US Home Equity ABS Risk Model

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We present the second-generation risk model for home equity asset-backed securities. The model continues the recent trend in Barclays Capital's credit risk modeling and relates risk to the level of spread and duration. Discrete rating levels are replaced as sources of risk by a continuous, market-based measure: duration times spread (DTS). We incorporate other risk sources, based both on analytics (e.g., average life) and collateral characteristics (e.g., delinquencies). Some risk sensitivities, such as average life, are non-linear in the main variable. These additional features capture out-of-sample the documented empirical relation between return volatility and certain characteristics. The enhancements deliver a model that performs well across different market environments.

INTRODUCTION[1]

The home equity ABS market has experienced structural changes along many dimensions over the past decade, some related to underlying loans and some related to deal structuring. Moreover, there has been a significant increase in the quantity and quality of available data and substantial progress in risk modeling. Given that the previous Barclays Capital USD ABS risk model was designed before some of these changes, we decided to re-evaluate the model.

The model has been redesigned following the duration times spread (DTS) concept, whereby spread risk is a linear function of DTS. However, empirical data show that risk is a function of other variables as well. We capture these relationships with factors based on measures such as average life, weighted average loan age, combined loan-to-value ratio, and delinquency rate. Risk sensitivities may be non-linear in the characteristics described. Idiosyncratic risk becomes a function of DTS as well, an improvement over the previous model, in which this risk was assumed to be flat (for a particular spread duration) across all spread levels.

In addition to incorporating new sources of risk, we expand the universe of securities used to calibrate the model to better reflect the current market. Floating-rate securities are included, along with non-index, lower quality ones.

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 ABS market and the data used to construct this model. The second describes the model starting with the systematic part and following with the idiosyncratic. It continues with a discussion of risk forecasts using the model. 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 Anthony Lazanas and Antonio Silva for their valuable comments and suggestions. Jerome Hauser, Chandra Koppella, and Gary Wang contributed to the development and implementation of the risk model in POINT.

THE US HOME EQUITY ABS MARKET

The market for home equity ABS has its origins in the consumer credit lines extended by banks and guaranteed with borrowers' residences, home equity lines of credit (HELOC). These loans amounted to 8% of total household mortgages outstanding in 1990, according to the Federal Reserve's "Flow of Funds" report. The growth of securitization meant that banks no longer had to keep these loans on their books. As with any securitized product, banks placed loans in structured vehicles and sold interest in those vehicles to investors.

Once a financial institution makes a mortgage loan, it can either keep it on its books, thus retaining all risk, or it can sell it to government sponsored enterprises (GSEs) and get paid an origination fee. In the early 1970s, banks held more than 70% of the outstanding mortgages on their books, but that share had dropped to 40% by 1990, since most mortgages were sold to the GSEs. Looking to deploy their capital, mortgage lenders sought to extend beyond typical GSE-guaranteed products, the so called "prime" market. Since HELOCs are a type of mortgage not guaranteed by GSEs and with significant risk of default by the borrower, one way to extend the mortgage market was to create a primary mortgage product similar to HELOCs and addressed to the non-prime market. The mortgage products targeted to borrowers with significant credit risk, or "subprime," became a significant part of the home equity market. Many of these loans were securitized, pushing the ratio of ABS-funded household mortgages to 20% by 2007. Since subprime loans were more likely to be securitized than HELOCs (historically, only 2-5% of the HELOC loans were held by ABS trusts), they came to dominate the home equity ABS (HE ABS) market. For example, in 2006, when there was a record $446bn in gross issuance, 96% of issuance was backed by subprime loans, 1.9% by second-lien loans, 0.3% by HELOCs, 0.5% by high loan-to-value loans, and 1.5% by other types, according to LoanPerformance.

Other parts of the non-GSE-guaranteed mortgage market are the alternative-A and jumbo markets. They are typically securitized as collateral mortgage obligations (CMOs). Since alt-As and jumbos were considered less prone to credit risk and more exposed to prepayment risk, CMOs have more complex payment structures than home equity ABS. HE ABS are structured broadly as water-flows, with interest and principal always allocated to certain tranches first. This structure allows a clear differentiation in credit risk across tranches and lends itself naturally to ratings by rating agencies.

Initially, most underlying mortgages included in HE ABS were fixed rate. Mimicking the underlying, most HE ABS bonds were fixed coupon. With the significant steepening of the yield curve in 2001-2004, adjustable-rate mortgages (ARMs) gained in popularity, and most of the origination for financially constrained subprime borrowers has been in the form of ARMs or hybrid ARMs. The HE ABS market followed, and most of the bonds issued carried a floating-rate coupon.

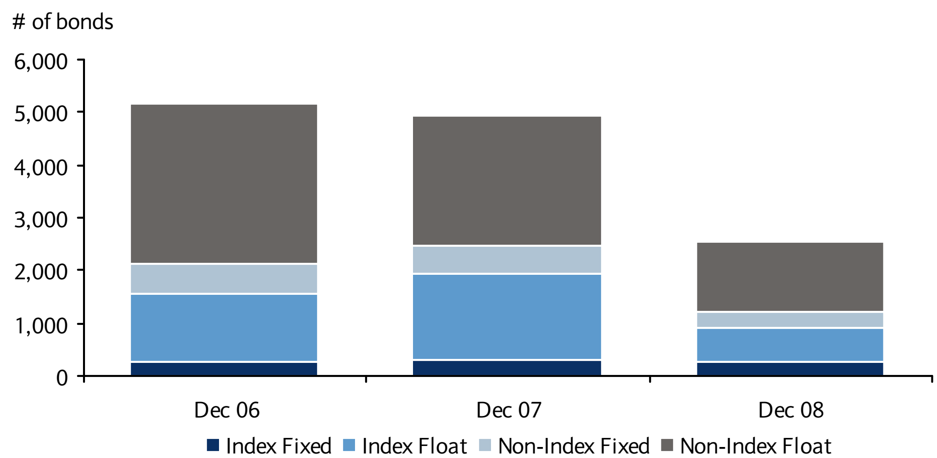
Barclays Capital, through its legacy Lehman Brothers unit, recognized the market shift and created the US ABS Floating Rate Index on January 2005. This index is composed of only floating-coupon bonds, with home equity being its major category. As of December 2008, the market value of the HE Floating Rate Index was $47bn, while the market value of the Home Equity Fixed Rate Index, created in December 1991, was $10bn. The new home equity ABS risk model also expands the universe it covers to include floating-rate ABS – the calibration universe for the previous model included only fixed-rate bonds.

Finally, note that both indices contain mostly AAA and AA rated securities, since they are deemed the most liquid. However, investors trade a more diverse set of securities, including those with lower ratings. Given that we have prices available for ABS with ratings as low as BBB, we expand the calibration universe to all securities with ratings BBB and above. The model does forecast the risk of below-BBB securities, but they are not used in its calibration.

Data

In our analysis, we use a sample that starts at June 2002 and includes only fixed bonds until March 2005. Before 2005, the sample size is around 1000 bonds per month, and after the size is around 5000 bonds per month (Figure 1). After 2005, most bonds are floating rate, and 20-30% are part of either the floating-rate or fixed-rate Barclays Capital US ABS Index. Given that POINT was previously using only fixed-rate index bonds for calibration, the two additions to the sample are significant. The sample size has been declining steadily from 2008. Note that we filter data for bad observations, especially along return, OAS, price, and OASD. Interest-only and residual bonds are excluded.

Figure 1: Market Structure of Calibration Sample, Select Dates

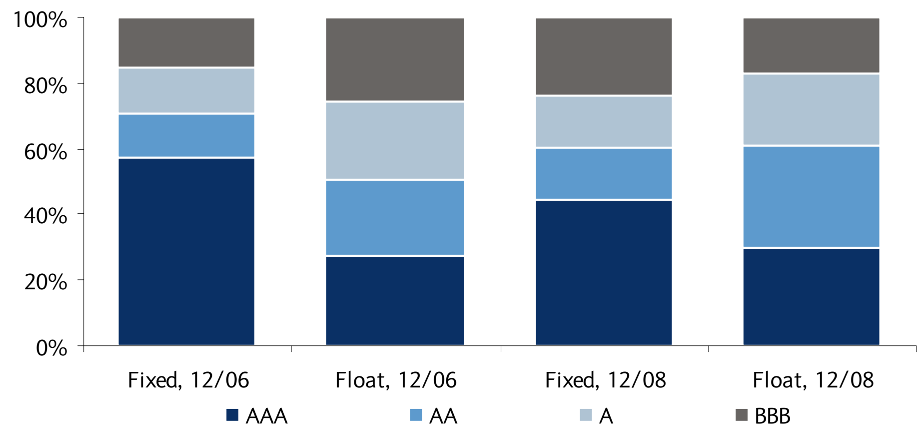


Source: Barclays Capital

Regarding the time series characteristics of a particular bond, half of the bonds have between 15 and 35 observations. Typical deals before 2003 have five bonds, and the ones after 2003 have ten bonds per deal. Concerning ratings distribution, in 2003, 70% of the bonds were AAA and 10% were in each of the other investment grade rating groups. In December 2006, 40% of bonds were AAA and each other rating group contained around 20% of the sample (Figure 2). Percentage-wise, the fixed-rate sample contains more AAA bonds than the floating-rate sample, even though the difference decreased recently.

Historically, ABS bonds were created to have very small loss probabilities. Any collateral loss would be assigned to junior bonds. Therefore, investment-grade ABS bonds enjoyed prices close to par. But since July 2007, ABS bond prices have registered dramatic decreases. When forecast losses on the underlying mortgages greatly exceeded the protection buffer available to the bonds, their prices fell sharply. Bonds previously priced around par have been quoted anywhere from 10 to 90 points. Initially, most declines occurred in lower-rated bonds. However, as loss expectations gradually increased, the senior bonds also started to register large negative returns. Therefore, in the time series, we may observe relatively different dynamics between the high and low ends of the ABS market.

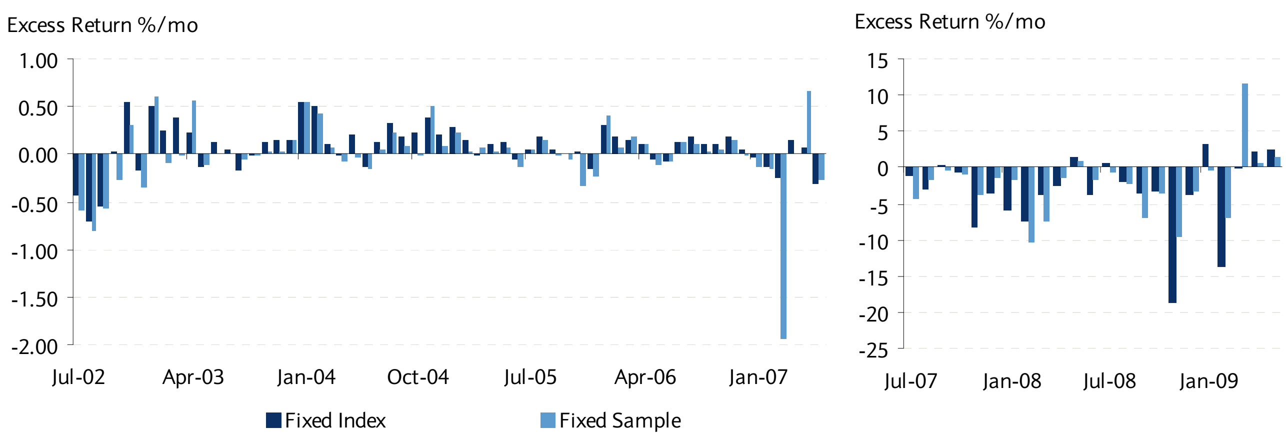
Figure 2: Calibration Sample Breakdown by Rating and Coupon Type, Select Dates



Source: Barclays Capital

This can be observed in Figure 3, which compares the fixed-rate index with a portfolio of all fixed-rate bonds in our universe. The index represents a higher quality sample. The two series tend to track each other, but the sample portfolio was the first to experience large negative shocks in March 2007 (see first panel); after late 2008, the index experienced larger shocks (see second panel).

