A Comprehensive Credit Assessment Framework
Overview and implications for the subprime crisis
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Abstract

This paper describes a Comprehensive Credit Assessment Framework (CCAF) for small business and consumer lending. CCAF is a unique rating system that extends existing credit scoring to embrace all relevant factors and business context so that lenders can classify credit risk and decide all transactions in a more effective, transparent and forward-looking manner. CCAF addresses the credit scoring limitations imposed by insufficient credit and market information, insufficient sampling time frames and static, data-driven factor selection and weightings. This robust and flexible approach can leverage alternative data and narrow the information gap in credit evaluation and loan underwriting practices. This will promote a new generation of credit models that possess greater transparency and, above all, ensure that the true risk is captured and the loan is affordable over its life. CCAF’s systematic segmentation approach has implications for both intervening in the mortgage crisis and preventing future financial disruption.
Executive summary

The magnitude of the current crisis makes it abundantly clear that there is significant room – and need – for improvement in current credit assessment approaches. There are two fundamental problems that contributed to the weakened underwriting standards and degraded loan quality.

First, credit scoring has not done an adequate job of assessing risk in the subprime mortgage market. The majority of the subprime mortgage underwriting systems were not, in fact, capturing “the full range of risk factors in the market,” particularly when their conventional risk models were applied to non-conventional loan products, which are associated with different payment terms and behavior. Lenders who depend on these credit scoring systems were measuring credit risk inaccurately and incompletely.

Second, there is a blind spot in today’s underwriting practices. That is, current practices overrely on quantitative models and automated underwriting systems. Technology has a vital role to play in boosting efficiency and helping measure and monitor credit risk. The models have their place and role to play. However, we need to control the models instead of the other way around. Loans need first to be properly classified, and then risk rated. Today’s process has that backward.

As the accuracy and power of the FICO score continue to be debated, new and improved ways for addressing limitations of credit scoring systems and how to better evaluate credit risk will be in demand. Simply recalibrating existing models and throwing technology at the problem will not fix it. A comprehensive new credit risk framework is needed—a hybrid approach that combines the best that technology can offer with expert human judgment. Such an approach can help deal with the current crisis and may lessen the extent of, or even prevent, the next one.

SAS has pioneered the Comprehensive Credit Assessment Framework (CCAF), which can get the job done. CCAF provides a consistent approach by using advanced computing technology and a sound, safe model development and validation process. CCAF naturally affords a sustainable and sensible segmentation based on all primary credit factors, and then offers a systematic means for taking appropriate actions relative to those identified segments as well as for ongoing monitoring of the impact of those actions in a comprehensive and efficient manner. Simply put, CCAF accomplishes this by:

• Expanding the boundaries of information.

• Appropriately segmenting loan applicants based upon primary factors.

• Layering in needed secondary qualification factors.

• Assigning actions for each identified segment.

• Putting in place an adaptable policy mechanism that is responsive to the evolving economic climate.
More specifically, CCAF improves current credit scoring from following three perspectives:

1. **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.**

2. **CCAF determines which risk factors pertain to the lending decision within the context of each borrower’s situation and the loan product parameters, then appropriately adjusts the factor weightings to produce the right outcome. This is in stark contrast to credit scoring, which has a fixed number of factors that have a constant set of point weightings that are automatically applied to every credit applicant regardless of their qualifications. Furthermore, CCAF uses a forward-looking approach and simulates future economic conditions, and its adaptive nature makes it more predictive over time, unlike credit scoring models.**

3. **CCAF systematically integrates judgmental components and proper context into the modeling process in a complete and transparent manner. Credit scoring systems lack context because they rely purely on the available data to determine what factors are considered. Credit scoring systems lack transparency because two individuals with identical credit scores can be vastly different in their overall qualifications, the credit score itself is not readily interpretable, and industry credit scoring models are maintained as proprietary, as are their development processes.**

To prevent future financial crises, it is absolutely necessary to improve the borrowers’ financial literacy, the lenders’ process of transparency and to better assess loan product affordability and suitability. CCAF achieves these goals through the following aspects:

- **Comprehensible classification to convey the essence of the borrower’s qualifications.** This allows risk rating credit transactions within that complete context, including transaction and borrower contours. It fosters financial education and literacy by letting the borrower know how he or she is classified and ranked according to relevant causally linked primary factors. It also shows borrowers how their proposed loan is classified vs. other possible loans for which they would be qualified.

- **Greater control of loan decisions.** This is through CCAF’s 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. Specific thresholds can be enforced at the segment level to limit risk exposure. As a result, significant overstatement or understatement of risk on individual loan transactions can be avoided, as can unacceptable levels of risk across all portfolio segment levels.
• **Easy identification of loans that are truly affordable relative to every borrower segment.** This drives product offering choices relative to specific credit risk segments. The most suitable mortgage products will vary widely by segment, and they may be neither the most profitable choices for the bank nor the most inexpensive for the consumer. This is a fundamental requirement for responsible lending in the aftermath of the subprime mortgage crisis, and it pertains to Alt-A and prime markets as well. In addition, there may be a positive net effect for fair lending performance relative to product steering.
Introduction

The current subprime crisis is significantly affecting the entire financial sector. With fallout from the 2007 mortgage market problems lingering into 2008, large investment banks and other institutions have been forced to sharply increase their write-offs on mortgage-linked assets on the scale of tens of billions of dollars. 1

As the subprime mortgage market crisis continues to unfold, lenders, investors and other market participants are exploring causes of and cures for the problems. It has been recognized that development in automated underwriting technology has played a significant role in encouraging lenders to penetrate deeper into the subprime loan pool. To a large extent, subprime lenders believed any additional risk they were taking on was covered using advances in credit scoring and scoring system policy overlays, which enabled them to effectively price that risk and charge borrowers on the basis of their fully quantified credit worthiness. This has contributed to the rapid development of the subprime loan market 2 and has created greater access to homeownership for some segments of borrowers, such as low-income and minority households.

It is now abundantly apparent that the majority of the subprime mortgage underwriting systems was not, in fact, capturing “the full range of risk factors in the market.” 3 This was particularly the case when conventional risk models were applied to non-conventional loan products, which were associated with different payment terms and behavior. Lenders who depended on these credit scoring systems were measuring credit risk inaccurately. Improper use of credit scoring and automated underwriting presented incomplete risk analyses and weakened underwriting standards and policy, and the end result has been a drop in loan quality. 4

As a result, lenders are now re-evaluating their lending procedures and tightening their lending standards in an effort to improve loan quality. This effort will inevitably involve underwriting technology improvement, which includes strengthening process integrity and upgrading scoring and automated underwriting system components. The system component upgrade will entail evaluation of the adequacy of data, current modeling practices and risk measurement frameworks.

Because of the virtual shutdown of the subprime mortgage lending market and general tightening of underwriting standards in 2007, we expect to see a significant increase in rate spread and denial ratios in the HMDA data scheduled for release later this year. 5

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2 Sandra Braunstein, Director of Consumer and Community Affairs for the Federal Reserve, the House Committee on Oversight and Government Reform, May 21, 2007, in Inside Mortgage Technology.
3 Patricia McCoy, professor, University of Connecticut Law School.
At a recent symposium, a panel made up of regulators representing OFHEO, FHFB, FDIC, OTS, OCC, and the NC Banking Commissioner discussed current responses to both housing-finance problems and housing problems. Some of the comments and advice that surfaced during the panel and the follow-up question-and-answer session included:

- “We need to think out of the box.”
- “We need to look at things we didn’t two years ago.”
- “Greater transparency is needed.”
- “Sunshine is the best disinfectant.”
- “A national lending standard is needed.”
- “There should be a level playing field where banks, mortgage companies and other mortgage originators follow the same rules.”

In this paper, we explain how a Comprehensive Credit Assessment Framework (CCAF) safely improves loan quality and preempts further financial disruption and regulatory pressure. We first define and describe the underwriting gap and its components in current lending practice. We then show how CCAF can address each of the gap components and facilitate the use of alternative data and model validation process. We also discuss how CCAF can leverage credit scoring as well as a judgmental system to achieve accurate and realistic risk measurement. A specific example of purchase mortgage fixed rate vs. ARM is provided for illustration purposes. This paper addresses key aspects of both crisis intervention and prevention relative to subprime mortgage lending, as well as CCAF’s implications for seizing revenue opportunities in emerging markets.

**Historical context**

Prior to the 1960s, consumer loans were made using loan officer judgment, with some guiding principles. Common practice was to consider The Five Cs of credit – Character, Capacity, Capital, Collateral and Conditions – when evaluating a consumer loan request. This approach looked at the ability of the borrower to repay the loan through income (Capacity) and, in the event of any interruption in income, their savings or liquid assets (Capital).

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8 Such as foreclosures, tightening credit standards, the impact of mortgage losses on lenders, mortgage modifications, and improving the mortgage origination process.
9 Such as housing affordability, impact of falling house prices on local communities, the availability of rental housing, and the slowdown in new home construction.
10 For examples of the Five Cs see Abrahams & Zhang (2008) pp. 185-186.
It also considered the borrower’s character by evaluating indicators of stability—his/her performance in meeting current and past credit obligations, the liquidation value of any collateral, and the borrower’s equity share in cases where the loan collateral was the property being financed—e.g. real estate, automobile, boat, etc. Finally, conditions were considered that related to the general economic climate and the terms of the loan agreement, such as loan amount, interest and fees, and repayment schedule. This represented a comprehensive approach that had been validated over a long period of time.

The judgmental approach, as practiced back then, was not without its shortcomings.\textsuperscript{11} Since each loan officer constituted “a system,” resulting loan decisions were sometimes inconsistent. That’s because the breadth and depth of experience varied by loan officer, and there was also a concern that bias might exist. Indeed, there is anecdotal evidence that some occupational biases existed by virtue of the Three Bs (“Never lend to beauticians, bartenders or barbers.”) or the Three Ps (“Never lend to preachers, plumbers or prostitutes.”)\textsuperscript{12}

Credit scoring appeared to offer a more objective approach that afforded consistency, speed and a quantification of the odds that a borrower might default on the loan. Furthermore, scoring was asserted to be more accurate; because no one loan officer could see all loans and contests to see who could best predict loans that would go bad, this invariably demonstrated the superior predictive ability of the scoring model over any particular loan officer.

This argument seemed to make sense. The loans that experienced loan officers failed to predict accurately were indeed real. However, there was more to the story that needs to be understood. The scorecards used for the comparisons were not modified to make the point values assigned to credit applicant attributes look reasonable. Nor were all relevant credit factors included—a fact that does not bother scorecard developers who assert that correlations make it unnecessary to consider more than seven to 10 factors. It is not surprising that given the scorecard factors, individual loan officers could not perform as well as the computer model. However, we assert that the conclusion that the scoring model is a better predictor of loan default does not follow if you widen the set of factors considered beyond those used in the scorecard and apply proven credit principles.

The apparent demonstrable superiority of credit scoring over judgmental methods was based on a comparison of credit scoring with individual loan officer judgment that was prevalent at the time, not systematic, judgmentally based rules like those making up the CCAF. At the issue’s core is the realization that credit scoring models are not causal models. In other words, although the factors used in credit scoring have correlations with loan default outcomes, they do not cause them to occur.

