The European Government Risk Model

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As concerns about European sovereign debt have increased, so has the awareness of the credit risk embedded in this market. The volatile dynamics of risk and return of these bonds in recent history have shown the need for a dynamic and flexible risk model that is able to capture individual circumstances across countries in the eurozone. Against this background, the POINT Global Risk Model (GRM) is adopting the DTS (Duration times Spread) approach to capture the risk dynamics of this market. The DTS approach has been successfully applied across other credit sensitive markets, such as global corporate credit, emerging markets, and securitized products.

The new model contains a Treasury-based DTS factor per European country, where the reference treasury curve is determined using the highest quality bonds available (i.e., German bonds). It accounts for the possibility of very low spreads and term structure effects in volatility that are specific to the European sovereign debt market. The new model improves the excess return volatility forecasts for European treasuries and agencies. Admittedly, the historical evidence for the model's performance during times of market stress is still limited as European debt markets have become significantly more volatile only recently. More importantly, the new model gives us increased flexibility to provide robust risk forecasts for both scenarios of continued turmoil or the possibility of an eventual return to a more stable environment. As the market situation evolves – framed by notable policy uncertainty – we monitor closely this model and its performance.

1. Introduction[1]

Credit concerns in European sovereign debt markets have increased and motivate a new risk modeling approach

The European sovereign market has become much more volatile since the credit crisis unfolded in 2008, and most investors now view the asset class as being driven by credit concerns. For years we have used DTS (duration times spread) models to capture the credit spread risk for a number of assets, such as corporate bonds, US ABS, municipal bonds, and emerging markets fixed income securities [see Gabudean (2009), Staal (2009) and Silva (2009)]. We now extend this approach to model sovereign spread risk across the eurozone[2]. The DTS model is built on the empirical finding that volatility of excess spread return is approximately linearly proportional to DTS for individual securities and at portfolio levels. Moreover, DTS factors are more stable and predictable over time than factors that are not conditioned on spread levels. Incorporating spread information explicitly in the DTS loading means that the model is very responsive to changing market conditions, thereby producing better volatility forecasts over relatively short time horizons.

As we adopt the DTS approach to model sovereign spread risk, there are two particular challenges we need to address. First, it is common for treasury bonds to have very low or even negative spread relative to a benchmark treasury curve (in our case the German treasury curve) for extended periods of time. Second, we find evidence that volatilities differ between portfolios of different maturities even after controlling for the DTS exposure, which is caused by volatility term structure effects. The new risk model tackles these challenges in two steps:

- We modify the DTS model by imposing a floor on the OAS component when constructing the loading. Our research suggests that this modified DTS model is robust and consistently captures spread risk over a wide range of scenarios including very low and negative spread cases.
- We calibrate adjustments on the DTS factor loading as a function of the instrument's maturity to take into account volatility term structure effects.

This adapted DTS model framework allows us to calibrate systematic factors and volatility term structure adjustments for individual countries in order to better capture heterogeneity of risk across issuers and maturities.

In the following we first briefly review the original DTS approach and highlight the additional challenges in modeling sovereign spread risk. We proceed to discuss the building blocks of the new model and our empirical findings. We conclude with a discussion on the improvements in historical risk forecasts that the model provides.

2. Review of the DTS Model and Empirical Analysis

Consider the excess return ($R_{i,t+1}$) due to spread change for an individual bond i at time t+1. The first order approximation of the excess return can be written as:

$$R_{i,t+1} = -OASD_{i,t} \times \Delta OAS_{i,t+1} = -(OASD_{i,t} \times OAS_{i,t}) \times (\Delta OAS_{i,t+1} / OAS_{i,t}) \quad (1)$$

where $\Delta OAS_{i,t+1}$ denotes the change in OAS from time *t* to *t+1*. We define DTS (duration times spread) as

[1] We thank Arik Ben-Dor, Albert Desclée, Jay Hyman and Anthony Lazanas for their comments and suggestions on earlier versions of this paper and research.

[2] For more evidence of the adequacy of the DTS approach for sovereign risk, please see Ben Dor et al. (2011).

$$DTS_{i,t} = -OASD_{i,t} \times OAS_{i,t} \tag{2}$$

then the spread excess return can be written in terms of DTS and the percentage spread change:

$$R_{i,t+1} = DTS_{i,t} \times (\Delta OAS_{i,t+1} / OAS_{i,t}) \tag{3}$$

Equation (2) and (3) are equivalent but the later has advantages for forecasting volatility. First, the volatility of percentage spread change is more stable than that of level spread change (as illustrated in empirical studies of a number of asset classes including corporate bonds and US municipal bonds). Second, the DTS loading incorporates the spread level explicitly in the bond sensitivity to percentage spread changes, thereby conditioning risk forecasts on current spread levels. In this approach the volatility of excess return can be written as

$$\sigma_t(R_{i,t+1}) = | DTS_{i,t} | \times \sigma_t(\Delta OAS_{i,t+1} / OAS_{i,t}) \tag{4}$$

where $\sigma_t(\ )$ denotes the volatility forecast conditional on time *t* information.

In order to impose a factor structure on the full universe of instruments, we decompose the percentage spread change of individual bonds into a systematic market factor (F_{t+1}) and an orthogonal idiosyncratic instrument specific component ($\varepsilon_{i,t+1}$) as follows:

$$\Delta OAS_{i,t+1} / OAS_{i,t} = F_{t+1} + \varepsilon_{i,t+1},$$

the volatility of excess return is then given by a linear DTS based factor model:

$$\sigma_t(R_{i,t+1}) \approx | DTS_{i,t} | \times \sqrt{\sigma_f{}^2 + \sigma_\varepsilon{}^2} \tag{5}$$

Since first implemented in POINT in 2006, the DTS model has proven to be a robust framework that provides accurate and timely risk forecasts across several asset classes. We will now examine its potential to model euro government spread risk.

Empirical Study of Excess Return Volatility and DTS

Volatility is not linearly proportional to DTS for low – and negative – spread Treasuries

Our empirical analysis uses all euro government securities data in POINT covering the historical constituents in Barclays Capital Euro Treasury Index and Euro Agencies Index from June 2004 to August 2011. We measure the spread risk of European sovereign securities against the German treasury curve. The data cover 16 countries as listed in Figure 1.

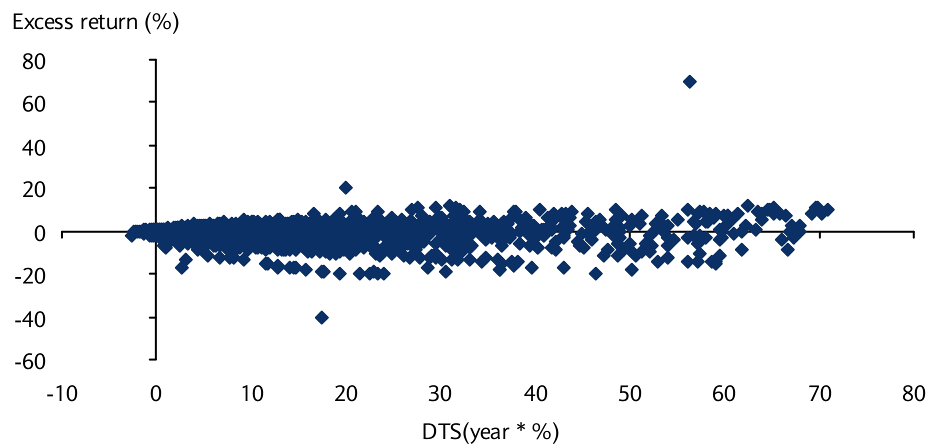
Figure 1: Sample Countries and the Average Number of Securities Available per Month

