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A Top-Down Approach to Stress-testing Banks *

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Abstract

We propose a simple, parsimonious, and easily implementable method for stress-testing banks using a top-down approach that evaluates the impact of shocks to macroeconomic variables on banks' capitalization. Our method relies on a variable selection method to identify the macroeconomic drivers of banking variables combined with a principal component analysis. We show how it can be used to make projections, conditional on exogenous paths of macroeconomic variables. We also rely on this approach to identify the balance sheet and income statement factors that are key in explaining bank heterogeneity in response to macroeconomic shocks. We apply our method, using alternative estimation strategies and assumptions, to the 2013 and 2014 stress tests of medium- and large-size U.S. banks mandated by the Dodd-Frank Act, and obtain stress projections for capitalization measures at the bank-by-bank and industry-wide levels. Our results suggest that while capitalization of the U.S. banking industry has improved in recent years, under reasonable assumptions regarding growth in assets and loans, the stress scenarios can imply sizable deterioration in banks' capital positions.

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1 Introduction

The most recent financial crisis and the subsequent bailouts of large financial intermediaries have brought policymakers' concern with the soundness of the banking sector into sharp relief. While interest in evaluating the robustness of a banking system's responses to macroeconomic shocks is quite old, practical implementation of banking stress tests has become a regulatory requirement only recently in the United States, with the passing of the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act or DFA) of 2010, motivated by the widely perceived success of the Federal Reserve's Supervisory Capital Assessment Program (SCAP) of 2009. Practical implementation of banks' stress testing directly related to the act (Dodd-Frank Act stress testing or DFAST) began in early 2011 with the first release of the Comprehensive Capital Analysis and Review (CCAR) stress scenarios by the Federal Reserve.[1] Since the law does not prescribe a particular way of conducting these stress tests and the literature on their optimal design is still emerging, our paper contributes to the ongoing discussion by proposing a simple, parsimonious, and easily implementable method. Our approach relies on publicly available data and can be used to assess the soundness of both individual banks or segments of the banking industry.

We first review the various approaches to stress tests of banking system soundness to provide context for our own contribution. The Financial Stability Assessment Program (FSAP) was one of the earliest initiatives to conduct a systematic, model-based evaluation of banks' responses to macroeconomic shocks. This initiative was conducted by the International Monetary Fund (IMF) in the late 1990s (see Blaschke et al., 2001, for an overview). Citing the FSAP, Sorge (2004) defines stress testing as "a range of techniques used to assess the vulnerability of a financial system to 'exceptional but plausible' macroeconomic shocks." The last decade has seen an explosion of interest from policy-makers and academics in developing tools that would allow an adequate assessment of the financial and banking system's resilience (Drehmann, 2009, provides an excellent overview). There is no consensus on what constitutes the best approach to conducting stress tests. The *direct* approaches to stress testing assess the effects of exogenous factors, such as macroeconomic variables, on banking variables. The two main types of direct approaches are *bottom-up* methods that estimate

[1] The 2011 CCAR contained only one stress scenario with nine domestic variables and was more limited in scope than it successors. The 2012 CCAR expanded the number of domestic variables, added international variables, and provided the series for both baseline and stressed scenarios. The now-standard format that includes baseline, adverse, and severely adverse scenarios first appeared in the 2013 CCAR.

the impact of exogenous drivers on banking variables at the highest levels of granularity, e.g. using loan-level data, and *top-down* methods that evaluate this impact on banking sector aggregates or individual bank's balance sheet or income statement categories. Constrained by the lack of publicly available data, the academic literature on bottom-up applications is sparse, whereas top-down approaches have recently received increased attention.[2] At the other end of the spectrum, work on *reverse stress testing* attempts to uncover scenarios likely to generate maximum distress for the banking system; see Breuer et al. (2009) and Glasserman et al. (forthcoming) for examples. Flood and Korenko (forthcoming) attempt to strike a middle ground between direct and reverse stress tests by searching for a range of scenarios that might inflict alternative degrees of distress on the banking system. In a similar vein, Pritsker (2012) studies implications of alternative risk scenarios on systemic risk within the banking industry.[3] Despite the legal mandate in the United States and the wide-ranging academic literature on stress testing, there is disagreement as to the usefulness of the enterprise. On one hand, Wall (2013) finds stress testing a useful macro-prudential complement to the Basel III capital regulations, while Borio et al. (2012) provide its critique.

We propose a simple, parsimonious and easily implementable top-down stress testing method and assess its usefulness from the perspective of regulators trying to judge the resilience of a *large* number of individual banks to macroeconomic shocks. We choose the top-down approach because of our interest in assessing the resilience of many banks simultaneously, using only publicly available financial statement data. This approach has the advantage of allowing the horizontal comparison of stress-testing models across banks. It also has the potential cost that bank-level aggregate data may miss banks' idiosyncratic characteristics that may be more clearly identified in a bottom-up approach based on detailed account and loan-level data for each bank. Indeed, while the CCAR stress tests on large bank holding companies in the U.S. (with assets above $50 billion) have required these banks to provide detailed information, the much larger set of banks (with assets above $10 billion) subject to the DFA stress testing are not required either to disclose detailed loan-level data

[2] For international applications of top-down approaches, see the following country studies: Andersen et al (2008) for Norway, Burrows et al (2012), Haldane et al (2007), Hoggarth et al (2005a,b) for the United Kingdom, De Bandt and Oung (2004) for France, Filosa (2007) for Italy, Kalirai and Schleicher (2002) for Austria, Van den End et al (2006) for the Netherlands, and Pesola (2007) for a cross-section of European countries, while Henry and Kok (2013) offer the European Central Bank perspective. Schuermann (2014) summarizes the stress tests conducted in the United States and Europe, using both top-down and bottom-up approaches, during the latest financial crisis.

[3] In a more general setting, Ergashev (2012) and Adbymomunov et al. (2014) apply scenario-based stress testing to operational risk management.

to regulators or to use a bottom-up approach for their internal stress testing models.[4] Following the DFA stress testing regulations, we study all *banks* with assets of more than $10 billion at any point in our sample. These banks today represent almost 80 percent of the total assets in the United States banking system.[5] We concentrate our analysis on banks instead of bank holding companies to mirror the interests of individual bank regulators. Nevertheless, our method could be applied easily to a larger set of banks or bank-holding companies, as well as to the banking system of any other country where similar data are available.

Our paper examines alternative ways of projecting for each bank its capital position for the 2013 and 2014 CCAR baseline and severely adverse scenarios. Our objective is to evaluate whether these projections can be informative in the sense of identifying the banks that would need larger capital injections under macroeconomic stress. As the 2013 and 2014 CCAR scenarios are hypothetical macroeconomic outcomes provided by the Federal Reserve, we use the 2008 crisis as the performance benchmark for our model in identifying banks under stress. Our model produces conditional forecasts for two key income statement quantities—pre-provision net revenue (PPNR) and net charge-offs (NCO)—and their responses to changes in the macroeconomic environment. We use NCO forecasts to model the provision for loan and lease losses and obtain projections for each bank's net income before taxes and extraordinary items.[6] We use these projections and standard accounting formulas to build stress paths for capitalization measures under alternative assumptions regarding growth in assets and loans.

The main contribution of our paper is to show that using readily available data and our fairly straightforward methodology, regulators can obtain information about the potential resilience of individual banks, as well as the overall banking system, to macroeconomic shocks. The main methodological challenge that existing literature on stress-testing faces has been finding a systematic way to identify the key macroeconomic factors that affect a bank's capital position and address bank heterogeneity in response to macroeconomic shocks. Our methodology attempts to address this challenge in three ways. First, to deal with the issue of model (variable) selection, we rely on a

[4] From a practical point of view, many of these banks do not have sufficiently long series of loan-level data available internally, for their own analyses.

[5] We do apply some sample selection rules on those banks, described in Section 2. The panel of banks we use in our sample represent 77 percent of the assets in the banking system in 2013, and 70 percent of the assets of the banking system from 2000 to 2013.

[6] While we rely on the conditional forecasts of only two variables to keep things simple, our methodology can be easily applied to a more disaggregated view of banks' financial statements.

least absolute shrinkage selection operator (LASSO) approach to selecting the key macroeconomic drivers of a given dependent banking variable. This allows us to summarize these drivers with an index variable given by the first factor from a standard principal component analysis. Second, we show how scenario projections for the underlying macroeconomic variables can be used to obtain corresponding scenarios for this index. Third, we deal with bank-response heterogeneity to macroeconomic shocks by allowing the effect of the macroeconomic index to differ for banks with different characteristics. We rely on the LASSO approach to identify the key balance sheet characteristics that describe bank heterogeneity associated with each dependent variable. The approach then produces an index measure of that heterogeneity by extracting the first principal component of the variables identified by the LASSO algorithm. We classify banks in groups, at each time period, based on the distribution of this measure. We then show that results improve in terms of in-sample fit when allowing heterogeneous effects of macroeconomic shocks, in particular for NCO.

Our paper is most closely related to the recent work by Guerrieri and Welch (2012), Covas et al. (2014), and Hirtle et al. (2014). These papers use data for large U.S. bank-holding companies or aggregate measures of the U.S bank-level data, and also rely on top-down approaches to stress testing. Guerrieri and Welch (2012) aggregate the bank-level data for the largest bank-holding companies into sector-wide time series, and argue that macroeconomic variables carry little to no predictive content in forecasting banking variables. They also find that even models that feature macroeconomic variables whose predictive content is the highest fail to generate meaningful stress under the 2012 CCAR exercise. In addition to estimating (mean) fixed effects models, Covas et al. (2014) use panel quantile regressions to derive density forecasts. Their conclusion, using the 2012 CCAR exercise, is that while fixed effects models predict relatively little stress, (simulated) density forecasts predict more severe stress to the banking system. Hirtle et al. (2014) use both aggregate time series and pooled quarterly observations for the 200 largest BHCs and banks in the U.S. banking system. They model detailed components of bank income, expense and loan performance, and evaluate stress scenarios based on the 2014 CCAR exercise. They find that the capitalization of the banking industry has improved since the crisis and that the capitalization gap under stress has fallen dramatically. Against this backdrop, we contribute in two ways. First, we provide a framework that allows for a more flexible provision for bank heterogeneity. Hirtle et al.

(2014) use aggregate and BHC-level data to estimate the parameters of interest necessary to describe industry-wide effects without allowing for any bank heterogeneity. The quantile regression approach of Covas et al. (2014) allows for heterogeneity in response to a particular macroeconomic driver, but it does not systematically identify the most important driver for each dependent variable. Our method, in contrast to these studies, examines a wide range of candidate sources of heterogeneity and provides a selection criterion for the subset that is relevant for a particular dependent variable. Second, the existing literature on top-down stress testing does not pay explicit attention to the key issue of model selection, particularly with respect to the macroeconomic drivers of banking stress. Our approach allows for selecting a parsimonious model linking each banking dependent variable with the subset of macroeconomic drivers relevant to that variable, chosen from a large pool of candidate variables. By including their lags and polynomial transformations of those candidate variables, we attempt to ensure that the model captures the dynamics and potential nonlinearities in the transmission of macroeconomic shocks to banking variables accurately.

The rest of this paper is organized as follows. Section 2 describes the data and outlines our empirical framework. Section 3 provides estimation results from several empirical models and discusses issues pertaining to model selection. Section 4 presents capital projections under alternative estimation models, both for stress scenarios under the 2013 and 2014 CCAR exercises and benchmark comparisons with the 2008 crisis. Section 5 concludes.

2 Data and Empirical Framework

2.1 Data

We use public data from quarterly financial statements (Call Reports) of the U.S. banks. We restrict our analysis to institutions with assets of $10 billion or above for at least one quarter during the period from 2000Q1 to 2013Q3, because only those banks are subject to stress-testing requirements (either DFAST or CCAR). We discard all banks with headquarters in the U.S. territories, uninsured institutions, trust companies, and U.S. branches of foreign banks. Of the 251 financial institutions with $10 billion in assets at some point in our analysis period, we drop 25 as a result of these rules. We also drop 13 institutions with less than $1 million in deposits during some point in the sample, to avoid including nontraditional banking institutions. Finally, we drop 57 banks, for which we do not have at least 25 quarters of data in our analysis period, so that we can estimate time series bank-specific models. We take into account any mergers that may have occurred but only when calculating lags; that is, lags are "merger-adjusted".[7] Our final sample comprises an unbalanced panel of 156 banks, of which 101 were still active as of 2013Q3.[8] The unbalanced nature of the panel is important because, by including in the analysis banks that disappear during the period (either due to mergers or failures), we avert obtaining results that may be subject to survivor bias. Note that for *estimation* of models associated with the 2013 CCAR exercise we only use data up to 2012Q3, while for models associated with the 2014 CCAR exercise we use data up to 2013Q3. We refer to these series as the 2013 vintage and 2014 vintage, respectively.

As explained in Section 1, we estimate our models for two variables: pre-provision net revenue (PPNR) and net charge-offs (NCO) on all loans and leases. The typical definition of PPNR in banking is PPNR=(interest income + noninterest income) − (interest expense + noninterest expense). We add realized gains or losses on securities to this standard definition. While it allows us to maintain a high degree of aggregation, the addition represents a minor change, as realized gains or losses account in the data for less than 5 percent of net income for the average bank and close to only 0.02 percent for the median bank. These figures are very similar for the 2008 crisis. To obtain a bank's net income before taxes and extraordinary items, the bank's provision for loan-and-lease losses needs to be subtracted from our definition of PPNR. As we explain in Section 4, we calculate this provision as a function of NCO. This is the main reason why we analyze PPNR and NCO separately instead of net income directly to better take into account the manner in which banks build loan losses into their provisioning decisions. After obtaining forecasts for PPNR and NCO and following mechanical assumptions explained in Section 4, we obtain projections for each bank's net income. As it is usually done in the banking literature, our models are estimated in ratios: PPNR/assets and NCO/total loan and leases (both multiplied by 100 to express them as percentages). We explain how we use these quantities to calculate bank capitalization measures in Section 4.

The evolution of the distributions of the PPNR-to-assets and NCO-to-loans ratios among the

[7] We "merger-adjust" lags by recalculating lags so that they reflect the composition of the bank during the current period.

[8] The panel is unbalanced also because there are a small number of missing values for some of the variables used in the analysis, for 87 out of 7,400 observations.

banks in our sample is presented in Figure 1. The graph shows that the 2008 crisis created large stress in the banking industry: PPNR fell and the NCO rate skyrocketed. While the change in PPNR was more pronounced in the lower quantiles of the distribution, changes in NCO happened in a very broad cross-section of the banking industry.

Translating these variables into capitalization measures requires us to discuss the possibilities for the alternative definitions of bank capitalization. There are three capitalization ratios of particular interest to regulators. We provide their computational details in Section 4.1. The Federal Deposit Insurance Corporation Improvement Act of 1991 deems an insured depository institution as *well capitalized* if its Tier 1 leverage ratio (T1LR) is at least 5 percent, its total risk-based capital ratio (TRCR) is at least 10 percent, and the Tier 1 risk-based capital ratio (T1RCR) is at least 6 percent.[9] Even though all three conditions need to be satisfied simultaneously for an institution to be deemed well capitalized, in our sample the T1RCR condition is never binding without one of the other two conditions also being binding. Thus, we focus our analysis on T1LR and TRCR.[10] Figure 2 provides a historical summary for these two variables. While there is a pronounced decline in the top quantiles of the distribution, there are no perceptible changes in the bottom quantiles during the crisis. This highlights the fact that regulatory capital ratios, which are based on the *book values* of capital and assets may not always accurately reflect their market values or the strength of a bank's capital position. In fact, most banks that experienced failure or assisted takeovers during the 2008 crisis had, in their last active quarter, capital ratios well above the regulatory minimums, at 7 percent and 12 percent for T1LR and TRBCR, respectively.

We use banks' balance sheet characteristics to control for bank heterogeneity and macroeconomic time series constructed by the Federal Reserve for the CCAR exercises as drivers of the PPNR-to-assets and NCO-to-loans ratios. For balance sheet characteristics and macroeconomic variables, it is unclear *a priori* which particular variables, among the large candidate sets, are relevant for explaining the two banking variables of interest. Thus, we propose a framework for selecting only the *relevant* variables and creating summary indexes of the selected variables. The

[9]The Tier 1 leverage ratio is defined as (Tier 1 capital)/(average assets net of disallowed amounts); the total risk-based capital ratio as (risk-based capital)/(risk-weighted assets); and the Tier 1 risk-based capital ratio as (Tier 1 capital)/(risk-weighted assets). Note that a bank can be deemed *adequately capitalized* if TRCR is at least 8 percent, and T1LR and T1RCR are at least 4 percent each.

[10]Guerrieri and Welch (2012), Covas et al. (2014), and Hirtle et al. (2014) focus their capitalization analysis on T1RCR.

following subsections detail this procedure and our empirical strategy.

