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Credit risk modeling during the COVID-19 pandemic:

Why models malfunctioned and the need for challenger models

December 2020

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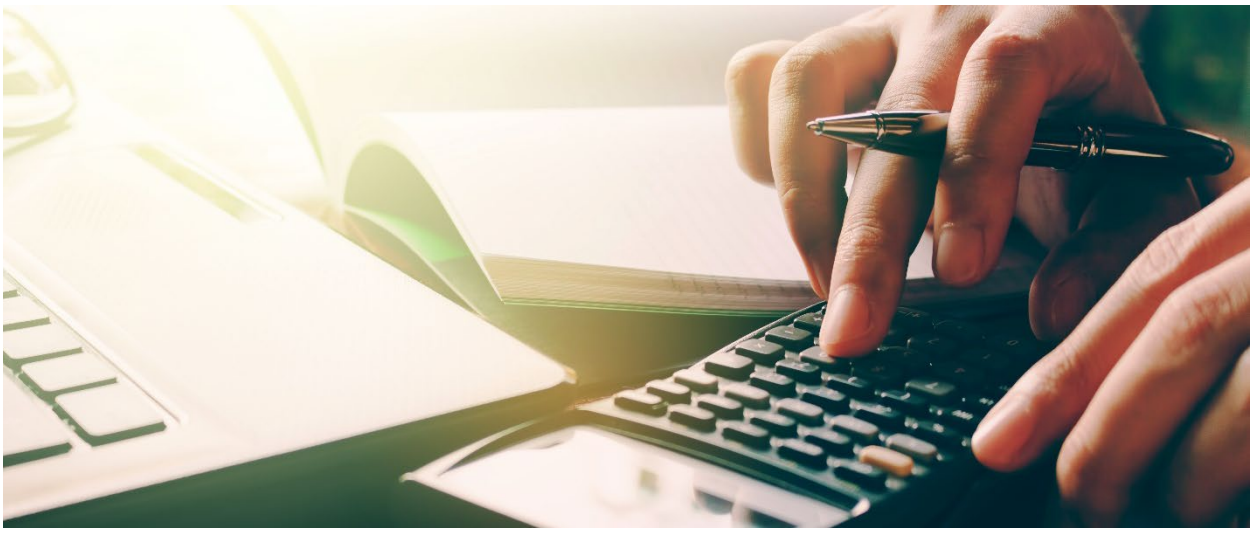
Introduction

Much effort went into developing CECL and IFRS 9 credit risk models that were supposed to hold up during the next economic crisis following the 2007-2008 Global Financial Crisis. Since that time, development and validation processes for econometric models have become longer and more highly regimented, resulting in exhaustive testing in development and production environments. In the end, models were approved and put into action. When the COVID-19 pandemic struck in early 2020, these models (based on their construction) were pushed beyond the boundaries for which they were developed.

In these times when primary models exhibit significant limitations, there has rarely been greater need for challenger models. Fortunately, there has never been an easier time to build challenger models. The road to CECL compliance involved significant investments in technology, data management, integration and process improvements. These investments have led to the creation of CECL modeling platforms that are flexible and can incorporate different types of model methodologies. Moreover, there are typically reliable, complete, and accurate data sets readily available for developing a challenger model.

In this white paper, we go over a few of the commonly used model methodologies, examine how the pandemic exposed significant model limitations, and finally, provide a practical solution to those limitations.

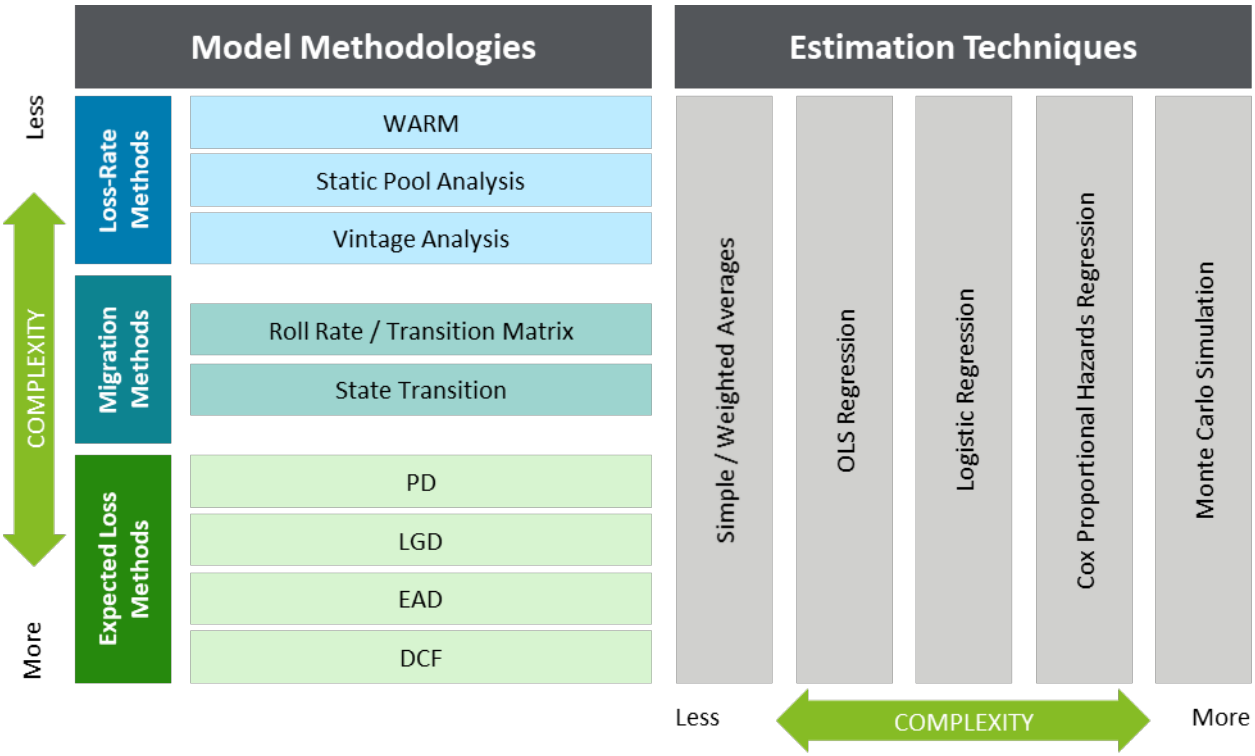
The solution described in this paper is a challenger model that does not have an overreliance on macroeconomic factors. The model is developed on prime auto loan performance data from Reg AB II filings with the SEC (a public data source). Data is restricted to prime loans because most loan portfolios are more heavily concentrated with higher quality loans than subprime loans.



