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Assessing financial stability: The Capital and Loss Assessment under Stress Scenarios (CLASS) model ☆

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ABSTRACT

The CLASS model is a top-down capital stress testing framework that uses public data, simple econometric models and auxiliary assumptions to project the effect of macroeconomic scenarios on U.S. banking firms. Through the lens of the model, we find that the total banking system capital shortfall under stressful macroeconomic conditions began to rise 4 years before the financial crisis, peaking in the fourth quarter of 2008. The capital gap has since fallen sharply, and is now significantly below pre-crisis levels. In the cross-section, banking firms estimated to be most sensitive to macroeconomic conditions also have higher capital ratios, consistent with a "precautionary" view of bank capital, though this behavior is evident only since the crisis. We interpret our results as evidence that the resiliency of the U.S. banking system has improved since the financial crisis, and also as an illustration of the value of stress testing as a macroprudential policy tool.

1. Introduction

Central banks and bank supervisors have increasingly relied on capital stress testing as a supervisory and macroprudential tool. The recent financial crisis highlighted the importance of the amount and quality of bank capital in ensuring public confidence in individual financial institutions and in the financial system as a whole. Stress tests have been used by central banks and supervisors to assess the resilience of individual banking companies to adverse macroeconomic and financial market conditions as a way of gauging additional capital needs at individual firms and as means of assessing the overall capital adequacy of the banking system. In the United States, the first formal bank supervisory stress tests – the Supervisory Capital Assessment Program (SCAP) – were performed during 2009, and stress tests have since been made permanent through the implementation of the stress test provisions of the Dodd-Frank Act (Dodd-Frank Act Stress Tests, or DFAST) and the introduction of the Comprehensive Capital Analysis and Review (CCAR)[1]. European banking supervisors conducted stress tests of the largest European banking companies in 2009, 2010, 2011 and 2014, with an additional round of tests planned for 2016.[2] A number of central banks have also constructed system-wide stress test frameworks to assess the robustness of their banking systems to adverse macroeconomic environments and stressed funding conditions.[3]

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1 See Board of Governors of the Federal Reserve System (2009a,b, 2012, 2013a,b) for more detail on the SCAP, CCAR and DFAST stress tests. Bookstaber et al. (2013) and Greenlaw et al. (2012) discuss use of supervisory stress tests for macroprudential purposes. Pre-dating the SCAP, regular supervisory stress tests of the housing government sponsored enterprises Fannie Mae and Freddie Mac were conducted by their regulator, the Office of Federal Housing Enterprise Oversight (OFHEO). Frame et al. (2015) present a detailed analysis of these tests and the reasons why they failed to forsee the insolvencies of Fannie Mae and Freddie Mac in 2008.

2 See Committee of European Banking Supervisors (2010) and European Banking Authority (2011) for details and results of the early European stress tests.

3 For instance, Kapadia et al. (2012) describe the RAMSI model developed by the Bank of England and Wong and Hui (2009) describe a model developed at the Hong Kong Monetary Authority to assess liquidity risk.

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In this paper, we describe a framework for assessing the impact of macroeconomic conditions on the U.S. banking system – the Capital and Loss Assessment under Stress Scenarios (CLASS) model. The CLASS model is a "top-down" model of the U.S. commercial banking industry that generates projections of commercial bank and bank holding company (BHC) income and capital under macroeconomic scenarios. These projections are based on regression models of components of bank income, expense and loan performance, combined with assumptions about provisioning, dividends, asset growth and other factors.

Projections from the CLASS model provide insight into the capital resiliency of the U.S. banking system against severely stressed economic and financial market conditions and thus into the stability of the broader financial system. Specifically, the CLASS projections suggest that the U.S. banking industry's vulnerability to undercapitalization has declined, not only relative to the financial crisis of 2007–09, but also relative to the period preceding the crisis. CLASS model projections indicate an increasing capital "gap" (a shortfall of capital under stressed economic conditions) starting as early as 2004, well before most market-based measures of capital adequacy began to deteriorate.

Looking cross-sectionally, CLASS model projections based on current industry data suggest that firms that are projected to experience large declines in capital under stressful economic conditions also tend to have higher current capital ratios. This relationship is consistent with a "precautionary" view of bank capital. That is, banking firms holding risky assets or engaged in risky income-producing activities also hold higher capital buffers to limit the likelihood of financial distress. This relationship has evolved over time, however. CLASS model results for years prior to the financial crisis do not show a consistent cross-sectional relationship between capital ratios and projected declines in capital under stress – instead we find evidence of this precautionary behavior only in the last part of our sample (2011–13). This finding further supports the idea that the capital strength and stability of the U.S. banking industry have improved relative to both the financial crisis period and the period leading into the crisis.

The CLASS model's top-down approach is intended to complement more detailed supervisory models of components of bank revenues and expenses, such as those used in the DFAST, CCAR, and European stress tests. Unlike such models, the CLASS model relies only on public information, namely, macroeconomic and financial market data combined with bank and BHC regulatory report filings. The use of regulatory report data allows the model to compute projections easily for a much larger number of firms and with greater frequency than is practical from detailed bottom-up analysis using supervisory data collected directly from BHCs. In addition, the CLASS framework is relatively simple to understand, and can produce income and capital projections in only a couple of minutes for a single macroeconomic scenario. As a result, it can be used either for simulations or to provide immediate back-of-the envelope estimates of the effect of a particular macroeconomic shock on the U.S. banking system.

Balanced against these advantages, the CLASS model's "top-down" approach also has some significant limitations. For example, it abstracts from many idiosyncratic differences between individual institutions. For this reason, while the model can reasonably be used to model aggregate net income and capital, and the overall distribution of capital across institutions, caution should be exercised in using the model to project the capital of a specific bank or BHC. In addition, the model does not currently incorporate any feedback from the banking system to the macroeconomy or to financial markets. Instead, the macroeconomic projections used as inputs to the model are treated as exogenous.

In spite of these limitations, we show that the CLASS model's projections of revenues, loan losses, and net income are positively and statistically significantly correlated with the Federal Reserve's DFAST projections, which are based on more detailed models and extensive confidential supervisory data. CLASS model projections for the financial crisis period are also positively correlated with actual outcomes for individual BHCs during this period. These results suggest that that the CLASS model is capturing some of the important firm-specific and economy-wide factors that generate differences in bank performance under stress.

The rest of this paper describes the CLASS model in more detail and presents model projections that provide insight into the evolution of the capital strength and financial stability of the U.S. banking system over time. Section 2 provides an overview of the CLASS model's framework and analytical approach and presents projections of industry aggregate revenue, losses, net income and capital ratios under a range of hypothetical scenarios, based on U.S. banking system data as of 2013:Q3. Section 3 shows how the CLASS model can be used to analyze trends in financial stability. Section 4 contains a detailed discussion of the data, specifications of the CLASS model equations and describes the auxiliary assumptions needed to complete the model. Section 5 reports specification tests comparing CLASS model results to those generated by the Federal Reserve in DFAST 2014 and to BHCs' actual experiences during the financial crisis and examines how different elements and assumptions of the CLASS model affect model output. Section 6 concludes.

2. Overview of the CLASS model framework and results

2.1. Framework and analytical approach

The CLASS model is designed to project net income and capital for individual banks and BHCs over a future period of 2–3 years (the "stress test horizon") under different macroeconomic and financial market scenarios. The macroeconomic scenarios are defined by a set of economic and financial market variables – such as GDP growth, the unemployment rate, housing prices, equity prices, short-term and long-term interest rates, and credit spreads – that are likely to influence the profitability of banking institutions. The key outputs of the CLASS model are projections of net income and capital given assumed paths for these economic and financial market variables over the stress test horizon.

Fig. 1 summarizes the CLASS model's structure and the main steps involved in generating income and capital projections. The model's core is a set of regression equations that are used to project how various financial ratios (e.g. the net interest margin (NIM), net charge-off rates on different types of loans) evolve over time, conditional on macroeconomic conditions, the lagged value of the financial ratio, and other controls.[4] These ratio projections are converted to dollar values by multiplying by loan balances (in the case of loan loss rates), securities balances (in the case of securities losses), or assets (in the case of revenue and expense items). The loss, revenue, and expense projections are then combined to compute projected pre-tax net income. Changes in regulatory capital and regulatory capital ratios are derived by combining these pre-tax net income projections with assumptions about dividends, taxes, and regulatory capital rules, along with assumptions about growth of risk-weighted assets (RWA). Details of the design and specification of the CLASS model equations and auxiliary assumptions are presented in Section 4 and the Appendix.

Net income and capital projections are computed for each of the 200 largest U.S. banking organizations (BHCs and independent banks) and for a hypothetical 201st firm representing the aggregate of the rest of the U.S. banking system. Individual firm projections are summed to generate system-wide results.

[4] As discussed in greater detail in Section 4, the regression equations have an AR(1) structure.

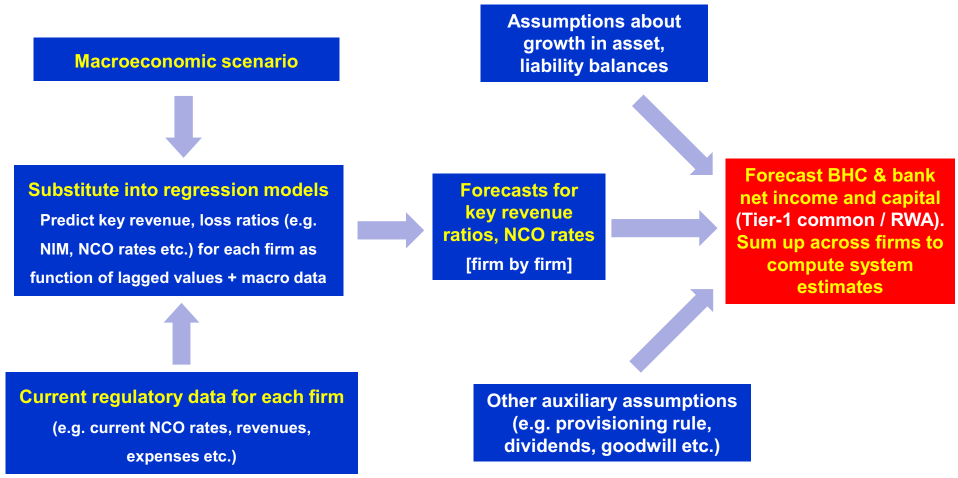

Fig. 1. CLASS model structure.

The CLASS model projects net income and regulatory capital ratios as they would occur over time under the particular macroeconomic scenario, rather than generating estimates of marked-to-market values of the banks' assets or capital or estimating the impact of an instantaneous roll-forward of peak-to-trough scenario conditions. As such, the CLASS model projections follow U.S. generally accepted accounting principles (GAAP) and U.S. regulatory capital rules. In particular, loss and revenue projections reflect the U.S. GAAP treatment of the underlying positions.

The CLASS model uses 22 regression equations to project the components of pre-tax net income. The first major component of income is pre-provision net revenue (PPNR), an accounting measure defined as: (1) net interest income (interest income earned minus interest expense) plus (2) non-interest income (including trading income, as well as non-trading noninterest income earned from fees and other sources), minus (3) non-interest expense (compensation, expenses related to premises and fixed assets, and other non-credit-related expenses).

The next net income component is provision expense for loan and lease losses. The CLASS model first computes projected net charge-offs (NCOs) based on NCO rates on 15 different categories of loans. CLASS includes a rule that then translates current net charge-offs and the level of loan loss reserves into provision expense, since under U.S. GAAP, it is provision expense rather than charge-offs that directly affects net income. This provisioning rule is described in Section 4.

Pre-tax net income equals PPNR minus provision expense for loan losses plus projected gains or losses on investment securities held in the firm's available-for-sale (AFS) and held-to-maturity (HTM) portfolios. The model includes an econometric model for AFS returns. Returns on HTM portfolios, which are generally small for most firms, are assumed to be zero. After-tax net income is calculated using a constant, assumed tax rate applied to all banks and BHCs. CLASS allows firms to accumulate deferred tax assets (DTAs) as a result of pre-tax losses incurred. However, since U.S. regulation limits the extent to which these DTAs can be recognized for regulatory capital purposes, CLASS includes an adjustment to recognize these limits.

In the final step, CLASS computes the evolution of capital for the firm, based on the path of net income combined with a behavioral rule for dividends and other distributions.[5] Following practice in the DFAST and CCAR stress tests, the primary capital metric in the CLASS model projections is Tier 1 common equity, defined as common equity minus the deductions from Tier 1 capital (such as certain intangible assets) required under U.S. regulatory capital rules. Capital ratios are calculated using the U.S. regulatory capital rules prevailing at the "as of" date of the projections (the last historical observation), including the definitions of regulatory capital and rules for calculating risk-weighted assets. The CLASS model results presented in this paper primarily reflect Basel 1 risk weights[6] and regulatory capital definitions, since these are the rules under which U.S. banks and BHCs calculated their risk-weighted regulatory capital ratios in 2013:Q3, the "as of" date of the projections. Future versions of the CLASS model will incorporate Basel 3 risk-weighted asset and regulatory capital definitions, as those come into force in the United States.

2.2. Net Income and capital projections

This section presents CLASS model net income and capital projections under two macroeconomic scenarios: a "baseline" scenario representing an expected or median path for the economy and financial markets, and a "crisis redux" scenario that replicates conditions experienced during the 2007–09 financial crisis. The baseline scenario is the scenario developed by the Federal Reserve for CCAR. The crisis redux scenario represents a repeat of the actual path of economic conditions experienced from the third quarter of 2007 onwards.[7] We seed the model with BHC and bank balance sheet and income data as of 2013:Q3. From this starting point, we use the CLASS framework to compute income and capital projections over the subsequent nine quarters under each scenario.[8] Macroeconomic and financial conditions under the baseline and crisis redux scenarios are summarized in Table 1.

