# Data Augmentation for CECL Compliance in Automobile Finance

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*Abstract*— ***Many new regulations have been enacted in response to the 2008 financial crisis. Most of these regulations prescribe further analysis and transparency of financial data to support better understanding of risks associated with various financial instruments. In fact, many industry experts have expressed an opinion that the crisis perhaps would have been less severe and happened quicker if we had better indicators to predict it.***

***Both the FASB and IFRS have recently issued pronouncements that require greater quantification associated with risks in lending. Stakeholders at all levels including regulators, investors and accountants are only beginning to understand the effects of these additional requirements on data requirements to support these directives.***

***This document outlines these new requirements and the derivative data implications for compliance. We further outline an approach for obtaining, segmenting and keeping the data current so that continuous risk assessment, reporting and quantification of financial exposure can be supported. Our approach focuses on integration of historical with forecasted information so that a valid, mathematical assessment can be performed as to the probabilities of default of loans in the automobile finance industry. We conclude with an example to support initial compliance with these standards.***

**Keywords— Data Analytics, Data Science, Data Sets, FASB CECL, IFRS 9, Predictive Analytics.**

## I. INTRODUCTION

As a result of the financial crisis of 2008, standard setting bodies were asked to research new pronouncements that would have perhaps detected sooner or averted such a catastrophic event. The Financial Accounting Standards Board ("FASB"; United States of America) and the International Accounting Standards Board ("IASB" scope is more world-wide in nature) both studied the issues and pronounced two sets of standards: FASB AU 2016-13; (topic 326: Credit Losses) and IASB IFRS 9. While both standards are similar they differ in the implementation of new methods for recognition of loan losses [2].

One of the top challenges in implementing these new measurement standards will be to select the appropriate data and to operationalize it into forward-looking models [1]. It will be particularly acute for organizations that do not have the data to begin with or do not have sufficient data to statistically support the loan provision numbers [3].

Our contribution in this document is to outline a potential set of tools for increasing the accuracy of the estimates by drawing on third party data sets. We first discuss the general background of the provisions and focus again in the methodologies that support these new standards. Next, we discuss some of the data sufficiency problems that could be associated with implementation in the automobile finance industry. We finally illustrate a potential way forward with proprietary data sets by means of a test case.

## II. BACKGROUND

The traditional method for recognizing loan portfolio losses is one that bases the amount to be written off on the prior experience of the lender. This method had been challenged for some time in the wake of the 2008 Financial Crisis [6]. Several shortfalls make the continued usage of this methodology a very risky proposition because it ignores key items such as current economic conditions and changes in risk profile of the borrowers. These issues are discussed below but first we begin with a review of the (until 2019 for major Financial Institutions) existing process.

### *A. The Current Process.*

As mentioned above, the current process of recognizing increases in loan loss provisions has been based on experience of the lender [9]. In addition, this is done for both reporting to investors under Generally Accepted Accounting Principles (GAAP) and under US Federal Tax Law [15] , [16]. The differences between the two are accounted for as a "timing difference" meaning the two sets of books keep track of this variation which, over time, should equalize [19].

In current practice, the "experience", meaning the rate of losses based on what has happened in the past is taken as a percentage of the overall outstanding balance in the portfolio. In the automobile industry that ranges from 10% to 12% of the balance as of 2018 [11]. This is a general average of the industry as a whole, in some cases, losses may be as small as 2-3% for prime lenders (to those borrowers with pristine credit) or much deeper for sub-prime lenders (those that accept borrowers with many recent derogatoriness, albeit at a much higher interest rate to compensate for the higher probability of default).

From a US Federal Tax perspective, the general practice is to take the average percentage of losses in regard to the outstanding portfolio balance over the past 5 years for "normal" tax or over the past 6 years for "alternative minimum" tax [15]. Certain membership-driven financial institutions (cooperatives, credit unions) may also elect up to an 8% deduction from income in alternative to the averaging method described above [16]. Up to this point, the GAAP and Tax methods have not been significantly different in most cases and as mentioned above, these timing differences equalize over time.

