Equifax AbsolutePD® Model

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Equifax AbsolutePD® Model provides consistency, transparency, and objectivity in the absence of financial statement information for private company obligors.

The AbsolutePD® Model (the Model) introduces a robust and consistent way to derive an absolute measure of the Probability of Default (PD) for private company obligors by using extensive obligor and contract-level history. The Model provides statistical estimates of Probabilities of Default, over various forecast horizons, of private firms, based on their payment histories and various macroeconomic variables. It is well suited to applications in which there are no timely borrower-level financial statement histories available.

The Model not only surpasses traditional scoring systems in its power to rank obligors, but it also implicitly targets the overall consistency between expected default frequency and the actual defaults. This consistency is at the foundation of Basel II IRB model criteria (Basel Committee on Banking Supervision, June 2006) and is critical in applications where estimation of expected loss of portfolios is necessary.

The AbsolutePD® Model represents a number of innovations, such as

- Unique blend of obligor-specific and macroeconomic covariates
- Nonparametric transform of covariates to adjust for sector-specific variations
- Explicit covariates to model sectoral idiosyncratic dynamics
- Self-correcting feature that learns from previous shortfalls
- Model trained on one of the most extensive data sets of private company obligors
- Independent of the availability of financial statements

The Model has originally been fitted to over three million private firm payments and default histories spanning over five years and was subsequently validated over a span of two years ('06-'08). The Model is reoptimized every quarter with one more quarter of additional data. Out of sample, back testing is performed for every historical quarter to date requiring iterative fitting of coefficients for each historical period.

The Model has originally been fitted to over three million private firm payments and default histories spanning over five years and was subsequently validated over a span of two years.

Some of the key advantages of the Model over traditional score-based models include the following:

- Absolute measure vs. comparative measure
- No need to set cutoff threshold subjectively
- Maintains calibration while maximizing power of prediction[1]

The estimated term structure of default probabilities for each obligor can be used as ingredients in such applications as credit-granting decisions; estimation of loss reserves on a portfolio of loans or accounts receivable; determination of the lender's economic or regulatory capital; and risk measurement, rating, and valuation of structured credit products whose collateral includes private-firm debt.

Introduction

Equifax AbsolutePD® represents a unified framework for PD estimation using one of the most comprehensive databases for private company loans.

Extensive Equifax obligor term loan database

"Internal estimates of PD, LGD, and EAD must incorporate all relevant, material and available data, information and methods . . . Where internal or external data is used, the bank must demonstrate that its estimates are representative of long run experience." - Basel Capital Accord, §448

Even the most sophisticated models, if they are not fitted with a comprehensive and representative data set, are not going to be able to generate consistent and robust forecasts. The more complex the credit model, the more observations of default events it needs over the sample period in order to adequately estimate the parameters, such that the response in-sample is representative of the empirical result and the forecast out-of-sample is robust and consistent under different scenarios.

[1] Here power refers to a model's ability to rank obligors from most likely to default to least likely to default. Calibration refers to the model's ability to generate PDs that match the actual default rate of a portfolio of loans. If a model scores high on both power and calibration, then we say the model has high consistency.

Behind the AbsolutePD® Model stands Equifax Commercial's proprietary private company loan database. Contributed by major lenders including 8 of the top 10 U.S. financial institutions, it encompasses more than 22 million current and historic contracts worth over $1.2 trillion in exposures. It is one of the largest of commercial term loans and leases in the U.S..

The data set used for Equifax AbsolutePD® has more than 3,000,000 unique obligors who operate in a wide range of business sectors spanning the full spectrum of four-digit NAICS codes. This granularity is crucial for a prediction model's power to differentiate between obligors.

"Irrespective of whether a bank is using external, internal, or pooled data sources, or a combination of the three, for its PD estimation, the length of the underlying historical observation period used must be at least five years for at least one source. If the available observation period spans a longer period for any source, and this data are relevant and material, this longer period must be used." - Basel Capital Accord, §463

"Internal estimates of PD, LGD, and EAD must incorporate all relevant, material and available data, information and methods."

Basel Capital Accord, §448

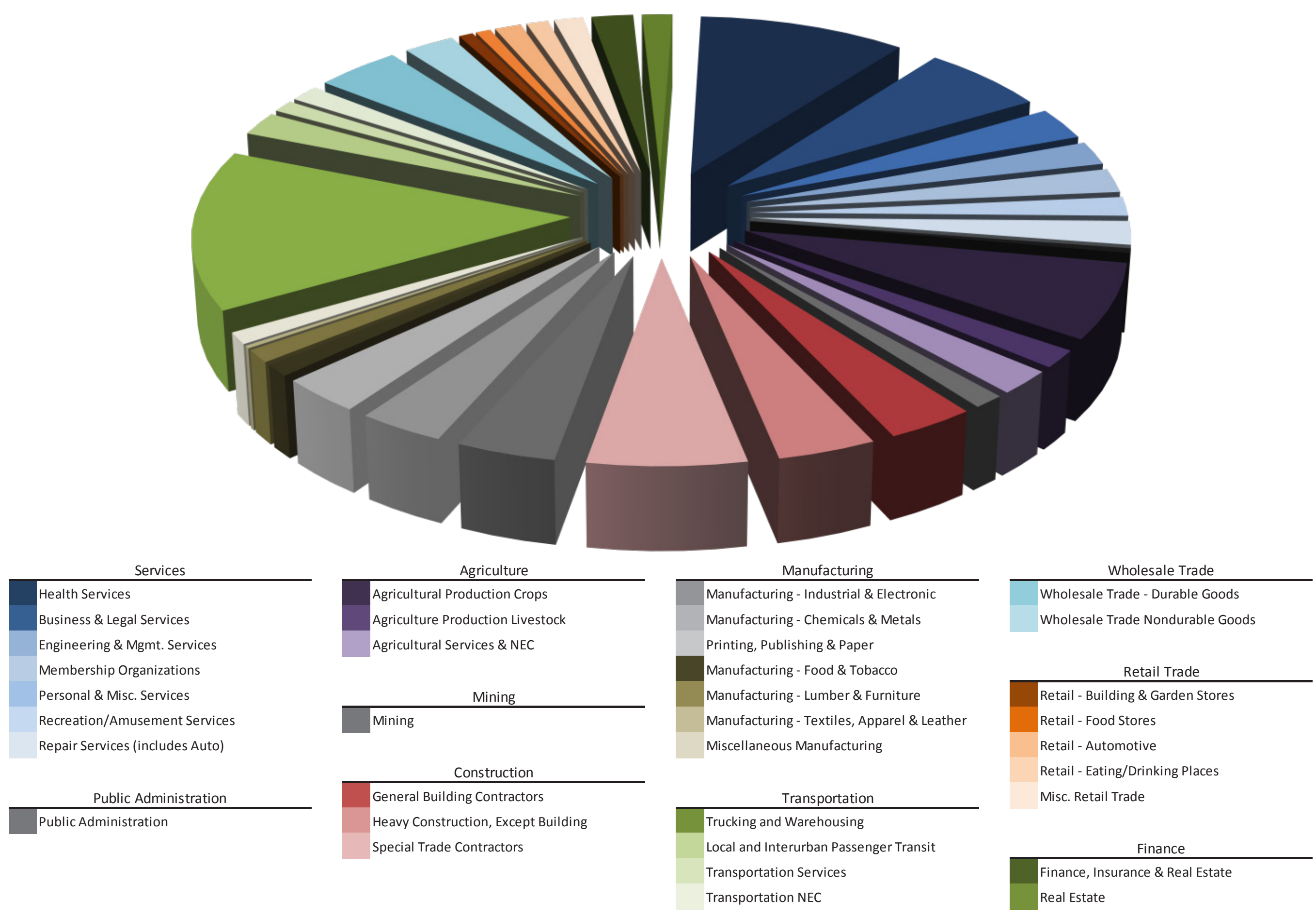

Figure 1. Database by industry

Equifax Commercial private obiligor database by industry category

With over 15 years of detailed borrowing history and with comprehensive monthly updates, the Equifax loan database is and remains one of the most comprehensive sources of data for private company obligors. This rich source of data forms a solid foundation for some of the covariates in the Model that depend on contract-level default dynamics. The overall goodness of fit of the Model not only depends on the number of obligors in the data set, but also on the degree of mix of default and non-default events under different obligor-specific circumstances and under different macroeconomic scenarios.

