Leveraged Loans

Model Insight

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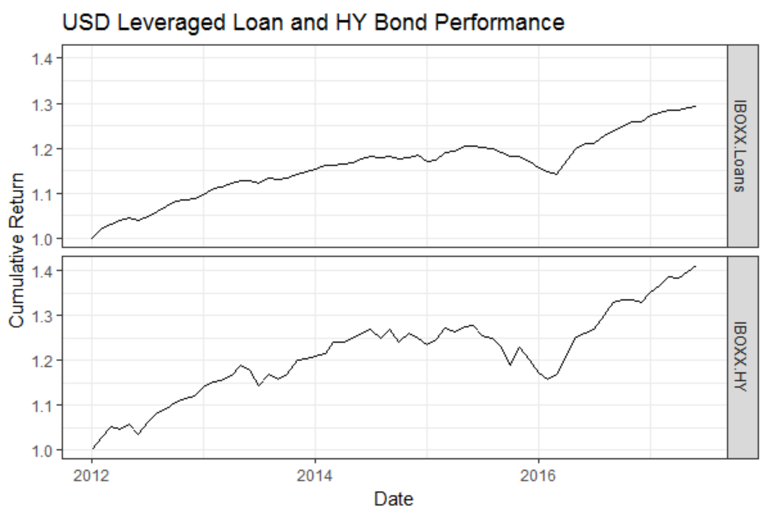
Executive Summary

Leveraged loans have emerged in the last decade as an attractive alternative to the typical high yield bond allocation. In periods of low and rising interest rates, the floating coupon of a leveraged loan portfolio offers an appealing combination of income and low duration. Indeed, loans have outperformed high yield bonds on a risk-adjusted basis in the recent past (Figure 1). As senior, secured obligations of corporate borrowers, loans also typically exhibit a high recovery in the event of default, and thus have a measure of downside protection.

Yet loan investors face distinctive risks. Loans are distinguished by a wide variety of embedded optionality, most importantly by their American calls and coupon floors. Most loan investors rely on rules of thumb when calculating analytics, but these can obscure important asset-level dynamics. Furthermore, bond-based proxies of loan risk can have biased correlation and volatility estimates due to differing liquidity profiles and market technicals.

To address these shortcomings, the new MSCI leveraged loan model takes the next step beyond trader heuristics to provide quantitative insight into the risk and performance of loans. We have partnered with IHS Markit to obtain class-leading data and coupled it to a novel pricing model with loan-specific risk factors. In total, our new offering provides next-generation analytics, purpose-built for loans.



2012-2017 Results	Loans	HY Bonds
Annualized Return	4.86%	6.55%
Annualized Volatility	2.59%	5.57%
Sharpe Ratio	1.88	1.18

Figure 1 – The risk-adjusted performance of leveraged loans exceeded that of high-yield bonds from Jan 2012 to May 2017. Source: IHS Markit, IBOXX USD Leveraged Loan Index and $ Liquid HY Index.

Insights from the Model

- The standard three-year call assumption can be misleading. Coarse rules of thumb for loan lifetimes ignore the market spread environment, which can significantly affect expected cash flow streams.
- Loan calls often are not exercised optimally and are best modeled in a behavioral framework. Ignoring the effects of callability can lead to badly distorted stress test results.
- Loan and bond spread returns are correlated, but only about 60%, so loan-specific risk factors add important detail. On-the-run CDX spread returns are not particularly correlated with loan spread returns.
- Loan returns exhibit smoothing and autocorrelation, likely due to illiquidity. Care should be taken in estimating longer horizon risk to avoid naïvely scaling daily return volatility.
- Stress tests simulating market wipeouts should include recovery rate shocks, as well as spread shocks. Otherwise, the high recovery rate of these senior secured instruments serves as a floor on price, leading to understated losses in a crisis scenario.

Methodology Overview

Market and Model Coverage

Leveraged loans generally are defined by reference to their credit quality. As a working definition, any syndicated commercial loan[2] rated BB+ or lower, or any loan priced at a spread over LIBOR of at least 125bp regardless of rating, qualifies as a leveraged loan [1]. Tracing its origins back to the leveraged buyout (LBO) boom of the 1980s, the global loan market has grown significantly since the 2008 credit crisis, topping $1 trillion outstanding in 2017 (see Table 4 in the appendix).

The mechanics of bank loan origination are similar to those of corporate bonds. A group, or syndicate, of lenders underwrites the initial loan and then sells these claims to institutional and private investors in the secondary market. There are of course important differences between loans and bonds. Loans are secured and offer stronger protection for investors in cases of credit events through liens, direct claims to issuer assets, and covenants. However, unlike corporate bonds, leveraged loans are uniformly callable.

Term loans are installment loans that require the issuer to repay either according to a schedule or as a lump-sum "bullet" payment at maturity. Amortizing term loans (or TLa) feature significant scheduled amortization and are usually retained by syndicating banks. They are commonly coupled to revolving lines of credit (RCs), which act as corporate credit cards that can be drawn and paid down rapidly. Institutional investors such as asset managers, structured investment vehicles, and hedge funds typically participate in bullet term loans (TLb), which feature little or no scheduled amortization.

[2] Note that this definition of leveraged loans excludes retail and peer-to-peer loans, as well as commercial real estate loans.

Data

Historically, syndicated loans were a quasi-private asset class. They retain distinctive practices with respect to terms and conditions dissemination and trade settlement that make data gathering difficult. In particular, loans may undergo terms and conditions modifications after issuance. Usually this is a result of a soft refinancing or "repricing" in which the loan's spread over LIBOR is adjusted, but also occasionally through other channels such as "amend-to-extend" agreements whereby lenders agree to extending a borrower's loan term in an attempt to stave off a default. Because of syndicated loans' quasi-private nature, only investors with active positions in a loan are able to access the so-called "post-trade" terms and conditions critical to the correct modeling of loan positions. Fortunately, through MSCI's partnership with IHS Markit, we have access to comprehensive post-trade loan terms and conditions and pricing data. As such, we are able to compute analytics using the most up-to-date spread, maturity, amortization schedule, soft call schedule, and all other terms[3].

Similarly we obtain prices from IHS Markit's loan pricing service, which aggregates dealer quotes. This feed provides us with bid and ask, as well as the number of dealers quoting a given name. Across all currencies and facility types we get around 6000 prices daily, with history extending back over a decade (see Figure 2)

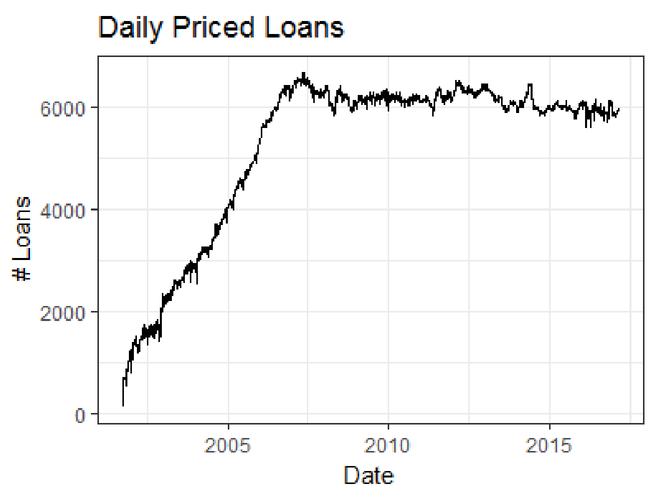


Figure 2 - Daily loan price counts over time.

Pricing

Loans are a challenging asset class to price because they feature multiple layers of optionality:

- Almost all have an American call option and as Figure 3 shows, the majority of leveraged loans are called prior to maturity. In many cases, loans feature a soft call protection fee on a step-down schedule. A typical example loan would be callable at 102 in the first year, at 101 the second year, then at par to maturity. The exercise of this option is often not optimal due to unobservable constraints on borrowers such as refinancing fees or covenants in the credit agreement.

[3] Markit receives these updates through agent notices. Note that some facilities are not tracked by Markit until the agent is directed by a loan participant to include Markit in the notice recipient list. Clients may need to initiate this process by contacting the facility agent.

- Base rate (LIBOR) floors, where the floating coupon is set to a spread over, for example, the larger of 3M LIBOR and 100bps.
- A draw option, for revolvers and some term loans, which enables borrowers to increase their borrowing up to a facility limit.
- Less commonly, loans can have negative amortization, a base rate switching, or irregular accrual options.

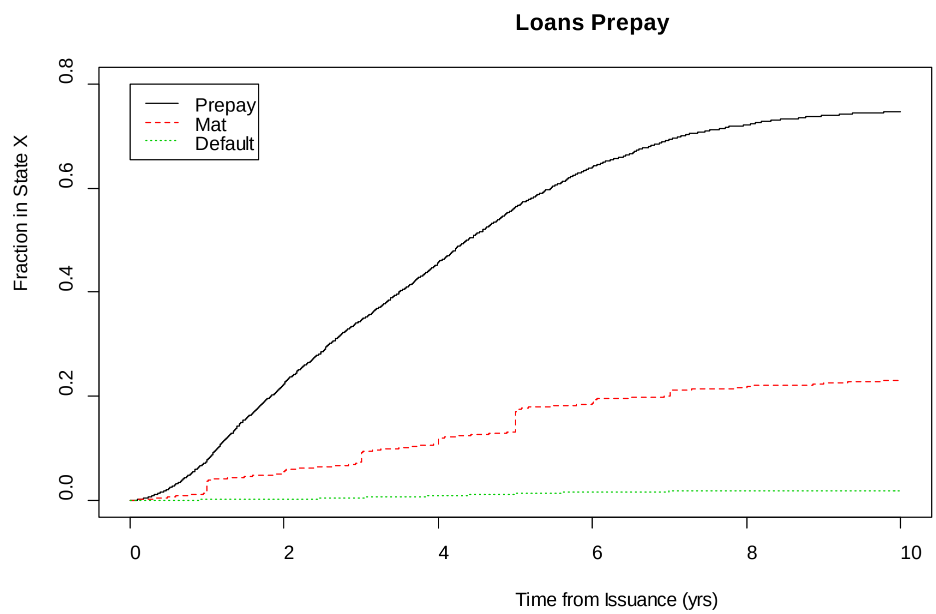


Figure 3 – Most leveraged loans prepay prior to maturity. The chart shows the prepaid/matured/defaulted status of a representative sample of term loans with scheduled maturity prior to 1 Jan 2017. Note that nearly 80% of loans pay off before their stated maturity. Common maturities are indicated by the step-like changes in the "Mat" trace. The total default rate in this sample is about 2%.

Given the features outlined above, loans price in both significant call (prepayment) risk as well as significant default risk. Traditional risk-neutral pricing approaches suffer from a number of drawbacks when it comes to valuing the call and default options embedded in loans. First, because loans are floating rate, they have little price sensitivity to interest rates, so pricing the call through simulation solely of interest rates does not capture the complete set of option drivers. Second, a more sophisticated model including a stochastic spread or hazard rate is difficult to calibrate. Finally, as noted above, issuers often do not optimally exercise the call option due to unobservable factors such as fees, covenants, or other constraints – indeed, loans trade above par for extended periods, as illustrated in Figure 4. To overcome these issues we use a behavioral model fit to historical loan performance data to measure and forecast the response of loan issuers to call incentives.

Combined with the calibration of default probabilities to the market price, we thus treat call and default risk jointly by applying a straightforward probabilistic approach, naturally extended from the reduced form Hull-White credit model used for risky bonds in RiskServer [3]. Both the value of the borrower's option to prepay and the probability of default are a function of the loan's spread, and so vary with loan price. The model also naturally handles non-optimality in call exercise through an explicit and user-tunable term capturing call friction.

