BLOOMBERG CREDIT DEFAULT RISK FOR GLOBAL NON-FINANCIAL PRIVATE COMPANIES DRSK<GO>

Framework, Methodology & Usage

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1.0 Introduction

Industry issues

Firms are facing more stringent regulatory requirements to enhance their risk management process. Investors require improved methods for measuring and managing risk. Risk officers need independent and timely evaluations of the credit health of their private counterparties, customers, and suppliers. For private companies that are largely unrated, CFOs and Treasurers need internal quantitative models or third party credit models to position themselves with their lenders and in capital markets.

Solution Overview

Private Company Default Risk (DRSK) provides an independent evaluation of a private company's credit health by combining fundamental data, industry risk, market sentiment and the business cycle in a quantitative model calibrated to our extensive private default database. DRSK is objective, with no subjective credit judgments. DRSK estimates a 12-month forward looking default probability (DP). Historical data is available back to 1999 for enterprise risk management calculations or investment strategy back-testing.

Private DRSK will be part of Bloomberg's credit risk solutions, which offer transparency, tools to understand capital structure and loan data, the ability to aggregate risk at the portfolio level, accurate and transparent credit pricing, sovereign risk analysis, and a proactive commitment to regulatory compliance. Clients can perform scenario analysis by overriding inputs such as leverage and profitability.

The remainder of the paper will proceed as follows: Section 2 describes our default probability model including the results of back-testing. Section 3 presents the Bloomberg default risk scale.

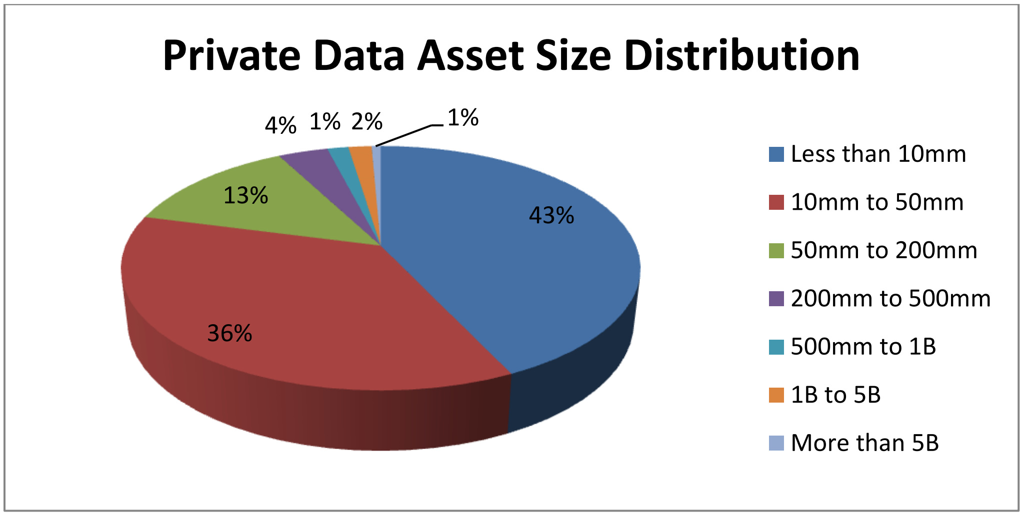
2.0 Private Company Default Risk Model - Methodology

2.0.1 Data

Bloomberg private data mainly comes from Dun & Bradstreet and other private data vendors. For large private companies with public debt and filings, Bloomberg collects the data directly from filings or the company website. In the global private data sample, asset sizes are distributed as follows:

< $10 million	- 43%
$10-50 million	- 36%
$ 50 - $200 million	- 13%
$200M - $1B	- 5%
> $1B	- 3%

Of note that majority of the private companies have total assets of less than $50 million.



2.0.2 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, bankruptcy filing. 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 during which 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 global non-financial default samples are distributed over time and Figure 3 shows how our default samples are distributed over industry globally. Figure 4 shows how DRSK default samples (1999-2015) are distributed by size, which does not support the "too big to fail" notion - big companies (more than 1 billion in assets) are 3% of sample but have 10% of total defaults. At the meantime, small companies (less than 10 million in assets) are 43% of sample and have only 32% of total defaults.