2.2 Identifying Macroeconomic Drivers of Banking Variables

The macroeconomic variables we consider are transformations of the 13 domestic variables provided by the Federal Reserve for the 2014 CCAR exercise (11 for the 2013 CCAR exercise). However, our procedure can be easily applied to a much larger number of candidate variables.[11] A key model selection issue is that, *a priori*, it is unclear what subset of the potentially highly collinear macroeconomic variables should be included. Additional complications arise if we want to capture the timing of the effects correctly, or if we want to evaluate nonlinear models. A total of 165 variables are generated by including all 13 macroeconomic variables with lags ranging from 0 to 4 and polynomial transformations of each of those series with orders from 1 to 3. Since we want to evaluate the impact of macroeconomic variables on time series regressions for *individual banks*, including all of them in a regression framework would not be possible. Thus, we rely on a variable selection method to identify the relevant macroeconomic drivers. There are numerous ways of approaching variable selection, and we rely on the least absolute shrinkage and selection operator (LASSO) approach proposed by Tibshirani (1996).[12] In a first step, we use this approach to identify the relevant macroeconomic drivers for each of the banking variables of interest (separately for each dependent variable) using the full panel of banks. In a second step, we use the set of variables identified by the LASSO approach as relevant for a dependent variable and generate an 'index of macroeconomic conditions, specific to the dependent variable, by extracting the first principal component of this set of macroeconomic variables. We refer to this index as MPCF (macroeconomic principal component factor) and sign it so that its highest values correspond to crisis conditions.

We operationalize the method that identifies the set of *relevant* macroeconomic variables as follows. First, we take the full panel of a banking variable of interest, Y_{it}, and remove variation

[11] Note that all the macroeconomic variables are standardized to be mean zero and standard deviation one, using the mean and standard deviation of the series from 1990Q1 to 2013Q3. Even though our sample only includes banks during the period 2000Q1 to 2013Q3, when standardizing and performing principal components analysis of the macroeconomic series, we use data from 1990Q1 to ensure that our procedure is based on the long-run properties of the series. We only use banking data from 2000Q1 because the banking industry underwent considerable structural changes during the 1990s, making that period less comparable to the present banking industry.

[12] Our results are driven by the use of a variable selection method, but using the LASSO method itself is not crucial. In analyses available upon request, we tried several alternative variable selection methods (Least Angle Regression, forward stagewise, forward and backward stepwise). We found that while the LASSO method weakly dominated those alternative methods in terms of in-sample fit, the differences were small.

associated with its own lag and fixed effects of individual banks by running the following regression, where $\tilde{Y}_{it}$ represents the residual variation in Y_{it}:

$$Y_{it} = \alpha_i + \beta Y_{it-1} + \tilde{Y}_{it}. \tag{1}$$

This step identifies the variation of the dependent variable not explained by its own lags and is standard in the macroeconomic forecasting literature.[13] Our selection of macroeconomic drivers on the basis of the residual variation of the dependent variable reduces the possibility that the variation of a selected macroeconomic driver picks up some of the variation in dependent variable that could be explained by its own lag. Second, we form two types of candidate variable pools: (a) "MPCF linear" includes concurrent macroeconomic variables and up to four lags; (b) "MPCF polynomial" includes the former set together with its squares and cubes to capture the possibility that nonlinear transformations of macroeconomic variables drive banking variables. Third, we employ the LASSO framework for variable selection and regress $\tilde{Y}_{it}$ on the set of K_z candidate variables to solve the following problem, with γ denoting the vector of coefficients associated with the candidate variables in the regression:

$$\min_{\gamma} \left\{ RSS + \lambda * \left(\sum_{k=1}^{K_z} |\gamma_k| \right) \right\}. \tag{2}$$

The parameter λ imposes a penalty factor on reducing the residual sum of squares (RSS) through additional regressors. As this parameter increases, the number of elements of the vector γ set to zero increases as well, signaling that the associated variable is not useful in reducing the residual sum of squares. Since there is no general guidance for the optimal choice of λ, we conduct a grid search over $\lambda \in [\lambda_{min}, \lambda_{max}]$, where λ_{min} (λ_{max}) is the minimum (maximum) value required to drop (keep) at least (at most) one variable from (in) the candidate pool. We *keep* all variables that appear at least 20 percent of the time over the entire grid. This implies that we only drop the macroeconomic variables that hardly ever explain a given banking variable.[14] Table 1 summarizes for each dependent variable and for each CCAR year, which variables are kept in the candidate set after

[13] For the theoretical motivation of this procedure, see Stock and Watson (2012).

[14] Our results are robust to other methods of forming the relevant set of macroeconomic variables. In an earlier version of the paper, we used an Elastic Net criterion in place of (2) that nests LASSO as a special case. Another alternative that we have considered is finding a particular penalty λ^* that results in the set of included variables being a fixed percentage of the number of total variables, e.g. 20 percent. Our choice of the selection algorithm is primarily driven by parsimony in the number of variables in the relevant set.

this process. In each case, an "X" indicates that at least some lag or polynomial transformations of the variable has survived (in several cases more than one lag or polynomial transformation of a variable survives). For the linear sets, we have 55 (65) candidate variables in 2013 (2014), of which 11 and 10 are included in the calculation of the PPNR- and NCO-specific MPCF, respectively, for both the 2013 and 2014 vintages of the data. For the polynomial sets, we have 165 (195) candidate variables in 2013 (2014), of which 9 (14 and 13) are selected using the 2013 (2014) vintage data for both (respectively) the PPNR- and NCO-specific MPCF. Hence our method indicates that a relatively small number of macroeconomic variables and their transformations should be considered as relevant for the evolution of the dependent variables of interest.

Once the set of relevant macroeconomic variables, $\mathbf{Z}$ (a matrix with dimensions given by the number of observations and the number of relevant macroeconomic variables), for a dependent variable has been identified, its singular value decomposition is given by:

$$\mathbf{Z} = \mathbf{F}\boldsymbol{\Sigma}\mathbf{V}', \tag{3}$$

where $\mathbf{F}$ and $\mathbf{V}$ are rotation matrices and $\boldsymbol{\Sigma}$ is a rescaling matrix. The columns of $\mathbf{F}$ are the principal component factors of $\mathbf{Z}$. For parsimony, important for the time series models, we focus on the first principal component factor, denoting it by f. Approaches of this kind have recently become popular in constructing indexes of financial stability or stress using a large number of macroeconomic and financial variables; see, for example, Hakkio and Keeton (2009), Kliesen and Smith (2010), and Brave and Butters (2011, 2012). One challenge that arises in evaluating hypothetical future macroeconomic scenarios is that these projections need to be consistent with the principal components obtained from the historical series. If we simply added the scenarios as new data to the historical series, the rotation and rescaling matrices would change and the resulting principal component factors associated with each scenario would have different paths over identical *historical* periods. To deal with this issue, we generate scenario-invariant rotation and rescaling matrices by relying on the historical series for $\mathbf{Z}$ up to the quarter prior to the first scenario period. Using these data, we obtain historical rotation ($\mathbf{V}^*$) and rescaling ($\boldsymbol{\Sigma}^*$) matrices. Then, we obtain principal components associated with a particular scenario s, $\mathbf{F}^{\mathbf{s}}$, which are consistent with the principal components of the historical data, by using $\mathbf{V}^*$, $\boldsymbol{\Sigma}^*$, and the macroeconomic data for the relevant macroeconomic variables during the scenario, $\mathbf{Z^s}$:

$$\mathbf{F^s} = \mathbf{Z^s V^* \Sigma^{*-1}}. \tag{4}$$

This adjustment allows us to obtain a first principal component factor f (or MPCF) that is the same in the historical portion of the data, across scenarios, and a principal component f^s for each scenario, used for forecasting purposes, which is consistent with f.

The above process is repeated for each candidate set and dependent variable, as well as for each vintage of the data. Figures 3 and 4 present the first principal component factor series under baseline and severely adverse scenarios, using linear and polynomial sets of macroeconomic candidate variables, for the 2013 and 2014 CCAR exercises, respectively.[15] The baseline scenarios imply factors that essentially continue most recent macroeconomic trends. During the last crisis, the PPNR-specific factors generally peaked a couple of quarters before the NCO-specific factors, while the severely adverse stress scenario projections imply that the peaks roughly coincide. This is consistent with Figure 1, which shows that while PPNR reached its nadir in the middle of the most recent recession, NCO rates peaked at the recession's very end. The severely adverse scenario factors generally do not reach the peaks obtained during the 2008 crisis, in part because the initial conditions prior to stress scenarios are milder than immediately prior to the most recent crisis. This is especially true for factors obtained with polynomial candidate sets. However, the effect of improved initial conditions is offset by these factors remaining at elevated levels for longer than they did during the 2008 crisis.

2.3 The Role of Balance Sheet Characteristics

To understand how the effect of macroeconomic shocks may vary by banks' heterogeneous characteristics, we consider a large set of income statement and balance sheet variables, X_{it}, that capture banks' business models, risk exposure, loan structure, etc. Table 2 shows the list of these variables. Even more so than with the macroeconomic variables in the previous section, including all of these variables in a regression model would be prohibitively expensive in terms of the degrees

[15] Although the adverse scenarios for these two vintages of the exercise capture different types of business cycle disruptions—an inflationary shock in 2013 and a credit risk shock in 2014—their effect on the macroeconomy and the shape of the respective factors make them fall between the baseline and the severely adverse factors in every case considered. Hence we chose to omit them from consideration to conserve space.

of freedom. To address this issue, we follow a strategy similar to the one involving macroeconomic variables and generate an index of income statement and balance sheet conditions with a second-stage application of the LASSO method. The method is used to select the sets of relevant dependent variable-specific income statement and balance sheet variables. These variables are then included in a principal components analysis; their first principal component factor (banking PCF or BPCF) is used as an index of bank heterogeneity. Using this measure of bank-heterogeneity, we can characterize each bank in every quarter. Instead of using its value directly, we rely on the distribution of this index immediately before the crisis to split banks into more homogeneous groups. We use the Schwartz information criterion (SIC) to determine the optimal number of groups for each dependent variable, and interact these group identifiers with the macroeconomic PCF for each dependent variable. This lets us economize on the degrees of freedom required to estimate the parameters of interest and while allowing for heterogeneity of dependent variable responses to a macroeconomic driver.

To carry out this part of our procedure, we first estimate the following fixed-effects model:

$$Y_{it} = \alpha_i + \beta Y_{it-1} + \sum_{p=1}^{P} \gamma_p f_t^p + \tilde{\tilde{Y}}_{it}, \tag{5}$$

where the last term represents variation in Y_{it} not explained by the lagged dependent variable and macroeconomic factors.[16] We then regress $\tilde{\tilde{Y}}_{it}$ on the vector of candidate variables X_{it}, with a number of columns K_x, to solve the following problem, denoting with δ the vector of coefficients associated with the candidate variables in the regression:

$$\min_{\delta} \left\{ RSS + \mu * \left(\sum_{k=1}^{K_x} |\delta_k| \right) \right\}. \tag{6}$$

Implementing a similar grid-search procedure as the one used in Section 2.2, we keep only those income statement and balance sheet variables that, for a given dependent variable, are not discarded in at least 20 percent of cases. Table 2 details the variables that survive this procedure and shows that of the 47 potential unique variables, 15 (2013) or 17 (2014) variables are selected for the PPNR-

[16]For the results we present in the paper, we set $p = 1$ and use the MPCF f_t based on the polynomial candidate set. Our results are similar using a nonlinear model or a different MPCF.

specific factor, and only 4 (2013 and 2014) are selected for the NCO-specific factor.[17] Next, we apply the singular value decomposition to the surviving subset of X_{it} to extract the first principal component factor for every bank. This parsimonious summary of the income statement and balance sheet conditions allows us to explore the effect of the heterogeneous response of PPNR and NCO to macroeconomic variables. The details of the heterogeneity-adjustment procedure are summarized in Section 2.4.

Figure 5 details the evolution of BPCFs and bank assignment to groups on the basis of their values. (Additional discussion of this figure is available in Section 3.) For both PPNR and NCO, the lightest shading corresponds to the quartiles that describe balance sheet characteristics least conducive to stress and the darkest shaded areas correspond to characteristics most conducive to it (the black lines are discussed below). The quartiles are formed based on the pre-crisis distribution of the BPCF values over the 2000q1—2006q4 time period. Note that in every quarter each bank is assigned to a group, based on the value of the BPCF for the bank in that quarter; hence group membership adds up to 100 percent. The figure shows that with the onset of the crisis, many banks switch from the safer groups to the riskiest one, signaling dramatic deterioration in their balance sheet characteristics. Since then, however, the reverse has taken place. The comparison of the top and bottom panels suggests that this process has notably accelerated during 2013, captured with the 2014 vintage data up to 2013Q3. The riskiest group membership fell from the crisis peak of about 80 percent to about 40 percent. Using the 2013 vintage, in contrast, the decline in the riskiest group membership is only to about 60 percent. Based on these results, one would expect, *ceteris paribus*, the 2013 CCAR severely adverse scenario to generate more stress in the banking system than its 2014 counterpart. Time variation of a bank's BPCF value suggests that the bank can have different trajectories for similarly structured stress tests performed in different years for reasons other than changes in the bank's dependent variable values. This feature has been absent from the previous literature on top down stress testing.

[17] Note that the procedure selects actually among potentially 163 variables, when lags are counted, and thus the number of variables used in the construction of the principal component factor are 24 (2013) or 26 (2014) for PPNR, and 6 (2013 and 2014) for NCO.

2.4 Estimation Framework

For each of our dependent variables (PPNR and NCO ratios), we estimate several specifications of the following general form:[18]

$$Y_{it} = \alpha_i + \beta_j Y_{it-1} + \sum_{p=1}^{P} \gamma_{j,p} f_t^p + \nu_{it}, \tag{7}$$

where $P = 1, 3$ allows for both linear and nonlinear specifications. The latter option may be interpreted as either capturing the differential effect of shocks of different sizes, as in Drehmann et al. (2007) among others, or as capturing the time-varying impact of the macroeconomic principal component on the banking (dependent) variable, as in the seminal contribution of Swamy (1970).

The subscript j associated with the coefficients β and γ reflects three alternative empirical strategies. First is the standard fixed-effects (FE) approach where only the vertical intercepts vary from one bank to another, i.e., $\beta_{(j)} = \beta$ and $\gamma_{(j)} = \gamma$. Second is the time series (TS) or bank-by-bank approach where all coefficients are estimated for individual banks, i.e., $\beta_j = \beta_i$ and $\gamma_j = \gamma_i$ for $i = 1, ..., n$. Third is the estimation of fixed-effects models, which allows coefficients to vary for groups of banks based on their income statement and balance sheet characteristics, i.e., $\beta_j = \beta_g$ and $\gamma_j = \gamma_g$ for $g = 1, ..., G$. The first approach imposes homogeneity in banks' responses to macroeconomic drivers and its own lagged dependent variable, the second allows for maximum heterogeneity, and the third strikes a middle ground. We perform the grouping procedure by using the dependent variable-specific BPCF, the first principal component factor extracted from income-statement and balance-sheet variables, explained in the previous subsection. For each dependent variable, we take for the *pre-crisis* period 2000Q1—2006Q4 the distribution of the relevant BPCF, and obtain threshold values corresponding to $q = 2, 3, 4, 5, 10, 20$ quantiles of that distribution. For each dependent variable and each q, we use these fixed thresholds to assign banks to $G = q$ groups of banks in *each* quarter. The groups should become more homogeneous as q increases. Each bank can be assigned to a different group in each quarter, based on its own quarterly value of the dependent variable-specific BPCF. For forecasting quarters during the stress scenarios, the last group assignment prior to the first scenario quarter is used. Note that, even though banks can

[18] We follow the existing stress testing literature in restricting our model to a dynamic panel model with only one lag of the dependent variable.

be assigned to different groups in each quarter, as we derive the thresholds from the distribution of BPCF for the pre-crisis period, we guarantee that membership to a particular group is driven by the pre-crisis distribution in characteristics. We estimate (7) as fully interacted models by using group dummies (allowing for group specific intercepts, in addition to α_i), and identify the number of groups that minimizes the SIC for the entire panel of banks (see discussion in the next section). We refer to this number of groups as optimal grouping (OG). Furthermore we define the optimality of FE, TS, or OG methods by comparing the SIC values across all these options for each dependent variable separately.[19]

3 Estimation Results

Our first set of results attempts to illustrate the degree of heterogeneity in the simplest possible setting, given by (7) with $P = 1$. We contrast the estimates of the coefficients γ associated to the MPCF in (7) using FE with the distribution of coefficients γ_i's from TS estimation. Figure 6 shows the results.[20] The figure makes two important points. First, the FE estimates of γ have the right sign but are small, implying a relatively muted response to macroeconomic shocks. Second, the distribution of γ_i's is wide enough for a number of coefficients to have the opposite sign to the one expected, which would make the banks' performance improve during stress episodes and may simply result from estimating the model on a relatively small number of highly idiosyncratic observations. The figure suggests that properly accounting for bank heterogeneity could, in principle, identify a set of relatively responsive banks and mitigate or eliminate econometric problems associated with TS estimation.

As highlighted in the previous section, accounting for modeling flexibility and bank heterogeneity implies that specifications may include many possibilities. The functional form can be either linear or nonlinear. The macroeconomic driver may be the first principal component from a linear or polynomial set of macroeconomic variables. Finally, there are three types of models: FE, TS, and OG strategies. To select the best model across all these possibilities, we follow Diebold (2012),

[19]Note that for parsimony we restrict all models to contain one macroeconomic PCF only. We did evaluate the use of a higher number of macroeconomic PCFs, with trivial improvements (less than 0.5 percent) in fit as measured by the SIC.