2.2.1. Income projections

Fig. 2 presents the industry-wide CLASS projections under these two scenarios for components of pre-provision net income, and for

[5] The behavioral rule for dividends is described in Section 4.

[6] An important exception is trading-related risk-weighted assets at the largest BHCs, which are calculated under "Basel 2.5" rules starting with the first quarter of 2013 and for all subsequent quarters. These rules significantly increase trading-related risk-weighted assets at these firms.

[7] Specifically, the crisis redux scenario uses the historical path for the *transformation* of each macroeconomic variable as it is used in the CLASS model. For example, one of the macroeconomic forcing variables in the CLASS model is the quarterly change in the unemployment rate. Correspondingly, for the crisis redux scenario, we set the *change* in the unemployment rate from 2013:Q2 onwards equal to the historical change in the unemployment rate from 2007:Q3 onwards.

[8] As explained in Section 4, our approach to modeling loan loss provisions uses projected *future* net charge-offs in the subsequent four quarters as an input into computing the value of ALLL at each point in time. Correspondingly, we actually project net charge-offs over a longer *thirteen* quarter horizon, in order to calculate provision expense and ALLL over the nine quarters of the scenario proper. For this reason, each macroeconomic scenario is actually specified to be thirteen quarters in length.

Table 1
Summary of macroeconomic scenarios.

Macro scenarios: selected variables	Historical	Baseline			Crisis redux		
	2013 Q3	First 3Q	Middle 3Q	Last 3Q	First 3Q	Middle 3Q	Last 3Q
Unemployment rate (end)	7.30	7.00	6.70	6.30	7.80	9.70	12.40
GDP growth (%, ann)	1.86	2.59	2.89	2.89	0.47	(2.87)	(1.54)
Equity prices (% ch)	19.44	(0.70)	4.00	4.08	(12.39)	(31.82)	19.39
Home price growth (% ch, ann)	10.90	2.52	2.64	3.07	(15.40)	(21.73)	(11.74)

Note: The historical data and baseline scenario reported here are based on the supervisory scenarios data posted by the Federal Reserve on November 1 2013 (see http://www.federalreserve.gov/bankinforeg/stress-tests-capital-planning.htm). They do not reflect any subsequent data revisions.

loan performance as measured by the net charge-off rate. Recall that the model projections are computed firm-by-firm and quarter-by-quarter; the model then calculates industry projections by summing all dollar projections across firms, and computing ratios based on these industry sums.

The upper panels of Fig. 2 present projections for different PPNR components: net interest margin, return on trading assets, and non-trading noninterest income and noninterest expense scaled by total assets. The green line in each graph represents baseline scenario projections, while the yellow line represents projections under the crisis redux scenario.

As the figure illustrates, the CLASS model projections are quite sensitive to the scenario, with the stressed economic and financial market conditions of the crisis redux scenario generating projections of losses, revenue, and expenses that are significantly more severe than those under the baseline scenario. In particular, with the exception of NIM, each component of PPNR deteriorates significantly under the crisis redux scenario. Projected trading income is volatile, and significantly negative in the worst quarters of the scenario, approximately matching its behavior during the financial crisis. Non-trading noninterest income also deteriorates, but is less volatile quarter-to-quarter due to the more highly autoregressive statistical model used for this category. In addition, noninterest expense scaled by total assets is significantly elevated under the crisis redux scenario. Aggregate PPNR (bottom left panel of Fig. 2) falls sharply in the crisis redux scenario and is actually projected to be negative at the worst point of the scenario, an outcome not observed at any point over our historical sample period.

The bottom-right panel of Fig. 2 plots the projected industry net charge-off ratio, a summary measure of realized credit losses. This ratio rises sharply under the crisis redux scenario, approaching, but not reaching, the peak NCO rate realized during the financial crisis. The NCO rate is essentially flat in the baseline scenario, implying that the NCO ratio as of 2013:Q3 is close to its long-term steady state value. Although not shown in the figure, provision expense, which is closely linked to NCOs, mirrors these patterns.

Fig. 3 plots annualized industry-level projected return on assets (ROA), defined as annualized net income as a percentage of total assets. Final net income reflects the sum of the income components presented in Fig. 2, as well as projections for other components of net income such as the model for AFS returns. ROA falls sharply under the crisis redux scenario, mirroring its realized path during the financial crisis itself, although with some differences. This variation between the historical crisis ROA and the projected ROA path under a repeat of the same macroeconomic conditions reflects two factors: first, some losses experienced during the crisis are not fully captured by the CLASS framework, for example because they occurred during quarters when the macroeconomic forcing variables did not deteriorate significantly, and second, the set of banking data that is used to seed the model is different, due to changes in the banking system between 2007 and 2013 (e.g. firm entry and exit, changes in the composition of banking system assets and income, and shifts in loan performance, ALLL, and income and expense ratios).

2.2.2. Capital projections

Fig. 4 presents CLASS model projections for the Tier 1 common equity capital ratio (Tier 1 common capital as a percent of risk-weighted assets) for the U.S. banking industry. Panel A of the figure presents the industry-level ratio, calculated as the weighted average for the BHCs and banks in the CLASS framework, using risk-weighted assets as weights. As illustrated in the panel, the industry-level Tier 1 common ratio rises slowly and steadily under the baseline scenario. This ratio declines sharply under the crisis redux scenario, however, from a historical value of 11.9% in 2013:Q3 to a level of 10.1% after the ninth quarter of the scenario. This drop approximately matching the magnitude of the decline in industry capitalization experienced during the 2007–09 financial crisis period.

The projections in Fig. 4 and elsewhere in this paper are point estimates that do not reflect the degree of statistical uncertainty around our conditional forecasts. The width of the confidence intervals will depend significantly on our estimates or assumptions about the *joint* variance–covariance matrix of the regression coefficients across all 22 CLASS model regression models. Currently, we do not estimate this joint matrix, since we estimate each equation separately, rather than as a system. Exploring these confidence intervals and the correlation of the equations using bootstrap methods represents an avenue for future work.

Panel B of Fig. 4 looks at the distribution of projected capital across the cross-section of BHCs and banks. Specifically, it plots the cumulative distribution function of capital: the percentage of industry assets that are held in banking firms with a Tier 1 common ratio lower than different thresholds between 0% and 15%, as plotted on the *x*-axis of the figure. For each scenario, we present this function during the "worst" quarter, that is, the quarter of the scenario in which the projected industry capital ratio is minimized. In practice, this is the first quarter of the baseline scenario and the ninth quarter of the crisis redux scenario.

The cumulative distribution of the Tier 1 common ratio is shifted significantly to the left under the crisis redux scenario relative to the baseline scenario. Reading off the figure, at the low point of the baseline scenario, around one-tenth of industry assets are owned by firms with a Tier 1 common ratio of less than 10%. But under the crisis redux scenario, more than three-quarters of industry assets are held in firms with a Tier 1 common ratio below this same threshold. Even under the crisis redux scenario, however, only a small fraction of industry assets are held in firms with a projected Tier 1 common ratio below 5%, the threshold referenced in the Federal Reserve's 2011 Capital Plan Rule.[9]

Note that the leftward shift in the distribution of capital under the crisis redux scenario (relative to baseline) is not entirely

[9] The Capital Plan Rule requires bank holding companies to demonstrate in their capital plans how the firm will maintain a minimum tier 1 common ratio of more than 5% under stressful conditions, and provides that the Federal Reserve will evaluate the firm's ability to do so in assessing the firm's capital plan. This rule applies to banking firms with at least $50 billion in total assets. See Board of Governors of the Federal Reserve System (2011).

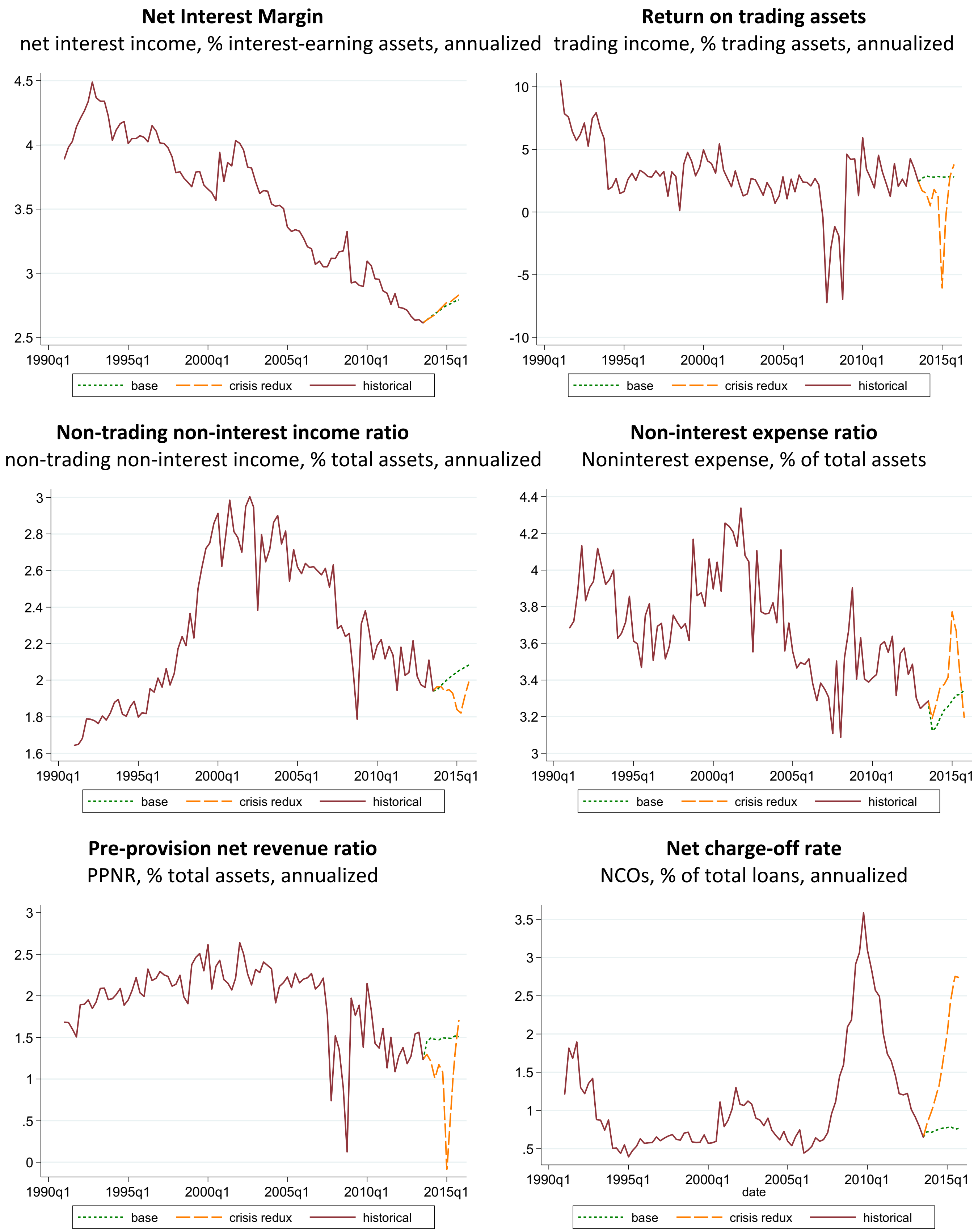

Fig. 2. CLASS projections of PPNR and loan performance.

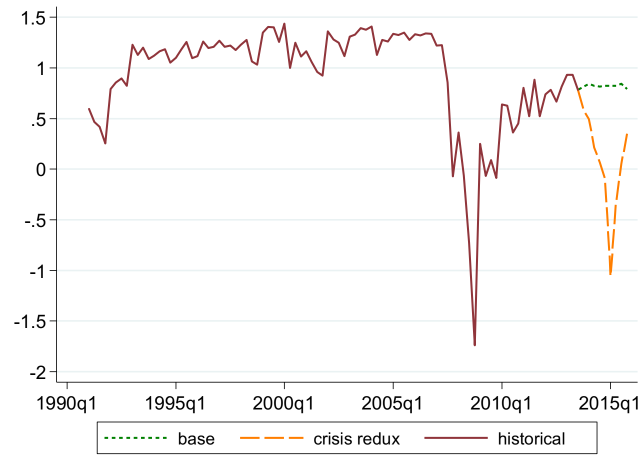

Fig. 3. Return on assets (annualized after-tax net income, % of total assets).

parallel – projected capital declines more significantly for some firms than others. Reflecting this, the variability in the final projected Tier 1 common ratio across firms is more diffuse under the crisis redux scenario than under the baseline scenario.

3. Using CLASS to analyze trends in financial stability

In this section we use the CLASS model as a tool to analyze trends in financial stability, with a focus on capital adequacy under stress. In the time series, we evaluate how the banking system has evolved in terms of being able to withstand a severe macroeconomic downturn without banks becoming undercapitalized or shrinking in size. We then look across the cross-section at the characteristics of banking firms that are particularly exposed to a macroeconomic downturn through the lens of the CLASS framework.

3.1. Evolution of the capital "gap"

As a summary measure of system-wide undercapitalization, we use the CLASS projections described above to compute an estimate of the total capital "gap" – that is, the projected dollar capital injection required to bring each BHC and bank up to a given threshold capital ratio under the scenario in question (or equivalently, the total dollar industry capital shortfall relative to this threshold). We calculate this capital gap firm-by-firm, and then sum across firms, reflecting the fact that capital is not fungible across institutions, and compute the gap in the quarter in which the industry capital ratio is minimized over the stress test horizon.

Fig. 5 plots the time series evolution of the capital gap under the crisis redux scenario, relative to two Tier 1 common/RWA thresholds, 5% and 8%. This figure is constructed by computing the CLASS projections repeatedly using different historical quarters of banking data to "seed" the model (we vary this every quarter between 2002:Q1 and 2013:Q3). We hold the model parameters and macro scenario constant across these runs, so variation in the results only reflects changes in the characteristics of the banking system over time. The time series path of the resulting capital gap can be viewed as an index of how the vulnerability to undercapitalization of the US banking system has evolved, measured under a given stressful macroeconomic scenario (i.e., in this case, the conditions experienced during the 2007–09 financial crisis).