Figure 3: Evolution of Excess Returns of ABS Home Equity Index and an Equal-Weighted Portfolio of All Fixed-Coupon Bonds within the Sample. First Graph Includes October 1999-June 2007, Second Graph Includes July 2007-May 2009

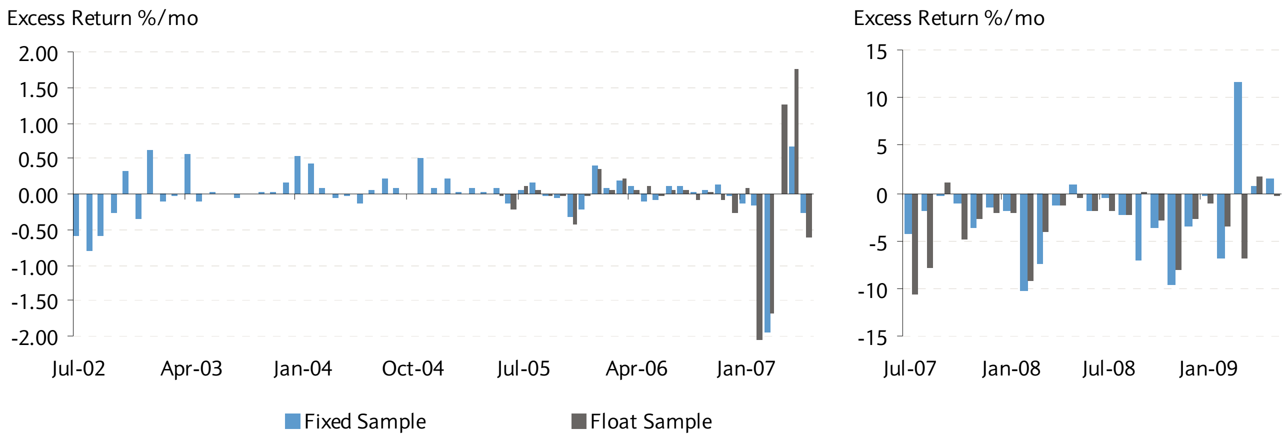


Source: Barclays Capital

Another observation from Figure 3 is the difference in return distributions between the pre- and post- July 2007 samples (see the difference in scale between the two panels). In the first panel, returns are typically 20-40bp. In fact, during the unusually calm period of 2005 and 2006, there were almost no months with returns larger than 20bp! By contrast, in the second panel, the typical return is about 5%. As we will see, this sharp contrast creates a big challenge in using historical data for calibration and back-testing.

Figure 4 shows the aggregate returns of all fixed-rate bonds and all floating-rate bonds. The two portfolios track each other, with the floating rate experiencing more negative moves, probably owing to higher uncertainty regarding the quality of their collateral. We can see the low volatility for the floating-rate bonds during 2005-2006, as well as the sharp increase in volatility after January 2007. Note that the big outliers observed at the end of the left panel (January-June 2007) are about 2% in magnitude, but in the right panel the magnitude is higher than 5% for many observations.

Figure 4: Evolution of Excess Returns of Equal-Weighted Portfolios of all Fixed-Coupon and all Floating-Coupon Bonds within the Sample. First Graph includes July 2002-June 2007, Second Graph includes July 2007-May 2009



Source: Barclays Capital

The analytics used in our risk model are based on a pricing model that forecasts prepayments, but not defaults. The analytics treat defaults as prepayments, in effect assuming a 100% recovery. As of 2009, heavy expected and realized credit losses have depressed prices. In our pricing model, this results in high spreads. Therefore, for modeling purposes, credit risk is fully embedded in spreads. This is important for the choice of systematic risk factors to explain the cross-sectional change in spreads.

Price dislocations also led to lower trading volume, which decreased pricing data quality. Thus, we filtered from our analysis any bonds with potentially stale prices, which account for up to 15% of the sample each month. Even after filtering, the market experiences large sudden jumps, between relatively calm periods, as seen in Figures 3 and 4.

Survivorship Bias

Approximately 1% of the bonds drop out of the sample each period without being paid off. We analyze whether there is a systematically important pattern for the drop-outs, inducing survival bias in our sample and therefore mischaracterizing risk. Most of the drop-outs are the result of our filtering process.[2] Many return to the sample at a later date. The bonds that disappear completely usually make up less than 0.2% of the sample. Overall, the results seem to suggest only a small effect due to survivorship, since most dropouts are actual payoffs. The dropouts due to downgrades usually have large OAS; therefore, their negative returns have largely been accounted for.

[2] They may not pass our filters, for example, if their OAS change is very different from the corresponding price change or if ratings drop below BBB.

THE US HOME EQUITY ABS RISK MODEL

The Systematic Risk Model

The Home Equity Asset Backed Securities (HE ABS) Risk Model is part of Barclays Capital's Global Risk Model (GRM) and follows its general linear factor-based approach.[3] 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 give the risk exposure of each security. Factor risk models reduce the dimensionality of the problem of calculating the joint risk 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

$f_{t+1} =$ systematic risk factor realization

$L_{i,t} =$ factor loading

$\varepsilon_{i,t+1} =$ remainder

Source: Barclays Capital

Systematic risk factors are grouped by types of risk: curve, swap spread, and spread related (Figure 6). The model uses the GRM's yield curve factors: six key rates (6m, 2y, 5y, 10y, 20y, and 30y) and one convexity. A bond's loadings to these factors are the key-rate durations and the option-adjusted convexity of that particular bond. Swap spread factors, which capture the risk of spread between the swap and treasury curve, receive a similar treatment.

Figure 6: Factor Breakdown

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

Source: Barclays Capital

Note that all fixed income securities can potentially load on these two sets of risk factors. However, the remainder of the common risk is modeled by spread factors specific to HE ABS bonds; that is, only HE ABS securities have exposures to these specific spread factors. That said, these factors may be (and typically are) correlated with the curve factors or spread factors specific to other asset classes (e.g., US credit). The choice of these factors and the construction of their loadings are the most complex part of this new model and its main contribution.

Spread return R^{Spread}_{it} contains common sources of risk originating from either risk to future cash flows or risk to their discount factor. Future cash flows change because of prepayments and defaults. Treasury and swap curves affect both cash flows and discount factors; thus, the effect of any spread factor should be in addition to those.

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

The pricing model used to calculate the analytics available in POINT and to calibrate this model accounts for projected prepayments, but not defaults. Therefore, the effects of prepayment surprises and defaults are reflected in spread changes. These effects can be triggered by many factors, namely the dynamic of home prices, credit standards, personal income, and demographics. Similarly, the discount rate has a component additional to Treasury yields, which measures the level of risk aversion. Thus, prepayment risk, default risk, and risk aversion are captured by the spread return. In fact, all other sources of risk are reflected there (e.g., liquidity).

Defaults

The notion of default for this asset class is different from its meaning in the corporate bond market. There are two notions of default for HE ABS bonds: default of the underlying loans and default of the ABS. The two measures are intertwined: as underlying loans default, it is less likely that ABS investors will recover their money. An ABS default is more complex than the default of a corporate bond. An ABS bond is usually a tranche of a deal of structured securities constructed using the same portfolio of underlying loans. The group may experience a "default event," which triggers changes in the cash flow allocations among securities, but does not necessarily lead to liquidation of any ABS. 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 is less clear cut than it is in the corporate world. Given these characteristics, we do not model default risk separately; we lump it into spread risk.

It is difficult to disentangle how much of the spread risk originates from each of the three sources mentioned: prepayment surprises, default, and risk aversion. In the HE ABS Risk Model, we treat these risk sources jointly. However, when researching specific risk factors, we look for variables that may account for all three risk sources.

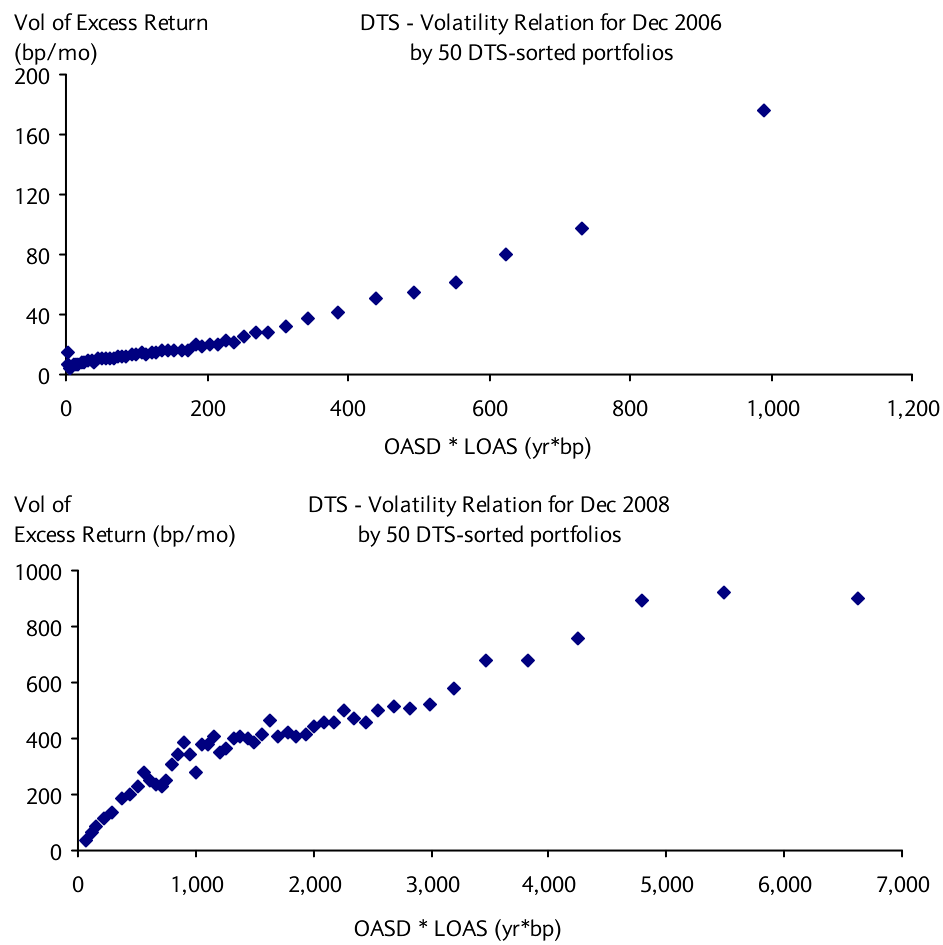
Risk Factors

Recent research (e.g., Dor, Dynkin et al. (2005)) suggests that spread volatility for 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 (2009) for a description of the implementation of DTS in POINT's credit risk model). It is therefore natural to investigate whether DTS is also a relevant concept for HE ABS.

For the HE ABS market, higher spreads are related to higher risk aversion, higher market expectations of default losses, higher cost for the prepayment option, etc. All these effects are 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.

Figure 7 shows the time-weighted realized volatility of 50 equal-weighted DTS-sorted portfolios of HE ABS bonds at two points in time. For each month, we sort all securities in our sample by the beginning-of-the-month (BOM) DTS and allocate them to 50 equal-weighted portfolios; thus, securities with DTS in the 1-2 percentile fall into portfolio 1, bonds with DTS in 3-4 percentile in portfolio 2, etc. For each portfolio, we register its return over the month. We obtain 50 time series of returns and BOM DTS values. For each of these time series, we can compute at various dates the time-weighted return volatility and the time-weighted mean DTS. We present these in Figure 7, showing average DTS on the horizontal axis and the volatility of excess returns on the vertical axis. As of 2006, we can see the quasi-linear relation between volatility and average DTS, with a slope of 0.2. As of December 2008 the relation is still monotonic, but the linearity is not perfect. The slope is around 0.4 for lower DTS, decreases to 0.1, and then flattens for very high DTS. Moreover, the DTS values are significantly higher and more dispersed than in 2006, mostly because of higher OAS. Overall, evidence seems to suggest a strong relationship between these variables.

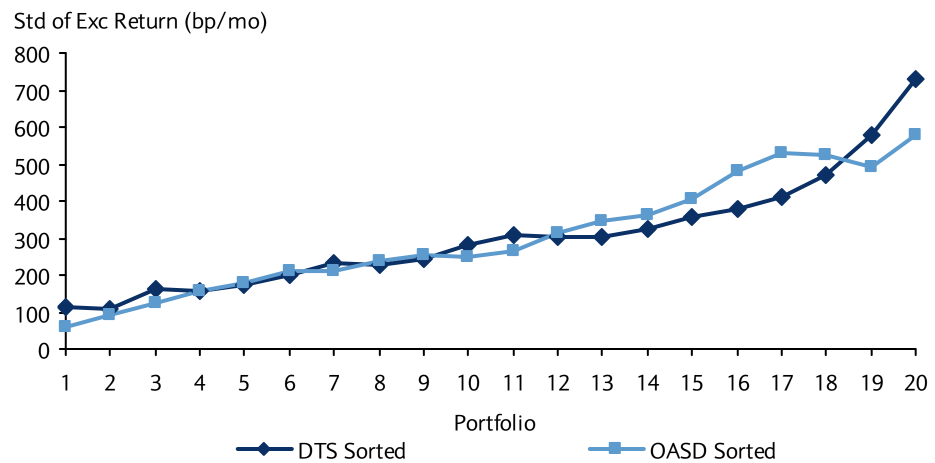
Figure 7: Relation between Time-Weighted Volatility of Excess Return and DTS



Source: Barclays Capital

As discussed earlier, a key motivation for using DTS is related to the properties of the risk factors derived from it. In our estimation procedure, the DTS is a loading to the risk factor. However, it is a known loading (at the beginning of every estimation period) and highly conditional (can change quickly on a daily basis). Therefore, if the cross-sectional variation of returns is associated with the DTS level of the bonds, the nature of the risk factor estimated with it is more robust and invariant. The relation between excess returns and DTS should be relatively stable, even if DTS values change significantly. Figure 8 complements the evidence above by showing the realized volatility on an unweighted basis (as opposed to time-weighted reported in Figure 7) from December 2005 to May 2009 for 20 DTS-sorted portfolios. Our previous analysis included 50 portfolios to show that the DTS relation is strong at a high level of detail, but for further analysis, we will retain the coarser partition of the sample. In Figure 8, we further document a strong positive relation between returns and OASD: similar to the DTS exercise, each month we create 20 OASD-sorted portfolios that we track over the month. In this way, we generate 20 monthly return time series from December 2005 to May 2009; we plot the volatilities of those series vs. their average OASD. This result will be referred to further in our analysis.

