Cox Proportional Hazards Model, Emerging Markets

An Application of the Cox Proportional Hazards Model

Analyzing Emerging Market Sovereign Bond Issuance

In September of 2016, Ghana issued $750 million in new debt at a 9.25% yield.

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Updated Dec. 20, 2016 6:33 a.m. ET

To gain a better understanding of emerging market economies and the financing of these countries, in this report, we will analyze what country-specific attributes impact the length of time until a country issues its first sovereign bond in the global debt market. In a previous report, we analyzed emerging market sovereign bond issuance with a Logistic Regression Model, where, for the i^{th} country, we denoted $Y_i = 1$ if the country issued sovereign debt between 1995 and 2013 and $Y_i = 0$ if the country did not issue sovereign debt between 1995 and 2013. In this analysis, we apply different methodology to the same general question: *what factors determine when a country first issues sovereign bonds in the global debt market?*

In this analysis, we will use the Cox Proportional Hazards Model, which is a part of the broader class of *survival models*. The Cox Proportional Hazards Model relates at least one covariate to the time that passes before a given event occurs. In this case, the event is initial sovereign bond issuance by a country, or the first time a country taps global debt markets. This model will help us better understand the evolving, growing global debt market.

As a note, *survival models* are frequently used in a variety of industries, as these models can be applied to analyze the time-to-onset for almost any event. The Cox Proportional Hazards Model, for instance, is used within the consumer-products industry to model device failure times and within the medical sphere to model the time until recurrence of a disease or illness. Similarly, Cox Models are often applied in the financial industry when analyzing the default rate of banks and other companies. Like the other scenarios described in this paragraph, initial sovereign bond issuance is a time-dependent event, too, explaining why I chose to implement the Cox Proportional Hazards Model in this setting.

All data used in this analysis was retrieved from the World Bank website, IMF reports, or the Federal Reserve Economic Data Catalog (FRED). For the i^{th} country in the dataset, we let T_i equal the time (in days since January 1^{st}2004) that elapsed until the first sovereign bond issuance for this country. As an example, if the i^{th} country in the dataset first issued sovereign debt on February 22^{nd}, 2004, then T_i would equal 52 days.

For each country in the dataset, T_i was retrieved from the IMF report found here. Countries in the dataset that still did not issue their first sovereign bond in the time period of this analysis, which we will call *right-censored* countries, were retrieved from the IMF report found here. To align our Cox Proportional Hazards Model with these two sources of data from the IMF, only the ten-year period between January 1^{st}, 2004 and December 31^{st}, 2013 was considered in this report. Any countries that issued sovereign debt before 2004 are consequently not considered in this dataset. Similarly, any countries that issued sovereign debt for the first time after 2013 do not have correct T_i values in this analysis, as this report only covers the ten year period ending in December of 2013.

Clearly, our dataset is relatively small in this analysis. However, we wanted to keep our source of data consistent to avoid discrepancies in determining exactly when each country officially issued its first sovereign bond. In future analyses, sovereign bond issuance over longer time periods could be studied using the Cox Proportional Hazards Model. Possibly, a more accurate, up-to-date Cox Model could even be constructed using data on initial sovereign bond issuance for all countries.

For each country in our dataset, we first need to encode whether or not the given country even issued its first sovereign bond between 2004 and 2013. Thus, in a similar methodology to Logistic Regression analysis, we let $status_i = 1$ if the country issued its first sovereign bond between 2004 and 2013 and $status_i = 0$ if the country did not issue its first sovereign debt between 2004 and 2013. Again, if $status_i = 0$, this i^{th} country *still* could have issued sovereign debt within the past three years, as this report only covers the ten year period from the start of 2004 to the end of 2013.

To further define the variables used in this snapshot report, we recall that, in previous analyses, we modeled the dependent variable in terms of entry-specific covariates. For example, in the previous Logistic Regression report analyzing whether or not a given IMF-designated Low-Income Developing Country (LIDC) issued a sovereign bond between 1995 and 2013, we encoded a variety of attributes about each country (e.g. Government Debt to GDP, GDP per Capita) as covariates in our Logistic Regression model.