The capital gap relative to an 8% Tier 1 common threshold is approximately $100 billion in 2002, and then rises over time, particularly during 2007 and 2008, reaching a peak of $540 billion in the fourth quarter of 2008. To reiterate, this value implies that if we substitute 2008:Q4 balance sheet and income data for banking firms into the CLASS model and compute capital projections under the crisis redux scenario, then by the low point of the scenario CLASS projects a shortfall of $540 billion in projected Tier 1 common equity relative to an 8% threshold.

This upward trend in the capital gap is reversed from 2009:Q1 onwards – the capital gap falls sharply between 2009 and 2013, reflecting equity issuance by firms, lower dividends and other capital distributions, as well as a return to profitability for most banks and BHCs. The measured capital gap as of 2013:Q3, the final bar on each graph, is $8.5 billion relative to an 8% capital ratio threshold. This is only about one-tenth of its value in 2002, even though industry assets have grown significantly over the intervening period.

Broadly similar trends are evident for the capital gap measured relative to a 5% threshold, although the level of the gap is mechanically smaller at each point in time. The capital gap relative to a 5% threshold is generally close to zero except in the period between late 2006 and 2011. This gap peaks at $304 billion, also in 2008:Q4.

A notable feature of Fig. 5 is that the estimated capital gap begins to increase in 2004, well before the onset of the financial crisis. This increase partially reflects growth in the nominal size

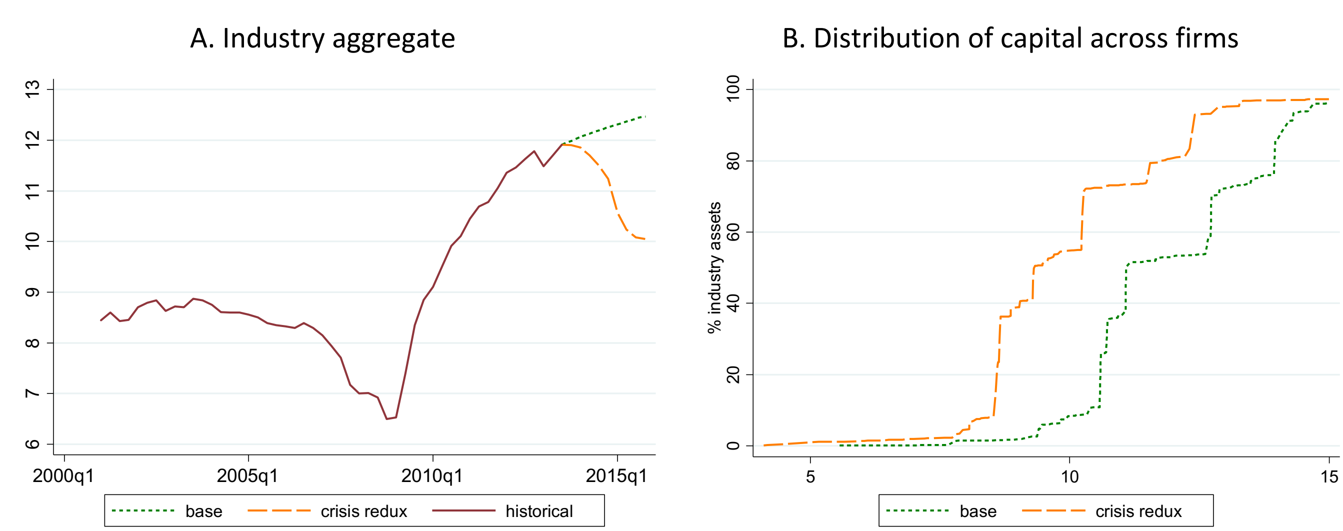

Fig. 4. Capital projections: Tier 1 common equity (percent of RWA).

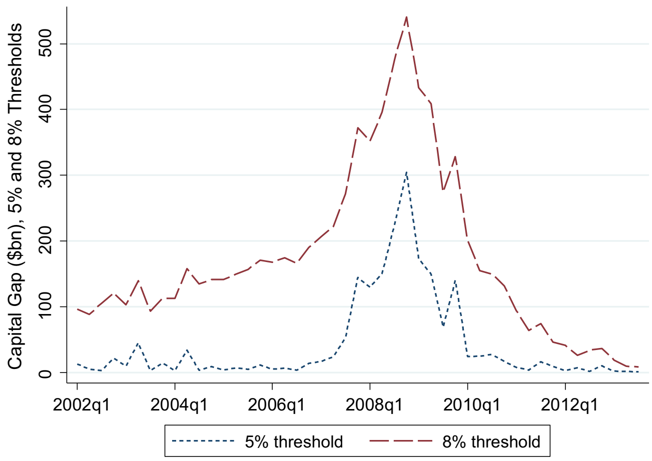

Fig. 5. Evolution of industry capital "gap".

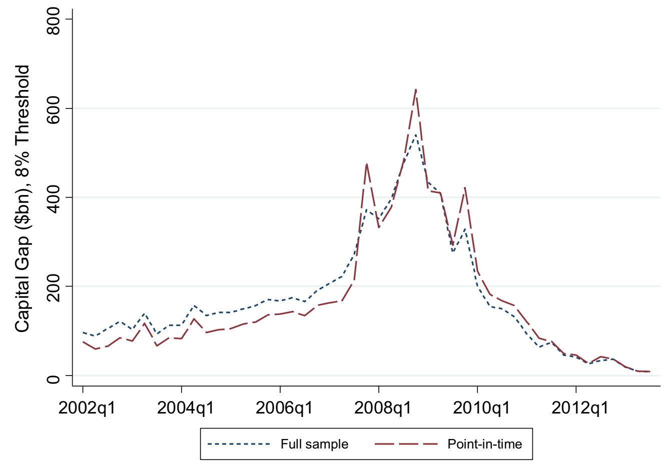

Fig. 6. Point-in-time and full sample industry capital "gap".

of the banking system, although this is not the main explanation: between 2004:Q1 and 2007:Q1 banking system assets increase by 33%, but the capital gap rises by a much larger 83% (from $113bn to $206bn). This time series path of the capital gap implies significant deterioration in the commercial banking industry's capital adequacy under stressful economic conditions in the years leading up to the financial crisis.

One caveat is that the capital gap path presented in Fig. 5 is based on the full-sample CLASS model econometric estimates, and thus is not truly "ex-ante" in nature. Would this upward trend in the capital gap prior to the financial crisis have been identifiable in real time using our framework? To answer this question, we computed a "point-in-time" version of this capital gap time-series, using regression models estimated *only* using data up to the quarter in question, rather than the full sample (e.g. the capital gap as of 2002:Q1 is computed using regression models based on data from 1991:Q1 to 2002:Q1 only). A comparison of the "point-in-time" and "full sample" versions of the industry capital shortfall is presented in Fig. 6. Note that we observe a very similar build-up in the capital gap using this point-in-time approach to the results based on full-sample estimates. For instance, the estimated real-time capital gap virtually doubles between 2004:Q1 and 2007:Q1 (from $82bn to $163bn), actually a larger percentage increase than the 83% change computed using the full-sample model.

The level of the measured capital gap prior to the financial crisis is lower under the point-in-time approach, reflecting that some of the econometric models underlying the CLASS framework are less sensitive to macroeconomic conditions when estimated over a sample period that does not include the financial crisis.[10] Once the financial crisis and Great Recession period is included, however, the projected capital gap based on the point-in-time and full-sample versions of the model are quite similar, and over the last 8 quarters or so of the sample are almost identical. This is consistent with our practical experience as we have updated the CLASS model progressively in recent periods. The financial crisis and Great Recession period has significant effects on many of our regression coefficients, because it represents a period of high volatility in earnings and macroeconomic conditions, helping to identify our parameter estimates. However, the models are relatively stable to the addition of new data points in recent years.

It is interesting to compare these projected capital gaps with market-based measures of stress capital adequacy. In Fig. 7, we compare the evolution of the capital gap from CLASS to the "SRISK" measure of capital shortfall developed by researchers at New York University (Acharya et al., 2012, 2013), and to credit default swap (CDS) spreads for U.S. investment banks and commercial banks, drawn from Bloomberg. (To compare these different measures on a common scale, we normalize each variable by its average value in 2002, the first year of the sample.) SRISK computes capital shortfalls for financial firms based on market equity values and time series models of stock returns. Two SRISK measures are presented, based on the GMES and MESSIM models maintained by the NYU Stern Volatility Lab. Measures shown are based on the same basic modeling approach, although they differ in some details.[11]

All these measures rise sharply as the financial crisis unfolds in 2007 and 2008, and the market-based measures peak at higher normalized values than the CLASS capital gap. But notably, the rise in the CLASS capital gap leads the increase in SRISK in the period leading up to the crisis, particularly so in 2006 and early 2007. And most strikingly, CDS spreads of large U.S. banking organizations were extremely low and actually falling in the period from 2004 until mid-2007, despite the risks building up in the system during this period (see also Eichengreen et al., 2012).

What explains these divergent trends? One plausible reason is the low risk premiums and high market valuations of U.S. banking firms prior to the financial crisis. Calomiris and Nissim (2012) document that the average market-to-book ratio for public banking firms exceeded 200% in the 7 years prior to the crisis, compared to around 100% in 2010 to 2011. Low risk premia for bank debt and equity, even if driven by speculative factors rather than fundamentals, will tend to improve market-based measures of financial stability. We interpret the results in Fig. 7 as evidence that careful analysis of bank accounting data, even without the benefit of confidential supervisory information, can help provide useful early warning signal information about capital adequacy under stressful conditions beyond information encapsulated in market prices.

3.2. Capital sensitivity to macroeconomic conditions: cross-sectional analysis

The sensitivity of projected net income and capital to macroeconomic conditions varies significantly across firms, due to

[10] For instance, residential mortgage credit losses are low and stable prior to the crisis, due to the rising home price environment. As a result, our residential mortgage net charge-off models exhibit little sensitivity to home price growth unless the crisis period is included in the regression sample.

[11] We thank Robert Engle and Viral Acharya for providing historical time series for these two measures. The GMES model is based on the Dynamic Conditional Beta approach of Engle (2014), measured relative to the MSCI World Index, while the MESSIM estimates are based on a simulation approach and capital asset pricing model measures of beta with respect to the S&P 500 index. Regularly updated SRISK estimates are publicly available on the NYU Stern V-Lab website: http://vlab.stern.nyu.edu/welcome/risk/.

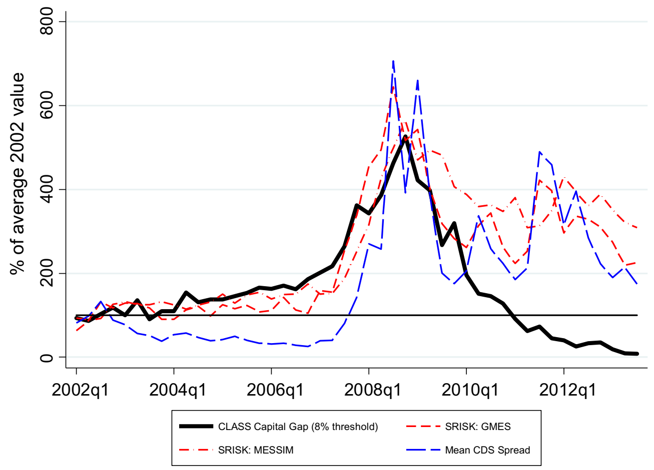

Fig. 7. Comparing measures of capital vulnerability. Each measure is normalized by its average value in 2002.

differences in firms' asset mix and income-generating activities. To examine this cross-sectional variation in more detail, we compute for each firm the change in the Tier 1 common equity ratio over the course of the nine-quarter crisis redux scenario (i.e., the difference between the firm's end-of-scenario ratio under the crisis redux scenario and their last historical Tier 1 common equity ratio). The more sensitive the firm's net income and capital are to adverse macroeconomic conditions, the more negative this change in capital will be. We do this firm-by-firm at different points in time between 2002 and 2013:Q3 for each of the 200 largest banking firms at each point in time (a total of 200 firms $\times$ 47 quarters = 9400 observations).

Table 2 illustrates correlations between the change in the capital ratio and various firm characteristics at different points in time, including: (i) the starting Tier 1 common equity ratio of the firm, (ii) a simple measure of asset liquidity, namely the sum of cash, interest bearing balances, securities and federal funds expressed as a percentage of total assets, (iii) a regulatory-based measure of asset risk, namely the ratio of risk-weighted assets to total assets, and (iv) firm size, measured by the log of total assets. In each case, we are interested in the overall cross-sectional correlation over the sample period, as well as whether the correlation has evolved in recent years due to the introduction of supervisory stress testing and other changes in the regulatory and economic environment. We measure this by including an interaction term between the banking firm characteristic and a dummy variable equal to one from 2011:Q1 onwards. All regressions also include time fixed effects, so that the correlations are identified only based on cross-sectional variation across banking firms, rather than time-series shifts in bank characteristics and capital stress. Our main results are robust to the exclusion of these time fixed effects, however. We cluster standard errors by entity.

Our primary finding from this analysis is that in the recent period (since 2011), the projected change in capital during the crisis redux scenario is significantly negatively correlated with the initial capital ratio – in other words, the capital ratio is projected to decline more steeply under stress for highly capitalized firms. This inverse relation is consistent with a "precautionary" view of bank capital structure (e.g. as discussed in Berger et al., 2008). Such a view argues that banking firms with more volatile or risky income will endogenously choose to hold a larger capital buffer, to reduce the likelihood of becoming undercapitalized. On the other hand, Berger and Bouwman (2013) argue that a risk-shifting view or moral hazard view would yield the opposite prediction, that less-well capitalized banks will be incentivized to hold riskier asset portfolios in equilibrium. This inverse relation is not observed prior to 2011 (in the earlier period the correlation is actually positive, although not statistically significant). The difference in the strength of this relationship, as measured by the interaction term, is statistically significant at the 1 percent level in each specification.

