Basel Loss Given Default Models for Retail Portfolios

Methodology Document

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Contents

1. Executive Summary

This Methodology Document describes the models used by American Express (AXP) to estimate account/client level Losses Given Default (LGD) to serve as inputs to Basel regulatory capital calculations for its retail portfolios. This document also serves as policies of model development standards for the suite of models governed by this methodology document.

The LGD estimates generated by the models are used also in other AXP business processes that require a long-term or Through-the-Cycle (TTC) measure of account/client credit risk. These include expected loss and economic capital calculations.

This methodology document presents the methodologies common across all Basel Retail PD models for consumer and small business portfolios, specifically U.S. Card Services (USCS), International Card Services (ICS), and Global Commercial Payment (GCP) for cardmember-level and client-level exposures.[1] Specifically, this methodology document summarizes the overarching model design; typical data employed; standards steps for calibrating and testing; and protocols for approving, implementing, and ongoing monitoring of the models. It does not present technical elements or results for particular LGD models; for these, consult model-specific model documents.

The central focus of this Methodology Document is the five step process through which AXP implements its Basel retail LGD models. The process involves (i) the segmentation of individual accounts/clients, (ii) the estimation of a predictive model of recovery rate for each segment, (iii) conversion of the resulting score to a through-the-cycle estimate, (iv) the mapping of accounts/clients into homogeneous segments, and (v) the assignment to each account/client of LGD based on historical LGD performance of the accounts/clients for the respective bucket.

Key choices made by AXP in developing the models covered here are:

- The first level of model segmentation is by business unit and product type. The second level is based on account attributes that are identified as important LGD drivers.
- The forecasting approach used to model LGDs is non-linear regression employing a logistic transformation of a linear combination of predictive variables. The fitting technique used is based on a Maximum Likelihood logistic regression algorithm also known as a fractional response regression technique.
- In calibrating its Basel retail LGD model to historical data, AXP allows for variations in market conditions by including time-varying effects. To obtain a TTC version of the model, suitable for calculating Basel LGDs, AXP averages these effects.
- Basel rules require that LGDs assigned to individual exposures are based on averages estimated for homogeneous account groups. AXP applies a decision tree algorithm to identify these homogeneous account groups.

The methodologies used in the above four steps are described in this Methodology Document and the assumptions made are discussed and justified by reference to regulatory expectations,

[1] GCP offers dual-liability products to its corporate clients, where an employee is responsible for balances that the employer does not accept responsibility (e.g. personal expenses). Credit risk due to client-driven and cardmember-driven defaults are addressed separately in capital calculations.

industry practice, academic analysis and AXP's own investigations of the relative performance of different approaches.

This Methodology Document also describes the data used in the LGD model calibrations. The data is derived from rich information on account and cardmember characteristics held within AXP's data systems. For some countries, the data also includes external credit bureau information (in particular, FICO scores for U.S. portfolios).

The Methodology Document lists the detailed steps that analysts follow in (i) compiling data, (ii) estimating models, and (iii) homogeneous segmentation and parameter assignment based on account-level LGD scores. In so doing, they are guided by policies on sampling and variable selection provided by the AXP's Modeling Strategy Committee (MSC). These policies are also followed by AXP in its Basel Probability of Default (PD) and Exposure at Default (EAD) modeling, which, therefore, share common features with the LGD approaches described here.

To take an example, variable selection, a central component of the LGD model design, is structured and systematized by AXP to ensure that a consistent and effective approach is used across multiple segments. The steps involved in selecting variables are: (i) exploratory data analysis, (ii) single factor analysis, (iii) variable transformation and treatment, and (iv) multi-factor analysis. Some steps make use of proprietary AXP algorithms. For instance, data transformations, caps and floors are generated using AXP's Modeling Automation Suite (MAS) application.

To assess the models, AXP tests their performance using out-of-sample and out-of-time validation. In both cases, performance measures (Gini Coefficients and Accuracy Scores) are calculated for observations excluded from the estimation dataset. The models' accuracy in rank ordering accounts by credit risk are also benchmarked by comparing performance with results obtained using earlier versions of the Basel retail LGD model.

Models may also be evaluated by analyzing key assumptions. AXP's choices in formulating the Basel retail LGD models are discussed in the Model Theory and Building the Model sections of the Methodology Document while a systematic listing and evaluation of assumptions is provided in the Assumptions and Limitations section.

In the latter, assumptions are examined from the point of view of (i) the rationale for the choice made, (ii) the risk associated with the assumption and its potential impact on model performance, (iii) testing performed during model development to validate the assumption, and (iv) AXP's approach to future monitoring including periodic reassessment of the validity of the assumption.

AXP follows a highly structured approach to model implementation, involving production model implementation, testing and approval. The bank also employs systematic frameworks for model governance, monitoring and control. These approaches and frameworks are described in Sections 8 to 10 of this Methodology Document.

2. Introduction

2.1. Introduction to the model

This methodology document describes the Basel retail Loss Given Default (LGD) models employed by American Express (AXP).[2] It explains the model design, the data employed, how the models are calibrated and tested, and the governance and other operational arrangements to which they are subject.

AXP uses the models to generate monthly, account-level or client-level LGD assignments for its retail portfolios. The models employ a combination of AXP internal data and external bureau data (when available) stored in AXP data warehouses. The LGDs generated are Through-the-Cycle (TTC) and so provide a long-run rather than a Point-in-Time (PIT) assessment of the credit standing of each account.[3]

This Methodology Document describes and justifies the steps for designing and calibrating the AXP Basel retail LGD models. In brief, AXP employs a non-linear regression approach in which the expected Recovery Rate (RR) for each account is estimated assuming that realized recovery rates equal an error term plus one minus the logistic transformation of a linear index of account characteristics. The LGD is then derived as 1 minus RR.

This model is created broadly in four steps.

1. **Classifying accounts/clients into segments.** The segmentation scheme is by business unit, product type, and others risk characteristics. It permits segmentation of accounts into two Basel categories: Qualifying Retail Exposures (QRE) and Other Retail Exposures (ORE).
2. **Estimating non-linear regression models.** AXP estimates non-linear regression models to obtain a PIT account-level or client-level LGD specific to each reference half-year period.
3. **Obtaining a TTC score.** AXP converts the PIT to a TTC by averaging time-varying constants appearing in the PIT model, thereby translating risk scores specific to each half-year period into a long-run risk score.
4. **Grouping by risk score.** AXP groups accounts/clients into homogeneous segments based on their long-run risk score using a non-parametric, decision-tree algorithm

[2] Retail is defined per the Basel Advanced Approaches. A general summary is that a retail exposure is to an individual person or persons; is comparatively low in value and large in number; and takes the form of following credit cards, installment loans, revolving credits, residential mortgages, or small business credit facilities.

[3] A Point-in-Time (PIT) LGDs measure expected loss given default conditional on all current information and, hence, are sensitive to variations in the macroeconomic environment. Through-the-Cycle (TTC) LGDs equal expected losses conditional on cross sectional borrower characteristics but not on the current state of the macro-economy.

and assigns each account/client an LGD estimate equal to the average of the segments into which it falls with cost adjustments.

2.2. Business problem solved by the model

The primary purpose of this model is to assign an LGD estimate to each retail account/client for which AXP calculates regulatory capital under the Basel Advanced Approaches. These LGDs, along with other input variables such as Probability of Default (PD) and Exposure at Default (EAD), determine risk weights and thus regulatory capital for AXP's retail portfolios. LGD represents the share of assets that AXP will not recover, and thus, the greater the LGD of an account/client, the higher the associated company's risk.

In addition, AXP uses the LGD models to calculate Expected Credit Losses (ECL). If ECL exceeds AXP's Allowances for Loan and Lease Losses (ALLL), deductions in available capital may result. Furthermore, the Basel retail LGD models provide inputs to AXP's calculation of economic capital, which is used as an input to important portfolio management and front-line business decisions. Table 2.1 lists the four main uses of outputs from the Basel retail LGD models.

Table 2-1: How outputs of the Basel retail LGD models are used

No.	Model	Description
1.	RWA Calculations	The model output is used to calculate risk-weighted assets (RWAs) for individual accounts, using the Basel II capital formulae for unexpected losses. This is the primary purpose of this model.
2.	Expected Credit Loss (ECL)	The model output is used to calculate Expected Credit Losses for each account, equal to the product of PD, EAD, and LGD.
3.	Economic Capital (EC)	The model output is used to calculate Economic Capital.

2.3. Background on recovery practices at AXP

2.3.1. Collection Process at AXP

When an account becomes delinquent, AXP first attempts to collect the balance by using its internal customer service staff. If unsuccessful, we typically contract with an outside agency to recover the owed balance. Outside agencies primarily use a "call and collect" approach, where staff call delinquent customers to request repayment. Alternatively, the agency may begin legal action based on considerations such as the cardmember's available assets and the size of the owed balance. Accounts associated with a bankruptcy filing, deceased notification, debt settlement case, or a consumer debt management plan (CDMP) follow different processes.

In general, U.S. accounts sent to outside agencies are put first in primary placement, which typically lasts four months or until the account is written off (officially defaults), whichever is sooner. Accounts that have not made payments in primary placement are successively placed in secondary placements (for four months) and tertiary placements (for six). Accounts in later placement tiers are generally less collectible. Collections efforts in international markets typically follow a similar progression, although the details vary by market.

2.3.2. Collection Cost

We divide the costs associated with recovering debt into fixed and variable costs. Variable costs rise and fall with the volume of recovered dollars.[4] Some variable costs occur before default, such as the expense we incur mailing delinquency letters. Because we do not track these internal costs by account, however, we treat them essentially as fixed costs—summing them by portfolio and then apportioning them evenly among accounts.

After default, our main variable costs are the fees we pay outside agencies. These fees vary based on the difficulty of collecting an owed balance, with later placement tiers generally costing more than earlier ones. Outside agencies subtract these fees by account from the dollars they return to us, so they are already netted out in the dependent variable.

Fixed costs are expenses that are independent of the volume of recovered dollars, at least in the short term. Before default, fixed costs include overhead expenses for our internal call center staff. After default, fixed costs include flat expenses such as vendor bonuses. When calculating LGD, we sum these at the portfolio level and then apportion them evenly by account. Table 2-1 summarizes.

[4] In general, variable costs are lower for charge accounts, which are easier to collect.

Table 2-1: Treatment of various recovery costs

	Variable costs	Fixed costs
Before default	Ex: The expense of mailing delinquency letters	Ex: Operating costs for our in-house collections center
	Summed by portfolio and then apportioned evenly among accounts	Summed by portfolio and then apportioned evenly among accounts
After default	Ex: Fees paid to outside agencies per account recovered	Ex: Lump-sum amounts paid to outside agencies
	Included in dependent variable	Summed by portfolio and then apportioned evenly among accounts

2.4. History of the LGD model at AXP

For the USCS and ICS portfolios, AXP has redeveloped Basel retail LGD models twice in the past three years in response to regulatory feedback. AXP initially developed the models in 2012, using a cardmember-level definition of default. Regulatory guidance AXP received in late 2012[5] triggered the development of models with an account-level default definition in 2013. In 2014, AXP received further regulatory feedback requiring modifications in AXP's default definition for Other Retail credit and charge card exposures. Specifically, regulators required that default should be defined as more than 180 days past due (rather than 120 days, as had been assumed earlier).[6] No further redevelopment is currently scheduled.

For the GCP portfolios, AXP has redeveloped Basel retail LGD models once for GCP cardmember and twice for GCP client in the past three years.

The GCP cardmember models were initially developed in 2012 using an account-level default definition. In 2014, Amex received regulatory feedback requiring modifications in its definition of default for its Other Retail credit and charge card exposures: specifically, that default should be defined as more than 180 days past due (rather than 120 days, as was earlier assumed).The GCP client models were initially developed in 2012. As per the guidance received from the EMVG team regarding the change in the Asset Classification logic, the models were redeveloped in 2013. In 2014, the models were redeveloped for the second time to incorporate the regulatory feedback requiring modifications in its definition of default for its Other Retail credit and charge card exposures.

2.5. Why the model is redeveloped

Future model redevelopment may be triggered by:

1. **Feedback from stakeholders**: These include issues raised by regulators, auditors, and internal validators.
2. **Additional data:** If, for example, a segment uses a short data window because of limited data, AXP may update the model as additional data accumulate over time. Also, AXP may

[5]The written guidance covering the October 2012 Regulatory IRB Retail review was transmitted in a letter dated March 6, 2013.

[6]The written guidance covering the 2014 review was transmitted in a letter dated April 9, 2014.

modify the model as richer data become available, e.g., further commercial credit bureau information.

3. **Monitoring alerts:** The model is redeveloped if its performance falls below acceptable levels. See Section 10 for more details.

2.6. Models encompassed by this document

This methodology document describes modeling decisions that are universal across Basel LGD models for consumer, small business and corporate portfolios globally. Details are provided in Table 2.2.

Table 2-2: Basel retail LGD models

Portfolio	Geographic market	Product	Model owner	Supervisor of model operations
USCS	US	CPS Charge; CPS Lending; OPEN Charge; OPEN Lending	Changbin Wang, Vice President	Pavel Gyrya, Director
ICS	Argentina, Australia, Austria, Canada, Finland, France, Germany, Hong Kong, India, Italy, Japan, Mexico, Netherlands, New Zealand, Singapore, Spain, Sweden, Taiwan, Thailand, UK	Consumer Charge; Consumer Lending; Small Business Charge; Small Business Lending	Changbin Wang, Vice President	Jessica Xu, Director
GCP	US and 68 International Markets	Corporate Charge; Corporate Purchasing Card; Global Dollar Card	Benjamin Chan, Vice President	Manas Mahajan, Director

Note: The portfolios covered by this methodology document comprise U.S. Card Services (USCS) and International Card Services (ICS). Twenty countries other than the U.S. are represented. Methodologies employed are broadly similar across countries except for Argentina, which is therefore excluded from this methodology document. Information on the products may be found in Section 16.

This methodology document describes the Basel retail LGD models for the four portfolios listed in Table 2.2, except for LGD models AXP's Argentina and International Currency Card (ICC) exposures. Data limitations require that the models for these exposures differ from those employed for other portfolios.

2.7. Relationship between Methodology Document and model document

This Methodology Document describes generic features of AXP's set of Basel retail LGD models. Because its focus is on common features, the Methodology Document does not cover results for particular Basel LGD models. Readers seeking such specific information should consult this Methodology Document together with the Model Document for the model of interest.

2.8. Intended audience

This Methodology Document is intended to meet the needs of multiple sets of readers. These include the staff of regulatory agencies, including the FRB, FDIC, and the OCC. Other stakeholders for whom the Methodology Document caters are model validators providing an independent review of the model's conceptual soundness and auditors determining compliance with governance procedures in line with AXP policies.

In addition, the Methodology Document is intended to serve the needs of (i) AXP management seeking to understand the model in sufficient detail to review critically its methodology and uses, (ii) AXP staff involved in modeling, wishing to comprehend modeling choices and approaches so as to facilitate continuity of operations, and (iii) new AXP hires involved in learning Basel LGD modeling approaches.

2.9. Organization of the document

The Methodology Document is organized as follows. Section 3 describes the theory behind the modeling approach, justifying the choices made and providing background on regulatory requirements and the academic literature. Section 4 provides information on the data used in the Basel retail LGD model calibrations. Section 5 details steps involved in building the model. Section 6 explains how the models are tested and benchmarked after implementation. Section 7 covers key assumptions and limitations. Section 8 describes AXP's organizational and systems arrangements for implementing the model. Section 9 provides information about how models are used and the impact on AXP's business. Section 10 summarizes governance, policies, and controls. Finally, a glossary lists key terms and acronyms while appendices provide descriptions of statistical techniques employed and of the portfolios covered.

3. Model Theory

3.1. Dependent variable

The statistical exercise described in this document involves the modeling of LGDs on AXP's retail portfolios. As such, it may be related to a substantial academic literature on the statistical investigation of LGDs or, equivalently, recovery rates on loans.

Numerous studies have investigated determinants of corporate debt LGDs. Specifically, Asarnow and Edwards (1995), Araten, Jacobs and Varshey (2004), Gupton, Gates and Carty (2000), Gupton and Stein (2005) have studied LGDs for US bank loans. Dermine and De Carvalho (2012) and Bastos (2010) analyse LGDs for Portuguese corporate loans. Grunert and Weber (2009) and Gurtler and Hibbeln (2013) study German corporate loan LGDs. Felsovalyi and Hurt (1998) analyse corporate loan LGDs using a substantial dataset of Citi defaulted loans across many Latin American countries. A substantial number of papers have analysed LGDs on corporate bonds. Of these, Carty and Lieberman (1996), Carty, et al (1998) and Hamilton and Carty (1999) focus on comparisons of LGDs on corporate bonds and loans using US data.