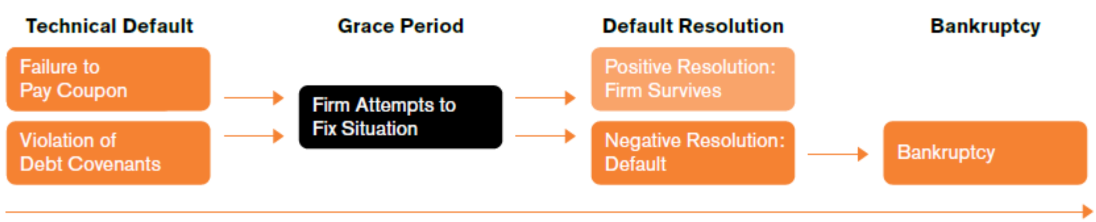


Figure 1 – Time line for default

Figure 2: Non-financial Default Distribution by year

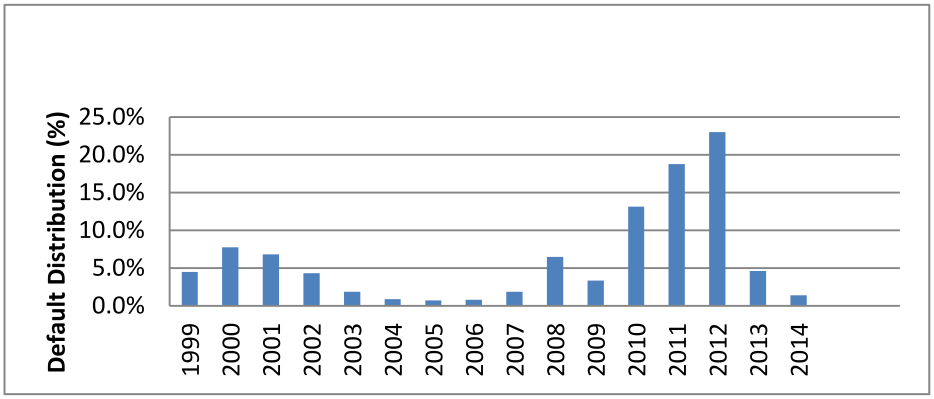


Figure 3: Default Distribution by Industry

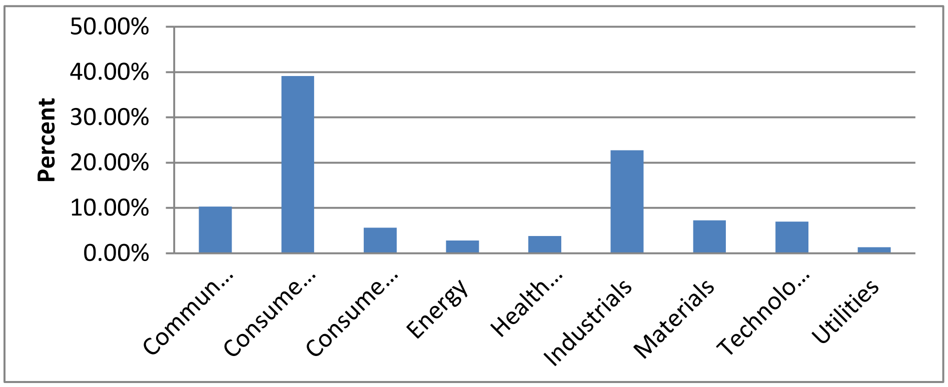
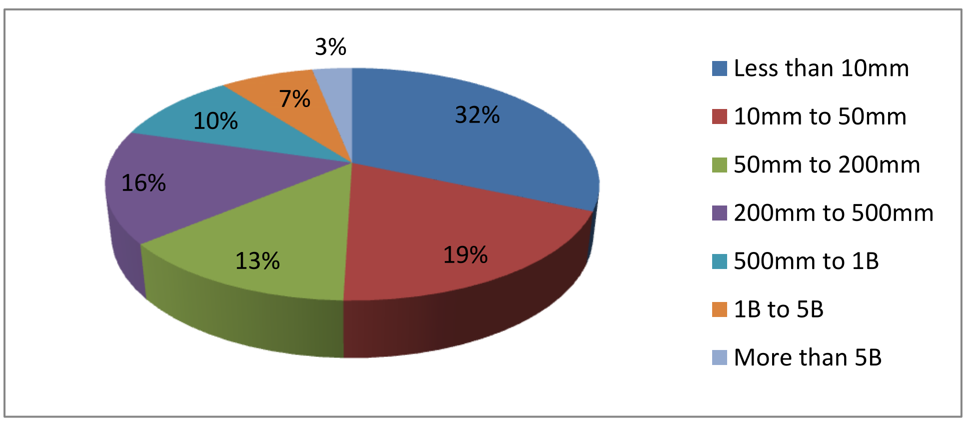


Figure 4: Empirical Default Distribution by Size



2.0.3 Drivers of Default

The Private DRSK framework incorporates fundamental factors with industry risk, market sentiment and business cycle in a quantitative model to determine the default probability of private companies. In this model, a firm's credit default risk is measured by combining its profitability, leverage, liquidity, activity, solvency and sector risk.

Fundamental And Market Input Factors

- Leverage ratios (measure of capital structure) -Total Asset/Total Liability, Book Equity/Current Liabilities
- Liquidity variables (ratio of liquid assets to liabilities or size)- Cash /Current liabilities
- Profitability ratios (earnings compared to expenses and investment) – ROA
- Activity ratios (operating efficiency) - sales “turnover” defined as total liabilities/sales
- Market information - industry average DD (Distance to Default)
- Insolvency proxy- book equity (negative book equity implies higher credit default risk)

Not every variable is available for all companies. Hence, the model balances coverage and performance. We tested a large number of factors and selected those that enabled the broadest coverage without sacrificing model performance. For similar measures, we use PCA (principle component analysis) to combine them.

Factor Analysis

For industrial firms, Return on Assets (ROA), defined as Net Income/Total Assets, significantly adds to the model performance. This factor is robust to a variety of specifications (namely, using Total assets or total equity in the denominator), however ROA provides better results, and is particularly helpful for firms with negative net income and negative book equity.

A plot of ROA versus actual default illustrates this relationship (Figure 5). Observations are grouped by ROA, and then the median ROA level is plotted against the number of firm-quarter default observations in that bucket. A clear pattern emerges of increasing default rates as ROA decreases. We performed similar tests to show the relationship of other factors to actual default rate. Figure 6-8 plot the Total Assets/Total Liabilities ratio, cash to current liabilities, total liabilities over sales, vs actual default.