We find relatively little correlation between the liquid asset ratio and the projected capital decline during the crisis redux scenario, although in column (7), firms with a high share of liquid assets are found to be less sensitive to macroeconomic conditions. Perhaps counter intuitively, firms with a higher ratio of risk-weighted assets to total assets actually experience a *smaller* projected decline in capital during the crisis redux scenario. This latter result suggests that the Basel I measure of risk weighted assets used over this sample period may be a poor, or at best noisy, measure of the sensitivity of a banking firm's assets to macroeconomic stress. For example, large diversified firms with significant trading operations and securities portfolios hold a smaller fraction of assets in the form of loans, which attract a higher Basel I risk-weight. But such firms tend to be significantly exposed to macroeconomic stress due to the volatility of trading income and other noninterest income. Finally, the projected capital decline is larger (i.e. more negative) for larger banking firms, particularly since 2011.

Complementing this table, Fig. 8 shows how the relationship between initial capitalization and the change in the capital ratio over the stress scenario has evolved quarter-by-quarter since 2002. As before, to construct this figure, we use the CLASS projections of capital (Tier 1 common equity, as before) under the crisis redux scenario for each of the 200 largest firms at each point in time between 2002:Q1 and 2013:Q3. We then regress the change in the ratio under the crisis redux scenario on the initial capital ratio in each quarter (i.e., 47 separate cross-sectional regressions). The figure plots the time-series evolution of the slope coefficient from that bivariate regression. Corroborating the evidence from Table 2, since 2011, firms with assets and income that are highly exposed to the crisis redux macro scenario consistently also have higher capital ratios. However, this is not true prior to 2011. During the 2008–2010 financial crisis period, such "exposed" firms were actually *less* well capitalized, likely reflecting that large losses experienced during the crisis had depleted their capital ratios. Prior to 2008 the relationship was either positive or at best weakly negative.

We highlight that caution should be exercised in applying a causal interpretation to these results, given that capitalization and other bank characteristics are endogenously chosen by the firm, and are likely to be correlated with a range of omitted variables. We also note that the overall R^2 of the regressions in Table 2 is quite low (ranging from 11.8% in column 2 to 19.3% for column 7), implying that these broad firm characteristics account for only a relatively small fraction of the variation in the sensitivity of capital to macroeconomic shocks estimated by the CLASS model.

Bearing these caveats in mind, however, the prima facie evidence that firms' capital policies have become more precautionary in nature in recent years appears encouraging from a financial stability point of view. One possible explanation *why* capital policy has evolved, at least for the largest firms, is the implementation of annual supervisory stress tests by the Federal Reserve. These tests are explicitly designed to ensure that all firms remain well-capitalized even under a severe macroeconomic downturn. Other changes since the financial crisis, such as improved risk management, greater awareness of downside risks, or changes in supervisory practices, may also have affected capital planning policies, especially among banking firms with riskier portfolios. While beyond the scope of this paper, investigating these issues in more detail would be an interesting topic for future research.

Table 2
Determinants of change in capital during stress scenario.

Dependent variable: change in Tier 1 common equity ratio during crisis redux scenario (projected minus historical)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm characteristics (last historical value)							
Tier 1 common ratio	0.033 (0.032)		0.028 (0.034)			0.025 (0.035)	0.039 (0.034)
Tier 1 common ratio × Post 2011Q1	−0.152*** (0.050)		−0.127** (0.051)			−0.182*** (0.048)	−0.160*** (0.043)
Liquidity ratio		0.006 (0.014)	0.004 (0.015)			0.004 (0.015)	0.041** (0.016)
Liquidity ratio × Post 2011Q1		−0.026*** (0.010)	−0.016 (0.010)			−0.003 (0.012)	0.029** (0.014)
RWA/total assets				1.742 (1.081)			4.749*** (1.135)
RWA/total assets × Post 2011Q1				1.711** (0.772)			2.536** (1.284)
ln(total assets)					−0.025 (0.075)	−0.010 (0.081)	0.110** (0.050)
ln(total assets) × Post 2011Q1					−0.133** (0.064)	−0.216*** (0.082)	−0.214*** (0.059)
Observations	9400	9398	9398	9400	9400	9398	9398
R^2	0.122	0.118	0.123	0.144	0.118	0.131	0.193
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Pooled regression is based on each historical quarter's projections of the change in the Tier 1 common equity ratio during the crisis redux scenario and firm characteristics as of that historical quarter. Variables are winsorized at their 1% and 99% values, to limit the influence of outliers. Clustered on entity. Observations are weighted by asset share. * Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

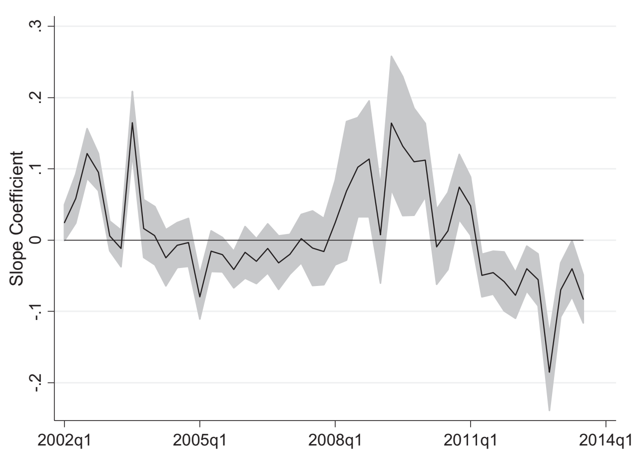

Fig. 8. Time series evolution of correlation between capital ratio and change in capital ratio under stress scenario. Each point on the line represents the point estimate from a cross-sectional regression of starting capital ratio against the projected change in the capital ratio under the crisis redux scenario. A negative value indicates that firms with capital ratios that decline sharply under the stress scenario also have higher starting capital ratios. A positive value indicates the reverse.

4. Model details

We now turn to a more detailed description of the structure of the CLASS model regression equations, the data used to estimate the equations, the resulting specifications and parameter estimates based on historical data through 2013:Q3, and the auxiliary assumptions needed to complete the CLASS model projections of net income and capital. Fig. 9 presents a detailed schematic of the CLASS model structure, including regression equations, calculation steps, and auxiliary assumptions.

4.1. Regression equation structure

Each CLASS regression equation models a key income or expense ratio as a function of an autoregressive (AR(1)) term and a parsimonious set of macroeconomic variables. Some equations are estimated as time-series models using historical data summed up across all BHCs and banks. Other models are estimated using pooled quarterly data on individual firms, allowing us to control for firm characteristics such as the composition of assets.

The time series specifications take the general form:

$$\text{ratio}_t = \alpha + \beta_1 \text{ratio}_{t-1} + \beta_2 \text{macro}_t + \varepsilon_t$$

where ratio_t is the financial ratio of interest and ratio_{t-1} is an AR(1) term, macro_t is the set of macroeconomic variables appropriate to that ratio. When statistically and economically significant, the equations also include a linear time trend in the specification.[12]

For the models estimated using pooled individual BHC and bank data, the specification is:

$$\text{ratio}_{t,\text{i}} = \alpha + \beta_1 \text{ratio}_{t-1,\text{i}} + \beta_2 \text{macro}_t + \beta_3 X_{t,\text{i}} + \varepsilon_{t,\text{i}}$$

where each observation is now indexed by firm i, and the equation includes $X_{t,\text{i}}$, a vector of firm-specific characteristics, such as shares of different types of loans in the loan portfolio[13] or the share of risky securities in the investment securities portfolio. Pooled regressions are estimated for the AFS returns equation, and for components of PPNR significantly affected by the composition of firm assets, such as net interest margin, compensation expense, and other non-interest expense. Standard errors are clustered by time.

The autoregressive nature of each equation implies that the projected ratio for each firm will converge slowly from its most recent historical value towards a long-run steady state value. These paths will be significantly influenced by the assumed macroeconomic scenario. The autoregressive structure also means that the CLASS model projections are sensitive to the lagged value of the ratio for each bank and BHC data, which are used to "seed" the model projections. The seed data is particularly important for income and expense categories that are estimated to be highly autoregressive (that is, with a large value of β_1); in such categories, a low or high ratio value in the historical quarter used to seed the model will have persistent effects on the projected income path over the stress test horizon.[14] On occasion, the autoregressive structure of the CLASS regression equations can create unrealistic shifts in projected income and capital in cases when an individual

[12] Time trends appear in three of the 22 CLASS econometric models, and are intended to capture long-term trends in particular financial ratios over our sample period (for example the secular decline in net interest margin). In each case, the time trend is normalized to zero in 1991:Q1 and increases by 0.25 each calendar quarter. When generating model projections, we hold the time trend constant at its most recent historical value, rather than assuming the trend continues over the forecast horizon.

[13] For example, the net interest margin (NIM) equation includes controls for the composition of the firm's loan portfolio. This is necessary because interest margins vary significantly across firms (e.g. margins are higher for firms with a high concentration of credit card loans, due to the high interest rates on credit card facilities). This implies that even the long-run NIM projection will vary across firms, reflecting differences in these portfolio shares.

[14] On the whole, this persistence is realistic, given the historical dynamics of bank income, and given that the regression models are estimated to maximize fit to the historical data.

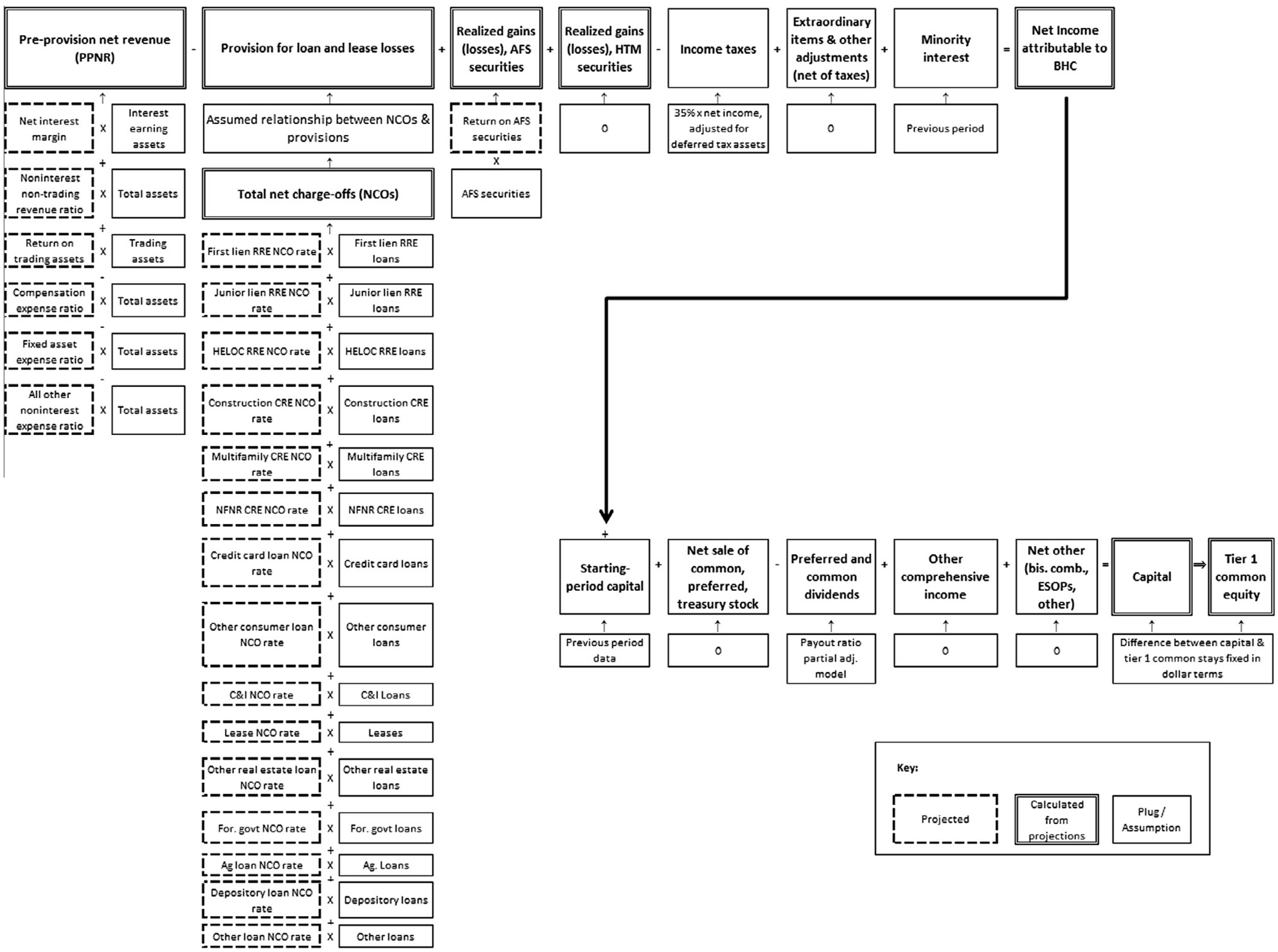

Fig. 9. Schematic, computation of net income and capital.

BHC or bank experiences an idiosyncratically large income spike that is unlikely to be repeated in future quarters (e.g. realization of a large loss related to a legacy acquisition). In such cases, we apply a correction to the model projections so that the shock in question does not have a persistent effect on projected income. In practice, we make such judgmental adjustments to the model projections only rarely.

4.2. Data

To estimate the equations described above, we combine two types of data measured at a quarterly frequency: regulatory report data on balance sheets, income and loan performance, and macroeconomic and financial market data used in the macroeconomic scenarios.