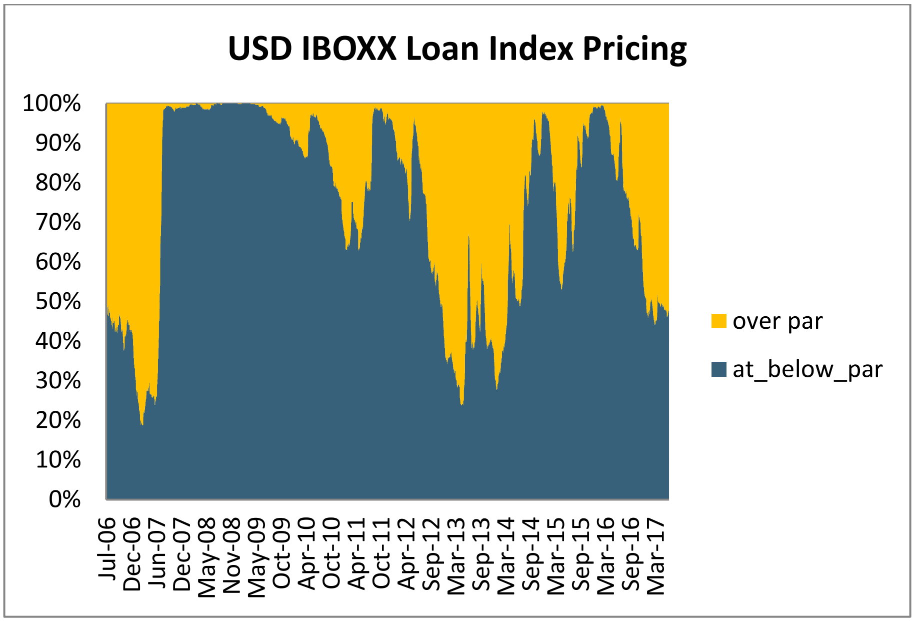


Figure 4 - Loans frequently trade above par despite low duration and callability.

Here, we outline the pricing model for leveraged loans at a high level. The details of the pricing model and its inputs are given in the Bank Loan Technical Note [4].

Cash Flow Model

Intuitively, we price a loan as the discounted expected cash flows from three channels: scheduled payments, calls, and defaults. Mathematically, this is given by:

$$P_{loan} = \sum_{i=1}^{N} D_i \left[P^s(t_i) C_i + P_i^p \left(k_i p_i + \frac{ai_i}{2} \right) + P_i^d \times RR \times \left(p_i + \frac{ai_i}{2} \right) \right]$$

where i indexes the N scheduled loan cash flows, which include both coupons and principal amortization; D_i is the riskless discount factor applying to the cash flow from period i, computed from the LIBOR/swap curve appropriate to the loan's currency; P_i^s is the probability of survival up to the scheduled cash flow; C_i. P_i^p is the probability of prepayment (call) between cash flows C_{i-1} and C_i; and P_i^d is the probability of default over the same interval. In the event of a call, the cash flow is the outstanding principal p_i multiplied by the prevailing call protection fee multiplier k_i plus the accrued interest. We approximate the timing of call and default as on average halfway between coupon dates; thus, the expected accrued in the call and default channels is $\frac{ai_i}{2}$. The default cash flow reflects the recovery of principal and accrued at a recovery rate RR. In line with market convention, we assume that the baseline recovery rate for first-lien loans is 70% and for second liens is 40%[4].

The call probabilities at each cash flow date P_i^p are given by the prepayment model outlined below. Default and survival probabilities P_i^d and P_i^s are calculated assuming a constant hazard rate of default calibrated to equate the input market price P_{mkt} with the model price P_{loan}.

Revolvers

Revolving lines of credit have somewhat more complex scheduled cash flows than term loans. These facilities typically entail a commitment fee paid on the undrawn fraction of the notional to keep the line of credit open, and in some cases include a credit enhancement fee paid on the drawn fraction in addition to the coupon. The total present value of a revolver thus includes the commitment fee, drawn fee, and coupon, in addition to both the scheduled and unscheduled return of drawn notional. Our terms and conditions data includes information on fees, but the model relies on client input for the drawn fraction and any view on its evolution over time. Given these ingredients, the model will calculate the scheduled cash flow stream[5]. Prepayment and default are interpreted as the close of the facility and thus the termination of all cash flow. We do not currently model borrow draw behavior in response to distress, i.e., the p_i are fixed in all scenarios.

[4] Assets trading below baseline recovery values use a lower recovery rate based on their market price; see [4].

[5] Note that the model interprets the input price for a revolver in terms of the current drawn notional. For example, a 50% drawn revolver priced at par would yield a PV of par with a cash flow stream reflecting principal and interest from the drawn half and the commitment fee on the undrawn half.

Prepayment

Loan market participants typically rely on rules of thumb for loan lifetimes when computing loan analytics, but these are coarse approximations. For example, the usual assumption for a term loan is an expected life of three years. Realized loan prepayment behavior shows that the median time to call of a five-year term loan is indeed about three years (Figure 5), but there is wide variation around this median. Moreover, characteristics such as facility type and original term strongly influence expected loan lifetimes. Relying on a blanket assumption oversimplifies the analysis and can provide misleading results in stress tests and risk forecasts (see Stress Tests on page 20 for illustrations of this). More sophisticated treatment with a callable bond model driven by stochastic interest rates can also be deceptive, as loans have little duration. The MSCI loan model offers a better solution by building on trader intuition to capture the influence of loan characteristics and credit conditions on borrower behavior.

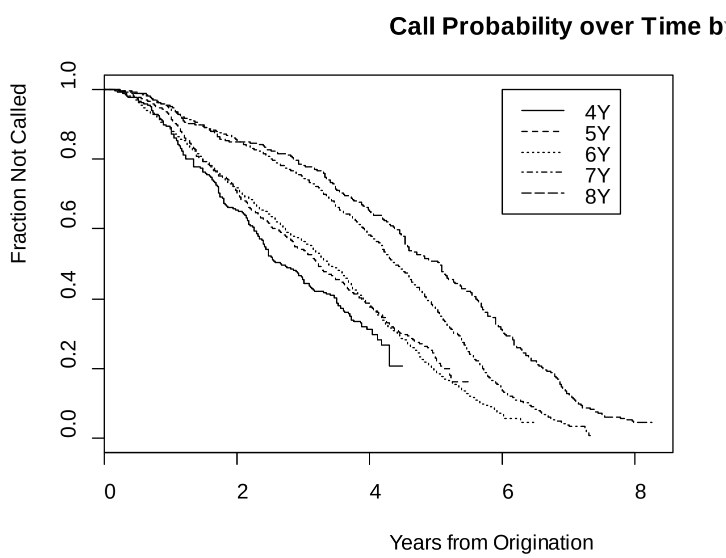


Figure 5 - Call probability depends on, among other factors, elapsed time from origination and term. Each curve represents the non-called fraction of a sample of institutional term loans bucketed by original term in a sample of Americas-domiciled issuance with scheduled maturity prior to 1 Jan 2017.

Intuitively, the model forecasts expected loan cash flows using a prepayment probability curve representing an average of similar loans that is scaled up or down to reflect the specifics of a particular loan. We include two drivers that influence the average prepayment curve in the model: a measure of the economic value of a lower spread, and the hedging benefit of locking in a refinancing spread prior to rolling over a loan at maturity. The first factor reflects the observation that a loan priced near or above its strike is more likely to be called than a loan priced at a discount to par – we will refer to this as the refinancing incentive factor. The second factor captures the link between higher spread volatility and a higher likelihood of refinancing as loans near their maturity dates[6] – we refer to this as the option value factor.

[6] The second factor also captures amend-to-extend refinancing, in which distressed borrowers roll over debt into higher coupon, longer maturity issues in lieu of default.

We estimate the refinancing incentive factor based on the difference between the implied coupon calculated as the asset spread S over the base rate Q (typically 3M LIBOR) and the contract coupon R_c. S is capped at a distressed spread level $S_d = 2000bps$. The factor explicitly accounts for prepayment penalties as well as unobservable frictions to refinancing with a fee term f_s. Finally, we assume that refinancing disincentive saturates at a floor[7] and accrue the refinancing advantage over the remaining time to maturity τ to compute the total incentive, yielding the refinancing factor definition

$$x_{refi} = \max\left[x_{refi}^{floor}, (R_c - Q - \min(S, S_d) - f_s)\right] \times \tau.$$

The refinancing factor exhibits a natural relationship to price, illustrated in Figure 6 for a broad panel of loan observations. Over time, the factor also responds intuitively to changes in the credit environment, as shown in Figure 7, where the refinancing incentive declines in bear markets and increases in bull markets.

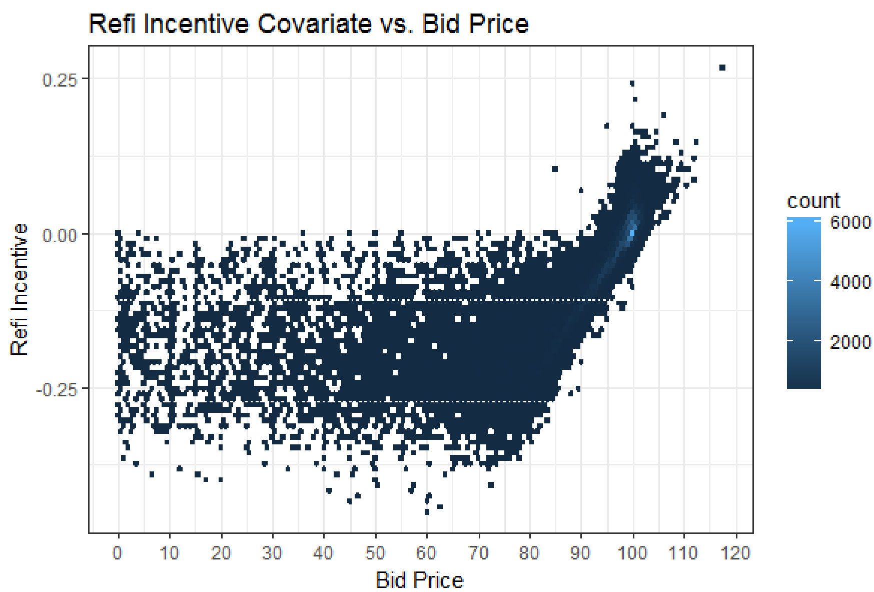


Figure 6 - Refinancing incentive as a function of bid price in a sample of first-lien term loans from 2005-2016. Each point represents a one dollar by 0.01 refi incentive bucket; brighter colors represent more observations in a given bucket. Par loans dominate the sample. Distressed loans with refinancing incentive around zero have very little remaining time to maturity.

[7] We tested various values of the floor x_{refi}^{floor} before settling at –0.500. This value yielded the best performance on tests of the proportional hazards assumption of the Cox regression model with little effect on forecasting accuracy. The model is not particularly sensitive to the value of x_{refi}^{floor}.