Country	Austria	Belgium	Cyprus	Finland
Treasuries	12	10	3	6
Agencies	12	3		2
Country	**Italy**	**Luxembourg**	**Malta**	**Netherlands**
Treasuries	27	1	2	10
Agencies	9	2		20
Country	France	Germany	Greece	Ireland
Treasuries	21	43	14	4
Agencies	57		1	4
Country	Portugal	Slovak	Slovenia	Spain
Treasuries	8	7	5	16
Agencies	5		1	22

Source: Barclays Capital

Figure 2 shows the scatter plot of the *ex post* excess return and the *ex ante* DTS of the treasury bonds in our sample. In general, we can see that the larger the DTS the wider the range of the realized excess returns, suggesting that the return volatility is positively related to DTS. We also notice that there is some volatility for close-to-zero spread and even negative spread cases.

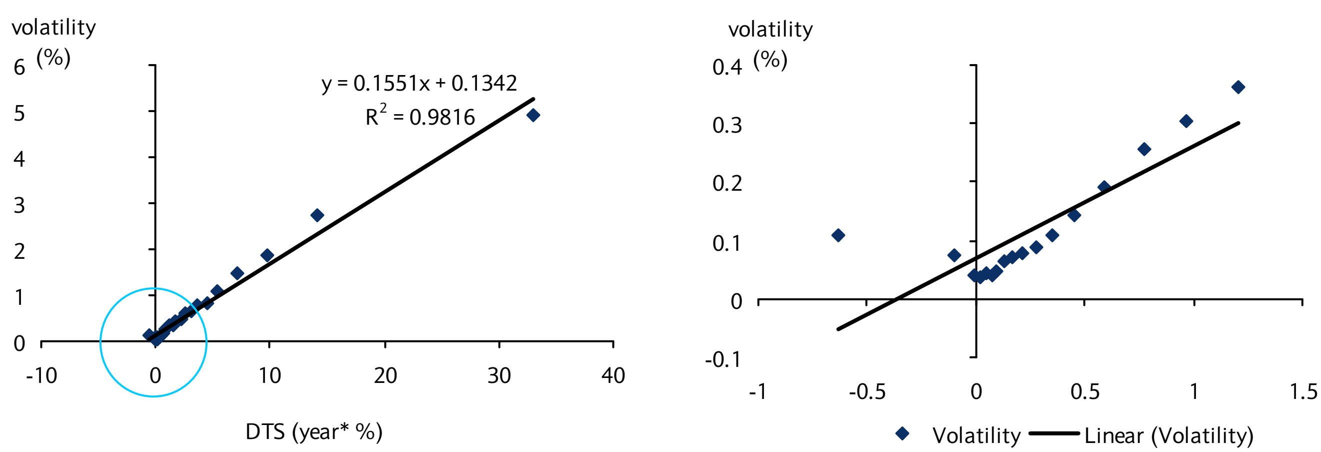
Figure 2: Scatter Plot of Excess Return and DTS for Pooled Sample



Source: Barclays Capital

To estimate the relation between volatility and DTS, we group the individual treasuries into different buckets based on the value of DTS. A total of 30 equally populated groups are created along the DTS dimension. The return volatility of each group is estimated by the mean of excess return in absolute value. The left panel of Figure 3 shows the estimated volatility plotted against the mean DTS for all buckets. A linear regression of volatility on DTS gives a good fit with a 0.98 R-square. But there is a sign of structural break for the very low and negative DTS buckets as shown in the right panel of Figure 3. The linear regression model will underestimate the volatility for treasuries with very low or negative spreads. In particular, volatility seems to flatten at about 10bp/month for low DTS levels.

Figure 3: Volatility of Excess Returns vs. DTS



Source: Barclays Capital

Negligible Spreads and Unstable Factor Realizations

Close-to-zero DTS may result in unbounded factor realizations, undermining the accuracy of volatility forecasting

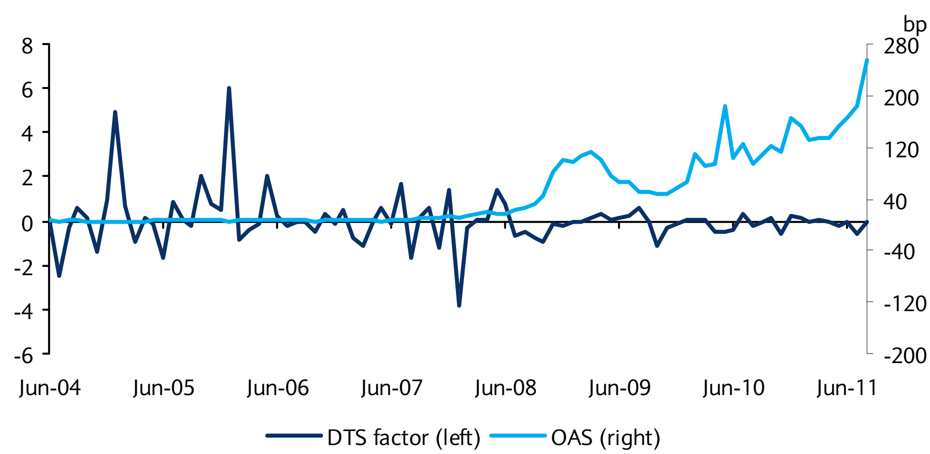
The presence of very small or negative sovereign spread suggests a practical concern – percentage spread changes may be ill-defined and very unstable when spreads are very low (dividing by zero is never a good idea). Specifically, small changes in spread near zero imply radically different percentage changes – a source of instability that is detrimental for forecasting purposes. The unbounded percentage change of spread may result in problematic realized factor estimate in the DTS framework undermining the accuracy of volatility forecasts.

Figure 4 illustrates this point, by showing the realized factor estimates from the DTS model described before, when applied to the European treasuries data. For reference, Figure 4 also shows the sample average OAS. Recall that the spread return of a security at time t+1 can be written in terms of DTS as

$$R_{i,t+1} = DTS_{i,t} \times (F_{t+1} + \varepsilon_{i,t+1}) \tag{6}$$

Thus the systematic factor may be estimated as the cross-sectional average of the normalized return ($R_{i,t+1} / DTS_{i,t}$). Figure 4 shows that factor realizations can reach values above 2 during very calm periods (e.g., 2005/06). These numbers contrast with values of 0.1-0.2 that we typically see on similar factors for credit securities and confirm our concern regarding the potential instability of the factor during periods of very low spreads. Moreover, the figure shows that the factor is more volatile in the pre-crisis period, which again is not very intuitive. In what follows we propose modifications to this DTS model that address these concerns.