### B. *Current Data Requirements.*

The current process requires that data be accumulated for loans that are considered in default (when it is evident that the borrower cannot fulfill their commitments, typically by missing several payments) or when collateral is secured, if any, and the balance written off versus the allowance for the losses. The data required is the portfolio balance for the prior years (the time is based on judgement for GAAP and either 4 or 5 years for US Federal Tax), and the corresponding amounts that have been charged off from the portfolios at that time. This method has been operational for some time and lenders' systems have been programmed to derive those results. The process requires portfolio "master data"; the balance of the portfolio and the loan loss reserve and "transactional data" for the individual charge-off amounts.

### C. *Reliability of Estimates.*

One of the principal challenges to the above methods in the wake of the 2008 Financial Crisis was the inability to incorporate changing future conditions into the analysis. Quite simply, the purely historical, based on percentage of balance does not take into consideration some of these major factors [10][4]:

- Changing economic environment and ability of borrowers to fulfill their obligations under loan terms.
- The "seasoning" of loans, meaning, the inclusion of the probability of default based on the stage of a loan in its life-cycle (for example, most borrowers will not default in the initial stages or the end stages of their loan).
- The inclusion of pre-payment assumptions; in the automobile business, most prime-credit will pay off the loan before maturity for a variety of reasons (more cash-flow, existence of lower rates, trade-in for a newer model etc.).

In view of the above reasons, it was felt that the new standards should incorporate greater input from risk analysis rather than a purely historical approach to provisioning for losses [2].

## III. ADOPTED CHANGES

The two main organizations for promulgating these standards are the Financial Accounting Standards Board (FASB) and the International Financial Reporting Standards Organization (IFRS). Post-2008 both organizations began projects to better understand and provide for more transparency into the risk associated with Loan instruments. The overwhelming feedback from the financial community was that incorporation of risk was very much needed in the provisions. We overview the general risk analysis that should be performed, the standards and their dates, and finally a brief discussion on rationale for these changes in the segments below.

### A. *Embedding Risk Analysis.*

Historical analysis is certainly a good place to begin when creating a set of estimates and a common practice. The main shortcomings with a purely historical analysis based on balances is that it does not take into consideration situational factors that could influence the behavior of a particular variable going into the future. In a very succinct view of credit, the incorporation of projections regarding economic conditions and their possible impacts on borrowers means that some reliable measures will need to be incorporated into a linear forecast (for a good overview of a linear forecast see [19]). The objective of incorporation of these measures is well spelled out into the standards, the mechanics however, are not. We next review what the standards require.

### B. *New Standard Requirements and Date Implications.*

As previously mentioned, there are two standards setting bodies. Both of these bodies have promulgated standards which require the estimation of Credit Losses based on the probability of a default. These Estimated Credit Losses (ECL) are computed as the probability of default (PD) multiplied times the Exposure at Default (EAD) or the amounts that would be charged towards the loan loss reserves net of recovery of collateral and expenses related to disposition and administration [5]. The two standards differ in their implementation as follows:

- The FASB standard requires the estimation of these ECL at the inception of the loan and to continue this estimation for subsequent reporting periods in order to provide more updated information from forecasted credit-related indicators.
- The IFRS standard requires the provision of ECL for the 12 months following the loan if it is in good status. If the loan falls into delinquent or other default

situation, the ECL should be estimated and booked for the remaining life of the loan.

Recommended implementation of the changes is for practical purposes for 2018 financial statements for those companies that wish to comply with IFRS. FASB requires compliance at 2020 for companies that are US SEC Registrants and 2021 for others.

### C. *Rationale for Changes.*

There were many reasons for recommending the change but perhaps the most important one was transparency for users of financial statements. A fundamental issue behind the new standard was to provide the investment and regulatory community with a quantifiable measure of the risks that were inherent in loan portfolios [12]. The standards contain some examples but the examples are somewhat broad and not necessarily specific to the auto lending industry. It is for this reason that we have prepared this document.

## IV. DATA SUFFICIENCY AND RELIABILITY

A major challenge in performing these analyses is the ability to source a data set with sufficient observations to derive supportable conclusions on loan defaults. Large organizations will typically have sufficient loans to perform vintage analysis but for the small to medium organizations this will prove a significant challenge. In this section we will overview the reasons for this data vacuum and the potential strategies to overcome it.