\textsuperscript{11} For a list, see Abrahams & Zhang (2008) pp. 187.
\textsuperscript{12} Ibid, p. 187, Figure 6.3, note (a).
Loan defaults are caused by a variety of circumstances, some of which are beyond the control of the borrower and not necessarily due to a deliberate failure to agree to repay an obligation. Examples are job loss, illness, an accident, marital dispute, etc. As an example, consider years at a job, which is a common underwriting factor. Because loss of a job is a leading cause of mortgage loan defaults, it stands to reason that the characteristic “years on job” is correlated with bad loan performance. As a result, usually the longer the time a borrower is at a job, the higher the number of points. This means that if you get a better job offer for greater salary and move to another job, you will be penalized, because the model fails to consider the context of your employment change. The threshold number on years on job for some mortgage issuers is 24 months – a rather long time to wait to get out of the penalty box for someone who voluntarily moved to take a better opportunity.

When a factor like years on job is in a scorecard, it usually exhibits illogical point assignments or reversals in point values. This is due to correlations with other variables. Credit scoring models do not necessarily make sense when you look at individual factors. The standard argument is that there is no single factor, or subset of factors, but rather it is all of the factors that combine to predict the creditworthiness of a loan. When scorecards are adjusted to make the value assignments for factors more palatable, the predictive power of the model can be significantly diminished. In other words, in the majority of cases, if the scorecard makes logical sense, it is less accurate than if one or more of the point values does not make sense!

As for the assertion that credit scoring is more consistent than judgment, in reality, the reverse is true if by judgment we mean systematic (vs. individual) judgment, as we will see later in this paper when we discuss scoring overrides. Finally, it is often noted that with credit scoring, two people with identical credit factors will have identical credit scores. It should come as no surprise that a formula applied to identical inputs yields identical results. The inverse, however, is not true. Two consumers with identical credit scores can be vastly different. So why does it matter if they are different if they have the same score? It matters because borrowers having significantly different capital positions or capacity have significantly different probabilities of default, which is what the credit score is supposed to measure.

Suppose borrower A has $1 million in capital, earns $200,000 a year, has $3,000 in additional credit card debt and $7,000 in additional installment debt and is purchasing a home as a primary residence that is priced at $390,000 with an interest-only 5/1 ARM. Borrower B has no capital, earns $100,000 a year, also has $3,000 in additional credit card debt and $7,000 in additional installment debt, and is purchasing a primary residence that is identically priced and financed and is in the same subdivision. While they both have identical credit bureau scores of 712 at one of the three major credit bureaus, borrower B intuitively has a higher probability of default.
With the general acceptance of credit scoring after decades of use, it should not be entirely surprising that some economists believe that some of the Five Cs aren’t predictive. We have been told by some that income was found to have no predictive value many years ago. In addition, it is believed in some circles that wealth (level of capital reserves) has also been found to have no predictive value, because some rich people don’t pay their bills either. Our responses to these counterintuitive assertions are as follows:

- Those who advocate that one or more of the Five Cs is no longer predictive will need to carefully qualify under what assumptions they expect that proposition to hold. The Five Cs have been around for a much longer time than credit scoring, and each one of the Five Cs has been considered and proven to be relevant to lending over centuries of commerce.

If income or wealth were found not to be predictive using scoring technology, then that should have cast a shadow on credit scoring, and not the other way around. The millions of foreclosures due to subprime mortgage loans that were all credit scored and application scored and turned out to be unaffordable could have used a bit more emphasis on borrower capacity, capital and collateral value. The result would have undoubtedly been a lower loss rate.

- Let’s examine history for some clues to the real answer. Scorecard development by the mid-1970s was performed during a prolonged high inflationary economic cycle in the US (partly a period of stagflation). Because income as a scorecard variable was deemed to be “inflation bound,” major scorecard developers chose not to include it in the scorecard.

In other words, scoring assigns points based on absolute thresholds, income that is indicative of good loan payment behavior today may prove to be insufficient in a relatively short period of time, and steady inflation would translate to steady performance degradation for the system. Because scoring systems can leverage on the correlation between different factors in predicting outcomes, the story line was that income was no longer predictive versus other alternatives. On that score, it is inaccurate to say that income is not predictive; rather, it was determined that surrogates for income existed that could be substituted in a model.

- Next, we need to examine what we mean by a bad loan. Scorecard developers lump a lot into this category, and that is what may be causing confusion and these counterintuitive propositions. The typical bad loan definition is a loan that, had you known what the ultimate performance would have been, you would not have approved. That is certainly a simple definition, but the translation to what the computer model can understand is the key.
Historically, scoring system developers were sample-bound on loan defaults. In other words, for a historical sample going back a few years, there are insufficient numbers of charge-offs to build a model. As a result, the definition of bad loan performance was stretched to include any accounts that were ever delinquent 90 days, twice delinquent 60 days, or three times delinquent 30 days. This is where we start to run into a problem. Today’s scoring systems still include in the bad loan sample “purely delinquent” as opposed to “actual defaulted” loans. Hence, wealthy people who choose to pay late for convenience (and don’t mind the late fee penalties) get thrown into the bad loan pool.

When a model is built on good and bad loans, then, it turns out that income and capital are not predictive! This is self-fulfilling based on the way the model samples are constructed. It is interesting to note that the most profitable credit card customers are those who revolve their balances and pay lots of late fees. But then, credit scoring is used to predict loans that will default rather than loans that will be profitable.

At this juncture it is important to say that while credit scoring is not perfect, we view it as a valuable tool. We believe credit scoring can be part of the solution, but not the solution itself. For example, as we explore the dimensions of a more comprehensive framework, we reserve the option to deploy individual credit scoring models to categorize and assess the risk of one or more dimensions in the framework. In this way, the credit bureau scores in use today may be used, possibly unmodified, to satisfy an important part of CCAF. Hence, CCAF may be viewed as an “enhancement” rather than a “replacement” of the current credit evaluation system.

The underwriting gap

There is a saying that “a problem that is well-defined is half solved.” This is particularly applicable to loan underwriting, because there are many givens that must be considered in contexts that take into account the borrower's circumstances, the lending institution's experience, the market conditions relative to competition and valuation of property being financed, laws and regulations, and general guiding principles of safe, sound lending. This points to the need for a framework that can support the kind of comprehensive and realistic view that is needed to render lending decisions.

Defining the underwriting gap

To develop an effective and comprehensive credit assessment framework, first we need to define and identify the underwriting gap and its components. The underwriting gap refers to the difference between the underwriting decision model and the borrower, business and market realities.
Narrowing the gap translates to more accurate loss predictions, fairer treatment of the customer and less reliance on the assumption that the past determines future outcomes. Moreover, the introduction of the CCAF will have an impact on even the more mainstream 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.

Many underwriting systems have become convoluted in the sense that they incrementally work from partial information along the decision-making process. As a result, consumers may be overcharged, or they may be approved for loans they cannot afford. When working with incomplete information, it is impossible to properly construct factor weights because their information value relative to predicting loan default can be significantly reduced by considering factors not included in the model.

For example, credit scores have a one-to-one correspondence with the odds that a loan will go bad, where the lower the score, the higher the likelihood of a bad outcome. Credit bureau scores in particular put substantial weight on payment history for credit accounts (35 percent) and on how much a consumer owes relative to how much credit is available (30 percent), and they also take into account the average age of the aggregate trade lines and the types of debt carried. As a result:

- Even mild, infrequent delinquency can significantly lower a credit score.
- Closing older, less-used accounts can both lower the average age of aggregate trade lines and increase the aggregate utilization rate – both of which can adversely affect the score.
- Opening new accounts will also lower the average age of aggregate trade lines, which can lower the score.
- Paying cash for cars or major appliances, or quickly paying them off, will adversely affect the credit score because of the lack of installment versus revolving debt.

Provided a borrower has sufficient liquid capital reserves (e.g., checking or savings account funds, short term CDs, T-bills) and/or capacity to repay the loan through sources of income (e.g., base salary, commissions, bonuses, earnings from investments), none of the factors cited should carry much weight, if any, relative to the likelihood of loan default. Yet the bureau credit score has a significant impact on how much consumers pay for their financing needs. Conversely, if a consumer has little capital or capacity, the risk is greater that the loan will default than the credit score would indicate, because it is based on a population of consumers having the full range of capital and capacity resources. The foregoing discussion points out ways that these gaps in the typical loan decision-making process can be addressed.

There are several technical underwriting modeling components that can be leveraged to close the gap: components for data, sampling/segmentation, model factor, model formulation and model construction. We review them after the next section. It is useful first to consider some examples of the outcomes associated with the gap, which impacts the full spectrum of borrowers.

First, let’s examine the case where a borrower is a well-established revolving credit user primarily for the rewards benefit, possessing very strong capacity and ample liquid capital reserves. Such a consumer has less motivation to use credit to finance automobiles or consumer durable purchases. As a result, a credit-bureau-based credit score may negatively assess a lack of, say, recent installment loan information, and thus be unable to calculate the ratio of revolving to installment debt, etc.

Such a consumer may also be found to have too many accounts reported or too many accounts with balances if they use several credit cards. Furthermore, some delinquency in credit payments may simply signify a willingness to pay late fees for convenience and not any greater risk of default. In this instance, the added lowering of credit score in addition to late fee assessment may overpenalize the borrower, and with credit-score-driven risk-based pricing, this consumer will pay more for their financing than is necessary or reasonable.

On the other end of the spectrum, let’s look at a thin-file borrower with a small amount of capital, a relatively small but steady income over several years and very little existing debt. In this instance, his/her payment history of meeting obligations must play a greater role. Other important considerations would be the amount of non-credit obligations (e.g., rent, utilities, telecommunications, insurance, subscriptions) relative to income and the impact of the proposed loan, or payment shock, relative to monthly cash outflows. Unfortunately, little to no use of credit in the past and fast repayment of any debt will likely hurt rather than help this borrower.

In addition, in the absence of alternative data on rent, phone, utility and other regular payments, it will be difficult for the borrower to obtain desired financing. Even if successful, these individuals will likely be required to pay more for their loans than the true default risk would dictate. This conclusion is consistent with the Federal Reserve Board’s recent report to Congress on credit scoring, which noted that the models assigned lower scores to recent immigrants and young people than appropriate given the actual performance of these groups.14

14 “Report to Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit,” Board of Governors of the Federal Reserve System, August 2007, p.117
Identify gap components

Typically, the underwriting gap consists of the following components:

Data component

It has often been said that a model is only as good as the data that goes into it. Currently, there is a significant gap in information captured by the large credit bureaus for those consumers having little or no credit history.

The information value contained in alternative data\textsuperscript{15} and community data\textsuperscript{16} has made it increasingly apparent that significant ground can, and must, be gained in enhancing the state of the art in consumer and small business lending relative to those segments in particular, and perhaps for all borrowers in general. Recent research conducted by the Political and Economic Research Council (PERC) and the Brookings Institution\textsuperscript{17} 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.

There are some hurdles to tapping this rich source of predictive information. Credit model developers will have to navigate challenges around alternative data acquisition, interpretation, normalization and validation. First, there is variation on what currently gets reported across and within industries (such as electric, gas, water, telephone, etc.). Some companies choose not to report due to the expense and time required. Those that do choose to report vary in practice relative to:

- How much is reported (e.g., positive and/or negative information).
- What information is reported (e.g., only balances greater than a policy-specified amount).
- When it is reported (e.g., if the number of days past due is greater than a set number of days, as determined by policy).

Furthermore, there are different jurisdictions (different states, for example) that have differing laws and regulations that affect reporting, such as forbearance policies that may not permit reporting in winter months (Wisconsin) or bans on reporting without first obtaining affirmative consent (California Public Utilities Commission, New Jersey, Ohio). Furthermore, federal legislation\textsuperscript{18} has had some privacy and data security issues around reporting alternative data. The upshot is that lenders who operate in multiple jurisdictions and whose prospective borrowing population uses different service providers that report alternative data differently have to address the issues of inconsistency in data availability, what ultimately gets reported and when!

\textsuperscript{15} 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.

