A New Data-Driven Fixed-Income Risk Framework:

Leveraging Advanced Statistical Methods to Construct Robust Issuer Credit Curves and Market Surfaces as the Basis for Granular, DTS-style Risk Modeling

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November 2019

1 Introduction

Modeling potential losses of a credit-risky bond portfolio based on granular, issuer-level return data is notoriously difficult. A myriad of data-quality concerns arise, driven by a vast, frequently illiquid market for which evaluated pricing is often stale, inconsistent or simply missing. Many issuers have only a small number of bonds outstanding. In fact, generally less than half of the issuers in USD high yield index portfolios have more than one bond outstanding that meets standard requirements for inclusion in a model estimation universe (sufficient maturity, etc.). Thus great care must be used to extract signal from data noise.

To produce consistent time series of returns for use in historical simulations or in constructing covariance matrices from parametric risk or Monte Carlo simulations, it is necessary to work with fixed-term spread returns (as opposed to bond price returns). Construction of an issuer spread term structure from bond prices is challenging due to the data issues mentioned above. Advanced modeling techniques are required to trim outliers and infer term structure shapes from limited and noisy data, so that the ultimate spread return time series used to measure volatility reliably captures issuer risk and not noise. It is also essential to have an issuer spread curve quality measure to assess when the issuer-specific data is of insufficient quality to produce reliable curves, and a market currency-region-sector-quality curve to serve as a more reliable proxy for risk assessment.

In this paper we describe Qontigo's next generation of fixed-income granular risk models based on a new proprietary methodology for constructing issuer spread curves and market surfaces. The time series of spread returns used in the risk analysis are computed as modified log returns[1], so that in the linear parametric model, the price return exposure to this risk is $-D \times S_{\text{oas}}$, i.e. duration times spread. Thus the new framework incorporates DTS-style risk models.

The paper is organized as follows. First, we address the fundamental question of what a bond issuer

[1] Modified log returns effectively give relative spread change returns above a user-specified spread threshold and absolute spread change returns below the threshold. See the section "Appendix: DTS Implementation" for more details.

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is by introducing the concept of Risk Entity and describing how we map a bond to an issuer, currency, country, rating and sector. Examples are provided to illustrate the advantages of our approach. Next, we discuss the importance of building issuer curves and highlight how the new methodology addresses some of the key data challenges. This is followed by a discussion of our implementation of DTS-style risk models. In the next section, we describe how issuer curves are used to build the risk models. The paper concludes with a discussion of backtest results that demonstrate the ability of the new methodology to accurately capture the risk of bond portfolios.

2 Why Risk Entities?

Risk Entity is the new framework for addressing the question of what constitutes a debt issuer and which bonds should be associated with an issuer in deriving issuer spread curves. The determination is based on a hierarchical rule-based framework that helps rationalize complex organizations with multiple subsidiaries, holding companies, financial arms and other structures that may issue debt. The process also identifies a unique sector and country of risk for each Risk Entity. There may be a number of different issuer spread curves associated with a Risk Entity, corresponding to debt issued in different currencies and at different seniority levels.

To address why it is necessary to have a rigorous process to identify debt issuers, we analyze the simplest mapping possible - assigning all bonds to the ultimate parent as the issuer. As an example, consider General Electric Co. as the ultimate parent and its 158 subsidiaries and sub-subsidiaries, which in some cases go six levels deep, and of which nine issue debt in addition to the parent company. Figure 1 provides a view of the corporate hierarchy of the debt-issuing subsidiaries. Suppose we are interested in building the USD senior spread curve. Three subsidiaries plus GE Co. issue USD Senior debt. As of September 2019, in total there were 94 USD Senior bond issues outstanding that met our criteria for inclusion in the bond construction universe. These criteria include maturity greater than six months, outstanding notional greater than $25 million, non-convertible, etc. The substantial majority (83) are issued directly by GE Co. It would be tempting to use all 94 bonds to construct a USD-SEN curve and associate all senior dollar bonds under the GE parent umbrella with this curve. However, one subsidiary, Baker Hughes Co., is significantly different. First, while GE is classified in the capital goods sector, Baker Hughes is in energy. Second, GE is rated BBB+/Baa1 by the major rating agencies, while Baker Hughes is rated A-/A3. Most significantly from a market perspective, each company issues its own equity, which trade separately. It is not surprising that the bond markets also regard the two companies as different, and there is a significant difference in how their debt trades. This can be clearly seen in Figure 2. The plot shows our estimate of the 5-year USD senior issuer spread for both companies. If all bonds were simply mapped to the ultimate parent, the spread would be dominated by the GE Co. bonds, and the during the fall of 2018, when the GE Co. spread blew out, the risk of the Baker Hughes bonds would be greatly overstated. It is clear that identifying GE Co. and Baker Hughes as separate debt issuers, contributing risk to different sectors and rating cluster curves, provides a more accurate picture of risk.

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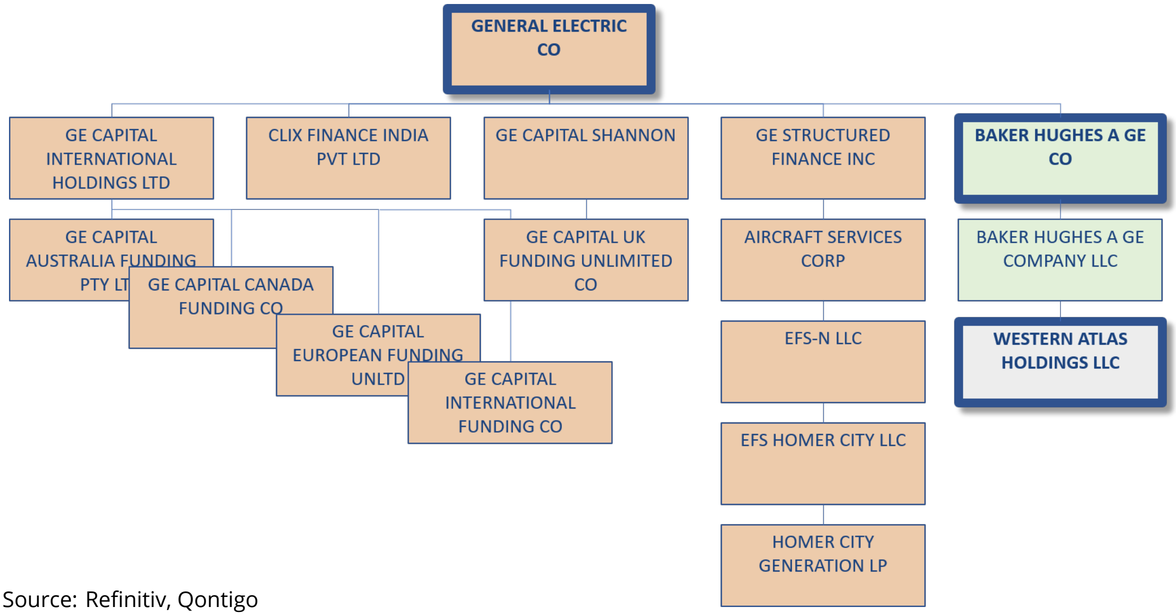

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Figure 1: *Hierarchy of debt-issuing subsidiaries of the ultimate parent General Electric Co, illustrating which subsidiaries belong to distinct Risk Entities.*

At the other extreme, one could also consider mapping each issuing subsidiary as its own Risk Entity. In the GE Co case, this would lead to 10 separate issuers as opposed to our current mapping of three issuers: GE Co (29 curves for various currency and seniorities); Baker-Hughes (1 curve); and Western Atlas Holdings (1 curve). The remaining seven are mostly local financing arms of GE that are very much tied to the performance of their parent; several of these subsidiaries have only a few outstanding bonds. Attempting to model issuer spread curves for these subsidiaries separate from the parent's curve of the same currency and seniority would add more noise to risk estimation for portfolios that include their debt, without adding additional insight into the signal. This level of granularity would also limit the usefulness of risk decomposition analysis by issuer for reporting and risk-management purposes.

