MODELING METHODOLOGY

Quantitative PPNR Modeling

Abstract

In this paper, we discuss various quantitative approaches for linking macroeconomic scenarios with PPNR items. Given the broad range of PPNR categories, each item requires special consideration when developing a modeling approach. Modeling approaches range in granularity and depend upon the availability and quality of historical data, statistical properties of the line item, business use and application, and model consistency across balance sheet and income statement items.

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1. Introduction

The Federal Reserve’s annual Comprehensive Capital Analysis and Review (CCAR) assesses the capital adequacy of large, complex US bank holding companies (BHCs) and the practices used to assess their capital needs. As a part of the CCAR process, institutions must demonstrate that they have sufficient capital to withstand a severely adverse operating environment and be able to continue operations. So far, institutions have mostly focused on developing quantitative models to describe potential credit losses, with expert judgment being more heavily relied upon for remaining balance sheet items. However, with the Federal Reserve increasing the required sophistication and precision of CCAR submissions, there is a growing need to gather data and develop quantitative models for the broad set of balance sheet and income statement items. Specifically, there has been more focus on developing quantitative models for pre-provision net revenue (PPNR), defined as interest and non-interest income, less interest and non-interest expense. PPNR represents a large number of disparate income statement items, ranging from interest income on loans, interest expenses related to retail deposits, compensation expenses, trading revenue and expenses related to operational risk. PPNR spans virtually every aspect of a financial institution, and the items can be disjointed in that available data, statistical properties and sensitivity to macroeconomic conditions can vary widely.

In this paper, we discuss various quantitative approaches for linking macroeconomic scenarios with PPNR items. Given the broad range of PPNR categories, each item requires special consideration when developing a modeling approach. The modeling approaches range in granularity and depend upon the availability and quality of historical data, statistical properties of the line item, business use and application, and model consistency across balance sheet and income statement items.

From a model accuracy perspective, granular, bottom-up style analysis can be ideal. For example, interest income on existing loans can be calculated by looking at the institution’s existing portfolio and modeling segment-level or even loan-level details. Unfortunately, for the majority of PPNR items, this kind of approach is not an option at most institutions. Compensation expenses, for example, are not generally tracked at a granular level with sufficient history and in a convenient format. When this is the case, it is natural to consider top-down approaches, where line-item time series for the entire organization is related to macroeconomic conditions. In many cases, one-time events (e.g., the sale or purchase of a branch or line of business) will result in volatile line items unsuited to statistical inference. Correcting for these events is frequently impractical, and sometimes not feasible. For example, historical data on a stand-alone branch may not be available to offset and disentangle the effect of its sale and the macroeconomic conditions that drive variation in deposits. In such cases, peer approaches can be utilized, where data from similar institutions are used to understand how line items relate to macroeconomic conditions. By using a peer group, it is easier to isolate the systematic drivers as idiosyncratic events are averaged out. This allows for a better representation of future dynamics when leveraging the models for the purpose of projecting items based on various macroeconomic scenarios. The use of external data to augment and extend internal data has been recognized by the Federal Reserve to represent stronger practice. Of course, care must be taken to ensure proper model use.

A separate consideration when using granular data is the extent to which segmentation aligns with business structure. In many cases, the organization is not aligned with reporting categories (e.g., FR Y-14A), with segmentation crossing business lines. This may result in challenges such as participation and buy-in by various stakeholders, especially if the customer segments are very distinct. This is related to consistency in modeling across balance-sheet items. For example, the modeling of new loan origination for the purpose of calculating interest income should be consistent with its modeling for the purpose of expected loss modeling. This is a subtle but important point given that higher balance suggests higher interest income and higher losses, all else being equal. To make matters more complicated, an organization should also recognize that loan origination impacts interest and non-interest expense as deposits, or other liabilities are needed to fund assets. These countervailing effects might motivate an institution to project higher loan origination for the purpose of interest income modeling, lower loan origination for the purpose of expected loss modeling, and lower loan origination for deposit growth modeling, which is against the spirit of the stress testing exercise. It is also inconsistent from an economic modeling perspective. Relating this back to the extent to which segmentation aligns with business practice, the organization must ensure that model ownership is well-defined and centralized, when the model applicability crosses functional boundaries. To this end, many organizations are structuring PPNR groups that are explicitly responsible for modeling consistency and coordination across the organization.

