S&P Global
Market Intelligence

# PD MODEL MARKET SIGNALS

## An Enhanced Structural Probability Of Default Model

## Introduction

**Authors**

**Giorgio Baldassarri, PhD**
Global Head of Analytic Development Group

**Alma Chen**
Head of Analytic Development Group, APAC

The recent turmoil experienced by global financial markets is characterized by highly volatile conditions that can quickly turn financially robust companies and financial institutions into weak ones, prone to default.

> In these conditions, it is critical that firms carefully monitor the evolution of the creditworthiness of their counterparties, by early screening and filtering of those clients or business partners that are less certain to fulfill previously agreed commitments in the future.

To do this, firms require access to an accurate econometric model that captures all relevant risks when calculating a counterparty's probability of default (PD) and/or distance to default (DD). Such a model can help firms take timely action (for example, reducing business with a single company or a portfolio of companies when market conditions worsen) and make informed decisions on a daily basis on their (potential) business partners.

Traditionally, “structural PD models” have found wide application in the industry because they can produce reliable and early warning signals useful for credit surveillance or quick initial screening. Structural models' transparent mathematical framework links a firm’s creditworthiness to market movements and their intuitive economic interpretation facilitates the analysis of a firm’s transactions (increased borrowing, share repurchases, acquisition of another firm, etc.).

However, current industry-standard structural models have severe limitations that lead to puzzling and/or user-unfriendly signals. They can be misleading because:

1) Abrupt market movement generates excessively volatile PD values or counterintuitive phenomena (namely an increasing PD when leverage decreases rapidly);

2) Country and industry risk dimensions may not be appropriately reflected, leading to possible overestimation/underestimation of a firm's creditworthiness; and

3) PD values are often floored at the sovereign rating (that is, they don't move lower than the PD implied by the sovereign rating). This masks valuable information about the behavior of a company's PD below the floor (whether it is still improving, or has started deteriorating, for example).

## S&P Global Market Intelligence’s PD Model Market Signals

S&P Global Market Intelligence has recently developed PD Model Market Signals for both corporates and financial institutions (including insurance companies), a structural model that produces PD values over a one- to five-year horizon for all public corporates and financial institutions, globally. PD Model Market Signals builds on a traditional structural framework with several enhancements that tackle the issues mentioned above.

## Iterative calculation method

Counterintuitive and excessively volatile PDs are removed by PD Model Market Signals' method of deriving its parameters, which are asset value and asset volatility. The iterative process employs an advanced approach for the identification and removal of asset value outliers.

## Distinct risk dimensions

All risk dimensions are separately captured and transparently integrated:

- In the non-financial corporate model, country and industry risk are explicitly included, for example via S&P Global Market Intelligence's Country Risk Scores[1] to produce PD values that better reflect, respectively, the business risk associated with each country and the way companies operate in each industry.
- For Banks in the Financial Institutions model suites, Banking Industry Country Risk Scores (BICRS) are used. BICRS are a combination of multiple factors that reflect the risk of the banking industry in a specific country. BICRS are used when evaluating banks to better capture the unique challenges and risk that this industry sector faces.
- The sovereign risk is combined with these other risk dimensions via Transfer and Convertibility (T&C) Risk Scores for non-financial corporates and via Sovereign Risk Scores for the financial institutions. Either is combined with daily changing probability of defaults implied by sovereign credit default swap spreads, provided that a liquid market exists for the country in which the company under investigation is based. All these sovereign risk components do not purely act as a fixed PD floor (or fixed cap of the implied credit risk score in letter grades). Instead, a more dynamic process has been implemented in order to account for fluctuations in a company's PD both based on company-specific input factors and based on sovereign risk. This unique feature gives users insight into the dynamics of a company's PD value, even below the conventional sovereign rating floor.

Thanks to these enhancements, PD Model Market Signals generates reliable market signals that clients can use to take consistent action.

PD Model Market Signals includes a pre-scored universe of more than 46,000 non-financial companies and more than 6,000 financial institutions extracted from the S&P Capital IQ platform, representing more than 99% of the global market capitalization of public corporates and financial institutions[2]. A firm's PD value is updated on a daily basis and mapped to a credit score, using lower-case.[3] PD Model Market Signals is fully

[1] See bibliography in the appendix.
[2] Pre-scored database is available for corporates and financial institutions via XpressFeed and the S&P Global Market Intelligence platform. Counts reported here are as of May 15, 2016.
[3] S&P Global Ratings does not contribute to or participate in the creation of credit scores generated by S&P Global Market Intelligence. Lowercase nomenclature is used to differentiate S&P Global Market Intelligence PD credit model scores from the credit ratings issued by S&P Global Ratings.

interactive with both CreditPro,[4] for the production of the PD-to-credit score mapping; and with the S&P Capital IQ platform,[5] for streaming the market-derived CDS signal produced for each country.

## The Basis of PD Model Market Signals Corporates and Financial Institutions

In the industry-standard structural model's classical formulation (the Merton model [1]), the credit risk of a company is characterized by postulating that a company's equity (E) is a call option on its assets (A). Hence, using the Black-Scholes call option formula:

$$E = A\,N(d_1) - D\exp(-rT)\;N(d_2)$$

Where: r is the risk-free interest rate; T is the time horizon (assumed to be equal to one year);
$d_1 = [\ln(A/D) + (r + \sigma_A^2 / 2)\,T] / (\sigma_A\,T^{0.5})$; D is the default point; $\sigma_A$ is asset volatility;
$d_2 = d_1 - \sigma_A T^{0.5}$; and N is the cumulative normal distribution function.

Under Merton's model, a firm defaults if the value of its assets is less than the value of its liabilities (D) by the time the debt matures. Hence, the distance to default (DD) is equal to:

$$DD = \frac{\ln(A/D) + (\mu - \sigma_A^2/2)\,T}{\sigma_A T^{0.5}}$$

DD represents the number of standard deviations that the firm's asset value is away from the default threshold (D). In PD Model Market Signals Corporates and Financial Institutions, the default point is initially fixed at 80%[6] of the total liabilities.

There are two unknowns in the DD definition: asset value and asset volatility. To find these unknowns, a standard approach is to introduce a second equation, based on Itō's lemma, and solve the two equations simultaneously in two unknowns. However, this approach tends to bias the DD values in exactly the wrong direction: when the market leverage decreases quickly (the credit profile is improving), the DD tends to be underestimated, which results in an inflated PD value; the opposite happens when the market leverage quickly increases.

## Enhanced Iterative Calculation Process

PD Model Market Signals Corporates and Financial Institutions uses an iterative process to calculate asset value and asset volatility, and this is enhanced by an ad hoc routine for the identification and removal of outliers.

