c,t} - s_{c,t}^{BC}$. Before fitting the model, the first principal component of credit spreads has variance of 6.09 which explains 80.9% of the total credit spread variation, suggesting that the country-level credit spread has a strong factor structure.

To understand the factor structure better, we run a univariate regression of the country-level credit spreads on the first principal component, and report the R-squared in Table 10. The results show that much of the variation in the UK, Germany, France and US is captured by the first principal component, while Japan and Canada have larger shares of idiosyncratic variance.

Next, we analyse the principal component from the country-level pricing errors, $s_{c,t} - s_{c,t}^{BC}$. The variance of the first principal component is estimated at 5.60, which does not differ much from the principal component of the credit spreads. An even more striking fact is that the first principal component still explains 73.1% of pricing errors, suggesting that the Black-Cox model does little in capturing the systematic variation in country-level credit spreads.

To put this number in perspective, Longstaff et al. (2011) emphasize that a single principal component accounts for 64% of comovement in sovereign CDS markets, while Collin-Dufresne et al. (2001) argue that the US credit spreads are subject to local supply/demand shocks because the first principal component captures 75% of the common variation. Since we have smaller cross-section of credit spreads than the previous two studies, one might expect an even stronger factor structure. However, we emphasize that the ratio of pricing error variance explained by the first principal component is high *relative to* the ratio for the credit spreads. These results are interesting because the inputs to the Black-Cox model, such as leverage and equity volatility, are determined by stock prices and thus correlated across countries. Therefore, should the model properly incorporate the important systematic shocks, the deviation from the model would be more idiosyncratic than in the raw data.

Figure 6 plots these country-specific pricing errors, the first principal component, and excess bond premiums of Gilchrist and Zakrajšek (2012), which is the pricing errors of US corporate bonds against the Merton model. The first principal component comoves with the US mispricing factor and excess bond premiums, with estimated correlation coefficient of 0.90 and 0.65, respectively. This high correlation is not mechanical for two reasons: First, we focus on domestic issuers in each country. Second, in forming the principal component, we put equal weight in each country by standardizing the country-level mispricing. Rather, it is an empirical finding that, despite different fundamentals, credit spreads comove across countries and with US, which goes beyond what is predicted from the comovement in stock prices, volatility, and leverage.

4.2 Pricing Errors and Macroeconomy

Another way to evaluate the economic significance of the pricing errors of the Black-Cox model is to study the link between the predicted/unpredicted components of credit spreads and economic growth in the future. If pricing errors carry systematic information about economic conditions, they would predict economic growth. For the Merton model, Gilchrist and Zakrajšek (2012) find that the pricing errors in US corporate bonds carry significant predictive power for the US economy, while Gilchrist and Mojon (2018) confirm the similar finding in Euro-area countries. As we use a different model and countries (Japan, Canada and the UK) than the previous study, it is interesting to see whether pricing errors predict economic growth or not.

To understand the link between fitting errors and economic growth, we combine the country-level data and run the following panel regressions of economic growth on a component of country c credit spread $x_{c,t}$,

$$\Delta_h Y_{c,t+h} = \alpha + \sum_{i=1}^{p} \beta_i \Delta Y_{c,t-i} + \gamma x_{c,t} + Controls_{c,t} + \varepsilon_{c,t+h}, \tag{8}$$

$$c = \{\text{Japan,UK,Germany,France,Italy,Canada}\} \text{ and } t = 1, \ldots, T$$

where Δ_h is the "h-period" lag operator, and the number of lags p is determined by the Akaike Information Criterion. For left-hand side variables, we follow Gilchrist and Zakrajšek (2012) and use real GDP growth rate in local currency, changes in unemployment rate and growth rate in industrial productions in each country to measure economic growth over the three- and twelve-month horizon ($h = 3, 12$). Our control variables are 1-year real risk-free rate, the difference between 10- and 1-year risk-free rate in each country, and country fixed effects. To avoid mechanically generating similar results to the previous study by Gilchrist and Zakrajšek (2012), the left-hand side variables are for the six countries excluding the US.

For regressor $x_{c,t}$, we use the median pricing errors of the Black-Cox model for each country, $s_{c,t} - s^{BC}_{c,t}$, the median prediction of the Black-Cox model, $s^{BC}_{c,t}$, as well as the first principal component of the pricing errors, PC_t. We use monthly (industrial production) or quarterly (unemployment rate and GDP growth rate) overlapping data, and thus standard errors are adjusted for both serial correlation and cross-sectional correlation.

Table 11 presents the estimated slope coefficients on pricing errors and model-predicted credit spreads as well as adjusted R-squared. For all specification, an increase in corporate bond mispricing predicts negative growth in economy. For example, a one-percentage point rise in mispricing predicts a 0.59 percentage point rise in unemployment rate, a 2.97 percent fall in industrial production, and a 1.69 percent drop in GDP growth rate over the next one year. Including control variables, adjusted R-squared ranges from 0.11 (industrial production) to 0.27 (unemployment rate) over the three-month horizon, and from 0.19 (industrial production) to 0.25 (GDP growth rate) for the one-year horizon.

The Black-Cox model-implied credit spreads also predict a contraction of the economies. However, the regression R-squared are somewhat lower than the regressions that use mispricing as a predictor in all specifications. When we use both mispricing $s_{c,t} - s^{BC}_{c,t}$ and the model-implied spreads $s^{BC}_{c,t}$ in multivariate regressions, the point estimates are greater in magnitude for mispricing than for the model-implied spreads, and the adjusted R-squares are mostly unchanged from the univariate regression using the mispricing only. These results show that the country-level pricing errors are strongly associated with the economic growth of *the* country.

Next, we repeat the exercise using the first principal component in pricing errors, or the global credit mispricing factor. In this regression, even though the left-hand side variables differ across countries, the right-hand side variables are common across countries. Table 11 shows that the first principal component extracted from the median pricing errors in the seven countries predicts economic growth negatively, regardless of the regression specification. Moreover, this global credit mispricing factor predicts economic growth just as well as the country-specific indices do. In many cases, the adjusted R-squared is higher than the regressions which use both country-specific mispricing and the Black-Cox model-based credit spreads. Therefore, the systematic factor that drives credit spreads across countries is strongly tied to economic growth in each country.

The negative correlation between the first principal component and global business cycle is not just a reflection of the global financial crisis in 2008, an unusual event in our relatively short sample period. We repeat the macroeconomic forecasting regressions in (8) excluding the observations in 2008 and 2009. We find that the estimated slope coefficients on PC_t, the associated t-statistics and regression R-squared are about unchanged from the main results for 12-month horizon. However, the forecasting results on PC_t over the 3-month horizon becomes weaker, with adjusted R-squared going down to 0.23, 0.05 and 0.11 for unemployment rate change, industrial production and GDP growth rate, respectively.

Overall, the evidence in this section suggests that the gap between corporate credit spreads and the prediction of the Black-Cox model carries important information for business cycle rather than simple measurement errors in the bond price data. Though the Black-Cox model also captures a part of business cycle signals, the significant fraction of the information in credit spreads is missed by the model, leading to the predictability of economic growth based on mispricing. Moreover, much of the economic predictability is driven by the global credit mispricing factor, or the first principal component of the country-level pricing errors.

4.3 Understanding Pricing Errors and Liquidity

In order to understand the source of mispricing, we attribute pricing errors of the Black-Cox models to security-level characteristics, global factors and liquidity measures. Specifically, we run a panel regression of pricing errors on a set of variables that are likely to be associated with errors, and explore why the Black Cox model does not work in our sample.

4.3.1 Security-Level Analysis

To begin the analysis, we consider the possibility of the model misspecification. If this is the case, the difference between the observed credit spreads and the model prediction is correlated with the inputs to the model. Thus, we use maturity, stock volatility, leverage, risk-free rates, and face value of the bonds as explanatory variables for mispricing.

With various characteristics of bonds, we analyse the source of pricing errors by running a panel regression of security-level pricing errors:

$$s_{k,c,t} - s_{k,c,t}^{BC} = b_0 + b_1 X_{k,c,t} + D_c + \xi_{k,c,t} \tag{9}$$

where D_c is the dummy variable for country c. In computing standard errors, we correct for cross-sectional correlation in the error term, and for serial correlation up to Newey-West 12 month lags.

Table 12 shows the estimated slope coefficients in (9) and adjusted R-squared. Since pricing errors are positive on average, negative slope coefficients show that an increase in the explanatory variable reduces pricing errors. We find that leverage is negatively associated with pricing errors, reflecting the fact that firms with low leverage and better credit quality have a more pronounced gap between data and the model. In addition, issue size is negatively related with the pricing error. As large issues are more liquid, these bonds have lower credit spreads than smaller issues.

The regression R-squared for (9) reported in Table 12 is 0.10, which is not very high. Still, the regression does a reasonable job in capturing the comovements in credit spreads. To support this argument, we repeat the principal component analysis in the previous section using the median regression residual $\xi_{c,t}$ in (9). The results in Table 10 show that the first principal component has variance of 3.96, which explains 58.4% of the total variance in $\xi_{c,t}$. Now the fraction of variance captured by the first principal component is much lower than the fraction for credit spreads (81.0%). These results imply that the simple reduced-form regression in (9) captures more common variation in credit spreads than the Black-Cox model does.

4.3.2 Country-Level Analysis

The results in 4.1 and 4.2 show that the country-level bond mispricing has an important systematic component that is correlated with business cycles. To better understand the driver of the country-level price errors, we consider global and liquidity factors that might drive these errors.

For this purpose, we use Goldman Sachs' commodity index (GSCI Commodity Index) and option-based uncertainty measures. Specifically, we use options on each country's stock index and construct the country-specific option-implied volatility and skewness measure following Collin-Dufresne et al. (2001).[10]

We also include proxies for corporate bond liquidity as additional explanatory variables. There is a strand of literature which highlights the importance of large transaction costs

[10] We fit a quadratic function on option implied volatility for one month options by

$$\sigma^{SPX}(m_k) = b_0 + b_1 m_k + b_2 m_k^2 + u_k$$

where m_k is moneyness of option k, and compute the skew by $\hat{\sigma}^{SPX}(0.9) - \hat{\sigma}^{SPX}(1.0)$.

in the US corporate bond market (e.g. Bao, Pan, and Wang 2011). These papers in turn argue that investors demand compensation for holding illiquid securities, which gives rise to illiquidity premiums that structural models of debt fail to capture. Therefore, proxies for illiquidity may be associated with mispricing of the Black-Cox model.

As we do not have transaction data for non-US corporate bonds that we analyse, we can not use proxies for corporate bond illiquidity measures devised for the US market. However, recently, Goldberg and Nozawa (2018) follow Hu et al. (2013) and propose to use yield curve fitting errors ('noise') of corporate bonds as a measure of illiquidity arising from dealer's inventory frictions. The advantage of the noise measure is that we do not need high-frequency transaction data to estimate it. Thus, we construct noise for each country, and use it as a proxy for illiquidity.[11]

In addition, we use TED spreads for each country as an alternative measure of illiquidity, as they capture the information about the funding market conditions for dealers. We use German TED spreads for all Euro-area countries.

With the country- and global-level explanatory variables, we run a panel regression of median mispricing in each country on the explanatory variables:

$$s_{c,t} - s_{c,t}^{BC} = b_0 + b_1 X_{c,t} + D_c + \eta_{c,t} \tag{10}$$

where D_c is the dummy variable for country c.

Panel A of Table 13 presents the estimated slope coefficients and regression R-squared. The estimated slope coefficients show that lower risk-free rate, higher noise and TED spreads, and option-implied volatility is associated with a greater gap between the observed credit

[11] Each month, we use security-level price data in Merrill Lynch[12] and fit the Nelson-Siegel curve for each issuer with more than 7 bonds outstanding, and the Nelson-Siegel-Svensson curve for each issuer with more than 15 bonds outstanding. As we focus on mispricing due to illiquidity, it is important to fit the curve issuer by issuer. Then we compute issuer-level root-mean squared fitting errors as

$$v_{j,t} = \sqrt{\frac{1}{n_j} \sum_k (ytm_{k,j,t} - ytm_{k,j,t}^{NS})^2}$$

and the country-level fitting errors are

$$Noise_{c,t} = \frac{1}{N_t} \sum_j v_{j,t}$$

In estimating illiquidity, we are agnostic about what drives bond fundamental values; instead, we capture mispricing of a corporate bond *relative to other bonds* with similar maturity by fitting a smooth curve. Grishchenko and Huang (2012) construct a similar "noise" measure for the TIPS market.

spreads and the Black-Cox model. This link between pricing errors and illiquidity measure is consistent with the idea of liquidity risk premiums that raise the credit spreads in data but do not affect the Black-Cox model estimates, since the model estimates depend on the stock market and accounting information.

The option-based uncertainty measures are positively related with the corporate bond pricing errors. Since the Black-Cox model assumes constant volatility in asset values, the option-implied volatility does seem to drive a wedge between the data and the model prediction. The link between the uncertainty measure and global credit spreads is consistent with the finding of Culp et al. (2018), who document a strong link between option prices in the US and credit spreads.

The heterogeneity among G7 countries is interesting since Canada is a net exporter of energy, while European countries and Japan are generally net importers. Thus, the commodity price index may have different impact on credit spreads. The loading on the commodity index and the interaction between the commodity index and the dummy variable for Canada in Table 13 supports this conjecture. The loading on the commodity index is significantly positive for countries excluding Canada, but Canadian credit spreads depend negatively on the commodity index. These coefficients suggest that a higher commodity price benefits energy firms in Canada, lowering the credit spreads on those firms. However, a rising commodity price generally hurts importer's economy, ultimately lowering the profitability of the firms in other countries.

The adjusted R-squared of the kitchen-sink regression is as high as 0.81. Though the regression does not tell anything about causality, it still sheds lights on the factors that are associated with the country-level mispricing. In particular, the risk-free yield curves, uncertainty, liquidity proxies and commodity indices explain much of the time-series variation.

Panel B of Table 13 runs monthly cross-sectional (univariate) regression in the spirit of Fama and MacBeth (1973). This regression asks what the key determinants of the difference in mispricing across countries are. We run univariate regressions because there are only seven observations in each month. The estimated coefficients suggest that the level and slope of the government yield curve and illiquidity measures explain the difference in the model performance across countries.

5 Conclusion

In this paper, we study the pricing mechanism of global corporate bond markets outside the US and conduct the out-of-sample test for "the credit spread puzzle" previously documented in the US corporate bond market. Specifically, we empirically examine two well-known models of risky debt pricing, the Merton (1974) and the Black and Cox (1976) models, using a sample of individual corporate bonds issued in the six non-US G7 countries—namely, Japan, UK, Germany, France, Italy and Canada. For each of the two models, we first match the $\mathbb{P}$-measure default probability implied from the model to the historical default frequency. We then test whether the model can generate the $\mathbb{Q}$-measure default probability consistent with the corporate bond price data in each country.

Our empirical findings are largely in line with those documented in Huang and Huang (2012) and Bai et al. (2018) that are based on the US data. For instance, we find that the Black-Cox model often underestimates credit spreads of corporate bonds, especially for highly-rated bonds with short maturity. We also examine CDS spreads that are less likely affected by liquidity premiums. We confirm that our findings are robust, though the magnitude of pricing errors are generally smaller for CDS spreads.

We argue that these pricing errors are unlikely to be a reflection of measurement errors in the data. Instead, they reflect systematic factors missed by the structural model of debt. To support this argument, we show that pricing errors are correlated with illiquidity measures (such as noise, TED spreads and issue size). Furthermore, the fraction of variance explained by the first principal component of pricing errors is as large as the fraction for credit spreads. Finally, we show that pricing errors are negatively associated with economic growth.

To summarize, this paper contributes to the literature by conducting an empirical analysis of structural models based on global corporate bond data and, importantly, by providing out-of-sample evidence for the credit spread puzzle.

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Table 1: Sample Selection

Firm Type	Bond Type	Industry	Count	Japan	UK	Germany	France	Italy	Canada	All
All Bonds			# Bonds	2,824	1,086	1,149	1,054	388	1,774	8,275
in ML Index			# Observations	178,139	79,948	61,576	63,764	21,167	127,403	531,997
Private			# Bonds	1,071	623	777	462	254	997	4,184
Firms			# Observations	52,823	48,066	42,100	29,452	13,106	78,119	263,666
Public			# Bonds	1,753	463	372	592	134	777	4,091
Firms			# Observations	125,316	31,882	19,476	34,312	8,061	49,284	268,331
Within	Noncallable, senior,		# Bonds	1,004	260	246	440	105	358	2,413
Public Firms	unsecured bonds	Nonfinancials	# Bonds	953	199	189	369	105	207	2,022
		Financials	# Bonds	51	61	57	71	0	151	391
	Others		# Bonds	749	203	126	152	29	419	1,678
	Total		# Bonds	1,753	463	372	592	134	777	4,091
Final Sample			# Bonds	953	199	189	369	105	207	2,022
			# Observations	58,007	15,870	9,673	23,440	6,344	16,735	130,069
			# Firms	108	60	47	52	17	48	332

Note: Table presents the sample selection process. The sample is monthly from January 1997 to December 2017.