With modeling methodology being the primary focus of this paper, the analysis is organized as follows: the next section discusses quantitative granular approaches to relating PPNR items with macroeconomic variables, followed by a section discussing top-down industry peer approaches to relating PPNR items with macroeconomic variables. We then explore applications of the model,

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and accounting for an organization’s strategic plans and incorporating expert judgment when projecting scenarios. The final section provides a recap and a glimpse of what the future might hold.

2. Granular Models

This section discusses a number of granular, bottom-up PPNR models. Here, granular refers to data available at a finer level than that reported at the bank- or BHC-level. Given that granular data are not typically available for non-interest income items, granular models are relevant for interest income and balance for categories such as commercial and industrial (C&I) and commercial real estate (CRE) loans, and, on occasion, for interest expense items. While institutions frequently have granular historical data related to interest expense, products change with sufficient frequency that it can be cumbersome to go develop a granular model. With that in mind, C&I balance and interest income (related to two FR Y-14A line items) are used to illustrate granular modeling given that granular data are commonly available.

There are at least two broad approaches to modeling balance: The first directly models balance for various segments of the portfolio (e.g., asset class, industry, maturity, credit rating), potentially having separate balance models for lines of credit and their usage. The second models various components of run-off and new origination for various portfolio segments. By explicitly modeling the components, one can ensure a more accurate estimate of balance sheet and income statement dynamics. For example, when computing interest income, one can differentiate between interest earned on existing loans and newly originated loans (assuming availability of models that differentiate interest charged on existing and newly originated loans). It also allows for a higher degree of consistency between PPNR calculations and loss estimation. For example, it is possible to account for changes in interest income resulting from non-accruals.

The choice of the direct balance or component approach should depend on the availability of data and analytics; modeling run-off requires accounting for prepayment, amortization, and loss. The choice of segmentation clearly depends upon available data, but should also depend upon the institution’s portfolio, along with the cross-segment variation in response to macroeconomic conditions.

Given that data availability is a major component of model design, the first part of this section focuses on data options and limitations, while the second part discusses a number of modeling considerations.

2.1 Data Options and Limitations

A number of data sources provide granular, loan-level data that can be segmented and provide a foundation for modeling balance, usage, new origination, and interest charged on new origination. Modeling run-off can be approached through empirical methods, or analytically through explicit modeling of drivers such as prepayment, loss and accounting for amortization and maturing assets for the existing book and newly originated assets.

Internal data for large C&I loans is frequently kept track of at a reasonably granular level. Institutions required to complete the FR Y-14Q may have loan details for C&I loans larger than $1 million going back a few years at best. While not sufficiently far back enough to build an econometric model, this data can provide the institution with an ability to model the existing balance by segment and potentially have appropriate data to model run-off from maturity and non-accruals. In some cases, the institution may have terms and conditions data allowing for modeling of run-off coming from prepayment. If sufficient internal data are not available, external data can be used as a supplement.

Moody's Analytics Credit Research Database (CRD) is an example of one dataset that contains information on C&I loans for non-public borrowers. The CRD contains data contributed by more than 45 financial institutions (including 15 US banks) and various external data sources. CRD participants provide quarterly portfolio snapshots with facility- and borrower-level data. The CRD contains data that can be used to infer time series dynamics of balance, new origination, interest charged on new origination, and usage. In addition, the CRD contains details that allow for loan segmentation based upon characteristics such as industry, credit quality, or loan type (e.g., term loan or line of credit).

2.2 Modeling Considerations

As discussed earlier, modeling approaches depend upon the availability and quality of historical data, statistical properties of the line item, business use and application, and model consistency across balance-sheet items. For the purpose of this section, we

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4 For an example of a model that allows one to describe loan prepayment dynamics, see a discussion of the lattice model in, Amnon Levy, “An Overview of Modeling Credit Portfolios,” Moody’s Analytics whitepaper, June 2013.

5 For further details around the CRD, as well as studies that leverage the data, please see:
assume the organization is structured so that models are coordinated across lines of business, and that segmentation decisions can be based upon data considerations (e.g., quality of historical data, statistical properties). With segmented data in hand, one can focus on the objective of designing models that can be applied to forecast changes in balance, usage, new origination, and interest charged on new origination under various macroeconomic scenarios, including the baseline, adverse, and severely adverse scenarios provided by the Federal Reserve, as well as custom scenarios that are specific to the institution. These model outputs can then be used in the calculation of FR Y-14A items.

