Quantitative precision for CECL

Expected Loss Model and Equifax's solution

Abstract

The Great Recession led to a belief that the incurred loss model caused insufficient loss reserve provisions in the case of a sudden and extreme downturn in credit risk. In response to criticism of the incurred loss model, the International Accounting Standards Board (IASB) published IFRS 9 with a new standard for accounting for expected credit loss. The U.S. Financial Accounting Standards Board (FASB) followed with a standard focusing on Current Expected Credit Losses (CECL). These standards shift the way financial institutions view and analyze risk of future losses. The standards emphasize a forward-thinking model forecasting loss over the life of a loan using historical and current information rather than occurred and observable evidence of credit loss. With various methodologies available to financial institutions, this white paper details the importance of a quantitative approach to calculating Expected Loss and the innovative elements of Equifax's Absolute Expected Loss Model for estimating Expected Loss (EL) to meet CECL standards.

Contents

Executive summary

Equifax's Absolute Expected Loss Model provides insight for optimal loss reserve along with valuable information about institutional portfolios.

FASB and IASB updated accounting practices away from trigger warnings to a forward-thinking practice due to the belief that an incurred methodology "delayed recognition of credit losses on loans and resulted in loan loss reserves that were not adequate" (Canals-Cerdá, 2019, p. 3). The implementation of Current Expected Credit Loss (CECL) and IFRS 9 seeks to balance loss recognition with regulatory priorities (Canals-Cerdá, 2019; Cohen & Edwards, 2017; Lucy, 2018) through forecasting potential loss utilizing historical and current information (Cohen & Edwards, 2017). Equifax's Absolute Expected Loss Model provides objective, consistent, and transparent contract-level estimates of lifetime expected credit losses derived from a suite of three individually built models: the Equifax AbsolutePD® (APD), Loss Given Default (LGD), and Exposure at Default (EAD) models.

Equifax's Absolute Expected Loss Model provides insight for optimal loss reserve along with valuable information about institutional portfolios. Because estimates are given at the obligation level, the model output can accurately rank order individual borrowers and aid in portfolio risk management. The Expected Loss Model represents a number of innovations, such as

- A unique blend of obligor-specific and macroeconomic covariates
- Explicit covariates to model sectoral idiosyncratic dynamics
- A self-correcting feature that learns from previous shortfalls built into the AbsolutePD® model
- A model trained on one of the most extensive data sets of private company obligors
- Predictions out to seven years from the quarter of prediction
- Independence from the availability of financial statements

Introduction

The U.S. Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB) published IFRS 9 and Current Expected Credit Loss (CECL) as new standards for understanding and provisioning Expected Loss. It is believed that during the Great Recession the incurred loss model was too slow in recognizing provisional needs due to acknowledging provisional needs only when trigger points, or observable evidence, demonstrated a risk of loss (Canals-Cerdá, 2019; Cohen & Edwards, 2017; Lucey & Change, 2018). The incurred loss method is a reactionary model, while IFRS 9 and CECL are forward-thinking models seeking to forecast probability of future credit loss with historical and current information “even if no such triggering events have yet occurred” (Cohen & Edwards, 2017). The new forward-thinking standards promoted by FASB and IASB encourage institutions to leverage their current credit risk frameworks and complement them with the use of historical, current, and future information.

Equifax’s Absolute Expected Loss Model is an ideal bottom-up approach that engages quantitative information to provide forward-thinking Expected Loss estimates to meet IASB and FASB standards.

Equifax’s Absolute Expected Loss Model is an ideal bottom-up approach that engages quantitative information to provide forward-thinking Expected Loss estimates to meet IASB and FASB standards. IASB and FASB do not prescribe a specific model for estimation of Expected Loss, instead allowing custom-built methodologies designed with reasonable and supportable information (Chae, Sarama, Vojtech, Wang, 2018; Cohen & Edwards, 2017). There are multiple methodological options to meet the Expected Loss requirements. However, an ideal methodology utilizes quantitative information and is based on empirically derived and statistically sound methodologies and analyses. An Expected Loss model methodology is a bottom-up approach that engages Probability of Default (PD) and Loss Given Default (LGD) from each individual loan to meet IASB and FASB standards (Lucey & Chang, 2017).

Equifax’s Absolute Expected Loss Model combines Equifax’s Absolute Probability of Default (APD), Loss Given Default (LGD), and Exposure at Default (EAD) models to provide Expected Loss (EL) for each contract as well as aggregated EL by various contract-level variables. Generating consistent and robust forecasts requires fitting the models on comprehensive and representative data. The data set used for Equifax’s Expected Loss Model has more than 300,000 discrete loss outcomes and 3,000,000 unique obligors that operate in a wide range of business sectors spanning the full spectrum of four-digit NAICS codes. This granularity is crucial for a model’s predictive power to differentiate among obligors. Fitting of the EL Model utilizes Equifax Commercial’s proprietary company loan database. The database includes eight of the top ten U.S. financial institutions and more than 22 million current and historic contracts with over $1.2 trillion in exposures. Lastly, the model engages and is fitted with obligor-specific circumstances and different macroeconomic variables.