The BHC and bank regulatory data are drawn from Federal Reserve Y-9C regulatory filings for BHCs and FFIEC Consolidated Reports of Condition and Income (Call Report) filings for commercial banks. The regressions are based on quarterly data from 1991 to the present for all BHCs that file the FR Y-9C, plus the subset of commercial banks that do not have a parent that files a FR Y-9C.[15] The data include all U.S.-headquartered, top-tier BHCs and independent commercial banks, as well as six large foreign-owned BHCs subject to CCAR in 2014. Other BHCs and commercial banks whose parent is domiciled outside the United States are excluded, as are two BHCs that are not engaged in traditional commercial banking activities: DTCC and ICE Holdings.

As noted above, the majority of the regression specifications are based on an aggregated time series for the banking system, calculated by summing data across the individual banking firms. These aggregate series are subject to breaks when new institutions become banks or BHCs or when a BHC makes a significant acquisition from outside the banking industry. For example, the conversion of Goldman Sachs and Morgan Stanley to bank holding companies significantly increased total industry assets (appearing in our data in 2009:Q1); similarly, acquisitions of non-bank financial firms, such as J.P. Morgan Chase's acquisition of Washington Mutual and Bear Stearns, and Bank of America's acquisition of Merrill Lynch, also create discontinuities. We do not make any adjustments for these sample breaks, in part because the pre-conversion or pre-acquisition data on the target firm needed to make such adjustments are not readily available in a format comparable with the Call and Y-9C reports. However, since the regression variables are specified as ratios – and the newly converted or acquired institution enters both the numerator and denominator of the ratio – the impact of these breaks is muted.

The regression specifications based on a pooled sample of firms rather than aggregate industry data are estimated using a panel of the 200 largest banking institutions by assets in each quarter. The remaining banks and BHCs are aggregated into a single observation, resulting in a total sample of 201 entities.

[15] This includes both commercial banks that are self-held and commercial banks that have holding companies that are too small to file a consolidated regulatory Y-9C filing.

The regression equations include parsimonious combinations of nine macroeconomic and financial market variables summarizing economic activity and financial market conditions. The final specification of each equation was based on a specification search based on measures of overall model fit (R^2 and adjusted R^2) as well as statistical significance of the macroeconomic variable, and accordance with economic theory (e.g., that chargeoff rates are positively correlated with poor economic conditions). The macroeconomic variables we use are a subset of those included in the scenarios provided by the Federal Reserve for the DFAST stress tests, and include the 10-year Treasury bond yield, the 3-month Treasury bill yield, the civilian unemployment rate, real gross domestic product (GDP), the CoreLogic U.S. home price index, the BBB bond index yield, commercial real estate prices and the U.S. Dow Jones Total Stock Market Index. Table 3 provides a full list of macroeconomic and financial market variables included in the CLASS model equations and describes the transformation of each variable used in the regressions (that is, whether the variable is expressed in levels, changes, percent changes, or some other form).

4.3. Regression model estimates

The CLASS model includes six regression equations for components of PPNR, fifteen equations for net charge-off (NCO) rates on different loan categories (e.g. first-lien residential real estate, construction loans, credit cards, C&I loans), and an equation for gains and losses on the AFS securities portfolio. Table 4 presents summary statistics for the twenty-two ratios that are projected as part of the CLASS framework. Table 5 summarizes the set of macroeconomic variables included in each equation, and indicates which are statistically significant. Full equation specifications and parameter estimates are presented in the Appendix.

The final model specifications used in the CLASS model represent the result of search of regression specifications over different combinations of macroeconomic variables and controls; in some cases we also varied other modeling choices such as the weighting of each observation in the regression sample or the functional form of the macroeconomic variable. The Online Appendix presents a more detailed description of how the specification search was conducted, and presents estimates for a number of the different specifications we tried (one table of specification searches per equation; 22 tables in total), as well as a graph of the in-sample fit of each preferred econometric model. In almost all cases, at least six different model specifications were estimated and considered for each equation. In choosing specifications, we put weight both on statistical fit and consistency with economic intuition, rather than relying on a purely mechanical approach to model specification such as LASSO. In part this is because of our concern that a purely statistical approach could lead to the risk of overfitting the relatively limited available time series history.

4.3.1. PPNR

The CLASS model contains six regression equations for components of PPNR, including net interest income (that is, interest income minus interest expense), trading income (which includes both mark-to-market changes in value of trading positions and derivatives as well as fee and spread income on trading activities), non-interest non-trading income (such as deposit fees, income from fiduciary activities, and revenues from investment banking and insurance), and three components of noninterest expense: compensation expense, expenses related to premises and fixed assets, and other non-interest expense.[16] Each of these components of PPNR is expressed as a ratio either of total assets (for non-interest, non-trading income, compensation expense, fixed asset expense, and other non-interest expense), trading assets (for trading revenue), or interest-earning assets (for net interest income).

Each PPNR equation except for return on trading assets is estimated by weighted least squares using the pooled regression approach, weighting by the institution's share of the relevant denominator asset balance (e.g. interest-earning asset share in the case of net interest margin). Pooled regressions include controls for the composition of firm assets and firm size: the ratio of residential real estate loans, commercial real estate loans, commercial and industrial loans, credit card loans, trading assets, and securities to interest earning assets, and the firm's assets scaled by industry assets in the quarter.

Given these controls, the projected PPNR ratio for each BHC or bank converges to the long-run conditional mean for firms with similar business focus and size, rather than the unconditional sample mean. These controls are particularly important for the net interest margin model, since the spread between borrowing and lending rates varies significantly across types of loans. For example, credit card balances historically have high net interest margins, compensating for the higher credit risk associated with these loans.

In our final specifications, the net interest margin is positively related to short-term Treasury yields as well as the slope of the yield curve, trading returns are sensitive to credit spreads (the change in the yield spread between BBB-rated corporate bonds and 10-year Treasuries), and non-trading noninterest income is sensitive to stock returns. Compensation expense is positively correlated with stock returns, while other noninterest expense is sensitive to credit spreads. As shown in the detailed results presented in Appendix A, most components of PPNR are highly autoregressive.

4.3.2. Loan net charge-Off rates

The CLASS model includes 15 net charge-off (NCO) models for major loan categories: first lien and junior lien residential mortgages, home equity lines of credit (HELOC), construction loans, multifamily and non-farm non-residential commercial mortgages, credit cards, other consumer loans, commercial and industrial (C&I) loans, leases, loans to foreign governments, loans to depository institutions, agriculture loans, other real estate loans, and all other loans. In each case, dollar net charge-offs are scaled by the corresponding loan balance, so that the regression dependent variables is a loss rate.

NCO rates on real estate loans are primarily associated with real estate price downturns. From a theoretical perspective, mortgage default represents a put option on the underlying real estate used to collateralize the loan (e.g., Kau et al., 1992). Consistent with this point, the empirical relationship between real estate price growth and real-estate loan charge-offs is highly non-linear, with real estate price declines having a much larger effect on charge-off rates than real estate price increases. For this reason, the final equations include an interaction between property price growth and a dummy variable for whether the change in the price index is less than zero. Quantitatively, this interaction term is the key macroeconomic determinant of mortgage NCO rates in the models.[17]

[16] We experimented with similar models for aggregate PPNR, however, explanatory power and sensitivity to macroeconomic conditions are lower for the aggregate model.

[17] Residential mortgage charge-offs in particular were low and relatively insensitive to macroeconomic conditions until the recent financial crisis. Although commercial real estate charge-offs were high in the early 1990s, NCOs in this category were also low between this episode and the recent crisis. We found that business cycle indicators such as the change in the unemployment rate were generally statistically insignificant once we controlled for real estate price growth; consequently these variables were not included in the final specifications.

Table 3
Summary statistics of macroeconomic variables.

Variable	Definition	2013:Q3 value	Historical mean	Historical SD
Term spread (10 year minus 3 months, pct. pt)	10 year Treasury Yield$_t$ – 3 month Treasury Yield$_t$	2.70	2.09	1.16
Quarterly growth in stock market returns (%, log change)	$[\ln(MKT_t) - \ln(MKT_{t-1})] \times 100$	5.49	1.92	8.50
Annualized real GDP growth (%)	$[\ln(GDP_t) - \ln(GDP_{t-1})] \times 400$	1.98	2.51	2.49
Annualized change in the civilian unemployment rate (%)	$[\text{Unemployment}_t - \text{Unemployment}_{t-1}] \times 4$	−1.20	0.05	1.20
3 month treasury yield (%)	3 month Treasury Yield$_t$	0.00	3.00	2.06
Spread of BBB bond index to 10 year treasury yield in percent	BBB Bond Yield$_t$ – 10 year Treasury Yield$_t$	2.20	1.72	0.92
Quarterly change in BBB bond spread (pct. pt)	BBB spread$_t$ – BBB spread$_{t-1}$	0.10	0.00	0.42
Quarterly change in 10 year treasury yield (pct. pt)	10 year Treasury Yield$_t$ – 10 year Treasury Yield$_{t-1}$	0.70	−0.06	0.38
Annual house price index (log change)	$[\ln(HPI_t) - \ln(HPI_{t-4})] \times 100$	9.85	3.13	7.55
Annual commercial property price index (log change)	$[\ln(CPPI_t) - \ln(CPPI_{t-4})] \times 100$	7.61	2.95	11.76

Table 4
Accounting ratios modeled in CLASS.

Variable	Definition	2013:Q3 Value	Historical Mean	Historical SD
Panel A: Components of PPNR and AFS returns (annualized, in percentage points)				
Net interest margin	$\frac{\text{Net Interest Income}}{\text{Interest Earning Assets}} \times 400$	2.61	3.57	0.51
Noninterest nontrading income ratio	$\frac{\text{Noninterest Income} - \text{Trading Income}}{\text{Total Assets}} \times 400$	1.94	2.28	0.39
Return on trading assets	$\frac{\text{Trading Income}}{\text{Trading Assets}} \times 100$	2.44	2.92	2.59
Compensation noninterest expense ratio	$\frac{\text{Compensation Expense}}{\text{Total Assets}} \times 400$	1.54	1.70	0.13
Fixed asset noninterest expense ratio	$\frac{\text{Fixed Asset Expense}}{\text{Total Assets}} \times 400$	0.30	0.45	0.09
Other noninterest expense ratio	$\frac{\text{Amortization Impair.} + \text{Goodwill Impair.} + \text{Other Noninterest Expense}}{\text{Total Assets}} \times 400$	1.45	1.55	0.20
Return on AFS securities	$\frac{\text{Realized Net Gains on AFS Securities}}{\text{Total Available For Sale Securities}} \times 400$	0.27	0.17	0.47
Panel B: Annualized net charge off (NCO) rates in percentage points				
First lien residential real estate	$\frac{\text{NCOs on First Lien RRE Loans}}{\text{First Lien RRE Loans}} \times 400$	0.36	0.42	0.56
Junior lien residential real estate	$\frac{\text{NCOs on Junior Lien RRE Loans}}{\text{Junior Lien RRE Loans}} \times 400$	2.38	1.66	2.22
HELOC residential real estate	$\frac{\text{NCOs on HELOC RRE Loans}}{\text{HELOC RRE Loans}} \times 400$	0.93	0.72	0.96
Construction commercial real estate	$\frac{\text{NCOs on Construction CRE Loans}}{\text{Construction CRE Loans}} \times 400$	0.27	1.42	2.01
Multifamily commercial real estate	$\frac{\text{NCOs on Multifamily CRE Loans}}{\text{Multifamily CRE Loans}} \times 400$	0.09	0.42	0.57
Non-farm non-residential commercial real estate	$\frac{\text{NCOs on NFNR CRE Loans}}{\text{NFNR CRE Loans}} \times 400$	0.21	0.41	0.50
Credit card	$\frac{\text{NCOs on Credit Card Loans}}{\text{Credit Card Loans}} \times 400$	3.27	5.15	1.77
Other consumer	$\frac{\text{NCOs on Other Consumer Loans}}{\text{Other Consumer Loans}} \times 400$	1.02	1.62	0.86
Commercial and industrial (C&I)	$\frac{\text{NCOs on C\&I Loans}}{\text{C\&I Loans}} \times 400$	0.27	0.87	0.67
Leases	$\frac{\text{NCOs on Leases}}{\text{Leases}} \times 400$	0.15	0.50	0.39
Other real estate	$\frac{\text{NCOs on Other Real Estate Loans}}{\text{Other Real Estate Loans}} \times 400$	0.48	0.43	0.55
Loans to foreign governments	$\frac{\text{NCOs on Loans to Foreign Gov'ts}}{\text{Loans to Foreign Gov'ts}} \times 400$	0.04	0.61	3.73
Agriculture	$\frac{\text{NCOs on Agriculture Loans}}{\text{Agriculture Loans}} \times 400$	0.06	0.21	0.19
Loans to depository institutions	$\frac{\text{NCOs on Loans to Depository Inst.}}{\text{Loans to Depository Institutions}} \times 400$	−0.04	0.21	0.47
Other	$\frac{\text{NCOs on Other Loans}}{\text{Other Loans}} \times 400$	0.20	0.36	0.40

For most other loan types, the change in the unemployment rate was generally the macroeconomic variable most correlated with loan losses, with an increase in the unemployment rate causing charge-off rates to increase. Across the entire spectrum of loan categories, net charge-off rates are highly autoregressive, with AR (1) coefficients ranging between 0.5 and 0.9.

4.3.3. Returns on available-for-sale (AFS) portfolios

Realized gains and losses in a banking firm's AFS securities portfolios occur only when the firm sells those assets or the securities are deemed to have experienced "Other Than Temporary Impairment" or OTTI. Under current GAAP accounting, OTTI status is determined only by credit factors, and need not incorporate changes in market prices due to interest rate risk, liquidity or other factors, until the bonds are sold. Realized AFS gains and losses thus reflect a combination of asset price shocks, credit events, behavioral decisions about asset sales, and accounting judgment. Historically, AFS returns are low and stable, but with occasional, large downward movements, particularly during 2008 and 2009.

Table 5
Model specifications.