The iterative process is similar to that discussed by Vassalou and Xing [2], and follows these steps:

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[4] CreditPro is a Web-based tool available on S&P Global Market Intelligence's Credit Analytics platform. It allows individuals to track ongoing default, transition, and recovery data on companies, securities, issues, and sovereigns.
[5] The S&P Capital IQ® platform is S&P Global Market Intelligence's dynamic web-based platform that provides, among others, real-time access to S&P Global Ratings credit ratings and research, market information, and risk analytics.
[6] We determine the initial default level, fixed for all firms, by optimizing the mapping between DD and PD, based on several performance metrics (i.e., monotonicity, uniqueness of values, and total range).

1) Assume $\sigma_A = \sigma_E$, where $\sigma_E$ is equity volatility and $\sigma_A$ is asset volatility;

2) Solve the Black-Scholes equation with respect to the asset value;

3) Repeat the process for each day within a specified time window;

4) Estimate the new $\sigma_A$ from the asset values just calculated;

5) Repeat steps two to five until the implied $\sigma_A$ converges (the precision is set at $10^{-3}$); and

6) Calculate the final asset volatility and asset return from the converged series of asset values; remove the outliers and correct the asset volatility and asset return estimates accordingly.

As we shall see later, this approach removes the inconsistent and counterintuitive behavior of PD values observed in the case of a company with sharply varying leverage.

A common industry variation of the Merton model includes a down-and-out call option approach, based on the idea that a firm can default at any point in time during a chosen time horizon. Tests performed by S&P Global Market Intelligence show that this alternative approach yields lower DD values than the classical models, but tends to be less robust in terms of the convergence of the iterative process and slightly slower than its traditional counterpart. On top of this, in both approaches the calculated DD values are empirically mapped onto the observed default rates (ODRs) from S&P Global Ratings rated universe, as we will show in the next section, and thus generate very similar PD values.

## Empirical mapping of DD values onto ODRs

Once the DD values have been calculated, PD Model Market Signals Corporates and Financial Institutions maps them to ODRs so that final PD values can be generated for the user. The empirical mapping is performed using historical default rates from the global universe of public corporates and financial institutions rated by S&P Global Ratings, from 1981 to the present. In order to create a stable DD/PD mapping and retain the long-term nature of the ratings, the historical ratings are transformed into through-the-cycle ODRs. We apply a logistic regression to the DD values and the ODRs, generating a “universal” mapping that collects all companies together, regardless of industry and country.[7]

## Enhanced Risk Dimensions

In order to generate PD values that properly reflect the creditworthiness of a firm, it is important to include industry, country, and sovereign risk components. Industry-standard models typically capture the industry and country risk components only implicitly, by combining the asset volatility obtained through an iterative process with industry, country, and size averages, or by adjusting the final PD values by the observed default frequency in a country. PD Model Market Signals explicitly isolates each risk dimension before combining them to generate more reliable PD values.

[7] A point-in-time mapping would generate additional volatility in the PDs, rendering them hard to interpret for the user.

## Industry risk

**Corporates**

Typically, companies operating in different industries will tend to operate at different leverage levels. For example, the services sector usually has a lower leverage than companies in the heavy manufacturing industries. Consequently, this should translate into different asset value threshold levels, below which a default could be triggered. Yet, industry-standard models assume a fixed threshold of short-term debt plus one-half of long-term debt, regardless of the company's sector.

By contrast, the non-financials corporates model takes into account different threshold levels in each industry. The "raw" DD calculated in the iterative process is adjusted by considering the short-term one-year ODR in each industry. This ODR is converted back into an implied distance to default, ($DD_{ind}$*), by inverting the empirical DD/PD mapping curve. Next, the median DD ($DD_{ind}$) of the companies in each industry sector is set as equal to the $DD_{ind}$* specific to each industry. Thus, the DD of a generic company in a specific industry is adjusted to be: $DD_{adj} = DD + (DD_{ind}^{*} - DD_{ind})$, and is finally transformed into a $PD_{adj}$. (See Figure 1 for PD Model Market Signals Corporates' DD adjustments by industry.) This is important because it accounts for differences in operating conditions of different companies and also reflects the point in time of the economic cycle for the specific industry.[8] The additional advantage of this approach is that it is transparent, easily explained, and does not require an iterative process for its implementation. The DD adjustments are updated on a regular basis.

Financial Institutions

For financial institutions, different operating leverage levels are also expected and observed. These industry-specifics are taken into account in the DD adjustments similar to the Corporates Model. The adjustments are carried out separately for a) commercial banks, b) investment banks and non-banking financial institutions and c) the insurance industry. Thus, the financial services sector gets a unique setting that differs from non-financial corporates in order to account for different 'acceptable' leverage threshold levels.

## Country risk

Corporates

Companies in the same industry sector but in different countries do not necessarily have the same risk profile because their operations will usually be affected by different legal, regulatory, business, and socioeconomic environments. This is especially evident for corporations in emerging and developing markets [3].

The Corporates Model distinguishes country risk, the risk of doing business in a country, from sovereign risk, the risk of the sovereign not meeting its debt obligations. (Country risk

[8] Not all industries follow the economic cycle in phase, and some industry sectors might be affected by worse economic conditions more than others. For example, the airlines industry tends to be cyclical (people are willing to travel more during good economic times), while educational services is widely considered to be countercyclical (during an economic contraction, adults tend to upgrade their education, to boost their competitiveness in the job market).

for selected countries included in the Corporates Model is shown in Figure 2.) The model adopts S&P Global Market Intelligence's "Country Risk Score Methodology": a country's country risk is first transformed into a $PD_c$ value specific to each industry, and each individual company $PD_{adj}$ is adjusted for the industry risk component as outlined above. These are subsequently combined to yield:

$$PD_{company} = f_1 (PD_{adj}, PD_c, \alpha).$$

This functional form ($f_1$) is empirically determined, so that companies operating in both an industry and a country with above-average risk are penalized. All else being equal, a company in a risky industry will tend to receive a higher $PD_{adj}$; the PD of the company will be further penalized if the country risk is worse than implied by a 'bbb' credit score, via the parameter α. This threshold of 'bbb' was selected because any country risk at this level or lower is not expected to have an adverse impact on a company's credit risk profile.

Financial Institutions

It is crucial to consider the environment in which a bank operates when constructing a global model. S&P Global Market Intelligence's Banking Industry Country Risk Scores[9] (BICRS) reflect the strengths and weaknesses of a country's banking industry within the context of its macroeconomic environment. A BICRS score is a combination of multiple factors reflecting a country's economy, financial regulatory infrastructure, and the credit culture of its banking industry. In order to achieve truly global coverage of all countries using these BICRS, the research includes comparing geographic location of countries, independence (or not) of their central banks, the degree and evolution of a country's economic development, and its type of political system. The model uses these factors to help depict the characteristics of a country's banking industry, its macroeconomic environment, and its degree of microeconomic development. (BICRS for selected countries included in the Financial Institutions Model is shown in Figure 3.)