Now, in this analysis, we want to model T_i in terms of the country-specific covariates $x_{i,1}$, . . . , $x_{i,p}$, where ‘p’ is the total number of covariates included in the model. For every country in the dataset, the following covariates were retrieved: Government Debt to GDP ratio (covariate 1, $x_{i,1}$), GDP per Capita (covariate 2, $x_{i,2}$), Resource Rich Developing Country (RRDC, covariate 3 $x_{i,3}$), the Annual Year-on-Year (YoY) growth rate (covariate 4, $x_{i,4}$), the unemployment rate (covariate 5, $x_{i,5}$), the YoY inflation rate (covariate 6, $x_{i,6}$), the current central bank interest rate (covariate 7, $x_{i,7}$), Government Effectiveness Index (covariate 8, $x_{i,8}$), Political Stability Index (covariate 9, $x_{i,9}$), Voice and Accountability Index (covariate 10, $x_{i,10}$), Regulatory Quality Index (covariate 11, $x_{i,11}$), Rule of Law Index (covariate 12, $x_{i,12}$), and the Control of Corruption Index (covariate 13, $x_{i,13}$). Thus, for each country, we encode thirteen different covariates into our Cox Proportional Hazards Model. As always, the initial data containing these covariate values for each country can be found at the bottom of the report.

The RRDC covariate was retrieved from the following IMF report found here. As written in the report, each LIDC is assigned a dummy variable of either 1 or 0, with a value of 1 indicating the country is resource rich, and a value of 0 indicating the country is not resource rich. The Government Effectiveness Index, Political Stability Index, Voice and Accountability Index, Regulatory Quality Index, Rule of Law Index, and Control of Corruption Index were all retrieved from the World Governance Indicators Initiative, a program run by the World Bank. These indices have been collected since 1996, and each index is a scaled value between -2.5 and 2.5. For those interested, an outline of the methodology for calculating each index can be found on the World Bank website, with all of these World Bank indices drawing on data from a variety of sources, including development banks (e.g. African Development Bank, Asian Development Bank). The remaining covariates used in this analysis (Government Debt to GDP ratio, GDP per Capita, Annual YoY growth rate, current unemployment rate, YoY inflation rate, and the current central bank interest rate) were retrieved from either the World Bank Data Catalog or FRED.

Now, let’s dive into an exploration of the theory of the Cox Proportional Hazards Model. In previous paragraphs, we defined $status_i$ as a binary variable and T_i as the time (in days) that elapsed until the first sovereign bond issuance for the i^{th} country. With the Cox Proportional Hazards Model, we treat T_i as a continuous random variable. For this random variable T_i, we define CDF = $F_i(t)$ and PDF = $f_i(t) = F'_i(t)$.

To further describe the Cox Proportional Hazards Model, we will introduce $\lambda_i(t)$ as the hazard function. With the Cox model, we will consider the distribution of T_i in terms of $\lambda_i(t)$. Intuitively, in this analysis, the hazard function $\lambda_i(t)$ represents the *instantaneous probability* that a given country issued its first sovereign bond at time 't,' and the formula for this hazard function $\lambda_i(t)$ can be seen below, where δ is a small constant. Note: conditional on a given country *not* having issued its first sovereign bond before time 't,' $\delta * \lambda_i(t)$ can be thought of as the probability that a given country in the dataset issued its first sovereign bond within the time window [t, t + δ].

$$\lambda_i(t) := \lim_{\delta \to 0} \frac{1}{\delta} \mathbb{P}[T_i \leq t + \delta \mid T_i \geq t]$$

This hazard function can easily be formulated with the CDF $F_i(t)$ and PDF $f_i(t)$ defined above.

$$\lambda_i(t) = \lim_{\delta \to 0} \frac{\mathbb{P}[t \leq T_i \leq t + \delta]}{\delta \, \mathbb{P}[T_i \geq t]} = \lim_{\delta \to 0} \frac{F_i(t + \delta) - F_i(t)}{\delta(1 - F_i(t))} = \frac{f_i(t)}{1 - F_i(t)}$$