Distinctly fewer studies have investigated retail loan LGDs. Caselli, Gatti and Querci (2008) look at LGDs for retail loans to Italian SMEs and households. Qi and Yand (2009) model LGDs on high loan-to-value residential mortgages. Crook and Bellotti (2012) model account level credit card LGDs using alternative techniques.

The dependent variable in the Basel retail Models is the account/client level recovery rate, denoted RR. Recovery rate refers to the fraction of the account/client balance at the default date that is recovered by AXP over a performance window of 24 months following default as a result of the bank's collection efforts. The recovery amount is equal to the total discounted cash flows after default.

The rate used in discounted future cash flow recoveries is 12% per annum. A number of alternative discount rates were considered, including (i) the cost of equity (CoE), (ii) the weighted average cost of capital, and (iii) the investment hurdle rate. Of these, option (iii) is used by AXP in discounting recovery cash flows. The hurdle rate, also referred to as a required rate of return or target rate, represents the minimum rate American Express expects to earn for an investment.[7] The value of the hurdle rate is 12% which is higher than the rates implied by the other options considered and, therefore, represents a conservative choice.

The recovery amount is based on cash flows recovered during a 24 month, post-default window. Using a 24 month window length is conservative as recoveries may continue to accumulate after the window ends. Analysis of past recoveries suggests that a 24 month window captures approximately 80-85% of ultimate recoveries.[8] Employing a window longer than 24 months would restrict the number of observations that can be employed because, for the most recent observations, such a window would be incomplete.

The US final rule states: *"The economic loss on an exposure in the event of default is all material credit related losses on the exposure including accrued but unpaid interest or fees, losses on the sale of collateral, direct workout costs, and an appropriate allocation of indirect workout costs."* [9]

The direct collection costs associated with recovering the debt are captured at the account-level. These are fees paid to outside agencies in the form of percentage for each dollar recovered. The indirect and pre-default costs are captured at the portfolio level and are allocated to LGD buckets during the quantification stage discussed in Section 0. These costs include expense for in-house work out, vendor management, and any other lump-sum costs that need to be allocated.

As discussed further below, the recovery rate dependent variable is capped at 100% and floored at 0%.[10] A small percentage of accounts show recovery rates outside the range 0%-100%. In the case of the US CPS lending portfolio, for example, such accounts represent less than 1% of the modeling dataset. Negative recoveries may result from account activity such as fees or a suspended amount that may be charged back to the account. Below is an example of monthly activity for one such account.

Consider an account that is written off in October 2009 for $2.95. The balance in file increases post default, however, because of a suspended amount of $628.95 which is charged back. This increase is counted as a negative cash flow associated with the account, and, thus, leads to a negative recovery rate if the recoveries observed in the subsequent 24 months prove insufficient to offset the negative amount of the suspended amount.

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[7] AXP uses this rate to discount future cash flows when determining whether to undertake a project. The hurdle rate roughly equals the bank's cost of capital, reflecting both the cost of equity and the cost of debt.
[8] This finding is based on historical averages for defaults on CCSG and OPEN portfolios with a minimum of three years of recovery history. The time period considered is 12/1/2004 to 9/1/2007
[9] 72 Fed. Reg. 69402
[10] The principal alternative dependent variable definition considered was an un-bounded LGD. It was not feasible to employ such a definition, however, because the estimation technique employed requires that observations lie between 0 and 1.

Table 3-1 Account with increase in balance due to suspended amount

Month	Written Off Status	Total Balance on File	Suspended Amount	Net Spending Amount
September 2009	No	$628.95	$17.95	$613.95
October 2009	Yes	$2.95	$628.95	$0.00
November 2009	Yes	$611.80	$0.00	$0.00

Note: The table shows the balance on file of an account with a suspended amount at the default month, October 2009. In this example, the suspended amount is charged back in the next month, thus, generating an increase in the balance from $2.95 in October to $611.80 in November. The increase in the balance is not driven by additional spending in November since the account has already been written-off.

3.2. Functional form

The recovery rate dependent variable, defined in Section 3.1, consists of a ratio taking values between 0 and 1. A non-linear regression approach employing a logistic transformation is used for modeling recovery rate. Specifically, the recovery rate (RR) at date t of exposure i, denoted as $RR_{i,t}$ is assumed to equal:

$$RR_{i,t} = \frac{exp\left(\beta_{0,t} + \sum_{j=1}^{N} \beta_j X_{i,j,t}\right)}{1 + exp\left(\beta_{0,t} + \sum_{j=1}^{N} \beta_j X_{i,j,t}\right)} \quad + \quad \varepsilon_{i,t} \qquad (3.1)$$

Here, $X_{i,j,t}$ for $j = 1,2,..,J$, are variables that are predictive of the recovery rate, $RR_{i,t}$. The parameters β_j for $j = 1,2,..,J$ reflect the degree to which the predictive variables influence the recovery rate. The parameters, $\beta_{0,t}$, represent constant, intercept terms. Note that these, unlike the parameters β_j for $j > 0$, depend on the time period, t, an issue that will be discussed further below. The error terms, $\varepsilon_{i,t}$ are assumed to be uncorrelated across i and t.

The parameters β_j for $j > 0$ and $\beta_{0,t}$ for different t are obtained by minimizing the least squares error of the model prediction. AXP estimates the parameters of the non-linear regression using the SAS logistic procedure described in Yang and Tkachenko (2012). This procedure fits a non-linear regression by maximizing a logit model likelihood function. In the standard logit model, the fractions of observations for a binary variable that equal the two possible values appear in the likelihood. The SAS procedure replaces these fractions with observations (in the unit interval) of a continuous variable and then maximizes the likelihood.[11]

This approach is a version of the fractional response regression technique. Fractional response regression techniques for continuous variables distributed on the unit interval are developed by Papke and Wooldridge (1993). Oberhofer and Pfaffermary (2012) provide a replication exercise for the original paper by Papke and Wooldridge (1993). Further recent advances in the technique are proposed by Papke and Wooldridge (2008) and Ramalho, Ramalho and Murteira (2011). Applications of these methods to modeling LGDs include Bastos (2010) and the paper by Yang and Tkachenko (2012) already cited. A recent application in another area of the finance literature is provided by Elsas and Florysiak (2015) who model corporate debt ratios.

[11] The use of SAS tools for modeling loan LGDs is discussed by Van Berkel and Siddiqi (2012) and Maldonado, Haller, Czika and Siddiqi (2013).

3.3. Rationale for selected methodology

3.3.1. Summary of the selected methodology

As mentioned in Section 2.1, Basel LGD quantification includes five steps. In each of these, AXP makes particular methodological choices. One may summarize the key methodological choices as follows:

1. **Define segmentation:** Retail accounts are classified using a segmentation that includes business unit and product, as well as account characteristics. Such segmentation allows us to separate accounts according to their Basel regulatory exposure category (either Qualifying Retail Exposure (QRE) or Other Retail Exposure (ORE)).
2. **Selecting the appropriate account characteristics:** As described in Section 3.2, the Point-in-Time (PIT) model used by AXP is a logit model in which the log odds ratio is a linear index of account characteristics. Important choices must be made in implementing such models in the form of the transformation and selection of explanatory variables, i.e., the account characteristics used as default predictors.
3. **Creating a Through-the-Cycle (TTC) model:** Converting the PIT model to a Through-the-Cycle (TTC) model generates a single long-run LGD score rather than a sequence of LGD scores specific to each time period. AXP accomplishes this by (a) implementing logit models with time-varying constants and then (b) calculating LGDs using a version of the model in which the time-varying constants are averaged.
4. **Identifying segments of homogeneous accounts:** AXP employs a decision tree algorithm based on the TTC LGDs obtained in step 3 to group accounts into segments or buckets.
5. **Quantifying LGD parameters for each homogeneous bucket:** AXP assigns an LGD to each account equal to the average LGD of accounts in the same segment adjusted by downturn and non-direct costs.

The subsections below discuss and justify the key methodological choices adopted by AXP.

3.3.2. Segmentation

The segmentation scheme of Basel retail LGD models is aimed at grouping cardmembers/clients that (i) respond similarly to the same set of explanatory factors and (ii) exhibit underlying behavioral characteristics that are distinct from other segments.

The first level of segmentation is by business unit (consumer or OPEN) and product type (lending and charge), i.e., OPEN Lending, OPEN Charge, CPS Lending, and CPS Charge. This segmentation is appropriate for LGD modeling because it captures the differences in payment structure between charge and lending cards which is a primary driver for the observed differences in recovery rates between those two types of products.

Specifically, most of the charge cards are pay-in-full products, while the lending cards require only minimum due payments (e.g. 2% of monthly balance) for the accounts to be in good standing. Once the accounts default, it is relatively easy to negotiate a payment sequence with charge customers in comparison to lending customers. Charge customers are at a relatively early stage of payment difficulties compared to lending customers that have exhibited difficulties to pay even the minimum due (2% of balance) much earlier.

The second level of segmentation (i.e., at each of the aforementioned 4 segments) is based on risk characteristics that have been identified as LGD drivers. In general, this second level differs from the approach used in PD modeling which is based on the segmentation scheme of AXP's Total Structural Risk (TSR) model.

The performance of alternative segmentation schemes has been evaluated by AXP in the past, and none yields better results than the current segmentation. Segment-level performance is examined quarterly as part of the model monitoring process and the implications of changes in performance for segmentation is investigated.

3.3.3. Selection of the functional form

A number of statistical approaches may be used to predict recovery rates. These approaches include:

1. Parametric regression approaches
    a. Linear model using recovery rate as dependent variable
    b. Non-linear regression using the recovery rate as dependent variable
    c. Two stage model. Stage 1 uses a logistic model to determine whether the account has recoveries, and stage 2 uses a linear regression to predict the corresponding recovery rate
2. Non-parametric regression approaches
    a. Decision tree model using recovery rate as dependent variable

AXP weighed the relative advantages of these approaches and chose the nonlinear regression model for Basel retail LGD models. The nonlinear regression is implemented using the events/trials syntax in the logistic procedure available in SAS. This corresponds to the fractional response regression technique originally proposed by Papke and Wooldridge (1993). The advantages of this approach are:

1. **Nature of output:** The nonlinear regression approach directly generates a number between 0 and 1 which is the typical case for recovery rates.
2. **Internal experience:** AXP has extensive experience of using the algorithms employed in fitting the nonlinear regression, namely the SAS logit model procedures.
3. **Available in the literature:** The application of quasi maximum likelihood techniques for fractional variables was proposed by Papke and Wooldridge (1993), further developed by, among other studies Papke and Wooldridge (2008) and Ramalho, Ramalho and Murteira (2011) and applied to estimation of bank loan LGDs by Bastos (2010) and Yang and Tkachenko (2012).
4. **Transparency:** The results from nonlinear regressions are likely to be transparent and easy to explain to internal stakeholders[12] thereby enabling better engagement of senior management and a robust ICAAP.[13]

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[12] Such internal audiences include: Modeling Strategy Committees (MSC) for individual and institutional portfolios; compliance group; fair lending group; and senior management.
[13] ICAAP refers to the company's Internal Capital Adequacy Assessment Process.

3.3.4. Account-Level modeling

When they were initially developed in 2012, AXP's Basel retail LGD models used cardmember-level data for all markets. Regulators required, however, that the LGD models be redeveloped based on account-level data. The key considerations in regulators' views were: [14]

1. Account-level modeling ensures greater consistency with other banking institutions;
2. Since one cardmember can have multiple accounts mapped to different Basel asset classes, account-level modeling may be viewed as more consistent with the Basel Final Rule.[15]

Since 2013, AXP has, therefore, performed account-level LGD modeling for Basel retail capital purposes.
Note that for GCP retail, Basel retail PD models are also developed at the client level.

3.3.5. Using cycle-cut data

To calibrate Basel retail LGD models, AXP employs historical cycle-cut data, i.e., using information available as of the account's billing date. AXP uses cycle-cut data due to operational considerations (the configuration of internal databases) and to ensure a consistent treatment of data for cardmembers that cycle at different dates.

There are two exceptions to the use of cycle-cut data in AXP's Basel modeling exercises. First, exposures are classified into Wholesale and Retail and then the latter are divided into Qualifying Retail Exposures and Other Retail Exposures based on month-end data. Second, the month-end balance of each account is used in the calculation of the EAD floor.

3.3.6. Modeling data window dates

AXP aims to employ a data window of seven years for calibrating Basel retail LGDs. Such a window is greater than the Basel Advanced approaches minimum requirement of five years. U.S. regulators recommend use of a longer data window to ensure that a full business or economic cycle is included in the sample.

The LGD data window is shorter than the eight years being used in PD modeling because for LGD an additional 24 months is required to measure recoveries. The LGD data window is a subset of the data window used for PD modeling.

3.3.7. Accounting for the impact of the external environment

Fluctuations in the economic or market environment affect recovery behavior in that recovery rates vary over time even if the characteristics of the portfolio do not change. Such fluctuations include decreases in recovery rates during economic downturns and increases in economic upturns.

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[14] The written guidance covering the October 2012 Regulatory IRB Retail review was transmitted in a letter dated March 6th, 2013.

[15] The Final Rule text includes the following: "A bank must classify each of its retail exposures into one of three retail subcategories— residential mortgage exposures; QREs, such as credit cards and overdraft lines; and other retail exposures. Within these three subcategories, the bank must group exposures into segments with similar risk characteristics. The bank must then assign the risk parameters PD, LGD, and EAD to each retail segment." (Basel II U.S. Final Rule 69294)

Recognizing the presence of such fluctuations, AXP considered three different approaches to reflecting this in LGD modeling:

1. To suppose that the intercept $\beta_{0,t}$ in equation (3.1) is constant, i.e., to suppose: $\beta_{0,t} = \beta_0$.
2. To allow the intercept $\beta_{0,t}$ in the linear index in equation (3.1) (i.e., $\beta_{0,t} + \sum_{j=1}^{N} \beta_j X_{i,j,t}$) to depend on the time period.
3. To replace the parameter $\beta_{0,t}$ in Section 3.3 with a linear function of macroeconomic variables including unemployment rate and GDP growth.

AXP decided to employ the second approach since it does not require the collection of macroeconomic data, which may be unavailable on a timely basis for some markets.

Note that time-varying dummies might be included in the model for different time periods. For example, constants could be introduced that are specific to each month. Alternatively, they could be held constant for three or six month periods. In selecting an approach, AXP considered the following objectives:

1. To capture the recovery rate variation over the development window with recovery rates distinctly different across time periods.
2. To ensure consistency across portfolios.
3. To ensure adequate default events per bucket per time period.

In light of these objectives, AXP chooses to employ quarterly time periods for LGD modeling for US portfolios, and semi-annual periods for ICSS (across markets) portfolios.

3.3.8. LGD segmentation (bucketing) based only on long-run LGD scores

Basel rules require that LGDs assigned to individual accounts/clients are the averages of those observed for homogeneous portfolios to which the account/client in question belongs.[16] Having estimated account-level or client-level LGDs, AXP must therefore (i) bucket the exposures into homogeneous segments or buckets, and then (ii) calculate representative LGDs for each bucket.

AXP employs the long-run Basel LGD model score for the segmentation variable in bucketing. Thus, accounts/clients with similar LGD scores are assigned to the same LGD segment. Basel LGD score is a natural choice for performing this segmentation, because:

1. It incorporates many key risk characteristics into one score.
2. It is based on long-term, through-the-cycle data.
3. It captures those risk characteristics which rank-order risk consistently over time.

To simplify segmentation, the LGD score is the only segmentation variable used. Each final segment was therefore defined by a range of LGD scores, with a lower bound and an upper bound, referred to as "LGD bucket."

[16] The Final rule states that a bank must have a system which "groups the retail exposures in each retail exposure subcategory into separate segments with homogeneous risk characteristics, and assigns accurate and reliable PD and LGD estimates for each segment on a consistent basis." "Final Rule" (22) (b) (3), 69407.

3.4. Regulatory requirements

Basel risk models must satisfy a number of explicit and implicit regulatory requirements, which shape multiple methodological choices.

The Basel retail LGD models conform to the Basel III Advanced Approaches rule. Table 3.2 provides references to some of the key requirements governing LGD models contained in the final rule. The modeling techniques also embody feedback from AXP's regulators, including the cumulative body of findings communicated through examinations and supervisory letters.

