LSEG StarMine

LSEG StarMine Sovereign Risk Model

By StarMine Research Team

Abstract

The LSEG StarMine® Sovereign Risk Model (SR) evaluates a wide array of macroeconomic, market-based and political data to estimate the probability that a sovereign government will default on its debt. The model produces updated estimates of the annualised probability of default for over 150 countries at six time horizons: one, two, three, five, seven and 10 years. The one-year default probabilities are also ranked to produce 1 to 100 scores and mapped to traditional letter grades. Historical model output is available starting from December 1994.

LSEG DATA & ANALYTICS

Contents

1. Introduction

Sovereign credit risk modelling has a history of several decades from the early work of Frank and Cline (1971) who used discriminant analysis to determine the rescheduling abilities of countries. The main inputs in sovereign default and rescheduling models typically include macroeconomic and political risk variables. The framework of logistic regression is commonly used to quantify sovereign default risk, from the early work of Feder and Just (1977) to the more recent work of Hilscher and Nosbusch (2010). Other examples of techniques used to determine sovereign risk are Principal Component Analysis, used by Dhonte (1975); Classification and Regression Trees (CART), used by Oral et al. (1992); Tobit Regression, used by Easton and Rockerbie (1999); and Artificial Neural Networks, used by Cooper (1999).

StarMine SR uses a logistic regression framework where the primary inputs of the model are macroeconomic data from Datastream®. Additional market-based inputs and political data inputs from LSEG World-Check® are also used to generate a comprehensive picture of sovereign risk. We consider as default events actual defaults (missed payments), distressed restructurings (debt reissued in less favourable terms) and debt rescheduling under the auspices of the Paris Club.[1] The model was trained on over 30 years of sovereign credit event data. We generate probability of default (PD) for six time horizons: one-, two-, three-, five-, seven- and 10-year tenors. The one-year PD is mapped to a letter grade using a simple look-up table such that the distribution of StarMine SR letter grades is similar to the distribution of sovereign letter ratings from major credit rating agencies.

According to our studies, the probability of default depends not only on the circumstances prevailing immediately before the default, but also on trends that are based on a relatively long period of time. Therefore, we group the variables of the model into two components: those that change quickly and those that tend to vary slowly over time, which we call the Short- and Long-Term Components, respectively. Defaults typically occur when a country is in poor overall financial health (low score on the Long-Term Component) and there is some trigger to push it over the edge, like a rapid currency devaluation or sudden drop in reserves (low score on the Short-Term Component). The components and one-year PDs are ranked to produce 1 to 100 percentile scores, with the lowest value of 1 corresponding to the countries with the most risk.

The remainder of the paper is organised as follows: Section 2 describes the overall construction of the model. Section 3 shows the model performance. Section 4 details the probability of default and letter-rating assignments. Section 5 shows the model output for selected defaults. Section 6 is dedicated to investigations on using StarMine SR in a CDS trading strategy and Section 7 to a bond trading strategy. Finally, we conclude in Section 8.

2. Construction of StarMine SR

StarMine SR uses a logistic regression framework to estimate default likelihoods, in which the probability of default, P, is modeled by the formula below, where α is the intercept term, β is a vector of coefficients and X is a matrix containing the explanatory variables.

$$P = \frac{1}{1 + exp(-(\alpha + X\beta))}$$

From this formula, we can obtain the probability that a sovereign government will default on its debt within one, two, three, five, seven or 10 years using a linear combination of our explanatory variables. The parameters are calibrated through maximum likelihood estimation.

Specifically, the inputs to StarMine SR are:

– **The level and change in the amount of government debt relative to GDP** – A high debt burden as percentage of GDP corresponds to a higher risk of default since there are fewer resources to service the debt. It is an input to the Long-Term Component

– **The level of credit provided by private banking** – As economic conditions weaken, demand for credit declines. Banks also tend to tighten lending standards in the face of uncertainty. It is an input to the Long-Term Component

– **The level and variability of foreign reserves** – A quick decrease in reserves points to difficult economic conditions. A large increase in reserves is often the result of debt issuance or loans received in difficult times from external agents. It is an input to the Short-Term Component

[1] The Paris Club, created in 1956, is an informal group of official creditors whose role is to find coordinated and sustainable solutions to the payment difficulties experienced by debtor countries (www.clubdeparis.org).