			Explanatory Variables														
			Macroeconomic Variables													Controls	
			Annualized Real GDP growth (%)	Term Spread (10 year minus 3 months, pct. pt)	3 Month Treasury Yield (%)	Quarterly change in 10 year Treasury yield (pct. pt)	Stock Market returns (quarterly, %)	Quarterly change in BBB bond spread (pct. pt)	Quarterly change in BBB Spread if change is positive (else zero)	Quarterly change in BBB Spread if change is positive x Risky AFS Ratio	Annualized change in Unemployment (%)	Home price growth (%, year-over-year)	Home price growth if growth is negative (else zero)	Commercial property price growth (%, year-over-year)	Commercial Property Price Growth if negative (else zero)	Time trend (annual)	Firm balance sheet controls
Modeled Variables	PPNR Specs	Net Interest Margin		■	■											■	X
		Noninterest Nontrading Income Ratio					■										X
		Return on Trading Assets						▨	■								
		Compensation Noninterest Expense Ratio					■										X
		Fixed Asset Noninterest Expense Ratio	▨													■	X
		Other Noninterest Expense Ratio						■									X
		Return on AFS Securities				■				■							
	Net Charge Off Specs	First Lien Residential										▨	■				
		Junior Lien Residential										▨	■				
		HELOC										▨	■				
		Construction													■		
		Multifamily													■		
		Nonfarm Nonresidential													■		
		Credit Card									■						
		Other Consumer									■					■	
		Commercial and Industrial									■						
		Leases									■						
		Other Real Estate												■	▨		
		Depository Institutions									▨						
		Agriculture									■						
		Foreign Governments									▨						
		Other Loans									■						

Legend
■ Included and signficant (10% level)
▨ Included but insignificant
X Firm controls included

The CLASS model's approach to modeling realized gains and losses on AFS securities recognizes the significant variation in the riskiness of these portfolios across firms and over time. Specifically, the model includes an interaction term between the share of AFS securities that are "risky" (that is, excluding U.S. government and agency securities) and increases in the credit spread (BBB minus Treasuries).[18] AFS returns are also found to be negatively correlated with the change in Treasury bond yields.

4.4. Auxiliary assumptions

4.4.1. Balance sheet growth and composition

As discussed above, the 22 regression equations produce projections of accounting *ratios* – losses, revenues or expenses scaled by a loan, securities or asset balance. To translate these ratios into dollar values in order to calculate net income, the CLASS model requires projections of the balance sheet over the stress test horizon. Balance sheet projections are also needed to project risk-weighted assets and to calculate capital ratios, since capital ratios have either risk-weighted assets or total assets in the denominator. Because of this mechanical relationship between capital ratios and asset balances, the results of CLASS and other stress testing models based on accounting data are highly sensitive to the growth path of assets over the stress test horizon, as illustrated in the sensitivity exercise presented in Section 5.

The CLASS model adopts a simple approach to balance sheet projections – each BHC or bank's total assets are assumed to grow at a fixed rate of 1.25% per quarter (5% per year) over the stress test horizon. This growth rate was chosen to be roughly consistent with the long-run nominal historical growth of assets in the U.S. banking industry. The same growth rate is assumed for all asset balances, implying that the composition of the balance sheet – that is, the proportion of total assets represented by different types of loans, securities, cash, trading positions, and other assets – stays fixed at its last historical value over the stress test. The composition of liabilities is also assumed to stay fixed, while the book value of liabilities is calculated so that the balance sheet identity (assets equal liabilities plus capital) holds at each point in time. If capital falls and assets increase, the difference is made up with additional liabilities, with constant mix as of the starting quarter.

Assuming that the growth rate of assets is the same for all institutions and for all scenarios is not "realistic" in the sense that

[18] Prior to 2001, BHCs and banks only reported the breakdown of risky securities into: securities issued by states and municipalities, foreign and domestic equity and debt securities. U.S. government agency and corporation obligations were reported without separately breaking out MBS. In the CLASS model, AFS securities backed by the U.S. government or government agencies are "safe" assets that are unlikely to experience credit impairment and thus incur OTTI. All other AFS securities are classified as "risky," including municipal bonds, non-agency mortgage-backed securities and asset-backed securities, and corporate debt. The aggregate fraction of AFS securities consisting of risky assets increased from less than 30 percent in 1994 to approximately half by 2010.

banking industry assets historically tend to grow more slowly in stressed economic environments than they do during expansions.[19] However, assuming that banking industry assets continue to grow during economic stress can be seen as rigorous from both microprudential and macroprudential perspectives. From a macroprudential perspective, it ensures that assessments of banking industry capital strength are made in the context of continued availability of credit[20], while from a microprudential perspective, firm-level capital projections are made under the assumption that the firm continues to function as an active financial intermediary.

Our assumption that balance sheet composition does not evolve with macroeconomic conditions is also not entirely consistent with historical experience. Incorporating scenario-dependent shifts in asset composition would have two main effects in the CLASS framework. First, changes in the relative share of risky and safe assets will affect projections of total net income via a composition effect. For example, a shift towards riskier loans types such as construction loans will increase the overall loan loss rate, holding fixed the projected loss rate *within* each loan category. Second, asset shares are used as control variables in several of our regression models, particularly for components of pre-provision net revenue. Thus, movements in these shares would have effects on the projected dependent variables in these equations (e.g., the net interest margin).

Enriching the CLASS model to explicitly incorporate these composition effects would be quite complex, and is outside the scope of the present paper. However, as a first step, the Online Appendix to this paper presents econometric estimates based on historical data showing how the share of industry assets in different asset categories evolves with macroeconomic conditions. The six categories we consider are cash and interest-bearing balances, loans, trading assets, securities, federal funds and repos, and other. Since the relationship between asset composition and macro variables might vary with banking firm characteristics such as size, we estimate these regressions for the industry as a whole, and then separately for the largest 10 firms (resorted by total assets each quarter) and for the remainder of the industry.

This preliminary analysis suggests that banking sector asset composition does indeed move with macroeconomic conditions historically, particularly with the term spread and with credit spreads (the difference between BBB corporate bond yields and 10-year Treasury yields). An increase in the term spread is associated with a contemporaneous shift from loans and trading assets to securities. An increase in credit spreads is associated with a statistically significant shift out of trading assets and fed funds and repos into securities portfolios and cash and interest-bearing balances. At least in the latter case, our expectation is that incorporating these composition shifts would be likely to slightly reduce banks' projected sensitivities to macroeconomic conditions somewhat (since in CLASS, projected losses on securities plus cash and interest bearing balances are low and relatively insensitive to credit spreads compared to losses on trading assets).

There is mixed evidence that these relationships are different between small and large banks; as shown in the Online Appendix, we find a statistically significant difference in the macroeconomic sensitivities between these two size groups (at the 5 percent level) in five of the twelve specifications. The evidence for heterogeneous sensitivities is strongest for trading assets, perhaps not surprisingly given that small firms have few trading assets regardless of macroeconomic conditions.

Summing up, this initial analysis suggests that allowing for asset composition to shift with macroeconomic conditions could be a useful extension of the CLASS framework. We do however also see possible pitfalls in relaxing our "constant shares" assumption. First, allowing for composition shifts adds significant complexity. Second, to the extent that historical shifts in asset shares during periods of stress represent flights to quality within bank portfolios that may not recur, it may be appropriate from a macroprudential perspective not allow for these channels when generating capital projections.

4.4.2. Allowance for loan and lease losses (ALLL)

The CLASS model's equations project total net charge-offs each quarter over the stress test horizon. However, under U.S. accounting rules, net charge-offs do not directly affect net income. Instead, accounting rules recognize the *provision expense* incurred to increase the allowance for loan losses reserve (the ALLL). This is not a straightforward exercise, however, since ALLL is estimated by the firm based on a set of accounting guidelines which leave scope for managerial discretion and judgment. As an empirical matter, the choice of provisioning rule has a quantitatively important effect on net income and thus on the regulatory capital projections (see Section 5).[21]

The CLASS model assumes that the ALLL is bounded in a range relative to projected future net charge-offs. If the ALLL is at least equal to the next four quarters of projected net charge-offs (under the macro scenario in question)[22] but not greater than 250% of that level, then provision expense in the quarter is set equal to current-quarter net charge-offs. If the ALLL is below four quarters of future charge-offs, then provision expense is set equal to an amount that would bring the ALLL to that level (so provisions would exceed net charge-offs for that quarter). However, if the ALLL is greater than twice four quarters of future net charge-offs, then provision expense is negative (an ALLL release), to bring the ALLL down to that level.[23]

4.4.3. Other significant CLASS model assumptions

Taxes: BHCs and banks are assumed to pay tax at the 35% statutory rate. Tax losses may be carried forward for regulatory capital purposes, subject to regulatory limits on qualifying deferred tax asset (DTA) balances. There are limits on the amount of DTA that can be counted as regulatory capital, as well as on the recognition of DTA relative to future taxable income. The CLASS model includes a calculation of qualifying DTA based on regulatory report data and the model's projections of future taxable income, although the calculation is necessarily a simplification due to the complexity of the accounting and regulatory capital rules.[24]

[19] Historical banking industry data illustrate that both the growth rate of bank assets and the composition of the balance sheet can vary significantly with economic conditions. For instance, Clark et al. (2007) document the cyclical variability in the share of retail-related loans such as mortgages and credit cards.

[20] Greenlaw et al. (2012) argue in favor of this approach.

[21] A detailed discussion of how we compute ALLL and provision expense is presented in the Online Appendix.

[22] Based on supervisory guidance suggesting that the ALLL should generally at minimum be sufficient to cover at least four quarters of recent charge-offs (Office of the Comptroller of the Currency et al., 2006; Federal Reserve Board, 2013).

[23] If necessary, we also adjust the ALLL at the *start* of the stress test horizon to ensure that the starting value of ALLL is inside this 100% to 250% range. To maintain the accounting identity that assets are equal to the sum of liabilities and equity, this also involves an equal corresponding adjustment to common equity. To avoid a discontinuity in equity capital, we treat this adjustment as an addition to provision expense which we apply evenly over the scenario horizon. See the Online Appendix for more details.

[24] Given constraints on the available data, we implement some simple limits on allowable DTA. First, working with information from the FR Y-9C reports, we compute net DTA as the maximum of deferred tax assets minus deferred tax liabilities, or zero. We then calculate allowable DTA as the difference between this value and disallowed DTA, which is reported directly on the Y-9C. Any allowed DTA below 10% of Tier 1 capital is deemed to be dependent on future taxable income. Any excess over 10% of Tier 1 capital is deemed to be recoverable through loss carry-backs. This latter category is held fixed over the stress test horizon, while any accumulated tax losses are applied to allowed DTA dependent on future taxable income at each point in the forecast. If at any point this balance reaches 10% of Tier 1 capital, further tax losses will not be able to be carried forward for regulatory capital purposes.

Dividends and Other Capital Distributions: As illustrated in Fig. 9, changes in equity and regulatory capital over the stress horizon are determined by two primary factors: after-tax net income and capital actions such as dividend payments on both common and preferred shares, share repurchases, and new share issuance. The CLASS model assumes that BHCs and banks do not issue new shares or make repurchases during the stress test horizon, and imposes a stylized rule for determining dividend payments, as illustrated in the sensitivity analysis presented in Section 5.

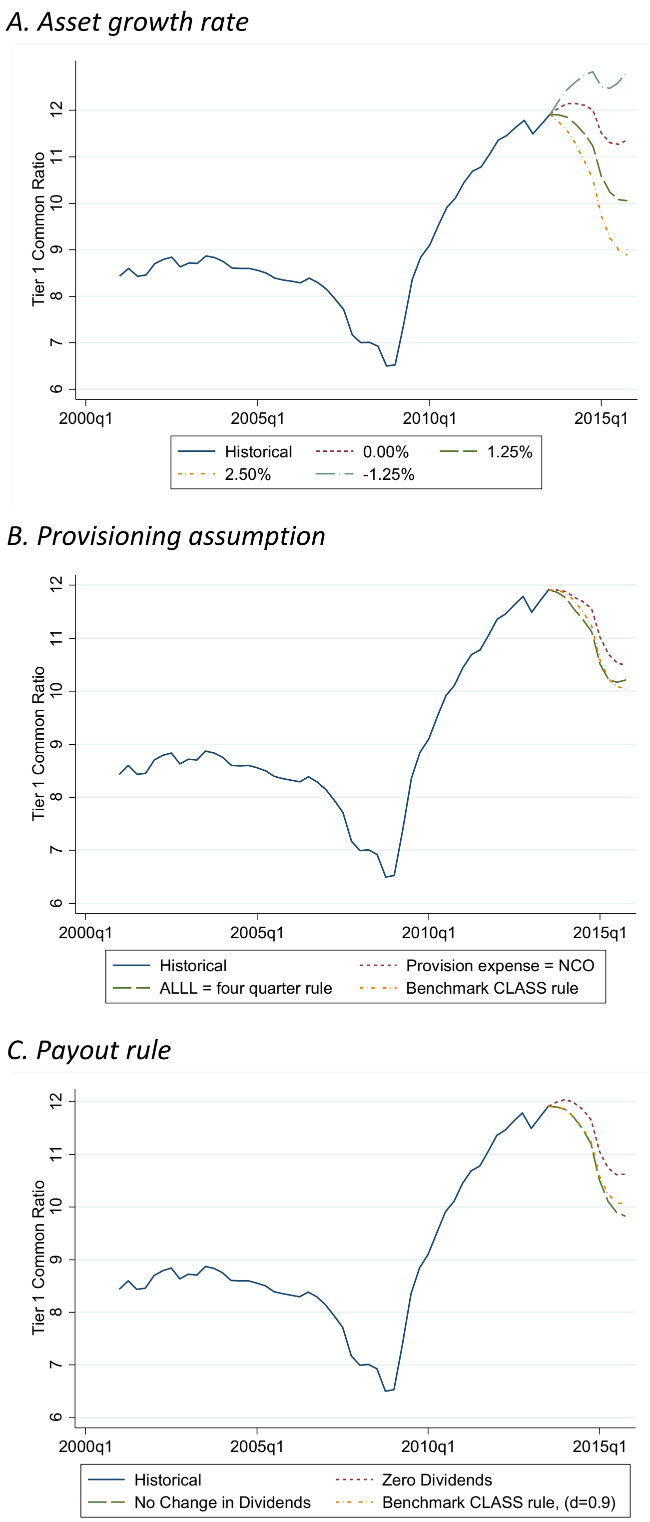

Fig. 10. Sensitivity to assumptions.

