Using Behavioral Models to Enhance ALM for Non-retail Instruments

BY ANDRE HOROVITZ

INFORMED BY BEHAVIORAL modeling, bank treasury professionals often adjust the duration of hedges for residential mortgages and retail deposits to better reflect the chance of consumers exiting these relationships.

This article argues for a need to develop similar behavioral models for "non-retail" assets and liabilities, and to augment the liquidity risk and interest rate risk management practices of such products accordingly.

Non-retail products that would most lend themselves to this approach include loans under prepayments, withdrawals from corporate term deposits, and drawdowns from credit facilities. Each is discussed below.

Loans Under Prepayments

Finance professionals since the 1970s have been applying "negative convexity" prepayment models to residential mortgages, in an attempt to model the volumes of "non-contractual" mortgage amortizations driven by refinancing at lower rates. Without such hedging, banks would be left with additional liquidity on their balance sheets to be deployed at these lower rates, eroding net interest margins.

While sensitivity to interest rates is seen as the main driver of decisions to prepay mortgages, the following additional motivations have recently been modeled:

- Relocation.
- Sale of property.
- Propensity to deleverage independent of rate changes.
- Personal events (births, deaths, divorce).

The Bond Market Association developed a model where prepayment volumes—modeled via conditional prepayment rates (CPR)—vary based on speeds of prepayment. The prepayment speeds themselves are derived from regional statistical data. From CPRs expressed as yearly estimates, banks derive single monthly mortality rates (SMM) using the widely used formula found in bank asset/liability management (ALM) applications:

$$SMM = 1-(1-CPR)^{1/12}$$

During the past three decades, banks have been augmenting CPR prepayment models through statistical models or stochastic models to account not only for the effects of the additional prepayment motivations enumerated above, but also for interest rate dynamics.

What, then, about the prepayments of corporate term loans?

Here, the current industry practice (and inherent in most off-the-shelf ALM software) is to work with contractual maturities with no adjustments for prepayments. However, experience points to the fact that some levels of prepayments do occur in such products, though possibly driven by factors other than those associated with residential mortgages.

Companies may prepay loans to deleverage their balance sheet in order to safeguard their credit standing, restructure liabilities in the event of a merger or acquisition, or as a result of a liquidity windfall.

While many credit agreements contain boilerplate language calling for prepayment penalties, such stipulations are often not enforced because banks fear losing their corporate and institutional clients to competitors. In fact, competitor banks occasionally offer to pick up prepayment fees if the corporations switch "prime brokerage" relationships.

As with residential mortgages, risk management of such loans may require appropriate "replicating portfolios," where the prepayment behavior is explicitly incorporated and based on specific customer data. While the interest rate sensitivity is generally lower than with retail fixed-rate mortgages, it is not negligible. Akin to when homeowners prepay mortgages to refinance at lower rates, corporate borrowers tend to prepay loans during times of economic contraction.

Indeed, when the demand for goods and services is lower, the velocity of working capital and inventory turnovers is typically also lower, requiring fewer financial resources. During such times, corporate credit standings (or investors' perception of them) often deteriorate, followed by adverse adjustments to the corporate credit spreads by lenders. It is understandable that corporate treasurers tend to prepay loans they deem unnecessary in such cases. Since periods of economic contraction are usually accompanied by lower interest rates, there is an implied sensitivity of corporate loan prepayments to interest rates.

While also important for the interest rate risk management of corporate loans—and the efficacy of the interest rate hedges assigned to them—the main value of developing and applying such models is to enhance liquidity risk management.

Many potential models describe prepayment behavior for corporate loans. This writer believes the following three are best

for these purposes: the Multinomial Logit Model, the Survival Analysis Model, and the Markov Chain Model.

Key features of the Multinomial Logit Model (MLM)

- MLM is an empirical model.
- The loan is mapped into a discrete finite number of states.
- The model is designed to predict the probability of occurrence of each state, given a set of explanatory variables.
- In a three-state illustration, mostly used in the industry, the dependent variable y takes three discrete values:

$$Y^3_{i,t} = \begin{cases} 1, & \text{if contractual payment} \\ 2, & \text{if prepayment} \\ 3, & \text{if default} \end{cases}$$

whereby the probability is given by

$$P\left(Y_{i,t} = j\right) = \frac{e^{x_{it}\beta_j}}{\sum_j e^{x'_{it}\beta_j}}$$

Key features of the Survival Analysis Model (SAM)

- SAM is also an empirical model.
- The model is designed to predict the probability distribution of the loan contract´s duration, based on a hazard rate model and contingent on a set of explanatory variables.
- The hazard rate λ is defined as the probability that the loan will be terminated for reason j, at time t, given the non-occurrence of this event until time t.

$$\lambda_j(t,x) = \lambda_{j0}(t)e^{-x'_{it}\beta_j}$$

Key features of the Markov Chain Model (MCM)

- MCM is likewise an empirical model.
- The loan is mapped into a discrete finite number of states.
- The model is designed to predict the probability of transitioning between states, via a transition matrix.

