>>

FIXED INCOME

A Bloomberg Professional Service Offering

BLOOMBERG CREDIT RISK DRSK <GO>

Framework, Methodology & Usage

Bloomberg

CONTENTS

INTRODUCTION

The Bloomberg credit risk function, DRSK <GO> provides transparent and timely quantitative estimates of an issuer's default probabilities, default risk and 5-year CDS spread.

The main model inputs are displayed on the screen, providing transparency into the drivers of credit risk; the inputs are also override-able, allowing users to perform scenario and sensitivity analyses (e.g., changes to capital structure or market conditions). DRSK <GO> currently covers about 8,365 U.S.—and–Canada domiciled companies, 6,362 Western European companies, 25,375 Asian companies and 1,154 Latin American companies.

The default likelihood model is based on the Merton distance-to-default (DD) measure, along with additional economically and statistically relevant factors. To ensure comparability across accounting/business models, reported financials are adjusted for operating leases and pensions/OPEB. Using the strong relationship between estimated default likelihoods and market CDS spreads, we also estimate 5-year CDS spreads, providing a valuable reference point for firms without traded CDS. Finally, firms are assigned a default risk measure as a high-level summary of their credit health using an explicit mapping from default likelihood to default risk. The complete term structure of default probability from 3 months through 5 years is estimated.

Estimating default likelihood is based on globally calibrated model which also retains region specific characteristics. This approach helps achieve enhanced comparability when investors need to know credit risks of same sector peer firms across different regions (e.g., Japan's Toyota Motor vs. Korea's Hyundai Motor vs. France's Renault vs. U.S.'s GM).

BLOOMBERG CREDIT RISK MODEL – METHODOLOGY

>>

DEFINITION OF DEFAULT

Default in the DRSK <GO> model is defined as the first of any of the following: failure to pay interest/principal on an interest-bearing bond or loan, bankruptcy filing or, for banks, FDIC takeover or government bail-out. A typical time line for default is shown below in Figure 1. Default is triggered by a firm's inability to pay a coupon on interest-bearing corporate debt or violation of a debt covenant. The firm enters a grace period where in it attempts to fix the situation. Then, the firm enters a default resolution phase that could result in a positive outcome(the firm survives unscathed) or a negative outcome (the firm files for bankruptcy). Figure 2 shows how our default samples are distributed over time.

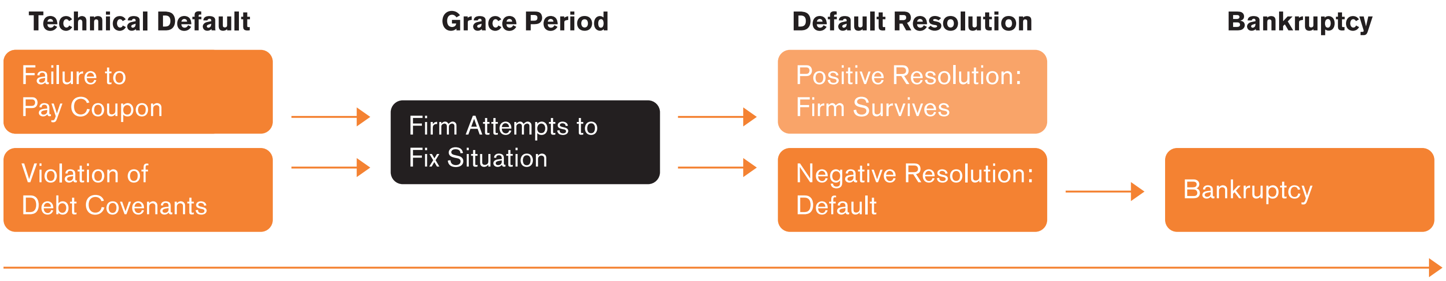

Figure 1 – Time line for default

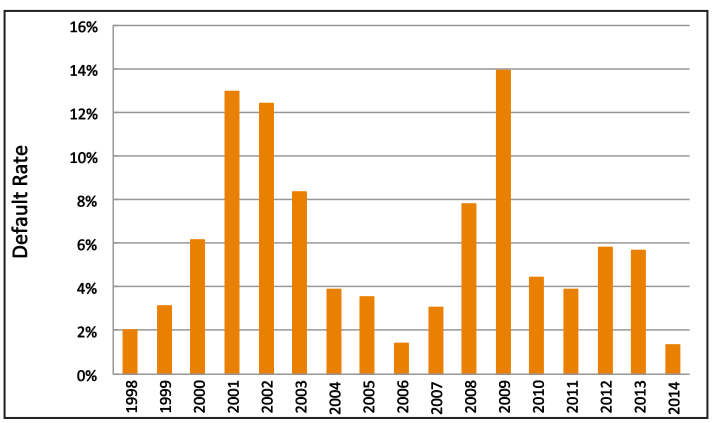

Figure 2 – Default Rate through Aug, 2014

Main Driver of Default: Distance-to-Default

The DRSK <GO> framework for modeling default has its origins in the structural model proposed by Robert Merton.[1] In this model, a firm is viewed as solvent as long as the value of the firm's assets is larger than the value of its liabilities. The issue is that the value of the assets of the firm is not observable and must thus be inferred. The Merton model links the value of the assets to the market cap and debt of a firm, both of which are observable. The key insight of the Merton framework is that the equity of the firm can be viewed as a call option on the total assets of the firm where the strike price is equal to its liabilities. This allows us to infer the value of the assets from the observed equity value using a Black Scholes option pricing approach.

