A Hybrid Consumer Credit Underwriting Decision System

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Abstract

Modern credit markets will derive significant benefits from credit assessment approaches that can overcome credit data limitations. This paper describes such an approach that combines judgmental factors with analytical methods to achieve a more complete and accurate credit assessment than is possible with today's typical loan underwriting systems. This approach leverages a comprehensive credit assessment framework to ensure that all relevant credit considerations and business contexts are brought into play in the decision process. This allows lenders to evaluate credit risk and decision all transactions in the most effective and transparent manner. This paper explores the method's operational form and explains how it can adapt to changes in market demand and credit quality. It also addresses the credit scoring limitations imposed by insufficient credit and market information and sampling timeframes, and static data-driven factor selection and weightings. This new and flexible approach will promote a new generation of credit models that can narrow the information gap in developing markets.

Introduction

In recent years, consumer credit portfolios have experienced extraordinary growth in developing countries. This represents huge revenue opportunities in auto loans, home loans, and credit cards, and has created a tremendous need for more efficient and cost-effective credit analysis systems. As a result, some leading software vendors, data management companies, and credit bureaus have partnered with some of the largest banks and credit card providers to develop credit analysis systems and to help automate the credit scoring process in many developing countries.[1] Several developing countries have already started the process to build credit bureaus that pool credit information across banks like those in the US.[2] As more retail credit information becomes available, some of the largest banks in developing countries will soon adopt some of the more widely used retail banking models such as credit scoring models (CSM) from the US, Canada, and European countries.

Despite some progress and significant potential, there remain challenges associated with improving loan underwriting in developing countries, including: 1) limited availability of timely, accurate, and reliable credit information, 2) inadequate credit reporting systems, 3) significant development costs associated with credit scorecard development, and 4) minimum, or reluctant,

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[1] For example, Fair Isaac Corp. has recently opened office in Beijing to promote credit scoring, in addition to their other Asian Pacific locations. See Switzky, Bryant Ruiz. "With expansion, Fair Isaac bets on China's consumer culture", St. Paul Business Journal, July 20, 2007.

[2] The benefits of using the data collected by a credit bureau have been widely recognized. See, for example, Miller (2003) and Miller, Mylenko, and Powell (2004). However, as pointed out by Luoto, McIntosh, and Wydick (2004), the development stages for information sharing mechanisms vary greatly among developing countries.

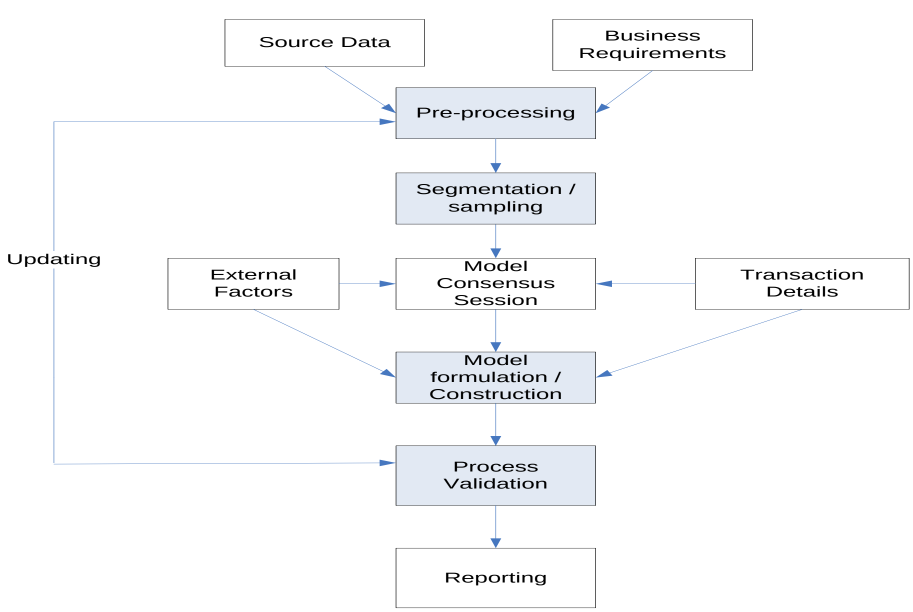
credit information sharing across banks.[3] These issues are impeding the progress of the development of credit measurement systems, as well as the implementation of Basel II's Internal Rating Based Approach.

To address the above challenges and issues, we present a Comprehensive Credit Assessment Framework (CCAF), which is an operational form of the risk evaluation and policy formulation system (REPFS). REPFS combines judgmental factors with analytical methods to achieve a more complete and accurate credit assessment than is possible with today's typical loan underwriting systems.[4] We will first describe the general nature of CCAF as well as each of the CCAF's key components. We then explain how credit scoring, alternative information, and judgmental factors can be leveraged to develop an effective and robust loan underwriting system. Some simple examples to illustrate the main concepts are provided. Finally, we discuss some of CCAF's implications for emerging markets, especially in light of the lessons learned from the current US financial markets. Our goal is to help lenders expand credit access in emerging markets while protecting loan quality and avoiding crises similar to that which has recently occurred in the United States that triggered even broader financial market disruption.