As such, in a three-state scenario,

$$Y^3_{i,t} = \begin{cases} 1, & \text{if contractual payment} \\ 2, & \text{if prepayment} \\ 3, & \text{if default} \end{cases}$$

The transition probability matrix P takes the form

$$P = \begin{pmatrix} P_{11} & P_{12} & P_{13} \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

with the general formulation:

$$\hat{P}_{ij} = \frac{N_{ij}}{\sum_j N_{ij}}$$

Whichever model is used, it will require calibration to a bank's internal historical prepayment data for the best goodness-of-fit results. Since it is expected that corporations will strive for early payments to maximize economic benefits, a good calibration would be achieved by a typically nonlinear OLS regression of prepayment volumes against the economic benefit achieved, as illustrated in the figure below.

Withdrawals from Corporate Term Deposits

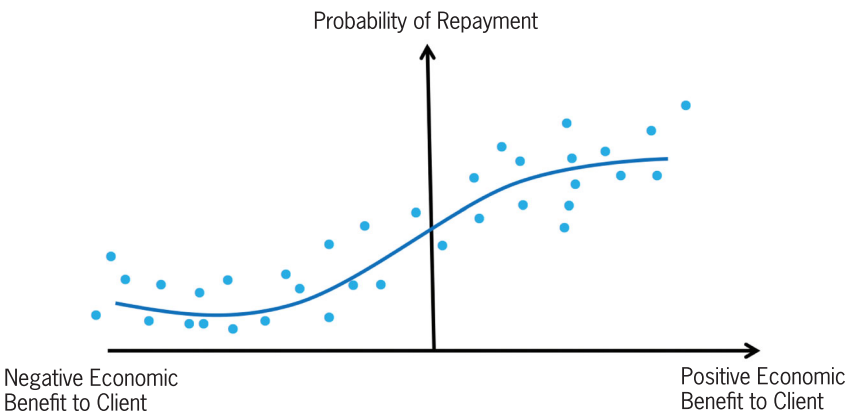
This piece is a focus of recent guidelines in Interest Rate Risk in the Banking Book (IRRBR).[1] Indeed, best-practice institutions have been investing significant effort and resources to build, parameterize, and validate models—mainly for consumer and retail deposits.

As in the case of early prepayments, this time in reverse, withdrawals are seen to be linked to interest rate levels—albeit in a more convoluted and interactive way. The customer and the bank have options embedded. In the case of a savings account, customers can withdraw some or all of their money while the bank can adjust rates. Withdrawals will be a function of the alternatives (for the same levels of risk) the depositor has at any point—alternatives to be explored both internally (other bank liability products offered) or externally (competitive offers from other banks).

Models used in the retail space can be split into four categories:

1. *Statistical models:* These models attempt to map withdrawals to changes in offered rates, to changes in reference rates in the economy, and to customer characteristics seen to be driving withdrawal decisions.

FIGURE: PREPAYMENT PROBABILITY IN RELATION TO THE ECONOMIC BENEFIT TO THE CLIENT



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2. *Nonlinear optimization models* (like the model proposed by Jacobs and Wilson): These models build replicating portfolios. The weights are built so they maximize/minimize an objective function (in the case of the Jacobs and Wilson model, they minimize the customer margin volatility) subject to liquidity constraints. A classic means of introducing practical constraints adapted to bank limit systems is the "market mixed method."

3. *Stochastic optimization models* (like the one introduced by Frauendorfer and Schuerle): These models augment the replicating portfolios by modeling the stochastic nature of the interest rate term structure and account for the implied correlations between term structure changes and withdrawal rates.

4. *Options-adjusted spread models* (like the one introduced by Jarrow and van Deventer): These models price the customer options via risk-neutral valuation means, akin to the pricing of traded spread options.

Unlike with corporate loan prepayments—where the case was made that interest rate sensitivity is low, though not negligible—withdrawals from corporate term deposits are driven significantly by interest rate changes (term structure evolutions as well as bank changes of product rates), but are also linked to idiosyncratic liquidity motivations (for example, a corporation attempts to use liquidity for business purposes and may not have access to a favorable credit facility at the time).

Prior to engaging any model, most practitioners split the volume of the bespoke deposits into "core" or "stable" components and "volatile" or "noncore" components. Volatile volumes are to be kept in cash or the shortest-term available instruments, very often not accumulating interest, to safeguard liquidity. Volumes subjected to replication are the "core" components.

The key question is, how large should the volatile component be? Naturally, the thinner the volatile component, the higher the risk of running out of liquidity should an unexpected withdrawal of significant size occur. However, more money will be left in the core component to be invested at advantageous rates, thus increasing the margin income.[2] It is best practice to determine the optimal threshold separating the two segments by subjecting the deposit volumes to stress events (ideally back-tested to past experiences) at a conservative confidence level congruent with institutional risk appetite.

For corporate term deposits, a similar analysis is performed. This writer proposes to build, for the core components, hybrid models that account for the rate evolution while augmenting the end results[3] via regression models, where liquidity motivations are entered as additional dependent variables. Several banking institutions are exploring the use of machine learning technology to identify liquidity-driven motivations from publicly available data, including financial reports and press releases.