\textsuperscript{16} For additional information see 1) www.socialcompact.org, 2) The Metropolitan Program at The Brookings Institution, which has produced numerous studies and performed pioneering research into consumer information gaps, such as Fellowes, Matt, “From Poverty, Opportunity – Putting the Market to Work for Low Income Families (2006), and 3) Abrahams and Zhang (2008) pp. 280-282.

\textsuperscript{17} See Turner, et al., 2006.

\textsuperscript{18} 2005 Energy Bill—FTC has significant rule making power, and the rules/timing were still at issue last year. The 2005 Broadband Bill requires consent in order to report.
These obstacles can be overcome, and the use of alternative data can shore up gaps in the credit evaluation process, especially relative to payment history for non-credit obligations and borrower capacity. Without changing any model factors, one can incorporate non-credit trade lines into the set of credit trade lines 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 from the non-credit trade lines. Similarly, the factor “number of satisfactory trade lines at least 24 months old” would be calculated the same, only now it would include non-credit trade lines as input to the calculation.

Finally, there is a gap in information in the insurance domain. Consumers and small business owners purchase a variety of policies for different types of coverage, including life (whole, term and possibly credit life), automobile (public liability and property damage, collision, theft), medical/dental/vision, income replacement insurance, homeowners and renters (hazard, theft), and umbrella policies that kick in when maximum coverage for designated policies is exceeded. These policies offer benefits, especially to those consumers who do not possess much of a capital cushion or an ability to quickly build cash-equivalent reserves. The main benefit is risk transfer in the event of a disruptive event such as job loss, illness, accident or death. In addition, some insurance products – such as whole life, variable annuity or single premium deferred annuities – can accumulate cash values that can be tapped if necessary. Insurance coverage addresses known causal factors associated with foreclosure and loan default in general. Specifically, some statistics on the causes of foreclosures are presented in Figure 1.

<table>
<thead>
<tr>
<th>Percentage</th>
<th>Cause</th>
</tr>
</thead>
<tbody>
<tr>
<td>19</td>
<td>Job loss</td>
</tr>
<tr>
<td>17</td>
<td>Cause unknown—no contact with loan servicer or response to delinquency notices</td>
</tr>
<tr>
<td>14</td>
<td>Health crisis, disability leave, workmen’s compensation (injury on the job), automobile accident</td>
</tr>
<tr>
<td>13</td>
<td>Poor money management, overspending</td>
</tr>
<tr>
<td>13</td>
<td>Divorce, separation</td>
</tr>
<tr>
<td>10</td>
<td>Borrower deceased, other death in family</td>
</tr>
<tr>
<td>6</td>
<td>Property repairs needed</td>
</tr>
<tr>
<td>3</td>
<td>Property tax, insurance, utility cost</td>
</tr>
<tr>
<td>4</td>
<td>Other</td>
</tr>
</tbody>
</table>

*Figure 1: Causes of foreclosures.*

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Material summarized from Consumer Bankers Association CRA Conference held at Ritz Carlton Pentagon City, Arlington, VA, April 23-25, 2006. Specific session entitled “Loss Mitigation Strategies” moderated by Deborah Oakley, SVP Home Ownership Preservation, National City Corporation, and presentations by panelists Heidi Coppola, VP & Director Public Policy, Citibank; Bonnie Boards, VP & Director, Chase Homeownership Preservation Office, JPMorgan Chase.
Clearly, the breadth (types of policies and corresponding risks covered) and depth (policy maximums, deductibles and coverage limits) of insurance possessed by a borrower should be accounted for in his/her risk profile, and, intuitively, it should improve their credit score. Consider subprime borrower A, who works for an employer that provides health and income-continuation benefits and carries higher-than-required maximums on auto insurance in addition to collision coverage. Compare to subprime borrower B, who has minimal or no insurance coverage.

If these borrowers are similarly situated otherwise, relative to creditworthiness, borrower B represents a higher risk than borrower A. Yet virtually no mortgage underwriting systems take insurance coverage into account. Ironically, credit bureau scores are often used to qualify consumers for these types of insurance policies! The authors suspect that if insurance information were captured, it would have significant predictive value relative to loan default in general.

**Model factor component**

This component is closely related to the data component. Maximizing the breadth of potential model 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. An example of just such an alternative data-based capacity factor might relate to simply an “obligation-to-income ratio” that combines a proposed loan payment with the sum of all payments of any kind in the numerator of the ratio.\(^{20}\)

Especially relative to the subprime crisis, examining future financial ratios as well as current ones is of key importance for adjustable rate mortgages (ARMs) and option-based mortgages. Here, behavioral and historical variables are needed to capture more than a snapshot.

For this purpose, current income and income 12 and 24 months ago are 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 valuations using best- and worst-case scenarios are most likely to come up with an estimate of the range of property values. This would 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.

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\(^{20}\) See Abrahams and Zhang (2008), p. 225, Chapter 6, Figure 6.29 for further details and examples.
Sampling/segmentation component

In addition to which factors are included in a model, another critical area is determining which observations are included. In this area, missing or insufficient 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. Hence, models based on data from non-representative time periods can also be misleading. To illustrate, an observation window based upon the past four or five years — when there has been a prolonged housing boom, the economy has been strong and interest rates were falling — would produce data-driven factor weightings that may not be a good indicator of how future loans will perform. This is especially true if the future reality becomes a recession with a housing slump and rising interest rates.

Another aspect of sample selection is concerned with how to classify observations based upon their performance — i.e., defining what constitutes a good or bad loan. This is discussed in the next section on model formulation, but it also has implications for sample construction. Inclusion of loans in various stages of delinquency in the bad loan category can pose problems that carry over to the model’s predictive power overall and individual factor weightings in particular.

Another hurdle is whether to define a good loan as any loan that is not a bad loan or attempt to define a third category corresponding to indeterminate performance. Indeterminate loans would have performance insufficient to be classified as either good or bad. In credit scoring models, samples are “factored up” to reflect the true proportion of good and bad credit applicants in the general, or through-the-door, applicant pool. At the end of that process, there are only good and bad loans in the reconstructed loan population. Exclusion of indeterminates can cause a gap in representation that is magnified when the sample is scaled up.

For example, in credit card scorecard development, as much as 40 percent of the sample can be lost to the “inactive” category of performance (insufficient account activity), 35 percent can be lost to the indeterminate category and 5 percent to other exclusions. The end result in such a case is a scorecard that is purported to have “reconstructed the total through-the-door applicant population” when in fact it has totally ignored 80 percent of the observations. This creates an overstatement of the system’s ability to decide which loans will turn out to be either good or bad. Granted, the resulting systems may still rank-order loans by default risk, but the associated estimated default probabilities may lack precision. We recognize the legitimate reasons for scoring system developers to restrict samples. We are simply pointing out possible consequences of those restrictions.
Model construction and formulation component

A fundamental question that must always be addressed in model building is, “What is the objective function?” Typical credit scoring systems are posed as discriminant analysis problems, where the objective function to be maximized measures the separation between observations that have been classified into “defaulter” and “non-defaulter” loan applicant groups. This approach carries with it assumptions concerning the form of the statistical distribution of the sample and general population of credit seekers, and also the properties of the score distribution, such as equal variance of “defaulter” (bad) and “non-defaulter” (good) groups.

There are other approaches that have modeled default risk as a propensity and have included expected profit as the outcome to be predicted. These models’ outcomes differ from those in standard use today, and they take into account a greater portion of the true business reality. CCAF is not dependent on distributional assumptions or properties of the sampled data. It can consider multiple objectives, including profitability, prepayment likelihood, spending propensity and default probability.

In model building, there is also 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. Failure to do so contributes to the gap.

Scoring system technology was originally sold chiefly on its ability to:

- Speed the process.
- Enforce consistency.
- Precisely quantify bad performance risk.
- Outperform individual loan officers on bad loan prediction.

On the first point, credit scoring was faster, even when performed in a manual environment, because it did not agonize at the cutoff-margin over who is good or bad – it simplified all those choices to a simple series of point assignments and totaling of the score. Scores at or above the cutoff were approved, and those below the score cutoff were declined. Choices around the threshold risk tolerance are always the most difficult ones.
On the second point, credit systems enforce consistency, because two consumers falling into the same categories for the factors being scored will get identical scores. However, two credit applicants falling into different categories for the factors being scored may still receive identical scores, because differences in point assignments for one factor may be offset by those on one or more other factors. The point is that two applicants may have identical scores, but not identical credit characteristics.

Relative to the third point, custom credit systems for specific lenders and loan products are capable of quantifying the odds of bad performance because they are developed based on the compilation of large numbers of similar loans where the historical performance is known. The same is true for bureau-based credit scores, except that they encompass multiple lenders and may span multiple loan products (revolving, installment, mortgage, etc.). The credit score is simply the odds of repayment, scaled to be a positive number that ranges within a few hundred points.

On the fourth point, historically when judgmental systems consisted of a collection of fairly autonomous loan officers, the scoring system always outperformed any individual loan officer. This was because it was based upon all, and not just some, of the cases to be decided. Hence, a loan officer may be correct in assessment but graded as a failure because in a particular instance in the past a loan went bad despite passing obvious tests. This is where credit granting has become a data mining exercise of separating out who did and did not repay in the past, irrespective of causality, and not a reasoned response to who will likely repay. The real issue is which decision is actually most likely to come true.24

Credit scoring models typically assign point values to perhaps six to 12 factors, and every credit applicant is considered on all factors, the same points assigned irrespective of the responses on any of the questions. The process of selecting variables often consists of picking the candidate variable that has the greatest predictive strength as the initial choice, then picking the next factor that jointly provides the greatest predictive strength. That means that the second variable selected may not be as predictive on its own as many of the other remaining candidate variables.

For example, suppose there are several variables to choose from, and the strongest variable represents the most severe credit delinquency during the past two years – so it gets selected first. Further suppose that debt ratio is the next most predictive factor among the remaining choices, but that it is obviously highly correlated with credit delinquency. The next variable to be included may be the number of years at address, although it is a much weaker predictor, because in combination with the first factor it provides the greatest lift. In other words, the length of time someone lives at an address does not cause them to perform well or poorly. It may be a measure of stability, but financial capacity and capital can arguably better determine ability to pay.

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24 For a detailed review of credit scoring and judgmental system, see Abrahams and Zhang, Fair Lending Compliance – Intelligence and Implications for Credit Risk Management, Wiley, 2008.
In addition, credit scoring system factors such as years at an address do not consider the circumstances associated with a residential move, such as whether it is due to a promotion and career advancement with greater pay, the loss of a job and a move to a lower-paying job, a move to a neighborhood that is zoned for better schools, or some other reason. Moreover, credit score point values associated with these factors may provide false signals if the borrowers they represent differ significantly in primary credit factors that are not included in the scorecard.

On a final note concerning years on job, years in profession, years at current residence and years at previous residence, there are frequently “reversals” in good/bad odds as the length of time increases. Often, scorecard developers will smooth out these irrational-looking patterns so that the likelihood of going bad decreases steadily as the length of time increases, which invariably reduces the predictive power of the system.

At any stage of variable selection, it is the marginal contribution with previously selected model factors that determines what, if any, factor is selected. It is entirely possible that debt ratio will not make it into the model, even though it is a key indicator of borrower capacity, and this does occur in fact with many underwriting scoring models. This points out the problem with letting the data drive what is in the model instead of proven principles that far surpass the time frames from which the model data are drawn. Alternatively, some of the more predictive factors may be withheld from selection until the end of the process because their early inclusion will result in only two or three factors being selected if correlations are high.