Figure 4: Realized DTS Factor Estimates and OAS level



Source: Barclays Capital

The Role of Swap Spreads

For the European government securities we use treasury-curve-based analytics to measure spread risk. That is, the OAS for a particular security is the difference between its yield and the German treasury curve. This treatment contrasts with the old model, in which country spread risk was measured against the Libor curve – with a swap spread factor plus a Libor-OAS based factor. There are a couple of major reasons for this change: first, the relative value of European government securities is now typically assessed against German bonds. Introducing Libor swap spreads into the analysis leads to uncertainty as to the source of the credit risk in sovereign bonds (bank risk versus sovereign risk). Second, the Libor market in Europe was extremely volatile during the 2008 credit crisis, a period of relatively homogeneous and stable behavior for government bonds. A split of the treasury spread risk into a Libor swap and libor-OAS components would be artificial risk decomposition at best during that period: it creates an extremely high negative correlation between the swap spreads and Libor-based DTS sovereign factors, as the treasury-based OAS does not move significantly. This lends unnecessary instability to the risk factors. It is hard to exclude the possibility of a repetition of this scenario. Therefore, we decided against the use of the previous swap spread plus Libor-OAS risk decomposition. Instead, we adopt the simpler treasury-based spread risk analysis.

3. Imposing a Floor on DTS

The modified DTS model imposes a positive constant floor on the OAS component in the DTS risk loading

As described above, a major concern that arises when considering a DTS model to capture the spread risk of European governments is its appropriateness to deal with low spread securities or environments. The close-to-zero and negative spread cases present a practical challenge because the DTS model may not be able to forecast volatility accurately in this scenario.

To deal with this issue we propose to modify the DTS used as the risk loading in our model. Specifically, we impose a positive floor on the OAS level used to compute a security's DTS. The modified/floored DTS loading is defined as:

$$\underline{DTS}_{i,t} = -OASD_{i,t} \times \underline{OAS}_{i,t} \tag{7}$$

where $\underline{OAS}_{i,t} = \max(OAS_{i,t}, C)$ is the maximum value between $OAS_{i,t}$ of security *i* in period *t* and the positive constant C. The excess return can be written as

$$R_{i,t+1} = \underline{DTS}_{i,t} \times [\Delta OAS_{i,t+1} / \underline{OAS}_{i,t}]$$

The expression in the squared brackets – a modified percentage change OAS – is now better defined, in the sense that the denominator on the expression is guaranteed to be sufficiently different from zero. Note that the denominator of the normalized return – $R_{i,t+1} / \underline{DTS}_{i,t}$ – is now guaranteed to also be bounded away from zero. In practice the floor is chosen to be 10 basis points, as supported by the empirical evidence presented in Appendix I. We use this value for the remainder of this note, except where explicitly noted otherwise.

The conditional volatility can now be written as

$$\sigma_t(R_{i,t+1}) = | \underline{DTS}_{i,t} | \times \sigma_{i,t}\left(\frac{\Delta OAS_{i,t+1}}{\underline{OAS}_{i,t},}\right) \tag{8}$$

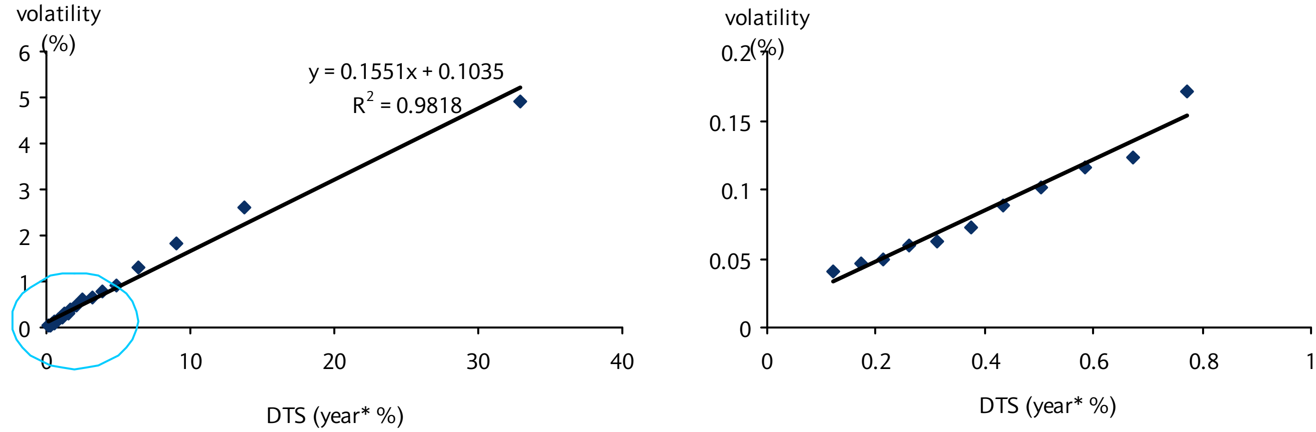
If the volatility of the modified percentage OAS change is stable then the return volatility is linearly proportional to the floored DTS loading. We test this hypothesis in the next section.

Empirical Study of Excess Return Volatility and Floored DTS

The volatility of excess return is linearly proportional to floored DTS loading

To study the empirical relation between excess return volatility and the floored DTS loadings we repeat the same analysis as described in Figure 3. Figure 5 plots the estimated volatility against the mean floored DTS. The linear regression of volatility on floored DTS has a good fit with R-square of 0.98. Both the low and high spreads samples are well fitted in the linear regression.

Figure 5: Return Volatility and Floor DTS Loading, C=10bp



Source: Barclays Capital

Factor Realizations

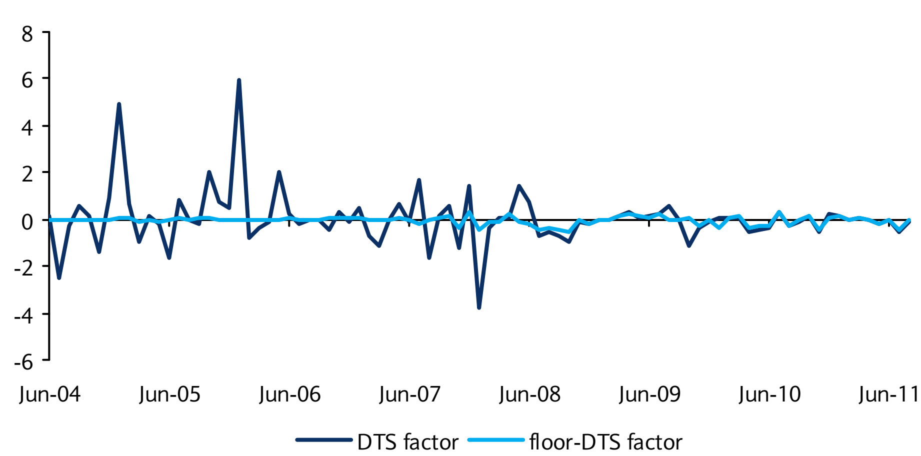
The realized factor from the floored DTS model is robust and stable over different regimes

To study the properties of the risk factor coming out of this modified DTS model, we first decompose the percentage spread change into its systematic and an idiosyncratic component as before:

$$R_{i,t+1} = \underline{DTS}_{i,t} \times (F_{t+1} + \varepsilon_{i,t+1}) \tag{9}$$

where the systematic factor can be estimated by a cross-sectional regression of the normalized return ($R_{i,t+1} / \underline{DTS}_{i,t}$) into a constant. Given that modified loading has a positive lower bound by construction, we expect the factor estimate to be less prone to outlier bias. Figure 6 compares the two different models by plotting the factor estimates from the original DTS model against the floored DTS model. The differences are readily apparent: the two estimates differ significantly before 2008 when spreads were low. Both factor estimates become very similar after 2010 when the sovereign spreads become large. This suggests that the modified model is working as predicted and is robust across spread environments. The floored DTS factor shows characteristics that are much closer to DTS factors from other asset classes.