The CLASS model uses a partial adjustment rule for dividends. In the long run, dividends converge to a payout ratio (a given fraction of net income). The industry payout ratio, computed as the sum of common and preferred dividends as a fraction of industry after-tax net income, averaged approximately 40–50% of net after-tax income prior to the financial crisis. Therefore, our baseline assumption is that total dividends converge to a long-run payout ratio of 45%, following a partial adjustment mechanism:

$$\text{Dividends}_t = \max(\delta\ \text{Dividends}_{t-1} + (1-\delta)[\text{Dividends}_t^* - \text{Dividends}_{t-1}], 0)$$

where $\text{Dividends}_t^* = 45\% \times$ after-tax net income$_t$, and δ is the speed-of-adjustment parameter. Dividends are also restricted to be non-negative at each point in time. Given observed inertia in dividends for banking firms (e.g. see Berger et al., 2008), we assume that dividends adjust slowly towards this target ratio. Our benchmark assumption is to set $\delta = 0.90$, meaning that ten percent of the gap between current and target dividends is closed each quarter (or 34% after 1 year).

5. Sensitivity analysis and specification tests

This section illustrates the sensitivity of the CLASS projections to different modeling assumptions. It also presents two external validity tests of the model's projections, comparing them to official DFAST supervisory stress projections, and to bank performance during the 2007–09 financial crisis.

5.1. Sensitivity analysis

The CLASS model projections are sensitive to a variety of modeling assumptions needed to link projections of loss, revenue and expense ratios to the model's ultimate projections of regulatory capital. This section highlights the sensitivity of the model's projections to assumptions about asset growth, loan loss provisioning, and capital distributions. These sensitivity results are summarized in Fig. 10.

The first panel of Fig. 10 presents the results for the asset growth rate assumption. Recall that the CLASS model assumes asset growth of 1.25% per quarter (5% per year). In the figure we compare our Tier 1 common equity ratio projections under this baseline assumption to projections under three other asset growth rates, ranging from 2.5% per quarter to −1.25% per quarter. As the figure shows, the path of the projected capital ratio is quantitatively very sensitive to which assumption is chosen – after nine quarters, the Tier 1 common equity ratio is around 13% under a −1.25% asset growth rate, but only 9% under a 2.5% growth rate. This variation is driven primarily by the mechanical fact that the Tier 1 common ratio is directly expressed as a ratio of risk-weighted assets – high asset growth thus acts to reduce the Tier 1 common ratio, while asset shrinkage increases it. Asset growth assumptions also affect the numerator of the capital ratio, through their effect on projected dollars of losses, revenues and expenses. For example a given projected ROA will by definition imply a higher dollar value of net income when assets are higher. However, this numerator effect turns out to be less important than the direct impact of the asset growth assumption on the risk-weighted assets denominator of the capital ratio over the

2–3 year timeframe over which CLASS model projections are calculated.[25]

Panel B of Fig. 10 illustrates how the model projections are affected by the choice of loan loss provisioning rule. We compare our benchmark assumption for provisions (that provision equal net charge-offs as long as the ALLL stays in a "tunnel" between 100% and 250% of the next four quarters of projected net charge-offs) to a "four quarter rule" that sets ALLL equal to the next four quarters of projected net charge-offs under the scenario in question, and to a rule that provision expense is always set equal to net charge-offs. (See the Online Appendix for a further discussion of the differences between these three approaches). Among these three approaches, the "provision expense = NCO" rule produces the smallest decline in the industry capital ratio, because it leaves ALLL constant at its last historical value, rather than revising ALLL upwards in line with the high projected future net chargeoffs as the adverse macroeconomic scenario plays out.

Finally, we vary the rule used for capital distributions, that is, the sum of dividends, share buybacks and equity issuance (panel C of Fig. 10). We consider three alternate capital distribution rules: (i) dividends remain fixed at their last historical value, (ii) dividends are equal to the benchmark rule used by the CLASS model (i.e. dividends adjust gradually towards a payout ratio of 45% of net income), and (iii) dividends are set equal to zero over the entire scenario. Comparing the two extreme scenarios under the crisis redux scenario, the industry Tier 1 common ratio is about 75 basis points higher under the "zero dividend" assumption than under the "constant dividends" assumption. The rule used by the CLASS model is in between these extremes, although closer to the "constant dividends" assumption, reflecting the model's assumption of a slow adjustment speed for dividends.

As this exercise illustrates, dividend behavior is quantitatively important for the path of capital during a period of stress. This point is relevant to discussions of the 2007 to 2009 financial crisis, a period when many commentators argue that banking firms were slow to cut dividends in response to large losses (e.g. see Acharya et al., 2009). The dividend rule machinery within the CLASS model enables a simple evaluation of the quantitative impact of different behavioral rules for capital distributions during a stressful macroeconomic event.

5.2. Comparing CLASS and DFAST projections

A natural benchmark for the CLASS model is the framework used in the Federal Reserve's DFAST and CCAR stress tests. At a conceptual level, the analytical approach in both sets of stress test calculations is the same: to project net income and post-stress regulatory capital ratios as they would occur, quarter-by-quarter, over the stress test scenario horizon, applying U.S. accounting and regulatory capital rules. However, there are important differences in implementation that affect the comparability of the results, as summarized in Table 6.

A first key difference is that the modeling approach used in CLASS is much more aggregated than the Federal Reserve's official stress tests. For the most part, the DFAST and CCAR stress test results are derived from "bottom up" models based on granular risk characteristics of the loan, securities, and trading portfolios, often at the individual borrower, loan or position level. These models use detailed data provided by the BHCs describing borrower characteristics, loan or securities structure, and other factors likely to affect the default probability, exposure at default, and loss given default of the positions. In contrast, the CLASS model uses a "top down" modeling approach based on the historical behavior of charge-offs, securities gains and losses, trading performance, and other revenue and expense variables. Although the CLASS models use firm specific regulatory report data, this information is much less granular than the confidential BHC-specific data used in the CCAR and DFAST stress tests.

In keeping with this very detailed supervisory approach, the DFAST and CCAR stress tests were originally performed on 18 individual large BHCs, and were expanded to a total of 30 BHCs with assets greater than $50 billion in 2014. In contrast, the CLASS model quickly generates results for each of the largest 200 commercial banking firms (BHCs and independent banks) and the sum of the remaining institutions which are aggregated into a single 201st proxy BHC.

There are also differences in some of the detailed modeling elements that affect both the nature of the loss projections and magnitude of the resulting post-stress capital ratios.

- *Trading and counterparty losses:* the DFAST and CCAR stress tests include an instantaneous global market shock on trading and counterparty positions at the largest BHCs, which is assumed to occur in the first quarter of the stress test horizon. The CLASS model does not include this trading shock specifically, though the trading revenue model is geared to produce the kind of large trading losses that were experienced during the recent financial crisis under a repeat of similar macroeconomic conditions. Even so, the additional global market shock included in the DFAST and CCAR stress tests is likely to generate larger trading and counterparty losses at the largest BHCs than the CLASS model.
- *Balance sheets:* the CLASS model includes stylized assumptions about balance sheet growth that do not vary across BHCs or across macroeconomic scenarios. In contrast, the CCAR and DFAST stress tests include balance sheet growth paths that vary across both these dimensions. As illustrated in Section 5, differences in balance sheet growth can have significant impacts on the resulting projections of post-stress capital ratios, largely due to the impact on projected RWA, the denominator of those ratios.
- *Dividend and capital distribution assumptions:* The CLASS model makes stylized assumptions about common stock dividends – linking these to earnings and an assumed long-run payout ratio – and repurchases. This means that the dividends in the CLASS model are sensitive to individual BHC performance and will change with the macroeconomic scenario; generally, dividends will be higher in good economic environments than in the stressed ones. The DFAST stress test results also make stylized assumptions about dividends and other distributions; dividends are assumed to be fixed at recent historical levels while repurchases are set to zero. Thus, distributions of capital to shareholders do not vary across or within macroeconomic scenarios in the DFAST stress tests.[26]
- *Regulatory Capital Rules:* The CCAR and DFAST stress tests incorporate RWA projections that capture the phase-in of any new capital regulations over the stress test horizon. In contrast, the

[25] As a numerical illustration, consider a firm that initially has $100bn in assets and $10bn in capital, and thus has a capital ratio of 10 percent. Assume for simplicity that the firm earns profit net of dividends equal to zero. For this firm, a 2.5% quarterly asset growth rate compounded over nine quarters amounts to cumulative asset growth of 24.9% and resulting total assets of $124.9bn. In contrast, compounded −1.25% asset growth amounts to cumulative growth of −11.0%, and resulting total assets of $89.0bn. Since capital after nine quarters is still $10bn, the capital *ratio* after nine quarters is significantly higher in the "asset shrinkage" case than the former "asset growth" case – 11.2 percent of assets in the former compared to 8.0 percent of assets in the latter.

[26] Capital distributions in the DFAST stress tests are equal to actual capital distributions in the first quarter of the stress test horizon (since these distributions have already taken place by the time the stress test calculations are being made) and are set at a constant level for the remaining 8 quarters of the nine-quarter stress test horizon.

Table 6
Comparison and differences between stress test frameworks.

	CLASS model	DFAST/CCAR
Modeling approach	Top-down models based on aggregated outcomes (e.g., net charge-offs) for broad income categories and loan and securities portfolios	Bottom-up models focused on the risk characteristics of individual loans, securities, and trading positions
Data	Publicly available balance sheet and income statement regulatory report data from Call and Y-9C filings	Detailed supervisory information from individual BHCs, often at the level of individual loans or securities
Coverage	The 200 largest BHCs and independent banks, plus the rest of the industry. Results reported at the aggregate industry level	30 BHCs with assets exceeding $50 billion (starting in 2014). Results reported in the aggregate and at the individual BHC level
Trading and counterparty	Trading revenue modeled based on the macroeconomic scenario	Separate instantaneous global market shock on the trading and counterparty positions of the 6 largest BHCs
Dividends	Stylized assumptions that result in dividends converging to a long-run average payout ratio relative to net income	For DFAST, stylized assumptions that hold dividends fixed at recent historical levels and assume no repurchases
Balance sheet growth	Stylized assumption for all institutions in all scenarios	Varies across institutions and across scenarios
Risk weighted assets	Changes proportionately with the balance sheet, implicitly carrying forward prevailing regulatory capital rules	Changes with the macroeconomic scenario, incorporating the phase-in of any new regulatory capital rules
Regulatory capital model	Captures key elements, but involves approximations of certain complex calculations	More detailed and precise calculations of regulatory capital

Table 7
Comparison between CLASS and DFAST projections under the DFAST severely adverse macroeconomic scenario based on data as of 2013:Q3 for the 30 firms subject to the 2014 CCAR and DFAST supervisory stress tests.

Income category	CLASS	DFAST	Difference	CLASS vs DFAST: across firms (CLASS = $\alpha + \beta$. DFAST + ε)	
				Slope coefficient (β)	R^2
PPNR/assets	1.97	1.57	0.39	0.845***	0.869
Provision expense/ assets	1.99	2.88	−0.89	0.729***	0.658[a]
Other/assets	−0.02	−0.26	0.24	−0.044	0.008
Net income before tax/assets	−0.05	−1.57	1.52	0.533***	0.338
Change in T1C/RWA	−1.77	−3.63	1.87	0.145	0.091

Note: PPNR is reported inclusive of trading and counterparty losses. DFAST projected trading loss is 0.86% of total assets. "Other" includes realized losses/gains on securities (AFS/HTM), as well as the projected change in fair value of loans held for sale and loans held for investment measured under the fair value option, and goodwill impairment losses. * Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

[a] Provision Expense R^2 is calculated from projections of Provision Expense/Total Loans.

CLASS model RWA projections implicitly carry forward the regulatory capital rules in place at the time of the last historical observation, since RWAs are assumed to grow proportionately with assets.

Bearing these differences in mind, Table 7 compares CLASS and DFAST projections as of 2013:Q3 for the 30 firms subject to the DFAST. This is done under the severely adverse macroeconomic scenario specified by the Federal Reserve as part of the DFAST and CCAR 2014 stress tests. DFAST projections are taken from the public information reported in Board of Governors of the Federal Reserve System (2014). The first three columns of results examine asset-weighted aggregate projections for the 30 firms for the change in the capital ratio (Tier 1 common/RWA) and for key components of income. The final two columns of results are the results of a cross-sectional regression comparing the CLASS and DFAST results across firms.

We highlight two key features of the comparison. First, CLASS and DFAST projections are significantly positively correlated for key components of income and loss. This association is strongest for PPNR – the regression comparing DFAST and CLASS projections has a slope coefficient close to unity (0.845) and an R^2 of 0.869. The association is also quite strong for provision expense as a percentage of total assets ($R^2 = 0.658$) and for pre-tax return on assets ($R^2 = 0.338$). For each of these categories, the association between the two sets of projections is positive and statistically significant at the 1% level, even with only 30 firms. The association for the change in the capital ratio over the scenario is also positive although no longer statistically significant ($R^2 = 0.091$). This less strong relationship, relative to net income, in part reflects the different assumptions for asset growth, dividends and other distributions underlying CLASS and DFAST, as well as the fact that DFAST incorporates some factors during the scenario which do not flow through net income but do affect regulatory capital over the DFAST projection horizon, such as fair value losses on securities portfolios for firms subject to advanced approaches under Basel II/III. (These are not reflected in the CLASS model projections, which are based on Basel I accounting only).