For the reasons illustrated in this example, we have developed an algorithm that seeks an optimal middle ground between the too coarse approximation of assigning all debt to a single ultimate parent issuer and the too granular approach of estimating issuer curves for each subsidiary that issues debt. A Risk Entity combines a set of subsidiaries and related legal structures, some of which have issued debt, that have substantially similar properties to create a single 'issuer' entity. This Risk Entity has a unique country of risk and sector that most appropriately capture the characteristics of the debt issuance associated with it. A common occurrence is for a bond issued by a financing arm subsidiary to have an industry group code of Diversified Financial; however, from a credit risk perspective, we often find such financing subsidiaries more appropriately belong to a Risk Entity higher up the tree and should inherit the industrial sector of the parent. Thus the sector to which a bond is mapped is not necessarily the same as the industry group code of the subsidiary that issued the bond. The same holds true for country of risk.

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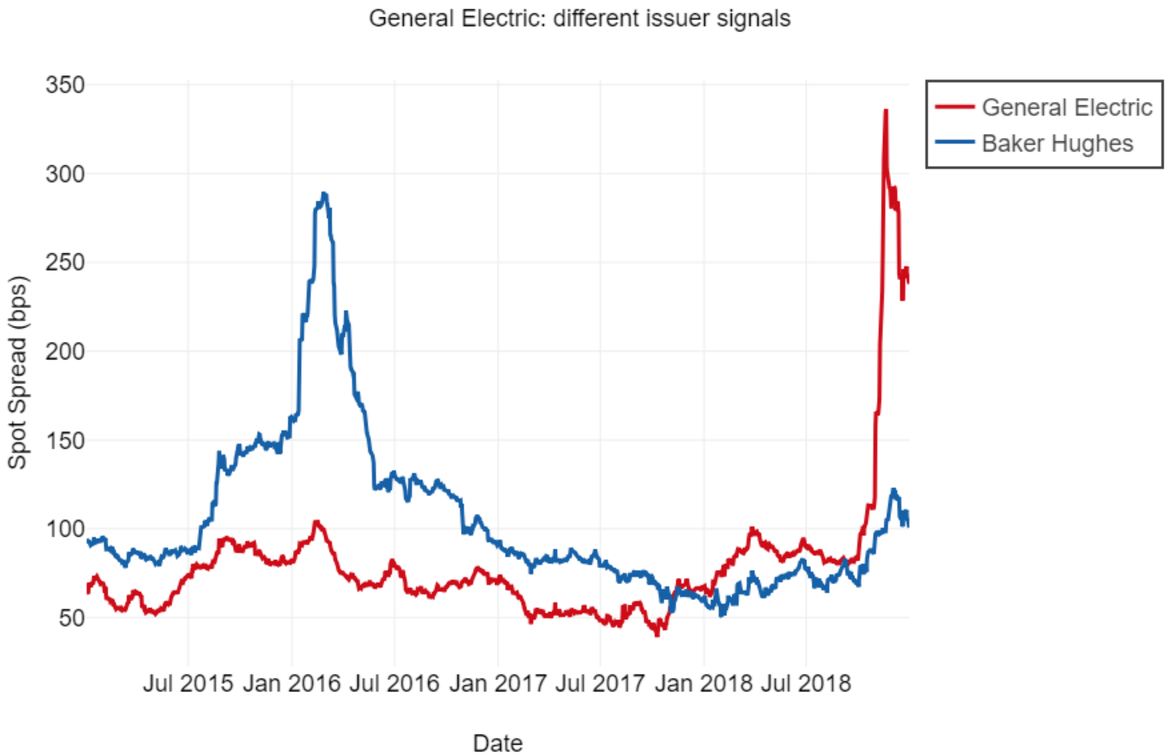

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Figure 2: *Time series of 5-year USD senior spread for GE Co and Baker Hughes.*

The algorithm that determines the Risk Entity structure of an organization considers a complex array of data and signals from several sources. There is generally no single indicator that can be used to determine entity groupings. In addition to the tree hierarchy of legal entities, signals considered include issued equity, traded CDS, ratings, quoted ticker and guarantor/related borrower relationships.

While the Risk Entity mapping is generally stable from day to day, it is far from static over time. Mergers, acquisitions and other corporate actions, together with varying forms of financing and degrees of implicit and explicit debt guarantees by parent units, mean that the relationships of subsidiaries and the identity of the issuer of a bond can change through time. We therefore recalculate the Risk Entity structure on a daily basis and monitor any changes, both to assess the impact of any corporate actions and to monitor data quality and consistency.

To illustrate the importance of monitoring and updating the Risk Entity structure, we consider the case of Deutsche Telekom and T-Mobile US, Inc. In 2001, Deutsche Telekom acquired VoiceStream Wireless and rebranded it as T-Mobile, which became a direct subsidiary of Deutsche Telekom. In 2012, T-Mobile merged with Metro PCS through a reverse takeover structure under the T-Mobile name and the combined entity issued public equity. The new company remained a subsidiary of Deutsche Telekom, which initially guaranteed the debt issued by the new T-Mobile. Due to this guarantee, T-Mobile was mapped to the same Risk Entity as Deutsche Telekom. Eventually, the guaranteed debt was retired, and currently the two companies have separately traded equity and significantly different credit ratings (BBB+

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for Deutsche Telekom and BB+ for T-Mobile). Therefore, the Risk Entity structure was updated and now reflects two separate Risk Entities with different countries of risk.

3 Why Curves?

With the problem of how to identify debt issuers resolved, the questions remain as to why it is necessary for risk management purposes to build full spread term structure curves and how such curves can be reliably estimated for issuers with only one or two bonds outstanding. Given the complexity of producing thousands of issuer curves on a daily basis, while maintaining an extensive curve history, it is important to understand the advantages of this approach.

As a preliminary comment, we consider the necessity of estimating risk through spread returns, as opposed to individual bond price returns. In a linear risk model, one could in principal decompose the price return into a sum of treasury, swap, volatility and credit price returns, then compute the covariance of each price return time series as a risk estimator for the bond. The difficulty stems from the need to use a lengthy time series of returns (generally at least one year, while four or five years is often used) to estimate volatility and correlation. Over such a period, the time to maturity of any individual bond shortens significantly (if it doesn't mature or default), and the volatility of the price returns changes through time due to this effect. If one instead works in rate and spread return space, much of this effect is eliminated by capturing the bond's shortening maturity in the exposure to the risk factors through the bond's durations. The effect can be further reduced by using a fixed term point on the spread curve to estimate the covariances instead of the individual bond's spread return, which will roll down the curve over time. There is also the difficulty that individual bond price or spread returns are often unreliable due to poor data quality or missing data, so that a more robust spread return estimation procedure ultimately captures the risk more accurately.