[20]The data used for this exercise come from the 2014 vintage. The results for the 2013 vintage are virtually identical.

who criticizes model selection based on "pseudo" out-of-sample criteria. He suggests using, when "true" out-of-sample data are not available as in our case, an information criterion based on the within-sample mean squared error (MSE) multiplied by a penalty that takes into account the number of coefficients estimated. We use the penalty usually associated with the SIC, under normality, which multiplies the MSE by $N^{K/N}$, where N is the sample size, and K is the number of coefficients estimated in the model. The model with the smallest value for this information criterion should be preferred.

We present the results for the SIC from estimating alternative models for PPNR and NCO in Figures 7 and 8 using the 2013 and 2014 vintages of the data, respectively. We note several regularities across different specifications. First, the SIC associated with any TS models is by far the largest. This suggests that the cost of estimating these models in terms of degrees of freedom is prohibitive. Second, linear specifications always have lower SICs than nonlinear (cubic) functional forms, suggesting that nonlinear or time-varying considerations are relatively unimportant in our setting. Third, models where the MPCF is extracted from the polynomial set of variables always have better fit. The difference between the FE and lowest SIC grouping model is small, with the strategy with two groups being slightly worse than the FE model for PPNR, and the strategy with four groups yielding the lowest SIC for NCO (but only slightly better than the FE model). Thus, we concentrate our analysis only on linear models, using the MPCF based on the polynomial set of variables, and we select as the optimal group (OG) two groups (i.e. above and below the median) for PPNR, and four groups (i.e. quartiles) for NCO. Returning to Figure 5, discussed in the prior section, the two groups under OG are shown by the black line. For NCO, the quartiles correspond to the optimal grouping strategy.

Table 3 shows the implications for the estimated coefficients using the FE or OG models. Although the interactions with the group dummies are not statistically significant for the lagged dependent variables, it is clear that for MPCF fully interacted regressions by group imply different coefficients that are statistically significant for most groups. For NCO, the OG model improves fit, as measured by the Adjusted R-Square, the RMSE and the SIC. For PPNR, the fit, as measured by the Adjusted R-Square and the RMSE, remains the same. The small deterioration in SIC is likely driven by the additional penalty on a larger number of regressors. Finally, for NCO, the direct effect of the group dummies is highly significant above and beyond the bank fixed effect, indicating that the grouping strategy captures relevant bank heterogeneity.

In the remainder of the paper, unless otherwise specified, we present results based on the estimated parameters from the optimal grouping (OG) strategies for two groups in the case of PPNR and for four groups in the case of NCO.

4 Projected Capital Under Stress

In this section, we discuss how we use the forecasts for NCO and PPNR under alternative stress scenarios to obtain projections for capitalization measures. As discussed above, we concentrate on two measures, the Tier 1 leverage ratio (T1LR) and the total risk-based capital ratio (TRCR), while excluding a third typically used measure, the Tier 1 risk-based capital ratio, which never appears as binding on its own in our sample period. For the two capital measures of interest, we consider the effects of using different minimum alternative thresholds, ρ. First, we rely on the regulatory threshold for an institution to be considered *well capitalized*, 5 percent for T1LR and 10 percent for TRCR, and denote it by ρ_1.[21] Second, we consider higher thresholds than the regulatory minimums. During the 2008 crisis banks that disappeared from our sample, as a results of failure or acquisition, had in their last active quarter average values of 7 percent and 12 percent for T1LR and TRCR, respectively. We refer to these values as ρ_2. Finally, the average values for T1LR and TRCR for all banks during the 2008 crisis were 8 percent and 13 percent, respectively, and are designated by ρ_3.

There are several important reasons for analyzing different capital thresholds, particularly above regulatory minimums. First, as Flannery (2013) points out, the DFA does not specify a well-defined quantitative criterion for passing a stress test. As a result, regulators have considerable discretion in evaluating stress-testing outcomes. Second, recent regulatory proposals have focused on the T1LR and advanced a variety of numerical values for minimum thresholds, generally pushing in the direction of higher requirements.[22] Third, the literature on the subject suggests that the socially

[21] The eight largest banks, part of bank holding companies with at least \$700 billion in total consolidated assets or at least \$10 trillion in assets under custody, will face a 6 percent T1LR threshold by 2018, according to a recently adopted rule (79 Federal Register, 2014). Given that the calculation of the supplementary T1LR required of these institutions includes off-balance sheet items, by the regulatory agencies calculations, the rule implies that the effective T1LR threshold for these institutions would have been around 8.5 percent in 2014.

[22] For example, Senators Sherrod Brown and David Vitter introduced a proposed bill in 2013, the Terminating Bailouts for Taxpayer Fairness Act of 2013, which would increase the minimum leverage ratio to 8 percent for financial institutions with over \$50 billion in total consolidated assets.

optimal bank capitalization level should be higher than the regulatory minimums (see Miles et al., 2013; Admati, 2014). Fourth, book values for balance sheet variables may lag their economic, market-value counterparts particularly during downturns. This implies that the market value of capital under stress is likely to be lower than what its book value suggests. Fifth, banks typically hold capital above regulatory thresholds (see Jackson et al., 2002, among others), in part because of the deteriorating access to credit markets implied by approaching these thresholds. Finally, as we have documented earlier, banks that ceased to exist during the most recent crisis had capital ratios well in excess of regulatory thresholds. The next subsection details the calculations for capital positions, relative to our thresholds of choice, that allow us to analyze the banks' potential performance during the two CCAR exercises, as well as during the 2008 crisis.

4.1 Capital Calculations

We mimic the requirements of the CCAR exercise, in calculating capital for a nine-quarter horizon, $h = 1, ..., 9$ quarters, under a stress scenario starting just after time period T.[23] We first calculate in each quarter the provision for loan and lease losses under the CCAR regulatory requirement that the allowance for loan and lease losses (ALLL) should cover at least the projected net charge-offs (NCO) for the subsequent four quarters:

$$\widehat{ALLL}_{T+h} = \sum_{\tau=1}^{4} \widehat{NCO}_{T+h+\tau} = \sum_{\tau=1}^{4} \left\{ L_T \prod_{\eta=1}^{h+\tau} (1 + g^L_{T+\eta}) \right\} \widehat{nco}_{T+h+\tau}. \tag{8}$$

Projections for the charge-off rate (as a share of loans), $\widehat{nco}_t$, are constructed by forecasts from the relevant model taking the CCAR stress scenario path as given, whereas the loan growth rates, g^L_t, are given by assumptions that we detail below; L_T represents the level of loans the quarter before the beginning of the stress scenario. Note that to obtain the ALLL for the nine quarters in the stress scenarios, (8) implies that we need to forecast NCO for 13 quarters. This allows us to construct estimates for the provision for loan-and-lease losses as follows:

$$\widehat{PROV}_{T+h} = \widehat{ALLL}_{T+h} - \widehat{ALLL}_{T+h-1} + \widehat{NCO}_{T+h}, \tag{9}$$

[23] Quantities all in uppercase are in terms of dollars; lowercase quantities are shares of total assets, A_t, except for net charge-offs that are shares of total loans, L_t.

where the formula reflects that current NCO and ALLL increase this quantity whereas the existing ALLL at end of the previous period reduces it. We assume that profits are taxed at the statutory rate:

$$\widehat{TAX}_{T+h} = 0.35 \times Max(0, \widehat{PPNR}_{T+h} - \widehat{PROV}_{T+h}), \tag{10}$$

where

$$\widehat{PPNR}_{T+h} = \left\{ A_T \prod_{\eta=1}^{h} (1 + g^A_{T+\eta}) \right\} \widehat{ppnr}_{T+h} \tag{11}$$

is driven by the assumptions on asset growth, g^A_t, over the stress period and the model-specific conditional forecasts for the ratio of PPNR to assets. Furthermore, we assume a constant dividend-to-assets ratio at the level of the last quarter prior to the first stress period, $\overline{div} = div_T$:

$$DIV_{T+h} = \left\{ A_T \prod_{\eta=1}^{h} (1 + g^A_{T+\eta}) \right\} \overline{div} \tag{12}$$

and a constant capital adjustment (as share of assets), $\overline{k^{t1l}} = k^{t1l}_T$, to obtain Tier 1 leverage capital:[24]

$$K^{t1l}_{T+h} = \left\{ A_T \prod_{\eta=1}^{h} (1 + g^A_{T+\eta}) \right\} \overline{k^{t1l}}. \tag{13}$$

Note that the median bank in our sample paid no dividends as of 2013Q3; hence capitalization numbers derived below cannot be improved much by assuming that banks would cut back on dividends under stress.

We calculate the path for equity as:

$$\widehat{EQ}_{T+h} = \widehat{EQ}_{T+h-1} + \widehat{PPNR}_{T+h} - \widehat{PROV}_{T+h} - \widehat{TAX}_{T+h} - DIV_{T+h} \tag{14}$$

and Tier 1 capital as:

$$\widehat{T1C}_{T+h} = \widehat{EQ}_{T+h} - K^{t1l}_{T+h}. \tag{15}$$

Finally, we obtain the Tier 1 leverage ratio by dividing Tier 1 capital by, A^{aa}, adjusted average

[24]The adjustment includes one-time items such as: losses in available for sale (AFS) securities, AFS equity securities, cash flow hedges, nonqualifying perpetual preferred stock, disallowed goodwill and intangible assets, cumulative change in fair value of financial liabilities, disallowed servicing assets and purchased credit card relationships, disallowed deferred assets, and the negative of qualifying minority interests in consolidated subsidiaries.

assets:[25]

$$\widehat{t1lr}_{T+h} = \frac{\widehat{T1C}_{T+h}}{A_T^{aa} \prod_{\eta=1}^{h}(1 + g_{T+\eta}^{A})}, \tag{16}$$

where for simplicity we assume that adjusted average assets grow at the same rate as quarter-end assets, an assumption that roughly holds in practice.

Similarly, we can calculate the total risk-based capital ratio. The main differences with T1LR is that this ratio is normalized by risk-weighted assets, A^{rw}, and requires a different adjustment from equity. In particular, the adjustment factor is given by:[26]

$$K_{T+h}^{tr} = \left\{ A_T^{rw} \prod_{\eta=1}^{h}(1 + g_{T+\eta}^{Arw}) \right\} \overline{k^{tr}}, \tag{17}$$

where the growth rate of risk-weighted assets, g_t^{rw}, is allowed to differ from that of assets. Total risk-based capital is given by:

$$\widehat{TRC}_{T+h} = \widehat{EQ_{T+h}} - K_{T+h}^{tr}. \tag{18}$$

The total risk-based capital ratio then is given by:

$$\widehat{trcr}_{T+h} = \frac{\widehat{TRC}_{T+h}}{A_T^{rw} \prod_{\eta=1}^{h}(1 + g_{T+\eta}^{Arw})}. \tag{19}$$

Our results will depend crucially on our assumptions regarding growth rates of assets and loans under stress. To place these assumptions within their historical context, Figure 9 describes the evolution of industry averages for four-quarter averages of these quantities over our sample.[27] We make two sets of assumptions regarding their trajectory over the nine-quarter stress period. First, we assume that the *path* of industry average growth rates during the 2007Q4—2009Q4 period will be replicated; we call this assumption Crisis Growth.[28] Second, we assume that the growth rates remain constant over the nine-quarter horizon, at the average industry level of the quarter preceding

[25]Adjusted average assets are calculated by subtracting from quarterly average total assets disallowed goodwill, other disallowed intangible assets, and disallowed deferred assets.

[26]The adjustment factor $\overline{k^{tr}}$ is calculated in period T as the sum of the Tier 1 capital adjustment (in terms of risk weighted assets), $\overline{k^{t1l}}(A_T/A_T^{rw})$, and deductions for total risk-based capital (as ratio of RWA or risk-weighted assets) and subtracting allowable Tier 2 capital and Tier 3 capital allocated for market risk (as ratios of RWA).

[27]We take four-quarter averages to smooth out extreme values. Our results are practically unaffected relative to those using quarterly growth rates.

[28]We use 2007Q4 as the beginning period associated to the 2008 crisis, because it coincides with the official starting point of the recession according to the NBER.

the first quarter of a particular stress scenario; for the 2013 CCAR, this corresponds to 2012Q3 and, for the 2014 CCAR, to 2013Q3. We refer to the latter assumption as Q3 Growth. Figure 9 shows the alternative assumptions imply distinct assumed growth rates. For the crisis period the growth rates for assets, loans and risk-weighted assets follow similar trajectories and remain close in 2012Q3; however, they differ substantially in 2013Q3.

Using the projected capitalization positions, we construct measures of expected capital shortfall as an approximation to the amount of capital necessary to recapitalize the banks under severe stress. First, we construct a measure of bank-quarter expected shortfall relative to a regulatory threshold ρ_r, $r = \{1,\ 2,\ 3\}$, for the T1LR as:

$$ES_{i,T+h}^{\rho_r,t1lr} = \left\{ A_T^{aa} \prod_{\eta=1}^{h} (1 + g_{T+\eta}^{A}) \right\} Max(0, \rho_r - \widehat{t1lr}_{T+h}). \tag{20}$$

For each bank i, we can obtain the maximum T1LR shortfall over the course of the stress testing exercise:

$$ES_i^{\rho_r,t1lr} = Max(ES_{i,T+1}^{\rho_r,t1lr}, \ldots, ES_{i,T+H}^{\rho_r,t1lr}). \tag{21}$$

We construct similar measures for the TRCR as:

$$ES_{i,T+h}^{\rho_r,trcr} = \left\{ A_T^{rw} \prod_{\eta=1}^{h} (1 + g_{T+\eta}^{Arw}) \right\} Max(0, \rho_r - \widehat{trcr}_{T+h}) \tag{22}$$

for the path of expected capital shortfalls for an individual bank and

$$ES_i^{\rho_r,trcr} = Max(ES_{i,T+1}^{\rho_r,trcr}, \ldots, ES_{i,T+H}^{\rho_r,trcr}) \tag{23}$$

for each bank's maximum TRCR shortfall over the stress path. We then construct the maximum capital shortfall for each bank as the largest of the T1LR and TRCR shortfalls:

$$ES_i^{\rho_r} = Max(ES_i^{\rho_r,t1lr},\ ES_i^{\rho_r,trcr}). \tag{24}$$

Finally, aggregating across banks, we can calculate a measure of shortfall for all banks in our sample (industry shortfall):

$$ES^{\rho_r} = \sum_{i=1}^{N} ES_i^{\rho_r}. \tag{25}$$

4.2 Projected Capitalization, Expected Shortfall, and Policy Implications

Table 4 reports the total expected capital shortfall (in billions of dollars) for the entire industry (i.e. the banks in our sample), given by (25), under several alternative scenarios. We first conduct a benchmarking exercise for the 2008 crisis. We take the full-sample parameter values (using the 2014 vintage of the data) estimated by our models and obtain forecast values for PPNR and NCO (in a recursive way) using the historical MPCF series for the nine-quarter (PPNR) and 13-quarter (NCO) periods starting in 2007Q4. We then calculate the expected shortfall at the three regulatory thresholds described above. We see in the top panel of Table 4 that the OG method generates larger shortfalls than the FE method for all regulatory thresholds and than the bank-by-bank TS method for all but one of the thresholds. Hence, adjusting for bank heterogeneity appears to generate substantially higher projected losses than the standard FE framework by about \$40 billion across all three thresholds. This suggests that the OG projections are about 10 percent higher for ρ_3 and 30 percent higher for ρ_1 than their FE counterparts. Quantitatively, our results for the 2008 crisis are consistent with the roughly \$245 billion disbursed under the two components of the Troubled Asset Relief Program (TARP) designed to assist the banking sector during the crisis, the Capital Purchase Program (CPP) and the Targeted Investment Program (TIP). These results suggest that the amounts disbursed by these programs should have been enough to recapitalize the system above the regulatory minimums, ρ_1, and even cover most of the gap with the average capitalization of institutions that disappeared during the crisis, ρ_2. Our model is agnostic regarding the source of funds for recapitalization. The expected shortfall indicates the amount banks would need to be able to recapitalize, from any source. Indeed, the above-mentioned programs were accompanied by multiple other emergency lending programs to support the banking system administered by the Federal Reserve. In addition, many banks resorted to private sources of recapitalization. In any case, the results in the top panel of Table 4 indicate that our model generates plausible predictions for the crisis period.