Table 2: Summary Statistics for Corporate Bond Data

		Bond characteristics by credit ratings							
		AA+	A	BAA	HY	AA+	A	BAA	HY
		Japan				*Germany*			
All	Credit Spreads (bps)	18	29	42	-	46	85	116	271
	Years to Maurity	6.5	5.1	4.1	-	3.8	4.7	4.7	3.7
	Issue Size (USDmil)	347	312	279	-	741	1102	917	831
	Average NObs	94.6	56.8	61.4	-	2.1	15.6	16.2	4.0
	NBonds/Issuer	13.5	7.6	5.4	-	1.8	4.2	3.0	2.4
Short	Credit Spreads (bps)	15	24	39	-	49	82	115	271
	Years to Maurity	3.0	3.0	2.9	-	3.1	3.2	3.0	2.9
	Issue Size (USDmil)	365	325	295	-	725	1127	941	856
	Average NObs	49.1	34.6	43.2	-	1.7	11.0	10.2	3.2
	NBonds/Issuer	12.9	7.0	5.1	-	2.0	4.3	3.0	2.5
Long	Credit Spreads (bps)	20	34	49	-	60	91	126	289
	Years to Maurity	7.6	7.4	6.9	-	6.9	6.8	6.8	6.4
	Issue Size (USDmil)	345	293	234	-	815	1098	912	786
	Average NObs	31.6	19.8	17.7	-	0.4	4.6	6.0	0.7
	NBonds/Issuer	13.2	8.2	5.9	-	2.2	4.7	3.0	2.9
SLong	Credit Spreads (bps)	25	41	91	-	-	-	-	-
	Years to Maurity	16.8	15.8	15.4	-	-	-	-	-
	Issue Size (USDmil)	243	231	199	-	-	-	-	-
	Average NObs	13.9	2.5	0.5	-	-	-	-	-
	NBonds/Issuer	14.4	9.5	6.1	-	-	-	-	-
		UK				*France*			
All	Credit Spreads (bps)	80	133	181	419	56	84	133	295
	Years to Maurity	7.2	11.4	8.5	8.6	5.1	6.0	5.6	4.0
	Issue Size (USDmil)	506	429	397	405	897	865	721	689
	Average NObs	3.6	25.3	17.5	3.8	7.8	34.9	39.6	10.1
	NBonds/Issuer	2.3	5.4	2.6	2.4	4.0	5.5	3.8	3.8
Short	Credit Spreads (bps)	67	109	163	390	52	75	118	266
	Years to Maurity	2.9	3.1	3.1	3.1	3.0	3.1	3.1	2.9
	Issue Size (USDmil)	531	403	379	406	889	809	712	735
	Average NObs	1.8	6.6	6.0	1.4	4.5	17.2	23.9	7.7
	NBonds/Issuer	2.2	5.5	2.3	2.5	3.8	5.0	3.5	3.7
Long	Credit Spreads (bps)	88	140	187	390	68	96	158	336
	Years to Maurity	7.8	8.2	8.0	7.5	7.5	7.2	6.9	6.7
	Issue Size (USDmil)	421	423	420	479	871	899	706	651
	Average NObs	1.1	8.9	7.9	1.5	2.6	15.0	14.3	2.4
	NBonds/Issuer	3.1	5.0	2.5	2.8	5.0	6.1	4.5	4.5
SLong	Credit Spreads (bps)	103	150	219	420	94	142	138	-
	Years to Maurity	19.5	19.3	17.2	15.9	20.4	19.3	19.5	-
	Issue Size (USDmil)	422	470	411	332	1152	1359	1169	-
	Average NObs	0.6	8.9	3.6	0.7	0.7	2.5	1.3	-
	NBonds/Issuer	1.9	5.6	3.7	3.9	7.9	9.5	6.9	-

Table 2 (continued)

		Bond characteristics by credit ratings							
		AA+	A	BAA	HY	AA+	A	BAA	HY
		Italy				*Canada*			
All	Credit Spreads (bps)	86	114	158	246	161	161	225	403
	Years to Maurity	10.0	7.1	6.8	6.2	14.7	16.6	8.5	4.7
	Issue Size (USDmil)	1336	1304	1066	706	93	146	215	181
	Average NObs	2.0	9.9	19.5	4.0	1.2	25.2	37.4	1.6
	NBonds/Issuer	3.6	5.8	4.8	6.2	6.0	12.9	4.4	1.5
Short	Credit Spreads (bps)	93	114	146	227	168	145	197	418
	Years to Maurity	3.3	3.5	3.3	3.1	3.4	3.1	3.0	2.9
	Issue Size (USDmil)	1416	1317	1141	674	92	131	219	156
	Average NObs	0.7	3.8	10.6	2.8	0.1	4.8	17.2	1.0
	NBonds/Issuer	4.8	7.7	5.1	6.1	5.6	12.2	3.5	1.4
Long	Credit Spreads (bps)	95	127	193	288	142	165	245	344
	Years to Maurity	7.0	7.1	7.2	6.4	8.7	8.0	7.3	7.5
	Issue Size (USDmil)	1448	1329	1038	905	82	135	269	243
	Average NObs	1.0	4.9	7.9	1.0	0.4	6.2	9.4	0.6
	NBonds/Issuer	4.2	5.9	5.2	7.4	7.4	13.2	4.0	1.9
SLong	Credit Spreads (bps)	68	145	218	-	153	166	351	-
	Years to Maurity	17.6	15.8	14.3	-	19.9	22.7	22.8	-
	Issue Size (USDmil)	1063	1073	823	-	93	155	180	-
	Average NObs	0.4	1.2	0.6	-	0.6	12.1	10.7	-
	NBonds/Issuer	1.8	7.2	5.7	-	5.6	13.0	6.8	-

Note: We sort bonds into portfolios based on credit rating and time to maturity every month, and compute simple average of characteristics across bonds every month. For maturity, bonds are sorted into three subsamples: short (less than 5 years to maturity), long (between 5 and 12 years) and slong (more than 12 years). We then take average over time for each portfolio and report the results in this table. Average N refers to how many bonds (per month) do we have in the portfolio. The sample is monthly from 1997 to 2017.

Table 3: Firm-Level Inputs to the Black-Cox Model

	Rating	NObs	Firm-level inputs by ratings					
			Mean	10%	25%	50%	75%	90%
Japan								
Leverage	AA+	31	0.44	0.21	0.33	0.42	0.55	0.73
	A	64	0.46	0.22	0.31	0.46	0.62	0.73
	BAA	63	0.52	0.32	0.42	0.52	0.62	0.71
	HY	0	-	-	-	-	-	-
σ^E	AA+	31	0.26	0.16	0.19	0.24	0.29	0.38
	A	64	0.31	0.19	0.24	0.29	0.37	0.46
	BAA	63	0.37	0.23	0.29	0.36	0.45	0.51
	HY	0	-	-	-	-	-	-
σ^A	AA+	31	0.15	0.05	0.13	0.15	0.17	0.22
	A	64	0.17	0.08	0.10	0.17	0.22	0.24
	BAA	63	0.18	0.10	0.14	0.17	0.21	0.23
	HY	0	-	-	-	-	-	-
Payout	AA+	31	0.009	0.004	0.006	0.008	0.012	0.016
	A	64	0.008	0.000	0.004	0.007	0.012	0.016
	BAA	63	0.005	0.000	0.001	0.004	0.008	0.012
	HY	0	-	-	-	-	-	-
UK								
Leverage	AA+	14	0.19	0.07	0.11	0.17	0.26	0.34
	A	39	0.34	0.15	0.22	0.32	0.47	0.55
	BAA	39	0.32	0.14	0.22	0.31	0.41	0.51
	HY	11	0.41	0.20	0.31	0.41	0.48	0.63
σ^E	AA+	14	0.27	0.17	0.20	0.27	0.32	0.37
	A	39	0.25	0.15	0.17	0.22	0.29	0.41
	BAA	39	0.28	0.17	0.20	0.24	0.32	0.45
	HY	11	0.39	0.23	0.27	0.33	0.41	0.64
σ^A	AA+	14	0.21	0.16	0.18	0.20	0.25	0.28
	A	39	0.17	0.12	0.14	0.15	0.18	0.22
	BAA	39	0.19	0.15	0.16	0.19	0.23	0.25
	HY	11	0.22	0.17	0.19	0.20	0.26	0.31
Payout	AA+	14	0.009	0.000	0.000	0.000	0.006	0.030
	A	39	0.019	0.000	0.000	0.000	0.042	0.048
	BAA	39	0.024	0.000	0.000	0.026	0.042	0.054
	HY	11	0.035	0.000	0.014	0.038	0.050	0.062

This table presents summary statistics for the firm-level inputs to the Black-Cox model for each country and for each credit rating. The statistics are computed using the panel data of bond issuers, and NObs is the number of firms that are in each category. The sample is from 1997 to 2017.

Table 3 (continued)

	Rating	NObs	Mean	10%	25%	50%	75%	90%
			Firm-level inputs by ratings					
Germany								
Leverage	AA+	9	0.35	0.11	0.16	0.21	0.73	0.75
	A	27	0.40	0.15	0.24	0.41	0.56	0.63
	BAA	35	0.38	0.12	0.22	0.37	0.50	0.66
	HY	9	0.42	0.25	0.32	0.41	0.50	0.61
σ^E	AA+	9	0.27	0.17	0.19	0.24	0.35	0.42
	A	27	0.32	0.18	0.23	0.28	0.37	0.51
	BAA	35	0.30	0.18	0.21	0.27	0.36	0.46
	HY	9	0.35	0.24	0.27	0.32	0.39	0.50
σ^A	AA+	9	0.19	0.05	0.07	0.20	0.28	0.29
	A	27	0.19	0.12	0.14	0.18	0.22	0.28
	BAA	35	0.18	0.10	0.15	0.16	0.23	0.28
	HY	9	0.21	0.16	0.18	0.21	0.23	0.25
Payout	AA+	9	0.015	0.000	0.000	0.007	0.024	0.040
	A	27	0.024	0.005	0.012	0.019	0.033	0.054
	BAA	35	0.035	0.010	0.016	0.033	0.055	0.067
	HY	9	0.032	0.019	0.024	0.028	0.040	0.050
France								
	Rating	NObs	Mean	10%	25%	50%	75%	90%
Leverage	AA+	9	0.24	0.07	0.14	0.21	0.28	0.48
	A	24	0.36	0.08	0.17	0.36	0.55	0.65
	BAA	38	0.39	0.16	0.25	0.39	0.52	0.59
	HY	18	0.54	0.27	0.42	0.54	0.67	0.78
σ^E	AA+	9	0.30	0.19	0.22	0.27	0.35	0.48
	A	24	0.28	0.17	0.20	0.25	0.31	0.43
	BAA	38	0.29	0.18	0.21	0.26	0.33	0.45
	HY	18	0.38	0.23	0.27	0.36	0.45	0.57
σ^A	AA+	9	0.21	0.15	0.18	0.22	0.25	0.29
	A	24	0.18	0.11	0.13	0.16	0.21	0.26
	BAA	38	0.18	0.11	0.14	0.18	0.21	0.25
	HY	18	0.19	0.11	0.14	0.17	0.23	0.26
Payout	AA+	9	0.024	0.008	0.014	0.022	0.028	0.045
	A	24	0.026	0.000	0.011	0.022	0.040	0.056
	BAA	38	0.025	0.003	0.015	0.021	0.035	0.049
	HY	18	0.020	0.005	0.009	0.015	0.026	0.045

Table 3 (continued)

	Rating	NObs	Firm-level inputs by ratings					
			Mean	10%	25%	50%	75%	90%
Italy								
Leverage	AA+	3	0.26	0.17	0.23	0.27	0.29	0.33
	A	12	0.41	0.27	0.30	0.41	0.52	0.58
	BAA	17	0.55	0.40	0.47	0.53	0.63	0.71
	HY	5	0.61	0.40	0.60	0.66	0.69	0.70
σ^E	AA+	3	0.24	0.12	0.16	0.21	0.28	0.48
	A	12	0.24	0.16	0.18	0.22	0.28	0.34
	BAA	17	0.26	0.18	0.20	0.25	0.30	0.35
	HY	5	0.33	0.27	0.29	0.33	0.36	0.44
σ^A	AA+	3	0.17	0.11	0.13	0.19	0.21	0.22
	A	12	0.15	0.11	0.13	0.14	0.16	0.18
	BAA	17	0.13	0.11	0.11	0.12	0.14	0.14
	HY	5	0.14	0.12	0.12	0.13	0.13	0.20
Payout	AA+	3	0.052	0.042	0.045	0.054	0.061	0.064
	A	12	0.047	0.023	0.044	0.050	0.055	0.061
	BAA	17	0.047	0.015	0.035	0.045	0.060	0.078
	HY	5	0.067	0.013	0.028	0.090	0.093	0.101
Canada								
Leverage	AA+	3	0.40	0.20	0.39	0.43	0.46	0.48
	A	17	0.37	0.20	0.32	0.37	0.42	0.47
	BAA	44	0.42	0.19	0.27	0.34	0.48	0.98
	HY	5	0.39	0.22	0.27	0.36	0.51	0.60
σ^E	AA+	3	0.22	0.11	0.13	0.25	0.28	0.31
	A	17	0.19	0.13	0.15	0.17	0.22	0.29
	BAA	44	0.21	0.11	0.15	0.18	0.26	0.33
	HY	5	0.34	0.19	0.22	0.31	0.41	0.50
σ^A	AA+	3	0.13	0.12	0.12	0.12	0.13	0.18
	A	17	0.12	0.10	0.11	0.12	0.13	0.14
	BAA	44	0.14	0.06	0.11	0.13	0.16	0.22
	HY	5	0.20	0.15	0.16	0.21	0.22	0.25
Payout	AA+	3	0.052	0.033	0.035	0.048	0.076	0.080
	A	17	0.039	0.017	0.027	0.039	0.048	0.056
	BAA	44	0.043	0.005	0.025	0.037	0.054	0.100
	HY	5	0.043	0.009	0.035	0.044	0.053	0.066

Table 4: Estimates for Country-Level Sharpe Ratio and Default Boundary

		Country					
		Japan	UK	Germany	France	Italy	Canada
Panel A: Sharpe ratios							
A1. Security Level Averages: All firms							
Number of Firms		4771	2711	987	991	439	3664
Mean Sharpe Ratio (annual)		0.23	0.35	0.27	0.28	0.19	0.28
Median Sharpe Ratio (annual)		0.19	0.28	0.22	0.28	0.17	0.23
Sample begins		1987	1987	1987	1987	1987	1984
A2. Security Level Averages: Bond Issuers Only							
Number of Firms		159	153	76	91	37	417
Mean Sharpe Ratio (annual)		0.21	0.42	0.37	0.32	0.27	0.34
Median Sharpe Ratio (annual)		0.22	0.29	0.30	0.29	0.19	0.32
Sample begins		1987	1987	1987	1987	1987	1984
Panel B: Default boundary estimates							
Same d for all firms	All	0.80	1.13	0.88	1.13	0.74	1.05
Heterogenous d	IG	0.80	1.12	0.85	1.01	0.66	1.05
	HY	-	1.14	1.22	1.18	0.76	1.09

Panel A presents the estimate for the Sharpe ratio on individual stocks in each country. We compute average annual returns and average volatility for each stock using the full sample of stock returns until 2017. We the compute the Sharpe ratio for each stock and compute mean and median across firms for each country.

Panel B reports the estimated default boundary (d) in Eq. (4) using the sample of firms that have at least a bond in Merrill Lynch data (including callable bonds). Three sets of the estimates are reported for each country: one for all firms, one for investment-grade (IG) firms, and one for high-yield (HY) firms.

Table 5: Cumulative Default Frequency: 1970–2016

Panel A: Outside the US

Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Aaa	0.00	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Aa	0.04	0.05	0.12	0.17	0.26	0.38	0.50	0.57	0.64	0.72	0.79	0.88	0.93	0.96	0.96	0.96	1.00	1.13	1.26	1.34
A	0.08	0.24	0.44	0.70	1.08	1.43	1.77	2.11	2.40	2.66	2.87	3.10	3.33	3.54	3.80	4.04	4.26	4.41	4.49	4.56
Baa	0.20	0.45	0.79	1.07	1.30	1.48	1.69	1.97	2.22	2.38	2.57	2.72	2.81	2.85	2.89	2.94	2.97	2.97	2.97	2.97
Ba	0.84	2.22	3.47	5.02	6.32	7.35	8.13	8.93	9.66	10.28	10.57	10.78	10.85	10.90	10.90	10.90	10.90	11.05	11.17	11.25
B	2.78	6.91	10.45	13.74	16.23	17.91	19.46	20.58	21.36	21.59	21.70	21.70	21.70	21.91	22.26	22.82	23.29	23.60	23.60	23.60
Caa-	16.78	26.45	32.83	35.97	38.08	39.55	41.86	43.59	44.90	46.15	47.47	47.81	48.29	48.29	48.29	48.29	48.29	48.29	48.29	48.29

Panel B: US

Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Aaa	0.00	0.00	0.00	0.06	0.17	0.30	0.42	0.54	0.66	0.77	0.89	1.00	1.11	1.17	1.22	1.28	1.33	1.33	1.33	1.33
Aa	0.01	0.03	0.13	0.31	0.47	0.61	0.72	0.83	0.92	1.01	1.13	1.30	1.47	1.64	1.78	1.89	2.01	2.15	2.40	2.59
A	0.04	0.13	0.32	0.49	0.68	0.89	1.14	1.39	1.65	1.88	2.10	2.30	2.52	2.73	2.96	3.20	3.43	3.69	3.95	4.23
Baa	0.18	0.48	0.86	1.28	1.71	2.13	2.50	2.86	3.29	3.77	4.26	4.73	5.19	5.63	6.07	6.47	6.87	7.22	7.49	7.76
Ba	1.17	3.19	5.36	7.67	9.75	11.62	13.25	14.83	16.35	17.83	19.29	20.77	22.11	23.53	24.81	25.93	26.83	27.80	28.78	29.52
B	3.83	8.64	13.10	17.01	20.45	23.56	26.27	28.55	30.73	32.74	34.33	35.58	36.81	37.87	38.82	39.50	40.20	40.77	41.22	41.73
Caa-	17.60	27.14	33.55	38.31	42.06	44.72	46.55	48.44	50.21	51.72	52.84	53.68	54.60	54.60	54.60	55.62	56.94	56.94	56.94	56.94

This table reports cumulative default frequency for the regions outside the US (panel A) and US (panel B) over the period 1970–2016. Every year, we form a cohort of firms with the same credit rating and keep track of the fraction of firms default for the subsequent 20 years. We then take average across cohort to estimate the cumulative default frequency. We compute using corporate credit ratings, excluding structured finance and real estate finance.