Commonly used model methodologies

The CECL standard does not require the use of any specific methodology. Commonly used methodologies fall under three categories: loss-rate methods, migration methods and expected loss methods. Figure 1 lists the most commonly used model methodologies and estimation techniques by order of complexity.

Figure 1: Model Methodologies and Estimation Techniques



Note: This figure is a generalization of the classification of methodologies and order of complexity and may not hold true in all cases. For example, depending on model specifications a vintage model could be more complex than a state transition model. Furthermore, methodologies are frequently combined such as using vintage rates or transition rates in a Discounted Cash Flow ("DCF").

Loss-rate methods generally can be estimated on portfolio or cohort (pools of loans that share similar risk characteristics) level data. The Weighted Average Remaining Maturity ("WARM") method estimates losses by multiplying average annual charge-off rates against the annual projected amortized cost, which is adjusted for prepayments, for the weighted average remaining life of financial assets in a pool. Static pool analysis and vintage analysis are essentially the same except that vintage analysis is based on the year of origination while static pool analysis is based on cohorts which share similar risk characteristics.

Migration methods can be estimated at the portfolio, cohort or loan-level. When at the portfolio or cohort level, the migration projection is commonly referred to as roll rates and presented in a transition matrix. Roll rates are the percentage of accounts that transition to a better, worse or remain in the same delinquency state. When at the loan-level, the migration method is referred to as a state transition model and transition rates are driven by factors such as loan specific characteristics and macroeconomic predictors.

Expected loss methods are more frequently estimated on loan-level data and depend on the aggregation of several component models' outputs to estimate losses. Component models include Probability of Default ("PD"), Loss Given Default ("LGD"), and Exposure at Default ("EAD").

$$Expected\ Loss = PD * LGD * EAD$$

A model methodology can be thought of as a type of model which can be estimated using a variety of statistical techniques that range in complexity.

A PD model, as an example, can be estimated using several techniques. On one end of the spectrum, PD rates can be estimated using simple averages. The number of defaulted accounts divided by the total number of active accounts equals the PD rate.

$$PD\ Rate_t = \frac{Number\ of\ Defaulted\ Accounts_t}{Total\ Number\ of\ Accounts_t}$$

Where t is the period which could be a month, quarter or year.

On the other end, since default is dichotomous (either a loan is in default or it is not) PD rates can be estimated using logistic regression. Probabilities are transformed to odds and set equal to a linear function of the predictor variables. For k predictor variables and $i = 1, \dots, n$ accounts, the model is

$$PD\ Rate_t = log\left[\frac{p_i}{1 - p_i}\right] = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik}$$

where p_i is the probability that $y_i = 1$. The expression on the left-hand side is referred to as the logit or log-odds. The predictors (x) on the right-hand side may be either quantitative variables or dummy (indicator) variables.

Frequently used predictors of default include macroeconomic factors (unemployment rates, home price index, gross domestic product, etc.) and loan characteristic variables (borrower FICO score, loan-to-value ratio, maturity term, etc.).

A logistic model has the benefit of directly incorporating past, current and future economic conditions. The model is estimated using historical data, run on the current portfolio, and used to project future losses based on reasonable and supportable forecasts.

There are, however, several limitations of a logistic model or other sophisticated methods which incorporate macroeconomic predictors directly. These limitations are explained in the next section where we examine how the pandemic exposed significant model deficiencies.

Four ways the COVID-19 pandemic caused models to malfunction

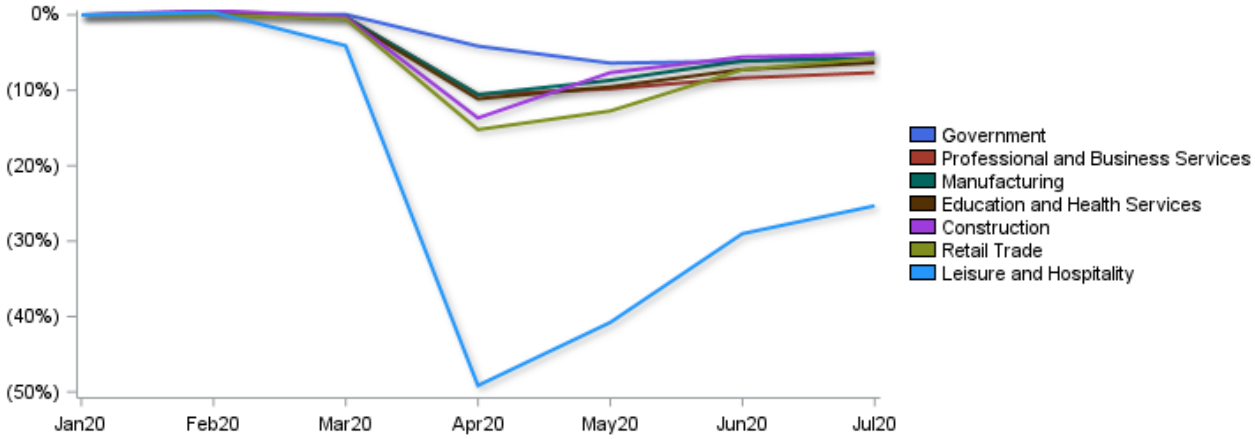
The pandemic wreaked havoc on econometric models in the following ways:

1. Government-imposed shutdowns and restrictions that disproportionally impacted leisure and hospitality industries
2. Extreme movements in economic series
3. Unprecedented amount of government support
4. Generous forbearance programs

1. Government shutdowns

Government-imposed shutdowns and restrictions related to businesses and individual citizens vary by state and local government. In general, these shutdowns and restrictions have included stay at home orders, limits on public gatherings, out-of-state travel restrictions, and closures of schools, daycares, restaurants/bars, and non-essential retail. Accordingly, these shutdowns and restrictions have disproportionally impacted leisure and hospitality industries and those states and localities that rely more heavily on these industries.

