BARCLAYS CAPITAL

US CMBS Risk Model

This paper presents the second-generation risk model for commercial mortgage-backed securities. The model continues the recent trend in Barclays Capital's credit risk modeling of relating credit risk to the level of spreads. It incorporates important innovations such as the use of Duration Times Spread (DTS) for this asset class, the use of higher-frequency proxy data to forecast monthly volatility, and a joint estimation of systematic and idiosyncratic parameters in an integrated framework. Aside from DTS, the model recognizes other sources of risk, which are based both on analytics (e.g., the estimated size of the payment window) and collateral characteristics (e.g., weighted average loan age). The predicted market volatility under this new model matches realized volatility more closely than the first-generation, ratings-based model.

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INTRODUCTION[1]

The CMBS market suffered major transformations during the financial crisis that started in 2007. Before the crisis, most of the assets traded were viewed as safe, investment grade bonds. Afterwards, however, this view changed radically. The same pre-crisis “almost-riskless” bonds have traded post crisis at deep and volatile discounts. In light of these developments, we decided to re-evaluate the previous Barclays Capital US CMBS risk model. While doing so, we also improved some technical components of the model construction and estimation, making the CMBS model more aligned with recent research and changes done across other asset classes.

The model has been redesigned following the duration times spread (DTS) concept, whereby risk is a linear function of DTS. Moreover, empirical data show that risk is a function of other variables as well. We capture these relationships with factors based on measures such as whether the security is paying principal, the size of the principal payment window, and the loan age of the collateral (WALA). Idiosyncratic risk becomes a function of DTS as well, an improvement over the previous model, in which this risk was assumed to be a function of ratings. In this work, we bring several refinements to the use of the DTS concept in risk. In particular for this market, where securities tend to move more closely than in other markets (e.g., credit), it was important to account for non-linearities in the DTS risk profile.

On the econometric front, we estimate the systematic and idiosyncratic model jointly, thus fully accounting for the modeled heteroskedasticity of the data. Therefore, bonds that have a higher idiosyncratic risk are given a lower weight in the parameter estimation[2].

We conduct extensive tests of the model to show its performance across various portfolios, either diversified, sorted by various characteristics or as long-short pairs.

The first section of this paper provides an overview of the CMBS market. The second describes the model and presents its behavior, starting with the systematic part and following with the idiosyncratic. Next, we treat several issues related to risk forecasting. The section ends with an out-of-sample analysis of the model performance for various types of portfolios. Section 3 concludes.

[1] The author would like to thank Antonio Silva for his extensive and valuable comments and suggestions. Gary Wang contributed to the development and implementation of the risk model in POINT.

[2] In previous specifications, we used robust regression to identify outliers, but did not incorporate information regarding idiosyncratic volatility to weight returns in the cross-sectional regression.

THE US CMBS MARKET

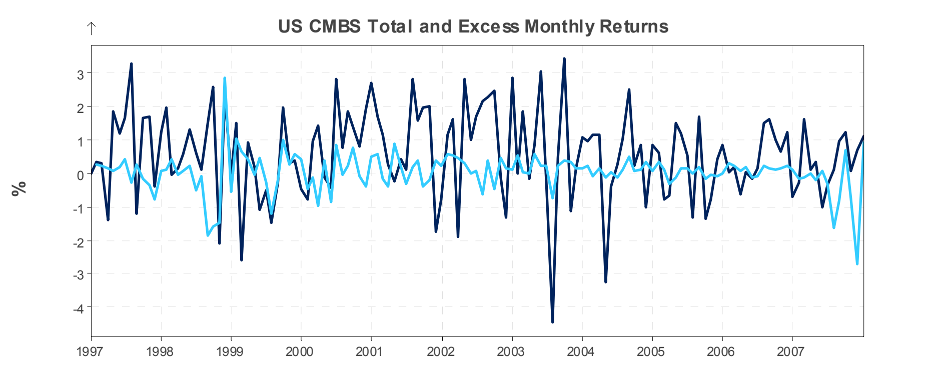
The Commercial Mortgage Back Securities (CMBS) are interests on a pool of commercial mortgages, which are secured typically by apartment buildings, office, industrial, or retail space properties. The market started in 1991 and grew exponentially in the mid-nineties. During that period there was a ready supply of commercial real-estate to be sold by the Resolution Trust Corporation in the wake of the savings and loan crisis. The only significant buyers of this large supply of commercial properties were non-traditional investment funds that looked for diversification and CMBS seemed a great vehicle to acquire it. Barclays Capital, recognizing the importance of the CMBS market, launched a set of benchmark indices[3] in January 1999.

The CMBS deals have been typically structured such that some securities (junior tranches) will absorb the initial losses from potential defaults of principal or interest shortfall. In practice, this allows the market to treat the senior tranches as relatively safe. Each security, or tranche, is targeted to a different type of investor, according to his or her risk preferences. Diverging from the MBS deals, CMBS deals include only a few transactions because commercial loans are much larger than residential ones, creating less diversification than in the MBS case.

Commercial loans are structured as balloons, with most principal paid at maturity and interest paid throughout the life of the loan. The borrower typically refinances, or rolls over, the loan at maturity. Reinforced by stiff pre-payment penalties for most loans, these characteristics create strong incentives for no loan prepayments. Although prepayment risk is mute, there is significant default risk at maturity when the loan must be rolled over.

Before the credit crisis that started in 2007, CMBS was considered a relatively safe, low-risk investment. This was true particularly for the highly rated tranches, the ones that are traded more extensively and found in the portfolios of many investors. The total and excess return for the Barclays Capital US CMBS Investment Grade Index (Figure 1) documents that fact: most of the volatility of the total return disappears once we subtract the return attributable to the movements in the Treasury curve. The remainder, the excess return, experienced very low levels of volatility (about 60bp/month).

Figure 1: The Total and Excess Return of Barclays Capital CMBS IG Index – 1997 to 2007



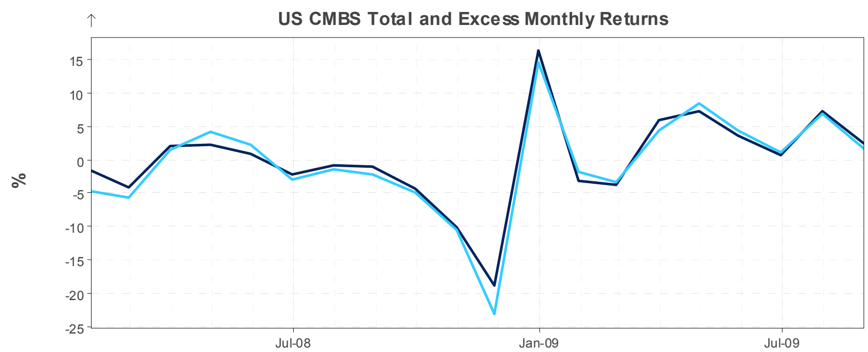
Key	Axis	Name	Last	Minimum		Maximum		Mean	SD
	Left	Inv Grade CMBS - Total Return	1.10	-4.46	07/31/2003	3.44	09/30/2003	0.57	1.32
	Left	Inv Grade CMBS - Excess Return	0.91	-2.70	11/30/2007	2.84	11/30/1998	0.03	0.59

Source: Barclays Capital Live

[3] Please refer to Baek and Golbin 1999 for more information.

During the credit crisis, the CMBS asset class went through an upheaval. Although the crisis began as a tail event during the second half of 2007, it quickly transformed CMBS into a highly volatile, credit-risk driven asset class, closer to distressed debt. Figure 2 shows that from 2008 onwards, excess return volatility differs by orders of magnitude from pre-crisis level: 7.58%/month vs. 0.59%/month. Moreover, excess return over Treasuries is now the main component of total return, contrary to what was seen in Figure 1.

Figure 2: The Return of Barclays Capital CMBS IG Index – 2008 to September 2009



Key	Axis	Name	Last	Minimum		Maximum		Mean	SD
	Left	Inv Grade CMBS - Total Return	2.49	-18.80	11/28/2008	16.45	12/31/2008	-0.07	6.96
	Left	Inv Grade CMBS - Excess Return	1.72	-23.19	11/28/2008	14.66	12/31/2008	-0.59	7.58

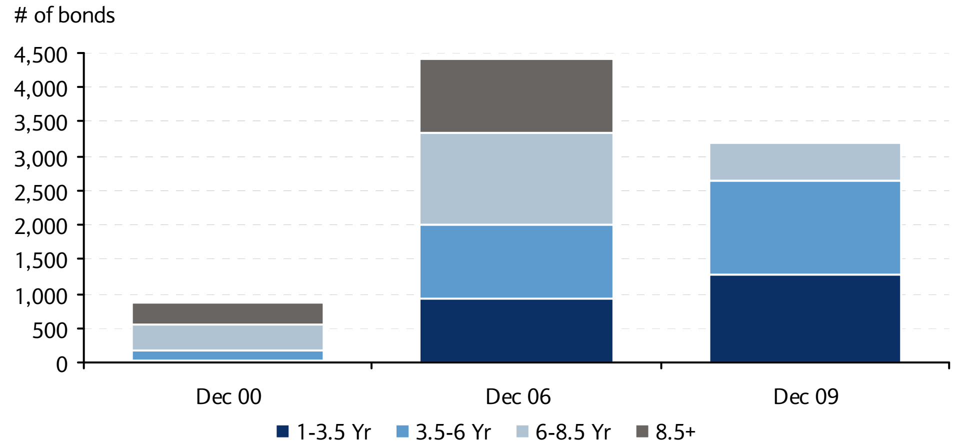
Source: Barclays Capital Live

The crisis affected the CMBS market in a very specific way. Contrary to what happened in the corporate debt market, the default rate on loans underlying CMBS was low by historical standards and driven mostly by the inability to refinance loans that were coming due, partly because credit was scarce in all markets and partly because underlying property values fell below loan balances. The longer the credit markets stayed frozen and the harder asset values fell, the bigger was the prospect of future defaults. This context dragged down the value of even the safest CMBS securities, even though they were not failing any scheduled payments. Thus, it was not only the decrease in future cash flows from the underlying properties that dragged down CMBS values, but also mainly the expectation that loans would not be refinanced when due. Moreover, because CMBS deals contain only a few loans, even one loan default would affect many tranches in a significant way, thus generating significant deal-specific risk.

Data

In our analysis, we use a sample that starts at August 1999 and includes only the bonds from Barclays Capital US CMBS Investment Grade Index. The sample size grew steadily from 600 bonds in 1999 to 1600 in 2004. The growth accelerated to 5,000 bonds as of 2007, due to a significant increase in issuance. This number started to decrease with the crisis – first with a freeze in issuance, and then followed by a large number of downgrades that prompted bonds to be dropped from the index. The index had 2,800 bonds as of middle of 2010. The evolution of sample breakdown by average life (Figure 3) reflects these market developments: in 2000 given that there are mainly new issues, many bonds have a long average life; in 2006, when the market matured there is a relatively even number of bonds in each bucket. By 2009, when new issuances have been suspended most bonds have a short average life.

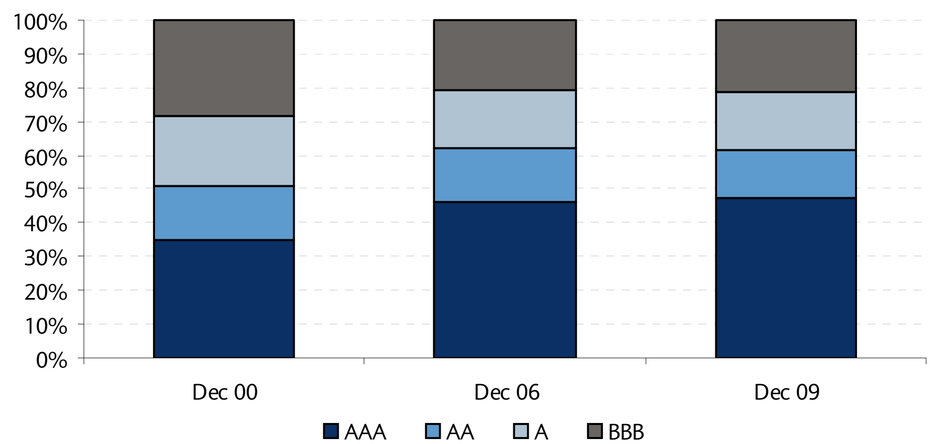
Figure 3: Calibration Sample Size and Breakdown by Average Life, Select Dates



Source: Barclays Capital

The sample breakdown by ratings is relatively stable over time, except for the beginning of the sample when there were more bonds of lower quality (Figure 4). The difference between the beginning of the sample and the other periods may be due to higher credit support for highly rated tranches during the early sample period, which translated into a lower issuance of these securities. This conclusion is supported by the size-weighted ratings breakdown of the sample (not shown). Another motivation for more AAA bonds later in the sample comes from issuers catering to investors' demand for more complex tranching of the high-quality part of the deal. The ratings breakdown of the index remained constant over the crisis, even though many bonds got downgraded, implying that each rating category suffered a similar ratio of downgrades.

Figure 4: Calibration Sample Breakdown by Rating, Select Dates



Source: Barclays Capital

Over the entire sample, there are 6,200 individual bonds and half of them have a history between 34 and 71 observations. In terms of deals, there are about 90 at the beginning of the sample, peaking at 450 in 2007 and decreasing to 350 in the middle of 2010. Typical deals before 2004 have six bonds in the sample, and the ones after 2004 contain between eight and eleven bonds.

Historically, CMBS bonds were created so that senior tranches have small loss probabilities. Any collateral loss would be assigned to junior bonds. Therefore, investment grade CMBS bonds enjoyed prices close-to and even above par. But since January 2008, CMBS bond prices have registered significant decreases, especially during the second half of that year, reaching a minimum of 61 for the index in November 2008.

The analytics used in our risk model are based on a pricing model that does not forecast defaults. During the crisis, heavy expected and realized credit losses have depressed prices. In our pricing model, these prices result in high spreads. Therefore, for modeling purposes, credit risk is fully embedded in spreads. This definition of spreads is widely used by market participants and it drives the choice of systematic risk factors to explain the cross-sectional excess return. Moreover, the pricing model assumes no prepayments: this assumption is reasonable, given that CMBS deals experience long lock-ups and there is little principal payment before maturity.

THE US CMBS RISK MODEL

The Systematic Risk Model

The Commercial Mortgage Backed Securities (CMBS) Risk Model is part of Barclays Capital's Global Risk Model (GRM) and follows its general linear factor-based approach.[4] Returns are represented as a linear combination of systematic factors, with pre-defined loadings, plus a security-specific remainder (Figure 5). Factors embody various sources of common, or systematic, risk across all securities, such as curve and spread. Loadings provide the exposure of each security to each risk factor. Factor risk models reduce the dimensionality of the problem of calculating the joint distribution of all securities in a particular universe by focusing on a smaller subset of systematic risk factors. Lastly, we must model the security-specific risk of the remainder, which tends to be diversified away for large portfolios.

Figure 5: General Structure of a Factor Risk Model

$$R_{i,t+1} = \mu_{i,t} + L_{i,t} \cdot f_{t+1} + \varepsilon_{i,t+1}$$

$\mu_{i,t} =$ carry

$f_{t+1} =$ factor realization

$L_{i,t} =$ factor loading

$\varepsilon_{i,t+1} =$ residual return

Source: Barclays Capital

In the GRM, systematic risk factors are grouped by types of risk: Treasury curve, swap spread, and spread related (Figure 6). For curve risk, the model uses seven risk factors: six key rates (6m, 2y, 5y, 10y, 20y, and 30y) and one convexity. The bond's loadings to these factors are the key-rate durations and the option-adjusted convexity, respectively. Swap spread factors receive similar treatment.

