Columbia SIPA Capstone Project

Measuring How Political Risk Affects Sovereign Bond Spreads

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I. ABSTRACT

This paper covers the work completed by the Columbia SIPA Capstone Team for BCG Platinion in the Spring Semester 2018. In the course of this project, the Capstone team identified the need for a more precise risk forecasting methodology on the directional movements of sovereign spreads, one that quantifies and includes political risk and uncertainty in addition to sovereign ratings. In order to do so a statistical model was developed to triangulate sovereign risk spread, sovereign credit ratings and political risk indices. The team aimed to more accurately forecast the directional movements of sovereign spreads by incorporating political uncertainty in addition to ratings, through the use of statistical methods. In the conclusion of the project, the team found that political risk does correlate with sovereign spreads. Within the developed model, political risk explains between 61% to 88% of variance depending on the country. This finding is more consistent with correlation than causation, and weaknesses in the model may be related to the political risk indices utilized, ICRG. Going forward, the Capstone Team believes BCG Platinion should find a more actionable and forward-looking measure of political risk that captures fluctuations at a more granular level, or find better proxy indicators for political risk that vary more over-time.

II. INTRODUCTION

BCG Platinion is working with non-financial institutions to complete a macroeconomic risk assessment on how to capture and measure political risk impacts to the firm. The SIPA Capstone team is tasked with researching and developing a forecasting methodology that incorporates political uncertainty into a probabilistic framework.The scope of the project views political risk as investment risk for U.S. institutions with subsidiaries in emerging markets.

III. PROBLEM DEFINITION

Political risk refers to the risk that a political event, government action, or societal outcome can have on a business.

Typically, investors consider risks associated with investments in emerging markets by utilizing sovereign credit ratings and sovereign spreads to determine an acceptable level of risk. Sovereign rating refers to a sovereign government's ability and willingness to service its debt in full and on time, and the sovereign credit spread is the difference between the yield on a bond issued by a developing country in USD and a US Treasury bond of similar maturity.

Even though it is generally understood that these types of investments are affected by political risk factors, the latter is rarely incorporated into a deterministic model in relationship to both the sovereign ratings and sovereign spreads. Hence, there is a need for a more precise risk forecasting methodology on the directional movements of sovereign spreads, one that quantifies and includes political uncertainty in addition to sovereign ratings.

IV. LITERATURE REVIEW

This gap in available market solutions was identified through a literature review of forty-five academic and industry-specific resources.

Through this process, the Capstone team distinguished two approaches to political risk analysis: (i) a structural approach that utilises static macroeconomic and political data to look at broader circumstances in a country; and (ii) an event-driven approach that utilises temporal and periodic data to analyse direct government action and economic functions.

The team identified several political risk indices: the Economist Intelligence Unit (EIU), Business Environment Risk Information (BERI) and Political Risk Service (PRS), and International Country Risk Guide (ICRG). ICRG political risk ratings were the most widely utilized political risk data set across academic literature.

The Capstone team also identified potential main output variables affected by political risk to include: Foreign Direct Investment (FDI), insurance pricing, strategic investing, and the stock market. The team only identified one researcher, Geert Bekaert et al., who used the political risk spreads extracted from sovereign spreads as the main output variable.[1]

V. METHODOLOGY

Seeking to fulfill this identified gap, the Capstone team worked to develop a statistical model to triangulate sovereign risk spread, sovereign credit ratings and political risk indices of South Korea, Russia, South Africa, Italy, India and Mexico, with United States as a baseline. These countries were chosen with the intention to focus on a select few emerging markets. However, the chosen countries were also contingent upon the availability of the data.

Given the theoretical relationship between ratings upgrades (downgrades) and reduction (increase) in spread, the team aimed to more accurately forecast the directional movements of sovereign spreads (dependent variable) by incorporating political uncertainty in addition to ratings.

[1] Geert Bekaert, Campbell Harvey, Christian Lundblad, and Stephan Siegel. (2016). "Political Risk and International Valuation", Journal of Corporate Finance", Vol. 37,Issue C (2016): 1-23.