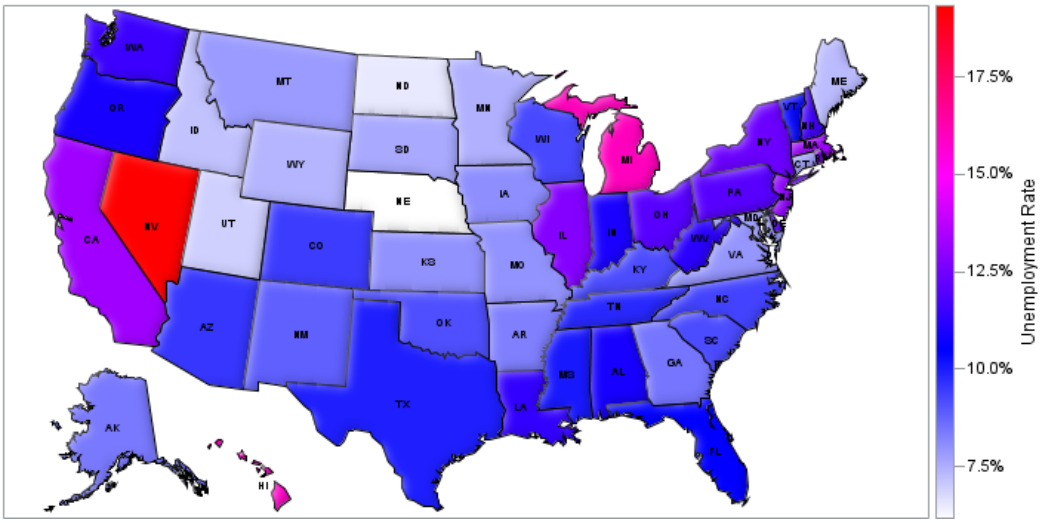
Figure 2: Percentage Change in Employees Since January 2020



Source: U.S. Bureau of Labor Statistics

Most credit loss models likely do not include predictors for borrowers' occupation or for government shutdowns – an extremely rare event. It is also not likely that many qualitative frameworks earnestly considered a pandemic-driven economic shutdown beforehand. However, it is common to use state level data for predictors such as unemployment rates. States that depend heavily on tourism, like Nevada, have had the highest unemployment rates during the pandemic.

Figure 3: Average State Level Unemployment Rates from March 2020-June 2020



Source: U.S. Bureau of Labor Statistics

State level unemployment rates can be considered somewhat of a proxy for occupation because states like Nevada depend more heavily on a specific industry such as leisure and hospitality. However, other states are less concentrated in a single industry and their unemployment rates are less useful as a substitute for occupation. A model ideally would include a predictor for borrower occupation and it would be refreshed every time a borrower changed employment – a fanciful idea but not viable. Furthermore, not all models use state level predictors and ones that use national level unemployment rates would be completely insensitive to localized unemployment trends.

2. Extreme movements

Credit loss models are inherently limited to understanding the behaviors observed in the historical economic series they are trained on. From the beginning of 2005 and up until the start of the pandemic, the largest year-over-year ("YoY") percentage change in unemployment rates was around 80% during the Great Recession (December 2007-June 2009). At April 2020, the YoY percentage change was over 300%. Consequently, the extreme movements pushed many credit loss models that use unemployment rates as a predictor beyond their limits. For example, it has not been uncommon for models predicting portfolio level net loss rates of the low single digits before the pandemic moving well into the double digits- i.e., values that are unreasonable and reflective of a model being used outside of the boundaries it was trained on.

Figure 4: Unemployment Rate YoY % Change (January 2005-July 2020)

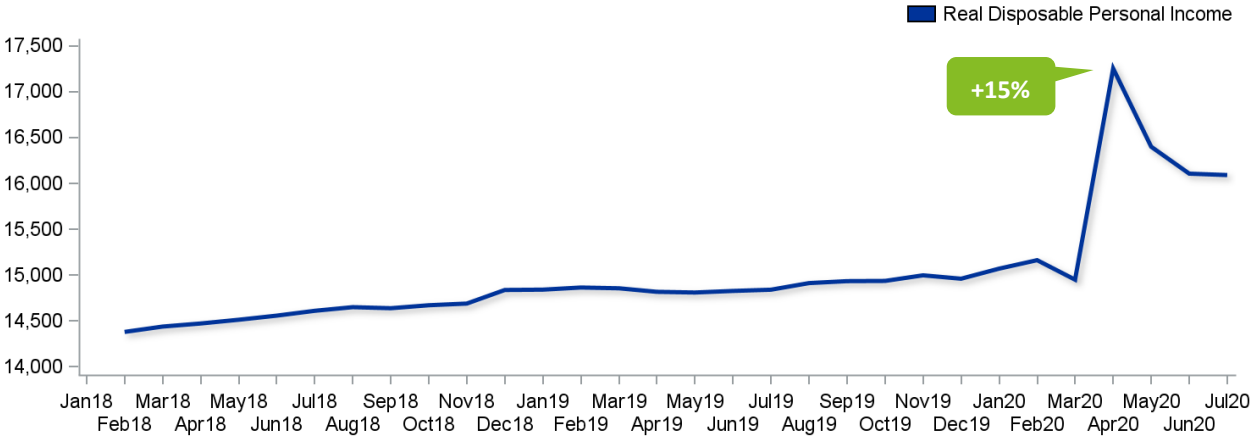
Source: U.S. Bureau of Labor Statistics, Unemployment Rate [UNRATE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UNRATE, September 3, 2020.

There were two forces that put the brakes on losses rising to a level that a 300% increase in unemployment rates normally would signal: government support and forbearance programs.

