MOODY'S ANALYTICS

Modeling Credit Card Losses Under CECL

Under the Financial Accounting Standards Board's new Current Expected Credit Loss accounting model, lending institutions must employ a new approach when making allowances on expected losses for loans and debt securities. With CECL, entities must recognize an allowance on the expected (remaining) lifetime credit losses when reporting. While the concept of lifetime is reasonably well understood for installment loans, it is more complicated for revolving products such as credit cards, which effectively have no term limit. To further complicate matters, borrowers can draw debt after the measurement date of the expected loss calculation. In other words, any credit card that has not been fully drawn could have higher losses than its measurement balance if the borrower keeps drawing and eventually defaults.

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Modeling Credit Card Losses Under CECL

BY DAVID FIELDHOUSE

Under the Financial Accounting Standards Board's new Current Expected Credit Loss accounting model, lending institutions must employ a new approach when making allowances on expected losses for loans and debt securities. With CECL, entities must recognize an allowance on the expected (remaining) lifetime credit losses when reporting.[1] While the concept of lifetime is reasonably well understood for installment loans, it is more complicated for revolving products such as credit cards, which effectively have no term limit. To further complicate matters, borrowers can draw debt after the measurement date of the expected loss calculation. In other words, any credit card that has not been fully drawn could have higher losses than its measurement balance if the borrower keeps drawing and eventually defaults.

Fortunately for most lenders, they need to make an allowance only for debt drawn—or committed—at the time of expected loss measurement. Provided that a card is unconditionally cancelable, a lender can terminate its obligation at any time and for no reason at all. In some cases, the issuer is nervous because the borrower is delinquent, bankrupt or overdrawn, or is failing to comply with the account agreement.[2] Alternatively, issuers may close an account if they see something that makes them nervous in their portfolio and want to reduce their overall exposure. The fact that the lender has the contractual right to cancel or freeze an account allows the institution this favorable treatment when calculating expected losses.

The practice of calculating expected losses on only committed debt is critical, because material losses on credit cards can occur for decades. Industry performance data reveal that cards booked prior to 1995 still have material losses today. Chart 1 shows accounts booked prior to 1995 averaged more than $100 million in monthly losses in recent years. As minimum payments to principal are required, it is reasonable to assume that most of the recent losses come from the uncommitted credit line at the time of booking.

Prior to CECL, lenders did not have the need to model committed and uncommitted losses separately. Modeling the evolution of committed debt presents a challenge to credit modelers, as even the largest institutions do not track losses by transaction. This paper answers the challenge of determining the lifetime of committed credit card debt. This analysis uses a dataset on U.S. credit cards from CreditForecast.com, a partnership between Equifax and Moody's Analytics. By combining this industry credit data with information about payment behavior based on data from the Consumer Financial Protection Bureau, we are able determine the lifetime of a credit card. Through this study, we illustrate the challenges for modelers under CECL and

Chart 1: Monthly Loss, Pre-95 Bookings
$ mil, monthly, NSA
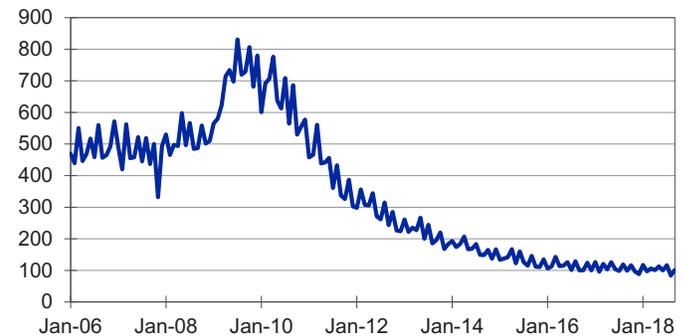
Sources: CreditForecast.com, Moody's Analytics

assess the impact of the new accounting standards.

Pay-down assumptions

The evolution of committed and uncommitted balances depends on the application of payments after the measurement

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1   We recognize that effective lifetime and contractual lifetime will differ.

2   There is some evidence to suggest that account closures are prevalent for riskier borrowers. In 2009, more than 10% of high-risk accounts were closed with zero balances. In 2017, more than 4% of these high-risk accounts were closed. This analysis uses data on U.S. credit cards from CreditForecast.com, a partnership between Equifax and Moody's Analytics. Here, we measure high-risk-using accounts with an updated Vantage credit score of 530 to 579.