Regulatory background

FASB and IASB implemented Current Expected Credit Loss (CECL) and IFRS 9 as new approaches to calculating allowances for credit losses. These two expected credit loss standards were implemented in response to previous loss calculations utilizing an incurred loss model that recorded probable losses based on "triggering" events having occurred, meaning it was concluded that an estimable probable loss occurred due to deterioration in risk characteristics (Chae, Sarama, Vojtech, & Wang, 2018; Cohen & Edwards, 2017; Covas & Nelson, 2018; Lucey & Chang, 2017; Ntaikou & Vousinas, 2018). The incurred loss model has been deemed "too little, too late," delaying recognition of losses resulting in inadequate loss reserves (Chae, et al., 2018; Cohen & Edwards, 2017; Covas & Nelson, 2018). These criticisms resulted in the Financial Stability Board (FSB) recommending alternative approaches to the incurred loss model.

Early recognition of potential credit losses is believed to anticipate EL and dampen the pro-cyclical nature of the incurred loss model. Pro-cyclicality is the demonstration that provisions fall in economic upswings and rise in economic downswings (Borio, Furfine, & Lowe, 2001), and utilization of the incurred loss model is believed to amplify this phenomenon (Chae, et al., 2018; Cohen & Edwards, 2017; Covas & Nelson, 2018; Lucey & Chang, 2018). Provision fluctuations of pro-cyclicality can result in insufficient funds at the onset of a downturn due to the lowered reserves held during upswings. In turn, higher provisions during downturns may render a lender more conservative with credit, which may lead to fewer originations and subsequently hinder economic recovery. Therefore, the forward-looking approaches of CECL and IFRS 9 are meant to forecast EL, helping to identify credit loss sooner and promote transparency for the regulatory priorities of safety and soundness (Cohen & Edwards, 2017; Lucey & Chang, 2017).

Forward-looking methodologies engage past events, historical experiences, current conditions, and reasonable and supportable forecasts, which include the utilization of forecasted macroeconomic variables to provide insight into what could happen given predictions of macroeconomic variables (Chae, et al., 2018; Cohen & Edwards, 2017; Lucey & Chang, 2017). This allows institutions to be proactive in provisioning for EL instead of reactive. Both CECL and IFRS 9 are similar in their forward-looking estimation of EL but demonstrate slight differences between risk and EL time-frame calculations.

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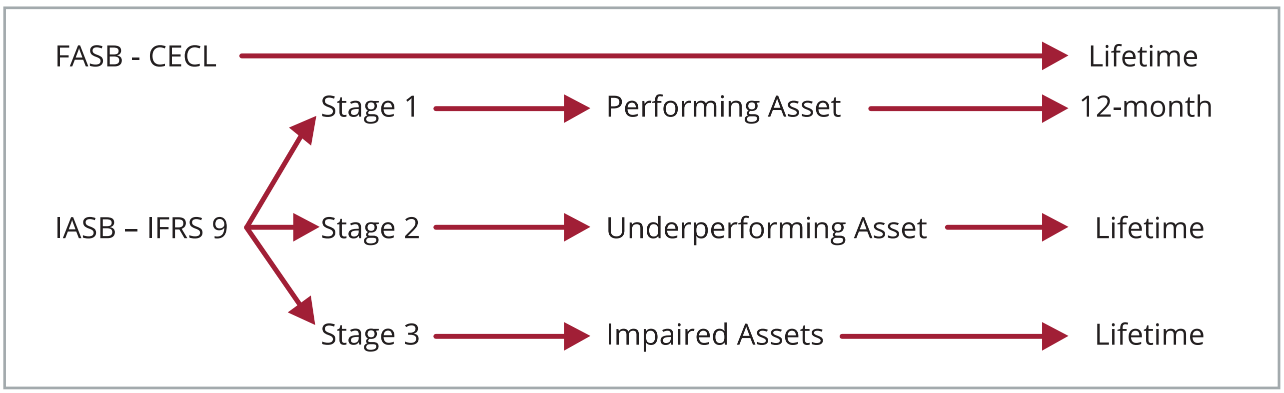
Figure 1 demonstrates the differences in term calculation of the EL models between CECL and IFRS 9. FASB standards provide that CECL Expected Loss models are calculated from the time of origination and over the life of a loan. IASB's approach with IFRS 9 is staggered into three stages. CECL's EL considerations are for all risk exposures and are expected to recognize credit loss earlier (Cohen & Edwards, 2017). IFRS 9 provides a benchmark for Expected Loss for standard risk by requiring a 12-month EL estimate at origination. When an asset is deemed to be underperforming, it is categorized as Stage 2. When an asset incurs credit loss or becomes credit-impaired, the financial asset is categorized as Stage 3[1]. Therefore, if an asset or portfolio of assets poses substantial default risk, then it is identified as Stage 2 or 3. These last two stages require full lifetime EL estimates (Cohen & Edwards, 2017). Substantial default risk is assumed when delinquency becomes 30 days past due.

Figure 1. Calculation term differences between FASB – CECL and IASB – IFRS 9 Expected Loss models



Regulation under FASB and IASB do not dictate the specific methodology for calculating EL. Institutions will be allowed to use various modeling methods as well as judgment for estimation methods that are appropriate for individual circumstances (Board of Governors of the Federal Reserve System, 2016). The new standards allow institutions to leverage previously established credit risk frameworks while engaging a broader range of data to provide an expected credit loss model on a collective or pooled basis of similar risk characteristics or on an individual asset basis when shared risk characteristics are not present (Board of Governors of the Federal Reserve System, 2016).