All fixed income securities (potentially) load on these two sets of risk factors: curve and swap spreads. In the GRM, all asset classes do load on them, including the new CMBS risk model. However, this is not the case for the spread return risk. For this, the GRM develops a specific set of spread factors designed to capture the specificity of this asset class. In this regard, only CMBS securities have exposures to the CMBS specific spread factors. These factors are typically correlated with the curve factors and spread factors specific to other asset classes (eg, US credit). The choice of these CMBS spread risk factors and the construction of their loadings is the most complex part of this new model and its main contribution.

Figure 6: Factor Breakdown

$$L_{i,t} \cdot f_{t+1} = R_{it}^{YC} + R_{it}^{SS} + R_{it}^{Spread}$$

Source: Barclays Capital

Spread return R_{it}^{Spread} contains common sources of risk (among securities in the same asset class) originating from either the risk to future cash flows or risk to their discount factor. Risk to the former, in the CMBS market, is due mainly to default. Regarding the

[4] Please refer to Dynkin, Joneja et al. 2005 and the Portfolio Modeling Group research papers for more information.

latter, the effect of any spread factor into the discount factor is in addition to the Treasury and swap curves.

The pricing model used to calculate the analytics available in POINT and to calibrate this model does not account for defaults, leaving all the effects of defaults or similar credit risk events to be reflected through spreads. These events can be triggered by many factors, namely a change in credit standards, underlying properties prices (e.g., hotels, office, industrial, and apartment buildings) or the income they generate. Similarly, the discount rate has a component additional to Treasury yields, which measures the level of risk aversion. Thus default risk and risk aversion are captured by spread return. In fact, other sources of risk (e.g., liquidity) are also reflected there.

Defaults

The notion of default for this asset class is different from its meaning in the corporate bond market. The nature of CMBS – a tranche of a deal of structured securities constructed from the same portfolio of underlying loans – creates two notions of default: of the underlying loans and of the CMBS. The two measures are intertwined: as underlying loans default, it is less likely that CMBS investors will recover their money. The deal may experience a "default event" that triggers changes in the cash flow allocations among securities, but does not necessarily lead to liquidation of any CMBS. Some default events may not affect all securities. Even when a security stops paying interest and/or principal, it may start paying again if the performance of underlying loans improves. Moreover, a missed payment is not always a default event. Thus, default for a CMBS bond is less clearly defined than in the corporate world.

It is difficult to disentangle how much of the spread risk originates from each of the two sources mentioned: default and risk aversion. In the CMBS Risk Model, we treat these risk sources jointly. When researching specific risk factors, we look for variables that may account for one or both risk sources.

The Relation between DTS and Spread Return Risk: Empirical Evidence

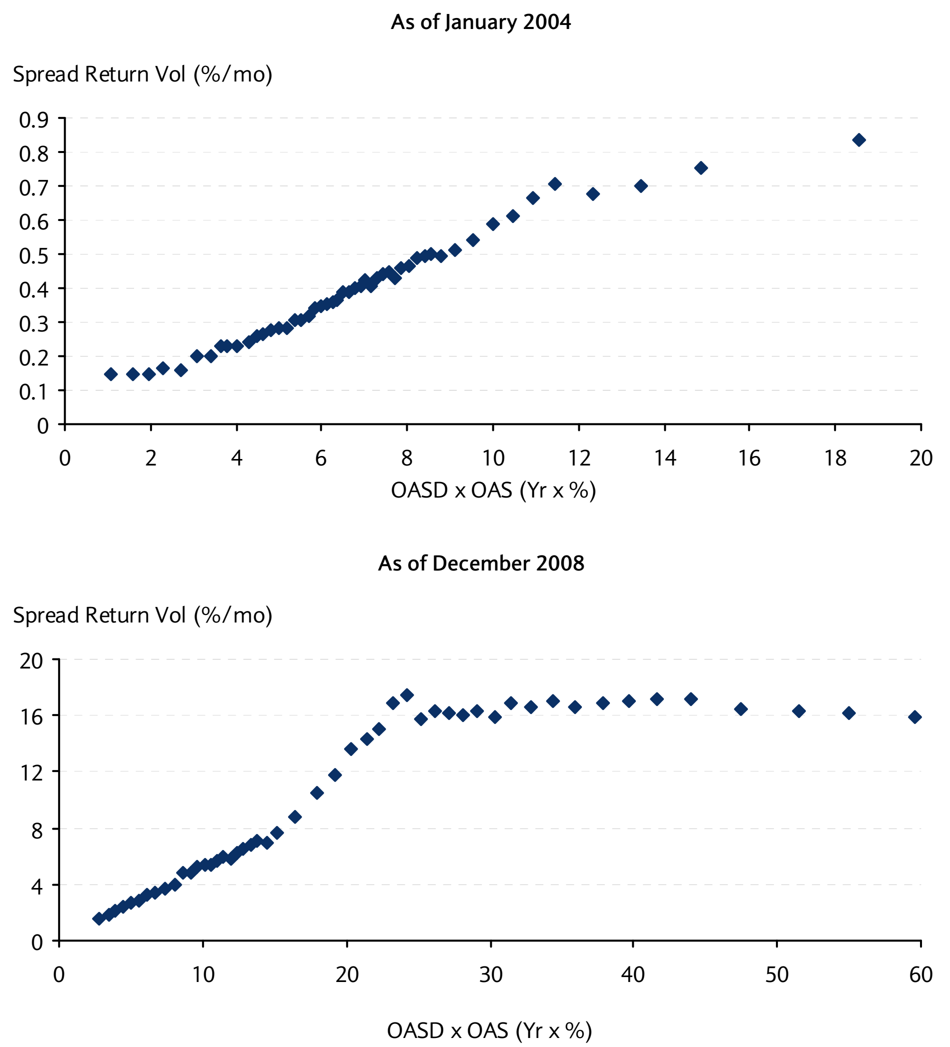
Recent research (e.g., Dor, Dynkin et al. [2005]) suggests that volatility of a particular bond can be well forecast by the bond's level of duration times its spread (DTS). Specifically, it seems that spread levels are a good predictor of near-term spread volatility, with a linear relationship between current spread levels and future spread volatilities. These findings make it attractive to model spreads changes as a log-normal process, rendering their estimation and forecasting more robust. Further research suggests that this result applies also to other assets classes. In POINT, this approach is already available in risk models for several asset classes (see Silva [2009a] for a description of the implementation of DTS in POINT's credit risk model, Gabudean [2009] for an implementation in the ABS Home Equity risk model and Silva [2009b] for an implementation in emerging markets risk model). It is therefore natural to investigate whether DTS is also a relevant concept for CMBS.

For the CMBS market, higher spreads are related to higher risk aversion or higher market expectations of default losses, for instance. All these effects are also commonly associated with higher volatility. Moreover, these effects are compounded by the spread duration of the bond: all else equal, the more distant the cash flows, the larger the effects. It is this intuition that gives DTS its appeal.

To illustrate the relationship between risk and DTS, each month we sort the sample universe by the beginning of the month DTS into 50 equal-weighted portfolios. Thus, securities with

DTS in the 0-2 percentile fall into portfolio 1, bonds with DTS in 2-4 percentiles in portfolio 2, etc. For each portfolio, we register its spread return (i.e., total return less carry and returns attributable to changes in Treasury curve and swap spreads) over the month. This spread return should contain mostly systematic risk, given that portfolio sizes are large (40 to 100). Repeating the exercise every month, we obtain 50 time series of returns and beginning-of-the-month DTS values. For each of these time series, we can compute at various dates the historical return volatility and mean DTS[5]. We present these in Figure 7, showing average DTS on the horizontal axis and the volatility of excess returns on the vertical axis for two different dates. As of 2004, top panel, we can see the quasi-linear relation between volatility and average DTS. While the relation flattens out for very high and very low DTS portfolios, all others are situated very close to a line with a slope of 0.06. The magnitude of the slope is comparable to the one found for corporate bonds (roughly 0.1) and other securities.

Figure 7: Relation between Time-Weighted Volatility of Spread Return and DTS, By 50 DTS-Sorted Portfolios



Source: Barclays Capital

The bottom panel of Figure 7 shows the volatility-DTS relation as of December 2008 (after the crisis). The linear relationship is still there, as predicted by the DTS. This result is

[5] In this illustration, we compute these statistics time-weighted, using an Exponential Weighted Moving Average (EWMA).

encouraging, showing that the concept is resilient to very different market conditions. However, there are also differences from 2004: the slope is much steeper, at 0.6, and the DTS relationship flattens out for high levels of DTS. The relationship is quite similar across other periods.

The above evidence suggests that DTS is a good starting point for modeling volatility forecasts. However, it does not clarify whether both variables (OAS and OASD) contribute to the relationship, or if we would have it using only one of them. To test that hypothesis, we perform the following exercise: separate the universe of securities into five equal-size OAS buckets, and then construct within each OAS bucket the DTS-sorted portfolios as described above. We use only 10 portfolios per OAS bucket, for the same total of 50 portfolios. If the linear relation is between risk and OASD (not DTS), the slope of portfolio spread return volatility to DTS should decrease with the OAS, as shown in equation (A) from Figure 8. That is, if OASD is the true risk driver, not DTS, we should expect each OAS bucket to have a different slope. If, instead, the linear relationship is between risk and DTS, we have the same relation between DTS and volatility, independently of the OAS bucket (equation (B) in Figure 8).

Figure 8: The Volatility-DTS Relation under Different Assumptions

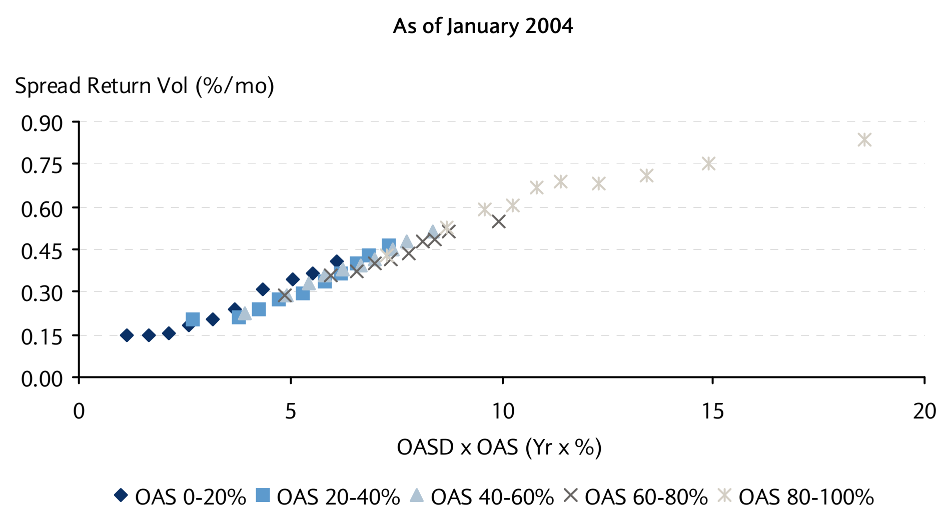
(A): $Vol(R_i) = const * OASD_i = \left(\frac{const}{OAS_i}\right) * DTS_i$

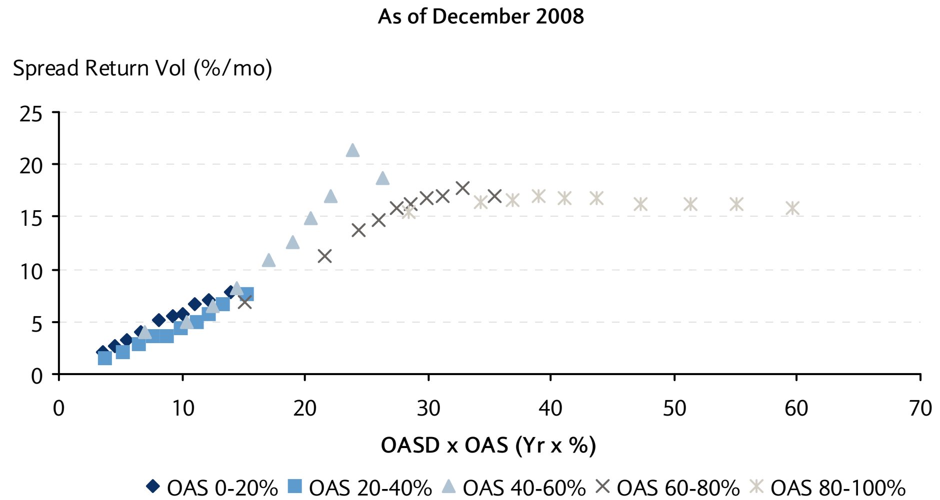
(B): $Vol(R_i) = const * DTS_i$

Source: Barclays Capital

In Figure 9, we plot the volatility of each portfolio from all OAS buckets versus the average DTS. The top panel shows that as of January 2004, the main driver is DTS, not OASD, because all portfolios are aligned on the same line, regardless of the OAS level. The conclusion does not change after the crisis, as the bottom of the figure illustrates. The relationship is just not that clear, due to the significant difference in the OAS levels between the buckets: the crisis significantly increased the range of OAS in the sample.

Figure 9: Relation between Time-Weighted Volatility of Spread Return and DTS, by 5 OAS Groups and 10 DTS-Sorted Portfolios within Each OAS Group

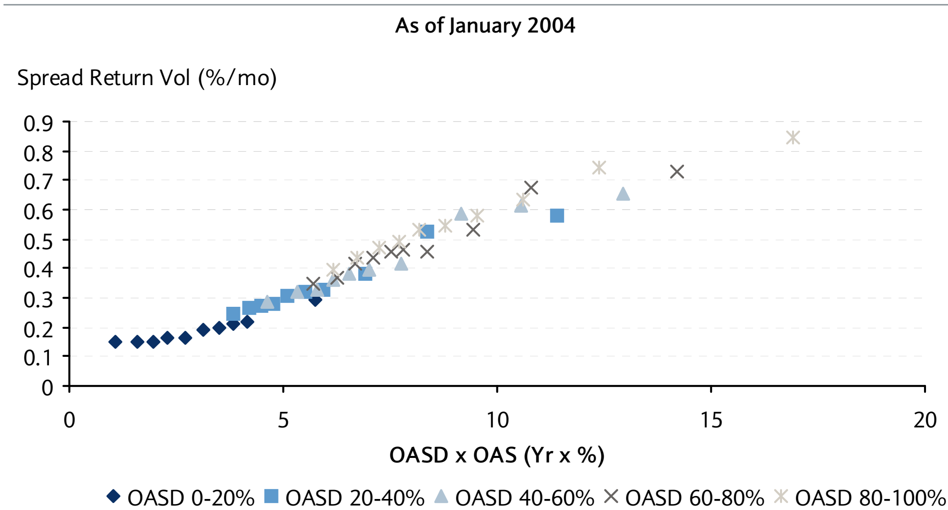




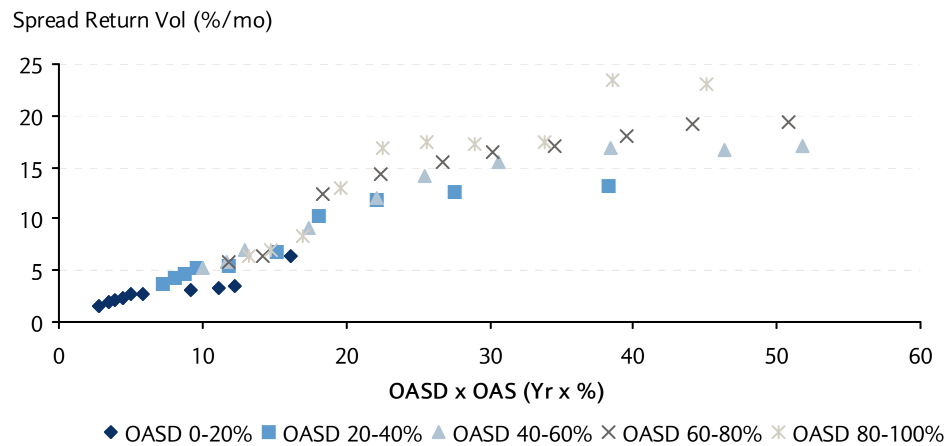
Source: Barclays Capital

A similar test can be constructed for the hypothesis that OAS is the main driver of risk, not DTS. We repeat the test described above, by switching OAS with OASD. Specifically, we now create five OASD, not OAS buckets. The results for January 2004 are shown at the top of Figure 10. Again, should the OAS be the important variable and not DTS, we would see the slope decreasing for higher OASD buckets. The results show that it is not the case, and the strong linear pattern is still observed. Results hold for December 2008 as well.