Chart 2: Total Balance Since Measurement

$
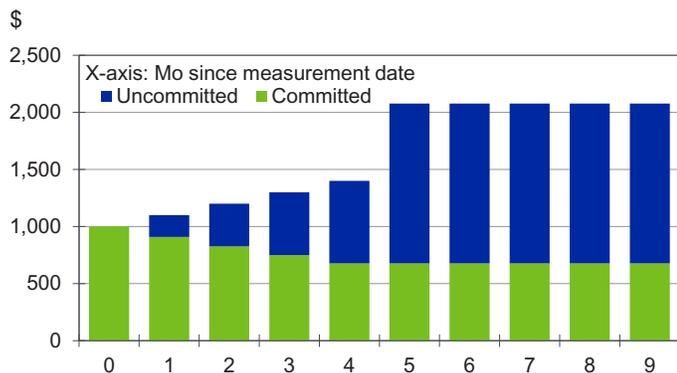
Source: Moody's Analytics

date. It is expected that most institutions will make assumptions about payments, because the appropriate transaction-level data are not available and forecasting committed payments is challenging, as we will discuss below.

Detailed payment data present the first challenge for a modeler. Most servicers do not provide account-level payment information back to the lender. Even if the lender had payment information, credit card debt is composed of the debt incurred from many transactions at different times. As a result, credit cards may have debt tiers that are associated with different interest rates. At the account level, interest rates can change from introductory to the regular interest rate. Another way account-level interest rates can change is if the rate is variable. Without information on how each payment is applied at the transaction level, though, a credit modeler must make an assumption of how payments are applied when interest rates change.

Legally, the CARD Act[3] requires issuers to apply principal payments to the outstanding balance with the highest interest rate first, until the highest rate balance is reduced to zero or the principal payment was fully utilized. However, the CARD Act is hard to follow in practice. Even if modelers had access to the appropriate data, they would have to forecast the size and payments to future interest rate tiers. Very quickly, this can be intractable, as many

potential interest rate tiers could be created.

A naïve approach to handling payments is FIFO, or first in, first out. Under FIFO, payments are applied first to the oldest balances.[4] This approach is much simpler and more practical to implement than the rules dictated by the CARD Act. However, larger institutions have received pushback on such a simple approach from regulators, as some payments are applied to future draw activity for reasons such as the CARD Act or because there could be changes in future payment activity. As a result, assuming payments are allocated by FIFO may artificially reduce the lifetime estimate by too much, especially for revolvers[5] who have a larger portion of uncommitted balances after the measurement date.

Instead of following FIFO or the CARD Act, many lending institutions are planning to use a modification of FIFO. One potential modification adjusts payment to principal by relating current debt to committed debt. More specifically, we define the proportional approach as

$$Committed\ Principal\ Payment =$$
$$Principal\ Payment\ *$$
$$min\left(1, \frac{Committed\ Debt}{Total\ Debt}\right)$$

This type of relationship is pinned in theory, because it assumes the proportion of payments is directly related to the proportion of committed debt to current total debt. In other words, each dollar paid has an equal chance to go to committed and uncommitted debt.

As a borrower draws more debt over time, a smaller proportion of payments to principal will be allocated to committed

debt and a larger proportion will be applied to uncommitted debt. Chart 2 illustrates how committed and uncommitted balances evolve each month after the measurement date for a hypothetical borrower who becomes delinquent in the five months after the measurement date.[6] In this case, the borrower makes both draws and payments after the measurement date. As a result, only a proportion of the total debt should be considered in the expected loss calculation under CECL.

Tables 1 and 2 illustrate the impact of different payment assumptions on committed losses. For exposition purposes, we abstract from interest and fees. In the tables, we motivate the fact that these assumptions may have a large impact on how one calculates a loss under CECL. In each table, a borrower makes payments and draws during the first four months after the measurement date. After four periods, the borrower stops paying and the account is eventually charged off. Under FIFO, the committed principal loss will be $600 as is shown in Table 1. In contrast, under the proportional approach (see Table 2), which is discussed above, the committed principal loss will be $677, as the payment assumption has become conservative and the borrower is drawing after the measurement date.