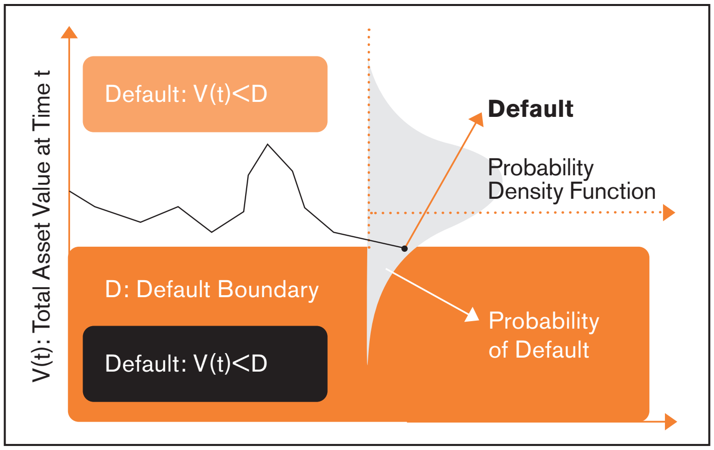

Figure 3 – Default of a firm in the option theoretic framework

The original Merton framework is limited in that it assumes that a firm can default only at the maturity of firm's liabilities, which are assumed to be zero coupon bonds. In reality, default can occur at any time. DRSK <GO> overcomes this limitation by treating equity as a 1-year barrier call option, explicitly incorporating the possibility that the firm defaults before the maturity of the debt. This approach is used to calculate the main output of the Merton model, the Distance-to-Default (DD).

DD is a leverage parameter that incorporates the ratio of firm value to debt, with an adjustment for market volatility and expected growth rate of the assets (Figure 3). As the name indicates, the smaller the DD, the closer the firm is to default. The DD that emerges from this option framework is the first key parameter in our default model.

It is well known that the default probability obtained from the basic Merton DD underestimates the true default likelihood over short horizons and for higher DD, or safe, firms. A crucial step in our process is, therefore, creating a mapping between DD and actual default rates, which allows DRSK <GO> to calculate an accurate default probability given a DD. This relationship is shown in Figure 4. The Default Probability is a nonlinear function of DD. The default probability can thus be expressed as follows:

Default probability = f(distance-to-default), where f is a nonlinear function.

If we now invert the above relationship and plot a transformation of the observed default frequency for many grouped firm observations against their Distances-to-Default, we obtain the graph shown in Figure 4.

Changes in DD and default likelihoods are largely driven by changes in market cap and equity volatility, making DRSK <GO> responsive to real-time changes in a firm's prospects. A natural outcome of this dependence on market cap and volatility is that default probabilities are also cyclical. Realized default rates correlate nicely with this result, rising during periods of overall economic distress and falling during expansions.

The definition of debt is straightforward for non-financial firms. For financials, especially banks and broker-dealers, the definition is more nuanced. After extensive testing, DRSK <GO> considers trading liabilities (repo, short sales and derivative liabilities) as important measures of credit risk alongside short-term debt. Customer deposits tend to be a special category—sharing some of the characteristics of debt (they are a liability), but having characteristics that are not debt-like—they tend to be stable over time, are viewed as a stable source of long-term funding and tend to have a significantly lower funding cost than debt. Finally, federal deposit insurance for deposits also affects customer perception of the risk of deposits. For all these reasons, we only include 50% of deposits in debt. Their inclusion in the debt calculation does not significantly change model performance in terms of the ability to discriminate between defaulting and non-defaulting banks—further supporting our hypothesis that they are not a significant source of leverage risk for a bank in the same sense that debt adds leverage.

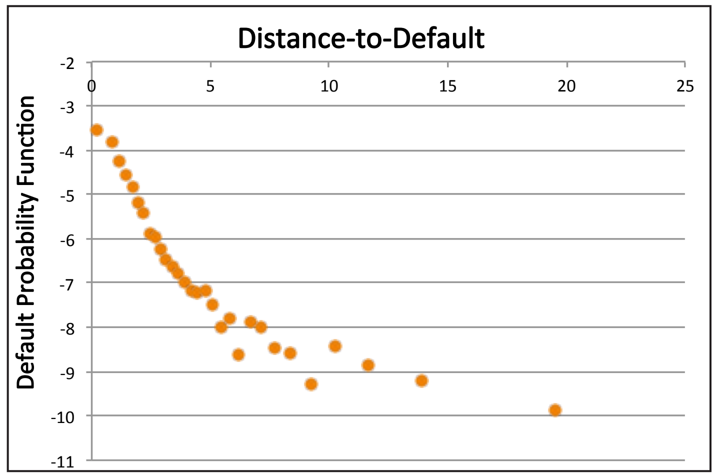

Figure 4 – The relationship between DD and a nonlinear transformation of default probability

Additional Drivers of Default

The Merton DD is a balance sheet–focused measure of credit risk. Bharath and Shumway,[2] show that while DD is a significant predictor of default, it is not a sufficient statistic. Consistent with this study, we find that supplementing the information in DD with information from other financial filings can significantly improve model performance. For each sector, we investigated metrics that should be related to the credit health of those firms. For example, for insurance firms we looked at measures of claims and reserves; for banks, non-performing loans, etc.

We find that for non-financial firms, interest coverage, defined as Trailing 12-month Cash Flow from Operations (CFO)/ Trailing 12-month Interest Expense, significantly adds to the model performance. This factor is robust to a variety of specifications (namely, using T12M EBIT or EBITDA in the numerator), however, CFO provides the best results, and is particularly helpful in identifying "true" interest coverage for firms with accrual (non-cash) income or high levels of capital investment. As CFO has taxes and interest expense removed from it, we add these amounts back to CFO before calculating our coverage metric.

A plot of interest coverage ratio versus actual default illustrates this relationship (Figure 5). Firm month observations are grouped by their coverage level, and then the median coverage level is plotted against the number of firm month default observations in that bucket. A clear pattern emerges of increasing default rates as coverage decreases.