Figure 10: Relation between Time-Weighted Volatility of Spread Return and DTS, By 5 OASD Groups and 10 DTS-Sorted Portfolios within Each OASD Group



As of December 2008



Source: Barclays Capital

Based on our research, partially presented above, we conclude that there is strong empirical evidence that the relationship between the risk of spread return and the DTS of the bond is linear in the CMBS market. We use this conclusion to construct our risk model.

The Relation between DTS and Spread Return Risk: Forecasting

Our starting point in creating a DTS-based model for the CMBS spread return R_i^{Sprd} volatility is the following:

$$R_i^{Sprd} \approx -OASD_i * \Delta LOAS_i = OASD_i \times LOAS_i \times \frac{-\Delta LOAS_i}{LOAS_i}$$
$$= DTS_i \times F^{DTS}$$

where F^{DTS} is the risk factor realization associated with the DTS factor and represents the negative percentage change in Libor OAS (LOAS). Although powerful, there are several limitations to this specification. We introduce additional features in the model to circumvent them. One such refinement is to recognize that for very low level of spreads (as shown in Figure 7), the relationship between risk and spreads may not follow the same linear function as for the rest of securities. For example, a security with a 5bp LOAS is unlikely to have half the spread risk of a security with 10bp LOAS. They probably would share very similar volatilities, but have differences in their duration and other technical considerations (liquidity, etc). Moreover, for bonds with negative spreads, DTS is ill-defined. Therefore, we must set a base level of risk that will be applied to all bonds, independently of their DTS level. This level of risk is a lower bound on the volatility of all CMBS bonds and the major risk component for bonds with very low DTS levels. Then, as the DTS of the bond increases, the risk associated with it increases linearly. For bonds with high DTS, the lower bound is negligible, and the majority of the volatility is driven by the DTS factor. Because the factor setting the base risk is the main source of spread risk for bonds with the lowest DTS, we call it the ultra high grade (UHG) factor. The loading to this base volatility is the OASD of the bond, similar to our other models of high quality bonds (e.g., agencies). With these considerations, the model specification is changed to:

$$R_i^{Sprd} \approx OASD_i \times F^{UHG} + DTS_i^* \times F^{DTS}$$

Where F^{UHG} is the UHG factor, $DTS_i^* = \max(DTS_i - \underline{DTS}, 0)$ and $\underline{DTS}$ determines the level of DTS above which the loading is non-zero.

For very high levels of DTS, Figure 7 shows that the relation between risk and spread is weaker. Thus, we cap the DTS at a particular level $\overline{DTS}$. This level defines the maximum loading attributable to the DTS factor, effectively capping the systematic risk a CMBS bond may have. Therefore, we now have a truncated (T) DTS loading:

$$R_i^{Sprd} \approx OASD_i \times F^{UHG} + DTS_i^T \times F^{DTS} \qquad (1)$$

where $DTS^T = \min\left[\max(DTS_i - \underline{DTS}, 0), \overline{DTS}\right]$.

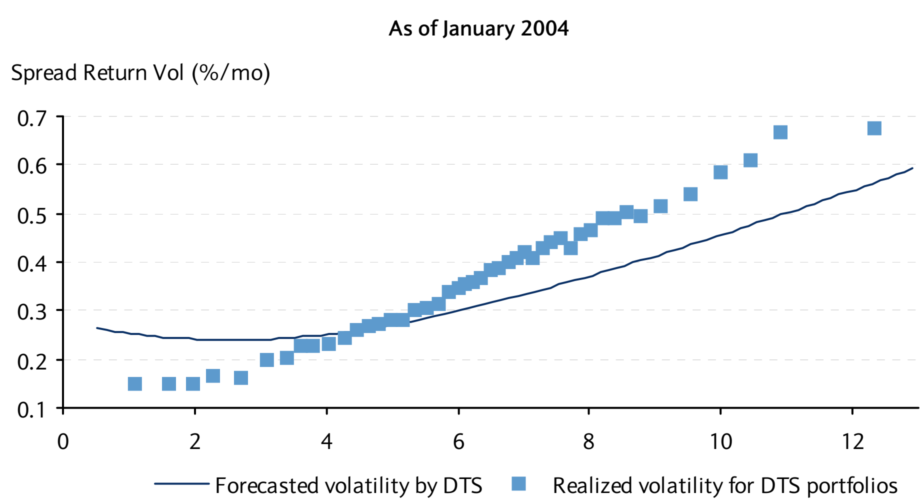
To forecast the spread return risk, each month we run a cross-sectional regression represented by equation (1), using OASD and DTS for each bond as of the beginning of the month. The result is a time series of risk factor realizations for F^{UHG} and F^{DTS}. From these factors' history, we can estimate their covariance matrix.

DTS Floor and Cap: Intuition

The previous model descriptions involve determining $\underline{DTS}$ and $\overline{DTS}$. To gain intuition regarding the effects of these parameters, we test them with different values, plot the implied risk profile of these securities versus their DTS level and compare it with actual data.

We start the exercise with one simple and appealing choice for $\underline{DTS}$ as 0 (i.e., all securities with negative LOAS have DTS of zero, loading only on the UHG factor) and $\underline{DTS}$ as the maximum observable value (i.e., no cap). We compute the forecasted volatility associated with these parameters for a set of portfolios with a typical OASD for lower DTS bonds and varying values of DTS. Figure 11 plots the volatility of these portfolios versus DTS using data up to January 2004. For easy comparison, we add to the graph the historical volatility of the DTS portfolios as displayed in Figure 7.

Figure 11: Forecasted Volatility of Spread Return Using a Zero Floor and No Cap on DTS for 50 DTS-Sorted Portfolios versus DTS, and Their Time-Weighted Realized Volatility



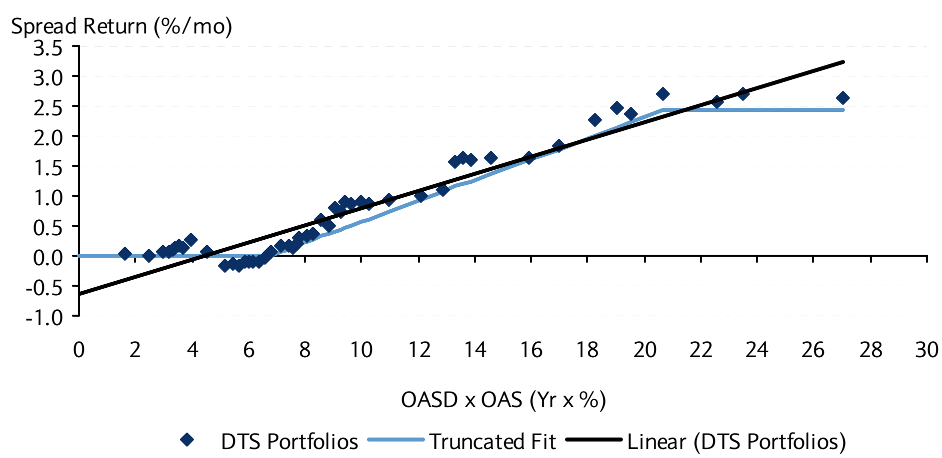
Source: Barclays Capital

There are two main differences between the forecasted volatility and volatility of the DTS portfolios: for low levels of DTS, the relationship between forecasted volatility and DTS is U-shaped, instead of flat, and the slope of the forecasted volatility is smaller than the empirical one.

The U-shaped relation between risk and DTS for low DTS comes from the negative correlation between the F^{UHG} and F^{DTS}. This u-shaped relationship is unintuitive, as one expects the volatility to be monotonically increasing with the spread level. That is, we expect that both higher and lower quality bonds move in a similar direction with the entire market, except for some intra-asset class flight-to-quality episodes.

To understand the source of negative correlation of factor realizations, consider how the chosen factor model – almost linear with the current settings for $\underline{DTS}$ and $\overline{DTS}$ – fits the hockey-stick profile of returns vs. DTS reported in Figure 7. If the market rallies, the model fits a positively sloped line through the data, as is shown in Figure 12. There we graph the actual spread returns on the 50 DTS portfolios for December 1999, together with the fit from the zero floor and no cap model (the Linear line). The two factors can be read approximately from the graph as follows: the intercept of the line with the Y-axis (DTS=0) is the value of the UHG factor, and the slope of the line is the value of the DTS factor. We can see that all low-DTS bonds have returns close to zero, but the fit is negative. Since the line slopes upwards, the lower the DTS, the more negative the returns, and at DTS=0, the fit is quite negative, resulting in a negative UHG factor. Over several months, such behavior generates an artificially negative correlation between the two factors and an artificially high volatility of the UHG.

Figure 12: Spread Returns of 50 DTS Portfolios, the Fit Using a Zero Floor and No Cap on DTS, and the Fit Using an Optimized Floor and Cap, December 1999

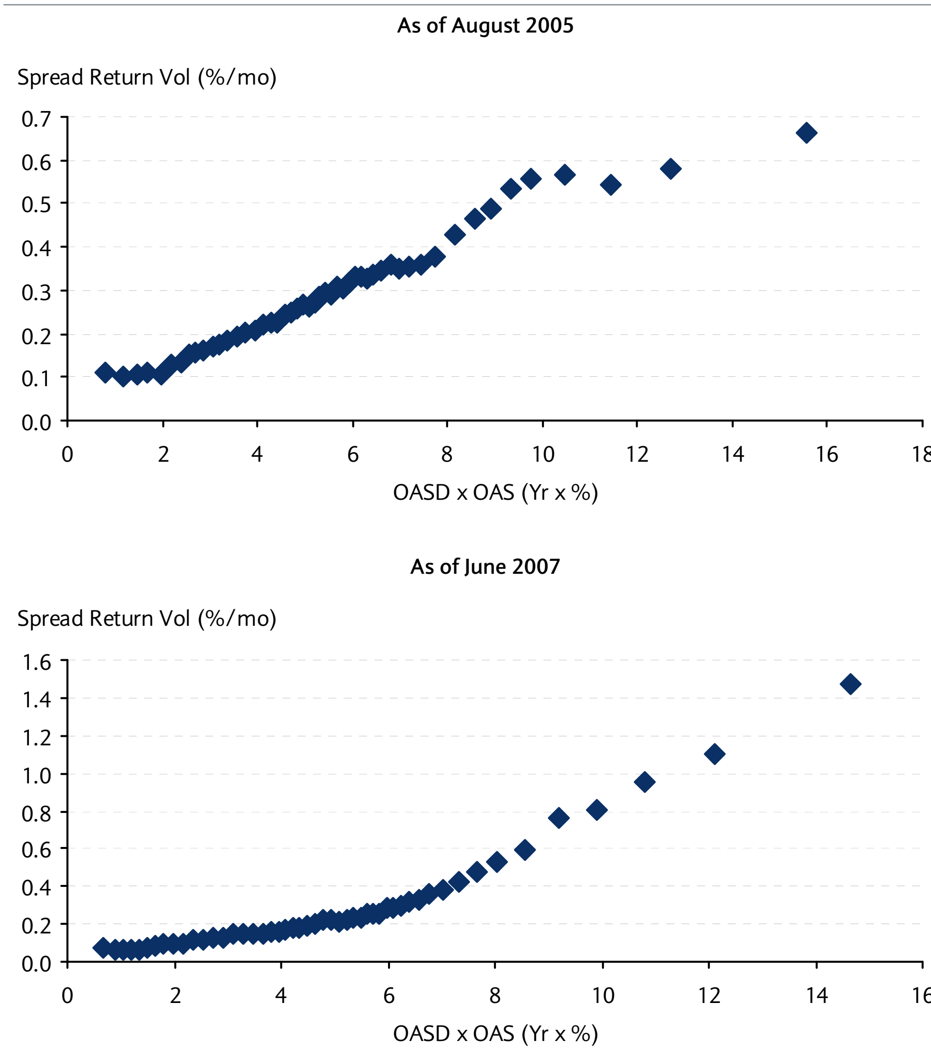


Source: Barclays Capital

The second anomaly in the forecasted volatility model – the flatter slope vs. DTS – can be understood by looking at high-DTS bonds. There, we see that ignoring the cap on the DTS-risk relation creates a smaller-sloped fit since it tries to fit the return on high-DTS bonds as increasing in DTS when they actually have a flat relation to DTS. Thus, the magnitude of the DTS factor (the slope) is lower than it should be. For comparison, we show in the same Figure 12 the fit from a model with appropriately chosen caps and floors (Truncated Fit). Notice the almost 0 value of UHG and the higher value of DTS factor (the slope).

Given the documented importance of setting the right caps and floors on DTS, we conduct an investigation into the evolution of observed values and whether there is a simple rule to forecast them. Building on the results in Figure 7, we look in Figure 13 at the DTS-realized spread return volatility for other dates and analyze the behavior of caps and floors. Comparing the two figures regarding the apparent DTS floor, we see that this is at about a DTS of 3 for January 2004, 2 for August 2005, but much higher for June 2007 (the point where the relation becomes steeper occurs at a DTS of 5). This suggests that the DTS floor can vary significantly across time. Similar analysis can be done with respect to the DTS cap. This suggests that the parameters should be allowed to vary across time. We allow for that variation through a proprietary estimation procedure. Broadly speaking, the procedure uses the central body of the DTS portfolios to estimate the slope of the relationship between DTS and volatility. We then gradually expand our analysis over the more extreme portfolios, comparing at each step the volatility of the portfolio with that implied by the DTS relationship, to decide whether the DTS still holds for that portfolio or whether we are entering a flattening zone. The procedure finishes – setting a cap and a floor – where the evidence for flattening is confirmed by a few set of portfolios.