Consequently, if the factors that are highly predictive on their own do make it into the model at a late stage, their weight will be substantially less than if they were allowed to enter the model without restriction. Unfortunately, factors that qualify as key credit indicators may be precluded from consideration for various technical reasons. For example, despite its obvious relevance, income may not be used because its thresholds for the point intervals can become less accurate due to inflation.

There is anecdotal evidence that a major mortgage underwriting system in use today does not include debt ratio as a factor because reportedly other model variables capture all of its predictive content. Other factors are abandoned by model developers due to the incidence of missing data, despite their relevance.

There are many choices that can be, and are being, made in model development. Weights may not be optimal, especially when you vary certain assumptions or drop into certain population segments. There may be regional differences, product differences, differences in customer culture or life cycle, etc. Perhaps consumers who use credit more sparingly are more disciplined to live within their immediate means and are more risk-averse. Models developed on a more mainstream population may tend to overestimate risk in such a segment.
Furthermore, one has to ask the question, “Is the object of the exercise purely to predict default risk, or should fair credit access also be part of the objective?” There are families of scorecards that perform very similarly relative to credit default prediction but differ significantly relative to acceptance rates for specific borrower population segments. This is often the case in underserved markets.

Finally, there is the issue of population performance definitions. These are necessary to create a development sample for a credit scoring system, and they relate to classification of observations into various performance categories: exclusions, inactives (for revolving credit), indeterminates, bads and goods. In addition to determining how observations are to be classified for modeling purposes, the performance definitions specify the time frame over which performance is to be observed and the behavior patterns that are indicative of class membership.

Interestingly, the time frame for delinquent behavior does not vary by severity of delinquency. In other words, consumers are penalized for having even mild late payments going back 24 months the same as for 60 and 90 day past-due occurrences. This means that borrowers who experience a temporary hardship for a few months but avoid severe delinquency have to wait two years for a clean slate even if they have been current with all accounts for the past year. As a result, it can take a long time for credit scores to improve, whereas the CCAF contours can change immediately when new information becomes available.

Population performance definitions will be different for a subprime lender than a prime lender. Subprime actually consists of layers of risk. Typically, borrowers with a credit bureau score of 660 or less are considered to be subprime. Within the subprime pool, one can further segment by credit history specifics by severity. Figure 2 provides an example of nine such layers.²⁵

<table>
<thead>
<tr>
<th>Severity High to Low</th>
<th>Performance Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Bankruptcy filed within the past five years.</td>
</tr>
<tr>
<td>2</td>
<td>Foreclosure public record filed during the past 24 months.</td>
</tr>
<tr>
<td>3</td>
<td>Judgment or tax lien or garnishment initiated during the past 24 months.</td>
</tr>
<tr>
<td>4</td>
<td>Repossession during the past 24 months based on the date reported in the trade line.</td>
</tr>
<tr>
<td>5</td>
<td>Charge-off during the past 24 months based on the date reported in the trade line.</td>
</tr>
<tr>
<td>6</td>
<td>Sixty days past due two or more times, or 90 days past due one or more times, during the past 24 months.</td>
</tr>
<tr>
<td>7</td>
<td>Sixty days past due one time during the past 24 months.</td>
</tr>
<tr>
<td>8</td>
<td>Thirty days past due three or more times during the past 12 months.</td>
</tr>
<tr>
<td>9</td>
<td>Thirty days past due two times during the past 12 months.</td>
</tr>
</tbody>
</table>

Figure 2: Credit history specifics segmented by severity.

²⁵ See Abrahams and Zhang (2008) op. cit. p. 309, esp. note 15, for a discussion of factors used by various players to assign loans to risk grades of Alt-A, B, C, and D. Specific definitions vary among subprime market participants.
An important consideration is how a particular subprime lender characterizes good and bad performance for the purposes of scorecard development and underwriting in general.

Subprime designation is given to loans that are perceived to have more risk. Because the current definition is primarily based on the bureau credit score, which mainly measures willingness to pay, it may fail to capture true default risk (overestimating or underestimating the risk). CCAF can define subprime based on primary credit qualifications that also take into consideration capital and capacity. This approach is more accurate for grading credit into A, Alt-A, B, C and D tiers so they can be properly priced. This will also result in a more clear and complete picture of riskier loans in the marketplace.

The Comprehensive Credit Assessment Framework

Overview of CCAF

To address the above underwriting gap, we present a Comprehensive Credit Assessment Framework (CCAF). The credit assessment framework offers a comprehensive rating system that enables lenders to classify credit risk and decide all transactions in the most fair, effective and transparent manner. Classification of credit transactions is performed sensibly and comprehensively using the Five Cs of credit (explained in footnote 28), and it requires that all primary underwriting factors be simultaneously weighed rather than letting a model dictate what is, and is not, important. The resulting distinctive pattern of values relating to the loan applicant is captured in what is termed their credit contour. Unlike a credit score, which is simply a numerical rating, the credit contour affords transparency and conveys the essence of the borrower’s qualifications.

CCAF risk rates credit transactions within the context of the borrower’s credit contour to avoid significant overstatement or understatement of risk on individual loan transactions. CCAF affords greater control of loan decisions 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 cutoff, which must be overridden from time to time.
In addition, CCAF’s transparent approach fosters the trust and confidence that come from knowing exactly how loans are evaluated and how credit quality and credit access will be maintained and improved. The result is a more flexible, adaptable, granular, powerful and enforceable lending system that can fairly and accurately evaluate credits, quantify transaction risk, maintain appropriate risk levels based on policy-dictated risk tolerances, and more effectively provide information used to monitor and manage loan portfolios. CCAF provides fair access to credit and ensures suitable loan products for consumers and a more profitable, safe and sound loan portfolio for lenders.

In terms of financial disclosure, CCAF provides consumers with their categorization relative to all primary underwriting factors via a transaction contour identifier. With this single number, strengths and weaknesses relative to the primary qualification criteria are immediately apparent. In addition, a simplified 10-point rating scale is used to describe the overall credit rating when all factors are combined. This rating is the same for all consumers sharing the identical transaction contour.

**CCAF addresses gap components**

CCAF development involves four milestones, each of which addresses different gap components. At a high level, Figure 3 describes the overall CCAF process:

![Diagram of Overall CCAF process](image)

*Figure 3: Overall CCAF process.*
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 sufficient for system construction.\textsuperscript{26}

The model consensus session (MCS)\textsuperscript{27} 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 Transaction Contour (TC), which will be described in detail in a later section. There, we also define a Borrower Contour (BC), which transcends all financial transactions for a particular borrower.

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.\textsuperscript{28} In addition to the action table, a series of additional tables are generated to allow for the maintenance and monitoring of the action table.\textsuperscript{29}

A comprehensive and transparent validation process is the next-to-last step in the CCAF process. It is essential in order to foster 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.\textsuperscript{30}

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 the current action table.\textsuperscript{31} In addition, alternative action tables associated with specific credit policy and marketing strategies can be produced, along with their system maintenance and operational reports. Because these reports can be regenerated and compared at two points in time, multidimensional variance reports can be produced to help spot issues early on in great detail using the TC as a basic frame of reference, and several such reports may be generated and visualized graphically to easily identify trends.

\textsuperscript{26} 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. For details specific to CCAF, see Abrahams and Zhang (2008), pp. 23-35, 201-202, 309-313, and 328-331.

\textsuperscript{27} Abrahams and Zhang (2008), pp. 158-159.

\textsuperscript{28} Ibid, pp. 203-216, 222-237, 250-264, and 329-332 describes in detail this process and the methods utilized.

\textsuperscript{29} Ibid, pp. 216-222

\textsuperscript{30} Ibid, Chapter 8, pp. 305-346 provides a detailed discussion of how this is performed. This topic is beyond the scope of this paper.

\textsuperscript{31} Ibid, pp. 209-210 shows examples of reports and an inventory of all multi-dimensional reports for a hypothetical action table.
The end result of CCAF is a more flexible and adaptable lending system that can accurately evaluate credits, quantify transaction risk, maintain appropriate risk levels based on policy-dicted risk tolerances, and more effectively provide information to monitor and manage loan portfolios. CCAF provides fair access to credit and ensures suitable loan products for consumers and a more profitable, safe and sound loan portfolio for lenders.

Now we describe how each of the four milestones addresses the underwriting gap components in more detail:

1. **Define objectives and identify required data sources.**

   CCAF starts with identifying business requirements and source data. CCAF can be used for different purposes such as managing credit risk 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:

   - An inventory of all current obligation terms, balances and monthly payment amounts with all lenders, service providers, landlords, insurers and counterparties.
   - Current sources of income and time in profession and with current employer.
   - Liquidity and value of personal assets and net worth.
   - 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).
   - Payment and delinquency history for credit and non-credit obligations and any past loan defaults.
   - Insurance coverage by type, including policy limits and cash values.
   - Loan conditions including maturity, loan amount, pricing mechanism, payment schedule and terms, and other borrower-elected or lender-specific transaction requirements.  

32 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 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.

33 For small business lending, additional factors play key roles, such as customer relationship, See Abrahams and Zhang (2008), pp. 225-234 for a detailed example.
2. **Determine segmentation and perform model consensus session.**

Sampling is an area where missing or insufficient 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. 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.

Credit scoring models are based on observed good/bad performance for a set period of time. If the observation window is the past four or five years – when times have been good for the economy, interest rates have fallen, etc. – then the information weights of evidence may not be a good indicator of how future loans will perform based on their scores if the reverse is true (e.g., a recession with rising interest rates, etc.). The weights of a hybrid model, in contrast, are tempered by logic and proven judgment. The argument that statistical credit model factor point assignments do not make sense, when viewed in isolation, can lead to the failure to detect the impact of shifting assumptions and givens.

A common consumer complaint relative to credit scores is that it takes a long time for their scores to improve – typically the performance window for past-due payments is 24 months. CCAF, in contrast, immediately recognizes changes in creditworthiness. For example, if one has an inheritance or bonus, or their capital position changes significantly, their credit contour immediately changes. The same would be true if they experienced a change in capacity. Also, with additional sources of information, their satisfactory trade line information can be bolstered, which will be explained in the next section on alternative data.

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 Cs of credit.\(^{34}\) The primary factors to encompass the first three Cs of credit can be extended to create a Borrower Contour (BC), which is a distinctive pattern of values relating to character, capacity and capital for a consumer or business. We can further introduce the notion of a lending transaction contour (TC), which is based on all Five Cs 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 can encompass BC, or it can operate across segments defined by BC. TC may also encompass channel and market factors.\(^{35}\)

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34 Character includes payment history, savings history, and 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 and physical properties. Conditions includes such factors as the loan amount, the term of the loan, the pricing mechanism, the payment schedule and payment options, the amount of down payment, applicable fees, etc.

35 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 Cs of the Five Cs of credit.
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 transaction contour identifier. With this single number, strengths and weaknesses relative to the primary qualification criteria are immediately apparent. In addition, a simplified 10-point rating scale is used to describe the overall credit rating when all factors are combined. This rating is the same for all consumers sharing the identical transaction contour.

To illustrate, we draw upon an example based loosely on 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 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 12 possible patterns, as shown in Figure 4, based upon:

- **Capacity (Income + Debt Ratio):** (High/Low)
- **Capital (Liquid Reserves + Percent Down Payment):** (High/Low)
- **Payment Performance (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 would be determined – perhaps 40 percent – to separate borrowers possessing high capacity from those with 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 12 unique segments (i.e., 1-Low, 2-Moderate, 3-High, 4-Severe) as indicated in Figure 4.
Within each segment, borrowers would be homogenous relative to primary credit strength. Lenders might regulate which products/programs would be 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 segment level using a referencing scheme known as a segment handle. 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. Behavioral and historical variables may be used to capture more than a snapshot—e.g., current income and income 12 and 24 months ago averaged to calculate average annual increase in the denominator for debt-to-income (DTI) projection for an ARM reset date, where the maximum rate on the reset date is also assumed. Yet another example would be property valuation using best case, worst case, most likely to come up with a future valuation of the asset's current price, less one standard deviation, and a conservative future value for the LTV calculation on an ARM.