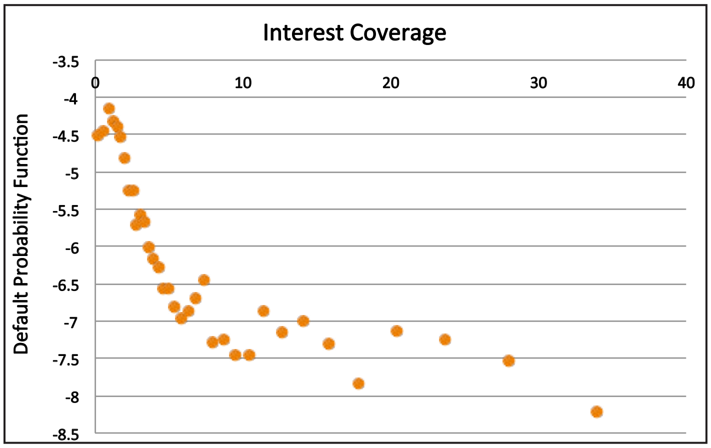

Figure 5 – Interest Coverage vs. Default Ratio

For banks, we find that the ratio of non-performing loans to loan-loss reserves provides incremental information beyond DD. Figure 6 shows the default rate across NPL/ groupings in our sample, indicating increasing default as the ratio increases. This ratio differentiates between firms with potentially conservative or aggressive accounting policies for deteriorating loan portfolios and/or sustainable profits. We also find that a negative value of return on assets adjusted for volatility to be significant for banks.

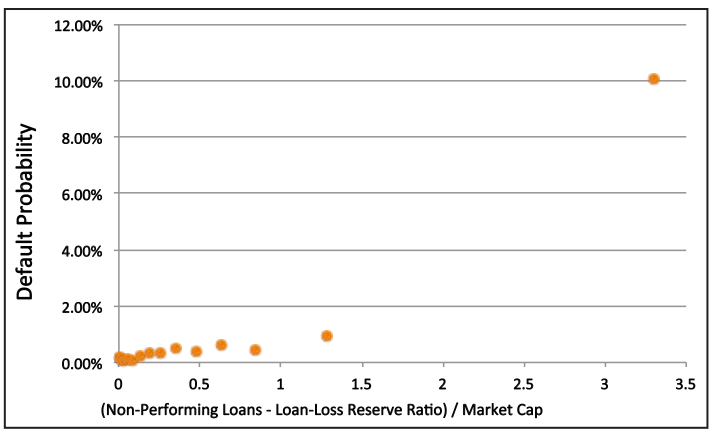

Figure 6 – (Non-Performing Loans – Loan-Loss Reserves)/Market Cap

Accounting Adjustments

Differences in accounting practices and off-balance-sheet activities can cause reported financial statements to misrepresent the true underlying economics. We adjust both the income statement and balance sheet to render the resulting fundamental information comparable across companies and obtain a true picture of the firm's financial condition. Specifically, we adjust both the balance sheet and income statement for:

» Operating Leases

» Pension Adjustments

These adjustments are described in detail below.

Operating Leases

Operating leases are contractual obligations of a lessee and are similar to debt payments. Choosing to classify a lease as operating rather than capital implies that debt levels and interest expenses are understated, as are various leverage ratios. To create a fair and accurate comparison between firms that use operating versus capital leases, we make the following adjustments to firms that utilize operating leases:

» **Balance Sheet –** The debt that results from the lease being capitalized is added to long-term debt. This is calculated by capitalizing the present value of the operating lease payments. The corresponding assets are added to property plant and equipment.

» **Income Statement –** The increased debt and assets result in higher interest expense and depreciation expense. Lease payments are removed from rental expense.

Operating lease adjustments are more significant for certain sectors such as retail, automotive and transportation. For example, Starbucks is a typical retail firm with heavy dependence on operating leases to finance its retail stores. The debt structure for Starbucks as of May 20 2014, is shown below:

» Short-Term Debt: $0B

» Long-Term Debt: $2.048B

» Operating Lease Equivalent Debt: $8.443B

Clearly, lease obligations are quite significant, and, in Starbucks' case, capitalization of lease obligations substantially increases default probability and credit risk (measure [measure drops by two notches, please see Table 1).

Adjustments	Default Probability	Bloomberg Credit Risk
Before	0.0047%	IG3
After	0.0192%	IG5

Table 1 – Impact of Lease Adjustments on Starbucks

Pension/OPEB Adjustments

"Defined benefit" pension plans represent a liability that a firm assumes in order to provide employees with health and pension benefits in retirement. These plans are becoming less common, but for mature manufacturing and industrial firms, legacy obligations can still be significant sources of risk. The law requires companies to provide funding to these plans to offset the liability arising from these benefits. However, the firm has some flexibility in how much to set aside, and some plans can become significantly underfunded. We reclassify the net unfunded obligation as long-term debt.

The exact adjustments are as follows:

» Pension & OPEB interest costs, and changes in asset values are reclassified as interest expense or non-operating income.

» Service costs (Pension & OPEB) are classified under operating costs.

» For accounting purposes, projected pension benefit obligations are netted against the fair value of plan assets. This net asset/liability is reclassified as long-term debt.

In the case of U.S., from 1980 through 2000, the number of employees of public companies covered by defined benefit pension plans in private industry shrank from 80% to 36%.[3] Hence, the number of firms that have such plans is dwindling and they tend to be concentrated in "old economy" companies.

Liabilities	$ (bn)
Short-Term Debt	38.88
Long-Term Debt	78.12
Pension liabilities = PBO−Fair Value of Plan Assets	14.86

Table 2 – Debt and Pension Liabilities for Ford

For Ford of the U.S., pension and OPEB represent almost 20% of total adjusted long-term debt (as of July 16 2014), as shown in Table 2, and have a meaningful impact on estimates of Ford's credit risk as shown in Table 3 below

Adjustments	Default Probability	Bloomberg Credit Risk
Before	0.147%	IG8
After	0.187%	IG9

Table 3 – Impact of Pension Adjustments on Ford

Liabilities	¥ (bn)
Short term debt (JPY)	171.87
Long term debt (JPY)	506.76
Pension Lib (JPY)	209.21

Table 4 – Impact of Pension Adjustment on Mitsubishi Electric

For Mitsubishi Electric Corp of Japan, pension and OPEB represent almost 41% of total adjusted long-term debt (as of July 16 2014), as shown in Table 4, and have a meaningful impact on estimates of Mitsubishi Electric Corp's credit risk as shown in Table 5 below.

