Stress-Testing U.S. Bank Holding Companies: A Dynamic Panel Quantile Regression Approach*

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Abstract

We estimate a fixed effects quantile autoregressive model with exogenous macroeconomic variables that is well-suited for capturing the nonlinear dynamics of revenues and bank profitability during periods of macroeconomic stress. We use the density forecasts generated by the quantile autoregression model to simulate capital shortfalls during the last financial crisis for some of the largest U.S. bank holding companies. We report that the capital shortfalls obtained using the quantile regression model are, for almost all banks in our sample, significantly higher than the capital shortfalls obtained using a linear dynamic panel data model with fixed effects. Our results indicate that relative to the quantile model the linear specification underestimates loan and trading book losses.

Keywords: Macroeconomic stress tests, dynamic panel quantile regression, density forecasting.

J.E.L. Codes: C32, G21.

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1 Introduction

Macro stress tests have become a key tool for the conduct of macroprudential policy in the United States and Europe.[1] Undoubtedly, the stress tests conducted in the U.S. have been responsible for the notable increase in bank holding companies' (BHCs) regulatory capital ratios since early 2009 (see Figure 1). An important novelty of U.S. stress tests is that the Federal Reserve constructs its own estimates of bank losses, revenues and regulatory capital ratios for each bank under a severely adverse macroeconomic scenario. In many instances, the models used by the Federal Reserve are estimated using data on individual portfolios and require a great deal of detailed information about loan characteristics which are provided by banks. Upon completion of the analysis, bank-specific results of the stress tests are released to the public. These disclosures have had a notable impact on banks' stock prices, suggesting that the announcements contain important information about the capital adequacy of banks (Peristiani, Morgan, and Savino 2010). Given the role of stress tests as an important policy tool, this paper evaluates the forecasting performance of "top-down" stress testing models. These approaches can be used to generate industry-wide losses and revenues using aggregate bank level data, hence require considerably less detailed data. In addition, top-down stress testing models are useful to benchmark aggregated results from the U.S. stress tests and also to evaluate banks' capital adequacy plans under different macroeconomic scenarios.

Top-down stress testing approaches map the paths of macroeconomic variables into bank outcomes using aggregate data. Although these models are used extensively by central banks and regulatory agencies around the world they have some important shortcomings. In particular, two often mentioned criticisms deal with misspecification issues and inability to capture the nonlinearity of bank losses during periods of macroeconomic stress. To mitigate some of these limitations, we estimate density forecasts of banks' regulatory capital ratios using dynamic panel quantile regressions. First, the quantile regression model is well-suited for capturing the nonlinear dynamics of bank losses during periods of macroeconomic stress. Second, in contrast to a point forecast, density forecasts provide an estimate of the probability distribution of all possible values of the

[1] For an overview of macroprudential policies and stress testing see, e.g., Hirtle, Schuermann, and Stiroh (2009), Hanson, Kashyap, and Stein (2011) and Greenlaw, Kashyap, Schoenholtz, and Shin (2011).

variables of interest. For example, density forecasts can characterize the uncertainty associated with the projection of banks' capital ratios under a severe macroeconomic scenario. Finally, we use the parameter estimates from the quantile regressions to assess the size of capital shortfalls at the onset of the last financial crisis using the density forecasts for the tier 1 common ratio (T1CR) generated using simulation methods.

The dynamic panel quantile regression model is able to generate density forecasts for losses that have fat tails in periods of macroeconomic stress, a distinct feature of the data that is impossible to capture with the standard linear regression framework. In particular, we observe a strong nonlinear effect in losses for several loan portfolios as well as trading losses, as the estimated impact of the lagged dependent variables in the quantile model are increasing in the quantiles of the dependent variable. This implies, that an adverse shock to the credit quality in, for example, the residential real estate portfolio will make the series more persistent and increase the heaviness of the right tail of the density forecast for residential real estate losses. Furthermore, as the out-of-sample forecast horizon expands, this mechanism is amplified as banks that draw a sequence of negative shocks would observe their losses escalate during a relatively short period of time. In contrast, the degree of persistence of the linear model is invariant to the size of bank losses, thus density forecasts generated using a linear panel regression have much thinner tails. As a result, in our projections, realized net charge-offs are usually inside the multi-step-ahead density forecasts generated using the quantile model during the last financial crisis whereas they are often outside the multi-step density forecast generated using the linear model, particularly for the portfolios most affected by the last financial crisis.

A key objective of macro stress tests is to analyze whether banks' capital ratios are always above a specified minimum requirement during a severe but plausible macroeconomic scenario. In particular, in the latest round of U.S. stress tests the Federal Reserve disclosed point forecasts of the T1CR for each of the 19 largest BHCs under a severe macroeconomic and financial market scenario. An important feature of our top-down stress testing approach, is that we use simulation methods to generate density forecasts for losses, net revenues and the T1CR and provide a complete description of the uncertainty associated with our forecasts conditional on a given macroeconomic scenario. Furthermore, having the distribution of all possible T1CR outcomes allows us calculate the probability a bank would violate a specified capital requirement. Moreover, we also calculate the expected capital shortfall, that is the amount of capital a bank would need, on average, to prevent it from ever violating the capital requirement under a given macro scenario.

To evaluate the methodology proposed in the paper, we estimate capital shortfalls for several large U.S. BHCs at the onset of the last financial crisis. First, the results from both the quantile and linear models indicate that relatively large fractions of banks would violate the minimum T1CR requirement of 4 percent during the last financial crisis. Projected losses for both the quantile and linear models are elevated enough that several banks have a relatively high likelihood of violating the 4 percent minimum T1CR requirement. Second, under a a 2 percent minimum T1CR requirement moderate fractions of banks would still have a fairly high likelihood of also violating this requirement, but only based on the density forecasts generated using the quantile model. In particular, several banks in our sample would violate the 2 percent T1CR requirement between 1 and 5 percent during the financial crisis. The probability of going below 2 percent in the linear model is zero for those same banks. Meanwhile, simulations based on the quantile model suggest that almost all banks in our sample would need to raise new capital to avoid violating the 2 percent minimum T1CR requirement during the financial crisis. In contrast, under the linear model specification just 1/4 of banks would need additional capital.

Several papers in the literature provide an overview of macro stress testing. For example, Sorge and Virolainen (2006) and Drehmann (2009) review the main methodologies used for macro stress testing, some of which are closely related to the class of models we use in our paper. Foglia (2009) reviews current stress testing practices across various jurisdictions and Cihák (2007) provides an overview of a typical stress testing process for both top-down and bottom-up approaches. Alfaro and Drehmann (2009) and Borio, Drehmann, and Tsatsaronis (2011) criticize the current state-of-the-art stress testing methodologies for not being capable of uncovering vulnerabilities to financial stability during good times. To address these concerns, Schechtman and Gaglianone (2012) suggest that stress testing exercises should turn their attention to the conditional right tail of credit losses. However, they find that the results obtained using the widely known reduced form stress testing approaches of Wilson (1997a) and Wilson (1997b) are very similar to the ones obtained using quantile regression. Our paper expands their basic idea of combining density forecasts and quantile regressions in several important directions and find that the dynamic panel quantile regression model generates density forecasts with fatter tails. First, we conduct our analysis using panel regressions. Second, we generate our results using multi-step forecasts, which are needed to generate significant differences to arise between the density forecasts derived from the quantile model and ones constructed using the linear model.

The rest of the paper is organized as follows. Section 2 motivates our paper and describes the stock market reaction to the disclosure of results from the latest round of U.S. stress tests. Section 3 describes the fixed effects dynamic panel quantile regression model. Section 4 describes the bank holding company data used in the analysis and presents the estimation results. Section 5 evaluates the out-of-sample forecast of the quantiles and linear model. Section 6 estimates capital shortfalls at U.S. BHCs at the onset of the last financial crisis and also for the last U.S. stress testing exercise. Section 7 concludes.

2 Some Implications of U.S. Stress Tests

In the U.S., stress tests are designed to carefully evaluate the capital adequacy of the 19 largest BHCs. In particular, the objective of stress tests is to evaluate whether these banks maintain sufficient capital to support the credit needs of borrowers under severe economic conditions. The results of the most recent U.S. stress tests—also known as Comprehensive Capital Analysis and Review (CCAR)—were released in mid-March of 2012. Prior to that, the capital adequacy of U.S. bank holding companies (BHCs) was also formally assessed in two other previous occasions, namely in March of 2011 and May of 2009.

The U.S. stress tests require a considerable amount of resources both at the banks and regulatory agencies and last for about four months. Initially, the Federal Reserve provides a severely adverse macroeconomic and financial market scenario to the participating BHCs. At the same time, the participating BHCs submit extensive data with information on their loan and securities portfolios to the Federal Reserve. These data is then used as inputs to a variety of models developed by staff at the Federal Reserve to generate projections for losses and net revenues. Meanwhile, banks submit their capital plans with proposed dividend payouts, share repurchases and redeemption of trust preferred securities. The Federal Reserve then uses their own projections for losses, net revenues and the banks' own capital plans to construct the path of the expected regulatory capital ratios under the supervisory stress scenario over the following 9 quarters. The key requirement for a bank to pass the stress test is that the projected tier 1 common capital ratio (T1CR) under the severely adverse macroeconomic scenario must stay above 5 percent throughout the forecasting horizon.[2]

Figure 1 plots the T1CR of the 19 largest U.S. BHCs between the first quarter of 2009 and the second quarter of 2012. During this period, the T1CR climbed from 5.5 percent in the first quarter of 2009 to about 11 percent in the second quarter of 2012. The increase in T1CR since the beginning of 2009 was mainly driven by the issuance of common equity and increased retained earnings at these BHCs. Restrictions in dividend payouts and share repurchases imposed by the Federal Reserve based on the outcomes of the three stress tests were, in most part, responsible for these increases.

In addition, the release of the U.S. stress test results to the public have also elicited a notable reaction by market participants. For example, there is some evidence of significant abnormal positive stock return performance for banks for which the Federal Reserve estimated relatively small declines in their T1CR under stressed economic conditions. Figure 2 reports the abnormal stock returns of each CCAR bank following the release of the CCAR 2012 stress test results against the projected decline in the bank's T1CR during the severe stress scenario.[3] The abnormal stock returns are defined as the residual of a capital asset pricing model estimated using banks' daily

[2]The bank has also to maintain tier 1 capital, total capital and the tier 1 leverage ratio above minimum regulatory capital ratios of 4, 8 and 4, percent respectively. The tier 1 common capital ratio (T1CR) is defined as tier 1 capital less non-common elements, such as qualifying perpetual preferred stock, qualifying minority interest in subsidiaries, and qualifying trust preferred securities. Common equity is the dominant for of capital in T1CR therefore this is the preferred capital ratio used by supervisors to evaluate the capital adequacy of U.S. BHCs. Also, the T1CR has a higher likelihood of binding during a severe stress scenario.

[3]The chart includes 18 of the 19 CCAR BHCs. Ally Financial Inc., is not a publicly traded BHC. Also, the regression results presented in the chart exclude MetLife since it is an insurance company and the firm's T1CR remained above 5 percent under the adverse economic scenario. Instead, the firm failed their total capital ratio and leverage ratio requirements.

stock returns in the 22-days prior to the release of the results. The event period includes the day of the release of the stress tests and the following day. As shown in Figure 2, banks that experienced relatively small declines in T1CR during the severe stress scenario experienced abnormal stocks returns in the range between 4 and 8 percent in the two days following the release of the results of the stress tests. In contrast, BHCs that experienced the largest declines in T1CR during the severe stress scenario had zero abnormal stock returns. Moreover, two of the banks that "failed" the stress tests had the lowest abnormal stock returns.

In summary, empirical evidence suggests that stress tests have strongly encouraged U.S. BHCs to increase their regulatory capital ratios notably over the last three years. In addition, there is some evidence that the disclosure of the stress test results to the public elicited significant reaction in stock markets and allowed market participants to better understand the risk profiles of each institution.

3 Econometric Methodology

In this section we introduce the fixed effects quantile autoregression model (FE-QAR) and the fixed effects dynamic linear panel model (FE-OLS). We use these models to generate h-step ahead predictions for net charge-offs of loan portfolios and subcomponents of pre-provision net revenue. These projections are key inputs to generate density forecasts for the tier 1 common regulatory capital ratio for each bank.

The dynamic panel quantile regression model is as follows:

$$Y_{it} = \alpha_i + \sum_{p=1}^{k} \phi_p(U_{it})Y_{it-p} + \beta(U_{it})'X_{it-1} + \theta(U_{it})'Z_t, \quad i = 1, \dots, N;\ t = 1, \dots, T, \tag{1}$$

where Y_{it} denotes, for example, annualized commercial and industrial (C&I) net charge-offs in period t for bank i, expressed as a percent of average C&I loans; α_i represents a bank fixed effect; Y_{it-p} is lag p of the dependent variable; X_{it-1} is a $(l \times 1)$-vector which includes observable bank-specific variables; Z_t is a $(k \times 1)$-vector of macroeconomic variables; U_{it} is a sequence of i.i.d. standard uniform random variables. In this context, the parameters $\phi_p : [0, 1] \to \mathbb{R}$, $\beta : [0, 1]^l \to \mathbb{R}^l$

and $\theta : [0,1]^k \rightarrow \mathbb{R}^k$ are unknown functions that must be estimated. Following Koenker (2004), we assume the bank specific effect is constant across the quantiles of the dependent variable. The bank fixed effects are intended to capture unobserved heterogeneity, so it might make sense to restrict the α_i to be constant across the quantiles of the dependent variable. The estimation of FE-QAR model solves the following minimization problem

$$(\hat{\alpha}, \hat{\phi}, \hat{\beta}, \hat{\theta}) = \min_{\alpha,\phi,\beta,\theta} \sum_{q=1}^{Q} \sum_{t=1}^{T} \sum_{i=1}^{N} \omega_q \rho_{\pi_q} \left(Y_{ij} - \alpha_i - \sum_{p=1}^{k} \phi_p(\pi_q) Y_{it-p} - \beta(\pi_q)' X_{it-1} - \theta(\pi_q)' Z_t \right) \quad (2)$$

where $\rho_\pi(u) = u(\pi - I(u < 0))$, denotes the piecewise linear quantile function of Koenker and Bassett (1978). As in Koenker (2004) the choice of the weights, ω_q control the relative influence of the Q quantiles on the estimation of the bank fixed effects, α_i. As for the standard errors of the parameter estimates we use the bootstrap. Generally, the FE-OLS and FE-QAR estimators are biased in the presence of lagged dependent variables as regressors. However, for relatively long panels the biases are negligible as the initial conditions have less of an effect on the fixed effect estimators.