Figure 5: ROA Ratio versus Actual Default

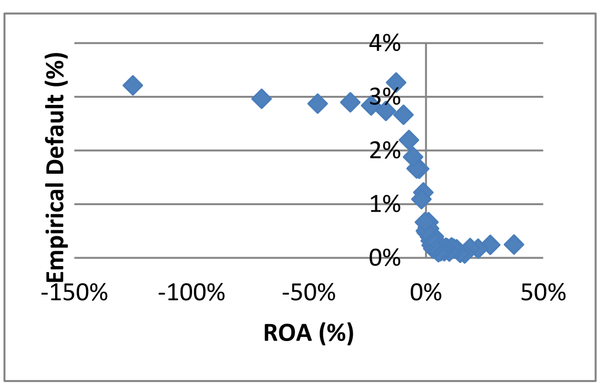


Figure 6: Total Assets/Total Liabilities Ratio versus Actual Default

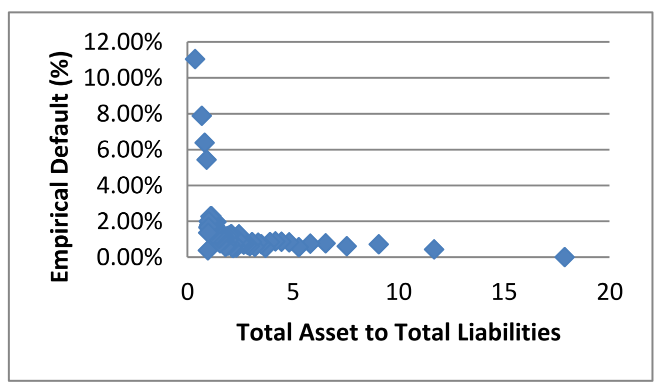


Figure 7: Cash/Current Liabilities Ratio versus Actual Default

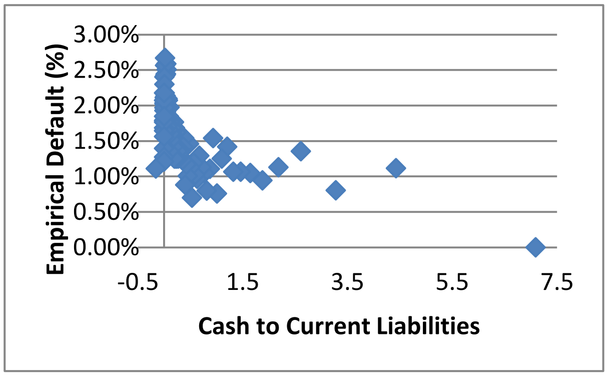
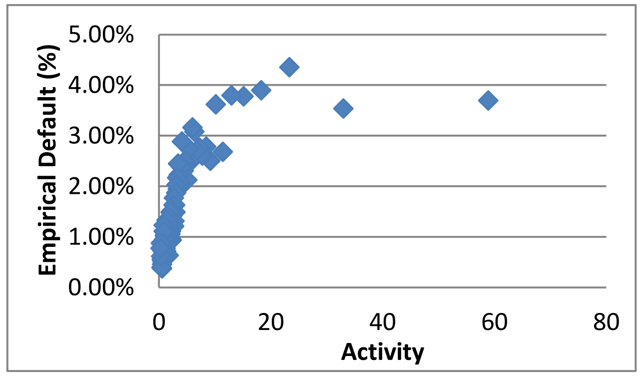


Figure 8: Total Liabilities/Sales Ratio versus Actual Default



2.0.4 Additional Drivers of Default

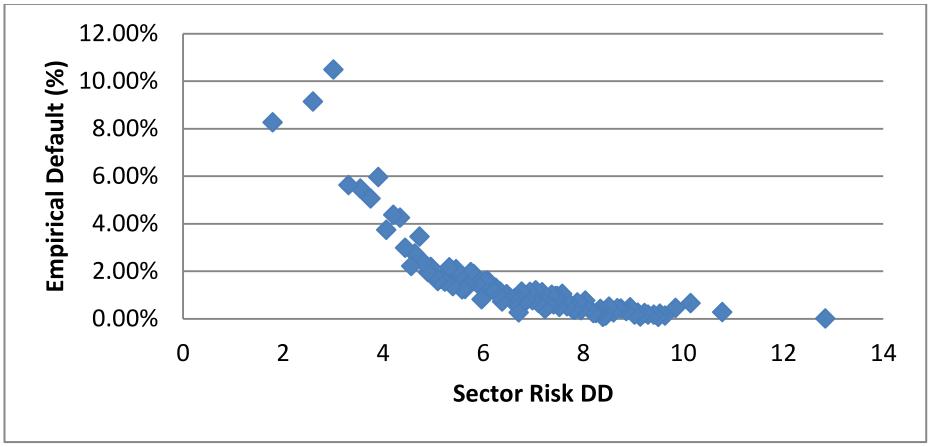
Fundamental credit analysis uses financial statement focused measures of credit risk, which reflect past information and are backward-looking. Therefore, we add a measure of industry market risk which is derived from our public company DRSK model, which is forward looking.

