PD MODEL FUNDAMENTALS: BANKS

A Pioneer Model For Assessing Bank Creditworthiness

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Introduction

During the recent global economic downturn, the number of banks that defaulted rose to unprecedented levels. However, the high default rate for banks was not captured by most existing models developed in the marketplace, be it by model vendors or internally by financial institutions, corporations, or investors. This is partly because many existing models are based on the historical financial data collected by banks, and don't take into account early warning signals or systemic risk factors such as the deterioration in the environment of a country's banking industry and economy.

S&P Capital IQ's new PD Model Fundamentals – Banks measures the creditworthiness of a bank in terms of its probability of default (PD) over a one-year time horizon. Our model is based on a new approach that combines cutting-edge modeling techniques with a comprehensive and up-to-date data set that goes far beyond standard financial ratios.

Scope of Application

The model applies to "Banks" or "Thrifts & Mortgage Finance", (see Appendix A) defined by Standard & Poor's Ratings Services' Global Industry Classification Standard (GICS®).

- **Financial and Macroeconomic Factors**
  Our model utilizes both financial data from banks and the most relevant macroeconomic data for the banking sector to generate what we regard as a reliable estimation of probability of default. Hence, it captures both market risk and industry-specific risk.

- **Global Coverage**
  As the world has become more interconnected economically, financial institutions, investors, and multi-national corporations have shown more and more interest in the creditworthiness of banks around the globe. Our model covers country and sovereign risk for all 247 countries to reflect their different operating environments and degrees of economic development. For country coverage, please refer to Appendix B.

- **Public and Private**
  Our model covers both private and public banks. Public banks are those listed on a stock exchange.

- **Model Output**
  The model's primary output is a one-year probability of default, which we then map to a credit score. The score is represented in the familiar nomenclature of letter grade symbols. They appear in lower case letters in order to clearly distinguish them from public credit ratings.

Absolute Contribution

Clients can assess the "weight" or importance of contribution of a risk factor to the current PD, through the Absolute Contribution (AC). The higher the contribution value, the more the input "contributes" to the model output. Absolute contributions of all input factors add to 100% and thus provide a straightforward means to identify the main input(s) that drive a model output.

How Do We Do Better?

Examined Defaulted Banks Globally

Some experts argue that it's difficult or even impossible to build a model that predicts defaults in banking because of a lack of historical default data. We were determined to find a way nonetheless. We searched for default information across the globe from regulators, central banks, universities, and research organizations. For example, we studied information from the Federal Deposit Insurance Corporation of the United States, the European Central Bank, and academic studies on African banking systems. We collected financials for about 500 defaulted banks from both North America and non-North America regions.

Comprehensive Financial Data

The data we used to develop the model goes back more than 10 years. So it tracks the experience and performance of banks through several industry and economic cycles. It thus captures better than ever before the characteristics of institutions that weathered various storms -- and those that didn't. We collected our data on a quarterly basis -- or as frequently as possible--for both public and private banks. We continue to do so, which allows us to refine the model rapidly if we spot new symptoms of default.

We collected the financial data with which we populate the model based on S&P Capital IQ's comprehensive standardized database, keeping in mind three key principles. We needed:

- Reliable and consistent data
- The largest possible target universe
- A sample that accurately represented our overall target universe

Table 1: North America Model Development Sample Country Summary

Country	Number of Observations	Number of Banks
Canada	502	41
United States	353,149	13,521
Total	**353,651**	**13,562**

Source: S&P Capital IQ as of 18 March, 2012

In the table above, "observations" refer to the financial statements of banks that we included in our model. For instance, if a specific bank issues quarterly statements, then over a period of 10 years data from this bank contributes to 40 separate observations. The lower number for

Canada stems mostly from the fact that the banking sector is less fragmented in that country than it is in the U.S.

The Non-North America Model Development Sample Country Summary is attached in Appendix C.

Table 2: Development Sample Entities by Region

Model	Region	Number of Banks
Non-North America	Africa & Middle East	342
	APAC	667
	Europe	1,081
	Latin America & Caribbean	213
North America	Canada, United States	13,562
Total		**15,865**

Source: S&P Capital IQ as of 18 March, 2012

The table above shows the number of banks whose data we included in the modeling sample. For all these banks the comprehensive set of data we needed was broadly available. Thus, the table above represents the cleaned dataset for modeling.