The Need for a New Framework

We introduce a Comprehensive Credit Assessment Framework (CCAF), a hybrid system that systematically combines judgmental factors with analytical methods to achieve more accurate credit assessment. CCAF offers an extended credit rating system that enables lenders to classify credit risk and decision all transactions in the most effective and transparent manner. Figure 1 depicts the key components of CCAF and how these components are structured for an effective and robust system.

Figure 1: CCAF Overview:



[3] See Wendel and Harvey (2006) for a description of challenges for small business credit scoring system.
[4] For a detailed discussion on REPFS, see Abrahams and Zhang (2008), pp. 200-222.

As is the case with typical loan approval system development using the standard credit scoring approach, requisite loan data, product data, policies, and business requirements must be sourced and pre-processed so as to create a base of information that is sufficient for system construction.[5]

The model consensus session (MCS)[6] is the core mechanism whereby CCAF ensures that classification of credit transactions is performed sensibly and comprehensively. Expert judgment, proven credit principles, and product and loan policy information are used, in addition to the available historical loan application and performance data. We call the resulting categorization a credit Transaction Contour (TC), a sub-component of which we term the Borrower Contour (BC). Both contours are described in detail in a later section.

Next, external factors relating to the economy, market states, and underlying asset valuation, are combined using a variety of modeling methods to arrive at a loan decision model in the form of an action table, which specifies an approve/decline decision for all borrowers relative to the credit transaction contour.[7] In addition to the action table, a series of additional tables are generated that allow for the maintenance and monitoring of the action table.[8]

An integrated and transparent validation process is the next to last step in the CCAF process. It \fosters trust and confidence that comes from knowing exactly how loans are evaluated and how credit quality and credit access will be maintained and improved. This step involves an examination and interpretation of underwriting model inputs, processing, and outputs[9]

The final step in the process is to produce various loan underwriting operational reports, such as multidimensional acceptee population mix reports and multidimensional acceptance rates tables associated with a particular action table.[10] In addition, alternative action tables associated with specific credit policy and marketing strategies can be produced, along with their system maintenance and operational reports.[11] These reports can be regenerated and compared at multiple points in time to easily identify trends.

The CCAF provides a more flexible and adaptable lending system that can accurately evaluate credits, quantify transaction risk, maintain appropriate risk levels based on policy-dictated risk tolerances, and more effectively provide information to monitor and manage loan portfolios. CCAF-based underwriting systems promote fair access to credit and ensure suitable loan products for consumers, and a more profitable, safe, and sound loan portfolio for lenders.

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[5] The details around the roles of individuals in a lending organization that are normally involved, the administration and planning of the project and the sampling and segmentation activities are not the focus of this paper. They are covered in detail in the literature and we mention them briefly in the next section as we describe certain aspects of CCAF in greater detail purely for completeness of the discussion. For typical scorecard development initiatives see Siddiqi, Naeem, Credit Risk Scorecards, John Wiley and Sons (2006), pp.1-71 and for details specific to CCAF see Abrahams and Zhang (2008) op.cit.,pp.23-35,201-202,309-313, and 328-331.

[6]op.cit. 158-159.

[7] This process, and the methods utilized are described in detail in Abrahams and Zhang (2008), op.cit., pp.203-216, 222-237, 250-264, and 329-332.

[8] Ibid, pp.216-222

[9] A detailed discussion of how this is performed is beyond the scope of this paper, but for the readers who are interested please see op.cit., Chapter 8, pp.305-346.

[10] Examples of reports and an inventory of all multi-dimensional reports for a hypothetical action table see op.cit. pp.209-210.

[11] For example, action tables can be constructed to target a particular loan default rate, or a specific acceptance rate, etc.

Key Development Milestones

As shown in Figure 1, CCAF contains four development milestones, namely: data and requirements sourcing, segmentation and sampling, model formulation, and process validation. Following are high level descriptions of what each milestone entails.

Data and Requirements Sourcing

CCAF starts with identifying business requirements and source data. CCAF can be used for different purposes such as managing credit risk[12] or fostering profitable growth. Preparation of data involves defining project scope, determining availability of information, and capturing current underwriting practices. The outputs from this step will be used as inputs for sampling, segmentation, and model formulation.