[1] Under IFRS 9, Stage 2 and Stage 3 must calculate lifetime Expected Loss. The difference between Stage 2 and Stage 3 is that when assets are flagged as Stage 3, interest revenue is calculated based on lower net amortized cost carrying amount (Cohen & Edwards, 2017).

Methodology and framework

A simple, precise, and quantitatively sound methodology to meet new Expected Loss standards is the Probability of Default/Loss Given Default methodology. The simplicity of this quantitative methodology is the conceptual framework of the solution that takes Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD) to calculate Expected Loss (EL).

Complexity of this quantitative methodology comes through the calculation of each individual input, PD, LGD, EAD. This methodology is considered a more comprehensive methodology given the amount of data used for modeling. Even when qualitative overlays are incorporated, such inclusion of these data points are determined by historical data. Therefore, this Loss Given Default Model reduces subjectivity in modeling for CECL compliance.

Equifax's Loss Given Default Model reduces subjectivity in modeling for CECL compliance.

Framework

Equifax's Absolute Expected Loss Model is comprised of three independently developed underlying models: APD, LGD, and EAD. This forward-looking model provides a bottom-up approach based upon the basic foundation of EL as the product of Probability of Default (PD) and Loss Given Default (LGD).

$$EL = PD \; X \; LGD$$

The basic model is further expanded to incorporate Exposure at Default (EAD), creating the following Expected Loss formula:

$$EL = PD \; X \; EAD \; X \; LGD$$

The theoretical framework calculates 28 quarters of predictions for APD, LGD, and EAD. Each quarter is multiplied together providing each quarterly EL estimate. Final quarterly estimates are then aggregated, yielding contract-level EL estimates that can then be segmented by various business-related variables.

Embedded within the EL equation are the calculations utilizing Equifax's Absolute PD®, LGD, and EAD models. Each model utilizes the same default definition: payment is 90 days past due. The 90 days past due definition provides a balance between being too quick of a trigger point and too late for default events, i.e., bankruptcy, litigation, repossession, or material loss (not just waiving of late charges).

Thus, default considers the entire borrower-lender relationship to determine if the average delinquency across all the contracts in the relationship, on a dollar-weighted basis, is greater than 90 days.

This theoretical framework engages a calculation that is independent of financial ratios by looking at a continuum of intrinsic propensities to failure through calculating probability of an obligor belonging to one of the two classifiers. The AbsolutePD®, LGD, and EAD models are themselves composed of dozens or hundreds of these generalized linear models, which allows them to produce different estimates based on the unique combination of factors specific to each borrower and forecast horizon.

Equifax's AbsolutePD® Model

The Equifax AbsolutePD® Model employs statistical techniques to estimate likelihood of default providing predictions based on borrower-by-borrower payment histories of three million distinct small-firm U.S. and Canadian borrowers collected by Equifax Commercial over 17 years. Payment histories are combined with sector-related macroeconomic variables, providing Probabilities of Default over quarterly forecast horizons of up to 28 quarters. Model validation and findings demonstrate a powerful and consistent portfolio analysis of Probability of Default. The basic model foundation is

$$L(p(X)) = \alpha + \sum_{j=1}^{n} f_j(X_j) + \varepsilon$$

where $L(\cdot)$ is the logit link function, $j = 1$, ..., n is each of the n covariates, f_j is the covariate-specific potentially nonparametric transformation, X_j is a list of explanatory variables, and ε is the model residual.

Covariates were chosen based on natural reasoning and common economic and literature assumptions. The coefficients for these covariates were then calculated utilizing Maximum Likelihood Estimation (MLE). Appropriate data selection and fitting are the basic foundations to estimating PD. Through expert decisions, literature, economic theory, and respective market and regional nuances, various data were analyzed to determine appropriate model fit. The MLE technique for the model analyzes obligor, lender, and macroeconomic data. The model includes Equifax's MasterScore® along with appropriate inputs determined from the previously mentioned areas. Further, the model incorporates an Excess Default Rate (EDR)[2] to adjust,

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when possible, for lender- and sector-specific over and under predictions. Therefore, the number of covariates, as well as the particular selection of covariates, can depend on industry sector and the number of forecasting quarters ahead.

After model fitting, the conditional probability of default is obtained by inverting the Link Function. Then, the probability that a given obligor defaults within k quarters is calculated via the following equation:

$$p_k = 1 - q_1 \times q_2 \times \ldots \times q_k$$

where q_1 is the probability of survival for one quarter, and q_i is the probability of survival from the end of quarter $i-1$ until the end of quarter i, conditional on survival to the end of quarter $i-1$. Each quarter-to-quarter conditional survival probability (q_i) is estimated through separate models; thus, each estimation utilizes historical dynamics for each separate estimation. The equation for q_i is therefore

$$q_i = 1 - L^{-1}\left[\alpha + \sum_{j=1}^{n} f_j(X_j) + \varepsilon\right]$$

Equifax's Loss Given Default (LGD) Model

Equifax's Loss Given Default (LGD) Model is a pooled-lender model that is estimated from hundreds of thousands of contract-level post-default repayment histories from two business cycles. Research and development identified the optimal segmentation for contracts based on LGD outcomes, borrow industry, collateral type, transaction size, facility type, and lender type. Analysis for Equifax's LGD Model encompassed 1,500 sub-models and 145 models representing different components of the loss spectrum for seven years of results from more than 300,000 unique contracts that cover the entire gamut of four-digit NAICS codes, 98% of U.S. counties, and over a decade and a half of time. During design, the developmental sample provided contract-level variables resulting in an ordinal logistic regression with nested linear regressions as the final model. When data are sparse, linear regression estimates are used.