Loan contracts are classified into industry categories based on the industry of the obligor. Figure 1 shows the proportional breakout of obligors by industry category represented in the Equifax loan database. Obligor industry determines which sectoral models will be applied within the AbsolutePD® Model.

A number of internal processes are put in place to improve data quality and integrity. Equifax filters data at multiple processing points prior to inclusion in the production database and flags suspect data for review by dedicated consultants. The consultant verifies the information before including it in the production database, which in turn forms the data set that the AbsolutePD® Model relies on. For more detail on data cleaning and integrity assurance procedures, please reach out to cmlmarketing@equifax.com.

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Basel abstract	Absolute Model feature
Borrower rating reflects economic conditions	AbsolutePD® Model explicity takes into account contemporaneous and forward-looking macroeconomic covariates. This helps the Model adapt to a wide range of possible economic conditions.
Meaningful and consistent quantitative estimation of risk	Based on established modeling framework for survival analysis, AbsolutePD® Model is both transparent and consistent. The covariates used in the Model are chosen based on a combination of economic intuition and empirical findings to avoid over-fitting.
Robust system to validate model	AbsolutePD® Model uses a rigorous empirical validating the model performance and the adequacy of choice of covariates using extensive in-sample vs. out-of-sample testing. Covariates are checked for their economic meaning, correlation with other covariates and stability.
Model of five years of historical observation	AbsolutePD® Model is fitted based on over five years of comprehensive obligor- and economic-level data is validated out-of-sample using two years of history.

Support for regulatory requirement

Implicit in the Basel II Accord is the evolution toward an internal credit risk model that aims to produce consistent treatment and assessment of credit exposure. The AbsolutePD® Model explicitly addresses some of the criteria laid out in the Accord.

Equifax AbsolutePD® Model innovation

AbsolutePD® Model represents a number of key innovations, both theoretically and practically, that differentiates the Model from its alternative solutions:

- AbsolutePD® Model gives both **obligor-specific default probability** and corresponding rank order by likelihood of default for up to eight quarters ahead. This enables one to derive a detailed PD term structure for each obligor.
- Rigorous and quantitative estimation of PD **independent of availability of obligor-specific financial ratios**. This is particularly important for private commercial loan obligors who do not have timely and reliable financial statements.
- **Reoptimization of the model covariates each quarter using an extensive database that is updated weekly**, in contrast to the yearly update of financial statements. Current version of the Model is fitted using over 3,000,000 unique borrowers with almost 4,000,000 borrowing relationships and an average default rate in the region of 4%.
- **Blend of obligor-specific and macroeconomic covariates** that combine to give a PD measure that self-adjusts under different economic environments.
- **Extensive model validation** using in-sample period for model fitting and out-of-sample period to test performance and validate choice of covariates.
- AbsolutePD® Model has embedded **self-correction** dynamics that both correct past prediction shortfalls and adjust for potential structural changes.
- Covariate momentum is addressed explicitly by incorporating **auto-regressive dynamics** in model specifications.
- Conditional default probability forecasts up to eight quarters ahead enable one to derive a detailed **PD term structure** for each obligor.

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Equifax AbsolutePD® Model framework

Equifax AbsolutePD® combines power and calibration in a unified, quantitative framework that delivers consistent estimation of PDs for private obligors.

A distinct model is designed and estimated for each of various industrial sectors. For a specified sector, at the end of some calendar quarter, the probability that a given obligor in that sector defaults within *k* quarters is modeled in the form

$$p_k = F_k\,(x_1,\ldots,x_n),$$

where $x_1, \ldots, x_n$ are obligor-specific and macroeconomic covariates that are selected based on the sector and the forecast horizon k, and where $F_k(\cdot)$ is a function that is statistically estimated.

We always include as a covariate the borrower's latest Equifax MasterScore®, a previously developed obligor-level credit score that is based on payment histories and other relevant variables. Details of the score construction process are described in a separate technical document. Current AbsolutePD® Model implementations are based on up to 10 covariates and up to a maximum forecast horizon of eight quarters.

Definition of default

To measure defaults, we utilize a definition that considers the status of the entire borrowing relationship between the lender and the borrower, rather than just looking at individual transactions in isolation, which can at times be misleading. It is rare that a lender will consider one contract with a borrower to be in default and simultaneously have another contract with that same borrower not deemed a default, so default is best viewed on an overall relationship basis. While lending institutions may have slightly different default criteria, in practice the differences are quite small because most "fairly bad" relationships soon become "quite bad" relationships. Moreover, material negative events, such as bankruptcy, litigation, repossession, or material loss (i.e., not just the waiving of late charges), are universally considered default events. Serious delinquency, however, is often an early default trigger, and 90 days past due strikes a good balance between being too quick to trigger and being too late. Though in order to consider the entire relationship (and avoid possible payment misapplication issues), we determine if the average delinquency across all the contracts in the relationship on a dollar-weighted basis is greater than 90 days.

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From Z-Score to Equifax AbsolutePD®

The increasing demand for credit exposure protection has attracted a number of different pricing frameworks for loans (Shek, Uematsu, & Wei, June 2007) and credit in general (Duffie & Singleton, 2003). One of the earliest and still often-quoted credit models is the Altman's Z-Score (Altman, September 1968). The Z-Score Model is a classification framework based on the theory of Multiple Discriminant Analysis (MDA) (Huberty & Olejnik, Second Edition, 2006), with the goal of grouping firms into default and non-default categories by using a number of financial ratios. These ratios—such as Total Assets, Total Liability, Sales, EBIT, and Working Capital—are calculated based on information available in standard financial statements. Despite the simplicity and ease of computation of the Z- Score Model and other scoring-based models, their shortcomings are well observed and acknowledged.

"Credit scoring models and other mechanical rating procedures generally use only a subset of available information. Although mechanical rating procedures may sometimes avoid some of the idiosyncratic errors made by rating systems in which human judgment plays a large role, mechanical use of limited information also is a source of rating errors." -Basel Capital Accord, §417

The shortfalls of the Z-Score framework are both practical and theoretical in the context of modeling private obligor defaults. On the practical level, most private obligors do not have timely available and reliable financial statements, if any at all. This means we have no means of obtaining inputs to the Z-Score Model. Even for those that do publish financial statements, they are often available only on an annual basis and with considerable lag. This means we have no means to update a Z-Score Model in a timely manner.