3. **Integrate business scenarios into analytical models.**

This addresses model construction and formulation components of the gap. In this stage, segmentation results including TC or BC will be integrated with proper business context or external factors relating to the economy, market states and underlying asset valuation 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 percent, so that the customer has an 80 percent 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:

  \[\text{DTI} = 20\%? \quad \text{DTI} = 40\%? \quad \text{DTI} = 60\%?\]

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

  \[\text{DTI} = 20\%? \quad \text{DTI} = 40\%? \quad \text{DTI} = 60\%?\]

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

  \[\text{DTI} = 20\%? \quad \text{DTI} = 40\%? \quad \text{DTI} = 60\%?\]

The foregoing scenarios could be repeated holding the value of DTI constant and 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.

To maintain or improve the risk measurement system’s accuracy, lenders must continuously improve model predictability over time as information accumulates. For most lenders, this means a constant burden of scorecard redevelopment every two years or so. Constant redevelopment of scoring models is very resource-intensive. 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 bad 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 5. The expected frequencies of credit applicants and the weights associated with CCAF factors by primary factor segment are updated dynamically as information becomes available.\textsuperscript{37} It allows for in-depth analysis of all possible multi-way primary-factor comparisons relative to the mix of accepted applicants and acceptance rates at any point in time.\textsuperscript{38} 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 a risk rating system for the banks that want to implement, or already use, Basel II’s Internal Ratings Based approach.

A typical validation process can be described as follows:

1. Create segment handle structure for input data if needed. When the system being validated is either purely 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 using 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 on availability.

\textsuperscript{37} Ibid, pp. 216-222 describes hybrid system maintenance.
\textsuperscript{38} Ibid, pp. 209-210 for specific examples and an enumeration of all possible combinations of these multi-dimensional acceptee mix and acceptance rate views.
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 them could improve model fit and reduce residual. This also can be performed to some degree by logical comparisons to identify disconnections between the observed risk and the predicted risk. 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 its 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. This allows a direct comparison between the observed risk in input data and the predicted risk in model outputs and, if necessary, the embedding of class priors by utilizing different thresholds and business policy. 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 handle structure. This is achieved by using variance reduction techniques\textsuperscript{39} to obtain maximum homogeneity in each handle segment. Simulation results from this step are also used to enhance lending policy rules.

\textsuperscript{39} 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.
Another key point is that the validation process is performed from both credit risk and compliance perspectives aided by an optimization process. The objective function is constructed based on results from steps 1 and 2 above. The goal is to select optimal thresholds to maximize model predictability for “good vs. bad” performance or to minimize disparate impact on all relative constituencies subject to a set of constraints on regulatory compliance and business requirements. A risk quadrants plot is used to balance the trade-offs between compliance risk and credit risk. The outputs from this optimization process can help banks make decisions on model update or rebuilding activities. A detailed example of the mathematical representation of the type of model compliance constraints that can be used in this context has been provided in the literature.\footnote{See Abrahams and Zhang (pp. 337-338).}

The connection between credit underwriting gaps and fair lending becomes more apparent when one attempts to balance credit access and credit risk in a more holistic framework as described. Fair lending self-evaluation normally entails systematic compliance testing for different outcomes (e.g., loan product selection, loan approval or denial, loan price) based on how loans are decisioned, but not necessarily based on who is actually most qualified. When significant findings persist, the final analysis involves construction of sets of similarly situated borrowers in different protected classes that can be compared with one another.
It is possible that even if borrowers are treated consistently by the underwriting system, individual matched-pair cases can be found where more qualified borrowers are disfavored over less qualified counterparts. In such instances, this may or may not involve protected vs. non-protected class differences; the differences may occur “in-class” as well. In situations where there is a difference in distribution for the protected and non-protected classes relative to the Comprehensive Credit Assessment Framework segmentation and those segments fall into “underwriting gap” categories, the results will signal potential discrimination.

In summary, adoption of the CCAF allows for improved credit default estimation, better identification of predatory lending patterns, the ability to assess whether predatory lending patterns cross over to fair lending problems, and immediate isolation of unfair lending patterns occurring within the homogenous risk classifications. This has implications for avoiding predatory and fair lending problems through predictive analytical approaches and optimization relative to the CCAF handle structure.

**Interplay of main elements**

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

Adoption of the CCAF allows for improved credit default estimation, better identification of predatory lending patterns, the ability to assess whether predatory lending patterns cross over to fair lending problems, and immediate isolation of unfair lending patterns occurring within the homogenous risk classifications.

---

*Figure 6: Interplay of main elements.*
Role of judgmental credit information

As shown in Figure 6, judgmental components play an important role throughout the CCAF development process. In fact, CCAF can be considered 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 and provide fast, consistent and efficient credit assessment. This can be crucial in the context of most consumer loans and some small business loans, and also for segmenting and monitoring micro-loans to lower origination and servicing costs and better price the risk.

CCAF is not an expert system. Like credit scoring, it treats everyone consistently. It is very flexible. It can be based on pure science, pure judgment (initially) or a combination of both. Judgment is not performed by CCAF based on individual opinions, as was the case prior to the age of credit scoring. Judgment is carefully and systematically deployed through consistent business rules that have stood the test of time and better fit the evolving nature of today’s business climate than a static and inflexible empirically based scorecard that diminishes in effectiveness from the day it is put into use.

The question of protected class treatment is a complex one. CCAF provides greater transparency than credit scoring or application scoring processes. If minorities are disadvantaged in any way, CCAF can better detect it and correct for it more effectively and precisely than any other method in use today. Furthermore, relative to Regulation B issue Section 202.P.iii, CCAF can be developed, like credit scoring models, on a data-driven basis.

The fact is that the credit scoring development process itself entails a host of judgmental decisions and has always been recognized by practitioners as being both an art and a science. In some cases the flavor of statistical methods used may differ, but that is of no consequence. In fact, CCAF may be based on a more general class of discrete multivariate models than the standard credit scoring regression models, and they are in many cases mathematically equivalent depending upon how the developer formulates the decision model.

Even if a CCAF system is developed using factors having purely judgment-based weightings that are applied universally, it should still fall into the statistical model category. An example might be quality of management for a small business loan. If there are well-defined descriptions of what constitutes strong (value of 3), fair (value of 2) or weak (value of 1) management based on objective criteria such as years of experience, education, track record, etc., then these numerical ratings can be treated as data just the same as with any other model factor. Customer relationship is another such factor that may depend on the length, depth and breadth of the loans, and the deposits and services a banking customer has with a particular financial institution. Again, business rules would be used to determine the value rating for customer relationship in the underwriting model.

41 Ibid, p. 187 for a list of shortcomings associated with a traditional judgmental system.
From a modeling perspective, the CCAF approach does more than simply introduce judgmental factors into the modeling process. More importantly, 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 cutoff, 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, low-side override rates can approach 5 percent and high-side override rates can approach 10 percent. For hybrid systems, the frequency of overrides can be less than 0.5 percent.43

Use of alternative data

The information value contained in alternative data44 and community data45 has made it increasingly apparent that significant ground can, and must, be gained in enhancing the state of the art in consumer and small business lending relative to those segments in particular, and perhaps for all borrowers in general.46 The use and understanding of IT for credit decisioning has developed so rapidly that few difficult barriers remain to spreading this financial innovation to non-credit economic transaction data and to most countries around the world. There are a number of benefits to the use of non-financial economic transaction data.47 Mainly, with use of non-credit transaction data, vast numbers of consumers can be brought into the financial mainstream and gain access to credit. With greater information, lending decisions become better, with lower rates of delinquencies, less overextension and an increase in the number of performing loans. This will shore up data gaps in the credit evaluation process, especially relative to payment history for non-credit obligations and borrower capacity.

43 Hybrid system estimated override performance is based on the authors’ expert opinions.
44 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.
45 See www.socialcompact.org for more information.
As shown in Figure 6, alternative data can be readily fed into CCAF’s handle structure for the purpose of segmentation and modeling. Without changing any model factors, one can incorporate non-credit trade lines into the set of credit trade lines 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 from the non-credit trade lines. The factor “number of satisfactory trade lines at least 24 months old” would be calculated similarly, except it would include non-credit trade lines as input to the calculation.  

**Role of credit scoring**

As shown in Figure 6, credit scoring can be mainly used to assist segmentation and model formulation. For example, credit score could summarize payment performance for both credit and non-credit trade lines. However, CCAF can extend credit scoring from three perspectives.

First, CCAF ensures inclusion of primary predictive factors that cover the full spectrum of relevant qualification criteria and both determine and reveal 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 (that is, credit scoring is not adaptive; its predictive strength diminishes over time). Even when credit scoring systems are redeveloped, 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. 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, ignoring 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.

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

49 Ibid, pp. 158-159, for a description of DCP and MCS.

50 Ibid, p. 117, Figure 4.21 for an illustrative mortgage pricing example that shows nine separate pricing offsets for a typical mortgage loan.
With CCAF, one can maximize the breadth of candidate model factors, which results in greater inclusiveness and accuracy. In addition, factor definitions may be tailored in order to maximize the information value of the data.

Third, CCAF integrates business context with the modeling process in a complete and transparent manner. Current credit scoring systems lack transparency because 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.

Simply put, the CCAF shores up the gaps in today’s prevailing loan decision processing. It accomplishes this via a complete credit categorization of borrowers prior to risk rating them, unlike current approaches that are piecemeal and risk rate certain aspects of borrower creditworthiness. Figure 7 provides a side-by-side comparison that highlights the most common shortcomings of today’s underwriting models and their corresponding CCAF remedies.

<table>
<thead>
<tr>
<th>Key U/W Factors</th>
<th>Typical U/W System</th>
<th>CCAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Character (payment history)</td>
<td>Credit history dominant, education, years in profession</td>
<td>Credit + cash payments, education, years in profession</td>
</tr>
<tr>
<td>Capacity (income, debt)</td>
<td>Documented/undocumented income, Credit obligations</td>
<td>Verified income, # dependents, Credit + alternative data (credit obligations), Future income stream</td>
</tr>
<tr>
<td>Capital (liquidity, net worth)</td>
<td>Checking, savings accounts, investments</td>
<td>Bank accounts, investment accounts, insurance products w/ cash values, insurance protection</td>
</tr>
<tr>
<td>Collateral (current/future value)</td>
<td>Current appraisal</td>
<td>Current appraisal, range of future scenario valuation</td>
</tr>
<tr>
<td>Conditions (product terms)</td>
<td>“Prime” borrowers can be sold, “subprime loans, risk-based mis-pricing, payment minimization focus</td>
<td>Match borrowers to right loan product, default odds geared to homogeneous handle groups, affordability/suitability focus, future payment stream</td>
</tr>
</tbody>
</table>

Figure 7: CCAF vs. status quo underwriting (U/W) model.  

Small business lending presents additional considerations that are covered by additional business-related key factors, such as industry, location, target market, external economic conditions, management strength, financial strength, and relationship with lender. For an example, see Abrahams and Zhang (2008), pp. 225-234.
While this summary is a generalization and simplification, it does convey some critical differences that we view as needed improvements in the way underwriting systems should work. There are obvious crossover effects between the Five Cs, such as the notion that the risk associated with a loan having undocumented income (Capacity) can adequately be quantified and priced for a subprime 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 subprime 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.