The Cox Proportional Hazards Model used in this analysis does not make any assumptions about the distribution of T_i. Rather, the Cox Model the defines hazard function $\lambda_i(t)$ as follows:

$$\lambda_i(t) = \lambda_0(t) \exp(\beta_1 x_{i1} + \ldots + \beta_p x_{ip})$$

As seen in past reports using Logistic Regression, the parameters $\beta_1, \ldots, \beta_p$ are the unknowns being solved for, and 'p' is the number of covariates (13 in this analysis). In the Cox Proportional Hazards Model, these unknown parameters $\beta_1, \ldots, \beta_p$ determine the effects of each covariate (x_i) on the predicted length of time T_i until a given country issues its first sovereign bond. Additionally, note that $\lambda_0(t)$ is the *baseline hazard function*, or the hazard function if all covariates are equal to zero. When using the Cox Proportional Hazards Model, $\lambda_0(t)$ is unknown, yet it is unnecessary to determine this baseline function to complete our analysis.

As further explanation of the Cox Model, we see that $\lambda_0(t)$ models the overall shape of the hazard function for all countries in this analysis. The factor containing the country-specific covariates, or $\exp(\beta_1 x_{i1} + \ldots + \beta_p x_{ip})$, only scales the hazard function for each individual country. Thus, although the shape of the baseline hazard function $\lambda_0(t)$ is exactly the same for all countries in this analysis, the scaling factor $\exp(\beta_1 x_{i1} + \ldots + \beta_p x_{ip})$ changes depending on the specific covariates of each country.

For two countries (e.g. country 'i' and country 'j'), the Cox Model assumes the hazard functions of each country differ only in scale, meaning $\lambda_i(t) \div \lambda_j(t)$ is constant for all times 't' in the analysis. This condition of the Cox Model is called the *proportional hazards assumption* . Since this condition is not trivial, this proportional hazards assumption can be analyzed using either *proc lifetest* in SAS or the *plot* function applied to a *survfit* object in 'R.' In this analysis, we will assume the proportional hazards assumption holds, enabling us to estimate the β coefficients for our thirteen covariates without consideration of $\lambda_0(t)$, the baseline hazard function. Note: this proportional hazards assumption is the first of two key conditions required for the results of the Cox Proportional Hazards Model to be safely applied. The second assumption of the Cox Proportional Hazards Model, which relates to *non-informative censoring*, will be described later in this report.

The Cox Proportional Hazards Model is slightly more complicated than the Logistic Regression Models and Linear Models used in previous reports. To address these complexities, we first realize that, in our Cox Model analysis, the time until first sovereign bond issuance T_i can be greater than the ten year period considered in this report. For instance, there are numerous countries that have still not issued sovereign debt, so the value of T_i is currently unknown (or undefined) for these countries. Since our analysis ends in December of 2013, our Cox Model cannot incorporate all true values of T_i for each country.

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In this report, for countries that did not issue their first sovereign bond between 2004 and 2013, we only observe $T_i > l_i$, where l_i is the length of the analysis (l_i = 10 years here). Note: l_i is a fixed, known constant. We call these observations with $T_i > l_i$ *right-censored* observations. Thus, for all countries in our dataset, we either observe an actual value of T_i that is less than or equal to l_i, or we simply observe that T_i is greater than l_i.

Following the procedures of the Cox Proportional Hazards Model, we must make the assumption that the true length of time until first sovereign bond issuance of a given country does not depend on l_i. This is the second key assumption of the Cox Proportional Hazards Model, where the first assumption (proportional hazards) was outlined in a previous paragraph. If this second condition holds, the Cox Proportional Hazards Model outlined below will naturally handle all right-censored observations in the dataset.

