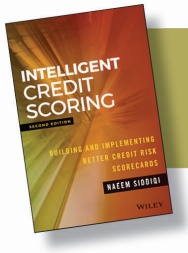
INTELLIGENT CREDIT SCORING

SECOND EDITION

BUILDING AND IMPLEMENTING BETTER CREDIT RISK SCORECARDS

NAEEM SIDDIQI

WILEY



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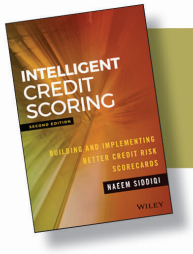

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CHAPTER 1

Introduction

"The only virtue of being an aging risk manager is that you have a large collection of your own mistakes that you know not to repeat."

—Donald Van Deventer

Much has changed since the publication of the first edition of this book in 2006. The use of credit scoring has become truly international, with thousands of lenders now developing their own scorecards in-house. As a benchmark, The SAS Credit Scoring[1] solution, which started out around that time, now has hundreds of customers—but more importantly, they are spread out across 60-plus countries. Many more banks, of course, use products from other vendors to build and use credit risk scorecards in-house, but in general, the trend has moved away from outsourcing the development of scorecards to internal builds. The following factors, listed in the order discussed, have led to more widespread usage of scorecards and the decision by banks to build them in-house.

Factors driving the increased use of scorecards include:

- Increased regulation.
- Ease of access to sizable and reliable data.
- Better software for building scorecards.
- Availability of greater educational material and training for would-be developers.
- Corporate knowledge management fostering retention and sharing of subject-matter expertise.
- Signaling capabilities to external and internal stakeholders.
- Efficiency and process improvement.
- Creating value and boosting profitability.
- Improved customer experience.

In the past decade, the single biggest factor driving banks to bring credit scorecard development in-house has been the Basel II Accord.[2]

Specifically, banks that have opted to (or were told to) comply with the Foundation or Advanced Internal Ratings Based approaches of Basel II were required to internally generate Probability of Default (PD) estimates (as well as estimates for Loss Given Default [LGD] and Exposure at Default [EAD]). Larger banks expanded their production and usage of credit scoring, and were compelled to demonstrate their competence in credit scoring. In many countries, particularly in Europe, even small banks decided to go for these approaches, and thus had to start building models for the first time. This led to some challenges—when you have never built scorecards in-house (and in some cases, not really used them either), where do you start? Many institutions went through significant changes to their data warehousing/management, organizational structure, technology infrastructure, and decision making as well as risk management cultures. The lessons from some of these exercises will be shared in chapters on creating infrastructures for credit scoring, as well as the people who should be involved in a project.

While there is a lot of variance in the way Basel II has been implemented in Europe, it is largely a finished process there.[3] Some of the lessons, from Basel II, specifically on how the default definition should be composed will be detailed in a guest chapter written by Dr. Hendrik Wagner. The implementation of Basel II is still ongoing in many countries, where the same exercise is being repeated many times (and in most cases, the same questions are being asked as were 10 years ago in Europe). Many institutions, such as retail credit card and automotive loan companies, that were not required to comply with Basel II, voluntarily opted to comply anyway. Some saw this as a way to prove their capabilities and sophistication to the market, and as a seal of approval on the robustness of their internal processes. But the ones who gained most were those who saw Basel II compliance not just as a mandatory regulatory exercise, but rather as a set of best practices leading to an opportunity to make their internal processes better. This theme of continuous improvement will be addressed in various parts of the book, and guidance given on best practices for the scorecard development implementation process.

In some countries where Basel II was not a factor, local banks decided to take on analytics to improve and be more competitive. In many developing countries, the banking industry became deregulated

or more open, which allowed international banks to start operating there. Such banks generally tended to have a long history of using advanced analytics and credit scoring. This put competitive pressures on some of the local banks, which in many cases were operating using manual and judgmental methods. The local banks thus started investing in initiatives such as data warehousing, analytics, and in-house credit scoring in order to bring costs down, reduce losses, and create efficiencies. Another factor that points to a wider acceptance of credit scoring is the tight market for scorecard developers globally. In almost all the countries, whether those with Basel II or not, the demand for experienced credit scoring resources has continued to be high.

