Stress Test Modeling in Cards Portfolios

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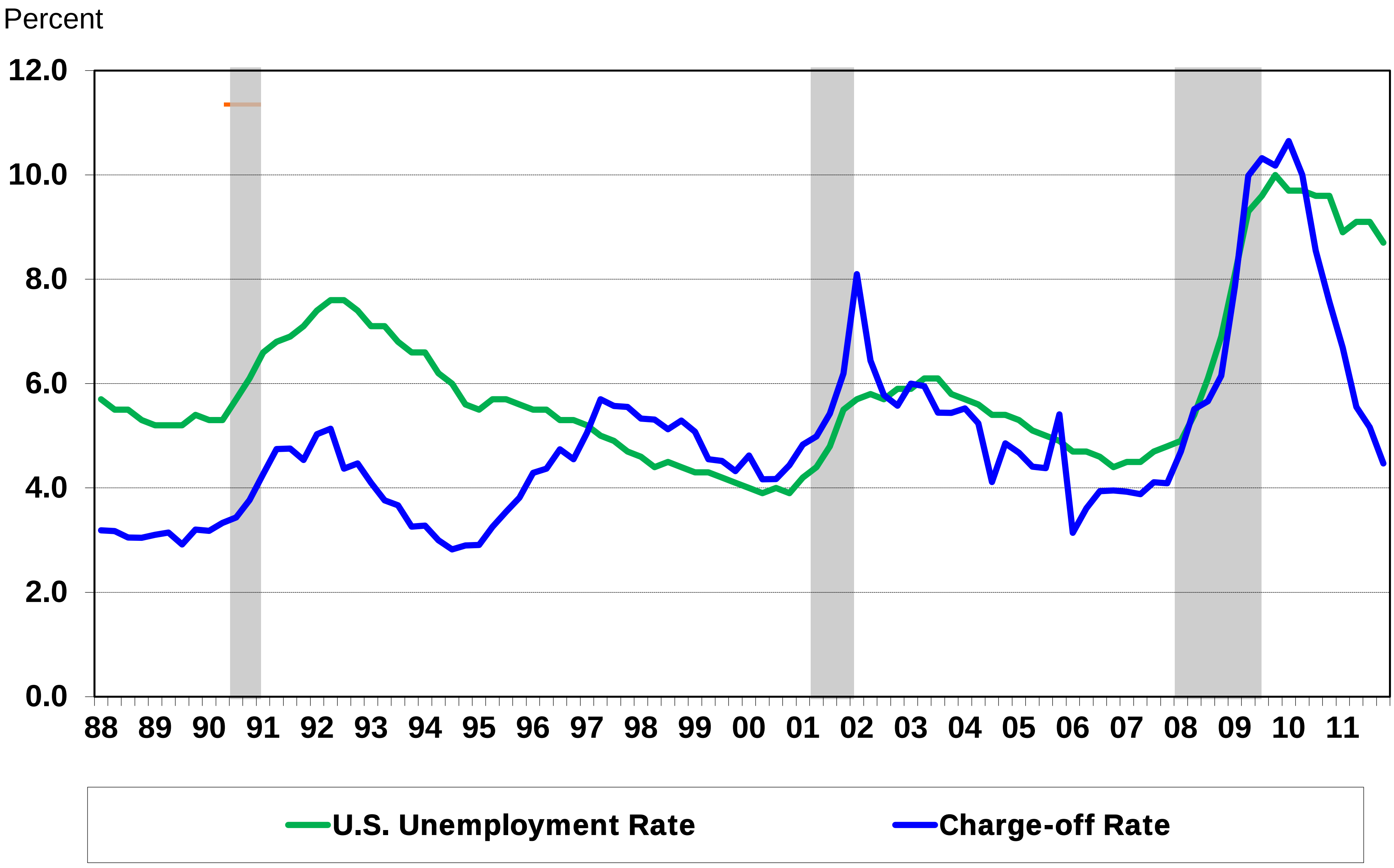