- **The level of government consumption relative to private consumption** – Low government consumption when private consumption is high normally indicates a difficult situation in the government finances. It is an input to the Long-Term Component
- **Imports of goods and services relative to GDP** – Low imports to GDP indicates loss of access to world financial markets. A higher ratio indicates capacity to obtain hard currency and therefore lower default risk. It is an input to the Long-Term Component
- **Inflation rate and purchasing power of the currency** – A high rate of inflation as well as inflation misalignment with the currency exchange rate change point to structural problems in government finances. It is an input to the Long-Term Component
- **The annual change in the exchange rate** – Fast currency devaluation is normally an indication of capital flight, and less availability of hard currency for debt servicing. It is an input to the Short-Term Component
- **Reserves over imports** – Low reserves in the face of high imports indicates less money to repay debt. It is an input to the Short-Term Component
- **The level of unemployment** – A low level of unemployment indicates a more flexible labour market making the country less vulnerable to changes in the global environment. It is an input to the Long-Term Component
- **GDP per capita** – A higher potential tax base of the borrowing country indicates a greater ability of the government to repay debt. It is an input to the Long-Term Component
- **Size and growth of the country's economy** – A country with a large economy normally indicates a diversified economy able to better absorb economic difficulties. High economic growth tends to decrease the relative debt burden and helps avoid insolvency. It is an input to the Long-Term Component
- **Integrated political risk as measured by World-Check** –Political risk indicates a possible unwillingness of the borrowing country to repay debt even when it has the capacity to do so. We use the following factors: Comprehensive Risk, Type of Governance, Government Effectiveness, Competitiveness, Political Stability and Regulatory Quality, which were chosen due to their significant correlation with CDS prices. It is an input to the Long-Term Component
- **Reserve currency indicator** – Countries whose currency is used as a reserve currency have a larger debt-carrying capacity. These countries currently include the United States, Germany, France, United Kingdom, Switzerland, Japan, Australia and Canada

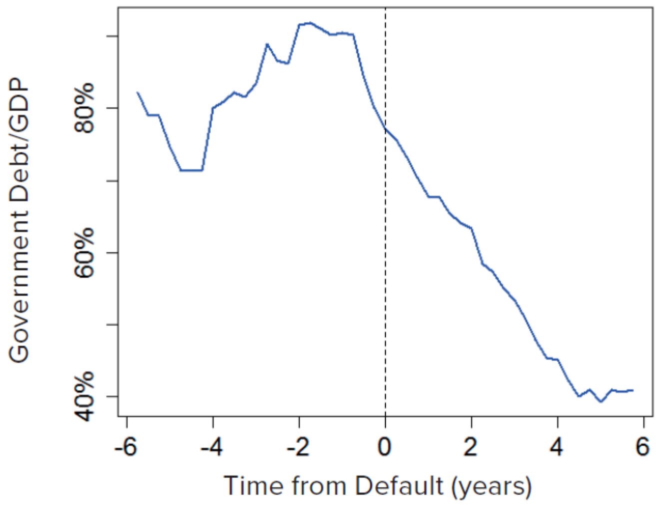
With respect to unemployment, if there is no data available for a given country, we use the median value of its geographic region. With respect to debt, we use overall debt – both foreign and domestic currency combined.

The frequency with which the input variables are updated varies from daily to annual, but most are monthly or quarterly. We use the most updated data available for each variable at a given point in time.