3. Government support

The U.S. government provided an unprecedented amount of support through the Coronavirus Aid, Relief, and Economic Security "CARES" Act that was enacted on March 27, 2020. The massive economic stimulus package (~$2 trillion of financial assistance) included $1,200 per adult for individuals whose income was less than $99,000 (or $198,000 for joint filers) and $500 per child under 17 years old – or up to $3,400 for a family of four[1]. In addition to the direct payments to individuals, states were given the option of extending unemployment compensation to independent contractors and other workers who are ordinarily ineligible for unemployment benefits[2]. Eligible individuals received an extra $600 weekly benefit for all weeks of unemployment from the beginning of April to the end of July 2020. The extent of government support is clearly visible when looking at real Disposable Personal Income ("DPI") which jumped 15% from March to April 2020.

Figure 5: Real DPI (January 2018-July 2020)



Source: U.S. Bureau of Economic Analysis, Real Disposable Personal Income [DSPIC96], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DSPIC96, September 7, 2020.

[1] https://home.treasury.gov/policy-issues/cares/assistance-for-american-workers-and-families
[2] https://www.dol.gov/coronavirus/unemployment-insurance

It is uncommon for models to account for government stimulus directly unless they happened to include personal income as a predictor variable, which is not as popular as using unemployment rate as a predictor, or some other predictor that serves as a proxy for government stimulus. Even if there were a predictor for personal income the accuracy of model output would depend heavily on the accuracy of the underlying macroeconomic forecast.

4. Forbearance programs

Lenders offered forbearance programs to borrowers in an effort to limit losses over the long-term. Principal and interest payments of federally-held student loans were automatically suspended through December 31, 2020[3]. Lenders holding federally-backed mortgages (FHA, VA, USDA, Fannie Mae and Freddie Mac) may suspend borrowers' payments for up to 360 days[4]. Some lenders also offered pandemic related forbearance programs for non-government backed and private loans such as auto loans.

A model could account for forbearance programs by segmenting the loan population by forbearance status or including a categorical predictor which flags accounts in forbearance. However, similar to how it is uncommon for models to account for government stimulus directly, it is also uncommon for models to control for forbearance directly. Historically there has hardly ever been a need for predictors of these types.

Summary of exposed model limitations

The four items discussed (government-imposed shutdowns, extreme movements in economic series, unprecedented amount of government support, and generous forbearance programs) demonstrate how a credit loss model can quickly be pushed beyond its limits. A 14% national unemployment rate must mean an increase in losses, right? Perhaps not when government support causes a 15% month-over-month increase in personal income. Not when borrowers can delay debt payments a month to even a whole year.

[3] https://www.consumerfinance.gov/coronavirus/student-loans/
[4] https://www.consumerfinance.gov/coronavirus/mortgage-and-housing-assistance/

Solutions for model limitations and the modeling conundrum

In the previous section we examined how the pandemic exposed significant model limitations. We also began providing a few suggestions on ways to improve model performance in pandemic like economic environments; a recap is as follows:

- Unemployment rates varied considerably among states since the start of the pandemic. States less sensitive to the shutdowns have had much lower unemployment rates than those that depend more heavily on industries like leisure and hospitality. For example, Nebraska's (agriculture-based economy) and Nevada's (tourism-based economy) average unemployment rates were 6.2% and 19.3%, respectively, from March to June 2020. These observations highlight the importance of using state level data.
- Extreme movements in economic series pushed models beyond the boundaries they were trained on. The 300% YoY percentage change in unemployment rates at April 2020 caused many models to predict nonsensical losses given the current environment (i.e., in light of government support and generous forbearance programs). The validity of relying on a model that directly incorporates macroeconomic predictors is questionable. Developers should explore alternative models that may be better suited for estimating losses for accounting purposes.
- Government stimulus has limited losses that usually would occur during periods of record high unemployment rates – at least for the short-term. Personal income economic predictors like Real DPI can help capture the extent of government stimulus. An econometric model with economic predictors for both unemployment rate and Real DPI would better be able to measure the offsetting effects of rising unemployment rates and rising incomes due to stimulus.
- The forbearance segment of a loan population has historically been insignificant. There is now a need to consider developing a model specific to the forbearance segment or including a categorical predictor which flags accounts in forbearance.

In addition to the recommendations above, model instability during changing economic environments can be mitigated several ways which deal with methodology choices.

One approach is to structure models in a way that they generalize well over many different types of environments. Models can be developed either on different segments or include categorical predictors that represent "clean" and "dirty" accounts. Clean accounts are those that are current, have never been delinquent and never modified as of the measurement date. Dirty accounts are those that are either currently delinquent, or current but at some point were delinquent or modified as of the measurement date. This setup is useful in the current environment because a model could better distinguish the risk between the unusually large segment of accounts in forbearance (dirty loans) and current (clean) accounts.

State transition models naturally account for various delinquency states (current, 30 days-past-due ("DPD"), 60 DPD, etc.) but come at the cost of added complexity. A larger quantity of sub-models is needed for transitions (current to 30 DPD, 30 DPD to current, current to 60 DPD, 60 DPD to current, etc.). With more sub-models it becomes more challenging to develop robust, stable estimates and sub-models that do not contradict one another. It is illogical to have a suit of state transition sub-models that includes a sub-model for current to 30 DPD that has a positive coefficient for unemployment rates and a separate sub-model for 30 DPD to 60 DPD that has a negative coefficient for unemployment rates. It is difficult to come up with a plausible explanation for why increases in unemployment rates sometimes coincide with increases and other times with decreases in the probability to transition to a worse state.

Both of the options described above (segmenting data between clean and dirty accounts and state transition models) deal with granularity. The overall loan population is segmented into smaller groups which share more delineated risk characteristics. Granularity is often preferable when there is sufficient quantity of data. However, a downside of granularity is that data becomes thinner the more it is segmented. Segments with fewer observations tend to be more volatile and difficult to model.

And this brings us to the modeling conundrum: no model is perfect and there is a give and take relationship when making modeling decisions. Developers strive to develop parsimonious models but must accommodate internal and external (regulatory) requirements within the constraints of model limitations.