On the theoretical level, some of the main assumptions behind MDA, such as Gaussian distributed ratios and absence of outliers, are simply not valid under normal circumstances (Hastie, Tibshirani, & Friedman, 2001). Furthermore, the model is static in nature in that it fails to capture the aggregate PDs over time because a firm with a certain set of variables will fail more frequently in a poor economic environment than during periods of broad base expansion. This systemic factor is absent in the establishment of Z-Score and, indeed, in most score-based models in general.

With the advent of increasing computational power and sophistication of statistical techniques, models based on more robust frameworks are gaining traction in real world applications. AbsolutePD® Model belongs to this latest generation of models. As one of the first PD models that is derived completely independent of financial ratios, it goes beyond the current paradigm, which relies heavily on publicly and timely available financial data for model estimation.

Rather than assigning obligors to a dichotomous default and non-default classifier, the AbsolutePD® Model looks at a continuum of intrinsic propensities to failure by calculating the probability of an obligor belonging to one of the two classifiers. This adds an extra layer of complexity to the model. Now we are not only concerned with Type I and Type II errors[2] of the model at various cutoffs, as in the case of the Z-Score; we are also implicitly taking consistency between expected probabilities and actual default rates into account. In other words, Z-Score targets default/non- default cutoff and the accuracy thereof, while the AbsolutePD® Model produces a distribution of Probability of Default that can be used not only for decision-making but also for estimating Expected Loss (EL).

AbsolutePD® Model produces a distribution of probability of default that can be used not only for decision making, but also for estimating expected loss.

Equifax's proprietary scoring system, MasterScore®, partially mitigates the biggest problem facing scoring systems similar to the Z-Score, namely the lack of timely and accurate financial statement information that drives the underlying model. Equifax MasterScore® uses extensive loan history, both on the obligor and on the loan contracts. This rich, multidimensional data give Equifax MasterScore® the ability to uncover information contents that simple financial ratios cannot match and to deliver superior performance in ranking obligors that operate in different sectors and under different economic conditions.

While Equifax MasterScore® delivers power of prediction, the AbsolutePD® Model adds calibration. This is better illustrated by observing the distribution of Equifax MasterScore® for the TRCK (Transportation) sector for the period from 2006 to 2008, as shown in Figure 2.

The kernel estimated density[3] curves in Figure 2 shows the distribution of the two sets of Equifax MasterScore®: one set belonging to the Equifax MasterScore® corresponding to events of default and the other set belonging to the Equifax MasterScore® corresponding to events of no default. We see that while the center of weights, i.e., the mean, of the two densities is sufficiently apart, there remains considerable overlap. In other words, there exists no Equifax MasterScore® that can completely separate the two groups.[4]

[2] Type I error is rejecting the null hypothesis when the null hypothesis is true. Type II error is accepting the null hypothesis when the null hypothesis is false. In our case, the null hypothesis would take the form of whether an obligor should be in default.

[3] Kernel estimation is an efficient way to extrapolate empirical frequency distribution. When we construct a histogram, we need to consider the width of the bins and the end points of the bins. As a result, the problems with histograms are that they are not smooth, and they depend on the width of the bins and the end points of the bins.

[4] This lack of separation means that we need to incorporate into the AbsolutePD® Model an efficient way to ensure our prediction achieves an optimal tradeoff between Type I and Type II errors.

It becomes a subjective exercise for credit officers to gauge the appropriate cutoff threshold, based on his or her experience and assessment of current and projected economic conditions. For example, the credit officer could pick 620 as the cutoff and assume all borrowers with lower than 620 to default and higher or equal to 620 to survive. This essentially assigns two PDs: 100% to the group of obligors with lower than 620 Equifax MasterScore®, and 0% to those with higher than 620 Score. This naïve score-to-PD mapping is obviously not ideal, as it does not take into account different shades of the likelihood of default but instead only explores the problem as dichotomous default vs. no default events.

Alternatively, the officer could bin the Equifax MasterScore® using the following scheme shown in Table 1.

While we have outlined one valid method to obtain PDs from scores, it relies on subjective measures such as one's assessment of the relative assignment of the PD range for each bin and of the overall average default rate.[5]

AbsolutePD® Model implicitly incorporates these decision criteria into the modeling framework. By choosing covariates based on obligor-specific information together with relevant macroeconomic variables and by applying appropriate transforms, the Model automatically adjusts each quarter to relative as well as absolute default distribution. On a national level, the Model will shift all PDs higher when the overall economic conditions worsen. The amount of shift depends on the specific sector in which the obligors operate. In addition, geographical variations under different macroeconomic conditions are also implicitly modeled by incorporating information such as regional historic default dynamics.

Theoretical foundation

The AbsolutePD® Model follows the theoretical framework of Generalized Additive Model (GAM) (Greene, 4th Edition), which has the following functional form:

where j= 1, … , n indicates each of the covariates, f_j is the covariate specific nonparametric transform, x_j is a list of model

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

This rich, multidimensional data give Equifax MasterScore® the ability to uncover information contents that simple financial ratios cannot match and to deliver superior performance in ranking obligors that operate in different sectors and under different economic conditions.

[5] Power of a model depends on the relative binning of PDs, whereas calibration depends on the overall average default rate.