In more recent times, the introduction of International Financial Reporting Standards (IFRS) 9 to calculate expected losses has expanded the usage of predictive models within all companies. Those institutions that have already invested in fixing their data problems and establishing sustainable and robust analytics functions will find it easier to comply.

In mature markets, banks that had been developing models and scorecards before have now been looking at how to make the process efficient, sustainable and more transparent. Investments in data warehousing, tools to enable analysts to access the data quickly and easily, integrated infrastructure to reduce model risk, governance processes, and other such areas have increased. Many banks that had invested a lot of money into data warehousing were also looking to increase return on investment (ROI). Credit scoring offered a quick and proven way to use the data, not just for reducing losses but also lead to greater profitability.[4]

Scarcity of modeling/credit scorecard (these two words are used interchangeably throughout this book) development resources has led institutions to try to reduce human resources risk by using modeling tools that encourage sharing and retention of corporate knowledge, reduce training cycles and costs, and are easier to use. Some of the challenges and risks of developing scorecards in-house will be discussed in the chapter on managing the risks of in-house scoring.

In other banks not specifically impacted by the preceding, increasing competition and growing pressures for revenue generation have led credit-granting institutions to search for more effective ways to attract new creditworthy customers and, at the same time, control losses. Aggressive marketing efforts have resulted in a continuously

deeper penetration of the risk pool of potential customers, and the need to process them rapidly and effectively has led to growing automation of the credit and insurance application and adjudication processes. The risk manager is challenged to produce risk adjudication solutions that can not only satisfactorily assess creditworthiness but also keep the per-unit processing cost low, while reducing turnaround times for customers. In some jurisdictions without a credit bureau, the risk manager faces an additional challenge of doing so using data that may not be robust or reliable. In addition, customer service excellence demands that this automated process be able to minimize denial of credit to creditworthy customers, while keeping out as many potentially delinquent ones as possible.

At the customer management level, companies are striving ever harder to keep their existing clients by offering them additional products and enhanced services. Risk managers are called on to help in selecting the "right" (i.e., low-risk) customers for these favored treatments. Conversely, for customers who exhibit negative behavior (nonpayment, fraud), risk managers need to devise strategies to not only identify them but also to deal with them effectively to minimize further loss and recoup any monies owed as quickly as possible.

It is in this environment that credit risk scorecards have continued to offer a powerful, empirically derived solution to business needs. Credit risk scorecards have been widely used by a variety of industries for predicting various types of payment delinquencies, fraud, claims (for insurance), and recovery of amounts owed for accounts in collections, among other things. More recently, as mentioned previously, credit scoring has been used widely for regulatory compliance. Credit scoring offers an objective way to assess risk, and also a consistent approach, provided that system overrides are maintained below acceptable policy-specified thresholds.

In the past, most financial institutions acquired credit risk scorecards from a handful of credit risk vendors. This involved the financial institution providing their data to the vendors, and the vendors then developing a predictive scorecard for delivery. For smaller companies, buying a generic or pooled data scorecard was the only option. While some advanced companies have had internal modeling and scorecard development functions for a long time, the trend toward developing scorecards in-house has become far more widespread in the past few years. Some of

the regulatory and operational reasons for this phenomenon were covered at the beginning of this chapter. Others will be discussed later.

First, there are more powerful and easy-to-use data mining software today than ever before. This has allowed users to develop scorecards without investing heavily in advanced programmers and infrastructure. Growing competition and the entry of several new data mining vendors made such tools available at ever cheaper prices. Complex data mining functions became available at the click of a mouse, allowing the user to spend more time applying business and data mining expertise to the problem, rather than debugging complicated and lengthy programs. The availability of powerful "point-and-click"–based Extract-Transform-Load (ETL) software enabled efficient extraction and preparation of data for scorecard development and other data mining. Second, advances in intelligent and easy-to-access data storage have removed much of the burden of gathering the required data and putting it into a form that is amenable to analysis. As mentioned earlier, banks and other lenders have made significant investments in data warehousing and data management, and are now looking to use that data to increase profitability.