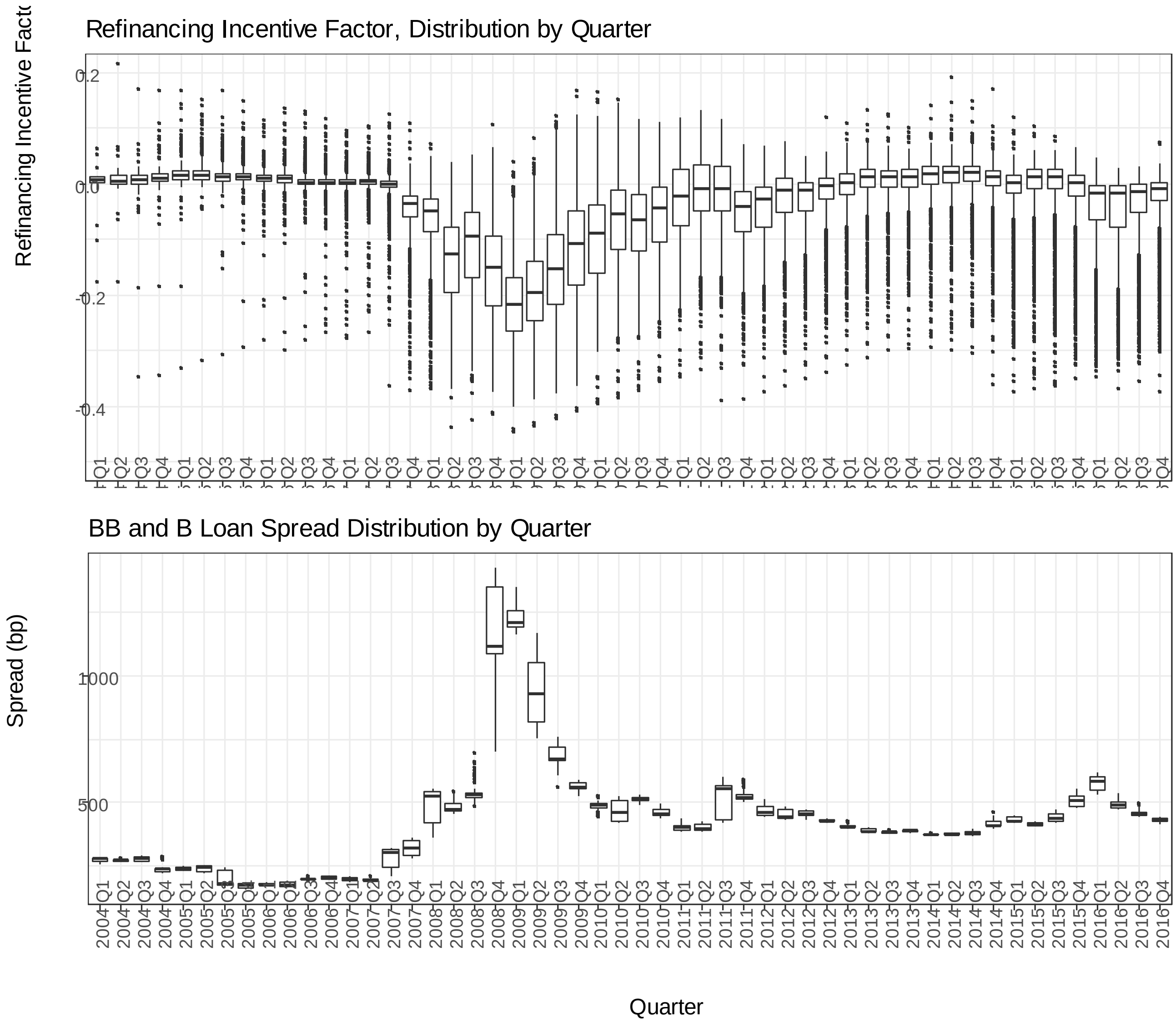


Figure 7 - Refinancing incentive factor distribution of a sample of first-lien term loans compared to the distribution of the average spread of loans rated BB and B, quarterly. Note the fall in refinancing incentive during periods of credit stress, such as during the 2008 crisis. Box top/bottom edges and centerlines represent the 75th, 25th, and 50th percentiles of the distribution, respectively; whiskers represent the 99th and 1st percentiles; dots are outliers. Note that the top panel reflects the distribution of individual loan refinancing incentive observations; the bottom represents the distribution of the daily average loan spread across the quarter.

The hedging value factor is defined by way of an analysis of the refinancing decision faced by a corporate issuer whose debt is priced below par. A borrower who knows that they will roll over their debt faces uncertainty regarding the future pricing of their new loan, meaning that there is potentially value in "locking in" the spread implied by the market on their debt. We view this as an option on the future (stochastic) spread at maturity S_τ struck at the current loan spread S, so we refer to this covariate as the "option value" factor. By refinancing at the current spread S, the borrower realizes a benefit proportional to the net new borrowing period and the expected value of the difference between S_τ and S, floored at zero. Mathematically,

$$x_{opt} = (\eta - \tau) \times E[\max(S_\tau - S, 0)],$$

where η is the expected new term of the loan, τ is the remaining time to maturity, and $E[]$ denotes expectation. We approximate the value of the expectation using standard Black-Scholes (see [4] for details of the derivation), yielding the final expression

$$x_{opt} = \sqrt{\tau}[\max(\eta, \tau) - \tau] \cdot \min(S, S_d).$$

In words, this says that the option value scales with the spread of the asset and saturates at a distressed spread S_d. The option value is zero if the time to maturity exceeds the new assumed term η, and it reaches a maximum value per basis point of spread at $\tau = \eta/3$. We tested several values for η and found that model performance was not particularly sensitive to the exact value, but that statistical tests and studies of the most common loan terms indicated that 7 years is a reasonable value.

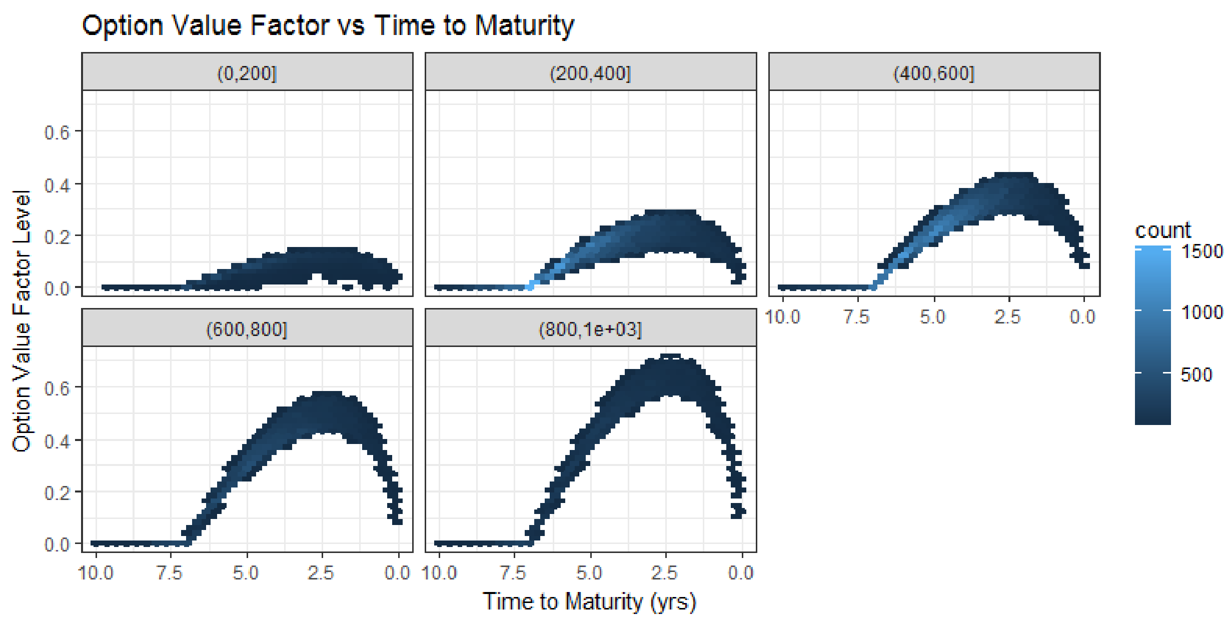


Figure 8 – Option value factor as a function of time to maturity (x axis) and spread (with different spread buckets in each panel) from a sample of first-lien term loans with an assumed new borrowing period η = 7 years. Each point represents a bin of quarterly loan observations. Each panel corresponds to 200bp-wide spread buckets. Note that the x-axis has a reversed scale. Most observations lie in the 200-600bp range.

We use a Cox proportional hazards approach [5] to estimate the strength of each factor in influencing the call decision. Mathematically, this is a regression of the change in the prepayment hazard rate $\lambda(t)$[8] onto the factors described above:

$$\log\left(\frac{\lambda(t)}{\lambda_0(t)}\right) = \beta_{refi}x_{refi} + \beta_{opt}x_{opt} + \epsilon.$$

$\lambda_0(t)$ is the time-dependent baseline hazard curve, and the other terms represent the two prepayment factors. Traditionally in survival analysis the factors are referred to as covariates, so we shall do so in the following

[8] The hazard rate is the probability of prepayment in the small period $[t, t + \delta t]$ conditional on not having prepaid up to time t.

development. This Cox regression yields an estimate of how strong of a response, i.e., how large of a β, the baseline hazard curve $\lambda_0(t)$ has to a change in each covariate. If an asset has both positive β and covariate values, then it indicates an increased incentive to prepay relative to the baseline and $\lambda_0(t)$ is scaled up, while an asset with negative covariate values will have a forecast scaled down from the baseline.

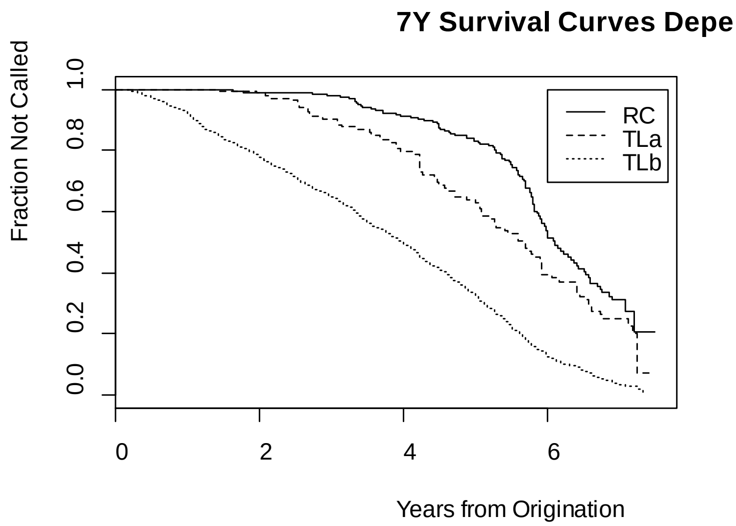


Figure 9 - Call probability forecasts depend on facility type. Revolving lines of credit (RC), amortizing term loans (TLa), and institutional term loans (TLb) have significantly different survival behaviors. Formally, a logrank test is used to reject the null hypothesis that the survival curves overlap.

The "proportional hazards" aspect of the Cox model means: 1) that the effect of a covariate is to scale up or down the baseline hazard, and 2) that the βs are independent of t. In other words, the strength of the effect of a change in covariate value is fixed over the life of the loan. We found that facility type, region, and original term also influence prepayment forecasts, but we do not include them as covariates in the Cox regression because doing so caused statistical tests of the proportional hazards assumptions fail. Instead, we estimate separate baseline hazard curves for each set of loans bucketed along those dimensions. Note that the values of the covariates x_{refi} and x_{opt} for a given loan vary through time, and the fraction of loans that prepay is not 100%. We account for these aspects of the data in estimating the model.

For the baseline hazard we found that the commonly used Weibull distribution

$$\lambda(t) = \lambda_0 p t^{p-1}$$

yielded a reasonable fit and tractable parameterization across facility type, region, and term buckets. For some facility types and regions, we used an ensemble of loans with similar original terms, e.g., 5- and 6-year TLs, as they had similar baseline hazard estimates. Figure 10 shows the final fit for a sample of 4-year TLb loans.

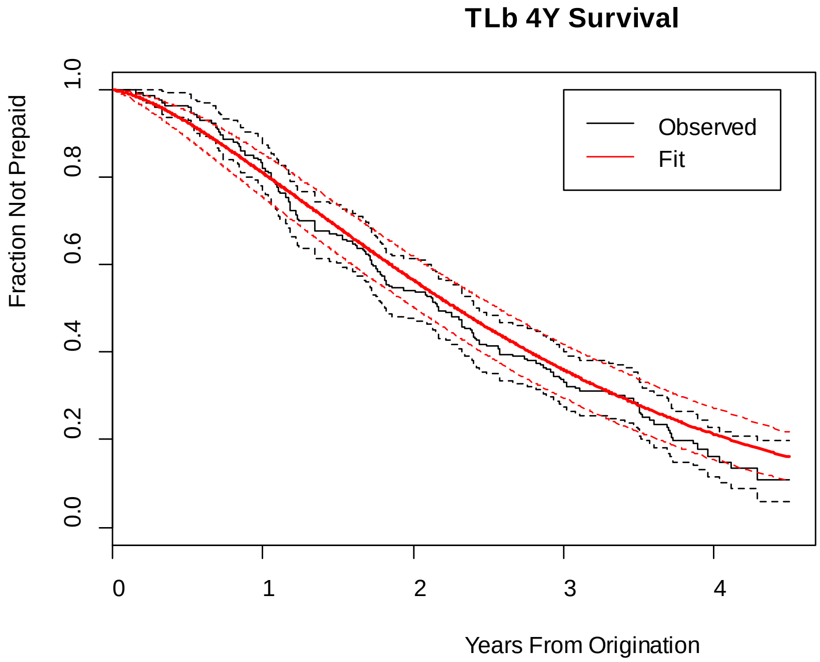


Figure 10 - Observed survival and Weibull proportional hazards model fit for a sample of first-lien four-year term loans. The dotted lines indicate 95% confidence intervals.