Systemic Risk Data

It is crucial to consider the environment in which a bank operates when constructing a global model. Standard & Poor's Banking Industry Country Risk Assessment (BICRA) score reflects the strengths and weaknesses of a country's banking industry within the context of its macroeconomic environment.

A BICRA 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 247 countries using these BICRA scores, 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.

Vigorous Variable Selection Process

We applied a vigorous, cutting- edge procedure for the variable selection process which helps to prescreen what could be included as input for the model. We have included both statistical analysis and some business judgment, and took the following into consideration:

Availability – All factors included in the model must be widely available on a consistent basis over time for banks. Some factors have a high predictive power but are seldom reported by companies (e.g. the proportion of interest-bearing debt). While these factors may help boost a model's performance, such a model would be irrelevant for banks that do not have detailed reporting. As a result, we drop factors with low availability to ensure the comparability of model outputs.

Correlation – Highly correlated factors do not provide additional insights and could distort the models. We use correlation analysis to weed out correlated variables.

Representation of All Relevant Risk Dimensions – We analyze the so-called risk dimension of each variable based on expert judgment. Then, we choose factors from a range of categories, including systemic risk factors, financial, and non-financial factors. Hence, the model outputs include the effect of the different types of drivers behind the creditworthiness of a bank.

Table 3: Risk Dimensions

Risk Dimension	Factors
Size	Total Adjusted Assets
Asset Quality	Loan Loss Provisions / Total Gross Customer Loans
Efficiency	Total Non-interest Expenses / Total Adjusted Assets
Profitability	Return on Total Adjusted Assets
	Retained Earnings / Total adjusted equity
Liquidity	(Total Adjusted Common Equity + Loan Loss Reserves) / Total Gross Customer Loans
	Tier 1 Capital Ratio
Systemic risk factors	Economic Risk Score for each country
	Industry Risk Score for each country
Company Type	Public or Private Banks

Source: S&P Capital IQ as of 18 March, 2015

Dummy Variable – We add slope dummy and pure dummy variables to the model, which help us check for:

- Potential differences in the explanatory power of factors between private and public banks.
- Early warning signals such as low values for tier 1 capital and liquidity ratios as defined by the latest regulatory guidelines.

Table 4: Types of dummy variables

Dummy Type	Factors
Slope Dummy	Company Type (Private / Public)
	Liquidity Ratio
Pure Dummy	Tier-1-Capital

Source: S&P Capital IQ as of 18 March, 2015

Integration of Most Recent Regulatory Developments

It is imperative for a model to evolve with the market. So we have added to the model factors that have become the focus of attention following changes in the regulatory environment (Basel III). An example is our use of the tier-1 capital ratio, the definition of which we've loosened sufficiently to ensure that it can be populated for almost any bank.

Sophisticated Methodology

The model uses a number of techniques, including variable transformations, which minimize the impact of extreme values. It also uses various constraints, which ensure robust treatment of outliers without any loss of data as well as a more accurate estimation of the beta parameters and PD.

Most existing models only employ simple logistic regression techniques. Our model employs a more sophisticated methodology, Maximum Expected Utility (MEU). The process of variable selection considers both linear terms and terms of higher order, and selects the final variables according to k-fold Greedy Forward Approach, a widely-used statistical method which ensures a good fit out-of-sample and out-of-time.

The model maximizes the Geometric Mean Probability (GMP), which is a transformation of maximum likelihood and uses the Akaike Information Criterion (AIC) to limit the maximum number of variables that are included (model parsimony), and a Tikhonov regularization to penalize extreme values for the parameters used in the model. This optimization is superior to the optimization of performance measures such as 'accuracy ratios' or the ROC curve (see below) as it exhibits greater stability and out-of-time performance.

We applied various statistical methods, including bootstrapping, a resampling technique to compensate for limited availability of defaulters from non-North America regions.

Sovereign Cap

We assume that a financial institutions' rating should not be better than the sovereign country rating at the same time. We apply this assumption to our result by capping any estimated PD by PD implied by the Standard & Poor's sovereign rating prevailing at that moment. The sovereign rating chosen is the one belonging to the country where the firm is headquartered.