Table 3-2: Specific regulatory requirements

Requirement	Citation	Regulatory text
Historical data requirements	"Final Rule" (22) (c) (6)	LGD estimates for retail segments must be based on at least five years of loss severity data.[17]
Conservative parameter estimation	"Final Rule" (22) (c) (3)	AXP's risk parameter quantification process must produce appropriately conservative risk parameter estimates where AXP has limited relevant data; any adjustments that are part of the quantification process must not result in a pattern of bias toward lower risk parameter estimates.
Downturn inclusion in modeling	"Final Rule" (22) (c) (7)	Default, loss severity, and exposure amount data must include economic downturn conditions, or AXP must adjust its estimates of risk parameters to compensate for the lack of data from economic downturn conditions.
Retail portfolio segmentation	"Final Rule" (22) (b) (3)	For retail exposures, AXP must have an internal system that groups retail exposures into the appropriate retail exposure subcategory, groups the retail exposures in each retail exposure subcategory into separate segments with homogeneous risk characteristics, and assigns accurate and reliable PD and LGD estimates for each segment on a consistent basis.
Drivers of retail segmentation	"Final Rule" Preamble Section III. B. 2	Examples of risk drivers could include loan-to-value ratios, credit scores, loan terms and structure, origination channel, geographical location of the borrower, collateral type, and bank internal estimates of likelihood of default and loss severity given default. Regardless of the risk drivers used, AXP must be able to demonstrate to its primary Federal supervisor that its system assigns accurate and reliable PD and LGD estimates for each retail segment on a consistent basis.
Capital calculation for segments of retail exposures	"Final Rule" (31) (e) (1) (i)	AXP must calculate the dollar risk-based capital requirement for segment of non-defaulted retail exposures by inserting the assigned risk into the appropriate risk-based capital formula specified in Table 2 and multiplying the output of the formula (K) by the EAD of the exposure or segment. Alternatively, AXP may apply a 300 percent risk weight to the EAD of an eligible margin loan if AXP is not able to meet the agencies' requirements for estimation of PD and LGD for the margin loan.
Reporting as of month-end	Y9-C-pg. 1 FEFIEC 101 - instructions, pg. 1	The institutions specified in Section A above must begin reporting on the FFIEC 101, Schedule A, except for a few specific line items, at the end of the quarter after the quarter in which the institution triggers one of the threshold criteria for applying the advanced approaches rule or elects to use the advanced approaches rule (an opt-in institution),and must begin reporting data on the remaining schedules of the FFIEC 101 at the end of the first quarter in which they have begun their parallel run period. All institutions specified in Section A will continue to file the regulatory capital schedule in the Call Report or FR Y-9C, as appropriate, as well as the FFIEC 101.

Note: the Final Rule may be retrieved from the original source at the following address: http://www.federalreserve.gov/generalinfo/basel2/FinalRule_BaselII/. The FEFIEC may be found at: http://www.ffiec.gov/forms101.htm.

4. Model Data

[17] Furthermore, PD estimates for retail segments must be based on at least five years of default data, EAD estimates for wholesale exposures must be based on at least seven years of exposure amount data, EAD estimates for retail segments must be based on at least five years of exposure amount data, and LGD estimates for wholesale exposures must be based on at least seven years of loss severity data.

This section provides a summary of data sourcing and transformation processes used during model development.

4.1. Data sources

Calibrating the Basel retail LGD model requires three types of information:

(i) Data on account default status, write-off amount, and recovery costs
(ii) Monthly internal behavioral characteristics associated with accounts/clients, such as the ratio of past payments to current balance
(iii) Monthly data on cardmember risk from external vendors, such as FICO

The first data source provides the information necessary to create the model's dependent variable, while the second and third sources provide the basis for constructing the independent or predictive variables used in the model. The data sources for (ii) and (iii) are the same as those used for PD modeling.

The modeling data for most portfolios are extracted from so-called APAC tables in AXP's Information Delivery Network (IDN) Warehouse.[18] IDN is a relational database containing internal AXP data including information on cardmember billings, A/R, delinquencies, fees, and payment histories.

The IDN and L2/GL2 files also contain consumer and small business credit bureau data, e.g., FICO scores and external balances for the US, CII and Delphi for the UK, and Global Bureau score in Argentina.

4.2. Creating the modeling dataset

4.2.1. Modeling population

For each relevant portfolio and Basel exposure category, AXP selects records and uses them to construct a master modeling dataset for Basel retail LGD modeling. As a first step, AXP excludes accounts/clients that do not satisfy modeling conditions specified in Table 4-1.

Table 4-1: Observations excluded to create the final dataset

Exclusion Rule	Description	Reason for Exclusion
Not in-base	Accounts that are not in-base as of the observation month (written-off accounts and cancelled accounts without balance)	No capital is required
Wholesale accounts	Wholesale accounts are excluded because they belong to a different Basel exposure category and will be modeled separately	Outside the model's scope
Lending ORE accounts	Lending Other Retail accounts (effective line exceeding $100,000).	Outside the model's scope
Defaulted accounts in observation amounts	The account is not in default as of the observation month based on the relevant Basel default definition.	Capital requirement is different
No future default	Excluded if the account did not default within 12 months of the observation month.[19]	Observing recoveries require a default event

[18] APAC stands for Advanced Performance Analytic Capability. It refers to tables that provide historical performance data sourced from the company's A/R systems and populated on a cycle basis. Data included are defaults, attrition, delinquency movements, write-offs, balances, spending, and more.

[19] Accounts that voluntarily attrite are excluded since it is not possible to observe whether they would have defaulted over a complete 12 month performance period. Accounts that default within 12 months

Less than 24 month post-default history	Excluded accounts with a default event but less than 24 months of post-default performance data	Post-default performance is needed for observing recoveries

4.2.2. Sampling

Two sampling approaches were considered for creating the LGD modeling dataset. One approach allows an account/client to appear multiple times in the modeling sample by taking a random sample of the accounts/clients in the LGD modeling population for each reference month. This approach will be referred to as "with repeats" because an account can be selected multiple times. Another approach randomly assigns a reference month among the 12 months before the default date. This approach is called "no-repeats".

The sampling approach "with repeats" will have some level of co-dependence among observations that may negatively affect model performance. The sample with "no-repeats" is preferable as it avoids incorporating additional co-dependence between observations. It also eliminates the possibility of the same default appearing more than once in the calculation of LGD assignments.[20]

The "no-repeats" sampling approach was used for creating a sample from the population. The resulting sample constitutes the master dataset that is used for the development and validation of the LGD model including (a) the development of the account-level model to predict recovery rates, (b) LGD bucketing, and (c) the corresponding assignments.

The steps taken in creating the master dataset are as follows. Starting with all the default events, a reference month between the 12 months before the default date is assigned randomly. AXP verifies that the randomly assigned reference month is part of the LGD modeling population. When a reference month does not satisfy any of the conditions that define the LGD modeling population, the observation is excluded from the sample.
Table 4-2 describes how the conditions that define the LGD modeling population are checked and provides examples of observations that do not satisfy those conditions.

Table 4-2: Conditions checked on the randomly assigned reference month

No	Condition	Reasoning
1	There are no other default events between the reference month and its corresponding default date	Some accounts show multiple default dates. In those cases, AXP keeps the randomly selected reference month if there is no other default event between the selected reference month and the corresponding default date.
2	In base in the reference month	This is a condition that defines the LGD modeling population.
3	Not in default status in the reference month.	This is a condition that defines the LGD modeling population.
4	Product type is in scope	This is a condition that defines the LGD modeling population.
5	Assigned reference month falls within the modeling window	The reference month is created randomly and could, therefore, fall outside the time window being used for modeling. For US, for example, the modeling data window dates start in January

cannot be labeled as attrition within the same 12 month period. Thus excluding voluntarily cancelled accounts does not reduce the number of defaults in the modeling population.
[20] In sampling, the approach "with repeats" is easier to refresh by adding additional months than the "no-repeat" approach. This is not a significant benefit, however, given the small size of the LGD dataset.

	2004. The first valid reference month for the LGD modeling population is, therefore, January 2004

4.2.3. Potential sources of bias

Several aspects of the Basel retail LGD modeling approach could lead to estimation bias. Table 4-3 describes these potential biases and how AXP eliminates or mitigates them.

Table 4-3 Sources of potential bias

Potential bias	Approach
Due to the use of a long-run, cyclical data series, segment size and default rates vary over time. This may lead to overweighting years for which a segment is larger or has a greater proportion of defaults.	Cyclicality is captured in the model by use of dummy variables. A set of binary dummy variables will be defined for each observation to indicate the time period of the observation. During multifactor analysis, the cyclical effect exerted by any particular period will be captured through the value of the coefficient associated with that period's dummy variable. To make the model suitable for scoring, the coefficients of the cyclical dummy variables are averaged. The fitted regression including this averaged coefficient represents a Through-the-Cycle (TTC) PD.
Within a given year, the month that an account is observed may influence default behavior during the performance period because of seasonal spending patterns. Seasonal effects may be correlated with cyclical effects.	Accounts are sampled from each month of each year included in the data window. For example, if five years of data are used, there are a total of 48 observation periods.
Including the same accounts multiple times would compromise the independence of observations, as one account's characteristics are likely to be similar over time.	A low and random sampling rate is employed to minimize repeat cases.

4.2.4. Creating independent variables

AXP follows specific policies for the selection of independent variables in its scoring exercises. Table 4-4 summarizes these policies and sets out the implications for the bank's Basel retail PD modeling.

Table 4-4: MSC variable analysis guidelines

Requirement	Implications
Capture all relevant categories of independent variables	Replicate existing TSR variables in the sample
Do not include more than 500 independent variables in the factor long list	This cap is sufficiently large to permit Basel PD models to utilize existing TSR variables, as well as 'must have' and 'must try' lists, and other raw variables available in the data
Perform data truncation (capping and flooring)	Perform data truncation, including capping and flooring, to select the relevant range for variable discrimination and optimize model performance
Organize independent variables by categorizes	Example categories include delinquency; spending patterns; customer profile (such as tenure); and bureau information.
Ensure adequate representation from most variable categories	Review the representation of different variable categories; investigate if one or more are missing
Include must-have variables	Must-have variables must be selected before any others in a category; exceptions require approval

Note: The source for these policies is AXP's Modeling Strategy Committee, or MSC.

All the independent variables are APAC replica of TSR variables. The difference is that variables used in Basel are based on the information available in the APAC table at cycle-cut, whereas the TSR variables are based on real-time information from AXP's Credit Authorization System (CAS).

4.3. Quality assurance

Recognizing that input data quality determines the quality of Basel capital calculations, AXP reviews and reconciles internal and external data. The tables below summarize these quality assurance steps. They are the same as those applied in PD modeling with the exception of the quality assurance of the dependent variable.

Table 4-4: Quality assurance (QA) checks for internal data

QA area	Activity
Data for the dependent variable	Check whether recovery rates are roughly consistent over time across the four datasets (the development, out-of-sample, out-of-time, and early validation datasets).
Data for independent variables	Perform univariate analysis, meaning a month-by-month comparison of the means, minima, maxima, number of missing values, number of zero values, and percentile distributions for each variable. For example, AXP confirms that account tenure does not carry any unreasonably high values. AXP conducts this analysis for all four datasets (listed immediately above). Investigate irregularities such as unexplained or counterintuitive variations. If AXP discovers any, their root causes are determined and appropriate correctives applied. For example, if AXP finds that the values of independent variables are unchanged across multiple months, AXP checks if the data was mistakenly duplicated.
Code check	Check logs of software code that retrieves internal data to search for errors.

Table 4-5: Steps for processing independent variables from credit bureaus or other external sources

Initial processing	Description
Initial processing	Confirm the data arrives in the expected format. Compare the number of records and file size against expectations. Convert from a ".dat" to a ".sas7bdat" format. As necessary, clarify with the bureau how compound variables were created. Check whether the construction of variables is appropriately documented.
Evaluation and cleansing	Evaluate variable means, minima, maxima, number of missing values, number of zero values, and percentile distributions to search for unexplained or counterintuitive variations. Confirm that the number of observations received matches the number of cardmembers in the sample. Look for and removing duplicate entries. Compare the rank-ordering of key risk scores with known instances of default.

5. Building the model

This section summarizes the LGD modeling approach including estimating the account-level expected LGD, the bucketing scheme and assignment of LGDs to individual accounts/clients. The approach to developing the account-level expected LGD is very similar to the approach used in Basel retail PD modeling. For bucketing, however, the use of a downturn period introduces differences between the LGD and PD approaches. See Section 5.6 for details.

5.1. Summary of model building steps

LGD model development requires six steps. These are summarized in Table 5-1 and further elaborated in the sections that follow. Note that the Basel retail LGD models are implemented using SAS, a software package that retrieves and processes data and performs statistical analysis.

Table 5-1: Model building steps

No.	Step		Description
1	Data creation and sampling		Retrieve and cleanse dependent and independent variables Select the sample of observations. Split into development and validation samples Select initial list of independent variables
2	Segmentation		Determine segments Prepare segment subsets of data from the master dataset
3	Variable selection	Single-factor analysis	Reduce list of independent variables based on their strength of relationship with Basel default Base expected sign on business intuition and correlation analysis Measure correlation among independent variables and exclude where it is too high
4		Variable treatment and transformation	Impute values where they are missing Apply caps and floors to control for outlier values Transform variables as necessary to ensure a linear relationship with default
5		Multi-factor analysis	Perform initial regression using stepwise procedure to identify the best subset of variables Exclude variables iteratively where: they are cross-correlated (VIF analysis) their signs are inconsistent over time they exhibit counter-intuitive signs they contribute only weakly to Gini Add time indicators, re-run the stepwise procedures, and re-check for cross-correlation
6	Model refinement		Conduct pre-validation (assess performance against out-of-sample data and prior version of the model)

Note: The table lists the common steps involved in creating Basel LGD models. Each of these steps is described at more length in sections 5 and 6. Model-specific details are provided in the individual model documents.

5.2. Segmentation

5.2.1. Guiding principles for segmentation

In this step, modelers divide the estimation sample into a number of subsamples corresponding to individual segments. Subsequent modeling steps are performed separately on these segment-level subsamples.

The first level of segmentation for Basel retail LGD modeling is based on each business unit/product type combination. This approach generates four groups: OPEN Lending, OPEN Charge, CPS Lending and CPS Charge.

The second level is based on account attributes that are identified as LGD drivers.[21] Segments are order dependent and mutually exclusive. They are sequenced in an "if-then-else" fashion, so that if an account is accurately described by the first segment, it is absorbed at that point. If not, the account proceeds through each successive segment until one matches.

[21] This differs from the approach employed for Basel retail PD modeling which replicates the scheme employed in AXP's TSR model. This latter scheme is designed to differentiate accounts based on default risk drivers.

The modeling team employs the following cross-term test to assess and compare the performance of various segmentation splits. In this test, many test regressions are built using an automated procedure for the purpose of identifying optimal segmentation variables. The steps involved in the cross-term test are:

1. Define key regression variables by building a model based on the overall population. For simplicity, missing imputation, cap/floor and transformation of these variables are also processed based on the overall population.
2. Define key segmentation candidates to be used as candidates for designing segmentation splits.
3. Prepare various candidate splits based on each segmentation candidate variable selected. For discrete variables, all unique values would be used as segment candidates. For continuous variables, each 5th percentile would be used as a candidate cut point for separating segments. If a segmentation candidate has some missing values, Missing/Non-missing split would always be considered as a separate sub-segment.
4. To select an optimal segmentation split among candidate splits defined in step 3, the algorithm would compare multiple regression models[22], each one built using its own binary segment split indicator as a class variable, and containing all the cross terms between regression variables and the selected binary split indicator.
5. An optimal segmentation split would be selected among those tested based on a pre-defined model performance metric. Business intuition is also considered, for example some segmentation candidate splits could be rounded to make segmentation more intuitive.

Given the specific features of the models covered by this document, modifications to the cross-term test described above may be applied. Such changes will be documented in the corresponding Model Document.

Following the guidance of MSC (Modeling Strategy Committee) and modelers' past experience, a PD modeling segment should have at least 1000 defaults in modeling data (development sample and validation sample combined) to ensure enough sample size for stable performance. Any deviation from the guidance will be documented and discussed in the portfolio specific model document.

5.2.2. Selected segments

For each model covered by this Methodology Document, the segments finally selected and the rationale for their selection are provided in the corresponding Model Document.

5.3. Variable selection

5.3.1. Data exploratory analysis

As a first step in variable selection, modelers:

1. Document whether all variable categories are represented
2. Note variables unavailable for the full duration of the modeling data window
    a. In most cases, exclude variables unavailable for the full window

[22] All the regression terms prepared were forced into regression model, even if insignificant

   b. If a variable is expected to be powerful, and is available for the Basel minimum 5 years, but not for the full data window duration, it may be included and the model appropriately adjusted
3. Exclude variables if they are not suitable for Basel LGD modeling (e.g. daily variables or closed loop variables[23]).

5.3.2. Single factor analysis

Prior to model development, for each segment, all the variables are checked for basic descriptive measures using the Enhanced Data Dictionary (EDD). The EDD is a spreadsheet containing summary profiles for each independent variable. Table 5-2 lists the fields provided for each variable by the EDD.