In the rest of the Table 4, the left panel presents results based on the observed average industry growth rates in loans and assets during the crisis, while the Q3 growth rates are used in the right panel. Not surprisingly, considering that assets affect the denominator in the capitalization formulas, the relatively higher growth rates of assets in the 2012Q3 and 2013Q3 periods, compared with the crisis period, imply milder across-the-board results in the right panels. The second and fourth panels show that capital shortfalls are negligible or small in the 2013 and 2014 baseline stress scenarios, with all three estimation methods delivering comparable results. Virtually no institutions are forecast to fall below the regulatory minimums[29] and the shortfalls at ρ_2 and ρ_3 appear to be small relative to the 2008 crisis levels. The severely adverse scenarios in the third and fifth panels, however, paint a different picture. For both CCAR exercises, OG estimates exceed their FE counterparts across the board, especially for the 2013 CCAR. The shortfall at ρ_2 is sizable albeit smaller than the amounts involved in the banking components of TARP discussed above: about \$150 billion for the 2013 exercise and a bit under \$100 billion for the 2014 one, which is 20 percent (in 2014) to 40 percent (in 2013) larger than the results obtained in the FE framework. Hence bank heterogeneity has continued to play an important role during the two most recent CCAR exercises. Improved capitalization across the industry and possibly a somewhat less stressful severely adverse scenario in the 2014 CCAR account for this reduction in one year. In addition, as discussed in the previous subsection, the asset growth rates assumed under the 2014 exercise are much lower than under the 2013 exercise when using Q3 growth rates (see Figure 9). This explains the even lower numbers in the right panel for the 2014 exercise. Finally, one cannot discount the possibility, highlighted by Bookstaber et al. (2013), that by this third iteration of the CCAR exercise, banks may have made progress in adapting toward scenario design, shaping their activities accordingly.

To provide a more complete picture of the degree of individual bank under-capitalization implied by our models during the crisis and under the two CCAR severely adverse scenarios, we construct empirical cumulative density functions (ECDFs) for the banks' T1LR and TRCR. Figures 10 and 11 describe the ECDFs for the two ratios for the 2008 Crisis benchmarking exercise. The figures show that even under the lowest threshold ρ_1, both for T1LR (Figure 10) and TRCR (Figure 11), a large percentage of banks is identified as not well-capitalized: more than 35 percent and 50 percent of the banks, respectively, using the OG results. The share of banks that the model identifies as

[29]The occasional \$1 billion numbers are the result of rounding up the sum of small positive values across several banks.

breaching the higher ρ_2 and ρ_3 thresholds climbs above 70 percent.

The same analysis can be replicated for each of the stress scenarios. Figures 12 and 13 describe the T1LR ECDFs under the Crisis Growth and 2012Q3 Growth assumptions, respectively, for the 2013 CCAR severely adverse scenario. The OG estimates for the number of banks falling below the thresholds of interest exceeds its counterpart generated by the FE model by as much as 10 percent of the sample at the two lower thresholds. About 20 percent of banks would not be deemed well capitalized because they would fall below the 5 percent threshold under the former growth assumption and about 15 percent under the latter. About one half of them would experience T1LR of less than 7 percent, the level exhibited on average by banks that exited the industry during the most recent crisis. Figures 14 and 15 convey similar information regarding the TRCR. Again, the OG ECDF lies above the FE one at low values of this ratio and overlaps at levels of about 11 percent and above. About one third of our sample would not be deemed well capitalized under the Crisis Growth assumption and well over a quarter under the 2012Q3 Growth assumption. Over one half of the sample would be at the average capitalization level experienced by the exiting banks during the 2008 crisis. Note that since the sets of banks experiencing under-capitalization according to these two ratios may be different in each figure, the total number of banks likely to have capitalization problems may be higher than the number implied by a particular measure. Also, the shares of banks breaching different thresholds are in general lower than those found for the historical period. This is not surprising given that the banks that survived the crisis may be stronger than the ones that did not. In addition, as discussed in Section 3 when analyzing Figure 5, a larger share of banks have shifted toward safer groups, as defined by our BPCF measure, in the last few years of the sample.

Figures 16, 17, 18, and 19 present analogous results for the 2014 CCAR severely adverse scenario. As was mentioned in the context of Table 4, the combination of better industry capitalization, possibly a less severe stress scenario, and different assumed asset growth rates in the 2013Q3 growth case, improves the capitalization outlook under stress for the banks in our sample. At most 10 percent to 15 percent would not be well capitalized, although the numbers breaching the ρ_2 thresholds remain quite high, in the range of 30 percent to 45 percent. The difference between the results generated by the three methods, especially FE and OG, also diminishes perceptibly relative to the 2013 CCAR.

To further analyze our bank-level results, we present in Table 5 the expected capital shortfall (in $ billions), given by (24), for some large individual banks (using the OG model). For each of the three periods of interest, we identify the largest ten institutions in terms of total assets (in the quarter just prior to the beginning of each episode). Since there is large persistence in the rankings of institutions by assets, we present results for 15 institutions. [30] The second column shows the starting assets (in $ billions) of each bank (rows within each panel are ordered by this amount), and, as before, we show the results for the three thresholds and for the two asset and loan growth assumptions in columns 4 to 9. To provide a benchmark for our results, in the top panel, for the 2008 crisis, column 3 provides the amount of government assistance received by the *bank holding company* (BHC) that owned each of the individual institutions at the beginning of each episode under the Capital Purchase Program (CPP) and Targeted Investment Program (TIP) components of the Troubled Asset Relief Program (TARP).[31] The top panel shows that our results for the crisis period, under ρ_2, are relatively close to the actual amounts received by the banks under the two programs, although our numbers are in general higher for ρ_3. We do not expect the CPP and TIP programs to match our results perfectly, given that banks had access to other sources of Federal Reserve-provided emergency lending, and in many cases resorted to private recapitalization operations. In addition, since these banks belong to BHCs that have direct access to capital markets and may have additional resources, our bank-level model cannot take this into account. This seems to be the case for JP Morgan Chase, for which the model implies a high level of recapitalization: If JP Morgan Chase's parent company can downstream capital easily to the bank, for such a large institution it may be optimal to keep less capital in the bank and more in the BHC. This shows a disadvantage of estimating a model, as we do in this case, purely at the bank level, ignoring the BHC information. Nevertheless, for the most part, our numbers seem reasonable and the share of assistance received by the banks in the list matches the shares projected by our model under the alternative thresholds and growth scenarios (as presented in the last row of the panel).

The second and third panels of Table 5 present similar results for the 2013 and 2014 severely adverse scenarios. In almost every case, the expected shortfall for a given bank in 2013 is higher

[30] This list of institutions includes Wachovia, which was severely distressed and underwent an unassisted merger with Wells Fargo, and Washington Mutual, which failed during the 2008 crisis.

[31] We concentrate on the CPP and TIP sources of government assistance because they are easy to track, even if provided at the BHC level, not at the bank level. Note that Wachovia and Washington Mutual did not receive any assistance, while HSBC and TD Bank were not recipients because they belonged to foreign bank holding companies.

than for 2014. The Q3 Growth assumptions generate smaller shortfalls. Nevertheless, the results show that several of the large institutions in the sample would still require a sizable capital injection to keep their capital levels with a reasonable buffer above the minimal regulatory thresholds. In summary, our results provide evidence in favor of using top-down stress testing as a tool to identify both industry and individual institution risks.

5 Conclusion

In this paper, we propose a simple, parsimonious, and easily implementable method for stress-testing banks and assess its usefulness for identifying under-capitalized banks under stressful macroeconomic conditions. We propose the use of a variable selection method for identifying the macroeconomic drivers of banking variables and use a principal components analysis to provide a parsimonious summary of these variables, through indexes of macroeconomic conditions. This method addresses the issue of variable selection that has not received adequate attention in the literature on stress testing. Furthermore, we explain how our method can be extended to make forward-looking projections, given the stress paths of macroeconomic variables. We apply a similar variable selection method and principal component extraction to create indexes of balance-sheet bank heterogeneity and form a series of groups of banks based on these measures.

We obtain projections for pre-provision net revenue (PPNR) and net charge-offs (NCO) under alternative stress scenarios, exploiting the indexes of macroeconomic conditions, and investigate the role of bank heterogeneity in dependent variable sensitivity to these indexes. We estimate bank-by-bank time series models, pooled fixed effects models, and models based on an optimal grouping strategy based on the generated indexes of balance sheet characteristics. When we translate the PPNR and NCO projections into paths for the Tier 1 capital leverage and total risk-based capital ratios, we can obtain results that are in line with observed experience during the 2008 crisis. Furthermore, for the 2013 and 2014 CCAR severely adverse scenarios, our results suggest that the capitalization of the banking industry has improved in recent years, but these scenarios can still imply sizable deterioration in banks' capital positions. This result holds at both the industry-wide and individual-bank levels.

Top-down stress testing is a relatively blunt regulatory tool, based only on public data. As such, it is encouraging that such a low-cost tool can generate results that closely match the last historical episode and sensible projections under hypothetical macroeconomic scenarios in a simple and parsimonious, yet flexible, approach. Our paper shows that careful model selection and allowing for bank heterogeneity are key to obtaining these results. Extending our methods to a much more disaggregated view of the banks' financial statements—and to a larger set of banks—is straightforward. Furthermore, larger sets of macroeconomic variables can be considered as candidates for macroeconomic drivers of banking variables, outside of the limited number considered in this article. All these are potential avenues that can build on the present work.

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Table 1: Variables Selected for Macroeconomic Principal Component Factors

Variable	PPNR				NCO			
	MPCF Linear		MPCF Polynomial		MPCF Linear		MPCF Polynomial	
	2013	2014	2013	2014	2013	2014	2013	2014
VIX Level	X	X	X	X				X
BBB Spread	X	X	X	X	X	X	X	X
CREPI Growth					X	X		X
DJIA Growth	X	X		X			X	X
HPI Growth	X	X	X	X	X	X	X	X
Mortg Rate Change	X	X		X				
10yr-TB Spread								
5yr-TB Spread*				X				
Prime-TB Spread*								
RDI Growth	X		X	X		X		X
RGDP Growth		X				X		
Unemp Rate Change		X		X	X	X	X	X
CPI Inflation	X	X	X	X	X			X

Note: * 2014 CCAR only

Table 2: Variables Selected for Banking Principal Component Factors

Variable	2013 vintage		2014 vintage	
	PPNR	NCO	PPNR	NCO
Concurrent variables				
Asset growth (4-quarter average)				
Loan growth (4-quarter average)				
One-bank holding company flag				
Multiple-bank holding company flag				
Bank specialization: C&I				
Bank specialization: Consumer & credit card				
Bank specialization group: Commercial real estate				
Bank specialization group: Mortgage				
Lagged variables (lags 1-4)				
Total equity / assets				
Tier 1 capital / assets	X		X	
Deposits / assets	X		X	
Brokered deposits / deposits	X		X	
Dividends / assets	X		X	
Compensation expenses / assets			X	
C&I loans / assets	X		X	
Consumer loans / assets				
Real estate loans / assets				
Other real estate owned / assets	X		X	
Total loans & leases / assets	X		X	
C&I loans / total loans				
Consumer (credit card) loans / total loans				
Consumer (non-credit card) loans / total loans		X		X
Real estate construction loans / total loans				
Real estate multifamily & commercial loans / total loans			X	
HELOC & Jr liens loans / total loans				
1-4 family residential loans / total loans				
Other loans / total loans				
30-89 days past-due loans / total loans	X	X	X	X
90+ days past-due loans / total loans				
Loans in non-accrual / total loans	X	X	X	X
Nonperforming assets / assets	X		X	
Share of assets with with 0% risk-weight				
Share of assets with with 20% risk-weight				
Share of assets with with 50% risk-weight				
Share of assets with with 100% risk-weight				
Trading account assets / assets				
Total available-for-sale securities / assets (fair market value)				
Total held-to-maturity securities / assets (amortized cost)		X		X
Auto loans securitization activity / assets	X		X	
C&I loans securitization activity / assets	X		X	
Credit Card loans securitization activity / assets	X		X	
Other consumer loans securitization activity / assets	X		X	
HELOC securitization activity / assets				
1-4 family residential loans securitization activity / assets	X		X	
Other loans & leases securitization activity /assets				
Total loan securitization activity / assets				
Securitization activity / assets				

Table 3: Coefficients from FE and OG regressions

Variable	PPNR				NCO			
	2013 vintage		2014 vintage		2013 vintage		2014 vintage	
	FE	OG	FE	OG	FE	OG	FE	OG
Lag 1 Y	0.212	0.208	0.224	0.214	0.427	0.259	0.438	0.278
	*0.012****	*0.028****	*0.012****	*0.027****	*0.011****	*0.111***	*0.010****	*0.107****
Lag 1 Y × group 2		0.004		0.011		0.041		0.021
		0.030		*0.029*		*0.126*		*0.120*
Lag 1 Y × group 3						0.011		-0.004
						0.117		*0.113*
Lag 1 Y × group 4						0.122		0.118
						0.111		*0.107*
MPCF Polynomial	-0.085	-0.075	-0.073	-0.068	0.089	0.002	0.086	0.004
	*0.006****	*0.012****	*0.006****	*0.012****	*0.004****	*0.011*	*0.004****	*0.011*
MPCF Polynomial × group 2		-0.017		-0.009		0.023		0.023
		0.015		*0.014*		*0.015*		*0.015*
MPCF Polynomial × group 3						0.041		0.038
						*0.015****		*0.015****
MPCF Polynomial × group 4						0.121		0.106
						*0.012****		*0.012****
Constant	0.476	0.470	0.465	0.464	0.148	0.068	0.140	0.065
	*0.009****	*0.017****	*0.009****	*0.017****	*0.004****	*0.012****	*0.004****	*0.012****
Constant × group 2		0.014		0.006		0.038		0.037
		0.022		*0.021*		*0.017***		*0.016***
Constant × group 3						0.071		0.069
						*0.017****		*0.016****
Constant × group 4						0.135		0.134
						*0.016****		*0.015****
Observations	6,907	6,907	7,313	7,313	6,907	6,907	7,313	7,313
Adjusted R-Square	0.579	0.579	0.578	0.578	0.587	0.602	0.592	0.605
RMSE	0.500	0.500	0.494	0.494	0.296	0.291	0.289	0.284
SIC	0.299	0.300	0.290	0.291	0.105	0.102	0.099	0.096

Note: Standard errors in italics below each coefficient; *, **, *** denote significant at 10%, 5% and 1% respectively.

Table 4: Expected Maximum Capital Shortfall (in $ billions)

Model	Maximum Shortfall ($b)					
	Crisis Growth Rates			Q3 Growth Rates		
	ρ_1	ρ_2	ρ_3	ρ_1	ρ_2	ρ_3
2008 Crisis						
FE	127	331	443			
OG	167	371	482			
TS	170	358	472			
2013 CCAR, Baseline						
FE	1	29	78	1	25	68
OG	0	30	79	0	25	68
TS	1	33	81	0	26	69
2013 CCAR, Severely Adverse						
FE	30	135	229	19	98	185
OG	48	181	273	34	142	233
TS	62	149	237	52	131	208
2014 CCAR, Baseline						
FE	0	18	54	0	14	46
OG	0	18	53	0	14	45
TS	0	25	61	0	17	49
2014 CCAR, Severely Adverse						
FE	12	108	200	3	58	128
OG	17	122	210	4	65	143
TS	48	126	208	41	93	158

Note: FE—fixed-effects models; OG—optimal grouping model; TS—time-series model. ρ_1—regulatory minimum rate; ρ_2—average rate for failed banks during the crisis; ρ_3—average rate for all banks during the crisis

Table 5: Expected Maximum Capital Shortfall for Largest Banks in the Sample (in $ billions)

Bank	Starting Assets	Assistance (CPP+TIP)[a]	Crisis Growth Rates ρ_1	Crisis Growth Rates ρ_2	Crisis Growth Rates ρ_3	Q3 Growth Rates ρ_1	Q3 Growth Rates ρ_2	Q3 Growth Rates ρ_3
2008 Crisis								
Bank of America	1,290	45.0	14.5	34.9	47.8			
JP Morgan Chase	1,244	25.0	33.1	71.2	90.2			
Citibank	1,233	45.0	19.0	44.7	57.6			
Wachovia[b]	557	-	17.0	25.9	30.3			
Wells Fargo	445	25.0	7.1	28.1	38.7			
Washington Mutual[b]	329	-	0.0	4.7	7.5			
U. S. Bank	226	6.6	1.4	7.3	10.2			
HSBC Bank	182	-	5.2	8.6	10.3			
Suntrust Bank	172	4.9	5.0	7.9	9.3			
FIA Card Services (BofA subsidiary)	149	-	0.0	0.0	0.0			
State Street[c]	131	2.0	0.0	3.5	5.4			
PNC Bank[c]	120	7.6	5.5	10.7	13.3			
Bank of New York Mellon[c]	113	3.0	0.0	4.3	6.9			
Capital One[c]	94	3.6	5.5	8.5	10.0			
TD Bank[c]	44	-	2.9	6.3	8.3			
Share of total in sample	**64.8%**	**68.5%**	**69.3%**	**71.9%**	**71.7%**			
2013 CCAR, Severely Adverse								
JP Morgan Chase	1,850		21.8	57.3	75.0	17.2	52.9	70.8
Bank of America	1,448		0.0	14.1	27.9	0.0	7.5	21.3
Citibank	1,365		0.0	8.6	21.9	0.0	3.2	16.6
Wells Fargo	1,219		2.4	22.3	32.3	0.0	16.1	26.1
U. S. Bank	343		0.0	3.2	5.9	0.0	1.3	4.0
PNC Bank	293		0.0	4.9	7.4	0.0	3.7	6.2
Bank of New York Mellon	265		0.0	4.0	6.4	0.0	3.4	5.8
State Street	201		0.0	1.0	2.9	0.0	0.1	2.0
TD Bank	201		2.1	5.2	7.1	1.2	4.4	6.2
HSBC Bank	196		0.7	4.4	6.3	0.1	3.9	5.8
Capital One[c]	235		3.0	5.5	6.7	2.1	4.6	5.8
Suntrust Bank[c]	169		3.4	6.1	7.4	2.8	5.5	6.9
FIA Card Services (BofA subsidiary)[c]	162		0.0	2.5	3.9	0.0	1.3	2.7
Share of total in sample	**71.8%**		**69.3%**	**76.9%**	**77.3%**	**68.2%**	**75.9%**	**77.4%**
2014 CCAR, Severely Adverse								
JP Morgan Chase	1,990		7.1	45.2	64.3	0.0	35.0	54.1
Bank of America	1,439		0.0	15.8	26.1	0.0	3.1	13.5
Citibank	1,345		0.0	5.4	18.3	0.0	0.0	8.7
Wells Fargo	1,328		0.0	8.9	19.5	0.0	0.0	9.7
U. S. Bank	357		0.0	0.0	2.4	0.0	0.0	2.0
PNC Bank	298		0.0	3.1	5.7	0.0	0.7	3.3
Bank of New York Mellon	291		0.0	4.2	6.9	0.0	3.9	6.5
Capital One	235		0.8	3.8	5.3	0.0	1.6	3.1
TD Bank	215		2.6	5.8	7.8	0.8	4.0	6.0
State Street	213		0.0	1.4	3.3	0.0	0.6	2.5
HSBC Bank[c]	180		0.0	2.2	3.9	0.0	1.2	2.9
Suntrust Bank[c]	168		0.0	1.6	3.0	0.0	0.1	1.5
FIA Card Services (BofA subsidiary)[c]	157		0.0	0.0	0.0	0.0	0.0	0.0
Share of total in sample	**71.9%**		**61.3%**	**80.0%**	**79.4%**	**18.9%**	**77.3%**	**79.7%**

Notes:
[a] Assistance was provided to the bank holding company (BHC) that owned the banks. We include only the assistance through the $205b Capital Purchase Program (CPP) and the $40b Targeted Investment Program(TIP), which were the programs within TARP directly oriented to shore up the BHCs balance sheet.
[b] Wachowia and Washington Mutual were acquired during the crisis by Wells Fargo and JP Morgan Chase, respectively.
[c] Denotes banks that are not part of the top 10 banks in assets at the beginning of that particular episode.