Figure 6: Realized Factor Estimates

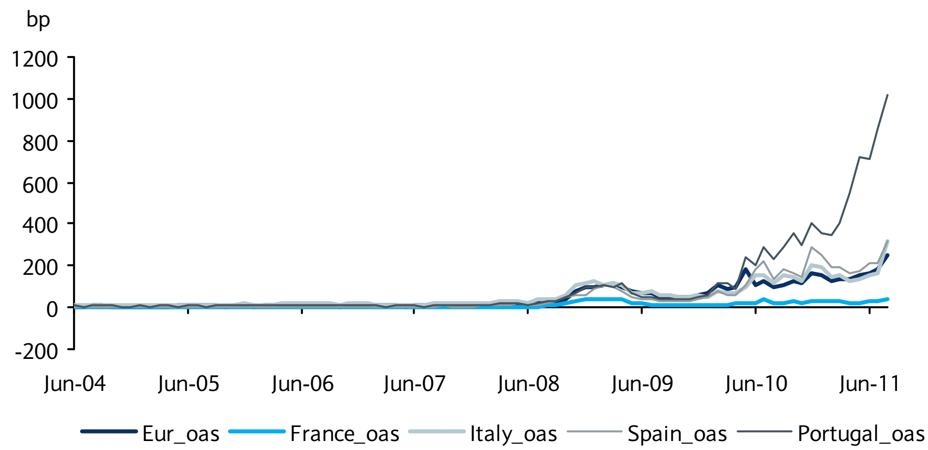


Source: Barclays Capital

4. Introducing Individual Country Factors

As described earlier, a major concern that arises when considering a DTS model to capture the spread risk of European government securities is its appropriateness to deal with low spread environments. However, there is another important fact that we want to address with the new model. Figure 7 shows a noticeable divergence in spread behaviour across countries after 2008.

Figure 7: Average Spread of European Treasuries (bp)



Source: Barclays Capital

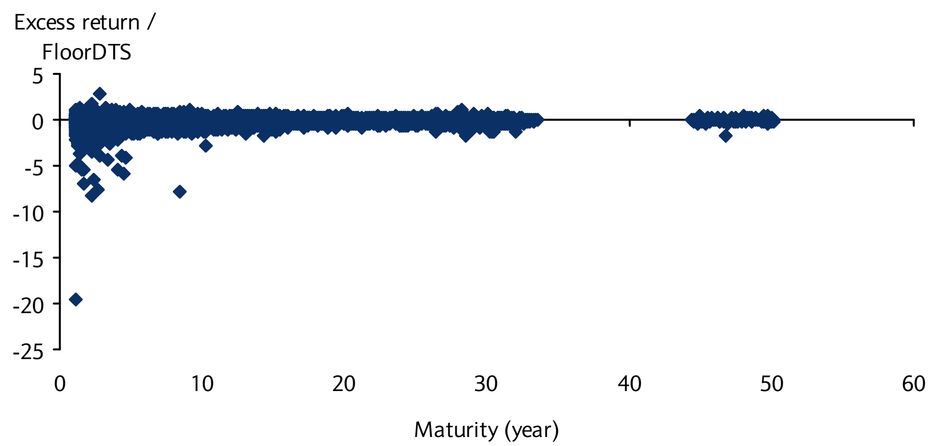
This discrepancy has emerged since the 2008 global crisis but became significantly more pronounced recently (and interestingly, resembles the diversity in spread levels seen before the introduction of the Euro). For instance, while the average spread between the Portuguese government bonds and the German treasury curve is more than 1,000bp as of November 2011, the spreads for some other countries can be very low – below 50bp for the Netherlands, for instance. To capture these historical diversions between country spread levels – as well as potential future ones – we introduce individual factors for each country in the new model. These country factors – in addition to the adoption of the DTS approach – allow us to capture different dynamics of the cross section of European bonds in a very timely fashion. Appendix I provides further empirical evidence.

5. Capturing Volatility Term Structure Effects

Another interesting feature of our European sovereign bond data is that shorter maturity portfolios tend to be more volatile than longer maturity portfolios, even after controlling for differences in DTS. The existence of this term structure effect may be driven by higher order effects, such as convexity, or by pricing models that do not explicitly consider credit risk embedded in prices. The linear risk factor model suggested so far may have problems capturing these effects. There are many different ways to deal with this shortcoming: for example, we could introduce additional factors to distinguish more precisely the different volatility dynamics of the long and short term of the spread curve. However, with limited data per country, the introduction of additional factors may lead to multi-colinearity issues that bring instability to the model. Therefore, we keep the one-factor per country structure and instead introduce a direct term structure adjustment to the DTS loading. This approach allows us to incorporate maturity related volatility effects in our risk model.

To illustrate this point, Figure 8 plots the normalized return ($R_{i,t+1} / \underline{DTS}_{i,t}$) against maturity for all bonds/periods in our sample. If the floored DTS loading fully captures spread risk, we expect to see the normalized return to be similarly volatile across maturity ranges. However, this is not the case. The figure shows that the volatility of the normalized returns is higher for short maturity securities and decreasing with maturity – even when controlling for differences in DTS.

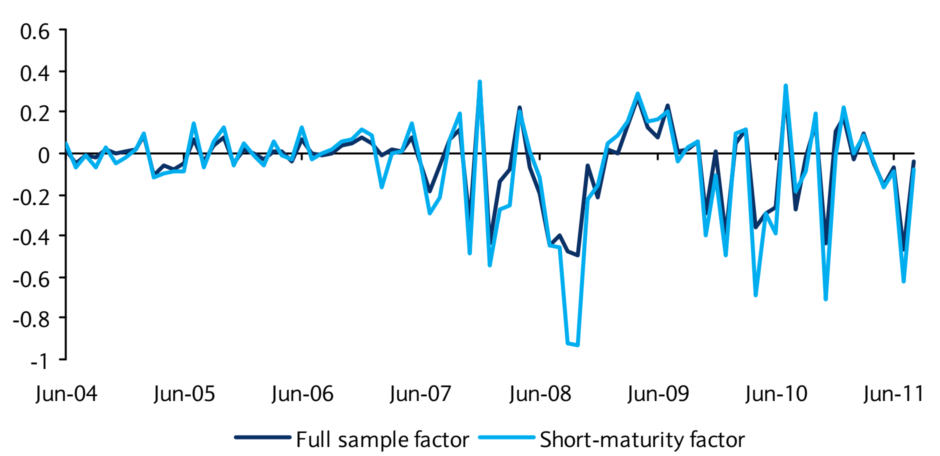
Figure 8: Floor-DTS-Normalized Return against Maturity



Source: Barclays Capital

To further examine this evidence, we estimate the monthly systematic risk factor realization [see equation (9)] for two different samples. The first includes all securities while the second is a subset that includes only instruments with shorter maturity (maturity less than the population average of eight years). Figure 9 presents the time series of the estimated factors for the two samples. The two factor realizations have very similar dynamics, suggesting that they are driven by the same source of systematic risk. In particular, the high colinearity between the two factors warns against a two-factor model – as discussed above. We do note however that the shorter-maturity factor realization is clearly more volatile than the full-sample factor.