Sovereign foreign currency ratings are used since local currency ratings may underestimate the credit risk in the country. The foreign currency sovereign credit rating is a current opinion of a country's overall capacity to meet its foreign currency-denominated financial obligations and is evaluated on the basis of the country's individual credit characteristics.

For countries without public sovereign ratings by Standard & Poor's Ratings Services, the proxy in terms of a sovereign risk score is provided which acts as a final cap in exactly the same way as the S&P foreign currency rating. These sovereign risk scores are provided by experts from S&P Capital IQ and maintained.

Model Performance

The model's performance can be measured by Receiver Operating Characteristic (ROC), which takes into account the true positive rate and the false positive rate. A higher ROC indicates better accuracy in predicting a bank default. The out-of sample testing result showed promising performance. The stability in the ROC value during the out-of-time testing over a tumultuous period for the financial industry indicates a strong performance of the PD Model - Banks Fundamentals.

Table 5a: The Model Performance

Performance Test	ROC
In-sample	86.31%
Out-of-sample	87.31%

Source: S&P Capital IQ as of 18 March, 2015

Model Validation

Since the release of PD Model Fundamentals - Banks, S&P Capital IQ has conducted a detailed performance evaluation annually, based on the actual performance data and provided the results of the validation to users. If a significant deterioration in model performance is observed, S&P Capital IQ will consider a recalibration of the parameters or a review of the risk drivers.

Below we report the AR and ROC of PD Model Fundamentals – Banks for the 2015 validation, specifically for the universe of companies rated by Standard & Poor's, where the default flags and the non-default flags are reliable, and no assumption is made when there is lack of default flags.

Table 5b: Overall AR and ROC of PD Model Fundamentals – Banks, for 2015 validation

	AR	ROC
2015 validation	63.27%	81.64%

Source: S&P Capital IQ as of 18 March, 2015

Typically, values of ROC between 0.7 and 0.8 are considered acceptable, between 0.8 and 0.9 are considered sign of good discriminatory power and above 0.9 are considered excellent.

More details can be found in the validation document, available to users upon request.

Pre-scored Database With Standalone Scores and Support Considerations

We provide clients with efficient access to estimates of creditworthiness for more than 4,000 banks globally. The pre-scored database includes both standalone scores, prior to parental and government support considerations, and after inclusion of support, that is modelled with a quantitative overlay. More details on the analytic methodology can be found in the corresponding technical documents.[1]

Sensitivity Analysis, Stress-Testing, Peer Comparison and Reporting

As for all our scoring and PD models, clients can score any bank from their own portfolio, even though it may not be in our pre-scored database, change input factors for a 'what-if' analysis or even stress-test input factors in order to generate stressed PDs.

In 'batch scoring', many banks can be scored simultaneously and results compared with each other. This user-friendly feature enables clients to upload a portfolio of banks at once and generate results instantly in an excel file.

For every analysis, reports can be generated with a comprehensive summary analysis.