Industry Risk Factor

Our industry risk factor is derived from a Merton model that derives the value of the assets (not directly observable) from 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. The Merton model infers the value of the assets from the observed equity value. DRSK for public companies treats equity as a 1-year barrier call option, explicitly incorporating the possibility that the firm may default 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. 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 for public companies. We use the average DD from public companies as an indicator of industry risk. Figure 9 shows that defaulted companies are related to average sector risk. The correlation is stronger when overall sector risk is high (DD is low), which could explain why companies failures cluster during the 2000 tech bubble and 2008 financial crisis. It also suggests that when the average sector risk is low (DD is high), the average default rate is lower and may be driven by factors other than sector risk.

Figure 9: Average DD and Empirical Default Rate



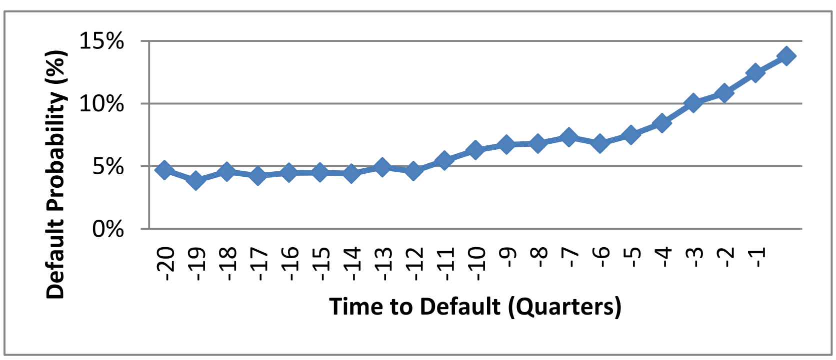
2.1 Model Validation

We validate our model using rigorous statistical tests, and use case studies to provide anecdotal evidence. The case studies illustrate our model's ability to provide early warning of credit default risk. We also illustrate the corporate actions that often result from deterioration in credit quality. Sections 2.1.1- 2.1.3 provide the illustrations. The illustrations are derived from back testing the model, which is instructive but not necessarily predictive of future action. Results of a comprehensive series of statistical tests of our model are found in section 2.1.4.

2.1.1 Early Warning of Distress: Time to Default[1]

We calculate the average (median) model default probability (DP) 20 Quarters (5 years) before the actual default time for defaulted companies. Figure 10 presents the result for the North American sample. We found that as far ahead as 20 quarters before actual default, the model's average DP rose over 4%. At, or close to, the time of actual default, model DP can go as high as 14%.

Figure 10: DRSK model DP for defaulting firms



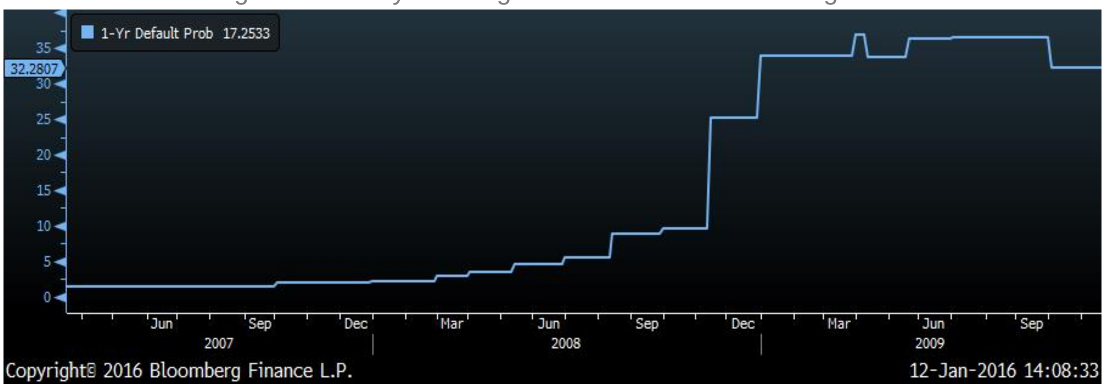
[1] Note that DRSK can only estimate the probability of default- it never predicts the actual occurrence of default. Actual default is a binary event- it either happens or does not happen. DRSK only estimates the probability of this binary event happening. There are many instances where model-driven, elevated credit default risk did not lead to a default event.

2.1.1.2 Early Warning of Distress: NTK Holdings, Deepocean Shipping and Caesars Entertainment Operation

NTK Holdings Inc. filed for bankruptcy in October 2009. NTK Holdings had negative Return on Asset (ROA), and negative book equity; Total asset over total liability is less than 1, and significant gap between cash and current liabilities. NTK Holdings had decreasing sales prior to default:

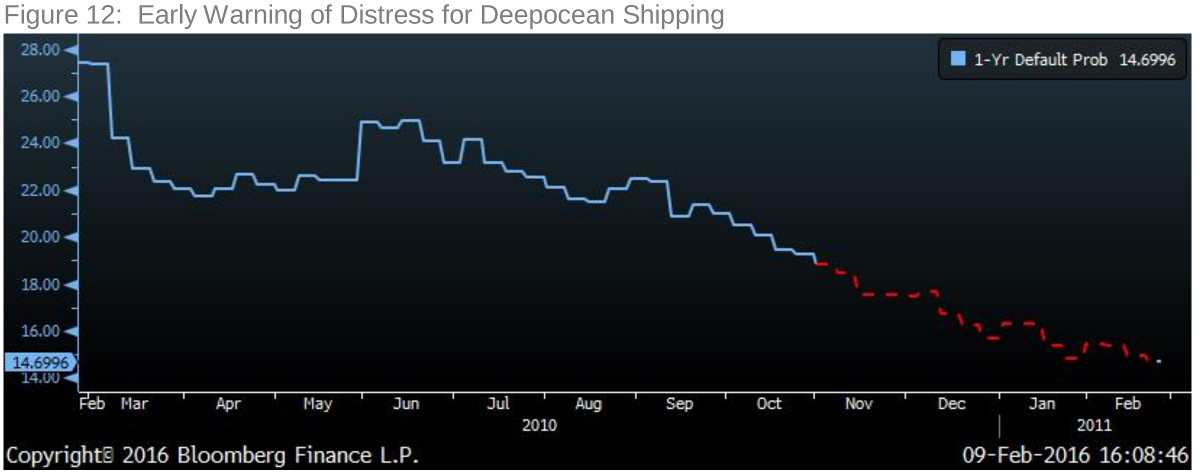
- Total equity was -$863 for Q1 2009
- Net income was -$48 M for Q1 2009
- Impaired goodwill written off from both income statement and balance sheet

Figure 11: Early Warning of Distress for NTK Holdings Inc.



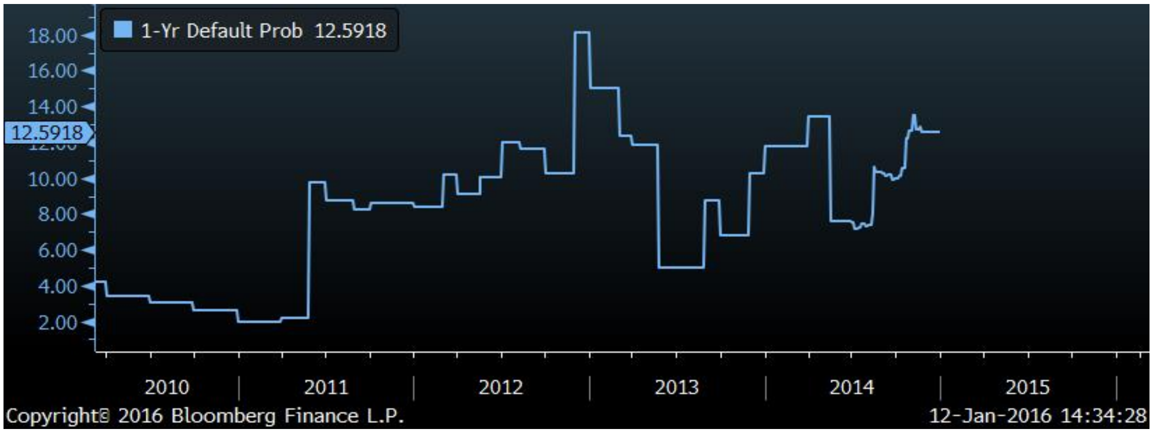
As early as October 2007, 2 years prior to bankruptcy, the default probability for NTK rose above 2% and up to above 35% in the months leading up to its default. Similarly, we found Deepocean Shipping was in deep distress (Default risk over 20%) before it filed bankruptcy in November, 2010, which had huge negative book equity, very high leverage, and big loss in income. Of note is that the decreasing DP of Deepocean was caused by the improvement of the transportation industry.

Figure 12: Early Warning of Distress for Deepocean Shipping



A more recent example is Caesars Entertainment Operation, which failed to meet covenants in October 2014, failed to make coupon payment in December 2014, and filed for bankruptcy on January 15, 2015. The financial statements showed a straight-line negative ROA, and negative book equity from 2010. Its financial situation started getting worse in Q2 2011 as book equity dropped further, and leverage rose.

Figure 13: Early Warning of Distress for Caesars Entertainment Operation



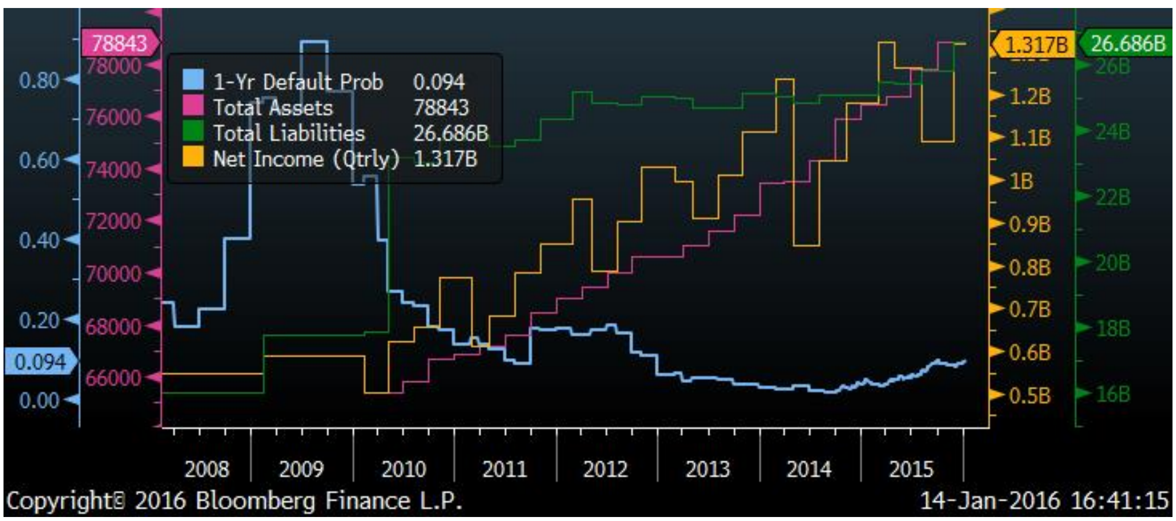
2.1.2 Identifying Firms with Good Credit Health: BNSF Railway