Table 6: Average Credit Spreads from the Black-Cox Model

		Credit spreads (bps) by credit ratings							
Maturity		AA+	A	BAA	HY	AA+	A	BAA	HY
		Japan				*France*			
All	Observed spreads	18	29	42	-	56	84	133	295
	Homogenous d	9	26	36	-	17	126	167	596
	Hetero d for IG/HY	9	26	36	-	10	79	109	744
Short	Observed spreads	15	24	39	-	52	75	118	266
	Homogenous d	2	15	26	-	14	108	154	669
	Hetero d for IG/HY	2	15	26	-	7	57	91	851
Long	Observed spreads	20	34	49	-	68	96	158	336
	Homogenous d	11	42	59	-	27	147	215	373
	Hetero d for IG/HY	11	42	59	-	17	101	154	420
SLong	Observed spreads	25	41	91	-	94	142	138	-
	Homogenous d	28	52	77	-	41	202	243	-
	Hetero d for IG/HY	28	52	77	-	27	154	209	-
		UK				*Italy*			
All	Observed spreads	80	133	181	419	86	114	158	246
	Homogenous d	7	47	65	280	3	13	47	133
	Hetero d for IG/HY	7	44	61	283	2	7	27	154
Short	Observed spreads	67	109	163	390	93	114	146	227
	Homogenous d	14	25	70	279	0	3	19	76
	Hetero d for IG/HY	13	22	65	284	0	1	7	93
Long	Observed spreads	88	140	187	390	95	127	193	288
	Homogenous d	3	54	67	275	3	15	102	316
	Hetero d for IG/HY	3	51	64	276	2	8	64	349
SLong	Observed spreads	103	150	219	420	68	145	218	-
	Homogenous d	5	62	75	280	7	55	137	-
	Hetero d for IG/HY	5	59	72	282	4	38	103	-
		Germany				*Canada*			
All	Observed spreads	46	85	116	271	161	161	225	403
	Homogenous d	3	47	54	143	53	30	87	253
	Hetero d for IG/HY	2	38	42	841	52	30	85	283
Short	Observed spreads	49	82	115	271	168	145	197	418
	Homogenous d	2	49	40	131	25	7	91	264
	Hetero d for IG/HY	1	40	28	880	24	7	88	299
Long	Observed spreads	60	91	126	289	142	165	245	344
	Homogenous d	15	56	83	115	54	28	89	168
	Hetero d for IG/HY	13	46	70	314	52	27	88	184
SLong	Observed spreads	-	-	-	-	153	166	351	-
	Homogenous d	-	-	-	-	49	67	151	-
	Hetero d for IG/HY	-	-	-	-	48	65	149	-

This table reports the credit spreads averaged within each category and over time. Specifically, separately for the data and for the Black-Cox model spreads (using either the same d for all firms or separate d values for IG and HY firms), we take average across bonds in each category every month, and then average over time to compute average credit spreads.

Table 7: Distribution of BAA Credit Spreads

	Mean	1%	5%	10%	50%	90%	95%	99%
	Japan							
Credit Spreads (bps)	42	6	11	14	32	86	108	151
BlackCox Model (bps)	43	0	0	0	13	111	178	415
Leverage	0.52	0.49	0.30	0.68	0.59	0.72	0.60	0.43
σ^A	0.18	0.12	0.16	0.08	0.18	0.16	0.19	0.41
Payout	0.005	0.004	0.009	0.000	0.006	0.006	0.003	0.022
	UK							
Credit Spreads (bps)	190	65	80	92	154	304	426	829
BlackCox Model (bps)	74	0	0	0	32	190	313	611
Leverage	0.32	0.04	0.32	0.31	0.24	0.40	0.46	0.67
σ^A	0.20	0.26	0.17	0.15	0.22	0.22	0.22	0.12
Payout	0.023	0.037	0.000	0.037	0.047	0.042	0.053	0.046
	Germany							
Credit Spreads (bps)	126	31	45	52	108	222	290	428
BlackCox Model (bps)	55	0	0	0	4	153	326	724
Leverage	0.38	0.17	0.06	0.20	0.37	0.69	0.74	0.87
σ^A	0.18	0.19	0.20	0.20	0.19	0.15	0.08	0.08
Payout	0.035	0.023	0.034	0.025	0.012	0.014	0.073	0.073
	France							
Credit Spreads (bps)	146	39	53	61	116	266	341	581
BlackCox Model (bps)	174	0	0	0	41	485	714	1692
Leverage	0.39	0.13	0.35	0.12	0.42	0.62	0.54	0.75
σ^A	0.18	0.18	0.10	0.23	0.17	0.10	0.17	0.11
Payout	0.025	0.013	0.000	0.023	0.000	0.043	0.066	0.060
	Italy							
Credit Spreads (bps)	156	43	57	64	116	320	394	509
BlackCox Model (bps)	56	0	0	0	8	195	319	545
Leverage	0.54	0.39	0.44	0.43	0.39	0.78	0.75	0.75
σ^A	0.13	0.13	0.10	0.12	0.14	0.13	0.12	0.12
Payout	0.047	0.038	0.067	0.038	0.051	0.050	0.080	0.081
	Canada							
Credit Spreads (bps)	248	65	106	133	236	369	421	633
BlackCox Model (bps)	106	0	0	0	6	147	314	2332
Leverage	0.35	0.17	0.27	0.32	0.28	0.41	0.54	0.92
σ^A	0.15	0.15	0.18	0.14	0.17	0.14	0.13	0.05
Payout	0.035	0.028	0.038	0.033	0.030	0.037	0.048	0.095
	US							
Credit Spreads (bps)	132	-75	-10	13	103	281	377	684
BlackCox Model (bps)	82	0	0	0	22	242	365	694
Leverage	0.31	0.06	0.09	0.27	0.15	0.49	0.69	0.33
σ^A	0.26	0.25	0.37	0.20	0.37	0.24	0.22	0.52
Payout	0.047	0.013	0.007	0.034	0.022	0.032	0.088	0.043

This table reports the distribution of credit spreads for the data and the model. For each percentile, we report the model inputs corresponding to the output credit spreads.

Table 8: Bond-Level Pricing Errors of the Black-Cox (1976) Model

Default boundary d used		Pricing errors by credit ratings							
		AA+	A	BAA	HY	AA+	A	BAA	HY
		Japan				*France*			
Constant d	MAE (bps)	16	27	40	-	48	132	158	440
	Avg Prc Errors (%)	110	104	103	-	87	169	133	167
Time-Varying d	MAE (bps)	18	30	45	-	49	125	150	448
	Avg Prc Errors (%)	118	116	110	-	90	152	116	157
Separate d values for IG and HY	MAE (bps)	16	27	40	-	49	97	128	566
	Avg Prc Errors (%)	110	104	103	-	87	125	102	222
		UK				*Italy*			
Constant d	MAE (bps)	78	99	134	212	82	102	122	207
	Avg Prc Errors (%)	97	80	77	55	96	91	86	83
Time-Varying d	MAE (bps)	76	110	177	223	71	88	151	207
	Avg Prc Errors (%)	96	86	100	55	83	84	111	79
Separate d values for IG and HY	MAE (bps)	78	100	135	212	84	106	135	214
	Avg Prc Errors (%)	97	81	77	55	98	94	91	85
		Germany				*Canada*			
Constant d	MAE (bps)	43	81	109	196	114	134	215	281
	Avg Prc Errors (%)	97	103	99	79	72	84	100	75
Time-Varying d	MAE (bps)	43	93	120	245	121	142	278	298
	Avg Prc Errors (%)	96	124	104	89	76	95	150	80
Separate d values for IG and HY	MAE (bps)	44	79	106	558	114	134	215	284
	Avg Prc Errors (%)	97	99	96	164	72	85	100	76

This table reports the bond-level pricing errors of the Black and Cox (1976) model under different default boundaries. MAE is Mean Abs Errors, or the average of $\epsilon_{k,t} = |s_{k,t} - s^{BC}_{k,t}|$ in basis points. Avg Prc Errors are the average of $\epsilon^p_{k,t} = \frac{|s_{k,t} - s^{BC}_{k,t}|}{s_{k,t}}$ in percent. The default boundaries considered include a constant d, separate (constant) d values for investment-grade (IG) and high-yield (HY) firms, and a time-varying d.

Table 9: CDS Spreads and the Black-Cox Model

		CDS spreads (bps) by credit ratings							
Maturity		AA+	A	BAA	HY	AA+	A	BAA	HY
		Japan				*France*			
All	Observed spreads	28	44	73	320	38	57	108	336
	BlackCox spreads	10	36	54	188	9	99	123	609
Short	Observed spreads	19	31	55	357	28	43	89	300
	BlackCox spreads	2	12	26	158	2	79	113	711
Long	Observed spreads	37	57	92	285	48	72	127	375
	BlackCox spreads	14	56	83	244	11	130	145	552
Slong	Observed spreads	47	71	109	263	55	79	140	391
	BlackCox spreads	26	75	96	205	22	120	127	411
		UK				*Italy*			
All	Observed spreads	22	55	102	236	28	77	126	276
	BlackCox spreads	2	20	93	396	2	16	53	224
Short	Observed spreads	16	40	83	218	22	61	104	191
	BlackCox spreads	0	4	76	404	0	2	20	74
Long	Observed spreads	25	68	123	286	32	94	146	363
	BlackCox spreads	2	29	110	401	2	22	87	386
Slong	Observed spreads	32	78	131	267	39	104	164	399
	BlackCox spreads	5	52	116	368	9	43	103	437
		Germany				*Canada*			
All	Observed spreads	38	63	94	320	-	73	102	363
	BlackCox spreads	20	33	72	104	-	13	68	375
Short	Observed spreads	30	48	75	288	-	57	84	337
	BlackCox spreads	6	15	35	75	-	2	44	394
Long	Observed spreads	44	77	114	361	-	89	119	370
	BlackCox spreads	30	50	110	141	-	18	88	391
Slong	Observed spreads	53	89	126	375	-	102	143	391
	BlackCox spreads	45	61	127	141	-	37	108	310

Note: Table reports the CDS spreads averaged within each category and over time. Specifically, separately for the data and for the Black-Cox model output, we take average across bonds in each category every month, and then average over time to compute average credit spreads. The sample is monthly from January 2001 to May 2015.

Table 10: First Principal Component of Credit Spreads and Pricing Errors

	Var. of PC_1	Fraction of Variance Explained by PC_1 (%)	Regression R^2 of Country-Level Variable on PC_1						
			Japan	UK	Germany	France	Italy	Canada	US
$s_{c,t}$	6.09	80.88	0.37	0.94	0.91	0.97	0.56	0.51	0.92
$s_{c,t} - s_{c,t}^{BC}$	5.60	73.08	0.11	0.94	0.93	0.81	0.49	0.31	0.89
$\xi_{c,t}$	3.96	58.42	0.18	0.70	0.83	0.74	0.35	0.00	0.81

The table shows the principal component analysis of country-level credit spreads, $s_{c,t}$, country-level pricing errors $s_{c,t} - s_{c,t}^{BC}$ and country-level panel regression residuals, $\xi_{c,t}$. The country-level variable is constructed as median values across bonds for each country. For each variable, we extract the first principal component of the country-level variables. Then we run regression of the country-level variable on PC_1 as

$$x_{c,t} = b_{c,0} + b_{c,1} PC_{1,t} + v_{c,t}$$

and report the R-squared.

Table 11: Pricing Errors and Economic Growth

$s_{c,t} - s_{c,t}^{BC}$	$s_{c,t}^{BC}$	PC_t	$\bar{R}^2$	$s_{c,t} - s_{c,t}^{BC}$	$s_{c,t}^{BC}$	PC_t	$\bar{R}^2$
3-month ahead growth				12-month ahead growth			
Panel A: Unemployment rate changes							
15.31			0.27	59.58			0.23
(2.25)				(3.24)			
	15.21		0.24		54.08		0.16
	(2.63)				(3.14)		
15.18	14.96		0.31	59.17	53.18		0.28
(2.70)	(4.10)			(4.07)	(6.57)		
		3.56	0.29			13.09	0.24
		(2.27)				(3.13)	
Panel B: Industrial production growth rate							
-1.27			0.11	-2.97			0.19
(-1.85)				(-1.99)			
	-0.63		0.07		-1.79		0.15
	(-2.34)				(-1.85)		
-1.26	-0.56		0.11	-2.93	-1.63		0.19
(-1.89)	(-2.30)			(-2.10)	(-2.95)		
		-0.51	0.21			-1.12	0.26
		(-2.05)				(-2.51)	
Panel C: GDP growth rate							
-0.57			0.19	-1.69			0.25
(-2.16)				(-3.24)			
	-0.42		0.12		-0.97		0.16
	(-2.65)				(-2.23)		
-0.57	-0.42		0.22	-1.69	-0.97		0.27
(-2.39)	(-4.20)			(-3.61)	(-4.89)		
		-0.17	0.27			-0.46	0.31
		(-2.14)				(-3.59)	

This table reports the predictive regressions of economic growth using average pricing errors,

$$\Delta_h Y_{c,t+h} = \alpha + \sum_{i=1}^{p} \beta_i \Delta Y_{c,t-i} + \gamma x_t + Controls_{c,t} + \varepsilon_{c,t+h}$$

where Δ_h is the "h-period" lag operator, and the number of lags p is determined by the Akaike Information Criterion. We the pricing error of the Black-Cox model averaged across bonds, $s_t - s_t^{BC}$, as well as the prediction of the Black-Cox model, s_t^{BC}, for the predictor, x_t. Control variables include 1-year real risk-free rate, the difference between 10- and 1-year risk-free rate, and country fixed effects. PC_t is the first principal component of the country-level pricing errors.

Table 12: Panel Regressions of Security-Level Pricing Errors

$\log Mat_{k,t}$	$\sigma^E_{k,t}$	$lev_{k,t}$	$R^f_t(1)$	$R^f_t(10) - R^f_t(1)$	$\log size_{k,t}$	
-0.02	1.24	-2.61	-0.13	0.01	-0.28	
(-0.55)	(2.66)	(-4.22)	(-4.18)	(0.09)	(-4.50)	
D_{Japan}	D_{UK}	$D_{Germany}$	D_{France}	D_{Italy}	D_{Canada}	D_{US}
3.81	3.49	3.34	1.71	3.94	3.82	4.80
(4.77)	(8.32)	(6.26)	(3.99)	(5.40)	(6.44)	(5.78)
$\bar{R} = 0.103$						

The table presents the estimated panel regression of pricing errors of control variables and country-fixed effects:

$$s_{k,c,t} - s^{BC}_{k,c,t} = b_1 X_{k,c,t} + D_c + \xi_{k,c,t}$$

$\log Mat$ is the log of years to maturity, $skew$ is the skewness of daily equity returns, $R^f(1)$ is 1-year risk-free rate, $R^f(10) - R^f(1)$ is the difference between 10-year and 1-year risk free rate, and $\log size$ is the log face value of the bond. Standard errors in parentheses are adjusted for cross-sectional correlation and serial correlation up to Newey-West 12 lags.

Table 13: Panel Regressions of Country-Level Pricing Errors on Macro-Variables

$R_t^f(1)$	$R_t^f(10) - R_t^f(1)$	$Noise_t$	TED_t	$Cmdty_t$	$D^{CAN} \cdot Cmdty_t$	IV_t	$SKEW_t$	$\bar{R}^2$
Panel A: Multivariate pooled OLS regressions with country fixed effects								
-0.10	0.00							0.55
(-4.15)	(0.07)							
		0.76	0.65					0.72
		(4.43)	(6.93)					
				0.07	-0.85			0.51
				(0.51)	(-3.50)			
						2.87	0.49	0.59
						(3.15)	(0.47)	
-0.09	0.02	0.42	0.59	0.25	-1.05	1.18	0.25	0.81
(-4.34)	(0.38)	(2.69)	(7.30)	(4.69)	(-5.79)	(4.09)	(0.51)	
Panel B: Fama-MacBeth cross-sectional regressions (univariate)								
0.36	0.23	0.89	1.44			-0.75	1.07	
(2.51)	(2.21)	(4.99)	(3.01)			(-0.58)	(0.28)	

The table reports the regression of country-level (median) pricing errors on explanatory variables. Panel A shows the multivariate panel regressions with country fixed effects.

$$s_{c,t} - s_{c,t}^{BC} = b_0 + b_1 X_{c,t} + D_c + \eta_{c,t}$$

Panel B shows the average slope coefficients from univariate monthly cross-sectional regressions of pricing errors on an explanatory variable. $Cmdty_t$ is the GSCI commodity index and D^{CAN} is a dummy variable for Canada. Standard errors in parentheses are adjusted for cross-sectional correlation and serial correlation up to Newey-West 12 lags.

Figure 1: Outstanding Debt Securities Issued by Non-Financial Corporations as a Fraction of GDP: the G7 Countries

This figure shows outstanding debt securities issued by non-financial corporations as a fraction of GDP in 1997 (in black) and 2017 (in purple) for seven different countries (the G7 countries). The data is from the Bank of International Settlements. The debt securities are debt instruments designed to be traded in financial markets including commercial paper, bonds, debentures and asset-backed securities.

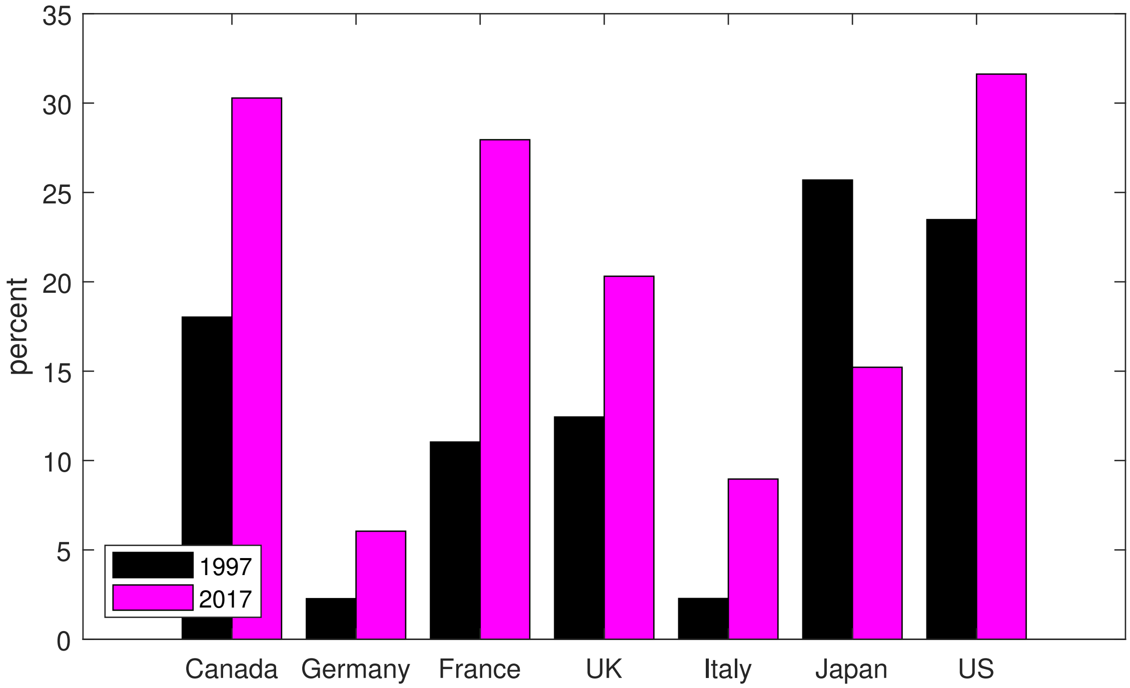


Figure 2: 5-Year Moving Average Recovery Rates

This figure plots the 5-year moving average (solid line) and one-year recovery rate (dotted line) of Moody's recovery rate for senior unsecured bonds at the global level.