3. Performance of StarMine SR

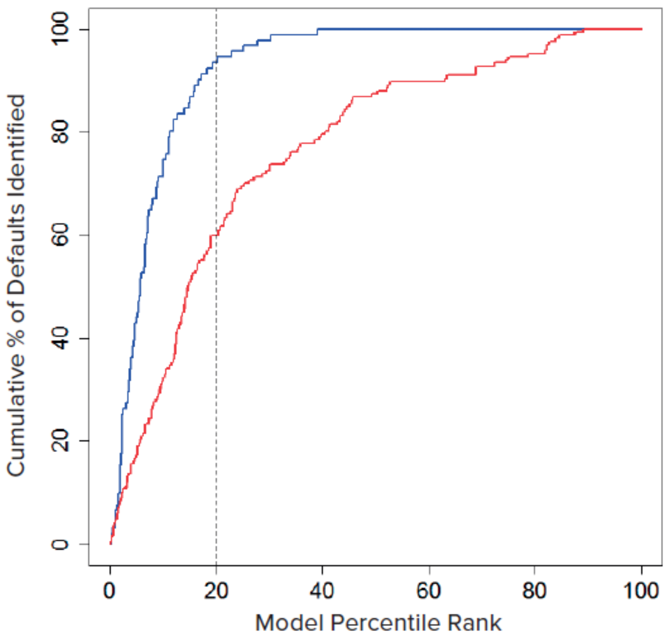
The most frequently cited measure of sovereign default risk, and the single most powerful individual variable in StarMine SR, is the government debt to GDP ratio. We therefore use this as a benchmark model against which we compare StarMine SR. In Figure 1, we plot the average value of the government debt over GDP as a function of the number of years from default, with year 0 being the default year. A negative time means time before the default, and a positive one means after the default. One can see from this figure that prior to default, countries typically have a debt to GDP ratio near 100%. After default, the ratio tends to decline as debt is restructured, forgiven or otherwise reduced.

Figure 1. Government debt to GDP as a function of the time from default. Sample period includes all defaults from 1990 to 2011.



We compare the default prediction power of the Debt/GDP benchmark to that of StarMine SR in Figure 2. We plot the Cumulative Accuracy Profile (CAP) curves for both models based on a one-year forecast horizon over the 1980 to 2011 period. StarMine SR produced an Accuracy Ratio (AR) of 84.3%, while the Debt/GDP benchmark generated an AR of 53.1%. The AR measures the extent to which a model correctly assigns countries that default to the “riskiest” part of the distribution. In the bottom quintile (20%), the StarMine SR captures 93.4% of default events while the benchmark captures 60% of default events.

Figure 2. Default prediction power of StarMine SR (blue) and the Debt/GDP benchmark (red) at the one-year forecast horizon. Sample period is 1980 to 2011.



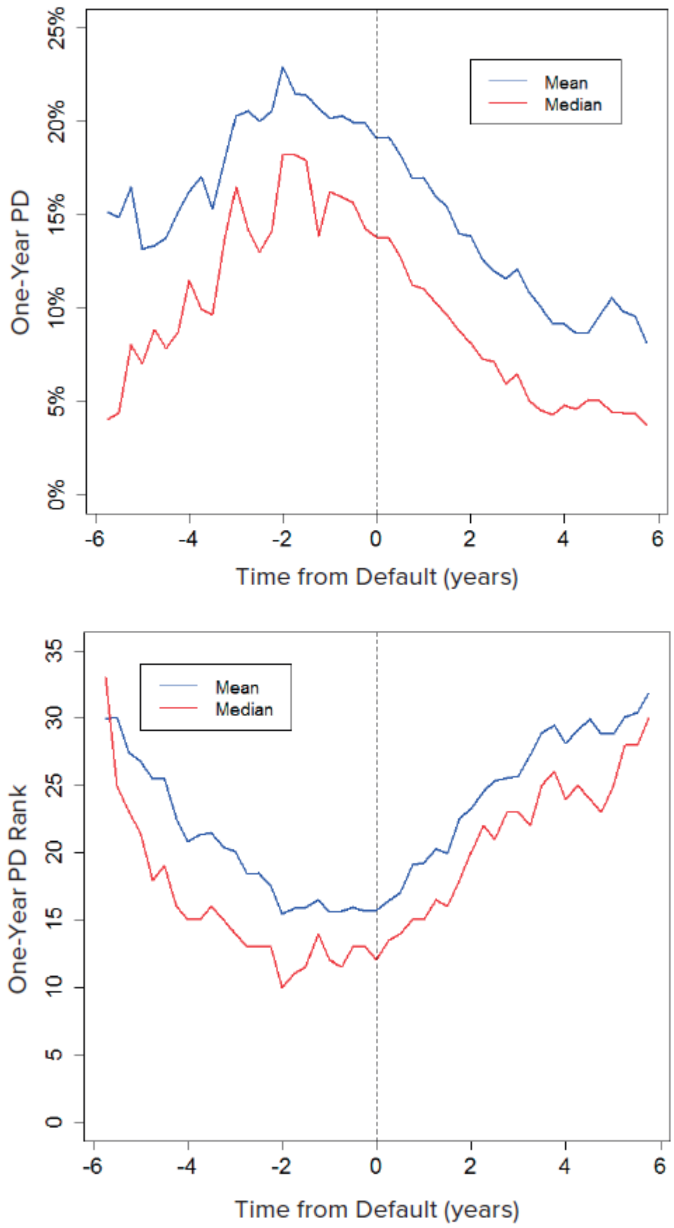
4. Probability of default and letter ratings