Figure 1. ICRG Political Risk Components

POLITICAL RISK COMPONENTS		
Sequence	Component	Points *(max.)*
* A	Government Stability	12
* B	Socioeconomic Conditions	12
* C	Investment Profile	12
* D	Internal Conflict	12
* E	External Conflict	12
F	Corruption	6
G	Military in Politics	6
H	Religious Tensions	6
I	Law and Order	6
J	Ethnic Tensions	6
K	Democratic Accountability	6
L	Bureaucracy Quality	4
Total		100

The team selected to use the International Country Risk Guide (ICRG) political risk ratings because it is the most widely utilized political risk data set across academic literature and has broad cross-country and cross-time coverage. It is also widely utilized because of its forward-looking nature and its quantification of political risk separate from macroeconomic factors. There are 12 political risk indicators, updated monthly: Government Stability (GS), Socioeconomic Conditions (SC), Investment Profile (IP), Internal Conflict (IC), External Conflict (EC), Corruption (CO), Military in Politics (MP), Religious Tensions (RT), Law and Order (LO), Ethnic Tensions (ET), Democratic Accountability (DA), Bureaucratic Quality (BQ).

The team also used sovereign ratings and sovereign spreads from 2000-2017 from S&P ratings, and the Global Financial Data respectively. Missing data values were statistically imputed on Excel using linear interpolation.

As for control variables, the team used economic and financial risk indicators from ICRG. The economic risk indicators combines GDP per Head, Real GDP Growth, Annual Inflation Rate, Budget Balance as a Percentage of GDP and Current Account as a Percentage of GDP. The financial risk indicators include Foreign Debt as a Percentage of GDP, Foreign Debt Service as a Percentage of Exports of Goods and Services, Current Account as a Percentage of Exports of Goods and Services, New international Liquidity as Months of Import Cover and Exchange Rate Stability. Furthermore, recent literature explored a global factor that may influence emerging market bond prices (Bekaert et al., 2012): the high yield spread.[2] Therefore, the team collected the Bank of America Merrill Lynch US High Yield BB Effective Yield over US 10-year government bond to explore the extent to which US credit risk pricing impacts emerging market bonds.

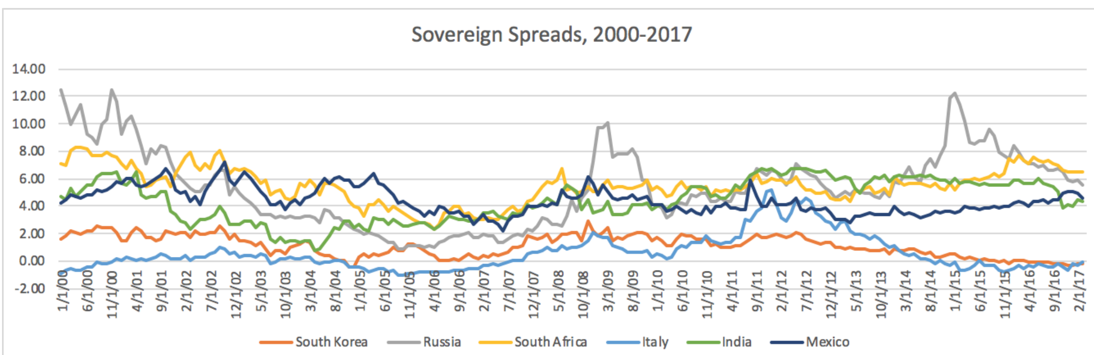
[2] Geert Bekaert, Campbell Harvey, Christian Lundblad, and Stephan Siegel. (2016). “Political Risk and International Valuation”, Journal of Corporate Finance”, Vol. 37,Issue C (2016): 1-23.

Due to time and resource constraints, other control variables were not pursued. Since most of the control variables also come from the ICRG dataset, it is expected that there is strong correlation between the Economic, Financial and Political risk indicators. It is important to note that between the Economic and Financial risk indicators, major macroeconomic indicators such as GDP growth, inflation and unemployment are incorporated.

Data Preparation

The Capstone team determined the dependent variable to be 10-year sovereign spread. The dependent variable "10yrspread" is the difference of yields of the 10-year treasury bond of each country and the United States. Figure 2 shows the time-series for the 10-year sovereign spreads for selected countries. For example, a positive spread indicates that a country has a higher 10-year yield than that of the United States, which indicates a relative higher risk of investment in that country. Conversely, a negative spread indicates relative lower risk of investment in that country in comparison to the United States.