Once these tools became available, in-house development became a viable option for many smaller and medium-sized institutions. The industry could now realize the significant ROI that in-house scorecard development could deliver for the right players. Experience has shown that in-house credit scorecard development can be done faster, cheaper, and with far more flexibility than any outsourcing strategy. Development was cheaper since the cost of maintaining an in-house credit scoring capability was less than the cost of purchased scorecards. Internal development capability also allowed companies to develop far more scorecards (with enhanced segmentation) for the same expenditure. Scorecards could also be developed more rapidly by internal resources using the right software—which meant that better custom scorecards could be implemented more rapidly, leading to lower losses.

In addition, companies have increasingly realized that their superior knowledge of internal data and business insights led them to develop better-performing scorecards. Seasoned modelers understand that the single biggest contributor to model quality is the data itself, followed by the knowledge level of the analyst of that data. This book will cover in detail how internal knowledge can be applied to build

better scorecards. In every phase of the project, we will discuss how appropriate judgment can be applied to augment statistical analyses.

Better-performing scorecards also came about from having the flexibility to experiment with segmentation and then following through by developing more finely segmented scorecards. Deeper segmentation allows for more fine-tuned predictions and strategies. Combined with software that can implement champion/challenger scorecards, this becomes a great way to experiment with different configurations of models. Performing such detailed segmentation analysis through external vendors can become expensive.

Banks have also realized that credit risk scorecards are not a commodity to be purchased from the lowest bidder—they are a core competence and knowledge product of the institution. Internal scorecard development increases the knowledge base within organizations. The analyses done reveal hidden treasures of information that allow for better understanding of customers' risk behavior and lead to better strategy development. We will cover some of this knowledge discovery in the section on model development, specifically the grouping process.

In summary, leaving key modeling and strategy decisions to "external experts" can prove to be a suboptimal route at best, and can also be quite costly.

This book presents a business-focused process for the development and usage of credit risk prediction scorecards, one that builds on a solid foundation of statistics and data mining principles. Statistical and data mining techniques and methodologies have been discussed in detail in various publications and will not be covered in depth here. I have assumed that the reader is either familiar with these algorithms, or can read up on them beforehand, and is now looking for business knowledge pertaining to scorecard development.

The key concepts that will be covered in the book are:

- The application of business intelligence to the scorecard development process, so that the development and implementation of scorecards is seen as an intelligent business solution to a business problem. Good scorecards are not built by passing data solely through a series of programs or algorithms—they are built when the data is passed through the analytical and

business-trained mind of the user. This concept will be applied in all the sections of this book—taking statistical analyses and overlaying business knowledge on it to create better results.

- Building scorecards is a business process—as much as we use statistical algorithms, simple or complex, to build models, at the end of the day it is a business exercise. The purpose of the exercise is to enable a better business decision and not merely the creation of a great formula. As such, each process—whether selecting a "bad" definition, deciding appropriate segmentations, best bins for attributes, or the best scorecard—will be viewed through the lens of a business decision.
- Collaborative scorecard development, in which end users, subject matter experts, implementers, modelers, validators, decision makers and other stakeholders work in a cohesive and coherent manner to get better results and avoid costly setbacks and potential disasters during the process.
- The concept of building a risk profile—this means building scorecards that contain predictive variables representing major information categories, usually between 8 and 15 variables. This mimics the thought processes of good risk adjudicators, who analyze information from credit applications or customer behavior and create a profile based on the different types of information available. They would not make a decision using four or five pieces of information only—so why should anyone build a scorecard that is narrow based? In statistics, parsimonious models are usually preferred. However, in this case, where the modeler is attempting to more fully capture the business reality, more variables are preferred in order to construct a proper and representative risk profile. The point of the exercise is to make the best decision-making tool possible, not just a statistical one.
- Anticipating impacts of decisions and preparing for them. Each decision made—whether on the definition of the target variable, segmentation, choice of variables, transformations, choice of cutoffs, or other strategies—starts a chain of events that impacts other areas of the company as well as future performance. By tapping into corporate intelligence and working in collaboration

with others, the user will learn to anticipate the impact of each decision and prepare accordingly to minimize disruption and unpleasant surprises.