From the cumulative probability equation given in Section 2, we calculate the PD for six different tenors. We display them in annualised form. The conversion to the annualised PD is done via the following equation

$$PD^{Cumulative} = 1 - (1 - PD^{Annual})^{Tenor}$$

where Tenor in our model can take the values 1, 2, 3, 5, 7 or 10. In Figure 3, we show the one-year PD of the model as a function of the time from default. We also plot the typical evolution of the StarMine SR score, which is simply the percentile rank of the one-year PD, in the bottom panel of Figure 3. As expected, we observe high PD values and low PD ranks as the default approaches. As the country moves away from default, the PD decreases and the rank increases. The fact that the one-year PD peaks two years before the default, and not one year, is likely to be due to delays between the country's worst economic conditions and arrangements for debt restructuring.

Figure 3. Top: One-year PD as a function of the time from default (mean and median). Bottom: One-year PD rank as a function of the time from default (mean and median). Low ranking means higher risk. Sample period is from 1990 to 2011.

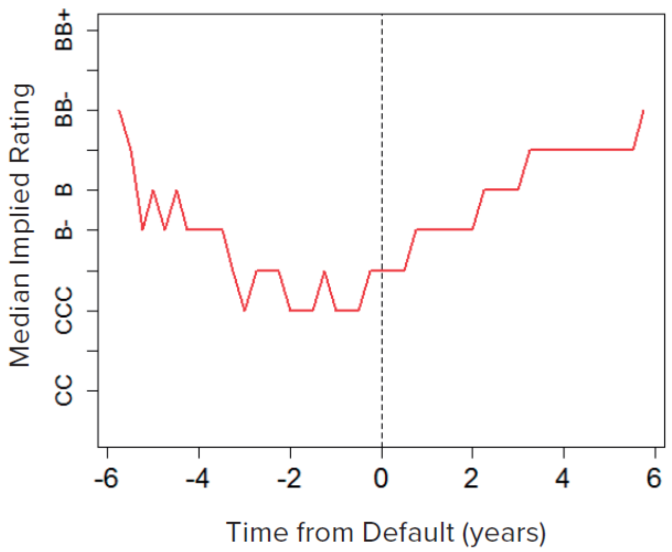


To enable comparison to agency ratings and allow ease of use for those who are calibrated to letter grades, we map our Sovereign one-year PD to letter grades using the mapping provided in Table 1. We created the cutoff points for each letter grade such that the distribution of StarMine SR letter grades roughly matches the distribution of agency ratings on a common universe of countries over the 2000 to 2013 period. In this way, we ensure that a difference between the StarMine SR letter grade and agency rating is due to differences in assessment of credit risk rather than to difference in distributions of ratings. We plot the median SR letter grade as a function of the time to default in Figure 4.