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[2] Excess Default Rate (EDR) is calculated for each lender and sector combination. It is also updated quarterly. When there are not sufficient data, additional history, all sectors, or both are utilized to achieve data sufficiency. If lender data are not sufficient for any modeling technique, a generic EDR is used that is calculated for each quarter and sector combined.

Equifax's LGD Model, when ample data are available, is a logistic regression producing estimates of the probability of a borrower experiencing one of two types of zero loss outcomes, a partial loss outcome, or a total loss outcome. The two types of zero loss outcomes are nuisance zero loss and recovery zero loss. The partial loss outcome is defined as losses greater than zero and less than 95% of Exposure at Default. The total loss outcome is defined as losses of 95% or greater of Exposure at Default. Linear regression is utilized with limited available data and produces either a nested LGD between 1% and 95%, which is LGD in the event of some loss, or the overall expected LGD.

> Equifax's LGD Model is a logistic regression producing estimates of the probability of a borrower experiencing one of two types of zero loss outcomes, a partial loss outcome, or a total loss outcome.

Within the model framework, a contract score is developed through the following equation:

$$s_i = \beta_0 + \sum_{j=1}^{J} \sum_{k=1}^{K_j} B_{jk} x_{ijk} + \sum_{h=1}^{H} \beta_h x_{ih}$$

where s_i is the score for contract i, J equals the number of discrete predictors, K_j is the number of bins for predictor j, B_{jk} is the weight for bin k of predictor j, x_{ijk} is the indicator variable for bin k of predictor j for contract i, H equals the number of continuous predictors, β_h provides the weight for continuous predictor h, and x_{ih} denotes the value of continuous predictor h for contract i.

The log-likelihood function is then maximized by

$$= \sum_{i=1}^{n} w_i \left[y_i \ln\left(\frac{e^{s_i}}{1+e^{s_i}} \right) + (1-y_i) \ln\left(1 - \left(\frac{e^{s_i}}{1+e^{s_i}} \right)\right) \right]$$

while the linear regression model minimizes the Sum of Squared Errors (SSE) via

$$SSE = \sum_{i=1}^{n} w_i (y_i - s_i)^2$$

where y_i provides the loss value of the i^{th} contract, w_i is the sample weight associated with contract i, and s_i denotes the score for contract i.

Model predictions were constructed through the design of cards that capture at least one of the zero loss, partial loss, or total loss outcomes mentioned above. Each card was designed through literature and a priori knowledge for respective variable inclusion and then validated through the Hooke and Jeeves direct pattern search methodology. Further, model fitting engaged a K-fold validation to control overfitting (logistic and linear). Variable categories identified through the model fitting process are demonstrated in Table 1.

Collateral	Size of contract	Contract characteristics
Historic and current pay-down	Repayments	Delinquencies
Default history	Repossession	Bankruptcy
Legal actions	Lender type	National economic variables
Industry economic variables	Geographic economic variables	

Table 1. Variables identified for Equifax's LGD Model through model fitting

The outcomes from each card capture four potential combinations of ordinal logistic regressions with nested linear regression models that result in the LGD estimate for a given contract. The four potential combinations of models are presented in Table 2. Each model is provided a respective weight accounting for strength, error, complexity, and a priori knowledge to provide a final LGD estimate.

<table>
<tr><th>Method I</th><th>Method II</th><th>Method III</th><th>Method IV</th></tr>
<tr><td rowspan="2">MODEL AB: Zero Loss (Nuisance or Recovery)</td><td>MODEL A: Nuisance Zero Loss</td><td>MODEL A: Nuisance Zero Loss</td><td rowspan="2">MODEL AB: Zero Loss (Nuisance or Recovery)</td></tr>
<tr><td>MODEL B: Recover Zero Loss</td><td>MODEL B: Recovery Zero Loss</td></tr>
<tr><td rowspan="2">MODEL CD: Some Loss (Partial or Total)</td><td>MODEL C: Partial Loss</td><td rowspan="2">MODEL CD: Some Loss (Partial or Total)</td><td>MODEL C: Partial Loss</td></tr>
<tr><td>MODEL D: Total Loss</td><td>MODEL D: Total Loss</td></tr>
</table>

Table 2. Four loss model combinations of the Equifax's LGD Model

Equifax's Exposure at Default Estimation

The third framework to Equifax's EL Model is Equifax's Exposure at Default Estimation. The expected Exposure at Default for a given transaction i is estimated as

$$EAD_i = F_k(x_1, \dots, x_n),$$

where $x_1, \dots, x_n$ are borrower- and contract-specific covariates that are chosen based on forecast horizon k, and are shown through out-of-sample validation to improve model accuracy. $F_k(*)$ is a function that is statistically estimated by a regression model. Exposure at Default estimates are given for up to 28 quarters.