For the banking industry, instead of adjusting the DD, the "raw" Probability of Default (PD) is adjusted by considering the relevant BICRS. The average value of economic and industry risk scores[10], which together form a BICRS score, is transformed into a PD value, and for countries with higher than average BICRS implied PDs, the bank's PD is penalized. The rationale for this threshold is the same as for corporates described above. The BICRS adjustment provides timely insight into the changes in a country's economy, legal and regulatory infrastructure in its financial system. The Algorithm for adjustment based on BICRS is as follow:

$$PD_{adj} = \max(PD, f(PD, PD_{BICRS}, \text{cut-off point}))$$

Where the cut-off point is selected based on the geographic region of the bank, and $PD_{BICRS}$ is the PD derived from the BICRS, and PD is the original PD before adjustment. The BICRS adjustment is a crucial factor that allows the model to accurately reflect the risk of the

[9] For all sovereign with a BICRA (Banking Industry Country Risk Assessment) from S&P Global Ratings the BICRS (Banking Industry Country Risk Scores) provided by S&P Global Market Intelligence is identical to its published BICRA. As of February 2013, BICRA are provided for around 90 countries by S&P Global Ratings. Thus, for the remaining circa 150 countries S&P Global Market Intelligence derives complimentary BICRS.
[10] Economic and Industry Risk scores are on a 1-19 scale, for example, 1 corresponds to an 'aaa' score, 2 to an 'aa+' etc.

banking industry for banks; as stated above, it is composed of both the relevant economic risk and industry risk of the country where the banks are based.

## Sovereign risk

Corporates

Sovereign risk refers to the possibility of a country not servicing its commercial debt obligations, which often diminishes the strength of its currency and limits capital flows. In addition to sovereign ratings, which reflect the sovereign's ability to service debt issued in a local or foreign currency, S&P Global Ratings provides transfer and convertibility assessments that reflect the likelihood of a sovereign limiting non-sovereign entities' access to foreign exchange. Moreover, the sovereign ratings reported by various rating agencies tend to be either a short-term or mid- to long-term view of the creditworthiness of a sovereign. In the corporate models from PD Model Market Signals, S&P Global Ratings mid- to long-term transfer and convertibility assessments on the sovereign is combined with a market-driven risk assessment, in this case a market-derived CDS signal, to obtain a more timely assessment of the sovereign risk component. Using the transfer and convertibility assessment brings into the corporates model the shield offered by monetary unions, such as the European Economic and Monetary Union (EMU or Eurozone).

Basically, the model assumes that a company's PD will not be lower (i.e. better) than a weighted average between the sovereign transfer and convertibility assessment, the market-derived CDS signal, and the company's PD:

$$PD = f_2\,(PD_{corporates},\ Sovereign\ TnC\ ,\ MDCDS\ ,\ \beta)$$

Where TnC is the sovereign transfer and convertibility risk score ; MDCDS is a market-derived CDS signal for sovereigns; and the parameter β is determined empirically and adjusted in case an MDCDS is not available.

We choose the sovereign transfer and convertibility assessment and sovereign CDS spread that belong to the country where the firm is headquartered.[11]

Financial Institutions

Financial institutions are often the largest buyers of sovereign debt, and their survivals are invariably linked to the financial health of their government. Due to its unique business nature and leverage, financial institutions tend to suffer the most during a sovereign crisis. As country's sovereign rating deteriorates, it could severely damage the quality of the financial institutions' asset. Therefore, it is necessary to reflect the sovereign risk that financial institutions are exposed to in the model.

For Financial institutions, the sovereign rating is used for a similar adjustment as it better reflects sovereign risk that financial institutions are exposed to. The model assumes that a

[11] Similar to the BICRA, whenever the TnC Assessments are not available from S&P Global Ratings, S&P Global Market Intelligence derives complimentary 'Transfer and Convertibility Risk Scores', that fulfill the same purpose. As of February 2013, around 115 sovereigns have a TnC Assessment from S&P Global Ratings. Thus, for around 125 countries S&P Global Market Intelligence derived complimentary TnC Risk Scores.

company's PD will not be lower (i.e. better) than a weighted average between the sovereign rating, the market-derived CDS signal, and the company's PD:

$$PD = f_2\ (PD_{financial\ institutions},\ \text{Sovereign Risk Score},\ MDCDS,\ \beta)$$

We choose the sovereign risk score and sovereign CDS spread that belong to the country where the firm is headquartered.[12]

# PD Scaling By Size

## Corporates

The model uses a universe of mainly large market capitalization companies to create the DD/PD mapping. To capture the size effect (whereby small companies tend to be more vulnerable to economic downturns and financial problems) we penalize the PD of companies with total revenues below a certain value. The penalty consists of increasing the PD by a PD-dependent scaling factor (sf) when total revenues are less than $5 billion. The rationale for the scaling is that greater PD levels (the equivalent of lower credit scores) are less affected by the size factor (which may be seen as a proxy for the firm's market share and overall degree diversification). This is applied at the very end of the model's calculation process, after the inclusion of all risk components.

The scaling factor was determined by studying the relationship between total revenues and credit scores for the global universe of unrated companies present in CreditModel.[13]

## Financial Institutions

Large asset-size financial institutions are more likely to survive an economic downturn and rarely default – even if only with government intervention as a 'strategically important financial institution - , while small financial institutions often show less resistance in a financial crisis, therefore, the PD of firms with size below a certain value is penalized. Slightly different from how corporates are handled, we choose 'total asset' as the criteria. Because of the excess use of leverage, financial institutions' revenue is not proportional to the asset that they hold. Furthermore, a financial Institution's revenue can show high volatility throughout the business cycle, and its high revenue now can also be followed by equally low revenue in the coming year. High revenue does not automatically guarantee their creditworthiness. Therefore, the model considers asset size as a more reliable measure of the size effect, a larger asset size provides a cushion during bad times, and banks that are "too big to fail" often get external help from the regulators when they need it.

The penalty consists of increasing the PD by a PD-dependent scaling factor (sf) when total asset for banks, diversified financials, and insurance companies are less than $50 billion,

[12] Similar to the TnC Assessment, whenever the sovereign ratings are not available from S&P Global Ratings, S&P Global Market Intelligence derives complimentary 'Sovereign Risk Scores', that fulfill the same purpose. As of February 2013, around 115 sovereigns have a sovereign rating from S&P Global Ratings. Thus, for around 125 countries S&P Global Market Intelligence derived complimentary Sovereign Risk Scores.

[13] CreditModel™ is a Web-based tool, available on S&P Global Market Intelligence's platform, which allows users to evaluate thousands of public and private firms using a unique series of newly retrained industry- and region-specific models. These models are based on the Primary Industry Classification Standard (PICS) to create credit scores represented by lower case letters to indicate that they are quantitatively-derived estimates.

$2 billion, and $100 billion respectively. The scaling factor was determined by studying the relationship between total asset and historical ratings for financial institutions.

## Model Performance

One way to assess the overall performance of a structural PD model is to see how successfully it distinguishes good companies from the default-prone. A theoretically perfect model would assign a higher PD to each defaulter than to any of the non-defaulters.