Next, we will dive into an explanation of how to calculate the Maximum Likelihood Estimators (MLEs) of each covariate in the Cox Proportional Hazards Model. Unlike in Logistic Regression and the Linear Model, we cannot perform standard statistical inference with the Cox Proportional Hazards Model by simply writing down the likelihood functions and setting partial derivatives equal to zero, as these likelihood functions for $\beta_1, \dots,$ β_p would depend on the baseline hazard rate function $\lambda_0(t)$, which is unknown in this analysis. Thus, we need to design a method of analysis such that $\lambda_0(t)$ cancels out when calculating the MLEs for $\beta_1, \dots, \beta_p$.

To eliminate the baseline hazard rate function $\lambda_0(t)$ from our analysis, we first condition the dataset on all distinct sovereign bond issuance times (e.g. $t_{(1)} < t_{(2)} < \dots < t_{(m)}$, where $t_{(1)}$ represents the shortest T_i observation and $t_{(m)}$represents the longest, *non right-censored* T_i observation in this analysis. Note: *'m'* represents the total number of *non right-censored* observations.

As stated previously, T_i is being modeled as a continuous random variable, so we can assume each observed initial sovereign bond issuance time $t_{(k)}$ corresponds to *only* one country in our dataset. In other words, we are assuming no two countries issued their first sovereign bonds on the exact same day. Then, for each $t_{(k)}$, we define a risk set $R_{(k)}$ as the set of all *non right-censored* countries that have still not issued a sovereign bond up to time $t_{(k)}$. Intuitively, $R_{(k)}$represents the set of possible countries that may issue their first sovereign bond at time $t_{(k)}$.

Then, conditional on the knowledge that some country in $R_{(k)}$ issued its first sovereign bond at time $t_{(k)}$, we define the probability that the issuing country was country $I_{(k)}$ as follows, where this probability is equivalent to the "instantaneous rate" of sovereign bond issuance for country $I_{(k)}$ divided by the sum of the instantaneous rates for all remaining candidate countries in $R_{(k)}$.

$$\frac{\lambda_{I_k}(t_{(k)})}{\sum_{i \in \mathcal{R}_{(k)}} \lambda_i(t_{(k)})}$$

In the Cox Proportional Hazards Model, this formula above is equivalent to the following formula:

$$\frac{\lambda_0(t_{(k)}) \exp(\beta_1 x_{I_k 1} + \ldots + \beta_p x_{I_k p})}{\sum_{i \in \mathcal{R}_{(k)}} \lambda_0(t_{(k)}) \exp(\beta_1 x_{i1} + \ldots + \beta_p x_{ip})}$$

We see that the baseline hazard rate function $\lambda_0(t)$ cancels out in the above formula, enabling us to write out the partial likelihood function for the ‘m’ *non right-censored* observations in the dataset. This partial likelihood function can be seen here:

$$\text{plik}(\beta_1, \ldots, \beta_p) = \prod_{k=1}^{m} \frac{\exp(\beta_1 x_{I_k 1} + \ldots + \beta_p x_{I_k p})}{\sum_{i \in \mathcal{R}_{(k)}} \exp(\beta_1 x_{i1} + \ldots + \beta_p x_{ip})}$$