One model can only do so much. So why just have one model?

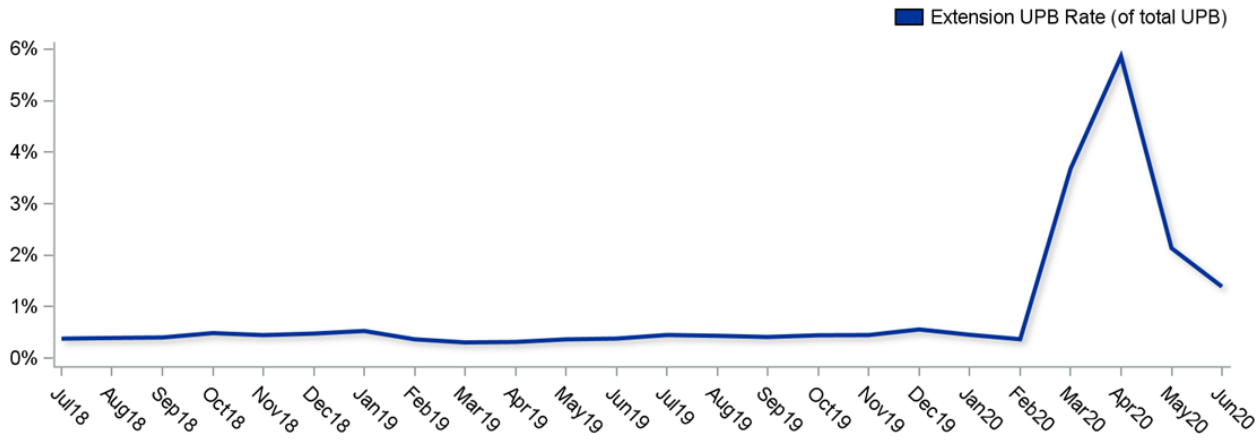
Expectations of the future environment are fluid. Attempting to fine-tune a primary model to handle whatever is thrown at it leads to overfitting and a loss of understandability because of the added complexity. Data sets have been scrubbed clean for CECL models and are readily available for other uses. Especially now in the pandemic environment there has never been a greater need for effective challenger models that help mitigate weaknesses in champion models.

Challenger model example using auto loan performance data

Need for a challenger model

A challenger model can be used to estimate losses of an entire portfolio or a specific segment. Based on pre-pandemic trends, generally speaking, accounts that were either currently or previously in forbearance represented a very small portion of a loan portfolio - likely not justifying the development of a forbearance model or incorporating forbearances directly in a champion model. For example, auto loan monthly extension rates averaged 0.4% leading up to the pandemic and jolted to 5.9% in April 2020.

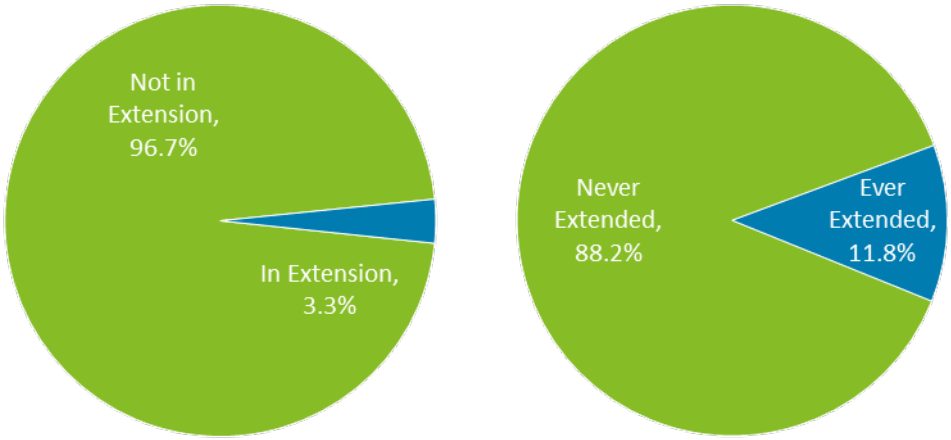
Figure 6: Auto Loan Extension Rate (July 2018-June 2020)



Note: An extension for an auto loan is akin to forbearance for mortgages in terms of payment deferrals.
Source: Reg AB II loan-level data filed with the SEC.

As of June 2020, 11.8% of active auto loans had been extended at some point and 3.3% were in extension status (on dollar basis).

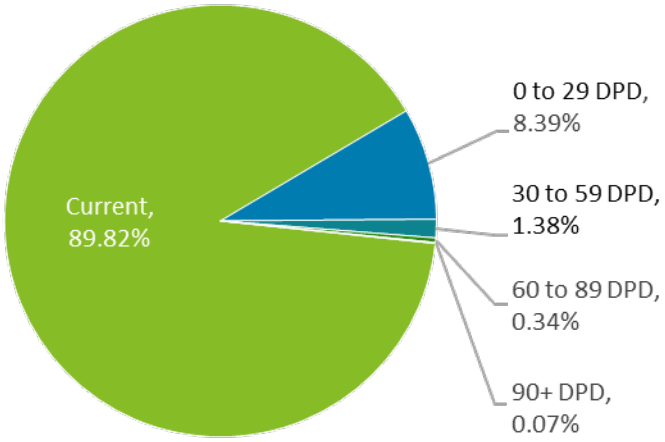
Figure 7: Auto Loan Extension/Forbearance Status (June 2020)



Source: Reg AB II loan-level data filed with the SEC.

Of the loans in extension status the majority are current (89.82%), 8.39% 1 to 29 DPD, 1.38% 30 to 59 DPD, 0.34% 60 to 89 DPD, and 0.07% 90+ DPD.

Figure 8: Auto Loan Delinquency Status of Loans in Extension/Forbearance (June 2020)



Delinquency State	Outstanding Balance (in millions of dollars)	% of Total
Current	$2,409 MM	89.82%
1 to 29 DPD	$225 MM	8.39%
30 to 59 DPD	$37 MM	1.38%
60 to 89 DPD	$9 MM	0.34%
90+ DPD	$2 MM	0.07%
Total	**$2,682 MM**	**100.00%**

Source: Reg AB II loan-level data filed with the SEC.