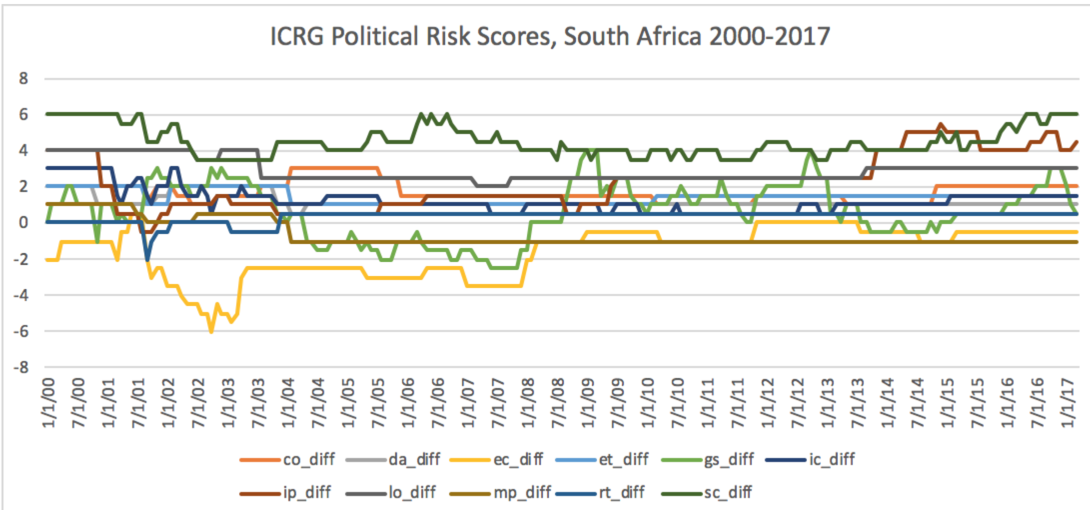
Figure 2. Sovereign Spreads, 2000-2017



The independent variables were derived from the following indicators: the 12 ICRG Political Risk Scores, ICRG Economic Risk Scores, ICRG Financial Risk Scores, high yield spread, and S&P Country Risk Ratings. The independent variables, labeled as "xx"_diff, were calculated by subtracting the score from each country from the same score of the United States. For consistency, the team took the difference between each ICRG political risk variable from that of the United States such that a positive difference reflected a greater political risk and a negative difference infers a lower political risk as compared to the US. For illustration purposes, on January 1, 2017, the Government Stability (GS) score of the US was 9 (out of 12), showing low levels of risk and 6 (out of 12) for South Africa, showing a medium level of risk. This difference of the US score and that of South Africa was 3 and reflects a higher political risk than that of the United States.

The Capstone team also combined the 12 ICRG variables by addition to create a composite score out of 100 and then calculated the difference of each country's composite score from that of the United States - whereby a higher composite score difference infers a higher overall political risk and a lower composite score difference infers a lower overall political risk. From the 12 ICRG Political Risk variables, the variable Bureaucratic Quality (BQ) was dropped due to its lack of change through the years in the individual variables analysis.

Figure 3. ICRG Political Risk Scores, South Africa 2000-2017



The team utilized ten year sovereign spread data instead of three year or five year sovereign spread data because of the availability of monthly data points and because the bond with the highest maturity is more conventionally used in the evaluation of the country's risk. Both the three year and five year spreads had many gaps in data, and the team was unable to reliably impute the data, as Credit Default Swap (CDS) rates for corresponding bond maturities also had many gaps. Additionally, the decision was made to not utilize lag variables as initially planned. Upon examination, it was determined that there was very little difference in the ICRG variables one, three, and six months apart, due to the structural nature of the data set. Consequently, the lag variables would have very little significance and therefore were not incorporated.

Figure 4. Raw correlation between ICRG Political Risk variables and sovereign spreads (South Africa)

	co_diff	da_diff	ec_diff	et_diff	gs_diff	ic_diff	ip_diff	lo_diff	mp_diff	rt_diff	sc_diff	comp_diff
10yr spread	-0.2135	0.4572	0.1935	0.636	0.5516	0.5645	0.385	0.6881	0.5325	-0.3484	0.2622	0.7752

The Capstone team first examined the correlation of each country's ICRG political risk variables and sovereign spreads. It was discovered that some correlations were counter-intuitive and thus further analysis was necessary. As seen by the above example of South Africa, Corruption (CO) and Religious Tension (RT) are negatively correlated with the 10 year spread.

Multicollinearity Testing

As the majority of the independent variables were obtained from the ICRG dataset, 11 of which are intended to measure political risk, the Capstone team decided to perform multicollinearity testing. The goal is to determine if any one of the variables in the model can be linearly predicted from the other variables with a substantial degree of accuracy. If such phenomenon exists, the coefficient estimates of the multiple regression may change erratically in response to small changes in the model or the data. A multivariate regression model with collinear variables can indicate how well the independent variables as a whole predict the outcome, but it may not provide accurate results about any individual variable.