Steps in the model development process should include both quantitative methods and economic judgment. The objective is to choose a model specification for each segment that has strong predictive power and that can be supported by economic judgment. Macroeconomic variables chosen by the FRB are candidates for explanatory variables in the regression analysis. However, there may be alternative variables that are relevant. For example, a portfolio heavily invested in oil companies should consider whether, say, an oil price index helps explain time series fluctuations in balance or any of the other variables. It is important to recognize that different models will have varying sensitivity to macroeconomic conditions. For example, interest charged on new origination is typically more sensitive to credit spread indexes than a balance model. Balance tends to be much slower moving, given that the loan book cannot be immediately rebalanced; the organization must wait for the existing book to run-off. Thus, lagged macroeconomic variables frequently perform well in describing balance.

It is important to allow economic intuition to enter into the modeling process. Given the large number of candidate variables, one can generally find statistical outliers where coefficients have signs that make little sense. We discuss this idea will in more detail later in the paper, when expert judgment is incorporated into the analysis. Care must be given to ensure that the variables have appropriate properties (e.g., stationarity, homoscedasticity), and that the properties are accounted for when making statistical inference. In addition, it is important not to over-fit the data, which is possible, given that many of the CCAR variables describe common economic environments (e.g., GDP and unemployment).

Transparency and parsimony are two additional properties that should be considered when proposing a model. Variables such as balance, usage, new origination, and interest charged on new origination are persistent. Linear growth or autoregressive models are specifications that are natural choices in this context. The choice of a growth model over an autoregressive model should be, in part, determined by whether the series exhibits a unit root. Using balance for term loans as an example, the autoregressive equation can be represented as something in the spirit of:

\[
\text{Balance}_t = AR_{\theta}(\{\text{Balance}_{t-k}\}, \{MV_{n,t-k}^{\text{CCAR}}\}, \{SC_{m,t-k}\}) + \epsilon_t
\]

And for growth, the equation can be expressed as something in the spirit of:

\[
\text{Balance Growth}_t = \frac{\Delta \text{Balance}_t}{\text{Balance}_{t-1}} = G_{\theta}(\{MV_{n,t-k}^{\text{CCAR}}\}, \{SC_{m,t-k}\}) + \epsilon_t
\]

where \(MV_{n,t-k}^{\text{CCAR}}\) are the selected set of macro and lagged macro variables used in the regression, \(\{SC_{m,t-k}\}\) represents the set of segment and lagged segment characteristics (e.g., maturity or average credit quality), and \(\epsilon_t\) represents an error term independent of the other explanatory variables. \(AR_{\theta}(\cdot)\) and \(G_{\theta}(\cdot)\) represent autoregressive and growth functions with parameters that need to be estimated. Ordinary least squares (OLS) can be used when the function is linear or some version of generalized least squares, such as a weighted least squares, if some data points are measured with a higher degree of accuracy, or if they are more relevant from an economic perspective. Non-linear specifications, such as panel quantile regressions, can also be explored. The chosen approach should consider the tradeoff between accuracy and complexity. In addition, care, of course, should be given to ensure that the error term is well behaved, and, if not, ensuring that their behavior is properly accounted for when making statistical inference.

In working through a specification, one should pool data to allow for robust statistical inference. For example, one can pool segments leveraging joint dynamics that are viewed to be common, allowing for a more accurate description of the relationship with macroeconomic variables. In other cases, it may make sense to estimate separate functions for each segment, as the dynamics across segments are too different from one another. For example, term loans and lines of credit are frequently modeled separately, given that lines of credit face an additional dynamic of potentially being drawn down.

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Under the direct balance approach, total interest-charged projections is needed to compute interest income. Conceptually, the interest charged at each point in time is a combination of interest charged on existing loans and new loans. This is likely to be difficult given that the balance model does not differentiate between new and existing loans. Instead, a conservative approach (from the perspective of stressing PPNR) can be taken where existing spreads can be applied to all loans. After all, spreads on newly originated loans tend to increase during downturns. This trait can be seen in Figure 1, which provides spreads for a sample of newly originated C&I loans from the CRD, along with fitted values and projections based upon the Federal Reserve 2013 baseline, adverse, and severe scenarios. By applying the spread associated with the last point in dataset, interest income will be lower under the adverse and severe scenarios.