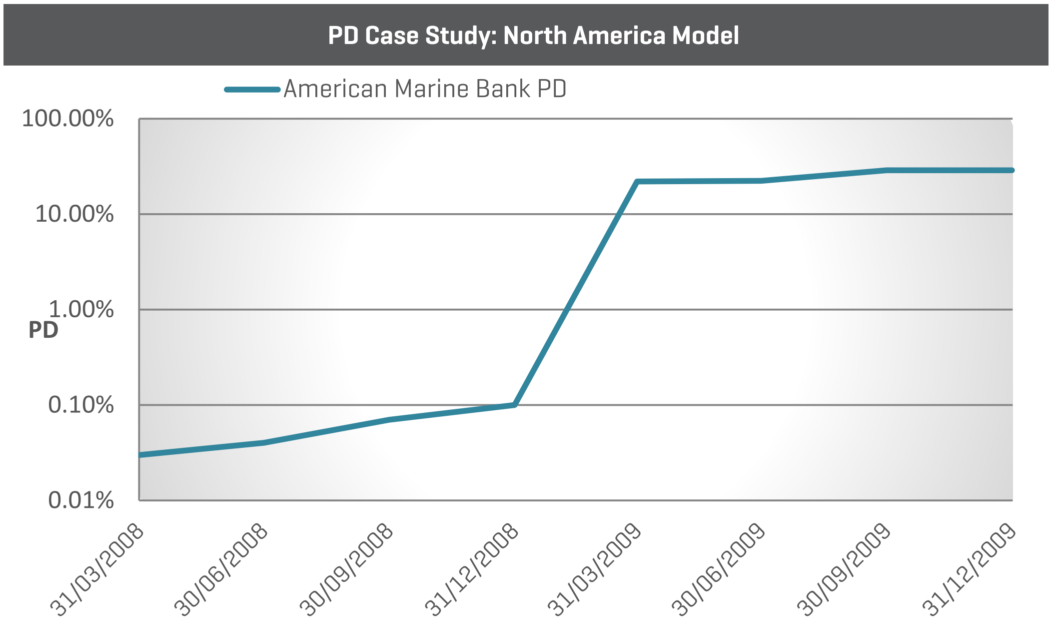
Case Study: North American Model

American Marine Bank was founded in 1948 and headquartered in Bainbridge Island, Washington, U.S. The bank offers personal and commercial banking services. On January 29, 2010, American Marine Bank was acquired by Columbia State Bank due to its distressed financials.

Figure 1 shows American Marine Bank's Probability of Default went up significantly during year 2009, which was also the period when the bank incurred significant losses after the global financial crisis. A series of financial ratios used in the model captured significant changes to this situation, which translate to credit assessment changes in the direction of increased PD. For example, the bank's 'Return on Total Adjusted Asset' dropped from 0.23% on December 31, 2008, to -5.13% on March 31, 2009. The substantial losses started to consume the bank's retained earnings, which resulted in a drop from 51.71% to -20.90% in 'Retained Earnings/Total Adjusted Equity' during the same quarter. As a result, our PD model was able to provide an early warning signal to users by significantly increasing the bank's PD from 0.10% to 21.90% during the same period. On September 30, 2009, when the bank was about 4 months away from being officially closed down by the FDIC, the PD model continues to reflect the bank's poor credit health by further increasing its PD. The PD model was able to utilize the fact that some key financials continued to show a downward trend. American Marine Bank's 'Loss Provisions/Total Gross Customer Loans' almost doubled from 7.25% to 12.10% on June 30, 2009. The bank's 'Retained Earnings /Total Adjusted Equity' dropped from -21.84% to -651.92% during the same period. At this point, the bank was already on the edge of collapsing. On December 31, 2009, just one month before the bank was officially closed down, the bank's PD increased to 28.82%, which is the highest PD recorded in the bank's own history ever.

[1] See S&P Capital IQ's "Quantitative parental support overlay" document, for the parental support methodology and S&P Capital IQ's "Quantitative support overlay for Government-related entities" document, for extraordinary government support methodology.

Figure 1: PD output changes before bank's bankruptcy – North America Model



Note: The PD axis uses a log scale to amplify the low percentage values.

Source: S&P Capital IQ, 15 March 2012.