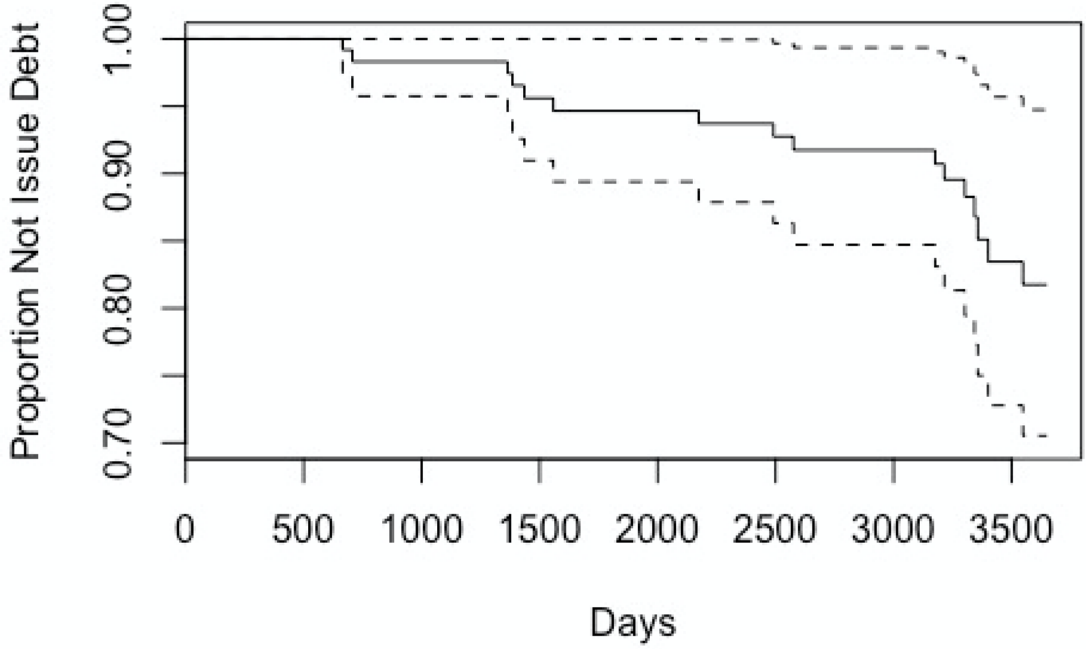
Similar to Logistic Regression analysis, we can estimate $\beta_1, \ldots, \beta_p$ by maximizing the partial likelihood for these unknown parameters. As usual, we introduce a logarithm to simplify the calculations:

$$l(\beta_1, \ldots, \beta_p) = \sum_{k=1}^{m} \left(\beta_1 x_{I_k 1} + \ldots + \beta_p x_{I_k p} - \log \sum_{i \in \mathcal{R}_{(k)}} \exp(\beta_1 x_{i1} + \ldots + \beta_p x_{ip}) \right)$$

Since we use thirteen different covariates in this analysis, ‘p’ = 13, and we calculate the MLEs for $\beta_1, \ldots, \beta_{13}$ by setting all thirteen individual partial derivatives with respect to each β_j equal to zero, as seen below. With thirteen partial derivative equations and thirteen unknown β_j values, we can solve for each β_j.

$$0 = \frac{\partial l}{\partial \beta_j} = \sum_{k=1}^{m} \left(x_{I_k j} - \frac{\sum_{i \in \mathcal{R}_{(k)}} x_{ij} \exp(\beta_1 x_{i1} + \ldots + \beta_p x_{ip})}{\sum_{i \in \mathcal{R}_{(k)}} \exp(\beta_1 x_{i1} + \ldots + \beta_p x_{ip})} \right)$$

Now that we have shown how to eliminate the unknown baseline hazard function $\lambda_0(t)$ and explained the fundamentals and assumptions of the Cox Proportional Hazards Model, let’s use the *survival* library in ‘R’ to dive into the data. First, we fit a Cox Model to the data with the *coxph* function, and a predicted distribution of survival times according to this model can be graphed using the *survfit* function in ‘R.’ We can see a graph of the predicted survival times below. The dotted lines represent a 95% confidence band.



Next, using the results of our Cox Model, we find the MLEs for the unknown parameters $\beta_1, \ldots, \beta_{13}$.