Figure 8: Unweighted Standard Deviation of Excess Returns of 20 Equal-Weighted Portfolios Sorted by Either DTS or OASD, December 2005-May 2009



Source: Barclays Capital

Given this evidence, the starting point for our risk model is that Libor spread (LOAS) changes can be modeled as

$$\Delta LOAS_i = LOAS_i \times F^{DTS}$$

where F^{DTS} is the risk factor realization associated with the DTS factor (percentage change in 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, 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 OAS is unlikely to have half the risk of a security with 10bp OAS. Moreover, for bonds with negative spreads, DTS is ill defined. Therefore, we set a base level of risk that will be applied to all bonds, independently of their spread level. Because it is the main source of spread risk for bonds with the lowest spread, we call the risk factor associated with it the ultra high grade (UHG) factor:

$$\Delta LOAS_i = F^{UHG} + LOAS_i^{+} \times F^{DTS}$$

Here, F^{UHG} drives the volatility of the very low spread bonds (UHG) and $LOAS^{+} = \max(LOAS, 0)$. Moreover, for very high levels of spread, Figure 7 shows that the relation between risk and spread is weaker. Thus, we cap the Libor OAS used to calculate the DTS of a security at a particular level $LOAS^{MAX}$, which caps the systematic risk.

$$\Delta LOAS = F^{UHG} + LOAS^{M+} \times F^{DTS}$$

Where $LOAS^{M+} = \min\left[\max(LOAS,0), LOAS^{MAX}\right]$. The parameter $LOAS^{MAX}$ is calibrated monthly. The LOAS cap dampens the influence of outliers in the systematic risk model. Typically, 1-3% of sample hits this cap.

Other Factors

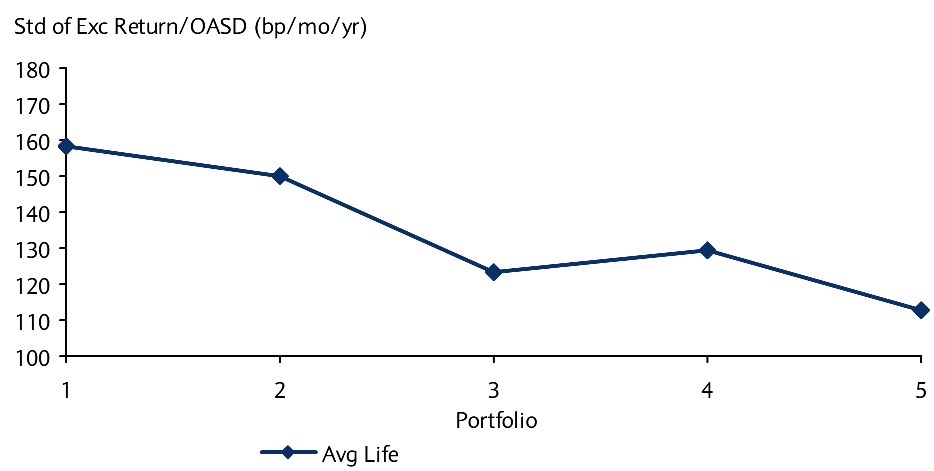
Our research shows that in addition to DTS, several other factors help explain the cross-section behavior of HE ABS bonds' spread returns. Below, we list the additional factors incorporated in the risk model:

- Average life (AL) slope: All else equal, bonds that have a longer expected life are thought to have a different risk profile than bonds with a shorter expected life, depending on the expected behavior over time of prepayment and default risk factors. Figure 9 plots the realized volatility of OASD-scaled returns from December 2005 to May 2009 for five AL-sorted portfolios. We scale returns by OASD, since AL is highly correlated with OASD and we already documented in Figure 8 a strong relation between returns and OASD. The short AL portfolios have significantly higher volatility than longer ones. We construct the loading on this factor to be nonlinear (we use the log function), since an increase in AL from one year to two years is more relevant than an increase from five years to six years. Finally, we normalize this loading so that a bond with median average life has a zero loading on this factor. Specifically, the loading to the AL factor is defined as:

  – OASD x (log(1+AL)-log(1+median AL))

  where OASD and AL are specific to the bond and median AL is the median average life on our estimation universe. Average life is represented in years.

Figure 9: Unweighted Standard Deviation of (Excess Return/OASD) of Portfolios Sorted by AL, December 2005-May 2009



Source: Barclays Capital

- Weighted average loan age (WALA): Figure 10 shows realized volatility for December 2005-May 2009 for five WALA-sorted portfolios. It is clear that more seasoned loans have less volatility, because the uncertainty regarding their prepayment and default profiles is smaller than for new loans. To account for this, we create two WALA factors, one short and one long. The two factors are important to capture different dynamics – not only different volatility levels – between these two set of bonds. All bonds load on the short factor, with loading capped at 24 months. Bonds with WALA higher than 24 months will also load on the long WALA factor. Specifically, the loadings are:

- Short WALA: OASD x max (WALA, 24)
- Long WALA: OASD x max (0, WALA-24)

where WALA is represented in months.

- Delinquencies 60+ (Delq): Bonds in deals experiencing more delinquencies are usually riskier. Figure 10 shows the realized volatility from December 2005 to May 2009 of five portfolios, sorted by level of delinquency. We scale this level by WALA, since we expect higher cumulative delinquencies as the loans age. In our model, the loading to this factor is:

  - OASD x delinquencies / WALA

  where delinquencies are measured as the percentage of loans delinquent by more than 60 days.

- Combined loan to value (CLTV): Loans with higher CLTV (more leveraged), especially higher than 80%, tend to have greater default risk and more difficulty refinancing. Therefore, bonds based on such loans tend to be riskier. Figure 10 confirms this intuition by showing that the realized volatility from December 2005 to May 2009 increases in CLTV. In our risk model, the loading to this factor is:

  - OASD x max (0, CLTV – 80)

  where CLTV is in percentage points.

- Full documentation loans (FullDoc): Loans without full documentation may be more subject to abuses by borrowers, which exposes them more to default risk. Therefore, bonds based on such loans tend to be riskier. Figure 10 shows that the realized volatility from December 2005 to May 2009 for five portfolios sorted by percentage of full documentation of underlying loans varies across portfolios. The variation is not as pronounced as for other characteristics, but there may be periods when this characteristic becomes important in explaining risk. The loading to this factor is set as:

  - OASD x (FullDoc – median FullDoc)

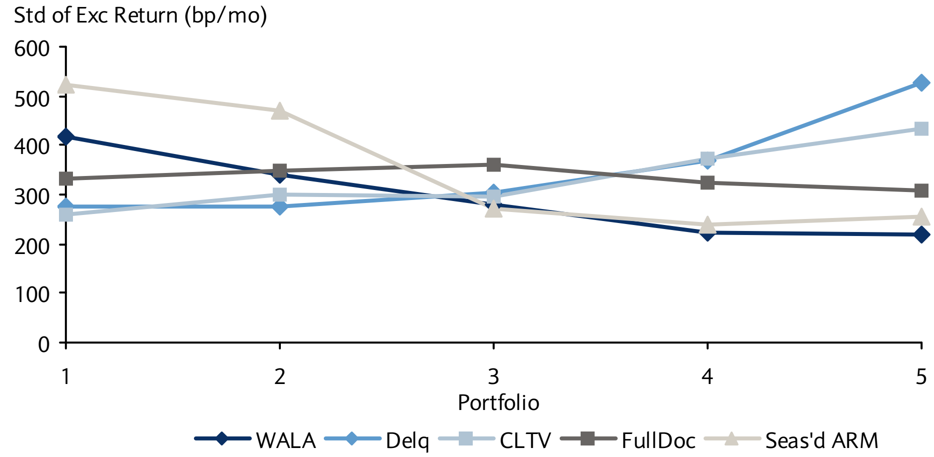
  where median FullDoc is the median percentage of loans with full documentation taken across all HE ABS bonds in our estimation universe. A bond based on a deal with median concentration of full documentation loans has a zero loading to this factor. FullDoc is represented in percentage points.

- Seasoned hybrid ARM loans (Seasoned ARM): Usually, there significantly higher uncertainty about the behavior of hybrid ARMs that are still in their rate-locked period. Mortgages that have passed their first coupon reset tend to behave in a more predictable way. Therefore, the concentration of seasoned ARM mortgages in the deal affects the risk level of a bond based on that deal. Figure 10 shows the unweighted realized volatility from December 2005 to May 2009 for five portfolios sorted based on the percentage of seasoned hybrid ARMs of underlying loans. As suggested above, the volatility decreases with the percentage of seasoned ARMs in the bond. The loading to this risk factor is:

  - OASD x Seasoned ARMs

  where the "Seasoned ARMs" are represented in percentage points as the percentage of seasoned ARM deals in the bond that have already reset.

Figure 10: Unweighted Standard Deviation of Excess Returns of Portfolios Sorted by Various Characteristics, December 2005–May 2009



Source: Barclays Capital

- Floating coupon (Float): Floating-coupon securities usually have underlying loans with characteristics that may be significantly different from fixed-coupon bonds. For example, floating-coupon ABS became very common in 2005-2007, when it is generally accepted that underwriting standards deteriorated. Figure 11 presents the unweighted volatility of excess returns for various portfolios for the entire sample period (December 2005-May 2009), as well as for three sub-periods. The "Float" ("Fixed") portfolios contain all of the floating (fixed) bonds in the sample. The volatility of the floating bond portfolio differs significantly from that of the fixed bond portfolio for both the entire sample period and its sub-periods. The numbers are consistent with Figure 4, which showed that the floating bonds' performance deteriorated earlier (in 2007) than the fixed rate bonds. In our risk model, only floating-coupon bonds load on this factor. The loading is the OASD of the security.

- Premium bond (Prem): A bond trading at a premium is very exposed to the prepayment option, since its coupon, often related to the coupon paid on underlying mortgages, is typically higher than current rates. However, bonds trading at discount may be less subject to prepayment risk, but more exposed to credit concerns. As Figure 11 shows, the unweighted return volatility of a portfolio composed of premium bonds differs significantly from a non-premium portfolio. For instance, for the first period under consideration, premium bonds had a volatility of 9bp/month, while non-premium bonds had a volatility of 26bp/month. For our risk model, the loading of this factor increases linearly from zero to the OASD as the price increases from 100 to 103. Bonds priced below 100 have a loading of zero to this factor, and bonds priced above 103 have their OASD as the loading. Note that while historically important, no bonds load on this factor as of May 2009.

Once all the loadings are identified, we are ready to estimate our risk factor monthly realizations. Specifically, each month, we regress the cross-section of realized excess returns over the month against the set of risk loadings, where loadings are as of beginning of the month. These regressions give us the monthly realizations of the risk factors that we aggregate into panel data. Their expected joint distribution, particularly the covariance matrix, is based on these historical observations, as specified in Dynkin, Joneja et al. (2005).

Figure 11: Unweighted Standard Deviation of Excess Returns for Various Portfolios by Sub-period (bp/month)

	All	Float	Fixed	NonPremium	Premium
12/05-05/09	273	294	349	305	133
12/05-01/07	14	14	16	26	9
02/07-03/08	359	384	310	415	183
04/08-05/09	232	260	504	231	107

Source: Barclays Capital

In-Sample Analysis

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

Figure 12 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 negative correlation between a bond's average life and its underlying loan age. This result is expected. The low level of correlation among the different loadings is a desirable characteristic, as it implies less co-linearity across the different risk factors and, therefore, more robust estimates.

Figure 12: Median of Cross-Sectional Correlations among Loadings/OASD, from December 2005 to May 2009

	DTS	WALA Sh	WALA Lg	AL	Float	Prem	Delq	CLTV	FullDoc	Seas'd ARM
DTS		0.03	-0.03	0.15	0.09	-0.02	0.49	0.24	-0.06	0.19
WALA Sh	0.03		0.46	-0.57	-0.12	0.24	0.11	-0.17	0.06	0.47
WALA Lg	-0.03	0.46		-0.34	-0.37	0.16	-0.1	-0.19	0.13	0.19
AL	0.15	-0.57	-0.34		-0.13	-0.01	0.02	0.21	-0.03	-0.25
Float	0.11	-0.12	-0.38	-0.13		-0.06	0.28	0.23	-0.27	0.14
Prem	-0.02	0.24	0.16	-0.01	-0.06		0.15	-0.02	0	0.16
Delq	0.49	0.11	-0.1	0.02	0.28	0.15		0.42	-0.14	0.39
CLTV	0.24	-0.17	-0.19	0.21	0.23	-0.02	0.42		-0.29	-0.03
FullDoc	-0.06	0.06	0.13	-0.03	-0.27	0	-0.14	-0.29		-0.09
Seas'd ARM	0.19	0.47	0.19	-0.25	0.14	0.16	0.39	-0.03	-0.09	

Source: Barclays Capital

Figure 13 shows the average incremental explanatory power (R-squared) for each variable, across all monthly regressions. These numbers are order-dependent, so they are presented in decreasing order of their univariate R-squared. Since returns differ by orders of magnitude before and after 2007, we analyze the two periods separately. Moreover, the AAA bonds had historically been targeted to a more general class of investors than non-AAAs, so we also separate the sample along that dimension. For the same reason, we conjecture that before 2007, the characteristics of the underlying (Delq, CLTV, FullDoc, Seas'd ARM) are more relevant for non-AAA bonds. The results show that the DTS factor explains a significant amount of cross-sectional volatility, underscoring the importance of adding the DTS factor to the model. On top of DTS, each additional variable increases the R-squared of the model. In general, variables have significant p-values more than 50% of the time (unreported). The exceptions are for FullDoc and CLTV, which may not be relevant as often, but they do matter on aggregate. Some variables, such as DTS, float, and average life, are particularly relevant.