Figure 1 C&I spread on newly originated term loans, fitted spread from spread growth model, and spread projections based upon Federal Reserve 2013 Baseline, Adverse, and Severe scenarios.

It is not surprising that consistent application of the direct balance model across the balance-sheet and income statement (e.g., when projecting credit losses) results in similar issues to those described when differentiating between spreads on existing and newly originated loans. To avoid these challenges, the component approach can be used, where separate projections are estimated for run-off and new origination for various segments. Functions similar to that described for balance (i.e., $ARt()$ and $Ga()$) would be explored and estimated for each component. For the purpose of, say interest income, spreads on newly originated loans would be associated with loans originated at each projected quarter and each segment.

An additional consideration when focusing on the component approach is its interaction with segmentation. This can be the case with new origination and spread charged on newly originated loans that feed into interest income projections. Another example is new origination for lines of credit, usage, and spread charged on newly originated lines that also feed into interest income projections. Differing dynamics may prevail across interactive models that may be countervailing, once segmentation is taken into account. These dynamics may be washed out and lost with the direct balance approach. For example, lines of credit tend to be drawn down as credit quality deteriorates. There is evidence to suggest that while smaller and lower-rated firms use their credit lines more intensively, in general, larger and higher-rated firms were more likely to draw on their credit lines during the financial crisis of 2007–08. A countervailing effect when calculating interest income on lines of credit is the more dramatic increase in rates charged to lower credit quality borrowers during the crisis. Thus, interest income may increase or decrease for various segments across the Federal Reserve’s scenarios. Similar patterns prevail for term loans where the response to the crisis was more pronounced for smaller entities and financial firms.

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Accounting for these differing patterns clearly allows for a more accurate description of interest income. In addition, it permits more accurate loss estimation when these cross-sectional patterns in new origination and usage are explicitly modeled.

As a final note, robust validation must be integrated into the model development process, where performance is assessed both within sample and out of sample. It is important to recognize that using external data does require additional analyses to ensure applicability to the institution. This can frequently be addressed by analyzing dynamics for the, perhaps more granular, external data under segmentation that conforms to data available for the organization, which allows for some level of statistical comparison.

3. Top-Down Industry Peer Models

In this section, we explore a number of top-down industry peer PPNR models. We present the models via a set of case studies, where specific PPNR items are analyzed. As discussed, there are several reasons to use top-down industry peer models: most non-interest income and expense items are not consistently tracked at a higher level of granularity than what is reported publicly or in regulatory filings; some interest income and expense items may have accurate granular historical data, but face the challenge that variation in product composition results in limited history, creating difficulties when attempting to quantitatively link variables with macroeconomic variables; finally, idiosyncratic variation in some line items makes statistical inference problematic. By using a peer group, it is easier to isolate systematic drivers as idiosyncratic events are averaged out, allowing for a better representation of future dynamics as they relate to macroeconomic scenarios. The remainder of this section is organized as follows: the first part focuses on data options and limitations and the second discusses a number of modeling options and considerations.

3.1 Data Options and Limitations

Given the objective of designing a quantitative model to produce projections for the FR Y-14A form, the challenge becomes finding data both relevant and available over a sufficiently long history. Within the context of top-down models, several datasets are worth noting. Financial institutions required to complete the FR Y-14Q will have historical data with the same line items as the FR Y-14A. However, the data are not public, thus not appropriate for peer modeling. In addition, data, at best, go back only to 2009. Given the limited history and idiosyncrasies in FR Y-14Q data, using additional data sources may improve the statistical soundness of the models. The following two data sources have proven to be useful.9

- FR Y-9C: Collected quarterly and reported publicly, the FR Y-9C is submitted at the consolidated level for the holding company and its subsidiaries. It is designed to parallel call reports for FDIC-insured banks. The report consists of financial data (balance sheet, income statement, and supporting schedules) for BHCs, SLHCs, and SHCs. When projecting most PPNR components, the Federal Reserve uses data on historical revenue, and operating and other noncredit-related expenses reported on the FR Y-9C report.10

- Call Reports: Call reports are similar to the FR Y-9C forms, in that, they contain basic financial data such as balance sheets and income statements. However, line items are reported on the bank level rather than the BHC level.