Data that are important for estimating loan default for consumers would include, but not be limited to, 1) an inventory of all current obligation terms, balances and monthly payment amounts with all lenders, service providers, landlords, insurers, and counterparties, 2) current sources of income and time in profession and with current employer, 3) liquidity and value of personal assets and net worth, 4) nature, and value of collateral (or asset being financed) based upon both current appraisal and future value ranges, and the amount/percent of loan down-payment (or loan-to-value ratio), 5) payment and delinquency history for credit and non-credit obligations and any past loan defaults, 6) insurance coverage by type, including policy limits and cash values, and 7) loan conditions including maturity, loan amount, pricing mechanism, payment schedule and terms, and other borrower elected or lender-specific transaction requirements.[13]

Segmentation and Sampling

Sampling is an area where missing, or too little, data can cause observations to be disproportionately excluded for certain population segments, which can result in a biased sample and unintended results. Time intervals over which samples are drawn may, or may not, reflect current conditions and hence models based on data from non-representative time periods can also be misleading. Sampling and segmentation go hand-in-hand. Segmentation can be used to account for a variety of structural differences in a sampled population, such as demographic differences, economic differences, product differences, channel differences, or differences in customer culture or lifestyles.

By way of a model consensus session (MCS), the CCAF affords a complete credit categorization of borrowers prior to risk rating them, unlike most of the prevailing approaches today, which are piecemeal and risk rate certain aspects of borrower creditworthiness. In contrast, the CCAF adopts a more holistic view, drawing upon the well known Five C's of credit.[14] The primary

[12] E.g. determining which credit applicants are sufficiently qualified for a loan, how to price the loan, how to monitor the loan portfolio relative to changes in borrower risk at a segment level, how to most determine the most effective collection strategies for past due loans or loans in recovery post charge-off, and estimating losses for all loan portfolio segments. Core to these activities is estimation of the probability of default for all loan segments.

[13] For small business lending, additional factors play key roles, such as customer relationship, See Abrahams and Zhang (2008) op.cit. pp.225-234 for a detailed example.

[14] Character includes payment history, savings history, stability measures such as years in profession, etc. Capacity is measured by such factors as income, debt obligations, cash obligations, living expenses, number of dependents, etc. Capital includes such factors as net worth, amount and liquidity of assets, etc. Collateral includes attributes of the property, including appraised value, sales price, age, location, physical properties, etc. Conditions includes such factors as the loan amount, the term of the loan, the pricing mechanism, the payment schedule and payment options, the

factors in encompassing the first three C's of credit combine to create a *Borrower Contour* (BC), which is a distinctive pattern of values relating to character, capacity, and capital for an obligor (i.e. a consumer or business). We can further introduce the notion of a lending transaction contour (TC), which is based on all five C's of Credit pertaining to a particular obligation. TC is a distinctive pattern of values relating to character, capacity, capital, collateral, and conditions for a consumer or business. TC encompasses BC, but it can also operate across segments defined by BC. TC also reflects channel and market factors.[15] It is essential that both TC and BC indicators are included in each loan application and origination record. This enables a comprehensive view of credit risk. As a result, lenders can evaluate and monitor lending practices to identify subprime credit deterioration, and potential predatory or discriminatory issues. In terms of financial disclosure, CCAF provides consumers with their categorization relative to all primary underwriting factors via a TC identifier. With this single number, strengths and weaknesses relative to the primary qualification criteria are immediately apparent. In addition, a simplified 1-10 rating scale may be used to describe the overall credit rating when all factors are combined. This rating is the same for all consumers sharing the identical TC.

To illustrate, we have constructed an example that is analogous to the way that credit bureau scoring is segmented in the United States. That scheme includes a combination of the extensiveness of the credit record (no/thin file, moderate file, or thick file) and the payment performance (good, mild delinquency, severe delinquency). In this case, the borrowers are grouped into distinct combinations, each having a distinct credit scoring model. This credit bureau segmentation, unfortunately, does not reflect comprehensively the borrower's ability to repay their debts.

In contrast, the CCAF utilizes the borrower contour based upon character, capacity, and capital in order to create a credit contour having twelve possible patterns, as shown in Figure 3 below, based upon:

- Capacity (Income +Debt Ratio): (High/Low)
- Capital (Liquid Reserves + Percent Down-payment): (High/Low)
- Payment History (Credit + Non-Credit): (Good/Fair/Poor)

Each of the primary categories is then assigned specific rating classifications based on factors causally related to them. For example, borrower capacity may be assessed by such factors as income, debt-to-income ratio (DTI), payment-to-income ratio (PTI), etc. In the simple case where just DTI is used, a threshold value (for example, 40%) would be determined to separate borrowers possessing high capacity from those having low capacity. This process would be repeated for the character and capital categories. The final step is to assign judgment-based, or empirically-based, ratings to each of the twelve unique segments (i.e. 1-Low, 2-Moderate, 3-High, 4-Severe), as indicated in Figure 2.