By imposing the constraint that the right-hand-side of the random coefficient specification (1) is monotone in U_{it} allows us to write the conditional quantile of Y_{it} as

$$Q_\pi(Y_{it} \,|\, Y_{it-1}, \ldots, Y_{it-k}, X_{it-1}, Z_t) = \alpha_i + \sum_{p=1}^{k} \phi_p(\pi) Y_{it-p} + \beta(\pi)' X_{it-1} + \theta(\pi)' Z_t \quad (3)$$

where $\pi \in (0,1)$ indexes the conditional quantile function of the dependent variable.[4] In equation (3), both the coefficient on the lagged dependent variable, the coefficients of the bank-specific variables and the coefficients on the exogenous macroeconomic variables are allowed to vary over the quantiles of Y_{it}. The variation in the coefficients on the exogenous variables shifts the location of the conditional distribution of Y_{it} in response to firm-specific and macroeconomic developments, whereas the variation in the coefficient on the lagged dependent variable allows for the change in the scale and the shape of the distribution over time. These types of distributional dynamics are

[4]We estimate the conditional quantile function for $\pi = 0.005, 0.010, 0.015, \ldots, 0.995$.

likely to be important during periods of severe economic and financial stress and are impossible to capture with the standard linear regression framework.

More specifically, suppose that the dependent variable is C&I net charge-offs, the model includes one lag of the dependent variable and that the coefficient $\phi(\pi)$ is an increasing function of π. In that case, an adverse shock to credit quality will increase the persistence of C&I charge-offs, a development that will ultimately increase the heaviness of the right-hand tail of the conditional distribution of charge-offs. In contrast, an unexpected positive development in credit quality will reduce the persistence of the series, thereby accelerating the reversion of charge-offs to their long-run mean.

This feature of the FE-QAR model allows it to capture the type of asymmetry that seems to be a distinctive characteristic of credit losses, which exhibit significant persistence during cyclical downturns but decline fairly quickly when economic conditions improve. Another attractive feature of the FE-QAR model is that it naturally generates a forecast of the entire distribution of Y_{it}. Density forecasts are important because they allow us to calculate value-at-risk and expected shortfalls, statistics of central importance in risk management and capital planning.[5] Of course, it is not necessary to estimate quantile regressions to produce density forecasts.

We also consider the dynamic panel linear regression with bank specific effects

$$Y_{it} = \alpha_i + \sum_{p=1}^{k} \phi_p Y_{it-p} + \beta' X_{it-1} + \theta' Z_t + \epsilon_{it}, \quad i = 1, \ldots, N;\ t = 1, \ldots, T, \tag{4}$$

where ϵ_{it} are idiosyncratic errors that change across bank and time. We estimate model (4) using ordinary least squares. Below, we also construct the density forecast of the FE-OLS model based on the normality assumption of the residuals and by using the bootstrap.

[5] For example, under Pillar I of the Basel II Capital Accord, banks are required to hold capital to cover unexpected losses up to the 99.9th percentile. Thus, our top-down approach that focuses on the loss/revenue estimates in the extreme tails of the distribution strikes us as a logical and reasonable way to assess the bank-specific capital needs.

Density Forecasting

To account for the uncertainty associated with our projections for losses and revenues we construct density forecasts through Monte Carlo simulations.[6] Specifically, for the FE-QAR model the one-step-ahead forecast is equivalent to a random draw from the conditional quantile function, which is calculated as

$$\widehat{Y}^m_{iT+1}(j) = \widehat{Q}^m_{U_{1i}}(Y_{iT+1} \,|\, Y_{iT}, \ldots, Y_{iT-k+1}, X_{iT}, Z_{T+1}), \tag{5}$$

where $\widehat{Q}^m$ is the conditional quantile of model m and U_{1i} is the j-th draw from an i.i.d. standard uniform distribution. Because we will need the forecasts of various loss and revenue subcomponents simultaneously, we let the uniform random draw be correlated across all loss portfolios and revenue subcomponents. Below we present the results under two different set of assumptions. The first approach uses the errors from each model specification m, to calculate the variance-covariance matrix, $\widehat{\Omega}$, and uses the multivariate uniform distribution to draw the shocks. The second approach, bootstraps the residuals from each model directly to generate the density forecast.

For the two-step-ahead forecast, we iterate equation (5) forward to calculate

$$\widehat{Y}^m_{iT+2}(j) = \widehat{Q}^m_{U_{2}i}(Y_{iT+2} \,|\, \widehat{Y}^m_{iT+1}(j), \ldots, Y_{iT-k+2}, X_{iT+1}, Z_{T+2}), \tag{6}$$

where U_{2i} is a new draw from the uniform distribution. Applying equation (6) recursively yields a sample path—for the j-th draw—of forecasts $(\widehat{Y}^m_{iT+1}(j), \widehat{Y}^m_{iT+2}(j), \ldots, \widehat{Y}^m_{iT+H}(j))$. To construct the conditional density forecasts, we repeat the above procedure 5,000 times. A potential problem with this approach is that the predicted density often exhibits, in finite samples, a "quantile crossing" problem—that is, the predicted conditional quantile function $\widehat{Q}^m_\pi$ is not monotonically increasing in π (i.e., $\widehat{Q}^m_\pi < \widehat{Q}^m_{\pi'}$ for some $\pi > \pi'$). To solve this problem, we rearrange the predicted quantile function to make it monotone.[7]

We also generate density forecasts for the FE-OLS model. The one-step ahead forecast from

[6] For a survey on density forecasting see Tay and Wallis (2000).

[7] For more details, see Chernozhukov, Fernandez-Val, and Galichon (2010). In particular, the paper shows that, in finite samples, the rearranged curve is closer to the true quantile function.

the linear model is:

$$\widetilde{Y}_{iT+1}^{m}(j) = \tilde{\alpha}_i + \sum_{p=1}^{k} \tilde{\phi}_p Y_{iT-p+1} + \tilde{\beta}' X_{iT} + \tilde{\theta}' Z_{T+1} + \epsilon_{iT+1}(j), \tag{7}$$

where $\epsilon \sim N(0, \tilde{\sigma}^2)$, and $\tilde{\alpha}_i$, $\tilde{\phi}_1, \ldots, \tilde{\phi}_k$, $\tilde{\beta}$, $\tilde{\theta}$ are the FE-OLS estimates. We can then apply equation (7) recursively to generate a sample path for the j-th draw forecasts $(\widetilde{Y}_{iT+1}^{m}(j), \widetilde{Y}_{iT+2}^{m}(j), \ldots, \widetilde{Y}_{iT+H}^{m}(j))$. To generate the density forecasts we present results both based on the variance-covariance matrix of residuals and a bootstrap approach using 5,000 simulations.

4 Data Sources and Estimation Results

Data sources. Our sample includes 15 bank holding companies (BHCs) over the 1997:Q1–2011:Q4 period listed in Table 1. We started by selecting all BHCs with total consolidated assets of $50 billion or more at the end of the sample period. We have excluded credit card and custodial banks, and did not include banks that have recently become BHCs (e.g., Goldman Sachs, Morgan Stanley, Ally Financial) for the following reasons. First, most of the banks we excluded have a very distinct business model relative to the BHCs included in the final sample. Adding those banks would require a wider range of models, perhaps by estimating different models for different bank types, which is beyond the scope of the paper. Second, the small time-series dimension of the recent BHCs likely requires an instrumental variable estimation approach to obtain consistent estimators for dynamic panel data models (Galvão Jr. 2011). For these reasons and to simplify the analysis we estimate both the FE-OLS and FE-QAR model specifications using a balanced panel with 15 BHCs. It would be, however, straightforward, to augment the models to different bank types and banks with shorter time-series.

We model net charge-offs for eight major loan portfolios and also split pre-provision net revenue (PPNR) into six subcomponents. For each of the fourteen series we estimate models (4) and (1) as described in the previous section. Net charge-offs are defined as charge-offs net of recoveries scaled by average loans during the corresponding quarter. We model net charge-offs for the following eight major loan categories: (1) C&I = commercial and industrial; (2) CLD = construction and land development; (3) MF = multifamily real estate; (iv) NFNR = nonfarm/nonresidential commercial real estate; (v) HLC = home equity lines of credit (HELOCs); (vi) RRE = residential real estate, excluding HELOCs; (vii) CC = credit card; and (viii) CON = consumer, excluding credit card loans. To speed-up the calculations we have only included the major loan portfolios. In particular, we excluded loans to depository institutions, loans to foreign governments, leases, farm loans and other loans from the analysis.

In addition, we also model the following six subcomponents of PPNR: (1) NIM = net interest margin; (2) TI = trading income; (3) ONII = noninterest income, excluding trading income; (4) CE = compensation expense; (5) FA = fixed assets expense; and (6) ONIE = other noninterest expense. All PPNR subcomponents are scaled by the average total assets during the corresponding quarter.[8] The series for each bank are expressed in annualized percent. All bank-level data were obtained from the FR-Y9C reports published by the Federal Reserve Board. To deal with the large number of mergers that occurred during the period of our analysis, we merger-adjusted the data by constructing a virtual bank that aggregates all entities that merged during our sample, to the extent data is available. Under this approach we combine, for example, Wells Fargo and Wachovia since the start of our sample. Once constructed, each series was seasonally adjusted using the X11 (additive) filter.

The set of macroeconomic variables used in our forecast exercise includes the following seven series: GDP_t = real gross domestic product; UR_t = (civilian) unemployment rate; P_t^{HP} = CoreLogic house price index; P_t^{CRE} = NCREIF transactions-based price index for commercial real estate; Treas_t^{3m} = 3-month Treasury yield; Treas_t^{10y} = 10-year Treasury yield; and BBB_t^{10y} = 10-year yield on BBB-rated corporate bonds. We restricted the set of macroeconomic variables to the ones available in the scenarios provided by the Federal Reserve to BHCs during previous comprehensive stress testing exercises.

Table 2 provides summary statistics for the set of variables used in the empirical analysis. It documents, for example, that loan losses are on average higher for credit card and construction

[8]Reported noninterest expense includes goodwill impairment losses, which have been especially large during the recent financial crisis, causing large—and hopefully one-off—swings in PPNR. To minimize the transitory noise associated with such accounting changes, we excluded goodwill impairment losses from the calculation of PPNR.

and land development loans. On the revenue side, about half of bank revenues are generated from interest income on loans, and noninterest/nontrading income, such as fiduciary income and investment bank fees, also accounts for a sizable share of revenues. On the cost side, the largest item of pre-provision net revenue is compensation expense. Finally, note that the sum of loan share for the median bank is about 70 percent, which indicates that the loan portfolios used in the analysis do not include all loan portfolios at banks. The remaining portfolios typically have very low charge-offs and exhibit a weak sensitivity to the business cycle.

Estimation Results

Before delving into our main results, we present in Table 3 the model estimates of the FE-OLS forecasting regression model for the eight loan loss series and the six subcomponents of PPNR. The lag order of the dependent variable is set equal to 4 following Guerrieri and Welch (2012). The remaining bank-specific variables and set of macroeconomic variables were selected using the Bayesian information criteria (BIC). We allowed lags of the macroeconomic variables to enter in each model specification, but in the large majority of models the BIC selected the contemporaneous value of the relevant macroeconomic variable.

As evidenced by the entries in the table, the coefficients on the bank-specific and macroeconomic variables have the economically intuitive sign and almost all are statistically significant at conventional levels. We enhance the robustness of the statistical inference by clustering standard errors by both bank and time. This two-way clustering has been discussed for example by Cameron, Gelbach, and Miller (2011). Moreover, all regressions fit the data relatively well, a result that is due in part to the presence of the lagged dependent variables, which captures the persistent dynamics of loan losses and most subcomponents of PPNR. For the estimation of the FE-QAR models we used the exact same covariates as the ones of the FE-OLS model specifications.

The nonlinear aspects of cyclical dynamics of credit losses is illustrated in the top left panel of the first row of Figure 3, which shows the sum of the estimated autoregressive terms increasing across the quantiles of the dependent variable for losses in the residential real estate portfolio (excluding HELOCs). Moreover, the degree of persistence of the dependent variable is higher across all quantiles of the dependent variable compared to the sum of the FE-OLS autoregressive coefficients reported in Table 3, and showed by the dashed line also in the top left panel. These empirical regularities are common across all eight net charge-off series. As discussed earlier, an attractive feature of the FE-QAR approach is that it allows the degree of persistence of the process to vary across the quantiles of the conditional distribution—that is, in periods of deteriorating credit quality, loss rates become considerably more persistent. At lowest quantiles, in contrast, loss rates exhibit only a moderate degree of serial dependence, implying a relatively quick reversion to steady state. However, as shown in the top right panel of Figure 3, the coefficient on house prices appears to vary less across the quantiles of the conditional distribution and is slightly smaller in magnitude relative to the FE-OLS coefficient reported in Table 3. As shown below, the projections for loan losses will be mainly driven by the degree of persistence of the process; the somewhat decreased sensitivity to the macro variables is more than compensated by the increase in persistence of the dependent variable, particularly when loan losses are elevated.

Compared with the net charge-off rates, the degree of persistence of the net interest margin—shown in the bottom left panel of Figure 3—varies a lot less across the quantiles of the dependent variable. In contrast, the degree of persistence of trading income—shown in the bottom right panel of Figure 3 decreases across the quantiles of the dependent variable. The intuition for this result is similar to what we estimated for loan losses since high trading losses correspond to low trading income. Thus, in periods of high trading losses the series becomes more persistent, which will increase the heaviness of the left-hand tail of the conditional distribution of trading income. For the remaining subcomponents of PPNR we do not reject the null hypothesis that the sum of the autoregressive terms is invariant across the quantiles of the dependent variable. The only other exception is noninterest expense, where the sum of the autoregressive terms increase somewhat across the quantiles of the dependent variable. The noninterest expense component includes charges for litigation risks associated with banks' mortgage portfolios. These charges have been elevated in the aftermath of the recent financial crisis.

5 Out-of-Sample Forecast Performance

To generate forecasts for the eight loss series and six subcomponents of revenues we need the estimated coefficients, the values of the bank-specific exogenous variables and the trajectory of macroeconomic variables over the forecast horizon. We assume that the values of the explanatory variables—with the exception of the lagged dependent variable—are equal to the realized values during the evaluation period. More specifically, for the FE-QAR model we need the coefficients of the underlying quantile process, $\hat{\alpha}_i$, $\hat{\phi}_1(\pi), \ldots, \hat{\phi}_4(\pi)$, $\hat{\beta}(\pi)$, $\hat{\theta}(\pi)$, for $\pi \in (0,1)$. With these inputs, and the values of the exogenous explanatory variables we construct the predicted conditional quantile function of Y_{iT+h}, denoted by $\widehat{Q}^m_{\pi,iT+h}$, for $\pi \in (0,1)$ and $h = 1, \ldots, 8$ as described in Section 3. The FE-QAR and FE-OLS models generate predictions for each bank, however to summarize the results in an efficient manner we report the forecasts by aggregating the projections across all banks in our sample. The aggregation is performed within each Monte Carlo simulation by adding losses and revenues across all banks, respectively. Each bank is weighted using the corresponding level of loans and total assets which is assumed to be known.

