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Prepared by Peter Mihaltian

Robust Models of Core Deposit Rates – II

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. We conclude that deposit modeling has not evolved significantly since 2000.

In our articles, we briefly discussed the conceptual flaws underlying common rate simulation practices employed in bank risk models and presented an alternative approach using the Excel SOLVER function.

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 and process limitations posed by the use of the Excel SOLVER.

We distinguish between the robust *analytical* strengths of SOLVER methodologies with the several *process inefficiencies* presented by SOLVER'S application when modeling many deposit products for monthly risk reports.

We conclude by showing that configuration transparency, together with simultaneous simulation of multiple, linked deposit rate models results in coherent rate structures that are *stable* over long periods, *persistent* across all

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

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modeled rate scenarios and *consistent* with historical evidence of rate structures. Finally, we observe that the methodology facilitates in-line back-testing and adjustment in the context of pricing history.

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 is adaptable to the widely documented observation that banks adjust deposit rates asymmetrically to changes in market rate (i.e., banks are slower to raise deposit rates when market rates rise than when market rates fall).

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

- First, there exists a *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). By adding Equation (2) we constrain target rates in low rate environments to account for the structural rate relationships identified in our earlier article 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. It is important to note that the degree of asymmetry varies by product and balance tier, with some products (i.e., Interest Checking and Savings) demonstrating much 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 $\boldsymbol{\lambda}$ 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 Estimates. The argument against econometrically estimated partial response models is based on how they are used in practice for simulating deposit rates. The observed deficiencies in current estimation-simulation practice appear to arise from the sequential use of incompatible methodologies: econometric estimation of historical pricing vs. their use in forward-looking simulations.

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; instead, there are 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.

We have also observed that when modelers use stochastic rate scenarios to model EVE, they frequently assume that historically fit econometric models will perform well because they see how well these models fit history. In fact, a simple graphical analysis would demonstrate that cross-product rate structures are violated sufficiently frequently as to invalidate the risk calculations under most risk governance standards, suggesting the econometric models can become *black boxes*.

Practical Limitations of the SOLVER or Other Optimization Algorithms. As we demonstrated in our BALM January 2017 article, models estimated using the Excel SOLVER, or an alternative non-linear optimizer, generate more realistic rate paths than do econometric models. 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 (i.e., 2004-2009).

Yet estimates derived from optimizing a simulation model also suffer from a drawback that potentially limits their 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.

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.

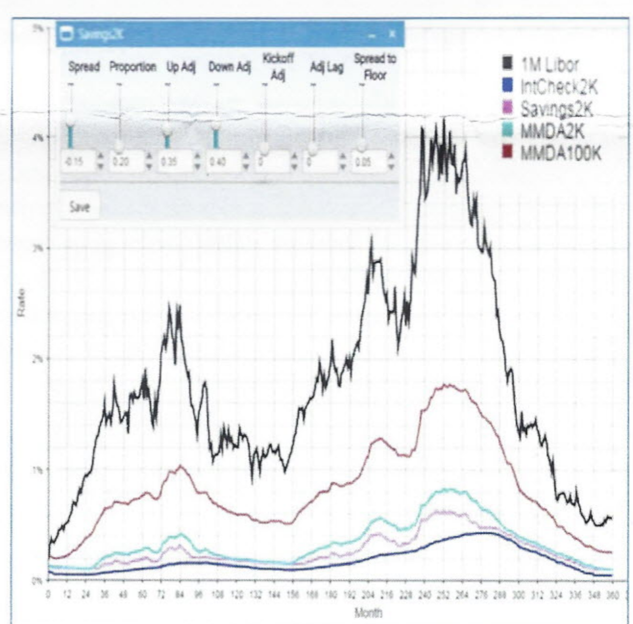
Parameter sensitivity occurs because the partial response model structure containing a simulated lagged dependent variable is *over-specified*. The model structure frequently generates a near *flat error surface*, which means, there are many sets of parameters that will *nearly* minimize the sum of squared 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 in a monthly ALCO reporting context. The SOLVER derived model will require 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.

Visualizing Deposit Rate Simulations. We undertook our search for a better rate simulation methodology with a goal of achieving first the transparency that is a key to building simulation models of deposit rates. Model users typically know what their rate structures *should* look like, but often don't confirm that the simulations meet this expectation, particularly if they are running many scenarios every month.