Risk Factors

To compute spread[9] factors, we bucket the loan universe along five dimensions: region, lien, loan type, sector/subsector, and credit quality. This differentiation reflects a practitioner's view of the structure of co-movement in loan spreads[10]. In determining the relevant dimensions for grouping loans, the primary use cases we considered were risk and stress testing, with pricing a secondary use case. In some cases, these dual goals result in tension: very granular spreads improve pricing accuracy but may compromise the robustness of correlation and volatility estimates or the availability of deep history, particularly for more illiquid assets. Sectoral effects, such as the energy-related wipeout at the end of 2015, are common through history yet difficult to predict, and they can lead to large shifts in bucket composition due to credit migration. Factor selection is thus a balance between explanatory power and stability.

A further complication in risk factor construction for the loan market is the degree of heterogeneity in size, bid-ask, and trading volume across issues. In 2016, the SEC classified bank loans as "less liquid" due to their longer settlement times compared to corporate bonds [2]. Indeed, from a market risk point of view, leveraged loans have lower trading volumes and less frequent price discovery compared to high yield corporate bonds.

[9] Risk factor spreads are defined as spreads to maturity. See [4] for the details of how spread-to-maturity returns are used to compute asset P&Ls.

[10] A list of available spread factors is given in the Appendix. Currently available curves are listed under Curves: Sector by Rating Range starting on page 33. Note that the more granular curves with subsector and rating-level detail will be released in Oct. 2017.

We emphasize more liquid names in curve construction by weighting assets proportional to liquidity, which we proxy by the number of dealers quoting a name. Quote depth correlates well with other measures of liquidity, such as bid-ask spread and frequency of price update. We also set thresholds on the minimum number of assets in a curve estimation universe to ensure sufficient diversification of idiosyncratic spread risk. Factors covering thinly traded or low-issuance sectors must be aggregated to generate broader curves that are not only well supported by current data but are also well supported for all available history.

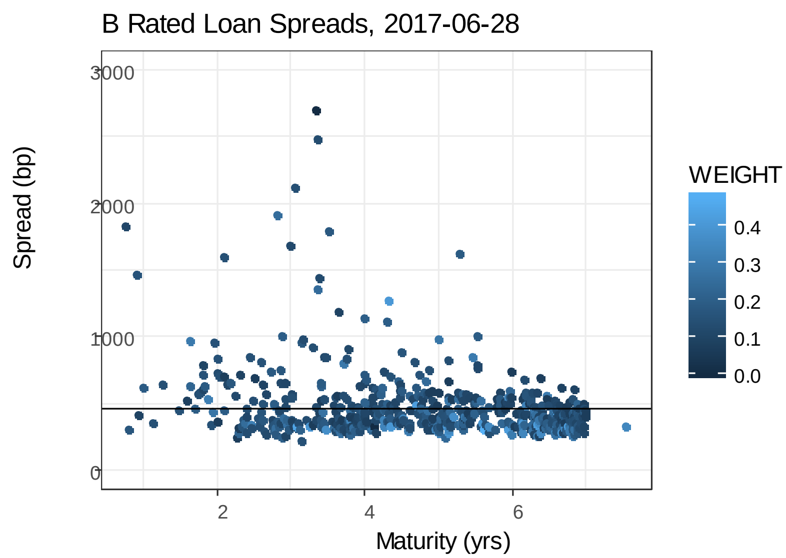


Figure 11 – B-rated loan spreads. This sample illustrates the flat term premium in loan spreads. In spread factor estimation, we emphasize liquid loans, which generally price at tighter spreads.

Curves adhere to naming conventions following this feature hierarchy. For example, AMER_1L_Term_Loan_ALL_B tracks the spread of first-lien term loan of B-rated loans from the Americas region across all sectors. Asset-to-factor mapping strives for the most granular curve possible, prioritizing subsector-by-rating curves. In cases for which a granular curve is not available, the mapping logic falls back to a less granular sector or all-rating curve, or rating range curve. Hence, the All Sectors curve guarantees coverage at a given credit quality.

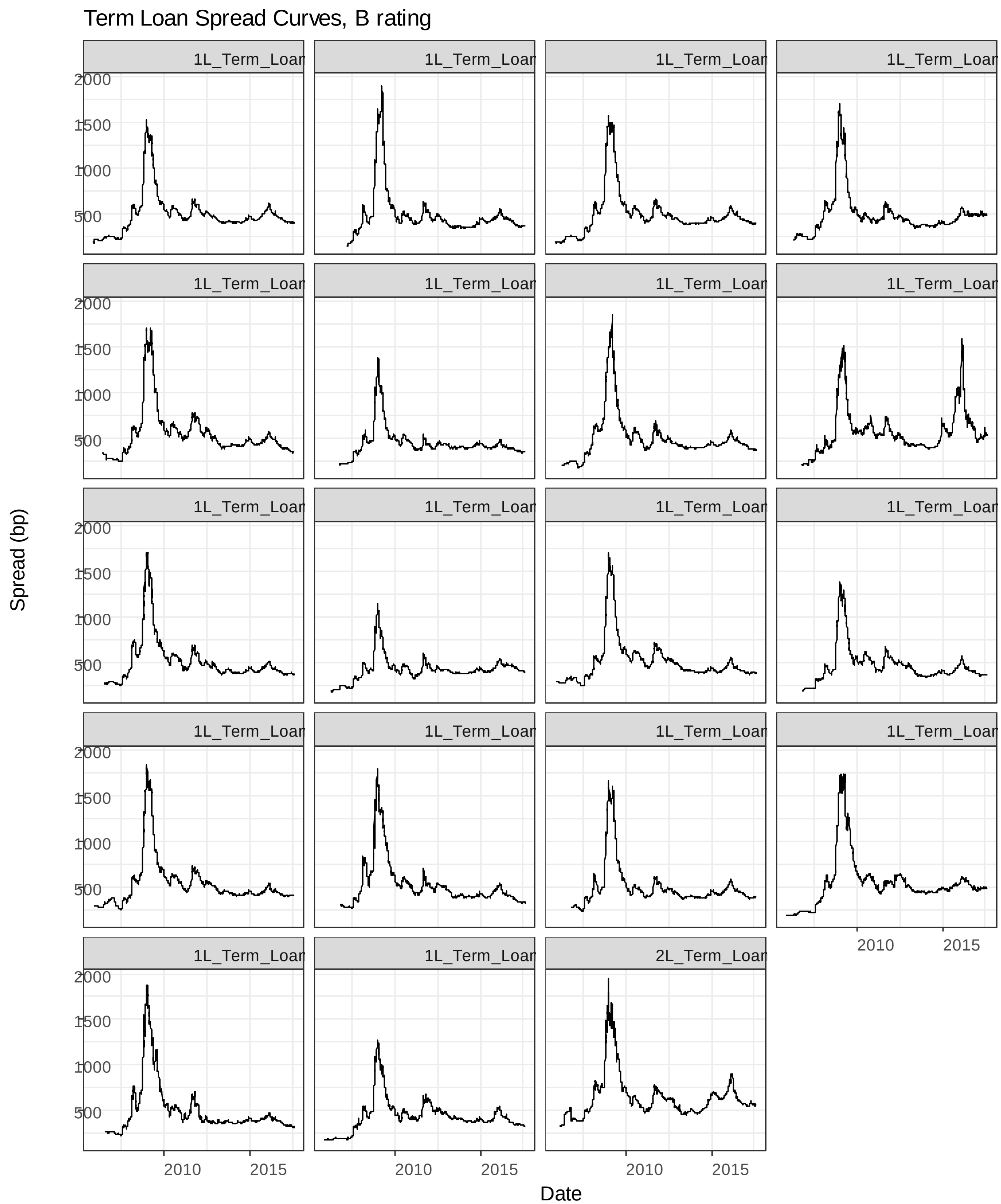


Figure 12 - A sample of US Term loan spread curves. While the 2008 crisis dominates these traces, sectoral and lien-dependent differentiation is clear. Note, for example, the behavior of energy sector spreads (1L_Term_Loan_ENGY_B) at the end of 2015, and the wider and more volatile nature of second lien spreads (2L_Term_Loan_ALL_B).

We build only curves that are well supported by a set of assets for a significant period. The criteria for this decision are that liquidity and issuer diversification meet minimum thresholds, that the sectoral price dynamics estimated from the curve constituents dominate idiosyncratic spread movement, and that both of these conditions are likely to hold going forward. If these conditions do not hold, then we do not estimate a curve for that bucket, and assets that fall into it will be modeled by a coarser sector or rating curve. For Americas-domiciled loans, we have broad coverage of subsectors and ratings, while in Europe, the curves are much broader due to the significantly smaller market.

In some cases, we also estimate curves covering rating ranges, such as the investment grade curve covering AAA through BBB– loans. This ensures the factor's robustness to changes in credit quality within sectors, which is especially important for historical stress testing or long-history risk reporting. In this sense, these aggregated factors maintain strong support even in periods of systemic stress; they respond to this stress by exhibiting a "blow-out" of spreads, but they do not succumb to idiosyncratic effects (i.e., they maintain a strong support through most likely periods).

Autocorrelation

We find that loan spread returns exhibit significant one-period autocorrelation (Figure 13). Practically, this has the effect that naïve scaling of volatility from daily to longer horizons is not appropriate. Users are advised to choose at least weekly or semimonthly returns in evaluating portfolio risk and designing VaR reports for longer horizons, or in defining the correlation matrix for predictive stress tests.

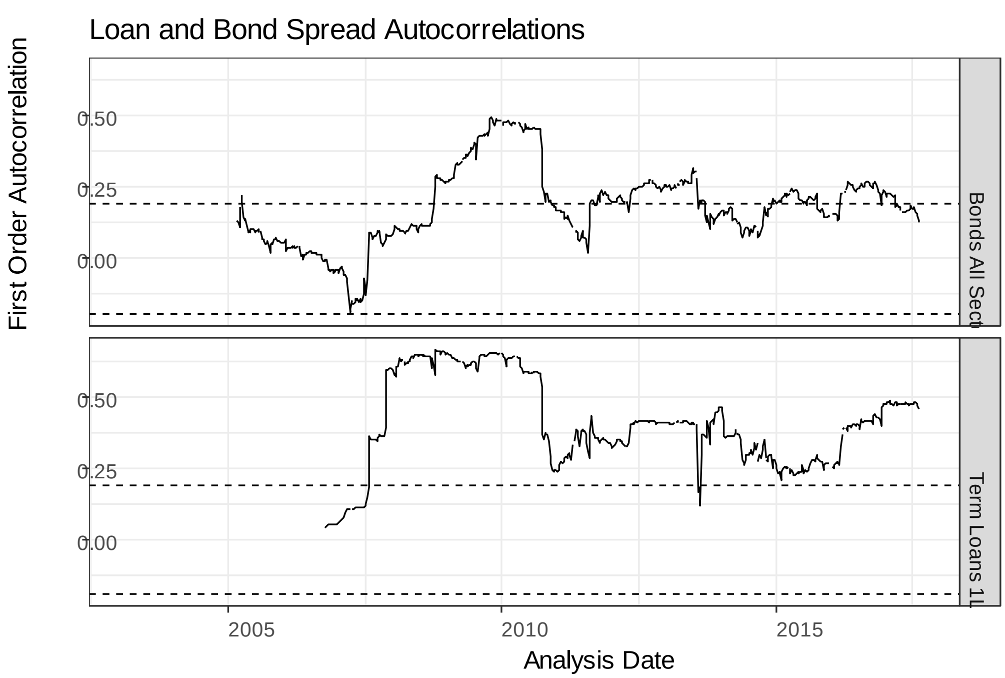


Figure 13 - Loan spread returns are more autocorrelated, on average, than bond spread returns of similar credit quality. Each graph shows the 104-week trailing first-order autocorrelation of weekly single-B bond and loan spread returns, with confidence intervals denoted by the dashed lines. Higher autocorrelation in loan factor spread returns implies that caution must be taken in the design of VaR valuation specifications in RiskServer.