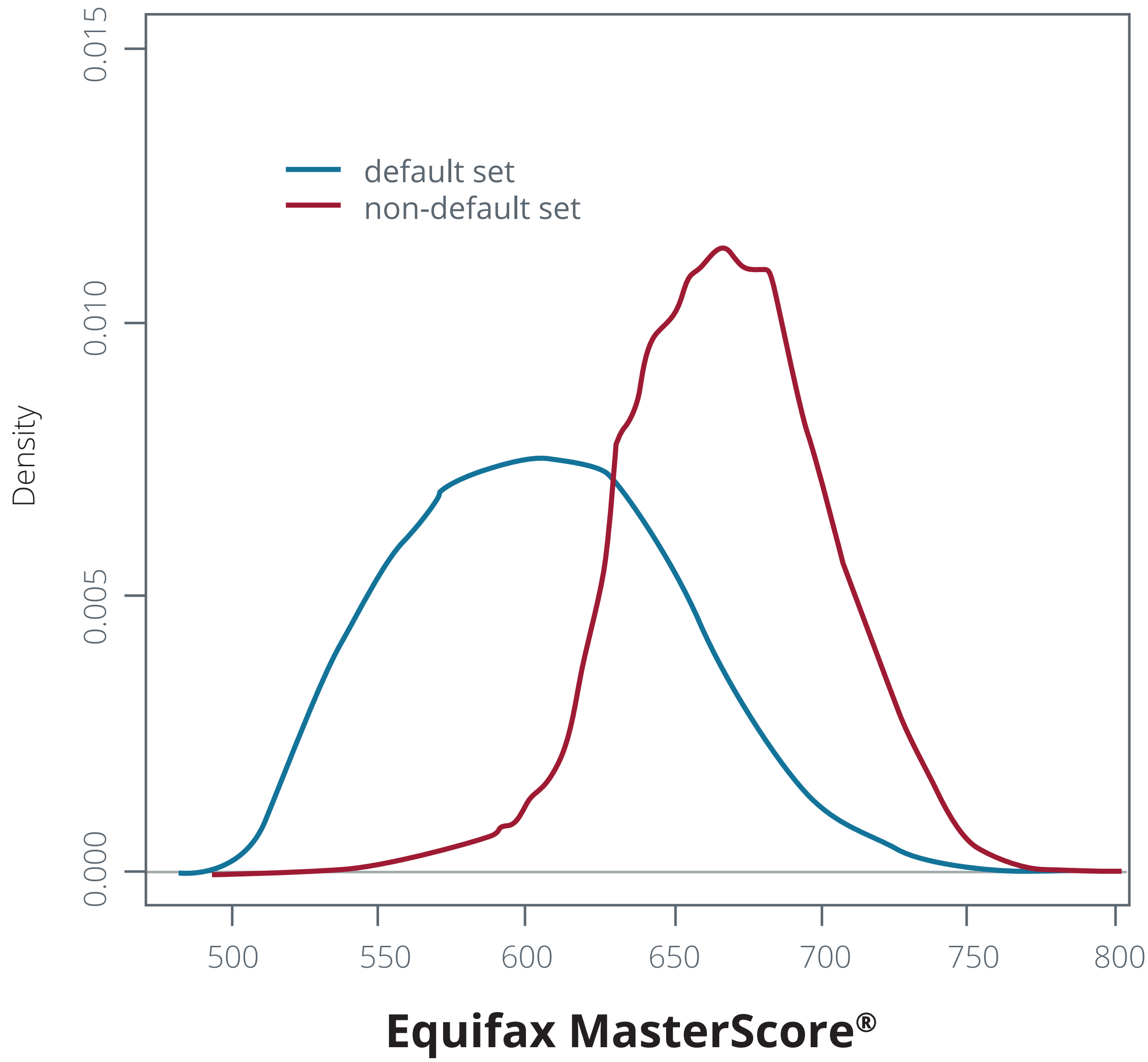

Figure 2. Equifax MasterScore®
Bimodal Equifax MasterScore® distribution for TRCK from 2006-2008

BIN	NORMAL ECONOMIC CONDITION	UNFAVORABLE ECONOMIC CONDITION	FAVORABLE
<500	85%	95%	75%
500-600	75%	85%	65%
600-700	50%	60%	40%
700-800	25%	35%	15%
>800	15%	25%	5%

Table 1. Deriving PDs using score binning method
The credit officer could bin the Equifax MasterScore® using this scheme.

covariates (explanatory variables), ε is the model residual, α a constant, *L* (·) is the Link function. For modeling binomial probabilities, popular choices for the Link function are *Logit* or *Probit*.[6] The choice between the two Link functions depends on the data set, its distribution, and the requirement for close form solutions. Nonlinearity of model covariates, such as the one shown in the next section, is explicitly addressed via the functional form of the Link function and the nonparametric transform, f_j, on the underlying covariates.

Once fitted, the conditional probability of default is obtained by inverting the Link function. Then the probability that a given obligor defaults within *k* quarters can be calculated using a mathematical result known as Bayes Rule, as

$$p_k = 1 - q_1 \times q_2 \times \cdots \times q_k,$$

where q_1 is the probability of survival for one quarter, and q_i is in general the probability of survival from the end of quarter $i-1$ until the end of quarter i, conditional on survival to the end of quarter $i-1$. Each quarter-to-quarter conditional survival probability, q_i, is obtained from a separately estimated model. Thus, an eight-quarter PD for a given sector calls for eight separately estimated models. One of the advantages of this term PD estimation procedure is that it does not rely on any analytical assumption of the underlying default term structure, but rather uses the data to empirically derive the underlying process. Estimated in this fashion, the Model implicitly takes into account historical dynamics of the underlying covariates.

One of the advantages of this term PD estimation procedure is that it does not rely on any analytical assumption of the underlying default term structure, but rather uses the data to empirically derivethe underlying process.

Each conditional survival probability, q_i, is specified to be of the form

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

The number of covariates, and the particular selection of covariates, can depend (and does depend, in our implementation) on both the particular industrial sector and on the number of forecasting quarters ahead. The coefficients for each of the covariates are chosen by application of the method known as Maximum Likelihood Estimation (MLE)[7], a standard approach to statistical fitting that, under data regularity assumptions, has desirable mathematical properties, as explained for example by Greene (Greene, 4th Edition).

[6] We follow the following definitions: Probit (p(X))=: Φ^{-1} (p(X)), where $\Phi^{-1}(\cdot)$ is the inverse Gaussian cumulative distribution function. Logit (p(X))=: ln $\left(\frac{p(X)}{1-p(X)}\right)$ where ln(·) is the natural logarithm.

[7] The MLE method has many large sample properties that make it attractive for use. It is asymptotically consistent, which means that as the sample size gets larger, the estimates converge to the right values. It is asymptotically efficient, which means that for large samples, it produces the most precise estimates. It is asymptotically unbiased, which means that for large samples one expects to get the right value on average.

Covariates

In addition to the transformed Equifax MasterScore®, we include obligor, lender, and macroeconomic level covariates that are suggested by judgment and by some preliminary model exploration. Nonparametric transform methods are used when necessary to address idiosyncratic behavior of specific covariates. We address the issues of over-fitting the data by avoiding covariates that are not suggested by natural reasoning, by avoiding extremely extensive trial-and-error model specification[8], and by excluding covariates that do not pass a reasonable test of statistical significance. In the end, we examine the out-of-sample performance of the model as a check on its robustness.

Macroeconomic covariates

The likelihood of default is affected by general economic conditions that are measured by directly observable macroeconomic variables. For the AbsolutePD® Model, we studied a wide range of macroeconomic variables that we deemed appropriate for the modeling framework, including GDP, unemployment, federal funds rate, distance to default, housing starts, fuel prices, a variety of regional statistics, and lender's own propensity to higher or lower default rates ceteris paribus. Suitability of inclusion of these covariates is based on economic intuition, frequency and availability of data, correlation of covariate to default, and potential multicollinearity[9] issues of the final pool of macroeconomic variables chosen. In addition, analysis is done on the choice of time lag necessary for each included covariate. For example, GDP might be a good predictor of default in the first four quarters, whereas the predictive power of the unemployment rate might only be significant over the next four quarters.

Self-learning mechanism covariates

For most statistical models that have static covariate coefficients and that are fitted using historic data, the resulting parameters of the model often can only capture the mean relationship between the response we aim to model and the underlying covariates. AbsolutePD® is an improvement over traditional models in that it incorporates self-learning and correcting features that systematically account for the model prediction error (the excess default rate, or EDR) by including the EDR as a separate covariate. This allows the model estimates to adjust to emerging economic environments

AbsolutePD® is an improvement over traditional models in that it incorporates self-learning and correcting features that systematically account for the model prediction error (the excess default rate, or EDR) by including the EDR as a separate covariate.

[8] There are systemic algorithms for selecting parameters, such as step-forward or step-backward covariate selection processes where, at each step, statistical tests are performed to judge the significance of a covariate's inclusion or exclusion. We avoid overreliance on such schemes, as when they are not used carefully, can easily lead to over-fitting.

[9] Multicollinearity is a statistical phenomenon that occurs when two or more covariates in the model are correlated and provide redundant information about the model response. Consequences of high multicollinearity include increased uncertainty of the estimate model parameters and could, in some cases, lead to counterintuitive results.

and improves the model's predictive performance throughout the economic cycle.