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amount of down-payment, applicable fees, etc. Conditions also include economic influences that may affect the borrower's employment, value of collateral, etc.

[15] In addition, a primary factor in mortgage lending is the ratio of the loan amount to the collateral market value (LTV), which actually spans collateral and conditions, the last two C's of the five C's of credit.

Figure 2: CCAF Segment Handle Specifications

Segment Handle	Capacity	Capital	Payment History	Risk Rating
1	H	H	G	1
2	H	H	F	1
3	H	H	P	2
4	H	L	G	2
5	H	L	F	3
6	H	L	P	3
7	L	H	G	2
8	L	H	F	2
9	L	H	P	3
10	L	L	G	3
11	L	L	F	3
12	L	L	P	4

Within each segment, borrowers are homogenous relative to primary credit strength. Lenders may regulate which products/programs are available within the segments based upon affordability concerns. It is important to note that the BC segments can be used to determine which products may be appropriate for certain groups of borrowers. For example, borrowers with little capital or capacity may not qualify for variable rate loans. Moreover, portfolio risk concentration/exposure limits could be managed at the BC and TC segment levels using a referencing scheme known as a segment *handle*.[16] After a certain frequency threshold is achieved, offerings could be restricted in a given segment. Using this approach, vulnerability metrics are applied to rank-order which cells will perform better under differing economic scenarios (e.g. housing slump, rising interest rates, etc.).

In addition to current financial ratios, future financial ratios are of key importance for certain types of loans, such as ARM and option-based mortgages. Here, behavioral and historical variables may be used to capture more than a snapshot. For this purpose current income and income 12 and 24 months ago averaged to calculate average annual increase in the denominator for debt-to-income, or DTI, ratio. For the numerator of the DTI ratio, the maximum rate on the next ARM reset date can be used to gauge the borrower's future ability to repay the loan. Property valuation can be performed using best case, worst case, most likely to come up with an estimate of the range of property values. This would

[16] See Abrahams and Zhang (2008), page 158 to for detailed description on the handle concept.

enable borrowers, and lenders, to view the range of possible loan-to-value (LTV) ratios that may result in the future, and hence how borrower equity may grow or evaporate.

Model Formulation

In this stage, segmentation results including TC or BC will be integrated within a proper context relative to internal business factors, or external factors relating to the economy, market states, and underlying asset valuation in order to fine tune model specifications. As a result of segmentation performed in the previous stage, this modeling process is significantly simplified. For example, when modeling with logistic regressions, each TC or BC will naturally correspond to a unique covariate pattern associated with a probability of default. The TC can accommodate changes in economic or business factors, such as the value of the underlying asset being financed, or the collateral pledged, for a secured loan transaction. For example, in the case of a mortgage, property reappraisal may result in a different LTV that can change the TC value. Another example would be a borrower’s working capital position, which may change due to assets being marked to market, or possibly due to longer term asset liquidations.

Specifically, this process is accomplished through a dynamic conditional process, in which the impact of business context or external factors is associated with each TC or BC to create conditional and interactive structure for model specifications. This is completed in two steps and is adaptive at different levels. Step one is to enumerate and separately consider all possible combinations of the primary variables. The actions taken in step two would depend upon how the borrower was initially classified according to the primary credit risk factors. To illustrate with a mortgage example, consider how one might appropriately decide what weight to apply on a value for the factor debt-to-income ratio (DTI) based on knowledge of the loan-to-value ratio (LTV). Consider the following three scenarios:

- Suppose you know that LTV is 20%, so that the customer has an 80% equity stake in the property being financed. Knowing this fact, how would you weigh the importance of DTI? How would you rate the following values of DTI, relative to risk in this case:
  DTI = 20%? DTI = 40%? DTI=60%?

- Next, suppose you know that LTV is 70%, so that the customer has a 30% equity stake in the property being financed. How would you rate the following values of DTI, relative to risk in this case:
  DTI = 20%? DTI = 40%? DTI=60%?

- Finally, suppose you know that LTV is 100%, so that the customer has no equity stake in the property being financed. Again, how would you rate the following values of DTI:
  DTI = 20%? DTI = 40%? DTI=60%?

The foregoing scenarios could be repeated holding the value of DTI constant and then varying the values of LTV under different scenarios. The point is that if you have a different weighting of one variable based on the value of another then the alternative approach should make business sense. This is achieved with a transparent model validation process as detailed in the next session. This is achieved with a transparent model validation process as detailed in the next session.

Process updating and validation

It is critical for a lender to continuously improve model predictability over time as information accumulates to ensure the expectations of the risk measurement system are met. However, for many lenders, the constant burden of scorecard redevelopment every two years or so, consumers a lot of resources. When the sample used is drawn during times of economic change, or transition, the future results of the scorecard produced can significantly vary from those of the holdout sample used to validate, and back-test the system. This is because credit payment behavior correlations change relative to the scorecard factors when new economic and demographic circumstances present themselves. In these cases, scorecard validation may not immediately surface the problem, and when the issues do become apparent, the scorecard will likely need to be replaced earlier than expected. Even then, the same sample issue can persist, and the cycle may repeat itself.