Table 5-2: Enhanced Data Dictionary fields

Field name	Description
Reference number	The numbering of the variable in the table
Variable name	Name of the variable
Group	The category/grouping of the variable
Variable description	Variable description
Type	Numeric or character
var_length	Length of the variable
n_pos	Position of the variable in the dataset
numobs	Number of observations
nmiss	Number of missing values
pzero	Zero rate
pmiss	Missing rate
Nunique	Number of unique values – for character fields only
mean_or_top1	Mean for numeric or most frequent value for character
min_or_top2	Minimum for numeric or 2nd most frequent value for character
p1_or_top3	1st percentile for numeric or 3rd most frequent value for character
p5_or_top4	5th percentile for numeric or 4th most frequent value for character
p25_or_top5	25th percentile for numeric or 5th most frequent value for character
median_or_top6	Median for numeric or 6th most frequent value for character
p75_or_top7	75th percentile for numeric or 7th most frequent value for character
p95_or_top8	95th percentile for numeric or 8th most frequent value for character
p99_or_top9	99th percentile for numeric or 9th most frequent value for character
max_or_top10	Maximum for numeric or 10th most frequent value for character

The EDD is run only on the estimation sample. The information it provides is used to highlight and exclude from subsequent steps any variables for which one of the following conditions is met:

- either missing rate above 60%
- trivial rate (Missing + zero) above 99.5%
- Non Trivial Count >= 250

Once the initial screening is complete, the remaining list of potential candidate variables is used to develop a model specific to the segment in question.

[23] Wherever AXP manages both the acquiring relationship with merchants and card issuing to consumers, it creates a "closed loop," in that access to information at both ends of the card transaction is available.

5.3.3. Variable transformation and treatment

The list of selected variables obtained from the previous step is inputted into the Model Automation Suite (MAS), an AXP proprietary data analysis application for data transformations. The objective of the MAS is to suggest the best transformation for an independent variable, where the transformations considered include (i) capping and flooring values, (ii) change of variable to linear, natural logarithm or square root of the original variable, and (iii) missing value imputation.

For example, cardholder balances vary over a wide range (often from a minimum of $10 to a maximum of $5 million). The logarithm of this variable is approximately linearly related to the ramp-up factor whereas the untransformed variable is not. In this instance, MAS would, therefore, suggest a logarithmic transformation.[1] The one variable that is not subjected to transformations using the MAS is the account FICO score.

To compute the preferred transformation for an independent variable (X), the following methodology is applied.

1. Three datasets are created corresponding to the linear (untransformed), log and square root of the variable. Perform the following steps for each of the three datasets.
2. Observations are split into K buckets based on the values of X. Each bucket contains an equal number of observations. The number of buckets K is determined by the user. Missing observations are treated as a separate bucket. The average value of the variable, X, denoted $\overline{\mathrm{X}}_{\mathrm{k}}$, for $k = 1,2,..,K$, is calculated for each bucket,.
3. The application computes a minimum permitted difference (D) between the minimum and maximum bucket-specific averages, $\overline{\mathrm{X}}_{\mathrm{k}}$. For any subset of buckets for which the difference in average values for the minimum and maximum values of $\overline{\mathrm{X}}_{\mathrm{k}}$ exceeds D, the following steps are followed:
    a. Calculate the fraction of the population, denoted P, contained in the buckets under consideration.
    b. For each bin, k, calculate the average EAD ramp-up factor $\bar{F}_k$. Calculate the difference, d, between $\bar{F}_k$ for the two bins for which $\overline{\mathrm{X}}_{\mathrm{k}}$ is highest and lowest
    c. Perform an ordinary linear regression of $\bar{F}_k$ on $\overline{\mathrm{X}}_{\mathrm{k}}$. Let R^2 denote the R-square statistic of this regression. The average of the dependent variable from the missing bucket, denoted $\bar{F}_0$, is inserted into the inverted regression equation to obtain an imputed value $\overline{\mathrm{X}}_0$ of the independent variable for the missing bucket.
    d. Calculate the MAS statistic defined as: $\text{MAS statistic} \equiv \mathrm{R}^2 \times \mathrm{d} \times \sqrt{\mathrm{P}}$
4. If the combination of bin range and functional form that gives the maximum MAS statistic contains the first or the last or both first and last buckets of the variable, further binning is performed in that the first two buckets or the last two buckets or both the first two and last two buckets are split and these additional bins are appended to the existing bins. Steps 1 to 5 are then repeated. Otherwise, the combination of transformation and set of bins that yields the maximum MAS statistic is selected.

[1] The MAS output serves as the starting point for analysis and also as a benchmark for comparing alternate transformations.

The selected transformation provides the functional form and the imputed value for missing values. The cap and floor values are the $\bar{X}_k$ corresponding to the minimum and maximum bins of the suggested transformation.

Caps and Floors
AXP decided to adopt the approach of restricting variable transformations to align with industry practice for Basel models. Where outliers exist, AXP may apply floors (minimum allowed values) or caps (maximum permitted values) to prevent bias and to avoid unreasonable results. Please refer to "20150430_AXP_Impact_of_transformations_vF.docx" mentioned in Bibliography.

Variable transformations would be restricted to generally have fraction of modeling population impacted by caps and floors be less than 5%. Where caps or floors affect more than five percent of observations, AXP analysts typically review the limits proposed by MAS and adjust the transformation based on trends in the variable and business knowledge. This adjustment would be explained in the corresponding modeling documentation, along with the rationale

Expected Sign
AXP assigns an expected sign for the dependence of the LGD on each independent variable. This expected sign is based on (i) business intuition, (ii) findings from past models, and (iii) portfolio-level correlations. Where no clear expectation exists, analysts remain agnostic and do not impose an expected sign.

5.3.4. Multi-factor analysis

Modelers first perform an initial regression with only behavioral variables using a stepwise procedure to identify the best subset of variables. Subsequently, modelers remove variables for which:

- **The coefficient sign is unreasonable or inconsistent over time**: Modelers remove variables for which the coefficient sign contradicts a priori intuition, beginning with the least significant. Counterintuitive signs may indicate multi-collinearity or other interactions that could destabilize results.
- **Variables are cross-correlated:** Modelers test for multi-collinearity using VIF and correct for it either by combining variables or by excluding the least influential one (identified based on the lowest Wald Chi-square score).[24]
- **Statistical significance drops:** After removing unreasonable or correlated variables, modelers re-estimate the model iteratively to check that the deletions do not reduce the significance of the remaining variables below the acceptable p-value threshold.
- **Variables contribute only weakly:** After cutting variables based on the above criteria, modelers discard variables if their removal does not significantly affect the Gini score.

[24] Multicollinearity occurs where two or more explanatory variables are highly correlated. It can cause coefficient estimates to behave erratically (for example, change sign) in response to small changes in values. One may test for multicollinearity using the Variance Inflation Factor (VIF).

- **Cross-term check:** For remaining variables, they were individually tested against yearly data, if any driver was found to be significant (p-value <1%) and the coefficient sign was found different to the base coefficient sign in at least 2 occurrences out of 8 (reference data consists of 8 years), such variables were removed. Finally, a few model refinement steps were performed, including adjusting variable transformations, and, for ICSS, regional time indicators

5.3.5. Model Refinements

The following model refinement steps were performed in order to review model quality, improve model fit and prepare model for long-run score adjustments.

Adjusting variable transformations
During this step, modelers reviewed bin plots for variables entering into the final model. A particular case is the adjustments to the FICO Score for US market transformation: in all cases a non-linear transformation was removed. Using a linear transformation is recommended because the non-linear transformation of bureau will have interpretation issues.

Including time indicators for Long run
In addition to the final set of independent variables, modelers included significant time period indicators into final round of refitting to capture cyclical effects and prepare the model for long-run score adjustments

Multi-collinearity, variable consistency and significance checks
Because including time indicators into regression model could potentially change sign, significance or multi-collinearity for the main modeling variables, these checks were re-done and only the variables that pass this test were included in the final LGD model.

5.4. Final model form and interpretation

5.4.1. Comparing the performance of the new and older models

In the Model Document, this section compares the performance of the new and previous versions of the Basel retail LGD model. Performance is typically measured using Gini and model accuracy measures.

5.4.2. Model results by segment

In the Model Document, this section presents the final model results by segment, including coefficients, transformation form, caps and floors, and p-values for each selected variable.

5.4.3. Business intuition of the selected variables

In the Model Document, this section provides an interpretation of the relationship between each variable and default based on the company's business experience.

5.5. Adjustments

The following adjustments are made to the RR scores to meet Basel purposes. They are applied in the order presented below.

5.5.1. Long-run or Through-the-cycle adjustments

Time indicators are constructed to capture cyclical effects in the modeling window/estimation period and prepare the model for long-run (LR) score adjustments. Time indicators are binary variables and are either quarterly indicators (or semi-annual indicators).

Time indicators are offered to the model along with other independent variables. Only the statistically significant one will be kept in the final model.

The statistically significant time indicators included in the final model are used to convert the point-in-time scores to long-run scores by adjusting the intercept of the estimation equation. First, we derive the weight to be applied to the coefficient of each significant time indicator to average out the time-varying constant. The weight is equal to the length of the period corresponding to the time indicator (such as one quarter for quarterly indicators) divided by the total length of the estimation period (such as 32 quarters). Second, we multiply the weight to the coefficient of each significant time indicator. Last, the adjusted coefficients are added to the intercept of the point-in-time estimation equation. The result is the through-the-cycle estimation equation.

Below is an illustrative example. In this example, the model development window is 32 quarters and there are 3 significant time indicators in the final point-in-time model equation. Therefore, the weight applied to each significant time indicator is 1/32, or 0.03125.

Table 5-1: Illustrative example of through-the-cycle adjustment using time indicators

Model Variables	PIT Equation	Weight	Adj. Coefficients	TTC LR Equation
Intercept	1.23	N/A	1.23	1.24
Customer tenure	-0.32	N/A	-0.32	-0.32
Balance (Int+Ext)	0.01	N/A	0.01	0.01
FICO	-4.13	N/A	-4.13	-4.13
#CPS Lending cards	-0.29	N/A	-0.29	-0.29
Total remittance- current month	-0.01	N/A	-0.01	-0.01
Time_Ind_Q22005	0.02	0.03	0.03125*(0.02)	-
Time_Ind_Q32008	0.22	0.03	0.03125*(0.22)	-
Time_Ind_Q12010	-0.05	0.03	0.03125*(-0.05)	-

5.5.2. Adjustments for CARE and Re-age accounts

Cardmember Assistance and Relief Environment (CARE) is a short term financial difficulty program that offers late fee suppression and lower APR for 12 months. Re-aging is a practice that provides assistance to cardmembers who have demonstrated a renewed willingness and ability to repay their debt. The Federal Financial Institutions Examination Council (FFIEC) has defined re-aging in the Uniform Retail Credit Classification and Account Management Policy as "returning a delinquent, open-end account to current status without collecting the total amount of principal, interest, and fees that are contractually due."

The current set of Basel models does not have specific segments for the Care and Re-age populations. Information on whether observations correspond to Care or Re-age accounts has not been reflected in the LGD model described above. To correct this, the PIT RR score is adjusted for Care/Re-age population.

To decide if RR score adjustments are necessary for these special account groups, modelers compared point-in-time predicted RR score, with actual recovery rate by business unit and product group, based on whether the account belongs to one or both of these special groups.

Buckets for which the RR score is significantly greater than the actual RR (at a 1% confidence level) are then adjusted by running a logistic regression with the log odds implied by the PIT prediction as the only independent variable.

The highlighted buckets in the following Table 5-3 need adjustment across business units and products.

Table 5-3: Identifying Care and Re-Age groups that need RR adjustments

Portfolio	Care / Re-Age program status	# Obs	Actual Default Rate	PIT RR	%Difference from Actual	P Value
Consumer Charge	Care Only	35,241	40.29%	29.95%	-25.66%	0.0%
	Re-age Only	969	8.35%	14.49%	73.53%	0.0%
	Care and Re-age	1,854	9.54%	13.28%	39.20%	0.0%
	Other	1,140,581	20.03%	20.35%	1.60%	
OPEN Charge	Care Only	15,576	46.77%	35.93%	-23.18%	0.0%
	Re-age Only	200	8.16%	10.97%	34.44%	1.5%
	Care and Re-age	361	8.03%	11.84%	47.45%	0.0%
	Other	359,530	23.92%	24.35%	1.80%	
Consumer Lending	Care Only	45,163	7.13%	7.28%	2.10%	2.2%
	Re-age Only	19,226	10.30%	11.19%	8.64%	0.0%
	Care and Re-age	18,641	8.72%	11.32%	29.82%	0.0%
	Other	2,103,181	9.01%	9.06%	0.55%	
OPEN Lending	Care Only	12,540	6.38%	5.80%	-9.09%	0.0%
	Re-age Only	3,473	7.85%	8.27%	5.35%	8.3%
	Care and Re-age	4,239	7.92%	8.47%	6.94%	1.5%
	Other	390,336	6.21%	6.23%	0.32%	

Note: The table shows the recovery rates for accounts in the each of the four USCS portfolios, with accounts in the Care and Re Age programs treated separately. The P statistics of a test to compare the actual RR with the PIT RR scores are also shown.

The following Care/Re-age adjustments were then developed for the population groups selected, using logistic regression with one independent variable (log odds of point-in-time RR score).

During Basel model scoring, these adjustments are intended to be applied to long-run Basel RR score.

For performing the adjustments, the RR score was converted into its logit(=log(p/(1-p)), and then a logistic regression was performed between actual default and the long-run average score. The slope and regression are summarized in the table below.

Table 5-4: Adjustments for CARE/Re-Age

Portfolio	Care / Re-Age program status	Adjustment Made	Intercept	Slope
Consumer Charge	Care Only	No		
	Re-age Only	Yes	-1.389	0.556
	Care and Re-age	Yes	1.175	0.562
	Other	No		
OPEN Charge	Care Only	No		
	Re-age Only	No		
	Care and Re-age	Yes	1.425	0.605
	Other	No		
Consumer Lending	Care Only	No		
	Re-age Only	Yes	0.894	0.605
	Care and Re-age	Yes	1.191	0.554
	Other	No		
OPEN Lending	Care Only	No		
	Re-age Only	No		
	Care and Re-age	No		
	Other	No		

Note: The table shows which accounts in the each of the four USCS portfolios received Care and Re Age adjustments. Where an adjustment was made, the slope and intercept of the logistic regression used for the adjustment is shown.

After the adjustments on logit, the logit scores were converted back into the probabilities.

5.6. Bucketing

To group accounts/clients into homogeneous pools or portfolios as required by Basel rules, AXP employs a Chi squared Automatic Interaction Detector (CHAID) based decision algorithm.[25] This is applied separately to each exposure classification (QRE/ORE), portfolio (Consumer/Small Business), and product group (Charge/Lending). The technique is implemented using the SAS Enterprise Miner application. The methodology used by the Enterprise Miner algorithm is described in an appendix.

The dependent variable employed in the sorting is the recovery rate (RR) while the independent variable consists of the long-term RR score after adjustments for CARE/re-age accounts as described in Section 5.5.2. The long-term Basel RR model score is used as the only segmentation

[25] Kass, Gordon V.; An Exploratory Technique for Investigating Large Quantities of Categorical Data, Applied Statistics, Vol. 29, No. 2 (1980), pp. 119–127.

variable. Thus, accounts/clients with similar RR scores are assigned to the same segment. The Basel RR score is a natural choice for performing this segmentation, because:

- It encapsulates all the key characteristics that drive the recovery rate into one score.
- It is based on long-term through-the-cycle data.
- It captures those characteristics which rank-order recoveries consistently over time.

To run the algorithm on a portfolio, the data is partitioned into a training set and a validation set using a 70% to 30% split as is common in such calculations.

The criterion for assessing whether to retain a split between two buckets used by the Enterprise Miner algorithm is the statistical F-test in which the null is that mean default rates in the child nodes are the same. To improve bucket stability, different criteria are applied so as to group some of the buckets.[26]

- Buckets with either less than 1000 observations in the dataset or less than 10 observations in the downturn period are grouped with neighboring buckets.
- A statistical two-sample Z-test is used to assess whether the average recovery rates for neighboring segments differ to a statistically significant degree.[27] When neighboring segments are not statistically different, they are merged into a larger bucket. This procedure is performed iteratively until all the neighboring segments are statistically different.

The algorithm produces buckets which exhibit the following properties with respect to a given target variable.

- Rank Order: Bucketing schema rank orders at an overall level and over time.
- Buckets are homogeneous within themselves and heterogeneous amongst. These properties of homogeneity or heterogeneity are demonstrated by the significant p-values of a Z test.

To assess the stability of the population schema at an overall level, the Population Stability Index (PSI) is checked for each reference quarter for the buckets generated by the above described approach. Any quarter with PSI greater than 10% is double checked, and some buckets may be further grouped if this is found necessary. A PSI index under 10% is usually considered small and, hence, such buckets are considered stable.