Figure 4 shows the out-of-sample density forecasts for net-charge offs over the 2005:Q1–2011:Q4 period. The top two panels depict the one-quarter-ahead forecasts and the bottom two panels display the four-quarters-ahead forecasts. The density forecasts are represented using several percentiles of the predicted density that range between the 1^{st} and 99^{th} percentiles. The left column shows the out-of-sample forecasts under the FE-QAR model and the right column the out-of-sample forecasts obtained using the FE-OLS model. These density forecasts were generated using the variance-covariance matrix of the residuals. For both the one- and four-quarters ahead forecasts the projected densities under the FE-QAR model exhibit fatter tails than the projected densities generated using the FE-OLS model, especially during the last financial crisis. For example, realized net charge-offs peaked in the first quarter of 2010, corresponding to the 98^{th} percentile of the density forecast generated using the FE-QAR model, however it is outside the density forecast generated using the FE-OLS model. More broadly, realized losses are outside the one-quarter-ahead density forecasts generated using the FE-OLS model in the second and third quarters of 2008, and in the first, second and third quarters of 2010. In contrast, realized losses are never outside the one-quarter-ahead density forecasts generated using the FE-QAR model.

The bottom two panels of Figure 4 plots the four-quarters-ahead forecasts of aggregate net-charge offs. Forecasting performance deteriorates somewhat as we increase the forecast horizon for both model specifications. In particular, the second, third and fourth quarters in 2008 and the first quarter of 2010 are outside the four-quarters-ahead density forecasts generated using the FE-OLS model. None of the quarters are outside the density forecasts of the FE-QAR model, however one quarter is above the 99^{th} percentile during the run-up of net charge-offs during 2008. It appears, both the quantile and the linear models had a tendency to understate loan losses during the last financial crisis, however this problem is ameliorated using the FE-QAR model since the projected density forecasts exhibit fatter tails. One reason to use the top percentiles of the density forecast during a crisis would be a reasonable approach for portfolios that did not experience meaningful losses during past recessions.

Figure 5 shows the out-of-sample density forecasts for PPNR. The actual PPNR series appears to behave a bit more erratic and therefore more difficult to forecast. In particular, there are very large swings in PPNR during the last recession, and there is some evidence the FE-QAR model captures slightly better that phenomenon. For example, the large swings in PPNR in 2008 and 2009 are usually inside the density forecast of the FE-QAR model, in contrast to what happens with the FE-OLS model. These density forecasts are also generated using the variance-covariance matrix of the errors of each model specification.

To formally assess the forecasting performance of each model, we calculate the realization of the process taken with respect to the estimated conditional density function. Specifically, for one-quarter-ahead forecasts, we calculate a sequence of statistics $z_t^h \in (0,1)$, for $h = 1, \ldots, 4$ and $t = 2005\text{:Q1}, \ldots, 2011\text{:Q4}$, where z_t^h solves the following equation:

$$Y_{t+h} = \int_0^{z_t^h} \widehat{P}^h(s)ds,$$

where Y_{t+h} denotes actual aggregate net charge-offs and pre-provision net revenue in quarter $t+h$

and $\widehat{P}^h$ represents the inverse of the cumulative distribution of the density forecast h-quarters-ahead. We use this sequence of statistics to test the null hypothesis that z_t^h is distributed according to an i.i.d. uniform distribution; the rejection of the null hypothesis is evidence that the density forecasts are not optimal.[9] We use the following two tests to test for the optimality of the density forecasts: (1) the χ^2 goodness-of-fit test, which compares the histogram of z_t^h with that of the standard uniform distribution; (2) the "Ljung-Box" test of serial correlation in $(z_t^h - \bar{z}^h)$. For test (1) the null hypothesis is that z_t^h is uniformly distributed; for test (2), the null hypothesis is that there is no serial dependence of up to four lags in the first moment of z_t^h. Table 4 provides the p-values for each of the two tests and forecast horizons.

Keeping in mind that the out-of-sample forecast evaluation period is quite short (i.e., we are using 28 quarters for out-of-sample evaluation), the p-values in Table 4 indicate that the near-term forecasts of aggregate net charge-offs have desirable statistical properties. For $h = 1$ we do not reject the null hypothesis of uniformity in z_t^h and there is little evidence of serial correlation. These statistical properties of the density forecasts of net charge-offs, however, deteriorate noticeably as the forecast horizon extends beyond the very near term, in particular beyond $h = 1$ the probability integral transform of the forecast exhibits a considerable amount of persistence. This is consistent with the out-of-sample forecasts depicted in Figure 4, which shows the realized net charge-offs with respect to the forecasted density consistently close to 1 during the financial crisis period. For aggregate pre-provision net revenue, the forecasts seem to be farther away from the "correct" density since we reject the null hypothesis of uniformity even at shorter horizons. In contrast, there is less evidence of serial correlation in the probability integral transform of the PPNR forecast.

6 Estimating Capital Shortfalls at U.S. BHCs

In this section we illustrate the potential of our "top-down" models to estimate the capital shortfalls of U.S. bank holding companies. We use the projections for net-charge-offs and pre-provision net revenue to simulate the T1CR for each BHC in our sample. We show that the projections obtained using the linear and quantile models result in sizable capital shortfalls at banks at the onset of

[9]The evaluation of densities is discussed by Diebold, Gunther, and Tay (1998).

the financial crisis. In addition, since the quantile model is better suited to capture some of the nonlinearities in credit losses and revenues, it generates fatter left tails for the distribution of T1CR and higher capital shortfalls. Just for benchmark purposes, and to report results based using the entire span of our data, we also construct the distribution of T1CR using the supervisory stress scenario provided to banks under CCAR 2012.

Capital calculator

We start by describing the mapping between the conditional forecasts of net charge-offs and pre-provision net revenue into the tier 1 common capital risk-based ratio. To focus on the differences between the quantile and linear model we constructed a relatively simple mapping between loan losses, net revenues and the evolution of bank equity. In particular, we assume the equity capital of bank i evolves as follows:

$$E_{it} = E_{it-1} + (1-\tau) \times \left(\sum_{j=1}^{6} \widehat{\text{PPNR}}_{it}^{j} \times \overline{\text{Assets}}_i - \sum_{j=1}^{8} \widehat{\text{NCO}}_{it}^{j} \times \overline{\text{Loans}}_i^{j} \right) - \overline{\text{Equity Payouts}}_i$$

where E_{it-1} denotes book equity of bank i at the beginning of period t, τ is the marginal tax rate, $\widehat{\text{PPNR}}_{it}^{j}$ and $\widehat{\text{NCO}}_{it}^{j}$ are the projections for net revenues and net charge-offs, respectively. Note that charged-off loans are taken directly from the allowance for loan and lease losses (hereafter loan loss reserves) and, therefore, do not impact earnings directly. Banks can increase loan loss reserves through provisions, which affect bank earnings directly. For simplicity we assume provisions are equal to net charge-offs. Furthermore, in the spirit of the U.S. stress tests we assume banks have to maintain lending capacity even under adverse economic conditions, thus we let assets and loans balances to remain constant throughout the projection period. Equity payouts are equal to dividends paid on common and preferred stock and repurchases of treasury stock, and we assume the bank is unable to issue new equity since during a stressful event it is prohibitively costly for a BHC to issue new equity. Also for simplicity, we assume equity payouts are constant. In a "live" exercise information on dividend payout and share repurchases is provided by banks to the Federal Reserve, and the stress testing results are conditional on requested dividend payouts.

As pointed out in Section 2, the T1CR is the capital ratio that is more likely to bind during an adverse macroeconomic scenario. This ratio is defined as the regulatory tier 1 capital less non-common equity elements. To map book equity to tier 1 common capital we subtract the dollar amount of regulatory capital deductions from total equity and assume deductions are constant throughout the projection period. Finally, we assume other comprehensive income, and other adjustments to equity capital to be zero over the projection period. Thus, the tier 1 common ratio in our exercise is defined as follows:

$$\mathrm{T1CR}_{it} = \frac{E_{it} - \overline{\mathrm{Deductions}}_i}{\overline{\mathrm{RWA}}_i}$$

where $\overline{\mathrm{Deductions}}_i$ includes all regulatory capital deductions under Basel I and additional tier 1 common deductions and $\overline{\mathrm{RWA}}_i$ denotes Basel I risk-weighted assets at the start of the exercise.

2007-2009 Financial Crisis

In our first exercise we start the projections of credit losses and revenue components in the first quarter of 2008. At the end of 2007 there was already evidence of signs of stress in financial markets. For example, the securitization market for non-conforming mortgages was essentially closed and delinquencies in residential real estate loans were increasing at a rapid pace. We estimate the FE-QAR and FE-OLS models until the fourth quarter of 2007 and use the realized macro variables to generate density forecasts for net charge-offs and pre-provision net revenue over the next 8 quarters until the end of 2009. Following that we apply the regulatory capital calculator and evaluate the distribution of T1CR at the end of 2009.

Table 5 provides selected moments of the T1CR distribution in the fourth quarter of 2009. The top panel shows the results based on Monte Carlo simulations generated using the variance-covariance matrix of the residuals and the bottom panel shows the results using bootstrapped errors. In both simulations we find that the FE-QAR model generates fatter tails for the T1CR distribution relative to the FE-OLS model. Namely, in the top panel the 1^{st} percentile of the T1CR distribution for all banks is 3.1 percent under the FE-QAR model and 3.7 percent under the FE-OLS model. Note that the differences in the first percentile of the T1CR distribution at the bank level are usually wider than the distribution for all banks since the aggregation of T1CR across banks makes the tail of aggregate T1CR distribution less fat-tailed since these shocks are independent and identically distributed. There is also a similar diversification effect in the aggregation of the various portfolios within a bank. The 5^{th} percentile is also lower for the FE-QAR model. However, the conditional mean prediction is slightly higher for the FE-QAR model, that is the FE-OLS model predicts a stronger decline in the mean T1CR. The results for all banks using bootstrap errors are similar to the results generated using the variance-covariance matrix of residuals, however there are differences at the bank level because under the bootstrap approach banks draw only from their own past shocks. For example, banks that experienced large trading and banking book losses simultaneously report a fatter left tail for the T1CR distribution at the end of the projection horizon.

The top panels of Figure 6 plot the density forecasts of aggregate net charge-offs for the quantile and linear models. Similarly, the bottom panels plot the density forecasts of aggregate PPNR. The fatter tails of T1CR in the FE-QAR model are explained by both higher fatter right tail for net charge-offs as well as higher left tail for net revenues. For losses, the difference arises mainly from the behavior of the autoregressive terms in the quantile model, particulary for the residential real estate portfolio, as suggested by the top panel in Figure 3. The heaviness of the right-tail of the density forecast is explained by the fact that the sum of the autoregressive terms in the quantile model is an increasing function of the level of net charge-offs. When an adverse shock leads to an increase in credit losses, the persistence of the series increases which amplifies the impact of the adverse shock on credit losses. Similarly, the lower percentiles of PPNR under the quantile model are almost entirely driven by losses in the trading book which are highly nonlinear. In the case of trading income, the sum of the autoregressive terms in the quantile model is a decreasing function of the level of trading income as shown in the bottom right panel of Figure 3.

Figures 7–8 display the T1CR distribution under the variance-covariance and bootstrap Monte Carlo simulation assumptions, respectively. The two panels confirm the findings presented in Table 5 which showed fatter tails for the T1CR based on the quantile regression model. The Figure also shows that the quantile model generates a distribution with a larger variance than the linear model. We believe that it can be attributed to the weak sensitivity of loan losses to changes in the macro variables when we estimate the models only using data until the fourth quarter of 2007. In particular, we do not observe a gap in the variance of the two distributions when the linear and quantile models are estimated using the full sample.

In stress testing the first important statistic is to know the probability a bank is unable to maintain its minimum regulatory capital ratio during a stressful event. Equally important, is to know the size of the capital shortfall, that is the average amount of capital a bank needs to avoid going below the minimum capital requirement. In risk management this statistic is known as the expected shortfall, which is defined as the expected amount of capital needed conditional on the capital ratio being below a certain requirement, τ. Specifically, letting $\widehat{p}_i^h$ denote the conditional density forecast of T1CR at the h-quarter-ahead horizon for bank i, the corresponding expected shortfall associated with capital level τ is calculated as

$$ES_{i\tau}^h = E[\widehat{C}_{iT+h} \,|\, \widehat{C}_{iT+h} \leq \widehat{C}^h(\tau)] = \mathrm{RWA}_{iT} \times \frac{1}{\tau} \int_{-\infty}^{\tau} [\tau - \widehat{p}^h(s)] ds. \tag{8}$$

where $\widehat{C}_{iT+h}$ represents the projected bank i tier 1 common capital in period $T+h$. Table 6 presents the probability banks are unable to maintain its minimum regulatory capital ratio and the expected capital shortfall. We consider a minimum capital requirement of 2 percent for T1CR, which is when the prompt corrective action provisions require supervisors to close a bank and a 4 percent requirement which was the minimum requirement adopted for the 2009 stress test exercise.

Looking first at the T1CR requirement of 2 percent, the average probability of failure is estimated to be 3 percent under the quantile model and 1 percent under the linear model. The aggregate number masks a significant amount of heterogeneity across banks. For example, C has a probability of failure of 23 percent at the end of 2009:Q4 using the quantile model and 17 percent using the linear model. In contrast, ZION has zero probability of failure according to the quantile and linear models. Because the quantile model generates T1CR distributions with fatter tails most banks have a nonzero probability of failure. Capital shortfalls based on the density forecast generated using the quantile model are also . For example, the estimated capital shortfall for C is about \$24 billion, that is the amount C would need to avoid violating the 2 percent T1CR constraint. The capital shortfall of JPM is \$15 billion, however the difference relative to C is that it reports a much lower probability of failing. Another interesting result is that the capital shortfall of the industry is lower than the sum of the capital shortfalls across all banks since the shocks used to generate the density forecasts are not perfectly correlated across banks.