Table 1. Mapping of StarMine SR PDs to letter grades.

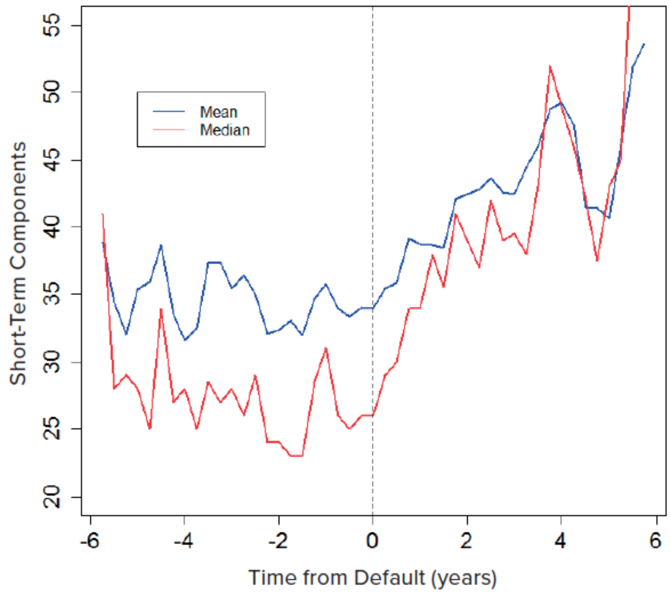
If one-year PD (%) is greater than	And one-year PD (%) is less than or equal to	Then Rating is
0.000	0.123	AAA
0.123	0.191	AA+
0.191	0.250	AA
0.250	0.332	AA-
0.332	0.504	A+
0.504	0.673	A
0.673	0.851	A-
0.851	1.087	BBB+
1.087	1.436	BBB
1.436	1.879	BBB-
1.879	2.420	BB+
2.420	3.222	BB
3.222	4.107	BB-
4.107	5.493	B+
5.493	7.993	B
7.993	12.052	B-
12.052	14.726	CCC+
14.726	18.274	CCC
18.274	20.973	CCC-
20.973	100.0	CC

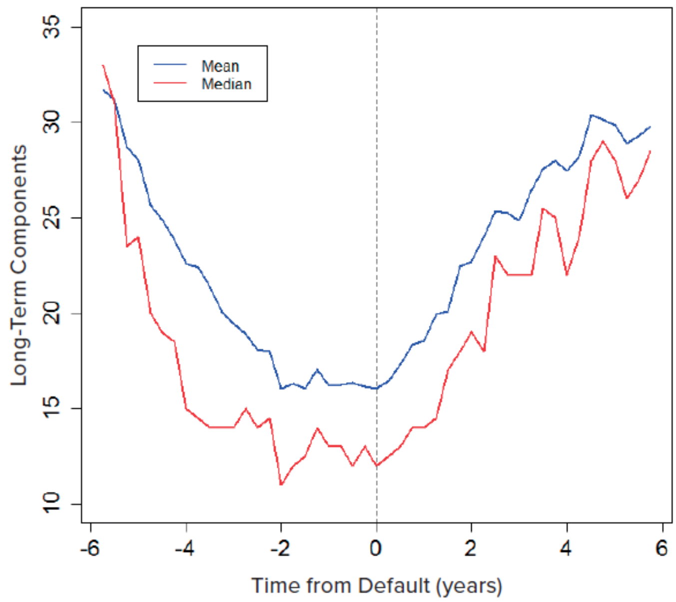
Figure 4. Median StarMine SR letter grade as a function of the time from default. Sample period is from 1990 to 2011.



The typical evolution of the Short- and Long-Term Components as a function of the time from default are shown in Figure 5. We see that, as expected, the Short-Term Component has considerable variability at relatively low values as the default approaches, whereas the Long-Term Component has a smoother and more pronounced convex shape around the default time. As the country emerges from default, both components tend to increase in value.

Figure 5. Top: Short-Term Component as a function of the time from default (mean and median). Bottom: Long-Term Component as a function of the time from default (mean and median). Sample period is from 1990 to 2011.