We next consider a common, simple approach to determining issuer spread, namely taking a notional-weighted average of the option-adjusted spreads (OAS) of the outstanding bonds associated with the issuer in a given currency. Typically the set of bonds included in this calculation is trimmed to remove bonds with short times to maturity (e.g. requiring the bond to have at least 6 months to maturity), small outstanding notional and any obvious outliers in OAS level. Although the spread level at a term of one year can be quite different from a term of 10 years, with differences often greater than 100 bp for investment-grade companies, the thought is that the primary risk lies in parallel shifts of the spread curve, and that volatility estimated from changes in the average spread adequately captures this risk, while eliminating much of the spurious noise and data errors.

While this is often a reasonable approach, there are two major challenges in this method that can lead to significant misestimation of risk. The first concerns the stability of the set of bonds for which the average spread is computed. For the bulk of issuers with relatively few bonds outstanding, the elimination of a single bond from one day to the next can lead to a substantial change in the estimated average spread. Such a jump then feeds into the volatility estimate, which is typically based on the spread return time

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series using an exponentially weighted moving average. The spread jump can create a volatility spike that persists until it decays away over several months or longer, although this is a completely artificial source of risk. Figure 3 illustrates this point for the company Loews Corp. The plot on the left shows the average bond OAS and the issuer spread curve, as well as the spreads of the set of issuer bonds used in the calculation, on September 14, 2015 and September 15, 2015, the day one bond drops out of the eligible estimation set due to shortened time to maturity. As the shorter maturity bond has a substantially lower spread of around 65 bp, the average spread jumps from around 159 bp to around 190 bp when it drops out of the average. However, the issuer curve at the shorter end barely moves from one day to the next. We consider the impact on volatility in the plot on the right. The yellow line represents the volatility of the changes in the average spread level. The large volatility spike from September 14^{th} to 15^{th} in the average level can clearly be seen; however, there is no noticeable impact on the issuer spread curve volatility, plotted here for both the 5-year and 20-year point.

The second challenge of using the average spread approach, compared with building the issuer spread curve, can also be seen in the plot on the right of Figure 3. We observe that the volatility at the shorter end of an issuer spread curve is often substantially higher than at the longer maturities. This effect is necessarily lost when the average spread is used to compute volatility. The impact can be seen over the period June 1 to June 2, 2015 in the volatility plot. On this date, a Loews bond with duration of around 7 years jumped from 96.6 bp to 110 bp and the short maturity bond went from 28.6 bp to 38.7 bp, while the long maturity bonds moved relatively little. The impact on the 5-year spread curve volatility is notable, while the effect on the 20-year spread curve volatility is small, as is the change in the average level volatility. The events of September 15 illustrate that the average spread method can lead to artificial spikes in volatility due to small numbers of bonds, while the events of June 2 show that the average method may miss significant increases in volatility at the short end of the curve if stabilized by the longer maturity bonds.

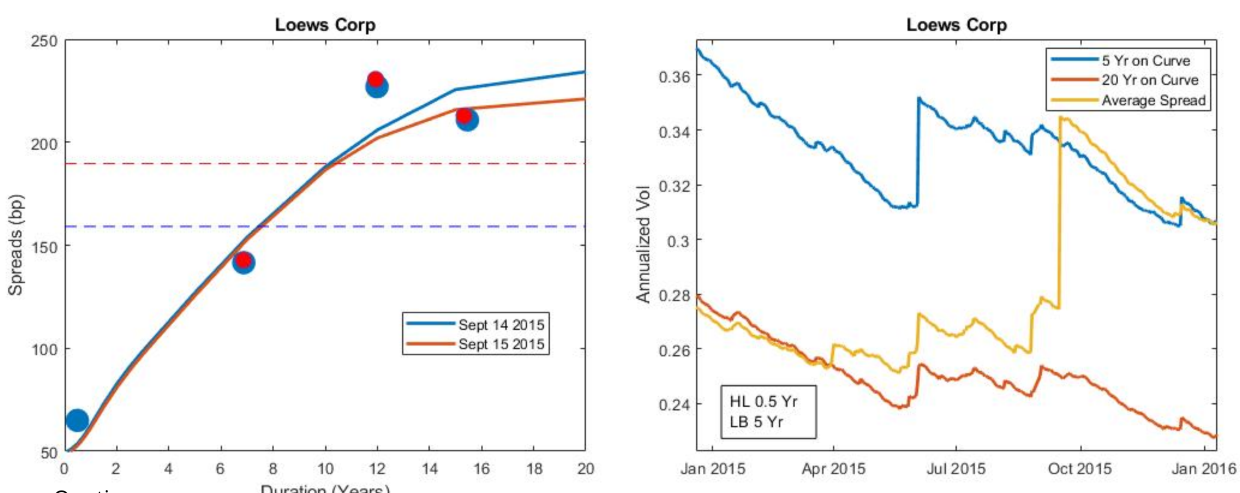

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Figure 3: *Issuer spread calculations for Loews Corp on Sept 14 and Sept 15, 2015 based on the average method (dotted line) and the new spread curve (solid line), and the impact on volatility estimation.*

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To further explore the importance to volatility estimation of modeling the full issuer spread term structure, we consider the high yield company Frontier Communications. Figure 4 shows a 12-year history of the issuer spread curve volatility at five maturities: 6 months, 1 year, 2 years, 5 years and 10 years. The volatility is computed from weekly overlapping log-returns (annualized by multiplying by $\sqrt{52}$) using an exponentially weight moving average estimator with a half-life of 0.5 years and a 5-year window. We see that the volatility at the 6-month point is often three to four times larger than the volatility of the 10 year point. We also see that volatility of the 10-year point tends to be more stable through time. This is an important effect to capture when using a duration-times-spread (DTS) exposure framework. Because the spread term structure is often substantially upward sloping, if a constant volatility is assumed across term, risk for shorter duration bonds could be substantially underestimated, while risk may be overestimated for longer duration bonds.

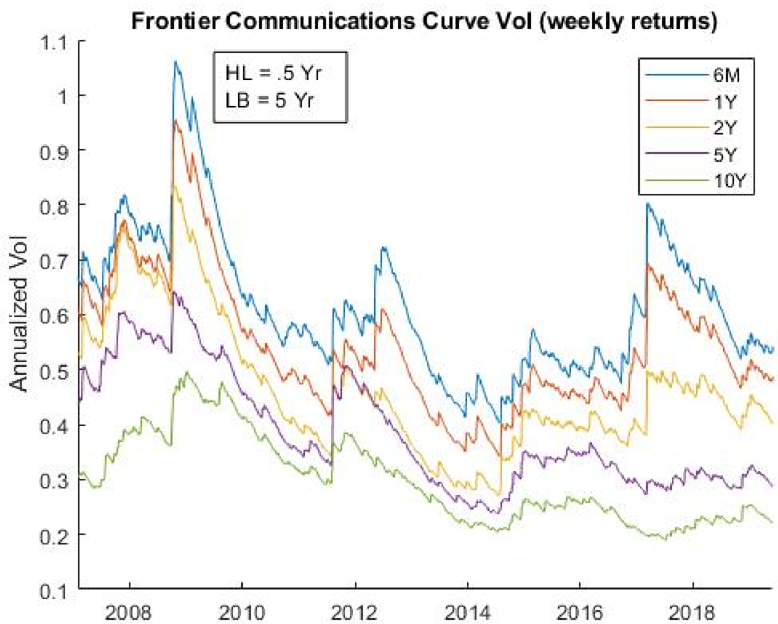

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Figure 4: *Time series of volatility at different maturities on the issuer spread curve for Frontier Communications.*

Another advantage of building curves concerns the noise inherent in bond spread data and its impact on covariance estimation. The process we have developed for building issuer curves is in many ways a method for extracting signal and de-noising the data. The curve structure itself is a key component in identifying outliers arising from bad pricing data. It may not be obvious from only looking at the spreads associated with an issuer as to whether a single spread is an outlier and should be removed or whether the term structure is steep or has an atypical shape and the bond should be included. When based on cleaner data and stronger signal, curve changes from day to day or week to week better reflect the true uncertainty stemming from changing market conditions and economic prospects of the issuer. When the average spread method is employed, there is additional data noise volatility introduced.