In CCAF, process validation is integrated into the entire framework as shown in Figure 3. The proven credit underwriting principles that underlie CCAF will enable its loan decision systems to better withstand any set of economic circumstances. The expected frequencies of credit applicants and the weights associated with CCAF factors, by primary factor segment, are updated dynamically as information becomes available.[17] It allows for in-depth analysis of all possible multi-way primary factor comparisons relative to the mix of accepted applicants and also acceptance rates at any point in time.[18] Because the credit segments are immediately interpretable and comparable to one another relative to credit risk, CCAF validation affords an additional measure of transparency and confidence that non-intuitive patterns can be detected, investigated, and remedied early on to head off unwanted consequences. This also presents a cost-effective approach to monitor and validate the consistency of risk rating system for the banks that need to implement Basel II's Internal Rating Based Approach.

A typical validation process can be described as follows:

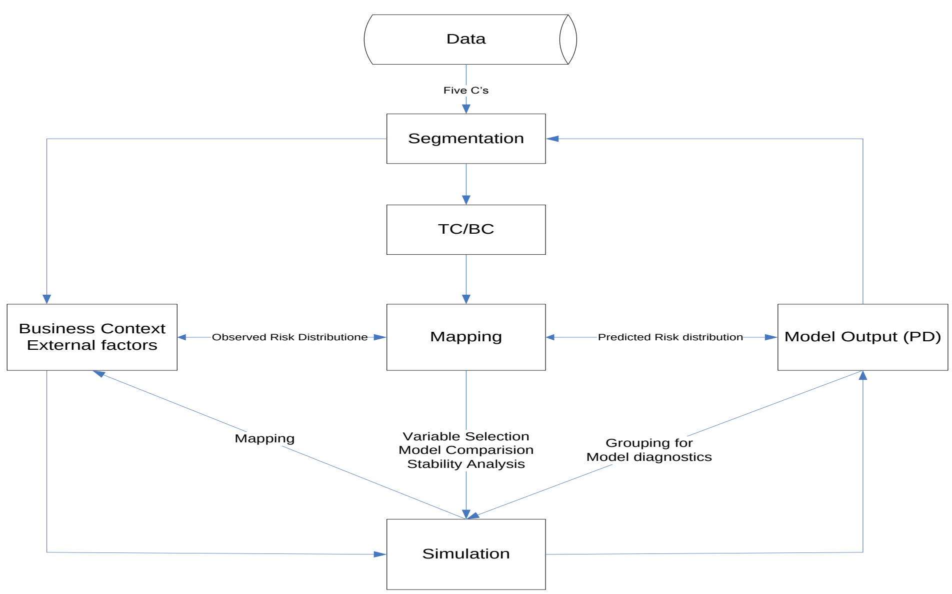
1. Create a segment handle structure for input data. When the system being validated is either pure judgmental, or credit scoring, an MCS is required to create the corresponding handle cells. The same approach can be used to segment model output associated with the probability of default.
2. Associate model output with model input through the handle structure. In this step, model results are analyzed by handle cells together with constructed business scenarios. At a minimum, rank orderings of the TC are verified both empirically and through expert judgment, and risk estimates are tested for validity using both holdout, and out-of-time, credit observations based upon availability.
3. Compute the residual score points for secondary factors, together with the system cut-off, and establish a "base" qualification rule within each cell. The residual between the predicted risk score and the input risk distribution (or profile) are further analyzed for root causes. In addition, outliers, or applicants that do not belong to that handle cell are identified and tested to determine how removing these outliers can improve model fit and reduce residuals. This also can be performed to some degree by logical comparisons to identify any cases where the observed risk, predicted risk,

[17] See op. cit. pp.216-222 regarding hybrid system maintenance for detailed coverage of this topic.
[18] See op. cit. pp.209-210 for specific examples and an enumeration of all possible combinations of these multi-dimensional acceptee mix and acceptance rate views.

or both are contrary to the categorical risk rankings of individual handle cells. For a concrete example, suppose a hybrid model shows handle cell 2 has an observed probability of default that is somewhat higher than predicted, and it's observed ranking is higher risk than handle cell 3, which is identical to it in all respects except that cell 3 has a poor, instead of fair credit history rating. In such a case, the higher than expected observed probability of default for handle cell 2 would be questioned because it was not only inconsistent with model predictions, but also because, all else being equal, applicants with poor credit histories should be riskier than those having fair credit histories.

