Robust Models of Core Deposit Rates – II

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Introduction and Summary

In a prior article[1], we presented results of our examination of national deposit pricing history from 1998 early 2016. We reported the evidence of "rate structures" characterized by hierarchical rate relationships among deposit products that are both robust (stable in all rate environments) and persistent (durable over time). We concluded these structures derive from pricing rules – express or implied – within bank deposit pricing committees.

We next examined[2] whether the rate structures are consistent with rate paths estimated by banks for purposes of risk modeling and reporting. We concluded they are not and presented examples of inconsistencies encountered in our model validation practice over nearly two decades; deposit modeling has not evolved significantly since 2000.

We briefly discussed the conceptual flaws underlying the most common rate simulation practices employed by bank risk models and the process challenges presented by alternative methodologies based on non-linear optimization (e.g., the Excel SOLVER) approaches.

Here we expand our discussion of the inherent *conceptual problems* arising from use of econometric estimations based on historical data when applied in forward-looking simulations.

We then examine further the strengths and limitations of optimization methodologies and narrate our (surprisingly successful) efforts to resolve the largely *process* (not conceptual) *limitations* that have heretofore prevented their widespread adoption.

We conclude by showing that simultaneous simulation of multiple, linked deposit rate models can generate rate structures that are *stable* over long periods, *persistent* across all modeled rate scenarios consistent and *consistent* with historical evidence of rate structures. Finally, we observe that the methodology facilitates in-line back-testing against history, wherein it demonstrates performance measures superior to widely-accepted econometric methodologies.

Partial Response Models that Incorporate Asymmetric Price Adjustment Speeds

Partial response models are used by economists when modeling economic variables characterized by known and observable lags in the target variable response to changes in the underlying independent variables. The model structure fits with observed deposit pricing behavior in banks and adaptable to the widely documented observation that banks adjust deposit rates asymmetrically to changes in market rate. Banks are slower to raise deposit rates when market rates rise than when market rates fall.

[1] BALM October 2016
[2] BALM January 2017

The deposit rate model described in Box A, below, is one representation of a pricing model. It incorporates two basic hypotheses regarding how banks price deposits.

First, there exists a long term *unique relationship* between the independent variable – in this case an indicative market rate – and the target deposit rate "in the long run." We describe this relationship with a linear equation (equation (1) in Box A). As indicated, by adding equation (2) we constrain target rates in low rate environments to account for the the structural rate relationships identified in our earlier paper and the zero rate boundary.

Second, as represented by equations (3) and (4), the deposit rate adjusts toward the target deposit rate with a *lag.* The lag is directionally asymmetric with deposit rates typically dropping more quickly as market rates decline and lagging in a rising market. It is important to note that the degree of asymmetry varies by product and balance tier, with some products (e.g. Interest Checking and Savings) demonstrating slower adjustment speeds, while others (MMDA and TD rates) adjust much more rapidly to changes in market rates.

We have found the general structure of the "Generic Asymmetric Partial Response Model" to be sufficient to simulate deposit rates under different rate scenarios – including stochastic rate scenarios – that are consistent with bank management expectations, past pricing histories, and requirements to report and manage income and economic value risks associated with changes in interest rates and economic conditions.

Box A

A Generic Asymmetric Partial Response Model of Deposit Rates

Let the target rate be described by

$D^*(t) = \mathbf{a} + \mathbf{b}\, M(t)$ represent the target rate equation …(1)

Potentially constrained by $D^*(t) \geq Z^*(t)$ …(2)

And dynamics

$\Delta(t) = [D^*(t) - D(t-1)]$ …(3)

$D(t) = D(t-1) + \lambda(\text{sign}(\Delta))\, \Delta(t)$ …(4)

Where,

$M(t)$=the market rate used to motivate changes in the deposit rate in month t

$D^*(t)$= the target deposit rate in month t conditional on the market rate $M(t)$

$Z^*(t)$ = a potential lower bound constraint to the target rate. It may be zero or another product's rate

$\lambda(\text{sign}(\Delta))$ = partial adjustment factor which varies based on whether the last value of the deposit rate is below or above the target rate.

a, **b**, and λ are parameters to be estimated

Modeling asymmetric lags and cross-product constraints must be part of any rate simulation, particularly when using stochastically generated market rate scenarios to simulate deposit rates. So the question is presented: What is the best way to estimate these models?