This information can be captured in a graph where all companies are ordered by decreasing PD value, and the cumulative percentage of defaulters is reported as a function of the cumulative percentage of all companies, as shown in Figure 4. This plot shows how the PD values of the defaulters rank among the PD values of all firms. A perfectly accurate model will be characterized by a very steep curve (purple line); conversely, a random model will assign random PD values to the defaulters, so that the curve will look like a straight 45 degree line (dark green line). The Corporates Model (light green line) shows a dramatic improvement versus the random model.

The Receiver Operating Characteristic (ROC) translates the pictorial information in Figure 4, which is shown here for illustrative purposes, into a quantitative measure of the model's accuracy. A model with ROC of 50% has no discriminatory power, i.e. it is a random model; conversely, the closer the ROC is to 100%, the more accurate the model.

Thanks to its enhancements, PD Model Market Signals achieved an overall ROC of 84% for all public entities globally and even 86% for public corporates, during model development.

The model is validated on an annual basis. The latest 2016 validation exercise shows the following results:

### Table 1: PD Model Market Signals validation

| PD Model Market Signals Validation | | 2015 | 2014 | Total (2014-2015) |
|---|---|---|---|---|
| Corporates | AR | 85.66% | 87.36% | 86.09% |
| | ROC | 92.83% | 93.68% | 93.04% |
| Financial Institutions (FIs) | AR | 96.29% | 97.62% | 96.88% |
| | ROC | 98.14% | 98.81% | 98.44% |
| All (Corporates + FIs) | AR | 87.74% | 88.88% | 88.11% |
| | ROC | 93.87% | 94.44% | 94.06% |

Source: S&P Global Market Intelligence, data as of Jan 14, 2016. For illustrative purposes only.

More details are available in the corresponding validation documents, available to users upon request.

# Additional Features

## PD mapping to credit score

PD Model Market assigns a credit score to each PD value, expressed via lower-case letters. The mapping is based on S&P Global Market Intelligence's global rated universe and spans a period of more than 30 years (starting 1981). We apply an exponential smoothing to the cumulative observed default rates (ODRs) for each rating category to ensure that higher-rated companies are assigned lower PD values (resulting in a "monotonic" structure).

## PD term structure pre-scored database

PD Model Market Signals yields a PD term structure with time horizons ranging from one to five years. The term structure is built by using the cumulative ODRs that are associated with each rating category in the S&P Global Ratings global rated universe for the corresponding time horizon; in particular, the logit-transform of the two-, three-, four-, and five-year ODRs are regressed against the exponentially smoothed one-year ODR mentioned in the previous paragraph, to yield a monotonic PD term structure.

## Pre-scored database

We provide clients access to both PDs and mapped credit scores (i.e., letter grades) for over 46,000 public corporates and more than 6,000 financial institutions globally from a pre-scored database.[14] Our data source is the S&P Capital IQ platform, which is the foremost provider of high-quality financial data of corporate firms and financial institutions companies. This database is updated frequently and implies that clients do not need to input any data themselves for their credit risk assessments. The table below shows the number of companies present in the pre-scored database, split by region.

## Corporates

Table 2: Number of companies in the pre-scored database, split by region

| Region* | Number of Companies |
|---|---|
| Africa & Middle East | 2,582 |
| APAC | 22,734 |
| Europe | 7,927 |
| Latin America & Caribbean | 1,042 |
| Canada, U.S. | 12,300 |
| **Total** | **46,585** |

*The full list of countries covered by the model is reported in the appendix, Table 4.

[14] As of May 15, 2016.

Source: S&P Global Market Intelligence, data as of May 15, 2016. For illustrative purposes only.

### Financial Institutions

Table 3: Number of financial institutions in the pre-scored database, split by region

| Region* | Number of Companies |
| --- | --- |
| Africa & Middle East | 857 |
| APAC | 2,079 |
| Europe | 1,187 |
| Latin America & Caribbean | 230 |
| Canada, U.S. | 2,206 |
| **Total** | **6,559** |

*The full list of countries covered by the model is reported in the appendix, Table 4.

Source: S&P Global Market Intelligence, data as of May 15, 2016. For illustrative purposes only.

## Case Studies

### Corporates

Compania Espanola de Petroleos, S.A. (CEPSA) is one of the largest energy companies in Spain.[15] Figure 5 shows CEPSA's historical market capitalization and total liabilities in the period from December 2009 to May 2011, during which CEPSA was operating as a public company.

For the same period, Figure 5 shows the one-year PD calculated by PD Model Market Signals Corporates on a daily basis, which we compare with a simulation of a typical industry-standard model that will serve as a benchmark.

It is clear that PD Model Market Signals Corporates produces higher PD values than the industry-standard model, due to its explicit and effective inclusion of all risk components. Starting from the left axis and moving to the right, there is a clear increase (or decrease) in PD values generated by PD Model Market Signals Corporates whenever the total liabilities remain constant and the market capitalization decreases (or increases). This is not well captured by the benchmark model, which generates volatile PD values that often do not reflect the decline in market capitalization. For example, on April 4, 2010, a sudden increase in total liabilities is reflected in a corresponding abrupt increase in PD Model Market Signals Corporates 's PD value, while the benchmark model shows a counterintuitive downward kink. As CEPSA's market capitalization approaches the 80% barrier, the PD values generated by

[15] Source: S&P Capital IQ platform: https://www.capitaliq.com/CIQDotNet/company.aspx?companyId=874195

both models tend to increase, as expected. On Oct. 4, 2010, total liabilities decreases, but PD Model Market Signals Corporates's PD value remains basically the same because market capitalization also decreases.

On Feb. 15, 2011, CEPSA announced that it would be acquired by International Petroleum Investment Company. As a result of the announcement, CEPSA's stock price jumped up and this was reflected in an abrupt increase in the market capitalization. The benchmark model then produced a fast increase in the PD, which remained very high for several days after the announcement. Whereas, a quick glance at the market capitalization shows that in the days following the announcement, volatility in fact decreased. One could argue that the benchmark model's increasing PD reflects the fact that announced acquisitions do not often proceed to completion or do not work well if they do complete. However, this is an ad hoc explanation that neglects the main aim of a structural model, which is translating market movements (and market perception) into an assessment of the probability of default. Since the market welcomed the acquisition announcement with a una tantum stock price increase, the only underlying measure of risk and uncertainty that remains in the Merton model is asset volatility. When the latter is calculated via the innovative iterative process, PD Model Market Signals Corporates produces PD values that are not biased and follow economic intuition and common sense, and that therefore decrease with higher market capitalization and lower asset volatility. However, in this example, the PD value is flattened out because volatility is so low (and thus the DD is so high) that $PD_{company}$ in the expression $f_2$ reported above becomes equal to zero.