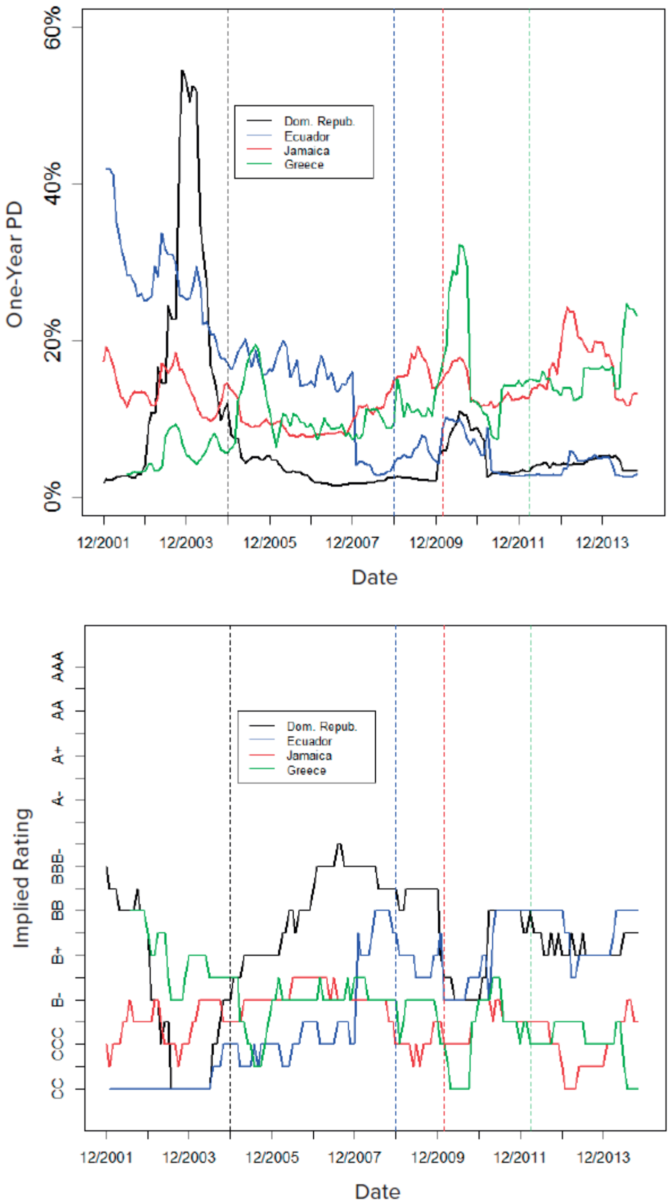




5. Analysis of selected defaults

For illustration purposes, we chose a sample of high-profile defaults that occurred after 2001 to show the time evolution of the model's one-year PD and letter grades in these cases in Figure 6. We generally see good predictive power, with high PD values and low letter grades as the default approaches. The default from Ecuador in 2008 is an exception, as that was a purely political default, caused by the unwillingness of the newly elected government to repay the debt incurred by the previous government.

Figure 6. One-year PD (top) and letter grades (bottom) as a function of time for selected defaults. The vertical lines mark the time of the default events, with the colour matching the respective country colour.