Figure 9: DTS Factor Realizations

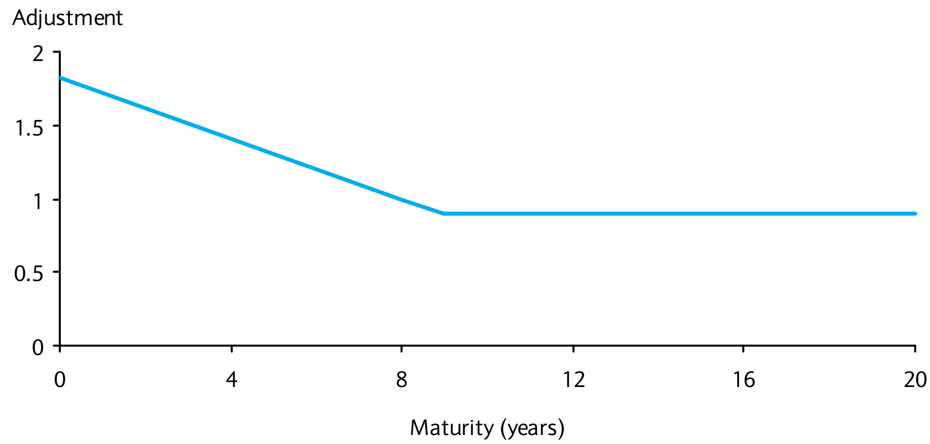


Source: Barclays Capital

The term structure effect is embedded as an adjustment to the DTS loading. In our model, this adjustment is a function of the instrument's maturity and is updated each period. We now describe how these parameters – one per country – are estimated.

The factor model described above is implemented in two steps: first, we use the cross-sectional regression to estimate the systematic factor using a floored DTS loading [see (9)]. Second, we estimate a term structure of volatility from the residuals of the first step. This term structure is captured by one parameter per country every month, and its time series is used to adjust the loading across the full maturity space. Upper and lower bounds are imposed on the function/parameter to ensure that the adjustment is robust, conservative and sensible. The details of the calibration – as well as the empirical test of the two-step model – are discussed in Appendix II. To illustrate, Figure 10 shows the adjustment function for Italy on August 2011.

Figure 10: DTS Term Structure Adjustment Function (August 2011)



Source: Barclays Capital

6. POINT Implementation

The European government securities DTS-based model integrated into the GRM in POINT has the following structure:

Systematic Risk

The risk model is calibrated in two steps:

1. The systematic risk factor is estimated from the cross-sectional regression of the normalized Treasury returns ($R_{i,t+1} / \underline{DTS}_{i,t}$) for each country.

2. An adjustment function per country ($\rho_{j,t}$) is calibrated from the residuals of the first step to take into account the term structure effects. Thus the loading for an instrument *i* of country *j* is given by

$$L_{i,t}^{DTS} = \rho_{j,t} \times \underline{DTS}_{i,t}$$

The simple one-factor structure allows us to calibrate country-specific risk factors and adjustment functions so that the heterogeneity of spread risk across issuers is properly captured.

Euro agency instruments load on the systematic factor estimated from treasuries to reflect the sovereign risk exposure. An alternative could be to estimate separately factors for agencies. Our research shows that this path leads to two major difficulties: first, many countries do not have a robust issuance of agency securities; second, for those that have, the factor estimated is highly collinear with the treasury one. In the current context sovereign spread risk dominates and propagates strongly to agencies. Therefore, we decided against having specific agency factors, choosing instead a more parsimonious model. Nonetheless, agency bonds are treated differently than Treasuries in what concerns idiosyncratic risk.

Idiosyncratic Risk

We apply the same DTS framework to model idiosyncratic risk of individual bonds, including the adjustments for term structure effects. Following equation (9) and the new loading specification the idiosyncratic risk can be written as:

$$R_{i,t}^{Idio} = L_{i,t}^{DTS} \times \varepsilon_{i,t} .$$

Further, we assume that the volatility of the idiosyncratic component is given by the product of the floored DTS loading and a country-specific parameter

$$\sigma(R_{i,t}^{Idio}) = L_{i,t}^{DTS} \times \phi_{j,t}$$

where $\phi_{j,t}$, is estimated from the history of residuals ($\varepsilon_{i,t}$) of bonds in country *j*. It measures the dispersion of the idiosyncratic components around the common factor for that country, adjusted for term structure effects. For each country, we estimate two idiosyncratic parameters: one for treasuries and one for agencies.

7. Back-testing the Model

Our DTS model provides better volatility forecasts at both the aggregate and country levels

In this section, we present some of the back-testing results for the new European government model. It allows us to understand how the model performed historically. We perform the tests over the period from January 2004 to August 2011[3]. This represents the period for which we have good cross sectional data and captures both regimes of low and high spread risk. We perform the tests both on the aggregate universe level as well as for specific countries, which allows us to account for the heterogeneous historical behavior of sovereign risk across issuers.

A simple test of volatility forecast is to examine the standardized return as defined by the Z-score:

$$Z_{i,t+1} = \frac{R_{i,t+1}}{\hat{\sigma}_t(R_{i,t+1})} \tag{10}$$

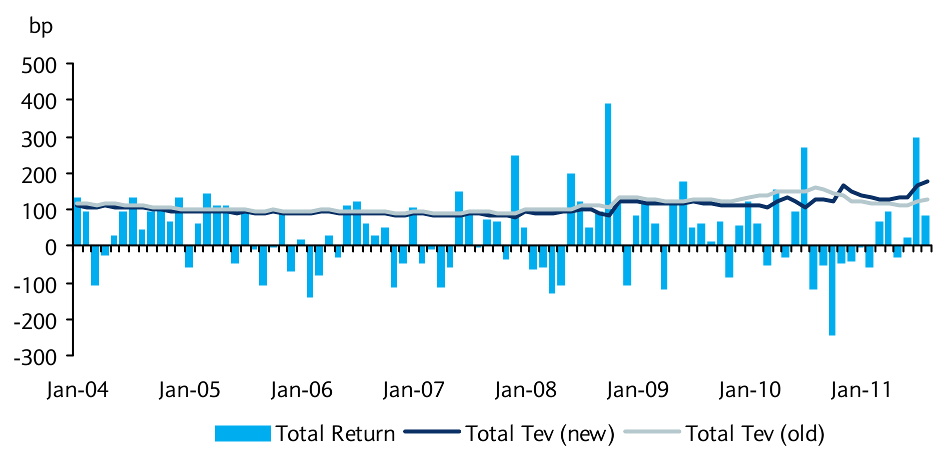
[3] For the out-of-sample test we are able to go back to January 2004 (instead of the June 2004 used before), due to less analytical requirements. The inclusion of these extra five months have no material impact on the results, but allow us to go as far back as possible for back-testing the model.

where $\hat{\sigma}_t(R_{i,t+1})$ is the one-step-ahead volatility forecast for return $R_{i,t+1}$ provided by our DTS model. If volatility forecasts are unbiased, the standard deviation of the Z-score over large samples should be close to 1. In addition to this statistic, we also analyze the full-time series results for the forecast overall performance.

Forecasting at the Aggregate Level

Figure 11 compares the actual returns for the European Treasury Index with the volatility forecast (TEV) under the old and the new versions of the European Government Risk Model. Before 2010 both models forecast almost the same TEV. But from 2010 onwards we see the difference becoming more apparent. In particular, as the European sovereign crisis evolves in 2011, the new model seems better prepared to capture the rising volatility.