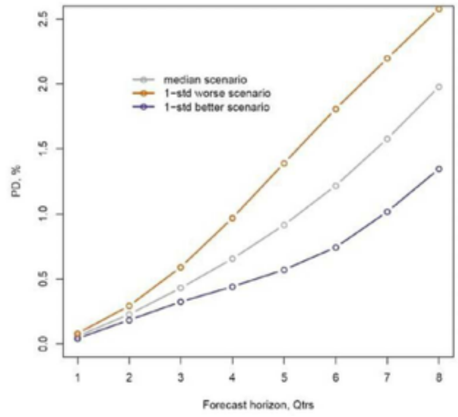

Figure 3. Term structure of default for TRCK

The excess default rate is calculated for each lender and sector combination and is updated quarterly where there are a sufficient number of observations of default in recent quarters. In cases where the underlying data are not sufficient to achieve such fine-tuned estimation, additional history, all sectors, or both are utilized to achieve data sufficiency. In instances where a lender's data are exceptionally thin, a generic excess default rate is used. The generic excess default rate is calculated for each quarter and sector combination over the set of lenders in the model.

This feature is important in capturing

- **Default momentum**, which manifests in occurrences where high level of defaults is followed by elevated rates of default for subsequent periods;
- **Forecast shortfall** to compensate the static nature of model parameters so as to minimize prediction error between each calibration; and
- **Serial correlation** of the fitted model residuals.

Estimation techniques

The MLE approach adopted by the AbsolutePD® Model estimation chooses those model coefficients that maximize the probability, based on the assumed model, of observing the particular survival and default outcomes that occurred historically, across time and across obligors. The main MLE assumptions are

- The given model of default probabilities applies at all times and to all obligors, and
- Conditional on the history of covariates of all of the obligors that have survived up to given quarter, the events of default or survival of the various obligors in all quarters are statistically independent of each other.

Although these data regularity assumptions are rarely satisfied in practice, the MLE method is nevertheless an accepted state-of-the-art methodology in settings such as this. See, for example, Campbell et al (Campbell, Hilscher, & Szilagyi, 2008). Further research may uncover new model approaches or fitting methodologies that are more accurate or robust than those adopted here. In the meantime, it is our judgment that the proposed Model and fitting method are reasonable and appropriate for the applications currently envisioned. After appropriate transforms, the underlying optimization problem can be cast as a weighted least squares problem and solved via an appropriate iterative algorithm, such as the modified conjugate gradient method.

Equifax AbsolutePD® term structure derivation

From the model output, we can calculate, for any obligor in any sector, the estimated conditional probability of default for each of the eight quarterly forecast horizons. From these conditional probability estimates, we derive the cumulative default probability at each horizon. This produces the term structure of default for the particular obligor. Figure 3 shows an example of a fitted term structure of default probabilities produced by the AbsolutePD® Model for TRCK. For a hypothetical obligor whose Equifax MasterScore® is 700 as of the date on which future PDs are to be estimated, this figure shows the estimated probability of default within one quarter, within two quarters, and so on up to eight quarters, for each of three possible macroeconomic environments.

The base-case environment, whose term structure of PDs appears as the central plot, has all of the covariates set at their respective sample medians. The figure also shows term structures of PDs that would apply for another two combinations of other levels of the underlying covariates: one to represent a favorable economic condition and another to represent an unfavorable condition.[10] For example, at an eight-quarter forecast horizon, an estimated PD of about 2.5% is shown for an adverse trailing-quarter sectoral excess-default rate, for an adverse macroeconomic growth scenario. The most favorable macroeconomic environment shown has a substantially lower estimated eight-quarter PD for the same Equifax MasterScore®, of about 1.25%.

Rating philosophy unified framework of Equifax AbsolutePD®

"Although the time horizon used in PD estimation is one year (as described in paragraph 447), banks are expected to use a longer time horizon in assigning ratings."
- Basel Capital Accord, §414

Traditional risk grading systems fall between the frameworks of Point-in-Time (PIT) and Through-the-Cycle (TTC) approaches.[11] For tasks such as credit approval, the PIT approach has distinct advantages, whereas for loss reserving and capital planning purposes, the case for cycle-neutral TTC approach is clear. The ability of a loan grading system to "look through the cycle" as an obligor's performance fluctuates is a challenge, but a necessary requirement of Basel II. It involves separating cyclical influences from those that are secular or seasonal, and segregating systematic factors from those that are idiosyncratic.

The ability of a loan grading system to "look through the cycle" as an obligor's performance fluctuates is a challenge, but a necessary requirement of Basel II.

[10] For both cases, we set the covariates one standard deviation away from their corresponding median levels.

[11] In brief, PIT seeks to explicitly estimate default risk over a fixed period, whereas TTC seeks to take cyclical volatility out of the estimation of default risk by assessing an obligor's performance across the business cycle.

In traditional risk grading, a common approach is to apply TTC scalar multipliers to the PIT PD estimates. The multiplier can either be derived based on historic data and then kept constant, or be allowed to vary with time. Essentially, this multiplier transforms the PD estimates produced by a PIT model to a long-run average of PDs, based on the relationship between long-term and relatively current default rates for a basket of obligors. Note that this is different from the IRB approach that calls for estimation of a long-run average default rate for each grade, pool, or score.

Clearly the choice of suitable scalar multipliers represents an important part of the transform. For example, it must be able to take into account changes in default risk that are not purely related to the changes in the cycle, and it should take into account obligor-specific factors in accordance with their riskiness.

Rather than conforming to the old paradigm of relying on a cardinal model to derive PIT PDs and then applying transforms based on subjective assessment of appropriate scaling factors to give TTC PDs, the AbsolutePD® Model represents a new paradigm that approaches the problem from the bottom up—by quantitatively estimating a time-specific and duration-specific conditional default probability for each individual obligor, while controlling for effects of cyclical and seasonal variations in the underlying default dynamics. This fine granularity of risk forecasts based on the bottom-up obligor level leads to a unified framework that satisfies both the PIT and TTC modeling requirements, together with added analytical benefits lacking in those two rigid approaches.

With AbsolutePD® Model, we can assign default probability for a specific obligor on a specific date over different time horizons. By incorporating appropriate macroeconomic covariates in the model estimation process, the AbsolutePD® Model enables the rating and default probabilities associated with each obligor to vary based on different stages of a typical business cycle. By NBER estimation, the average business cycle lasts around 16 quarters. So by setting the forecasting period theoretically to 16 quarters ahead in the Model, the resulting PD term structure will then give a direct measure of probability of default for each individual obligor through various stages of a complete business cycle.

Model validation

"Banks must have a robust system in place to validate the accuracy and consistency of rating systems, processes, and the estimation

By incorporating appropriate macroeconomic covariates in the model estimation process, the AbsolutePD® Model enables the rating and default probabilities associated with each obligor to vary based on different stages of a typical business cycle.

of PDs. A bank must demonstrate to its supervisor that the internal validation process enables it to assess the performance of internal rating and risk quantification systems consistently and meaningfully."
- Basel Capital Accord, §302

Not only is the validation process part of the Basel requirements, but it is also an integral part of any rigorous quantitative prediction model development process if models are to be accepted and used to support decision making. It ensures that the model meets its intended requirements in terms of the methods employed and the results obtained.

Validation can be done in a variety of ways, ranging from the simple to the complex. We can perform validation

- Only on the model development sample;
- On a sample of obligors that is not used to develop the model, but is taken from the same period of time;
- On a single holdout sample from the time period outside the model development period; and
- As a step-through simulation process across multiple time periods while recalibrating the model.