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The process is quite complex to generate thousands of stable issuer spread curves that give spread time series that accurately capture spread-change risk. For some issuers, such as General Electric Co., there may be more than 80 USD senior bonds over a wide range of maturities with which to build a curve, so that most approaches would produce a reasonable curve. However, the majority of issuers are more like Loews Corp. with three or four (or fewer) bonds in the estimation set. For these issuers it is essential to use peer information to determine how the market is pricing similar bonds across currency, sector, credit quality, liquidity and maturity to determine the shape of the credit curve, which is then adjusted to best fit the available spread data for the issuer. We employ a proprietary weighted optimization method to fit curves in log-spread space to hundreds of similar bonds (weighted by closeness in a measure of similarity) and adjusted for average level. Crucial to this process is the removal or down-weighting of bonds of questionable data quality in the estimation set. We also filter by both comparable spread level and comparable spread change level in identifying potential outliers. Weighting towards consistent spread change is particularly important in accounting for stale quotes for illiquid bonds. For example, if a bond's spread does not move when most of its peers' spreads substantially tighten, it may be a sign that the price was not correctly updated. As a final step, a statistical scoring method is applied to each curve to rate the curve's quality. Only curves of sufficient quality are used directly in the risk model.

In addition to issuer curves, a set of 'cluster curves' are produced on a daily basis. These are spread term structures constructed by averaging all available issuer curves belonging to a group defined by currency, region, sector, and rating. The various rating curves in a currency-region-sector cluster are adjusted to create a smooth surface in rating-maturity space, such that the spread increases monotonically with deteriorating credit quality as defined by rating. Fitting a smooth surface has the important benefit of limiting downgrade spikes to rating curves when a major issuer's rating is downgraded and a large percentage of bonds making up the universe of one rating-sector move to a different rating-sector universe. In Figure 5 we observe this effect for the BBB Euro-Sovereign curve when Greece was downgraded from BBB+ to BB+ by S& P in April 2010. The cluster curves remain stable while the average spread of the BBB Euro-Sovereign universe blows out then sharply tightens after the downgrade.

The rules that determine whether a bond is mapped to an issuer curve or a cluster curve are based on the quality of the issuer curve, as measured by the combination of a density score and an outlier score. The density score is simply the percentage of days over the last year where there was at least one bond price available to build the issuer curve. The outlier score is determined by evaluating curve movements relative to a curve-specific projected distribution of probability-weighted curve movements. A bond is mapped to a cluster curve when its issuer curve receives a low quality score. In addition, the cluster curves are used to augment the issuer-curve history and fill in gaps for the purposes of risk estimation.

As a result of this process, Qontigo produces over 11,000 spread curves, corresponding to around 6,000 issuers, over 30 currencies and multiple subordination tiers, on a daily basis as sufficient data allows. More than 6,000 cluster curves across over 30 currencies, 9 regions, 21 ratings and multiple sector/industry levels are available as proxies and rating benchmark curves.

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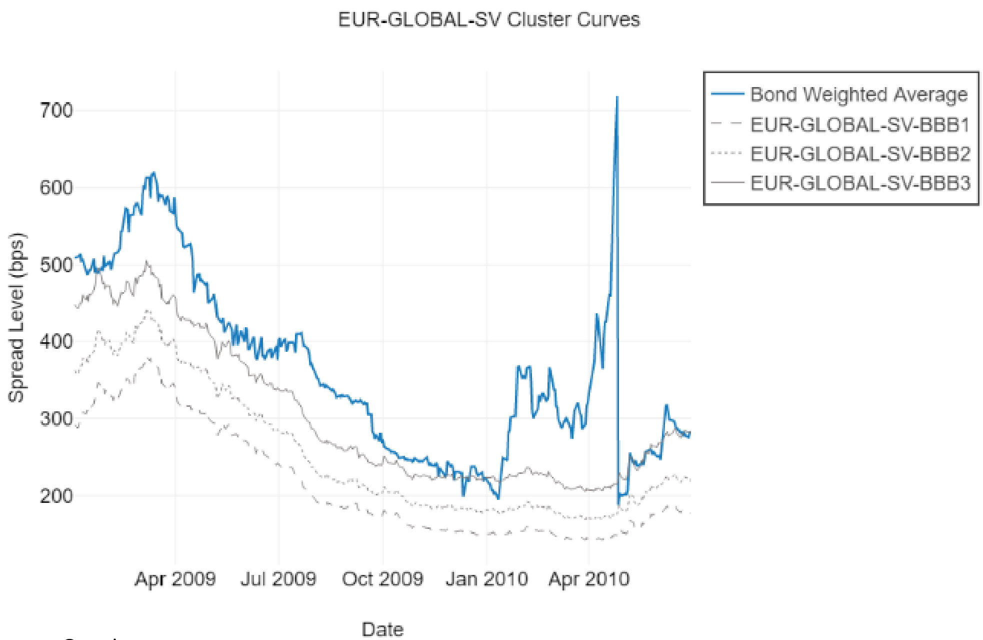

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Figure 5: *Stable cluster curves for BBB Euro-Sovereigns in April 2010 compared with the average spread for the cohort driven by the deteriorating credit quality of Greek sovereign debt followed by its downgrade.*

To compute individual bond analytics, such as spread duration, the issuer spread curve is adjusted by a parallel shift in spread chosen such that when the bond is priced using the shifted curve, the market price is recovered. Durations, etc., are then computed as numerical derivatives (i.e., through 1 bp shocks up and down) to the adjusted issuer spread curve as appropriate using a variety of pricing methodologies depending on instrument features (callable, convertible, floating-rate, etc.).

4 Why DTS?

Once we have established a substantial library of daily issuer spread term structures, the question remains as to the best method of estimating bond price risk that leverages the issuer spread curves. Under traditional bond modeling, the percentage price change of a bond subject to a small parallel shift to its spread curve ΔS can be expressed (under linear approximation) as

$$\frac{\Delta P}{P} = -D_{\text{eff}}\,\Delta S \tag{1}$$

where D_{eff} is the effective spread duration of the bond. For this model the credit spread risk component of the bond price risk is determined by the volatility of its absolute spread changes with exposure given by the effective duration. Alternatively, this can be expressed as

$$\frac{\Delta P}{P} = -\left(D_{\text{eff}} \times S_{oas}\right)\frac{\Delta S}{S_{oas}}. \tag{2}$$

Under this formulation, the credit spread risk is determined by the volatility of the relative change in spread, while the exposure is now the effective duration times the bond's option-adjusted spread.

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This idea of Duration Times Spread, or DTS, as a better measure of spread risk exposure for corporate bond portfolios was introduced in early 2007 in a paper[1] by several Lehman and Robeco researchers. The intuition is that the level of spread change volatility should be proportional to the spread level, so that one would expect a bond trading at a 2,000 bp spread to have substantially higher absolute spread change volatility than a bond trading at a 100 bp spread. In other words, looking at relative spread changes is a more meaningful way to measure risk than looking at absolute spread changes. This is borne out in empirical studies showing that for higher spread bonds, price volatility is proportional to spread level. From a statistical perspective, this means that for higher spread levels, the time series of relative spread changes is more stationary (i.e., the volatility of the time series is more stable through time) than the time series of absolute spread changes.