In order to test for multicollinearity, the Capstone Team tested the variance inflation factor (VIF). VIF is the ratio of variance in the model with multiple terms, divided by the variance of a model with one term alone. This method quantifies the degree of multicollinearity within a regression analysis. VIF provides a value that indicates how much of the variance of a regression coefficient is related to collinearity. The rule of thumb is that if the average VIF value of each variable in the model is greater than 10, then multicollinearity is high. If the average VIF of each variable in one model is less than 4, then multicollinearity is low.

Stepwise Analysis

After cleaning the data, the Capstone team decided to utilize Stepwise Analysis, which is a conventional method to to counter multicollinearity. Stepwise regression is a methodology that works to fit a regression model by choosing which independent variables have the most explanatory power through an automatic process. The Capstone Team chose the backward elimination in which all independent variables are tested and the variable with the least statistical significance is deleted. This process is repeated until no other variables can be deleted without losing statistical significance of fit.

To further counter multicollinearity, and because the ratings did not change significantly over the years, the team decided to treat the S&P ratings as dummy variables into ratings upgrades and ratings downgrades.

Principal Component Analysis (PCA) and **Factor Analysis (FA)**

Another way to counter multicollinearity is through Common Factor Analysis (CFA) and Principle Component Analysis (PCA). Both methods explore the correlation between the model's independent variables to see if variables can be reduced into sets of groups which are distinct from each other. Using PCA, one can either combine highly correlated factors into several categories, or eliminate factors that can explain the variance of other independent variables more than dependent variables. Hence, it is a way to reduce the influence of multicollinearity on independent variables. While PFA has a different theory, both PCA and PFA results in similar conclusions.

Autocorrelation and Durbin Watson Test Statistic

Temporal Autocorrelation occurs when there is Omitted Variable Bias (OVB) and can affect the confidence interval of statistical estimates. In this case of a time series, there is often a very high correlation between T1 and T2, which are temporarily organised as if they are not independent of each other. Consequently, the Capstone team ran a Durbin Watson test, which tests the null hypothesis that the residuals from an ordinary least-squares regression are not auto-correlated against the alternative that they are. The Durbin-Watson (DW) test statistic ranges in value from 0 to 4. A value close to 2 indicates non-autocorrelation; a value close to 0 indicates positive autocorrelation; a value close 4 indicates negative autocorrelation.[3]

VI. RESULTS

Our key regression took the following form:

$$10yrspread = constant + \boldsymbol{\beta X} + \boldsymbol{\gamma Z} + \epsilon$$

Where ***X*** represents a vector of political risk indicator variables, ***Z*** represents a vector of other control variables.

The Capstone team arrived at the following three models with different political risk variables:

Model 1: 11 ICRG sub-components

$$\begin{aligned} 10\widehat{yrspread} = \widehat{constant} &+ \widehat{\beta_1} co\_diff + \widehat{\beta_2} da\_diff + \widehat{\beta_3} ec\_diff + \widehat{\beta_4} et\_diff + \widehat{\beta_5} gs\_diff \\ &+ \widehat{\beta_6} ic\_diff + \widehat{\beta_7} ip\_diff + \widehat{\beta_8} lo\_diff + \widehat{\beta_9} mp\_diff + \widehat{\beta_{10}} rt\_diff \\ &+ \widehat{\beta_{11}} sc\_diff + \widehat{\gamma_1} er\_diff + \widehat{\gamma_2} fr\_diff + \widehat{\gamma_3} highyield + \widehat{\gamma_4} ratingchange \end{aligned}$$

[3] "Durbin-Watson Significance Tables", University of Notre Dame, https://www3.nd.edu/~wevans1/econ30331/Durbin_Watson_tables.pdf