Our approach is a combination of the third and the fourth methods. We divide the sample time series into its in-sample and out-of-sample populations. The in-sample population is first used for model analysis and parameter fitting. The fitted model and parameters are then applied to data taken from the out-of-sample population. This method minimizes over-fitting[12] and is the most efficient way to ascertain whether the level of accuracy remains the same from year to year—an indication of how stable the model may be over time. Every quarter, we reassess the model covariates and reestimate the parameters taking into account latest updates to obligor information, new defaults that occurred over the last period, new readings for our macroeconomic indicators, and the latest measure of performance of the model over the previous quarters. This continuous validation and calibration process ensures the AbsolutePD® Model gives the most up-to-date default prediction.

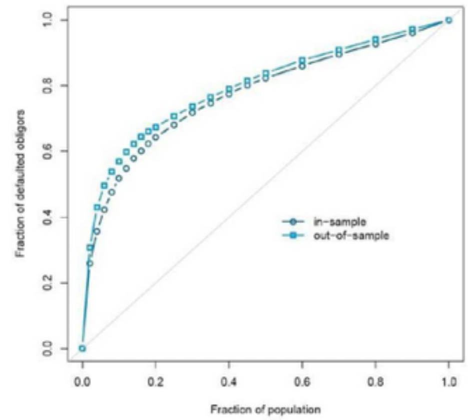

Figure 4. PowerCurve for TRCK, in-sample vs. out-of-sample, averaged over four quarters

[12] Over-fitting is the phenomenon of building a model that agrees well with the observed data but has no or significantly reduced predictive ability when applied to real, unseen data. Some causes of over-fitting include incorporating too many correlated covariates, capturing spurious relationships due to data problems, and incorporating a model too rich to be supported by either the data set or the underlying economic realm.

In-sample vs. Out-of-sample comparison

In order to boost the sustainability of the Model's predictive ability, we allow different sets of covariates to be used when making forecasts for different horizons.

Equifax AbsolutePD® Model: Power

An industry-standard method for visualizing the ability of a model to rank obligors by credit quality is the Power Curve (PC). We emphasize that the PC differs from another standard method, the Receiver Operating Characteristic (ROC). The two methods are similar in concept and the usual metric, Area-Under-Curve (AUC), for the two methods are linked by a factor proportional to the rate of defaults.[13] (See Engelmann, Hayden, & Tasche, January 2003 for a more in- depth analysis.)

In order to construct the Power Curve, we first sort the firms according to their PDs. For each number f between 0 and 1, we can set aside the "higher-PD group," containing a fraction f of the total population of firms, and consisting of these firms whose PDs are higher than those in remaining fraction 1 - f of the population. For example, if f = 0.20, then the higher-PD group consists of the 20% of the population that is most likely to default, according to the AbsolutePD® Model. We can then calculate the fraction of all defaulting firms in the higher-PD group. This "captured fraction" is shown on the vertical axis of the Power Curve. For example, if

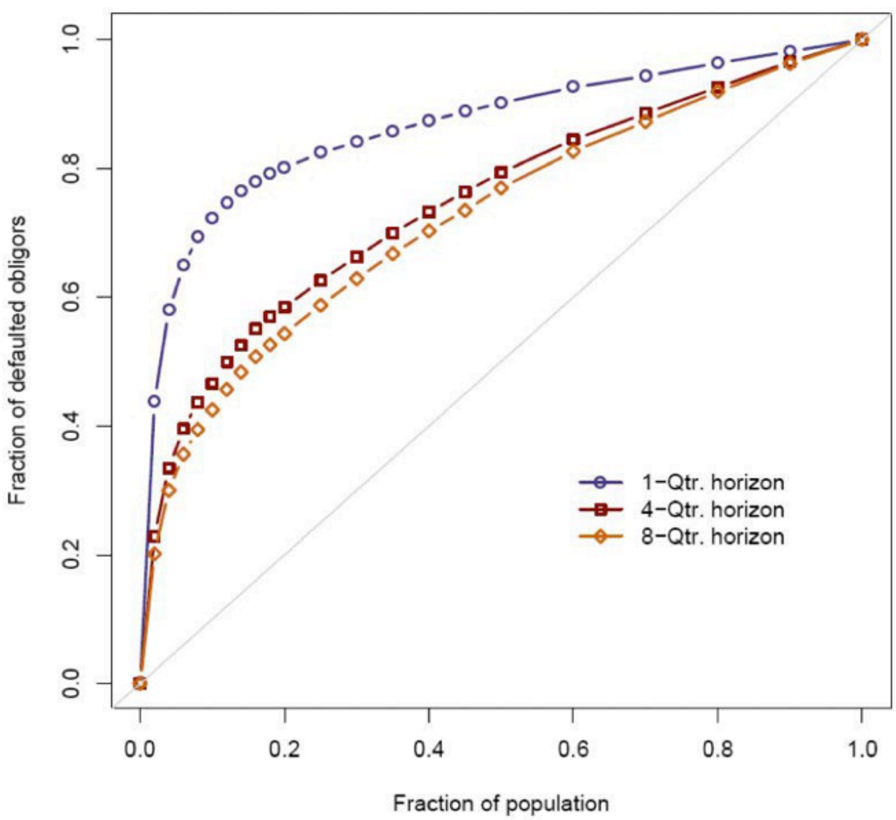

Figure 5. PowerCurve for TRCK, in-sample vs. out-of-sample, for one-, four-, and eight- quarter horizons

Figure 5 shows the out-of-sample Power Curve for the one-, four-, and eight-quarter horizons. This out-of-sample PC is produced by first fitting the Model on the in-sample population. Then we use the same fitted parameters of the Model to produce PD forecasts over eight different horizons.

[13] Define AUC as the area between the Power Curve or ROC curve and the diagonal line. Then we have $AUC_{PC} = (1 - N_{ND}/N)\, AUC_{ROC}$ where the ration of the number of non-defaulter, N_{ND}, to the total population, N, is the default rate.

1,000 firms defaulted within the one-year forecast horizon, and if 600 of these firms were in the higher-PD group of $f = 0.20$, then the corresponding point on the Power Curve at $f = 0.20$ is 0.60.

Figure 4 shows two Power Curves based on an experimental version of the AbsolutePD® Model specification.[14] For this, we average the captured fraction f, over four quarters, first across the "in-sample period," the period for which data were used to estimate the model coefficients, in order to obtain the in-sample PC; then across the "out-sample period," the period for which data were used to validate the fitted model coefficients, in order to obtain the out-of-sample PC.

In general, we would like the Power Curve to be as high in the north-west direction as possible, such that the area between the curve and the diagonal is as large as possible. A better PD model is one that is able to more accurately split firms into a group that is more likely to default and a group that is less likely to default. A model that assigns PDs based on no ability to discriminate among borrowers would have a Power Curve that is expected to lie on the 45-degree line. For example, from a pool of 100,000 borrowers, a model with no explanatory power would assign 20,000 firms at random into the "worst 20%" group, and these firms would be expected to include 20% of the firms that ultimately defaulted within the forecast horizon.

Figure 5 shows the out-of-sample Power Curve for the one-, four-, and eight-quarter horizons. This out-of-sample PC is produced by first fitting the AbsolutePD® Model on the in-sample populations.