Effective lifetime of credit cards

When calculating committed losses, it is important to consider payment behavior and the heterogeneity of borrowers. Keys and Wang (2016)[7] characterize a distribution of payer types and behavior. Using their characterization of the credit card market, we simulate committed and uncommitted debt by borrower type. More specifically, we forecast payments for four types of borrowers. Payments then become conditional on borrower type with each type having a different chance of not making a payment. Next, we track the bor-

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3   Credit Card Accountability Responsibility and Disclosure Act of 2009

4   For the purposes of this discussion, we assume that payments are net of interest and fees. Consequently, payments are applied to unpaid principal balance.

5   Borrowers who carry balances month to month.

6   The detailed calculation is shown in Table 2.

7   Benjamin J. Keys and Jialan Wang, "Minimum Payments and Debt Paydown in Consumer Credit Cards," *National Bureau of Economic Research Working Paper Series* (October 2016).

Table 1: Example of FIFO Payment Allocation

Mo	Unpaid principal balance	Draw	Principal payment	Com. payment	Com. bal	Com. total charge-off	Total charge-off bal
0	1,000				1,000		
1	900	0	100	100	900		
2	800	0	100	100	800		
3	700	0	100	100	700		
4	600	0	100	100	600		
5	600						
6	600						
7	600						
8	600						
9	600						
10	600					600	600

Source: Moody's Analytics

rowers over time and identify individuals who default. By studying the defaulter population, we are able to determine the proportion of the charge-off balance that belongs to committed debt at the time of measurement.

Chart 3 plots the proportion of committed debt compared with total default balance by month since measurement date. We consider four types of borrowers: Those who typically (1) pay in full (transactors), (2) pay the minimum, (3) pay near the minimum and (4) mixed payers or those who do not consistently pay within one of these categories at least half the time. The y-axis shows the proportion of committed debt to total debt at the time of default, while the x-axis shows the month since measurement when the default occurred. Our analysis reveals that losses on committed debt are likely to be material for minimum payers. Even for borrowers who were likely to make full payments, our analysis reveals that material losses on committed debt can still be discharged around the two-year mark in the event of a default.

One way to understand the effective lifetime of a credit card is to understand the distribution of the months it takes for a committed dollar to default. Table 3 shows information on the number of months to default broken out by borrower type and for the

portfolio overall. In our analysis, the average committed dollar defaults at 8.85 months after the measurement date while the 95th percentile occurs at the 28th month.[8] It is reasonable to forecast any credit model for 28 months. After that time period, the data become much noisier and forecast accuracy will deteriorate. Consequently, a model owner may use some type of gross-up factor to capture losses beyond the forecast horizon.

While one might be tempted to forecast committed losses over a two- or three-year horizon, it is important to recognize that losses can occur much further out as shown in Chart 3 and Table 3. Depending on the borrower type, the material loss window can differ dramatically. Borrowers who typically make the minimum payment default 18.2 months after measurement, while transactors default on average after 5.3 months since measurement. The upshot is that portfolios with a high concentration of revolvers could have an 85% longer forecasting window. Even if one forecasts out 52 months, the lender will still need to account for the remaining 5%.[9]

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8 For this analysis we assume that the population consists of 9% minimum payers, 20% near minimum payers, 45% mixed payers and 26% transactors.

9 It is reasonable to apply some gross-up factor to capture the terminal losses if forecasting further presents a challenge.

Losses on committed balances

We are able to calculate the losses on committed debt at the quarterly booking cohort level by combining the results of the simulation with the CreditForecast.com data. To illustrate the results, we focus on cards booked in the fourth quarter of 2009 with a measurement date of June 2010. Chart 4 shows committed losses against actual losses against losses under CECL. To illustrate the importance of using a FIFO or proportional assumption, we present both. The analysis reveals that that committed losses are substantially less than actual losses because they exclude future draws beyond the measurement date. Furthermore, our calculations reveal that losses can occur as late as eight years after the measurement date. These delayed losses would be driven from borrowers who only made the minimum payment.

While illustrative, Chart 4 obscures the impact of payment assumptions. Minor differences, month after month, can build up. Chart 5 shows the cumulative committed loss for the same analysis. By the end of available history, the proportional approach results in 12% more losses than the FIFO approach. Clearly, the assumptions used to calculate expected credit losses are not trivial and must be considered carefully.