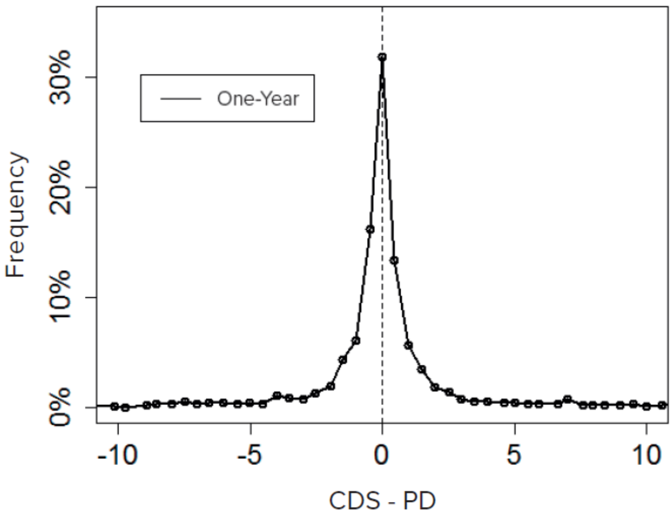
6. Credit default swap strategy

As shown in Hull et al. (2000), the probability of default and credit default swap (CDS) spreads are related by the formula below, where the main approximation used in this formula is to consider the risk-free rate to be zero. If we assume that *Recovery Rate 0*, one has *CDS PD*.

$$CDS \approx (1 - Recovery\ Rate) * PD$$

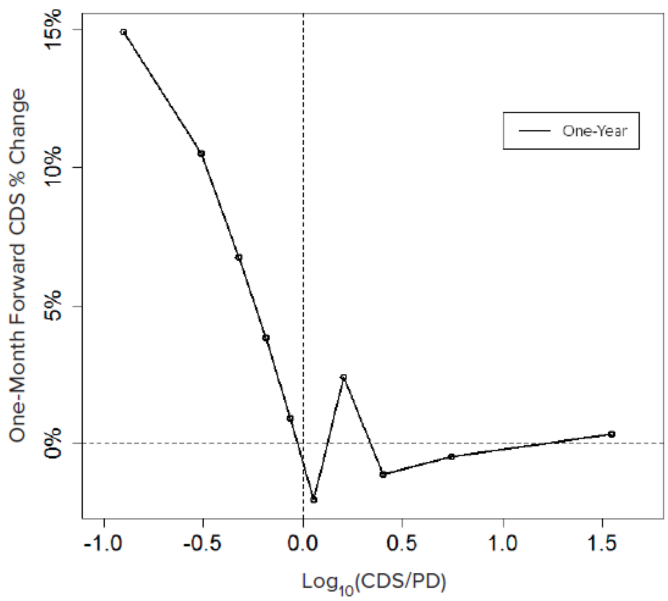
The approximations used in this formula become less valid as the tenor increases, and therefore we focus on the one-year PD from StarMine SR. We test this relationship in our sovereign model with respect to Senior Unsecured Full Restructuring CDS prices in USD for a period of nearly seven years and plot the distribution of this difference in Figure 7. As we can see, this equation is well obeyed in our model, resulting in the central peak, but there are outliers in the tails of this histogram, which suggests the potential for profitable strategies when the two are in disagreement.

Figure 7. Histogram of the difference CDS – PD for the one-year tenor of StarMine SR. Period is from January 2008 to November 2014.



One strategy we examine is to look at the CDS price when the PD and CDS are significantly different. For this, we plot the average one-month forward one-year CDS price change as a function of the one-year CDS price to the one-year PD in Figure 8.We use a logarithmic scale on the x-axis so negative values in the x-axis correspond to the CDS being less than the PD, and we see that, on average, the CDS price increases over the following month in these cases. We also see that the rise in the CDS price increases as the ratio becomes smaller. When CDS ≈ PD/10, the average increase in the CDS price is approximately 15%. In other words, when StarMine SR PD is ten times larger than the CDS price, on average, we see the CDS price increase by about 15% during the following month. As one crosses to positive regions of the x-axis, we see that the average CDS price change is essentially zero, indicating the CDS price tends not to decline when the StarMine SR PD is lower than the CDS price. A total of 66 countries were covered in the CDS data.

Figure 8. One-month forward one-year CDS price change as a function of the logarithm of CDS/PD for the one-year tenor of StarMine SR. Sample period is January 2008 to November 2014.



