#### **Robust Models of Core Deposit Rates**

by

Michael Arnold, Principal ALCO Partners, LLC & OLLI Professor Dominican University Bruce Lloyd Campbell Principal ALCO Partners, LLC

Introduction and Summary

Our recent analysis of historical deposit pricing across the country (BALM October 2016) revealed a structure of relationships between and among bank core and time deposit rates. This structure is persistent and stable, even in the most recent (post-crash) period of extremely low rates, where differences among products are compressed and the relationships are less visibly evident.

The history suggests that bank liability pricing committees have, implicitly or explicitly, adopted industry-wide deposit pricing practices incorporating relative cross-product pricing constraints (caps, floors, and asymmetric pricing lags) within a framework of absolute product price tiering (rates crossing).

Based on observations of deposit modeling techniques made in the course of the many validations we have performed in banks of all sizes, the rates modelers incorporate into deterministic scenarios utilized in analyses of interest rate risk (IRR) generally conform to the observed historical deposit pricing structures.

On the other hand, we have observed that when stochastic interest rates are employed to calculate EVE-at-Risk for core deposits, the deposit rate simulations frequently violate these pricing structures. In particular, we have observed that the estimated models generate deposit rates that cross more than occasionally, particularly in downward scenarios. This persistent divergence from pricing norms raises questions as to the validity of simulations based on models estimated using standard econometric techniques, even when estimated from historical pricing data preceding the financial meltdown of late 2008. Moreover, we have noted that modelers typically do not graph or otherwise analyze their stochastic rate paths and are unaware of these anomalies.

We discuss the origins and nature of this divergence below.

We begin with a comparison of simulation results obtained using a proxy partial adjustment model and standard econometric techniques with those generated using the same model but with coefficients estimated using SOLVER, the non-linear optimization algorithm embedded in Excel, that minimizes the sum of squared errors to a within sample forecast. The purpose of this comparison is to demonstrate that econometric techniques typically seen in the industry to estimate deposit rate models will typically fit history well if sufficient history exists to perform the test, but will perform relatively poorly as soon as the econometric models are used in a

simulation context based over that same history. The tests we perform demonstrate that these models tend to drift around historical turning points in rates.

Using a different estimation methodology may improve simulations, but neither method will produce deposit rate paths that do not cross in stochastic rate scenarios. In order to accomplish this objective, we propose that cross product constraints be added to the deposit rate equations embedded in ALM models.

Fitting History and Simulating Deposit Rates with Partial Adjustment Models

In this section we report results from the use of a standard partial adjustment model fit to history estimated using two different procedures: econometric and simulation. The partial adjustment model, described in Box A, is commonly employed, and typically fits deposit rate histories extraordinarily well.

| Let,  | Box A<br>A Partial Adjustment Model of Deposit Rates   |  |  |  |  |
|---|--|--|--|--|--|
|   | $D_t = a + b D_{t-1} + c M_t + e_t$  |  |  |  |  |
| Where,  |  |  |  |  |  |
| M <sub>t</sub> =the ma  | posit rate in month t<br>arket rate used to motivate changes in the deposit rate in month t<br>are parameters to be estimated<br>or term |  |  |  |  |
| Textbook analyses of the model structure above usually indicate the presence of serial correlation (i.e., $e_t = \rho e_{t-1} + u_t$ ) and can easily be corrected, leaving us with the constrained form: |  |  |  |  |  |
|   | $D_{t} = \alpha + \rho D_{t-1} + \gamma (M_{t} - \rho M_{t-1}) + u_{t}$  |  |  |  |  |
|   | Where $\alpha = a(1-\rho)$   |  |  |  |  |

We applied the model to the histories of four deposit product rates listed in Table 1 and obtained incredibly good statistical results from monthly data over a 17 year time period (January 1998-February 2016). The  $R^2$  from the model fits are reported in Table 1 and for the econometric model (col a), are all above 99%. The parameter estimates are reported in Appendix A.