Case Study: Non-North America Model

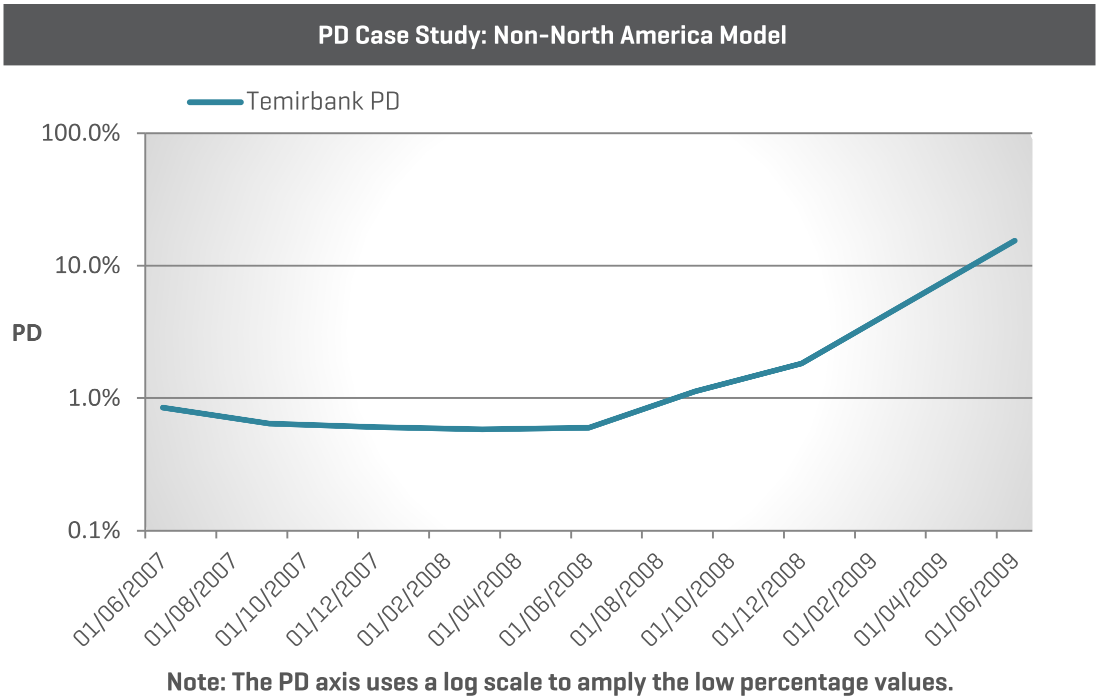
Temirbank JSC was founded in Kazakhstan in 1992 and it offers retail and corporate banking products and services to corporate and individual clients in Kazakhstan. On November 30, 2009, the bank and its debt obligations were downgraded by Standard & Poor's to "D".

Figure 2 shows the PD for Temirbank JSC increased dramatically in 2009, which coincided with bank's failure in interest payment and default on payments due to its major shareholder and announcement of debt obligation restructuring.

From our model, the bank's Total Adjusted Assets showed a decreasing trend during 2008 to 2009 together with significant changes in the following ratios: Return on Total Adjusted Assets decreased during 2008 and changed from positive to negative in late 2008 followed by a significant decrease from -1.24% on December 31, 2008 to -29.62% on June 30, 2009, while Loan Loss Provision/Total Gross Customer Loans also showed a downward trend in 2008 and was also increased from 3.09% on December 31, 2008 to 27.91% on June 30, 2009. As a result, our PD model reacted to this trend in 2008 and showed investors the PD of Temirbank increased from 0.60% in mid-2008 to the an 8-year high 1.83% on December 31 2008 and further provided an early warning signal to investors by increasing the PD of the bank on June 30, 2009 to a record-high 15.44%. Five months later, the bank was reported to have defaulted on two related-party deposits of 7.7 billion KZT (approx. 51.3 million USD) due to its major shareholder BTA Bank JSC and have missed interest payment to its senior notes pursuant to Temir Capital B.V.'s 1.2 billion USD global medium-term note program and to 300 million USD senior notes.

Followed by that, Temirbank JSC officially announced a debt obligations restructuring and was downgraded by Standard & Poor's to "D" from "CC"

Figure 2: PD output changes before bank's bankruptcy – Non-North America Model



Source: S&P Capital IQ, 15 March 2012.

Conclusion

We developed a global probability of default model for banks utilizing a state-of-the-art statistical framework, a project which was often labeled 'mission impossible' in the past. Input factors are both financials, which are updated with the highest possible frequency, i.e. every three months in our pre-scored database, plus a range of systemic risk factors that are 100% tailored to this specific asset class and which account for country, sovereign, economic, and industry risks.

Next, we will develop a model to capture short term indicators from the market, for example stock price and volatility. We'll do this first for public banks and later extend to private banks via suitable market signal proxies. Subsequently, we will combine such quick response features with the existing fundamentals-based models.

APPENDIX A

PD Model Fundamentals: Banks – Supported Industry

Industry	GICS Code	Sub Industry
Banks	40101010	Diversified Banks
		Large, geographically diverse banks with a national footprint whose revenues are derived primarily from conventional banking operations, have significant business activity in retail banking and small and medium corporate lending, and provide a diverse range of financial services. Excludes banks classified in the Regional Banks and Thrifts & Mortgage Finance Sub-Industries. Also excludes investment banks classified in the Investment Banking & Brokerage Sub-Industry.
	40101015	Regional Banks
		Commercial banks whose businesses are derived primarily from conventional banking operations and have significant business activity in retail banking and small and medium corporate lending. Regional banks tend to operate in limited geographic regions. Excludes companies classified in the Diversified Banks and Thrifts & Mortgage Banks sub-industries. Also excludes investment banks classified in the Investment Banking & Brokerage Sub-Industry.
Thrifts & Mortgage Finance	40102010	Thrifts & Mortgage Finance
		Financial institutions providing mortgage and mortgage related services. These include financial institutions, whose assets are primarily mortgage related, savings & loans, mortgage lending institutions, building societies and companies providing insurance to mortgage banks.