Figure 13: Average R-squared (in percent) in Cross-Sectional Regressions

	Full Sample		Non-AAA Sample	
	All data	Before Jan-07	All data	Before Jan-07
All vars	**23.3**	**19.2**	**21.7**	**19.0**
Only DTS	12.6	8.7	10.4	7.5
+Float	14.0	9.9	11.8	8.7
+WALA Sh & Long	16.1	12.1	14.9	11.9
+AL	18.7	15.2	17.3	14.5
+Premium	20.6	17.5	18.0	15.5
+Delq&Seas'd	21.4	17.8	19.0	16.3
+CLTV&FullDoc	23.3	19.2	21.7	19.0

Source: Barclays Capital

Next, we compare the performance of the old and new models. But before that, we want to succinctly describe the first generation ABS risk model in POINT (i.e., the old model). In this model the expected magnitude of spread changes – which is an approximation for excess returns divided by OASD – was assumed to depend mainly on whether a bond is AAA-rated. Other characteristics differentiating risk across bonds were average life, WALA, price, and OAS. The loadings on these factors were computed net of the median of the respective characteristics for the universe. For example, the loading on the WALA factor was the bond's WALA less the median WALA across all ABS bonds in the index. Thus the risk of a bond with typical price, WALA, OAS, and AL characteristics is given only by whether it is AAA, scaled by OASD. In a nutshell, the factors of the old model capture changes on OAS, while the DTS factor of the new model captures percentage changes in OAS.

We note that OAS was part of the risk factors in the old model. However, this does not mean it was a DTS model, mainly because the OAS was net of median OAS. In such a setting, given a bond that always has an OAS close to the median OAS over all bonds, when the entire market experiences a large increase in OAS, the risk of this bond does not change because its loading on the OAS factor is small. In contrast, a DTS model scales the bond's risk with the total change in OAS. An additional issue with this factor comes from the collinearity with the price risk factor, which is the result of the high correlation between prices and spreads. When spreads were not the overwhelming contributor to risk, this correlation may have been lower, but in the environment after 2007, it became close to one.

To gauge the relative performance of the new and old models, we compare different statistics of both models extensively across different subsamples. Figure 14 reports some of these statistics, for three different periods and three different samples. The first period, 2003-2004, includes only fixed-rate bonds in a relatively mild volatility environment. 2005-2006 contains mostly floating-rate bonds, and the environment is marked by very low volatility. The last period was marked by high levels of volatility. For the different samples, the analysis is conducted for index and non-index bonds. For the index bonds we report separately the results for fixed-rate bonds because the index sample is dominated by floating-rate bonds.

Comparing the first two columns of Figure 14, we see that the new model explains more of the realized returns than the old one, especially in the early and late periods. The total explanatory power is high for the entire sample, with 60-70% correlation levels corresponding to 35-50% R-squared. The old model fits better with the fixed-rate index subsample, since that is the sample used to calibrate it and this analysis is purely in-sample. All of the index data fit particularly well with the new model in the high volatility period of 2007-2009, benefiting from the DTS specification.

The third column compares regression-fitted returns from the old and the new models. The correlations are low, always below 50%. They are generally higher for fixed-rate index bonds, since both models use them for calibration.

Figure 14: Select Correlations among Realized Returns, Fitted Returns, and Residuals; Regressions Use Either the New or Old Model, by Sub-periods and Subsamples

	Actual vs. Fitted Returns (old)	Actual vs. Fitted Returns (new)	Fitted Return Old vs. New
2003-04			
Fixed index	35%	38%	38%
All Index	35%	38%	38%
All Sample	2%	58%	19%
2005-06			
Fixed index	31%	20%	31%
All Index	31%	24%	31%
All Sample	29%	69%	37%
2007-08			
Fixed index	67%	42%	47%
All Index	35%	58%	43%
All Sample	25%	68%	31%

Source: Barclays Capital

The Idiosyncratic Risk Model

Not captured in systematic risk is the risk corresponding to the residual, name-specific, or idiosyncratic return. By definition, this risk should be uncorrelated across securities and with systematic risk. We model this risk in reduced form only. We assume that the only driver of idiosyncratic risk is the spread level (DTS). We also allow for a separate base line idiosyncratic risk for fixed- and floating-coupon securities (Figure 15).

Figure 15: Equation of Idiosyncratic Risk Model

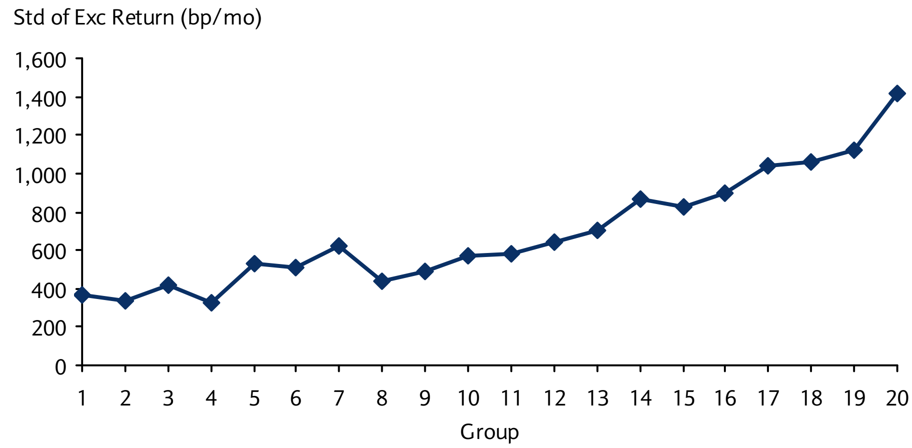
$$Var\left(\varepsilon_{i,t+1}\right) = OASD_{i,t}^{2}\left(1_{isFixedRate} \cdot P^{Fix} + 1_{isFloatRate} \cdot P^{Float}\right) + DTS_{i,t}^{2} \cdot P^{DTS}$$

Source: Barclays Capital

The justification for the relation between idiosyncratic risk and spread level is similar to the systematic case: higher spread securities have higher idiosyncratic prepayment risk or default risk. Moreover, when we relate both the systematic and idiosyncratic risk to spread levels we keep the ratio of systematic to idiosyncratic risk constant, an empirical regularity we want to capture.

Figure 16 presents evidence of the strong positive relation between DTS and idiosyncratic volatility: we plot the average realized volatility of DTS-grouped long-short portfolios. For each of the 20 DTS groups, we select for each month ten random portfolios composed of two securities. In each portfolio, we go short one security and long the other. Because they belong to the same DTS group, their DTS exposure should be comparable. Since DTS is the largest component of systematic risk, these long/short portfolios should have low systematic risk exposure and high idiosyncratic risk. We can then calculate the volatility of the (mainly idiosyncratic) returns of all these portfolios for each DTS group. Figure 16 shows the relationship between the DTS and the idiosyncratic return volatility for each group. It documents a strong monotonic relationship between these two variables. The model in Figure 15 captures this idea.

Figure 16: Unweighted Standard Deviation of Excess Returns of 10 Long/Short Portfolios by 20 DTS Groups, December 2005-May 2009



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 (in either direction) from the average return of high DTS bonds than the individual returns of low DTS bonds. One factor relates the means of the return distributions of high DTS bonds and low DTS bonds; the other factor relates their standard deviations.

Each month, we estimate the three idiosyncratic parameters (*P's)* from residual returns. To estimate the idiosyncratic risk over the next month, we take their historical average and use those averages in conjunction with the formula above (Figure 15).

Figure 17: Sources of Idiosyncratic Risk, Two Dates

	Square-root of Parameter Mean	Square-root of Average Loading	Risk bp/month
As of Jan 2007			
Fixed Intercept	3.32	1.12	3.7
Floater Intercept	2.45	2.13	5.2
DTS Sq	0.73	2.62	1.9
As of Jan 2009			
Fixed Intercept	113	1.60	180
Floater Intercept	144	2.39	344
DTS Sq	12.88	41.30	532

Source: Barclays Capital

To provide a sense of the importance of various components to total idiosyncratic risk, Figure 17 shows the square-root of average loadings and time-weighted average parameters at two dates. We show the square-root of the averages to make the numbers comparable with previous tables. Floating bonds have a higher idiosyncratic volatility than fixed-rate bonds, for similar DTS levels. For example, the idiosyncratic risk of a floating coupon bond with an OASD of 2.4 years and DTS exposure of 41.3 (bp/mo/%) was on January 2009 the square root of the sum of 344^2 and 532^2, which is 633bp/month. While idiosyncratic risk was very small before the crisis, it has increased 100-fold since. Moreover, DTS became the most important source of idiosyncratic risk. The parameter mean of DTS has increased significantly together with the average loading.

A model with a good fit should result in residuals that are uncorrelated in the cross-section and over time. However, the analysis of the residuals in our sample points to residual correlation among securities. Pair-wise correlations of residual returns for securities with at least 12 overlapping observations are, on average, slightly positive, and the right tail is larger than the left one (see first row in Figure 18) Thus, there may be some (non-spurious) residual correlation between securities in our sample.

We could try to address this correlation in the systematic model. However, adding a factor for each cluster of securities with correlated idiosyncratic returns results in over-fitting the model. Moreover, these clusters are small in size, which places their additional risk in between the systematic and idiosyncratic risk. We concluded that the most parsimonious way to address the issue is in the idiosyncratic model.

We model these leftover idiosyncratic correlations as a function of whether the securities belong to the same deal, whether they are at the same position in the capital structure (i.e., have the same rating), and the interaction between the two. In particular, securities that are part of the same deal and are on the same level of the capital structure (0.06% of the pair-wise correlations) have a high correlation of the residuals, at 43%. Securities that are part of the same deal have 17% correlation, and securities that are at the same level in the capital structure have a 10% correlation. Once we account for these features, the distribution of the correlations becomes more regular, and closer to what we would expect of a distribution of correlations from random draws of independent series (e.g., spurious correlations only). The second row of Figure 18 documents that.

Figure 18: Distribution of Pair-Wise Correlations of Idiosyncratic Returns, before and after Modeling

Variable	Mean	StdDev	5% Right - Left Tail	1% Right - Left Tail	0.5% Right - Left Tail	0.1% Right - Left Tail
Corr	1.0%	29%	6.5%	12.5%	13%	11%
Corr-Model Corr	0.0%	29%	2.7%	4.3%	3%	-2%

Source: Barclays Capital

In the following sections we will compare the behavior of new with the old, first generation risk model. While we have already briefly described the old systematic model, we made little mention of the old idiosyncratic model. This old model simply assumes that the idiosyncratic risk of spread changes is the same for all ABS bonds. Thus the idiosyncratic risk is just a linear function of a bond's OASD.

Risk Forecasting

In this section, we detail the characteristics of the risk predictions from our new model.

Factors Distribution and Risk

The summary statistics of the new risk factors realizations are shown in Figure 19 for two periods. The first refers to statistics before January 2007, the second to the whole sample.