- View of scorecards as decision support tools. Scorecards should be viewed as a tool to be used for better decision making and should be created with this view. This means they must be understood and controlled; scorecard development should not result in a complex model that cannot be understood enough to make decisions or perform diagnostics.

Individual scorecard development projects may need to be dealt with differently, depending on each company's unique situation—for example, amount and type of data available, knowledge level, staff, and regulatory limitations. This methodology should therefore be viewed as a set of "best-practice" guidelines rather than as a set of definitive rules that must be followed. Many processes and calculations described in this book can be changed and customized by individual users once they understand what is going on. Finally, it is worth noting that regulatory compliance plays an important part in ensuring that scorecards used for granting consumer credit are statistically sound, empirically derived, and capable of separating creditworthy from noncreditworthy applicants at a statistically significant rate.[5] Users should be aware of the regulations that govern models in their jurisdictions, and change the process accordingly.

SCORECARDS: GENERAL OVERVIEW

Credit risk scoring, as with other predictive models, is a tool used to evaluate the level of credit risk associated with applicants or customers. While it does not identify "good" (no negative behavior expected) or "bad" (negative behavior expected) applications on an individual basis, it provides statistical odds, or probability, that an applicant with any given score will be "good" or "bad." These probabilities or scores, along with other business considerations such as expected approval rates, profit, churn, and losses, are then used as a basis for decision making.

In its simplest form, a scorecard consists of a group of characteristics, statistically determined to be predictive in separating good and bad accounts. For reference, Exhibit 1.1 shows a part of a scorecard.

Exhibit 1.1 Sample Scorecard (Partial)

LTV	LTV< 89	41
	89<= LTV< 98	27
	98<= LTV< 111	18
	111<= LTV< 119	11
	119<= LTV, _MISSING_	7
Mth_oldest_trade	Mth_oldest_trade< 42, _MISSING_	16
	42<= Mth_oldest_trade< 58	17
	58<= Mth_oldest_trade< 86	19
	86<= Mth_oldest_trade< 125	20
	125<= Mth_oldest_trade< 178	22
	178<= Mth_oldest_trade< 216	26
	216<= Mth_oldest_trade	29
Total_lim_cc	Total_lim_cc< 1100, _MISSING_	15
	1100<= Total_lim_cc< 1902	16
	1902<= Total_lim_cc< 3970	18
	3970<= Total_lim_cc< 12500	20
	12500<= Total_lim_cc< 21218	25
	21218<= Total_lim_cc	31
Utilisation	Utilisation< 2, _MISSING_	20
	2<= Utilisation< 12	29
	12<= Utilisation< 27	25
	27<= Utilisation< 39	24

Scorecard characteristics may be selected from any of the sources of data available to the lender at the time of the application. Examples of such characteristics are demographics (e.g., age, time at residence, time at job, postal code), existing relationship (e.g., time at bank, number and types of products, payment performance, previous claims), credit bureau (e.g., inquiries, trades, delinquency, public records), real estate data, and so forth. The selection of such variables and creation of scorecards will be covered in later chapters in much more detail.

Each attribute ("age" is a *characteristic* and "23–25" is an *attribute*) is assigned points based on statistical analyses, taking into consideration various factors such as the predictive strength of the characteristics, correlation between characteristics, and operational factors. The total score of an applicant is the sum of the scores for each attribute present in the scorecard for that applicant.

Exhibit 1.2 is an example of the gains chart, one of the management reports produced during scorecard development.

The gains chart, which will be covered in more detail in later chapters, tells us the expected performance of the scorecard. Several things can be observed from this exhibit:

- The score bands have been arranged so that there are approximately 10 percent of accounts in each bucket. Some analysts prefer to arrange them in equal score bands.
- The marginal bad rate, shown in the column "marginal event rate," rank orders from a minimum of 0.2 percent to a maximum of about 15.7 percent. There is some variability between the bad rate based on counts and the predicted bad rate from the model (average predicted probability) due to low counts.
- For the score range 163 to 172, for example, the expected marginal bad rate is 5.31 percent. This means 5.31 percent of the accounts that score in that range are expected to be bad.
- For all accounts above 163, the cumulative bad rate, shown in the column "cumulative event rate," is 2.45 percent. This would be the total expected bad rate of all applicants above 163.
- If we use 163 as a cutoff for an application scorecard, the acceptance will be about 70 percent, meaning 70 percent of all applicants score above 163.