This out-of-sample PC is produced by first fitting the model on the in-sample population. Then we use the same fitted parameters of the Model to produce PD forecasts over eight different horizons. Finally, we compare the ranks of the predicted PDs with the actual defaults. We observe that as the forecast horizon shortens, the power of the Model increases accordingly. In other words, the PC for shorter horizons dominates that for longer horizons. This result is intuitive as the forecasting power of the covariates is most potent and relevant for making predictions at horizons closest to the model valuation date.

A powerful and consistent model generates predictions that are consistent over a broader range of forecasts. This is the key advantage of the AbsolutePD® Model over traditional score-based predictions.

[14] Production version may have different covariate specifications and hence different PC profiles.

In order to boost the sustainability of the Model's predictive ability, we allow different sets of covariates to be used when making forecasts for different horizons. The economic intuition behind this feature is as follows. For example, GDP may have better predictive power at close range, so we might use it instead of a correlated covariate such as the fed funds rate, which may have a longer lasting power and generally operates with a lag, so it will be used for forecasts further out.

A model that suffers from over-fitting might have a relatively high in-sample PC, but a lower (poorer) out-of-sample PC. One way to assess any presence of over-fitting is by overlaying both in-sample and out-of-sample PCs, as shown in Figure 4, to see if there exists any significant deterioration of power when the model is applied to the out-of-sample holdout population. Our result indicates that the out-of-sample PC for the AbsolutePD® Model is comparable to the in-sample PC, indicating no evidence of over-fitting and showing that the ability of the Model to rank firms is sustained over time, at least for the indicated sector and period. This procedure is methodically carried out for all separately defined sectors to detect any sign of over-fitting. The result of this analysis determines both the number of covariates and the specific choice of covariates used in the final production version of the Model.

It is simple to show[15] that PC and the corresponding frequency of default for a given cutoff are related. The link for the two values is the mean probability of default. Consistency, as discussed in the next section, is at the heart of models that can better estimate this mean probability of default. Two models can have the same power, but if they have different degrees of consistency, then the derived probability of default could be significantly different.

[15] By definition, for any cutoff C, the power at that cutoff is given by $P(M_D < C) =: \frac{X_1(C)}{N_D} = \frac{\sum_{i=0}^{C} Pr(i)}{\sum_{i=0}^{1} Pr(i)}$ *m* where $X_1(C)$ is the number of obligors who are predicted to default actually defaulted, N_D is the total number of defaulted obligors, M_D is the set of score/PDs belonging to defaulted obligors, and *Pr(i)* is the default frequency for cut off *i*. From this we see that $Pr(C) = \sum_{i=0}^{1} Pr(i)\,[P(M_D < C) - P(M_D < C - 1)]$, where $\sum_{i=0}^{1} Pr(i)$ is the mean default probability.

COVARIATES				
Fit 1	Z_t			
Fit 2	Z_t	W_t^R		
Fit 3	Z_t	W_t^R	GDP_t	
Fit 4	Z_t	W_t^R	GDP_t	Z_t-Z_{t-1}

Table 2. Covariates used on successive model fits

The output is a sequence of four different versions of the Model, adding an additional covariate for each fit, as shown in Table 2. Note that Z_t is the transformed Equifax MasterScore® and the other covariates are as defined earlier in this paper.

MODEL	FIT 1	FIT 2	FIT 3	FIT 4
1 Qtr. Forward	0.245	0.207	0.209	0.208
2 Qtr. Forward	0.381	0.335	0.323	0.313
3 Qtr. Forward	0.425	0.354	0.344	0.297
4 Qtr. Forward	0.497	0.437	0.429	0.372
5 Qtr. Forward	0.586	0.555	0.546	0.525
6 Qtr. Forward	0.545	0.542	0.538	0.538
7 Qtr. Forward	0.407	0.411	0.410	0.397
8 Qtr. Forward	0.366	0.367	0.366	0.345
1 Year Forward	4.090	3.190	2.940	2.550

Table 3. In-sample AMSE (x10000) of AbsolutePD® Model for each covariate specification

Table 3 shows the in-sample period (2001-07-01to2006-04-01)AMSEof the Model for sector TRCK from one quarter forward to eight quarters forward, together with result for the one-year fit.

MODEL	FIT 1	FIT 2	FIT 3	FIT 4
1 Qtr. Forward	4.850	2.680	1.680	1.080
2 Qtr. Forward	6.510	5.270	5.030	3.370
3 Qtr. Forward	7.070	6.130	6.030	4.290
4 Qtr. Forward	7.890	7.120	7.050	5.120
5 Qtr. Forward	9.100	8.460	8.370	6.940
6 Qtr. Forward	11.480	11.290	11.230	10.780
7 Qtr. Forward	11.780	11.610	11.590	12.270
8 Qtr. Forward	-	-	-	-
1 Year Forward	50.100	42.100	38.100	27.700

Table 4. Out-of-sample AMSE (x10000) of AbsolutePD® Model for each covariate specification

Table 4 shows the corresponding table for the out-of-sample period (2006-07-01 to 2008-04-01). Here we see striking improvement of the AbsolutePD® Model over a score-based approach.

A powerful and consistent model generates predictions that are consistent over a broader range of forecasts. This is the key advantage of the AbsolutePD® Model over traditional score-based predictions.

Power comes from better prediction of the shape of the underlying distribution of the likelihood of default for a portfolio of obligors.

Equifax AbsolutePD® Model: Calibration

In this section we analyze the accuracy of the Model in terms of Average Mean Squared Error[16] (AMSE), defined for a given sample by

$$AMSE =: \frac{\sum_t \left(\sum_{i=1}^{N_t} y_{i,t} - \sum_{i=1}^{N_t} p_{i,t}\right)^2}{\sum_t N_t^2}$$

Where N_t is the total number of obligors in the sample in quarter t, and $p_{i,t}$ and $y_{i,t}$ are, respectively, the Model predicted default probability and the actual default indicator for obligor i in quarter t.

The output is a sequence of four different versions of the Model, adding an additional covariate for each fit, as shown in Table 2. Note that Z_t is the transformed Equifax MasterScore® and the covariates are as defined earlier in the paper.

Table 3 shows the in-sample period 2001-07-01 to 26-4-1 AMSE of the Model for sector TRCK from one quarter forward to eight quarters forward, together with results for the one-year fit. We observe that the successive addition of appropriate covariates reduces the AMSE and that the AMSE of the "full" model is significantly lower than that of the model using information encapsulated in Z_t alone. Note, although these models might have comparable power in ranking obligors, the reduction in AMSE comes from the superior calibration of the AbsolutePD® Model.

Table 4 shows the corresponding table for the out-of-sample period (2006-07-01 to 2008-04-01). Here we see striking improvement of the AbsolutePD® Model over a score-based approach. This dramatic pickup in consistency comes from the Model's ability in adapting to different economic conditions, in continuously learning and adjusting based on past prediction shortfall, and in archiving an optimal trade-off between Type I and Type II errors.

This analysis demonstrates how the numerical accuracy of the Model improves as we move from a basic model, based on only Z_t to progressively richer specifications. Overall, the results show a significant improvement in AMSE as additional covariates are added to the model, both in-sample and out-of-sample.