Figure 19: Summary Statistics for the Risk Factor Realizations, Selected Dates

Variable	Units	N	Mean	Std Dev	50 Pct	10 Pct	90 Pct
A: Before January 2007							
UHG	bp/(mo*Yr)	54	5.9	11.4	6.0	-5.0	20.8
DTS	bp/(bp)	54	0.00	0.15	0.00	-0.14	0.20
WALA Sh	bp/(mo*Yr^2)	54	0.4	0.7	0.1	-0.2	1.3
WALA Lg	bp/(mo*Yr^2)	54	0.0	0.2	0.1	-0.3	0.2
AL	bp/(mo*Yr*Ln(Yr))	54	-4.5	11.4	-5.9	-16.7	11.3
Float	bp/(mo*Yr)	23	-2.5	7.2	-3.7	-11.3	5.8
Prem	bp/(mo*Yr)	54	-17.2	17.4	-12.0	-48.9	0.6
Delq	bp/(mo*%)	54	8.6	26.4	7.2	-24.6	50.0
CLTV	bp/(mo*Yr*%)	54	0.1	1.5	0.1	-1.9	2.0
FullDoc	bp/(mo*Yr*%)	54	0.0	0.4	0.0	-0.4	0.6
Seas'd ARM	bp/(mo*Yr*%)	54	0.0	0.3	0.0	-0.2	0.4
Adj RSQ		54	19%		14%	5%	39%
B: All Data							
UHG	bp/(mo*Yr)	83	-37.1	174.1	3.3	-188.2	26.4
DTS	bp/(bp)	83	-0.02	0.15	-0.03	-0.15	0.19
WALA Sh	bp/(mo*Yr^2)	83	1.4	3.7	0.3	-0.4	5.7
WALA Lg	bp/(mo*Yr^2)	83	0.1	2.0	0.0	-1.2	1.2
AL	bp/(mo*Yr*Ln(Yr))	83	15.7	41.7	0.9	-15.2	58.6
Float	bp/(mo*Yr)	62	-11.5	112.2	-1.5	-88.0	70.5
Prem	bp/(mo*Yr)	83	-5.1	170.0	-9.8	-50.4	107.1
Delq	bp/(mo*%)	83	-9.8	85.4	5.8	-62.0	60.4
CLTV	bp/(mo*Yr*%)	83	-0.2	4.1	0.0	-3.9	2.3
FullDoc	bp/(mo*Yr*%)	83	0.1	1.6	0.0	-0.7	2.1
Seas'd ARM	bp/(mo*Yr*%)	83	-0.2	0.8	0.0	-0.8	0.5
Adj RSQ		83	23%		15%	5%	60%

Source: Barclays Capital

As expected, there is a significant change in factor distribution once we add observations after January 2007. In addition, for the whole sample and apart from the UHG, all factors are centered at close to zero, and the 10^{th} and 90^{th} percentiles are roughly symmetric around the median. The UHG is positively skewed before 2007 and negatively so afterward.

To gauge the (isolated) risk contribution from each factor, we add to the analysis the magnitude of the risk factors' loadings. This is done in Figure 20 where for each factor we show its time-weighted volatility, the size of its loadings, and the product of the two. The loadings' size is the average loading for factors with positive loadings, (e.g., UHG, DTS, AL) and the average of absolute values for factors with loadings centered near zero (e.g., Full

Doc, Delq). For CLTV, we average the loadings only for bonds with CLTV>80% (i.e., strictly positive values). The analysis is shown for January 2007 and January 2009.

Figure 20: Uncorrelated Time-Weighted Risk of Each Factor, Two Dates

	Std Dev	Loading	Risk (bp/month)
January 2007			
UHG	9.0	2.0	18.4
DTS	16.3	1.6	25.7
WALA Sh	0.5	31.1	16.8
WALA Lg	0.2	6.1	1.2
AL	9.5	0.8	8.0
Float	8.1	1.7	13.3
Prem	14.5	0.2	3.4
Delq	19.6	1.2	23.4
CLTV	1.1	12.8	14.0
FullDoc	0.2	16.2	3.9
Seas'd ARM	0.2	29.5	5.9
January 2009			
UHG	257.2	2.6	661
DTS	16.4	41.2	674
WALA Sh	6.0	61.5	368
WALA Lg	3.0	63.8	194
AL	37.1	1.4	53
Float	100.4	1.8	179
Prem	133.6	0.0	7
Delq	131.4	1.6	213
CLTV	5.1	9.7	49
FullDoc	2.4	20.1	48
Seas'd ARM	1.1	29.5	32

Source: Barclays Capital

The differences between the two snapshots are large. In some cases, the factor volatilities did not change significantly, but loadings did. In others, we see the opposite changes. The volatility of the DTS factor changed little, but its average loading increased 25 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. This was driven by the tremendous market shift for high-rated bonds. WALA factor loadings also increased, since there have been no new originations and the sample inevitably gets more seasoned. Regarding the relative rankings, both DTS and the UHG have a large effect on risk, followed by WALA, Float, and Delq. The other three characteristics are only somewhat important on aggregate, but they may be relevant for specialized sub-portfolios.

To better assess the aggregate effect of each factor on overall risk, we add factor correlations to the analysis. Figure 21 reports the time-weighted correlation across all risk factors. Again, the analysis is made as of January 2007 and January 2009. There are some strong negative correlations, suggesting that hedging effects may reduce the (isolated) aggregate risk reported in Figure 20.

Figure 21: Time-Weighted Factor Correlations, Two Dates

	UHG	DTS	WALA Sh	WALA Lg	AL	Float	Prem	Delq	CLTV	FullDoc	Seas'd
As of Jan 2007											
UHG		-56%	-23%	-34%	18%	-45%	26%	26%	47%	6%	2%
DTS	-56%		12%	35%	-70%	30%	-44%	-29%	-25%	-15%	4%
WALA Sh	-23%	12%		-15%	-5%	-27%	-69%	-15%	-17%	0%	17%
WALA Lg	-34%	35%	-15%		-9%	25%	-14%	-7%	-13%	-18%	-15%
AL	18%	-70%	-5%	-9%		-22%	29%	34%	8%	9%	-33%
Float	-45%	30%	-27%	25%	-22%		15%	7%	-24%	-24%	11%
Prem	26%	-44%	-69%	-14%	29%	15%		33%	24%	-11%	-10%
Delq	26%	-29%	-15%	-7%	34%	7%	33%		55%	-25%	-34%
CLTV	47%	-25%	-17%	-13%	8%	-24%	24%	55%		-21%	-10%
FullDoc	6%	-15%	0%	-18%	9%	-24%	-11%	-25%	-21%		-35%
Seas'd ARM	2%	4%	17%	-15%	-33%	11%	-10%	-34%	-10%	-35%	
As of Jan 2009											
UHG		-26%	-87%	-75%	-21%	8%	-41%	-26%	28%	-11%	26%
DTS	-26%		12%	18%	-23%	19%	-6%	-11%	12%	-12%	3%
WALA Sh	-87%	12%		52%	20%	-36%	37%	17%	-23%	20%	-11%
WALA Lg	-75%	18%	52%		-11%	1%	-10%	45%	-10%	-8%	-39%
AL	-21%	-23%	20%	-11%		30%	49%	-1%	-14%	3%	-28%
Float	8%	19%	-36%	1%	30%		-13%	13%	14%	11%	12%
Prem	-41%	-6%	37%	-10%	49%	-13%		0%	-38%	29%	-19%
Delq	-26%	-11%	17%	45%	-1%	13%	0%		6%	50%	10%
CLTV	28%	12%	-23%	-10%	-14%	14%	-38%	6%		-7%	13%
FullDoc	-11%	-12%	20%	-8%	3%	11%	29%	50%	-7%		46%
Seas'd ARM	26%	3%	-11%	-39%	-28%	12%	-19%	10%	13%	46%	

Source: Barclays Capital

Before the crisis, negative correlations were particularly strong between the DTS and UHG factors, factors with a large univariate effect on risk. On the other hand, delinquencies and CLTV factors seem to compound risk, given their 50% correlation. The DTS correlations in January 2009 are much smaller in the absolute value; hence, DTS relative contribution to risk is expected to be more significant than before. In 2009, the factors proxying underlying characteristics increased their correlation as well; thus, their effect on total risk is expected to be higher than observed two years earlier.

The UHG factor has strong negative correlations with the WALA factors in 2009. This is important, since all these factors are major risk contributors in Figure 20. The large negative correlation is driven somewhat by the steady increase in WALA over time, which makes it difficult to differentiate bonds among WALA dimension. Since all loadings, including UHG, are scaled by OASD, it generates significant positive correlation between the UHG and WALA loadings, and more so for WALA Short. Thus, multi-collinearity leads to large observations with opposite signs in UHG and WALA. Since we do not expect new issuances anytime soon in this market, this problem is bound to persist. One method to address it is to turn off the WALA Short factor and capture all volatility in the UHG. In effect, this redefines the security whose risk is captured by the UHG: before implementation, there was a security with low DTS, newly issued, fixed rate, non-premium, median average life, no delinquent loans, CLTV less than 80%, median %FullDoc loans and no seasoned ARMs; after implementation, the base security is not newly issued anymore, but aged 24 months. Since the transition from one base security to another is done gradually, the risk from the WALA

Short factor is expected to decrease and shift gradually toward the UHG. During the shift, the total risk will not change compared with a case in which the WALA Short factor continues to be calibrated. Simulation tests show that within a year, a third of the individual risk adjustment occurs, and within two years, two-thirds of the adjustment occurs.

Figure 22 shows the correlation between the new ABS spread factors and relevant risk factors from other asset classes for two dates: January 2007 and 2009. Of special relevance is the correlation with all yield curve factors. This is because total systematic risk for HE ABS bonds includes the effects of both curve and spread. The figure shows that correlations between spread and curve factors are not particularly strong for January 2007. This means that the total return variance for generic ABS bonds is close to the sum of the curve-implied variance and the spread-implied variance. For January 2009, correlations were still low, except for UHG, which is negatively correlated with the curve factors. This means that total risk is expected to be smaller than the sum of the risks from these two components. Figure 22 also analyzes correlations with other securitized asset classes. The relationship has been weak historically. More recently, the correlation between the UHG and other securitized asset classes is higher. Other factors have experienced shifts in correlation signs, but levels have remained low. More important, the DTS factor – a major risk factor in the new model – has low correlations with other asset classes in 2009 and weak correlation in 2007.

Figure 22: Time-weighted Factor Correlations with Other Asset Classes, Two Dates

	UHG	DTS	WALA Sh	WALA Lg	AL	Float	Prem	Delq	CLTV	FullDoc	Seas'd
As of January 2007											
KR 6 mo	15%	-12%	17%	-27%	12%	-22%	-10%	-5%	-7%	20%	-1%
KR 2 yr	33%	-6%	19%	**-54%**	-15%	-30%	-34%	-8%	0%	25%	4%
KR 10 yr	18%	1%	16%	-36%	-6%	-20%	-30%	-5%	5%	24%	-3%
KR 30 yr	13%	0%	9%	-22%	1%	-15%	-23%	-3%	10%	20%	-7%
SS 6 mo	36%	-19%	-9%	-31%	-10%	-18%	6%	18%	22%	-6%	-9%
SS 10 yr	-12%	6%	-5%	9%	24%	3%	22%	6%	-1%	10%	-9%
SS 30 yr	0%	5%	14%	-19%	12%	-21%	-4%	-2%	0%	9%	0%
ABS	-14%	29%	23%	-8%	-35%	-3%	-32%	-18%	12%	-5%	31%
MBS	-36%	27%	-3%	35%	5%	37%	26%	11%	-9%	-16%	5%
CMBS	-31%	28%	-18%	**50%**	6%	36%	35%	7%	-5%	-8%	-15%
Hybrid ARMs	6%	14%	24%	-29%	-28%	-7%	-9%	-8%	6%	10%	25%
Strip IO	-8%	25%	1%	-1%	-15%	2%	4%	-3%	18%	-8%	14%
As of January 2009											
KR 6 mo	**-42%**	1%	34%	21%	35%	20%	**44%**	-1%	-11%	9%	-21%
KR 2 yr	**-51%**	-6%	**45%**	18%	**46%**	-1%	**61%**	-1%	-34%	12%	-30%
KR 10 yr	**-46%**	-2%	34%	**45%**	19%	-28%	**45%**	28%	-30%	2%	**-41%**
KR 30 yr	**-45%**	-4%	29%	**53%**	30%	-6%	**45%**	35%	-27%	9%	**-51%**
SS 6 mo	0%	-9%	20%	23%	-11%	**-43%**	-29%	5%	18%	-21%	-12%
SS 10 yr	**-53%**	2%	**53%**	32%	25%	17%	28%	9%	0%	19%	-3%
SS 30 yr	**-64%**	9%	**65%**	30%	2%	-26%	31%	12%	-8%	12%	8%
ABS	**59%**	0%	**-61%**	**-53%**	-28%	16%	-24%	-4%	-2%	16%	40%
MBS	**88%**	-11%	**-78%**	**-67%**	-29%	18%	**-52%**	-29%	15%	-4%	**43%**
CMBS	**59%**	1%	**-47%**	**-48%**	**-52%**	-25%	**-48%**	-4%	19%	-2%	**52%**
Hybrid ARMs	27%	-6%	-15%	-8%	-33%	-21%	-28%	23%	-2%	17%	16%
Strip IO	1%	5%	-10%	10%	-10%	-29%	17%	22%	-24%	-1%	-16%

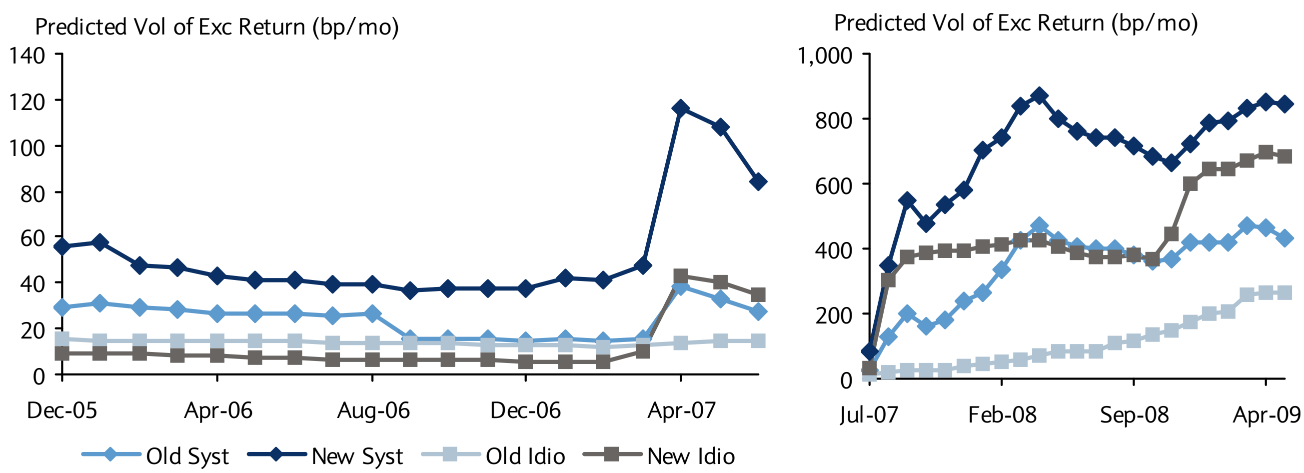
Source: Barclays Capital

Evolution of Systematic and Idiosyncratic Risk

In what follows, we present the time-series evolution of model predictions about the systematic and idiosyncratic risk for a typical bond. For comparison, we also report the predictions for the old model (Figure 23). The forecast had been relatively stable from 2005 to 2007, with the new model forecasting higher systematic risk and lower idiosyncratic risk than the old one. Because of large return realizations, the predicted systematic volatility changed sharply in the second half of 2007, from 20-60bp/month to 400-900bp/month. The new model has continued to predict higher systematic volatility levels than the old one.