The model utilizes linear regression for periods in which the response variable is best described by a linear relationship with the predictor variables. Linear regression modeling estimates coefficients b that minimize the sum of squared errors:

$$SSE = \sum_{i}^{n} (y_i - x_i^T b)^2,$$

where y_i are the response variables for transactions $i = 1, \dots, n$ and x_i are the predictor variables for transaction i.

For periods that demonstrate a nonlinear relationship between the response and predictor variables, functional form framework resulted in

$$\mathrm{L(p(X))} = \alpha + \sum_{\mathrm{j}} \mathrm{fj(Xj)} + \varepsilon$$

where j=1,...,n indicates each of the n covariates, fj is the covariate specific nonparametric transform, Xj is a list of model covariates (explanatory variables), ε is the model residual, α is a constant, and $L(\cdot)$ is the link function. A conservative variant of the Hooke and Jeeves direct pattern search method provided bin constraints for the LGD Model variables. Where sufficient data were present, model parameters were generated using K-fold estimation techniques, with the parameter values chosen based on the average of each fold's estimated coefficient value.

Equifax's Absolute Expected Loss (EL) Model

Equifax's Absolute Expected Loss (EL) Model provides a quantitative methodology that engages three data-driven models and creates a bottom-up approach providing a forward-thinking EL estimation for IASB and FASB standards. There are multiple methodological options to meet the EL requirements, but the best methodology utilizes quantitative information based on empirically derived and statistically sound methodologies and analyses. The Probability of Default Model is an ideal methodology for meeting IASB and FASB EL standards as a bottom-up approach that engages Probability of Default (PD) and Loss Given Default (LGD) based on the respective information of each individual loan (Lucey, 2017).

The data set used for Equifax's Expected Loss Model has more than 300,000 discrete loss outcomes and 3,000,000 unique obligors that operate in a wide range of business sectors spanning the full spectrum of four-digit NAICS codes. This granularity is crucial for a prediction model's power to differentiate between obligors. Fitting of the EL Model utilizes Equifax Commercial's proprietary private company loan database that includes eight of the top ten U.S. financial institutions and more than 22 million current and historic contracts with over $1.2 trillion in exposures. Lastly, the model engages and is fitted with obligor-specific circumstances and different macroeconomic variables. Thus, Equifax's Absolute Expected Loss (EL) Model provides a reasonable and supportable EL option that estimates the effects of potential future Probability of Default on EL.

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Expected Loss Model scope

CECL and IFRS 9 seek to provide transparency of expected credit loss during the life of the loan through greater interaction and analysis of historical and current data along with reasonable and supportable future data. The scope of Equifax's Absolute Expected Loss (EL) Model is an estimate of EL through statistical analysis of 28 quarters, or seven years, of contract-level data. Equifax's model provides contract-level estimates, but the scope and power of the model is in the portfolio-level estimates. The model is designed to provide U.S. lending and banking institutions with a statistically sound EL methodology that utilizes Equifax, industry-specific, and macroeconomic data for transparency. Further, the model will help institutions understand EL at the contract and portfolio levels while helping understand changes to EL at every reporting period[3].

[3] Financial Accounting Standards Board (2016, June). Financial instruments—credit losses (topic 326): Measurement of credit losses on financial instruments. Financial Accounting Series, 248. www.fasb.org/jsp/FASB/Document_C/DocumentPage&cid=1176168232528

Equifax's Expected Loss (EL) Model, validation, and findings

Internal validation demonstrated strong Absolute EL Model estimates compared to lender-reported losses.

Equifax's EL Model estimates EL for seven years along with cumulative estimates for 4, 8, 12, 16, 20, 24, and 28 quarters. Equifax's EL Model engages an incremental and cumulative approach for each quarter. EL percentage is calculated with the cumulative EL estimate of the respective time frame and divided by current transaction balance. Estimates are then provided at the contract level, gathered into portfolio-level pooled aggregations, and segmented by region, state, industry, and collateral.