Exhibit 1.2 Gains Chart

Gains Table

Bucket	Score Bucket	Data Role	Count	Cumulative Count	Event Count	Non-Event Count	Cumulative Event Count	Cumulative Non-Event Count	Marginal Event Rate	Marginal Non-Event Rate	Cumulative Event Rate	Cumulative Non-Event Rate	Average Predicted Probability	Low Predicted Probability Threshold	High Predicted Probability Threshold	Cumulative Approval Rate
10	Score >= 232	TRAIN	2465.5	2465.5	5	2460.5	5	2460.5	0.202799	99.7972	0.202799	99.7972	0.004772	0.00312	0.006819	10.60852
9	220 <= Score < 232	TRAIN	2315	4780.5	16	2299	21	4759.5	0.691145	99.30886	0.439285	99.56072	0.008167	0.006419	0.010231	20.56947
8	207 <= Score < 220	TRAIN	2263.75	7044.25	36	2227.75	57	6987.25	1.590282	98.40972	0.809171	99.19083	0.012515	0.009648	0.01603	30.30991
7	193 <= Score < 207	TRAIN	2425.25	9469.5	55	2370.25	112	9357.5	2.267807	97.73219	1.182745	98.81726	0.019892	0.014836	0.02602	40.74524
6	182 <= Score < 193	TRAIN	2349.75	11819.25	84	2265.75	196	11623.25	3.574848	96.42515	1.658312	98.34169	0.03	0.023839	0.037466	50.85572
5	172 <= Score < 182	TRAIN	2331.75	14151	85	2246.75	281	13870	3.645331	96.35467	1.985725	98.01427	0.042729	0.034268	0.051626	60.88874
4	163 <= Score < 172	TRAIN	2297.5	16448.5	122	2175.5	403	16045.5	5.31012	94.68988	2.450071	97.54993	0.058533	0.047773	0.068489	70.77439
3	154 <= Score < 163	TRAIN	2328.5	18777	191	2137.5	594	18183	8.202706	91.79729	3.163445	96.83656	0.07829	0.065195	0.092712	80.79343
2	143 <= Score < 154	TRAIN	2214.5	20991.5	248	1966.5	842	20149.5	11.19892	88.80108	4.011147	95.98885	0.104679	0.086111	0.131602	90.32196
1	Score < 143	TRAIN	2249.25	23240.75	354	1895.25	1196	22044.75	15.73858	84.26142	5.146133	94.85387	0.168506	0.12092	0.277842	100

Based on factors outlined above, as well as other decision metrics to be discussed in the chapter on scorecard implementation, a company can then decide, for example, to decline all applicants who score below 163, or to charge them higher pricing in view of the greater risk they present. "Bad" is generally defined using negative performance indicators such as bankruptcy, fraud, delinquency, write-off/charge-off, and negative net present value (NPV).

Risk score information, combined with other factors such as expected approval rate and revenue/profit potential at each risk level, can be used to develop new application strategies that will maximize revenue and minimize bad debt. Some of the strategies for high-risk applicants are:

- Declining credit/services if the risk level is too high.
- Assigning a lower starting credit limit on a credit card or line of credit.
- Asking the applicant to provide a higher down payment or deposit for mortgages or car loans.
- Charging a higher interest rate on a loan.
- Charging a higher premium on insurance policies.
- Adjusting payment terms for business customers.
- Asking the applicant to provide a deposit for water/electricity utilities services, or for landline phones.
- Offering prepaid cellular services instead of postpaid, or offering a lower monthly plan.
- Denying international calling access from telecommunications companies.
- Asking high-risk applicants for further documentation on employment, assets, or income.
- Selecting applicants for further scrutiny for potential fraudulent activity.