## Financial Institutions

First Sound Bank provides various commercial banking services for small and medium-sized businesses, organizations, not-for-profits, and professionals in Washington, the United States. Its deposit products include personal and business checking and savings accounts. The company was founded in 2004 and is based in Seattle, Washington.

Figure 6 shows the result from our DD Merton Model for First Sound Bank. The Market Capitalization of First Sound Bank starts to decline gradually from around 40 million USD, to around 13 million USD in 2009. The Bank lost more than half of its market capitalization in two years. One can see the significant change in PD value, right before the bank capitalization drops significantly. Meanwhile, the bank's total liabilities continue to rise to a higher level. The 80% of total liabilities increased from 22.55 million USD in 2007 to 173.86 million USD in 2009. These factors combined together form a clear market signal that the bank was not doing so well, and our model was able to capture that signal. At the end of 2008, the bank was forced to be bailed out by the U.S treasury due to its distressed balance sheet, and received capital from the Troubled Asset Relief Program (TARP).[16] In fact, starting from late 2008, the bank began losing millions as defaults rose in a leasing portfolio they acquired, at the same time the bank's market capitalization decreased at an accelerating speed. As the bank's financial situation deteriorating, the PD of First Sound Bank's rose significantly to more than 10%, i.e. several times the industry average.

[16] Source: S&P Capital IQ platform: https://www.capitaliq.com/CIQDotNet/company.aspx?companyId=10906511&fromSearchProfiles=true

## Summary

Risk managers may find it hard to reliably screen good companies from bad ones and monitor the evolution of the business partners' creditworthiness. This is especially true in volatile market conditions. Current industry-standard models tend to capture only marginally the contribution of each risk dimension. Incumbent models also typically generate noisy signals that are hard to interpret and may inform wrong decisions or inconsistent actions.

S&P Global Market Intelligence has developed PD Model Market Signals, an innovative structural model that blends several market signals and risk dimensions. PD Model Market Signals' methodological enhancements and iterative techniques remove the weaknesses of common industry-standard models described above, while retaining a high level of accuracy. The integration of this model into a platform allows users to access a global pre-scored database with more than 40,000 public companies to obtain daily changing PD values and mapped credit scores with and without implied sovereign risk for a single firm or a batch (possibly the universe).[17]

[17] As of May 14, 2016.

# Glossary

Itō's lemma. A mathematical identity that, in the context of this model, links equity volatility and asset volatility to equity value and asset value. [4]

Down-and-out call option. A variation of the "plain" call option where the call ceases to exist when the price of the underlying security hits a specific barrier price level. If the price of the underlying does not reach the barrier level, the investor has the right to exercise their down-and-out call option. Used as a proxy for a firm's equity in the context of the Merton model, it means that as soon as the asset value drops below the barrier level, this triggers a default, without the need to wait for the expiration date. [4]

A monotonic function. Any function that generates steadily increasing or decreasing values.

A logistic regression. A special kind of regression, based on the formula: $y = 1 / [1 + \exp(a + b\,x)]$.

A logit transform. A transformation by: $y = \log [x / (1 – x)]$.

# Endnotes

[1] R.C. Merton, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," Journal of Finance, Vol. 29, No. 2, (May 1974), pp. 449-470.

[2] M. Vassalou and Y. Xing, "Default Risk and Equity Returns," The Journal of Finance, LIX (2), (2004), pp. 831-868

[3] M. Heinrichs and I. Stanoeva, "Country risk and sovereign risk – building clearer borders," Euromoney Risk Management Handbooks, (2012).

[4] J. C. Hull, "Options, Futures, and Other Derivatives," Prentice Hall (2006).

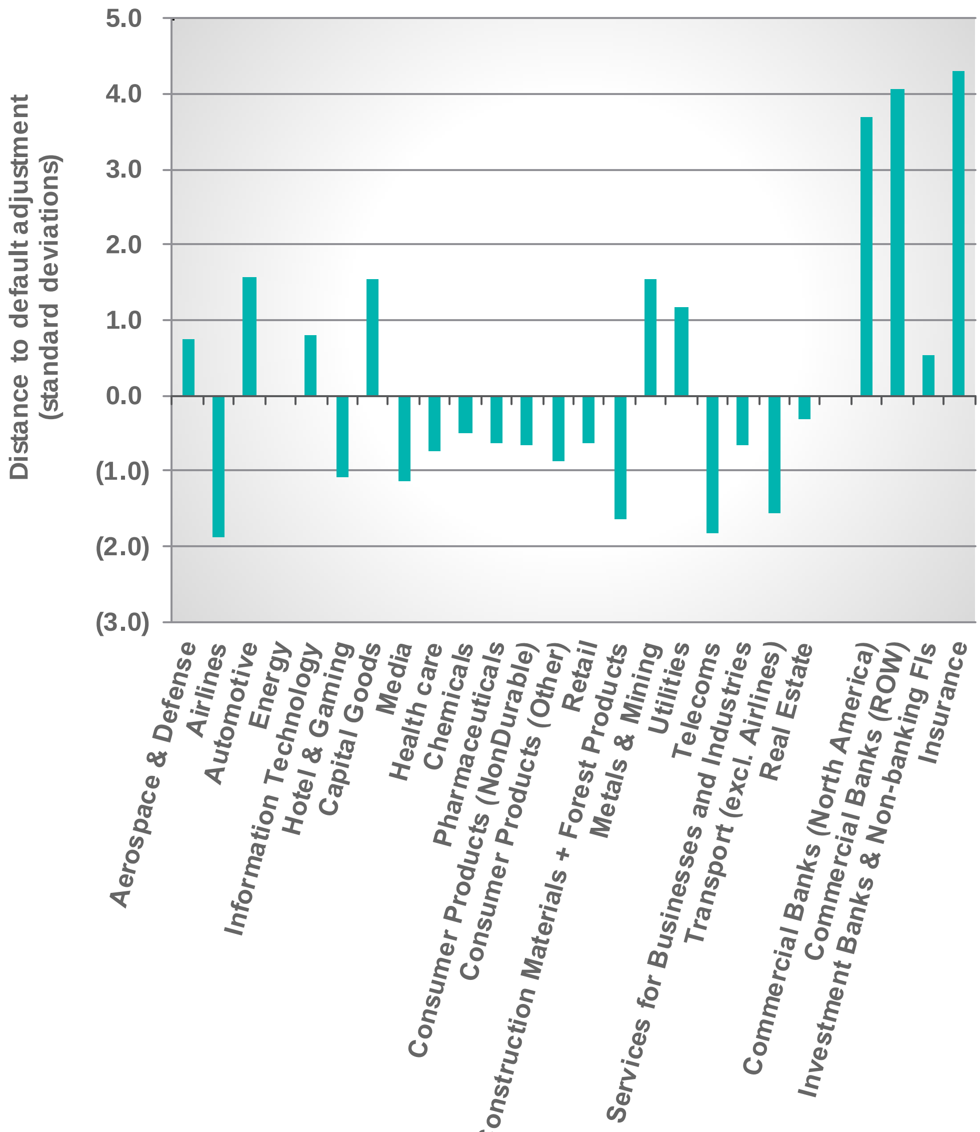
### Table 4: Country Coverage – PD Model Market Signals[18]