Model 1	Greece	South Korea	Russia	South Africa	Italy	India	Mexico
Adj. R-Squared	0.6902	0.7661	0.9019	0.7910	0.7475	0.7996	0.6781
Correlation between Predicted and Actua	0.8308	0.8753	0.9497	0.8894	0.8646	0.8942	0.8234
Mean VIF	3.4904	2.6709	3.3047	2.7622	2.5814	3.0700	3.2244
D-W	1.9916	1.9632	2.1059	2.0345	1.7729	2.0898	2.5321
Percent ICRG Political Indicators Explain							
co_diff	11%	1%	1%	7%	3%	9%	15%
da_diff	5%	8%	5%	0%	14%	3%	2%
ec_diff	1%	0%	11%	1%	0%	26%	4%
et_diff	1%	0%	0%	1%	1%	7%	7%
gs_diff	0%	0%	4%	9%	2%	3%	12%
ic_diff	0%	2%	3%	1%	0%	16%	2%
ip_diff	29%	10%	2%	14%	37%	5%	8%
lo_diff	5%	4%	4%	9%	0%	4%	5%
mp_diff	1%	6%	24%	18%	4%	10%	5%
rt_diff	0%	9%	0%	2%	2%	0%	2%
sc_diff	10%	25%	11%	1%	26%	3%	1%
SUM	**63%**	**65%**	**65%**	**63%**	**89%**	**85%**	**63%**

Model 1 Standardized Coefficients

lm(tenspread ~ co_diff+da_diff+ec_diff+et_diff+gs_diff+ic_diff+ip_diff+lo_diff+mp_diff+rt_diff+sc_diff + er_diff + fr_diff + highyield + ratingchange)

co_diff	0.3618	-0.0934	0.0607	0.2144	-0.2385	-0.2213	0.3358
da_diff	-0.2408	-0.2924	0.1519	0.0227	-0.4951	-0.1192	-0.1250
ec_diff	0.1233	0.0167	0.2226	0.0711	0.0751	0.3723	0.1799
et_diff	0.1145	-0.0523	-0.0285	0.0723	-0.1397	-0.1972	-0.2254
gs_diff	-0.0402	0.0717	0.1339	0.2322	0.1769	0.1295	0.3061
ic_diff	-0.0190	-0.1344	-0.1132	-0.0913	-0.0162	0.2920	-0.1116
ip_diff	0.5923	0.3221	0.0847	0.2934	0.8158	0.1585	-0.2479
lo_diff	0.2389	0.2048	-0.1307	0.2313	0.0027	-0.1498	-0.1906
mp_diff	0.1185	0.2446	0.3365	0.3356	0.2798	-0.2289	0.2048
rt_diff	-0.0408	0.3100	-0.0420	0.1105	0.2046	0.0427	0.1261
sc_diff	0.3548	-0.5058	0.2309	0.0559	-0.6805	-0.1279	-0.1020
er_diff	0.3832	-0.1424	0.1100	0.2255	-0.0157	0.1974	0.0847
fr_diff	-0.3055	0.1815	0.2369	0.1423	0.0683	0.1813	0.3661
highyield	0.3436	0.2948	0.1643	0.2743	0.3666	-0.0608	0.3150
rating_downgrade	0.3068	0.3790	0.2420	-0.2727	0.1076	0.0421	0.1074
rating_upgrade	-0.0078	-0.2740	-0.1075	-0.1025	-0.2319	0.0455	0.1676

Model 2: with Composite ICRG scores

$$\widehat{10yrspread} = \widehat{constant} + \widehat{\beta_1} comp\_diff + \widehat{\gamma_1} er\_diff + \widehat{\gamma_2} fr\_diff + \widehat{\gamma_3} highyield + \widehat{\gamma_4} ratingchange$$

Model 2	Greece	South Korea	Russia	South Africa	Italy	India	Mexico
Adj. R-Squared	0.6005	0.5773	0.8862	0.7532	0.3932	0.2477	0.4366
Correlation between Predicted and Actua	0.7749	0.7598	0.9414	0.8679	0.6271	0.4977	0.6607
Mean VIF	1.4525	1.3862	1.6758	1.5181	1.3372	1.5999	1.2847
DW	1.9806	1.7498	2.0564	1.8587	1.1647	0.6762	1.8466
Percent ICRG Political Indicators Explain							
comp_diff	**22%**	**1%**	**6%**	**41%**	**1%**	**1%**	**11%**
er_diff	19%	0%	0%	18%	0%	0%	6%
fr_diff	1%	5%	2%	3%	0%	1%	71%
highyield	1%	5%	1%	17%	1%	0%	6%
rating_downgrade	2%	44%	1%	21%	0%	1%	2%
rating_upgrade	54%	45%	90%	0%	98%	97%	5%