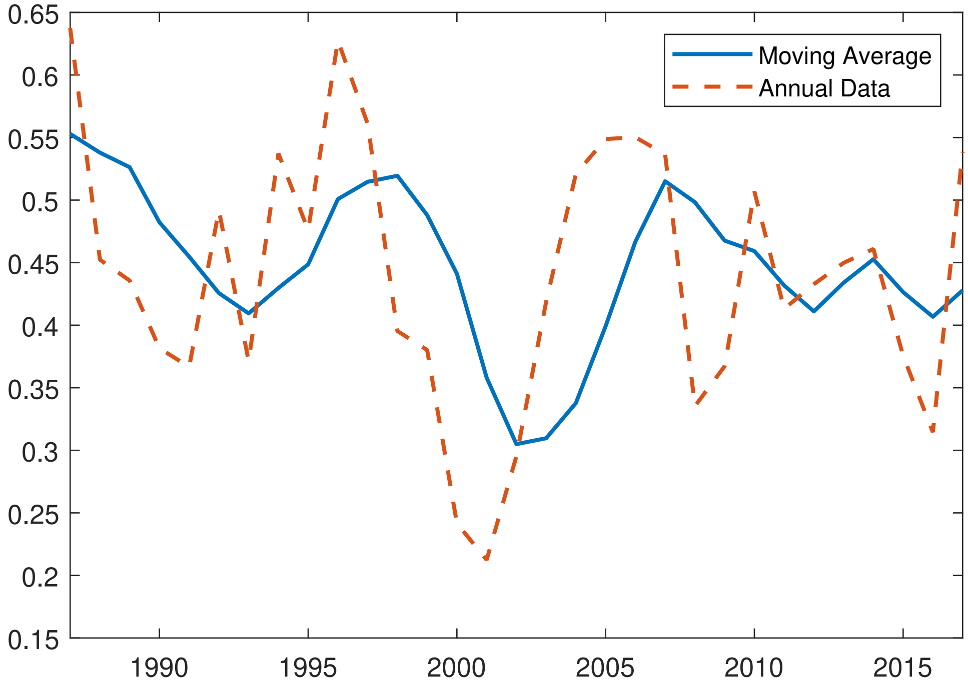


Figure 3: P-Measure Default Probability: Constant d

These figures show the Black-Cox model-implied $\mathbb{P}$-measure probability of default (star), which is computed by taking average across firms and time for each rating and maturity bin. The lines show the Moody's historical default frequency from 1920 to 2017. The 95% confidence interval (dotted line) is computed based on the simulation method described in Section 3.2.3.

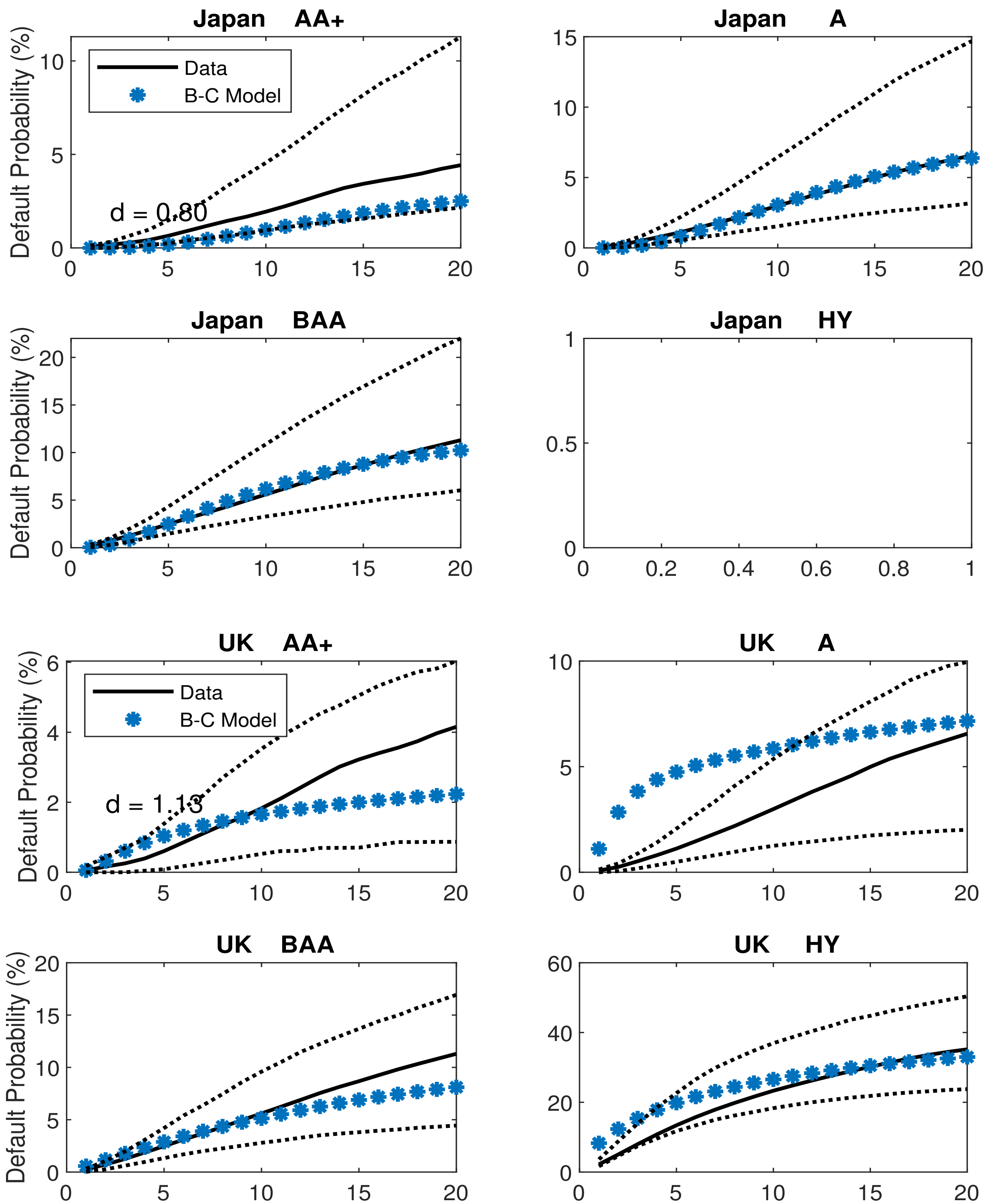


Figure 3 (continued)

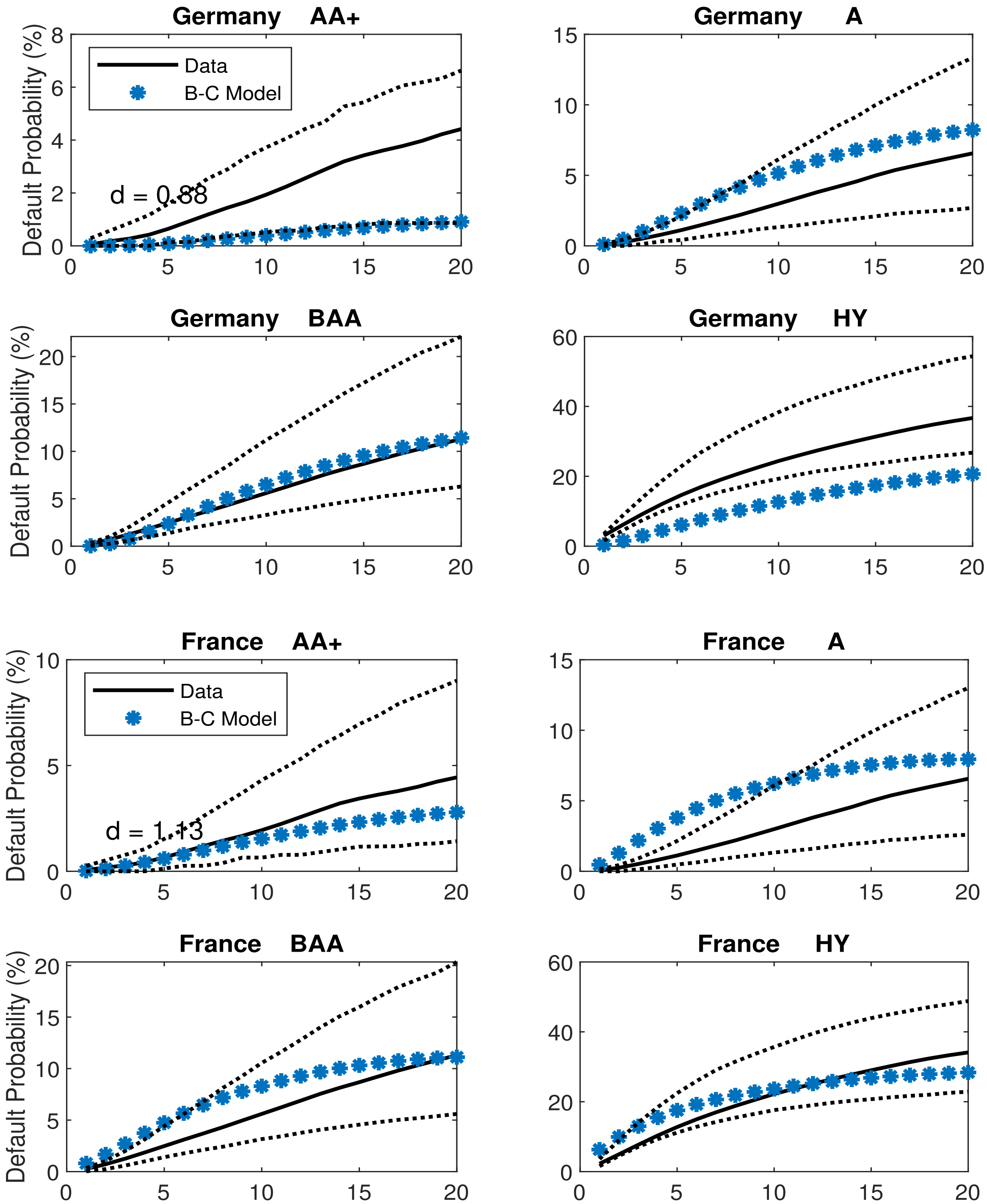


Figure 3 (continued)

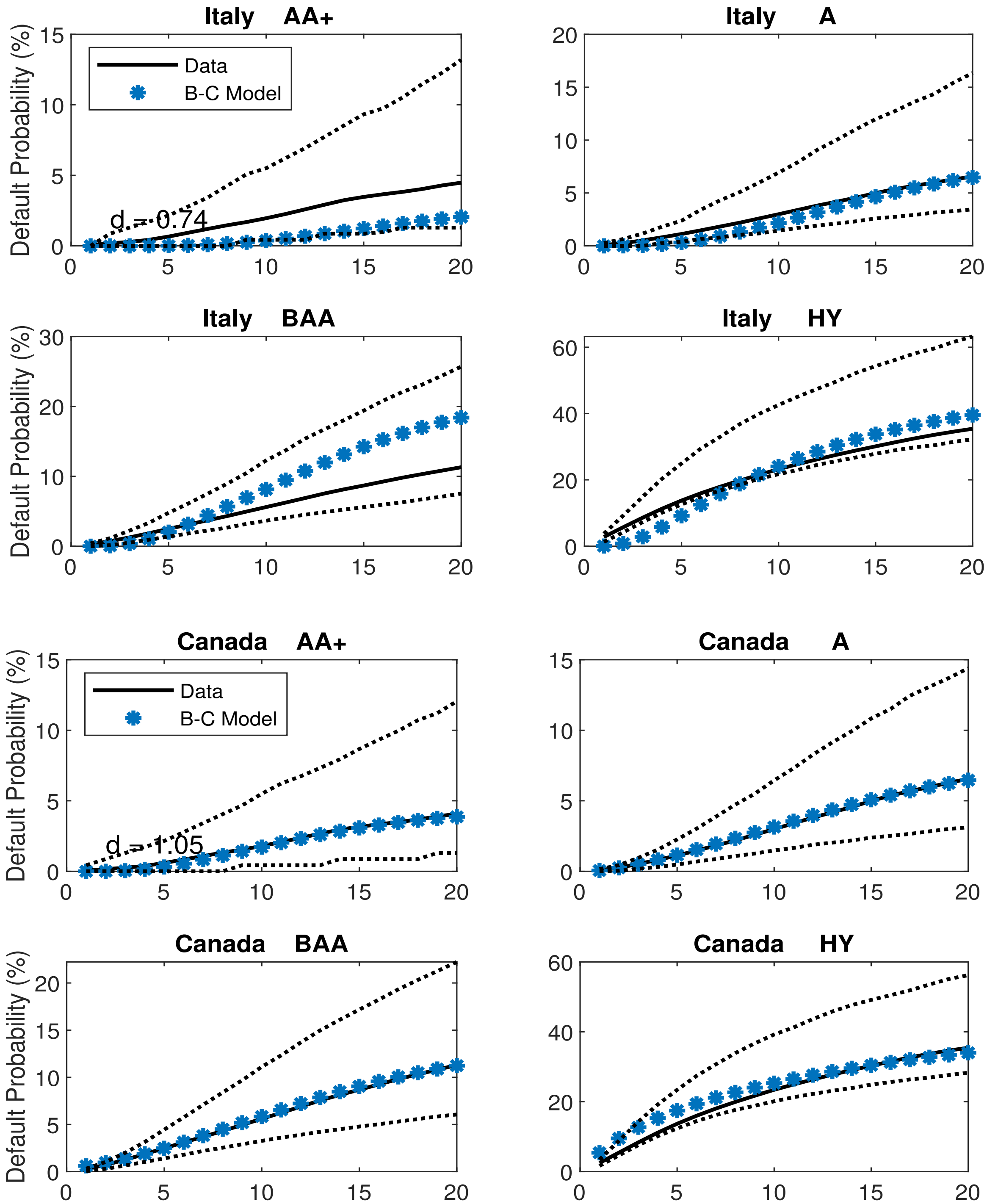
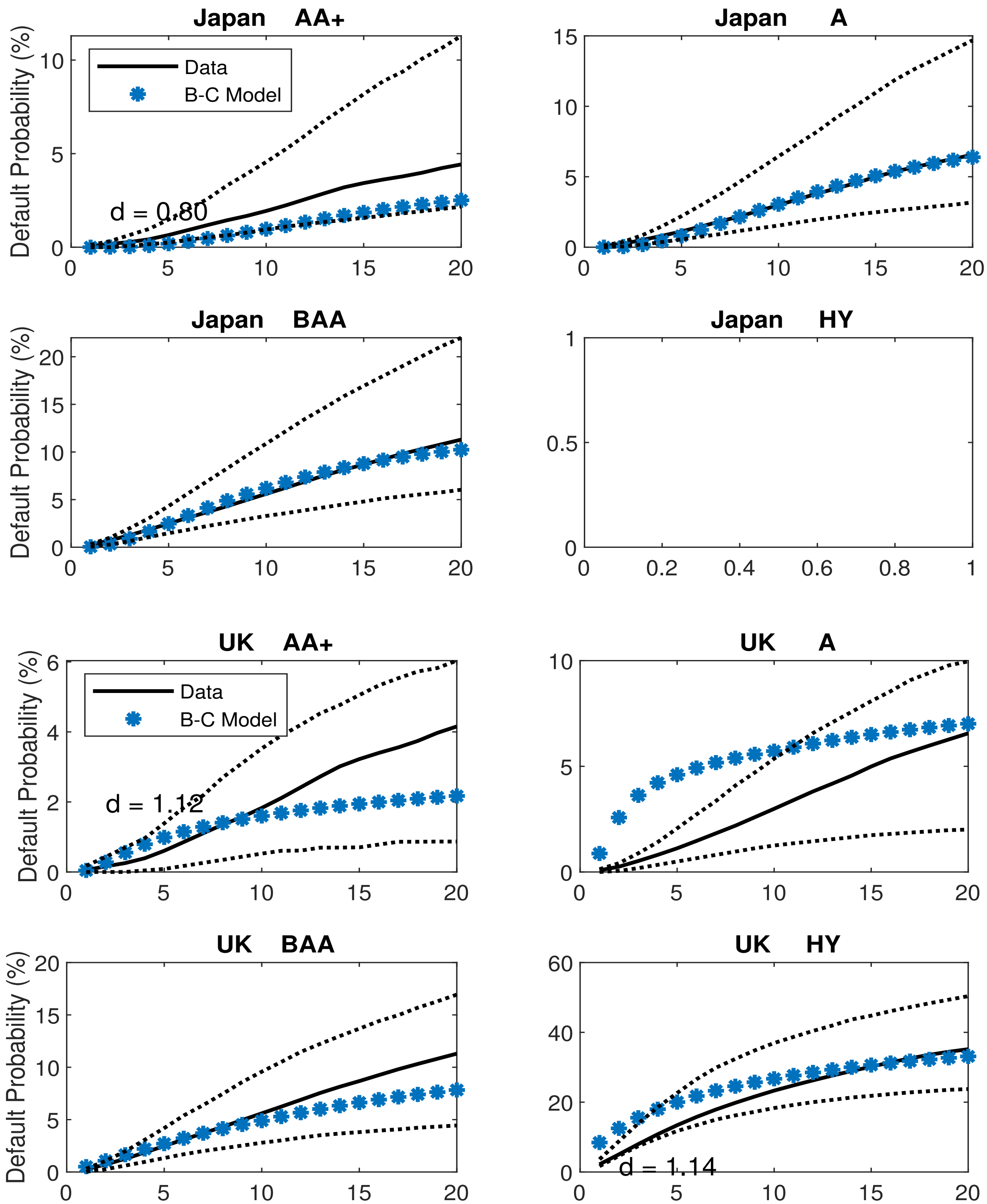


Figure 4: P-Measure Default Probability: Heterogeneous d for IG and HY

We estimate optimal values of default boundary d separately for IG and HY issuers in each country. These figures show the Black-Cox model-implied $\mathbb{P}$-measure probability of default (star), which is computed by taking average across firms and time for each rating and maturity bin. The lines show the Moody's historical default frequency from 1920 to 2017. The 95% confidence interval (dotted line) is computed based on the simulation method described in Section 3.2.3.