BNSF Railway provides railroad transportation services and was viewed as a stable low credit default risk by DRSK after 2008 financial crisis. Key financial factors are shown below:

- Return on Assets has always been positive and has kept rising since Q1 2011
- Leverage dropping over time
- Positive revenue growth

The history of default probability levels is displayed in Figure 14 below:

Figure 14: Default Probability history for BNSF Railway



DRSK default probabilities remained low (associated with Bloomberg 1-Yr Default Risk of IG-9 or higher), from 2011 onwards. In this example, DRSK identifies the high credit health of BNSF

Railway.[2]

2.1.3 High Default Probability as a Precursor to Corporate Action [3]

Table 1 below shows a sample of firms with high default probabilities on Dec 31, 2011. In general, these companies engaged in corporate actions indicating financial distress after that date.

Table 1: High DRSK Model Default Probabilities and Subsequent Corporate Actions

Firm	Ticker	Default Prob.	Corporate Action
Texas Competitive Electric	68662Z US Equity	6.6%	Chapter 11, April 2014
Beechcraft Holdings	3641803Z US Equity	14.4%	Chapter 11, May 2012
Reddy Ice	3662090Z US Equity	4.5%	Chapter 11, April 2012
Outdoor Group	1318338Z LN Equity	18.6%	Chapter 11, January 2012

2.1.4 Comprehensive Statistical Tests

The primary focus of DRSK is to discriminate between firms with higher and lower credit default risk. To this end, we evaluate its performance by calculating the Accuracy Ratio, or Cumulative Accuracy Profile. 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 compare it 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 ability of the model to rank order defaults. This test penalizes the model for assessing excessive default risk (type II error) or inadequate default risk (type I error). The AR is calculated as follows:

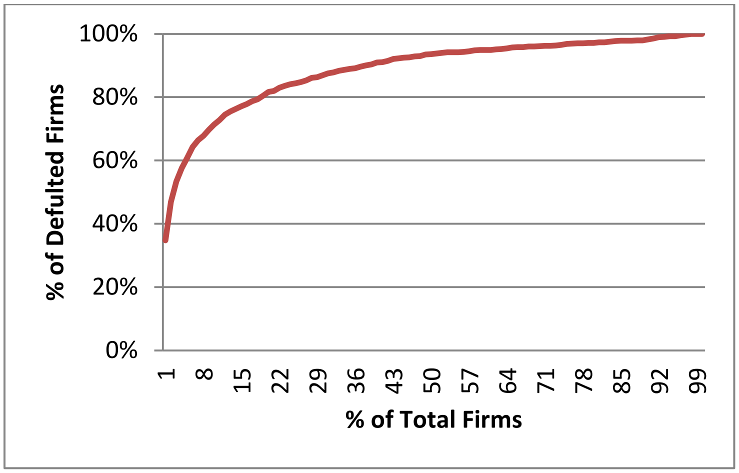
- Rank firms by decreasing default probability.
- Draw firms in order of decreasing default rank without replacement. On the y-axis mark the percentage of defaulted firms that have been removed, and on the x-axis mark the percentage of the total number of firms that have been removed.
- After completing the draw, plot the curve (Cumulative Accuracy Profile). Compute the area under the curve. This is the Accuracy Ratio. For 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 tests indicate that DRSK global non-financial private model has an accuracy ratio of 81% (figure 15).

[2] Similar to its inability to predict default, DRSK cannot predict that a default will not occur. There are many instances of model-driven, low credit default risk leading to a default event.

[3] DRSK cannot predict corporate actions. There are many instances of model-driven, elevated credit default risk leading to no corporate actions.

Figure 15: Non-Financials In-sample Cumulative Accuracy Profile (Accuracy Ratio Test)



DRSK also performs out-of-sample or walk-forward accuracy ratio tests to evaluate the performance of the model in time periods not used in the estimation of the model. We use data through the end of 2009 to estimate our model, and then apply that model to the 2010-2015 time periods. Table 2 is the summary of the walk-forward accuracy ratio tests. All out-of-sample accuracy ratios indicate that our model has good out-of-sample performance. If our in-sample were to exclude the 2008 financial crisis, a large portion of failed companies would leave the model, which would suffer from an insufficient test sample and loss of predictive power out-of-sample.