However, it is also empirically true that at lower spread levels, spread change volatility does not appear to be consistently proportional to spread level. This effect was also discussed in the Lehman and Robeco paper. While spread change volatility varies across names, there is no clear trend that higher spreads mean higher volatility for bonds with spreads below a certain threshold. Figure 6 illustrates this point over a large universe of bond issuers. The plot shows issuer spread volatility versus spread level. We see that below a threshold of around 100 bp, there is on average no relationship between volatility and spread level, while above this threshold a linear relationship appears. As a specific example, consider the daily 5-year spread level over the period January 2017 to August 2019 of Cargill (spreads ranging from 62 bp to 100 bp) and Johnson & Johnson (spread ranging from 10 bp to 62 bp) . The Cargill spread is on average 3.1 times larger; however, the annualized volatility of daily returns over this period for Cargill is around 31%, compared with an annualized volatility of daily Johnson & Johnson returns of around 33%.

In the new granular fixed-income risk models, the DTS framework is expanded in several significant ways. First, we have extended DTS to multiple views of risk, including application to both granular issuer spreads and the rating/sector cluster spreads. Second, we have extended the application of DTS shocks to multiple risk nodes along the credit spread curves through the introduction of key rate DTS durations for parametric models. In addition we allow the transition threshold from absolute to relative returns to be set as a user-defined parameter in the granular risk model, although based on our research, we set the default value to 100 bp. The final key innovation extends the methodology to simulation. The name DTS inherently suggests a linear risk model with the credit spread factor exposure given by 'duration times spread'. However, for a full-repricing Monte Carlo or historical simulation, it is also possible to sample the spread risk factor returns as relative changes above a threshold and absolute changes below. The shocked spread curve for a bond can then be computed based on the spread shocks corresponding to the sampled risk factor returns, and the bond can be repriced under the shocked curve. Thus the DTS idea extends to full repricing, even when a duration exposure is not part of the calculation.

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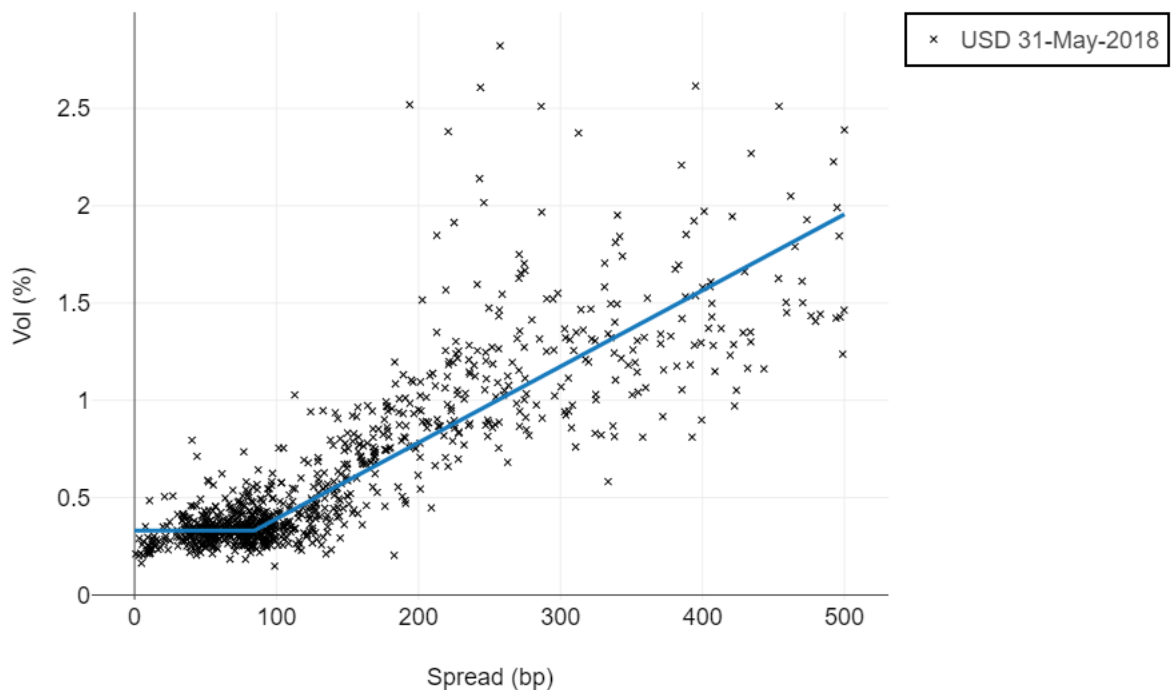

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Figure 6: *Issuer spread change volatility plotted against spread level. The results show that above a certain spread level, volatility is proportional to spread level, while below this threshold, volatility does not scale with spread level.*

5 Building Granular Risk Models

Once a daily production process and history of robust, stable and reliable issuer spread curves and cluster curves is available, risk factors associated with the spread curves can be combined with government rate, swap rate and rate volatility risk factors to build a sophisticated granular risk model for a portfolio of bonds. In this model, each bond for which there is an associated issuer spread curve is mapped as having exposure to changes in selected treasury rates, swap rates, rate volatility (for bonds with optionality) and a set of user-specified nodes (e.g. the 2-year and 5-year points) on the issuer spread curve, where the rates and curve correspond to the appropriate properties of the bond. For bonds for which there is no available issuer spread curve, any spread risk is captured through mapping to the appropriate cluster curve.

A key risk analysis that is enhanced through the availability of the new issuer spread curves is granular historical simulation. In addition to the historical data available for rates and volatility, we have time series data going back as far as July 2002 for many of the new issuer and cluster curves. To compute the historical simulation we first select a set of historical dates from which to sample the returns of the risk factors. This could be specified as one contiguous period (e.g. the most recent five years or July 1, 2007 to July 1, 2009) or a set of time periods that are combined for purposes of the simulation. For each date in the set, we compute the desired returns - e.g. daily, 5-day (weekly) or 20-day (monthly) - for all

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risk factors relevant to the portfolio, then update the levels of all the risk factors (rates, spreads, etc.) under the return 'shock' for this specific date, starting from the risk factor levels given on the analysis date. Thus for each historical date, we have a sampled set of new levels of the risk factors, based on the historical returns. Each position in the portfolio is then repriced under the new levels, and a price return for each position under the historical spread return scenario can be computed. In this way, a distribution of individual bond returns and the portfolio return can be computed with each sample point corresponding to the risk factor returns of a specific historical date. One advantage to this method is that the return distribution can be constructed without relying on distributional modeling assumptions or parameter estimation.