The forbearance segment of the portfolio is now large enough to justify the use of a challenger model specific to the segment. Furthermore, in the current pandemic environment one of the main modeling questions we are trying to answer is what portion of the forbearance population will ultimately turn into losses? An underlying assumption of this being a key question is that those borrowers who have been impacted negatively by the pandemic would have already taken advantage of forbearance programs. Of course, this will not always be the case. Some borrowers may not be savvy enough to be aware of forbearance or to sign up even if they were aware. Some borrowers may be financially stable today, but the domino effect of the pandemic and economic recession will cause new job losses and financial hardships.

In times of uncertainty it is helpful to use modeling techniques that are straightforward rather than convoluted. The pandemic has already caused enough confusion so we should not add to it by using some obscure approach. Roll rate (or transition rates) methodology is a classic framework and one that key stakeholders (management, internal/external auditors, regulators, etc.) can quickly grasp. A challenger model that uses roll rates can fairly quickly be developed and at a minimum can be used to help guide forbearance related qualitative adjustments to the champion model output.

Challenger model overview

The potential challenger model uses a transition matrix (roll rate methodology) estimated from the observed transition rates of the ever-dirty accounts segment of the prime auto loan population to develop low, mid and high net loss estimates for prime auto loans in forbearance as of June 30th, 2020. The roll rate methodology is used for a 24-month Reasonable and Supportable ("R&S") forecast period. Beyond the R&S period net losses are estimated by reverting immediately to the average historical net loss rate which is applied to remaining amortizing balances until the segment's end of life.

The transition matrix includes the following states: current, 1-29 DPD, 30-59 DPD, 60-89 DPD, 90+ DPD (default/terminal state) and paid (terminal state). Transition rates are calculated using simple averages like in the following formula:

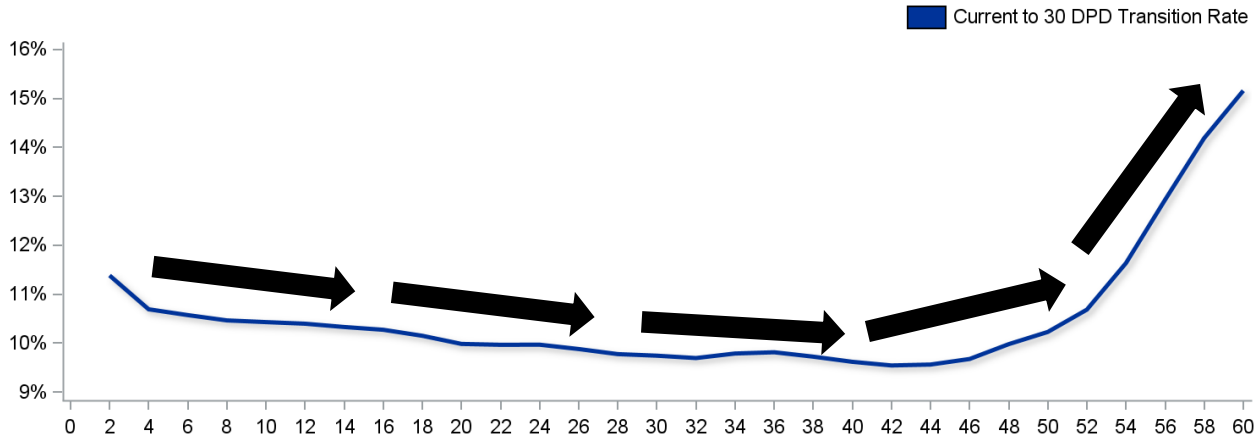
$$Transition\ Rate_{\text{1-29 DPD to 30-59 DPD}} = \frac{Number\ of\ Accounts\ Transitioning_{\text{1-29 DPD to 30-59 DPD}}}{Total\ Number\ of\ Accounts_{\text{1-29 DPD}}}$$

Transition rates are held constant throughout the 24-month R&S forecast horizon except for current to paid, which represents amortizing payments plus prepayments, and current to 1-29 DPD, which is dependent on loan age.

Current to 1-29 DPD is viewed as a key factor in the model because it represents new entries to delinquency and therefore flows through to all subsequent delinquency states. Also, balances becoming delinquent results in slower principal payback since payments are calculated only for current balances.

Figure 9 shows current to 1-29 DPD transition rates by loan age. The first part of the curve from 0 to 46 months shows declining delinquency rates which is consistent with the intuition that as borrowers demonstrate their ability to continue to make payments and build equity they are less likely to miss payments. However, this trend reverses after 46 months and delinquency rates quickly rise. At first glance this may seem counterintuitive, but it is reflective of the quality of loans that survive to older ages and is a relationship that has been noted in research on auto loan defaults.[5]

Figure 9: Current to 1-29 DPD Transition Rate by Loan Age



Source: Reg AB II loan-level data filed with the SEC.

This challenger model applies transition rates to amortizing balances, which include prepayments, using matrix multiplication and assuming a Markov process. A stochastic process has the Markov property if the conditional probability distribution of future states of the process depends only on the present state. In other words, predicting the next delinquency state depends only on the current state, and not the states that came before the

[5] Wu, Deming and Fang, Ming and Wang, Qing, An Empirical Study of Bank Stress Testing for Auto Loans (June 1, 2018). Journal of Financial Stability, Forthcoming, Available at SSRN: https://ssrn.com/abstract=2591361

current state. This "memoryless" property is an attractive feature of using transition rates because at any given point in time you only need to know the current state.

After the 24-month R&S period net losses are estimated by applying the average historical net loss rate to the remaining amortizing balances until the end of the segment's life. Finally, net losses estimated for the R&S period and reversion period are added together to form the lifetime expected loss estimate.

Low, mid, and high estimates are developed by varying the rate at which loans become delinquent and prepayment speeds.