Problems with Econometric Methodologies

The argument against current estimation methodology begins with the empirical observation that results are typically and unpredictably flawed. Two examples will suffice.

First, we observe that when modelers are using stochastic rate scenarios to model EVE, they frequently assume that historically fit econometric models will perform well in these kinds of scenarios. In essence, the econometrically estimated models become "Black Boxes." Simulated paths are typically not reviewed or otherwise validated and it has been our experience that modelers are nearly always surprised when shown modeled rate paths that are inconsistent with their history (structures) and their expected rate setting behavior. Cross-product relationships break down particularly at turning points in the rate cycle, where crossing rate paths conflict with pricing practices, reporting and governance standards.

The observed deficiencies in current estimation-simulation practice appear to arise from the sequential use of incompatible methodologies: econometric estimation of historical pricing vs. forward-looking simulation.

Econometric models estimated from time series data provide a robust methodology when used to fit and explain history. In other words, the methodology can "explain" the evolution of the dependent variable with a high degree of confidence, as measured by the impressive R^2 values and small coefficient standard errors

Partial response models fit history well because deposit rates are correlated with past values. In forward looking simulations with horizons incorporated in bank risk models, there are no actual lagged dependent variables, only simulated lagged dependent variables. As we demonstrated in our January BALM article, the econometric models perform poorly as soon as the underlying market rate scenario has turning points, such as those contained in stochastically generated rate scenarios.

From a practitioner's point of view, a second flaw in the methodology is even more fatal: it ignores the rules evident in and implied by the historical rate structures: hierarchy and cross-product and boundary constraints.

Practical Limitations of the SOLVER or Other Optimization Algorithms

While econometric estimations frequently produce model results that fail to pass reasonableness tests in simulations and/or back-tests, models estimated using the Excel SOLVER (or other non-linear optimizer) provide better parameters and more realistic rate paths. They also perform better in out-of-sample simulations, particularly when the cross-product constraints are applied and estimated from a rate history containing turning points (e.g., 2004-2009).

Unfortunately, estimates derived from optimizing a simulation model suffer from a drawback that potentially limits its general application: estimated parameters are not stable from one time period to the next or are highly sensitive to the specific time period used to derive the estimated model.