We then simulated the deposit rates over the same time period with the estimated models, replacing the lagged dependent variable in Box A, with the simulated lagged dependent variable, a procedure which replicates what occurs in an out-of-sample simulations such as those utilized to measure IRR over multi-year periods. As reported (col b), we noted significant deterioration in model performance as measured by the decline in  $R^2$ .

As a final step, we then estimated the same model in simulation "mode" using the Excel nonlinear optimizer ("SOLVER") to estimate model parameters, minimizing the sum of squared errors as the objective. Those results are shown in the last column (col c) of Table 1.

## Table 1

| Product                | (a)<br>Economet<br>ric | (b)<br>Simulated<br>(Unadj) | (c)<br>Simulated<br>(Adj) |  |
|------------------------|------------------------|-----------------------------|---------------------------|--|
| Interest Checking 2.5K | 0.997                  | 0.956                       | 0.973                     |  |
| Savings 2.5K           | 0.998                  | 0.959                       | 0.969                     |  |
| MMDA 2.5K              | 0.999                  | 0.920                       | 0.960                     |  |
| MMDA 100K              | 0.998                  | 0.848                       | 0.954                     |  |

# **R**<sup>2</sup> from Partial Adjustment Model Simulations

As further illustration of the decline in performance, we have graphed the four results on the following page. While the estimated rates from the econometric model are so close to the history that they can't be seen on the graphs, the simulated rates from the econometrically estimated models don't past a "visual" reasonableness test. However, the models optimized for this purpose perform quite well.

Our explanation for these results is something that hasn't been noted in the econometric modeling literature, possibly because the application of long-term simulations (e.g., 360 months) is outside the province of most economists researching the topic.

Our conclusion is that deposit rate models that include lagged deposit rate variables as explanatory variables are going to usually fit history quite well because of the stickiness of deposit rates, but will simultaneously not be optimized for their intended use—that is, for simulating deposit rates over long horizons. On the other hand, the same structural models estimated using optimization procedures, may not fit history as well as econometric models, but will out-perform the econometric models when used to generate deposit rate simulations embedded in bank IRR measures.

# *Observed Deposit Rate Modeling Practices in Deterministic Rate Shock Scenarios vs. Stochastic Scenarios*

When using deterministic scenarios to calculate IRR, from either an earnings or economic value perspective, balance sheet modelers across the industry typically incorporate the observed pricing structures across the deposit products that we identified in our prior analysis. This conformity appears to be robust, even when econometrically estimated models are used to simulate the deposit rates using deterministic scenarios to measure IRR. This may occur because deterministic scenarios typically contain no turning points or because modelers may be adjusting deposit rates manually in deterministic scenarios to conform to known structural pricing relationships.

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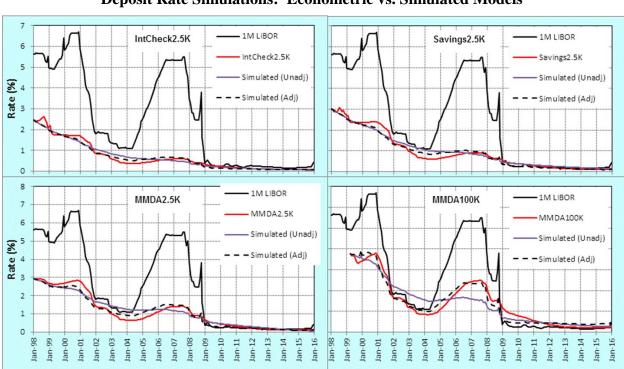


Fig. 1 Deposit Rate Simulations: Econometric vs. Simulated Models

On the other hand, as we noted above, these same models will perform poorly in scenarios with multiple turning points such as stochastically generated rate scenarios. While opting for a different estimation technique from history may improve simulation performance the estimation technique alone won't prevent rates crossing in volatile scenarios generated by stochastic processes. To consistently obtain results conforming to pricing norms requires additional interventions when simulating deposit rates.