During bucketing, development accounts/clients with low EAD may be excluded because they tend to have volatile LGD rates and impact the simple average calculations. In the US portfolio, for example, accounts/clients with EAD less or equal than $10 were excluded from the dataset. The threshold is market specific and it is chosen to ensure that the exclusion does not make any significant impact in terms of recovery amount, EAD, and number of accounts/clients.

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[26] The criteria are similar to those used for PD bucketing with the addition of a rule based on the number of observations during the downturn period. Such a rule has been added to ensure the stability of the initial RR assignment.

[27] The null of the Z-test is that the default rates for a pair of neighboring buckets are identical. Let d_j be the average default rate for bucket j, let σ_j be its standard deviation and suppose that N if the number of observations. The Z statistic is: $(d_2 - d_1)/\sqrt{(\sigma_1 + \sigma_2)/N}$. Buckets are combined if the P-value of the test is greater than 1% and less than 99%.

5.6.1. Downturn Period Identification

AXP has developed a downturn identification methodology in compliance with the US Final rule and regulatory guidelines mentioned in BCC 14-3.

The Final rule defines an economic downturn as follows:

The proposed rule defined economic downturn conditions with respect to an exposure as those conditions in which the aggregate default rates for the exposure's entire wholesale or retail subcategory held by the bank (or subdivision of such subcategory selected by the bank) in the exposure's national jurisdiction (or subdivision of such jurisdiction selected by the bank) were significantly higher than average.

The regulatory guidance in BCC 14-3 further states:

When assessing whether a banking organization's reference data cover a reasonable "mix of economic conditions ... over the economic cycle" the following criteria should be applied:

1. *The reference data should include at least one period when aggregate default rates within an exposure subcategory (or subdivision selected by the banking organization) were significantly higher than average.*
2. *Significantly higher-than-average default rates in the reference data should coincide with a period of adverse economic conditions (such as high unemployment or falling home prices) that affect borrowers' ability and willingness to repay debts within an exposure subcategory (or subdivision selected by the banking organization).*
3. *The reference data used for calculating long-run averages should not place undue weight on periods of favorable or benign economic conditions relative to periods of economic downturn conditions.*

For purposes of LGD and EAD quantification, the downturn period should consist of consecutive quarters encompassing the peak default-rate quarter of the cycle. Downturn identification should begin with a one-year period encompassing the peak, extending outward beyond one year subject to criteria 1 and 2. In recognition of the uncertainty regarding the precise beginning and ending dates of the downturn period, a banking organization is expected to carry out a rigorous sensitivity analysis of the LGD and EAD impact of alternative downturn specifications to ensure the risk parameter estimates are appropriately conservative. Typically, downturn periods are one to two years in length. A downturn period exceeding two years is subject to close supervisory scrutiny, especially if it captures on the back end a period of clearly improving economic conditions in the relevant markets.

The Final rule requires identification of a downturn period for each exposure subcategory in a national jurisdiction. AXP takes a more granular view and determines a downturn for each market portfolio combination.

In accordance with the guidelines mentioned in BCC 14-3, the downturn identification process AXP proposes ensures that the following criteria are met.

- Downturn Period was between 1-2 years in length
- Downturn Period was caused due to deteriorated macroeconomic conditions
- Downturn Period was a period when the default rates were significantly different from the long run average default rates.
- For market portfolios that did not show a pronounced downturn period, market intelligence from similar market portfolios were leveraged to identify peak default rates and make upward adjustments to the Basel risk parameters.

The methodology for identifying downturn periods comprised of several steps. In step 1, we first identify periods of the significantly higher default rate for a given market portfolio combination. Then in step 2, we separately identify periods of adverse macroeconomic conditions for the market in consideration by observing the trends of real GDP growth and unemployment rates over the modeling windows. Then in step 3, we identify downturn period by incorporating information from the previous steps. Detailed methodology for each steps are summarized below:

<u>Step 1: Identify Periods of Significantly Higher Default Rate</u>

- For a given reference month, fix the number of accounts/clients(cohort) for that month and calculate the ratio of the number of accounts/clients in the cohort that went into default in the next 12 months to the total number accounts/clients in the cohort for that month(i.e. defaulters in the next 12 months and non defaulters as well).[28]
- Perform a one proportion z-test with 5% significance to identify the months with significantly higher default rates:

<u>Step 2: Identify periods of adverse macroeconomic conditions</u>

- We identify adverse macroeconomic condition of a market by observing the trend of real GDP growth rates and unemployment rates during the modeling window. Typically decline in real GDP is accompanied by an increasing trend of unemployment rates for most markets.
- Next, for each market, we first identify the period where GDP started to decline in consecutive quarters and then overlay this information with the trend of unemployment rate. We chose the adverse macroeconomic time period to be the *maximum* time period in which either GDP started to increase or unemployment rate started to fall from its peak.
- The methodology of identifying adverse macroeconomic condition involves some subjective judgment at times, particularly for markets in which no clear recession period is observed as in the case of Australia. Germany is a case of a market for which the period of adverse macroeconomic conditions was chosen to be different from the official recession, this was done after careful consideration of unemployment rate data and official economic outlook reports relevant to the reference periods published by organizations like the OECD. In these cases, trends in unemployment rates became the

[28] This process is done on the full population data.

primary drivers to determine adverse macroeconomic conditions. Details of identifying periods of adverse macroeconomic conditions can be found in "AXP Basel Downturn Identification Methodology.docx".

Step3: Identify Downturn period for a market and portfolio combination

- Choose months that with significantly higher default rates that are in the vicinity of adverse macroeconomic conditions. In general it is a six month vicinity.
- Ensure that the chosen months above are between 1-2 years in length and are consecutive.
  - Conducted a sensitivity analysis to compare recovery rates in the downturn period identified from above procedure and by forcing the length of the downturn period to be the same as the length of the macroeconomic recession.
- For market portfolios where the above process does not yield a downturn, leverage downturn intelligence from a similar market portfolio to make upward adjustments to Basel risk parameters.

5.6.2. Assignment

Once buckets have been defined, AXP assigns an LGD to each bucket as follows. AXP starts with an initial assignment which is calculated as the minimum between the simple average of RR values calculated over the complete modeling window and the simple average of RR over a downturn period. The recovery rate used for parameter assignment does not include any transformations in that it is not floored/capped at 0/1. Such transformations are only applied during the development of the account-level model.

The final RR assignment is equal to the initial RR assignment minus an adjustment factor which reflects recovery cost that were not included in the definition of the dependent variable for LGD model development. The LGD assignment is equal to one minus the final RR assignment. The derivation of the cost adjustment is explained below.

5.6.3. Cost Adjustment Factor

AXP divides the costs associated with recovering debt into fixed and variable costs. Variable costs rise and fall with the volume of recovered dollars. Some variable costs occur before default, such as the expense AXP incurs mailing delinquency letters. Because AXP does not track these internal costs by account, AXP treats them essentially as fixed costs, summing them by portfolio and apportioning them evenly among accounts/clients.

After default, the main variable costs are the fees AXP pays to outside agencies. These fees vary based on the difficulty of collecting an owed balance, with later placement tiers generally costing more than earlier ones. Outside agencies subtract these fees by account from the dollars they return to AXP, so they are already netted out in the dependent variable.

Fixed costs are expenses that are independent of the volume of recovered dollars, at least in the short term. Before default, fixed costs include overhead expenses for AXP's internal call center staff. After default, fixed costs include flat expenses such as vendor bonuses.

As shown in Table 5-5, the independent variable does not include all the recovery costs.

Table 5-5 Treatment of various recovery costs

	Variable costs	Fixed costs
Before default	Ex: The expense of mailing delinquency letters Summed by portfolio and then apportioned evenly among accounts/clients	Ex: Operating costs for our in-house collections center Summed by portfolio and then apportioned evenly among accounts/clients
After default	Ex: Fees paid to outside agencies per account recovered Included in dependent variable	Ex: Lump-sum amounts paid to outside agencies Summed by portfolio and then apportioned evenly among accounts/clients

Recovery costs not included in the dependent variable are incorporated at the bucket level by calculating an adjustment factor that is applied when deriving the LGD assignment. For each bucket, the adjustment factor is equal to the cost allocated to a given bucket divided by the total EAD in the corresponding bucket. The allocation rules of the costs are based on the characteristics of each bucket, for example, number of accounts/clients, total outside agency cost pre-default, etc. The specific rules vary by portfolio, and thus, they are described in the corresponding Model document.

As an illustration, the derivation of the final RR assignment for a hypothetical bucket in the US Consumer Lending portfolio is discussed below. The example shows the derivation of initial RR assignment, adjustment factor, and final RR assignment.

The initial RR assignment is derived by taking the minimum of the average long-run recovery rate and the average recovery rate in the economic downturn, as follows:

$$Min\ (average\ RR_{long-run}, RR_{downturn})$$

For this example, the calculation becomes:

$$Min\ (19.44\%, 13.55\%)$$

This yields an initial assigned recovery rate of 13.55 percent. The derivation of the recovery costs associated to the bucket is shown in Table 5-4. The total costs amount to $ 7,602,423.
To obtain the final assigned recovery rate, AXP divides the total cost by the bucket's total owed balance. This gives a cost adjustment of 3.87 percent:

$$\frac{\$\ 7{,}602{,}423}{\$184{,}970{,}476} = \ 3.87\%$$

The bucket's final assigned recovery rate is the initial rate less this cost adjustment:

$$13.55\% - 3.87\% = 9.68\%$$

Table 5-6 Total recovery costs not included in the dependent variable

Timing	Type	Category	How the expense is calculated	What determines cost at	Actual cost for the bucket

				the bucket level	
Before default	Fixed	Outside agency costs	Flat cost of $3,854,500	Flat cost by bucket	$3,854,500
		Operating expenses for in-house collections	$18.30 per account for consumer lending portfolio	Number of accounts	$18.30 x 45,020 = $1,275,089
	Variable		$8 per servicing month x (avg. no. of months of servicing) x no. of accounts	Number of accounts	$8 X 3.34 X 45,020 = $1,221,684
After default	Fixed	Lump sum payments to outside agencies after default (such as bonuses)	13.50% of outside agency cost	Outside agency cost	13.50% x $9,267,777 = $1,251,150

6. Testing the Model

6.1. Overview

The estimated model is evaluated by:

- Assessing how well it forecasts recovery rates for data not used in the estimation, specifically out-of-sample and out-of time data
- Comparing its estimates with those implied by alternative models including an earlier version of the same model

Testing is performed at both a portfolio and segment-level. The comparisons are based on statistics including Gini coefficients and an Accuracy Index. The Gini coefficient shows how well a model rank-orders cardmembers by RR. The Accuracy Index evaluates how well predicted RRs match actual recovery rates. More detail on each validation activity is provided in an appendix.

6.2. Out-of-sample validation

Several tests are performed to evaluate performance using out-of-sample data. The tests are performed using the long-run RRs without other score adjustments (notably the adjustment for CARE and the Re-age program). The out-of-sample validation results for the overall portfolio and for individual segments are presented in the portfolio-specific model documents.

6.3. Out-of-time validation

The same tests performed for the out-of-sample validation are conducted on out-of-time data. Because this data comes from a later time period than the development dataset, these tests provide evidence on the model's stability over time. Poor testing results could indicate that the model is over-fitted for the particular period used in estimation. The out-of-time validation results for the overall portfolio and for individual segments are presented in the portfolio-specific model documents.

6.4. Sensitivity analysis

Sensitivity analyses are conducted to gauge how much the dependent variable varies in response to changes in inputs and whether this variation is reasonable. For a simple linear regression, the marginal sensitivity of the dependent variable to a change in an independent variable is directly reflected in the latter's coefficient.

The dependence of RRs on the independent variables is nonlinear. Furthermore, sensitivities are affected by data transformations, capping and flooring. The interpretation of the coefficient is, therefore, less straightforward in the current context and so, sensitivity is, gauged through the steps described below.

1. **Change one variable:** Change one input variable by a defined increment (+5%, -5%, +10%, or -10%)
2. **Cap and/or floor to valid range:** Apply the cap or floor of the valid range
3. **Apply variable transformation:** Apply the final variable transformation
4. **Apply final model to re-score the data:** Calculate through the final model equation to obtain the new Basel retail LGD score
5. **Compare the relative difference:** Compare the relative difference between the new and original score; differences are typically presented as a comparison of means

In the course of model tracking, changes in Basel retail LGD independent variables are monitored to ensure their behavior remains within acceptable tested limits.

6.5. Benchmarking against alternatives

The model's estimates are compared with estimates obtained using an earlier version of the Basel retail LGD model. This validation focuses on which model rank-orders by risk better. The benchmarking results are presented in the portfolio-specific modeling documents.

7. Assumptions and limitations

7.1. Key assumptions

This section provides a summary of key assumptions that are made during development of Basel retail LGD models. Model owners are responsible for assessing these assumptions and documenting any exceptions that arise during the development of individual models.

Assumptions may be categorized according to whether they are related to (i) data, (ii) methodology or (iii) implementation. In assessing the assumptions, the following factors should be considered:

- The rationale for making the assumption
- The risk associated with the assumption and its potential impact on model performance
- The testing performed during model development to validate the assumption
- Future monitoring including periodic reassessment of the validity of the assumption

Table 7-1: Summary of modeling assumptions and their assessment

Modeling Assumption	Assessment of impact on model performance	Details
Data window: The selected historical data window comprises full economic cycle and is	Category: Data Rationale: To use maximum amount of available historical data relevant for current portfolio, and consistent with full-cycle identification and regulatory requirements[29].	Sections 3.3.6, 10.4.3

[29] Three basic regulatory requirements outlined in the "Final rule" are: (1) must be relevant to the current exposures, (2) must be based on at least five years of default data, and (3) must include periods of economic downturn.

appropriate for assessing future credit risk.	Risk: Inaccurate estimation of TTC LGD due to (a) incorrect full-cycle and downturn period identification in historical dataset, and (b) irrelevance of historical data for assessing future risk. Developmental testing: Data window setting is reviewed during model recalibration. Window selection is tested based on historical macroeconomic analysis. General guidelines are documented in "Model window-setting."[30] Future monitoring: Data used to develop the model is reviewed periodically. Ongoing monitoring is used to identify model performance deterioration related to changes in macroeconomic environment and population changes.	
Cycle-cut data: Cycle-cut data is acceptable for modeling month-end regulatory capital requirement.	Category: Data Rationale: Long-run historical data for risk management purposes is collected and stored as of cycle-cut dates. Month-end data has insufficient historical coverage to ensure proper TTC calibration. Risk: Potentially missing risk-driver dynamics can results in an inaccurate model. Development testing: The impact of using cycle-cut vs. month-end data has been assessed on a sample portfolio during early stages of Basel credit models development.[31] Any impact of using cycle-cut data was found to be inconsequential. Future monitoring: N/A – no structural differences are expected for other portfolios. Possibility of switch to month-end data will be revisited in the future when historical coverage is sufficient for proper TTC calibration and satisfies minimum regulatory requirements.	Section 3.3.5
Management strategy: Historical business management strategy is consistent with current strategy.	Category: Data Rationale: To use maximum amount of available historical data consistent with regulatory requirements. Risk: Calibration of models on historical data corresponding to different business practices (account terms, underwriting standards, collection practices, etc.). Development testing: Out-of-sample and out-of-time testing is used to ensure model performance stability across population and through time. Future monitoring: Ongoing monitoring is used to identify model performance deterioration on existing products.	Sections 6.2, 6.3, 10.4.3
Product stability: Future product features are similar to those in the development dataset	Category: Data Rationale: To use maximum amount of available historical data consistent with regulatory requirements. Risk: Calibration of models on irrelevant historical data. Development testing: Out-of-sample and out-of-time testing is used to ensure model performance stability across population and through time. Future monitoring: Ongoing monitoring is used to identify model performance deterioration on existing products.	Section 10.4
Vendor data: Data sourced from external vendors is reliable and consistent within development dataset and appropriate for future use.	Category: Data Rationale: To use maximum amount of diverse historical data consistently. Risk: Biased model performance due to calibration on inconsistent or irrelevant historical data. Development testing: Out-of-sample and out-of-time testing is used to ensure model performance stability across population and through time. In particular, analysis of potential impact due to inconsistency of historical FICO scores has been performed during early stages of model development.[32] Future monitoring: Ongoing monitoring is used to identify model performance deterioration and to assess impact of external data. External data is centrally managed and used consistently both by BAU and Basel models. Any changes to the quality and/or consistency of such data is monitored by CDIT.	Section 10.4.1
Data exclusion and sampling: Model performance on excluded population is similar to development sample.	Category: Data Rationale: Random sampling is used to minimize dependency between different observations used in model calibration. Risk: Calibration of models on data inconsistent with excluded population. Development testing: Detailed comparison of sample and population data characteristics is performed. Out-of-sample and out-of-time testing is used to	Sections 4.2.2, 10.4.3