$$\hat{\beta}_1 = \hat{\beta}_{\text{Gov't Debt to GDP}} = 1.008$$
$$\hat{\beta}_2 = \hat{\beta}_{\text{GDP Per Capita}} = 7.068 * 10^{-5}$$
$$\hat{\beta}_3 = \hat{\beta}_{\text{RRDC}} = 7.351 * 10^{-1}$$
$$\hat{\beta}_4 = \hat{\beta}_{\text{YoY Growth Rate}} = 3.109 * 10^{-2}$$
$$\hat{\beta}_5 = \hat{\beta}_{\text{Unemployment Rate}} = -2.681 * 10^{-2}$$
$$\hat{\beta}_6 = \hat{\beta}_{\text{YoY Inflation Rate}} = -7.351 * 10^{-2}$$
$$\hat{\beta}_7 = \hat{\beta}_{\text{Central Bank Interest Rate}} = 7.210 * 10^{-2}$$
$$\hat{\beta}_8 = \hat{\beta}_{\text{Gov't Effectiveness Index}} = 2.395$$
$$\hat{\beta}_9 = \hat{\beta}_{\text{Political Stability Index}} = -1.348$$
$$\hat{\beta}_{10} = \hat{\beta}_{\text{Voice and Accountability Index}} = 1.5601 * 10^{-1}$$
$$\hat{\beta}_{11} = \hat{\beta}_{\text{Regulatory Quality Index}} = -3.163$$
$$\hat{\beta}_{12} = \hat{\beta}_{\text{Rule of Law Index}} = 2.177$$
$$\hat{\beta}_{13} = \hat{\beta}_{\text{Control of Corruption Index}} = -1.091$$

Then, similar to Logistic Regression analysis, for each of the thirteen covariates used in this analysis, 'R' was used to complete a Generalized Likelihood Ratio Test (GLRT) for the following null and alternative hypotheses: H_0: $B_j = 0$ and H_1: $B_j \neq 0$, for j = 1...13. Using a significance level of $\alpha = 0.05$, the GLRT rejected any null hypothesis with $p < 0.05$, where, as usual, p is the probability of a Type 1 Error. As seen in the hypotheses above, the GLRT is used to study whether a given covariate has a statistically significant effect on when a country issued its first sovereign bond. If we fail to reject H_0 for a given covariate, then the β for this covariate is not statistically significantly different than zero, and, according to the Cox Proportional Hazards Model, this covariate does not have a statistically significant effect on when a country issued its first sovereign bond.

Implementing the thirteen GLRTs in 'R' for each H_0: $B_j = 0$ and H_1: $B_j \neq 0$, we discover that four of the thirteen covariates have a statistically significant effect on when a country issued its first sovereign bond according to this Cox Proportional Hazards Model. These four covariates are GDP per Capita ($p = 0.025 < \alpha = 0.05$), the World Bank Government Effectiveness Index ($p = 0.031 < \alpha = 0.05$), the World Bank Political Stability Index ($p = 0.031 < \alpha = 0.05$), and the World Bank Regulatory Quality Index ($p = 0.0029 < \alpha = 0.05$). For the other nine covariates with $p > \alpha$, we do not reject H_0, and the Cox Proportional Hazards Model for this dataset does *not* support that these covariates have a statistically significant effect on when a country first issued sovereign debt.

According to the Cox Proportional Hazards Model, for a unit increase in covariate x_i, the log hazard rate is increased by β_i, or, equivalently, the hazard rate $\lambda_i(t)$ is increased by $\exp(\beta_i)$. Thus, as an example of how to interpret these thirteen MLEs, since our Cox Model finds that $\beta_{\text{Government Debt to GDP}}$ is positive, as Government Debt to GDP increases, the hazard rate $\lambda_i(t)$ increases in our analysis. On the other hand, since our model finds that $\beta_{\text{Regulatory Quality}}$ is negative, as regulatory quality increases, the hazard rate $\lambda_i(t)$ decreases. Note: a decreasing hazard rate function implies a longer time 't' until initial sovereign bond issuance for a given country in the dataset.

Looking at the MLE results of this analysis, we can see that many of these covariate relationships found using the Cox Proportional Hazards Model are not trivial. For example, since $\beta_{\text{Government Effectiveness Index}} = 2.395$, as government effectiveness improves, the hazard rate $\lambda_i(t)$ increases, implying a shorter time 't' until initial debt issuance. In some ways, this result makes logical sense - if a country has a very effective government (high $x_{\text{Government Effectiveness Index}}$ value), it should be easier for this country to tap debt markets, as investors would consider this country safer and more trustworthy, leading to higher demand for the country's debt. On the other hand, a negative $\beta_{\text{Government Effectiveness Index}}$ could also make logical sense, as emerging markets with more effective governments may be less dependent on external funding. Thus, the thirteen MLEs found with this Cox Proportional Hazards Model are clearly not all intuitive.