Conversely, high-scoring applicants may be given preferential rates and higher credit limits, and be offered upgrades to better products, such as premium credit cards, or additional products offered by the company.

Application scores can also help in setting "due diligence" policies. For example, an applicant scoring very low can be declined outright, but those in middling score ranges can be approved but with additional

documentation requirements for information on real estate, income verification, or valuation of underlying security.

The previous examples specifically dealt with credit risk scoring at the application stage. Risk scoring is similarly used with existing clients on an ongoing basis. In this context, the client's behavioral data with the company, as well as bureau data, is used to predict the probability of ongoing negative behavior. Based on similar business considerations as previously mentioned (e.g., expected risk and profitability levels), different treatments can be tailored to existing accounts, such as:

- Offering product upgrades and additional products to better customers.
- Increasing or decreasing credit limits on credit cards and lines of credit.
- Allowing some revolving credit customers to go beyond their credit limits for purchases.
- Allowing better customers to use credit cards even in delinquency, while blocking the high-risk ones immediately.
- Flagging potentially fraudulent transactions.
- Offering better pricing on loan/insurance policy renewals.
- Setting premiums for mortgage insurance.
- Deciding whether or not to reissue an expired credit card.
- Prequalifying direct marketing lists for cross-selling.
- Directing delinquent accounts to more stringent collection methods or outsourcing to a collection agency.
- Suspending or revoking phone services or credit facilities.
- Putting an account on a "watch list" for potential fraudulent activity.

In addition to being developed for use with new applicants (application scoring) or existing accounts (behavior scoring), scorecards can also be defined based on the type of data used to develop them. "Custom" scorecards are those developed using data for customers of one organization exclusively, for example, if a bank uses the performance data of its own customers to build a scorecard to predict bankruptcy. It may use internal data or data obtained from a credit bureau for this purpose, but the data is only for its own customers.

"Generic" or "pooled data" scorecards are those built using data from multiple lenders. For example, four small banks, none of which has enough data to build its own custom scorecards, decide to pool their data for auto loans. They then build a scorecard with this data and share it, or customize the scorecards based on unique characteristics of their portfolios. Scorecards built using industry bureau data, and marketed by credit bureaus, are a type of generic scorecards. The use of such generic models (and other external vendor built models) creates some unique challenges as some of the know-how and processes can remain as black boxes. We will discuss how to validate and use such models in a guest chapter authored by experienced industry figures Clark Abrahams, Bradley Bender, and Charles Maner.

Risk scoring, in addition to being a tool to evaluate levels of risk, has also been effectively applied in other operational areas, such as:

- Streamlining the decision-making process, that is, higher-risk and borderline applications being given to more experienced staff for more scrutiny, while low-risk applications are assigned to junior staff. This can be done in branches, credit adjudication centers, and collections departments.
- Reducing turnaround time for processing applications through automated decision making, thereby reducing per-unit processing cost and increasing customer satisfaction.
- Evaluating quality of portfolios intended for acquisition through bureau-based generic scores.
- Setting economic and regulatory capital allocation.
- Forecasting.
- Setting pricing for securitization of receivables portfolios.
- Comparing the quality of business from different channels/ regions/ suppliers.
- Help in complying with lending regulations that call for empirically proven methods for lending, without potentially discriminatory judgment.

Credit risk scoring, therefore, provides lenders with an opportunity for consistent and objective decision making, based on empirically derived information. Combined with business knowledge, predictive

modeling technologies provide risk managers with added efficiency and control over the risk management process.

Credit scoring is now also being used increasingly in the insurance sector for determining auto[6] and home insurance[7] premiums. A unique study conducted by the Federal Reserve Board even suggests that couples with higher credit scores tend to stay together longer.[8]

The future of credit scoring, and those who practice it, is bright. There are several issues, discussed later, that will determine the shape of the industry in the coming 5- to 10-year span.