[30] BII Individual Modeling window-setting analysis documentation July 1 2013.pdf
[31]AXP025_20110725_Cycle_vs_Calendar_Final.doc
[32]20130403_Basel_Individual_Modeling_update_vfinal.pptx

	ensure model performance stability across population and through time. Future monitoring: Ongoing monitoring is used to identify model performance deterioration.	
Bucketing and LGD scale: LGD buckets and scales created for individual segments are homogeneous over time.	Category: Methodology Rationale: Bucketing is based on RR score and results in proper segmentation into groups with homogeneous risk characteristics. Risk: RR score does not differentiate accounts with heterogeneous risk characteristics. As a result, RR scale and underlying buckets are unstable and result in volatile model outcome. Development testing: Homogeneity and stability of bucketing scheme for individual segments is assessed on the development dataset. Future monitoring: Homogeneity and stability of bucketing scheme for each segment is monitored on ongoing basis with population stability and bucket migration analysis	Section 10.4.3
Model misspecification: Regression model is properly specified and includes all key drivers and interactions.	Category: Methodology Rationale: Stepwise selection of regression structure is widely used for multi-factor modeling. Risk: Model has sub-optimal performance on out-of-sample and/or out-of-time data due to violation of underlying assumptions or over- or under-fitting. Development testing: Out-of-sample and out-of-time testing is used to ensure that model has acceptable performance. VIF analysis is used to identify multi-colinearity. Benchmarking against alternative approaches is used to confirm selected model. Future monitoring: Ongoing monitoring is used to identify model performance deterioration.	Section 10.4.3
Bank differentiation: Populations from AECB and FSB banks have similar risk profiles.	Category: Methodology Rationale: There is no significant difference in terms of the cardmember acquisition, behavior or performance across banks. Risk: Model has sub-optimal performance on one or both bank populations due to significantly different population risk profiles or business management standards (account terms, underwriting standards, collections, etc.). Development testing: Model performance has been assessed on the overall population and on individual bank level. No significant difference has been observed between two sub-populations. Future monitoring: Model performance differences are tracked as part of on-going monitoring process. Any significant differences will trigger reassessment of this assumption in the future.	Section 10.4.3
Implementation: Production model is implemented correctly.	Category: Implementation Rationale: Production model is implemented within the standard analytics suite. Risk: Model is not implemented correctly in production. Development testing: Extensive UAT testing is performed before production model implementation is approved for use. Future monitoring: Periodic regression testing is performed to confirm model implementation integrity.	Section 10.4.3
Dependent variable: The recovery rate in the account-level RR score models is floored/capped at 0/1	Category: Methodology Rationale: The logit model assumes that the dependent variable is in the range [0,1]. Risk: The RR score models are not able to discriminate accounts with recovery rate outside the interval [0,1]. This could reduce the stability of the bucket definition. Development testing: The cases with recovery rates outside the range [0,1] represent a small percentage of the modeling dataset; for example, in US such a percentage is 1.3%. Future monitoring: The stability of the buckets is tracked as part of on-going monitoring process. Any significant change in bucket migration will trigger reassessment of this assumption in the future.	Section 10.4.3
Data exclusion during bucketing Accounts with low EAD can be excluded during the development of the bucketing scheme and assignment	Category: Methodology Rationale: Low EAD translates into volatile recovery rates (recovery amount divided by EAD), which in turn, leads to unstable LGD assignments because they are calculated as a simple average of the recovery rates. Risk: The materiality of the accounts with low EAD could increase, and thus, the bucketing scheme will not reflect the characteristics of the AMEX portfolio. Development testing: The definition of the low-EAD threshold is based on an	Section 10.4.3

	analysis that shows the improvements in the robustness of the LGD parameters as well as the low materiality of the corresponding group of accounts. Future monitoring: The stability of the buckets is tracked as part of on-going monitoring process. Any significant change in bucket migration will trigger reassessment of this assumption in the future	

Note: Model assumptions undergo rigorous risk assessment, development testing and monitored during future model use.

7.2. Key limitations

This section provides a summary of key model limitations and weakness categorized based on their source: (i) Data, (ii) Methodology or (iii) Use. Model owners are responsible for monitoring risks associated with these weaknesses and limitations, and continual assessment of effectiveness of corresponding mitigating controls during the use of the individual models.

Table 7-2: Summary of model limitations and mitigating controls

Model limitation	Risk and mitigating control	Details
Model use: Basel LGD model is not a Point-In-Time model and should not be used when it is necessary to estimate absolute levels of loss given default under given macroeconomic conditions.	Category: Use Cause: Modeling choice. Risk: Inappropriate use of the model output will result in unpredictable consequences. Control: Only approved downstream models can use Basel LGD model output.	Section 9.1
Segments with data limitations:	Category: Data Cause: Segments may have insufficient quantity and/or low quality of modeling data. Risk: Model performance can become unstable going forward if modeling data used for development is not sufficiently robust. Control: Model performance monitoring is used to ensure that weakly performing segments do not have material impact on the regulatory capital.	Section 10.4.3
Segments with weak performance:	Category: Methodology Cause: Model may show weak performance on development sample for particular segments due to methodological limitations. Risk: Model can have unacceptably low performance on some segments. Control: Model performance monitoring is used to ensure that weakly performing segments do not have material impact on the regulatory capital.	Section 10.4.3
Historical data consistency:	Category: Data Cause: Historical data can become inconsistent with future data inputs. Risk: Model performance can be compromised if model inputs in the future become inconsistent with historical data. Control: Data monitoring process is used to track any changes in data consistency.	Section 10.4.1
Overreliance on external data: External bureau data (e.g. FICO) has dominant impact on model performance.	Category: Data Cause: Lack of control over external data sources, methodology and quality. Risk: Model performance can be compromised if model inputs sourced from external data become unreliable. Control: Data monitoring process is used to track any changes in consistency of the externally sourced data.	Section 10.4.1
Availability of external data: Lack of commercial bureau coverage.	Category: Data Cause: Lack of control over external data sources and their future availability. Risk: Model performance can be compromised if model inputs sourced from external data become unavailable. Control: Exceptions related to temporary (up to one month) discontinuity in external data are generally addressed by using the last available data. Permanent loss of data source or an extended period of data discontinuity will result in identifying another provider with equivalent data. If no satisfactory alternative source can be found, this would trigger model redevelopment.	Section 10.4.1

Costs not included in the account-level recovery rates	Category: Data Cause: Some recovery costs were not included in the dependent variable for RR scores because they are not available at account level. Those costs include vendor management cost or global collection operating expense, other lump sum costs, pre-default costs related to OA, and internal servicing costs both pre and after default. Risk: The LGD models are not accurately reflecting AMEX's recovery rates, Control: The costs are incorporated by using adjusting to the assigned LGD after the bucketing scheme has been defined.	Section 5.6

Note: Model weaknesses and limitations are assessed in terms of potential adverse impact on calculation of regulatory capital. Mitigating controls are implemented to minimize corresponding risks.

8. Implementing the model

Basel models are developed and implemented in accordance with modeling standards established by the Modeling Strategy Committee. These standards are used across all modeling at AXP and include both BAU as well as Basel models. The following sections provide details on the implementation platform, UAT testing, production implementation approval and data load and storage. The same process is used for all retail Basel models: PD, EAD, and LGD.

8.1. Implementation platform

Basel LGD models are developed and implemented on the company's Information Delivery Network ("IDN"). IDN is the core in-house data and analytics platform. It is used in AXP for the bulk of internal modeling. The platform is integrated with various data sources and has a range of capabilities for data sourcing, data management, quality assurance, model execution and reporting. The functions of the IDN platform that are relevant for Basel LGD model implementation are summarized in Table 8-1.

Table 8-1: Modeling requirements and IDN platform capabilities

Modeling Requirement	IDN Capability
Sourcing of historical and future data	Data Management Platform
Data transformation and repository	Data Warehouse Platform
Segmentation definition	Analytical Environment
Model development	Modeling Environment and ARC
Model validation and governance	ARC / Enterprise Model Manager
Model deployment	Model Deployment Environment
Model execution	Scoring Environment

Note: IDN is a comprehensive platform that satisfies all core requirements for Basel model development, implementation, validation, execution and monitoring.

In addition to its comprehensive capabilities, the IDN platform was designed to provide efficient modeling environment and has the following advanced features:

- Minimal duplication of data
- Scalability to match wide range of portfolios and historical datasets
- Multiple environments to allow efficient development, test and production
- Task scheduling and reuse of resources to allow periodic re-run capabilities

8.2. Production implementation process, testing and approval

Contingent on model certification by EMVG[33] and approval by Basel MSC, the model is deployed in IDN production environment. To initiate the deployment process, the modeling team submits a Risk Change Management (RCM) request to American Express Technologies (AET) – the technology team responsible for model deployment in production. The request is reviewed and approved by the Vice President managing the effort. The history of RCMs is used to track model changes, justification, test results, signoffs, and approvals.

8.2.1. Production implementation process

Implementation of the final model is performed using AXP's Automated Modeling Capability (AMC) application. This internally developed application is used to generate the underlying model code, which is then uploaded into pre-production environment in IDN by AET team.

The model code contains complete model specification including the following components:

- Final model structure:
    - List of independent variables
    - Transformation specifications for the independent variables
    - Model scoring coefficients
    - Segmentation logic

8.2.2. UAT testing

Pre-production model implementation undergoes rigorous User Acceptance Testing (UAT) prior to going live to ensure that the implementation meets business requirements and satisfies model specifications provided by the model developers. UAT is performed by an independent Model Implementation Testing team on a random sample of account records.

Testers perform the following series of steps: (i) obtain implementation of the model in SAS from model developers, (ii) independently derive input data, (iii) generate model output using development code and (iv) compare it to production output generated and provided by the Advanced Risk and Capabilities (ARC) team. Any mismatches in output are investigated until all inconsistencies are satisfactorily resolved.

In addition, UAT's quality control checklist includes the following tasks:

1. Assessment of the random sample used in testing in terms of its size and coverage;
2. Comparison with in-sample model output produced by model developers; and
3. Comparison of pre-implementation UAT results with post-implementation validation (PIV).

Upon successful completion of UAT testing, the model code and specification is locked and transferred to live production environment in CAS.

8.2.3. Model execution in production

Basel LGD models are executed automatically at every month end. Production run consists of the following stages:

[33] IDN is also used to upload the model into EMVG's model inventory Enterprise Model Manager (EMM) to facilitate independent validation.

1. **Data load:** snapshot of IDN Analytics Data Warehouse is loaded into production environment.
2. **Data management:** additional data used by the model is generated from the raw data snapshot.
3. **Model execution:** Basel credit models are executed and any necessary overlays are applied.
4. **RWA calculation:** model output is used as input to RWA models and results are loaded to ODS/Finance systems.

Each stage of the production run generates an execution log and all the intermediary data is stored in IDN production database. Final Basel LGD model output is copied to IDN Data Warehouse in analytics environment and is made available for future model development.

Model output is monitored by automated Continuous Data Integrity Tracking system and any issues are escalated to model owners. For more details on data monitoring, calculation verification and model performance tracking see Section 10.4.

9. Model use and business impact

9.1. Model use

The primary use of Basel LGD models is to assign LGD parameter to each account in the retail portfolios for which AXP calculates regulatory capital under the Basel Advanced-IRB approach.

These LGDs, along with such other parameters as Probability of Default (PD) and Exposure at Default (EAD) are used to calculate risk weights and, hence, regulatory capital for AXP's retail portfolios.

In addition, the LGD models are used by AXP in calculating Expected Credit Losses (ECL). Differences between ECL and the bank's Allowances for Loan and Lease Losses (ALLL) can result in deductions or credits to AXP's available capital.

Furthermore, the Basel retail LGD models provide inputs to the bank's calculation of economic capital. The latter is a key metric as return on economic capital affects important portfolio management and front-line business decisions.

The uses of outputs from the Basel retail LGD models are listed in Table 9-1.

Table 9-1: Model use and model output consumers.

Model use	Details	Output consumers
Basel A-IRB RWA calculations	The primary model use is to provide PD parameter input for calculating risk-weighted assets, as specified in the Final Rule. See Section for further details.	Finance
Expected Credit Loss calculation	LGD parameter is used as one of the inputs to ECL calculation. See "Expected Credit Loss model documentation" for further details.	Finance
Economic Capital	LGD parameter is leveraged as one of the inputs for calculating Economic Capital. See "Economic Capital Individual	Finance

Credit Risk Model Documentation" for further details.

Note: This table shows the downstream models which depend on the Basel LGD model. Each is described in detail in the documents referenced.

9.2. Impact of redeveloping the model on capital requirements

Capital impact assessment is performed for any significant change to modeling methodology, underlying data or implementation. Capital on the appropriate population is calculated with the new model and then compared to the capital based on the current risk parameter inputs. An illustrative example of such calculations is shown in Table 9-2.

Table 9-2: Assessment of capital impact due to model change

Metric	Current Model	New Model	Change
Average PD, %	1.43%	1.43%	+0.03%
Total EAD, $	$36.9Bn	$36.9Bn	-
Average LGD, %	84%	85%	-
Capital, $	$3.07Bn	$3.11Bn	+$0.05Bn
RWA, $	$38.35Bn	$38.81Bn	+$0.46Bn

Note: This table shows the capital impact of a Basel LGD model change in USCS Consumer Charge portfolio. This is a hypothetical example for illustration purpose and please do not cite the numbers.

In the above example, as a result of a hypothetical LGD model change for USCS consumer charge portfolio, average LGD increased from 84% to 85% while the EAD and LGD parameters stay the same. Capital impact due to this model change is an increase of 0.46Bn, calculated as the difference of capital under current models (LGD = 84%) and capital under the new model (LGD =85%).

10. Governance, policies and controls

The contents of this sections are common across all the retail Basel models.

10.1. Guiding standards

Basel LGD models are created in an operational context defined by *American Express Management Policy 50: Enterprise-wide Risk Management* (January 1, 2016) and *American Express Management Policy 55: Model Governance and Validation* (July 15, 2015). In addition, feedback from AXP's regulators influence (i) modeling techniques, (ii) practices followed in development, (iii) implementation, (iv) testing and (v) model use. This feedback includes regulatory expectations communicated generally to the industry, for example views expressed in *Supervision and Regulation Letter 11-7, Supervisory Guidance on Model Risk Management* (April 4, 2011). The feedback also includes the cumulative body of supervisory findings communicated through examinations and supervisory letters.

The content of this document complies with the *Model Documentation Standards* published by AXP's Enterprise Model Validation Group (June 15, 2015).

10.2. Governance framework

Governance framework around Basel credit models is designed to minimize adverse impact due to uncertainty in model development, implementation and use. Summaries of the key roles and responsibilities of the parties involved are provided in Table 10-1.

Table 10-1: Summary of governance framework

Role	Responsible party	Responsibility
Model Developer	Decision Sciences Director	Model scoping Assessment of available options to achieve modeling objective Development of model and comparison of different options Data sourcing, assessment and processing Developmental testing
Model Owner	Decision Sciences Vice President	Review and approve methodological choices, data sources and processing. Understand key modeling assumptions and limitations. Review and approve model output and appropriateness of model use. Review and approve model changes Regulatory compliance
Expert Panel	Subject matter experts from appropriate Bus	Provide guidance in model selection, development and assessment Review and approve modeling choices Review and assess key modeling assumptions and limitations Review and assess model implementation Review and assess ongoing monitoring
Model Technology	American Express Technology	Responsible for model implementation on production systems
Model Oversight	Model Strategy Committee	Review and challenge by executives from a variety of business lines who possess regulatory knowledge and depth of industry experience
Model Validation	EMVG	All aspects of independent model validation of newly developed models, periodic re-validation of existing models, model change and ongoing monitoring Certification of models for business use Maintain model inventory
Assurance	IAG	Ensure compliance of all responsible parties with model governance framework

Note: The model governance framework involves a range of stakeholders responsible for managing model risk at various stages of model development, implementation, use, validation, approval and oversight.

10.3. Regulatory feedback

The modeling techniques used by the bank embody feedback from its regulators, including the cumulative body of findings communicated through examinations and supervisory letters. AXP has redeveloped Basel retail LGD models twice in the past three years in response to this feedback. The models were initially developed in 2012 employing a cardmember-level definition of default. Regulatory guidance received in late 2012[34] led to the development in 2013 of models that employed an account-level default definition. In 2014, Amex received further regulatory

[34]The written guidance covering the October 2012 Regulatory IRB Retail review was transmitted in a letter dated March 6th, 2013.

feedback requiring modifications in its definition of default for its Other Retail credit and charge card exposures: specifically, that default should be defined as more than 180 days past due (rather than 120 days, as was earlier assumed). No further redevelopment is currently scheduled.

10.3.1. Summary of regulatory findings and their resolution

The following findings applying to all the models in scope have been provided by the regulators and resolved in this version of the models.