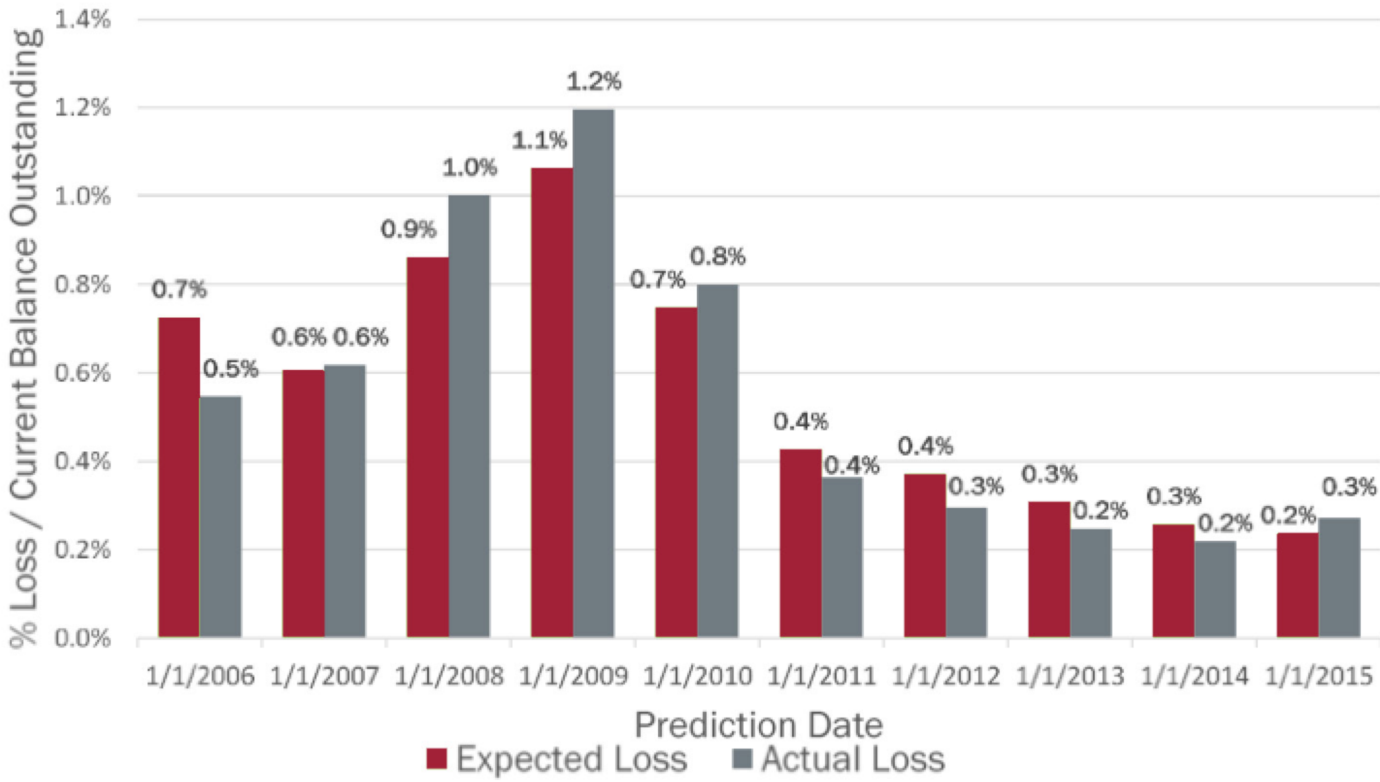
APD and LGD models have been validated[4]. Model validation is a cyclical process that is continuous through the lifespan of model use. The EL Model was conceptually reviewed through the lens of theory and practice, model data, estimation, testing, and documentation. It was then validated through analysis of the modeling process and assessment of the EL Model. Each validation piece is crucial in not only fitting an appropriate model, but also providing consistent, reliable, and purposeful results.

A pooled analysis was used to examine model performance. Pooled analysis analyzed the predictability of Equifax's Absolute EL estimates through internal validation comparing estimates to lender-reported losses. Internal validation provides one-year, three-year, five-year, and seven-year analysis on contracts $1 million and under. Lender-reported percentage loss is the sum of reported loss for the given time frame divided by the sum of the current transaction balance.

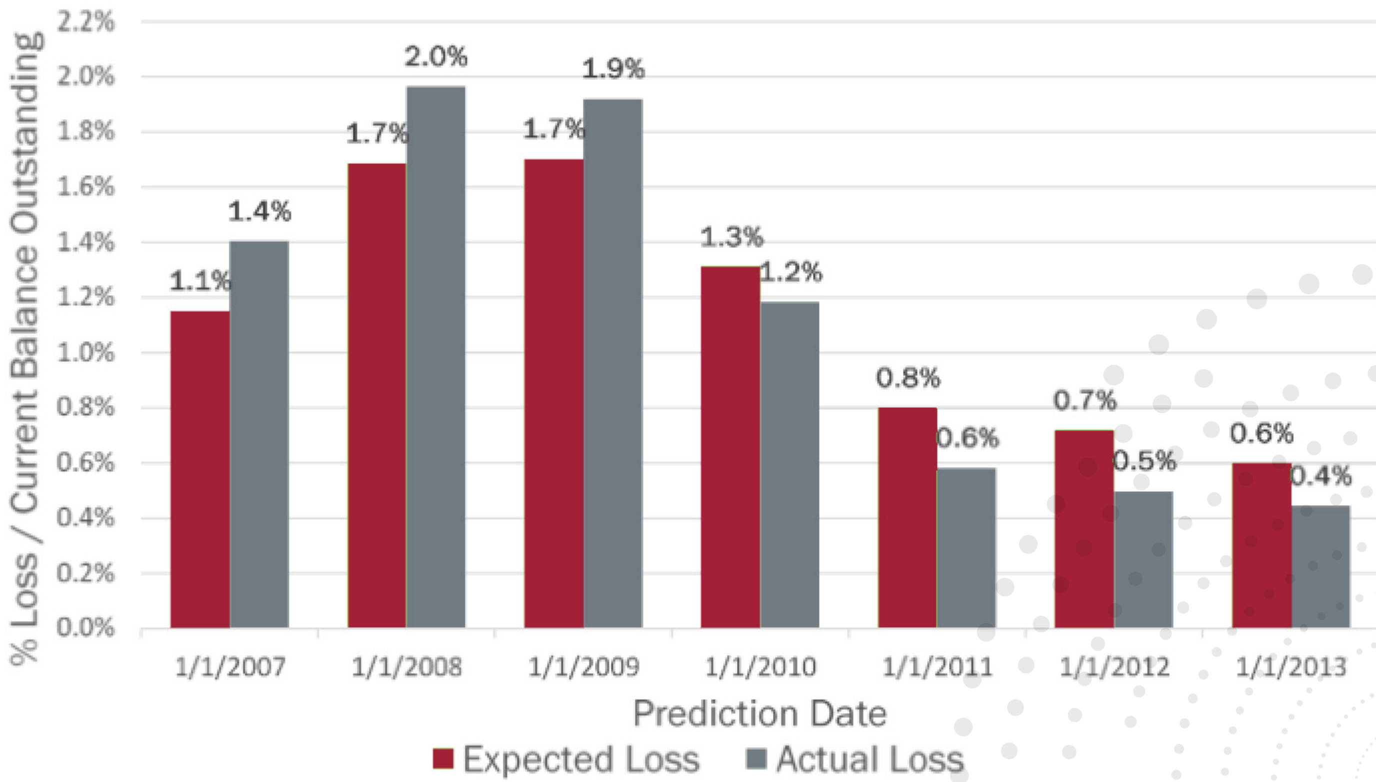
Internal validation demonstrated strong Absolute EL Model estimates compared to lender-reported losses. The pooled validation demonstrated model learning associated with the changing economy, Graphs 1-4. Graphs 1-3 show how the model slightly underpredicts EL by at most 0.3% until the end of the Great Recession. After 2009, the model takes that information and trends to slightly overpredict EL by at most 0.2% compared to reported losses. Graph 4 demonstrates the slight overprediction of the model by 0.2% after 2009. Thus, a potential correction that could potentially be supported and reasonable is a 0.2% qualitative overlay to minimize the slight overprediction.