| | | | |
|---|---|---|---|
| Afghanistan | Fiji | Marshall Islands | Sri Lanka |
| Algeria | Finland | Mauritius | Sudan |
| Anguilla | France | Mexico | Sweden |
| Argentina | Gabon | Moldova | Switzerland |
| Australia | Georgia | Monaco | Syria |
| Austria | Germany | Mongolia | Taiwan |
| Azerbaijan | Ghana | Morocco | Tanzania |
| Bahamas | Gibraltar | Mozambique | Thailand |
| Bahrain | Greece | Namibia | Togo |
| Bangladesh | Greenland | Netherlands | Trinidad and Tobago |
| Barbados | Honduras | New Zealand | Tunisia |
| Belgium | Hong Kong | Nicaragua | Turkey |
| Belize | Hungary | Niger | Turks & Caicos Islands |

[18] As of May 15, 2015.

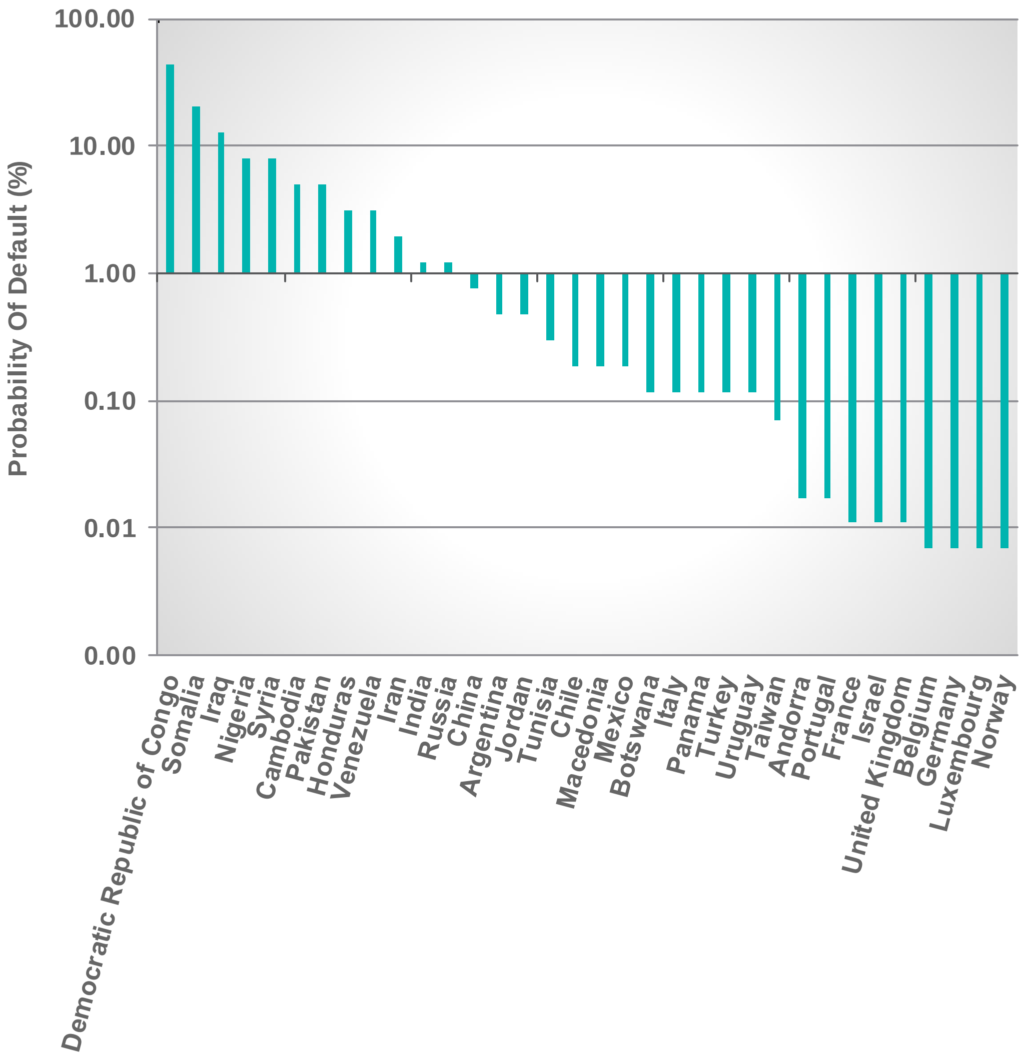
| | | | |
|---|---|---|---|
| Benin | Iceland | Nigeria | Uganda |
| Bermuda | India | Norway | Ukraine |
| Botswana | Indonesia | Occupied Palestinian Territory | United Arab Emirates |
| Brazil | Iran | Oman | United Kingdom |
| British Virgin Islands | Iraq | Pakistan | United States |
| Bulgaria | Ireland | Panama | United States Virgin Islands |
| Burkina Faso | Isle of Man | Papua New Guinea | Venezuela |
| Cambodia | Israel | Peru | Vietnam |
| Cameroon | Italy | Philippines | Zambia |
| Canada | Jamaica | Poland | Zimbabwe |
| Cayman Islands | Japan | Portugal | |
| Chile | Jordan | Qatar | |
| China | Kazakhstan | Réunion | |
| Colombia | Kenya | Romania | |
| Costa Rica | Kuwait | Russia | |
| Côte d´Ivoire | Laos | Samoa | |
| Croatia | Latvia | Saudi Arabia | |
| Curaçao | Lebanon | Senegal | |
| Cyprus | Libya | Serbia | |
| Czech Republic | Liechtenstein | Sierra Leone | |
| Denmark | Lithuania | Singapore | |
| Dominican Republic | Luxembourg | Slovakia | |
| Ecuador | Macau | Slovenia | |
| Egypt | Malawi | South Africa | |
| El Salvador | Malaysia | South Korea | |
| Estonia | Malta | Spain | |

Figure 1: Distance To Default Adjustments (2015) By Industry for Non-Financial Corporates