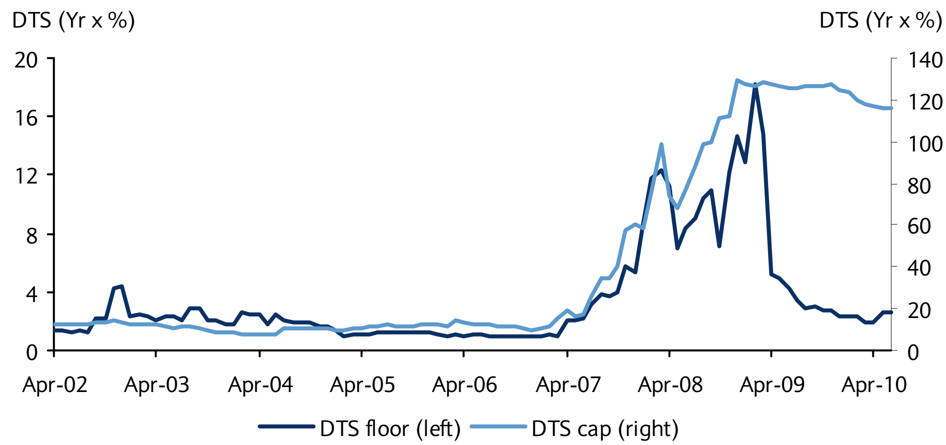
Figure 13: Relation between Time-Weighted Volatility of Spread Return and DTS, by 50 DTS-Sorted Portfolios, Other Dates



Source: Barclays Capital

In Figure 14, we show the evolution of caps and floors. In particular, it is interesting to note how the floor increased dramatically over the crisis. This is just the result of having the whole market – including the bonds considered the safest – moving in tandem and less dependent on the particular spread level. As markets stabilized, the floor came down, reflecting a larger diversity of behavior across different levels of DTS. Note that that cap did not decrease, given the persistent presence of highly distressed bonds.

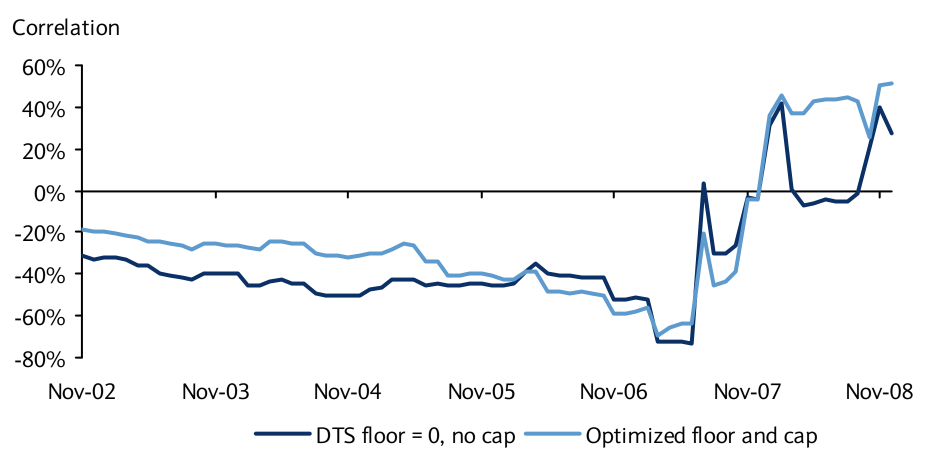
Figure 14: The Evolution over Time of Fitted DTS Floors (left axis) and Caps (right axis)



Source: Barclays Capital

To see the effect of the chosen caps and floors on forecasted volatility, we show in Figure 15 the evolution of correlation between the resulting factors and contrast it with the correlation between factors obtained by setting the floor to zero and no cap. As described above, in the latter case the correlation between factors is negative even before the crisis. It reaches extreme negative levels at the beginning of the crisis and afterwards turns positive. When we optimize the caps and floors, the evolution of correlation is much smoother and it does reach less extreme levels. This evidence suggests that our model of choosing caps and floors is a step in the right direction.

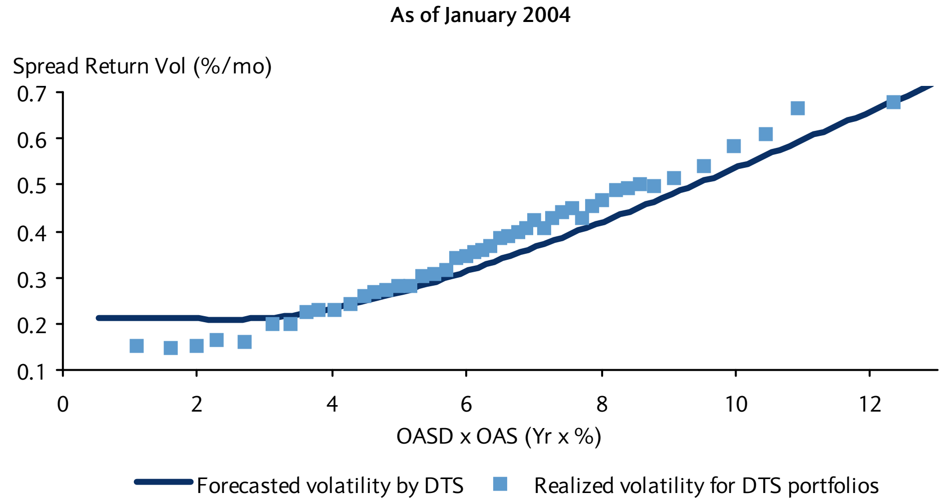
Figure 15: The Evolution of Time-Weighted Correlation between the UHG and DTS Factors Using Various Models for DTS Floor and Cap



Source: Barclays Capital

We can also construct the profile of volatility forecast vs. DTS using the estimated floor and cap, as done in Figure 11 for the basic floor and cap. The results are presented in Figure 16. The forecasts with estimated floors and caps match past realizations more closely, suggesting that there is value added in allowing for a richer specification.

Figure 16: Forecasted Volatility of Spread Return Using a Model with Optimized Floor and Cap on DTS, and Time-Weighted Realized Volatility of 50 DTS-Sorted Portfolios versus DTS



Source: Barclays Capital

Other Risk Factors

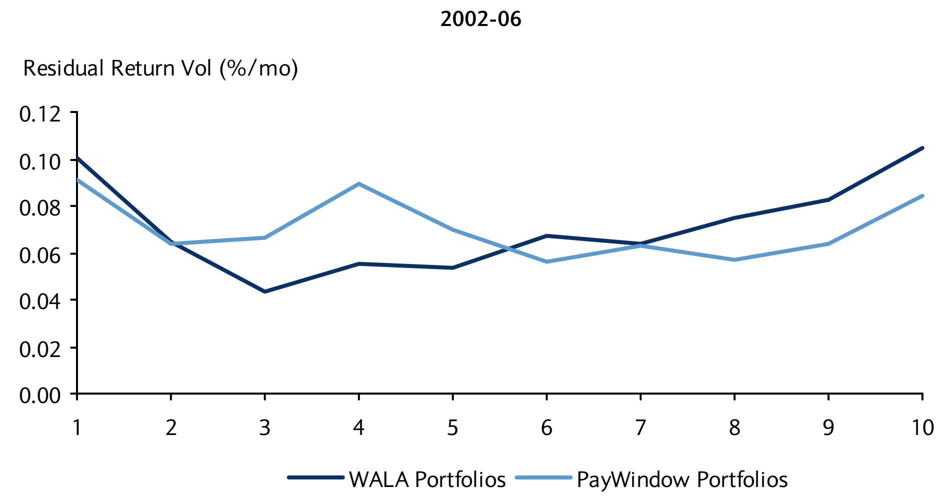
Our research shows that in addition to DTS, several other factors help explain the cross-sectional behavior of CMBS bonds' spread returns. To study these effects, we construct characteristic-based portfolios and investigate the returns' volatility pattern across these characteristics. The return used is net of the UHG and DTS factors studied above. For each attribute, we construct the portfolios by sorting the CMBS universe along that characteristic. They are then formed based on that sort, usually divided into 10 portfolios with increasing level of the characteristic. They are composed of a large number of securities, to ensure little idiosyncratic risk. Below, we list the additional factors incorporated in the risk model:

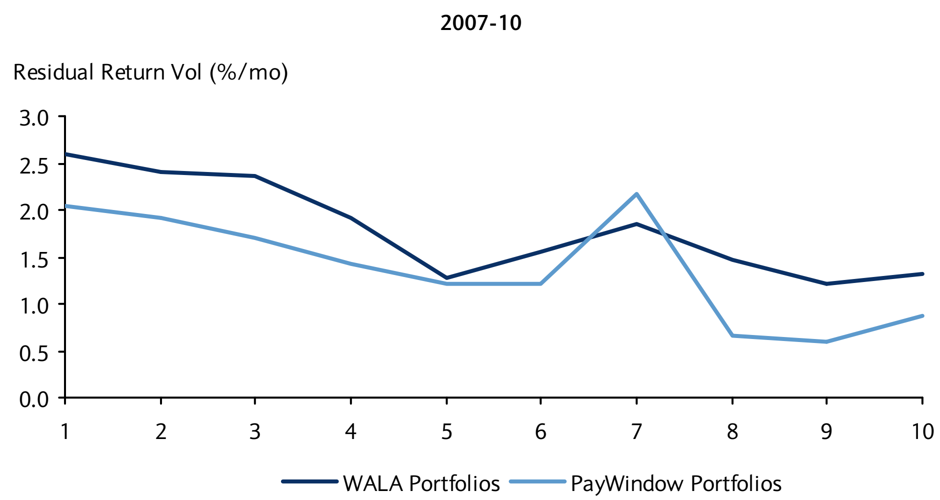
- Weighted average loan age (WALA): As for all mortgage products, seasoning affects commercial mortgages as well, even though in different ways. CMBS backed by seasoned mortgages may experience higher uncertainty than less seasoned ones as the refinancing window approaches. In Figure 17, we show the volatility of residual return (after accounting for DTS) of 10 portfolios created by sorting the CMBS universe based on WALA. The volatility is computed separately for two periods, one from 2002 to December 2006 and the second from 2007 to 2010. We see a U-shaped pattern in volatility before the crisis (top panel), signalling that both newer and very seasoned bonds are more volatile than others. During the credit crisis the newer bonds experienced more volatile returns, even after adjusting for their DTS. This may be due to the looser credit standards allowed at the boom of the market in 2006-07. The evidence seems to suggest different systematic volatility patterns across the 10 portfolios. Therefore, we introduce a WALA factor into our model. The loading to this factor is expressed as a deviation from the median WALA across all CMBS bonds, implying that a diversified portfolio would have an almost 0 loading on this factor. Specifically, the loading is:

- OASD x (WALA – median WALA)

where WALA is represented in months.

Figure 17: Unweighted Volatility of Residual Returns of Portfolios Sorted by Various Characteristics, for Two Time Periods





Source: Barclays Capital

- Principal Payment Window (Window): Borrowers with mortgages locked-out behave differently than the rest, making investors account for the lock-out feature when they price CMBS bonds. One dimension of the lock-out is captured by the length of the principal payment window and investors may differentiate among bonds if some are unlocked for a longer period than others. We may see this behavior reflected into risk. To test for it, we compute the residual return's volatility of a set of 10 portfolios created based on window length. The unweighted volatility of those portfolios is shown in Figure 17 for two separate periods. As with WALA, we note a variation in volatility across portfolios, even after accounting for DTS, which leads us to incorporate a

"Principal Payment Window" factor in our model. The loading is defined relative to the median payment window across all bonds, implying that a diversified portfolio would have a loading close to 0 on this factor. The loading is defined as:

– OASD x (Window – median Window)

where Window = Years to last payment – Years to first payment

- Is Paying Principal (IsPay): This factor captures a different effect of the lock-out period. All else equal, bonds that are outside the lock-out period are less desired by investors that the ones locked-out because the latter have more predictable cash flow. This difference in investor preferences should translate into a different behavior of returns on the two bond types. Looking at the behavior of residual returns from the DTS model for a portfolio that contains all bonds not paying principal compared with a portfolio of all other bonds, we see in Figure 18 that before the crisis, the locked-out bonds had a much lower volatility than the ones paying principal. This effect is not visible after the crisis, potentially due to the general spike in volatilities. We decided to add an IsPay factor to our model. The loading is defined as:

  – OASD x $1_{\text{Tranche Factor} <1}$

Figure 18: Unweighted Volatility in %/Month of Residual Returns of a Portfolio of All Bonds Not Paying Principal Vs. a Portfolio of All Bonds Paying Principal, for Two Time Periods

	No Princ Pay	Princ Pay
1999-2006	0.02	0.09
2007-2010	0.75	0.78

Source: Barclays Capital.

With the addition of these factors, the final form of the factor model for systematic spread return for CMBS bonds is given by Figure 19.

Figure 19: The Spread Return Factor Model, Systematic Component

$$R_i^{Sprd} = OASD_i F^{UHG} + DTS_i^{Adj} F^{DTS} + \\ + OASD_i \left[\left(WALA_i - \overline{WALA} \right) F^{WALA} + \left(Window_i - \overline{Window} \right) F^{Window} + IsPay_i F^{IsPay} \right]$$

Source: Barclays Capital.

In Sample Analysis

In this section, we analyze statistics related to the research and testing of the CMBS model. This allows us to understand the main characteristics and relative strength of each variable/factor in the model.

Figure 20 shows the median cross-sectional correlations among the different factor loadings used in the model. For a more straightforward comparison, results are shown for the value of the loadings before being multiplied by OASD. In general, correlations are below 50% in magnitude. The exception is the positive correlation between the length of the payment window and whether a bond pays principal. This result is expected since bonds with short lock-out periods (long payment windows) are more likely to pay principal. Overall, the level of correlations is low enough for us to avoid significant multicollinearity problems.

Figure 20: Average of Cross-Sectional Correlations among Loadings/OASD

	DTS	WALA	Window	IsPay
DTS		-0.24	-0.40	-0.42
WALA	-0.24		-0.09	-0.03
Window	-0.40	-0.09		0.75
IsPay	-0.42	-0.03	0.75	

Source: Barclays Capital

Figure 21 shows the average explanatory power (R-squared) across all monthly regressions, for DTS factor and all variables in the model. These numbers are order-dependent. Because returns differ by orders of magnitude before and after 2007, we analyze the period before and after separately. The results show that DTS factors explain a significant amount of cross-sectional volatility, underscoring the importance of adding the DTS factors to the model. On top of DTS, the additional variables (WALA, Window, and IsPay) increase the model's adjusted R-squared. While the total explanatory power of the model is the same before and during the crisis, DTS became more prominent during the crisis, with the DTS adjusted R-squared increasing from 27% to 32%. This is not surprising, as the market shifted concerns to the creditworthiness of the bonds, something primarily captured by the DTS factor.

Figure 21: Average Adjusted R-squared in Cross-Sectional Regressions

	Before Jan07	Since Jan07
DTS	27.2	31.7
All Variables	35.0	36.5

Source: Barclays Capital

The Idiosyncratic Risk Model

The idiosyncratic return (also called name-specific or residual return – see Figure 5) of a bond is the part of the return not captured by the systematic factors analyzed before. By definition, this risk is uncorrelated across securities and with systematic risk. In our model, idiosyncratic risk is a function of two parameters – constant across all CMBS bonds – and the specific DTS level of the bond, as in Figure 22. The idiosyncratic model is calibrated using a large sample of historical idiosyncratic returns across all CMBS bonds. As with the systematic model, there is a lower bound on the idiosyncratic volatility of the bond, given by the UHG parameter. The justification for the relation between idiosyncratic risk and spread level is similar to the systematic case: higher spread securities have higher idiosyncratic risk; that is, they tend to move less in tandem with the market. This is a reasonable assumption, given that those high-DTS securities tend to experience more relevant idiosyncratic events (e.g., lenders fail to agree on a debt restructuring with the property owners, owners get closer to default, inability to refinance, etc).