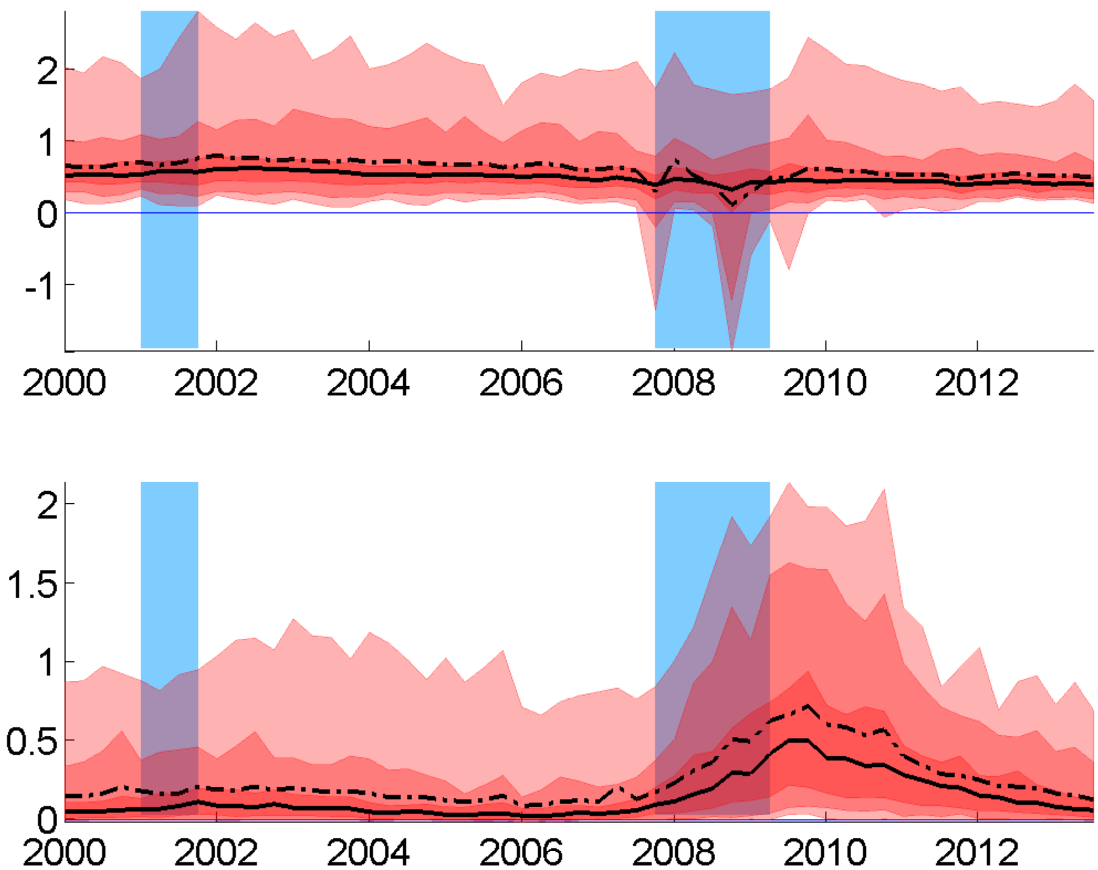


Figure 1: Top panel: PPNR/Assets*100; bottom panel: NCO/loans*100. Light/Medium/Dark red areas: 5th—95th/10th—90th/25th—75th percentiles; Punctuated black line—mean; Solid black line—median; Blue shaded areas—NBER-defined recessions

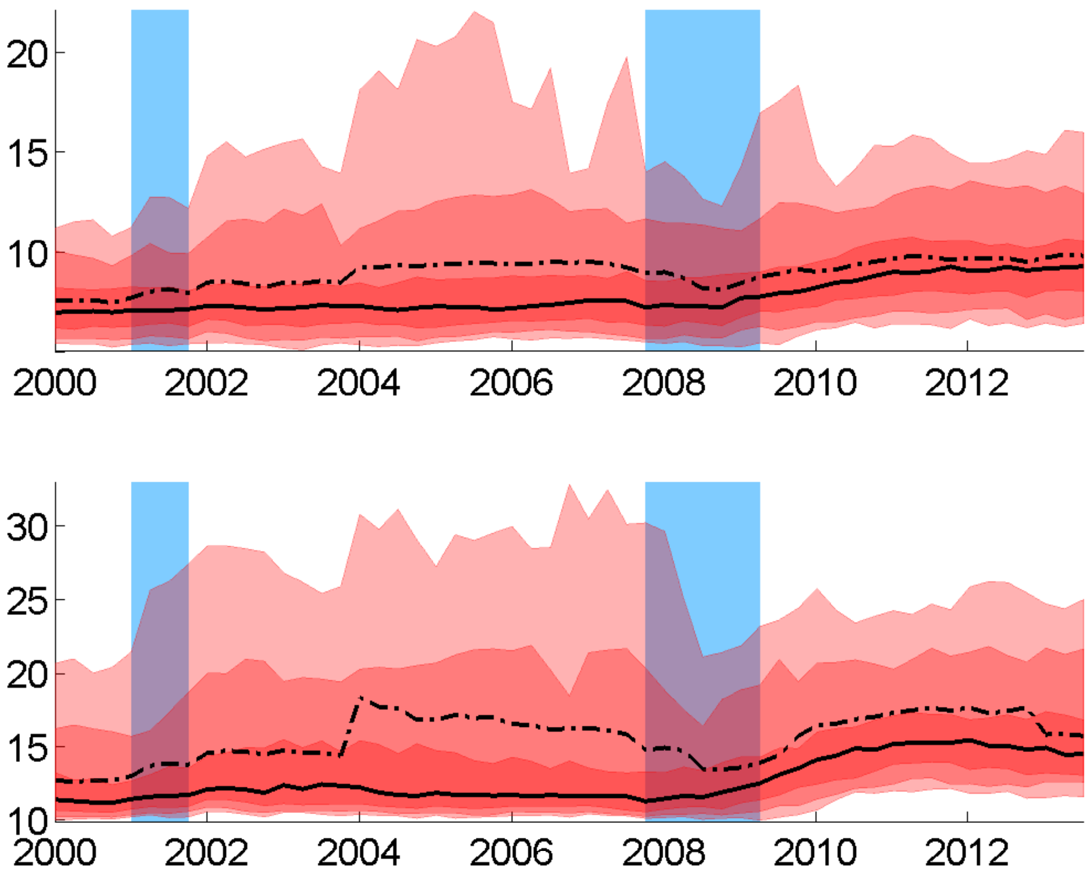


Figure 2: Top Panel: Tier 1 Leverage Ratio (%); bottom panel: Total Risk-based Capital Ratio (%). Light/Medium/Dark red areas: 5th—95th/10th—90th/25th—75th percentiles; Punctuated black line—mean; Solid black line—median; Blue shaded areas—NBER-defined recessions

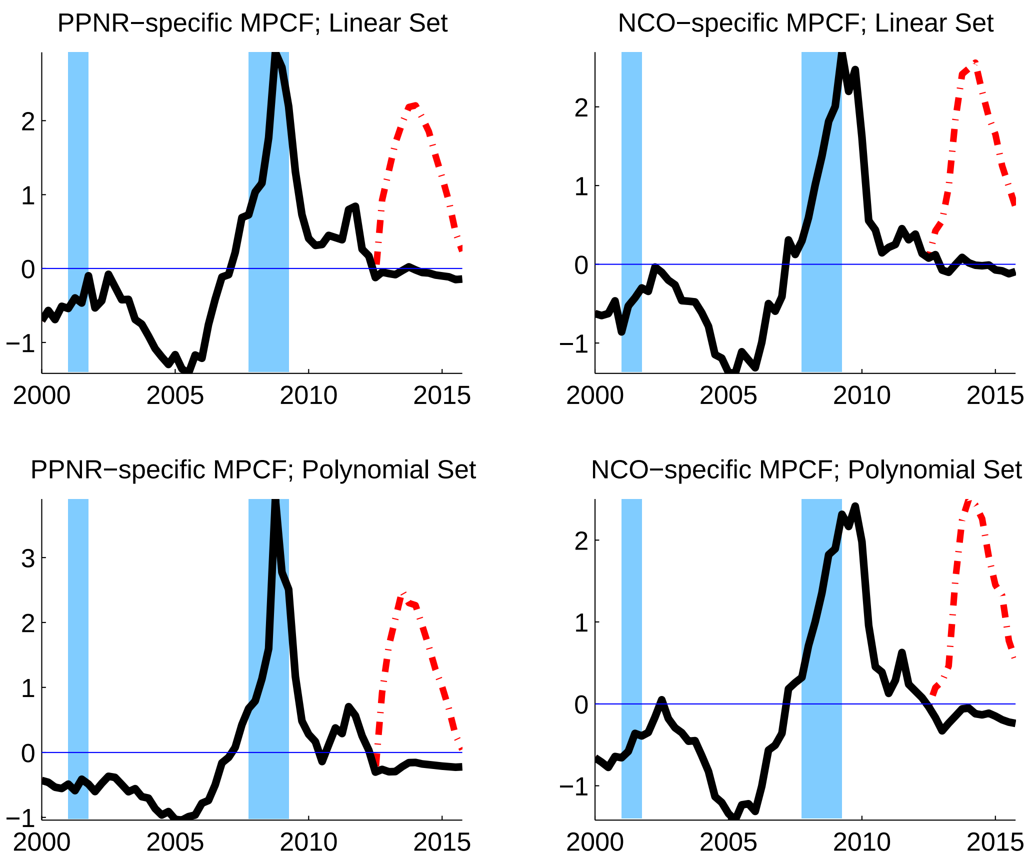
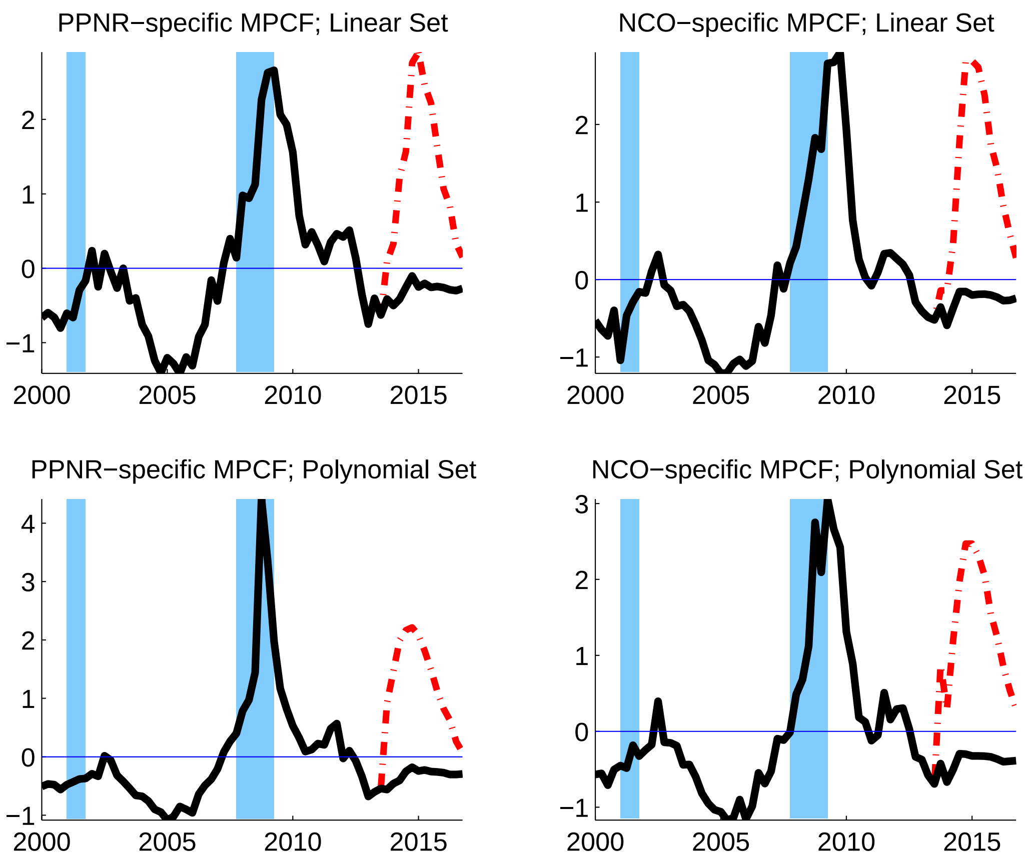


Figure 3: Principal Component Factors and the 2013 CCAR; Solid black line—historical series and the baseline stress scenario; Punctuated red line—severely adverse stress scenario; Blue shaded areas—NBER-defined recessions



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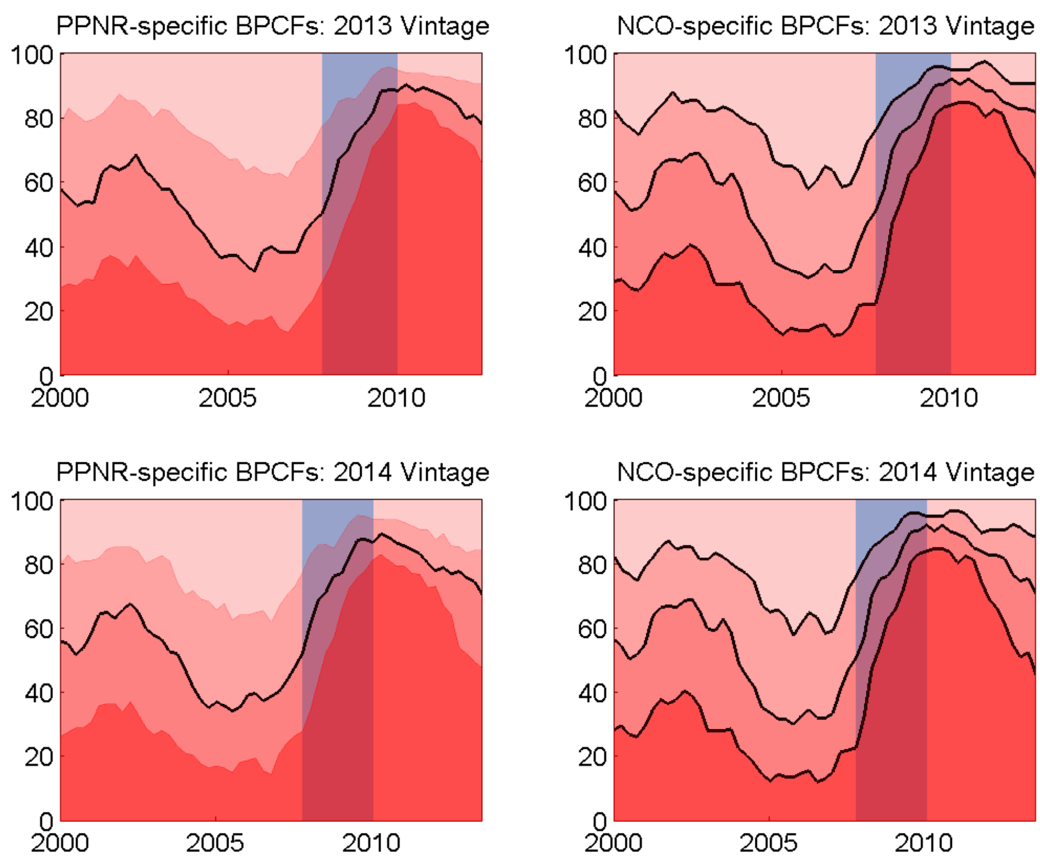