To illustrate in more detail, we consider a specific granular risk model defined by the choice of risk factors for the treasury, swap, credit and volatility risk components. We describe how the risk model is applied to a historical simulation of a US high yield corporate bond benchmark portfolio using monthly (20 trading days) returns over a fixed period, say April 1, 2013 to March 31, 2018, with a portfolio analysis date of March 31, 2018. For the US treasury risk, we select six key rates - the 6 month, 1 year, 2 year, 5 year, 10 year and 30 year rates - for which the monthly returns are computed as absolute rate changes and the new treasury rate curve under the return shock is computed as the treasury curve as of March 31, 2018, plus linearly weighted rate changes interpolated between the key rate nodes. For swap rate risk, we use absolute change returns of the 5-year node on the swap spread over treasury curve. The new levels of the swap spread over treasury curve are computed based on the March 31, 2018 swap spread over treasury curve and the sampled return. For bonds with options, the volatility risk factor is taken as the 2 yr x 2 yr at-the-money swaption volatility level, and the risk factor return is computed as the monthly log-returns of this volatility level, and the shocked volatility level is computed as the March 31, 2018 volatility level times the exponential of the historical log-return. For the credit spread risk, the issuer credit risk factor is the 5-year credit spread taken from the issuer curve (or appropriate cluster curve when no issuer curve is available). The monthly return of the spread factor is computed as the modified log return of the spread level evaluated at the end and beginning of the month period. Given the sampled return of the 5-year point, a new issue-specific spread curve is generated for each bond, as described in the appendix.

Once the new treasury rate curve, swap spread curve, volatility and credit spread curve are computed based on returns from a given historical date, the bond is repriced, and the return relative to the bond price on March 31, 2018 is computed. This provides a set of potential monthly returns for the bonds in the portfolio on the analysis date, and the corresponding portfolio return sample. When all dates in the 5-year analysis window are computed, there are approximately 1,260 samples of individual bond and portfolio returns, making up the return distribution which can be used for risk analysis, such as determining portfolio volatility or Value at Risk. The total number of risk factors used in this example is 6 treasury factors, 1 swap factor, 1 volatility factor, and $N_I + N_C$ credit spread factors, where N_I is the number of unique issuer spread curves available for the portfolio and N_C is the additional number of unique cluster curves required to complete coverage.

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The granular framework can also be used for Monte Carlo simulation or linear parametric portfolio risk analysis. For these methods, the same risk factors and return calculations are employed as in the historical simulation. However, the returns are ordered from most recent to oldest in the analysis window, and the exponentially weighted moving average (EWMA) method is used to compute the covariance matrix of the factor returns. For these calculations it is necessary to specify a half-life and look-back window (the analysis period). In order to increase the sample size for estimating the covariance parameters, weekly overlapping returns may be used with appropriate auto-correlation corrections to compute the covariance matrix for the desired risk horizon (e.g. one month). For the Monte Carlo simulation, the covariance matrix is used to sample factor returns, which are then used to compute bond prices and portfolio returns in the same way as in the historical simulation. For the linear parametric method, for each bond in the portfolio a linear exposure to each risk factor is computed as key rate durations for the treasury and swap factors, vega for the volatility factor and spread duration times the bond's credit spread (or the threshold), i.e., the DTS exposure.

6 Testing the Model

To study the granular model, we first consider the historical simulation of the US high yield corporate bond benchmark described in the preceding section. Figure 7 shows the probability density function of the portfolio returns for a month horizon based on five years of 20-day historical returns with daily overlap through the end of March 2018. A probability density function based on Monte Carlo simulation returns is also plotted, where the associated covariance matrix is computed using 5 years of monthly overlapping returns with a one-year half-life. For comparison, the distribution corresponding to the linear parametric risk model based on the same covariance matrix is also plotted. We observe that while the portfolio return volatility of the historical and Monte Carlo simulations are similar, the historical simulation has a significantly different shape with a much larger down-side risk tail than the linear model or the Monte Carlo simulation. The ability to capture this asymmetric behavior of portfolio returns through historical simulation in a DTS-based framework is a key advantage of the new risk model.

Table 1 shows a risk decomposition of annualized portfolio price return volatility in percent by sector using various methods for the US high yield benchmark as of end of March 2018, as computed using the historical simulation above. The Risk Contribution column is additive by sector to the total portfolio volatility, capturing the volatility of the sector and the covariance with other sectors. The Stand-alone Risk column provides the volatility of the sector weighted by its relative exposure weight in the portfolio. It is not additive, but if an average sector correlation of 77% is assumed, the total portfolio risk can be recovered. The fact that the Risk Contribution and Stand-alone Risk numbers are quite similar implies that the actual sector correlations do not deviate greatly from this average. This is consistent with empirical estimates of US high yield sector cluster curve spread return correlations. The final column, Sector Volatility, provides the volatility of each sector sub-portfolio as computed separately from other sectors (i.e., without adjusting for the sector weight in the portfolio). Comparing the Sector Volatility numbers, assuming equal weighting by sector, with the Stand-alone Risk numbers indicates that on a

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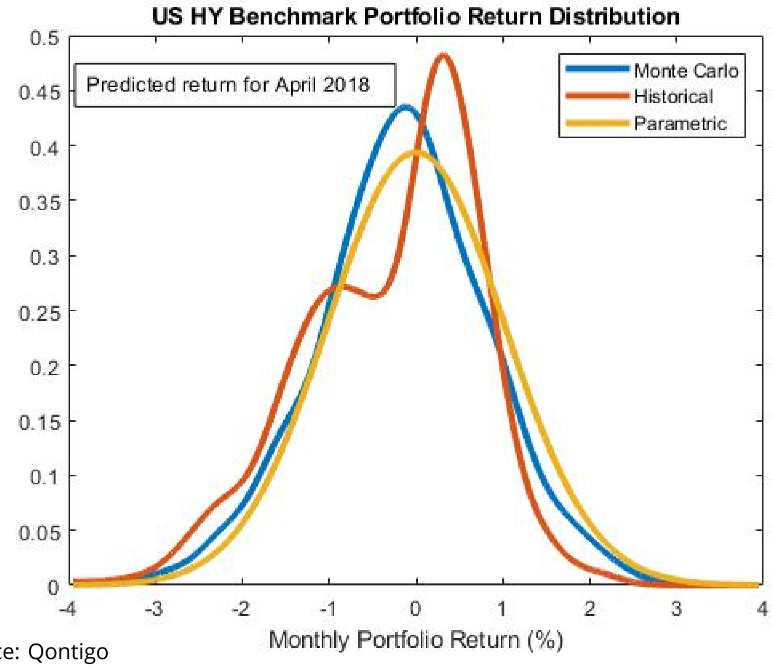

Source: Qontigo

Figure 7: *Return distribution for US high yield benchmark computed through historical and Monte Carlo simulation.*

risk-basis, the benchmark is substantially overweight in energy and overweight in communication, consumer discretionary and financials, and somewhat underweight in consumer staples and health care.

	Risk Contribution	Stand-alone Risk	Sector Volatility
Total	3.55	3.55	3.55
Communication Services	0.46	0.51	4.48
Consumer Discretionary	0.35	0.42	3.22
Consumer Staples	0.12	0.13	4.11
Energy	1.10	1.25	7.19
Financials	0.34	0.35	2.92
Health Care	0.21	0.26	3.79
Industrials	0.27	0.28	2.63
Information Technology	0.15	0.17	2.55
Materials	0.34	0.36	3.60
Real Estate	0.10	0.11	2.84
Utilities	0.11	0.11	3.79

Source: Qontigo

Table 1: *Annualized portfolio risk by sector of US High Yield benchmark as computed by historical simulation.*

We now illustrate the predictive power of the granular risk model through a series of backtests. The results are shown in Figure 8c. To illustrate the flexibility of the risk factor selection, we have also run a monthly back test from January 2006 through May 2019 on the US high yield benchmark using a linear