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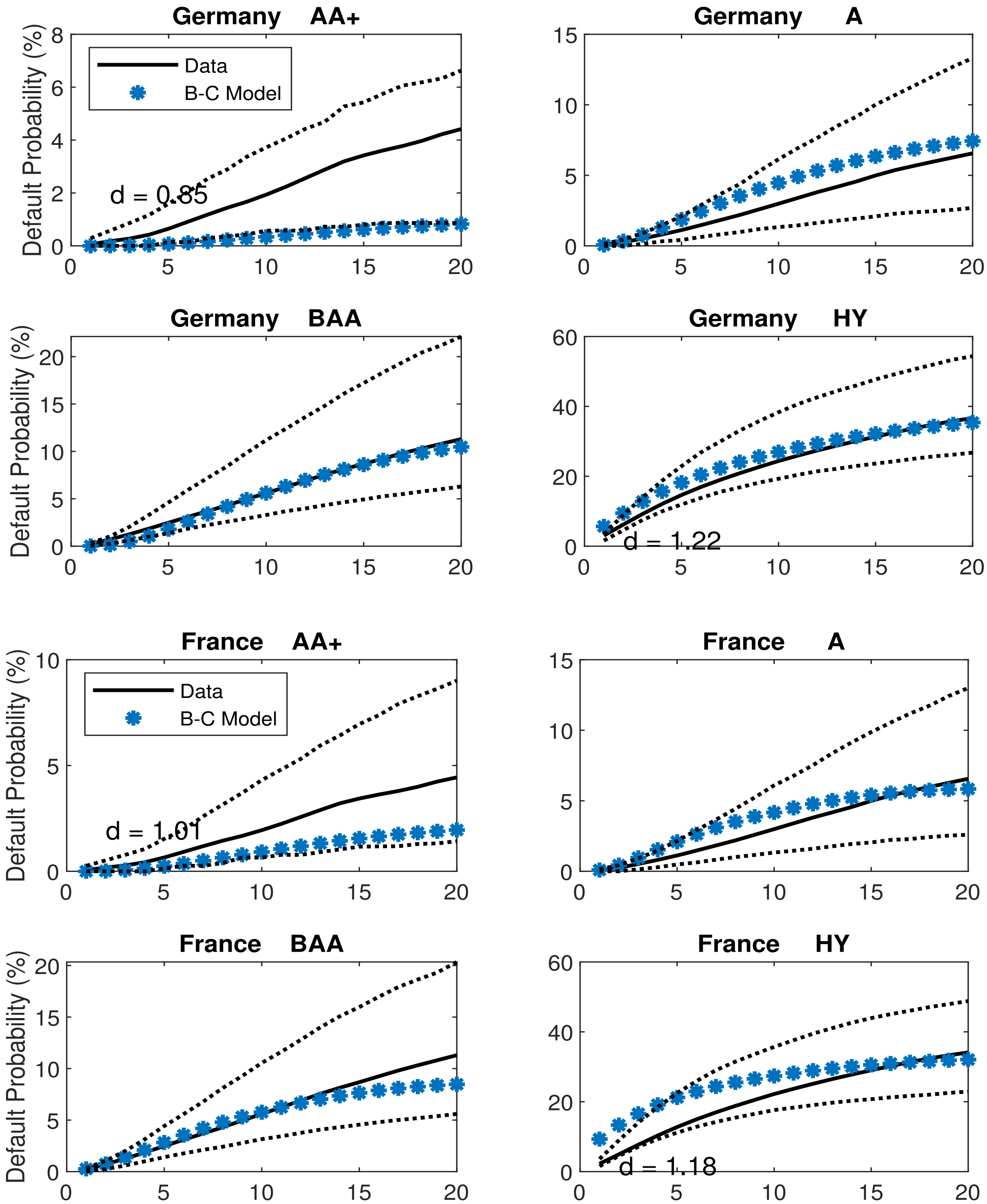

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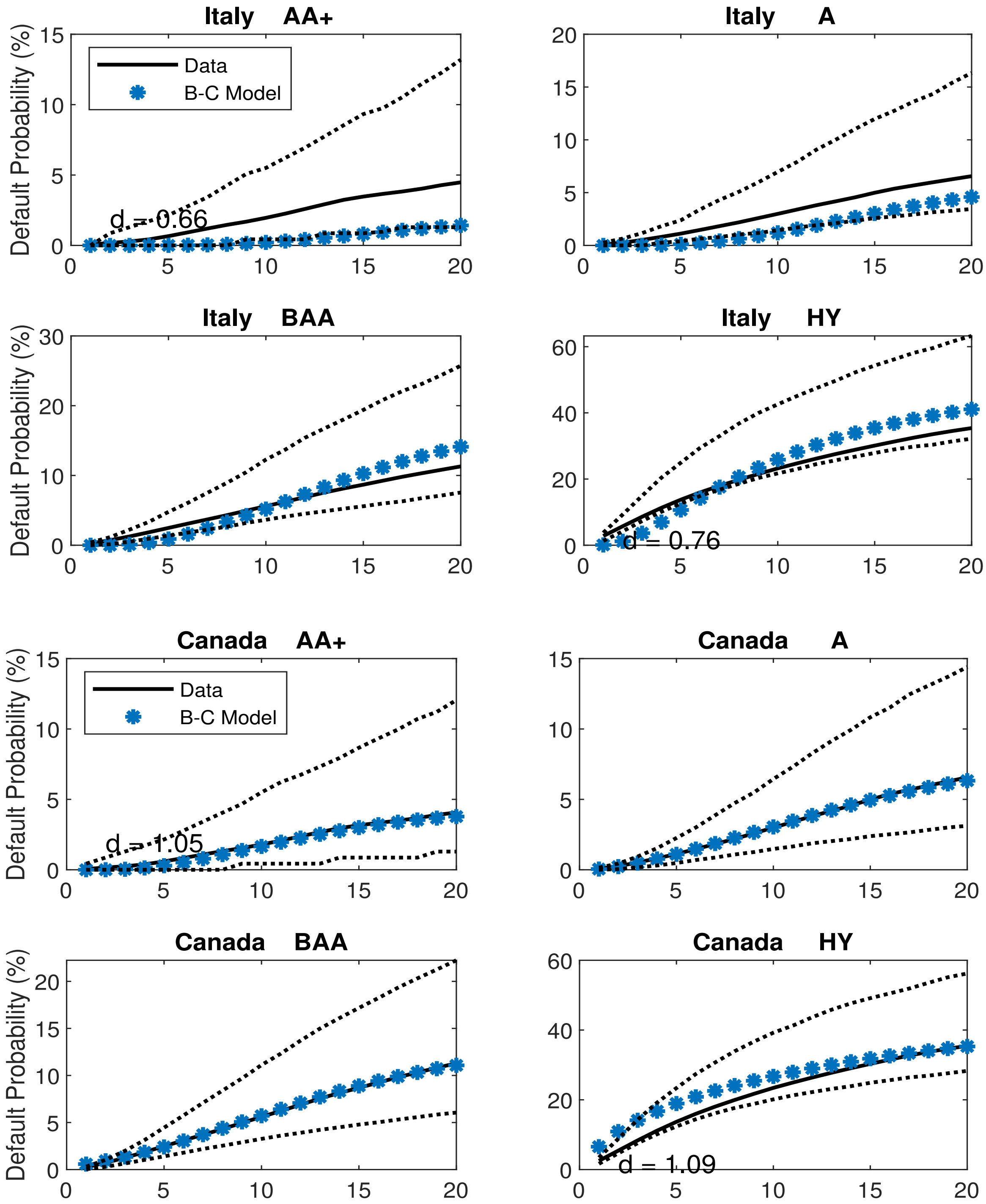


Figure 5: Monthly Observed and Black-Cox Credit Spreads

This figure plots the monthly observed and Black-Cox (1976) model-implied credit spreads over time. The blue line shows corporate credit spreads averaged across bonds in each country, and the red line shows the prediction of the Black-Cox model.

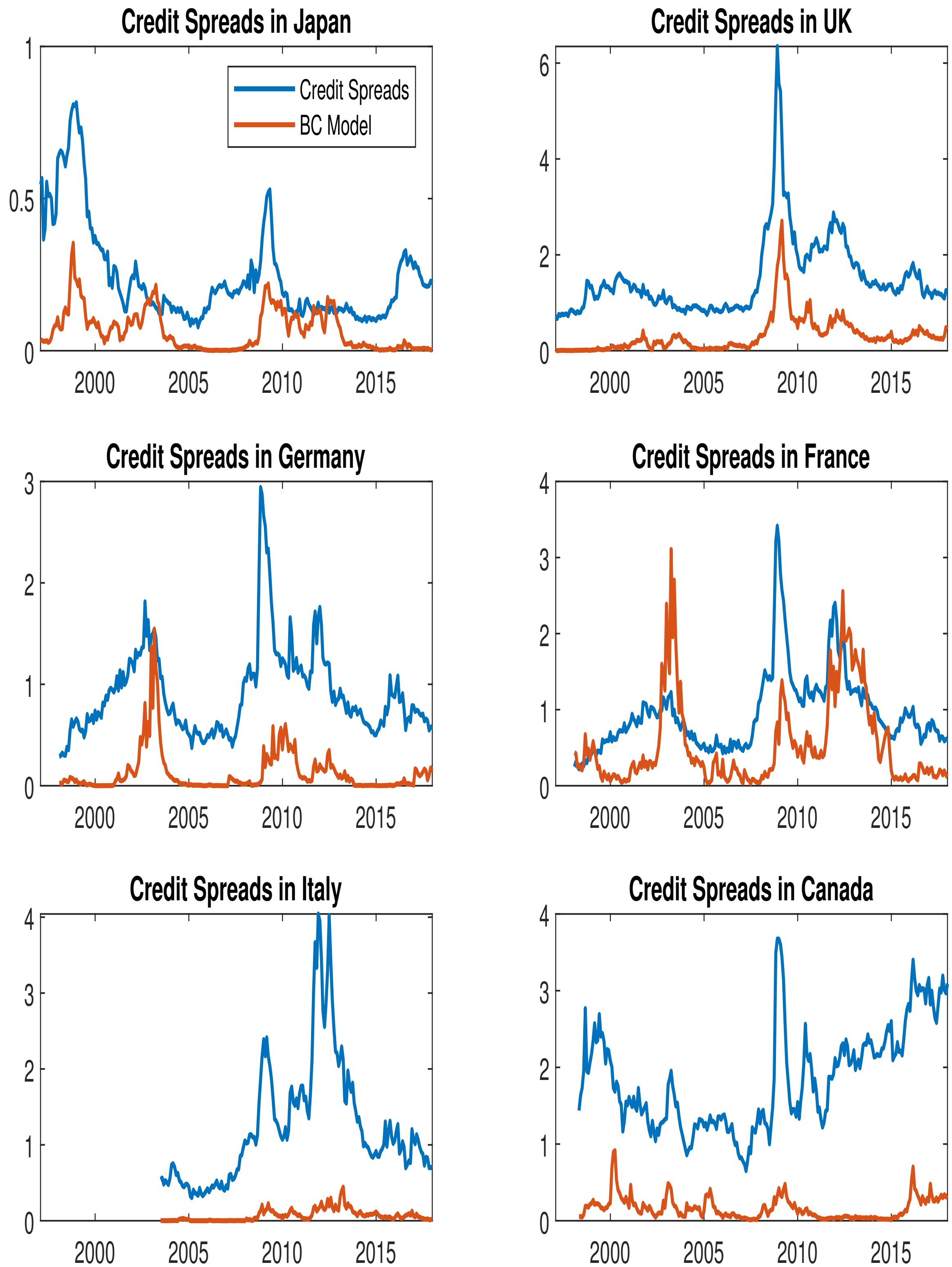
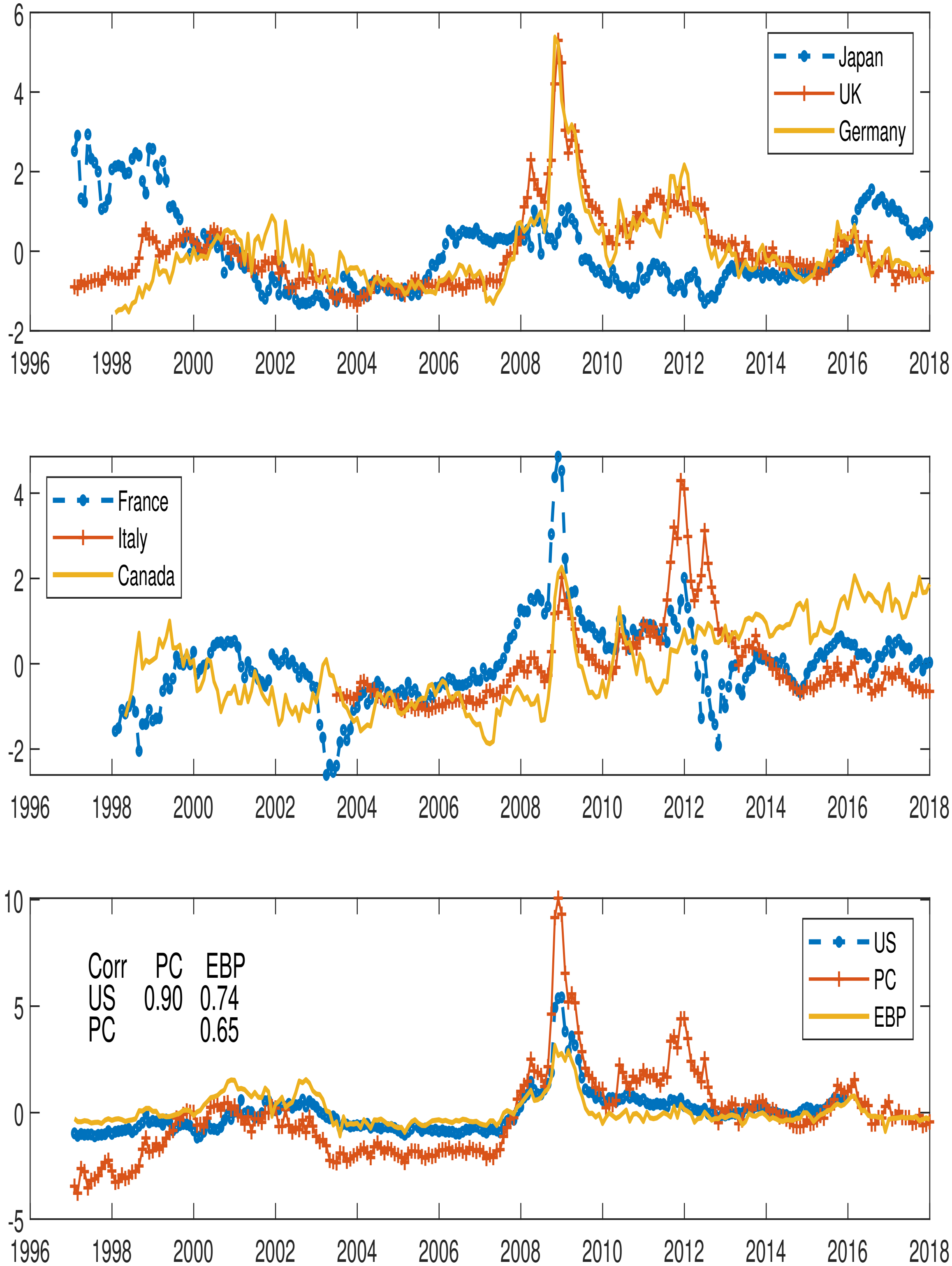


Figure 6: Country-Level Pricing Errors, Principal Components and Excess Bond Premium

The top two panels plot the standardized median pricing error from the Black-Cox (1976) model for each country. The bottom panel plots the standardized median pricing errors for US, the first principal component extracted from 7 countries, and excess bond premium of Gilchrist and Zakrajšek (2012)



Appendix A Explaining Changes in Credit Spreads

Collin-Dufresne, Goldstein and Martin (2001) attempt to explain changes in credit spreads using the inputs to the Merton (1974) model. Rather than estimating the Merton model, they run regressions of monthly changes in credit spreads, effectively freeing the parameters of the model to increase the chance to fit the data. Using the sample of US bonds, Collin-Dufresne, Goldstein and Martin (2001) find that the regression R-squared is quite low, suggesting that there may be a bond-market specific factor driving credit spreads.

Now we turn to the international evidence using the bond-level regressions of monthly credit spread changes in the spirit of Collin-Dufresne, Goldstein and Martin (2001),

$$\begin{aligned}\Delta CS_{k,t} = b_{k,0} + b_{k,1}R_{k,t} + b_{k,2}\Delta r_t^{10} + b_{k,3}(\Delta r_t^{10})^2 + b_{k,4}\Delta slope_t \\ + b_{k,5}\Delta vol_{k,t} + b_{k,6}R_{INDEX,t} + b_{k,7}\Delta skew_{k,t} + \nu_{k,t}\end{aligned} \tag{11}$$

where R_k is a stock return on the bond issuer, r^{10} is 10-year risk-free yields in each currency, $slope$ is the difference between 10 and 2 year yields, vol is the issuer's stock volatility, R_{INDEX} is the return on the country's major stock index, and $skew$ is the skewness of issuer's stock return.[13] and examine whether the regression R-squared is sufficiently large.

Table A1 reports the estimates for (11) averaged across bonds together with t-statistics. Following Strebulaev and Schaefer (2007), we account for cross-sectional correlation in credit spread changes in computing standard errors for slope estimates. For each country, we reports the coefficients averaged across all bonds. In addition, we report the results for bonds with below-median leverage and above-median leverage separately.