The idiosyncratic risk of the old model was about 50% of the systematic risk during 2006 and then dropped to less than 15% during 2007, as the slow ramp-up in idiosyncratic risk did not keep up with the increase in systematic risk. Toward 2009, it increased back to 60% of the systematic risk. The new model predicted extremely low idiosyncratic risk during 2006, as spreads were very compressed, and increased rapidly during 2007, reaching a level of 70% of the systematic risk. Since early 2007 it has overtaken the idiosyncratic risk predicted by the old model and it has been significantly higher since.

Figure 23: Evolution of Predicted Systematic and Idiosyncratic Risk for an Average Bond, New and Old Model



Source: Barclays Capital

Portfolio Back-testing

Given our limited time-series sample, we cannot perform exhaustive out-of-sample tests spanning multiple market conditions. Moreover, the nature of the returns in this asset class – with its abrupt structural break after 2007 – renders the test statistics described below less revealing. Even with all these caveats, the tests are important, as they help frame the performance of the new model. We investigate the out-of-sample behavior of the model for several portfolios over the December 2005 to May 2009 period (42 months). The test of choice is studying the distribution of unit-scaled returns. Using the risk model, at the beginning of each month *t,* we forecast the spread (excess of curve) return volatility of each portfolio *p*, $\sigma^t_{p,forecast}$. We then compute the unit-scaled (standardized) return, u^t_p as the spread return scaled by the forecast volatility:

$$u^t_p = \frac{r^t_p}{\sigma^t_{p,forecast}}$$

If the volatility forecasting model is good, the volatility of standardized returns u^t_p should be close to one. The standard deviation of these returns - $\theta_{pt} = std(u^t_p)$ - is the *bias test statistic* we use later in this section. For a larger sample, one may study other properties of the u^t_p distribution, such as how close it is to a normal or Student-t.

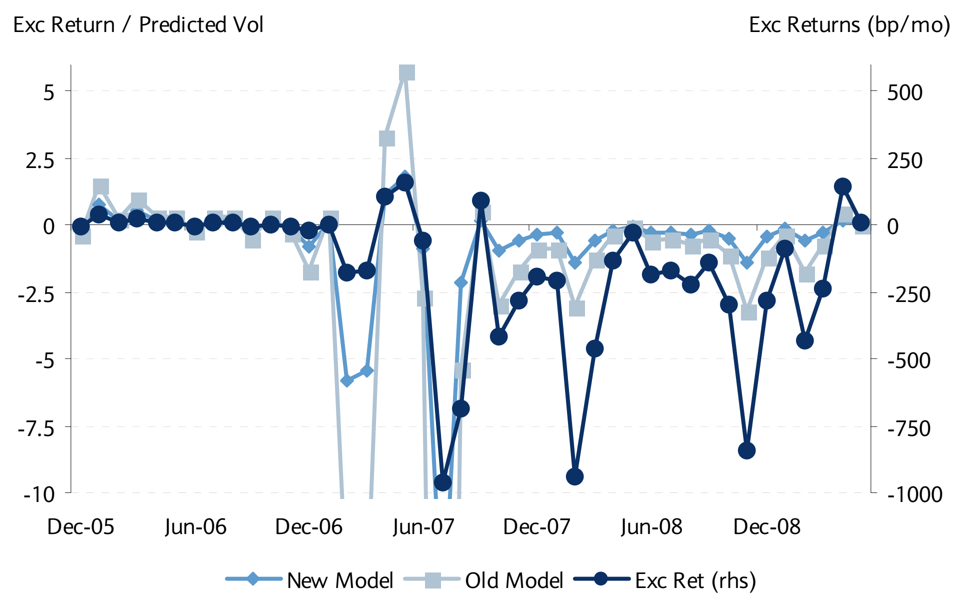
Market Portfolio

To study the systematic volatility model, we start with the most diversified portfolio possible – the "market" portfolio – that includes all bonds in the sample. Figure 24 plots the time series of the market portfolio's standardized returns on the left axis and the actual returns on the right axis. The returns are standardized by either the old (non-DTS) or the new models. There are three distinct volatility periods in the sample. First is the extremely low volatility period of 2006. During this period, standardized returns are very small, and both new and old models over-predict volatility. In the second period, after the major shocks of February and March 2007, volatility picks up. 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 extreme volatility of 2007-2008. For example, August 2007 was a 2 standard deviation event in the new model and a 5.5 standard deviation event in the old one, even after registering 5+ standard deviation events for five months. This means that the old model was struggling significantly to keep up with the sudden and continuous changes in environment.

At the start of the third period, the shock of February 2008 pushed the new model volatility above 7%, which turned out to be relatively high when compared with subsequent monthly returns. Nevertheless, similar, more liquid instruments, such as various AAA ABX indices, experienced regularly monthly returns above 10% in absolute terms after February 2008. The new model seems to do a better job in understanding the latent high volatility environment created by the 2007 events. This is achieved with the introduction of the DTS factor.

The bias test statistic θ for the market portfolio is reported in Figure 33, under the "All sample" column. The results show that the new model underpredicts risk by a ratio of 2.67:1. Yet, the 95% confidence interval regarding this number, obtained via bootstrapping, is so wide that it includes the ideal model value of 1. The wide confidence interval is a result of both the small sample we use for the test and of the non-normal characteristics of the test statistic distribution. In contrast, the old model underpredicts risk by a much wider margin of 8.24:1. Moreover, the 95% confidence around this number does not include 1.

Figure 24: Time-Series of Excess Returns and Standardized Returns of the Entire Sample Portfolio. Returns Standardized by Predicted Volatility from either New or Old Risk Model. December 2005-May 2009



Source: Barclays Capital

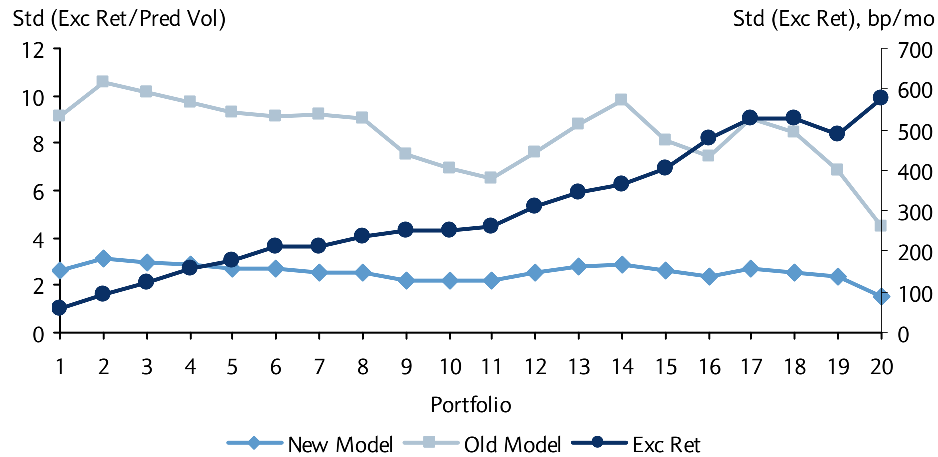
Characteristics-Sorted Portfolios

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 the model's cross-sectional behavior, we construct diversified portfolios sorted by various characteristics. If the risk model does a good job in capturing cross sectional systematic differences in volatility associated with the characteristic, we should not see any systematic pattern in the bias test for these diversified portfolios. For instance, if we form portfolios based on WALA and we see that the bias test statistic θ is systematically increasing with the WALA portfolios, then one could argue that the model does not fully capture differences in that characteristic on the cross-section.

To evaluate this reasoning, Figures 25 to 32 plot on the left axis the volatility of standardized excess returns (θ) using predictions from either the old or the new model and on the right axis the unweighted volatility of returns. The figures present these statistics for the different characteristics-based portfolios.

The first variable we investigate is OASD, which is the loading of the UHG factor and scales the loadings of all other factors. Securities are grouped in 20 portfolios sorted each month by their OASD. Figure 25 shows that the relationship between the volatility of standardized returns from the new model and OASD is much weaker (almost flat) than the relation between the volatility of excess returns or the old model with OASD. Thus, the new model captures reasonably well the risk-OASD relation and it does so better than the old model, which has OASD-scaled factors as well.

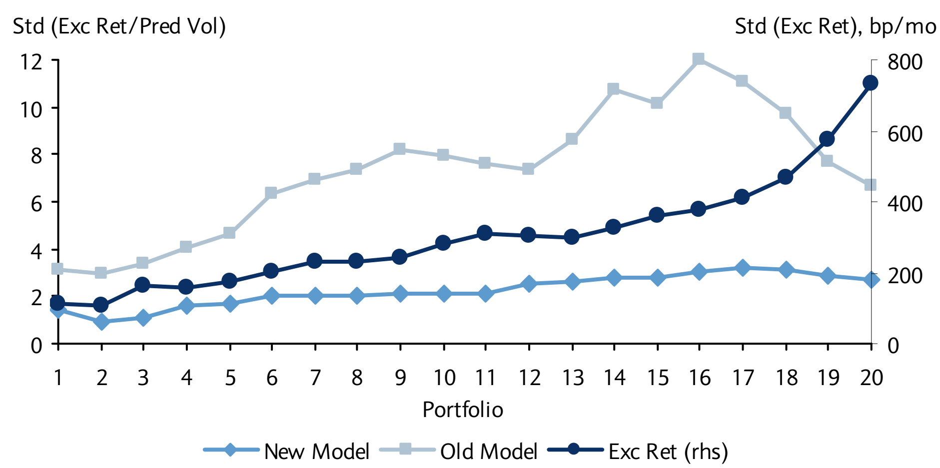
Figure 25: Standard Deviation of Standardized Returns (left) and Excess Returns (right) for 20 Portfolios Sorted by OASD, December 2005-May 2009



Source: Barclays Capital

Next, we study the relation between returns and DTS. As Figure 26 shows, the new model captures the risk-DTS relationship fairly well, although not completely: there is still a monotonic relation between standardized return volatility and DTS. This relation is much weaker than the results from the old model, which proves that our DTS factor improves the risk model along this dimension. This model feature has important consequences for forecasting, given that the volatility of high-DTS portfolios can be 3-4 times the volatility of low-DTS portfolios. A non-DTS model, such as the old one, fails to forecast that difference, since the volatility of standardized returns still exhibit in Figure 26 a strong increasing pattern.