Figure 22: The Equation of Idiosyncratic Risk Model

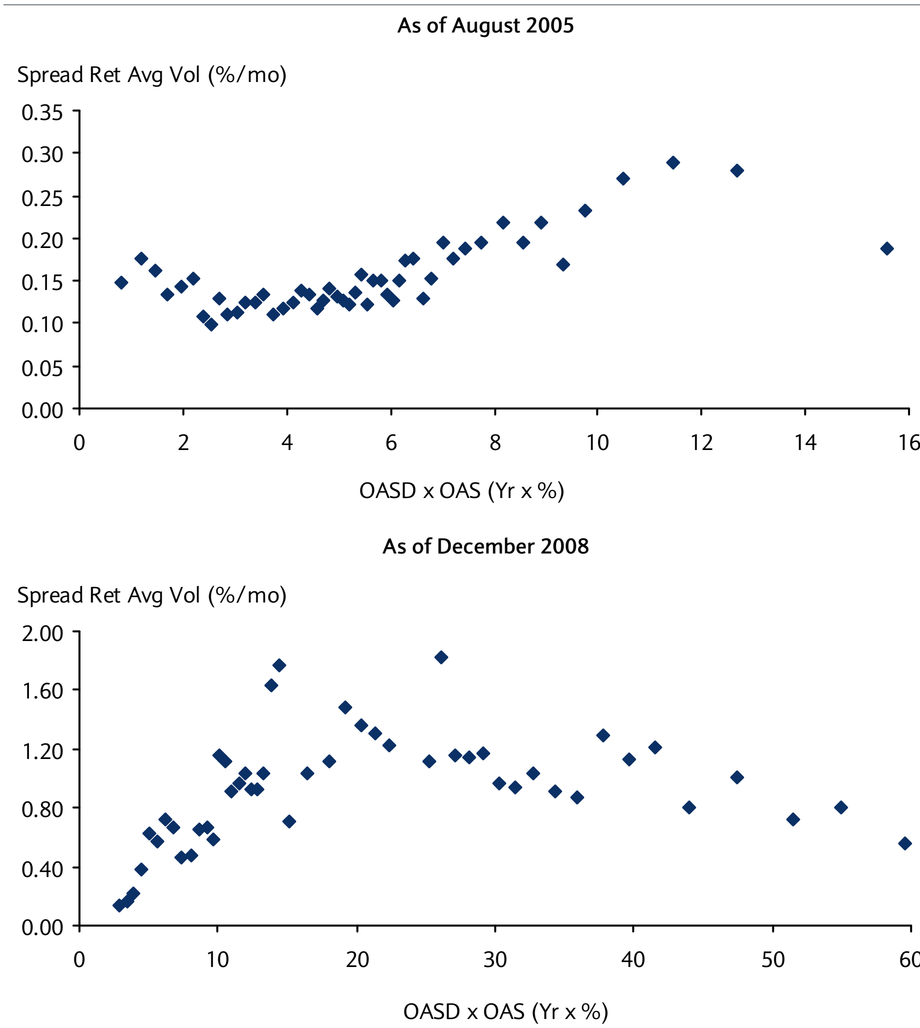
$$Vol\left(\varepsilon_{i,t+1}\right) = \sqrt{P^{UHG} + \left(DTS_{i,t}^{T}\right)^{2} P^{DTS}}$$

Source: Barclays Capital

To produce empirical evidence for the relationship between DTS and idiosyncratic volatility, we follow the empirical analysis done in the previous sections while studying the systematic risk. Specifically, each month, we sort the universe of bonds into 50 groups based on their beginning-of-the-month DTS. Within each group, we select 100 random portfolios composed of a long and a short security. Since both bonds on each portfolio are from the same bucket, they should hedge each other relatively well in regards to systematic risk (remember that DTS is the major source of systematic risk). However, the portfolio should have significant idiosyncratic risk, due to the lack of diversification.

Next, we compute the average variance of spread returns across all portfolios within a bucket, at each point in time, giving us a bucket variance for that month. From there we compute a time-weighted average volatility for the typical portfolio of each bucket, where averaging is done both across portfolios within a bucket and across time. The resulting average volatility is plotted in Figure 23 versus the average DTS of each bucket. The top graph shows that the relationship between the DTS and the idiosyncratic risk is linear across the majority of the buckets before the crisis. The slope, at about .03, is less steep than what we encountered for systematic risk during this period. The relationship becomes much stronger after the advent of the crisis, with a slope of 0.7 (note the difference in the scale of the x-axis between the periods).

Figure 23: Time-Weighted Average Standard Deviation of Spread Returns across 100 Random Long/Short Portfolios within Each of 50 DTS Groups, Various Dates



Source: Barclays Capital

How does one interpret the presence of a similar factor in both systematic and idiosyncratic risk models? The systematic DTS captures the fact that high DTS bonds go up or down at the same time and by a greater magnitude than low DTS bonds. The idiosyncratic DTS expresses the intuition that the individual returns of high DTS bonds can deviate more from the average return of high DTS bonds than the individual returns of low DTS bonds deviate from their average return. The systematic factor relates the means of the return distributions of high DTS bonds and low DTS bonds; the idiosyncratic factor relates their standard deviations.

Each month, we estimate the idiosyncratic parameters P jointly with the systematic factors, a procedure that we describe further below. To forecast the idiosyncratic risk over the next month, we average the parameters over their history and use those averages in conjunction with the formula above (Figure 22). To provide a sense of the importance of the different components to total idiosyncratic risk, Figure 24 shows the average loadings (not the squares) and the square-root of the time-weighted average of parameters at two dates. Column three, the product of the first two columns, shows the idiosyncratic risk for a typical bond if it was exposed only to that idiosyncratic factor.

Figure 24: Sources of Idiosyncratic Risk, Two Dates

	Sqrt Parm Mean	Avg Loading	Risk bp/month
January 2007			
UHG	14.83	1.0	14.8
DTS	0.03	307.6	10.7
January 2009			
UHG	82.30	1.0	82
DTS	0.13	5900.3	739

Source: Barclays Capital

Both parameters increased significantly over the crisis, together with the associated risk. Before the crisis, both factors had a similar contribution to the idiosyncratic risk (UHG contributed 15bp/month and DTS 11bp/month), but after the crisis, DTS dwarfs in importance the UHG factor (739bp/month for DTS, compared with only 82bp/month for UHG).

Risk Forecasting

Factors Distribution and Risk

The summary statistics of the new risk factors realizations are shown in Figure 25 for two periods, before January 2007 and after[6]. The volatility of all factors except the DTS differs by orders of magnitude between the two samples. For example, UHG has a standard deviation of 5.9bp/month before the crisis and 81bp/month after. The volatility of the DTS factor increases three times, even though there were extreme market dislocations over the period. This change is large, but significantly less than what is experienced by the other factors. This is one of the attractive points of the DTS methodology: it delivers relative stable factors across very different market environments. We also note that the mean of each factor is significantly less than its standard deviation, effectively close to zero. We note a significant skew in the DTS factor after January 2007. The IsPay and Window factors exhibit some skewness as well.

[6] All factors are represented in bp/month, except for the DTS that has no scaling (e.g. DTS = 0.07 means 7%).

Figure 25: Factor Summary Statistics

Variable	N	Mean	Std Dev	50 Pct	10 Pct	90 Pct
A: Before January 2007						
UHG	90	-0.06	5.92	0.03	-6.85	6.82
DTS	90	0.01	0.07	0.01	-0.07	0.09
IsPay	90	-0.94	4.12	-1.20	-5.26	4.45
Window	90	0.06	0.54	0.04	-0.53	0.66
WALA	90	0.01	0.05	0.01	-0.06	0.08
B: After January 2007						
UHG	41	-3.16	81.34	0.13	-76.99	62.04
DTS	41	-0.10	0.21	-0.02	-0.39	0.05
IsPay	41	-9.38	66.25	-1.75	-52.30	27.14
Window	41	2.11	7.77	0.34	-2.29	7.86
WALA	41	-0.15	0.84	-0.04	-0.96	0.45

Source: Barclays Capital

To better assess the (isolated) risk contribution from each factor, we add to the analysis the magnitude of the risk factors' loadings. In Figure 26, we show the time-weighted volatility of each factor, its loadings size, and the product of the two. The loadings' size is the average loading for factors with positive loadings, (i.e., UHG, DTS, IsPay) and the standard deviation for factors with loadings centered at zero (i.e., Window, WALA). The analysis is shown for January 2007 and January 2009.

The differences between the two dates are large. In some cases, the factor volatilities did not change drastically, but loadings did. In others, we see the opposite changes. The volatility of the DTS factor changed somewhat, but its average loading increased 20 times. This is the expected behavior of DTS, with its highly conditional loading. The opposite happened with the UHG factor, with loadings staying low but factor volatility increasing significantly, which was driven by the tremendous market shift for high-rated bonds. Regarding the relative rankings, both DTS and UHG have a large effect on risk, followed by Window, WALA, and IsPay. The non-DTS factors are only somewhat important on aggregate, but they may be relevant for specialized portfolios, such as DTS-hedged ones or portfolios benchmarked to a market index such as Barclays Capital CMBS index.

Figure 26: Uncorrelated Time-Weighted Risk of Each Factor, Two Dates

	Std Dev	Loading Size	Risk(bp/month)
At Jan 2007			
UHG	4.10	5.0	20.3
DTS	0.07	307.6	20.9
IsPay	3.14	0.3	1.0
Window	0.35	9.7	3.4
WALA	0.05	125.1	6.3
At Jan 2009			
UHG	89.50	3.1	276
DTS	0.24	5900.3	1397
IsPay	70.16	0.3	19
Window	8.18	7.4	60
WALA	0.36	76.3	27

Source: Barclays Capital

To assess the aggregate effect of each factor on overall risk, we add factor correlations to the analysis. Figure 27 reports the time-weighted correlation across all risk factors. As in previous cases, the analysis is made as of January 2007 and January 2009. There are some strong negative and positive correlations, suggesting that hedging effects may change the (isolated) aggregate risk profiles reported in Figure 26.

Figure 27: Time-Weighted Factor Correlations, Two Dates

	UHG	DTS	IsPay	Window	WALA
January 2007					
UHG		**-56%**	-31%	-10%	**-45%**
DTS	**-56%**		**58%**	-28%	**59%**
IsPay	-31%	**58%**		**-73%**	34%
Window	-10%	-28%	**-73%**		-29%
WALA	**-45%**	**59%**	34%	-29%	
January 2009					
UHG		**53%**	**72%**	**-64%**	22%
DTS	**53%**		**62%**	**-67%**	**62%**
IsPay	**72%**	**62%**		**-82%**	**54%**
Window	**-64%**	**-67%**	**-82%**		**-52%**
WALA	22%	**62%**	**54%**	**-52%**	

Source: Barclays Capital

Before the crisis, DTS and UHG experienced negative correlations, as discussed previously. These correlations would have been even more negative had we not accounted for the floor and cap of the risk-DTS relation. DTS is significantly correlated with IsPay and WALA as well. The largest correlation is between Window and IsPay, and strongly negative. This correlation should affect only bonds that load on both factors, and those are bonds that pay principal and are either close to maturity (very short window) or very far from maturity (very long window). Bonds with a loading only on one of the factors (e.g., they do not pay principal yet or they have a typical length of the payment window) would not be affected by their correlation. After the crisis, correlations generally increased and some experienced changes in sign.

To conclude the investigation into the properties of the new risk factors, we show in Figure 28 the correlations between the new factors and other representative fixed income factors. Those before the crisis are low, except for the UHG factor, which is mildly negatively correlated with Treasury factors. This is in line with the correlations between the Treasury curve and other high-quality spread factors (e.g., agency). After the crisis, they are higher, UHG and DTS being negatively correlated with the curve and with the long swap spreads, a clear indication of flight to quality. There are two factors in Figure 28 that we want to highlight: the CMBS factor from the now “old” CMBS model (replaced by the model described in this paper) and the DTS factor for the US credit market. The previous CMBS model can be interpreted as the monthly changes in the average level of spreads for CMBS bonds (in contrast with the DTS factor, which can be interpreted as the monthly average *percentage* change in spreads). Before the crisis, this factor had a mildly positive correlation with UHG and DTS. That correlation became much stronger afterwards. This positive relation shows that both UHG and DTS capture the market-wide effects, but in a fundamentally different manner. Regarding the credit DTS factor, it is positively related to both UHG and DTS, especially after the crisis started. This expected result shows that the DTS model is well suited to drive correlations across asset classes.

Figure 28: Time-Weighted Factor Correlations with Other Asset Classes, Two Dates

	UHG	DTS	IsPay	Window	WALA
January 2007					
KR 6 mo	-21%	2%	-2%	9%	5%
KR 2 yr	-32%	2%	-4%	14%	7%
KR 10 yr	-29%	-6%	-8%	17%	2%
KR 30 yr	-22%	-10%	-10%	16%	-1%
SS 6 mo	-7%	3%	1%	2%	3%
SS 10 yr	-25%	12%	4%	5%	11%
SS 30 yr	-23%	11%	4%	4%	10%
MBS	12%	-10%	-4%	0%	-7%
CMBS (Old Model)	34%	26%	22%	-32%	7%
US Credit DTS	23%	13%	12%	-18%	2%
January 2009					
KR 6 mo	-34%	-32%	-31%	28%	-18%
KR 2 yr	-32%	-41%	-32%	32%	-24%
KR 10 yr	5%	-40%	-9%	19%	-25%
KR 30 yr	9%	-36%	-5%	15%	-23%
SS 6 mo	23%	11%	18%	-14%	6%
SS 10 yr	-68%	-35%	-53%	43%	-19%
SS 30 yr	-70%	-37%	-55%	44%	-19%
MBS	43%	25%	35%	-29%	14%
CMBS (Old Model)	66%	59%	59%	-55%	33%
US Credit (DTS)	43%	34%	37%	-33%	19%

Source: Barclays Capital.

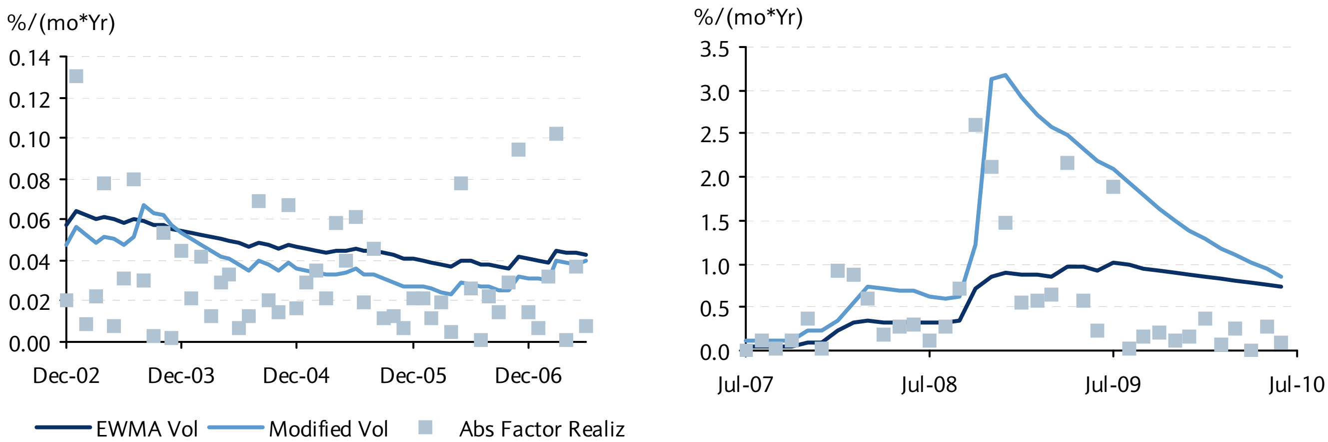
Volatility Forecast of the Ultra-High Grade Factor

As Figure 25 illustrates, the non-DTS factors experienced a very large increase in volatility during the crisis. Given the direct link between factor volatility and risk, we need good factor volatility forecasts to forecast risk appropriately. In what follows, we focus on the UHG factor as it is a major non-DTS driver of risk, as shown in Figure 26.