Simulation

Loan risk factor returns are simulated by the RiskServer engine using standard methodologies for calculating distributional and stress test statistics[11]. Importantly, the loan risk model differs from our standard corporate bond risk model in that spread factor returns are applied to the total asset spread, which means that both the systematic and idiosyncratic spread components are shocked. Practically, this means that higher spread assets will display higher risk, all other things equal.

Both the prepayment probability, through changes in the prepayment model factors, and default probability, through changes in default hazard rate, are affected in all simulated scenarios. This has important ramifications for exposure calculation, VaR, and stress testing, which are highlighted in the Use Cases section below.

Use Cases

Risk Exposures

One of the bank loan model's most important innovations in risk estimation is in the modeling of prepayment risk. The prepayment model is fundamentally behavioral in that it models prepayment as a hazard process with two risk factors, but it also has a tuning parameter (included in the refinancing fee term f_s) that augments assets' strike prices to better reflect the unobservable costs for issuers to refinance.

For assets that are priced above par, this refinancing friction increases the effective strike prices in its call schedule, reducing the probability of prepayment. This, in turn, extends the asset's projected cash flow stream, resulting in a larger spread duration and higher risk. Throughout the research process, both through empirical investigations and client discussions, we have found that a refinancing fee of 2% both best represents the real-world refinancing constraints of issuers and tunes the model's spread duration estimation to empirically observed spread durations.

[11] By default, loan spread risk factors have a log return type. See [7] for the details of factor return simulation.

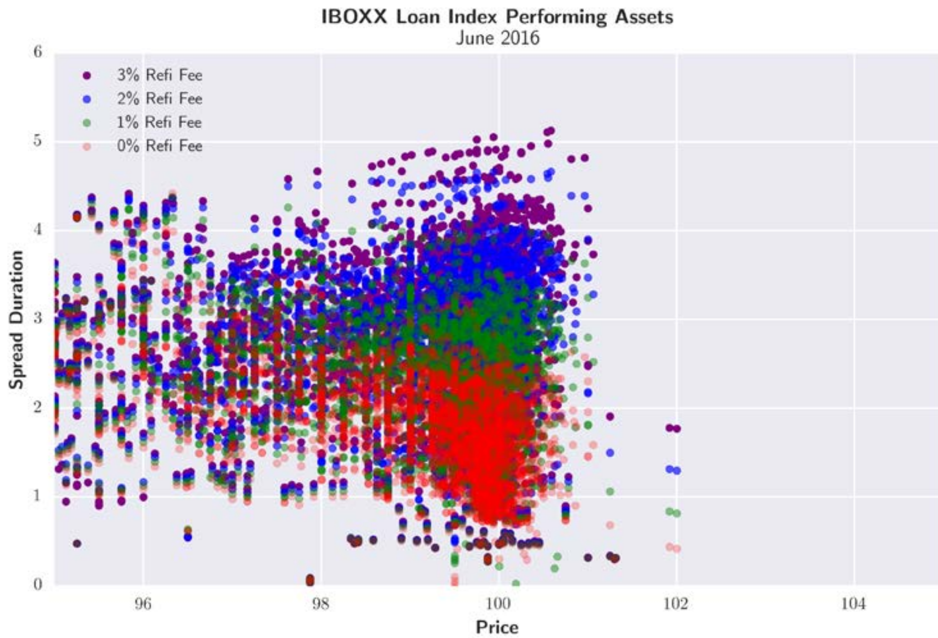


Figure 14: Price against spread duration with varying refinance fees for IBOXX assets priced at 95 or higher

Figure 14 illustrates the effects of varying the refinance fee parameter for performing IBOXX loans in June 2016. We can see that increasing the fee parameter represents a level shift in spread duration for assets priced near, at, or above par. However, for assets sufficiently distant from par, the larger refinancing friction's effects are insignificant.

Risk

Value at Risk

Backtesting the model's performance in a Value-at-Risk (VaR) context illustrates its efficacy for most clients' primary use case. The following results are based on Markit Partners' IBOXX Leveraged Loan Index and its constituent subindexes in conjunction with a filtered historical simulation VaR methodology using five years of returns[12]. We find the model passes coverage tests for both 99% and 95% daily VaR, as illustrated in Figure 15 and Table 1.

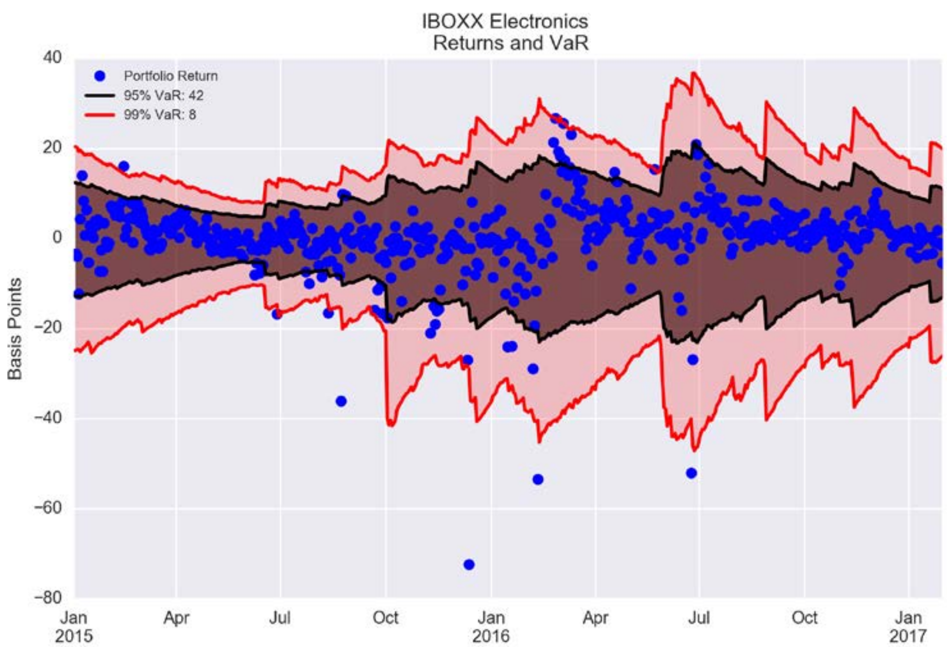


Figure 15: Example of an extended VaR backtest with two-sided exceedance counts. The test portfolio is the Electronics subindex of the IBOXX Leverage Loan index. For a two-year window, the range of two-sided exceedance counts are [2, 18] at 99% and [32, 70] at 95% confidence.

We conducted backtests for longer sample periods and found similar results. In some cases, we found bias within these longer samples stemming from a lack of dynamic risk factor mapping[13]. To minimize the effect of this bias on our evaluation of the model, we focus on 1 Feb 2016 to 30 Jan 2017 as our sample period.

[12] For details on scenario generation and asset P&L computation for risk, see [4].

[13] An asset's risk factor assignment is guaranteed to be valid for analysis dates within the past three months, but not for analysis dates in the distant past, when changes to T&C or credit rating become more pervasive, leading to biased factor mapping in some cases. For instance, many Oil & Gas loans are currently mapped to *CCC* ratings curves due to the sectoral shock in the fall of 2015 and subsequent ratings downgrades, but the corresponding risk factor during that historical period reflected contemporaneous, often higher, ratings. This mismatch of risk factors causes a bias in coverage tests that cover that sample period.

Table 1: VaR Violations for IBOXX Leveraged Loan Indexes (Feb 2016 - Feb 2017).

Index	95% VaR	99% VaR
IBOXX	6	2
B	6	2
BB	8	2
CCC	4	3
Chemicals Plastics and Rubber	7	1
Diversified Conglomerate Service	6	1
Electronics	4	2
Healthcare Education and Childcare	7	0
Oil and Gas	10	2
Retail Stores	14	2

Table 1 provides confirmation that the model backtests well. For most credit qualities and sectors, the model passes coverage tests for one-sided VaR[14], while in some cases it is slightly conservative. These results are meant only to be illustrative – both the portfolio holdings and VaR methodology will strongly affect backtest results.

Pricing

A VaR backtest is a joint test of pricing model, risk factors, and VaR methodology. To isolate the first two components, we also conduct pricing backtests in which we directly compare model returns against market returns. The pricing backtest provides insight into how the modeled return distribution compares to the market return distribution for a given portfolio, as opposed to the VaR coverage test, which focuses only on exceedances at the tails. In addition to its usefulness in isolating particular dimensions of the model's performance, this particular backtest is often an important consideration in regulatory evaluation of risk modeling.

We conduct this backtest by comparing the realized returns of loan portfolios over a given period, denoted r_{market}, to portfolio returns computed by applying an historical risk factor stress test covering the same period, denoted r_{model}. We use estimates of β and R^2 from the regression $r_{market} = \beta r_{model} + \epsilon$ to evaluate the performance of the model in capturing asset returns. To avoid biasing our results with stale returns or interpolated returns, we conduct the backtests at a weekly frequency. Moreover, we set the call protection fee schedule to 2% (the MSCI-recommended value) in these backtests.

[14] The acceptance intervals for 95% and 99% VaR exceedances are [7, 20] and [0, 5], respectively.

Table 2: Regression Statistics for IBOXX Indexes

Index	β	R^2
IBOXX	1	0.94
B	0.93	0.96
BB	1	0.99
CCC	0.84	0.86
Chemicals Plastics and Rubber	0.97	0.96
Diversified Conglomerate Service	0.98	0.99
Electronics	1.02	0.97
Healthcare Education and Childcare	0.82	0.87
Retail Stores	1	0.97

Table 2 illustrates the results of this backtest. We see near-uniform levels for the regression coefficient and R-squared, both of which hover around one. An important caveat in interpreting regression statistics is their sensitivities to outliers. Given this caveat, high R-squared numbers tell us that portfolio returns are highly correlated with risk factor returns, and β near 1 tells us that the magnitude of risk factor-driven model returns are very similar to that of the realized portfolio returns. The model's performance in these backtests provides evidence that, independent of the VaR methodology, the pricing model and risk factors are well specified for risk estimation.

Stress Tests

Another common use case for our risk models is stress testing, with which clients evaluate how shocks on different risk factors affect the value of their portfolio. In this section, we present six different tests, along with their results under both the new Bank Loan and the alternative Generic Bond model. We also highlight key considerations to be taken when defining these tests. As reference, we look at the loan-only portfolio comprising the 297 loans on the iBoxx BB USD Leveraged Loan Index as of 31 January 2017 (a static snapshot of the index). We generate and analyze the following scenarios:

1. Generalized parallel shifts on all IR term structure curves [–500bp, +500bp].
2. Generalized parallel shifts on all Credit Spread curves [–500bp, +500bp].
3. Predictive stress test on the CDX.NA.HY series [–10%, +10%].
4. Predictive stress test of the iBoxx USD Liquid Leveraged Loan Index [–1%, +1%].
5. Predictive stress test of the AMER_1L_Term_Loan_ALL_HY spread curve [–10%, +10%].
6. Historical stress tests corresponding to the periods of the Global Financial Crisis (2008/06 – 2009/03), the European Sovereign Debt crisis (2011/04 – 2011/10) and the latest oil and energy crisis (2015/07 – 2016/02).

Table 3 summarizes the main descriptive statistics of the test portfolio under the different model settings.

Table **3**: IBOXX BB Leverage Loan Index Statistics by Model

	Legacy Model	BankLoan Model
PV	4510.71	3580.50
Weighted Avg. Life	3	2.959
Effective Duration	0.6526	0.2083
Spread Duration	2.8051	2.6602
Effective Convexity	0.6477	-1.1923

Generalized Stress Tests

First, we examine the effect of credit spread shocks on loans by applying stresses to all spreads, illustrated in Figure 16. Spread shocks have a much larger effect on loan prices than rate shocks, but with the new bank loan model, the upside is limited. This is because the model captures the influence of a tightening spread environment on the incentive to refinance, driving up call exercise probability and causing price gains to saturate. The refinancing friction term affects the spread level at which the P&L rolls off.