Figure 5: Distribution of BPCFs by quartile; Black lines designate optimal grouping borders; Blue shaded area—Crisis Period

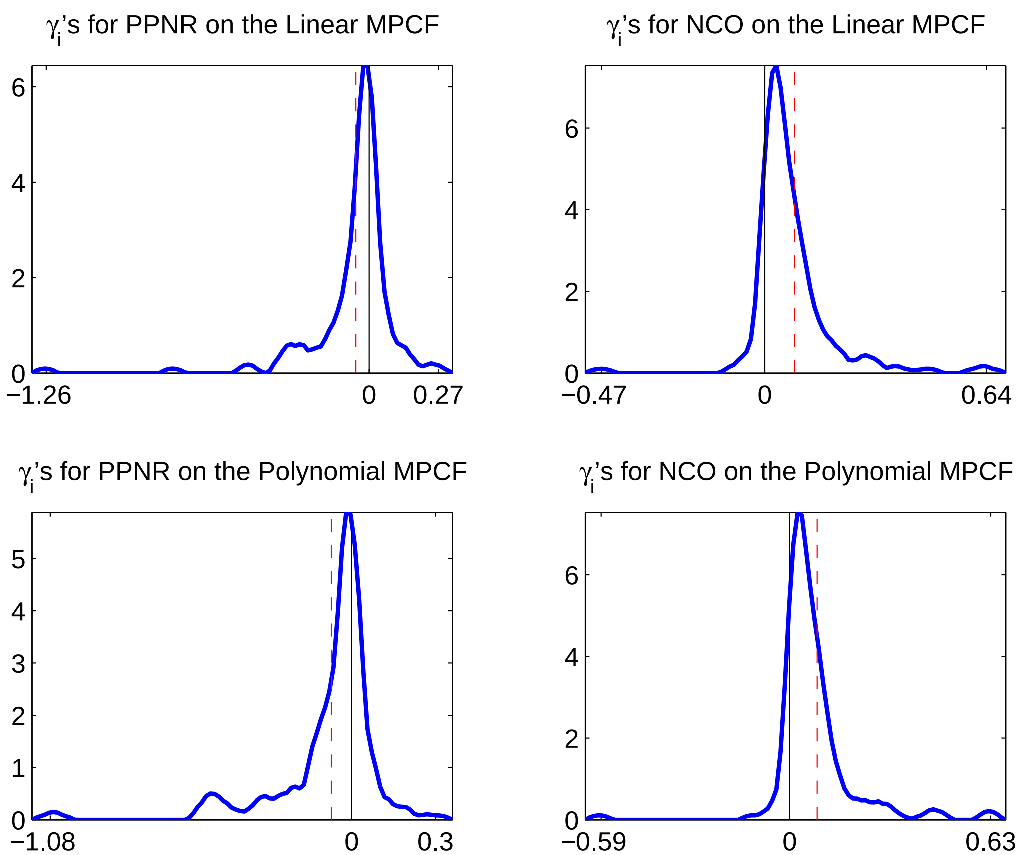

Figure 6: Blue solid line—Coefficients from bank-by-bank regressions; Red dashed line—Coefficients from FE regressions

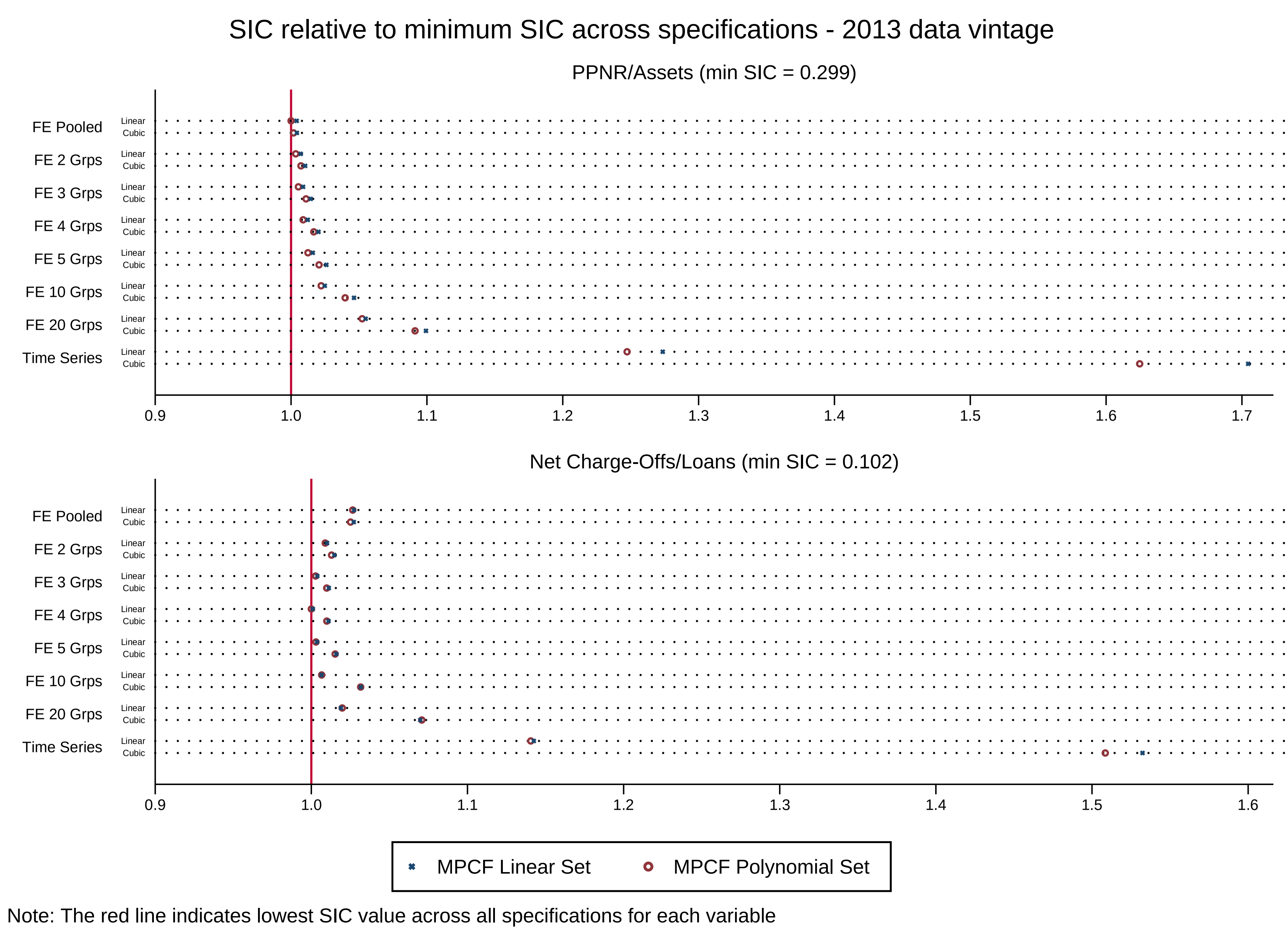

Figure 7: Schwartz information criterion for alternative models: 2013 data vintage

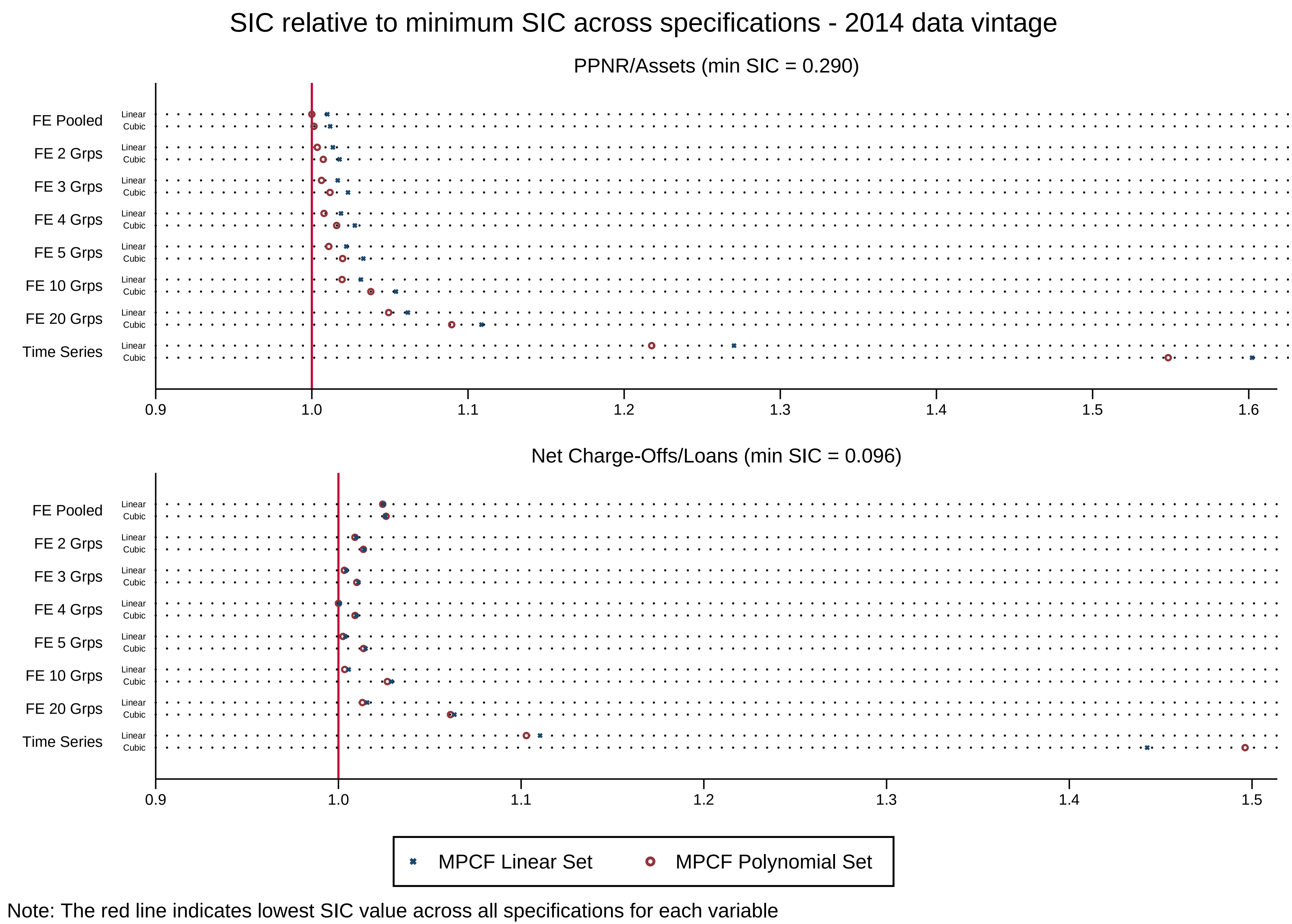

Figure 8: Schwartz information criterion for alternative models: 2014 data vintage

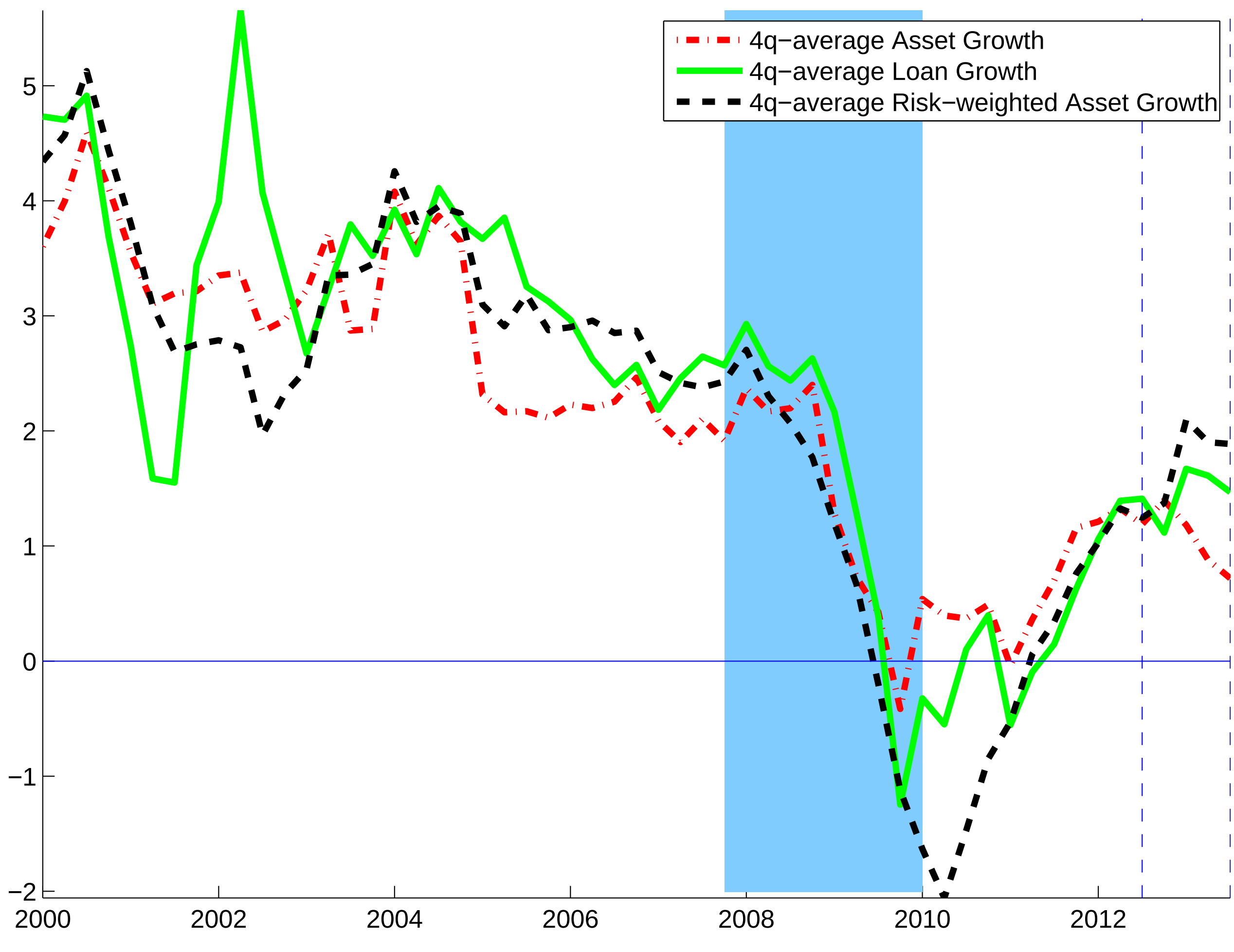

Figure 9: Historical Industry Average 4-quarter Asset and Loan Growth Rates; Periods for asset and loan growth assumptions: Blue shaded area—Crisis Period, vertical dashed lines at 2012Q3 and 2013Q3

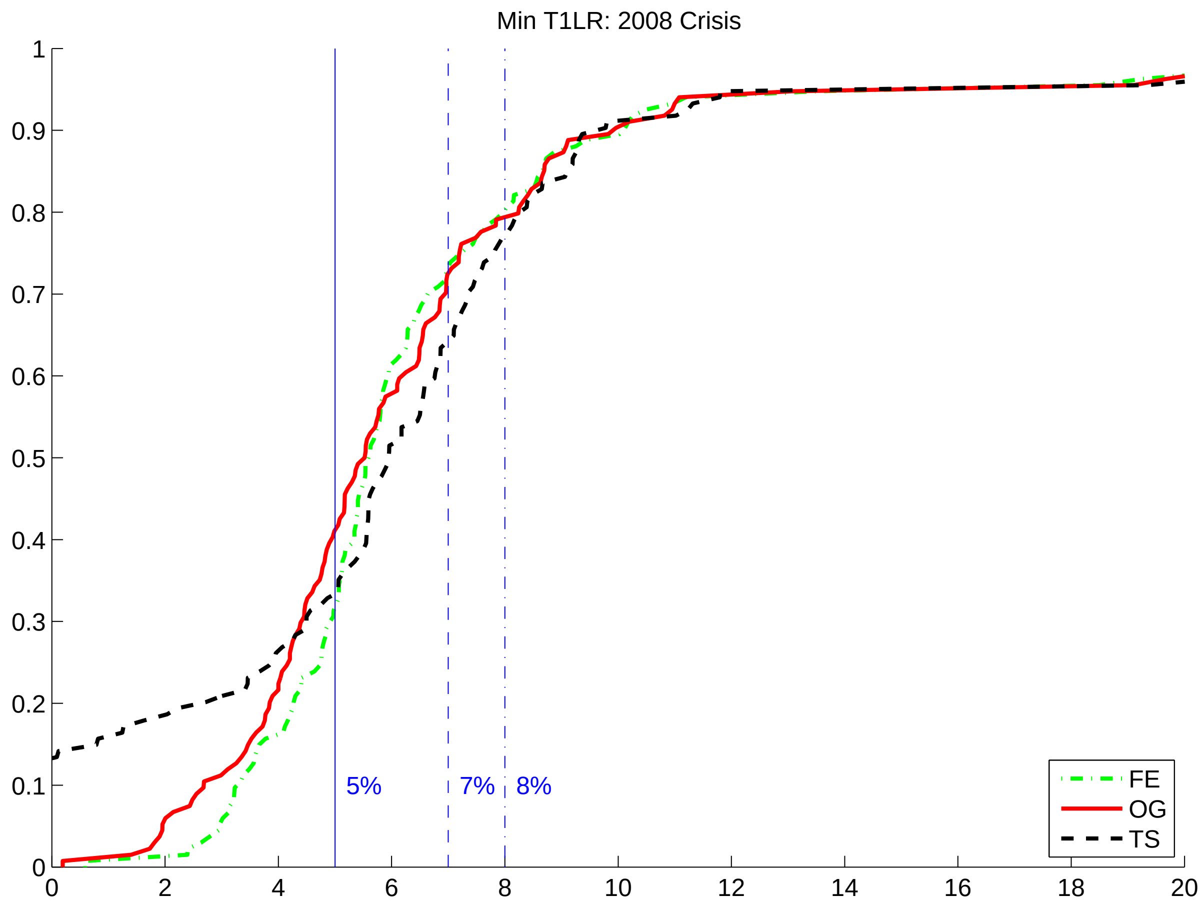

Figure 10: 2008 Crisis; Horizontal axis: T1 Lev Ratio (%); Vertical axis: cumulative frequency