Figure 11: Total Return TEV for Euro Treasury Index



Source: Barclays Capital

The standard deviation of the Z-scores for this index – as well as for the European Agencies Index – is reported in Figure 12. We present the results for both the full sample, as well as for its two halves. The analysis shows that at the aggregate level, both models are performing very similarly. This is not surprising given the fact that historically the spread levels (and therefore the DTS loadings of this index) were consistently low. However, the two models position the forecasts very differently as we move the analysis either to more distress countries or for higher spread level environments, as we see in what follows.

Figure 12: Standard Deviation of Z-score for Different Models, Aggregate Level (January 2004 – August 2011)

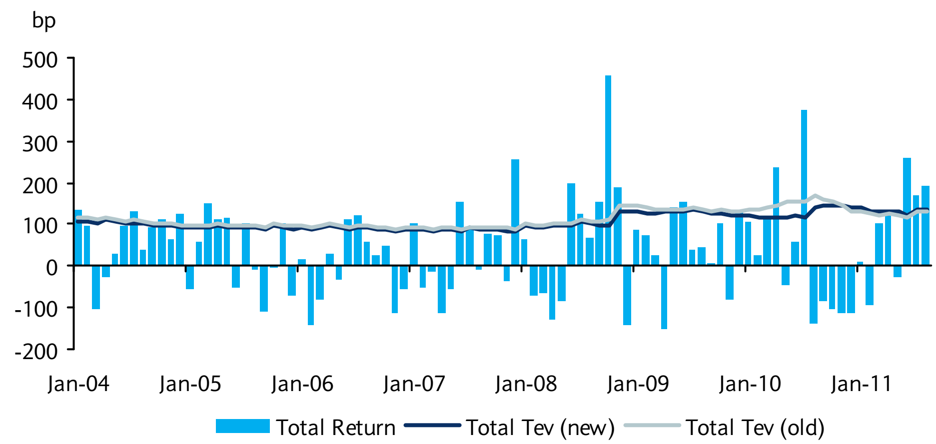
	Euro Treasury Index		Euro Agencies Index	
Model	old	new	old	new
2004.01-2011.08	0.96	1.07	0.89	1.00
2004.01-2007.12	0.85	0.90	0.81	0.86
2008.01-2011.08	1.08	1.22	0.97	1.11

Source: Barclays Capital

Forecasting at the Country Level

In this section we focus our analysis on three countries with varying level of perceived credit risk – France, Italy and Spain. Figures 13 to 15 compare the actual return with both the volatility forecasts from the old and new model for each of these countries separately.

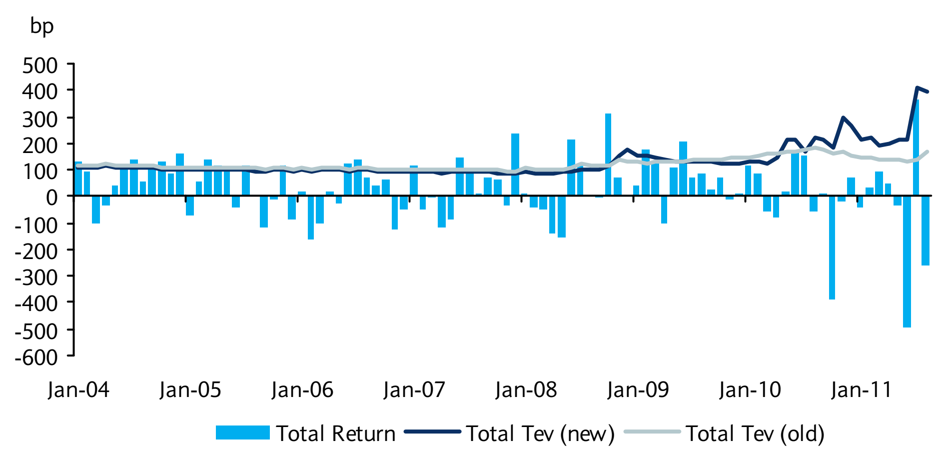
Figure 13: Total Return TEV for Euro Treasury France Index



Source: Barclays Capital

For French treasury bonds, there is not much difference in the TEV forecasts between the two models. French bonds during this period experienced relatively low levels of spread, making the distinction unnecessary.

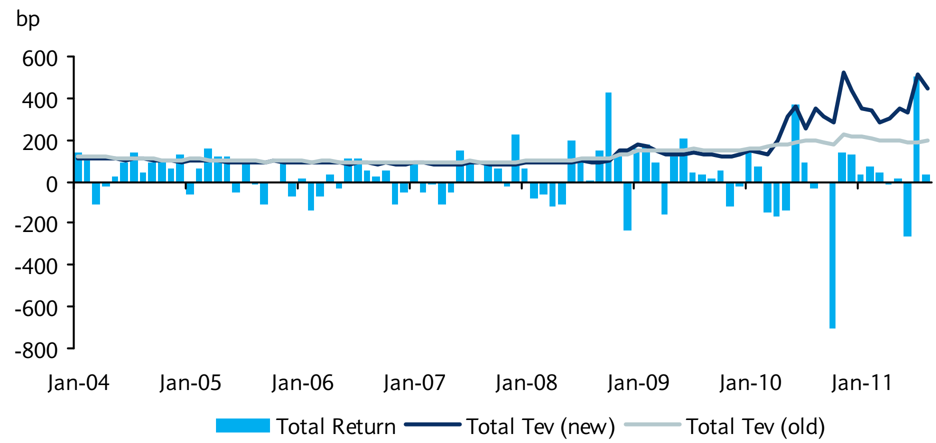
Figure 14: Total Return TEV for Euro Treasury Italy Index



Source: Barclays Capital

On the contrary, for both Italy and Spain, the differences in forecasts over the past several months are quite clear. As spreads increased significantly for these two countries, so did the predicted volatility. At the end of the period under consideration, the new model forecasts a volatility that is almost double the forecast coming from the old model. The difference is due to the timely reaction of the new model to the market dynamics as captured by the DTS loading.

Figure 15: Total Return TEV for Euro Treasury Spain Index



Source: Barclays Capital

Figure 16 reports the standard deviation of the Z-score for these three countries, again for both the entire sample as well as for its both halves. The results seem to suggest that the new model has successfully corrected the downward bias on forecasted volatility of the old model in the recent high spread market conditions. It does that without jeopardizing forecast ability under low spread regimes, as seen in the first half of the sample.

The robustness of the forecasts from the new model to different spread scenarios seem to suggest that it is well positioned to absorb rapid environment changes we may observe in the future. The old model does not offer that flexibility.

Figure 16: Standard Deviation of Z-score for Different Models, Country Level (January 2004 – August 2011)

	Euro Treasury France		Euro Treasury Italy		Euro Treasury Spain	
Model	old	new	old	new	old	new
2004.01-2011.08	1.01	1.11	1.03	0.98	1.08	1.04
2004.01-2007.12	0.86	0.91	0.85	0.92	0.83	0.89
2008.01-2011.08	1.16	1.28	1.20	1.05	1.30	1.19

Source: Barclays Capital

8. Concluding remarks

This paper describes our DTS modeling approach for capturing the spread risk of European government securities. We study in detail the challenges in modeling these instruments, especially as related to the significant regime shifts this market has gone through. We adapt the DTS approach implemented for other asset classes in our global risk model by introducing a positive floor on the OAS used to construct the DTS risk loading. This allows us to capture the risk implications of close-to-zero and negative spread cases. We further introduce an adjustment function to take into account volatility term structure effects. Finally, we estimate specific factors for each country in order to better capture the heterogeneity of risk across issuers in the eurozone. The model performs well historically and is robust over time and across countries. Importantly, the model is well positioned to accurately capture future developments in the European sovereign market. It gives portfolio managers a tool that can help them understand and manage their sovereign risk exposures in greater detail and with greater accuracy than before.