4. Analyze declined applications, including inferences about how the declines would have performed had they been accepted. If the system is a hybrid, then the process is streamlined, and the only basis for analysis of declined applicants would be system overrides. Here a direct comparison is made between the observed risk in input data and the predicted risk in model outputs. If necessary, class priors may be embedded by utilizing different thresholds and business policies. This, to a certain degree, overcomes the common weakness associated with the standard validation metrics, and allows more accurate, and explicit, testing of model discriminatory power. In addition, the handle method creates a natural grouping definition for statistical testing and its effectiveness does not depend on binning.
5. Perform simulation and optimize the handle structure. This is achieved by using variance reduction techniques[19] to obtain maximum homogeneity in each handle segment. Simulation results from this step are also used to enhance lending policy rules.

Figure 3: Model Validation Process

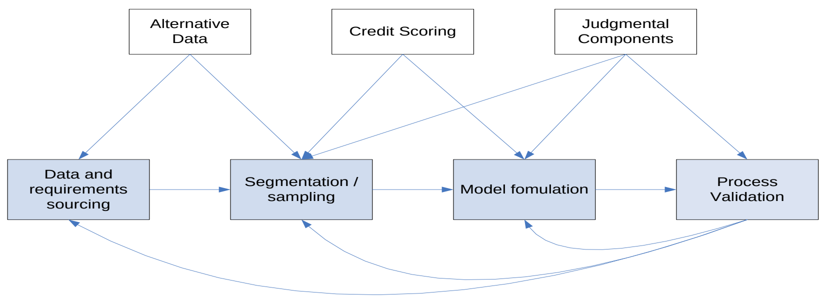


[19] Variance reduction procedures, such as importance sampling and stratified sampling, are typically used to improve model estimation precision. For detailed discussion on this topic, see, for example, Ross, Sheldon. *Simulation*, Harcourt/Academic Press, 1997, pp. 131-180

Interplay of Main Elements

To improve efficiency, transparency, and accuracy, CCAF utilizes alternative data, credit scoring, and judgmental components. We now briefly describe how these elements relate to the four development milestones.

Figure 4: Interplay of main elements



Utilizing alternative data

The information value contained in alternative data[20] and community data[21] has made it increasingly apparent that significant ground can, and must, be gained in enhancing the state-of-the-art in consumer lending relative to non-mainstream segments in particular, and perhaps for all borrowers in general.[22] There are a number of benefits to the use of non-credit transaction data,[23] which can enable vast numbers of consumers to gain access to credit. With greater information, lending decisions will improve and result in lower rates of delinquencies, less overextension, and an increase in the number of performing loans. Alternative data can shore up gaps in the credit evaluation process, especially relative to payment history for non-credit obligations and borrower capacity.

[20] Recent research conducted by PERC and the Brookings Institution, produced compelling empirical evidence that noncredit payment data can help predict credit risk, which, in turn, can help qualify consumers for loans provided that they pay their cash obligations as agreed**.** For a list of alternative data, see Information Policy Institute, "Giving Underserved Consumers Better Access to Credit system — the Promise of Non-Traditional Data," July 2005, p. 11.
[21] See www.socialcompact.org for more information.
[22] See Turner, et al., 2006.
[23] See Turner, Michael, S. Alyssa Lee, Ann Schnare, Robin Varghese, and Patrick D. Walker. "Give Credit Where Credit Is Due—Increasing Access to Affordable Mainstream Credit Using Alternative Data," Political and Economic Research Council and The Brookings Institution Urban Markets Initiative, ©2006.

As shown in Figure 4, alternative data can be readily feed into CCAF's handle structure for the purpose of segmentation and modeling. Without changing any model factors, one can incorporate non-credit tradelines into the set of credit tradelines usually considered for payment history. In this way, the credit factor "number of times 30-days past due" will be calculated identically, because it will simply include counts form the non-credit tradelines. Similarly, the factor "number of satisfactory tradelines at least 24 months old" would be calculated the same, only now it would include non-credit tradelines as input to the calculation. With CCAF, alternative data will be used not only for risk rating, but more fundamentally for segmentation where all forms of payment are considered.

Studies have already shown that alternative data has significant lift when it is allowed to substitute for credit data using the existing credit scorecards. It stands to reason that even greater lift can be realized if models are optimized for use with alternative data, and CCAF promises to improve predictive power even further.[24]

Extending Credit Scoring System

As shown in Figure 4, credit scoring can be mainly used as one or more of the input factors to assist segmentation and model formulation. For example, a payment score could summarize payment performance for both credit and non-credit tradlines. CCAF actually extends credit scoring from three perspectives. First, CCAF ensures inclusion of primary predictive factors that cover the full spectrum of relevant qualification criteria, and both determines, and reveals, how they combine, to produce outcomes. Credit scoring, which relies on historical data, does not have this capability, nor does it possess a feedback mechanism to adjust factor weightings over time as experience accumulates (e.g. credit scoring is not adaptive, rather its predictive strength diminishes over time). Even when credit scoring systems are re-developed the factors are again considered one at a time and selected in a particular sequence.