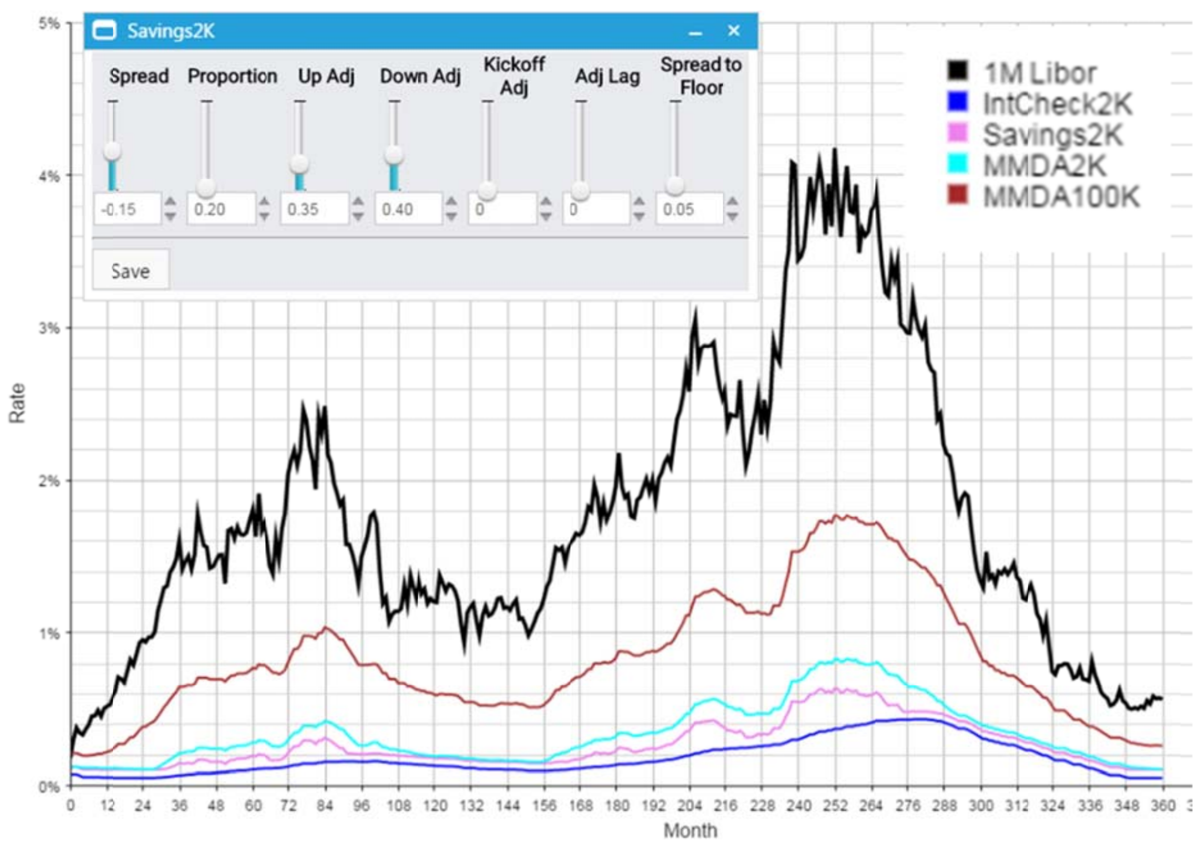
Parameter sensitivity occurs because the partial response model form with simulated lagged dependent variables is "over-specified" when a simulated lagged deposit rate is utilized in the model. The model structure frequently results with a near "flat error surface," which means, there are many sets of parameters that will *nearly* minimize the sum of squared errors (or maximize R^2). As a consequence, when users select a different historical period, or if they change the current deposit rate just slightly, a completely new and different set of parameters may result.

This condition is highly unsatisfactory when used in a continuous monthly reporting context. The SOLVER requires analytical constraints to work consistently in a bank environment that frowns on models with changing parameter values. With the large number of deposit rates to be estimated using the SOLVER function, it simply isn't feasible for modelers to constantly *re-estimate models*, *report results* to a governance body and *obtain the required permissions* to change parameters.

A Serendipitous Discovery of Robust Deposit Rate Models

In attempting to resolve at least the problem of modeling transparency, we constructed a rate simulation model that allows the modeler to directly control pricing parameters at the product level, and features a visual feedback mechanism allowing the user to see and interact with the resulting structure. Figure 1, below presents images of these key features.