**Examples**

The following CCAF example is for home purchase mortgages originated through a lender’s branch retail channel. Models for refinancings or home improvement loans would have differing sets of criteria, as would wholesale channel mortgages.

**Capturing payment history**

Figure 8 shows an example of the payment history, or “character” dimension, of the Five Cs of credit.

<table>
<thead>
<tr>
<th>Delinquency Time Frame</th>
<th>Mortgage Trades Severity</th>
<th>Installment/Revolving Trades Severity</th>
<th>Alternative Cash Payment Trades Severity</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td><strong>LESS THAN 12 MONTHS</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 days past due</td>
<td>G</td>
<td>F</td>
<td>F</td>
</tr>
<tr>
<td>60 days past due</td>
<td>G</td>
<td>P</td>
<td>P</td>
</tr>
<tr>
<td>90 days past due</td>
<td>G</td>
<td>P</td>
<td>P</td>
</tr>
<tr>
<td><strong>12-24 MONTHS</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 days past due</td>
<td>G</td>
<td>G</td>
<td>F</td>
</tr>
<tr>
<td>60 days past due</td>
<td>G</td>
<td>P</td>
<td>P</td>
</tr>
<tr>
<td>90 days past due</td>
<td>G</td>
<td>P</td>
<td>P</td>
</tr>
<tr>
<td><strong>MORE THAN 24 MONTHS</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30 days past due</td>
<td>G</td>
<td>G</td>
<td>G</td>
</tr>
<tr>
<td>60 days past due</td>
<td>G</td>
<td>F</td>
<td>P</td>
</tr>
<tr>
<td>90 days past due</td>
<td>G</td>
<td>P</td>
<td>P</td>
</tr>
</tbody>
</table>

*Figure 8: Payment history dimension – ratings for three categories of trade lines.*
A COMPREHENSIVE CREDIT ASSESSMENT FRAMEWORK

Figure 9 shows how payment history rating can be collapsed based on time and trade line categories.

<table>
<thead>
<tr>
<th>Case</th>
<th>Overall</th>
<th>Mortgage</th>
<th>Install/Rev</th>
<th>Cash Pay</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>G</td>
<td>G</td>
<td>G</td>
<td>G</td>
</tr>
<tr>
<td>2</td>
<td>F</td>
<td>G</td>
<td>G</td>
<td>F</td>
</tr>
<tr>
<td>3</td>
<td>P</td>
<td>G</td>
<td>G</td>
<td>P</td>
</tr>
<tr>
<td>4</td>
<td>F</td>
<td>G</td>
<td>F</td>
<td>G</td>
</tr>
<tr>
<td>5</td>
<td>F</td>
<td>G</td>
<td>F</td>
<td>F</td>
</tr>
<tr>
<td>6</td>
<td>P</td>
<td>G</td>
<td>F</td>
<td>P</td>
</tr>
<tr>
<td>7</td>
<td>P</td>
<td>G</td>
<td>P</td>
<td>G</td>
</tr>
<tr>
<td>8</td>
<td>P</td>
<td>G</td>
<td>P</td>
<td>F</td>
</tr>
<tr>
<td>9</td>
<td>P</td>
<td>G</td>
<td>P</td>
<td>P</td>
</tr>
<tr>
<td>10</td>
<td>F</td>
<td>F</td>
<td>G</td>
<td>G</td>
</tr>
<tr>
<td>11</td>
<td>F</td>
<td>F</td>
<td>G</td>
<td>F</td>
</tr>
<tr>
<td>12</td>
<td>P</td>
<td>F</td>
<td>G</td>
<td>P</td>
</tr>
<tr>
<td>13</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>G</td>
</tr>
<tr>
<td>14</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>F</td>
</tr>
<tr>
<td>15</td>
<td>P</td>
<td>F</td>
<td>F</td>
<td>P</td>
</tr>
<tr>
<td>16</td>
<td>P</td>
<td>F</td>
<td>P</td>
<td>G</td>
</tr>
<tr>
<td>17</td>
<td>P</td>
<td>F</td>
<td>P</td>
<td>F</td>
</tr>
<tr>
<td>18</td>
<td>P</td>
<td>F</td>
<td>P</td>
<td>P</td>
</tr>
<tr>
<td>19</td>
<td>P</td>
<td>P</td>
<td>G</td>
<td>G</td>
</tr>
<tr>
<td>20</td>
<td>P</td>
<td>P</td>
<td>G</td>
<td>F</td>
</tr>
<tr>
<td>21</td>
<td>P</td>
<td>P</td>
<td>G</td>
<td>P</td>
</tr>
<tr>
<td>22</td>
<td>P</td>
<td>P</td>
<td>F</td>
<td>G</td>
</tr>
<tr>
<td>23</td>
<td>P</td>
<td>P</td>
<td>F</td>
<td>F</td>
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<td>24</td>
<td>P</td>
<td>P</td>
<td>F</td>
<td>P</td>
</tr>
<tr>
<td>25</td>
<td>P</td>
<td>P</td>
<td>P</td>
<td>G</td>
</tr>
<tr>
<td>26</td>
<td>P</td>
<td>P</td>
<td>P</td>
<td>F</td>
</tr>
<tr>
<td>27</td>
<td>P</td>
<td>P</td>
<td>P</td>
<td>P</td>
</tr>
</tbody>
</table>

Figure 9: Payment history rating collapsing on time and trade line categories.

As one might expect, payment history is a primary underwriting factor in mortgage lending and includes delinquent or derogatory performance, and the typical credit trade lines have been expanded to include alternative data trade lines.\(^{52}\)

\(^{52}\) It should be noted that the occurrence of a bankruptcy, judgment, lien, foreclosure, repossession or significant dollar charge-off, within set periods of time, can automatically put the borrower in the poor performance category.
30-year fixed rate vs. five-year ARM home purchase mortgage

Continuing with our example, Figures 10 and 11 provide primary factors for a home purchase mortgage, and Figure 12 shows the corresponding handle structure for both a 30-year fixed-rate mortgage and a five-year adjustable-rate mortgage (ARM).

<table>
<thead>
<tr>
<th>Primary Factors</th>
<th>Categories, Definitions &amp; Value Assignments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital</td>
<td>G: High net worth &amp; liquidity</td>
</tr>
<tr>
<td></td>
<td>F: Moderate net worth &amp; sufficient liquidity</td>
</tr>
<tr>
<td></td>
<td>P: Low net worth &amp; minimal savings</td>
</tr>
<tr>
<td>Character: Payment history for all credit and cash trade lines</td>
<td>G: Based on past due occurrence for &lt;1 yr, 1-2 yrs, &gt;2 yrs separated by trade line</td>
</tr>
<tr>
<td></td>
<td>F: Based on past due occurrence for &lt;1 yr, 1-2 yrs, &gt;2 yrs separated by trade line</td>
</tr>
<tr>
<td></td>
<td>P: Based on past due occurrence for &lt;1 yr, 1-2 yrs, &gt;2 yrs separated by trade line</td>
</tr>
<tr>
<td>Capacity</td>
<td>H: DTI &lt;45% or discretionary monthly income &gt;2x mortgage payment</td>
</tr>
<tr>
<td></td>
<td>L: DTI 45%+ and discretionary monthly income &lt;2x mortgage payment</td>
</tr>
<tr>
<td>Collateral &amp; conditions exposure</td>
<td>L: LTV 80% or less</td>
</tr>
<tr>
<td></td>
<td>H: LTV 81%+</td>
</tr>
</tbody>
</table>

**Figure 10: Home purchase mortgage loan primary factors – 30-year fixed-rate.**

<table>
<thead>
<tr>
<th>Primary Factors</th>
<th>Categories, Definitions &amp; Value Assignments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital</td>
<td>G: High net worth &amp; liquidity</td>
</tr>
<tr>
<td></td>
<td>F: Moderate net worth &amp; sufficient liquidity</td>
</tr>
<tr>
<td></td>
<td>P: Low net worth &amp; minimal savings</td>
</tr>
<tr>
<td>Character: Payment history for all credit and cash trade lines</td>
<td>G: Based on past due occurrence for &lt;1 yr, 1-2 yrs, &gt;2 yrs separated by trade line</td>
</tr>
<tr>
<td></td>
<td>F: Based on past due occurrence for &lt;1 yr, 1-2 yrs, &gt;2 yrs separated by trade line</td>
</tr>
<tr>
<td></td>
<td>P: Based on past due occurrence for &lt;1 yr, 1-2 yrs, &gt;2 yrs separated by trade line</td>
</tr>
<tr>
<td>Capacity</td>
<td>H: DTI &lt;40% or discretionary monthly income &gt;3x mortgage payment</td>
</tr>
<tr>
<td></td>
<td>L: DTI &gt;40% + and discretionary monthly income &lt;3x mortgage payment</td>
</tr>
<tr>
<td>Collateral &amp; conditions exposure</td>
<td>L: LTV 75% or less</td>
</tr>
<tr>
<td></td>
<td>H: LTV 76%+</td>
</tr>
</tbody>
</table>

**Figure 11: Home purchase mortgage loan primary factors – five-year ARM.**

---

53 Includes alternative data tradelines, e.g., rent, utility payments, telecommunications payments, etc.
54 DTI calculated as the ratio of current total monthly debt payments to current gross income; monthly mortgage payment includes taxes and insurance.
55 LTV Ratio calculated as loan amount divided by the market value of the collateral.
<table>
<thead>
<tr>
<th>Handle</th>
<th>Capital</th>
<th>Character: Payment History</th>
<th>Capacity</th>
<th>Collateral/Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>G</td>
<td>G</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>2</td>
<td>G</td>
<td>G</td>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>3</td>
<td>G</td>
<td>F</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>4</td>
<td>G</td>
<td>F</td>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>5</td>
<td>G</td>
<td>P</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>6</td>
<td>G</td>
<td>P</td>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>7</td>
<td>F</td>
<td>G</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>8</td>
<td>F</td>
<td>G</td>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>9</td>
<td>F</td>
<td>F</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>10</td>
<td>F</td>
<td>F</td>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>11</td>
<td>F</td>
<td>P</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>12</td>
<td>F</td>
<td>P</td>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>13</td>
<td>P</td>
<td>G</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>14</td>
<td>P</td>
<td>G</td>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>15</td>
<td>P</td>
<td>F</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>16</td>
<td>P</td>
<td>F</td>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>17</td>
<td>P</td>
<td>P</td>
<td>H</td>
<td>L</td>
</tr>
<tr>
<td>18</td>
<td>P</td>
<td>P</td>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>19</td>
<td>G</td>
<td>G</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>20</td>
<td>G</td>
<td>G</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td>21</td>
<td>G</td>
<td>F</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>22</td>
<td>G</td>
<td>F</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td>23</td>
<td>G</td>
<td>P</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>24</td>
<td>G</td>
<td>P</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td>25</td>
<td>F</td>
<td>G</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>26</td>
<td>F</td>
<td>G</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td>27</td>
<td>F</td>
<td>F</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>28</td>
<td>F</td>
<td>F</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td>29</td>
<td>F</td>
<td>P</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>30</td>
<td>F</td>
<td>P</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td>31</td>
<td>P</td>
<td>G</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>32</td>
<td>P</td>
<td>G</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td>33</td>
<td>P</td>
<td>F</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>34</td>
<td>P</td>
<td>F</td>
<td>L</td>
<td>H</td>
</tr>
<tr>
<td>35</td>
<td>P</td>
<td>P</td>
<td>H</td>
<td>H</td>
</tr>
<tr>
<td>36</td>
<td>P</td>
<td>P</td>
<td>L</td>
<td>H</td>
</tr>
</tbody>
</table>
Examples of secondary factors are shown in Figure 13. The current subprime crisis has seen certain loan products villianized, such as low- or no-documentation loans, option-adjustable priced mortgages, interest-only ARMs, 40-year mortgages, etc. In the case of some of the variations on ARMs, the issue is more with how those products were administered than the products themselves. A five-year ARM may make sense for borrowers having a strong capital position and adequate reserves. Borrowers who lack strong capital but have strong capacity may still be good candidates if they have a strong savings rate and they agree to build an adequate reserve over time to immunize themselves against the imbedded interest rate risk in their ARM (see last example listed in secondary factors).