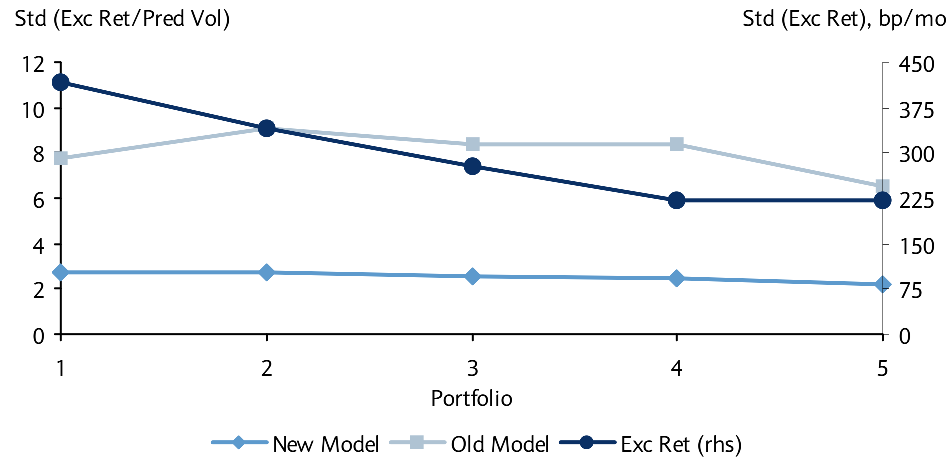
Figure 26: Standard Deviation of Standardized Returns (left) and Excess Returns (right) for 20 Portfolios Sorted by DTS, December 2005-May 2009



Source: Barclays Capital

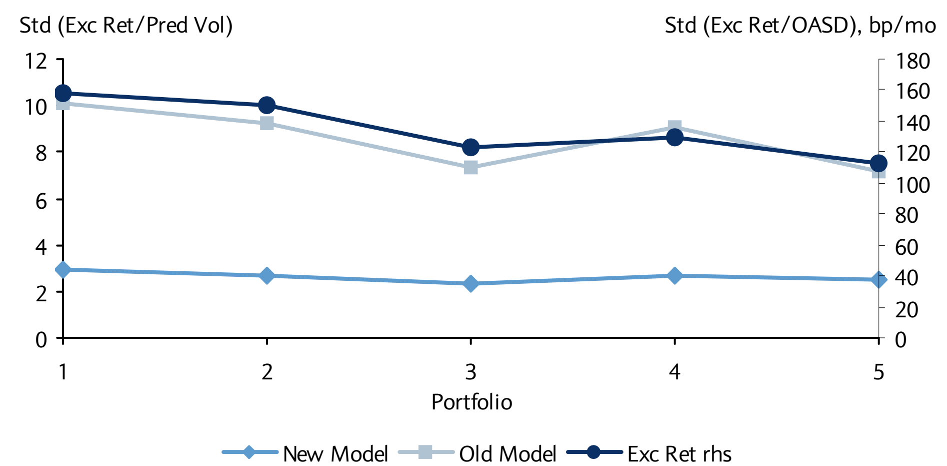
The risk of excess returns exhibits a monotonic pattern compared with WALA. The old model, which includes a WALA factor, captures some of that pattern (Figure 27), yet the intermediate WALA portfolios have a higher volatility of standardized returns than the low or high WALA. Thus, the old model underpredicts the volatility of intermediate WALA portfolios relatively to low or high WALA ones. The risk profile across WALA of the new model is flat, showing that the breakdown of WALA risk into high and low, an innovation of the new model, captures the empirical feature missed by the old model. Instead of 20 portfolios, we break down the sample more parsimoniously into only five portfolios. We used 20 portfolios for DTS and OASD because these are major characteristics and we wanted to show that our model captures their risk well, but here, five portfolios are enough to document the patterns.

Figure 27: Standard Deviation of Standardized Returns (left) and of Excess Returns (right) for Five Portfolios Sorted by WALA, December 2005-May 2009



Source: Barclays Capital

Figure 28: Standard Deviation of Standardized Returns (left) and Excess Returns/OASD (right) for Five Portfolios Sorted by AL, December 2005-May 2009

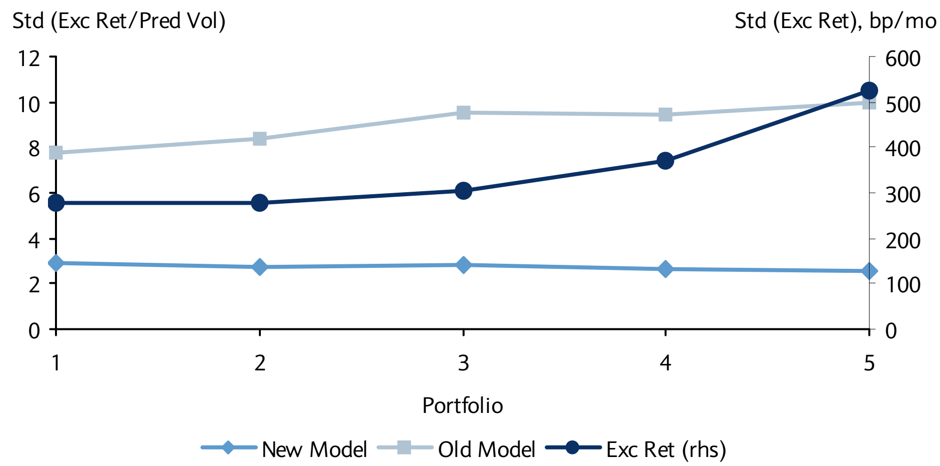


Source: Barclays Capital

The new model also forecasts appropriately the relation between risk and average life (Figure 28). The profile of volatility of standardized returns across AL-sorted portfolios is flat in the new model, but downward sloping in the old one. The old model includes an AL factor as well, but the new model uses a non-linear loading, which may capture the properties of risk better. The AL of the five portfolios is not linear, even though the realized volatility is close to linear.

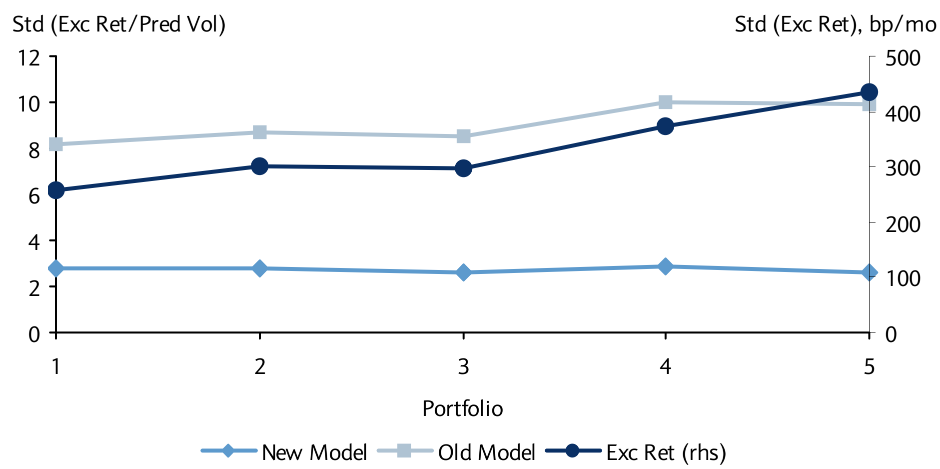
Figure 29 shows that the low-delinquency portfolios have half the excess return volatility of high-delinquency ones. This fact underscores the importance of accounting for the risk-delinquency relation. Results show that our model captures it well. The old model, which does not have such a factor, captures some of the relation through other factors, but the monotonic pattern remains.

Figure 29: Standard Deviation of Standardized Returns (left) and Excess Returns (right) for Five Portfolios Sorted by 60+Delinq/WALA, December 2005-May 2009



Source: Barclays Capital

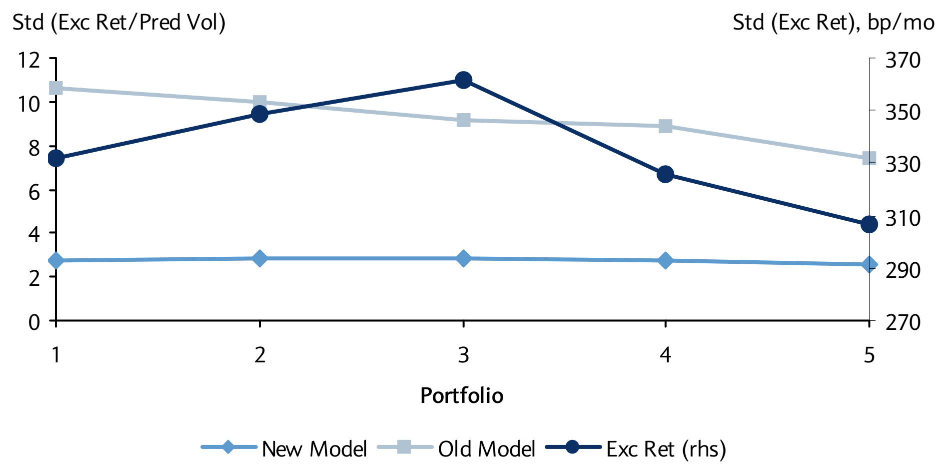
Figure 30: Standard Deviation of Standardized Returns (left) and Excess Returns (right) for Five Portfolios Sorted by CLTV, December 2005-May 2009



Source: Barclays Capital

Another factor describing the quality of the underlying collateral, CLTV, has also a monotonic relationship to risk (Figure 30). The new model accounts for this very well, while the old model does so only partially. Even though the results for CLTV and Delq-sorted portfolios are similar, the two factors do not fully overlap. A bond's loading on Delq changes monthly, while the loading on CLTV stays constant. Thus, the ratio of uncorrelated CLTV-risk of two bonds stays constant (up to changes in OASD), while the ratio of Delq risk does not. Moreover, looking at the profile of realized risk, it is linear across CLTV-sorted portfolios but non-linear across Delq-sorted ones. We also see in Figure 21 that the correlation between these two factors is small recently, indicating they do capture different dynamics.

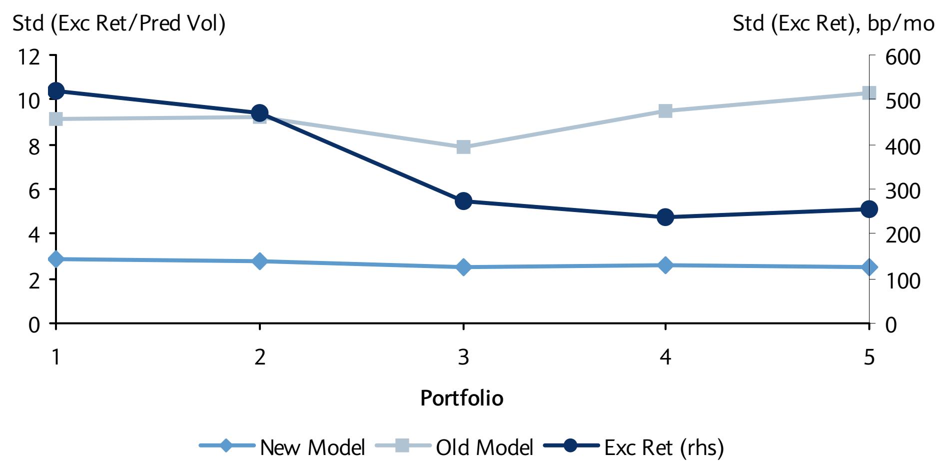
Figure 31: Standard Deviation of Standardized Returns (left) and Excess Returns (right) for Five Portfolios Sorted by FullDoc, December 2005-May 2009



Source: Barclays Capital

Figure 31 illustrates the results for FullDoc-sorted portfolios. While the excess return volatility-FullDoc relationship looks non-monotonic, the new model fully accounts for it since the profile of the volatility standardized returns across the FullDoc-sorted portfolios is flat. In contrast, the old model produces volatilities of standardized returns that are monotonic across portfolios.

Figure 32: Standard Deviation of Standardized Returns (left) and Excess Returns (right) for Five Portfolios Sorted by Seasoned ARMs, December 2005-May 2009



Source: Barclays Capital

The risk-Seasoned ARMs relation is significant in magnitude, with bonds backed by more ARMs before first reset having up to double the risk of bonds backed by less seasoned ARMs (Figure 32). The new model captures the feature well. The old model does so also, but overstates the volatility of the middle portfolio by 20% relative to the other ones.

The results from this analysis seem to suggest that the innovations incorporated - from the DTS framework to non-linear loadings – in the new model account well out of sample for the empirical relations previously documented between risk and various bond and collateral properties. The model seems to do a good job in explaining well differences in volatility in the cross-section associated with the bonds characteristics.

Separating the sample between fixed- and floating-rate bonds, Figure 33 shows that a portfolio of fixed-rate bonds has a higher level of risk than a portfolio of floating-rate bonds The new model captures the risk of both the fixed- and floating-rate bonds, but the forecast is better for fixed-rate bonds.

Figure 33: Standard Deviation of Excess Returns and of Standardized Returns (the test statistic) for Portfolios Created Based on Various Subsamples, December 2005-May 2009

	All Sample	Float	Fixed	Premium	NonPrem
Exc Ret (bp/month)	273	294	349	133	305
New Model Statistic	2.67	2.90	1.12	2.61	2.91
Old Model Statistic	8.24	9.51	3.53	6.92	8.54

Source: Barclays Capital

Lastly, we analyze the risk of the premium vs. non-premium sample. The risk of non-premium bonds is significantly higher. The new model, which includes both DTS and a special factor for premium bonds, accounts for the difference fairly well. Using data only before the crisis (not shown), when premium-ness was linked strongly to prepayment risk, the new model still performs well. The old model, which includes a price factor, forecasts a large part of the observed relation as well: notice the small difference between the old model's test statistic for premium and non-premium samples.