Second, CCAF uses a dynamic conditional process (DCP) in modeling decision factors.[25] In model building there is always the dilemma of what factors to include and how much weight to put on them individually. This is complicated by the reality that many credit factors are correlated with one another. The simple fact is that the primary underwriting factors possess deep interrelationships and, as such, their interactions and conditional nature should be reflected in the model formulation to the greatest extent possible. The selection of factors for scorecards does not require that all primary factors be considered, and often they focus on payment history, search for credit, and type/mix of credit used and ignore factors that have a direct relationship to ability to repay the loan, such as capacity and capital. When included, factors relating to capacity, capital, collateral and conditions, or some combination of them, are often applied serially after a credit score is produced, and those factors are usually considered as distinct and independent overlays (sometimes two, or at most three factors are considered jointly for risk-based pricing adjustments to mortgage points). The result can be a series of adjustments that can mount up to large incremental pricing offsets.[26] With CCAF, one can maximize the breadth of candidate model

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[24] For more detailed examples on how alternative data are used for loan underwriting, see Abrahams and Zhang (pp. 234-237).

[25] See Abrahams and Zhang (2008), pp. 158-159, for a description of DCP and MCS.

[26] Ibid, p117, Figure 4.21 for an illustrative mortgage pricing example that shows nine separate pricing offsets for a typical mortgage loan.

factors makes for a more inclusive and accurate model. Also, the ability to tailor factor definitions is important in order to maximize the information value of the data.

Third, CCAF integrates business context with modeling process in a complete transparent manner. Current credit scoring systems lack transparency as industry models are maintained as proprietary property of the companies that develop the scorecards and those that gather and report credit data and credit scores, which are simply a numerical rating. CCAF uses the BC to convey transparency and the essence of the borrower's qualifications. As CCAF rates credit transactions within the context of the TC, it can help avoid significant overstatement or understatement of risk on individual loan transactions.

Figure 5 provides a side-by-side comparison that highlights the most common shortcomings of today's underwriting models and their corresponding CCAF remedies. While this summary is a generalization and simplification, it does convey some critical differences which we view as needed improvements in the way underwriting systems should work. There are obvious crossover effects between the Five C's, such as the notion that the risk associated with loan having undocumented income (Capacity) can adequately be quantified and priced for a sub-prime option-type mortgage (Conditions), or that there are reserves (Capital) that can be tapped if necessary in the future due to rising property valuations (Collateral). The sub-prime mortgage crisis, and spill-over effect to prime mortgage loans, can be traced to many of the shortcomings summarized here and to combined assumptions across key underwriting factors.

Figure 5: CCAF vs. Status Quo Underwriting (U/W) Model

Key U/W Factors	**Typical U/W System**	**CCAF**
Character (Payment History)	Credit History Dominant, Education, Yrs in Profession	Also include Cash Payments
Capacity (Income, Debt)	Documented/Undocumented Income Credit Obligations	Verified Income, # Dependants, Credit + Alternative Data (Cash Obligations) Future Income Stream
Capital (Liquidity, Net Worth)	Checking, Savings Accounts, Investments	Also include, Insurance Products w/Cash Values, Ins Protection
Collateral (Cur/FutureValue)	Current Appraisal	Also include Range of Future Scenario Valuation
Conditions (Product Terms, economic state)	"Prime" Borrowers can be sold "Sub-Prime" Loans, Risk-Based Mis-Pricing, Payment-Minimization Focus	Match Borrowers to Right Loan Product, Default Odds Geared to Homogeneous Handle Groups, Affordability/Suitability Focus Future Payment Stream

Systematic integration of Judgmental Credit Information

As shown in Figure 4, judgmental components play an important role throughout the CCAF development process. In fact, CCAF can be considered as a "systematic" judgmental decision process that can be fully automated and updated after initial judgmental factors are integrated. Since it can be executed in a similar automated fashion as credit scoring, it can overcome some shortcomings inherent with traditional judgmental systems,[27] and provide fast, consistent, and efficient credit assessment. This can be crucial in the context of most consumer and some small business loans, and also for micro-loans, where the cost of origination and servicing can easily make such loans infeasible at reasonable interest rates.