Adjustments	Default Probability	Bloomberg Credit Risk
Before	0.046%	IG7
After	0.059%	IG7

Table 5 – Impact of Pension Adjustment on Mitsubishi Electric

CDOs, Trusts & Conduits

For large banks, a potentially significant portion of risk may reside off-balance sheet in SPV/SIVs, CDOs, trusts or conduits. Although technically off-balance sheet and bankruptcy remote, during the credit crisis, several banks stepped in to support their SPVs. While we did not find a systematically appropriate way to add a portion of off-balance-sheet risk to the default barrier, we do make these values over-ridable by the user to facilitate scenario analysis.

Users can choose to include a fraction of these off-balance-sheet items as part of long-term debt by overriding the long-term debt value.

Term Structure of Default Probabilities

The term structure of default probabilities is necessary for applications with differing time horizons. Besides the 1-year default probability, DRSK <GO> also provides default probabilities for a spectrum of tenors from 3, 6, 9 months to 2, 3, 4, 5 years. Similar to the term structure of interest rates, the term structure of default probabilities can be expressed in cumulative (CDP), annualized (ADP) or forward (FDP) terms, conditional on no default in previous years.

To ensure consistency between default probabilities at various tenors, DRSK <GO> uses the forward conditional default probability estimation methodology. The steps are as follows:

» At the 3-month tenor, DRSK <GO> directly estimates the probability of default within 3 months (CDP_{3m}).

» At the 6-month tenor, DRSK <GO> estimates the forward default probability from 4th month to 6th month—given no default in the first 3 months (FDP_{6m}). The cumulative 6 months default probability (CDP_{6m}) is, therefore, calculated as $CDP_{6m}=1-(1-CDP_{3m})(1-FDP_{6m})$.

» This is similarly done for 9 months and 1 year. Beyond 1-year, DRSK <GO> uses a 1-year interval to derive 2-, 3-,4- and 5-year forward default probability and then calculates cumulative default probability.

» From cumulative default probabilities, the annualized default probabilities can be easily obtained using the following formula:

$$ADP_T=(1-CDP_T)^{1/T}$$

Where T is 3m, 6m, 9m, 1y, 2y, 3y, 4y, 5y serially.

Model Validation

We validate our model using rigorous statistical tests; we employ case studies to provide anecdotal evidence. The case studies illustrate our model's ability to provide early warning of credit deterioration as well as improvement. We also illustrate our model's ability to forecast corporate actions resulting from deterioration in credit quality. The illustrations are derived from back testing the model. We have also provided results of a comprehensive series of statistical testsof our model.

Early Warning: Eddie Bauer, Lehman Brothers & OGX

Eddie Bauer was part of Spiegel and went through a bankruptcy in 2003 before being reconstituted as a separate entity in May 2005. Eddie Bauer relied on funding primarily through a variety of long-term instruments immediately prior to default:

- Revolver $150M size, with $31.9M outstanding and maturity 2010.
- PIK term loan, with $225M tranche size and $188M outstanding, maturity 2014.
- Senior unsecured convertible debt of $75M, 5.25% coupon, maturity 2014.

There were short-term funding instruments in place ranging from $20–30M. Eddie Bauer defaulted on June 17, 2009 .

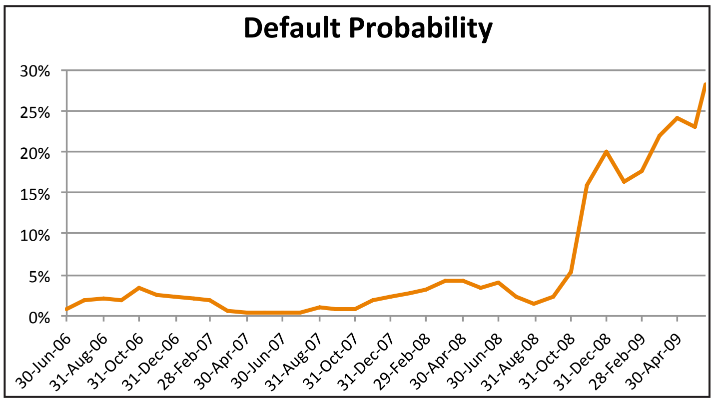

Figure 7 – Early Warning for Eddie Bauer

Figure 7 shows that as early as August 2007 the default probabilities for Eddie Bauer began increasing and rose to 5% in 2008 and to above 28% in the months leading up to its default.

In the financials space, we highlight the DRSK <GO> model of default likelihood for Lehman Brothers. Lehman filed for bankruptcy on Sept. 15, 2008, with more than $600B in assets, $388B in short-term borrowings (including repo, stock loans and other trading liabilities) and $128B in long-term borrowings.

The high level of credit risk posed by Lehman's leverage is apparent throughout the history, with the default probability never falling below 1% (HY2). In Figure 8 below, the default risk is shown to rise fairly steadily from a low of ~1.5% in 2006 to higher than 15% in the summer of 2008.