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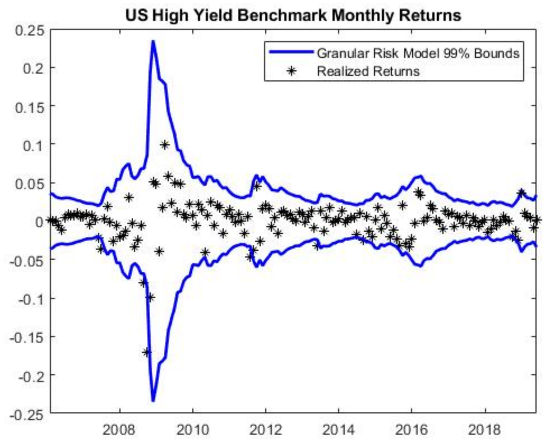
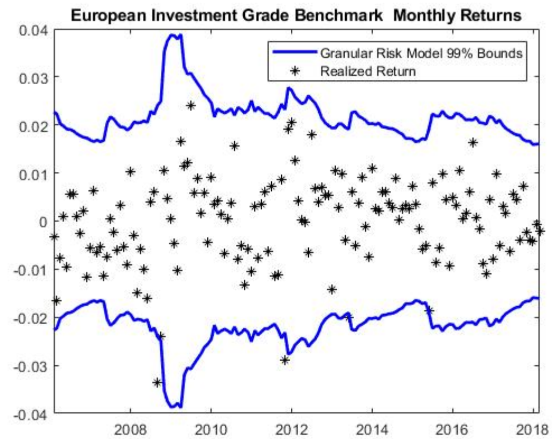
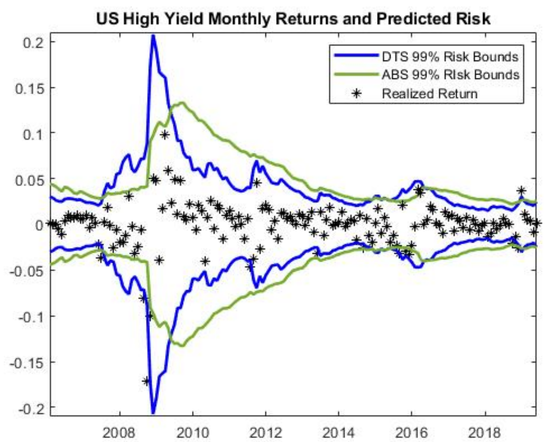


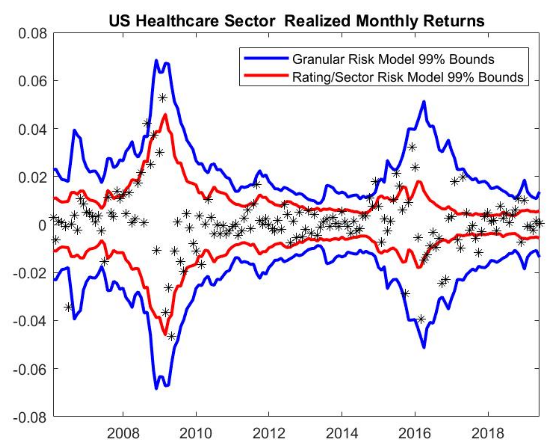
(a) *US high yield benchmark*



(b) *European investment grade benchmark*



(c) *DTS vs absolute change risk models*



(d) *Active sector risk for granular vs aggregate risk models*

Source: Qontigo

Figure 8: *Backtest results highlighting some of the advantages of the new granular fixed-income risk model and issuer spread curves.*

parametric risk analysis based on the same treasury and volatility risk factor settings as the historical simulation, but now using the 3-year node of the swap and issuer credit spread curves. The 3-year tenor is chosen to better match the average duration of the benchmark. For this case, the covariance matrix is estimated using the EWMA method from monthly (20 day) overlapping returns with a look-back period of four years and a half-life of one year. Here we compare the predicted two-side 99% confidence interval (computed as 2.58 times the predicted monthly portfolio return volatility under the assumption of Normality) to the one-month forward-looking realized portfolio return. Figure 8a shows these results. It is clear that the predicted risk tracks the return volatility, with a small number of returns near the 99% risk boundary. While there are eight exceedances of the boundary in 161 monthly observations, five are relatively small, consistent with expected Normal distribution exceedances. The largest exception

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is for October 2008 following the Lehman default. Two other exceptions are connected to the on-set of the sub-prime mortgage downgrades and the impact on sub-prime lenders in July 2007, and the sharp increase in high yield risk in August 2011, tied in part to the US government downgrade from AAA.

We can also test the accuracy of our risk prediction by computing the bias statistic for the model. This is defined as the standard deviation of standardized realized returns, where the returns are scaled by the predicted volatility for the return period. Under a perfect model, the true standard deviation would be exactly 1, with the sample standard deviation $1/\sqrt{2N}$ based on N independent observations under the assumption of a Normal distribution. A bias statistic substantially greater than one indicates a risk model that underestimates risk, while a bias statistic much lower than one indicates over prediction of risk. For the US high yield benchmark risk analysis, the granular model gives a bias statistic of 1.21, which indicates reasonable agreement of predicted and realized risk, although it would be rejected in a hypothesis test. This is mainly driven by the three large event-driven outliers mentioned above. If those months are removed from the sample, the bias statistic is 1.07, well within the confidence bonds for the model and indicating good predictive performance.

The new granular risk model also performs well on investment-grade portfolios and in other geographies. To demonstrate this, we consider a similar back test of returns versus predicted risk over the period January 2006 to February 2018 for a European investment-grade benchmark portfolio. Figure 8b shows the returns plotted together with the predicted two-sided 99% confidence interval computed for the linear parametric risk model under the same EWMA settings for covariance estimation. The result again show that the predicted risk tracks the realized return volatility well, and that the 99% risk boundary captures the extreme returns accurately with three relatively small exceedances over the 146 months. The bias statistic over this period is 1.05, consistent with an accurate risk model.

The next test studies the importance of using a DTS-based risk analysis in the new risk model framework. The results can be seen in Figure 8c. Here we compare the realized total benchmark returns versus predicted risk for a high yield USD benchmark portfolio for two linear parametric risk models with credit risk factors determined by the 5-year point on the associated spread curves. For this analysis, we map all bonds to their rating/sector cluster curves. For the first risk model, we used DTS exposures (effective spread duration times option-adjusted spread) and compute covariances based on modified log returns of the 5-year spread. The second model uses the effective spread duration as the exposure and uses the time series of absolute spread changes of the 5-year spread to compute the covariance matrix. For both models, monthly (20-day) overlapping returns are used to compute the covariance matrix, based on a five-year look-back period and a one-year half-life. Figure 8c plots realized monthly portfolio price return against the predicted two-sided 99% confidence interval for each model. The results clearly show that the DTS-based risk model more accurately predicts the realized risk. Particularly during the run-up to the global financial crisis, the non-DTS model indicates a moderate increase in risk from mid-2007 through September 2008 (3.9% annualized volatility to 5.7%), while risk under the DTS-based model increases by almost a factor of four before spiking in October 2008 and subsequently decaying over the next year. Under the non-DTS model, risk continues to be underestimated until mid-2009. However, the

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memory of the financial crisis persists much longer in the non-DTS model, so that risk is substantially overstated once the crisis has passed until the end of 2013. Moreover, the DTS-based model is much more responsive to the rapidly changing risk in the high yield market. This can be seen in September of 2011, when the DTS-based model shows a rapid increase in risk with subsequent correspondingly larger realized returns, while the non-DTS model shows little change.