Increasing the target T1CR from 2 to 4 percent rises the probability of failing the stress test from 3 to 30 percent. Based on the T1CR density forecasts the target of 4 percent is no longer at the tail of the distribution, hence the linear model generates, on average, a higher probability of violating this requirement. Recall also that Figure 7 showed that the T1CR distribution generated using the linear model has lower variance than the one generated using the quantile model. Because with the higher T1CR capital requirement several banks are expected to violate that target simultaneously, the capital shortfall is about \$29 billion for both model specifications. At the bank level, the expected capital shortfall is in almost all cases higher for the quantile regression model, in particular for the cases where the probability of violating the 4 percent T1CR threshold is not close to 1.

The stress tests conducted in the U.S. use the conditional mean forecast of regulatory capital ratios to evaluate whether a bank passes or fails the stress test. Based on the results of our model a bank may "pass" a stress test by having the mean T1CR above the minimum requirement, but still report a nonzero capital shortfall. For example, BAC's mean T1CR reported in Table 5 was 4.3 percent at the end of 2009. Since the ratio is above the threshold of 4 percent, BAC would have "passed" the stress test. However, as shown in Table 6, there is still a 31 percent probability BAC would end up the period below 4 percent in the fourth quarter of 2009, which generates a capital shortfall of \$12.3 billion. The density forecast of T1CR gives a more complete capital adequacy assessment because it also incorporates information about the uncertainty surrounding our estimates. Another advantage of this approach is that it creates less incentives for banks to submit capital plans that are just enough to pass the stress test. That is, even if the average T1CR is above the minimum requirement, as long as there is a nonzero probability of violating the T1CR requirement a bank would have a capital shortfall. In that case, the bank would be required to review its capital plan and reduce the capital shortfall to zero.

CCAR 2012

In our second exercise we simulate losses and net revenues over 9 quarters starting in the fourth quarter of 2011 and until the end of 2013. For the path of the macro variables we use the severe adverse stress scenario provided to banks by the Federal Reserve for CCAR 2012. The goal of this exercise is re-estimate the top down models including all data until the third quarter of 2011 and verify if the quantile model still generates fatter tails than the linear model.

Table 7 summarizes our findings. As reported in the table the 1^{st} and 5^{th} percentiles of the T1CR distribution are lower using the quantile model. This finding confirms our previous result that the quantile model generates fatter tails than the linear model. In addition, the change in conditional mean prediction is now about the same for the two models. For example, according to the quantile model the severe adverse macro scenario would cause the mean T1CR of all banks in our sample to fall from 9.7 to 7.1 percent. The Monte Carlo results based on the bootstrap approach, shown in the bottom panel of Table 7, are also similar to the results obtained using the variance-covariance approach.

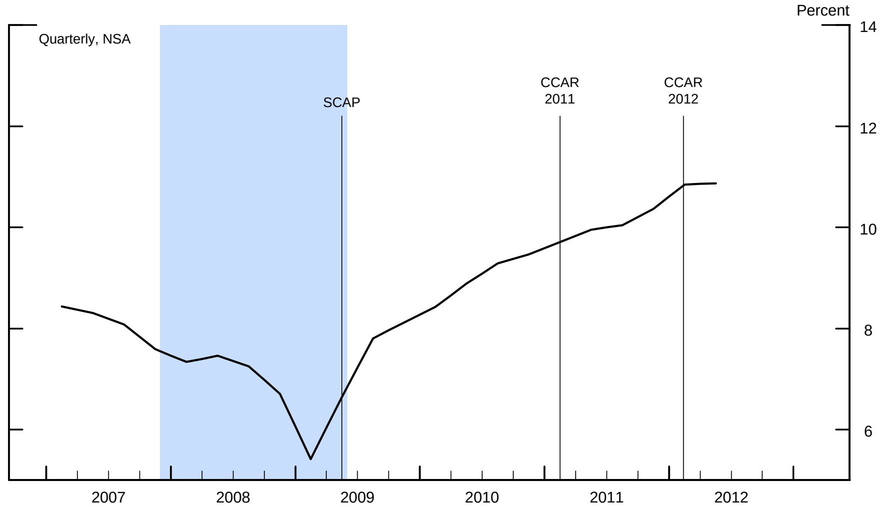
The top panel of Figure 9 plots the density forecasts of aggregate net charge-offs under the quantile and linear models, respectively. The gap in the right tail of aggregate net charge-offs is less wide using the full sample, because the inclusion of the financial crisis in the sample improved the sensivity of losses in the residential real estate portfolios to house prices and unemployment in the linear model. The bottom panel displays the projections for aggregate PPNR under the quantile and linear models, respectively. Again, differences between the models are not as dramatic as in the previous exercise, however the left tail of PPNR is considerably more heavy under the quantile model.

Currently, U.S. bank holding companies' T1CR are at historically high levels. This is in part due to existing restrictions on capital distributions that are in place at some of the largest BHCs. Because the T1CR is considerably higher in the third quarter of 2011 than at the end of 2007 we considered a minimum capital requirement of 5 percent for T1CR—as in CCAR 2012—and a minimum requirement of 8 percent, which is closer to a G-SIFI capital requirement. In the simulation of T1CR we used the same dividend payouts as in the previous exercise. Alternatively, we could have assumed the same dividend payouts as in 2011, but thought it would be more interesting to compare the distributions of T1CR under a similar set of assumptions for capital distributions. Overall, we arrive at very similar conclusions as in the previous exercise with the quantile model generating fatter tails than the linear model as shown in Figures 10–11. In addition, even at today's levels of regulatory capital ratios banks in our sample would be expected to violate the 5 and 8 percent T1CR minimum capital requirements 28 and 77 percent of the time under a severe macroeconomic scenario, respectively. But of course we assumed equity payout ratios set at 2006 levels, which is probably not very realistic in the current environment.

7 Conclusion

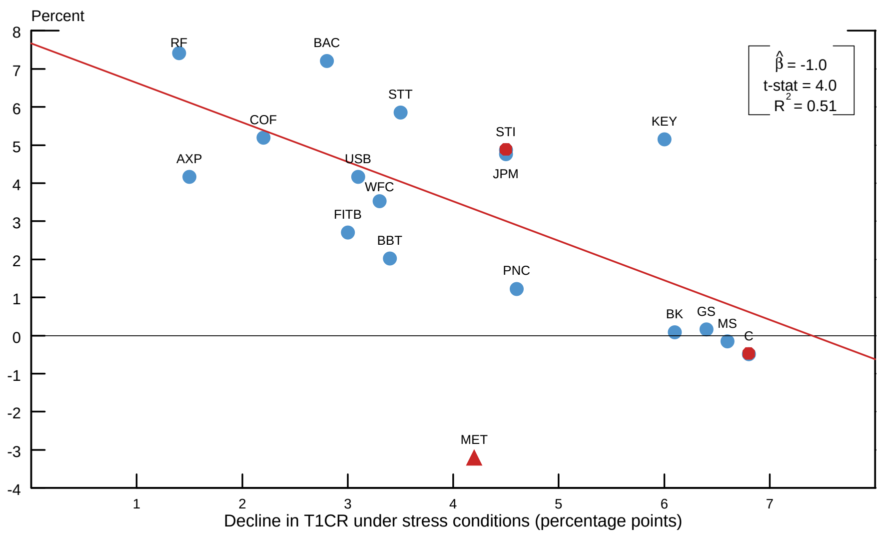
Macro-stress testing is becoming a key element of the macroprudential toolkit. The results of stress tests tell whether banks have enough tier 1 common equity to absorb losses incurred during a severely adverse macro scenario without triggering an excessive reduction in assets. We have shown that dynamic panel quantile regression models are well-suited in capturing nonlinearities observed between bank losses and macroeconomic outcomes. In particular, the density forecasts of T1CR generated using the quantile model exhibit fatter left tails relative to the density forecasts constructed using the linear model. Thus, "top-down" stress-testing models based on quantile regressions have higher odds of identifying vulnerabilities in financial stability than linear models. Moreover, our approach generates density forecasts for bank losses, revenues and regulatory capital ratios. These are important because not only they provide a complete description of the uncertainty surrounding our projections, but they also allow the calculation of the capital ratios associated with particular percentiles of the distribution and the expected capital shortfall. These are important statistics in our view for at least two reasons. First, having a density forecast gives a range of possible T1CR outcomes, which can be very useful to assess the outcomes of bottom-up approaches and the estimates submitted by the banks. Also, as pointed out by Pritsker (2011), the macro and financial variables used in U.S. stress tests may not capture enough risks banks are exposed to. Second, under current stress tests a bank gets a pass if its mean projected T1CR is above the minimum requirement set by regulators. This criteria creates an incentive for a bank to submit a capital distribution plan that would just be enough to receive a pass in the stress test. By using a density forecast to evaluate a bank's capital plan, regulators would reduce the incentive for banks to adopt this strategy, since a bank that would just pass the stress test in a conditional mean sense would still have a sizable capital shortfall based on the density forecast approach. Finally, "top-down" models can be very useful in the design of stress scenarios since they allow to assess the sensitivity of the size of capital shortfalls to the severity of macro scenarios.

Figure 1: Tier 1 Common Ratio, CCAR BHCs



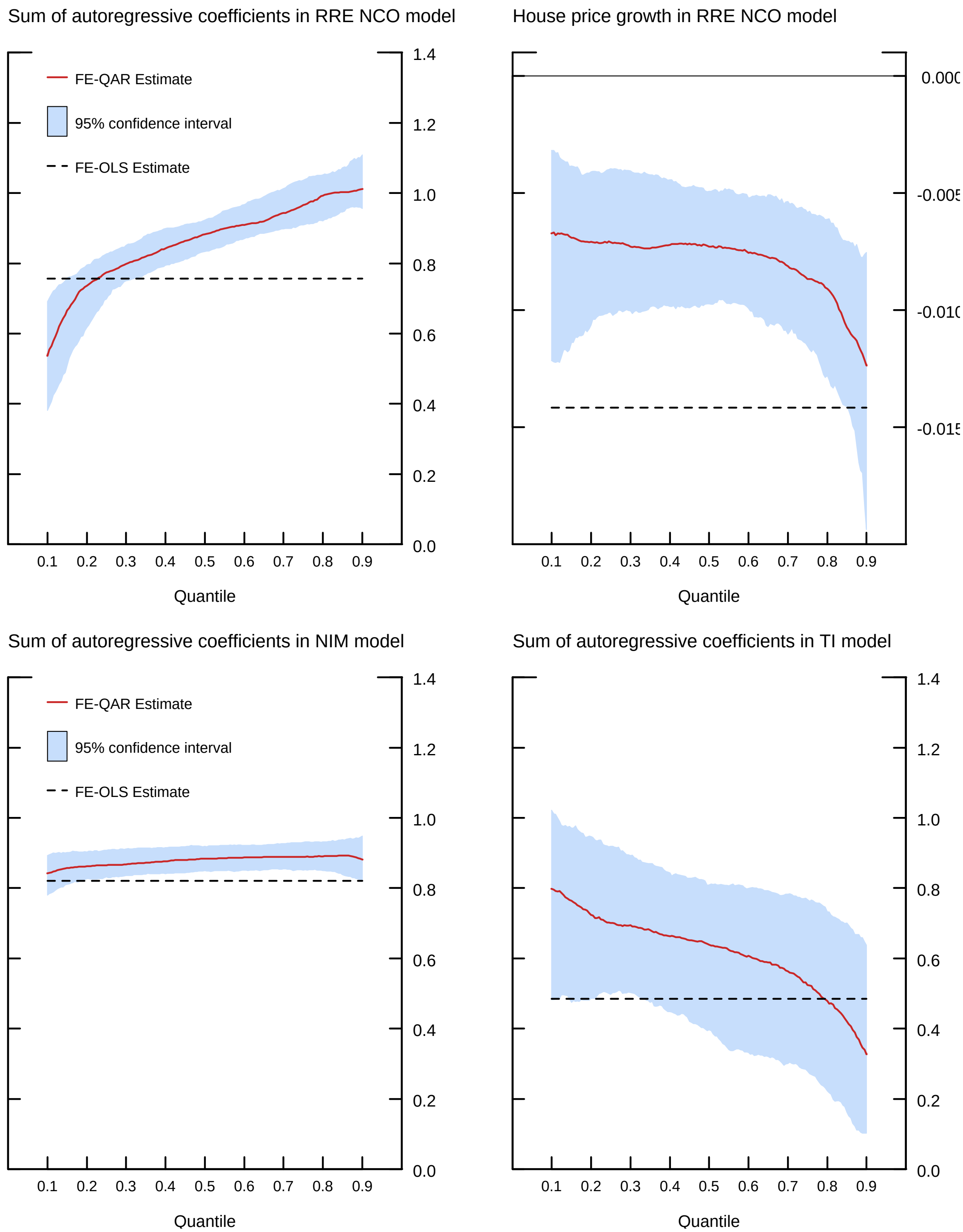
NOTES: (1) Tier 1 common ratio means the ratio of tier 1 common capital to its total risk-weighted assets. Tier 1 common capital is calculated as tier 1 capital less noncommon elements in tier 1 capital, including perpetual preferred stock and related surplus, minority interest in subsidiaries, trust preferred securities, and mandatory covertible preferred securities; and (2) the BHCs that participated in SCAP, CCAR 2011, and CCAR 2012 are Ally Financial Inc. (formerly known as GMAC LLC), American Express Company, Bank of America Corporation, The Bank of New York Mellon Corporation, BB&T Corporation, Capital One Financial Corporation, Citigroup Inc., Fifth Third Bancorp, The Goldman Sachs Group, Inc., JPMorgan Chase& Co., Keycorp, MetLife, Inc., Morgan Stanley, The PNC Financial Services Group, Inc., Regions Financial Corporation, State Street Corporation, SunTrust Banks, Inc., U.S. Bancorp, and Wells Fargo & Company.