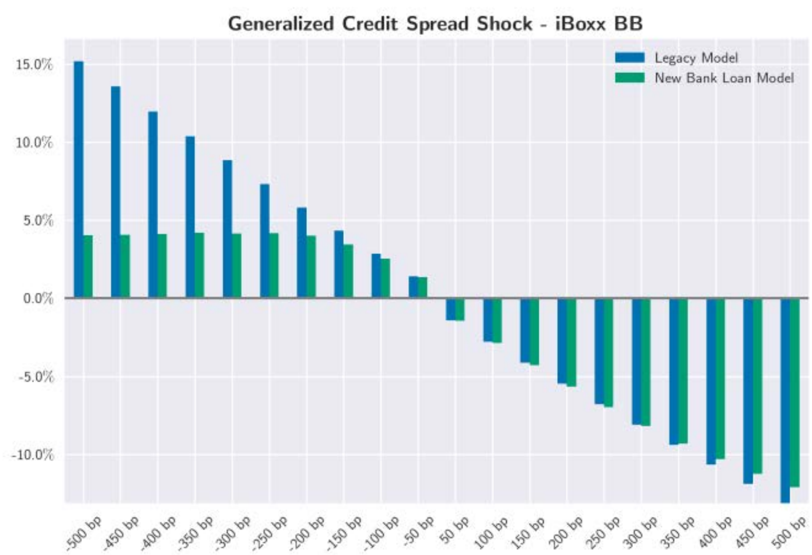


Figure 16: Generalized Credit Spreads Stress Test on iBoxx BB Leverage Loans

Now we turn to the effect of generalized parallel shifts on all IR curves, ranging from –500 to +500bp. Figure 17 shows the percentage changes of our portfolio value under both models.

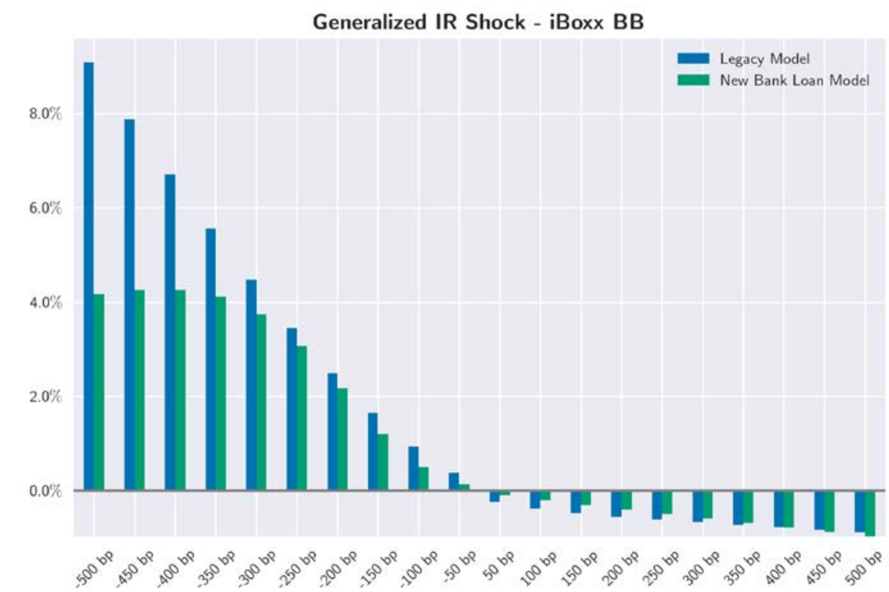


Figure 17: Generalized IR Stress Test on iBoxx BB Leverage Loans

When rates rise, we observe a limited downside effect on the portfolio value due to the floating rate nature of the instruments. The upside effect, however, is non-negligible, which might seem unintuitive considering that we are keeping spreads constant. The explanation of this phenomenon is specific to the rate environment during the analysis period: LIBOR rates were ~1.70% at the time, so shocks greater than –200bp effectively turn the loans into fixed-rate instruments when they start hitting their coupon floors. Note the distorted results of the legacy model for large rate shocks. The limited gains in a declining-rate environment reflect the incentive to refinance when loans approach their strike price. Incorporating this cap on returns is crucial for accurate forecasting and risk reporting, as a model that ignores the callable nature of loans will overestimate potential gains.

Specific Stress Tests

Moving to correlated stress tests, now we look at the effect of shocking the spread levels of the CDX.NA.HY and the iBoxx USD Liquid Leveraged Loan Total Return Index. We start with the CDX.NA.HY series, a commonly used benchmark on the high yield space. We will compare the results of the tests under both models with a target value, defined as (β * % shock), for which beta is estimated by regressing the portfolio returns against index returns. Although this is a linear approximation, this value should give us a rough estimate of the expected P&L for each of the shock levels. In Figure 18, we observe that the new Bank Loan model is significantly more responsive to shocks on this index, with the results being much in line with those predicted by the target value. The effect on the portfolio value is still small, as historically CDX.NA.HY has exhibited moderate correlation with loan portfolios (~50%) and low beta.

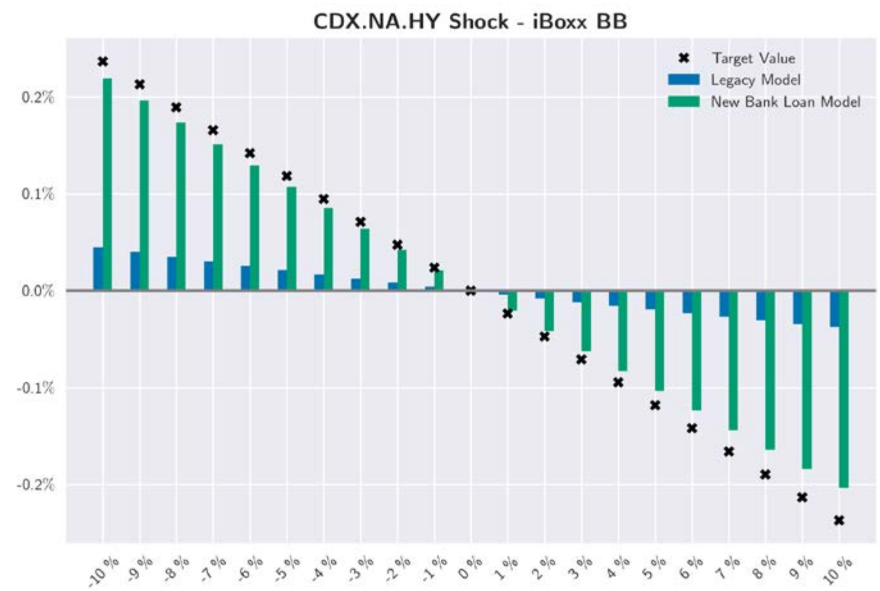


Figure 18: CDX.NA.HY Spread Stress Test on iBoxx BB Leverage Loans

A more natural choice for evaluating the performance of loans on periods of distress is the iBoxx Leveraged Loans index itself, which exhibits a correlation of 92% with our analysis portfolio of BB loans. In Figure 19, we observe that the new leveraged loan model provides much better responsiveness to shocks on this benchmark compared to the legacy approach. We should note that in this case the range of shock goes from ±1%. This might seem like a conservative level, but indeed this range corresponds to two standard deviations on the index weekly returns for the last couple of years of history.

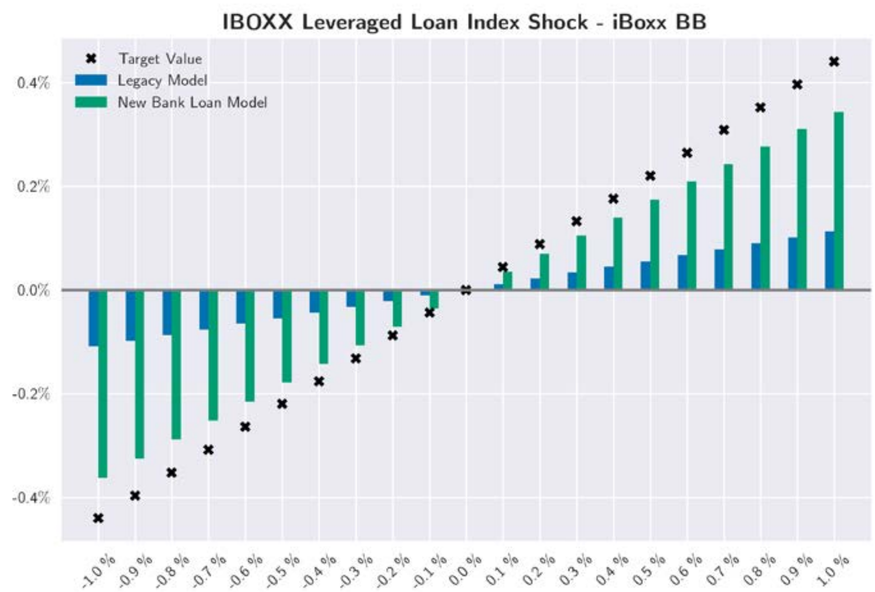


Figure 19: iBoxx Liquid Leverage Loan Index Stress Tests on iBoxx BB Leverage Loans

Historical Stress Test

Historical stress tests provide a picture of how a portfolio would perform under scenarios of significant market distress. Figure 20 shows how the Bank Loan model (green) reprices our portfolio during the Global Financial Crisis (2008/06 - 2009/03), the European Sovereign Debt crisis (2011/04 - 2011/10), and the latest oil and energy crisis (2015/07 – 2016/02). In orange, we also show the realized historical returns of the iBoxx BB loans during these same periods, which match closely with the modeled ones.

Note that the figure shows two versions of the Global Financial Crisis stress test: one in which we simply define the historical period of interest, and a second one for which we also apply a recovery rate shock. Taking as reference a study performed by Moody's [6], we select an average shock of –17% for 2008-2009. Clients should take this parameter into consideration when building their own stress tests, particularly when the simulated market shocks are large.

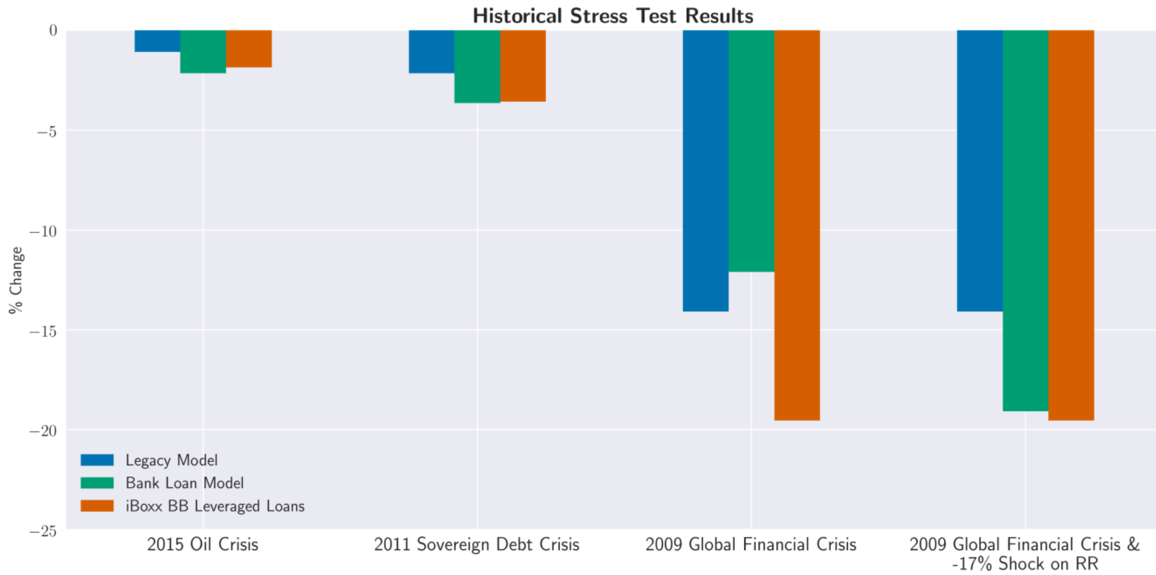


Figure 20: Historical Stress Tests, iBoxx BB Leveraged Loans

Loan-Level Stress Test Analysis

Finally, in Figure 21 we look at how the new Bank Loan model takes into account instrument-specific attributes when estimating the effect of credit shocks on loan prices. Intuition tells us that default and prepayment risk should be larger when considering long-maturity instruments, as the uncertainty of receiving future cash flows is greater for these instruments. The Bank Loan model incorporates these two sources of risk into account, and indeed when looking at the loan level results for a generalized credit shock (±250bp), we observe that the predicted effect is largely dependent on the expected time to maturity (in this case WAL) of the instruments.