Typically, in the monthly horizon Global Risk Model, we forecast factor volatilities as the exponentially weighted moving average of past monthly data, using a set of weights with a decay parameter of 12 months half-life. Such a model will experience significant difficulty accommodating changes in volatilities as high as what we see for the UHG factor (from 6 to 81bp/month, Figure 25). Moreover, a simple adjustment to the decay parameter would not be satisfactory, since using a set of weights that decay faster decreases the precision of our forecast and makes it very volatile from month to month. Thus, we developed a more responsive method that can cope better with the extreme movements in the market. The model uses weekly data from the Barclays Capital CMBS AAA Index to construct a monthly volatility forecast for the UHG factor in the CMBS risk model. The use of higher frequency data allows us to increase the responsiveness of the forecast without compromising its robustness. Specifically, we construct the volatility forecast as an EWMA with a 26-week decay parameter, which is both more precise and more aggressive than the EWMA with 12-month decay, corrected for potential autocorrelations that may exist at the weekly level.

In Figure 29, we plot the absolute factor realizations against the volatility forecast using the initial EWMA model and our mixed frequency model. The figure shows clearly the benefit of

Figure 29: Volatility Forecast of the UHG Factor Using Either the EWMA Model or a Proxy-Derived Model, Together with the Absolute Value of UHG Factor Realizations



Source: Barclays Capital

the model with the quicker adjustment, especially after the financial crisis (second panel). The model is quicker to capture the increase in volatilities in the second half of 2008, but also accommodates downward trends quickly once the underlying volatility decreases.

Joint Estimation of the Systematic and Idiosyncratic Models

When estimating the systematic factors described in Figure 19, an optimal procedure calls for weighting returns based on their precision: we should give higher importance to data coming from securities with more precise returns. One way to measure this precision is to use the idiosyncratic risk associated with that security. In this context, we would give a higher importance to bonds that have lower idiosyncratic risk. The issue is that idiosyncratic risk is estimated from residual return after accounting for the systematic component that we want to estimate. To solve the issue, we estimate the idiosyncratic and systematic model jointly, using a Full Information Maximum Likelihood (FIML) framework. The FIML procedure assumes that the spread return is normally distributed, with a mean given by the systematic return (as previously shown in Figure 19) and volatility given by the volatility of the idiosyncratic component (Figure 22). The framework produces the estimates of the seven parameters our model has: five are the realizations of the systematic factors and two are the realizations of the idiosyncratic parameters.

This estimation method presents an alternative to robust regressions and other methods to reduce the influence of outliers. However, FIML has the practical advantage of providing the estimates of idiosyncratic model parameters together with the systematic ones, while the other methods require an additional step. Moreover, robust regressions tend to cap the outliers, meaning that above a certain threshold, a large observation has exactly the same influence as a larger observation. In contrast, in FIML a larger observation has a bigger influence on the results, although the increase in its influence is not as big as the increase in its magnitude. Finally, the threshold required by robust regressions is another parameter that needs to be calibrated, complicating the estimation.

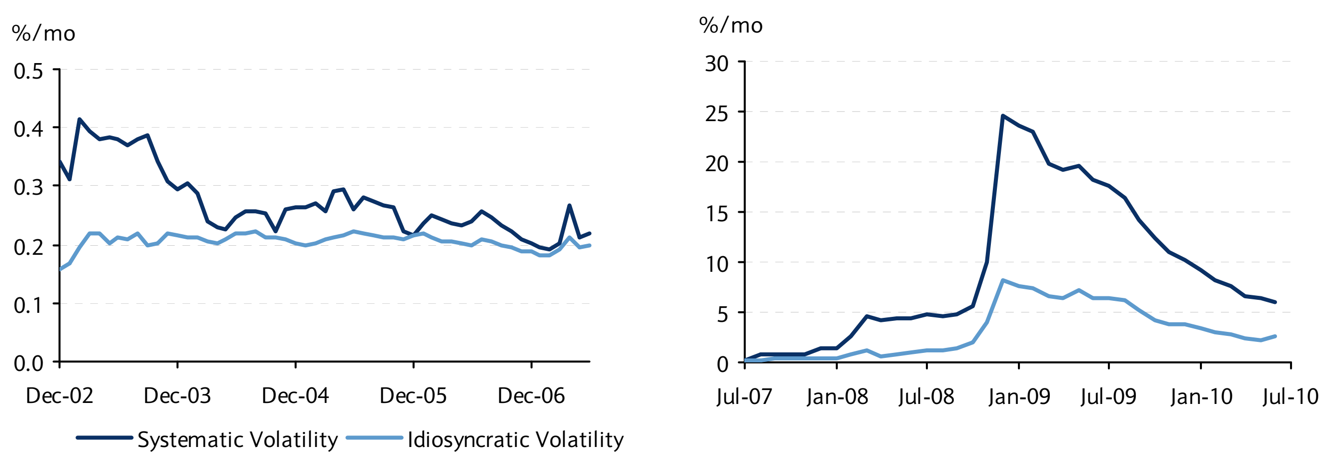
Evolution of Systematic and Idiosyncratic Risk

We use the model described thus far to predict the risk, or expected volatility, of various bonds and portfolios. All risk forecasts use the time-weighted forecast of volatility. We begin the analysis of model predictions by showing in Figure 30 the evolution of systematic and idiosyncratic risk for a typical bond. We present the results from the old model, too, for comparison. Because of large return realizations, the predicted volatility changed sharply in the second half of 2007, from 20-40bp/month to 5-25%/month. This dramatic change leads us to do the analysis separately for the two periods.

The systematic and idiosyncratic forecasts of the new model had a relatively similar magnitude of 20-40bp/month before the crisis, as shown in the left panel of Figure 30. The systematic risk adjusted quickly to the low-risk environment of 2004-06. However, the idiosyncratic risk did not decrease from its 2002 level. The forecast behavior after the crisis changed sharply, as shown on the right panel, with large increases in both the systematic and idiosyncratic risk. The jump in systematic risk was much higher than the one in the idiosyncratic one, showing that the crisis, viewed through the lenses of our risk model, was more systematic than idiosyncratic in nature. The systematic risk reached a peak of 25% on December 2009, when the whole market was in disarray, and decreased sharply afterwards. The idiosyncratic risk peaked at 8% during the same period and decreased significantly afterwards, but less so than the systematic one.

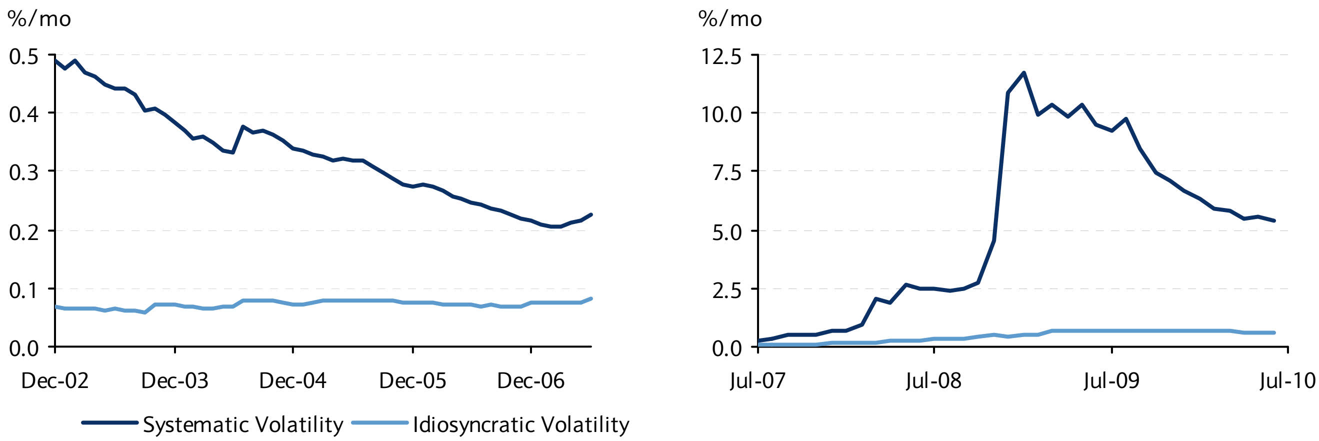
We contrast the behavior of the forecast from the new model with the one from the old model in Figure 31. Before the crisis, the systematic forecast was similar in magnitude between the two models, the major difference being that the new model provided a quicker adjustment to the low-volatility environment of 2004-06. The old model reached the 20bp/month forecast of the new model only in July 2007, right before the crisis. The benefits of the quick adjustment of the new model were tempered by its more volatile nature, with the forecast varying more from month-to-month than the old one's. During the crisis, the systematic risk from the old model increased sharply, too, but only at about half the level of the new model forecast. The risk decreased much slower after the peak, and as of June 2010, the two models again forecast a similar level of systematic risk for a typical bond in our sample. The dynamics, though, have been different. Regarding idiosyncratic risk, the old model's forecast before the crisis was much lower than new one, and it remained such throughout the crisis. As of 2010, the new model forecasts an idiosyncratic risk an order of magnitude higher than the old one.

Figure 30: Evolution of Systematic and Idiosyncratic Volatility Forecast for a Typical Bond Using the New Forecast Model



Source: Barclays Capital

Figure 31: Evolution of Systematic and Idiosyncratic Volatility Forecast for a typical Bond Using the Old Forecast Model



Source: Barclays Capital

Portfolio Back-Testing

Given our limited time-series sample and the nature of the abrupt disruption in the market during 2007 and 2008, we cannot perform exhaustive out-of-sample tests spanning multiple market conditions. We investigate the out-of-sample behavior of the model over 2002-2010, encompassing 91 months. The test of choice is studying the distribution of unit-scaled residuals. Using the risk model, at the beginning of each month *t,* we forecast the spread (excess of curve and swap spread) return volatility of each portfolio $\sigma_{t,p,forecast}$.

We record the realization of the spread return scaled by forecast volatility, called the standardized return $u_{t,p}$:

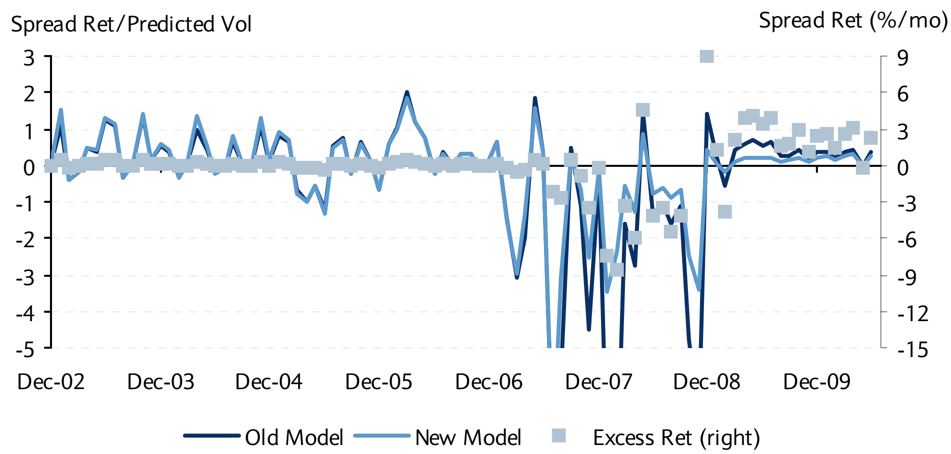
$$u_{t,p} = \frac{r_{t,p}}{\sigma_{t,p,forecast}}$$

If the forecast model is correct, the volatility (unweighted or weighted) of standardized returns $u_{t,p}$ should be one. The standard deviation of the standardized return is only one of the metrics used. In particular, one should look at the entire time series of these returns, looking for patterns or outliers, for instance, if the distribution has fat tails, systematic biases across the business cycle, etc. We do not attempt this here because of our limited sample and its nature.

Market Portfolio

To study the systematic spread return volatility model, we start with the most diversified portfolio possible, including all bonds from the sample, or "the market portfolio." Figure 32 plots the time series of the market portfolio's standardized returns (spread returns divided by spread return volatility forecast) on the left axis and the actual returns on the right axis. The returns are standardized by either the old (non-DTS) model or the new model. There are three distinct volatility periods in the sample. First, the low volatility period of 2003-2006, when returns are very low even by non-crisis standards. During this period, standardized returns are very small, and both new and old models over-predict volatility.

Figure 32: Time-Series of Spread Returns and Standardized Returns of the Entire Sample Portfolio, Returns Standardized by Predicted Volatility from either New or Old Risk Model, December 2002-June 2010



Source: Barclays Capital

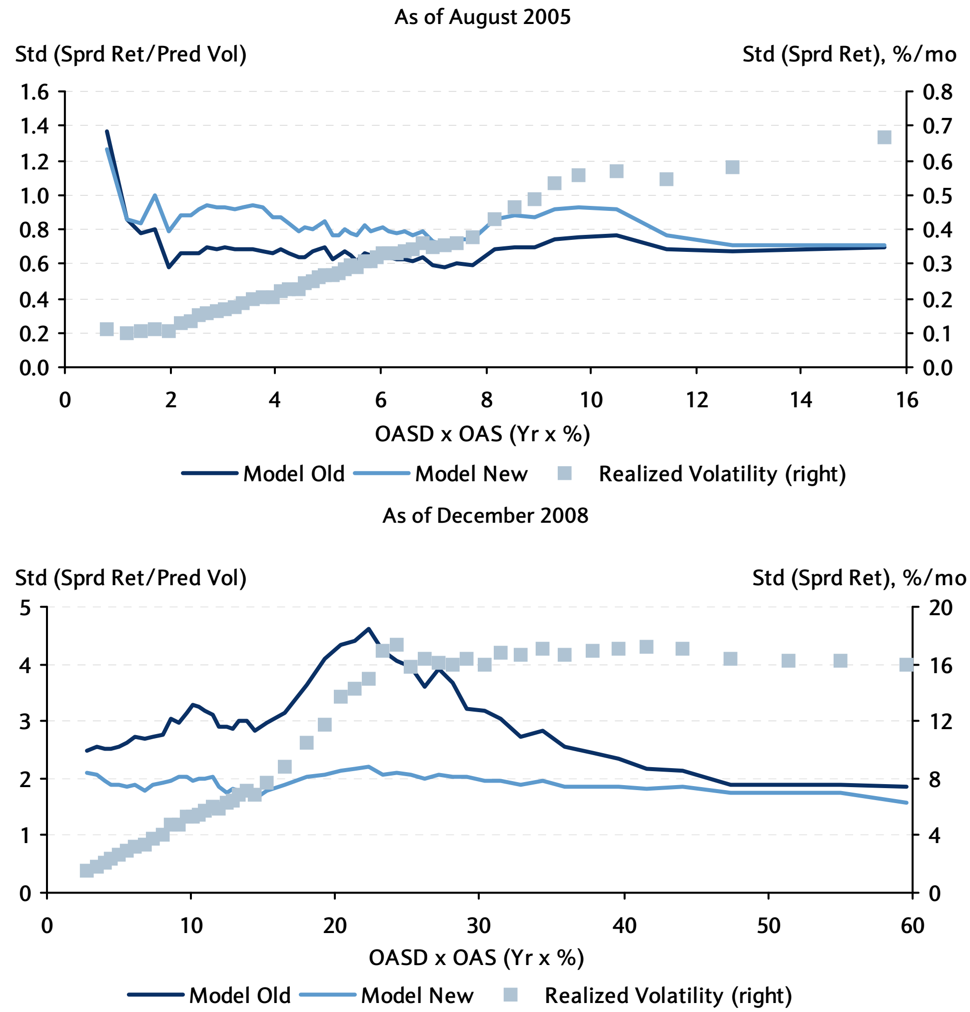
After the major shock of February/March 2007, volatility picked up significantly. Interestingly, even though both models gave similar forecasts during calm times, the new model handled the initial shock of 2007 better and adjusted more quickly to the large volatility of 2007-08. For example, the return for August 2007 was a 3.1 standard deviation event in the new model and a 5.5 standard deviation event in the old one. Both models already registered a similar 8 standard deviation event during the previous month. Over the twelve months between March 2007 and February 2008, the old model experienced five 4+ standard deviation events, while the new model only one. The October/November 2008 period is also better forecasted by the new model, shown as a 2.5-3.5 standard deviation event, as opposed to a 5-7 standard deviation event when viewed through the old model.