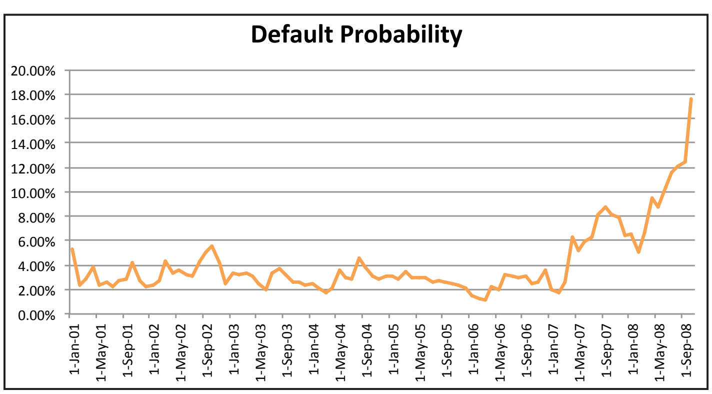

Figure 8 – Lehman Brothers Default Likelihood History

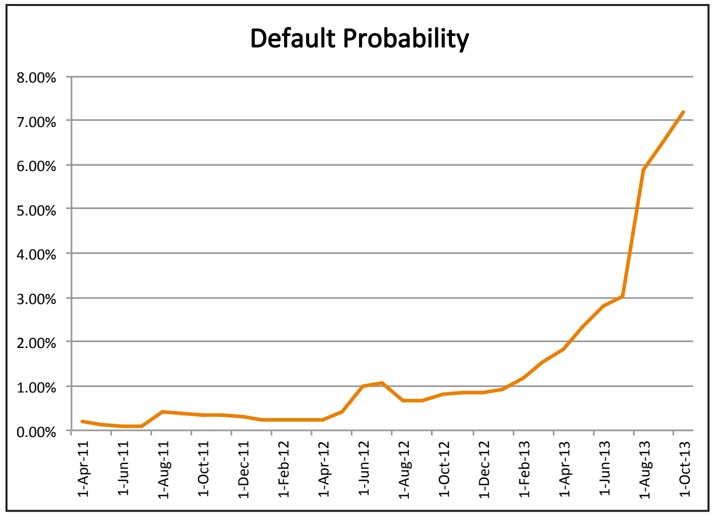

Figure 9 – Early Warning for Oleo e Gas Partipacoes S.A.

Figure 9 shows default probability of Oleo e Gas Participacoes S.A. (OGX) of Brasil. OGX filed for bankruptcy on Oct 31, 2013, which is the largest bankruptcy in Latin America economies. Default probability was already over 1% since summer 2012, then fast rose to over 7% one month prior to its bankruptcy.

Identifying Firms That Are in Good Credit Health: Genzyme

After adjusting for operating leases, Genzyme represented a stable and safe credit in the DRSK <GO> model as early as 2003. Sources of long-term funding are shown below:

» Revolver $350M size, with $12M outstanding and maturity 2011
» Secured debt, size $18M, 5.57% coupon, maturity 2020
» Capital Leases: $107M
» Senior unsecured debt $6M, 3.86% coupon, maturity 2013

A history of default probability levels is displayed in Table 6.

Date	DRSK Model Default Probability
12/28/08	0.07% (IG7)
1/31/08	0.01% (IG4)
3/31/05	0.02% (IG5)
7/28/03	0.10% (IG8)
5/29/03	0.14% (IG8)

Table 6 – Default Probability for Genzyme

DRSK <GO> default probabilities remained low (associated with Bloomberg 1-Yr. Credit Risk of IG-7 or higher) from at least 2003 onwards. In this example, DRSK <GO> identifies the high credit quality of Genzyme.

High Default Probability as a Precursor to Corporate Action

Table 7 below shows a sample of firms with high default probabilities on Dec. 31, 2008. In general, these companies engaged in corporate actions indicating financial distress after that date.

Firm	Ticker	Default Probability	Corporate Action
Aemetis Inc.	AMTX	49.75%	Default, May 2009
Nova Biosource Fuels Inc.	NBFAQ	24.68%	Chapter 11 Bankruptcy, Mar 2009
Vineyard National Bancrop	VNBCQ	35.67%	Chapter 11 Bankruptcy, July 2009
Corus Bankshares	CORSQ	48.91%	FDIC arranged deposit sale, Sept 2009
Eimskipafelag Islands HF	HFEIM IR	8.09%	Filed for Composition on July 1, 2009

Table 7 – High Default Probabilities and Subsequent Corporate Actions—North America examples

Table 8 below shows default probabilities at six months prior to corporate actions of Asian firms. Corporate actions include defaults/bankruptcy, creditor's capital injection and creditor take-over after long period of distress.

Firm	Ticker	Default Probability	Corporate Action
Shanghai Chaori Solar Energy/China	002506 CH	2.11%	Default, Mar 2014
Sino Forest Corp/China	TRE CN	6.89%	Default, Mar 2012
STX Corp/ Korea	011810 KS	2.84%	Creditor takeover, Jan 2014
Elpida Memory/ Japan	6665 JP	7.31%	Creditor capital injection, Aug 2009

Table 8 – High Default Probabilities and Subsequent Corporate Actions—China, Japan, Korea examples

Comprehensive Statistical Tests

The primary focus of DRSK <GO> is to determine firms likely to default and those unlikely to do so. To this end, we evaluate its performance by calculating the accuracy ratio, or cumulative accuracy profile. This test quantifies a model's ability to identify defaulting firms as more risky than non-defaulting firms. After correctly ordering firms based on default risk, the model should also predict the default rate among a group of firms. To test this, we perform a goodness-of-fit test by plotting model-implied default rates against realized rates, and comparing results with a 45% degree line. Finally, we evaluate our model's overall ability to provide early warning of default.

ACCURACY RATIO (AR) TEST

The accuracy ratio measures the quality of the ordering of a default probability model. This means that the model is penalized both for assessing safe firms as too risky and vice versa (type I and II errors). The calculation is as follows:

» Rank firms by decreasing default probability.

» Draw firms in order of decreasing rank without replacement. On the y-axis, mark the percentage of defaulted firms that have been removed; on the x-axis, mark the percentage of the total number of firms that have been removed.

» After completing the draw, plot the curve (cumulative accuracy profile). Compute the area under the curve. This is the accuracy ratio. In a model that is generating random results, the cumulative accuracy profile is a 45 degree line. For a perfect model, the line would rise almost vertically (the exact angle would depend on the overall default rate) until it intersects the 100% level and then would form a horizontal line.

This test can be performed both in-sample and out-of-sample. In-sample accuracy ratio (AR) tests indicate that non-financial model has an accuracy ratio of 92.43% (Figure 10) and financial model has an AR of 91.78%.