Figure 2: Abnormal Stock Returns, CCAR 2012 BHCs



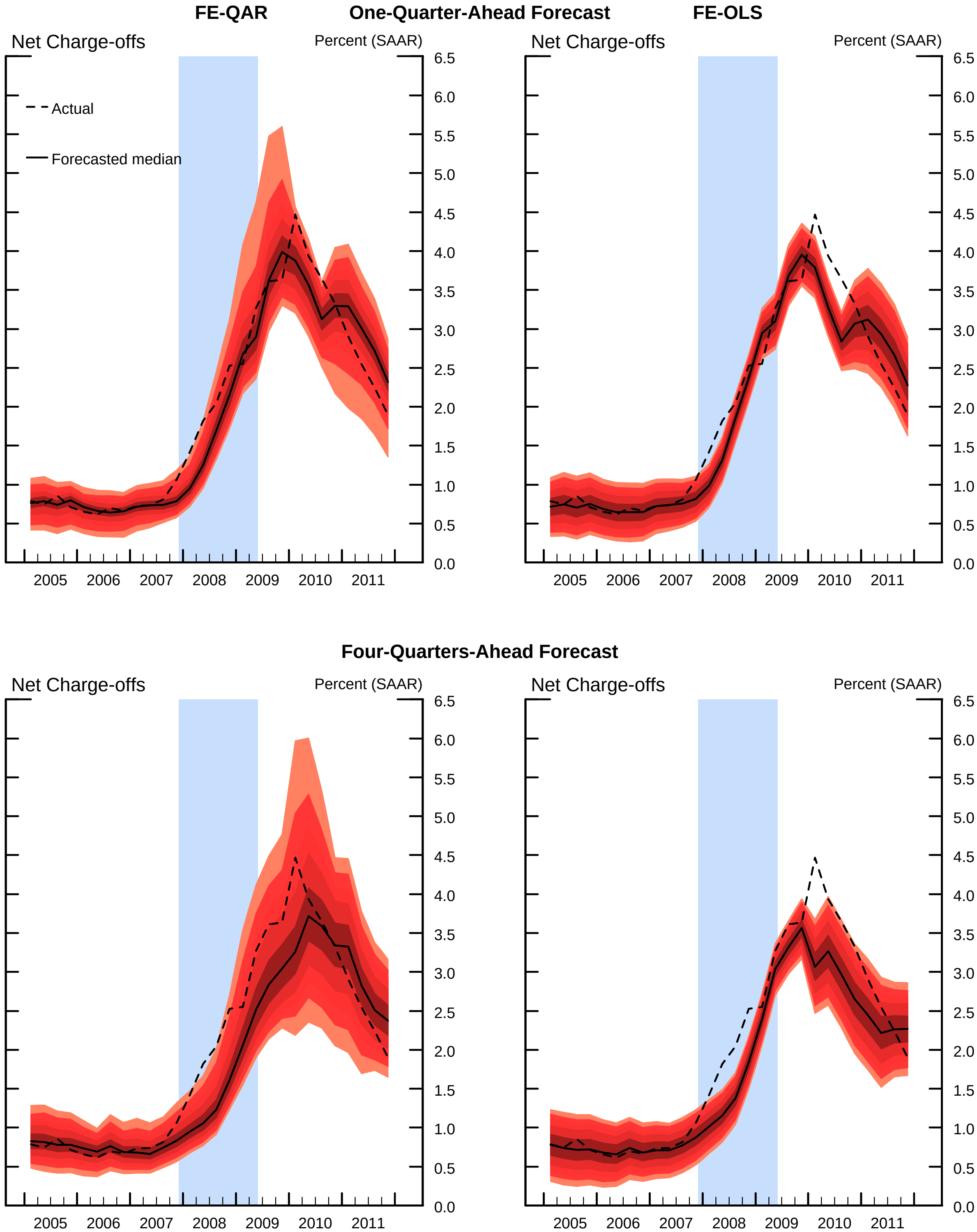
NOTES: Abnormal stock returns are estimated using the capital asset pricing model on daily stock returns between February 8, 2012 and March 12, 2012. The event period is two days, March 13-14, 2012. The decline in T1CR is defined as T1CR in Q3 2011 less the Minimum Stressed T1CR as reported in Board of Governors of the Federal Reserve System (2012). The regression results reported in the top right of the chart exclude MetLife (see text for details). The red symbols represent the banks for which the Federal Reserve objected to their capital plans.

Figure 3: Selected Coefficients of Various FE-QAR Model



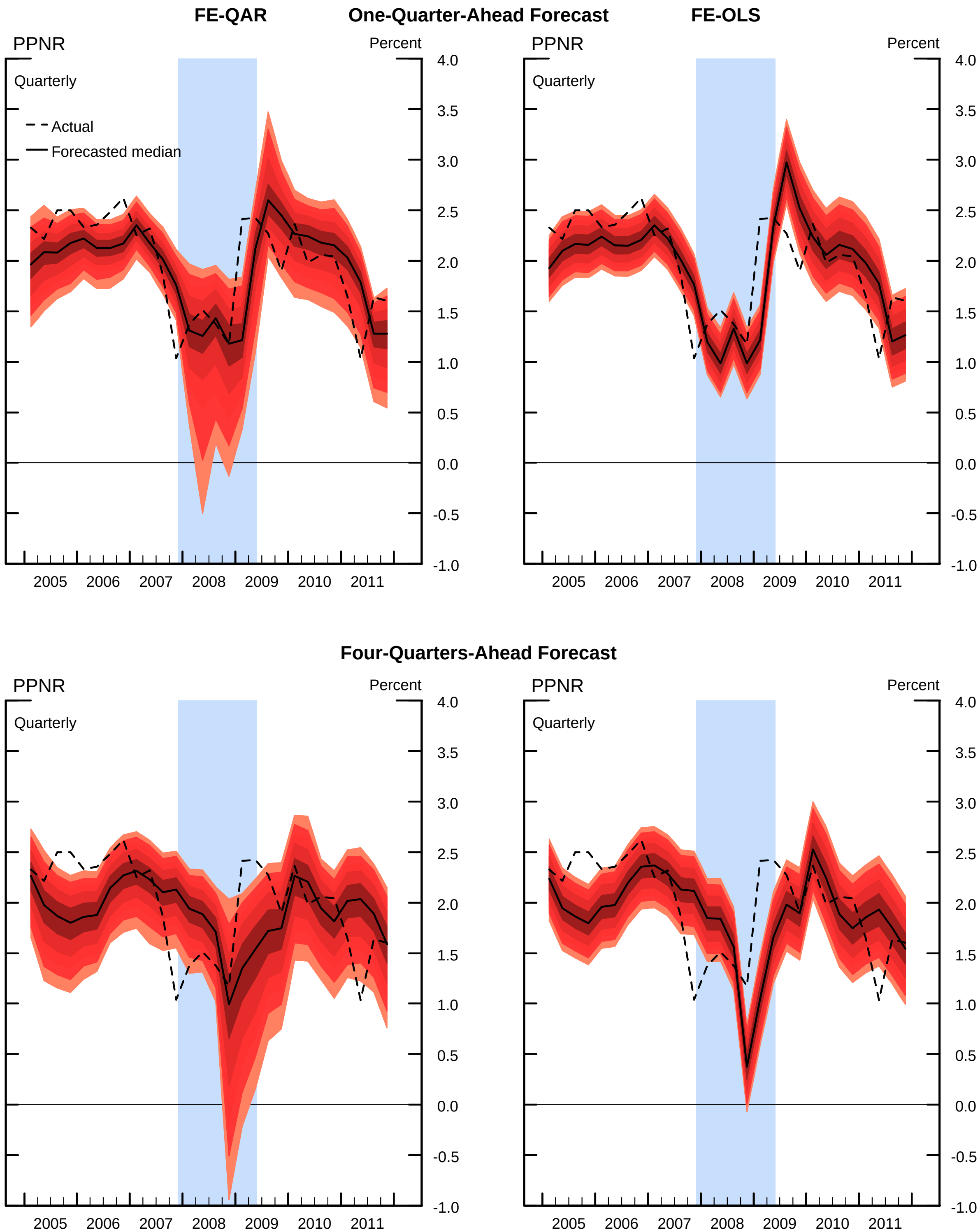
NOTE: The solid line in each panel depicts the estimate of the coefficients of the quantile process given by equation (1) for selected series. The shaded bands represent 95-percent confidence intervals obtained using a bootstrap Monte Carlo procedure.

Figure 4: Out-of-Sample Forecasts for Aggregate Net Charge-Offs



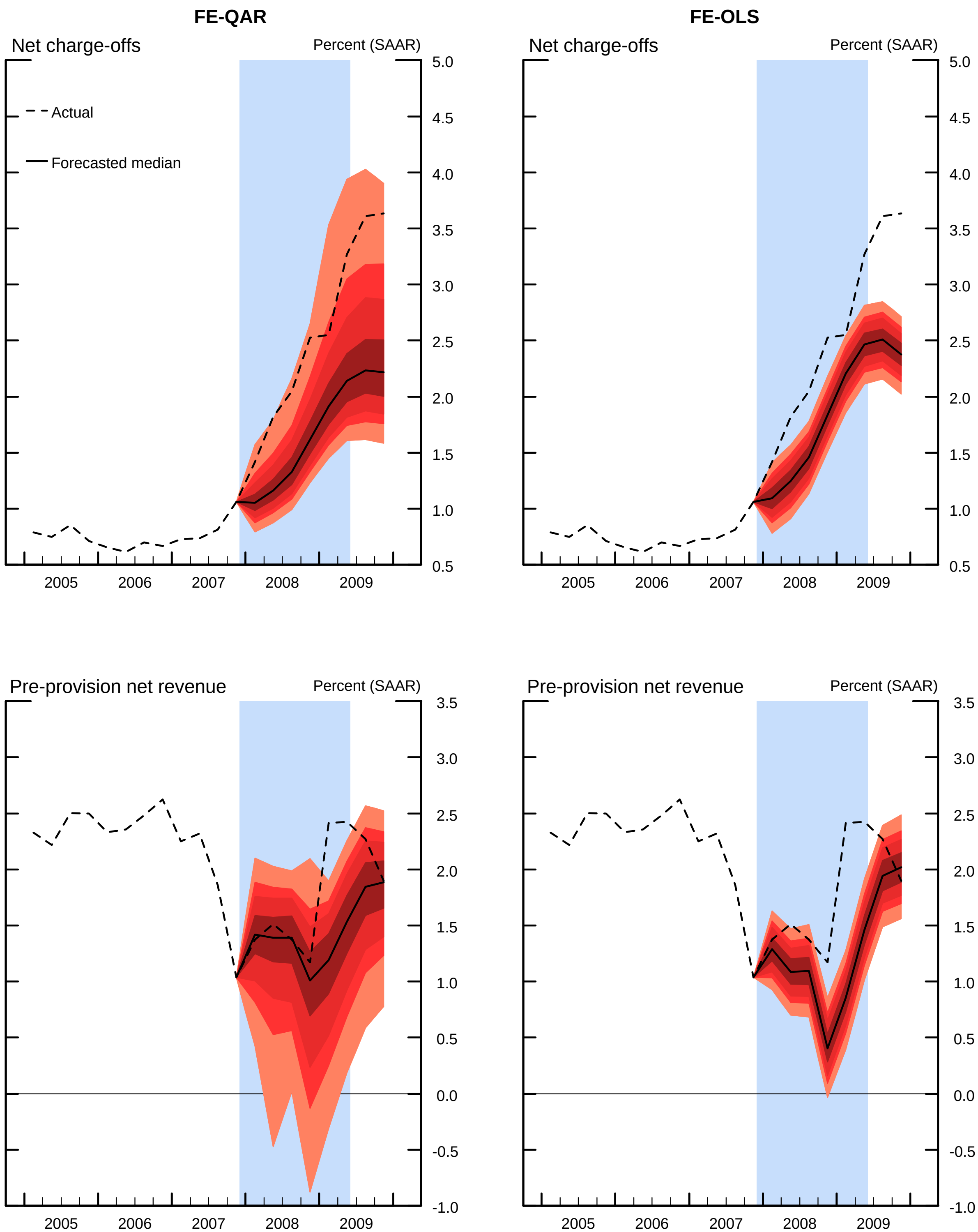
NOTE: The dashed line in each panel depicts the realized value of the specified series. The shaded areas in each plot represents the 1st/2.5th/5th/10th/25th/50th/75th/90th/95th/97.5th/99th percentiles of the density forecast. The shaded vertical bar denotes the 2007-09 NBER-dated recession.

Figure 5: Out-of-Sample Forecasts for Aggregate Pre-Provision Net Revenue



NOTE: The dashed line in each panel depicts the realized value of the specified series. The shaded areas in each plot represents the 1st/2.5th/5th/10th/25th/50th/75th/90th/95th/97.5th/99th percentiles of the density forecast. The shaded vertical bar denotes the 2007-09 NBER-dated recession.

Figure 6: Projections for All BHCs During 2008:Q1–2009:Q4



NOTE: The shaded vertical bar denotes the 2007-09 NBER-dated recession.

Figure 7: Empirical Density of Projected T1CR in 2009:Q4 - Variance Covariance Approach