Characteristics-Sorted Portfolios

The market portfolio describes the aggregate, time-series behavior of the systematic model. Apart from the time-series behavior, the model should also capture cross-sectional features of risk. To study this aspect, we construct diversified portfolios sorted by various characteristics. The standardized returns of these portfolios should show whether the model captures well out of sample the empirical relationships documented above between volatility and various characteristics. In particular, because we work with standardized returns, we expect the risk profile to be stable across characteristics: all differences should have been captured by the forecasted volatility used to construct the standardized return. Figures 33-38 plot on the left axis the volatility of standardized returns using predictions from both the old and the new model. On the right axis, we show the time-weighted volatility of returns, given as reference.

The first characteristic-risk relationship investigated is the DTS. For the analysis, we use the portfolios previously constructed to document the relationship between DTS and risk, as shown in Figure 7 and Figure 13. We plot in Figure 33 the time-weighted volatility of the standardized returns by DTS portfolios for two different periods: before and during the crisis.

Figure 33: Time-Weighted Standard Deviation of Standardized Returns (Left) and Spread Returns (Right) for 50 Portfolios Sorted by DTS, Select Dates

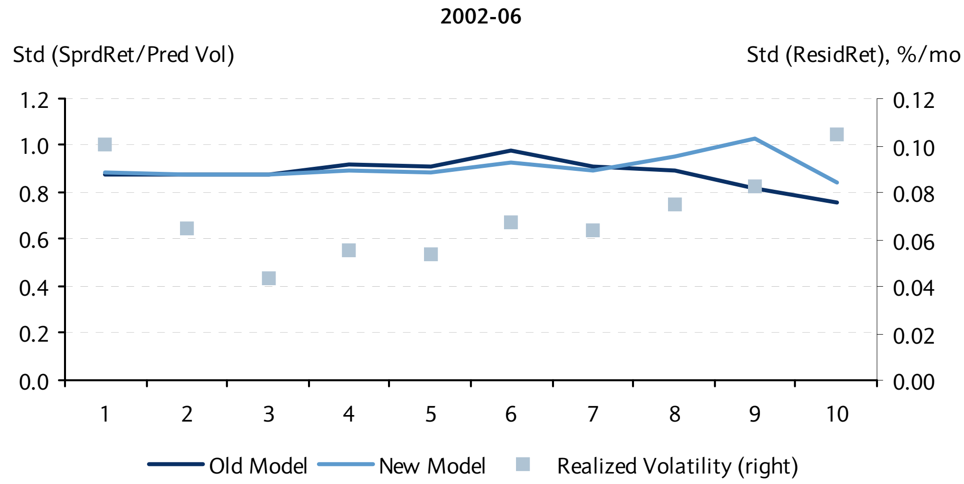


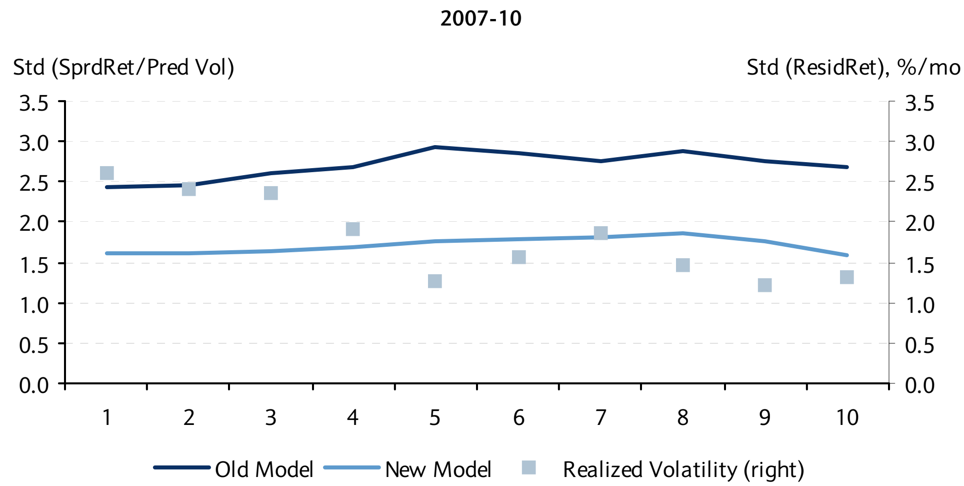
Source: Barclays Capital

The results show that the new model captures well the risk-DTS relationship out of sample: there is no monotonic relation between standardized return volatility and DTS. The old ratings-based model also captures the relationship well before the crisis. However, the model struggles to capture well the relationship after the crisis, especially for medium-level DTS portfolios. The overall level of the volatility of standardized return also differs between the two models. The old model overestimates volatility before the crisis (standard deviation of standardized returns is around 0.8 instead of 1) and underestimates it significantly during the crisis (standard deviation at 2.5-4.5). The new model captures well the volatility before the crisis (standard deviation at 1) and it underestimates – although to a lower extent – during the crisis (standard deviation at 2). We believe the new model performs well, given the violence of the crisis.

Next, we investigate in a similar fashion the out-of-sample performance of our model for portfolios sorted by the other characteristics we found to be relevant for risk: WALA, the length of the payment window and whether it pays principal. For the first two, we use the 10 portfolios shown in Figure 17. We present the results separately for the "WALA" and "Window" portfolios, for clarity, in Figure 34 and Figure 35.

Figure 34: Standard Deviation of Standardized Returns (Left) and of Residual Returns (Right) for Ten Portfolios Sorted by WALA, Two Periods





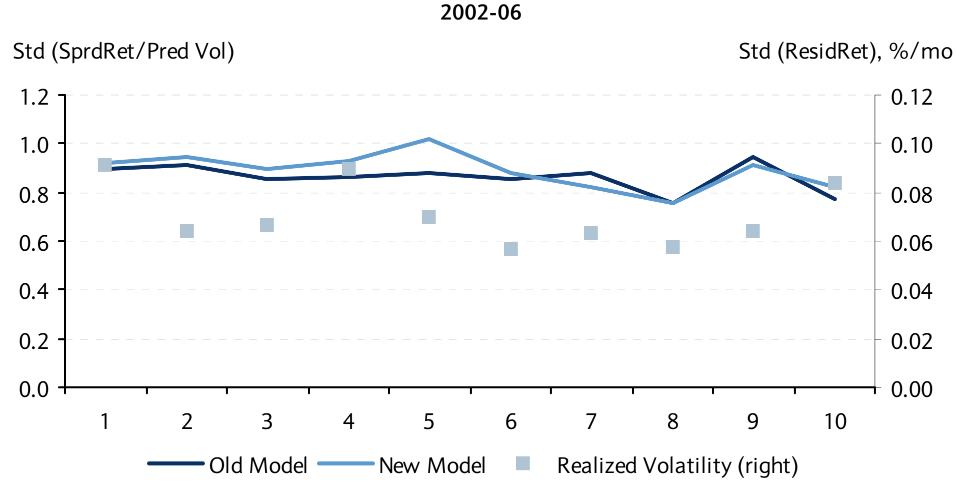
Source: Barclays Capital

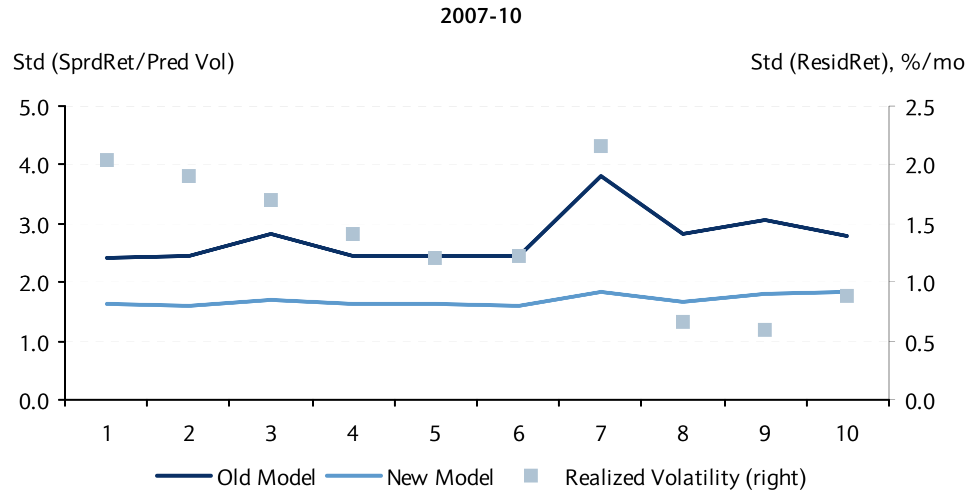
For each characteristic, we plot for two subsamples the standard deviation of spread returns standardized by the volatility forecast of each model. For comparison, we also show the standard deviation of the residual returns (after we subtract the effect of DTS), as reported in Figure 17.

The observed pattern in the WALA-residual risk relationship is well captured by the WALA-based factor of our model, as shown by the flat line in Figure 34. There is little difference in the standard deviation of standardized returns across WALA portfolios, either before or during the crisis. The old model also captures the relationship well, as it also has WALA-based factors. As with the DTS analysis, the overestimation of risk is significantly higher for the old model during the crisis.

The same analysis for the "Window" characteristic is reported in Figure 35. Before the crisis, the addition of the "Window" factor smoothes the jagged pattern in the risk-Window relationship, and both models fare well. During the crisis, the pattern of residual risk-Window is much stronger (see the pattern in returns). The new model does not exhibit any biases and again underestimates risk by a significantly smaller margin than the old one.

Figure 35: Standard Deviation of Standardized Returns (Left) and of Residual Returns (Right) for Ten Portfolios Sorted by "Window," Two Periods





Source: Barclays Capital

The third non-DTS characteristic, whether a portfolio pays principal, is investigated in Figure 36. The previous results from Figure17, repeated for convenience in the last column, show a large difference between the residual volatility of a portfolio composed of all bonds that do not pay principal and a portfolio containing the ones that pay. Before the crisis, both models show similar results for the standardized returns, with a slight performance advantage for the new model. During the crisis, the new model shows a much smaller difference between the two portfolios. The level of the standard deviation is also smaller, pointing to a lower degree of under-prediction of risk.

Figure 36: Standard Deviation of Standardized Returns and of Residual Returns for a Portfolio That Pays Principal and for One That Does Not, Two Periods

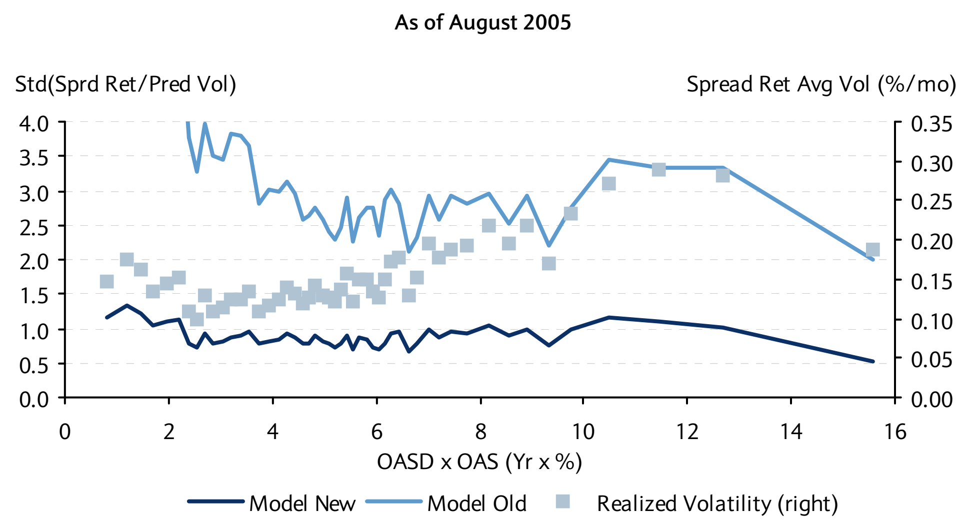
	Old Model	New Model	Realized Vol
2002-06			
No Principal Pay	0.88	0.88	0.02
Principal Pay	0.74	0.79	0.09
2007-10			
No Principal Pay	2.72	1.67	0.75
Principal Pay	2.14	1.54	0.78

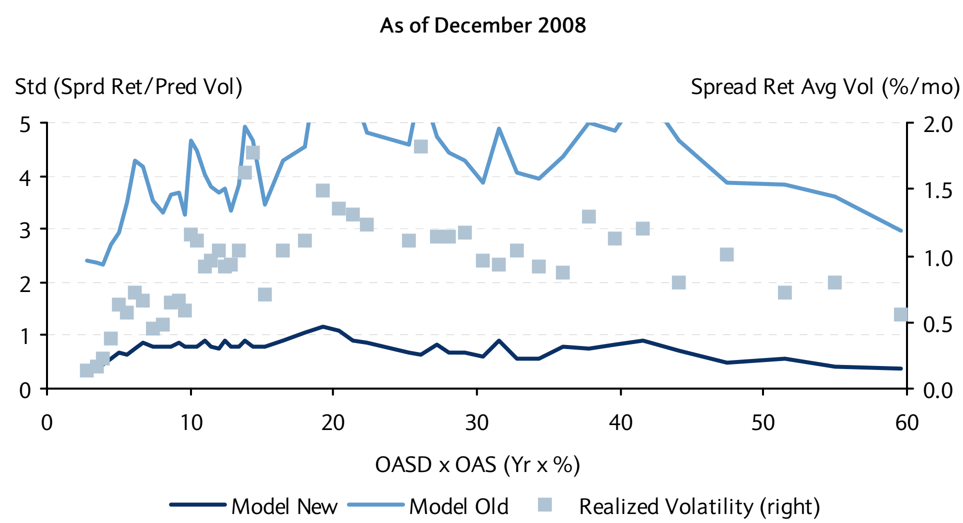
Source: Barclays Capital

Long-Short Portfolios

In this subsection, we analyze the performance of the idiosyncratic model. To do that, we resort to the long-short portfolios previously constructed to investigate the relationship between DTS and idiosyncratic risk. To recapitulate, we create one hundred random portfolios each period for each of 50 DTS-sorted groups of securities. Each portfolio contains a long and short position in two securities from that group. Given that the two securities are matched on DTS, the portfolios should have a low exposure to systematic risk and a large one to idiosyncratic risk. Similarly to previous back-tests, we compute the time-weighted standard deviation of the standardized returns of each set of one hundred portfolios, where returns are standardized using either the old or the new model. The measure is taken simultaneously across portfolios and across time, by averaging the squared returns across portfolios within each group and for each period, and then take the square-root of a time-weighted average of those averages. Figure 37 shows the results on the left axis. For convenience, we repeat the results for spread returns (shown on the right axis) from Figure 23.