Table 10-2: Summary of regulatory feedback

Source	Requirement	Resolution Details
April 2014 MRIA-1	Define "Other Retail" Default as Required by the Final Rule 1. revise models with new default definition for ORE for credit & charge cards to 180 dpd	Default definition for ORE portfolios has been changed to 180DPD.
April 2014 MRA-3	Improve Transparency and Develop Comprehensive Data Controls, Data Quality ("DQ") and Data Validation Processes	Summary of Data monitoring can be found in Section 10.4.1.
April 2014 MRA-4	Enhance Model Development Documentation 4.01 Waterfall from the source data (Source (Triumph)) to IDN to APAC to Modeling), with clear description of data exclusions and justification for such exclusions.	Source data waterfall is provided in respective model documents for individual models.
April 2014 MRA-4	Enhance Model Development Documentation 4.02 Sampling distribution and population distribution of accounts and receivables by key risk attributes for all USCS lending and charge products	Comparison of the sample and population distribution of accounts and AR across key attributes FICO, Balance, Tenure and Delinquency is available in respective model documents for individual models.
April 2014 MRA-4	Enhance Model Development Documentation 4.03 Details and narrative on procedures used to determine automated variable transformation using MAS (e.g. floor, caps) 4.04 Details and narrative on variable transformations based on modeler judgment and/or all over-rides of the automated process that is used in the models	Summary of variable transformation techniques can be found in Section 5.3.3. Detailed documentation of techniques implemented by MAS can be found in "MAS Modeling Document"[35]
April 2014 MRA-4	Enhance Model Development Documentation 4.05 Business intuition and narrative on regressors used in the models.	Final model interpretation and business intuition is provided in respective model documents for individual models.
April 2014 MRA-4	Enhance Model Development Documentation 4.06 Details and narrative on variable transformations done for scoring the current portfolio for capital calculation, if any.	Production model is based on the same logic as used in model development..
April 2014 MRA-4	Enhance Model Development Documentation 4.07 Details and narrative on model fit statistics.	Model fit statistics are provided and discussed in respective model documents for individual models.
April 2014 MRA-4	Enhance Model Development Documentation 4.08 Details and narrative supporting choice of LGD adjustment factors for the CARE, tenure, and re-age.	CARE and re-age adjustments are explained in detail in Section 5.5.2. Tenure adjustments were removed from this version of the model.
April 2014 MRA-4	Enhance Model Development Documentation 4.x1 duplicated content; model developers are required to be concise	Deficiencies have been addressed in this round of documentation exercise.
April	Enhance Model Development Documentation	Deficiencies have been addressed in this round of

[35] Enhanced MAS Modeling Document.docx

Source	Requirement	Resolution Details
2014 MRA-4	4.x2 details on critical components of the model development processes and narratives or discussion of quantitative results are missing	documentation exercise.
April 2014 MRA-4	Enhance Model Development Documentation 4.x3 inconsistencies in references made on sample size across various model documents	Inconsistencies have been addressed in this round of documentation exercise.
April 2014 MRA-4	Enhance Model Development Documentation 4.x4 failure to provide sufficient details to support the conclusions referenced from prior analysis done by the Bank	Conclusions from prior analyses are periodically reviewed. In addition, any significant changes in assumptions would manifest in model performance deterioration, which is actively monitored (Section 10.4.3).
April 2014 MRA-7	Develop and Enhance the Framework for On-Going Monitoring of Basel Models	Summary of Data monitoring can be found in Section 10.4.1. Details are available in "Model Monitoring and Control Process for Basel Credit Risk Models". [36]
October 2014 MRA-5	Identify, increase transparency, demonstrate reasonableness and assess impact underlying automated variable transformations using MAS (e.g. floors, caps, manual adjustments)	Summary of variable transformation techniques can be found in Section 5.3.3. Detailed documentation of techniques implemented by MAS can be found in "MAS Modeling Document"[37]

10.3.2. Outstanding regulatory findings

We received below MRAs in the January 2016 transmittal letter.

Source	Requirement	Resolution Details
April 2014 MRA-4 (past due)	Enhance Model Development Documentation	• Final model estimates and corresponding narratives are included in the respective model document, such as "20160930 USCS PD Model Document vF", "20160930 ICS PD Model Document vF. • Description of collection processes and associated variable and non-variable costs of collection is included in Section 2.3 "Background on recovery practices at AXP" of "20160930 Retail LGD Methodology Document vF". • Description of how LGD is measured, explanation of variable and non-variable collection costs/adjustments and how they are included in LGD measurement is discussed in Section 3.1 of "20160930 Retail LGD Methodology Document vF". • Supporting analysis such as benchmarking and sensitivity analysis is documented in Section 6.4 and 6.5 of respective model document for each portfolio (such as USCS, ICS) • Explanation of time dummies to adjust for long run effects are described in Section 5.6.1 of retail PD, EAD, LGD methodology document.
April 2014 MRA-7 (past due)	Develop and Enhance the Framework for On-Going Monitoring of Basel Models	An enhanced on-going monitoring framework is proposed and is pending EMVG and committee review and approval. Details of the proposal can be found in "20160930_Basel_Credit_Risk_Enhanced_Ongoing_Monitoring_Framework vF"

[36] 20150920 AXP Model Monitoring and Controls vF.docx
[37] Enhanced MAS Modeling Document.docx

Source	Requirement	Resolution Details
October 2014 MRA-5 (past due)	Identify, increase transparency, demonstrate reasonableness and assess impact underlying automated variable transformations using MAS (e.g. floors, caps, manual adjustments)	• Details underlying automated design of variable transformation used in the modeling process have been included in Section 5.3.3 of PD, EAD, LGD Methodology document. • Details on variable floors and caps, percentage of observations affected by flooring or capping, and manual overrides by modelers (if any) have been documented in Section 5.3.3 the respective model document for each portfolio. Impact analysis for the most truncated variables is provided in Appendix of respective model document for each portfolio.
January 2016 MRA-1	Investigate, analyze, and address the cause of the instability of retail risk segments	• An enhanced on-going monitoring framework is proposed and is pending EMVG and committee review and approval. Details of the proposal can be found in "20160930_Basel_Credit_Risk_Enhanced_Ongoing_Monitoring_Framework vF". • For detailed review of key model performance monitoring alerts please refer to "20160920_Basel_MRA_Instability_of_Retail_Segments_vF". • The Point-in-time models for USCS PD have been updated to ensure adequate alignment between predicted and observed default rates to avoid any potential systemic biases. Details of the update are documented in Section 5.1.1 of "20160930 USCS PD Model Document".

10.4. Model Monitoring and Control Framework

American Express has well established procedures and processes for model monitoring and maintenance for all decision making models. The results of model monitoring and maintenance are reported to the Basel Modeling Strategy Committee and to US Banks CRC where applicable.

The AXP Basel Credit Models leverage these existing capabilities and methodologies for ongoing monitoring of input data quality, independent variable creation, model score calculations and model performance. Additional customizations are made to the tracked metrics of Basel Credit Models. Guidance on monitoring and controls is summarized below. Details of these procedures and the rationale behind the approach may be found in *Model Monitoring and Control Process for Basel Credit Risk Models*.

The three main components of the model control framework are:

1. **Data monitoring:** to ensure input data quality and consistency,
2. **Calculation verification:** to ensure accurate calculations and
3. **Model performance tracking:** to ensure quality and reliability of model output.

10.4.1. Data monitoring

Data monitoring is implemented by the Continuous Data Integrity Tracking (CDIT) system. CDIT allows for continuous tracking of data and generates "Out of pattern" alerts for key decision items or components of the data accuracy. This process is run automatically after every quarterly execution of the Basel Credit Models by the IDN Model Scoring Engine (MSE).

CDIT uses recent historical data observed over the latest one year period to identify significant deviations of new observations from historical distributions. Generally, thresholds are set at *three standard deviations* around the moving average of the corresponding metric. The following components are tracked by CDIT:

1. **Exposure Categorization:** Percentage of accounts in each exposure category at portfolio level.
2. **Default Classification:** Percentage of defaults at portfolio level.
3. **Variables:** Average value over the portfolio, percentage of accounts with missing value, percentage of accounts with zero value.
4. **Model Output:** Average score by modeling segment.

CDIT alerts are emailed to process owners and displayed on web-portal. Process owners are responsible for review and resolution of all alerts. Any fixes required are reviewed and approved by the IDN and Data Governance team through RCM or IMR.

10.4.2. Calculation verification

Calculation verification, similarly to data verification, is implemented by CDIT and ensures a one-to-one match between production and offline calculations at an account level for a random sample of accounts.[38] This process is run automatically after every quarterly execution of the Basel Credit Models by IDN Model Scoring Engine (MSE).

The following components are tracked by CDIT:

1. **Exposure Categorization:** tested for exact match.
2. **Default Classification:** tested for exact match.
3. **All variables:** tested to match at four decimal places.
4. **Segmentation variables:** tested for exact match.
5. **Modeling Segment Assignment:** tested for exact match.
6. **Bucket mappings:** tested for exact match.
7. **Model output:** tested to match at four decimal places.

CDIT alerts are emailed to process owners and displayed on web-portal. Process owners are responsible for review and resolution of all alerts. Any fixes required are reviewed and approved by IDN and Data Governance team through RCM or IMR.

10.4.3. Model performance tracking

Model performance tracking is performed on a quarterly basis and covers the following measures:

1. **Discriminatory power:** quantified by Modified Gini Coefficient.
2. **Accuracy:** quantified by Modified Accuracy Index and Customized Accuracy Deviation.
3. **Population stability:** quantified by Population Stability and Bucket Migration Indices.

The model's discriminatory power is monitored at the individual model segment level. Each quarter, the Gini coefficient is calculated based on the data in the current quarter and compared

[38] Size of the random sample of accounts used for calculation verification varies between 1% and 5% and depends on the size of underlying portfolio.

with distribution of Gini coefficient values in the model development sample. If the Gini coefficient in the current quarter falls outside of historical average minus three standard deviations and the relevant change is greater than 25%, the model segment is considered as "Need Improvement". The modeling team will conduct root cause analysis, and the model segment will be escalated to Basel MSC (Model Strategy Committee) if it meets materiality threshold.

The model's accuracy is monitored at the individual model segment level. Each quarter, the accuracy index is calculated based on the data in the current quarter and compared with distribution of accuracy index values in the model development sample. If the accuracy index in the current quarter falls outside of historical average plus three standard deviations and is greater than 25%, the model segment is considered as "Need Improvement". The modeling team will conduct root cause analysis, and the model segment will be escalated to Basel MSC (Model Strategy Committee) if it meets materiality threshold.

Model's population stability is monitored at bucket (retail segment) level and compares the current quarter's vs. previous quarter's population distributions across buckets. Distributions are computed using both the dollar value of ARs as well as the number of accounts. Breach of the threshold results in the corresponding action. Population Stability Index (PSI) of greater than 25% will be investigated and resolved by the model owners.

Table 10-3: Population stability thresholds

Metric	Benchmark	Threshold	Rating
Population Stability Index: For PD and LGD: use #accounts and AR For EAD: use #accounts only	Current Quarter vs. Previous Quarter Current Quarter vs. Modeling Development Sample Current Quarter vs. Same Quarter previous year	>25%	Needs Improvement
		[10% , 25%]	Requires Attention
	Using Buckets, and modeling segmentation	<10%	Satisfactory

10.5. Change control management

Production model code is locked and secured from any modification. Changes to the code can be initiated only through a proper RCM request approved by modeling VPs and the governing bodies. Change request can be triggered by issues identified by ongoing model performance monitoring process, due to regulatory findings or issues identified by EMVG group. All model changes have to follow model development and implementation guidelines outlined in this document.

11. Key terms

Table 11-1: Definitions of common terms

Term	Definition
ADSS	The Acquisition Decision Support System, an internal model used by AXP to evaluate credit applications for first-time cardmembers. ADSS measures the probability that a new account will enter default in either the next 12 months (for charge) or 24 months (for lending). Lower scores generally represent increased creditworthiness. Also called Q-score.
AECB	American Express Centurion Bank, one of AXP's two U.S. bank operating subsidiaries. AECB issues AXP's proprietary credit cards and certain consumer charge cards. In addition, AECB offers loans through its lending-on-charge program.
A/R	Accounts receivable, which generally represents the total outstanding amount due from cardmembers at a given time for charges made on AXP cards.
Authorization	The process of granting merchants permission to accept an AXP charge for payment. The process begins when the cardmember attempts payment. The payment request is transmitted to AXP, which calculates the transaction risk and, if the transaction is approved, reserves the sales amount on the cardmember's account. See CAS.
Balance transfer (BT)	The reassignment of part or all of a cardmember balance from another institution into an AXP account, often as part of an initiative to attract new cardmembers or increase A/R growth.
CARE	The Cardmember Assistance and Relief Environment, an AXP program intended for cardmembers experiencing financial hardship. CARE lowers the required minimum due amount for a limited time and enables cardmembers to remain in their current delinquency stage if they fulfill the program's terms.
CAS	The company's Credit Authorization System, which authorizes transactions for cardmembers globally. CDSS scores are inputs into DAC (below), which operates on CAS.
Case set up	A flag on an account indicating an AXP cardmember service representative should contact the cardmember to request a payment. Case set ups are generally initiated because the account is overdue or high-risk (even if current).
Credit Bust Out (CBO)	Where cardmembers acquire cards with no plan to repay their balance. In these instances, cardmember generally acquire cards from various issuers, and, once their credit history is established, quickly ramp up their expenditure ("bust out"), often using bounced checks to maximize spending.
Credit limit	The pre-established amount of money a cardmember may charge to an account at a given time.
CPS	Consumer Products & Services, the AXP business unit encompassing card products for individual U.S. cardmembers (rather than businesses).
Co-brand	See SAC.
DAC	Dynamic Authorizations Capability (DAC), an information processing system on CAS. For each incoming transaction, DAC makes an authorization decision by comparing TSR, CDSS, and FICO scores to pre-established business rules that weigh the balance of profitability and risk. Referral Reduction Rules – provide the ability to override the original decline decision by DAC depending on user defined rules
Delinquent	An AXP account is typically considered delinquent when the owed balance is 60 or more days past the billing date (30 or more days past the due date).
EMVG	Enterprise Model Validation Group (EMVG), the business unit responsible for validating the statistical models AXP uses to make business decisions.
FICO	A quantitative measure of an individual's risk of default, based on consumer files at a credit bureau. A higher score generally represents increased creditworthiness.
FSB	American Express Federal Savings Bank, one of AXP's two U.S. bank operating subsidiaries. FSB issues OPEN charge and credit cards as well as U.S. consumer co-branded credit cards. In addition, FSB has outstanding lines of credit in association with certain OPEN and consumer charge cards and offers loans through its lending-on-charge program.
Global limit (GL)	A communicated spending limit that AXP imposes on a small proportion of higher-risk charge accounts to control exposure. AXP manages the limits based on cardmember risk and economic conditions. Cardmembers' transactions may be declined if their balance hits the global limit. As such, global limits operate as a temporary de facto credit limit.
Lending cards	Credit cards, which allow cardmembers to make purchases and either pay the balance in full each month or revolve the balance month-over-month and keep making charges up to the credit limit (so long as they pay the required monthly minimum due).
LOC	Lending-on-charge, a feature on some charge cards that enables cardmembers to revolve certain balances (that is, carry these balances over from one billing cycle to the next).

MAS	Modeling Automation Suite, a proprietary tool used widely in AXP's risk management practice. The tool recommends the most predictive initial logistic regression model by identifying an optimal subset of independent variables.
MR	Membership Rewards points, which cardmembers earn through eligible spending on AXP cards. MR points are redeemable for a wide array of rewards, including travel, retail merchandise, and dining and entertainment.
MSC	The Modeling Strategy Committee, a body of RIM executives that convenes roughly monthly. Forthe models within its purview, MSC evaluates the model logic and input data; tracks model performance; directs corrective action where performance deteriorates; and ensures models comply with relevant laws and regulations.
OPEN	The AXP business unit encompassing card products for U.S. small businesses.
Portfolios	Groupings of accounts by business. An example portfolio is consumer proprietary lending cards. A portfolio may encompass multiple segments.
Proprietary lending cards	Credit cards that solely carry the AXP brand, in contrast to strategic alliance and co-brand (SAC) cards. AXP bears the full cost of marketing, operations, member rewards, and credit risk associated with proprietary cards.
Re-age	Reclassifying an account's delinquency status (for example, reclassifying a delinquent account as current). Cardmember accounts are typically re-aged when they enter a hardship program (see definition for CARE, above).
Responsible lending actions (RLA)	Actions taken by AXP management to control exposure by re-pricing or restricting credit. Examples of RLA actions are reducing credit lines, imposing global limits, canceling cards, and suspending the LOC feature on charge cards.
Revolvers	Cardmembers who typically roll over unpaid balances from one billing cycle to the next.
Segments	Categories of accounts with common risk characteristics (for example, FICO score less than 700). Segments are typically subsets of portfolios.
Strategic alliance co-brand (SAC) (also known as co-brand)	Cards that are issued by AXP under co-brand marketing agreements with U.S. companies. Cardmembers earn rewards based on spending through the partners' loyalty programs, for example, frequent flyer miles, hotel loyalty points, or cash back. Generally, AXP's partner is responsible for providing rewards and AXP retains the credit risk.
Transactors	Cardmembers who typically pay their full balance at the end of each billing cycle.
TSR	Total Structural Risk, the model used by AXP to assess the probability that AXP cardmembers will enter default on any of their relationships both within and outside AXP in the next 18 months. TSR differs from CDSS in that it depends more heavily on external data.
United States	U.S. states plus territories, including Puerto Rico, U.S. Virgin Islands, American Samoa, Guam, Northern Mariana Islands, Marshall Islands, Palau, and Micronesia.
Q-score	See ADSS.
Write-offs	Accounts receivable (A/R) that is recorded as a loss, either due to prolonged delinquency or a cardmember's bankruptcy, death, or settlement agreement. Synonymous with charge-offs.