Table 2: Example of Proportional Payment Allocation

Mo	Unpaid principal balance	Draw	Principal payment	Com. payment	Com. bal	Com. total charge-off	Total charge-off bal
0	1,000				1,000		
1	1,100	200	100	100*1000/1100=91	909		
2	1,200	200	100	100*1000/1200=83	826		
3	1,300	200	100	100*1000/1300=77	749		
4	1,400	200	100	100*1000/1400=71	677		
5	1,400						
6	1,400						
7	1,400						
8	1,400						
9	1,400						
10	1,400					677	1400

Source: Moody's Analytics

Impact analysis

To understand the impact of CECL on the credit card industry overall, we forecast the expected loss on committed credit balances at different measurement dates and compare these expected losses to the incurred loss approach.[10] The committed loss forecast is constructed from using the CreditForecast.com credit card loss forecast and assuming the proportional approach defined above.

Chart 6 shows the increase in expected credit loss, or ECL, relative to the incurred loss approach at different points in time. During the last recession, with perfect foresight, we would expect allowances to have increased by 90% if CECL had been in effect.[11] Of course, much of the impact reflects the fact that economic conditions heading into the financial crisis would be considered under CECL and not under the incurred loss approach. If we used economic forecasts that underestimated the severity of the recession, the impact would have been less on reserves. Looking at more recent data, we see a smaller impact from CECL. In June 2018, allowances would have been 34% higher using Moody's Analytics economic forecasts. Finally, in January 2020 allowances are expected to increase by 36% relative to incurred losses.

In general, we expect credit supply to become slightly more limited under CECL in the card market. Compared with other consumer credit products, the change in reserves is fairly modest and in line with the overall impact of IFRS 9 in Europe.[12] Our research in other lending products such as mortgage and auto suggests that the typical allowance for installment debt could double.[13] Of course

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10   The incurred loss approach is approximated by taking the loss rate in the prior year and applying it to balances in the first 12 months of the evaluation year.

11   We assume that there are no substantial changes to accounting practices other than the switch to CECL.

12   Alain Laurin, Maria Mazilu, Claudia Silva and Nick Hill, "Limited Impact From IFRS 9 First Time Adoption, but Disclosure Uneven So Far," *Sector In-Depth for Financial Institutions* (April 30, 2018).

13   Deniz Tudor and Timothy Daigle, "How Much Will CECL Impact Reserves for First Mortgage Portfolios?" *Moody's Analytics white paper* (December 2017); Evan Andrews, "CECL Impact on Credit Loss Allowances for U.S. Auto Loans" *Moody's Analytics white paper* (August 2018).

Chart 3: Committed Portion of Total Default

%

X-axis: Mo since measurement

Legend: Min payers, Near min, Mixed, Transactors
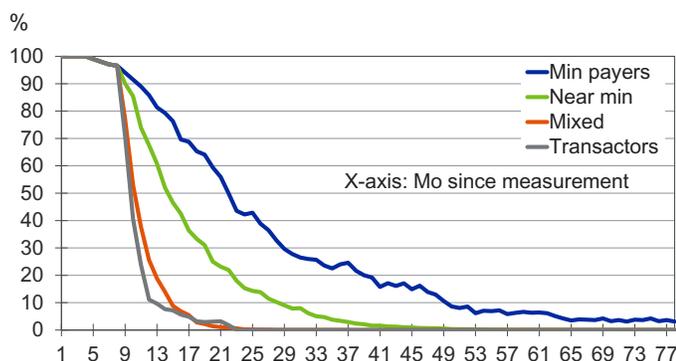
Source: Moody's Analytics

Chart 4: Monthly Loss, 2009Q4 Booking

$ mil, 2010Q2 balance sheet date, NSA

Legend: Total, FIFO committed, Proportional committed
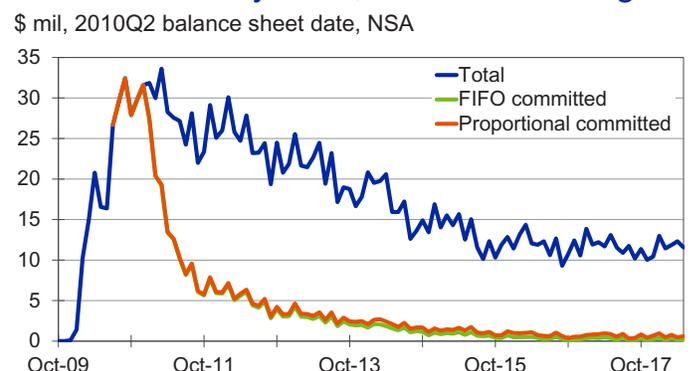
Sources: CreditForecast.com, Moody's Analytics