Advantages of this challenger model setup include its ability to account for: the current composition of the forbearance segment at a granular level (by delinquency state); the effects loan age has on transition rates from current to 1-29 DPD (i.e., becoming delinquent); amortizing balances which are adjusted for assumed prepayment speeds; and a methodology that is easily understood and appropriate for short-term forecasting. This challenger model also does not have an overreliance on macroeconomic factors which have caused a lot of noise in models during the pandemic environment.

Challenger model mechanics

First, a delinquency transition matrix is built on data for only those accounts that had ever been dirty (i.e., delinquent or modified). The ever-dirty population includes loans that were in forbearance and also loans that were just delinquent at some point. Even though the transition rates will be used for the forbearance segment, the inclusion of delinquent accounts makes for a richer data set (i.e., more observations). It also helps reduce the noise from accounts transitioning to a better state because of modification and not because of the borrower's ability to pay. Since transition rates will be used for the forbearance segment (accounts that have elevated credit risk) it is more appropriate to use the ever-dirty segment than to use all accounts in the population which would include low-risk accounts.

Figure 10: Prime Auto Loan Delinquency Transition Matrix for Ever-Dirty Accounts

		Ending State					
		Current	**1-29 DPD**	**30-59 DPD**	**60-89 DPD**	**90+ DPD**	**Paid**
Beginning State	**Current**	**x**%	**y**%	0%	0%	0%	**z**%
	1-29 DPD	38%	54%	8%	0%	0%	0%
	30-59 DPD	21%	23%	36%	20%	0%	0%
	60-89 DPD	18%	9%	15%	29%	29%	0%
	90+ DPD	0%	0%	0%	0%	100%	0%
	Paid	0%	0%	0%	0%	0%	100%

Note: Transition rates calculated using data from December 2016 to June 2020. Depending on data availability the data look-back period could be longer in order to have a richer data set (Reg AB II loan-level data is available beginning December 2016). The look-back period could be shortened if it was desirable to capture more recent trends and there was a sufficient quantity of observations.
Source: Reg AB II loan-level data filed with the SEC.

The transition matrix shows that when account balances are current, in the next month they stay current **x** percent of the time, move to 1-29 DPD **y** percent of the time (which is dependent on loan age), and move to the paid terminal state **z** percent of the time. When accounts are 1-29 DPD, 38% of the time they move to current, 54% of the time they stay 1-29 DPD, and 8% of the time they move to 30-59 DPD. And so on.

A state for paid has been added to capture principal payments and voluntary prepayments made on current balances. This state is not calculated on observed rates but instead on an assumed amortization schedule. Payment rates are projected by assuming amortizing loan payments based on the forbearance segment's weighted average coupon rate ("WAC") and WARM, plus an assumed Constant Prepayment Rate ("CPR").

Next, the delinquency transition matrix is combined with the initial vector of starting delinquency states (percentage of in-extension balances by delinquency state at June 30, 2020) to forecast the percentage of balances that will be in default at specific points in time of the forecast horizon. To get the delinquency states of accounts after one month the following matrix multiplication is performed:

$$States = [Current \quad \text{1-29}\ DPD \quad \text{30-59}\ DPD \quad \text{60-89}\ DPD \quad \text{90+}DPD \quad Paid]$$

$$[89.82\% \quad 8.39\% \quad 1.38\% \quad 0.34\% \quad 0.07\% \quad 0\%] * \begin{bmatrix} 86.84\% & 9.98\% & 0\% & 0\% & 0\% & 3.18\% \\ 38\% & 54\% & 8\% & 0\% & 0\% & 0\% \\ 21\% & 23\% & 36\% & 20\% & 0\% & 0\% \\ 18\% & 9\% & 15\% & 29\% & 29\% & 0\% \\ 0\% & 0\% & 0\% & 0\% & 100\% & 0\% \\ 0\% & 0\% & 0\% & 0\% & 0\% & 100\% \end{bmatrix}$$
$$= [80.63\% \quad 14.74\% \quad 1.22\% \quad 0.37\% \quad 0.17\% \quad 2.86\%]$$

Thus, at the end of the first month (percentages are of the June 30, 2020 outstanding balances):

- 80.63% of outstanding balances are current
- 14.74% of outstanding balances are 1-29 DPD
- 1.22% of outstanding balances are 30-59 DPD
- 0.37% of outstanding balances are 60-89 DPD
- 0.17% of outstanding balances are 90+ DPD (in default)
- 2.86% of outstanding balances are paid

To get the delinquency states of accounts after two months the following matrix multiplication is performed:

$$[80.63\% \quad 14.74\% \quad 1.22\% \quad 0.37\% \quad 0.17\% \quad 2.86\%] * \begin{bmatrix} 86.81\% & 9.96\% & 0\% & 0\% & 0\% & 3.23\% \\ 38\% & 54\% & 8\% & 0\% & 0\% & 0\% \\ 21\% & 23\% & 36\% & 20\% & 0\% & 0\% \\ 18\% & 9\% & 15\% & 29\% & 29\% & 0\% \\ 0\% & 0\% & 0\% & 0\% & 100\% & 0\% \\ 0\% & 0\% & 0\% & 0\% & 0\% & 100\% \end{bmatrix}$$
$$= [75.12\% \quad 17.11\% \quad 1.67\% \quad 0.35\% \quad 0.28\% \quad 5.74\%]$$

Thus, at the end of the second month (percentages are of the June 30, 2020 outstanding balances):

- 75.12% of outstanding balances are current
- 17.11% of outstanding balances are 1-29 DPD
- 1.67% of outstanding balances are 30-59 DPD
- 0.35% of outstanding balances are 60-89 DPD
- 0.28% of outstanding balances are 90+ DPD (in default)
- 5.74% of outstanding balances are paid

Notice that the current to 1-29 DPD transition rate is 9.98% in the first month and 9.96% in the second month. This transition rate is not constant and is time-variant. Similarly, the paid transition rate is 3.18% in the first month and 3.23% in the second month.

Matrix multiplication is performed iteratively until the end of the 24-month R&S period. The cumulative amount in the default state at the 24th month equals total gross losses for the R&S period. Net losses are then calculated by applying a recovery rate assumption to gross losses.