References

Ben Dor, A., Desclee, A., Hyman, Jay., and Polbennikov, S. (2011), *"Managing European Sovereign Spread Risk,"* Quantitative Portfolio Strategy, Barclays Capital.

Gabudean, R. (2009), *"US Home Equity ABS Risk Model",* Portfolio Modelling, Barclays Capital.

Lazanas, A., Silva, A., Gabudean, R., and Staal, A. D., (2011), *"A Portfolio Manager's Guide to Multi-Factor Fixed Income Risk Models and Their Applications,"* Portfolio Modeling, Barclays Capital.

Silva, A. B. (2009), *"Emerging Markets Risk Model: G4-Denominated Fixed Income Securities,"* Portfolio Modelling, Barclays Capital.

Staal, A. (2009), *"US Municipal Bond Risk Model,"* Portfolio Modelling, Barclays Capital.

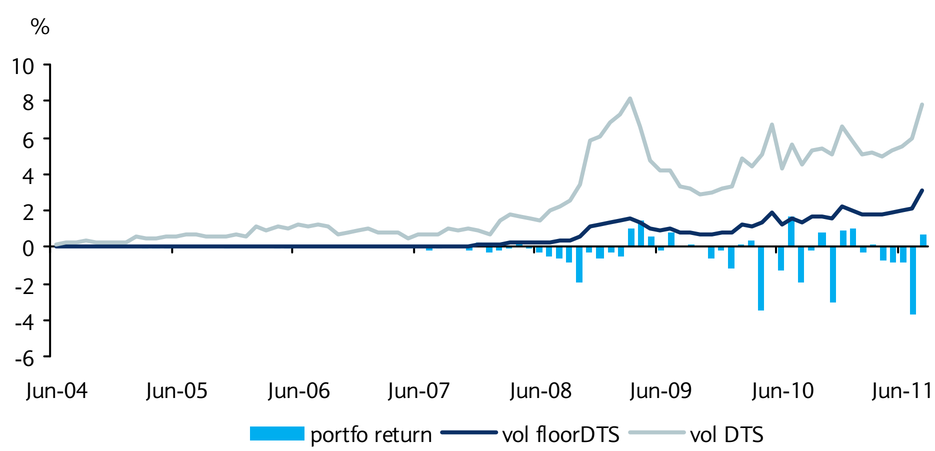
Appendix I: Testing Different Specifications of the Floor

This section examines different parameterizations for the floored DTS model, by examining the quality of their conditional volatility forecasts. We analyze both aggregate and country-specific portfolios, over the period from June 2004 to August 2011. We analyze the results using both the Z-scores introduced previously [see (10)] as well as the full time series of the forecasts against actual returns.

The Aggregate Level

We start the analysis by considering an equal-weight portfolio of all Euro treasuries. A time series plot of the portfolio excess return and volatility forecasts from both the DTS and the floor DTS models are shown in Figure 17. The DTS approach (without modification on OAS) has a significantly higher volatility forecasts when compared with the alternative calibration.

Figure 17: Return and Volatility Forecasts of the Aggregate Portfolio of Euro Treasuries



Source: Barclays Capital

The standard deviation of the Z-score, summarized in Figure 18, confirms that the DTS model is overestimating significantly the volatility due to the upward bias in the factor estimate (discussed before – see Figure 6). Moreover, the floored DTS model has better volatility forecasts when the floor threshold is C=10bp, against higher floor alternatives. In particular, the table seems to suggest that a relatively low floor is enough to avoid problems with DTS factor estimation. When the floored DTS parameter (and therefore the DTS loading) is adjusted too high, we quickly fall into the other extreme, ending up with an underestimation of the factor volatility (e.g., for c=30bp, we underestimate risk on average by 56%).

Figure 18: Standard Deviation of Z-score for Different Models, Aggregate Level

DTS	FloorDTS c=10bp	FloorDTS c=20bp	FloorDTS c=30bp	FloorDTS c=40bp
0.19	1.16	1.42	1.56	1.62

Source: Barclays Capital

The Country Level

We now analyze the results from a similar approach, but applied to country-specific portfolios. Three countries are studied: France, Italy, and Spain. The analysis of the Z-scores for these portfolios is summarized in Figure 19 and follows closely the results for the aggregate portfolio.

Figure 19: Standard Deviation of Z-score for Different Models, Country Specific Portfolios

	France	Italy	Spain
DTS	0.43	0.22	0.20
FloorDTS c=10bp	1.44	1.10	1.18
FloorDTS c=20bp	1.55	1.29	1.32
FloorDTS c=30bp	1.61	1.41	1.40
FloorDTS c=40bp	1.63	1.47	1.45

Source: Barclays Capital

Overall, the floored DTS model with C=10bp seems to perform better in terms of volatility forecast across countries. The standard deviations of the Z-score are significantly less than 1 from the simple DTS model suggesting that model forecasts are significantly overestimated. We again see an increasing tendency for underestimation as we increase the parameter used to define the floor. Even with c=10, the table seems to suggest that we are underestimating risk, sometimes significantly (e.g., France). The other adjustments introduced to the model help to significantly reduce this bias, as shown in Figure 19.

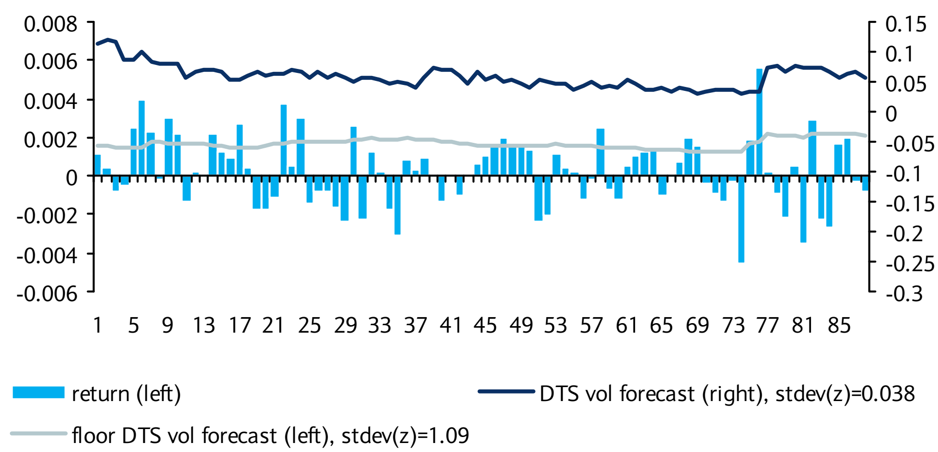
Robustness Test in Simulated Scenario

The floored DTS model is designed to robustly capture a wide range of sovereign spread risk and the above empirical evidence suggests that it is able to significantly improve the volatility forecast. But given the short history of the sample and that the low-spread treasuries account for only a fraction of the sample, it is useful to conduct robustness test in some extreme scenario where most of the securities have very low spreads. This section examines the model's forecasts for simulated observations where the spread of each individual security is very close to zero.