### A. *Sufficient portfolio data might not exist.*

There are a variety of reasons why sufficient data that provides meaningful historical information for executing the ECL analyses. Firstly, the number of loans in the particular time-frame vintage might not be enough to provide statistical significance. Below are some challenges associated with such situations:

- If the time-boxing algorithm corresponds to months, the number of loans made in that month might be less than 30 or as the vintage seasons, there may not be enough observations to understand the propensity to pay offs or charge offs to be able to adjust estimates accordingly.
- Following on the immediate previous, if the bucketing of loans is made with more time intervals (months or quarters), then the accuracy when predicting the vintage behavior will decrease since the subpopulations within the vintage might be significantly different.
- The credit policies enacted by management may have changed signaling a different population. For example, if management relaxed credit standards for borrowers we might be dealing with a different sub-population that might not be similar to the rest of the portfolio (in fact a different portfolio might have been created).
- The credit cycle might be longer than the amount of history available; loan history might not be available during a complete credit cycle to understand what changes will be inherent in the population when conditions change.

The above situations affect smaller lenders in greater proportion than those organizations that may have larger volumes or data facilities.

### B. *Forward-looking (Forecast) Data.*

A second challenge in obtaining relevant data is the type of forecasting index that will be selected. Most of the relevant literature will point to employment data as a meaningful set of values for assessing general economic conditions. While this will be true on an overall country-based basis, the impact of such factors may differ significantly by state or postal code for example. One would want to obtain the index and model it for the regions where the borrowers were located. In another example, the value of collateral may also vary by geography (SUVs may be more popular in the Mid-Western US and may therefore command a higher price) or by units of production being delivered (in a high gas price situation compact cars will typically command a higher price than their pre-high gas price offer).

Perhaps the key characteristic of the forecast data to be selected is the specificity that allows for greater accuracy in the future values to be predicted.

### C. *Data Selection.*

As detailed above, the data challenges associated with accurate modeling will lead the credit scientist through a careful procedure for obtaining the relevant data and forecasts to predict the behavior over time of the loans.

In our experience the first place to begin is to obtain an inventory of the available data from the portfolio. In addition to securing a dataset from the legacy systems, the researcher should interview relevant sources from management to determine the composition of their credit granting programs in the past and future to determine impacts on the independent data draw. Our experience has indicated that the following independent attributes make for a more accurate draw.

Data that is predictive of credit default can typically be classified into three categories:

1. Individual consumer (specific to lender)
2. Aggregate portfolio (specific to lender)
3. Exogenous (both macro-economic and industry related that influence the lender's baseline or à priori loss odds)

The most important elements in predicting a lender's level of credit default come from attributes that are unique to the individual consumers that comprise the portfolio. These include each individual's loan payment history, level of debt and income stability.

**Figure 1. Individual Consumer Risk Measurement**

| Variable | Input 1 | Input 2 | Source |
|---|---|---|---|
| Maturity | Months in Credit File | Number of Tradelines | Credit Bureau |
| Recency | Months since recent delinquency | Months since recent trade opened | Credit Bureau |
| Burden | Installment Debt | Revolving Debt | Credit Bureau |
| Derogatory | Number of 90 day past due trades | Number of Bankrupt Tradelines | Credit Bureau |
| Loan Structure | Loan to Value Ratio | Down Payment Percent | Loan Contract |
| Stability | Months at Current Employer | Months at Current Address | Loan Application |

The level of defaults experienced by a particular lender is also influenced by loan origination strategies, collection practices and changes in the regulatory environment. These factors determine the subset of loans the lender is likely to acquire, the effectiveness of collecting delinquent dollars and the limits placed on the company by the regulators.

**Figure 2. Aggregate Portfolio Risk Measurement**

| Variable | Input 1 | Input 2 | Source |
|---|---|---|---|
| Growth | Annual growth in dollar volume | Geographic Concentration | Loan Origination System |
| Competition | Loan Closure Rate | Pricing (APR, Discount, Participation) | Loan Origination System |
| Underwriting | Policy Exception Rates | Shifts in credit score distributions | Loan Origination System |
| Regulation | Usury Rates | Collection Practices | C.F.P.B, F.D.I.C., State Regulations |
| Collections Effectiveness | Ratio of dollars collected to outstanding | Ratio of payment promises kept vs. broken | Loan Management System |
| Servicing Strategy | Days past due at repo assignment | Dollars deferred as a percentage of the portfolio | Loan Management System |

Finally, credit default levels are influenced by exogenous factors, such as a shift in the availability of debt or lower recovery rates caused by a drop in used vehicle values. These external influencers can shift the total number, dollar magnitude of defaults and timing of credit defaults a lender experiences.