While the FR Y-9C and call report data have the benefit of containing a rich history for peer institutions, there is the disadvantage that line items do not align with many of the FR Y-14A line items. This issue is particularly relevant for the non-interest income and expense line items. In addition, FR Y-9C and call report data structures themselves change over time, with some line items dropped and others added. Finally, institutions have flexibility in choosing which line item to associate reporting various non-interest income and expenses, making peer comparisons difficult.

To address this challenge, institutions can aggregate line items by broader category classification comparable across the FR Y-14A and FR Y-9C (or call reports). To ensure the classification makes sense, one can compare the historical dynamics of the FR Y-14Q and FR Y-9C (or call report) over the (limited) historical data for one’s organization.

3.2 Modeling Considerations

With a panel of peer data from the FR Y-9C and call report in hand, one can begin exploring the relationship between macroeconomic variables and industry peer PPNR category classification. It is important to recognize that it is unlikely for a single relationship to prevail across all PPNR categories. For example, CRE interest income is likely driven to a large degree by the CRE

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9 The historic FR Y-9C and call report datasets do not account for mergers and acquisitions. Therefore, certain banks and BHCs may see random jumps in historical segment values that are not immediately explainable and need to be corrected. The first step in correcting the historical time series for mergers and acquisitions is to examine the bank and BHC merger data. The merger and acquisition database files produced by the Federal Reserve identifies mergers and acquisitions for banks and BHCs from 1976 through the present. See “Bank Merger Data,” Chicago Federal Reserve. http://www.chicagofed.org/webpages/publications/financial_institution_reports/merger_data.cfm and “BHC Merger Data,” Chicago Federal Reserve.

price index, which may not play as much of a role with C&I interest income or compensation expense. In addition, a separate modeling framework may be needed for BHC and bank, with different macroeconomic drivers. This is relevant when the holding company contains a number of banks or other entities with substantive values for line items that feed into the category. Peer groups may need to be constructed for each entity level and each category—peers should be chosen to most closely resemble activities in that area. In addition, in some cases business lines might associate a different set of peers for the same line category classification. With these issues in mind, this section outlines several classes of specifications found to describe top-down peer relationships between many PPNR categories and macroeconomic scenarios.

There are many similarities between statistical approaches used in top-down peer approaches and those used in granular bottom-up approaches. However, important differences exist. First, one should recognize that there are differences across institutions used in estimating the model. While those behavioral differences ought to be minimized through proper peer selection, there will undoubtedly be variances that, when possible, need to be accounted for. Second, when developing autoregressive models, it is natural to explore the dynamics of items scaled by, say, assets. This scaling allows for easier comparison across peers. Otherwise, nominal series (i.e., unscaled) when applied to autoregressive models, for example, tend to have observations of very different orders of magnitude, driven by the wide range of values that prevail on bank’s balance sheets. Such a wide range makes statistical inference more complicated. If one models categories scaled by assets, a separate asset model is needed. The scaled model, along with the asset model and starting values, allows one to project the category. If one were to model line item growth directly, rather than scaled values, the additional growth model for the numerator (e.g., asset growth) is not needed. We now turn our attention to the representation of top-down peer regression models. Since growth models are sufficiently similar to those described above in the granular case, our focus is entirely on autoregressive asset-scaled category models:

\[
\text{Category}_{p,t-k}/\text{Asset}_{p,t} = AR\left(\left\{\text{Category}_{p,t-k}/\text{Asset}_{p,t-k}\right\}, \left\{\text{MV}_{n,t-k}\right\}, \left\{\text{PC}_{p,t-k}\right\}\right) + \epsilon_{p,t}
\]

where \(\text{Category}_{p,t-k}/\text{Asset}_{p,t-k}\) represents a lagged asset-scaled category balance, \(\text{PC}_{p,t-k}\) represents peer characteristics (e.g., peer dummy), \(p\) represents peer, and other variables are defined as above. Since some categories follow a seasonal process, the modelling approach may also include quarter dummies to capture possible cyclicity.