<table>
<thead>
<tr>
<th>MONTHS OF RESERVES</th>
<th>G- 6 months +</th>
<th>F- 3-5 months</th>
<th>P- 2 months or less</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIMILAR HOUSING EXPENSE</td>
<td>G- 120% or less of previous payment</td>
<td>F- &gt;120-135% of previous payment</td>
<td>P- &gt;135% of previous payment</td>
</tr>
<tr>
<td>TIME IN PROFESSION</td>
<td>G- 5 yrs +</td>
<td>F- 3-4 yrs</td>
<td>P- &lt;3 yrs</td>
</tr>
<tr>
<td>STRONG LIQUID ASSETS</td>
<td>G- &gt;10% Loan Amt.</td>
<td>F- 5 to 9% Loan Amt.</td>
<td>P- 4% or less Loan Amt</td>
</tr>
<tr>
<td>HISTORY OF HANDLING HIGHER DEBT</td>
<td>G- 3+yrs</td>
<td>F- 1-2yrs</td>
<td>P- &lt;1yrs</td>
</tr>
<tr>
<td>DISCRETIONARY INCOME</td>
<td>G- &gt; $2M/mo.</td>
<td>F- $1 to 2M/mo.</td>
<td>P- &lt;$1M/mo.</td>
</tr>
<tr>
<td>RELATIONSHIP</td>
<td>G- 2+ loan, deposit, investment accounts</td>
<td>F- 1 loan, deposit, or investment account</td>
<td>P- None</td>
</tr>
<tr>
<td>MANDATORY RESERVE OR PRINCIPAL PAYDOWN W/ RE-AMORTIZATION AT RESET DATE IF HIGHER PAYMENT REQUIRED</td>
<td>G- Additional 20% of monthly payment set in reserve or paid towards principal each month for first 30 months</td>
<td>F- Additional 10% of monthly payment set in reserve or paid towards principal each month for first 30 months</td>
<td>P- None</td>
</tr>
</tbody>
</table>

Figure 13: Secondary factors: Weight in final decision of 5 percent to 15 percent each.

The primary factors and secondary factors are combined to render a loan-underwriting decision. Figure 14 specifies the two-stage action table for this example. There are 36 primary handle cells based on the handle dimensions.  

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56 For an explanation of why there are 72 entries in the table, see Abrahams and Zhang (2008), p. 223.
<table>
<thead>
<tr>
<th>Capital</th>
<th>Payment History</th>
<th>Capacity</th>
<th>Low Expo Coll/Cond</th>
<th>High Expo Coll/Cond</th>
<th>Low Expo Coll/Cond</th>
<th>High Expo Coll/Cond</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>Good</td>
<td>Low</td>
<td>1 Accept</td>
<td>19 Accept</td>
<td>37 n/a</td>
<td>55 n/a</td>
</tr>
<tr>
<td>Good</td>
<td>Good</td>
<td>High</td>
<td>2 Accept</td>
<td>20 Stage 2</td>
<td>38 n/a</td>
<td>56 Denial</td>
</tr>
<tr>
<td>Good</td>
<td>Fair</td>
<td>Low</td>
<td>3 Accept</td>
<td>21 Stage 2</td>
<td>39 n/a</td>
<td>57 Denial</td>
</tr>
<tr>
<td>Good</td>
<td>Fair</td>
<td>High</td>
<td>4 Stage 2</td>
<td>22 Stage 2</td>
<td>40 Denial</td>
<td>58 Denial</td>
</tr>
<tr>
<td>Good</td>
<td>Poor</td>
<td>Low</td>
<td>5 Accept</td>
<td>23 Stage 2</td>
<td>41 n/a</td>
<td>59 Denial</td>
</tr>
<tr>
<td>Good</td>
<td>Poor</td>
<td>High</td>
<td>6 Stage 2</td>
<td>24 Denial</td>
<td>42 Denial</td>
<td>60 n/a</td>
</tr>
<tr>
<td>Fair</td>
<td>Good</td>
<td>Low</td>
<td>7 Accept</td>
<td>25 Accept</td>
<td>43 n/a</td>
<td>61 n/a</td>
</tr>
<tr>
<td>Fair</td>
<td>Good</td>
<td>High</td>
<td>8 Accept</td>
<td>26 Stage 2</td>
<td>44 n/a</td>
<td>62 Denial</td>
</tr>
<tr>
<td>Fair</td>
<td>Fair</td>
<td>Low</td>
<td>9 Accept</td>
<td>27 Stage 2</td>
<td>45 n/a</td>
<td>63 Denial</td>
</tr>
<tr>
<td>Fair</td>
<td>Fair</td>
<td>High</td>
<td>10 Stage 2</td>
<td>28 Stage 2</td>
<td>46 Denial</td>
<td>64 Denial</td>
</tr>
<tr>
<td>Fair</td>
<td>Poor</td>
<td>Low</td>
<td>11 Accept</td>
<td>29 Stage 2</td>
<td>47 n/a</td>
<td>65 Denial</td>
</tr>
<tr>
<td>Fair</td>
<td>Poor</td>
<td>High</td>
<td>12 Stage 2</td>
<td>30 Denial</td>
<td>48 Denial</td>
<td>66 n/a</td>
</tr>
<tr>
<td>Poor</td>
<td>Good</td>
<td>Low</td>
<td>13 Accept</td>
<td>31 Stage 2</td>
<td>49 n/a</td>
<td>67 Denial</td>
</tr>
<tr>
<td>Poor</td>
<td>Good</td>
<td>High</td>
<td>14 Accept</td>
<td>32 Stage 2</td>
<td>50 n/a</td>
<td>68 Denial</td>
</tr>
<tr>
<td>Poor</td>
<td>Fair</td>
<td>Low</td>
<td>15 Stage 2</td>
<td>33 Stage 2</td>
<td>51 Denial</td>
<td>69 Denial</td>
</tr>
<tr>
<td>Poor</td>
<td>Fair</td>
<td>High</td>
<td>16 Stage 2</td>
<td>34 Denial</td>
<td>52 Denial</td>
<td>70 n/a</td>
</tr>
<tr>
<td>Poor</td>
<td>Poor</td>
<td>Low</td>
<td>17 Stage 2</td>
<td>35 Decline</td>
<td>53 Denial</td>
<td>71 n/a</td>
</tr>
<tr>
<td>Poor</td>
<td>Poor</td>
<td>High</td>
<td>18 Stage 2</td>
<td>36 Decline</td>
<td>54 Denial</td>
<td>72 n/a</td>
</tr>
</tbody>
</table>

Figure 14: Two-stage action table for mortgage loan examples.\(^\text{57}\)

It is necessary that every handle cell relationship to secondary factors be defined, even if the definition specifies to approve or decline with no secondary factors required, or a general rule such as any two secondary factors with good (G) ratings. A more in-depth discussion of how the secondary factors would be applied to the primary factor combinations (handle cells) for a similar example can be found in the literature.\(^\text{58}\)

\(^{57}\) Note that in this particular example the primary (stage 1) factors are identical, with identical actions, but the stage 2 factors will not be the same for a 30-year fixed-rate mortgage versus the five-year ARM.

\(^{58}\) See Abrahams and Zhang (2008), pp. 222-228.
Summary and subprime implications

A re-engineering of the credit evaluation process is needed to eliminate the possibility of future crises and also speed assessment and provide relief to those who are experiencing, or will experience, significant hardship. We say “will” because there are large numbers of mortgage loans that are due for their first rate resets between the second quarter of 2008 and the summer of 2012.

There are many theories concerning the causes of the subprime crisis. There have been many allegations floating around, and the list of suspects is long. Some examples include:

- Products (put consumers in a debt trap).
- Consumers (knew what they were signing up for and threw caution to the wind).
- Speculators (evidenced by non-owner-occupied property purchases).
- Appraisers (inflated valuations fueled a market bubble).
- Builders (housing is overbuilt on the high end and overpriced).
- Real estate agents (up-selling – stretching borrower to their max).
- Interest rates (increase after a prolonged period of decline).
- Lenders/brokers (commission-driven behavior).
- Housing market (downturn to blame for 90 percent of problem).
- Regulatory and internal controls (massive failure in such a highly regulated industry raises questions of oversight adequacy and safeguard sufficiency). For example:
  - Where was risk limitation addressed, and what were the key risk indicators?
  - What were the thresholds, who set them, and how were they determined?
  - How often was risk monitoring performed, at what level, and by whom?
- Rating agencies and investment bankers (inadequate understanding of imbedded risk in structured debt obligations).
- Underwriting standards (failure to gauge borrower ability to repay).

It is easy to fall into a loop of blame and to penalize suspected offenders. Unfortunately, there are segments of borrowers who no longer have access to credit and who had no part in the current crisis. In some circles, there is a rationalization that some people are not worthy of owning their residence and that they should be renters for life. There is a difference, though, between choosing to rent for life and not being given the chance to be a homeowner. Furthermore, the act of becoming a homeowner can be transformational by itself, which makes it difficult to predict how someone will behave once they have an owner stake in a property or an enterprise.
This paper has focused on the last bullet. It is essential to correct the problem of underwriting standards as early in the loan origination process as possible to avoid fallout that can mushroom and cascade over time. By putting in place controls that remove some broker and lender discretion, and also some borrower choices, the creation of debt traps and credit time bombs can be avoided. The CCAF borrower contour determines what products are available to borrower segments according to their credit qualifications. Even if there are bad actors that want to sell consumers products that will put them into a debt trap, CCAF will not allow them to succeed, nor will it allow consumers to pick financing that will prove too costly for them. Because CCAF is comprehensible, it will be easy for lenders to explain to consumers what is available to them and why.

CCAF ensures comprehensive classification of borrowers and loans relative to the major categories of factors linked to loan default risk as a prerequisite to risk quantification. It avoids substituting payment habit and loan preference history factors as proxies for debt ratio and income, net worth, liquid reserves and payment shock because they are clearly out of context relative to the broad categories of capacity and capital. The fact that CCAF is validated from both a qualitative and quantitative basis and monitored for any signs of predictive decay or compliance violations ensures that it will perform at least as well as expected relative to credit risk measurement, responsible lending, and fair lending. Because of CCAF’s adaptive, forward-looking nature, it will perform acceptably under all economic and sector cycles.

**Intervention**

A primary contributory factor to the current subprime crisis was the failure of current lender 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. In other words, a loan that looks good today can in reality be 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.

For example, suppose a borrower wanted to buy, rather than rent, housing while attending medical school for four years. Further suppose that he/she found a home selling for 85 percent of appraised value, and on the lower end of property values in the neighborhood. In this case, a 5/1 interest-only ARM with a monthly payment amount that is 50 percent of the prevailing rate for a comparable rental unit makes perfect sense. Any principal repayments made by the borrower immediately reduce the next month’s interest payment, due to the simple interest feature of this type of loan. Even without additional paydowns, the 5/1 I/O ARM is more affordable than a conventional loan and will be liquidated prior to the five-year reset date in this example.

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Even if there are bad actors that want to sell consumers products that will put them into a debt trap, CCAF will not allow them to succeed, nor will it allow consumers to pick financing that will prove too costly for them.