Model 2 Standardized Coefficients							
lm(tenspread ~ comps_diff + er_diff + fr_diff + highyield + ratingchange)							
comp_diff	0.4785	-0.1372	0.4925	0.5267	0.3967	0.2341	-0.231
er_diff	0.4469	0.0636	0.1046	0.3468	0.225	0.0562	0.1652
fr_diff	-0.114	0.3684	0.2812	0.1509	0.1121	0.2105	0.5832
highyield	0.1109	0.3648	0.1727	0.3331	0.5304	-0.061	0.1672
rating_downgrade	0.131	1.0834	0.1673	-0.3712	0.2294	-0.254	-0.097
rating_upgrade	-0.75	-1.1054	-1.874	-0.041	-5.366	-2.187	0.1537

Model 3: 11 ICRG subcomponents stepwised

$$\begin{aligned}10\widehat{yrspread} = \widehat{constant} &+ \widehat{\beta_1}co\_diff + \widehat{\beta_2}da\_diff + \widehat{\beta_3}ec\_diff + \widehat{\beta_4}et\_diff + \widehat{\beta_5}gs\_diff \\ &+ \widehat{\beta_6}ic\_diff + \widehat{\beta_7}ip\_diff + \widehat{\beta_8}lo\_diff + \widehat{\beta_9}mp\_diff + \widehat{\beta_{10}}rt\_diff \\ &+ \widehat{\beta_{11}}sc\_diff + \widehat{\gamma_1}er\_diff + \widehat{\gamma_2}fr\_diff + \widehat{\gamma_3}highyield + \widehat{\gamma_4}ratingchange\end{aligned}$$

Model 3 (Stepwised)	Greece	South Korea	Russia	South Africa	Italy	India	Mexico
Adj. R-Squared	0.6833	0.7624	0.9014	0.7867	0.7442	0.7952	0.6706
Correlation between Predicted and Actua	0.8266	0.8732	0.9494	0.8869	0.8626	0.8917	0.8189
Mean VIF	2.1440	2.5506	2.7655	2.0820	2.2269	3.3834	2.1465
D-W	1.9809	2.0127	2.0825	1.9541	1.7721	2.0979	2.5624
Percent ICRG Political Indicators Explain							
co_diff	7%	1%	1%	5%	3%	9%	9%
da_diff	7%	9%	5%	0%	15%	3%	0%
ec_diff	0%	0%	13%	0%	0%	25%	2%
et_diff	0%	0%	0%	0%	1%	5%	6%
gs_diff	0%	0%	5%	12%	2%	3%	17%
ic_diff	0%	2%	3%	0%	0%	13%	0%
ip_diff	36%	12%	2%	18%	38%	6%	18%
lo_diff	4%	6%	3%	7%	0%	4%	8%
mp_diff	0%	6%	19%	24%	5%	19%	3%
rt_diff	0%	7%	0%	3%	2%	0%	2%
sc_diff	8%	23%	10%	0%	22%	0%	0%
Sum	**62%**	**65%**	**61%**	**69%**	**88%**	**88%**	**64%**

Model 3 Standardized Coefficients							
co_diff	0.2942	-0.0674	0.0585	0.1770	-0.2418	-0.2276	0.2520
da_diff	-0.2843	-0.2787	0.1443		-0.5468	-0.1312	
ec_diff			0.2337			0.3669	0.1124
et_diff					-0.1023	-0.1686	-0.1991
gs_diff			0.1416	0.2705	0.1995	0.1208	0.3433
ic_diff		-0.1358	-0.1082			0.2715	
ip_diff	0.6464	0.3212	0.0934	0.3318	0.8607	0.1805	-0.3498
lo_diff	0.2092	0.2319	-0.1127	0.1999		-0.1453	-0.2344
mp_diff		0.2297	0.2788	0.3790	0.3108	-0.3249	0.1468
rt_diff		0.2479		0.1411	0.2008		0.1207
sc_diff	0.3150	-0.4488	0.2083		-0.6515		
er_diff	0.3619	-0.1386	0.1022	0.2108		0.2118	
fr_diff	-0.3043	0.1964	0.2372	0.1626		0.1488	0.3480
highyield	0.3329	0.3086	0.1589	0.2323	0.3969		0.3046
rating_downgrade	0.3277	0.2824	0.2464	-0.2349	0.0893		0.0560
rating_upgrade	0.0123	-0.2808	-0.1075	-0.1100	-0.2694		0.1719

Overall, Models 1 and 3 had comparable adjusted R-squared, correlation between Predicted and Actual spreads, Durbin-Watson statistics, and percentage of variation in spreads that ICRG can explain. However, Model 3, the step-wised model, had a lower mean VIF score than Model 1, indicating lower multicollinearity. Hence, Model 3 was chosen. Model 2 was not chosen because the ICRG political risk indicators only explain 12% of the variations in 10 year spreads.