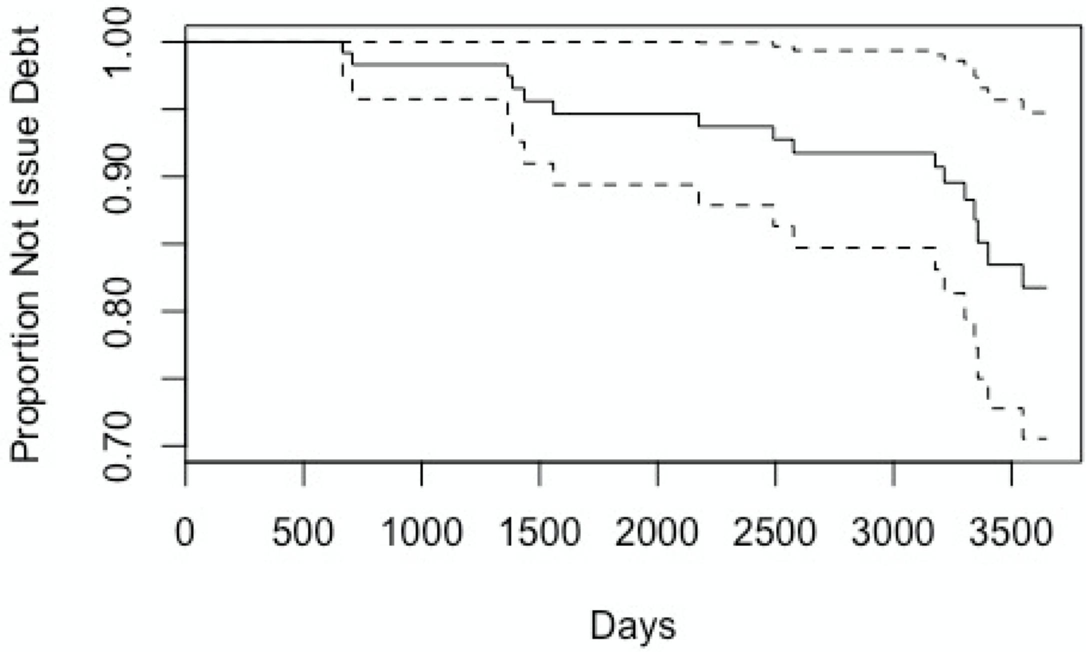
Now, we will compare the results of this Cox Proportional Hazards Model to the previous report analyzing emerging market sovereign bond issuance using Logistic Regression and Machine Learning. These reports are similar for three main reasons. First: both reports analyzed sovereign bond issuance in emerging markets. Second: some covariates overlapped both analyses, such as the World Bank Government Effectiveness Index and GDP per Capita. Third: the IMF was used as the source of data for both analyses.

As a recap, in the previous Logistic Regression report, we utilized data from the IMF to determine whether or not a given country in the dataset issued a sovereign bond between 1995 and 2013. In our dataset, we included all countries designated by the IMF as Low Income Developing Countries (LIDCs). In this Logistic Regression Model, for the i^{th} country in the dataset, Y_i is defined such that $Y_i = 0$ if the country did not issue a sovereign bond between 1995 and 2013 and $Y_i = 1$ if the country did issue a sovereign bond between 1995 and 2013. Using the Generalized Likelihood Ratio Test with this Logistic Regression Model, our analysis showed that only GDP per Capita was a statistically significant covariate in determining whether or not a given country issued a sovereign bond between 1995 and 2013 (with $p < \alpha$). However, the GLRT in this Logistic Regression analysis also found that $p_{Gov't\ Effectiveness} = 0.071$. Although this World Bank Government Effectiveness Index was not a statistically significant covariate in the Logistic Regression model (since $p > \alpha = 0.05$), we should note that this p-value was still relatively small and close to the $\alpha = 0.05$ threshold significance level.