We find that the loading on each factor is generally sensible: higher stock returns on issuer's stock are negatively correlated with credit spread changes as they reflect improving firm value. Except for Japan and Canada, a rise in 10-year risk-free rate is negatively related with credit spread changes, while a rise in yield curve slope is positively associated. Rising volatility leads to an increase in credit spreads as they reflect increasing risk of firm values. A positive overall stock market returns are negatively correlated with credit spread changes even after controlling for individual stock returns.

For non-Japanese bonds, the adjusted R-squared averaged across bonds are comparable to the levels in the US, ranging from 0.22 to 0.33. If the Merton model holds, these R-squared

[13] Collin-Dufresne, Goldstein and Martin (2001) use option-based volatility and skewness measures as right-hand side variables. As we do not have reliable option data for those six countries, we rely on realized volatility and skewness from daily stock returns.

must be close to one, and they are clearly below one. The average R-squared for bonds in Japan is unusually low, estimated at 0.06 using all bonds.

Since we are using the same data source for all countries, low R-squared for Japanese bonds cannot be explained by the difference in data quality. One potential reason is that the level of credit spreads in Japan is generally much lower than other countries, and that monthly changes are small and dominated by measurement errors. In addition, the average number of issues per issuer is much higher in Japan (nearly 10 issues per firm) than other countries, and fragmentation of bonds makes Japanese bonds less liquid than other countries.

Although the low R-squared in regression (11) is compelling, one may be concerned about the potential nonlinear relationship between credit spreads and their determinants, which can be missed by regression in (11). To address this concern, we run a complimentary regression of credit spread changes on changes in distance to default,

$$\Delta CS_{k,t} = b_{k,0} + b_{k,1}\Delta DD_{k,t} + \nu_{k,t} \tag{12}$$

where $DD_{k,t}$ is distance to default of the bond's issuer.

Table A2 reports the average coefficients and R-squared for (12). Consistent with the prediction of the model, an increase in distance to default are negatively correlated with credit spread changes. However, after accounting for a potential nonlinearity, adjusted R-squared is disappointingly low, ranging from 0.02 in Japan to 0.07 in Italy.

Based on the reduced-form analysis, we do not see convincing evidence for the performance of structural models of debt in explaining the time-series variation in credit spreads. The analysis in this section, however, does not answer the question as to whether structural models can match the average level of credit spreads. We will turn to this question in the next section.

Appendix B Match in P-Measure Default Probability

Consider all issuers of corporate bonds. Tables A3 present summary statistics for non-financial firms matched to all bonds, including callable bonds. We do not use callable bonds in computing credit spreads, but we still use these firms in estimating default boundary. Comparing Table 3 and Table A3, we find that the characteristics of the firms are similar between these two samples, which justifies our choice of finding default boundary using the larger sample.

Appendix C Robustness Test for Default Boundary

In this section, we run a robustness test using different values of d. In particular, we estimate separate values for d for AA+, A, BAA and HY and 3 maturity categories (Short, Long, SLong) that are held fixed across countries.

Table A4 shows the estimated default boundaries that vary across credit ratings and maturities. Figure A7 plots the historical default rates and $\mathbb{P}$-measure default probabilities under the Black-Cox model. The resulting credit spreads are presented in Table A5. In addition, Table A6 shows the security-level pricing errors. These results show that the main conclusion of the paper is robust to the alternative default boundary used here.

Appendix D Results from the Merton Model

Many previous studies on the credit spread puzzle, including an earlier version of Feldhutter and Schaefer (2018), use the evidence from the Merton model as their benchmarks. In this appendix, we apply to the Merton model the procedures as outlined in Section 3.2 and examine the performance of resultant "optimal" default boundaries.

It follows that switching to the Merton model leads to the following boundaries for each countries:

- 0.89 (JPN), 1.03 (UK), 1.02 (GEM), 0.96 (FRN), 0.88 (ITY), 1.21 (CAN).

Comparing them with the results tabulated in Table **??**, we find that the Merton model generally needs a higher boundary to fit the historical default rates, except for UK and France. This finding reflects the economics under the Black-Cox model, which extends the original Merton model by allowing for defaults prior to the maturity date. Even with uniformly higher estimates of default boundary, nevertheless, the Merton model has difficulty in matching the slope of the term structure of physical default rates, as shown in Figure A8. In particular, the model-implied term structure generally exhibits excessive degree of convexity, such that it tends to underfit at the short and long ends and overfit in the middle.

Table A7 presents the Q-measure performance of the Merton model. We find that the model overwhelmingly under-predicts the credits spreads for all countries except Japan. Note that the Black-Cox model has the best pricing performance in Japan, and increasing the default boundary by about 9% (from 0.80 to 0.89) would further boost the model-implied spreads. As a result, the Merton model fits well the yield spreads of $AA+$ bonds and even overshoots in the A and BAA categories. Regarding other countries, the degree of overpricing is greater for IG bonds compared to HY bonds, consistent with the results from the Black-Cox model.

Finally, the security-level pricing errors are summarized in Table A8. Judging from absolute pricing errors, we find that the pricing performance of the Merton model is comparable to that as documented in Table 8 for high-quality (AAA-A) bonds, though it is slightly worse than the Black-Cox model in terms of percentage fitting errors. On the other hand, the Black-Cox model outperforms in pricing BAA and HY bonds, no matter in the absolute term or in the percentage term. These findings indicates that, for firms with a large distance-to-default (in terms of the face value of debts), the location of default boundary is a more important determinant of default risk than the possibility of default before debt maturity, and vice versa.

Appendix E Swap Rates as Risk-Free Rates

In this section, we treat swap rates as risk-free rates, and repeat the main exercise. Since swap rates are for uncollateralized loans among banks, it reflects the default risks of banks. As such, swap rates tend to be higher than government bond yields on average.

Table A9 presents the average corporate credit spreads for each rating and maturity, compared with the Black-Cox implied spreads. As expected, using swap rates lowers the observed corporate credit spreads. Therefore, the difference between the average credit spreads and the average model prediction becomes narrower. In particular, in Japan and France, the model credit spreads sometimes exceed the data.

Table A10 presents the security-level pricing errors. In contrast to Table A9, the percentage security-level errors are in fact larger if we treat swap rates as risk-free rates. This is because the denominator becomes smaller, and thus the errors as a fraction of observed credit spreads are more pronounced.

Table A1: Bond-by-Bond Time-Series Regression of Credit Spread Changes on Their Determinants: Monthly 1997-2017

	All	High Lev	Low Lev	All	High Lev	Low Lev	All	High Lev	Low Lev
	Japan			*UK*			*Germany*		
R	-0.13	-0.04	-0.22	-0.29	-0.21	-0.39	-0.40	-0.33	-0.48
	(-3.23)	(-1.37)	(-3.71)	(-2.04)	(-1.72)	(-2.07)	(-2.43)	(-2.35)	(-2.19)
Δr^{10}	0.01	-0.02	0.03	-0.38	-0.29	-0.49	-0.33	-0.31	-0.35
	(0.09)	(-0.54)	(0.38)	(-4.33)	(-3.92)	(-4.58)	(-2.75)	(-3.59)	(-2.13)
$(\Delta r^{10})^2$	0.09	0.20	-0.01	0.06	0.02	0.10	0.03	0.03	0.03
	(0.21)	(0.66)	(-0.02)	(0.22)	(0.09)	(0.32)	(0.07)	(0.07)	(0.06)
$\Delta slope$	0.04	0.05	0.03	0.36	0.26	0.49	0.34	0.30	0.37
	(0.71)	(1.43)	(0.36)	(3.25)	(3.01)	(3.13)	(2.56)	(2.98)	(2.17)
Δvol	0.02	0.01	0.03	0.45	0.28	0.68	0.35	0.28	0.43
	(0.67)	(0.38)	(0.80)	(4.48)	(3.04)	(4.84)	(2.55)	(2.70)	(2.16)
R_{INDEX}	0.01	-0.06	0.07	-0.87	-0.82	-0.92	-0.82	-0.48	-1.20
	(0.05)	(-0.81)	(0.43)	(-1.73)	(-2.00)	(-1.46)	(-1.84)	(-1.45)	(-1.99)
$\Delta skew$	0.01	0.00	0.01	0.02	0.00	0.05	0.00	0.00	0.00
	(2.01)	(-0.50)	(2.54)	(3.21)	(-0.69)	(4.06)	(0.19)	(0.35)	(0.03)
$\bar{R}^2$	0.06	0.08	0.05	0.25	0.25	0.26	0.25	0.23	0.27
N	876	440	436	172	97	75	168	88	80
	France			*Italy*			*Canada*		
R	-0.55	-0.32	-0.81	-0.35	-0.61	-0.08	-0.69	-0.43	-0.95
	(-3.61)	(-2.13)	(-4.76)	(-1.33)	(-2.18)	(-0.27)	(-2.04)	(-1.61)	(-2.08)
Δr^{10}	-0.42	-0.28	-0.57	-0.53	-0.46	-0.61	0.49	0.58	0.40
	(-4.01)	(-3.22)	(-4.58)	(-3.95)	(-3.75)	(-4.04)	(4.36)	(4.80)	(3.73)
$(\Delta r^{10})^2$	0.19	0.03	0.37	0.55	0.41	0.69	0.17	0.19	0.15
	(0.16)	(0.05)	(0.22)	(0.99)	(0.68)	(1.25)	(0.38)	(0.41)	(0.32)
$\Delta slope$	0.44	0.29	0.61	0.80	0.67	0.94	-0.40	-0.44	-0.35
	(3.70)	(2.84)	(4.36)	(4.92)	(4.56)	(5.17)	(-2.96)	(-3.00)	(-2.84)
Δvol	0.23	0.15	0.32	0.44	0.28	0.61	0.50	0.48	0.52
	(2.10)	(1.44)	(2.56)	(2.22)	(1.40)	(2.62)	(2.28)	(2.53)	(1.74)
R_{INDEX}	-0.98	-0.88	-1.10	-1.33	-0.80	-1.89	-1.16	-1.32	-0.99
	(-2.28)	(-2.61)	(-2.07)	(-3.08)	(-2.15)	(-3.80)	(-2.81)	(-2.98)	(-2.47)
$\Delta skew$	0.01	0.01	0.01	-0.01	0.00	-0.01	0.01	0.00	0.01
	(0.92)	(0.98)	(0.61)	(-0.40)	(-0.23)	(-0.40)	(0.90)	(-0.01)	(1.27)
$\bar{R}^2$	0.26	0.22	0.30	0.31	0.29	0.33	0.25	0.24	0.25
N	365	191	174	99	51	48	155	78	77

Note: We run time-series regression of monthly changes in credit spread (in percent) for bond k as

$$\Delta CS_{k,t} = b_{k,0} + b_{k,1} R_{k,t} + b_{k,2} \Delta r_t^{10} + b_{k,3} (\Delta r_t^{10})^2 + b_{k,4} \Delta slope_t$$
$$+ b_{k,5} \Delta vol_{k,t} + b_{k,6} R_{INDEX,t} + b_{k,7} \Delta skew_{k,t} + \nu_{k,t}$$

where R_k is a stock return on the bond issuer, r^{10} is 10-year risk-free yields, *slope* is the difference between 10 and 2 year yields, *vol* is the issuer's stock volatility, R_{INDEX} is the return on the country's stock index, and *skew* is the skewness of issuer's stock return. This table reports the average slope coefficients and average adjusted R-squared.

Table A2: Bond-by-Bond Time-Series Regression of Credit Spread Changes on Distance to Default: Monthly 1997-2017

	All	High Lev	Low Lev	All	High Lev	Low Lev	All	High Lev	Low Lev
	Japan			*UK*			*Germany*		
DD	-4.51	-2.43	-6.65	-23.93	-17.60	-32.13	-25.91	-17.26	-35.42
	(-1.67)	(-1.61)	(-1.44)	(-3.25)	(-3.14)	(-3.16)	(-2.48)	(-2.92)	(-2.12)
$\bar{R}^2$	0.02	0.02	0.02	0.04	0.04	0.04	0.05	0.05	0.06
N	864	438	426	172	97	75	168	88	80
	France			*Italy*			*Canada*		
DD	-21.17	-9.31	-34.67	-42.36	-29.22	-56.31	-12.78	-8.09	-17.40
	(-2.49)	(-1.49)	(-2.58)	(-3.29)	(-2.95)	(-3.30)	(-2.99)	(-1.68)	(-3.56)
$\bar{R}^2$	0.04	0.03	0.05	0.07	0.06	0.08	0.04	0.02	0.05
N	357	190	167	99	51	48	153	76	77

Note: We run time-series regression of monthly changes in credit spread (in percent) for bond k as

$$\Delta CS_{k,t} = b_{k,0} + b_{k,1}\Delta DD_{k,t} + \nu_{k,t}$$

where DD_k is distance to default of the bond issuer. This table reports the average slope coefficients and average adjusted R-squared.

Table A3: Summary Statistics: All Non-Financial Bond Issuers

	Rating	NObs	Mean	10%	25%	50%	75%	90%
	Japan							
Leverage	AA+	32	0.41	0.09	0.21	0.41	0.63	0.73
	A	68	0.44	0.18	0.26	0.42	0.62	0.74
	BAA	63	0.51	0.28	0.41	0.52	0.63	0.71
	HY	0	-	-	-	-	-	-
σ^E	AA+	32	0.26	0.15	0.19	0.24	0.31	0.39
	A	68	0.31	0.18	0.23	0.30	0.37	0.45
	BAA	63	0.37	0.23	0.28	0.36	0.46	0.54
	HY	0	-	-	-	-	-	-
σ^A	AA+	32	0.16	0.06	0.07	0.15	0.21	0.28
	A	68	0.17	0.07	0.10	0.18	0.22	0.26
	BAA	63	0.18	0.11	0.14	0.17	0.21	0.25
	HY	0	-	-	-	-	-	-
Payout	AA+	32	0.009	0.000	0.006	0.009	0.012	0.017
	A	68	0.009	0.000	0.005	0.008	0.012	0.016
	BAA	63	0.005	0.000	0.000	0.004	0.008	0.012
	HY	0	-	-	-	-	-	-
	UK							
Leverage	AA+	15	0.19	0.05	0.08	0.18	0.28	0.35
	A	50	0.30	0.10	0.16	0.25	0.41	0.52
	BAA	51	0.31	0.12	0.19	0.29	0.41	0.53
	HY	26	0.42	0.14	0.23	0.39	0.57	0.78
σ^E	AA+	15	0.26	0.16	0.19	0.25	0.33	0.39
	A	50	0.26	0.14	0.18	0.24	0.32	0.42
	BAA	51	0.28	0.17	0.20	0.24	0.32	0.45
	HY	26	0.46	0.24	0.28	0.36	0.53	0.84
σ^A	AA+	15	0.21	0.16	0.17	0.21	0.25	0.28
	A	50	0.19	0.11	0.15	0.18	0.22	0.30
	BAA	51	0.20	0.14	0.16	0.19	0.23	0.25
	HY	26	0.27	0.18	0.20	0.23	0.30	0.32
Payout	AA+	15	0.010	0.000	0.000	0.004	0.010	0.038
	A	50	0.017	0.000	0.000	0.000	0.029	0.051
	BAA	51	0.026	0.000	0.000	0.029	0.042	0.053
	HY	26	0.034	0.000	0.000	0.032	0.052	0.081

Table A3 (continued)

	Rating	NObs	Mean	10%	25%	50%	75%	90%
	Germany							
Leverage	AA+	10	0.44	0.10	0.13	0.34	0.74	0.76
	A	28	0.36	0.12	0.20	0.34	0.48	0.62
	BAA	40	0.33	0.10	0.16	0.29	0.49	0.64
	HY	26	0.41	0.23	0.30	0.39	0.50	0.59
σ^E	AA+	10	0.25	0.16	0.18	0.22	0.32	0.40
	A	28	0.29	0.17	0.20	0.26	0.35	0.45
	BAA	40	0.29	0.18	0.21	0.26	0.35	0.45
	HY	26	0.36	0.22	0.27	0.32	0.41	0.54
σ^A	AA+	10	0.15	0.06	0.06	0.15	0.23	0.28
	A	28	0.19	0.13	0.15	0.18	0.21	0.27
	BAA	40	0.19	0.11	0.15	0.19	0.24	0.29
	HY	26	0.22	0.16	0.19	0.22	0.24	0.27
Payout	AA+	10	0.012	0.000	0.000	0.007	0.021	0.034
	A	28	0.024	0.004	0.012	0.019	0.033	0.051
	BAA	40	0.028	0.008	0.014	0.022	0.041	0.056
	HY	26	0.030	0.002	0.018	0.029	0.040	0.050
	France							
Leverage	AA+	11	0.33	0.07	0.14	0.22	0.57	0.74
	A	28	0.29	0.08	0.14	0.26	0.43	0.59
	BAA	42	0.34	0.13	0.20	0.32	0.46	0.56
	HY	23	0.44	0.19	0.30	0.45	0.59	0.71
σ^E	AA+	11	0.28	0.17	0.20	0.26	0.35	0.43
	A	28	0.28	0.17	0.20	0.25	0.33	0.45
	BAA	42	0.29	0.17	0.21	0.26	0.34	0.47
	HY	23	0.39	0.22	0.27	0.36	0.47	0.59
σ^A	AA+	11	0.19	0.07	0.11	0.21	0.26	0.29
	A	28	0.20	0.12	0.15	0.19	0.24	0.27
	BAA	42	0.20	0.12	0.15	0.19	0.23	0.26
	HY	23	0.22	0.14	0.17	0.21	0.25	0.27
Payout	AA+	11	0.024	0.000	0.007	0.020	0.033	0.050
	A	28	0.021	0.000	0.009	0.018	0.029	0.045
	BAA	42	0.022	0.002	0.014	0.020	0.029	0.042
	HY	23	0.023	0.001	0.011	0.019	0.031	0.048

Table A3 (continued)

	Rating	NObs	Mean	10%	25%	50%	75%	90%
	Italy							
Leverage	AA+	3	0.27	0.12	0.22	0.28	0.33	0.36
	A	11	0.39	0.21	0.29	0.41	0.51	0.58
	BAA	18	0.54	0.37	0.46	0.53	0.62	0.72
	HY	10	0.63	0.34	0.45	0.66	0.77	0.90
σ^E	AA+	3	0.21	0.12	0.14	0.17	0.22	0.43
	A	11	0.24	0.15	0.17	0.21	0.28	0.37
	BAA	18	0.26	0.18	0.21	0.24	0.30	0.37
	HY	10	0.40	0.28	0.31	0.36	0.44	0.53
σ^A	AA+	3	0.15	0.11	0.11	0.13	0.21	0.21
	A	11	0.14	0.11	0.13	0.13	0.16	0.18
	BAA	18	0.13	0.11	0.12	0.13	0.14	0.17
	HY	10	0.16	0.12	0.13	0.15	0.21	0.21
Payout	AA+	3	0.049	0.000	0.044	0.055	0.060	0.063
	A	11	0.037	0.013	0.019	0.042	0.052	0.061
	BAA	18	0.038	0.010	0.026	0.038	0.048	0.064
	HY	10	0.037	0.000	0.014	0.028	0.051	0.092
	Canada							
Leverage	AA+	3	0.30	0.12	0.19	0.23	0.43	0.47
	A	30	0.34	0.12	0.20	0.34	0.44	0.52
	BAA	66	0.34	0.14	0.20	0.29	0.43	0.59
	HY	29	0.38	0.13	0.20	0.32	0.55	0.70
σ^E	AA+	3	0.25	0.11	0.14	0.27	0.31	0.33
	A	30	0.24	0.14	0.16	0.21	0.30	0.35
	BAA	66	0.25	0.14	0.17	0.22	0.30	0.39
	HY	29	0.43	0.20	0.25	0.34	0.49	0.62
σ^A	AA+	3	0.15	0.12	0.12	0.12	0.19	0.20
	A	30	0.16	0.10	0.11	0.13	0.21	0.29
	BAA	66	0.17	0.08	0.12	0.17	0.21	0.27
	HY	29	0.24	0.16	0.20	0.23	0.27	0.29
Payout	AA+	3	0.048	0.022	0.026	0.042	0.075	0.085
	A	30	0.038	0.012	0.019	0.040	0.050	0.066
	BAA	66	0.035	0.000	0.019	0.033	0.047	0.068
	HY	29	0.041	0.013	0.024	0.039	0.055	0.070

This table presents summary statistics for non-financial firms matched to all bonds, including callable bonds. We do not use callable bonds in computing credit spreads, but we still use these firms in estimating default boundary.