As seen, the model generated by stepwise analysis fulfilled the standard of VIF, addressing the issue of multicollinearity. Below are the VIF test results for each respective country for Model 3 :

Figure 5. Mean variance of inflation factor (VIF) scores for Model 3

	Greece	South Korea	Russia	South Africa	Italy	India	Mexico
Mean VIF	2.14	2.55	2.77	2.08	2.23	3.38	2.15

The benefits of utilizing a stepwise regression is that it allowed the Capstone team to identify the independent variables with the highest statistical significance, generating an "optimized" model. This type of analysis allows for the creation of country specific models, where the variables most relevant to a specific country were identified. It also served the function to reduce multicollinearity of the original model as identified by the VIF testing.

The drawbacks of utilizing a stepwise regression include that it is a brute force method that may over-simplify the real models of the data. It may overfit the data and the results must be examined closely to identify false correlation.

Figure 6. Durbin Watson (DW) statistics for Model 3

	Greece	South Korea	Russia	South Africa	Italy	India	Mexico
DW	1.98	2.01	2.08	1.95	1.77	2.10	2.56

The DW statistics for all countries show values close to 2 that indicate non-autocorrelation. The DW values range from 1.77 to 2.56.

Figure 7. Correlation between Predicted and Actual Spreads for Model 3

	Greece	South Korea	Russia	South Africa	Italy	India	Mexico
Corr. predicted and actual spreads	0.8266	0.8732	0.9494	0.8869	0.8626	0.8917	0.8189

Overall, the model demonstrate good predict properties, as seen in Figure 7, with low multicollinearity and reasonable DW test statistics that suggests low autocorrelation.

VII. CASE STUDIES

The Capstone Team chose three countries to test Model 3 in a more detailed way: Russia, South Africa, and India. The team specifically looked at how much variation in the 10 year spread the ICRG political risk indicators can explain and what are the key drivers of political risk in each respective country.

Russia

A stepwise regression of Russia's 10-year bond spreads and its Political Risk composite score difference alongside other control variables indicated that the ICRG political risk indicators can help explain 61% of the variations in the 10 year spread in Russia between 2000 and 2017. The key drivers of political risk in Russia were found to be: External Conflict (13%) [Coefficient: 0.321], Military in Politics (19%) [Coefficient: 0.728], and Socioeconomic Conditions (10%) [Coefficient: 0.282]. Lastly, it was found that there is a 95% correlation between predicted and actual sovereign bond yield spreads in Russia when utilizing ICRG to predict yield spread.

South Africa

A stepwise regression of South Africa's 10-year bond spreads and its Political Risk composite score difference alongside other control variables indicated that the ICRG political risk indicators can help explain 69% of the variations in the 10 year spread in South Africa between 2000 and 2017. The key drivers of political risk in South Africa were found to be: Government Stability (12%) [Coefficient: 0.183], Investment Profile (18%) [Coefficient: 0.223], and Military in Politics (24%) [Coefficient: 0.628]. Lastly it was found that there is a 89% correlation between predicted and actual sovereign bond yield spreads in South Africa when utilizing ICRG to predict yield spread.

India

A stepwise regression of India's 10-year bond spreads and its Political Risk composite score difference alongside other control variables indicated that the ICRG political risk indicators can help explain 69% of the variations in the 10 year spread in India between 2000 and 2017. The key drivers of political risk in India were found to be: External Conflict (25%)[Coefficient: 0.360], Internal Conflict (13%) [Coefficient: 0.468], and Military in Politics (19%) [Coefficient: -0.536]. Lastly it was found that there is a 89% correlation between predicted and actual sovereign bond yield spreads in India when utilizing ICRG to predict yield spread.

VIII. DUE DILIGENCE

In view of the results, the Capstone Team performed several due diligence tasks to understand why certain ICRG indicators are negatively correlated with sovereign spreads.