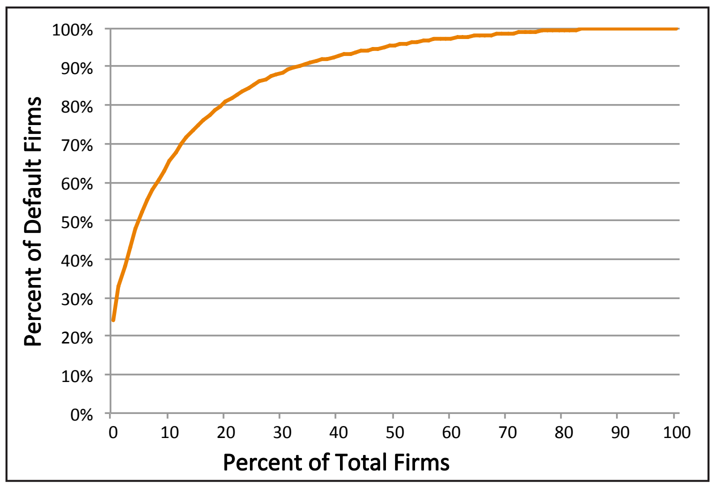

Figure 10 – Accuracy Ratio Test for Non-Financial Sectors

GOODNESS OF FIT TEST

The goodness of fit was tested by:

» Grouping firm-level observations of default by default probability across the universe of firms being considered.

» Plotting the calculated default probabilities on the x axis and the actual default rates from default data on the y axis. These represent ex-ante versus ex-post default probabilities, respectively.

The curve that is generated (Figure 11) lies close to the 45 degree line, indicating that the model estimation is free of bias.

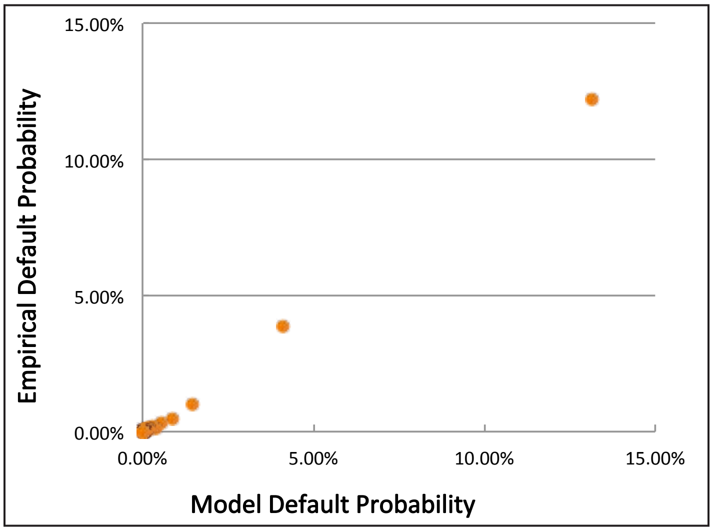

Figure 11 – Realized Versus Model Default Probability

EARLY WARNING PERFORMANCE

For the sample of firms that defaulted, we calculated the mean and median default probabilities in the months prior to their eventual default (Figure 12). The DRSK <GO> model calculated that the default probability increases steadily as default approaches, rising from ~4%, one year before default up to ~17% one month before default.

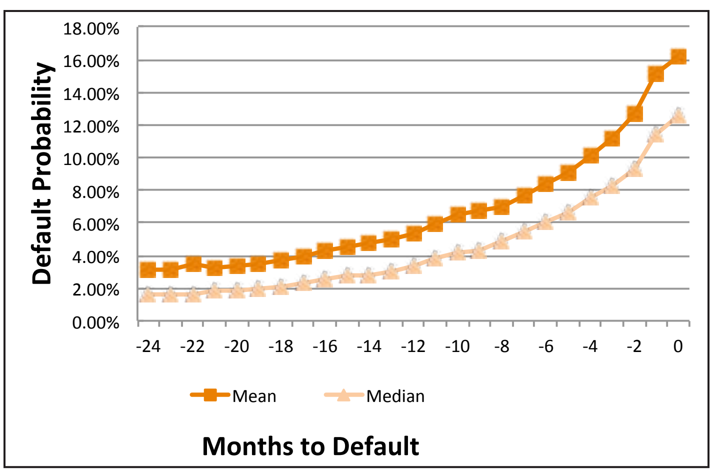

Figure 12 – DRSK <GO> Early Warning of Defaulting Firms

Term Structure of Default Probability—Validation

If a risky firm does not default, chances are that management is taking steps for the business to become less risky. For such firms, we would expect the default probability to fall eventually. For a safe company, the default probability should rise slowly—as asset volatility increases the chances of default over longer periods of time. Figure 13 confirms this intuition. In this figure, companies are sorted and grouped by their 1-year default probability, where Group 1 is the safest in the near term and Group 5 is the riskiest. While Group 5 clearly shows a downward trend in its predicted annualized default probabilities, the other safer groups are predicted to become riskier over time, exactly as our intuition suggests.

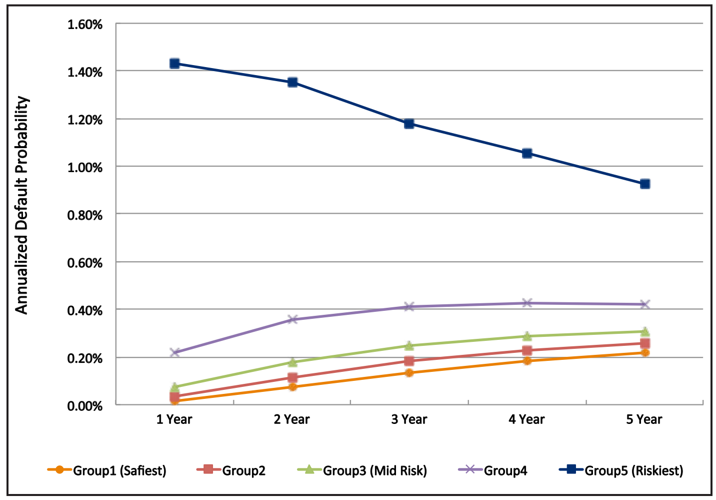

Figure 13 – Stylized Term Structure of Annualized Default Probabilities

BLOOMBERG 1-YEAR CREDIT RISK SCALE

The Bloomberg Credit Risk Scale is shown to the right in Table 9. The Bloomberg Credit Risk Scale is an explicit mapping from the DRSK <GO> model default probability to a credit risk measure. The credit risk bands are chosen so that the default rate in each band is broadly consistent with the 1- year probability of transition to default across major NRSRO ratings of a comparable level. The safest credit risk measure is IG-1, with the riskiest non-defaulted firm credit risk measure being DS5. Defaulted firms are assigned the credit risk measure DDD. The default probabilities associated with the credit risk measure bands are fairly stable over time but are subject to minor modifications.