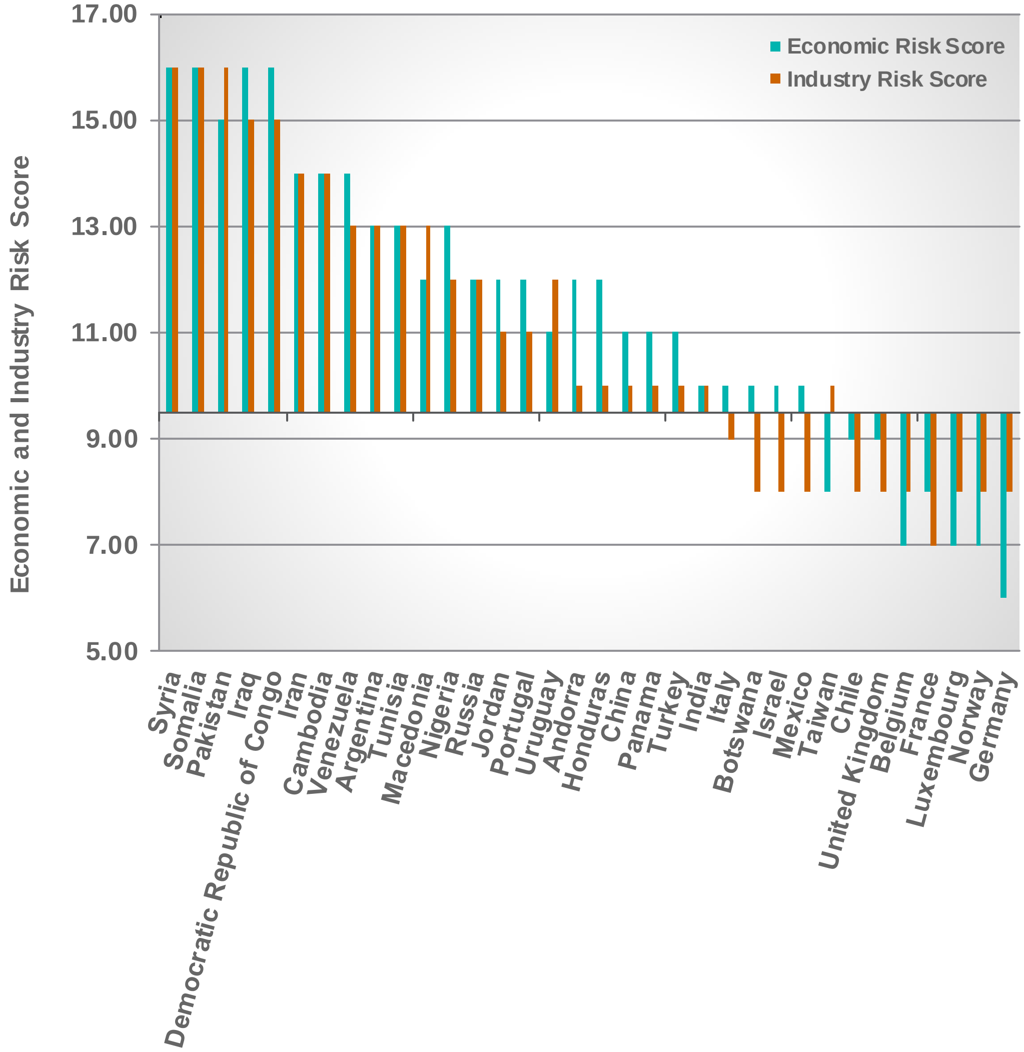

Source: S&P Global Market Intelligence, as of 1 January 2015. For illustrative purposes only.

Figure 2: 2015 Probability Of Default According To Country Risk



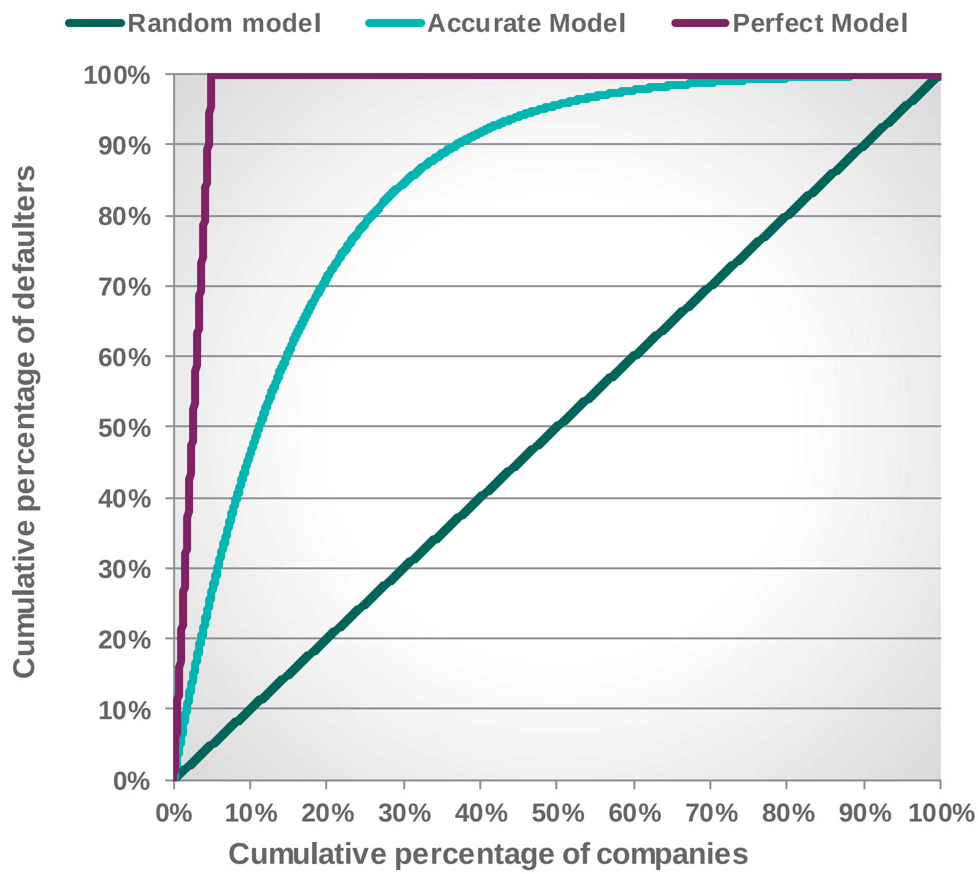

Source: S&P Global Market Intelligence, as of 1 January 2015. For illustrative purposes only.