We have regularly observed that when modeling deposit rates in stochastic scenarios, modelers regularly add a zero or a small bp boundary constraint on all of the deposit products to prevent simulated deposit rates from becoming negative. At the same time, we have not observed cross-*product* constraints being applied. We believe the absence of cross product constraints is the primary source of the observed inconsistencies in deposit rate structures when stochastic scenarios are used to measure IRR.

#### Adding Cross Product Constraints to Simulation Models

Structural pricing constraints that we identified in our prior BALM article can be extraordinarily difficult to estimate in econometric models because, unless one explicitly accounts for them, the models will fit the history without the constraints. This is easily achieved by incorporating cross product pricing constraints into the simulation models.

Modelers who replace econometric model estimation techniques with optimization techniques may, under certain circumstances, be required to factor other real-world adjustments when performing back tests. Some cases where these adjustments may be appropriate are:

- When modelers are asked to "stress test" deposit rates in economic or bank-specific stress conditions that haven't existed in prior periods
- When the bank's historical data on which simulation is based includes pricing responses that are inconsistent with current pricing practices, such as when a bank has had a "rate sale."
- When the financial markets are disrupted, such as in the six month period following the collapse of Lehman Brothers.
- In post-acquisition or branch/deposit purchase analysis involving rates set through dissimilar pricing practices and histories.

In such cases, models designed to simulate rates in the future should not be expected fit the historical periods well. Work-arounds include exclusion of the non-conforming rate histories from the back tests or potentially applying ad hoc weighting schemes to historical periods.

## SOLVER Caveats

The Excel SOLVER tool is a powerful estimation tool within Excel. When using it to simulate deposit rates using historical data, modelers will find that the estimation surfaces associated with partial adjustment simulation models are relatively flat. This means that multiple sets of parameters can provide very similar outcomes in the objective function. Modelers who rely on these techniques need to be aware of these sensitivities while recognizing the lessons above. Fitting to these models to history should be considered, but used only as a guide for determining a robust set of parameters to simulate deposit products under most interest rate scenarios.

### Conclusion

The pricing structures among the many deposit products offered by banking institutions leads to a set of a common form of partial adjustment models that can be used to simulate deposit rates in the most interest rate scenarios required for internal and regulatory risk reports. Our analyses have led us to conclude:

- Over-reliance on econometric methodologies for fitting models to history is an inferior approach to building the models necessary to measure and report risk.
- Cross product pricing constraints, when integrated into partial adjustment models can improve the simulations of deposit rates consistent with historical pricing practices, currently observed in the banking industry.

# Appendix A

#### **Parameter Estimates**

## (See Model in Box A)

| Variable | Interest Checking<br>2.5K |        | Savings 2.5K |         | MMDA 2.5K |         | MMDA 100K |        |
|----------|---------------------------|--------|--------------|---------|-----------|---------|-----------|--------|
|          | Econ                      | Sim    | Econ         | Sim     | Econ      | Sim     | Econ      | Sim    |
| α        | 0.0000                    | 0.0005 | 0.0000       | -0.0002 | -0.0037   | -0.0011 | 0.0009    | 0.0094 |
| γ        | 0.0295                    | 0.0798 | 0.0475       | 0.1057  | 0.0800    | 0.2014  | 0.1384    | 0.3584 |
| ρ        | 0.9826                    | 0.9790 | 0.9860       | 0.9841  | 0.9918    | 0.9879  | 0.9857    | 0.9707 |
| а        | 0.0006                    | 0.0257 | 0.0006       | -0.0097 | -0.4548   | -0.0888 | 0.0609    | 0.3213 |

Notes:

Econ = econometric estimate using lagged dependent variable

Sim = SOLVER estimate

The value of a is provided because the estimate of  $\alpha$  is so small.