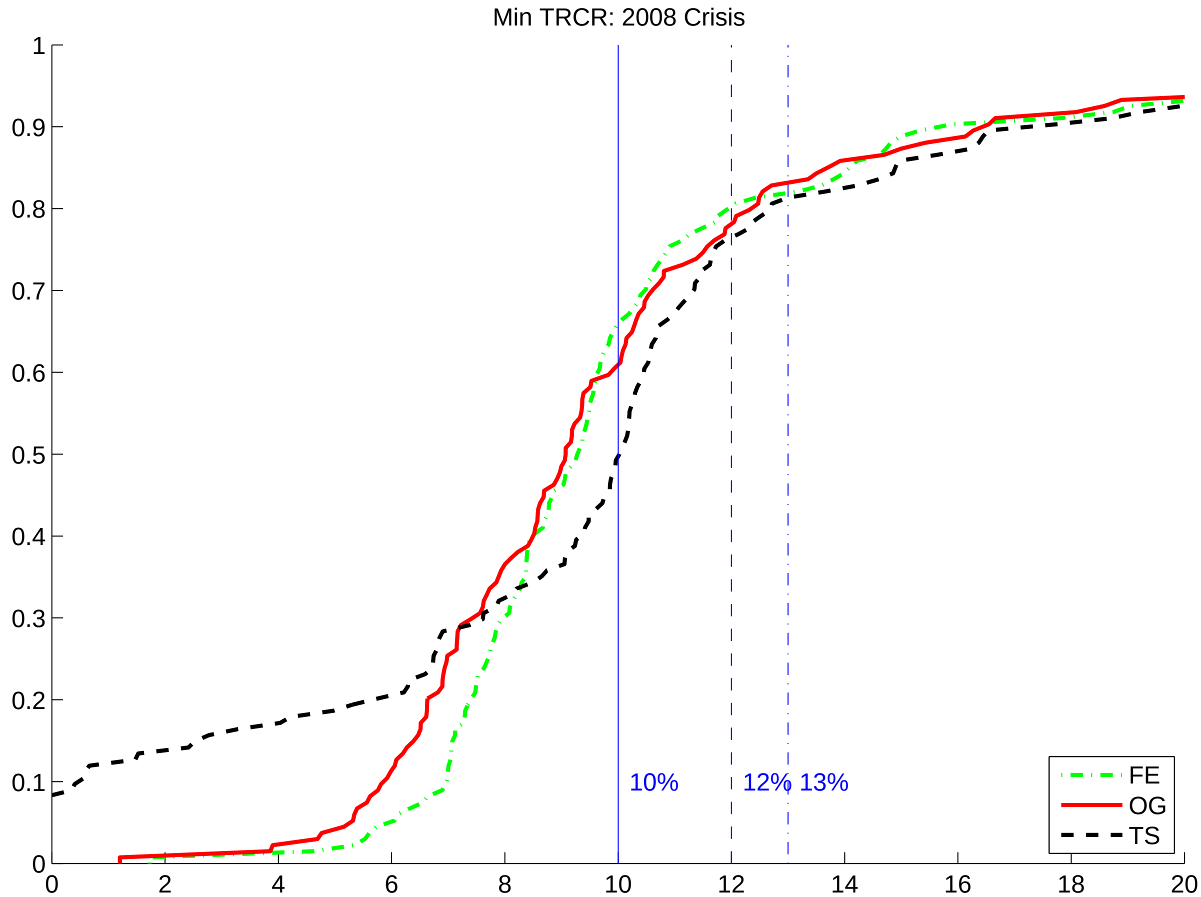

Figure 11: 2008 Crisis; Horizontal axis: Tot Risk-based Cap Ratio (%); Vertical axis: cumulative frequency

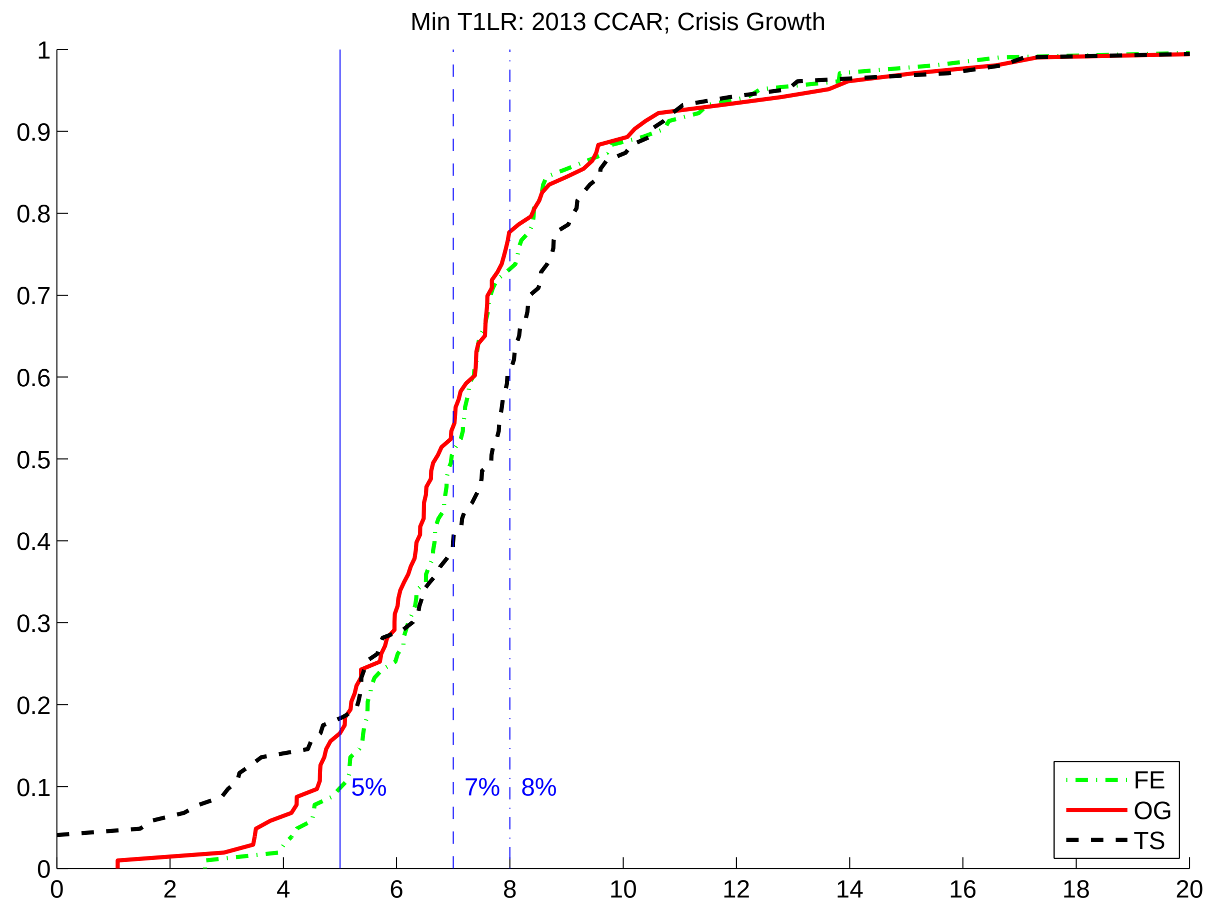

Figure 12: 2013 CCAR Severely Adverse Scenario; Crisis Growth Rates; Horizontal axis: T1 Lev Ratio (%); Vertical axis: cumulative frequency

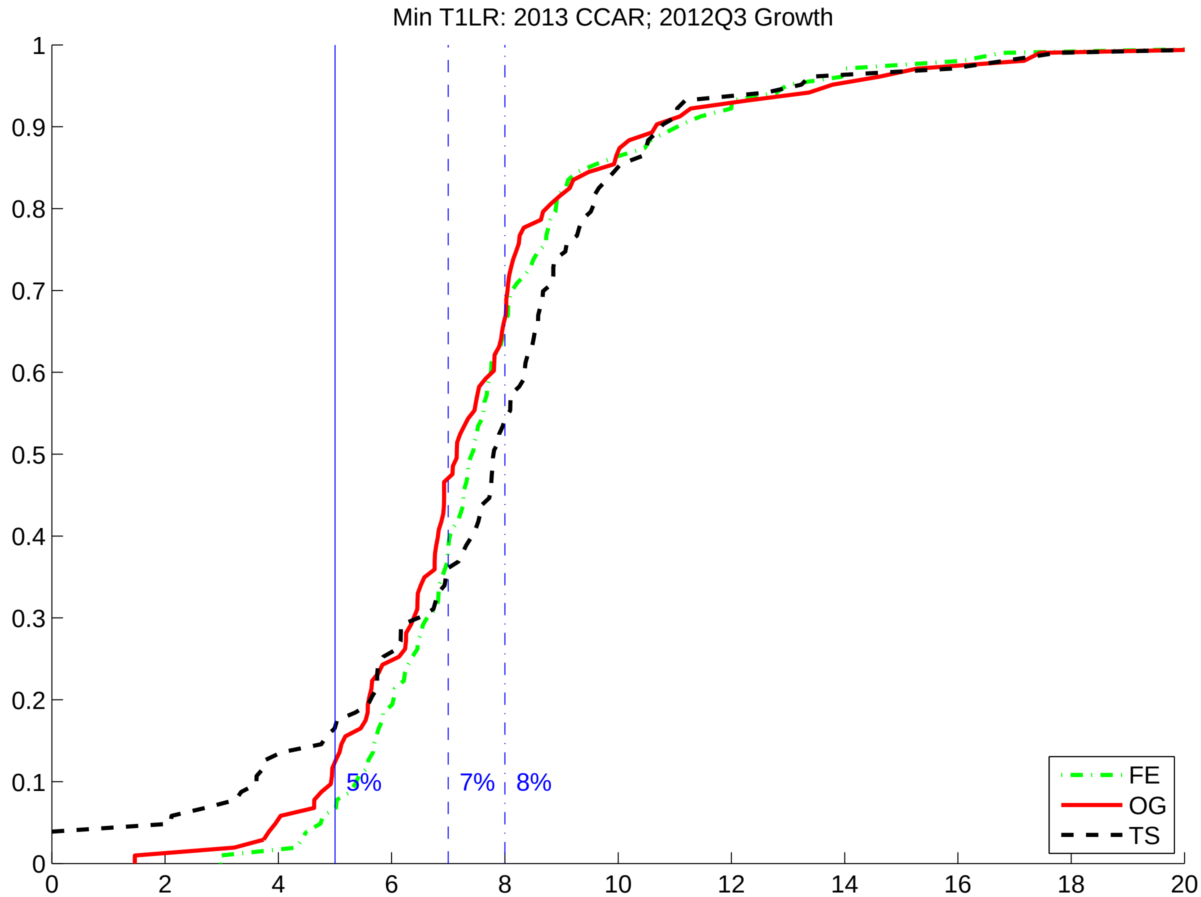

Figure 13: 2013 CCAR Severely Adverse Scenario; 2012Q3 Growth Rates; Horizontal axis: T1 Lev Ratio (%); Vertical axis: cumulative frequency

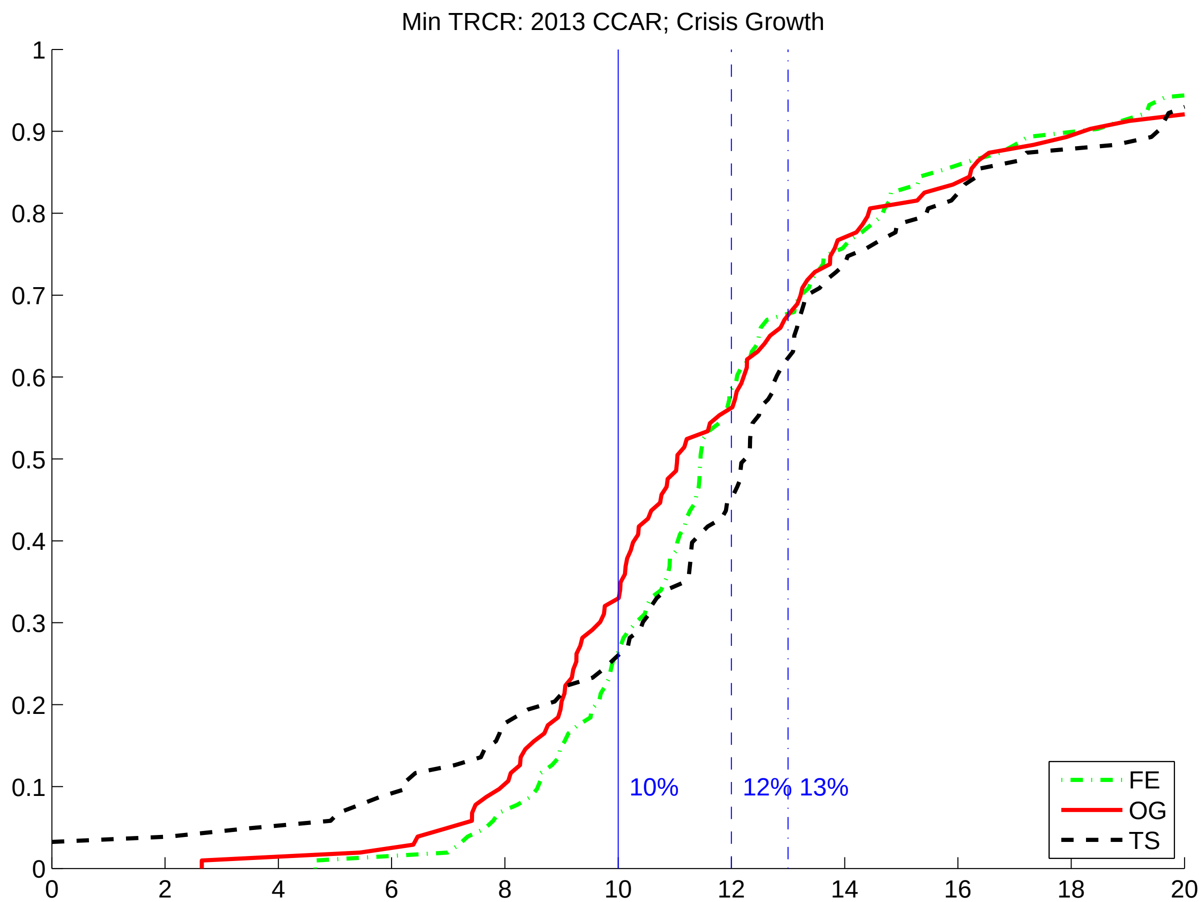

Figure 14: 2013 CCAR Severely Adverse Scenario; Crisis Growth Rates; Horizontal axis: Tot Risk-based Capital Ratio (%); Vertical axis: cumulative frequency