---

59 This is not uncommon for properties held in corporate relocation programs or in bank OREO portfolios.
The borrower is positioned to realize a gain on sale if the property value goes up, but is also protected if there is some depreciation (up to 15 percent in this case) if property values are depressed at the time of liquidation. Again, the cost of renting in this example is twice that of financing the purchase, with no possibility of any capital appreciation on a comparable home over the same period of time. Furthermore, it is unfortunate that these same products, which are either no longer available or have a tarnished name, are precisely the type of loans that would offer advantages to a very broad segment of home buyers when the housing market is in a slump and home values are significantly depressed! Sadly, the removal of these types of financing vehicles will serve only to drive real estate prices down even further and lengthen the time it takes to sell the oversupply of housing stock that continues to be fueled by foreclosures.

The magnitude of the current crisis makes it abundantly clear that there is significant room and need for improvement in current credit assessment approaches. Various solutions have been suggested to deal with subprime issues, but a common theme has been the establishment of long-term segmentation solutions coupled with more systematic approaches. The credit assessment framework naturally affords a sustainable and sensible segmentation based on all primary credit factors, and it offers a systematic means for taking appropriate actions relative to those identified segments and for ongoing monitoring of the impact of those actions in a comprehensive and efficient manner. CCAF accomplishes this by expanding the boundaries of information associated with existing variable-rate mortgage holders, appropriately segmenting them based upon primary factors, layering in needed secondary risk mitigation factors, assigning actions for each identified segment, and putting in place an adaptable policy mechanism that is responsive to the evolving economic climate. More specifically, the application of CCAF to 1) identify borrowers who need assistance and loans that can be salvaged to avoid foreclosure, 2) measure the impact of strategies on foreclosure and loss exposures, and 3) continuously update required actions to achieve the best possible outcomes in these difficult circumstances, entails the following steps:

1. Apply CCAF to current population of mortgage holders “at risk” now, or in the next “n” months.
2. Identify primary factors that will define the transaction contour.
3. Assign actions for each identified segment.
4. Determine mitigation rules as secondary (stage 2) factors.
5. Put in place an adaptable policy mechanism that is responsive to the evolving economic climate.

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60 This example is based on an actual market analysis and loan originated in the Atlanta metropolitan area in 2006.
61 David Nason, Assistant Treasury Secretary for Financial Institutions, recently said that the industry has “to be able to segment a population in a way that can create long-term solutions.” At a Nov. 8, 2007, Joint Economic Committee hearing, Federal Reserve Board Chairman Ben Bernanke said, “We support scaling up these efforts, and the best way to do that is by creating more systematic approaches.”
62 Both prime and subprime borrowers who either have experienced, or will be experiencing, an increase in their monthly payment amount.
63 Such as behavioral factors based upon alternative data, up-to-date information, and projected risk metrics.
6. Update the system continuously using the system maintenance techniques described to ensure data are timely and complete.

7. Monitor results regularly for accuracy and measure success using the system validation techniques described and simple trend analysis (is risk increasing, stable, or decreasing?).

8. For low- and no-documentation loans, consider augmenting with alternative data. Attempt to determine actual capacity and capital to classify relative to the borrower contour.

A credit assessment framework that is sensible, transparent and comprehensive is needed for both crisis intervention and prevention. Widespread use of flawed models – not the loan products themselves – is a root cause of the problem. The comprehensive credit assessment framework (CCAF) offers lending institutions the ability to approve and better price credit through the use of alternative data and new, improved models. It enables the construction of credit profiles across multiple categories and factors and puts credit profiles in an appropriate context for assessment of borrower creditworthiness and loan repayment performance.

CCAF uses advanced analytical models to estimate risk and forecast performance. It does so by leveraging a more meaningful segmentation coupled with expanded source data that has been integrated with judgmental factors and policy thresholds. CCAF’s systematic segmentation approach has implications for both intervention in the mortgage crisis and prevention of future financial disruptions.

**Prevention**

CCAF can be used not only to deal with the current crisis but also to prevent future financial crises. Classification of all credit transactions at their inception may be performed sensibly and comprehensively using CCAF and the Five Cs of credit. In preliminary discussions with major industry groups, it has been suggested that standardization of the credit assessment framework would pay huge dividends, as opposed to the case where each lending institution invents its own version of the primary factors and their associated thresholds. We agree and see great value in such a framework from several directions. Before discussing those advantages, we examine briefly what a standard framework might look like.

For a borrower contour, we have the example previously described in Figure 4. Agreement would need to be reached on the exact factors that would be used to determine payment performance, capacity and capital. Once the factors are agreed upon, thresholds relative to those factors would need to be specified to determine how many distinct classifications would be required for each of the three major categories and how borrowers would be assigned to them.
Once this system is put into place, lenders could capture and verify the credit contour for loans that are approved and report it to the credit bureaus along with the first report on that loan’s payment performance. The credit bureaus would then possess a common definition of borrower qualification that is consistent and that would have immediate interpretation for the consumer. The consumer could request their credit bureau borrower contour to verify that it is accurate. There would be no need to keep the definitions secret.

The transaction contour would be constructed by augmenting the borrower contour relative to the last two Cs of credit: collateral and conditions. This process would be specific to the type of loan, e.g., credit card, auto loan, mortgage, etc. For a credit card, the additional categories might relate to features such as line amount and pricing tiers. For a mortgage loan, collateral categorization might be determined by the borrower’s equity position relative to property valuation that is based on either current appraised value for fixed-rate loans or estimated future value for variable-rate loans. The thresholds might fall into three classifications: for example, weak (less than 15 percent), moderate (15-30 percent) and strong (greater than 30 percent).

For a mortgage loan, the conditions category might classify loans according to whether they are fixed- or variable-priced and whether they are conforming, which would lead to four possible values, e.g., fixed and conforming, etc. For a home equity loan, a similar scheme to that of mortgages might be used, where borrower equity would need to take into consideration any/all senior lien positions for the equity position calculation and possibly whether the loan is a piggyback, whether the purpose of the loan is to improve the underlying loan collateral, and/or possibly whether the collateral is the borrower’s primary residence.

Having CCAF in place would be advantageous not only to lenders for more accurate pricing of the true transaction risk, but also for creating homogeneous pools of assets for securitization and sale. With CCAF, the composition of securitized pools, or loans bundled for sale (with servicing retained or released), could be regulated by the transaction contour classifications. In the credit card arena, the credit score plays a dominant role in pricing the risk for sale to investors in the capital markets. CCAF contours would provide greater information and deliver superior pool performance over time, which would lower risk due to better diversification, lower cost in fees charged by credit enhancers and insurers, and improve returns due to more reliable and sustainable cash flows. We see the secondary market players embracing CCAF in time as a best practice.
Another important related concern has been discussed relative to the need to be able to trace loans in investor pools back to their source through a unique identifier, like the nine-character CUSIP associated with all North American securities that facilitates clearing and settlement of trades. We advocate that, in designing the identifier, additional thought be given to building in some extra intelligence. To uniquely identify a loan, the originating institution, the loan booking system, and the original loan number would need to be codified at a minimum.

We would like to see the transaction contour also imbedded in the universal loan identifier. The power afforded by having the contour in the identifier would be substantial. Pool performance could be monitored at the loan level and improved projections on delinquency, loss and prepayments would be possible by building separate models based upon the contour segments.

Furthermore, the borrower contour can drive product offering choices relative to specific credit risk segments. Presumably, the most suitable mortgage product will vary widely by segment and may not be the most profitable loan for the bank or the most inexpensive loan for the consumer. For the lender it avoids financial disruption through the use of forward-looking criteria and helps manage reserves, gauge suitability and affordability of different financial products, and captures early warning signals during the analysis process. In addition to early warnings, CCAF can be used to impose limits on portfolio segments so that crises can be averted and performance problems minimized.

Portfolio limits can be based upon more granular regulatory guidelines made possible by CCAF, in addition to the institution’s experience using CCAF, which will afford greater information for portfolio management over time and stronger internal controls that can head off trouble before it cascades into huge losses for the institution. Based upon these facts, CCAF offers superior risk measurement through a sensible and transparent process that best serves the broadest spectrum of today’s credit market, prime and non-prime alike.

64 CUSIP is an acronym for Committee on Uniform Security Identification Procedures. It is owned by the American Bankers Association and operated by Standard & Poor’s.

65 In some lending institutions, separate instances of the loan booking system are used in separate regions or states, which means that a region or state identifier also needs to be appended. In short, lenders need to come up with a unique identifier that can then be associated with their lending institution code to make unique identification possible.

66 Building in this intelligence can be accomplished either through a coding algorithm that can accept an alphanumeric string of digits and decipher it, or by designating a position in the string of digits where the transaction contour will reside so it can be easily retrieved.

Conclusion

Based on pragmatic market analysis, we identified some of the most important properties of a credit underwriting system. They are listed below, along with key capabilities of CCAF that relate to each one.

1. **Accurate.** Affords better risk estimation because it is a closer fit to the business reality.

2. **Fast.** Computer-driven decisions, data and policy maintenance, operational and management reporting.

3. **Cost-effective.** Fewer models required and model redevelopment costs virtually eliminated.

4. **Flexible.** Best of art and science – rules coexist with formulas.

5. **Consistent.** Systematic and more consistent than credit scoring because there are virtually no system overrides.

6. **Reliable.** Validated from both a quantitative and qualitative standpoint.

7. **Easy to understand.** BC/TC interpretable and fosters borrower financial literacy.

8. **Based on proven lending principles.** Five Cs and common sense.

9. **Rates the borrower’s ability to repay the loan.** Capacity and capital required as primary factors.

10. **Able to be effectively monitored.** Handle, and related multi-factor views, provide contextual meaning relative to acceptance rates, applicant population mix, and borrower segment performance relative to default risk, delinquency, pre-payment, profit, etc.

11. **Provides adequate controls to limit risk.** Policy caps can be enforced to avoid unwanted concentrations at the handle cell level.

12. **Adaptive and easily updated.** More, not less, predictive over time!

In summary, CCAF’s holistic classification affords transparency, conveys the essence of the borrower’s qualifications, and risk rates credit transactions within that complete context. As a result, significant overstatement or understatement of risk on individual loan transactions can be avoided. CCAF affords greater control of loan decisions 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. This allows for efficiency, transparency and accuracy.
CCAF transparency fosters financial education and literacy relative to the underwriting process and enables easy identification of loans that are truly affordable relative to every borrower segment. Having a standardized version of CCAF could enable regulators to make comparisons across lenders and more explicitly examine safety and soundness of loan underwriting practices and product offerings. It could also enable them to monitor the diversity and vulnerability of loan portfolios in advance of adverse loan quality trends that not only occur during typical economic downturns, but also surface unexpectedly – like the subprime mortgage crisis.

References


“Report to Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit,” Board of Governors of the Federal Reserve System, August 2007, p.117.


68 There are additional areas that consumers need to consider such as the pros and cons of products, escrow options, tax nuances, and negotiation strategies. See Abrahams, Clark R., Interpreting the New HMDA Pricing Data, SAS Institute White Paper ABA Regulatory Compliance Conference program presentation script for Breakout Sessions 7C and 8F, June 14, 2006.
Information Policy Institute, “Giving Underserved Consumers Better Access to the Credit System: The Promise of Non-Traditional Data,” © July 2005; and “Give Credit Where Credit is Due: Increasing Access to Affordable Mainstream Credit Using Alternative Data,” © December 2006.


Siddiqi, Naeem, Credit Risk Scorecards; Developing and Implementing Intelligent Scoring, John Wiley & Sons, Inc., © 2006.