[4] See individual Equifax Commercial white papers for the respective models.

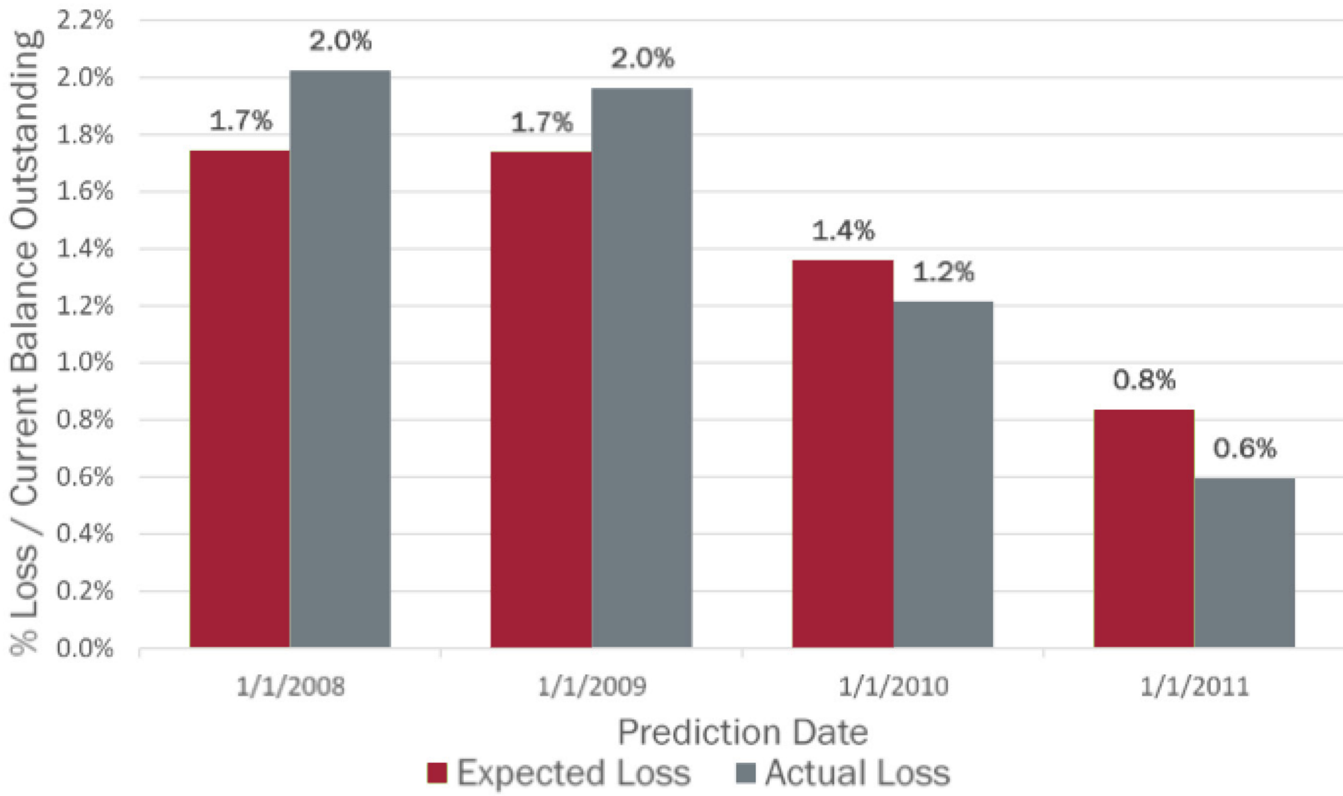
Graph 1. All industry – 4-quarter EL prediction vs. actual