APPENDIX B

PD Model Fundamentals: Banks – Global Coverage

Country	Country	Country	Country
Afghanistan	Dominica	Lithuania	Saint Martin
Åland Islands	Dominican Republic	Luxembourg	Saint Pierre & Miquelon
Albania	Ecuador	Macau	Saint Vincent & Grenadines
Algeria	Egypt	Macedonia	Samoa
American Samoa	El Salvador	Madagascar	San Marino
Andorra	Equatorial Guinea	Malawi	Sao Tome and Principe
Angola	Eritrea	Malaysia	Saudi Arabia
Anguilla	Estonia	Maldives	Senegal
Antarctica	Ethiopia	Mali	Serbia
Antigua & Barbuda	Falkland Islands	Malta	Seychelles
Argentina	Faroe Islands	Marshall Islands	Sierra Leone
Armenia	Fiji	Martinique	Singapore
Aruba	Finland	Mauritania	Sint Maarten
Australia	France	Mauritius	Slovakia
Austria	French Guiana	Mayotte	Slovenia
Azerbaijan	French Polynesia	Mexico	Solomon Islands
Bahamas	Gabon	Moldova	Somalia
Bahrain	Gambia	Monaco	South Africa
Bangladesh	Georgia	Mongolia	South Georgia & the South Sandwich Islands
Barbados	Germany	Montenegro	South Korea
Belarus	Ghana	Montserrat	South Sudan
Belgium	Gibraltar	Morocco	Spain
Belize	Greece	Mozambique	Sri Lanka
Benin	Greenland	Myanmar	Sudan
Bermuda	Grenada	Namibia	Suriname
Bhutan	Guadeloupe	Nauru	Svalbard & Jan Mayen
Bolivia	Guam	Navassa Island	Swaziland
Bonaire, Sint Eustatius & Saba	Guatemala	Nepal	Sweden
Bosnia-Herzegovina	Guernsey	Netherlands	Switzerland
Botswana	Guinea	New Caledonia	Syria
Brazil	Guinea-Bissau	New Zealand	Taiwan
British Indian Ocean Territory	Guyana	Nicaragua	Tajikistan
British Virgin Islands	Haiti	Niger	Tanzania
Brunei	Heard Island & Mc Donald Islands	Nigeria	Thailand
Bulgaria	Honduras	Niue	Timor-Leste
Burkina Faso	Hong Kong	Norfolk Island	Togo
Burundi	Hungary	North Korea	Tokelau

Cambodia	Iceland	Northern Mariana Islands	Tonga
Cameroon	India	Norway	Trinidad & Tobago
Canada	Indonesia	Oman	Tunisia
Cape Verde	Iran	Pakistan	Turkey
Cayman Islands	Iraq	Palau	Turkmenistan
Central African Republic	Ireland	Palestinian Authority	Turks & Caicos Islands
Chad	Isle of Man	Panama	Tuvalu
Channel Islands	Israel	Papua New Guinea	Uganda
Chile	Italy	Paraguay	Ukraine
China	Jamaica	Peru	United Arab Emirates
Christmas Island	Japan	Philippines	United Kingdom
Cocos (Keeling) Islands	Jersey	Pitcairn Islands	United States
Colombia	Jordan	Poland	United States Virgin Islands
Comoros	Kazakhstan	Portugal	Uruguay
Cook Islands	Kenya	Puerto Rico	Uzbekistan
Costa Rica	Kiribati	Qatar	Vanuatu
Côte d'Ivoire	Kuwait	Republic of the Congo	Vatican City
Croatia	Kyrgyzstan	Réunion	Venezuela
Cuba	Laos	Romania	Vietnam
Curaçao	Latvia	Russia	Wallis & Futuna
Cyprus	Lebanon	Rwanda	Western Sahara
Czech Republic	Lesotho	Saint Barthélemy	Yemen
Democratic Republic of the Congo	Liberia	Saint Helena, Ascension & Tristan da Cunha	Zambia
Denmark	Libya	Saint Kitts & Nevis	Zimbabwe
Djibouti	Liechtenstein	Saint Lucia	