Table 2: Walk-forward Accuracy Ratio Tests

In-sample range (year)	Out-of-sample (year)	AR for out-of-sample (%)
1999-2009	2010-2015	78.1
1999-2010	2011-2015	79.5
1999-2011	2012-2015	81
1999-2012	2013-2015	83.9
1999-2013	2014-2015	89

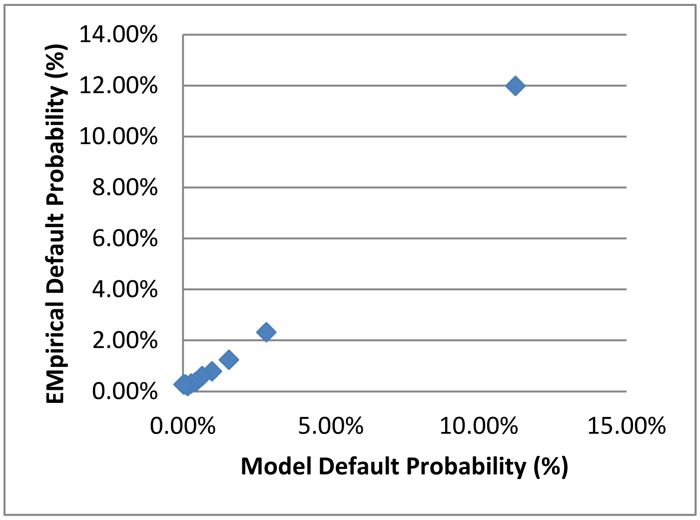
GOODNESS OF FIT TEST

The goodness of fit was tested as follows:

- Group firm level observations of default by default probability bucket across the sample
- Plot calculated default probabilities on the X axis, and 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 (Figure16) lies close to the 45 degree line indicating the model estimation reduces bias.

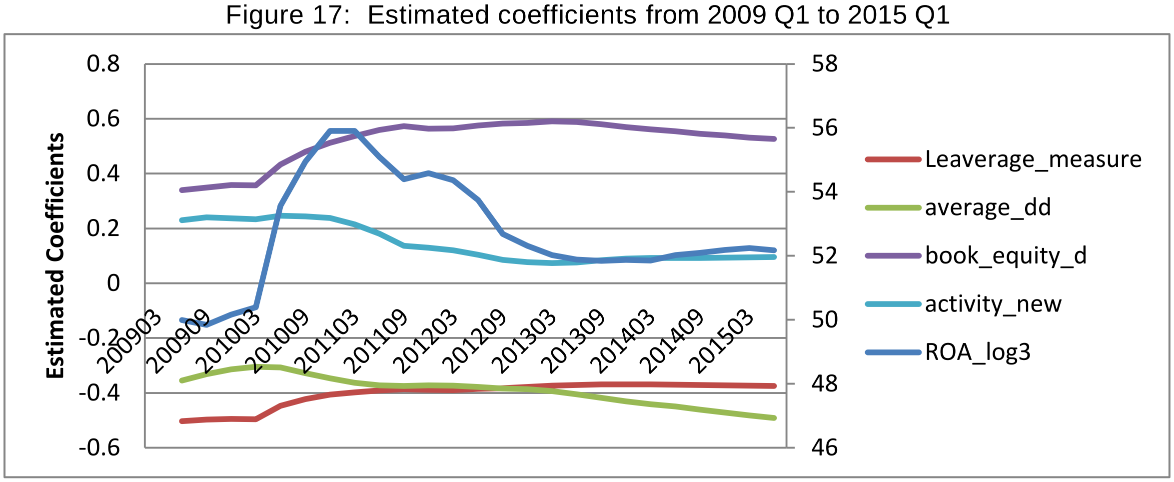
Figure 16: Global Non-financial Realized versus Model Default Probability



MODEL STABILITY TEST

Model stability implies estimated coefficients are stable over time and free from sample selection bias. DRSK conducts recursive estimations beginning in 1999. The first set of coefficients are estimated for the sample from 1999 Q1 to 2009 Q1, the second set of sample 1999 Q1 to 2009 Q2, and so on, to Q1 2015. Figure 16 shows the evolution of estimated coefficient from 2009 Q1 to 2015 Q1. All factors use left (primary) axis, except ROA uses right axis. All estimated coefficients are stable over time. As stated earlier, our calibration sample needs to include a “complete” credit cycle to reduce bias. In our calibration sample, we have the 2000 technology bubble and the 2008 financial crisis. It could explain why our estimated coefficients are very stable after 2010 when most of the defaults are already included in the sample.

Figure 17: Estimated coefficients from 2009 Q1 to 2015 Q1



2.1.5 Default Probabilities vs Size: Through the Crisis

Figures 18 & 19 show default risk vs size after the crisis. Median DRSK Default Probability (Figure 18) is highest in 2009, and keeps dropping after that for all size buckets. The largest companies (total assets over 5 billion) have the highest DP in 2009 and similar DP in other years. The average DP in Figure 19 for the same size buckets tells a similar story. The average risk goes up a little bit as size goes up and then goes down when the scale of economy takes effect (bigger companies have easier access to capital market and more choices of financing).