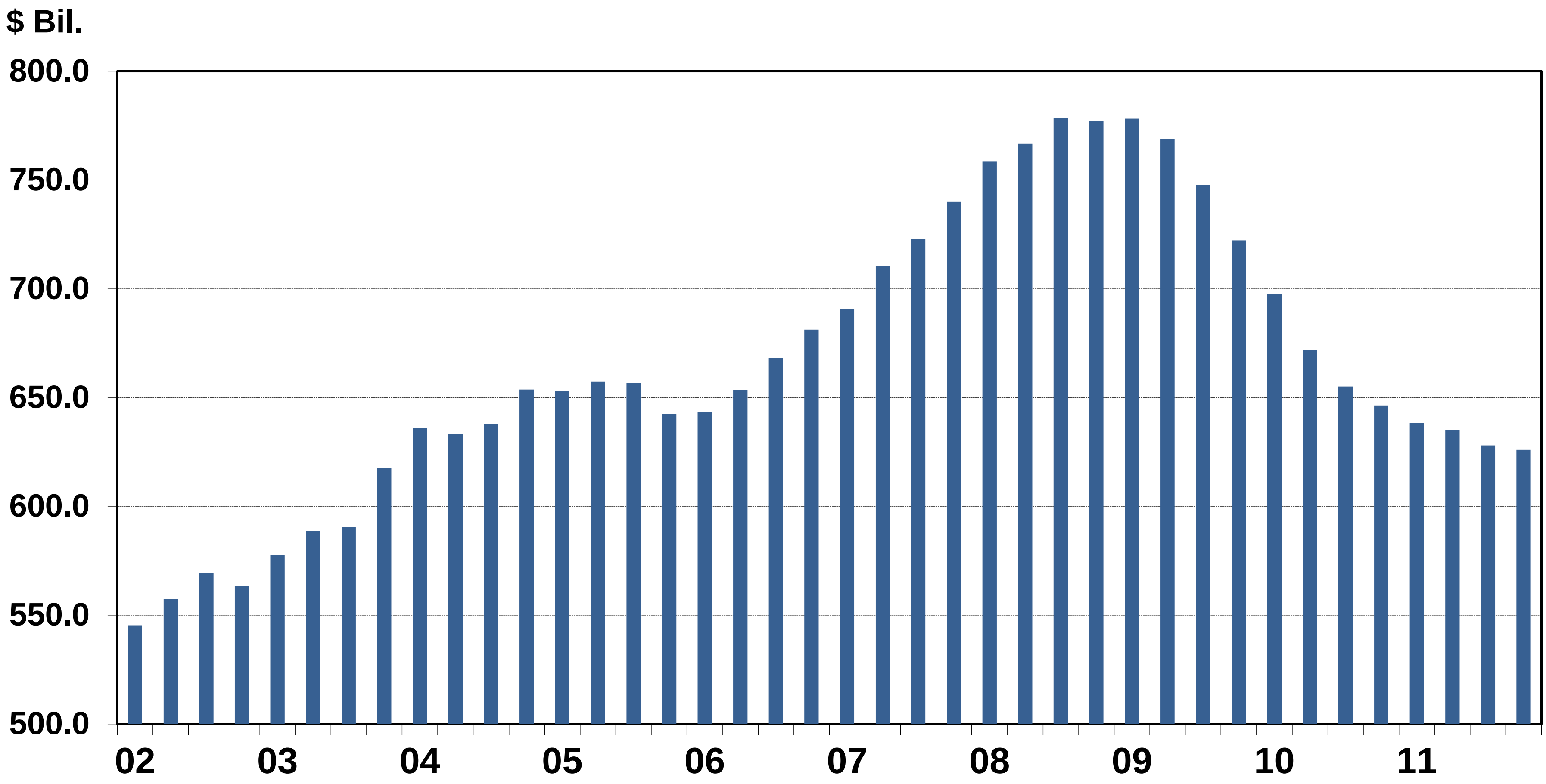
The views expressed here are my own and not necessarily those of the Federal Reserve or its staff.