Chart 5: Cumulative Loss, 2009Q4 Booking

$ mil, 2010Q2 balance sheet date
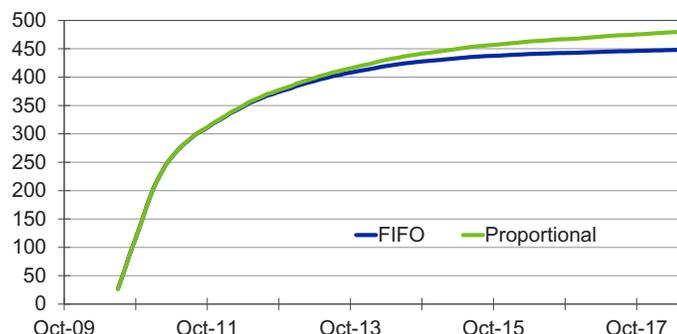
Sources: CreditForecast.com, Moody's Analytics

Chart 6: Increase in ECL Under CECL

Relative increase over incurred loss approach, %
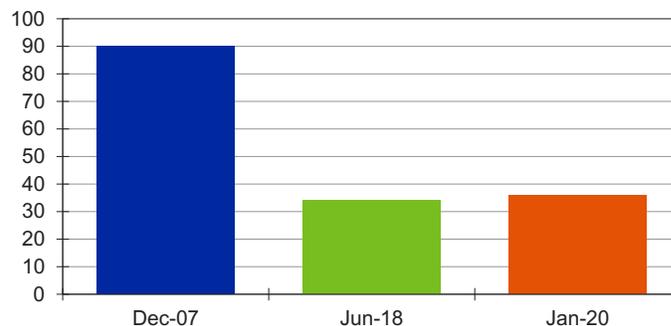
Sources: CreditForecast.com, Moody's Analytics

this analysis here is ceteris paribus. It is certainly possible that lenders might substitute away from installment loans because they will be cheaper under CECL compared with other products.

Results will vary at the portfolio level. Perhaps the biggest determinant of the CECL impact on allowances is the composition of revolvers and transactors. Because revolvers have a much longer life than transactors, portfolios with a higher concentration of revolvers are much more likely to experience a larger impact when adopting CECL. Conversely, a portfolio with a high concentration of transactors may potentially end up with lower allowance numbers.

Of course, our assessment about the potential impact from CECL is subject to several risks and assumptions. Larger lenders may be forced to apply a more conservative payment approach. On the other hand, smaller lenders may face fewer restrictions, which may result in a smaller impact as they choose a methodology that is less onerous. Lenders may also change their credit management policy to minimize CECL's impact on loss reserves. For example, there may also be a greater emphasis on mitigating losses through the extension of smaller credit lines and a greater emphasis on loss mitigation programs to curb borrowing when borrowers become delinquent.

As we head toward CECL adoption, it is critical that we highlight a couple of important issues and themes. Lenders must absolutely exclude future draws beyond the measurement date when calculating their ECL; otherwise they will be at a competitive disadvantage. Next, modelers must carefully construct and defend their committed pay-down curves to a variety of stakeholders. The model owners will need to prepare for regulatory scrutiny and examinations by validators and auditors. The analysis of this paper shows that subtle decisions over payment decisions can still have a moderate impact on loss reserves and the model owners need to understand their decisions. New monitoring tools need to be developed to ensure that CECL models are and continue to be accurate as they pertain to committed losses. Finally, lenders need to prepare for portfolio loss reserves that will be volatile. Heading into any recession, lenders should expect the population of revolvers to rise. A quick change in the portfolio composition can drive large increases in allowances that each lender must be prepared to cover.

Table 3: Months to Default of Committed Dollars*

Segment	Avg	95th Percentile
Portfolio	8.9	28
Min payers	18.2	52
Near min payers	10.7	26
Mixed payers	6.5	14
Transactors	5.3	13

*These statistics are weighted by default balances.

Source: Moody's Analytics

About the Author

David Fieldhouse is a Director in the Content, Economics and Structured Analytics Division of Moody's Analytics. His responsibilities include developing and validating models of retail loan performance for financial institutions. He also provides regular analysis and commentary on consumer credit markets. David has a PhD from the University of Western Ontario.

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