The CCAF approach does more than simply introduce judgmental components and other factors into the modeling process. More important, it affords the simultaneous consideration of all relevant factors via the handle cell. This allows for both a conditional structure and interaction effects that scorecards simply cannot capture with their "one-size fits all" assignment of points. It can also perform the standard risk grouping and ranking of handle cells using actual data. This way, CCAF affords greater control of loan decisioning through its ability to integrate expert judgment with statistically based criteria in the risk evaluation process, which encompasses not only default risk, but also concentration risk, fair lending non-compliance risk, and a host of other important objectives. In this way, CCAF loan decisioning is not restricted to a numerical score cut-off, which must be overridden from time-to-time. By systematically integrating judgmental elements, CCAF is in fact more consistent than credit scoring because it can greatly minimize, or eliminate entirely, system overrides. For example, in practice, with credit scoring, lowside override rates can approach 5% and highside override rates can approach 10%. For hybrid systems, the number of overrides can be less than 0.5 percent.[28]

Summary and Policy Implications

In this paper, we have introduced a Comprehensive Credit Assessment Framework (CCAF), which is a robust credit risk rating system designed for consumer lending. CCAF expands the boundaries of information associated with existing variable rate mortgage holders[29]. It naturally affords a sustainable and sensible segmentation based on all primary credit factors, and then layers in needed secondary risk mitigation factors[30]. It offers a systematic means for taking appropriate actions relative to those identified segments, and for on-going monitoring of the impact of those actions in a comprehensive and efficient manner. It enables the construction of credit profiles across multiple categories and factors and puts credit profiles in an appropriate context for underwriting performance. CCAF's transparency fosters financial education/literacy relative to the underwriting process and enables easy identification of loans that are truly affordable relative to every borrower segment.

[27] See Abrahams and Zhang (2008), p. 187 for a list of shortcomings associated with a traditional judgmental system.
[28] Hybrid system estimated override performance is based on the authors' expert opinion.
[29] Both prime and sub prime borrowers who either have experienced, or will be experiencing, increase in their monthly payment amount
[30] Such as behavioral factors based upon alternative data, up-to-date information, and projected risk metrics.

With CCAF, regulatory agencies could pool data from all lenders, as well as from secondary market conduits, to monitor industry exposure as part of an early warning system. This could also provide a benchmark to measure individual lenders and secondary market players relative to credit exposures in sub-prime and other market segments. For example, individual limits could be imposed at portfolio segment levels as defined by the transaction contour. Segments may be further aggregated into broader categories such as subprime. The monetary exposure in these categories can viewed relative to bank capital to better ensure that corporate portfolio quality standards and regulatory guidelines are satisfied.

CCAF is highly applicable to building an effective credit risk management system in developing countries or emerging markets. CCAF's unique modeling approach allows lenders to fully utilize all forms of data including both traditional and non-traditional information to conduct an accurate and effective credit assessment. This is particularly important for developing countries where consumer credit information may be limited or unavailable for typical credit scoring. Its systematic judgmental system can provide a consistent initial assessment based upon lending policy and expert rules in lieu of data. As developing markets mature, however, CCAF will help strengthen underwriting standards as lenders recognize the benefits of putting borrowers, and their credit transactions, in the proper context before attempting to determine creditworthiness or how much to charge for a particular loan.

The magnitude of the current crisis in US house market makes[31] it abundantly clear that there is significant room, and need, for improvement in current credit assessment approaches. The lessons learned from the US subprime market crisis are directly applicable to developing countries. A contributing cause of this market failure is the inability of loan underwriting practices to take into account all relevant risk factors that would have effectively signaled borrower vulnerability to the payment shock associated with adjustable rate or option-priced mortgage loans.[32] A loan that looks good today is in reality a "credit time bomb." While these innovative loan products create some additional risks, they are not the cause of the problem, and they may represent the best alternative for certain segments of qualified borrowers. Therefore, new metrics and methods that address limitations of credit scoring systems are needed to evaluate credit risk in an efficient and transparent manner. Lack of transparency in mortgage loan underwriting system further hindered investors' ability to properly evaluate risk associated with the underlying loans.

It is also recognized credit assessment is not simply a modeling process based on historical data. Loan underwriting process should not be purely data driven and one should not be controlled by the models and over-rely on automated underwriting system. Rather, it should be dictated by business judgment and continuously validated against business reality, and updated with dynamic economic factors using a forward-looking approach. Therefore, it is critical for developing countries to design and refine a credit assessment framework that can meet their unique requirements, instead of wholesale adoption of the prevailing methods such as those used in the United States.

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[31] According to a recent article by Felesky and Locke, over the last few months, total losses announced by financial institutions related to mortgage-backed securities (MBS) investment have exceeded $50 billion; the number will increase every day. This crisis has also affected banks outside US and has become a global financial downturn. For example, Bank of China's subprime hit may be $2 billion (Wall Street Journal, January 22, 2008 by Jason Leow in Beijing and James T. Areddy).

[32] Traditional credit scoring has been less effective in credit assessment for new and innovative loan products. For example, 'the once-vaunted FICO credit scoring system' is now being blamed for failing to signal risky borrowers in the mortgage market. See Foust and Pressman (2008).

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