**Figure 3. Exogenous Risk Measurement**

| Variable | Input 1 | Input 2 | Source |
|---|---|---|---|
| Availability of Credit | G19 Report | Growth Rate in Auto Financing | Federal Reserve, Experian Automotive |
| Vehicle Values | Manheim Index | JD Power Index | JD Power, Manheim Consulting |
| Vehicle Demand | Days Inventory | New and used sales volume | NADA, NIADA. Federal Reserve |
| Economic Cycle | Treasury Yield Curves | Employment Levels | Federal Reserve, BLS |
| Market Credit Performance | Prime ABS Index | Subprime ABS Index | Fitch Ratings, S&P, Moody's |

Each of the three categories of data (individual, portfolio and exogenous) represent factors that are largely independent of each other and compensatory in nature. For example, the twenty-seven percent increase in used vehicle values from 2009 to 2011 [18] contributed to record low levels of credit defaults for lenders on loans originated during the Great Recession, where the incidence of default was increasing. Credit scientists must be careful to select significant inputs from each of the three categories in order to achieve the most accurate estimates.

## V. MODEL BUILDING

Models are representations of reality that help us understand certain phenomenon. We build models to try and predict the behavior of a variable (in this case the probability of default for a loan or a loan vintage). The next discussion focuses on an approach to model building that we have found to be successful in the automobile near-prime finance industry.

### *A. Historical: A Place to Start.*

The majority of data contributing to a lender's loss forecast will come from either their own experience, or from data that represents a close proxy in the event the lender does not have enough data for a statistically meaningful model.

The key forecasted elements that historical analysis should produce are:

- Cumulative unit default by loan origination vintage (PD – Probability of Default by month)
- Default timing (hazard curves) by origination vintage

- Principal outstanding at default (EAD – Exposure at Default)
- Loss severity at default (by month of default). This includes both the vehicle value depreciation net of recovery and the impact of loan structure. (LGD – Loss Given Default)
- The impact of seasonality on performance

These elements are combined to produce an origination-time forecast from which actuals are measured against and remaining losses may be estimated.

### B. *Integrating Forward Looking Features.*

Historical credit performance is a function of a number of independent and often compensating elements. As such, it is necessary for credit scientists to decompose historical performance into their constituent categories [7].

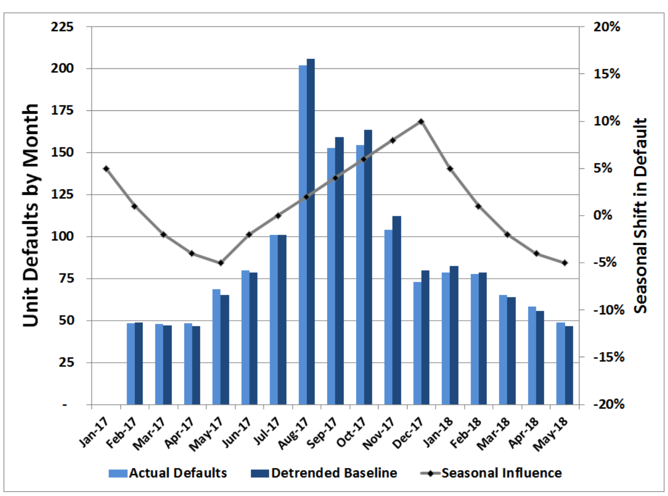
As mentioned above, credit performance is influenced by:

- Individual consumer risk
- Aggregate portfolio trends
- Exogenous factors

We will now begin to incorporate historical data which must be analyzed as a time series in order to determine how the influence of each factor, and then de-trend the data in order to arrive at an environmentally neutral loss estimate.

To illustrate this, refer to the data in Graph 1, which represents defaults by month for a pool of 10,000 loans originated in January 2017. Consumer auto loans tend to experience seasonality that leads to fewer defaults in the second quarter and increased defaults in the fourth quarter. To estimate the most accurate loss expectation at the point of origination, seasonal affects (that are independent of the risk of the individual consumer) must be removed.