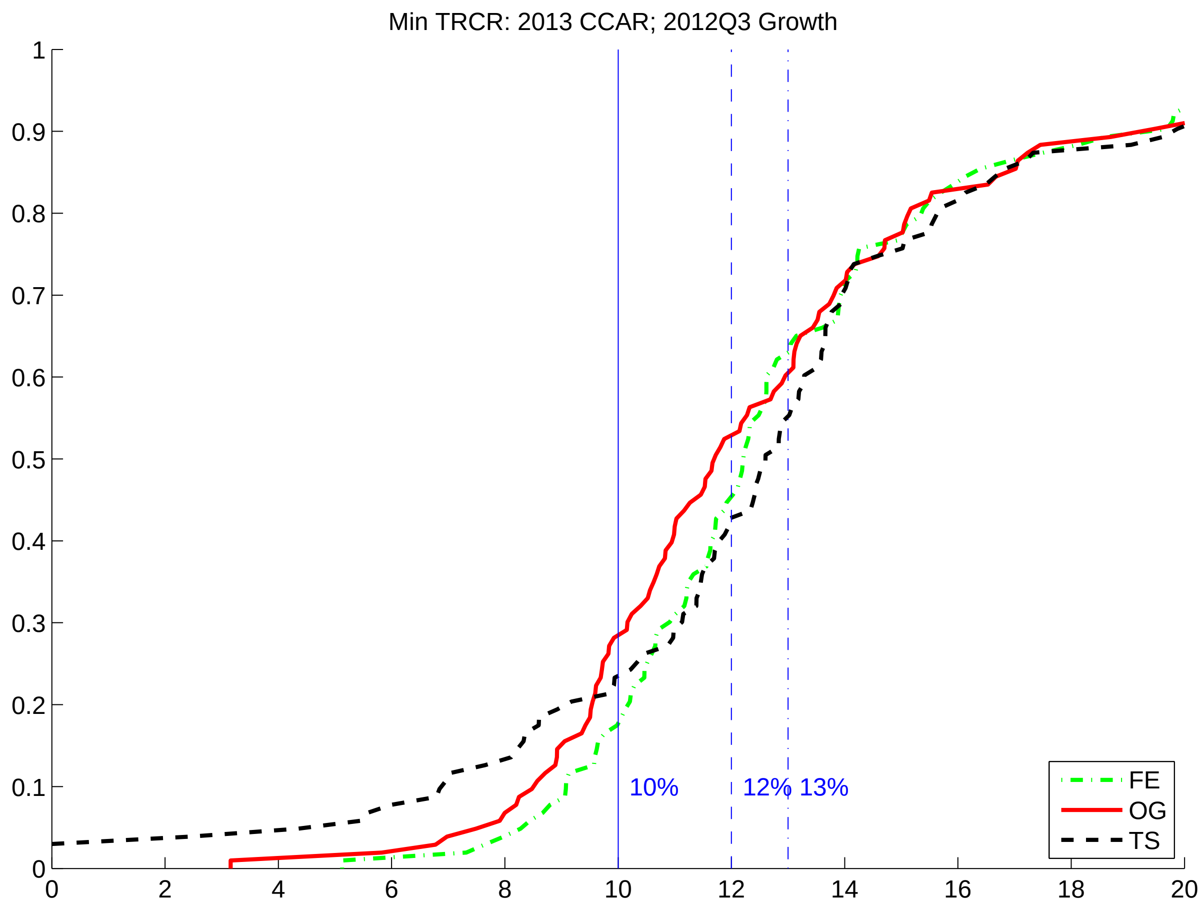

Figure 15: 2013 CCAR Severely Adverse Scenario; 2012Q3 Growth Rates; Horizontal axis: Tot Risk-based Capital Ratio (%); Vertical axis: cumulative frequency

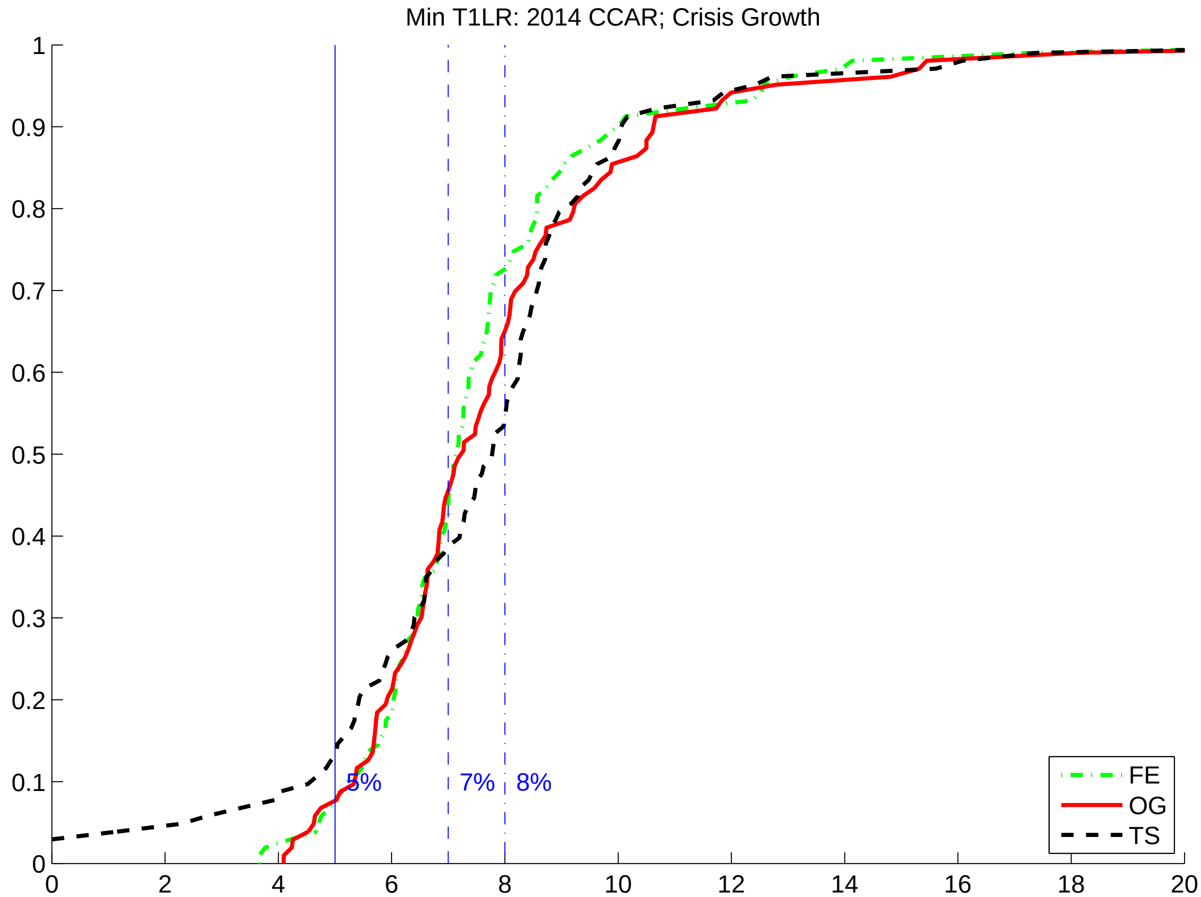

Figure 16: 2014 CCAR Severely Adverse Scenario; Crisis Growth Rates; Horizontal axis: T1 Lev Ratio (%); Vertical axis: cumulative frequency

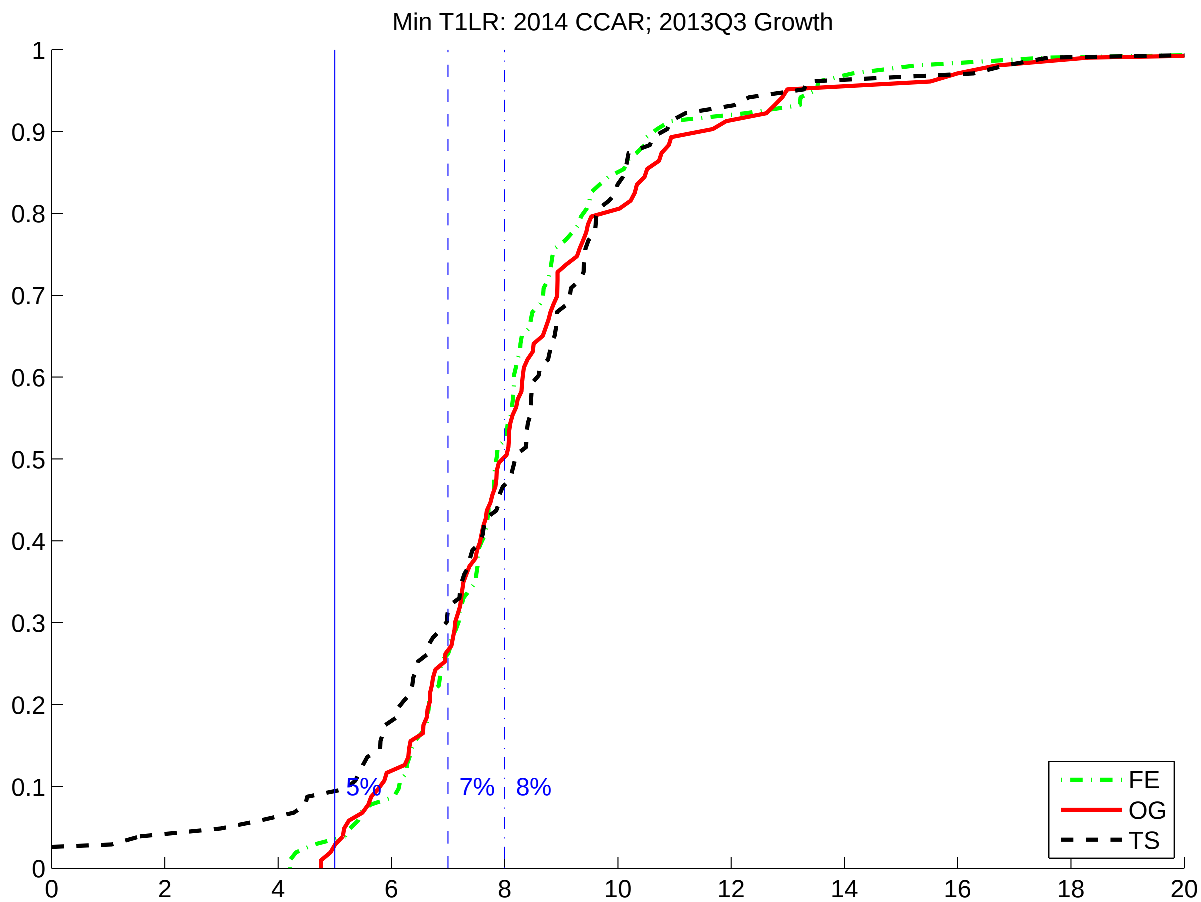

Figure 17: 2014 CCAR Severely Adverse Scenario; 2013Q3 Growth Rates; Horizontal axis: T1 Lev Ratio (%); Vertical axis: cumulative frequency

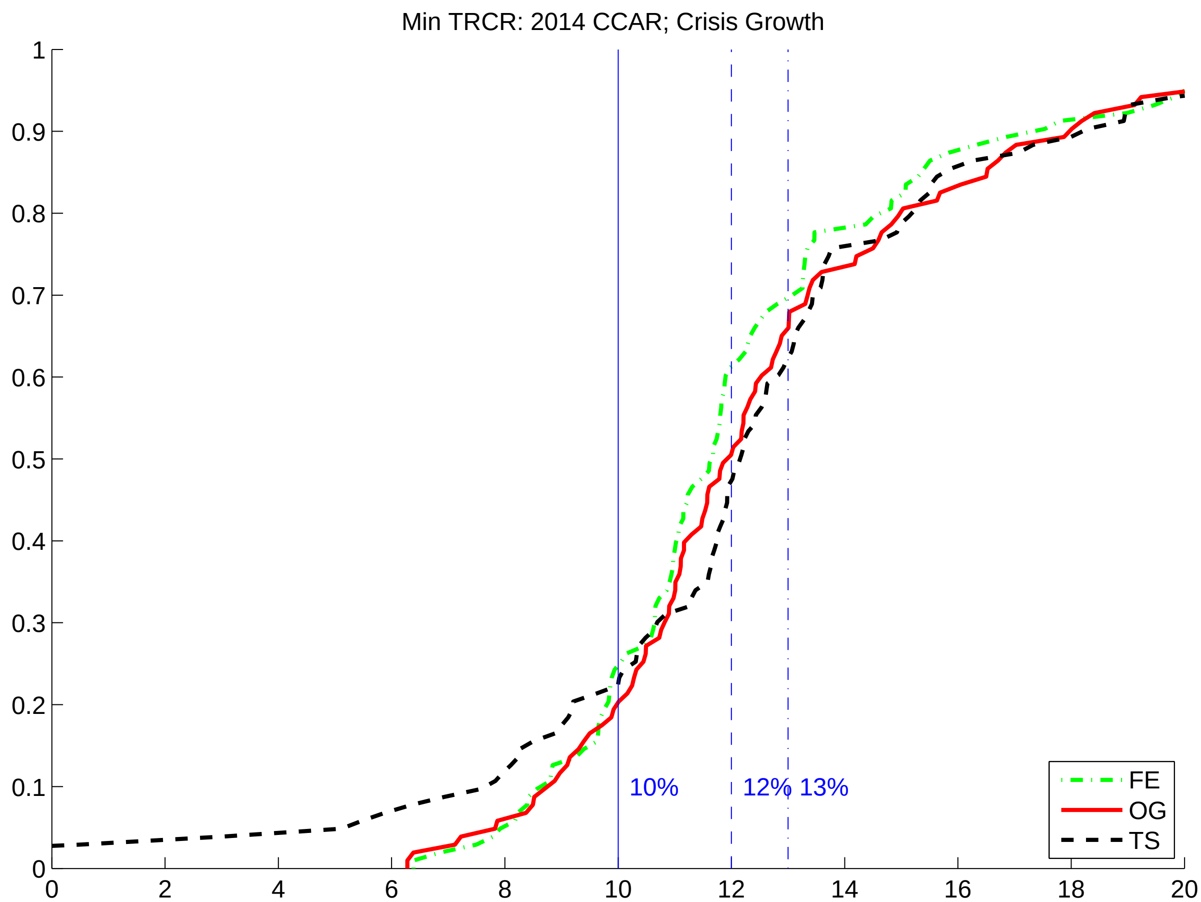

Figure 18: 2014 CCAR Severely Adverse Scenario; Crisis Growth Rates; Horizontal axis: Tot Risk-based Capital Ratio (%); Vertical axis: cumulative frequency

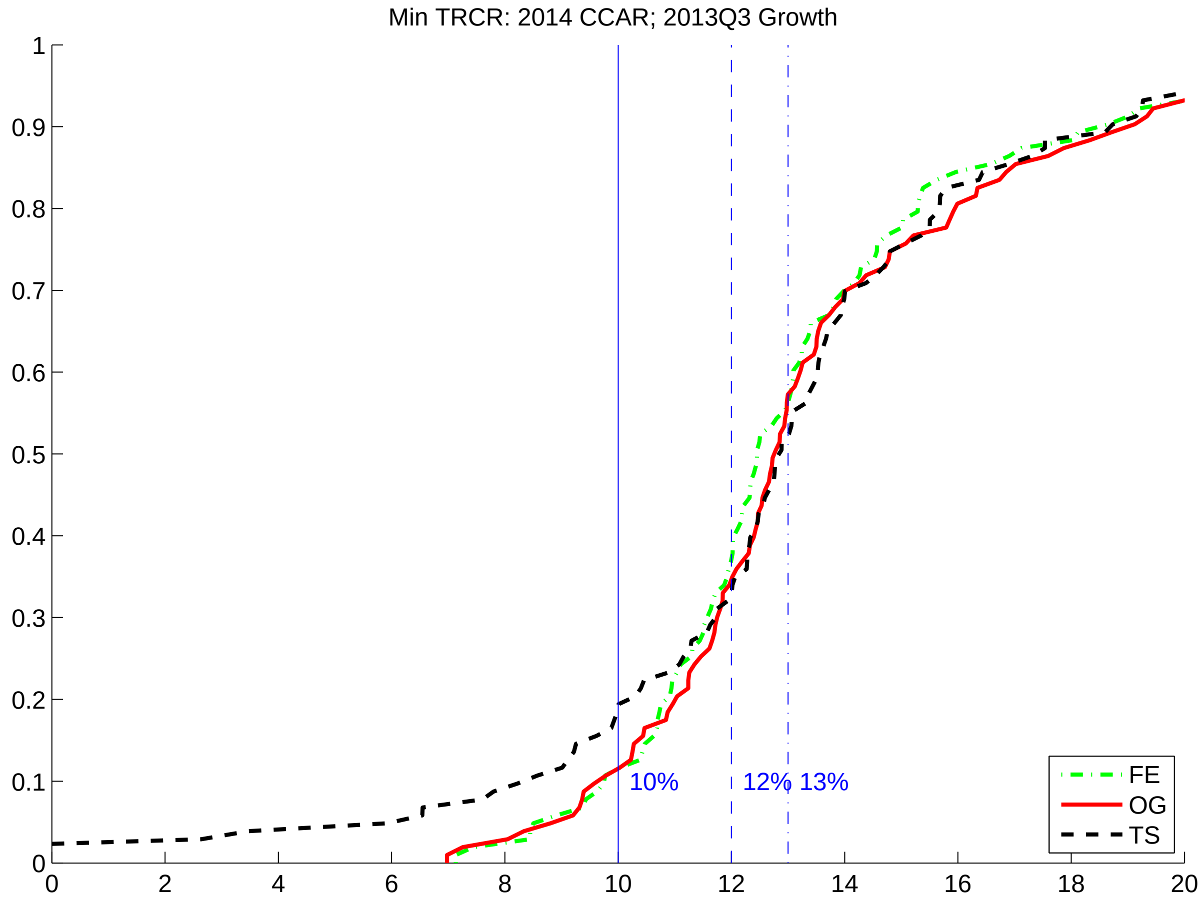

Figure 19: 2014 CCAR Severely Adverse Scenario; 2013Q3 Growth Rates; Horizontal axis: Tot Risk-based Capital Ratio (%); Vertical axis: cumulative frequency