Consequently, the team leveraged a range other tools to yield better regression results, measured by a higher R-squared:

(1) Attempted a 1 month lag for 10yrspread to see if the top quintile of ICRG political risk variables had an impact on the 10yrspread
(2) Dummied the ICRG political risk variables to see if a movement in the increase of a variable had an impact on the 10yrspread
(3) Used composite score difference, dummying composite score movements
(4) Grouped of different ICRG scores according to PFA
(5) Manually dropped variables that are negatively correlated with the spread before and after performing stepwise regression
(6) Inverted ICRG variables such that a higher individual ICRG component score also related to higher risk
(7) Correlated the negative variables

The results of these due diligence did not significantly improve the model. The PCA and CFA groups did not reflect intuitive real-life groupings.

IX. CONCLUSION & RECOMMENDATIONS

Figure 8. Summary Explanatory Power of ICRG political risk indicators

	Greece	**South Korea**	**Russia**	**South Africa**	**Italy**	**India**	**Mexico**
Sum	62%	65%	61%	69%	88%	88%	64%

The team found that political risk does correlate with sovereign spreads. For Greece, on average, political risk explains 62% of the variance in sovereign spreads, for South Korea 65%, Russia 61%, South Africa 69%, Italy 88%, India 88% and Mexico 64%. In our model, political risk explains between 61% to 88% of variance depending on the country. Overall, the model demonstrates good predictive properties and R^2 value, with low multicollinearity and autocorrelation.

However, this finding is more consistent with correlation than causation. Some countries were more weakly correlated, potentially suggesting that political risk matters less for these countries' market outcomes. It is also possible that the weaker correlation is a function of the subcomponents of ICRG political risk scores not having much explanatory power. The fact that Corruption (CO), Military in Politics (MP), Religious Tensions (RT), Law and Order (LO), Ethnic Tensions (ET), and Democratic Accountability (DA) ranges from 0-6 instead of 0-12 like the other subcomponents means that the former will vary less. Torrez (2002) has argued that precisely because of this, ICRG does not have the variation of other datasets. [4]

Less intuitive are the negative correlations between some ICRG political risk indicators and sovereign spreads. Despite running several due diligence tests to counter these negative correlations or attempt to explain them, the team was ultimately unable to. This is more likely a reflection of the measurement qualities of the ICRG index than the model itself.The ICRG data does not change much over time, hence why lagging the political risk variables were ineffective. Diamonte, Liew and Stevens (1996) also noted that ICRG data changes too slowly.[5] The methodology of Political Risk Services (PRS), the group behind the ICRG dataset, is opaque and unknown. Torrez (2002) has even suggested that PRS concentrates its resources in certain countries and may not have the same quality of data for all countries.

Other researchers have also commented on the shortcomings of the ICRG dataset. Olson et al. (2000) noted that ICRG is ultimately subjectively measured by PRS, and it is important to see how the data correlate with some objective measures.[6] For instance, Bräutigam and Knack (2004) supplemented the ICRG data with other indices and correlated the ICRG data to see fit.[7]

The team therefore concludes that ICRG is more fitting for an academic and structural approach to data for macro-level decisions and not a practical tool for event-driven prediction.

Going forward, BCG Platinion should find a more actionable and forward-looking measure of political risk that captures fluctuations at a more granular level, or find better proxy indicators (e.g., polling data, social media) for political risk that vary more over-time.

ICRG Political Risk data provides a good basis to understand the relationship of specific political risk factors and sovereign spread. However given that this data is provided by a single source, it may lack reliable forward-looking power. The team therefore recommends supplementing the ICRG data with real-time data of Google Mentions, or other actionable data sources. Using python, a sentiment analysis can be conducted whereby top daily Google news articles can be extracted, cleaned and analysed based on major keywords as to whether a story is positive, neutral or negative. Furthermore, daily sovereign yields and spreads data can be

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[4] Jimmy Torrez, “The Effect of Openness on Corruption”, Journal of International Trade & Economic Development, 11:4 (2002): 387-403.

[5] Robin L. Diamonte, John M. Liew and Ross L. Stevens, “Risk in Emerging and Developed Markets”, Financial Analysts Journal, Vol. 52, No. 3 (1996): 71-76.

[6] Mancur Olson Jr., Naveen Sarna and Anand V. Swamy, “Governance and Growth: A Simple Hypothesis Explaining Cross-Country Differences in Productivity Growth”, Public Choice, Vol. 102, No. 3/4 (2000): 341-364.

[7] Deborah A. Bräutigam and Stephen Knack, “Foreign Aid, Institutions, and Governance in Sub- Saharan Africa”, Economic Development and Cultural Change, Vol. 52, No. 2 (2004): 255- 285.

obtained to gain greater predictive power.

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