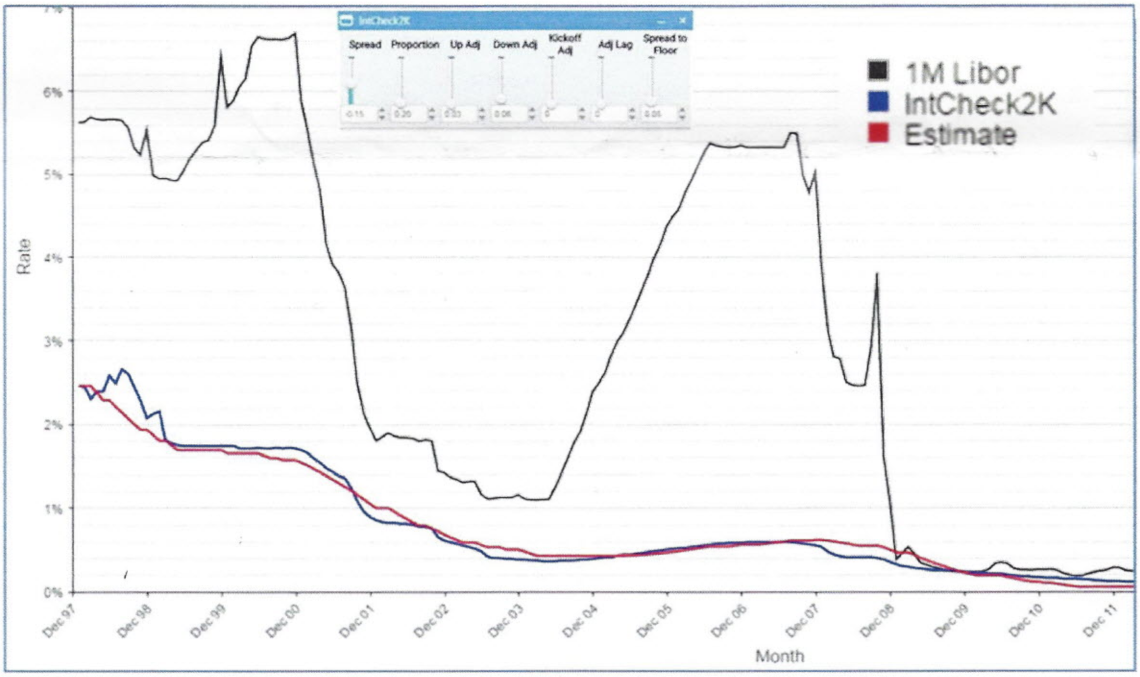
To eliminate this problem and support a more accurate and transparent process, we built product-specific configuration panels that contain *value dials*, allowing users to control model parameters, while watching and interacting with the simulations. Figure 1, below, presents an example of a four-product group being modeled for 360 months against a stochastically generated 1 Month LIBOR rate and the parameter box for the Savings 2K rate.

Figure 1. DDA Analytics Deposit Rate Simulation Model



In-line Back-testing of Deposit Rate Models. Regulators require banks to back-test rate models. However, in reality there is great variance among banks regarding the frequency and consistency such tests are performed. We found, however, that loading rate histories for simulation purposes allowed us to convert the data to simultaneously use to back-test the models. We found that making parameters adjustments in the in-line back-tests further facilitated the understanding of how they impacted simulations and vice versa. The in-line feature from this model is displayed in Figure 2.

Figure 2. Example of Back Test of US Average Interest Checking Rates with Minimum Balances of $2K



A Serendipitous Discovery of Robust Deposit Rate Models. In using the model described above and the associated visualization tools, we discovered that the modeling process yielded what we have termed **robust deposit rate models**: that is, models that will work *over time* and, if desired, fit historical pricing responses reasonably well in forward looking simulation tests.

The process itself consistently produced better simulation results than those estimated using econometric methods and produced far more stable results than those estimated using the SOLVER.

Concluding Thoughts. We conclude that interactive configuration and simultaneous calculation of linked deposit products, guided by history:

- Can replace flawed and *black box* methodologies with a methodology consistent with transparency and control.
- Will synchronize deposit rate paths and cross-product structures with actual pricing history and practices.
- Apply across virtually any rate and stress scenario.
- Support required in-line back-testing.

— Michael Arnold, Ph.D. &
Bruce Lloyd Campbell
ALCO Partners, LLC

Liquidity Takes Center Stage

While the common notion of a Federal Reserve tightening cycle focuses on the pace and extent of interest rate increases, the real impact for banks involves draining liquidity. The money supply (M2) adjusted for inflation grew at an annual rate of roughly 5% from the middle of 2011 to late 2016. In the last few months, the money supply growth rate has declined to about 3.5%. If the Fed is true to their projections of ongoing normalization of the overnight rate to the end of 2019, it is likely that the growth in the real money supply will fall even further.