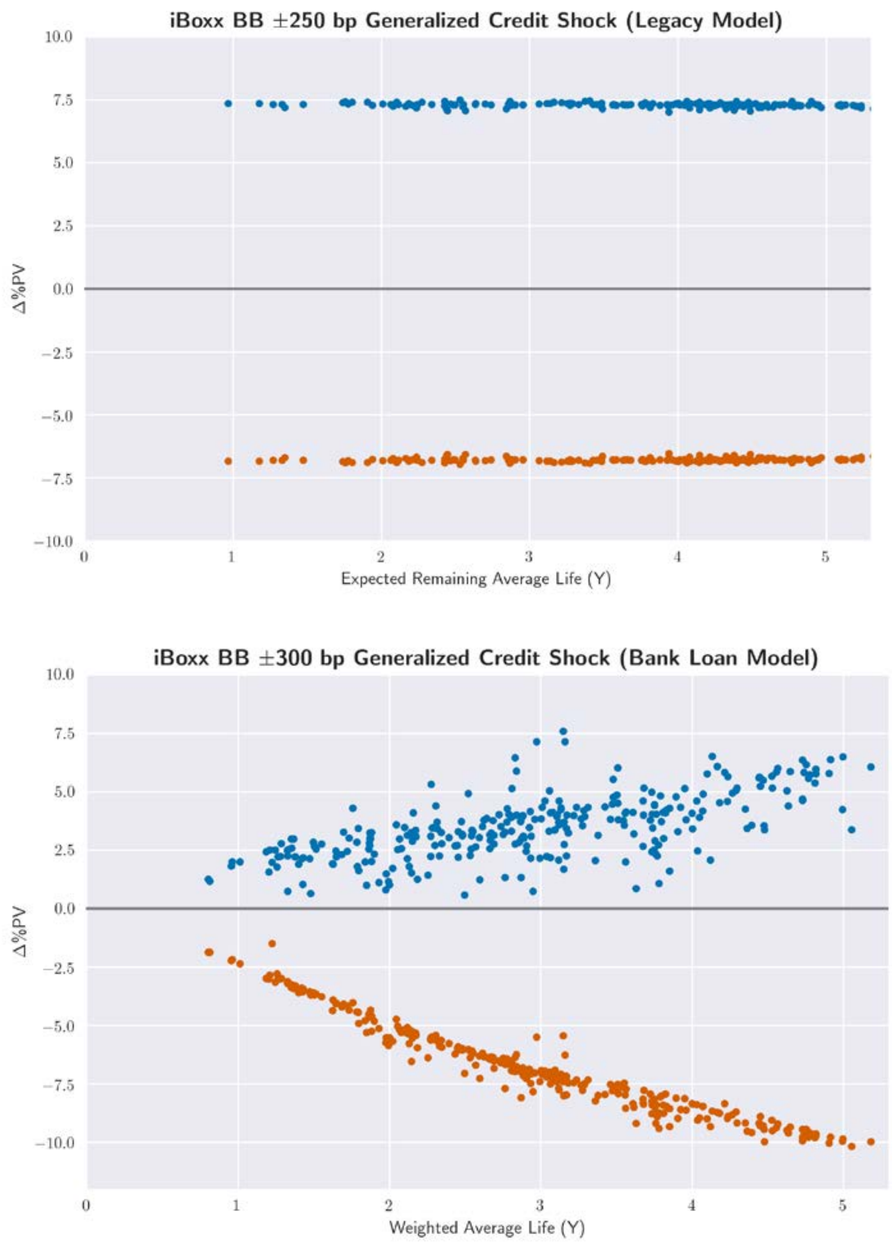


Figure 21: Credit Shock Effect vs. Expected TTM/WAL, iBoxx BB Leverage Loans

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Appendix

Loan Universe

Table 4 - Loan Outstanding by Currency as of 2017-August (source: IHS Markit)

Currency	Outstanding (BB)
USD	1272.3
EUR	115.1
GBP	15.9
JPY	10.0
NOK	6.8
SEK	2.6
DKK	2.4
CAD	0.8
AUD	0.3
CHF	0.0

Prepayment Model Details

Estimation

To handle time-dependent refinancing incentive and option value, we discretize each loan's history into quarterly observations of covariate values and prepaid status. βs are estimated by maximum likelihood based on the cohort of loans at risk of prepayment at any given time from origination. We treat maturing and defaulting loans as "censored" observations for the purpose of model estimation. Given that a large majority of loans prepay prior to maturity, and that the large majority of censored observations overall stem from the (arbitrary) study period ending, we assume that the influence of matured and defaulted loans on parameter estimation is negligible. For details on Cox model estimation with time-dependent covariates in the presence of censoring, see [5].

For all groups of loans defined by original term, region, and facility type, we estimated both stratified models, in which loans with different baseline forecasts λ_0 are grouped together and a shared set of βs are estimated, and separate models, with separate λ_0 and βs for each group. We ran statistical tests to determine whether to reject the null hypothesis that there is no interaction between the strata and the β estimates. In cases for which we were unable to reject the null hypothesis, we used a stratified model, i.e., the same β but different baselines for different terms.

Validation

To validate the prepayment model, we performed a number of statistical tests, including tests of the proportional hazards assumption, tests for whether it was feasible to use the same Cox βs for multiple baseline buckets, tests of the significance of Cox regression estimates, bootstrapped resampling to check for overfitting of parameter estimates, and out-of-sample forecasting performance. We illustrate the last test in Figure 22, which compares forecast vs. realized prepayment behavior. On each analysis date, we form a cohort of active loans. The prepayment model gives us the prepayment probability at the end of the quarter for each loan. Since any given loan either prepays or survives with a different predicted probability, the percentage of the cohort that is forecast to prepay will have Poisson binomial statistics. We evaluate the predictive power of the model by comparing the realized number of prepayments among the cohort of loans to the 95% confidence interval of the portfolio forecast computed using a bootstrap resampling approach. In most cases, the model does well, given the assumption embedded in the forecast of a constant asset spread. Periods of tightening or widening spread have less accurate forecasts, but in practice, the model is updated daily, and prepayment probabilities would adjust to follow market spread movements.

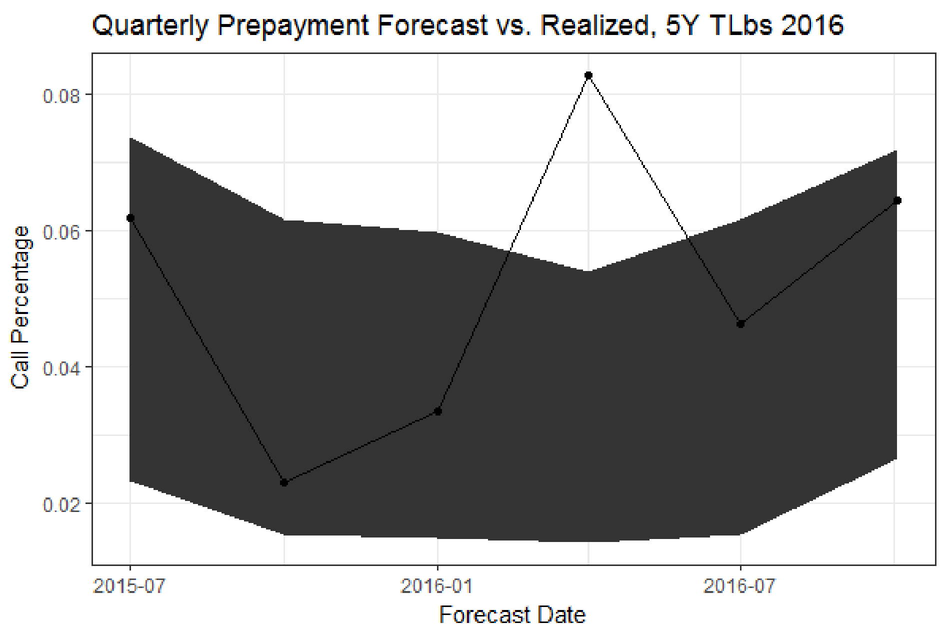

Figure 22 – The prepayment model generally forecasts prepayment well, up to the effect of significant spread movement over the forecast period. This figure illustrates an out-of-sample test of prepayment forecasting for a sample of 5Y term loans. We form cohorts on the forecast date and compute prepayment probabilities from asset prices and T&C as of the beginning of the period using the prepayment model estimated from data through 2014. The gray ribbon represents the bootstrapped 95% confidence interval of the one-quarter prepayment forecast for each cohort of loans. The solid line represents the realized prepayment of that cohort over the following three months. The sustained recovery in spreads over Q2 2016 drove higher than forecast prepayments over that period; in practice, daily reports would have shown increased prepayment probability.

Loan Curve Details

Curve Estimation

Liquidity and trading activity vary widely across loan names and facility types. We observe that about 50% of rated loans have day-over-day stale prices across 80% of observed history. As such, the construction of sensible risk factors depend heavily on a robust treatment of the data, balancing the marginal information gains presented by lightly traded issues against the possibility of increased noise in the estimation. Since even those loans that have large current commitments, and active ratings can exhibit stale pricing, boundary conditions alone are insufficient, and some care must be exercised in setting the appropriate weights to the basket constituents.

We subject the estimation universe to the following filters. First, all loans considered must be no fewer than 6 months from maturity. Second, only loans for which a credible rating can be sourced are included. Finally, loans for which more than 85% of all available return data is stale are removed. This ensures that the curves are fit to the most actively traded names.

Given a basket definition, we collect the set of all reported prices and associated quoting depth information, which we use as a measure of liquidity. We then find the best-fit constant spread over the LIBOR/swap curve as follows: For each individual constituent loan, we first calibrate a spread to maturity to the market price. Then, we compute a rolling liquidity score on a per-asset basis, defined as:

$$L = \frac{1}{N} \sum_{t=-N-1}^{0} (d_t + 1)\,, N = \min(60, length(price\ hist))$$

from the quote depth history $\{d_t\}$. Finally, we compute the weighted average spread with liquidity-score weighting over the assets in the universe. As noted above, the weighting is intended to minimize the effect of illiquid names on risk factor volatility estimates. In combination with the top-level exclusion rules, it ensures a minimum of manual interventions in spread curve constituents.

Quality Assurance

Loan curves are fully integrated in the MSCI time series data QA model. Exceptions from both the generic QA process and the timeseries multivariate model are evaluated by analysts daily and escalated and resolved appropriately.

Loan Factor Time Series Properties

The long-run correlation of a sample of loan spread curves, broad-market bond, and CDS index spread, as well as loan index prices, is shown in Figure 23. This figure captures equal-weighted correlations over the period from 2007 to 2016. Broadly, sectors are highly correlated.