Credit Card Performance: Charge-off Rate



Sources: Aggregated Call Report data for insured commercial banks, Bureau of Labor Statistics, Haver Analytics

Credit Card Performance: Outstandings



Seasonally Adjusted Managed Card Outstandings

Source: Aggregated Call Report data for insured commercial banks.

Credit Card Performance: Observations

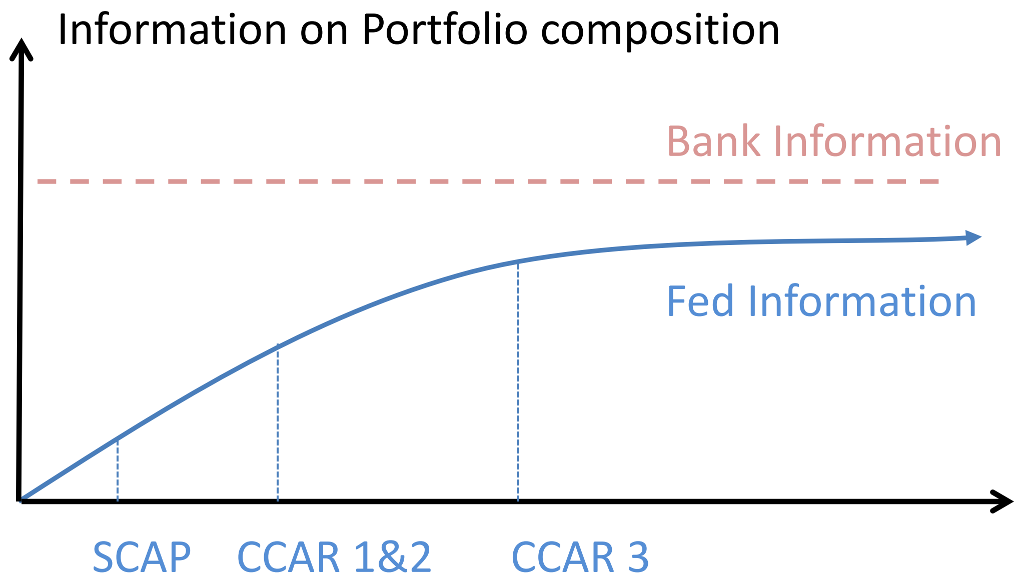
We observe:

- Significant changes in delinquency behavior.
- Significant changes in portfolio composition.

Thus:

- Understanding customer and firm behavior, and portfolio dynamics, is needed to produce reasonable medium and long run loss projection estimates under stress economic conditions.
- Access to granular historical information can be of great help. Banks have been collecting this information for years to aid their Risk Management and Marketing efforts.
- The Fed and other regulators are making efforts to improve the quality and granularity of their information on portfolio characteristics and historical portfolio dynamics.

From SCAP to CCAR 2013



• For SCAP the Fed had access to aggregated summary information on portfolio characteristics, but limited disaggregated information.

• As a result, it was difficult to differentiate among potentially dissimilar portfolios with comparable aggregated characteristics.

• A goal of the data collection efforts in CCAR 1 and 2 and the upcoming CCAR 2013 has been to improve the quality and granularity of information on Banks' portfolios.

Stress Testing Framework – Assumptions and Implications

The objective of the loss projection exercise is:

To project EXPECTED losses as a function of MACROECONOMIC RISK DRIVERS conditional on the portfolio's risk profile and growth projections.

A "SIMPLE" CONCEPTUAL FRAMEWORK:

LOSS UNDER STRESS AS A FUNCTION OF

- OBSERVABLE & UNOBSERVABLE PORTFOLIO CHARACTERISTICS
- RISK
- UNCERTAINTY

Where,

Risk: Foreseeable and measurable loss events

Uncertainty: Unforeseeable and immeasurable loss events

The Stress Testing Framework – Implicit Assumptions

- A1: After controlling for observable portfolio characteristics, unobserved portfolio characteristics do not introduce a significant bias in:

  (1) The measurement of risk as a function of macro factors

  (2) The measurement of portfolio loss in general

- A2: Risk can be characterized as a function of specified macro factors.

- A3: Uncertainty has an insignificant impact on results (i.e. it is ignored in this framework).

- A4: The specified stressed macroeconomic conditions are sufficiently severe to encompass the average projected losses of most plausible stress scenarios.

Examples of Industry Practice
– without an implicit or explicit endorsement of any specific approach

• Stress Factor: postulates an increase in the portfolio loss rate by a given stress factor (either empirically or judgmentally based).

Argument - Implicitly assumes that there is no relationship between macro scenarios and risk or that the adjustment factor represents a loss upper bound (i.e. conservative).

• Vendor Models developed by a third party.

Argument - Implicitly assumes that a generic model using generic, or perhaps bank-specific, data represents an adequate stress testing framework for the institution.

• Models that assume that losses can be modeled at an aggregate level (portfolio or segment) and macro risk drivers are the only drivers of loss.