[16] An alternative measure, MSE, is defined by $MSE =: \frac{\sum_t \sum_{i=1}^{N_t} \left(y_{i,t} - p_{i,t}\right)^2}{\sum_t N_t}$ The AMSE is a more revealing measure of model error than the MSE in settings such as ours because, in expectation, it isolates the squared error in the default probabilities.

Next, we dig a bit deeper into understanding the driving factors behind the superior performance of the AbsolutePD® Model. We start by referring back to the twin pillars under model consistency—power and calibration.

Power comes from better prediction of the shape of the underlying distribution of the likelihood of default for a portfolio of obligors. Figure 6 plots the predicted distribution for some 300,000 obligors in the TRCK sector. The horizontal axis gives the predicted PD; the vertical axis gives the corresponding density, which indicates the fractional count of obligors associated with a particular PD. We observe that the overall shape of the PD distribution changes over time. This is partially a consequence of the mathematical relationship between conditional default and cumulative default. But more importantly, it also reflects the impact of obligor- and lender-specific covariates that help the Model differentiate among obligors in the same sector under different economic environments.

Calibration, on the other hand, comes from the ability of a model to predict PD that matches actual default in aggregate. In other words, the mean of the predicted PD distribution when compared to the actual default rate gives an indication of the overall calibration of a model. In Figure 6, we see that the sample mean of the predicted PD tracks that of the actual default rate closely, even at horizons beyond four quarters.

Also in Figure 6, we see effects of the self-correction mechanism embedded in the Model. We observe that as the Model slightly undershoots the actual default rate in the first quarter, it progressively self-adjusts and zooms in on the actual default rate after three quarters.

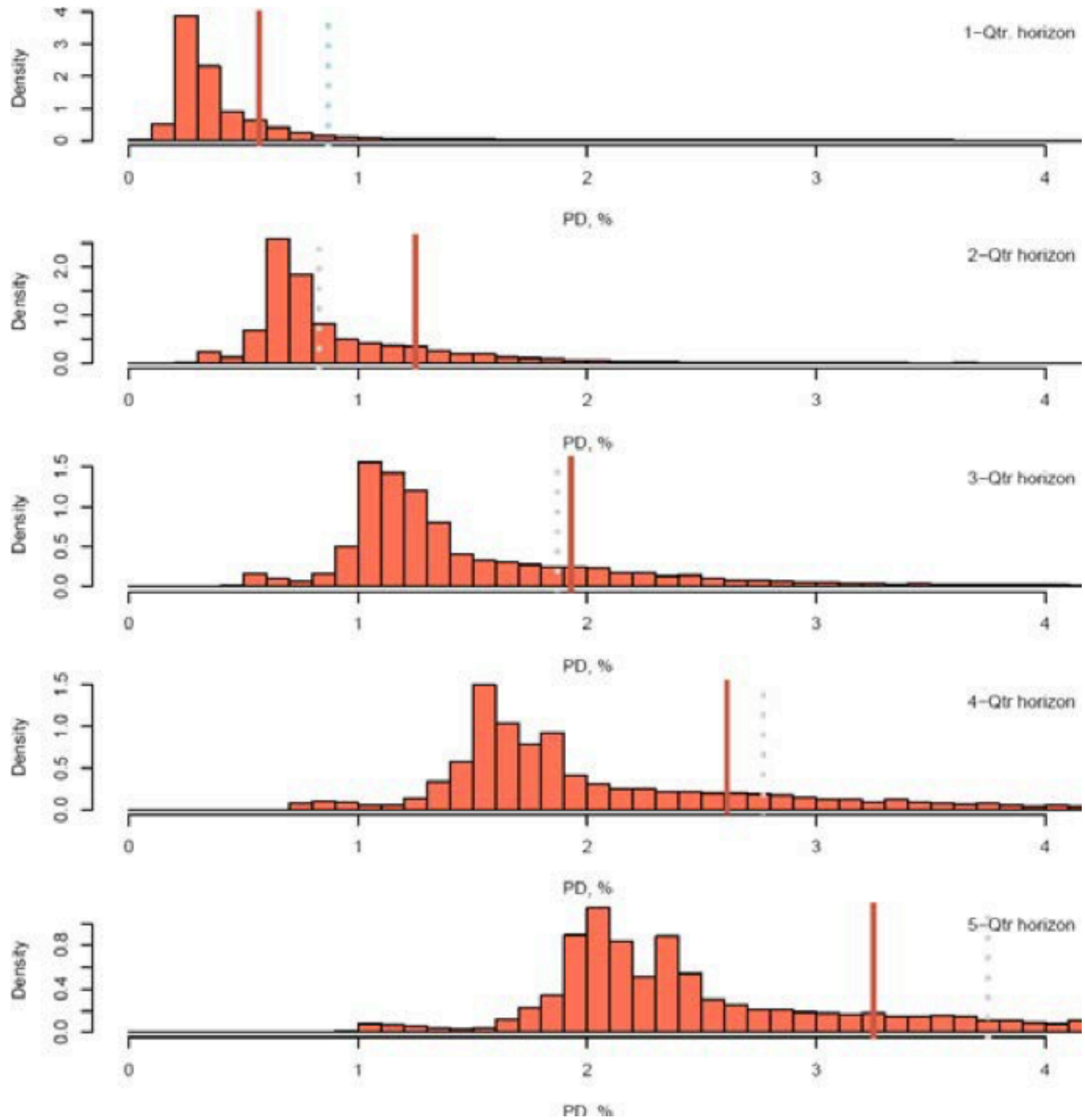

Figure 6. **TRCK sector out-of-sample PD distribution for one- to five-quarter hoirzons**

Figure 6 plots the predicted distribution for some 300,000 obligors in the TRCK sector. The horizontal axis gives the predicted PD; the vertical axis gives the corresponding density, which indicates the fractional count of obligors associated with a particular PD. (Note that dotted lines show the actual realized default rate over the same horizon, and solid lines indicate the predicted mean rate of default.)

Summary and conclusions

Equifax AbsolutePD® delivers a statistically and quantitatively advanced default forecast model for obligors without reliance on financial statements.

Through extensive research and analysis, the AbsolutePD® Model breaks new ground with the statistical analysis of the likelihood of default based on borrower financial condition, size, and industry sector, as well as lender portfolio default rate and overall economic cycle.

One innovation of the AbsolutePD® Model is that it does not rely on availability of financial statements, making it a tool particularly suitable for analyzing private obligors for whom current or accurate financial statements are not available. For large, publicly traded firms with marketable credit derivative instruments, such as Credit Default Swaps, one can readily infer the implied risk neutral probability of default. For other large- to medium-size firms with publicly available financial statements, there are also models available that use financial ratios to help make default predictions. AbsolutePD® Model is unique in that it uses transaction history and obligor-specific characteristics together with relevant macroeconomic data as supplementary input.

We have demonstrated in this analysis that the AbsolutePD® Model complements and enhances the Equifax MasterScore® in a number of ways. One, it boosts predictive power by incorporating macroeconomic covariates. Second, the framework enables one to deduce a term structure of probability of default for specific obligors. Third, it features a self-correcting mechanism by incorporating historic forecast errors as an explicit input covariate.

Overall, the AbsolutePD® Model succeeds in delivering superior prediction of PDs that is both powerful and consistent.

AbsolutePD® Model is unique in that it uses transaction history and obligor-specific characteristics together with relevant macroeconomic data as supplementary input.

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The AbsolutePD® Model succeeds in delivering superior prediction of PDs that is both powerful and consistent.

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