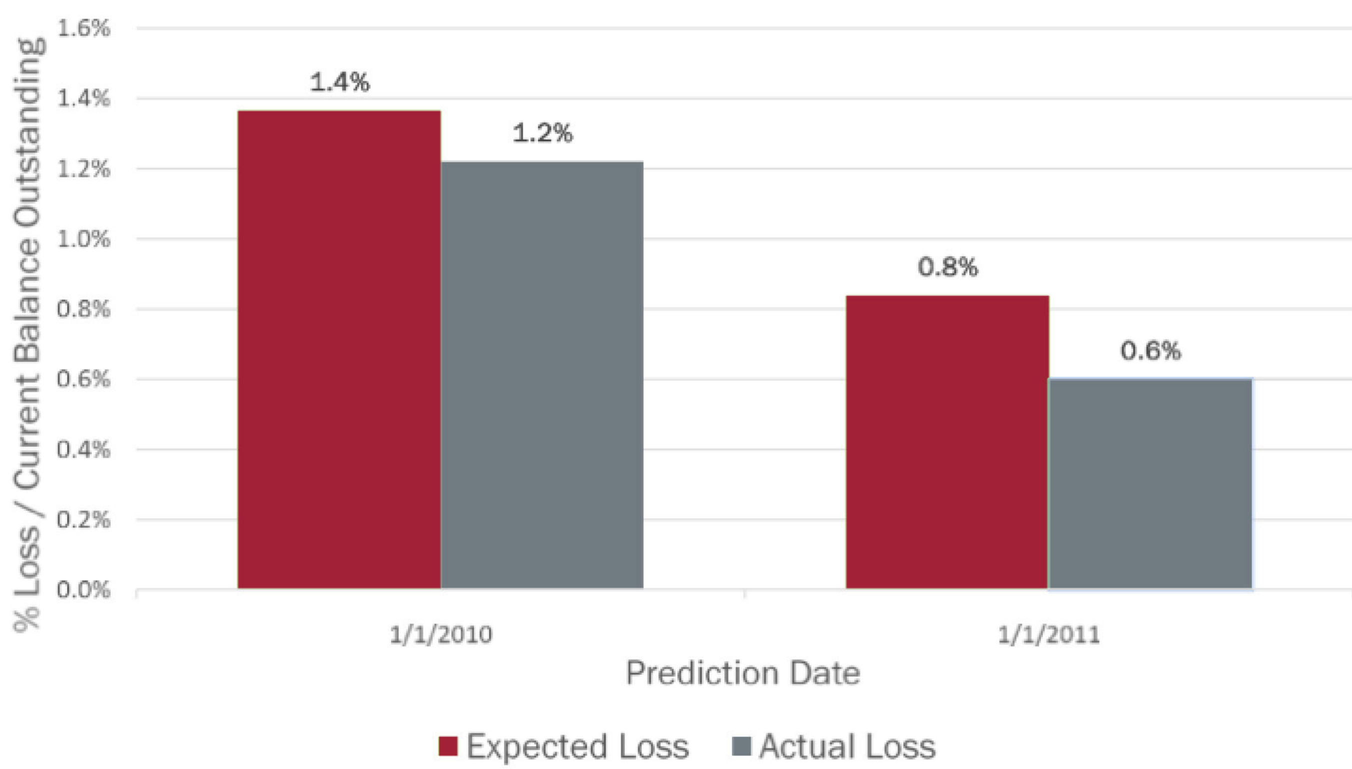
Graph 2. All industry – 12-quarter EL prediction vs. actual



Graph 3. All industry – 20-quarter EL prediction vs. actual



Graph 4. All industry – 28-quarter EL prediction vs. actual



Limitations

As is the case with every statistical model, Equifax's Absolute Expected Loss (EL) Model should be used within its intended scope and the limitations of its power. Equifax's EL Model is trained on data from Equifax's robust database. Utilizing a commercial loan-focused data set limits the strength of the model when deviating outside the data domain, such as to consumer data. Currently, when an asset goes into default, that asset is removed from the EL Model. When an asset is reported as having gone into default, the asset is removed from the model without a calculated EL from that given model estimate. Therefore, there may be some definitional limitations in estimating EL for certain assets.

In much the same way a meteorological model provides some level of accuracy two weeks out but degrades beyond this prediction window, economic forecasts can be reasonably made over only two to three years. Beyond that time horizon, gaining insight on human behavior and economic activity is difficult. The EL Model covers seven years, thus placing bounds on the accuracy of the economic forecasts that impact most of the later periods.

The current model does not engage forecasted economic variables from an internal or external forecasting model. The current model estimation does not afford for scenario testing. Thus, it does not provide an opportunity for qualitative overlays of the model.

866.825.3400
cmlmarketing@equifax.com

Summary

Equifax's Absolute Expected Loss (EL) Model was developed as a forward-thinking quantitative methodology to help businesses meet CECL and IFRS 9 standards. The model's theoretical framework is founded in the basic Expected Loss formula of $EL = PD\ X\ EAD\ X\ LGD$ complemented by Equifax's Absolute Probability of Default, Loss Given Default, and Exposure at Default models. Each individual foundation of the model was tested and validated as part of the development process. The overall EL Model has undergone an internal pooled data validation. The pooled data validation demonstrated the predictive nature of the EL estimates, yielding a quantitatively sound model that has the ability to predict current and future EL to meet compliance obligations.

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