Argument - Assumes that the impact of macro drivers is homogeneous at the portfolio or segment level, and that past loss experience at an aggregate level provides the relevant information for the analysis of loss projections.

• Models that assume that losses can be modeled at a certain level of aggregation and include macro risk drivers and portfolio characteristics as drivers of loss.

Argument - Assumes that the heterogeneous impact of macro drivers and portfolio characteristics can be accurately measured at a certain level of aggregation and that past loss experience at an aggregate level provides the relevant information for the analysis of loss projections.

Examples of Industry Practice (cont.)

- Loan level models where Loss is derived as a function of its components.

EL = PD * LGD * EAD

Each component is analyzed empirically in terms of observable portfolio characteristics and macro risk drivers.

Argument: usually assumes independence across loss components after accounting for relevant drivers of loss and other observable portfolio characteristics. Additional functional form assumptions are imposed in most cases.

The Fed's loss projection strategy is consistent with this approach:

We consider the transition to default across delinquency states (PD), the loss rate for defaulted accounts after accounting for recoveries (LGD) and the projected changes in balances resulting from transitions across delinquency states (EAD).

Models are consistent with the relevant empirical literature.

Loss Projections

- Models are estimated using industry data from a time interval up to time t.

- Models are applied to:

  - Fed defined stress macro projections.

  - A Bank' portfolio characterized by its observable characteristics (i.e. FR Y-14Q in CCAR2012 or FR Y-14M in CCAR 2013)

  - Portfolio Balance Projections.

- In order to generate:

  - Portfolio Loss projections up to 9 quarters into the future.

- FR Y-14Q represents a significant improvement over data collection efforts for SCAP. Our expectation is that FR Y-14M will represent an additional step forward in our understanding of relevant portfolio characteristics.

- Differences in loss profiles across portfolios are captured in the analysis to the extent that they are reflected in the portfolio characteristics collected in the FR Y-14Q at the segment level, or in the FR Y-14M at the loan level for future Stress Test analysis.

Some Observations

• In our experience certain macro risk drivers have a stronger impact over certain components of loss (PD, LGD) than over others (EAD).

• The impact of policy risk drivers is potentially heterogeneous with respect to account characteristics.

• The relevant literature (e.g. from the literature [1], [3]), and our own analysis, suggest that model parameters, for macro drivers in particular, are sensitive to the time period in the estimation sample, and potentially also to the sample geographic coverage.

• Conceptually, the data time coverage period may impact model coefficients through the “risk channel” (the degree of coverage of the distribution of risk drivers) or through the “uncertainty channel” (e. g. recent experience may exceed prior expectations of portfolio stress loss).

• This suggests that a data coverage period that encompasses at least a full economic cycle can strengthen the empirical framework.

• Small variations in model structure may have a second order impact on results, assuming a robust model specification (e.g. from the literature [2], [4],[8] and [9]).

Enhancements to the Fed Methodology

Our expectation is that the new FR Y-14M and enhanced FR Y-14A will allow us to:

- Enhance the model specification with additional relevant variables available in the FR Y-14M schedule. Also, allow for a more granular segmentation along observable dimensions (credit card type, card activity, product type, loan source/channel, etc.). This will mitigate the potential reliance on assumption A1.

- Allow for further development of a time variant coefficient specification structure.

- Offer additional tools for the analysis of measurement error across the overall sample or of problem variables at specific institutions.

- Contribute to a better understanding of a bank's portfolio balance growth projections, disaggregated according to existing portfolio and new account originations.

- Contribute to improvements in the process of outcomes analysis.

- Analyze the level of consistency within a bank's risk management framework, in particular through the analysis of Basel II parameters from specific institutions.

- Also, we will continue to strive to adhere to the principles of SR 11-7 (Model Risk Management guidance) with assistance from the Fed's Model Validation Unit.

Thank you.

Some Relevant Literature

[1] Agarwal, S. and C. Liu, (2003). “Determinants of Credit Card Delinquency and Bankruptcy: Macroeconomic Factors.” Journal of Economics and Finance 27 (1): 75-85.

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[6] Qi, M. (2009) "Exposure at Default of Unsecured Credit Cards," W.P. Office of the Comptroller of the currency.

[7] Qi, M., Yang, X., (2009). Loss give default of high loan-to-value residential mortgages. Journal of Banking and Finance 33, 788–799.

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