To reduce the frequency of one notch changes in default risk when a firm's default probability is on or near the boundary between risk bands, we apply a risk watch when the move into a new risk band is very slight. This situation is displayed on the screen by the addition of */+ for improving credit health and */– for worsening credit health.

As an example, imagine Google has a 1-year default probability of 0.0022% and is rated IG-2. The next day the stock rises and DD increases, reducing default probability to 0.0019%. While this is technically in the IG-1 band, it is close enough to the IG-2 lower bound of 0.002% that normal daily volatility in the equity could cause the firm to move back to IG-2 the next day. We thus signify the potential improvement by calling Google IG-1 */+ until it has moved far enough into the higher band to suggest that the move was not caused by short-term volatility in the stock price. If Google fell back into the IG-2 band the following day, the risk watch would be removed. Large moves in default probability that push a firm into a significantly higher or lower risk band are considered informative (and not noise) and hence the default risk is immediately moved to the new band.

Credit Risk Measure	Default Probability Lower Bound	Default Probability Upper Bound
IG - 1	0.000%	0.0020%
IG - 2	0.0020%	0.0040%
IG - 3	0.0040%	0.0080%
IG - 4	0.0080%	0.0152%
IG - 5	0.0152%	0.0286%
IG - 6	0.0286%	0.0529%
IG - 7	0.0529%	0.0960%
IG - 8	0.0960%	0.1715%
IG - 9	0.1715%	0.3000%
IG -10	0.3000%	0.5200%
HY - 1	0.5200%	0.88%
HY - 2	0.88%	1.50%
HY - 3	1.50%	2.40%
HY - 4	2.40%	4.00%
HY - 5	4.00%	6.00%
HY - 6	6.00%	10.00%
DS - 1	10.00%	15.0%
DS - 2	15.0%	22.0%
DS - 3	22.0%	30.0%
DS - 4	30.0%	50.0%
DS - 5	50.0%	100.0%
DDD	Defaulted	Defaulted

Table 9 – Credit Risk Band Mapping

CDS MODEL

CDS spreads are largely indicators of default risk (Longstaff, Neis, Mithal[4]). We use our estimated 1-year default probabilities as the driving factor in a simple econometric model of CDS spreads. Naturally, the DRSK <GO> output is "real-world," physical or "P-measure" whereas CDS implied default probabilities are "risk-neutral" or "Q measure." The risk premium inherent in the conversion between the two measures is implicit in our regression framework, allowing the market data to specify the appropriate conversion as well as the market assumed recovery rate.

The DRSK-implied CDS spread is not intended to be value fitted to the current market, but, rather, to be an estimate of the intrinsic value of the spread. It is an estimate based on an empirical measure of default risk in the real world (not credit market–implied). The model is fit over a rolling window, which provides a smoothed estimate of this conversion between DRSK <GO> default probabilities and market CDS. Thus, the implied spread can deviate from the market value when either the market moves quickly (especially variation in the market credit risk premium) or when the DRSK <GO> default probability ordering disagrees with the market's ordering.

Correlation Test

We test the performance of our CDS model by doing out-of-sample correlation tests with the market spreads. We find that implied CDS spread has a 63.4% rank correlation with the actual spreads and a 64.8% linear correlation. These numbers suggest a strong relationship between the DRSK <GO> model and market spreads.

DRSK FUNCTION

>>

The Bloomberg Credit Risk Model and the CDS Spread Model can be accessed through DRSK <GO>. This section describes the function and its capabilities.

The function has four key areas. The top left corner has the key outputs:

» Credit Risk

» Default Probability

» CDS Spreads

The model table has DRSK <GO> outputs for three key credit measures: 1-year credit risk, 1-year default probability and 5-year CDS implied spread. The 5-year market CDS and market/model CDS ratio are displayed beneath the model CDS.

Inputs

The key model inputs are displayed in the middle left section of the screen underneath the model outputs. Inputs are either derived from market data or the company's financials.

The market data category includes two inputs: share price/ market cap and price volatility. Within the financials category are effective short-term debt, long-term debt, T12M interest expense and T12M Adj. CFO. For financial firms, interest coverage fields are removed and replaced with factors that are meaningful for that type of firm, for instance, non-performing loans and loan loss reserves for banks. To help understand leverage, market cap is shown in the same currency as the fundamentals, whereas the share price is stated in the trading currency. Both market and fundamental inputs can be overridden by the user. This enables the user to study the sensitivity of the credit risk measures and CDS spreads to the key drivers of default as specified in the model.

Scenario Analysis by Overriding Inputs

The user must bear in mind that while inputs may be changed one at a time, in real life, multiple inputs would change simultaneously. For example, a sudden drop in market cap should be accompanied by an increase in volatility. Thus, changing only one input without considering the concurrent movement of other inputs will likely misrepresent the true impact of the desired scenario.

The top right corner of the screen can plot default probability and/ or any reference variables (selected from model outputs and inputs sections of the screen). The graphing tool helps identify the source of changes to model default likelihood by showing model inputs and outputs, over time, on the same screen. By switching from "History" to "Term Structure" in the combo box on top of this part of the screen, users can see either the cumulative and annualized default probabilities at the current date from 3m, 6m—–up to 5y tenors.

Accounting Adjustments

Under 97) Settings on the top of the screen, a check box can be used to switch off the accounting adjustments if desired, and recalculate the default probabilities, credit risk measure and CDS spread. The screen wakes up with the accounting adjustments switched on.

To make our tool as timely as possible, we incorporate preliminary filings into the model. Not all financial line items are released in the preliminary filing, so you may see cases where some fields reflect data from the preliminary and the other fields show input from the previous quarter's filing (and not yet released this quarter). To notify you of this event a "P" for Preliminary, is displayed next to the fundamentals header.