Next, to demonstrate the value of using the fully granular issuer curves as the basis of the risk model, compared with a more traditional risk model based on exposure to rating and sector buckets, we compute a back test of the active risk of a high yield single sector portfolio, compared with the high yield benchmark. The issuer-specific risk captured by the issuer curves tends to dominate the active risk (i.e., volatility of the portfolio return in excess of the benchmark return) as much of the systemic rating and sector risk is missing from the excess return. We therefore anticipate that the traditional rating/sector bucket risk model will substantially underestimate risk in the active space, compared with the richer granular issuer model. Figure 8d shows that this is indeed the case. In this chart we consider a portfolio consisting of all the bonds in the health care sector of a US high yield benchmark portfolio with risk computed relative to the benchmark return. For the granular model, the bonds in the health care portfolio are mapped to their issuer curves, while in the rating/sector model, they are mapped to their corresponding cluster curve. Monthly active returns going back to January 2006 are plotted against the 99% risk confidence bounds for each risk model. Clearly, the granular model risk is significantly higher than the rating/sector model risk. Particularly in the global financial crisis (2008-2009) and during the energy sector crisis (2016), we observe that the realized active returns are often substantially larger than 99% estimate of the rating/sector model, while the granular model risk captures the extreme returns, with exceedances at the 99% level being rare and relatively minor. In terms of the bias statistic, the granular model has a value of 1.11, which is within the acceptable range for a valid risk model. The rating/sector model, however, has an active bias statistics of 3.62, indicating severe underestimation of risk. This demonstrates the power of modeling individual issuer risk through the granular model.

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7 Conclusions

With the introduction of the new granular fixed-income risk model derived from thousands of issuer spread curves, Qontigo provides portfolio and risk managers with an unprecedented ability to analyze fixed-income portfolios with credit-risky assets from a bottom-up issuer level perspective. Major challenges that arise in other fixed-income risk models, such as thin sector factors, strong sensitivity to ratings migration, volatility estimates dominated by noisy data instead of risk signals, etc., have been addressed through sophisticated data processing and advanced curve-construction techniques. Key innovations of the risk model include:

> **Risk Entity:** New issuer classification scheme that maximizes the number of relevant bonds used to construct issuer spread curves, while separating out bonds with different risk characteristics.

> **Issuer Curves:** New methodology allows the construction of over 11,000 full term structure issuer curves on a daily basis with a 15-year history, leveraging sophisticated outlier detection to produce robust, market-consistent spread curves that are stable through time. Aggregation of issuer spread curves when grouped by currency, region, rating and sector, combined with a smoothing algorithm, allows for the introduction of over 6,000 'cluster curves' for use when an issuer curve is not available.

> **Choice of Credit Risk Factor Term:** The full term structure of the issuer curves and extensive history allow users to select different points along the curve as a risk factor and directly measure credit risk differences from short, medium and long horizon cash flows.

> **Issuer Specific Risk:** The issuer-specific risk is captured natively in the granular model by directly measuring the spread volatility of issuer spread curves. The noise introduced with other sector-average models with spread residuals as specific risk is greatly reduced in this approach.

> **DTS with Issuer Risk Factors:** By using relative returns applied to the individual issuer spread curves, bond-specific duration times spread exposure naturally pairs with the issuer spread volatility risk factor. Here the exposures are computed as price sensitivities to relative changes in spread at key nodes, which is approximately the negative of spread duration times option-adjusted spread (i.e. DTS). Moreover, through the use of relative return shocks to the credit spread curve, the DTS framework can also be used in historical and Monte Carlo simulations.

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[1] A. Ben Dor, A. et al. DTS (Duration Times Spread) - a new measure of spread exposure in credit portfolios. Journal of Portfolio Management. Winter 2007. Available on ssrn.com.

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Appendix: DTS Implementation

This section provides a formal description of how spread returns are computed to allow a smooth transition between absolute change returns below a specified threshold α and relative returns above the threshold. This methodology allows us to extend the basic DTS framework of linear exposure (given by $-D \times S$)) for a single credit spread risk factor return R to a richer risk factor framework with multiple nodes on issuer and cluster credit spread curves and to full repricing simulations.

We begin by defining the modified log function as

$$\text{mlog}(S) = \begin{cases} \log(S/\alpha) + 1 & S > \alpha \\ S/\alpha & S \leq \alpha. \end{cases}$$

Here α is a spread threshold, above which log returns are used and below which absolute returns are used. The modified log return over the period $(t, t + \Delta t)$ is simply

$$R(t, t + \Delta t) = \text{mlog}(S(t + \Delta t)) - \text{mlog}(S(t)).$$

The inverse of the modified log function is the modified exponential function defined as

$$\text{mexp}(y) = \begin{cases} \alpha \exp(y - 1) & y > 1 \\ \alpha y & y \leq 1. \end{cases}$$

A spread shock ΔS corresponding to a spread level S and a specified return R is then given by

$$\begin{aligned} \Delta S &= \text{mexp}\left(\text{mlog}(S) + R\right) - S && (3) \\ &\approx \max(\alpha, S)\, R. && (4) \end{aligned}$$

We can now combine the spread return modeling described by Equation 1 for low spreads and Equation 2 for higher spreads, to give the updated price return equation for a parallel spread shock under the linear approximation as

$$\frac{\Delta P}{P} = -DTS_{\text{eff}}\, R$$

where

$$DTS_{\text{eff}} = D_{\text{eff}} \times \max(\alpha, S_{oas})$$

and R is the $mlog$ return. When multiple tenors on the issuer spread term structure are selected as risk factors, the resulting credit spread shock price return formula becomes

$$\frac{\Delta P}{P} = -\sum_{i=1}^{N} DTS_i \left(\text{mlog}(S(\tau_i) + \Delta S(\tau_i))) - \text{mlog}(S(\tau_i))\right)$$

Here DTS_i is the key rate DTS duration at risk factor node τ_i. This is computed as the numerical derivative of the bond price with respect to the return by applying a return shock $\pm R$ at the node, with linear

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interpolation in tenor of the return shock size down to zero at adjacent key rate nodes, to construct a shocked spread curve derived from the adjusted bond issue spread curve (i.e., the parallel shift of the issuer curve adjusted to match the bond price) using Equation 3 at all cash flow tenors between the key rate nodes. The bond is repriced with the up and down shocked spread curves, and the price difference is divided by $2R$ to estimate the derivative. Note that if the bond cash flows correspond exactly to the risk factor nodes, then $DTS_i \approx D_i \times \max(\alpha, S_i)$, where D_i is the key rate spread duration of the bond and S_i is the spread of the adjusted bond issue spread curve at the tenor τ_i.

For simulations, we sample the returns for each risk factor, either through the covariance matrix (for Monte Carlo) or from historical factor returns, and, in a similar manner, use the sampled returns to construct shocked bond-specific spread curves for repricing to compute price return samples. For each bond j in the portfolio, the return $R_j(\tau)$ at each cash flow date τ of the bond is computed from the return shocks to each risk factor node, using a weighted average return for cash flow dates between factor node tenors (weighted by the relative distance in time to the adjacent factor node tenor). The updated adjusted issue-specific credit spread shock is computed from the adjusted issue-specific spread level $S_j(\tau)$ through the formula in Equation 3. The updated issue-specific spread curve is determined by these shocks at each cash flow date. Note that this is the simulation equivalent of the DTS approach for linear parametric risk in that above the spread threshold, the size of the spread curve changes and the corresponding price return shocks are directly a function of the current spread level.

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By Qontigo GmbH
First published October 2019
This version published 8 November 2019
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