Table A4: Default Boundary Estimates by Ratings and Maturity

	Default Boundary Estimates			
Maturity	AA+	A	BAA	HY
Short	0.93	0.84	0.85	1.01
Long	0.94	0.84	0.86	1.10
Super long	0.97	0.90	0.93	1.19

Note: Table reports the optimal value of default boundary in Eq. (4)) using the sample of firms that have at least one bond in Merrill Lynch data (including callable bonds). The estimates of the default boundary d are obtained by maturity and credit ratings, not by countries. That is, the estimated d is the same across six countries for a given maturity and credit rating.

Table A5: Average Credit Spreads from the Black-Cox Model: Separate d for 4 Ratings/3 Maturities But Held Constant Across Countries

		Average credit spreads (bps)							
Maturity		AA+	A	BAA	HY	AA+	A	BAA	HY
		Japan				*France*			
All	Observed spreads	18	29	42	-	56	84	131	295
	BC-Fixed d	9	26	38	-	62	231	110	353
	Hetero for Rtg/Mat	19	32	52	-	40	118	57	379
Short	Observed spreads	15	24	39	-	52	75	118	263
	BC-Fixed d	2	16	28	-	61	306	93	378
	Hetero for Rtg/Mat	7	19	40	-	36	122	41	382
Long	Observed spreads	20	34	48	-	66	96	155	335
	BC-Fixed d	11	43	63	-	71	174	150	281
	Hetero for Rtg/Mat	25	51	81	-	52	129	86	360
SLong	Observed spreads	25	41	92	-	94	142	138	-
	BC-Fixed d	29	54	79	-	27	144	212	-
	Hetero for Rtg/Mat	52	73	115	-	23	104	186	-
		UK				*Italy*			
All	Observed spreads	80	129	183	408	86	113	157	236
	BC-Fixed d	4	38	100	282	6	32	93	256
	Hetero for Rtg/Mat	2	21	69	328	14	45	146	863
Short	Observed spreads	69	106	165	376	93	109	150	217
	BC-Fixed d	6	10	96	310	2	13	58	182
	Hetero for Rtg/Mat	3	3	59	301	7	24	117	837
Long	Observed spreads	88	134	191	382	95	127	193	284
	BC-Fixed d	2	39	95	281	8	39	178	507
	Hetero for Rtg/Mat	1	17	62	316	17	54	237	1002
SLong	Observed spreads	103	146	222	428	68	145	218	-
	BC-Fixed d	3	68	106	362	8	107	173	42
	Hetero for Rtg/Mat	3	52	90	452	21	144	239	374
		Germany				*Canada*			
All	Observed spreads	47	85	120	267	161	162	222	396
	BC-Fixed d	8	64	79	143	28	38	206	283
	Hetero for Rtg/Mat	9	51	66	321	16	10	139	258
Short	Observed spreads	49	82	118	267	168	145	197	418
	BC-Fixed d	2	69	62	131	14	54	178	309
	Hetero for Rtg/Mat	2	55	46	303	3	2	73	254
Long	Observed spreads	65	92	128	289	142	165	238	338
	BC-Fixed d	37	69	116	144	28	7	244	210
	Hetero for Rtg/Mat	40	57	103	285	12	2	218	228
SLong	Observed spreads	-	-	-	-	153	167	275	-
	BC-Fixed d	-	-	-	-	30	41	344	-
	Hetero for Rtg/Mat	-	-	-	-	21	27	326	-

Note: Table reports the credit spreads averaged within each category and over time. Specifically, separately for the data and for the Black-Cox model output, we take average across bonds in each category every month, and then average over time to compute average credit spreads.

Table A6: Bond-Level Pricing Errors From the Black-Cox Model: Separate d for 4 Ratings/3 Maturities But Held Constant Across Countries

		Black-Cox bond-level pricing errors							
Maturity		AA+	A	BAA	HY	AA+	A	BAA	HY
		Japan				France			
All	Mean Abs Errors (bps)	22	30	46	-	72	155	112	255
	Avg Pct Errors (%)	173	118	127	-	122	216	88	91
Short	Mean Abs Errors (bps)	16	25	42	-	71	170	105	260
	Avg Pct Errors (%)	158	109	122	-	119	263	90	99
Long	Mean Abs Errors (bps)	25	38	57	-	77	158	128	205
	Avg Pct Errors (%)	170	139	144	-	122	186	85	69
SLong	Mean Abs Errors (bps)	35	48	80	-	71	78	124	-
	Avg Pct Errors (%)	195	118	84	-	77	60	91	-
		UK				Italy			
All	Mean Abs Errors (bps)	78	117	185	270	70	88	127	772
	Avg Pct Errors (%)	97	93	105	73	82	85	89	465
Short	Mean Abs Errors (bps)	65	105	184	409	86	90	128	779
	Avg Pct Errors (%)	95	99	113	112	93	89	97	502
Long	Mean Abs Errors (bps)	87	122	183	254	76	95	149	798
	Avg Pct Errors (%)	99	93	102	71	84	80	79	359
SLong	Mean Abs Errors (bps)	100	124	172	117	47	75	151	-
	Avg Pct Errors (%)	98	85	78	30	71	61	79	-
		Germany				Canada			
All	Mean Abs Errors (bps)	47	94	111	216	145	161	274	252
	Avg Pct Errors (%)	121	114	100	83	90	101	137	68
Short	Mean Abs Errors (bps)	46	98	106	225	164	145	231	287
	Avg Pct Errors (%)	96	125	95	80	98	101	118	73
Long	Mean Abs Errors (bps)	70	91	125	118	130	164	336	182
	Avg Pct Errors (%)	200	100	108	54	91	99	164	57
SLong	Mean Abs Errors (bps)	-	-	-	-	133	166	338	-
	Avg Pct Errors (%)	-	-	-	-	86	100	174	-

This table reports the bond-level pricing errors of the Black and Cox (1976) model. Mean Abs Errors are the average of $\epsilon_{k,t} = |s_{k,t} - s_{k,t}^{BC}|$ in basis points. Avg Percentage Errors are the average of $\epsilon_{k,t}^{p} = \frac{|s_{k,t} - s_{k,t}^{BC}|}{s_{k,t}}$ in percent.

Table A7: Average Credit Spreads from the Merton Model

Maturity		AA+	A	BAA	HY	AA+	A	BAA	HY
		Average credit spreads (bps) by ratings							
		Japan				**UK**			
All	Observed spreads	16	27	42	NaN	80	133	181	419
	Model spreads	16	44	81	NaN	2	20	29	141
<5yr	Observed spreads	15	24	39	NaN	67	109	163	390
	Model spreads	9	29	65	NaN	2	7	27	127
5-12yr	Observed spreads	20	24	49	NaN	88	140	187	390
	Model spreads	14	44	81	NaN	2	16	29	143
> 12yr	Observed spreads	25	41	91	NaN	103	150	219	420
	Model spreads	35	41	55	NaN	3	29	29	120
		Germany				**France**			
All	Observed spreads	46	85	116	271	56	84	133	295
	Model spreads	9	77	79	121	12	43	47	172
<5yr	Observed spreads	49	82	119	271	52	75	118	266
	Model spreads	8	80	71	114	7	23	32	174
5-12yr	Observed spreads	60	91	126	289	68	96	158	336
	Model spreads	9	77	79	121	11	41	46	172
> 12yr	Observed spreads	NaN	NaN	NaN	NaN	94	142	138	NaN
	Model spreads	NaN	NaN	NaN	NaN	31	100	96	NaN
		Italy				**Canada**			
All	Observed spreads	86	114	158	246	161	161	225	403
	Model spreads	14	22	53	288	36	39	69	145
<5yr	Observed spreads	93	114	146	127	168	145	297	418
	Model spreads	11	13	35	217	41	15	80	204
5-12yr	Observed spreads	95	127	193	288	142	164	245	344
	Model spreads	15	20	52	290	32	22	71	145
> 12yr	Observed spreads	68	145	218	NaN	153	166	351	NaN
	Model Spreads	10	49	112	NaN	40	57	70	NaN

This table shows observed corporate yield spreads and the credit spreads predicted by the Merton model. We use monthly quotes provided by Merrill Lynch (ML) on senior unsecured bonds. Further sample selection criteria are: the bond issuer can be matched unambiguously with a company in Compustat Global; the bond is issued by a non-financial corporation; the bond does not have any option-like embedded features; and the bond has an initial maturity of at least 12 months. Bond observations are grouped into groups where the issued bond is rated as $Aaa\&Aa$, A, Baa or speculative grade, and where it has remaining maturity $<$ 5yr, $5-12yr$, or $>$ 12yr. All entries in the table are the average across bonds in a rating/maturity group. The sample period spans from 1987 to 2017.

Table A8: Bond-Level Pricing Errors From the Merton Model

Maturity	AA+	A	BAA	HY	AA+	A	BAA	HY	AA+	A	BAA	HY	AA+	A	BAA	HY
	Panel A: Mean Absolute Pricing Error								Panel B: Mean Absolute Percentage Pricing Error							
	Japan				**UK**				**Japan**				**UK**			
All	22	44	62	NaN	60	96	133	294	109	159	182	NaN	96	89	88	74
<5yr	19	37	58	NaN	44	86	131	335	121	152	193	NaN	97	97	93	81
5-12yr	21	44	62	NaN	54	97	130	306	104	161	183	NaN	96	93	89	75
> 12yr	25	32	43	NaN	83	95	141	254	139	112	61	NaN	97	80	85	69
	Germany				**France**				**Germany**				**France**			
All	41	91	136	181	44	77	102	172	94	99	123	77	91	122	104	71
<5yr	42	97	140	184	44	71	96	169	94	102	122	81	95	109	103	73
5-12yr	41	91	136	181	43	78	102	172	94	99	123	77	93	126	104	71
> 12yr	NaN	NaN	NaN	NaN	50	60	108	NaN	NaN	NaN	NaN	NaN	72	55	110	NaN
	Italy				**Canada**				**Italy**				**Canada**			
All	37	74	74	248	77	84	182	224	74	47	491	218	111	79	119	77
<5yr	36	63	55	202	81	69	181	233	74	44	7	167	145	106	154	74
5-12yr	39	74	71	246	75	74	174	224	83	58	509	219	127	92	135	77
> 12yr	26	75	165	587	77	95	205	NaN	31	100	205	92	97	66	78	NaN

The table reports the pricing errors of corporate yield spreads under the Merton model. Pricing errors are calculated as the absolute differences, $\epsilon_{k,t} = |s_{k,t} - s^{BC}_{k,t}|$, or as the absolute percentage differences, $\epsilon^p_{k,t} = \frac{|s_{k,t} - s^{BC}_{k,t}|}{s_{k,t}}$, between the model implied and observed spreads. Bond observations are grouped into groups where the issued bond is rated as $Aaa\&Aa$, A, Baa or speculative grade, and where it has remaining maturity $<$ 5yr, $5-12yr$, or $>$ 12yr. All entries in the table are the average across bonds in a rating/maturity group. The sample period spans from 1987 to 2017.

Table A9: Average Credit Spreads from the Black-Cox Model: Swap Rates as Risk-Free Rates

		Credit spreads (bps) by credit ratings							
Maturity		AA+	A	BAA	HY	AA+	A	BAA	HY
		Japan				*France*			
All	Credit Spreads (bps)	3	12	26	-	24	53	100	259
	Homogenous d	9	23	33	-	16	119	161	580
Short	Credit Spreads (bps)	-1	8	23	-	18	41	83	229
	Homogenous d	2	13	25	-	13	102	149	652
Long	Credit Spreads (bps)	5	19	33	-	38	65	127	301
	Homogenous d	11	39	55	-	25	138	206	358
Slong	Credit Spreads (bps)	14	26	75	-	74	122	119	-
	Homogenous d	27	54	76	-	39	195	237	-
		UK				*Italy*			
All	Credit Spreads (bps)	32	97	141	387	51	84	120	202
	Homogenous d	7	44	60	273	3	12	42	122
Short	Credit Spreads (bps)	22	64	119	346	47	70	101	183
	Homogenous d	13	23	65	268	0	2	17	69
Long	Credit Spreads (bps)	34	104	150	361	56	95	155	245
	Homogenous d	3	50	62	267	3	12	92	292
Slong	Credit Spreads (bps)	60	122	199	418	48	134	197	-
	Homogenous d	4	59	74	281	6	54	130	-
		Germany				*Canada*			
All	Credit Spreads (bps)	24	51	83	230	136	135	197	373
	Homogenous d	3	44	50	136	48	28	84	246
Short	Credit Spreads (bps)	23	46	81	227	146	111	164	389
	Homogenous d	1	47	37	125	23	6	87	256
Long	Credit Spreads (bps)	33	59	94	253	116	136	214	319
	Homogenous d	13	51	77	108	47	25	86	164
Slong	Credit Spreads (bps)	-	-	-	-	132	152	342	-
	Homogenous d	-	-	-	-	44	63	149	-

This table reports the credit spreads averaged within each category and over time. Specifically, separately for the data and for the Black-Cox model spreads (using constant d for each country), we take average across bonds in each category every month, and then average over time to compute average credit spreads. In this table, we treat swap rates as risk-free rates.

Table A10: Bond-Level Pricing Errors of the Black-Cox (1976) Model: Swap Rates as Risk-Free Rates

	Pricing errors by credit ratings							
	AA+	**A**	BAA	HY	AA+	A	BAA	HY
	Japan				*France*			
MAE (bps)	11	21	31	-	23	116	142	432
Avg Prc Errors (%)	559	539	303	-	208	462	327	225
	UK				*Italy*			
MAE (bps)	34	70	103	192	49	73	91	179
Avg Prc Errors (%)	187	85	77	56	95	90	85	88
	Germany				*Canada*			
MAE (bps)	23	59	82	167	100	110	190	269
Avg Prc Errors (%)	135	201	120	79	75	93	146	78

This table reports the bond-level pricing errors of the Black and Cox (1976) model under constant default boundaries. MAE is Mean Abs Errors, or the average of $\epsilon_{k,t} = |s_{k,t} - s_{k,t}^{BC}|$ in basis points. Avg Prc Errors are the average of $\epsilon_{k,t}^{p} = \frac{|s_{k,t} - s_{k,t}^{BC}|}{s_{k,t}}$ in percent. In this exercise, we treat swap rates as risk-free rates.

Figure A7: P-Measure Default Probability: Constant d Across Countries, Different for Maturities/Ratings

We estimate optimal values of the default boundary d separately by maturities and credit ratings across different countries. That is, the default boundary for a given maturity-rating bin is the same across different countries. These figures show the Black-Cox model-implied $\mathbb{P}$-measure probability of default (dashed line), which is computed by taking average across firms and time for each rating and maturity bin. The solid lines show the Moody's historical default frequency from 1920 to 2017.