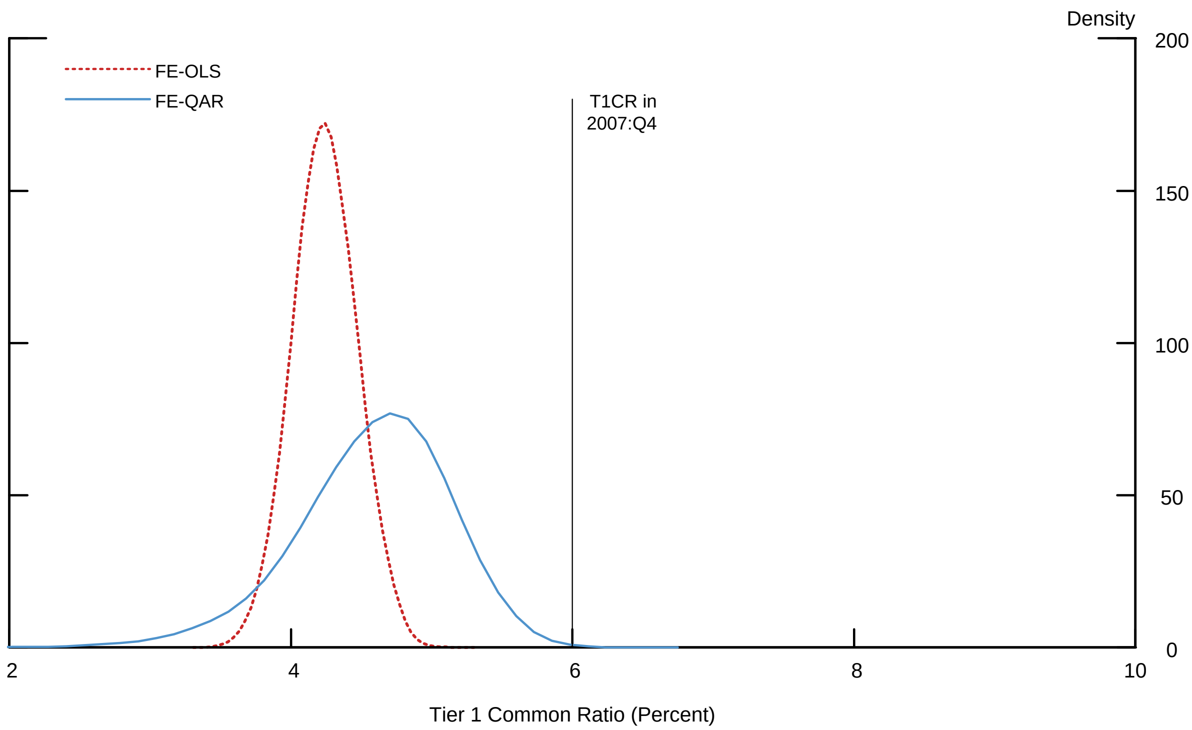


Figure 8: Empirical Density of Projected T1CR in 2009:Q4 - Bootstrap Approach

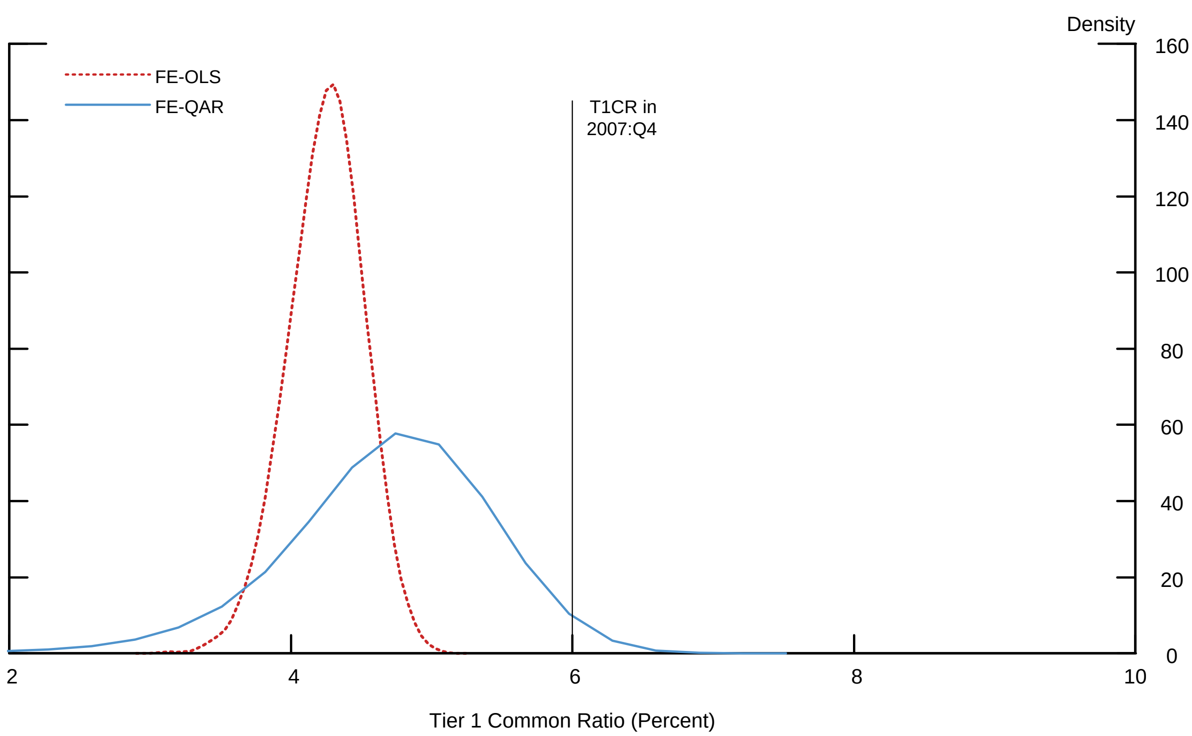
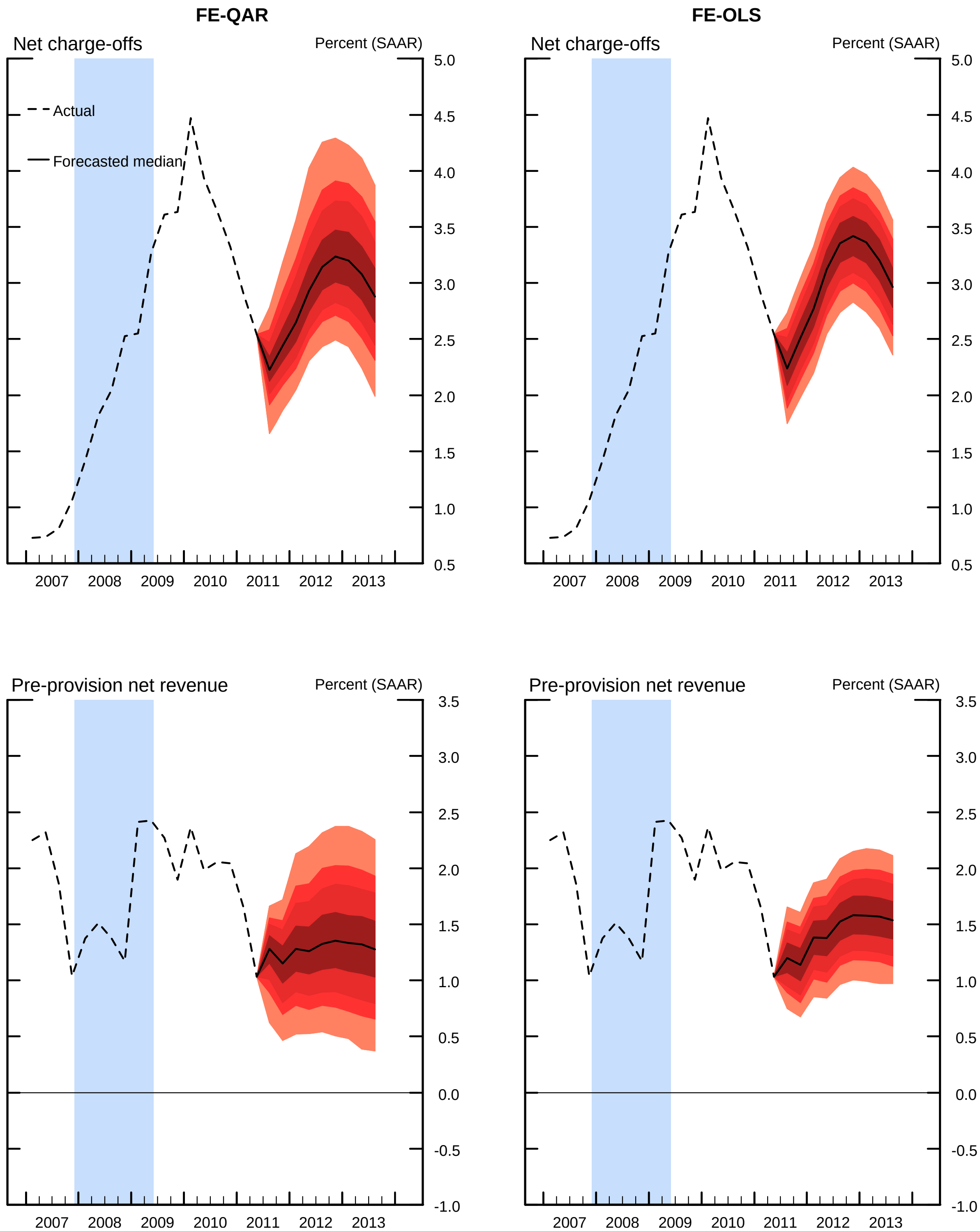


Figure 9: Projections for All BHCs During 2011:Q4–2013:Q4



NOTE: The shaded vertical bar denotes the 2007-09 NBER-dated recession.

Figure 10: Empirical Density of Projected T1CR in 2013:Q4 - Variance Covariance Approach

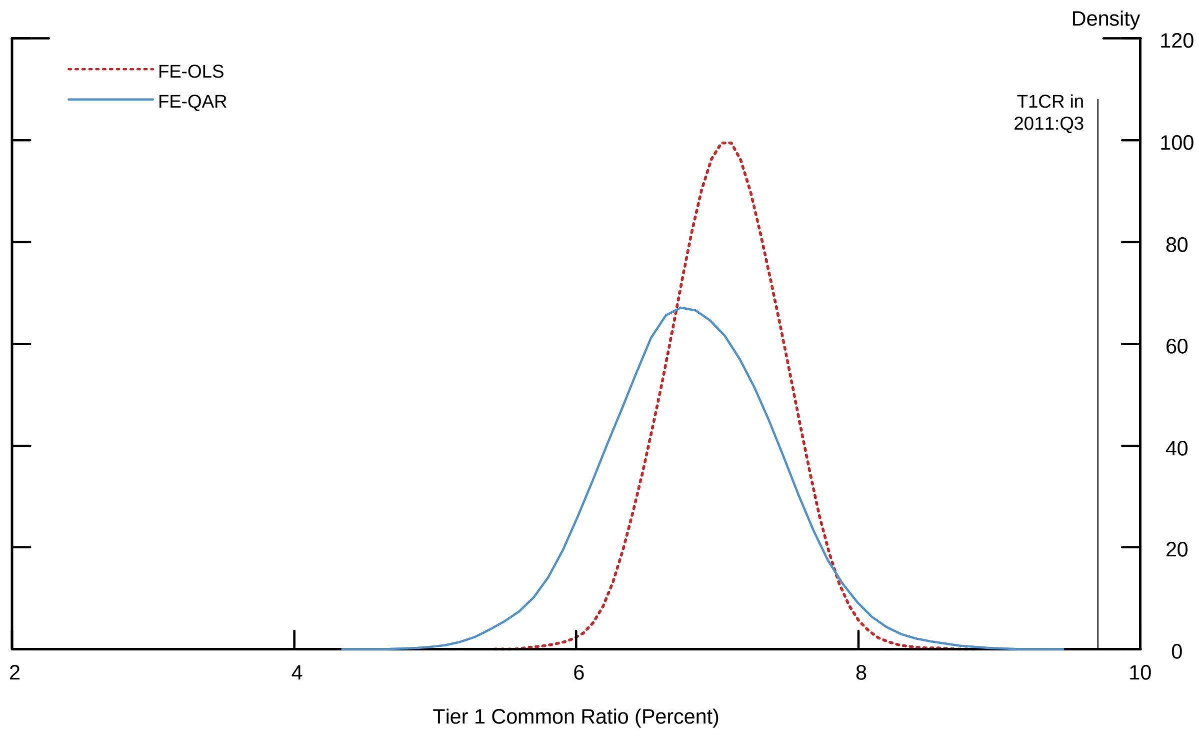


Figure 11: Empirical Density of Projected T1CR in 2013:Q4 - Bootstrap Approach

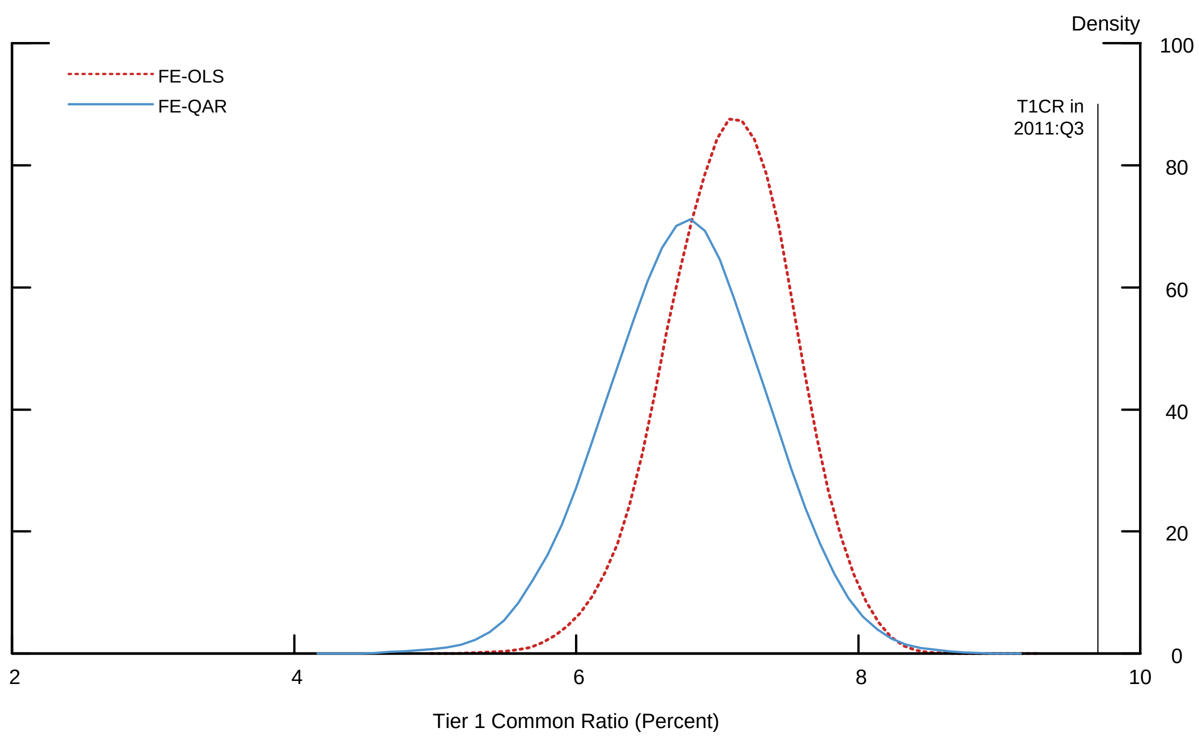


Table 1: List of Bank Holding Companies

Bank Holding Company	Ticker	Start	End	N
Bank of America	BAC	1997:Q1	2011:Q4	60
BB&T Corporation	BBT	1997:Q1	2011:Q4	60
Citigroup Inc.	C	1997:Q1	2011:Q4	60
Citizens Financial	RBS	1997:Q1	2011:Q4	60
Comerica Inc.	CMA	1997:Q1	2011:Q4	60
Fifth Third Bancorp	FITB	1997:Q1	2011:Q4	60
JPMorgan Chase & Co.	JPM	1997:Q1	2011:Q4	60
KeyCorp	KEY	1997:Q1	2011:Q4	60
M&T Bank Corp.	MTB	1997:Q1	2011:Q4	60
PNC Financial Services Group	PNC	1997:Q1	2011:Q4	60
Regions Financial Corporation	RF	1997:Q1	2011:Q4	60
SunTrust Banks Inc.	STI	1997:Q1	2011:Q4	60
U.S. Bancorp	USB	1997:Q1	2011:Q4	60
Wells Fargo & Company	WFC	1997:Q1	2011:Q4	60
Zions Bancorporation	ZION	1997:Q1	2011:Q4	60