Figure 18: Median DRSK DP for different sized companies

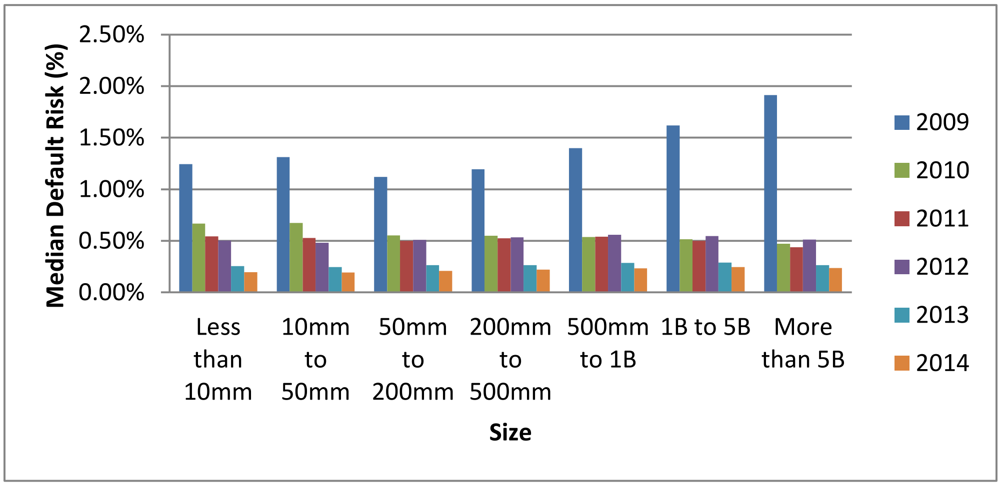
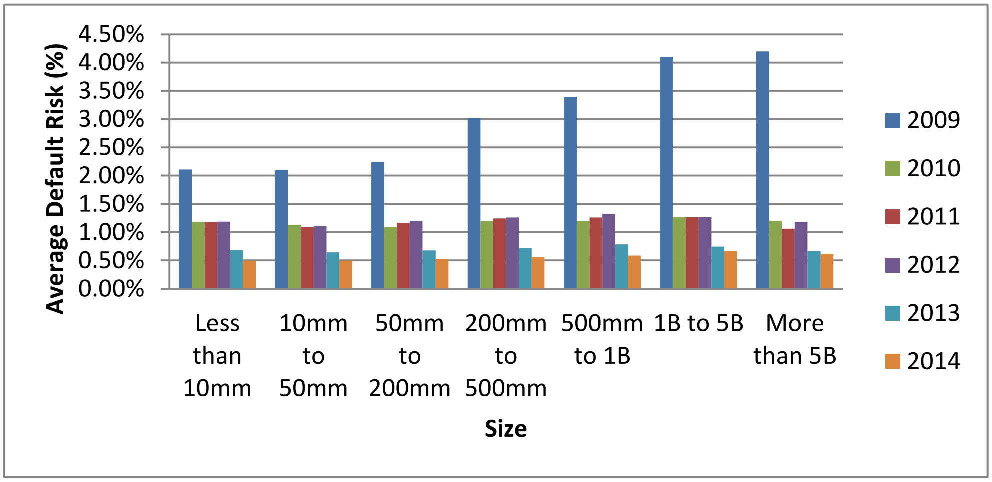


Figure 19: Average DRSK DP for different sized companies



3.0 Bloomberg 1-Year Default Risk Scale

The Bloomberg private company Default Risk Scale is identical to the scale for public companies. The Default Risk Scale is an explicit mapping from DRSK model default probability to a credit risk measure. The credit risk classes are chosen so that the default rate in each class is broadly consistent with the 1-year default probability observed across major NRSRO ratings of a comparable level. The lowest credit risk measure is IG1, with the highest 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.

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%

4.0 Private Company DRSK Function

The Bloomberg private Default Probability Model can be accessed through DRSK<GO>. This section describes the function and its capabilities.

4.1 Inputs and Outputs

The function has four key areas.

The top left corner has the key outputs:

- Default Risk
- Default Probability

In the future, we will also calculate a model CDS, and compare to market CDS where available.

Model inputs are displayed on the upper left corner of the screen (from Fundamental data FA<GO>)

4.2 Overriding Inputs

DRSK enables the user to study the sensitivity of the credit risk measures to the key drivers of default specified in the model. Each input line item can be changed independently. Please note that when you override a line item, it does not necessarily change balance sheet totals.

- The model accepts current liabilities, total liabilities, and equity as inputs for the right hand side of the balance sheet
- It accepts Cash on the left hand side.

- Total assets are calculated as: Total Assets = Total Liabilities + Equity. Total assets are not overridable
- Internally, Other assets are calculated as Total Assets – Cash
- If you increase current liabilities only, the total liabilities and total assets do not change. Since total liabilities were not simultaneously increased, the model assumes some items were shifted from long term to short term liabilities
- If you increase book equity and total liabilities, then Total Assets increase according to the formula above

Here are some examples:

- For a non-financial firm, assess the effect of swapping some short-term debt into long-term debt. Decrease “Current Liabilities”. In this case, the total liabilities do not change. And total assets do not change. The model DP goes down.
- Assess the effect of adding short-term debt. Increase current liabilities, and increase Total Liabilities by the same amount. DP goes up. Total assets automatically increase by the amount of debt added.
- Assess the effect of recognizing off- balance sheet debt on the balance sheet. Increase Total liabilities by the off-balance sheet amount. DP increases. Total assets automatically increase by the amount of off-balance sheet to the balance sheet debt added.

4.3 Custom Data Uploader

DRSK enables the users to input their own data and calculate Default Probability. Under “97) Upload” on the DRSK screen, there is an excel template which accepts selected financial data to provide a default risk estimate. Users can fill the template and drag the data into the Bloomberg screen. Custom tickers (based on the ticker requested by the user) will be created and data will be uploaded. The created ticker can be used in DRSK and other Bloomberg functions that support custom tickers. Custom data is only visible to users from the same company.

5.0 Bibliography

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