**Graph 1. The Impact of Seasonality on Default for January 2017 Originations**




Once this is done, the credit scientist must evaluate elements that may cause future deviations from the neutral baseline. These factors include the influence of competition, strategy, vehicle values and recession. Analysis produced in this stage is used to flex total portfolio performance based on estimates of the expected duration of the exogenous influence.

### C. *Model Back Testing.*

Each of the components of loss, such as seasonality, is modeled separately due their independent influence on performance and the lack of sufficient data to model every contingency simultaneously. In practice, however, these components must be re-integrated and applied to historical data when producing forward looking estimates.

To ensure a robust fit, the forecasting model must be back-tested using only what was known at origination (loan inception) for the following factors:

- Individual applicant's probability of default
- Likely loss timing and recovery value given vehicle information
- Estimates of forward looking factors, such as the economy, competition, demand and debt levels

Historical data must be aggregated into vintage cohorts so as to reduce issues related to sample size. In addition, vintages must be removed from analysis where sufficient seasoning has not occurred.

Model fit must be done with consideration given to sample size and the distribution of the data [14]. Data related to consumer credit performance rarely tends to be normally distributed, which is why non-parametric measures tend to be the standard These measures include the Kolmogorov-Smirnov (K-S) [13], Gini Coefficient [13] and the Anderson-Darling Test [17].

### D. *Model Calibration.*

Once back testing is complete, the final model must be calibrated to most closely match the state of the portfolio going forward. This involves adjusting the baseline loss estimate to account for adverse or positive selection bias, current origination practices, market pressure, collections practice and vehicle value trajectory [8]. An additional component of calibration is the weighting of forward looking factors, which may change based on where the lender sits within the credit cycle. The credit scientist must endeavor to minimize the weighting of portfolio, industry and market factors so as to minimize any non-random variation between expected and observed results identified in the back-testing phase [8].

## VI. BUILDING THE CUSTOMIZED DATA SET - AN AUTOMOBILE FINANCE EXAMPLE

We modeled an example based on historical data, the results of which follow. Five years of lender performance data were selected from a non-prime automobile finance company with an active loan portfolio totaling $100 million. The data was comprised of origination-time credit, loan structure and application data for 11,226 fundings. Credit performance data was also included for each loan by month. Performance data included payoff date, charge-off date, gross charge-off dollars, vehicle recovery dollars, and net charge-off dollars. The active portfolio, for which the CECL provision would be estimated, consisted of 5,817 loans.

A. ***The Static Model.***

All of the funded loans were grouped into vintage cohorts based on the month of origination. Cumulative unit losses, gross dollar charge-offs and net dollar charge-offs were then aggregated by month from origination for each vintage, and were used to create generic loss timing, amortization and vehicle recovery curves for vintages with sufficient seasoning.

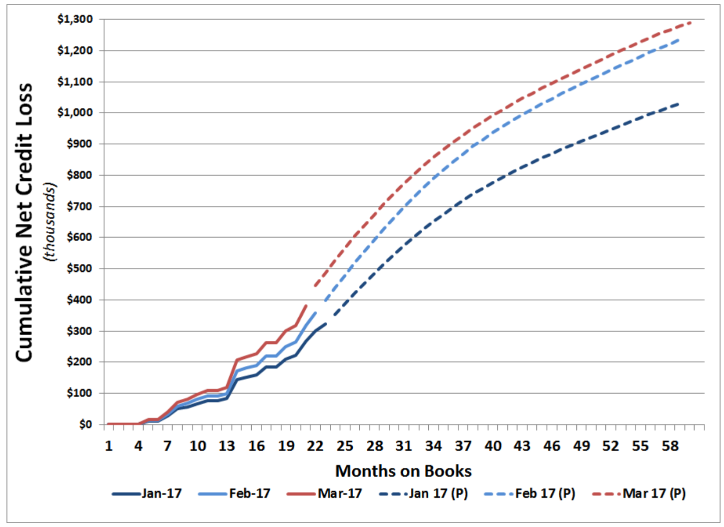
Credit bureau, loan structure and application factors for each funded applicant were regressed against the incidence of default to create an index, or score, that was used to assess the unique risk associated with every individual vintage. The index was then calibrated to align with the historical cumulative unit default rate of fully seasoned cohorts. In practice, many lenders have their own custom models to serve this purpose, or a national credit score is used as a proxy.