Figure 37: Average Time-Weighted Standard Deviation of Standardized Returns (left) and Spread Returns (right) for 100 Long-Short Portfolios within Each DTS Group, Select Dates





Source: Barclays Capital

The new model captures well the documented strong relationship between DTS and idiosyncratic risk: the relationship between the volatility of standardized returns and DTS is almost flat, both before (top panel of Figure 37) and during the crisis (bottom panel). The standardized returns from the old model still exhibit a strong pattern across DTS groups, implying that the model does not fully capture the structure of the idiosyncratic risk. In absolute terms, the new model does significantly better than the old, ratings-based non-DTS idiosyncratic model during both periods. The standard deviation of standardized returns is about 0.8-1.2 using the new model but 2.5-7.0 using the old one.

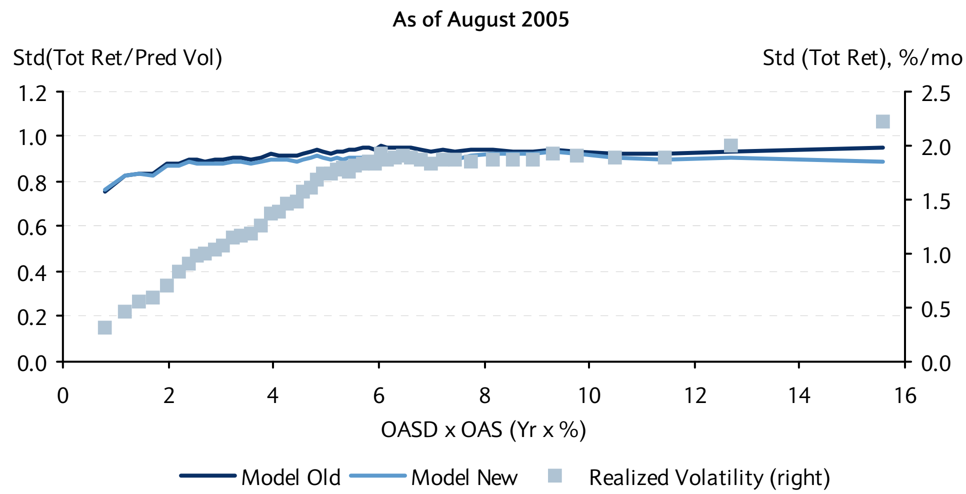
Total Return Portfolios

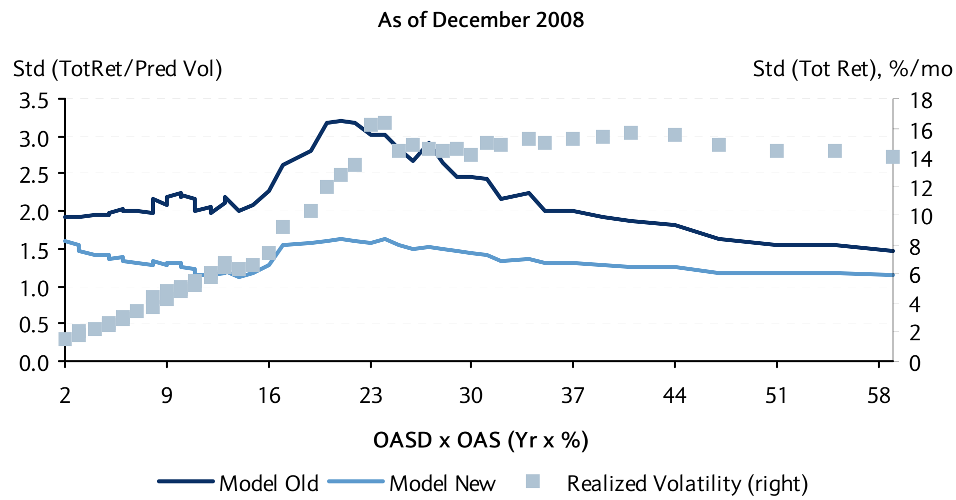
Although our focus thus far has been the spread return over the curve, many investors are concerned about total returns as well. Moreover, because the complex nature of these securities makes it difficult to capture their exact sensitivity to the curve, it is important to gauge the model performance on a total return basis.

We analyze the 50 DTS-sorted portfolios as in Figure 33 using total returns instead of spread returns and present the results in Figure 38. Before the crisis, most of the risk and return comes from the Treasury component of total returns. We can see that by comparing the right scale of this figure with the one from Figure 33. Given that spreads were very low and that OAD levels were similar to OASD levels, the DTS-sorted portfolios are mostly OAD sorted for low-DTS levels. Since the Treasury return is linearly related to OAD, we expect a linear relationship between DTS and the volatility of total return, at least for low DTS (low OAS) portfolios. We observe precisely that relation in the top panel. Moreover, because both models have the same model for curve (Treasury) risk, we expect both models to show a similar performance, as they do. Both capture the total return volatility before the crisis very well, with standard deviation of standardized returns of close to 1.0 for most portfolios.

During the crisis, the spread return became the most important component of total return and the main driver of risk. Thus, the results for total return should follow a pattern similar to the spread return that we analyzed before. The bottom panel of Figure 38 shows that to be the case, where total returns exhibit a risk-DTS relationship, and that relationship is accounted for well by the new model, but not by the old one. Moreover, the underestimation of risk is more severe in the old model than the new one.

Figure 38: Time-Weighted Standard Deviation of Standardized Returns (Left) and Total Returns (Right) for 50 Portfolios Sorted by DTS, Select Dates





Source: Barclays Capital

We want to test how the two models capture the relation between spread return and curve return; we therefore analyze the relation between total return and excess return. The former incorporates that relation but the latter return does not. We cannot compare directly the performance of each model in forecasting total returns because we know that the new model is better at forecasting spread returns, so even if it is not better at forecasting the spread-curve relation, it could still perform better than the old model. However, if we can see that the new model's improvement at forecasting total return risk is even higher than its improvement at forecasting spread risk, then it must be that the additional improvement comes from capturing the spread-curve relation better. The improvement could not come from improvement in curve risk only, since both models have an identical forecast.

This is precisely what we see: over 2007-10, the old model overestimates total return risk by a magnitude of 2.0 and the new model gets the average right, but the ratio of the overestimation of spread return risk between the old and new model (not shown) is 2.8 to 1.7, which is lower than 2:1. This ratio can be interpreted as the improvement of the new model versus the old one. Thus, based on the analysis above, the new model captures better the correlation between curve risk and spread return risk.

Access in POINT

The new CMBS risk model is implemented in POINT – Barclays Capital's portfolio analytics platform – as part of the Global Risk Model (GRM). The risk report package in POINT delivers a very detailed view of the different sources of risk. For more details on GRM and its reports, please refer to Joneja, Dynkin et al. [2005]. Below, we focus on only two reports from the report package: the risk summary report and the factor exposure report.

In Figure 39 we present the top of the first page of the risk report, the "Portfolio Risk Summary Report." It shows the risk of the Barclays Capital CMBS Investment Grade Index versus cash, as of June 30, 2010. The new risk factors are captured under the "Spread Securitized" group in the factor partition presented.

Figure 39: Partial View of the "Portfolio Risk Summary Report" of the POINT Risk Report for the Barclays Capital CMBS Investment Grade Index versus Cash, on June 30, 2010

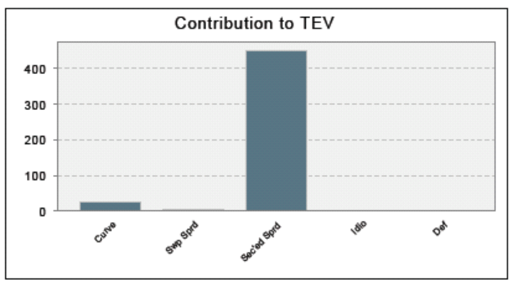
POINT® **Global Risk Model**

Portfolio Risk Summary Report

Portfolio: US CMBS (Statistics)
Index: USD Cash
Reporting Units: Returns in bps/month

Run Date: 08/04/2010
As of Date: 6/30/2010
Base Currency: USD

Factor Partition Summary	Contrib to TEV	Isolated TEV	Systematic Beta
Total	482.4	482.4	0.0
Systematic	482.3	482.3	0.0
Curve	26.3	158.0	0.0
Swap Spreads	6.0	38.7	0.0
Spread Securitized	450.0	477.3	0.0
Idiosyncratic	0.1	8.1	-
Credit default	0.0	0.0	-



TEV Summary	
Total TEV	482.4
Systematic TEV	482.3
Idiosyncratic TEV	8.1
Default TEV	0.0

Portfolio Info	
Last Transaction	N/A
Total MV (MM$)	473.6
Cash MV (MM$)	0.0
Total Notional (MM$)	487.3
Positions Included	2,817
Positions Excluded	5

Source: Barclays Capital POINT

The "TEV Summary" on the top-right corner shows that the total risk of the index is 482.4bp/month, with 482.3 coming from the systematic factors, 8.1 from idiosyncratic (we have no risk from defaults because we do not use explicit default probabilities for the CMBS market; default risk is captured directly through the systematic and idiosyncratic components of the report). Moreover, the "Factor Partition Summary" shows that as of the report date and for this index, the "Spread Securitized" systematic factor group overwhelmed the other two factor groups, namely "Curve" and "Swap Spreads," as source of risk for the portfolio.

In Figure 40 we show the "Risk Factor – Full Detail" section of the same report package. The section (partially shown) presents the set of systematic spread factors the portfolio and benchmark load on. We specifically focus on the set of factors associated with the new model. For each factor, the report shows the nature of the exposure, its value for the portfolio and benchmark, the volatility of the factor, and several risk analytics associated with that factor. As described in the paper, this is the list of systematic spread factors one should expect a CMBS portfolio to load on.

Figure 40: Partial View of the "Factor Exposure – Full Details" of the POINT Risk Report for the Barclays Capital CMBS Investment Grade Index versus Cash, on June 30, 2010

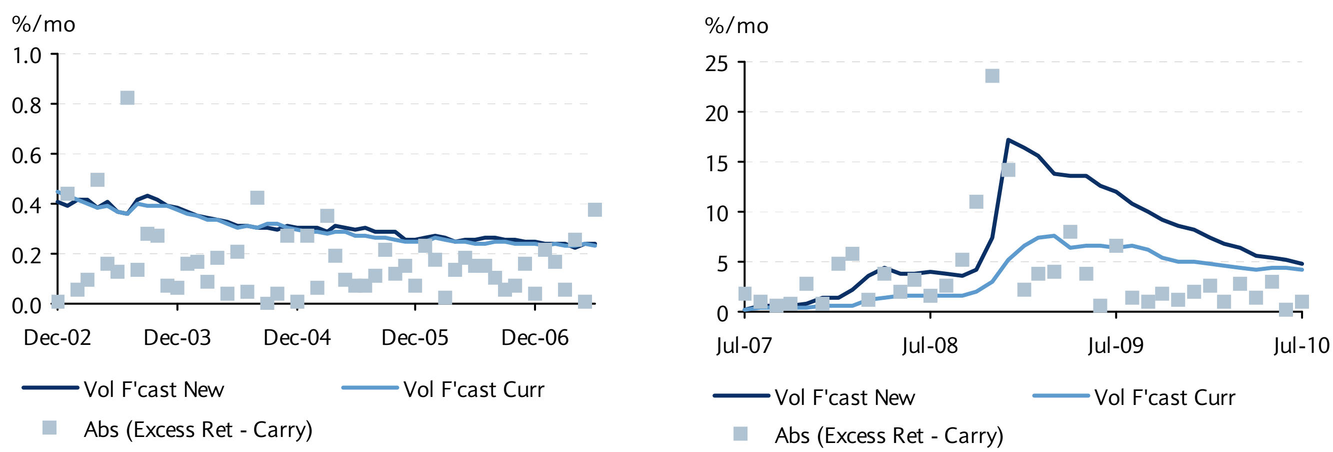
Factor name	Sensitivity/Exposure	Portfolio exposure	Benchmark exposure	Net exposure	Factor volatility	TE impact of an isolated 1 std. dev. up change	TE impact of a correlated 1 std. dev. up change	Marginal contribution to TEV	Percentage of tracking error variance (%)	Contribution to TEV
CMBS SPREAD										
USD CMBS Ultra High Grade	OASD (Yr)	3.783	.000	3.783	86.33	-326.63	-409.16	73.226	57.43	277.04
USD CMBS DTS	DTS Shifted (Yr*%)	12.679	.000	12.679	20.26	-256.90	-301.52	12.665	33.29	160.57
USD CMBS IsPay	OASD (Yr)	.695	.000	.695	68.12	-47.35	-11.71	1.653	.24	1.15
USD CMBS Paym Window	OASD*(PayWin-AvgPayWin) (Yr^2)	6.385	.000	6.385	8.25	-52.66	45.15	-.772	-1.02	-4.93
USD CMBS WALA	OASD*(WALA-AvgWALA) (Yr*Mo)	-51.280	.000	-51.280	.97	49.81	156.21	-.314	3.34	16.13

Source: Barclays Capital POINT

Next, we show an application in POINT of the new model and compare the results with the old model. We forecast the excess-of-curve risk of the US CMBS IG Index vs. cash and compare it with the realized carry-adjusted excess return of that index over the next month. The excess return can be defined as the total return less the return attributable to changes in the Treasury curve and curve-associated carry. Thus our carry-adjusted excess return encompasses the return due to changes in the swap curve and unexpected spread return.

The results confirm our previous findings. The two models forecast very similar TEV in excess of curve until the crisis starts in 2007. Afterwards, the new model forecasts a sharper increase in risk than the old one, with both forecasts peaking in December 2008. Since then, the new model has adjusted risk down significantly and as of June 2010 both models forecast again a similar level of risk, at about 4.5% per month. The new model is more aggressive in adjusting the forecasts to market conditions, in environments of both low and high volatility.

Figure 41: Evolution of the TEV Net of Curve for US CMBS IG Index Using Either the Old or the New Risk Model, and the Evolution of the Absolute Value of Index Excess Return Net of Carry



Source: Barclays Capital

CONCLUSION

The second-generation Barclays Capital CMBS Risk Model incorporates important innovations such as a carefully researched and constructed relationship between both systematic and idiosyncratic volatility and Duration Times Spread (DTS); the use of higher-frequency proxy data to forecast monthly volatility; and a joint estimation of systematic and idiosyncratic parameters in an integrated framework.

We detailed several empirical relationships between risk and various measures. Our model forecasts these relationships appropriately. In particular, the observed risk-DTS connection is well captured in this framework. We also show that the model adjusts risk quickly both to the post-2007 high-volatility environment and to the new low volatility environment that followed.

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Analyst Certification(s)

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