Last, the average historical net loss rate is applied to the remaining balances not in the two terminal states (90+ DPD or paid) and assuming amortizing payments until the end of the WARM.

Challenger model loss estimate

Now that we have detailed the mechanics of this challenger model, we are ready to project losses of the prime auto loan in-forbearance segment as of June 30, 2020.

The challenger model requires the following inputs:

- In-forbearance Outstanding Principal Balances ("UPB") by delinquency state:
  - Current
  - 1-29 DPD
  - 30-59 DPD
  - 60-89 DPD
  - 90+ DPD
- WARM
- WAC
- CPR
- Recovery rate
- Transition matrix
- Transition rates for Current to 1-29 DPD by loan age
- Average historical net loss rate (ideally over a complete economic cycle)

Step 1: Segment the loan population by forbearance status. The forbearance population is then further segmented by delinquency state (current, 1-29 DPD, 30-59 DPD, 60-89 DPD, or 90+ DPD). The remainder of the population, which represents the majority of the portfolio, can be modeled as usual but with adjustments for the pandemic as needed.

Step 2: Calculate WARM and WAC of the loan-level data for the in-forbearance segment as of June 30, 2020.

Step 3: Develop a prepayment assumption specific to the in-forbearance segment. We use the average observable CPR of the prime auto loan ever-dirty accounts over the past 12 months as the baseline expectation (or mid estimate). For the low estimate we increase prepayment speeds by 10% under the assumption that borrowers are more able to prepay which decreases the amount of balances that could default. For the high estimate we decrease prepayment speeds by 10% under the assumption that borrowers are less able to prepay which increases the amount of balances that could default. We acknowledge this method is rudimentary. A more sophisticated approach could incorporate management judgment, correlations between prepayment speeds and a macroeconomic factor such as unemployment rates, or modeled prepayment speeds.

Step 4: Develop a recovery rate assumption specific to the in-forbearance segment. We use the average observable recovery rate of prime auto loans over the past 3 months as the baseline expectation (or mid estimate). For the low estimate we increase recovery rates by 10% under the assumption that used vehicle prices will increase. For the high estimate we decrease recovery rates by 10% under the assumption that used vehicle prices will decrease. A more sophisticated approach could incorporate forecasts of used vehicle values such as the Manheim Index.

Step 5: Project cash flows under three scenarios (low, mid and high) based on period-end values (UPB, WARM and WAC) and transition rates for the 24-month R&S period. For the low estimate we decrease the rate current loans transition to delinquency by 10% under the assumption that borrowers are better able to pay which decreases the amount of balances that could flow through to default. For the high estimate we increase the rate current loans transition to delinquency by 10% under the assumption that borrowers are less able to pay which increases the amount of balances that could flow through to default. Similar to our comments on the prepayment assumption a more sophisticated approach could (and probably should) be used to develop a more robust assumption here. The cumulative amount in default at month 24 is the gross loss for the R&S period. Apply the recovery rate assumption to gross losses to calculate net losses.

Step 6: Project cash flows under three scenarios (low, mid and high) using the same WAC as step 5, but the remaining maturity and UPB at month 25, and using the average historical net loss rate as the loss assumption.

Step 7: Add net losses estimated for the R&S period (step 5) and reversion period (step 6) to get the lifetime expected loss estimate.

Figure 11 shows the challenger model's low, mid and high loss estimates for the in-forbearance segment as of June 30, 2020.

Figure 11: Challenger Model Estimates for Prime Auto Loan Forbearance Segment (June 2020)

Scenario	Shock to Current to 1-29 DPD Transition Rate	CPR	Recovery Rate	WAC	WARM	Annualized Historical Net Loss Rate	24-Month R&S Net Loss Estimate	Remaining Life Net Loss Estimate	Total Net Loss Estimate ($)	Total Net Loss Estimate (%)
Low	-10%	18	48%	4.22%	47	1.64%	$44 MM	$17 MM	$61 MM	2.29%
Mid	0%	16	44%	4.22%	47	1.64%	$52 MM	$18 MM	$70 MM	2.61%
High	+10%	14	40%	4.22%	47	1.64%	$60 MM	$19 MM	$79 MM	2.94%

Source: Reg AB II loan-level data filed with the SEC.

How can you fine tune loss estimates and decide where in the range is most appropriate? The range is meant to be a starting point and other factors such as loan concentration in states with high unemployment rates, FICO distribution of loans, or the percentage of loans in forbearance which have been modified multiple times can be used to justify where within the range is best for the specific portfolio being analyzed.

Concluding thoughts

Since the Great Recession, many have been anticipating how CECL and IFRS 9 credit loss models would perform during the next economic crisis. A lot of hard work went into developing robust models that would output credible estimates in the good and bad times.

Due to the ongoing COVID-19 pandemic, many existing models have been pushed beyond their boundaries. Government shutdowns, extreme movements in economic series, unprecedented levels of government support, and generous forbearance programs are unlike anything we've seen before in history. The reality is that some of these pandemic driven factors may require model redevelopment – not an easy task and one which takes time both for relationships to be observable in data and for a model to be rebuilt.

One lesson the pandemic has taught us is the importance of having readily available challenger models. There is no one-size-fits-all approach to modeling. Some models perform better in certain economic conditions and other models perform better in others. As of late, many econometric models have projected unrealistic loss estimates because of the extreme movements in economic predictors. Having alternatives to these complex econometric champion models, which perform adequately in most environments, puts us in a better place to estimate a range of reasonably expected losses given the current environment and reasonable and supportable forecasts. A challenger model that excludes macroeconomic predictors – which is not a requirement of the CECL standard – could help bridge the gap between champion model loss estimates and reality.

In this article we have demonstrated, using prime auto loan performance data from Reg AB II filings, a GAAP compliant challenger model that can be used to estimate losses of the forbearance segment of a loan portfolio. The example described herein follows a systematic and repeatable approach that incorporates a range of plausible estimates.

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Data
ABS asset-level prime auto loan data pulled from EX-102 data files that are available through the Regulation AB II Asset-level disclosure requirements.

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