The cumulative unit loss estimate for each vintage was applied to the loss timing curve in order to project an origination time expectation for the life of each pool. Gross and net charge-off curves were also estimated using expected principal outstanding and vehicle recovery estimates for each month.

Analysis was performed to determine the independent effect of shifts in used vehicle values on recovery and net loss rates over time. In addition, analysis was also performed to measure the impact of seasonality on the incidence of default. This information was used to de-trend the historical data in order to arrive at projections that a static, or neutral, to the environment.

The static projections were then integrated with cohorts that are not fully seasoned in order to estimate the amount of remaining losses for each vintage. This is illustrated in Graph 2, where the cumulative net losses for loans funded in the first quarter of 2017 are shown, along with their respective forward looking estimates. Projections are denoted with (P).

**Graph 2. Cumulative Net Credit Loss for Q1-2017 Vintages**




The cumulative net loss projections for vintages that are not fully seasoned were aggregated to produce the static expected credit defaults remaining in the active portfolio.

B. ***The Dynamic Model.***

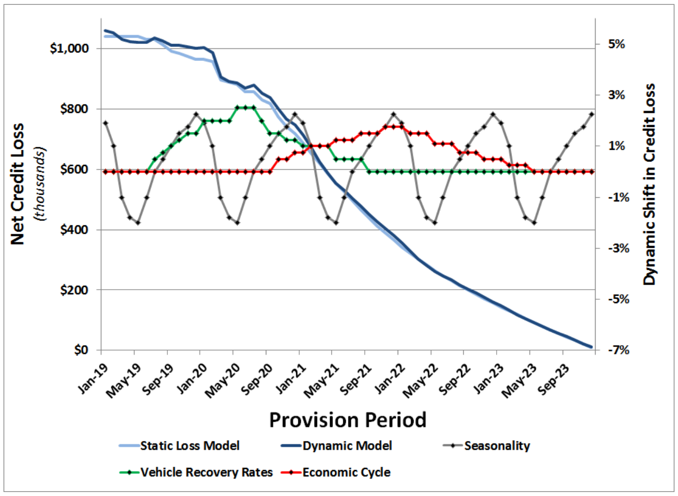
Exogenous factors, such as vehicle values and unemployment, will influence future performance apart from risk factors related to the underlying portfolio. In practice, lenders will use quantitative forecasting models in conjunction with reasonable and defensible management assumptions to stress the static model appropriately.

For this example, we assume the following:

- The impact of seasonality will remain consistent with historical trends.
- Vehicle values will decline beginning in June 2019, leading to an increase in net loss that will peak at 2.5 percent in June 2020. Values will return to baseline levels over the following 12 months.
- A recession will begin in October 2020, leading to an increase in losses over the following 14 months, peaking at a 1.75 percent increase in net losses by December 2021. Values will return to baseline levels over the following 18 months.

The impact of these dynamic assumptions against the static model is illustrated in Graph 3.

**Graph 3. Static Loss with Dynamic Effects**




In the above, revised forward looking net loss estimates from the dynamic model would be used as the estimate for the total provision. The prior period's provision would be adjusted to reflect the current estimate.

In practice, lenders should revise these estimates either monthly or quarterly, depending on data and resources available. In addition, model assumptions should be tested periodically in order to ensure that actual performance continues to align with forecasted values.

# VII. Future Work

The above discussion is an initial work on the estimation of Credit Losses and the implications on data sets required to execute a statistically significant analysis on them. One of the principal factors in determining the behavior of the loss however is the ability to forecast meaningful indexes (and economic conditions such as recession). This task may be a daunting one but one which all preparers of financial statements will need to do.

Forecasting is a science onto itself and in this document, we have only skimmed that topic. In fact, probably the toughest item to overcome for the researcher is the determination of which forecast to use (single or combination) in order to determine the ultimate monetary provision to be accrued. Within reason, the risk of selection and derivation of said forecast will need to be minimized in order to more accurately predict these losses. We plan to prepare a follow-up document that assists credit scientists in determining the quantification and mitigation of said risks.

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