Figure 3: 2012 Economic and Industry Risk Scores for the Banking Industry



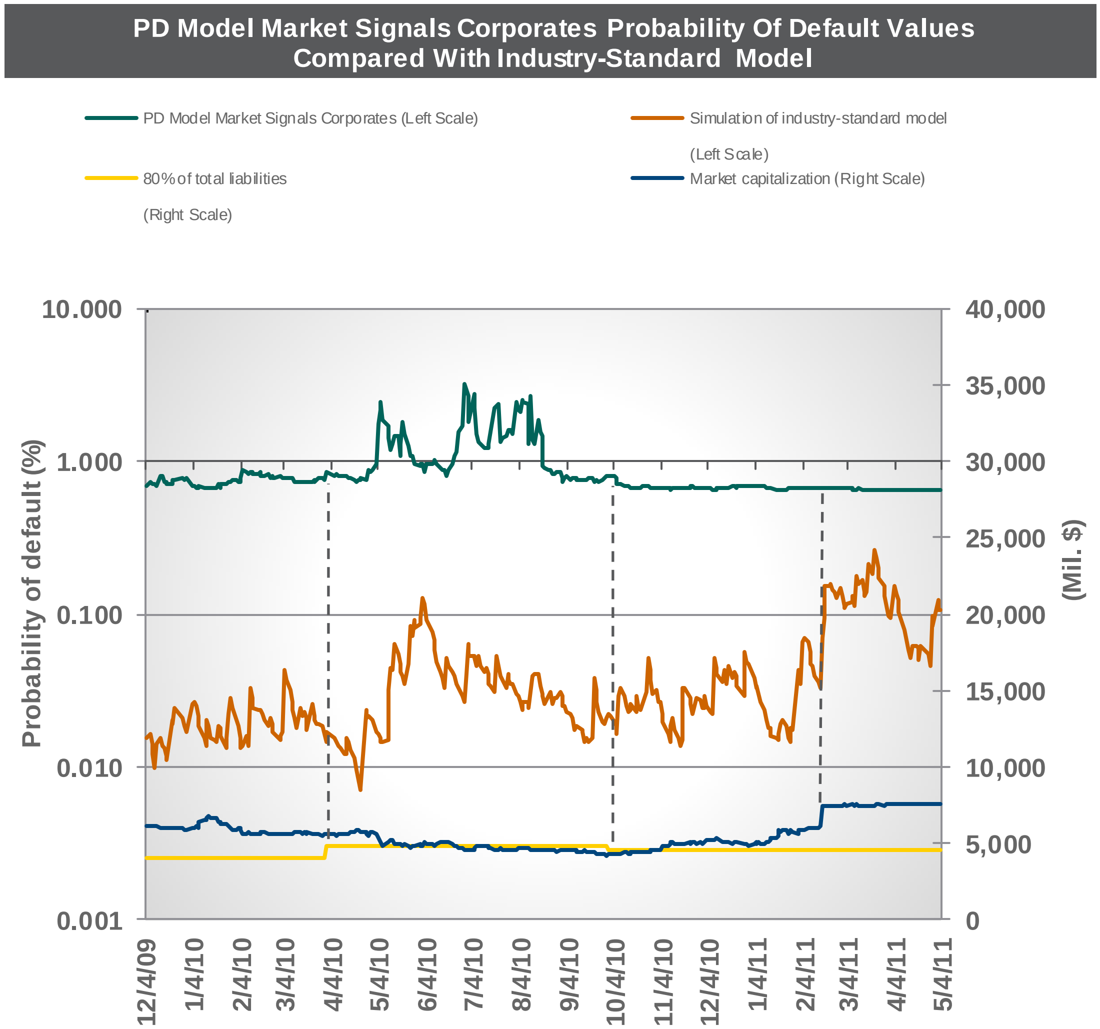

Source: S&P Global Market Intelligence, as of 1 January 2012. For illustrative purposes only.
Economic and Industry Risk scores are on a scale of integers from 1-19, that can be associated with letter grades: 1 = aaa, 2 = aa+ etc. hese scores act like anchor points, representing the median risk of a bank in a country, the best score is 6 = a, and the w orst score is 16 = b-.

Figure 4: Receiver Operating Characteristics (ROC) For A Probability Of Default Model




Source: S&P Global Market Intelligence, as of 1 January 2012. For illustrative purposes only.

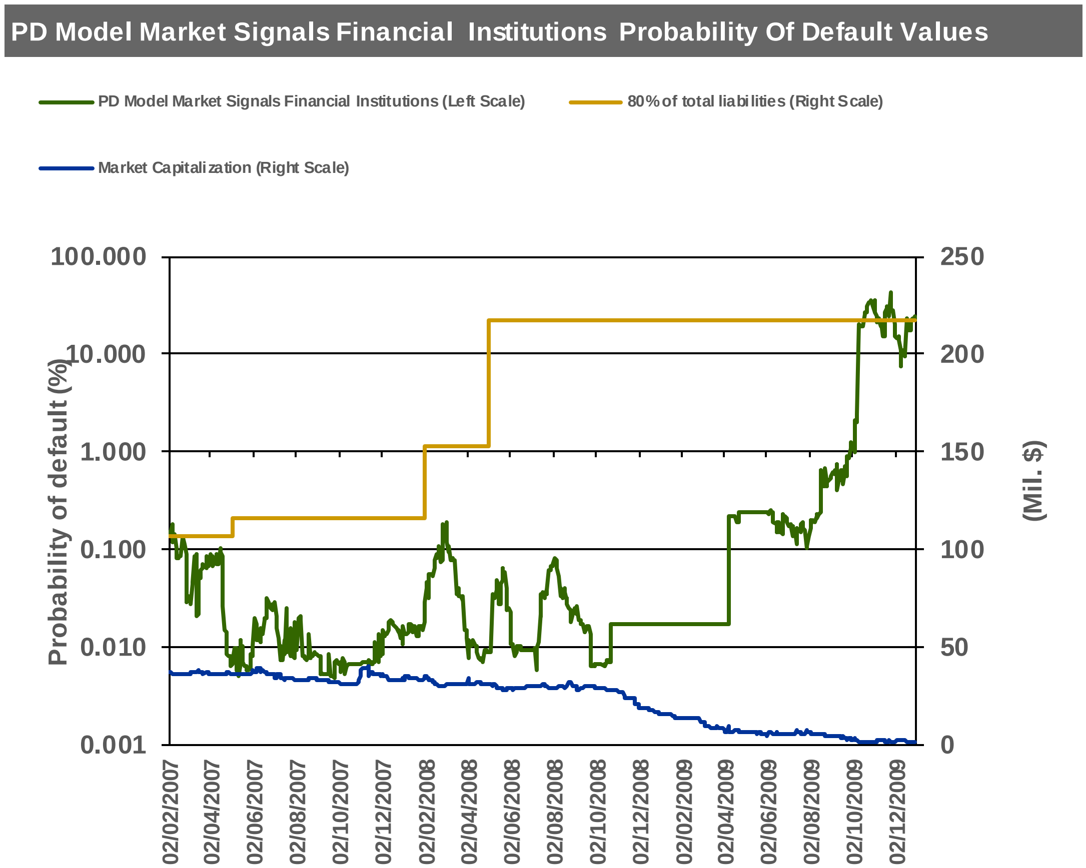
Figure 5: Compania Espanola de Petroleos




Note: The probability of default axis uses a semi-log scale to amplify the low percentage values.

Source: S&P Global Market Intelligence, as of 1 January 2012. For illustrative purposes only.

Figure 6: First Sound Bank




Note: The probability of default axis uses a semi-log scale to amplify the low percentage

Source: S&P Global Market Intelligence, as of 1 January 2012. For illustrative purposes only.

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Contact Us

Americas
+1 212 438 8701

Europe, Middle East and Africa
+44 (0)20 7176 1234

Asia Pacific
+852 2533 3565

credit_analytics@spcapitaliq.com

www.spglobal.com/marketintelligence