Thus, the results of our Cox Proportional Hazards Model are fairly similar to the results of our Logistic Regression Model. The only statistically significant variable in the Logistic Regression Model is also statistically significant in the Cox Model (GDP per Capita). Additionally, the next covariate closest to being statistically significant in the Logistic Regression Model with p = 0.071 (World Bank Government Effectiveness Index) is statistically significant in our Cox Model, too.

As a side note, the Cox Proportional Hazards Model and the Logistic Regression Model are inherently different with different assumptions, so we do not expect the results of each model to be identical. Additionally, different datasets were used for both analyses. Although both reports utilized data retrieved from the IMF, the Logistic Regression analysis incorporated data from 1995 to 2013, but this current Cox Proportional Hazards Model only analyzes the ten-year period between 2004 and 2013. Thus, it is not surprising that these two models yield somewhat different statistically significant covariates.

In my opinion, the most important knowledge that can be gained from this Cox Proportional Hazards Model is seen in the graph of predicted survival times. Although this graph is already shown above, for convenience, the graph is also shown below. Again, the dotted lines represent a 95% confidence band.



As seen in this graph, after the financial crisis, as time *t* increases towards the end of 2013, more and more countries began to issue sovereign debt for the first time. We may wonder - *why did numerous countries begin to take on sovereign debt for the first time between 2010 and 2013*? In my opinion, there is one main reason for this increased sovereign debt issuance after the financial crisis: record-low bond yields in developed countries.

The main reason for increased sovereign debt issuance is record-low bond yields in developed countries. In the past few years, unprecedented asset purchase programs were initiated by various Central Banks, including the Federal Reserve, the Bank of Japan, and the European Central Bank. This global quantitative easing has led to plummeting bond yields around the world, forcing investors still looking for a decent return to purchase bonds from issuers with lower credit ratings. Although yields have risen slightly in the past few months after Trump was elected, borrowing costs around the world are still abnormally low compared to historical levels.

With such low borrowing costs, numerous emerging market countries are seizing the opportunity to issue bonds in global debt markets. For example, this September, only weeks after Ghana requested a bailout from the IMF, the country sold $750 million worth of debt at a 9.25% yield. Although Ghana still has high inflation and high debt, investors seemed to shrug these issues off; investors wanted any security with yield, and bonds from Ghana offered these investors a high-yield opportunity in a world of low and negative rates. Amazingly, before 2006, South Africa was the only sub-Saharan African country to have issued a sovereign bond denominated in a foreign currency. Since 2006, though, *at least* fourteen additional countries in sub-Saharan Africa have issued sovereign bonds, including countries that rely heavily on external aid (e.g. Rwanda). In 2013, sub-Saharan Africa managed to issue a record $4.6 billion in new sovereign debt.

At first, emerging market bond issuance seems like a win-win situation for investors and issuers. For example, Ghana is able to raise capital in global markets, and investors are able to find a decent return in a world of low and negative yields. However, I believe the current pace of emerging market debt issuance is a problem. Debt issuance requires emerging market countries to have strong political will and financial discipline, yet many of these countries do not have these qualities. For many of these emerging markets, sovereign debt issuance is a short-term drug, allowing countries to push off economic reforms for the time being. With changing financial and political conditions, repaying this debt can become *extremely* difficult for some emerging market countries. For instance, in 2008, Seychelles defaulted on its sovereign debt, mainly due to years of excessive government spending.

Thus, I believe this increased debt issuance from emerging market countries should worry investors and economists. A high percentage of emerging market debt is set to mature in the early to mid 2020s, and many of these new emerging market bond issuers may have trouble repaying this debt. After Donald Trump was elected in November of 2016, the dollar has strengthened, too, moving towards parity with the Euro. As the dollar strengthens, external debt becomes more expensive for emerging markets to service, since the debt is typically denoted in U.S. dollars. Thus, in upcoming years, with more protectionist policies under the new Trump administration and a strengthening dollar, we may find that emerging market economies have difficulty repaying investors, leading to increased defaults in the next few years. Just something to keep an eye on...

Click here to download the data used in this snapshot financial report.