APPENDIX C

Non-North American Model Development Sample Country Summary

Country	Number of Observations
Albania	87
Algeria	9
Andorra	11
Angola	43
Argentina	531
Armenia	254
Australia	714
Austria	462

Country	Number of Observations
Azerbaijan	164
Bahamas	27
Bahrain	310
Bangladesh	306
Barbados	39
Belarus	229
Belgium	162
Belize	40
Benin	17
Bermuda	88
Bolivia	13
Bosnia-Herzegovina	55
Botswana	90
Brazil	1,511
Bulgaria	225
Cambodia	23
Cameroon	13
Cape Verde	6
Cayman Islands	13
Channel Islands	30
Chile	266
China	511
Colombia	268
Costa Rica	39
Croatia	253
Cyprus	153
Czech Republic	487
Denmark	1,602
Ecuador	37
Egypt	314
El Salvador	48
Equatorial Guinea	3
Estonia	217
Ethiopia	18
Fiji	9
Finland	182
France	1,489
Gabon	7
Georgia	163
Germany	1,671
Ghana	96
Gibraltar	40

Country	Number of Observations
Greece	443
Honduras	4
Hong Kong	716
Hungary	289
Iceland	109
India	1,352
Indonesia	678
Iran	5
Iraq	18
Ireland	210
Israel	355
Italy	1,298
Ivory Coast	32
Jamaica	114
Japan	4,591
Jordan	239
Kazakhstan	456
Kenya	186
Kuwait	194
Laos	3
Latvia	533
Lebanon	187
Libya	13
Liechtenstein	48
Lithuania	259
Luxembourg	214
Macau	5
Macedonia	109
Madagascar	10
Malawi	13
Malaysia	641
Mali	4
Malta	153
Mauritius	56
Mexico	808
Moldova	204
Monaco	12
Mongolia	17
Montenegro	21
Morocco	173
Mozambique	20
Namibia	36

Country	Number of Observations
Nepal	21
Netherlands	320
New Zealand	289
Niger	12
Nigeria	240
Norway	1,138
Oman	214
Pakistan	694
Palestinian Authority	7
Panama	142
Papua New Guinea	20
Peru	497
Philippines	699
Poland	699
Portugal	425
Qatar	218
Romania	154
Russia	596
Rwanda	14
Saudi Arabia	391
Senegal	25
Serbia	114
Singapore	140
Slovakia	134
Slovenia	218
South Africa	403
South Korea	415
Spain	1,181
Sri Lanka	342
Sudan	37
Sweden	522
Switzerland	758
Syria	2
Taiwan	1,145
Tanzania	72
Thailand	602
Togo	33
Trinidad & Tobago	66
Tunisia	164
Turkey	707
Uganda	26
Ukraine	333

Country	Number of Observations
United Arab Emirates	677
United Kingdom	1,307
Uruguay	4
Uzbekistan	10
Vanuatu	7
Venezuela	219
Vietnam	79
Western Samoa	10
Zambia	43
Zimbabwe	57
Total	**44,815**

About S&P Capital IQ

S&P Capital IQ, a business line of The McGraw-Hill Companies (NYSE:MHP), is a leading provider of multi-asset class and real time data, research and analytics to institutional investors, investment and commercial banks, investment advisors and wealth managers, corporations and universities around the world. We provide a broad suite of capabilities designed to help track performance, generate alpha, and identify new trading and investment ideas, and perform risk analysis and mitigation strategies. Through leading desktop solutions such as the S&P Capital IQ, Global Credit Portal and MarketScope Advisor desktops; enterprise solutions such as S&P Capital IQ Valuations, and Compustat; and research offerings, including Leveraged Commentary & Data, Global Markets Intelligence, and company and funds research, S&P Capital IQ sharpens financial intelligence into the wisdom today's investors need.

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