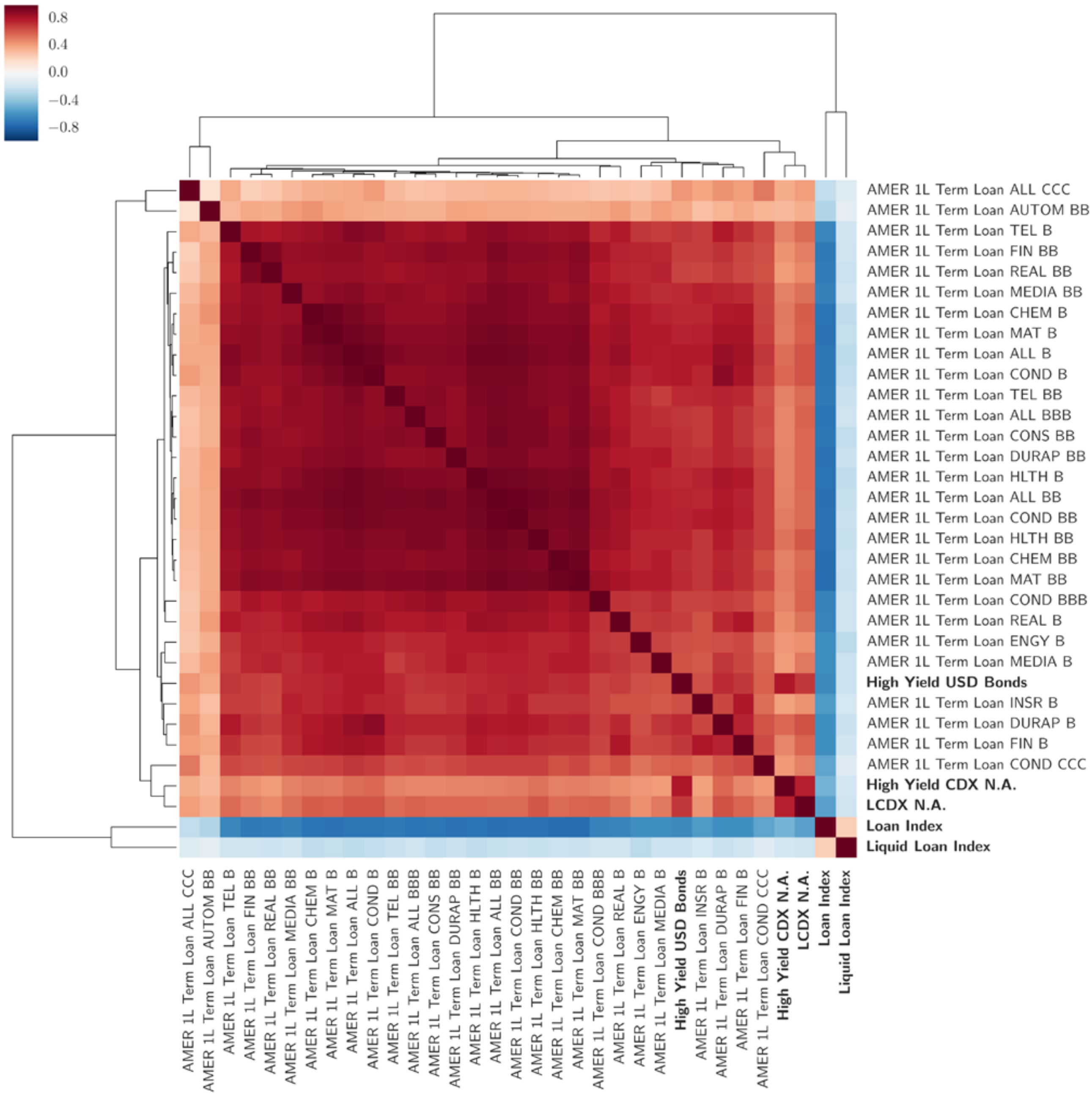

Figure 23 - Correlation of weekly loan sector spreads with broad credit index spreads and prices. Note that the price indices exhibit the familiar negative correlation with spreads.

Curves: Subsector by Rating[15]

RM Name	Lien	Loan Type	Sector/Subsector	Rating
AMER_1L_Revolver_ALL_B	First Lien	RC	All	B
AMER_1L_Revolver_ALL_BB	First Lien	RC	All	BB
AMER_1L_Revolver_COND_B	First Lien	RC	Consumer Discretionary	B
AMER_1L_Revolver_COND_BB	First Lien	RC	Consumer Discretionary	BB
AMER_1L_Revolver_FIN_B	First Lien	RC	Financial	B
AMER_1L_Revolver_HLTH_B	First Lien	RC	Healthcare	B
AMER_1L_Revolver_MEDIA_B	First Lien	RC	Media	B
AMER_1L_Revolver_MEDIA_BB	First Lien	RC	Media	BB
AMER_1L_Term_Loan_ALL_B	First Lien	TL	All	B
AMER_1L_Term_Loan_ALL_BB	First Lien	TL	All	B
AMER_1L_Term_Loan_ALL_BBB	First Lien	TL	All	BBB
AMER_1L_Term_Loan_ALL_CCC	First Lien	TL	All	CCC
AMER_1L_Term_Loan_AUTOM_BB	First Lien	TL	Auto	BB
AMER_1L_Term_Loan_CHEM_B	First Lien	TL	Chemicals	B
AMER_1L_Term_Loan_CHEM_BB	First Lien	TL	Chemicals	BB
AMER_1L_Term_Loan_COND_B	First Lien	TL	Consumer Discretionary	B
AMER_1L_Term_Loan_COND_BB	First Lien	TL	Consumer Discretionary	BB
AMER_1L_Term_Loan_COND_BBB	First Lien	TL	Consumer Discretionary	BBB
AMER_1L_Term_Loan_COND_CCC	First Lien	TL	Consumer Discretionary	CCC
AMER_1L_Term_Loan_COND_RET_B	First Lien	TL	Retail	B
AMER_1L_Term_Loan_COND_RET_BB	First Lien	TL	Retail	BB
AMER_1L_Term_Loan_COND_SERV_B	First Lien	TL	Services	B
AMER_1L_Term_Loan_COND_SERV_BB	First Lien	TL	Services	BB
AMER_1L_Term_Loan_CONS_B	First Lien	TL	Consumer Staples	B
AMER_1L_Term_Loan_CONS_BB	First Lien	TL	Consumer Staples	BB

[15] Subsector by rating curves will be released in Oct. 2017.

AMER_1L_Term_Loan_DURAP_B	First Lien	TL	Consumer Durables and Apparel	B
AMER_1L_Term_Loan_DURAP_BB	First Lien	TL	Consumer Durables and Apparel	BB
AMER_1L_Term_Loan_ENGY_B	First Lien	TL	Energy	B
AMER_1L_Term_Loan_FIN_B	First Lien	TL	Financial	B
AMER_1L_Term_Loan_FIN_BB	First Lien	TL	Financial	BB
AMER_1L_Term_Loan_HLTH_B	First Lien	TL	Healthcare	B
AMER_1L_Term_Loan_HLTH_BB	First Lien	TL	Healthcare	BB
AMER_1L_Term_Loan_IND_B	First Lien	TL	Industrials	B
AMER_1L_Term_Loan_IND_BB	First Lien	TL	Industrials	BB
AMER_1L_Term_Loan_IND_CAPGD_B	First Lien	TL	Capital Goods	B
AMER_1L_Term_Loan_IND_CAPGD_BB	First Lien	TL	Capital Goods	BB
AMER_1L_Term_Loan_IND_SERV_B	First Lien	TL	Industrial Services	B
AMER_1L_Term_Loan_IND_SERV_BB	First Lien	TL	Industrial Services	BB
AMER_1L_Term_Loan_INSR_B	First Lien	TL	Insurance	B
AMER_1L_Term_Loan_MAT_B	First Lien	TL	Materials	B
AMER_1L_Term_Loan_MAT_BB	First Lien	TL	Materials	BB
AMER_1L_Term_Loan_MEDIA_B	First Lien	TL	Media	B
AMER_1L_Term_Loan_MEDIA_BB	First Lien	TL	Media	BB
AMER_1L_Term_Loan_REAL_B	First Lien	TL	Real Estate	B
AMER_1L_Term_Loan_REAL_BB	First Lien	TL	Real Estate	BB
AMER_1L_Term_Loan_TEL_B	First Lien	TL	Telecommunications	B
AMER_1L_Term_Loan_TEL_BB	First Lien	TL	Telecommunications	BB
AMER_2L_Term_Loan_ALL_B	Second Lien	TL	All	B

Curves: Sector by Rating Range

Note that for loans in the Americas/First Lien/Term Loan/High Yield Speculative/Health and Telecommunications sectors and Americas/First Lien/Term Loan/ High Yield Speculative/Energy and Materials sectors, insufficient loans exist to support individual curves for each sector; however, the combination of these sectors into two curves provides a better modeled curve than the alternative All Sector High Yield Speculative curve (AMER_1L_Term_Loan_ALL_HYS). As such, two supersectors, COMM (commodity-related: Energy + Materials) and REGUL (Regulated: Health and Telecommunications), are defined for which the RM Names "AMER_1L_Term_Loan_COMM_HYS" and "AMER_1L_Term_Loan_REGUL_HYS" are produced.

RM Name	Lien	Loan Type	Sector	Rating
AMER_1L_Term_Loan_ALL_IG	First Lien	Term Loan	All	AAA - BBB-
AMER_1L_Term_Loan_ALL_HY	First Lien	Term Loan	All	BB+ - B-
AMER_1L_Term_Loan_ALL_HYS	First Lien	Term Loan	All	CCC+ - C-
AMER_2L_Term_Loan_ALL_HY	Second Lien	Term Loan	All	BB+ - B-
AMER_2L_Term_Loan_ALL_HYS	Second Lien	Term Loan	All	CCC+ - C-
AMER_1L_Revolver_ALL_IG	First Lien	Revolver	All	AAA - BBB-
AMER_1L_Revolver_ALL_HY	First Lien	Revolver	All	BB+ - B-
AMER_1L_Revolver_ALL_HYS	First Lien	Revolver	All	CCC+ - C-
AMER_1L_Revolver_UTL_HY	First Lien	Revolver	Utilities	High Yield
AMER_1L_Revolver_TEL_HY	First Lien	Revolver	Telecommunications	High Yield
AMER_1L_Revolver_COND_HY	First Lien	Revolver	Consumer Discretionary	High Yield
AMER_1L_Revolver_CONS_HY	First Lien	Revolver	Consumer Staples	High Yield
AMER_1L_Revolver_ENGY_HY	First Lien	Revolver	Energy	High Yield
AMER_1L_Revolver_FIN_HY	First Lien	Revolver	Financial	High Yield
AMER_1L_Revolver_HLTH_HY	First Lien	Revolver	Health	High Yield
AMER_1L_Revolver_IND_HY	First Lien	Revolver	Industrial	High Yield
AMER_1L_Revolver_MAT_HY	First Lien	Revolver	Materials	High Yield
AMER_1L_Revolver_TRANS_HY	First Lien	Revolver	Transportation	High Yield
AMER_1L_Term_Loan_COND_HYS	First Lien	Term Loan	Consumer Discretionary	High Yield Speculative
AMER_1L_Term_Loan_COMM_HYS	First Lien	Term Loan	Commercial	High Yield Speculative

AMER_1L_Term_Loan_REGUL_HYS	First Lien	Term Loan	Regulated	High Yield Speculative
AMER_1L_Term_Loan_COND_HY	First Lien	Term Loan	Consumer Discretionary	High Yield
AMER_1L_Term_Loan_CONS_HY	First Lien	Term Loan	Consumer Staples	High Yield
AMER_1L_Term_Loan_ENGY_HY	First Lien	Term Loan	Energy	High Yield
AMER_1L_Term_Loan_FIN_HY	First Lien	Term Loan	Financial	High Yield
AMER_1L_Term_Loan_HLTH_HY	First Lien	Term Loan	Health	High Yield
AMER_1L_Term_Loan_MAT_HY	First Lien	Term Loan	Materials	High Yield
AMER_1L_Term_Loan_UTL_HY	First Lien	Term Loan	Utilities	High Yield
AMER_1L_Term_Loan_TRANS_HY	First Lien	Term Loan	Transportation	High Yield
AMER_1L_Term_Loan_TEL_HY	First Lien	Term Loan	Telecommunications	High Yield
AMER_1L_Term_Loan_IND_HY	First Lien	Term Loan	Industrial	High Yield
EMEA_1L_Term_Loan_ALL_EUR	First Lien	Term Loan	All	High Yield
EMEA_1L_Term_Loan_COND_EUR	First Lien	Term Loan	Consumer Discretionary	High Yield
EMEA_1L_Term_Loan_HLTH_EUR	First Lien	Term Loan	Health	High Yield
EMEA_1L_Term_Loan_IND_EUR	First Lien	Term Loan	Industrials	High Yield
EMEA_1L_Revolver_ALL_EUR	First Lien	Term Loan	All	High Yield
EMEA_1L_Revolver_COND_EUR	First Lien	Term Loan	Consumer Discretionary	High Yield
EMEA_1L_Revolver_CONS_EUR	First Lien	Term Loan	Consumer Staples	High Yield
EMEA_1L_Revolver_HLTH_EUR	First Lien	Term Loan	Health	High Yield
EMEA_1L_Revolver_IND_EUR	First Lien	Term Loan	Industrials	High Yield
EMEA_2L_Term_Loan_ALL_EUR	Second Lien	Term Loan	All	High Yield

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