Table 2: Summary Statistics

Variable	N	Mean	S.D.	Min	0.25	0.50	0.75	Max
Net Charge-offs:								
Commercial & Industrial	900	1.08	1.37	-0.33	0.34	0.67	1.37	12.98
Construction & Land Development	900	1.36	3.33	-3.03	0.00	0.09	0.92	45.25
Multifamily Real Estate	900	0.51	1.61	-1.15	-0.01	0.04	0.23	26.76
Nonfarm/Nonresidential CRE	900	0.41	1.11	-4.37	0.01	0.10	0.37	14.60
Home Equity Lines of Credit	900	0.64	1.01	-0.29	-0.09	0.19	0.73	7.00
Residential Real Estate (excl. HELOCs)	900	0.64	0.96	-0.77	0.07	0.20	0.76	9.12
Credit Card	720	4.38	3.71	-18.80	2.11	3.93	5.52	43.24
Consumer (excl. CC)	900	1.23	1.21	-0.67	0.45	0.90	1.57	8.71
Pre-Provision Net Revenue:								
Interest Income (% Assets)	900	3.28	0.60	1.42	2.92	3.32	3.68	4.98
Trading Income (% Assets)	900	0.09	0.24	-2.51	0.02	0.05	0.12	0.92
Noninterest/Nontrading Income (% Assets)	900	2.01	0.71	-0.61	1.56	1.92	2.41	5.84
Compensation Expense (% Assets)	900	1.59	0.25	-0.16	1.47	1.61	1.74	2.66
Fixed Assets Expense (% Assets)	900	0.41	0.08	0.15	0.35	0.40	0.47	0.68
Other Noninterest Expense (% Assets)	900	1.17	0.41	-0.16	0.92	1.11	1.33	3.67
Loan/Asset Shares:								
C&I (% Loans)	900	16.6	8.3	1.9	11.8	15.6	19.5	48.8
CRE (% Loans)	900	17.3	10.3	0.6	11.0	15.9	23.5	49.4
RRE (% Loans)	900	21.3	7.9	4.6	16.3	21.0	25.8	49.4
CC (% Loans)	900	2.4	3.2	0.0	0.3	1.0	3.9	18.9
Consumer (excl. CC) (% Loans)	900	8.0	3.5	0.8	5.7	8.1	10.4	18.6
Trading Assets (% Assets)	900	5.2	9.5	0.0	0.3	1.0	4.5	53.4
Macroeconomic Variables:								
$\Delta^4\text{GDP}_t$	60	2.30	2.14	-4.69	1.59	2.46	3.88	5.24
$\Delta^4\text{UR}_t$	60	0.24	1.10	-0.87	-0.47	-0.23	0.43	3.94
$\Delta^4 \log P_t^{HP}$	60	3.48	9.18	-18.97	-3.03	6.94	9.37	16.57
$\Delta^4 \log P_t^{CRE}$	60	4.76	13.42	-44.15	0.58	8.07	13.33	22.68
Treas_t^{3m}	60	2.78	2.03	0.01	0.92	2.71	4.83	6.02
$[\text{Treas}_t^{10y} - \text{Treas}_t^{3m}]$	60	1.93	1.26	-0.24	0.78	1.85	3.08	3.76
$[\text{BBB}_t^{10y} - \text{Treas}_t^{10y}]$	60	1.93	0.98	0.72	1.33	1.77	2.19	5.74
$\Delta[\text{BBB}_t^{10y} - \text{Treas}_t^{10y}]$	60	0.03	0.49	-1.57	-0.10	0.02	0.13	2.53
VIX_t	60	30.86	13.23	12.67	21.85	28.82	34.70	80.86

Table 3: Linear Forecasting Models

	Net Charge-Off Rate by Type of Loan								PPNR Subcomponents					
Explanatory Variable	C&I	CLD	MF	NFNR	HLC	RRE	CC	CON	NIM	TI	ONII	CE	FA	ONIE
ϕ_1	0.427	0.251	0.213	0.443	0.588	0.464	0.373	0.431	0.498	0.251	0.357	0.558	0.461	0.340
	[5.2]	[2.7]	[1.4]	[4.1]	[12.0]	[4.0]	[6.7]	[5.4]	[6.5]	[1.7]	[5.4]	[7.8]	[7.7]	[14.9]
ϕ_2	0.266	0.265	0.287	0.314	0.376	0.355	0.133	0.250	0.370	0.279	0.204	0.340	0.302	0.238
	[3.6]	[5.5]	[3.8]	[3.2]	[7.0]	[7.9]	[1.9]	[3.7]	[9.4]	[3.2]	[3.3]	[6.0]	[6.4]	[6.5]
ϕ_3	0.102	0.134	0.136	0.108	0.057	-0.013	0.040	0.085	0.108	0.013	0.169	0.041	0.206	0.209
	[2.7]	[4.0]	[1.8]	[1.3]	[1.0]	[0.2]	[0.9]	[1.6]	[1.3]	[0.3]	[2.6]	[0.9]	[3.8]	[4.8]
ϕ_4	-0.090	0.031	0.003	-0.123	-0.138	-0.049	0.105	-0.043	-0.155	-0.058	0.001	-0.095	-0.083	-0.034
	[1.5]	[0.8]	[0.1]	[1.3]	[4.0]	[1.4]	[1.4]	[1.0]	[2.7]	[0.9]	[0.1]	[1.7]	[2.0]	[1.2]
$\Delta^4 GDP_t$	-	-0.157	-	-	-	-	-	-0.103	-0.024	0.015		-	-	0.018
		[2.3]						[5.3]	[3.1]	[2.2]				[2.1]
$\Delta^4 UR_t$	0.198	-	-	-	0.043	-	0.904		-	-	-	-	-	-
	[3.5]				[2.0]		[4.5]							
$\Delta^4 \log P_t^{HP}$	-	-	-0.022	-	-0.011	-0.014	-	-	-	-	-	-	-	-
			[1.8]		[3.6]	[4.3]	-							
$\Delta^4 \log P_t^{CRE}$	-	-0.039	-0.012	-0.014	-	-0.008	-	-	-	-	-	-	-	-
		[2.7]	[1.8]	[3.9]		[4.0]								
Treas_t^{3m}	-	-	-	-	-	-	-	-	0.039	-0.024		-	0.003	-
									[2.5]	[2.8]			[2.1]	
$[\text{Treas}_t^{10y} - \text{Treas}_t^{3m}]$	-	-	-	-	-	-	-	-	0.068	-0.042	-0.023	-	0.004	-
									[2.8]	[2.6]	[1.8]		[2.4]	
$[\text{BBB}_t^{10y} - \text{Treas}_t^{10y}]$	0.101	-	-	-	-	-	-	-	-0.068	0.046	-	-	-	-
	[2.5]								[3.5]	[2.4]				
$\Delta[\text{BBB}_t^{10y} - \text{Treas}_t^{10y}]$	-	-	-	-	-	-	-	-	0.034	-0.098	-0.127	-0.038	-	-0.059
									[1.6]	[2.9]	[2.4]	[3.3]		[2.2]
VIX_t	-	-	-	-	-	-	-	-	-	-	-	-	-	0.004
														[3.3]
Obs.	840	840	840	840	840	840	672	840	840	840	840	840	840	840
R^2	0.78	0.49	0.40	0.61	0.92	0.79	0.52	0.78	0.93	0.50	0.71	0.80	0.86	0.65

NOTE: Sample period: 1997:Q1–2011:Q4; Series: C&I = commercial & industrial; CLD = construction & land development; MF = multifamily real estate; NFNR = nonfarm/nonresidential commercial real estate; HLC = home equity lines of credit (HELOCs); RRE = residential real estate (excl. HELOCs); CC = credit card; CON = consumer (excl. CC); NIM = net interest margin; TI = trading income; ONII = other noninterest income; CE = compensation expense; FA = fixed assets expense; ONIE = other noninterest expense. All dependent variables are expressed in annualized percent. Entries in the table denotes OLS estimates of the coefficients associated with the explanatory variables; absolute t-statistics reported in brackets are based on standard errors clustered by bank and time. Almost all PPNR subcomponents include as explanatory variables lagged bank specific portfolio shares.

Table 4: Specification Tests for the Optimality of Density Forecasts

	Specification Tests			
Forecasted Series	KS		LB(4)	
Net Charge-Offs	FE-QAR	FE-OLS	FE-QAR	FE-OLS
Monte Carlo: Variance-Covariance Matrix				
h=1	0.07	0.13	0.10	0.03
h=2	0.19	0.02	0.00	0.01
h=3	0.10	0.02	0.00	0.01
h=4	0.09	0.00	0.00	0.00
Monte Carlo: Bootstrap				
h=1	0.02	0.01	0.12	0.05
h=2	0.07	0.00	0.00	0.01
h=3	0.06	0.00	0.00	0.01
h=4	0.01	0.00	0.00	0.00
Pre-Provision Net Revenue	FE-QAR	FE-OLS	FE-QAR	FE-OLS
Monte Carlo: Variance-Covariance Matrix				
h=1	0.01	0.01	0.16	0.32
h=2	0.02	0.00	0.02	0.04
h=3	0.01	0.00	0.01	0.01
h=4	0.02	0.00	0.00	0.00
Monte Carlo: Bootstrap				
h=1	0.02	0.01	0.16	0.31
h=2	0.02	0.00	0.02	0.04
h=3	0.01	0.00	0.01	0.01
h=4	0.01	0.01	0.00	0.00

Note: Entries in the table denote the p-values associated with the following specification tests of the FE-QAR and FE-OLS models: (KS) the Kolmogorov-Smirnov χ^2 goodness-of-fit test; (LB) the Ljung-Box test for serial correlation of $(z_t - \bar{z}^h)$. The rejection of the null hypothesis is taken as evidence against the optimality of the density forecasts (see text for details).

Table 5: Selected Moments of the Tier 1 Common Distribution

	T1CR Distribution in 2009:Q4						
	1st Percentile		5th Percentile		Average		Memo: T1CR
Banks	FE-QAR	FE-OLS	FE-QAR	FE-OLS	FE-QAR	FE-OLS	in 2007:Q4
Monte Carlo: Variance-Covariance Matrix							
All banks	3.1	3.7	3.6	3.9	4.6	4.2	6.0
BAC	0.7	2.7	2.4	3.1	4.3	4.0	5.5
BBT	3.8	4.9	5.1	5.2	6.4	6.1	7.0
C	-3.6	1.1	-0.7	1.5	3.1	2.7	5.1
CMA	3.8	4.1	4.5	4.4	5.3	5.0	7.0
FITB	3.6	4.2	4.4	4.4	5.2	5.0	6.8
JPM	0.2	3.0	2.2	3.4	4.9	4.4	7.0
KEY	2.9	3.4	3.7	3.7	4.6	4.3	6.0
MTB	3.4	3.9	4.4	4.3	5.4	5.0	6.5
PNC	1.1	1.9	2.0	2.1	3.2	2.9	5.5
RBS	2.0	3.0	3.2	3.4	4.5	4.3	7.3
RF	1.5	2.5	2.7	2.8	3.8	3.6	6.6
STI	1.6	2.7	2.6	3.0	3.9	3.7	5.3
USB	1.9	3.0	2.8	3.3	4.1	4.0	5.9
WFC	3.6	4.6	4.8	4.9	6.0	5.7	6.4
ZION	5.8	6.1	6.7	6.4	7.6	7.2	6.5
Monte Carlo: Bootstrap							
All banks	2.7	3.6	3.6	3.8	4.7	4.2	6.0
BAC	1.9	2.8	3.0	3.2	4.5	4.0	5.5
BBT	5.8	5.3	6.2	5.5	6.8	6.1	7.0
C	-7.8	-0.1	-2.7	0.9	2.6	2.7	5.1
CMA	3.6	4.3	4.4	4.5	5.2	5.0	7.0
FITB	4.0	4.1	4.5	4.4	5.4	5.0	6.8
JPM	3.3	3.0	3.9	3.4	5.4	4.4	7.0
KEY	3.3	3.2	3.8	3.5	4.6	4.3	6.0
MTB	4.0	3.8	4.6	4.3	5.4	5.0	6.5
PNC	1.4	1.3	1.9	1.8	3.0	2.9	5.5
RBS	-0.6	3.3	2.3	3.6	4.3	4.3	7.3
RF	2.9	3.0	3.3	3.2	4.0	3.6	6.6
STI	1.4	3.1	2.6	3.3	3.9	3.7	5.3
USB	3.1	3.0	3.6	3.4	4.4	4.0	5.9
WFC	4.9	4.2	5.3	4.7	6.2	5.7	6.4
ZION	6.4	6.2	6.8	6.5	7.6	7.2	6.5

NOTE: Projection period: 2008:Q1–2009:Q4. Bank names: BAC = Bank of America Corporation; BBT = BB&T Corporation; C = Citigroup, Inc.; CMA = Comerica; FITB = Fifth Third Bancorp; JPM = JPMorgan Chase & Co.; KEY = KeyCorp; MTB = M&T Bank Corp.; PNC = PNC Financial Services Group, Inc.; RBS = Citizens Financial; RF = Regions Financial Corporation; STI = SunTrust Banks, Inc.; USB = U.S. Bancorp; WFC = Wells Fargo & Company; and ZION = Zions Bancorporation.