Further, on the bottom of the screen, we provide a concise version of industry comparison, which leads to the full version of industry comparison with 20 <GO> or a click on the title of the section. This section provides key ratios for the firm and the industry to which it belongs. Key ratios cover liquidity, leverage and earnings, including:

» Debt to Equity

» Interest Coverage

» EV/EBITDA

» Realized 1-Yr Vol (%)

» Implied 1-Yr Vol (%)

Both median and sales-weighted mean measures of industry-level ratios are shown under the range column of the table.

Additionally, under the default risk distribution, we display how many entities under the selected industry are classified into the seven different risk groups (IG1, IG2–IG4, IG5–IG7, IG8–IG10, HY1–HY3, HY4–HY6, DS1–DS5).

Figure 14 — Home Screen for Harley Davidson with History View

Figure 15 — Home Screen for Harley Davidson with Term Structure View

Accounting Adjustments for Operating Leases Starbucks finances its coffee outlets through operating leases. SBUX EQUITY <GO> brings up the DRSK <GO> screen in Figure 16 as of May 14 2015, with a credit risk of IG4 and a CDS spread of 39 bps. There is no market CDS quote. Toggling off the accounting adjustments under "97) Settings" results in long-term debt falling from $11.915B to $2.049B and improves the credit risk to IG2. The change in long-term debt is the estimated amount of debt that Starbucks would have to issue to finance its stores without leases. The adjusted T12M interest expense, which was adjusted to account for the increased interest expense because of added debt at the prevailing cost of debt, drops from $388M to $66M. We can thus estimate the effect of operating leases on the credit health of the firm.

Figure 16 — SBUX with Accounting Adjustments

Capital Structure Adjustments

Starbucks had a credit risk of IG4 as of May 14, 2015. If the treasurer wants to issue debt to pay a special dividend, but still maintain credit risk at a similar level, he/she could use DRSK <GO> to estimate how much debt can be issued. By issuing $4B in debt, the credit risk remains at IG4 while the CDS spread increases to 46 bps. The post-issuance scenario is shown in Figure 17 below.

Figure 17 — SBUX Debt Issuance

Analysis of CDS Spreads

Consider Goldman Sachs Inc as of the end of 2011. GS's default risk was IG9, market CDS spreads fell from ~300 bps to the CDS-implied spread of 150 bps in late 2012, however, during this time, spreads tightened as economic recovery in the U.S. led to a "risk-on" attitude and an increase in market cap. The DRSK <GO> model spread has also narrowed. In the figure below, the analysis indicates market cds converges to model cds over time.

Figure 18 — Goldman Sachs Credit Risk Measure and Share Price

APPENDIX

>>

Notes

1. Robert Merton, “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates,” *Journal of Finance* 29, 449–470.
2. Sridhar Bharath and Tyler Shumway, “Forecasting Default with the Merton Distance to Default Model,” *The Review of Financial Studies* 21, 1339–1369.
3. Bryandt Dickerson, Bureau of Labor Statistics website, http://www.bls.gov/opub/cwc/cm20030325tb01.htm
4. Francis Longstaff, Eric Neis, and Sanjay Mithal, “Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit-Default Swap Market,” *Journal of Finance* 60, no. 5, 2213–2253.

Appendix 1 – Technical Details of the Merton Model

The development of the option theoretic approach or the structural model for default is described in Merton [1]. Under the assumption of:

» Frictionless Markets

» Continuous Trading

» Short Sales

» Geometric Brownian Motion of the assets $dV=\mu V dt+\sigma V D w$

denote total debt as D. Considering equity as a call option on the assets of the firm we have:

$$E_t=E^P[\max(V_T-D,0)]$$

In this framework, default can only occur at the expiration date T. DRSK employs a more flexible specification by defining equity as a barrier option, allowing default to occur at any point in time from t to T.

$$E_t=E^P[\max(V_T-D,0)]1_{MIN(Vt)>D}$$

where 1 represents the indicator function.

Given a time series of firm market cap-and debt-level observations, we back into the asset level and volatility implied by the formula above. The key output of the model is then the distance to default (DD), which is defined as:

$$DD=\frac{\ln\left(\frac{V_0}{D}\right)+\left(\mu-\frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

Where:

V_0: Total Merton assets of the firm at time 0

σ : Asset volatility

μ : Asset drift

D : Debt liabilities of the firm

T : Time to maturity

DD: Distance to Default

Appendix 2 – Interpreting the Accuracy Ratio

Accuracy ratios are designed to highlight the ability of a credit model to discriminate between defaulting and non-defaulting firms correctly. If we view default as a positive event and survival as a negative event, the accuracy ratio contains information about false and true positives as shown in Figure 19. Any point on the accuracy ratio curve has a y coordinate that is a measure of true default, while the x coordinate is a measure of false default (since, in the event of a perfect model, the x coordinate should be almost zero). The complements of these quantities on the x and y axis represent true survival and false survival, respectively. Figure 19 shows that false positives and false negatives are a function of the default probability level. The figure also shows that the more powerful the model, the more concave the profile in the graph below.

Figure 19 – Description of the Cumulative Accuracy Profile/Accuracy Ratio

>>>

The Bloomberg Professional® service for corporate finance, treasury and investor relations not only helps address the needs you have today, but also prepares you for those to come. To learn more about what the Bloomberg Professional service can do for you, email our corporations team at corporations@bloomberg.net.

>>

BEIJING
+86 10 6649 7500

FRANKFURT
+49 69 9204 1210

LONDON
+44 20 7330 7500

NEW YORK
+1 212 318 2000

SÃO PAULO
+55 11 2395 9000

SYDNEY
+61 2 9777 8600

DUBAI
+971 4 364 1000

HONG KONG
+852 2977 6000

MUMBAI
+91 22 6120 3600

SAN FRANCISCO
+1 415 912 2960

SINGAPORE
+65 6212 1000

TOKYO
+81 3 3201 8900

bloomberg.com