Note: The table shows the terms and acronyms used by AXP throughout this document.

12. Appendix: Multivariate logistic regression

12.1. Specification

The fractional response regression approach was developed for modeling continuous variables distributed on the unit interval by Papke and Wooldridge (1993). These authors also suggest that it be estimated using Quasi Maximum Likelihood techniques.

Employing a logistic transformation of a linear index of explanatory variables, the regression model is as follows. Consider n independent response variables, $Y_1, \dots, Y_n$, where each response variable Y_i is dependent on m predictor variables taking values $x_{i,1}, \dots, x_{i,m}$. Each Y_i takes values in the range 0 to 1. Our modeling assumption is that

$$E(Y_i|\mathbf{x}_i) = \frac{\exp(\beta_1 x_{i,1} + \cdots + \beta_m x_{i,m})}{1 + \exp(\beta_1 x_{i,1} + \cdots + \beta_m x_{i,m})} = \frac{\exp(\boldsymbol{\beta}' \cdot \mathbf{x}_i)}{1 + \exp(\boldsymbol{\beta}' \cdot \mathbf{x}_i)}, \qquad \text{(A12.1)}$$

Here, $\mathbf{x}_i = (x_{i,1}, \dots, x_{i,m})'$ and $\boldsymbol{\beta} = (\beta_1, \dots, \beta_m)'$.

12.2. Quasi-maximum likelihood estimation

For each i let y_i be the observed value of the variable Y_i, and let $\mathbf{y} = (y_1, \dots, y_n)'$. To estimate the value of the parameters $\beta_1, \dots, \beta_m$, a quasi-maximum likelihood estimator may be used. The Bernoulli log-likelihood, given by

$$L_i(\boldsymbol{\beta}) = y_i \log\left(\frac{\exp(\boldsymbol{\beta}' \cdot \mathbf{x}_i)}{1 + \exp(\boldsymbol{\beta}' \cdot \mathbf{x}_i)}\right) + (1 - y_i) \log\left(1 - \frac{\exp(\boldsymbol{\beta}' \cdot \mathbf{x}_i)}{1 + \exp(\boldsymbol{\beta}' \cdot \mathbf{x}_i)}\right) \qquad \text{(A12.2)}$$

is a member of the linear exponential family, hence the quasi-maximum likelihood estimator, $\widehat{\boldsymbol{\beta}}$, is given by:

$$\widehat{\boldsymbol{\beta}} = \arg\max_{\boldsymbol{\beta}}\left(\sum_{i=1}^{n} L_i(\boldsymbol{\beta})\right) \qquad \text{(A12.3)}$$

One may show that this estimator is consistent and asymptotically normal.

12.3. Diagnostics

12.3.1. Wald statistics

The Wald test is used to compare the maximum likelihood estimate for a distribution parameter with a proposed value. Suppose that $\hat{\theta}$ is the maximum-likelihood estimate for a parameter and that θ_0 is the proposed value of the parameter, then the Wald statistic is defined as

$$W = \frac{(\hat{\theta} - \theta_0)^2}{\operatorname{var}(\hat{\theta})}. \qquad \text{(A12.4)}$$

The statistic is compared to a chi-squared distribution to determine whether to reject the hypothesis that $\hat{\theta} = \theta_0$.

12.3.2. Variance inflation factors

The variance inflation factor measures the inflation of the variance of a regression coefficient due to correlation with other regression coefficients. Suppose there are $m+1$ predictor variables, $X_0, \ldots, X_m$, with regression coefficients $\beta_0, \ldots, \beta_m$. Then the variance inflation factor of β_i is given by the formula

$$VIF_i = \left(1 - {R_i}^2\right)^{-1} \tag{A12.5}$$

where ${R_i}^2$ is the coefficient of determination of X_i regressed on the remaining predictor variables. If $VIF_i > 10$ then the multicollinearity is high.

12.3.3. Hosmer-Lemeshow test

The Hosmer-Lemeshow test may be applied to a collection of variables taking one of two outcomes. To apply the Hosmer-Lemeshow test, the observations of these variables are first ordered by their fitted probabilities. They are then divided into N groups of sizes $M_1, \ldots, M_N$. The group sizes should be approximately equal.

Let $y_{i,j}$ denote the outcome of the j^{th} observation in the i^{th} group, and let $\hat{\pi}_{i,j}$ denote the fitted probability. The Hosmer-Lemeshow statistic is defined as

$$HL = \sum_{i=1}^{N} \frac{\left(\sum_{j=1}^{M_i} y_{i,j} - \sum_{j=1}^{M_i} \hat{\pi}_{i,j}\right)^2}{\left(\sum_{j=1}^{M_i} \hat{\pi}_{i,j}\right) \cdot \left(1 - \left(\sum_{j=1}^{M_i} \hat{\pi}_{i,j}\right)/M_i\right)}. \tag{A12.6}$$

The asymptotic distribution of this statistic is approximately chi-squared.

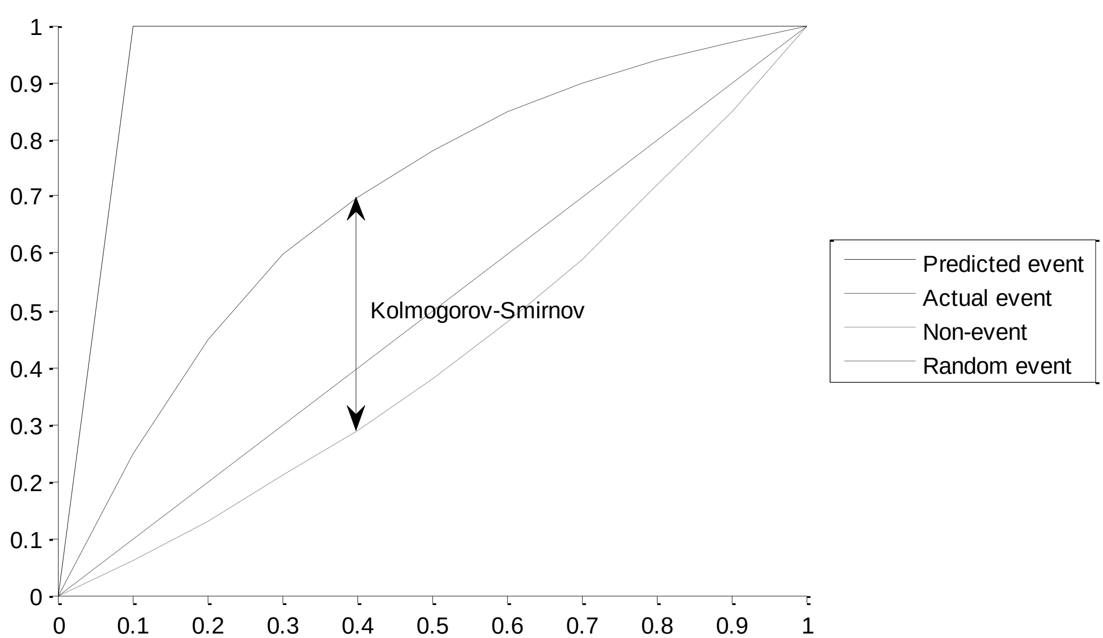
13. Appendix: Model performance metrics

To evaluate model performance on a dataset containing both predicted and actual metrics, the dataset is separated into n rank-groups (normally 20) based on the predicted metrics. These rank-groups are ordered.

For each $0 \leq i \leq n$ let x_i be the fraction of the population falling within the first i rank-groups. Suppose we have some subset of the population for which a specified event occurs, then for each $0 \leq i \leq n$ let y_i be the fraction of this subset of the population that falls within the first i rank-groups. The Lorenz curve for this event is constructed by plotting the points (x_i, y_i) and interpolating linearly between adjacent points.

Such Lorenz curves could be constructed for any event including predicted events, actual events, negative of actual events, or random events. In such cases we will use the notation: $y_i^{predicted}$, y_i^{actual}, $y_i^{non-event}$ and y_i^{random}.

Figure 13-1: Lorenz curve example



The area enclosed between the actual event line and the random event line will be denoted A_{actual}, and the area between the predicted event line and the random event line will be denoted $A_{predicted}$. The area of the half of the graph above and to the left of the random event line is denoted B; clearly $B = \frac{1}{2}$.

Let z_i denote the actual outcome of the i^{th} observation, and let z_i' denote the predicted outcome. Let N be the total number of observations. In the context of Lorenz curves such as those shown above, the following model performance metrics may be constructed and are widely used throughout this document:

- Gini coefficient (G_{actual}): This is defined as the ratio of A_{actual} to B. This simplifies to the formula
$$G_{actual} = 2 \times A_{actual}. \tag{A13.1}$$
- Maximum possible Gini coefficient ($G_{predicted}$): This is defined as the ratio of $A_{predicted}$ to B. This simplifies to the formula
$$G_{predicted} = 2 \times A_{predicted}. \tag{A13.2}$$
- Modified Gini coefficient (G_{mod}): This is defined as the ratio of A_{actual} to $A_{predicted}$. This can be reformulated as
$$G_{mod} = \frac{G_{actual}}{G_{predicted}}. \tag{A13.3}$$
- Spearman's rank correlation (r_s): Suppose each observation is ranked based on predicted and actual outcomes, and that d_i is the difference between the two ranks for the i^{th} observation. Spearman's rank correlation is given by the formula
$$r_s = 1 - \frac{6\sum_{i=1}^{N} {d_i}^2}{N^3 - N}. \tag{A13.4}$$
- Accuracy index (a): Let $z_{j,k}$ denote the actual outcome of the k^{th} observation in the j^{th} rank-group, and let $z_{j,k}{'}$ denote the predicted outcome. For each $1 \leq j \leq n$ let M_j be the size of the j^{th} rank-group. The accuracy index is given by the formula
$$a = \frac{N}{n} \times \frac{\sum_{j=1}^{n} \frac{\left|z_{j,k} - z_{j,k}{'}\right|}{M_j}}{\sum_{j=1}^{n} \sum_{k=1}^{M_j} z_{j,k}}. \tag{A13.5}$$
- Modified accuracy index (a'): This is given by the formula
$$a^{'} = a \times \min\left(1, \sqrt{\frac{\sum_{i=1}^{N} z_i}{1000}}\right) \tag{A13.6}$$
where $\sum_{i=1}^{N} z_i$ is the total number of defaults.
- Kolmogorov-Smirnov (KS): The maximal distance between the actual event line and the non-event line. It is given by the formula
$$KS = \max_{0 \leq i \leq n} \left| y_i^{actual} - y_i^{non-event} \right|. \tag{A13.7}$$
- Root-mean-square error ($RMSE$): A measure of the difference between the actual outcomes and the predicted outcomes. It is given by the formula
$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (z_i - z_i{'})^2}{N}}. \tag{A13.8}$$

14. Appendix: Population stability measures

Segmentation stability is measured by tracking quarter-over-quarter changes in percentage of overall population falling within each segment, and then aggregating changes over all segments using the following metric, constructed to be non-negative:

$$PSI = \sum_s [w_s(t) - w_s(t')] \times \ln \frac{w_s(t)}{w_s(t')} \qquad \text{(A14.1)}$$

15. Appendix: Decision trees and bucketing

15.1. Decision Tree algorithm in SAS Enterprise Miner

The Decision Tree algorithm in SAS Enterprise Miner employs data divided into (i) Training and (ii) Validation subsets. The Training subset is used to grow a "Maximum Tree" while the Validation subset is used to prune the tree to a stable size. For generating an LGD assignment segmentation tree, the following version of the algorithm applicable to a continuous dependent variable is employed. Before applying the algorithm, a continuous variable is converted into a category variable by partitioning the range of all possible values into a number of smaller ranges.

When the variable is continuous, by default, an ANOVA F test is used in the training process to identify the best split from all the inputs. The Average Square Error is then employed to test the Maximum Tree and prune it.

15.2. Splitting the data

During the training process, "Worth of Split" was calculated based on a one way ANOVA performed on the split. The F statistic for a split is computed as: (Sum of Square Error between the resultant buckets / (number of resultant buckets - 1))/(Sum of Square Error within resultant buckets / (number of observations in original bucket - 2)).

More formally, if a split creates k buckets from an original bucket, we have:

$$F = \left(\frac{\sum_{i=1}^{k} (\bar{y}_i - \bar{y})/(k-1)}{\sum_{i=1}^{k} \sum_{j=1}^{n} (y_{ij} - \bar{y})/(n-2)} \right), \qquad \text{(A15.1)}$$

where n_i is the number of observations in the i^{th} new bucket, $\bar{y}_i$ is the mean of target in the i^{th} new bucket, $\bar{y}$ is the mean of target in the original bucket, y_{ij} is the value of target variable for j^{th} record in i^{th} new bucket, n is the number of observations in original bucket. Let

$$\text{p} - \text{value} \equiv \Pr(\text{F} > \textit{calculated}\ \text{F statistic} \mid \text{null hypothesis is true})$$

The "Worth of Split" is defined as $-\log_{10}(\text{p} - \text{value})$. The smaller the p-value, the greater the Worth of Split. All possible splits of all inputs are tested. The one with highest Worth of Split is selected. If the split cannot fulfill the constraints set by the user, the tree will stop growing.

15.3. Pruning the tree

During the validation process, the segmentation logic from the training data was applied to the validation data. If a certain split increased the overall Average Square Error for a tree or sub-tree, the correlated split was pruned. For the t^{th} bucket, the Average Square Error is given by:

$$\frac{1}{n_t}\sum_{i=1}^{n_t}(y_{it} - \overline{y_t})^2 \tag{A15.2}$$

Here, y_{it} is the actual value of the target variable for the i^{th} record in the t^{th} bucket, and $\overline{y_t}$ is the expected value of the target for the t^{th} bucket calculated from training dataset. The overall Average Square Error for a tree or sub-tree is the weighted average of the average square error of the individual leaves, which is

$$\sum_{t=1}^{T}\frac{n_t}{n}\left[\frac{1}{n_t}\sum_{i=1}^{n_t}(y_{it} - \overline{y_t})^2\right] \tag{A15.3}$$

16. Appendix: Product background

AXP credit and charge cards

AXP's principal products are charge and credit payment cards. Credit cards, internally called lending cards, allow cardmembers to make purchases and either pay the balance in full each month or revolve it month-over-month and keep making charges up to the credit limit.

Charge cards generally carry no preset spending limit and are intended as a method of payment rather than a way to finance purchases. They are designed to be paid in full each month, but may include a lending-on-charge (LOC) feature, which enables cardmembers to revolve certain balances. Cardmembers enrolled in lending-on-charge may choose to automatically "sweep" all charges of a specific type or over a designated amount (for example, $100 or $500) into their revolving balance. The intent of this feature is to help when traveling or to extend repayment for a larger purchase.[39]

To remain current, lending cardmembers must pay their minimum due payment on time; charge cardmembers must pay their pay-in-full monthly balance and make minimum due payments on the lending-on-charge portions of their accounts.

Proprietary versus co-branded cards

AXP offers both proprietary and co-branded cards, which are also called Strategic Alliance and Co-Brand (SAC) cards. An example of a proprietary card is Blue Cash Everyday®; an example of a co-branded card is Gold Delta SkyMiles® Credit Card from American Express.

Corporate card programs and corporate purchasing card programs

[39] AXP typically caps the maximum revolving LOC balance to $35,000 to $50,000 and communicate this limit through terms and conditions. This limit is not a committed line of credit and can be suspended at AXP's discretion.

Global Commercial Payments (GCP) provides corporate card programs (CC) and corporate purchasing card programs (CPC) to business clients around the world. The majority of GCP clients use charge cards to allow employees to charge incidental business-related expenses (e.g. travel and entertainment (T&E) expenses). GCP products also allow corporate clients to use charge cards as a means of financing working capital needs e.g. to purchase components or materials for products they produce or re-sell, to manage and pay their office supplies and vendor charges.

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