Drawdowns from Credit Facilities ("Evergreen Facilities")

Experience points to differences in customer decisions to withdraw from brokered deposits as opposed to committed credit facilities.[4] This writer believes they both should be subjected to separate examination. Given the rather significant size of committed facilities on banks' balance sheets, these models have attracted attention from developers, examiners, and regulators during the past few decades.

Some banks take the very conservative approach to account for the full volumes to be withdrawn at any time, since customers can exercise these options at their own leisure. However, this approach proves too conservative even under some of the most stressed scenarios. Indeed, even during the Great Recession, fewer than 30% of corporate customers accessed the credit facilities at their disposal, according to U.S. data. In fact, it can be proven that, during an economic contraction where the demand for goods and services is universally shrinking, corporations tend to use liquidity facilities less than during expansions.

One of the most comprehensive approaches to modeling drawdowns of credit facilities is offered in a book by Antonio Castagna and Francesco Fede.[5] They present a doubly stochastic, intensity-based model (sometimes referred to as a "double hazard rate model") for the joint behavior of loan commitments—one that is simple and analytically tractable and incorporates the critical features of loan commitments observed in practice:

- Multiple withdrawals by the borrower.
- Interaction between the probability of default and the level of credit line usage.
- Impacts on the funding and liquidity buffers to back up the withdrawals.

In addition, the authors designed a specific tractable, dynamic, and common-factor model for the defaults of several borrowers by allowing them to be correlated. Even though many banks use a Gaussian copula model to parameterize this correlation effect, Castagna and Fede opted for a reduced-form approach to modeling defaults. It proved to be more reflective of reality during validation on historical withdrawal data sets.

A precise specification of the bespoke model can be found in Castagna and Fede's book. Here, it is sufficient to mention the key results that align to observations on drawdowns from many portfolios of credit commitments:

1. There is a demonstrable positive correlation between withdrawal intensity (credit line usage) and credit standing as illustrated by borrowers' credit spreads.
2. The joint distribution of credit line withdrawals is a direct function of the degree of credit risk concentration in the portfolio.

In practice, the above model gives superior results—compared with other models

employed by asset/liability managers, many of them adapted from credit-card behavioral models. And the two main metrics associated with credit line withdrawals—usage and loan equivalent exposure—achieve best fits to historical withdrawal data in many implementations.

This writer does not propose to enhance or modify the model mentioned above, but rather would point to the practical challenges of implementing it in traditional ALM engines such as quantitative risk management. As often encountered in ALM projects, the devil was in the details. Some of the challenges encountered were as follows:

- Bootstrapping and interpolating the term structures as well as the credit spread curves.
- Accounting for multiple withdrawals over short time periods.
- Parameterizing the idiosyncratic evolution of credit spreads.
- Ascertaining the correlation between the idiosyncratic credit spread changes and the credit spread changes in the overall economy.
- Depicting the relevant triggers for corporations' decisions to access liquidity through credit line usage.
- Accessing and processing (cleaning) customer data.

Conclusion

While most behavioral models currently applied in the banking industry focus on retail and consumer assets and liabilities, it is worth applying similar models for those corporate and institutional balance-sheet items rendering themselves to behavioral modeling.

The advantages for bank asset/liability managers and risk managers could include the following:

- Bank treasurers will have tools at their disposal to better model the behavioral nature of corporate financial assets and liabilities and to employ more effective hedging techniques based on behavioral durations akin to the methods used for retail and consumer products.
- Internal controllers will have better instruments (assuming that the resulting replicating portfolios are appropriately transported into internal FTP systems) to ascertain corporate asset and liability profitability against objective market-based benchmarks.
- Financial accountants and capital managers will allocate regulatory and economic capital in a way that is better aligned with the interest rate risks of bank balance-sheet instruments containing institutional exposures that render themselves to behavioral modeling.

WHILE MOST BEHAVIORAL MODELS CURRENTLY APPLIED IN THE BANKING INDUSTRY FOCUS ON RETAIL AND CONSUMER ASSETS AND LIABILITIES, IT IS WORTH APPLYING SIMILAR MODELS FOR THOSE CORPORATE AND INSTITUTIONAL BALANCE-SHEET ITEMS RENDERING THEMSELVES TO BEHAVIORAL MODELING.

This article presented best-practice models for addressing the critical corporate and balance-sheet items in commercial banks. These items include loans under prepayments, corporate term deposits, and credit facilities ("evergreen").

Based on this writer's experience in working with asset/liability and risk managers at several institutions, the main challenge of employing new behavioral models is their implementation into legacy ALM and risk systems and, to a lesser degree, appropriate parameterization and validation of the models. ®

Notes

1. Basel Committee on Banking Supervision, April 2016.
2. The margin income is the difference between the income generated on the core components´ investments and the interest paid to the customers.
3. This is analogous to the "market mixed method" applied to replicating portfolios.
4. With committed credit facilities, borrowers pay commitment fees for the option to use the facilities when necessary.
5. See Antonio Castagna and Francesco Fede, *Measuring and Managing Liquidity Risk*, John Wiley & Sons, 2013. This book enjoys wide usage among asset/liability managers worldwide.

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