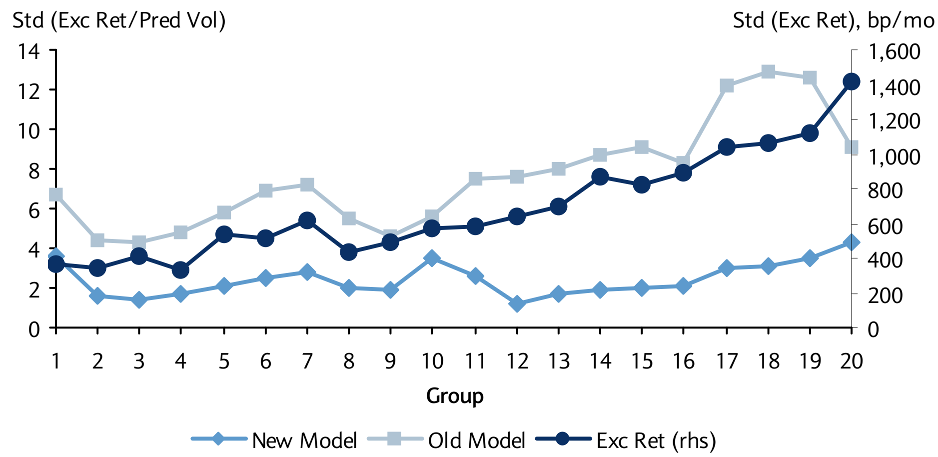
Long-Short Portfolios

In this subsection, we analyze the performance of the idiosyncratic model. For that, we construct ten random portfolios each period for each of 20 DTS-sorted groups of securities. Each portfolio contains a long and short position in two securities from that group. The portfolio return is assumed to be the return on the long security less the return on the short security. Given that the two securities are closely matched on DTS and the OASD is correlated with DTS by construction, the portfolios should have a low exposure to both the DTS and UHG factors. Since these two factors are the biggest sources of systematic risk, these portfolios should be much more exposed to idiosyncratic risk than to systematic risk.

At every month, we have the realized returns for the 10 portfolios in each of the 20 DTS groups. Each realized return is divided by its beginning of month forecast volatility to compute the standardized returns. Finally, we calculate the bias test statistic across portfolios and time for each DTS group. Specifically, note that for each of these 20 groups we use 420 observations (10 portfolios times 42 months) to calculate the bias test statistic. Figure 34 shows these statistics for the 20 groups.

As previously documented (Figure 16), there is a strong relationship between DTS and idiosyncratic risk. The new model captures this very well across DTS portfolios, as the standard deviation of standardized returns does not show any systematic pattern across DTS groups. The old risk model forecasts idiosyncratic risk as the average cross-sectional residual return per rating bucket, scaled by OASD. The use of OASD only does not capture the risk-DTS relation, and it also understates the overall level of idiosyncratic risk by a significant margin.

Figure 34: Standard Deviation of Standardized Returns (left) and Excess Returns (right) by DTS-Sorted Group for Ten Long-Short Portfolios, December 2005-May 2009



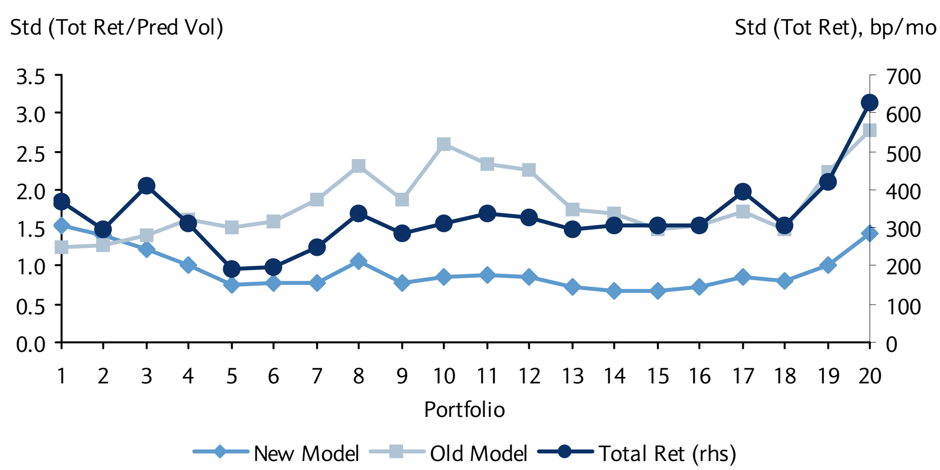
Source: Barclays Capital

Total Return Portfolios

While our focus thus far has been the excess return over the curve, many investors are concerned about total returns as well. Moreover, since 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 also on a total return basis.

We analyze 20 DTS-sorted portfolios as we did in Figure 26, but now using total returns. One issue with such a test is the nature of our sample, composed mostly of floating-rate bonds. For these bonds, the total return and its forecast risk typically do not differ significantly from the excess return measures, since they have little theoretical exposure to the curve. Thus, in what follows, we perform the analysis using only the fixed-rate bond sample.

Figure 35: Standard Deviation of Standardized Returns (left) and Total Returns (right) for 20 Portfolios Sorted by DTS, Fixed-Rate Bonds Only, December 2005-May 2009



Source: Barclays Capital

Figure 35 shows that the DTS nature of returns for this subsample is a bit weaker, and inexistent for the low DTS portfolios. This result for low DTS portfolios comes from the fact that the main source of total risk for those portfolios is the curve, which does not depend on spread level. Overall, one can see that the new model performs well across all DTS groups, both on an absolute and relative terms. The old model has a more volatile behavior, significantly under predicting risk for medium DTS level groups. This is true even though the old model is calibrated using this sub-sample only.

The overall level of under-/over-predictability is small, but even the risk for excess returns is more precisely forecast for this subsample, as shown in Figure 33 ("All Sample" vs. "Fixed").

Access in POINT

The new HE ABS risk model is implemented in POINT – Barclays Capital's portfolio analytics platform – as part of the Global Risk Model[4] 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 three reports from the report package: the risk summary report, the factor exposure report, and the portfolio issue-specific risk report.

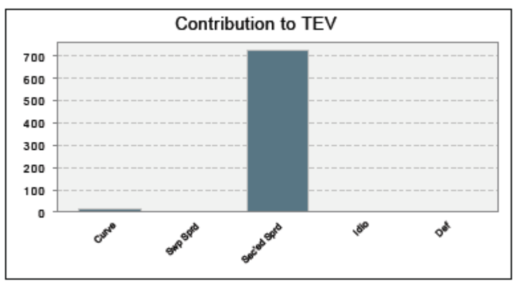
Figure 36: Partial View of the "Portfolio Risk Summary Report" of the POINT risk report for the Barclays Capital ABS Floating Rate Home Equity Index vs. cash, on December 31, 2008

Portfolio Risk Summary Report

Portfolio: US ABS Floating Rate: Home Equity (Statistics)
Index: USD Cash
Reporting Units: Returns in bps/month

Run Date: 09/28/2009
As of Date: 12/31/2008
Base Currency: USD

Factor Partition Summary	Contrib to TEV	Isolated TEV	Systematic Beta
Total	737.1	737.1	0.0
Systematic	736.0	736.5	0.0
Curve	11.3	38.4	0.0
Swap Spreads	1.3	13.1	0.0
Spread Securitized	723.4	725.0	0.0
Idiosyncratic	1.0	27.4	-
Credit default	0.0	0.0	-



TEV Summary	
Total TEV	737.1
Systematic TEV	736.5
Idiosyncratic TEV	27.4
Default TEV	0.0

Portfolio Info	
Last Transaction	N/A
Total MV (MM$)	29.8
Cash MV (MM$)	0.0
Total Notional (MM$)	46.8
Positions Included	653
Positions Excluded	0

Source: Barclays Capital

In Figure 36 we present the top of the risk report first page, which is the "Portfolio Risk Summary Report." It shows the risk of the Barclays Capital ABS Floating Rate Home Equity Index vs. cash, on December 31, 2008. The new risk factors are captured under the "Spread Securitized" group in the factor partition. The "TEV Summary" on the top-right corner shows that the total risk of the index is 737.1bp/month, with 736.5 coming from the systematic factors, 27.4 from idiosyncratic, and none from default since we capture the entire default risk for this asset class in the systematic and idiosyncratic parts. 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."

In Figure 37, we show a snapshot of the "Risk Factor – Full Detail" section of the same report package. The section (partially shown) presents the set of systematic factors the portfolio and benchmark loads 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

[4] Running a risk report on a portfolio containing USD securities with Class 4 equal to "ABS" and Collateral Type equal to "HOMEEQU" accesses the model for those securities.

associated with that factor. As described in the paper, this is the list of systematic factors one should expect an HE ABS portfolio to load on.

For example, the second row shows the DTS factor, named "USD ABS HEL DTS." Its sensitivity is in Yr*%, since DTS is OASD*OAS. The value of DTS loading is 36.4 for this index as of December 31, 2008. Further, the forecasted volatility of the factor as of that date is 16.35, which means that for every 100bp increase in OAS, we expect a 16.35bp increase in spread change volatility. This is how the "TE impact of an isolated 1std. dev. up change" is computed, by multiplying the "Factor Volatility" with "Net Exposure." Thus, if the DTS factor experiences a 1 std. dev. increase, the tracking error of this index increases 595.9bp.

Figure 37: Partial View of the "Factor Exposure – Full Details" of the POINT risk report for the Barclays Capital ABS Floating Rate Home Equity Index vs. cash, on December 31, 2008

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
ABS SPREAD										
USD ABS HEL Ultra High Grade	OASD (Yr)	2.500	.000	2.500	257.17	-642.96	-101.21	35.314	11.98	88.29
USD ABS HEL DTS	DTS (Yr*%)	36.457	.000	36.457	16.35	-595.91	-532.37	11.806	58.40	430.42
USD ABS HEL Short WALA	OASD*WALA (Yr*Mo)	59.658	.000	59.658	5.99	-357.11	151.01	-1.226	-9.93	-73.17
USD ABS HEL Long WALA	OASD*WALA (Yr*Mo)	52.199	.000	52.199	3.04	-158.76	17.12	-.071	-.50	-3.69
USD ABS HEL Avg Life	OASD*(F(AL)-AvgF(AL)) (Yr*LogYr)	.481	.000	.481	37.08	-17.82	193.22	-9.721	-.63	-4.67
USD ABS HEL Floating Coupon	OASD (Yr)	2.500	.000	2.500	100.39	-251.00	-361.19	49.197	16.69	123.00
USD ABS HEL Delinquencies	OASD*Delinquencies/WALA (Yr*%/Yr)	1.820	.000	1.820	131.41	-239.18	-182.42	32.524	8.03	59.20
USD ABS HEL CLTV	OASD*CLTV (Yr*%)	8.092	.000	8.092	5.08	-41.08	-276.25	1.903	2.09	15.40
USD ABS HEL Full Doc	OASD*(FullDoc-AvgFD) (Yr*%)	-5.308	.000	-5.308	2.40	12.74	-139.25	.454	-.33	-2.41
USD ABS HEL Seasoned Hybrids	OASD*%ResetARM (Yr*%)	176.877	.000	176.877	1.10	-193.84	-346.12	.515	12.35	91.03

Source: Barclays Capital

Lastly, we (partially) show the "Portfolio Issue-Specific Risk" part of the risk report, which details the idiosyncratic risk of the top securities by market value (Figure 38). According to this report, the security with the largest market value as of the report date is "OOMLT06-1:1A1", which is an Option One mortgage loan trust. It has an OAS of 1098bp and a market value equal to 1.04% of the total index. The systematic TEV associated with this issue is 3.35bp/month and the idiosyncratic TEV is 2.57bp/month.

Figure 38: Partial View of the "Portfolio Issue-Specific Risk" of the POINT risk report for the Barclays Capital ABS Floating Rate Home Equity Index vs. cash, on December 31, 2008

Identifier	Ticker	Description	Currency	Coupon (%)	Maturity	Current OAS (bps)	MV issue weight (%)	MV issue net weight (%)	MV issuer net weight (%)	Marginal systematic TEV	Systematic TEV	Idiosyncratic TEV	Issuer idiosyncratic TEV
OOMLT06-1:IA1	OOMLT	Option One Mortgage Loan Trust	USD	.69	1/25/2036	1,098	1.04	1.04	1.04	3.1384	3.35	2.57	2.57
CWL06-25:1A	CWL	CWABS Asset-Backed Certificate	USD	.61	7/25/2035	774	.91	.91	.91	5.8071	6.31	3.89	3.89
ARSI05-W2:A1	ARSI	Argent Securities Inc., Asset-	USD	.73	10/25/2035	1,034	.84	.84	.84	6.3889	5.59	4.18	4.18
CWL06-18:2A2	CWL	CWABS Asset-Backed Certificate	USD	.63	5/25/2033	2,471	.79	.79	.79	7.1880	5.76	3.40	3.40

Source: Barclays Capital

CONCLUSION

The second-generation Barclays Capital US Home Equity ABS Risk Model incorporates important innovations such as the relationship of both systematic and idiosyncratic to the Duration Times Spread (DTS) and the addition of factors based on the characteristics of the underlying collateral. The resulting model is significantly more responsive and adjusts risk forecasts quickly to the post-2007 high-volatility environment. It also explains well the cross sectional variation in volatilities. Out-of-sample tests suggest the model performs significantly better than the legacy one.

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Analyst Certification(s)

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