With the autoregressive scaled model estimated, we turn our attention to the modeling the scaling variable. If assets are used in scaling, growth models are a natural choice, given that asset levels are not typically stationary. Asset growth would be applied to the scaled model projections in order to come up with category projections in dollar terms. Asset growth can be modeled as something along the lines of:

\[
\text{Asset Growth}_{t} = \frac{\Delta \text{Asset}_{t}}{\text{Asset}_{t-1}} = G\left(\left\{\text{MV}_{n,t-k}\right\}, \left\{\text{PC}_{n,t-k}\right\}\right) + \epsilon_{t}
\]

The spirit of this overall approach is in-line with that of the Federal Reserve, where most PPNR items are categorized, scaled and modeled through an autoregressive process.\(^{11}\)

As a final note for this section, and similar to the discussion in the section that outlines granular modelling approaches, robust validation ought to be integrated into the model development process, where performance is assessed both within sample and out of sample.

4. Application and Accounting for the Operating Plan and Expert Judgment

This section will discusses the mechanical application of the model for the purpose of scenario projections in a format in line with FR Y-14A line items, and approaches to accounting for an organization’s strategic plans and incorporating expert judgment into the projections.

The mechanical application of the model involves several steps. First, multiple models may need to be combined to generate projections. Such was the case with the scaled autoregressive top-down industry peer models that needed to be combined with an asset growth model. Second, a starting point is needed for the growth and autoregressive models. Third, when categories are modeled, a decomposition schema is needed to allocate the category classification across the various FR Y-14A line items within the category. An organization then needs to consider the extent to which strategic plans align with the quantitative model projections, and the degree to which they may want to consider adjustments or overlays so that the two align.

The discussion of the mechanical application of the models for projecting FR Y-14A items is presented within the context of the top-down industry peer model described above. This is of particular relevance for non-interest income and expense where

\(^{11}\) See Federal Reserve Board, “Dodd-Frank Act Stress Test 2013: Supervisory Stress Test Methodology and Results,” March 2013.
autoregressive scaled category models and asset growth models need to be combined to estimate each of the nine quarter projections. Future asset values can be estimated recursively, and then used to calculate the predicted category totals.\(^\text{12}\)

\[
\text{Category}_{pt} = \frac{\text{Category}_{pt}}{\text{Asset}_{pt} \times \text{Asset}_{pt-1}} \times \text{Asset Growth}_{pt}
\]

Here, hatted variables represent fitted modeled values. In some instances, the model might describe dynamics of an observed variable that does not exactly align with the required FR Y-14A item. This is the case with balance where the most precise data may be balance levels, which is different from the FR Y-14A required item that is averaged over the quarter. While the growth or autoregressive projection model can be applied to the starting average balance value, the organization should recognize the limitation of the model’s application.

The next step is the disaggregation of projections to the FR Y-14A line-item level. Disaggregation can be carried out proportionally, based upon the relative size of the FR Y-14A items. A more involved procedure would allocate the projection based upon the proportion of variation coming from each FR Y-14A item—perhaps by leveraging the FR Y-14Q history.

Prior to deciding upon the final set of models and projections, it is important to review results with economic judgement. There will be instances where seemingly similar variables will have opposite reactions to a macroeconomic stress. The challenge is to differentiate between legitimate candidate models and models with coefficients that are statistical outliers and may even have coefficients with signs opposite to that which most closely represents reality and the spirit of the exercise. An example of two variables that seem similar, but have legitimate opposite reactions to stressed macroeconomic environments are checking and time deposits. The two figures below are based upon call report data for the banking industry and represent dynamics for checking and time deposits along with fitted modelled values and projections. The opposite reaction of checking and time deposits to the severe scenario is consistent with historical flight to quality patterns seen during economic downturns (checking) and movement toward higher paying investments (time deposits) seen during upturns.\(^\text{13}\)

Figure 2 Checking deposits, fitted deposits from growth model, and projections based on the Federal Reserve 2013 Baseline, Adverse, and Severe scenarios.

\[^{12}\text{In some cases, it makes sense to account for nonlinear and cross effects related to projections. For example, cross-model error terms may be correlated, resulting in an augmentation to the expected value of the projection.}\]

Figure 3  Time deposits, fitted deposits from growth model, and projections based on the Federal Reserve 2013 Baseline, Adverse, and Severe scenarios.