Table 6: Estimated Capital Shortfalls in 2007:Q4

	2% T1CR Requirement				4% T1CR Requirement			
	Prob. Violate		Expected Shortfall		Prob. Violate		Expected Shortfall	
Banks	FE-QAR	FE-OLS	FE-QAR	FE-OLS	FE-QAR	FE-OLS	FE-QAR	FE-OLS
Monte Carlo: Variance-Covariance Matrix								
All banks	0.03	0.01	6.9	0.9	0.27	0.36	28.6	28.1
BAC	0.03	0.00	15.2	0.6	0.31	0.48	12.3	6.0
BBT	0.00	0.00	0.5	–	0.01	0.00	1.1	–
C	0.23	0.17	24.4	5.1	0.65	0.97	25.4	18.4
CMA	0.00	0.00	0.2	–	0.01	0.00	0.5	0.1
FITB	0.00	0.00	0.6	–	0.02	0.00	1.0	0.2
JPM	0.04	0.00	15.2	–	0.20	0.26	13.8	3.6
KEY	0.00	0.00	0.5	–	0.11	0.21	0.5	0.2
MTB	0.00	0.00	0.3	–	0.02	0.01	0.6	0.1
PNC	0.05	0.02	2.5	0.6	0.93	1.00	3.7	4.6
RBS	0.01	0.00	1.4	–	0.20	0.28	0.7	0.4
RF	0.02	0.00	1.1	0.1	0.59	0.82	0.7	0.7
STI	0.02	0.00	1.1	–	0.54	0.78	1.1	0.8
USB	0.01	0.00	1.6	–	0.39	0.52	1.4	0.8
WFC	0.00	0.00	14.6	–	0.02	0.00	13.0	1.3
ZION	0.00	0.00	–	–	0.00	0.00	0.2	–
Monte Carlo: Bootstrap								
All banks	0.03	0.02	11.3	2.4	0.22	0.36	30.7	27.7
BAC	0.01	0.00	8.7	–	0.21	0.46	9.2	5.4
BBT	0.00	0.00	–	–	0.00	0.00	–	–
C	0.31	0.24	35.9	9.5	0.65	0.93	35.9	19.4
CMA	0.00	0.00	–	–	0.03	0.00	0.3	0.0
FITB	0.00	0.00	–	–	0.01	0.01	0.5	0.2
JPM	0.00	0.00	–	–	0.06	0.26	4.0	3.8
KEY	0.00	0.00	0.8	–	0.11	0.26	0.4	0.3
MTB	0.00	0.00	0.0	–	0.01	0.02	0.3	0.2
PNC	0.07	0.08	1.3	1.2	0.95	0.97	4.2	4.8
RBS	0.04	0.00	2.2	–	0.21	0.23	1.4	0.3
RF	0.00	0.00	–	–	0.48	0.95	0.4	0.5
STI	0.02	0.00	1.4	–	0.48	0.90	1.1	0.6
USB	0.00	0.00	–	–	0.16	0.47	0.8	0.7
WFC	0.00	0.00	–	–	0.00	0.01	4.9	3.7
ZION	0.00	0.00	–	–	0.00	0.00	–	–

NOTE: Projection period: 2008:Q1–2009:Q4. Bank names: BAC = Bank of America Corporation; BBT = BB&T Corporation; C = Citigroup, Inc.; CMA = Comerica; FITB = Fifth Third Bancorp; JPM = JPMorgan Chase & Co.; KEY = KeyCorp; MTB = M&T Bank Corp.; PNC = PNC Financial Services Group, Inc.; RBS = Citizens Financial; RF = Regions Financial Corporation; STI = SunTrust Banks, Inc.; USB = U.S. Bancorp; WFC = Wells Fargo & Company; and ZION = Zions Bancorporation. Expected shortfall is in billions of dollars.

Table 7: Selected Moments of the Tier 1 Common Distribution

	T1CR Distribution in 2013:Q4						
	1st Percentile		5th Percentile		Average		Memo: T1CR
Banks	FE-QAR	FE-OLS	FE-QAR	FE-OLS	FE-QAR	FE-OLS	in 2011:Q3
Monte Carlo: Variance-Covariance Matrix							
All banks	5.5	6.2	5.9	6.4	6.8	7.1	9.7
BAC	1.1	2.2	2.2	2.9	4.3	4.4	8.7
BBT	4.7	5.9	5.6	6.4	7.6	7.9	9.8
C	5.7	7.1	6.8	7.8	9.5	9.6	11.7
CMA	4.9	5.5	5.6	5.9	6.9	6.9	10.6
FITB	2.1	3.1	2.8	3.6	4.2	4.7	9.3
JPM	4.8	6.7	6.0	7.4	8.6	9.1	9.9
KEY	5.7	6.1	6.3	6.6	7.7	7.7	11.3
MTB	2.3	2.7	3.0	3.2	4.4	4.4	6.9
PNC	2.8	3.5	3.4	4.0	5.0	5.1	10.5
RBS	5.0	5.7	5.7	6.2	7.3	7.5	13.3
RF	-0.9	0.5	0.1	1.1	2.0	2.4	8.2
STI	3.1	4.1	3.9	4.6	5.8	5.9	9.3
USB	3.8	4.9	4.6	5.4	6.3	6.6	8.5
WFC	4.2	5.2	5.0	5.7	6.8	7.0	9.2
ZION	6.1	6.8	7.0	7.4	8.6	8.8	9.5
Monte Carlo: Bootstrap							
Industry	5.5	6.0	5.8	6.4	6.8	7.1	9.7
BAC	0.9	1.6	2.1	2.6	4.3	4.5	8.7
BBT	5.8	6.7	6.4	7.1	7.6	7.9	9.8
C	4.6	5.3	6.1	6.5	9.3	9.7	11.7
CMA	5.2	6.1	5.7	6.4	6.7	7.0	10.6
FITB	0.6	2.1	2.1	2.9	4.3	4.7	9.3
JPM	5.7	7.0	6.4	7.6	8.5	9.1	9.9
KEY	4.7	5.6	5.7	6.3	7.6	7.7	11.3
MTB	3.3	3.2	3.7	3.6	4.7	4.4	6.9
PNC	2.7	3.1	3.3	3.7	5.1	5.1	10.5
RBS	5.2	6.3	5.9	6.7	7.3	7.5	13.3
RF	-0.4	1.2	0.4	1.6	2.0	2.5	8.2
STI	3.9	4.4	4.6	4.9	6.1	5.9	9.3
USB	4.6	5.3	5.3	5.8	6.5	6.6	8.5
WFC	4.2	5.1	5.1	5.8	6.6	7.0	9.2
ZION	6.6	7.1	7.3	7.6	8.8	8.7	9.5

NOTE: Projection period: 2011:Q4–2013:Q4. Macro scenario is based on the supervisory stress scenario provided by the Federal Reserve. Bank names: BAC = Bank of America Corporation; BBT = BB&T Corporation; C = Citigroup, Inc.; CMA = Comerica; FITB = Fifth Third Bancorp; JPM = JPMorgan Chase & Co.; KEY = KeyCorp; MTB = M&T Bank Corp.; PNC = PNC Financial Services Group, Inc.; RBS = Citizens Financial; RF = Regions Financial Corporation; STI = SunTrust Banks, Inc.; USB = U.S. Bancorp; WFC = Wells Fargo & Company; and ZION = Zions Bancorporation.

Table 8: Estimated Capital Shortfalls in 2011:Q3

	5% T1CR Requirement				8% T1CR Requirement			
	Prob. Violate		Expected Shortfall		Prob. Violate		Expected Shortfall	
Banks	FE-QAR	FE-OLS	FE-QAR	FE-OLS	FE-QAR	FE-OLS	FE-QAR	FE-OLS
Monte Carlo: Variance-Covariance Matrix								
All banks	0.28	0.25	18.5	13.7	0.77	0.75	98.2	86.2
BAC	0.72	0.72	17.8	13.6	0.99	1.00	50.4	48.4
BBT	0.02	0.00	0.7	0.1	0.66	0.55	1.3	0.9
C	0.00	0.00	7.9	–	0.17	0.07	9.0	4.6
CMA	0.01	0.00	0.3	0.1	0.93	0.96	0.8	0.7
FITB	0.81	0.69	1.1	0.7	1.00	1.00	3.9	3.4
JPM	0.01	0.00	7.5	–	0.35	0.14	13.1	6.3
KEY	0.00	0.00	0.3	–	0.66	0.68	0.6	0.5
MTB	0.77	0.78	0.7	0.6	1.00	1.00	2.5	2.5
PNC	0.53	0.45	1.7	1.1	1.00	1.00	6.8	6.5
RBS	0.01	0.00	0.6	0.1	0.79	0.76	1.1	0.8
RF	0.99	1.00	2.8	2.4	1.00	1.00	5.5	5.2
STI	0.24	0.12	0.9	0.5	0.97	1.00	3.0	2.8
USB	0.10	0.01	1.3	0.8	0.94	0.97	4.8	3.8
WFC	0.05	0.00	4.8	2.4	0.87	0.91	14.9	11.5
ZION	0.00	0.00	0.3	–	0.25	0.18	0.3	0.2
Monte Carlo: Bootstrap								
All banks	0.26	0.25	17.8	13.4	0.79	0.76	97.6	86.4
BAC	0.70	0.68	17.6	13.6	1.00	1.00	50.1	47.9
BBT	0.00	0.00	0.2	–	0.71	0.57	0.9	0.5
C	0.02	0.01	6.7	7.7	0.25	0.16	11.8	11.3
CMA	0.01	0.00	0.2	–	1.00	1.00	0.8	0.6
FITB	0.72	0.66	1.3	0.9	1.00	1.00	3.8	3.4
JPM	0.00	0.00	8.0	–	0.36	0.11	10.2	5.5
KEY	0.02	0.00	0.4	0.3	0.65	0.64	0.8	0.6
MTB	0.73	0.90	0.4	0.4	1.00	1.00	2.3	2.5
PNC	0.48	0.46	1.9	1.4	0.99	1.00	6.6	6.5
RBS	0.01	0.00	0.3	–	0.81	0.84	1.0	0.6
RF	1.00	1.00	2.8	2.4	1.00	1.00	5.6	5.1
STI	0.12	0.07	0.6	0.4	0.97	1.00	2.5	2.8
USB	0.03	0.00	1.2	0.5	0.97	1.00	4.0	3.7
WFC	0.04	0.01	5.7	3.7	0.94	0.95	14.4	10.8
ZION	0.00	0.00	–	–	0.20	0.14	0.2	0.1

NOTE: Projection period: 2011:Q4–2013:Q4. Macro scenario is based on the supervisory stress scenario provided by the Federal Reserve. Bank names: BAC = Bank of America Corporation; BBT = BB&T Corporation; C = Citigroup, Inc.; CMA = Comerica; FITB = Fifth Third Bancorp; JPM = JPMorgan Chase & Co.; KEY = KeyCorp; MTB = M&T Bank Corp.; PNC = PNC Financial Services Group, Inc.; RBS = Citizens Financial; RF = Regions Financial Corporation; STI = SunTrust Banks, Inc.; USB = U.S. Bancorp; WFC = Wells Fargo & Company; and ZION = Zions Bancorporation. Expected shortfall is in billions of dollars.

References

ACHARYA, V., L. PEDERSEN, T. PHILIPPON, AND M. RICHARDSON (2009): "Regulating Systemic Risk," in *Restoring Financial Stability: Policy Recommendations from NYU Stern*, ed. by V. Acharya, and M. Richardson.

ALFARO, R., AND M. DREHMANN (2009): "Macro stress tests and crisis: what can we learn?," *Bank of International Settlements Quarterly Review*, pp. 29–41.

BASEL COMMITTEE ON BANKING SUPERVISION (2010): "Results of the Comprehensive Quantitative Impact Study," `http://www.bis.org/publ/bcbs186.pdf`.

BOARD OF GOVERNORS OF THE FEDERAL RESERVE SYSTEM (2012): "Comprehensive Capital Analysis and Review 2012: Methodology and Results for Stress Scenario Projections," `http://www.federalreserve.gov/newsevents/press/bcreg/bcreg20120313a1.pdf`.

BORIO, C., M. DREHMANN, AND K. TSATSARONIS (2011): "Stress-Testing Macro Stress Testing: Does it Live Up to Expectations?," Bank of International Settlements, Mimeo.

CAMERON, A. C., J. B. GELBACH, AND D. L. MILLER (2011): "Robust Inference with Multiway Clustering," *Journal of Business and Economic Statistics*, 29, 238–249.

CHERNOZHUKOV, V., I. FERNANDEZ-VAL, AND A. GALICHON (2010): "Quantile and Probability Curves Without Crossing," *Econometrica*, 78, 1093–1125.

CIHÁK, M. (2007): "Introduction to Applied Stress Testing," IMF Working Paper.

DIEBOLD, F., T. GUNTHER, AND A. TAY (1998): "Evaluating Density Forecasts with Applications to Financial Risk Management," *International Economic Review*, 39, 863–883.

DREHMANN, M. (2009): "Macroeconomic stress-testing banks: a survey of methodologies," in *Stress-testing the banking system*, ed. by M. Quagliariello. Cambridge University Press.

DREHMANN, M., A. PATTON, AND S. SORENSEN (2007): "Non-Linearities and Stress Testing," in *Proceedings of the Fourth Joint Central Bank Research Conference on Risk Measurement and Systemic Risk*. European Central Bank.

FOGLIA, A. (2009): "Stress Testing Credit Risk: A Survey of Authorities' Approaches," *International Journal of Central Banking*, 5, 9–45.

GALVÃO JR., A. F. (2011): "Quantile regression for dynamic panel data with fixed effects," *Journal of Econometrics*, 164, 142–157.

GREENLAW, D., A. K. KASHYAP, K. SCHOENHOLTZ, AND H. S. SHIN (2011): "Stressed Out: Macroprudential Principles for Stress Testing," Mimeo.

GUERRIERI, L., AND M. WELCH (2012): "Can Macro Variables Used in Stress Testing Forecast Banking Conditions?," FEDS Working Paper XX.

HANSON, S. G., A. K. KASHYAP, AND J. C. STEIN (2011): "A Macroprudential Approach to Financial Regulation," *Journal of Economic Perspectives*, 25, 3–28.

Hirtle, B., T. Schuermann, and K. Stiroh (2009): "Macroprudential supervision of financial institutions: lessons from the SCAP," Federal Reserve Bank of New York, Staff Reports: 409.

Koenker, R. (2004): "Quantile Regression for Longitudinal Data," *Journal of Multivariate Analysis*, 91, 74–89.

Koenker, R., and G. Bassett (1978): "Regression Quantiles," *Econometrica*, 46, 33–49.

Koenker, R., and Z. Xiao (2006): "Quantile Autoregression," *Journal of the American Statistical Association*, 101, 980–990.

Kuritzkes, A., and T. Schuermann (2008): "What We Know, Don't Know and Can't Know About Bank Risk: A View From The Trenches," in *The Known, The Unknown and The Unknowable in Financial Risk Management*, ed. by F. Diebold, N. Doherty, and R. Herring. Princeton University Press.

Peristiani, S., D. P. Morgan, and V. Savino (2010): "The Information Value of the Stress Test and Bank Opacity," Federal Reserve Bank of New York Staff Report no. 460.

Pritsker, M. (2011): "Enhanced Stress Testing and Financial Stability," Mimeo.

Schechtman, R., and W. P. Gaglianone (2012): "Macro Stress Testing of Credit Risk Focused on the Tails," *Journal of Financial Stability*, 8, 174–192.

Sorge, M., and K. Virolainen (2006): "A comparative analysis of macro stress-testing methodologies with application to Finland," *Journal of Financial Stability*, 2, 113–151.

Tay, A. S., and K. F. Wallis (2000): "Density Forecasting: A Survey," *Journal of Forecasting*, 19, 235–254.

Wilson, T. (1997a): "Portfolio Credit Risk (I)," *Risk*, pp. 111–117.

——— (1997b): "Portfolio Credit Risk (II)," *Risk*, pp. 56–61.