The rise of alternate data sources, including social media data, will affect the industry. In reality, the change has already begun, with many lenders now starting to use such data instead of the more traditional scores.[9] This issue will be discussed in more detail in several chapters. In many countries, the creation of credit bureaus is having a positive impact on the credit industry. Having a centralized repository of credit information reduces losses as lenders can now be aware of bad credit behavior elsewhere. Conversely, it makes it easier for good customers to access credit as they now have strong, reliable evidence of their satisfactory payment behavior. In addition, the access to very large data sets and increasingly powerful machines has also enabled banks to use more data, and process analytics faster. We will cover this topic in more detail in its own chapter authored by Dr. Billie Anderson.

Regulatory challenges will continue, but banks are better prepared. Basel II has overall improved the level of analytics and credit scoring in banks. It has introduced and formalized repeatable, transparent, and auditable processes in banks for developing models. It has helped create truly independent arm's-length risk functions, and model validation team that can mount effective challenges. Basel II, as well as Basel Committee on Banking Supervision (BCBS) regulation 239,[10] has also made data creation, storage, and aggregation at banks far better than before. IFRS 9 and other current regulatory initiatives such as Comprehensive Capital Analysis and Review (CCAR), Current Expected Credit Loss (CECL), and stress testing, as well as their global equivalents, will continue to expand and challenge analytics and credit scoring.

One factor that users of credit scoring will need to be cautious about is the increasing knowledge of credit scoring in the general population. In particular, in the United States, knowledge of bureau scores such as

the FICO score, is getting very common. This is evidenced by the number of articles, discussions, and questions on how to improve the score (I personally get such questions via e-mail and on social media at least every week or two weeks—questions such as "How do I maximize my score in the shortest time?"; "If I cancel my card, will it decrease my score"; etc.). This factor can work in two ways. On the positive side, it may drive people to improve their payment and other credit habits to get better scores. On the negative side, this may also lead to manipulation. The usage of robust bureau data will mitigate some of the risk, while the usage of unreliable social media or demographics data may not.

The ever-present discussion on newer, better algorithms will continue. Our quest to explain data better, and differentiate useful information from noise, has been going on for decades and will likely go on for decades more. The current hot topic is machine learning. Whether it or the other more complex algorithms replaces the simpler algorithms in use in credit scoring will depend on many factors (this topic will also be dealt with in the later chapter on vendor model validation). Banks overwhelmingly select logistic regression, scorecards, and other such methods for credit scoring based on their openness, simplicity, and ease of compliance. Complex algorithms will become more popular for nonlending and nonregulatory modeling, but there will need to be a change in regulatory and model validation mind-sets before they become widely acceptable for the regulatory models.

The credit crisis of 2008 has been widely discussed and dissected by many others. Let us firstly recognize that it was a complex event and its causes many. Access to cheap money, a housing bubble in many places, teaser rates to subprime borrowers, lack of transparency around models, distorted incentives for frontline staff, unrealistic ratings for mortgage-backed securities, greed, fraud, and the use of self-declared (i.e., unconfirmed) incomes have all been cited.[11] Generally, I consider it a failure of both bankers in exercising the basic rules of banking, and risk management in failing to manage risks. Some have even suggested that models and scorecards are to blame. This is not quite accurate and reflects a failure to understand the nature of models. As we will cover in this book, models are built on many underlying assumptions, and their use involves just as many caveats. Models are not perfect, nor are they 100 percent accurate for all times. All models describe historical

data—hence the critical need to adjust expectations based on future economic cycles. The amount of confidence in any model or scorecard must be based on both the quality and quantity of the underlying data, and decision-making strategies adjusted accordingly. Models are very useful when used judiciously, along with policy rules and judgment, recognizing both their strengths and weaknesses. The most accurate model in the world will not help if a bank chooses not to confirm any information from credit applicants or to verify identities. As such, one needs to be very realistic when it comes to using scorecards/models, and not have an unjustified level of trust in them.

> *"… too many financial institutions and investors simply outsourced their risk management. Rather than undertake their own analysis, they relied on the rating agencies to do the essential work of risk analysis for them."*
>
> —Lloyd Blankfein, CEO Goldman Sachs
> (*Financial Times*, February 8, 2009)

NOTES

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