Turning attention to model application and use, several issues are worth thinking through. First, from a statistical standpoint, there is the question of the extent to which projections make sense, given that historical data is used in estimation. For example, average C&I loan balance growth has been substantial over the last 12 or so years, in-line with the substantial growth in the banking sector. It is questionable whether this level of growth is expected to persist in the coming years. The model might provide good insight on co-movement between balance and macroeconomic conditions, but it may not provide a reasonable baseline projection. As an example, the figure below presents historic balance levels for a sample of C&I loans, fitted values, and projections for the Federal Reserve baseline, adverse, and severely adverse 2013 CCAR scenarios using data from Moody’s CRD (2003 is set to 100).
Figure 4  C&I Balance Levels (June 2003 = 100), fitted balance from balance growth model, and balance projections based on the Federal Reserve 2013 Baseline, Adverse, and Severe scenarios.

The time series dynamics conform to the dramatic pre-crisis growth in C&I lending with a sharp reduction as the crisis unfolded and a more recent recovery. Focusing on projections, the dramatic increase in balance under the baseline projection is striking. While the pattern conforms to historical patterns, it may not be in line with the institution’s strategic plans. In fact, in this example, the baseline is sufficiently rosy, so much so that the adverse scenario looks rather appealing as well, and not in the spirit of the exercise if the model is applied to, say, interest income.

In such cases, it may be most natural to overlay the projections onto the organization’s annual operating plan (that accounts for strategic initiatives), so that the augmented model has baseline projections that align with the operating plan. An example is scaling projections by the ratio of the institution’s operating plan growth rate and the model’s unadulterated baseline projection. This will result in changes to the dispersion across the three scenarios. For example, if the organization’s baseline is greater than the modeled baseline, projections under the Federal Reserve scenarios will be scaled up, and dispersion will be greater than that implied by the unadulterated model. Alternatively, one can shift projections by the difference between the institution’s operating plan growth rate and the model’s unadulterated baseline projection, keeping the dispersion in projection unchanged.

Figure 5 provides an example of such an overlay. One can see the muted growth under the baseline and the, perhaps more realistic, adverse scenario.
The choice of overlay should depend upon the extent to which the organization believes scaling or shifting best reflects the dynamics in the projections; back-testing may allow one to understand the most appropriate approach.

In addition, the organization may have views on the strategic actions it plans to take under the various scenarios that do not conform to historical patterns. In these situations, it may make sense to further adjust projections. One approach is for the organization to quantify historical strategic decisions. While involved, in that it requires heavy input from the lines of business, it can provide a quantification mechanism for strategic overlays more precisely and dynamically. Given that the process of bringing in strategic plans is both a quantitative exercise as well as a qualitative one, a narrative is needed to explain discrepancies and any resulting adjustments.

5. Recap and a Glimpse of the Future

PPNR covers a wide range of disparate items, with modeling that relies on a wide range of data sets with differing statistical properties. While disparate, there are a few points that are relevant for all PPNR line items.

First, the organization must understand what data options (internal and external) are available and how the options align with the organizational structure so that relevant stakeholders can be identified. Second, with data options in hand, segmentation and categorization of FR Y-14A line items must be determined. This will be done in conjunction with designing modeling specification and macroeconomic variable selection. Statistical analysis, along with validation will ensure a robust statistical methodology (or at least a methodology that is superior to practical alternatives). Third, it is necessary to demonstrate that the quantitative model is appropriate for CCAR projections. The organization must, at some level, reconcile strategic plans and the quantitative model when submitting the final projections. This is both a quantitative exercise, as well as a qualitative one, as a narrative is needed to explain discrepancies and any resulting adjustments.

With these points in mind, we should recognize that PPNR modeling is in its early stages. Institutions have only just begun exploring datasets and modeling approaches. Collection and reporting of FR Y14-Q data, for example, will eventually produce time-series sufficiently long enough to allow institutions to more accurately describe PPNR line items. While peer models will likely be used for many items that have volatile dynamics resulting from idiosyncratic events, the lengthier FR Y-14Q time-series
will certainly provide more options. In addition, there will likely be demand for data consortiums where granular anonymized data is collected, similar in spirit to loan level datasets such as the CRD, that will allow for much more accurate modeling.

Beyond the modeling, there is the question of application. Once sufficient data is available, and once the organization is able to develop models of sufficient accuracy, model use should move toward strategic decision making. The organization will be able to measure the extent to which various activities consume CCAR-capital. While some organizations are beginning to recognize this variability when stress testing loan portfolios, organizations have not yet fully integrated this thinking when considering the application of PPNR models.
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