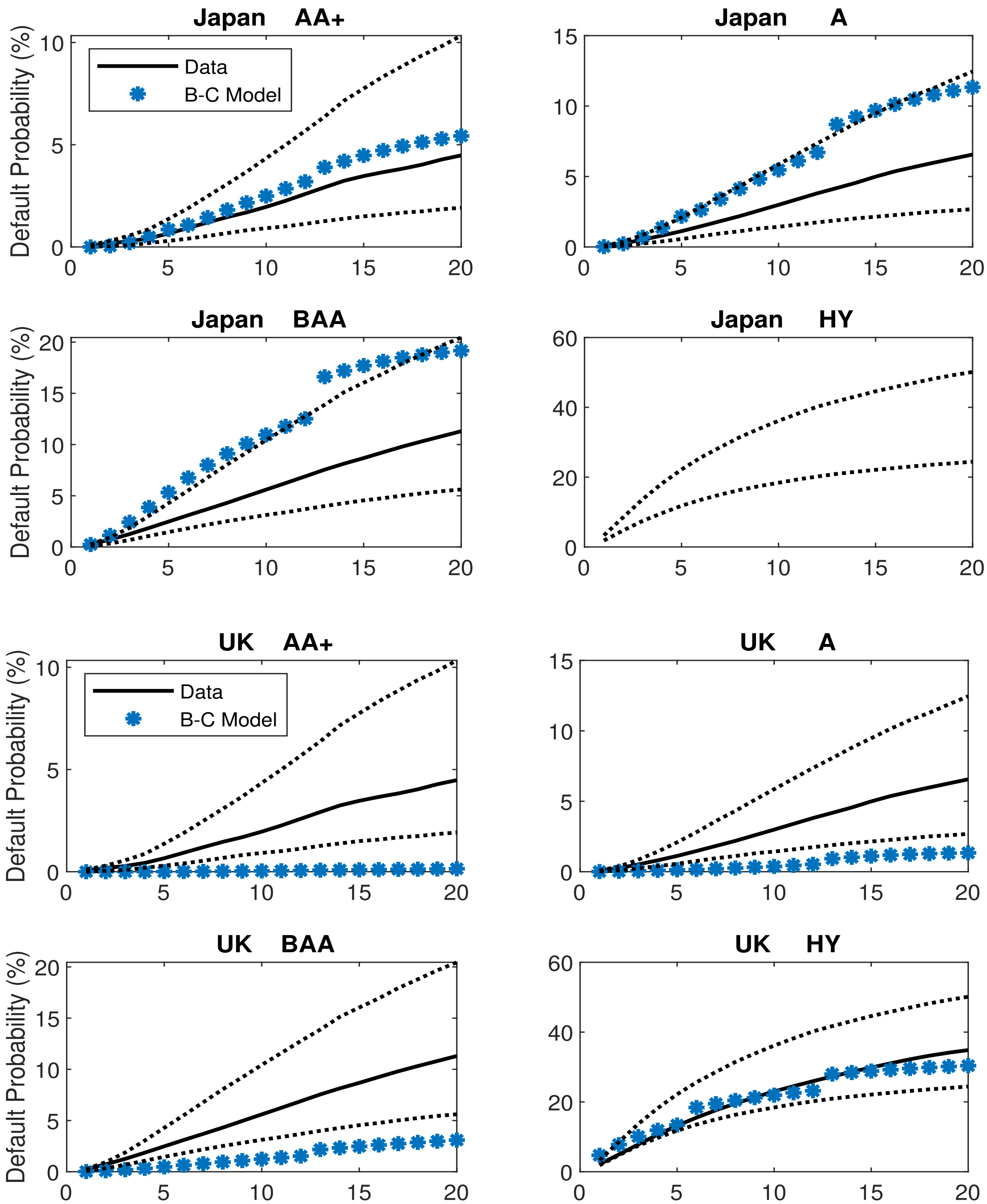


Figure A7 (continued)

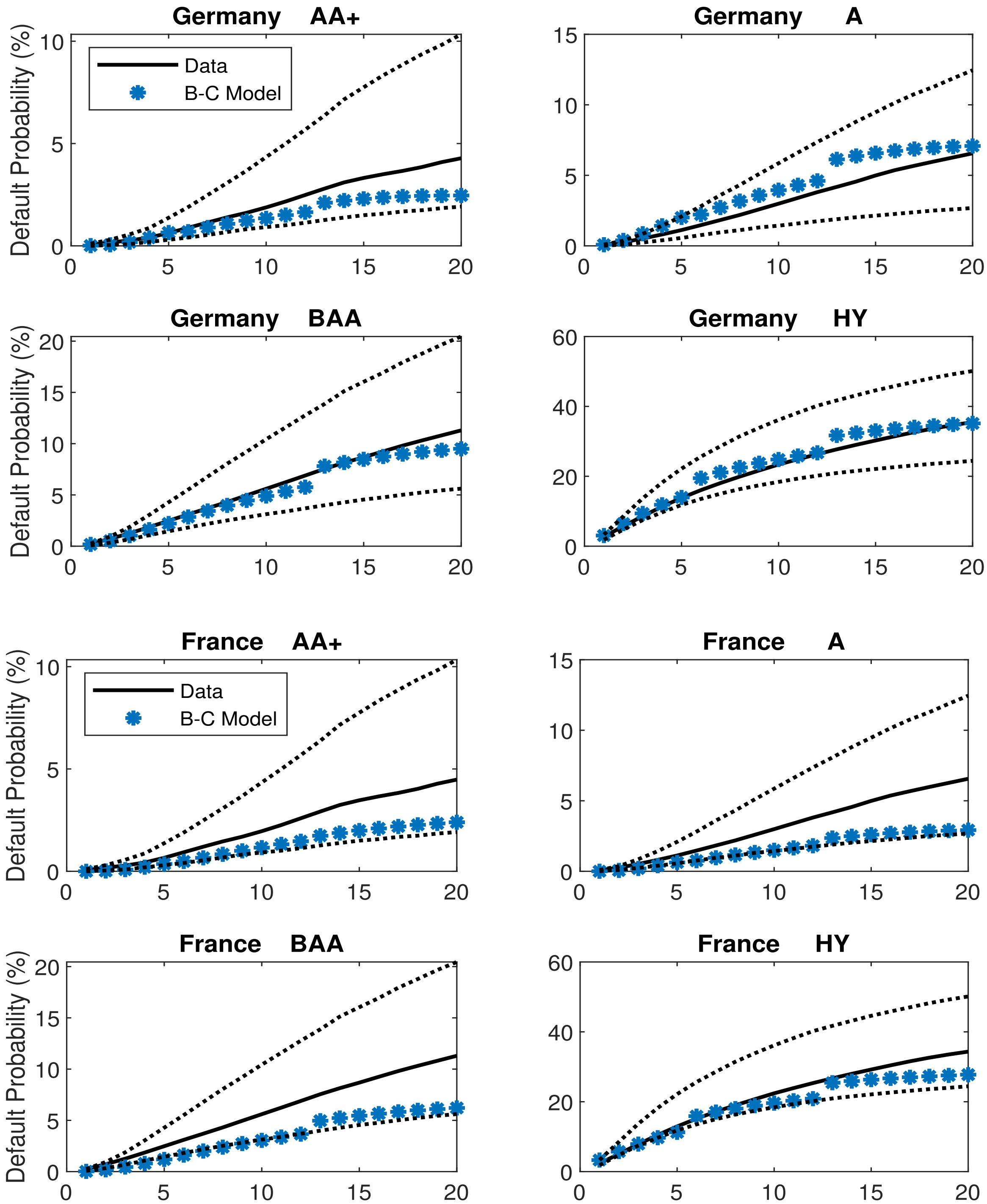


Figure A7 (continued)

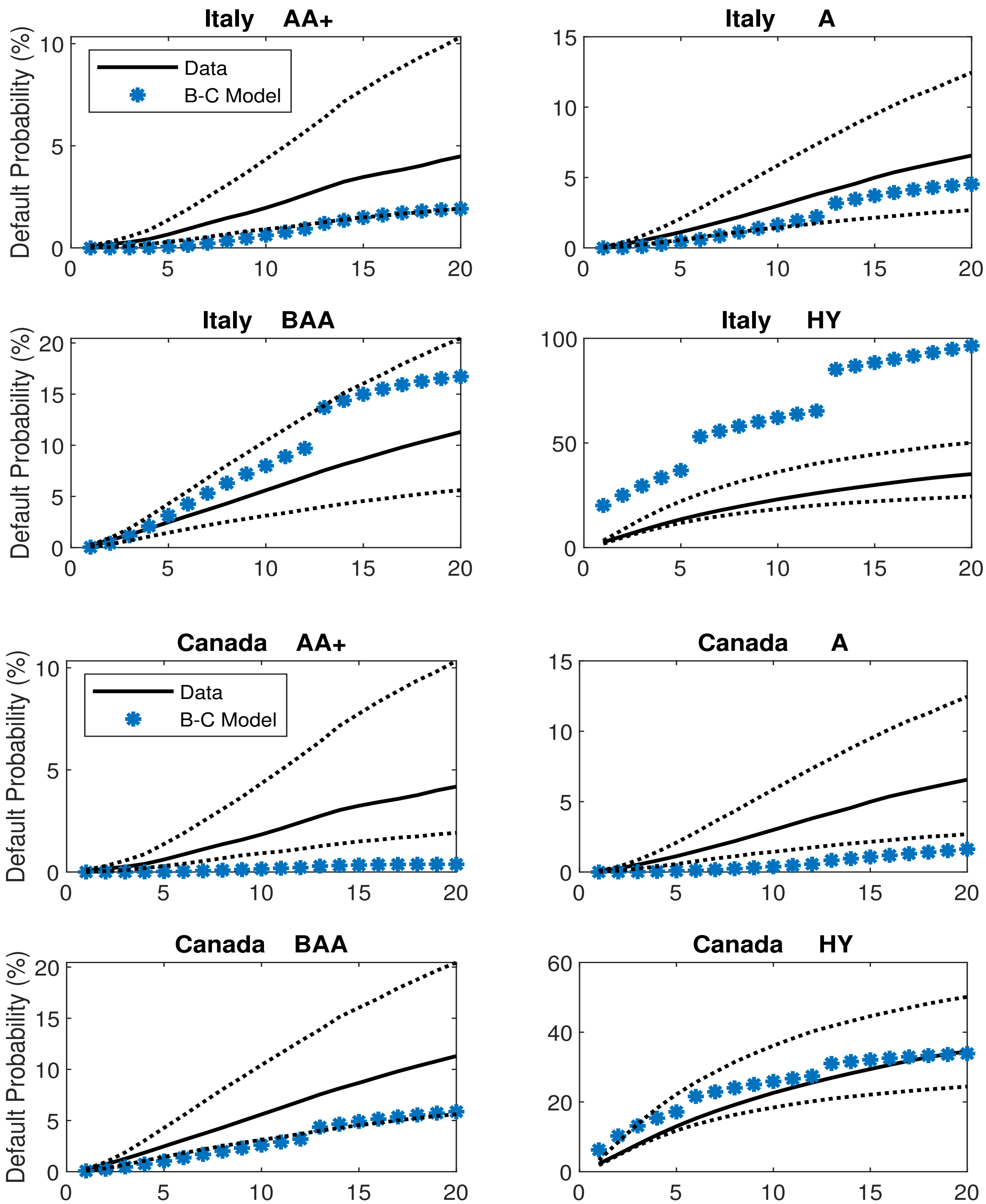
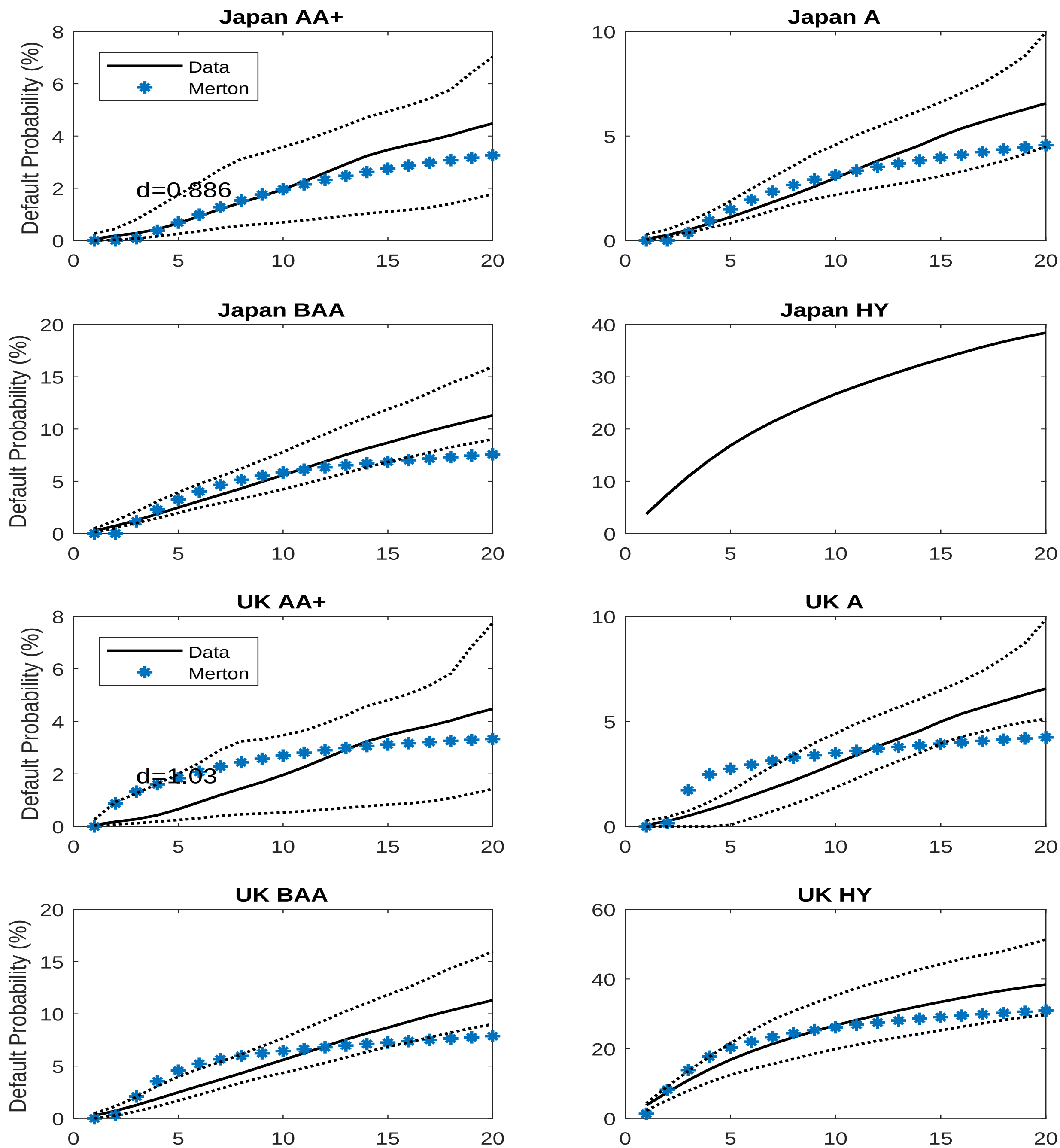


Figure A8: Historical Default Rates and the Merton $\mathbb{P}$-Measure Default Probabilities

This figure plots the term structure of $\mathbb{P}$-measure default probabilities under the Merton (1974) model, along with Moody's average global default rates from 1920 to 2017. The data set underlying the Merton probabilities is constructed by merging firm data from Compustat Global with the Moody's ratings included in the Merrill Lynch corporate bond database. For every firm and every year from 1997 to 2017, we calculate a 1-, 2-, ..., 19-, 20-year default probability in the Merton model with the default boundary of 0.899 for Japan, 1.012 for UK, 0.937 for Germany, 0.943 for France, 0.791 for Itay, 1.022 for Canada. A 95% confidence band for the historical default rates is calculated following the approach of Feldh$\ddot{u}$tter and Schaefer (2018).



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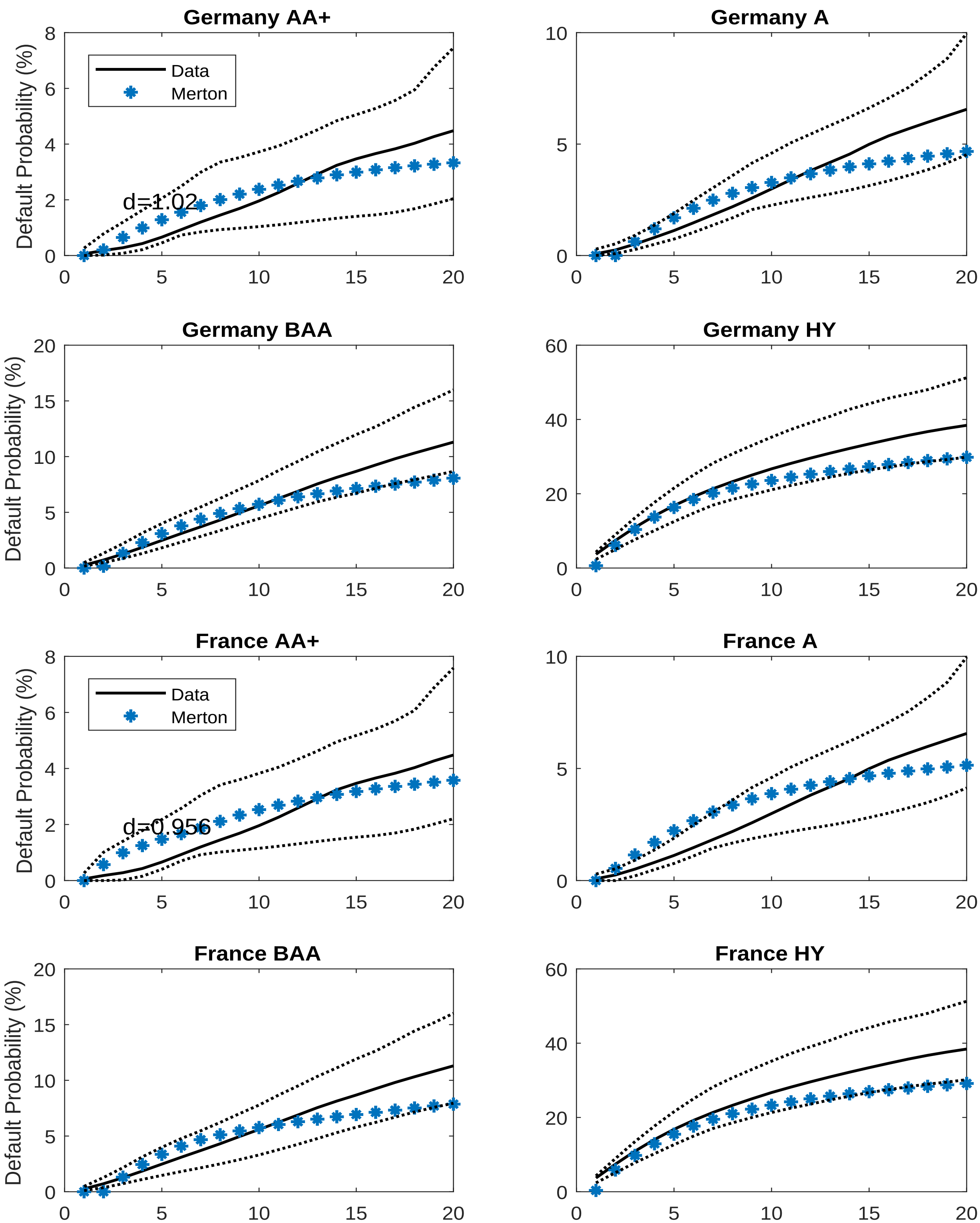

Figure A8 (continued)