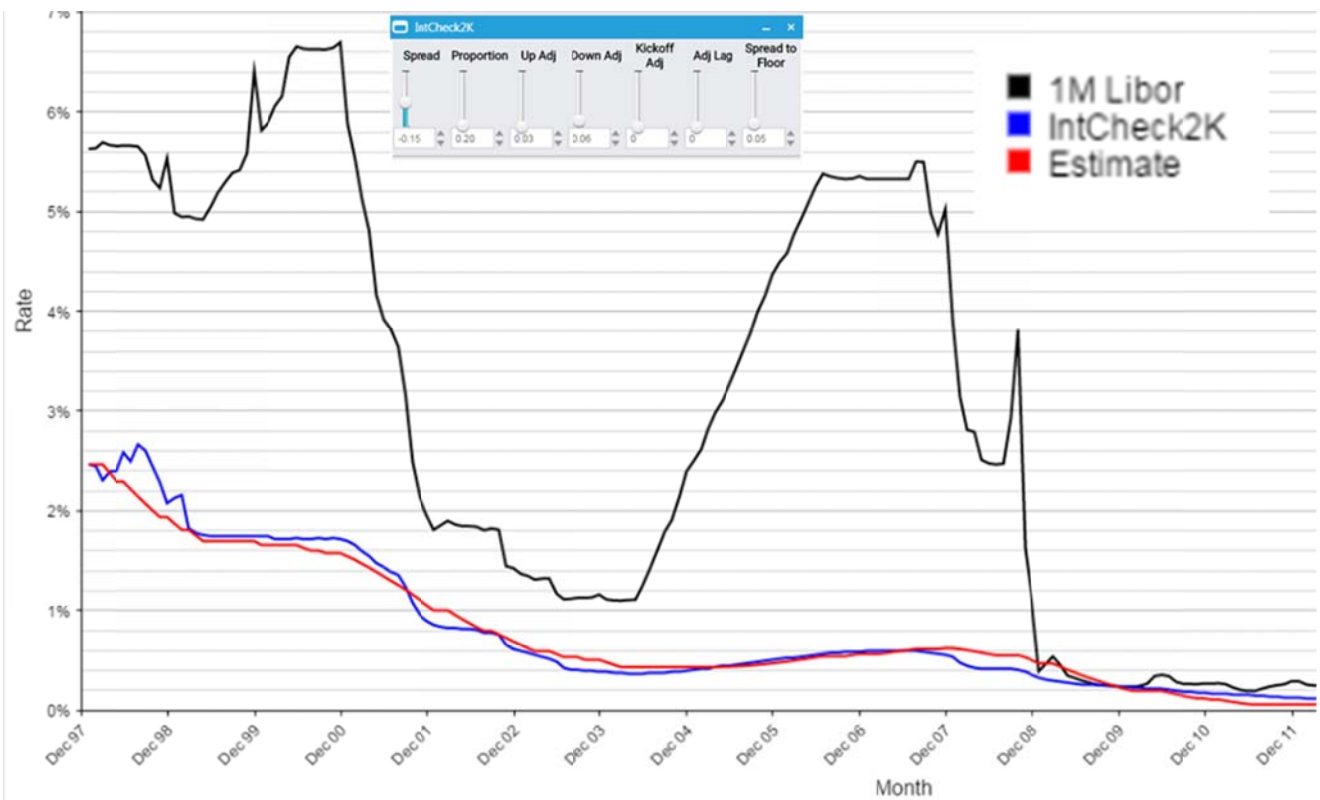
Figure 1 – DDA Analytics Deposit Rate Simulation Model



Next we considered how to achieve parameter stability such that we could model linked product groups (e.g., Interest Checking, Savings, MMDA and associated balance pricing tiers) simultaneously and across all expected interest rate (stress) scenarios. At the same time we included a back-testing visualization tool, so that modelers could see how various parameters fit the rate histories, such as shown in Figure 2 below.

Figure 2

Example of Back Test of US Average Interest Checking Rates with Min Balances of $2K



We then discovered that shifting from *sequential* modeling of *individual* products to *simultaneous* modeling of *linked product groups* provided insight and parameter stability, particularly when historical pricing was used as a *guide* to parameter selection. In other words, parameters that were selected did not maximize R^2, but were sufficiently close to capture bank pricing responses, such as those in Figure 2.

We believe this discovery has widespread application within the industry, because the goal of these models isn't to meet statistical objectives. It is to have models of deposit rates that senior management find credible and useful for making judgments about their bank exposures or economic value and income to changes in market rates.