We consider zero coupon bonds for simplicity assuming the maturity is 20 years and the base curve rate is 2%. At each period we simulate 1000 securities of which the spreads are randomly drawn from a uniform distribution with range [-10bp, 30bp]. The change in spread for each securities is randomly drawn from a uniform distribution with range [-50bp, 50bp]. Thus a large number of simulations will have very large percentage spread change. The returns are calculated by the zero-coupon bond pricing formula plus a random noise which is normally distributed with zero mean and a volatility of 5bp. We estimate the factor from the cross-sectional regression and we run the simulation for 100 periods. We then compare the volatility forecasts for an equally weighted portfolio of the simulated securities.

The forecasting performance is assessed by the normalized return (Z-score) which is shown in Figure 20 along with the plot of return and volatility forecasts. The Z-score from the DTS model is very small with a standard deviation of 0.038 because the volatility forecast is significantly biased upwards (notice the right scale). This is because the systematic factor estimate is skewed by the outliers which have close-to-zero DTS loadings. On the other hand, the floored DTS loading ensures that the factor estimate is sensible and robust, and the volatility forecast is much better as the corresponding Z-score has a standard deviation of 1.09. The results do depend on the settings chosen for the exercise, but the need to impose a floor is clear.

Figure 20: Z-scores for the Equally Weighted Portfolio, Simulated Sample, C=10bp. DTS Volatility Right Scale; Floor DTS Volatility Left Scale.



Source: Barclays Capital

Appendix II: Calibrating the Adjustment Function for Volatility Term Structure

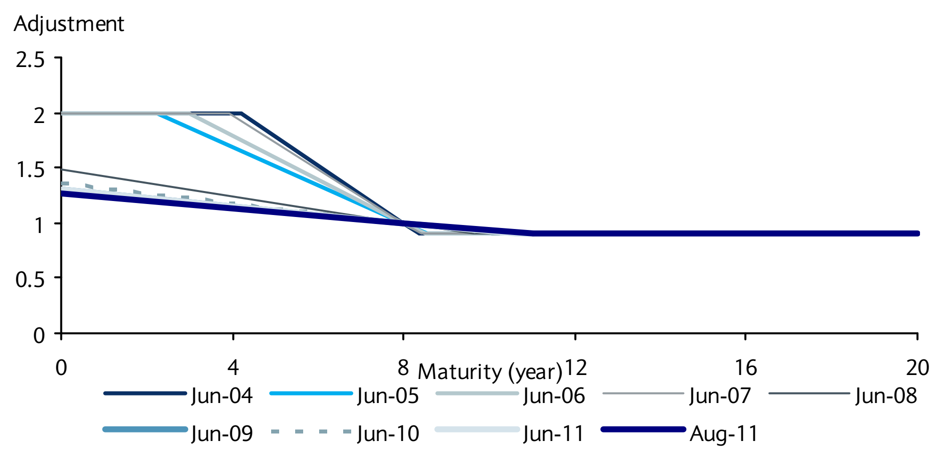
As discussed earlier, shorter maturity portfolios in this market tend to be more volatile, even after controlling for differences in DTS. This suggests that the linear risk factor model may have problems capturing this feature of the data and lead us to introduce an adjustment to the DTS loading used in the model. In this section we discuss how we calibrate the parameter used in this adjustment and look at the improvements on the out-of-sample results of the model.

Recall that we calibrate the model in two steps: we estimate the country DTS factors by cross-sectional regression in the first step; we then use the residuals from this first step to calibrate the term structure parameter. By construction, the sum of the residuals over all the securities in the country is zero. If the country DTS risk factor captures all systematic components of the risk, the cross section average of the residuals should be random across any particular dimension. Our research shows that this is not the case. Residuals tend to be higher (in absolute terms) for shorter maturity bonds. Note that this is the case, even though these residuals are obtained controlling for DTS differences (as we use the DTS as the loading in the regression). Moreover, this is not an issue of heteroskedasticity: the average residual is not zero for shorter maturities. The residuals for short-maturity securities are not only more volatile, but also have averages that are systematically different than zero.

This evidence suggests this behavior represents systematic risk not captured by the DTS factor.

To incorporate this systematic term structure effect, we create a short-maturity systematic factor by adding the non-zero mean of the residuals over short-maturity securities to the country DTS factor. Then the ratio between the volatilities of these two factors is used to calibrate the adjustment function used in the instrument's loading. A linear interpolation is applied to derive the adjustment function spanning the full maturity space. Figure 21 plots the adjustment function for several periods as estimated at the aggregate portfolio level (note that upper and lower bonds are imposed in the function, for added robustness). We can see that the adjustment function is decreasing over maturity and changing over time. This simple yet robust approach is used to calibrate country-specific adjustment function in order to handle the heterogeneity of sovereign risk across regions better. In what follows we study the improvements on the performance of the model brought by this adjustment.

Figure 21: Adjustment on DTS Loading as a Function of Maturity



Source: Barclays Capital

Empirical Performance

The empirical performance of the two-step approach is examined by studying the volatility forecasts for three portfolios, both at the aggregate and country levels, of equally weighted securities over the period from June 2004 to August 2011. We again use Z-scores to report the results of the analysis [see (10)] focusing on the portfolio excess return.

The three equally-weighted portfolios considered for testing are as follows: a pooled sample portfolio, a short maturity portfolio consisting of the half of the pooled sample that is below the average maturity, and a long maturity portfolio consisting of the other half. The forecast performance measured by the standard deviation of the Z-score is summarized in Figure 22. The one-step model – that does not consider term structure effects – significantly underestimates the volatilities for the short maturity portfolios. The two-step approach corrects this bias satisfactorily while preserving the robust forecasts for the pooled sample portfolios. The two-step allows for a robust performance in both the aggregate and country levels[4]. Notice that we calibrate the adjustment function for each country separately so that

[4] The results seem to suggest that we still tend to underestimate volatility for short maturity portfolios. This may be due to the conservative estimation approach we use - imposing a cap on the adjustment factor. Although a more aggressive cap may correct this bias, we feel the current calibration adds needed robustness to the analysis of this market that is under significant change. Please also note that the Z-score presented here is sensitive to outliers and is only one of the many analyses we perform to gauge the quality of the model and to decide on what calibrations to use.

the heterogeneity across them is properly handled. Moreover, the adjustment factor is updated every month, by adding to the analysis the behavior of the residuals for that country for that incremental month.

Figure 22: Standard Deviation of Z-score for Portfolios of Different Maturity (June 2004 – August 2011)

Sample	Model	Aggregate	France	Italy	Spain
Pooled	One-step	1.16	1.44	1.10	1.18
	Two-step	1.12	1.48	1.13	1.16
Short maturity	One-step	2.04	1.88	2.02	1.86
	Two-step	1.37	1.41	1.48	1.30
Long maturity	One-step	1.06	1.54	1.06	1.19
	Two-step	1.12	1.63	1.14	1.20

Source: Barclays Capital

Analyst Certification(s)

We, Dapeng Gu, Antonio Silva and Arne D. Staal, hereby certify (1) that the views expressed in this research report accurately reflect our personal views about any or all of the subject securities or issuers referred to in this research report and (2) no part of our compensation was, is or will be directly or indirectly related to the specific recommendations or views expressed in this research report.

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