7. Bond yield spread strategy

Because a CDS contract provides insurance against a bond default, a portfolio consisting of a CDS and a par yield bond issued by the reference entity is very similar to a risk-free rate bond. This results in a theoretical relationship between CDS; the bond par yield, y; and the risk-free rate, r, given by

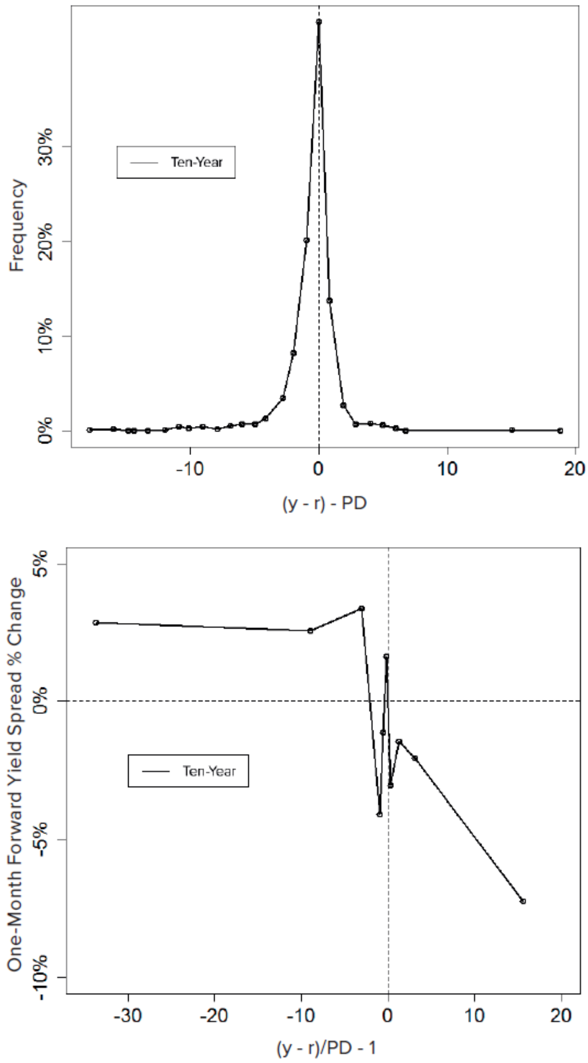
$$CDS \approx y - r$$

The approximations and assumption used in the above equation are detailed in Hull et al. (2004). They also find the relationship to be well-observed in practice. In this equation, *CDS, y* and *r* have the same maturity. The quantity $y - r$ is typically referred to as the bond yield spread or bond credit spread. Since $CDS \approx PD$, as we have seen in Section 6, we conclude from this equation that

$$PD \approx y - r$$

We test our model in this expression for the 10-year tenor, where we use for the risk-free rate the 10-year par yield of the U.S. The histogram of $(y\text{-}r)$ – PD is shown in the top panel of Figure 9. As we can see, this equation is well-obeyed in our model, resulting in the central peak. However, there are outliers, suggesting the possibility of exploring these anomalies in strategies for the yield spread. We studied how the one-month forward yield spread changes as a function of $(y\text{-}r)$/PD and observed the results shown in the bottom panel of Figure 9.We see that yields go up when PD is much larger than the yield spread and vice versa. In contrast with the CDS case, we observe that there are profitable strategies on both sides: when PD > $y\text{-}r$ and when PD < $y\text{-}r$, as shown at the bottom panel of Figure 9. A total of 51 countries were covered in the bond data.

Figure 9. Histogram of the yield spread minus the PD (top) and one-month forward yield spread percent change versus (y-r)/PD -1 (bottom) for the 10-year tenor. Sample period is January 2008 to November 2014.



8. Conclusion

StarMine SR provides robust estimates of the probability of default of sovereign nations over multiple time horizons using a broad spectrum of data inputs. The model's main drivers are macroeconomic data, but it also considers political risk factors from World-Check as well as market-based inputs from the FX markets. The one-year default probabilities are also ranked to produce 1 to 100 scores and mapped to traditional letter grades. Backtests of trading strategies in the CDS and fixed-income markets using StarMine SR show profitable strategies for forecasting one-month forward CDS price changes and for government bond yield spread changes.

StarMine SR is currently available in LSEG Eikon and will be available as a Datafeed in LSEG DataScope Select in the near future. History files are also available for those who wish to backtest the model.

9. References

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