Second, CLASS projections are less conservative than DFAST for both PPNR and provision expense, and also project a significantly smaller decline in industry capitalization than DFAST. This difference reflects differences in methodology and data availability, as well as the fact that CLASS does not model some loss and components of loss projected in DFAST – such as the short run "trading shock" applied to firms with large trading portfolios, and fair value unrealized losses on available-for-sale securities portfolios. It also reflects other modeling differences, such as the fact that DFAST holds firm dividends constant under the scenario, while CLASS assumes that payouts adjust slowly to changes in net income according to a partial adjustment mechanism.

We interpret the positive correlations between CLASS and DFAST projections as encouraging evidence that CLASS provides a reasonable proxy as to how more detailed stress tests might have performed prior to the financial crisis or if applied to a broader range of firms. CLASS should not necessarily be viewed as a good tool for measuring the absolute *level* of any undercapitalization in the banking system, given its more optimistic projections relative to DFAST. However, our interpretation is that CLASS is likely to be useful in evaluating how capital adequacy under stress evolves over time or how it varies across firms.

5.3. Comparing CLASS to the 2007–09 crisis experience

In similar vein, we compare CLASS projections as of 2007:Q2 to ex-post realized firm performance during the financial crisis period. We conduct this comparison over nine quarters for net income components, and over six quarters for firms capital ratios' (i.e. the change in the capital ratio from 2007:Q2 to 2008:Q4). We stop at the end of 2008 for the capital comparison because it is the point at which industry capitalization was minimized – banking sector capital ratios increased sharply in 2009 as firms recapitalized by issuing equity and cutting dividends, in significant part due to the 2009 SCAP. To compute CLASS projections, we seed the CLASS

Table 8
Comparing CLASS projections to performance during the financial crisis.

	Industry values			Actual vs predicted: across firms (actual = $\alpha + \beta$. predicted + ε)[a]			
				Weighted		Unweighted	
	Model	Actual	Difference	Slope coefficient (β)	R^2	Slope coefficient (β)	R^2
Income and loan performance (9 quarter cumulative, annualized)							
PPNR/total assets	1.54	1.47	0.07	0.552***	0.223	0.194***	0.068
Net chargeoff rate	1.93	1.99	−0.05	1.284***	0.674	0.609***	0.120
Return on assets	0.13	−0.05	0.18	0.558***	0.094	0.229**	0.025
Change in T1C/RWA (6 qtr)	−1.12	−1.77	0.65	0.593***	0.079	0.288***	0.086

Note: CLASS projections are compared to the actual evolution of capital over the six quarters between 2007:Q3 and 2008:Q4, and the actual evolution of net income over the nine quarters from 2007:Q3 to 2009:Q4. * Significant at 10% level; ** significant at 5% level; *** significant at 1% level.
[a] Based on winsorized OLS (winsorized at 2% and 98%)

model with 2007:Q2 banking data and project forward using the actual realized path of macroeconomic and financial market conditions from 2007:Q3 onwards. We then compare the resulting CLASS projections to realized accounting data. This is done for each of the 200 largest banking firms in 2007:Q2 that are still active in the data six quarters later (164 entities in total).

Results of this comparison are presented in Table 8, which follows a similar format to Table 7. As the table shows, the model projections are quite similar to realized performance for PPNR, net chargeoffs and net income. CLASS somewhat under-predicts total industry realized losses – annualized cumulative ROA projected by CLASS is 0.13%, compared to a realized value of −0.05% (note: both these values are much lower than annualized industry ROA in the period prior to the crisis, which generally ranged between 1% and 1.5%). CLASS also projects a smaller decline in the industry ratio of Tier 1 common equity to RWA, in part due to the difference in projected ROA, and in part due to the fact that net capital distributions (dividends and share repurchases net of issuance) declined in net terms more slowly than the partial adjustment rule embedded in the CLASS model.

Looking cross-sectionally, CLASS projections and are significantly positively correlated with actual outcomes during the financial crisis for several key financial ratios: PPNR as a percentage of total assets, for the net chargeoff rate on loans, return on assets, and for the change in the capital ratio.[27] Interestingly, the correlations are also stronger when we compute them weighted by total assets rather than on an unweighted basis – in other words, CLASS projections are more correlated with actual realized performance among larger firms. Our interpretation of this finding is that CLASS performs reasonably well in picking up differences in risk across different types of assets (e.g., construction loans versus Treasury securities), but is less useful in identifying differences in risk within a particular asset class, given the lack of detailed risk information such as geography, credit scores or loan-to-valuation ratios on individual loans. This is likely to make CLASS more effective for firms engaged in a range of activities, rather than smaller firms which may be relatively more concentrated in particular types of lending or lending in a particular geographic region. Similar to our comparison between CLASS and DFAST, CLASS projections of capital are less correlated with actual realizations for the capital ratio than for the components of net income – reflecting that firms' capital policy during this period did not always closely correspond to the partial adjustment assumption used in the CLASS framework.

We view these results as encouraging evidence that CLASS, while a simplified framework that abstracts from many features of bank risk, performs reasonably well as a tool for projecting the evolution of net income and capital under stressful macroeconomic conditions.

6. Summary and conclusions

The CLASS model is a top-down capital stress testing framework designed to provide insights into the stability and capital resiliency of the U.S. banking system against stressed economic and financial market conditions. The CLASS model is based on simple econometric models and publicly available regulatory data, rather than the more detailed confidential data that underpins the DFAST and CCAR supervisory stress tests. One advantage of this approach is that model projections can be generated quickly, making the CLASS framework amenable to conducting a range of "what if" analyses. For example, by adjusting key assumptions in the model – such as those governing the rate of asset growth or the amount and timing of capital distributions – the model can be used to assess how the banking industry capital might change under different circumstances, as well as provide some insight into how these assumptions might affect the more detailed, firm-specific stress test results generated by supervisors and banks. The model is also useful as a benchmark framework against which other top-down models (e.g., Covas et al., 2013; Kapinos and Mitnik, 2015) can be compared. For example, Covas et al. adapt many features of the CLASS framework, but use a quantile regression approach, rather than OLS, in modeling the effect of macroeconomic conditions on banking system income and capital.

The CLASS model projections suggest that the vulnerability of the U.S. banking industry to under-capitalization in stressed economic conditions has declined significantly since the financial crisis of 2007 to 2009. This result is consistent with the increases in regulatory capital ratios that have occurred since this period. What is perhaps less obvious is that CLASS model projections show increasing capital vulnerability starting as far back as 2004, well before either regulatory capital ratios or market indicators suggested a capital shortfall in the industry. Although our baseline projections are based on the CLASS model estimated on data incorporating the financial crisis period itself, this rising vulnerability is still observed if we estimate the same models based only on data available at the time.

In the future, we plan to further refine the CLASS model to account for the risk sensitivities of individual banks and BHCs. For instance, loan loss rate projections might be better tailored to individual institutions by including firm-specific information about non-performing loans to supplement lagged net charge-off rates in "seeding" the projections. The models for projecting PPNR could be made more granular by further disaggregating the various PPNR sub-components (e.g., separately projecting interest income on loans and interest expenses on deposits). Another avenue for future development is to explore different approaches to projecting the balance sheet, some of which would allow individual balance sheet

[27] As a robustness test, we repeated the results shown in Table 8 using a "point-in-time" version of the CLASS model estimated using data only up to 2007:Q2, rather than the full sample. Even under this version of the model, CLASS income projections are significantly positively correlated across firms ROA and its major components (e.g., the R^2 for the asset-weighted ROA in the "full sample" and "point-in-time" versions is 0.094 and 0.082, respectively, and is 0.025 and 0.079, respectively in the unweighted case).

components to grow at different rates in different scenarios (e.g., to capture shifts between loans and securities over the business cycle).

It would also be of interest to conduct additional out-of-sample testing of the CLASS framework. Guerrieri and Welch (2012) present cautionary evidence that for "top-down" models of the type estimated in this paper, macroeconomic variables only modestly improve out-of-sample forecasting power. That said, we find in Section 5.3 of this paper that CLASS projections are positively correlated with bank performance during the financial crisis period, even when the model is estimated only using pre-crisis data. It would be interesting, although outside the scope of the present paper, to also test whether CLASS projections are also correlated with bank financial distress or failure during the crisis. That said, a difficult challenge for testing CLASS out-of-sample is that our sample period contains only one period of significant macroeconomic and banking system distress. We have no data (yet) to tell us whether models estimated using a sample period including the 2007–09 crisis perform well in projecting banking sector performance during the next crisis or severe recession. This is a general problem for stress testing models – the goal of such models is to project losses in the tails of the distribution, which by definition are rarely observed.

Several other avenues for model development also seem promising. One would be to streamline the model in a way that would allow us to run many scenarios very quickly and thus to take a statistical approach to determining the underlying vulnerabilities of the banking system (e.g., to explore the characteristics of scenarios that generate capital declines in the tail of the distribution, to see what these scenarios have in common). Another would be to integrate liquidity stress into the model, for example using a framework like Eisenbach et al. (2014). In short, the CLASS model is a living framework that is expected to evolve and develop over time.

Appendix A. Estimated econometric models

Appendix Table 1: PPNR components and securities specifications.

	Net interest margin	Noninterest nontrading income ratio	Return on trading assets	Compensation noninterest expense ratio	Fixed asset noninterest expense ratio	Other noninterest expense ratio	Return on AFS securities
Macroeconomic variables							
Annualized real GDP growth (%)					0.000552		
					(0.000665)		
Term spread (10 year minus 3 months, pct. pt)	0.0426***						
	(0.0139)						
3 month treasury yield (%)	0.0220**						
	(0.0106)						
Quarterly change in 10 year treasury yield (pct. pt)							−0.580***
							(0.161)
Stock market returns (quarterly, %)		0.00407*		0.00345***			
		(0.00245)		(0.000886)			
Quarterly change in BBB bond spread (pct. pt)			−0.671			0.179*	
			(0.452)			(0.0939)	
Quarterly change in BBB Spread if change is positive (else zero)			−2.559***				
			(0.588)				
Quarterly change in BBB Spread if change is positive × risky AFS ratio							−0.0291***
							(0.00328)
Time-series controls							
Lagged dependent variable	0.793***	0.904***	0.284	0.894***	0.853***	0.816***	0.128
	(0.0390)	(0.0143)	(0.181)	(0.0175)	(0.0221)	(0.0340)	(0.0951)
Time trend (annual, 1991:Q1 = 0)	−0.00528*				−0.00186***		
	(0.00317)				(0.000348)		
Balance sheet ratios (as % of interest earning assets)							
Residential real estate loans	0.00476***	−0.00155		−0.000722	−0.000321	−0.00227	
	(0.00141)	(0.00185)		(0.000918)	(0.000207)	(0.00211)	
Commercial real estate loans	0.00648***	−0.00364**		−0.00109*	−0.000328	−0.000938	
	(0.00162)	(0.00174)		(0.000647)	(0.000201)	(0.00136)	
Commercial and industrial loans	0.00685***	−0.000877		−0.000229	−0.000470*	−0.00171	
	(0.00134)	(0.00189)		(0.00147)	(0.000252)	(0.00202)	
Credit card loans	0.0184***	0.00990***		−0.00115	−0.000554***	0.0153***	
	(0.00369)	(0.00245)		(0.00105)	(0.000170)	(0.00337)	
Trading assets	−0.00626***	−0.00146		−0.00252**	−0.00129***	−0.000807	
	(0.00161)	(0.00223)		(0.00110)	(0.000459)	(0.00201)	
Securities	0.00393***	0.00309		−0.00172*	−0.000853***	0.00886***	
	(0.00118)	(0.00201)		(0.00103)	(0.000244)	(0.00241)	

(continued on next page)

Appendix A (*continued*)

	Net interest margin	Noninterest nontrading income ratio	Return on trading assets	Compensation noninterest expense ratio	Fixed asset noninterest expense ratio	Other noninterest expense ratio	Return on AFS securities
Other							
Asset share (firm assets as % of industry)	0.00743***	−0.00581***		−0.0000207	−0.0000756	−0.00369**	
	(0.00141)	(0.00181)		(0.00084)	(0.000159)	(0.00175)	
Constant	0.234*	0.233*	1.989***	0.261***	0.130***	0.148	0.272***
	(0.124)	(0.127)	(0.602)	(0.0964)	(0.0253)	(0.111)	(0.0535)
Observations	17,565	17,565	67	17,565	17,565	17,565	12,875
R^2	0.885	0.876	0.449	0.828	0.835	0.772	0.0352

* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Appendix Table 2. NCO specifications.

	Residential real estate			Commercial real estate			Commercial and industrial
	First lien residential	Junior lien residential	HELOC	Construction	Multifamily	Nonfarm nonresidential	
Lagged dependent variable	0.884***	0.867***	0.893***	0.801***	0.776***	0.823***	0.798***
	(0.0776)	(0.0847)	(0.0501)	(0.0887)	(0.105)	(0.0990)	(0.0680)
Home price growth (%, year-over-year)	−0.00147	−0.0153	−0.00492				
	(0.00200)	(0.0109)	(0.00330)				
Home price growth if growth is negative (else zero)	−0.0192**	−0.0671***	−0.0284***				
	(0.00756)	(0.0212)	(0.00831)				
Commercial property price growth if negative (else zero)				−0.0473**	−0.0114**	−0.00928***	
				(0.0222)	(0.00467)	(0.00343)	
Annualized change in unemployment (%)							0.133***
							(0.0338)
Constant	0.0231	0.176*	0.0528*	0.113*	0.0480**	0.0395*	0.164***
	(0.0168)	(0.0994)	(0.0287)	(0.0657)	(0.0218)	(0.0229)	(0.0488)
Observations	90	90	90	90	90	90	90
R^2	0.917	0.911	0.955	0.878	0.765	0.797	0.820

	Consumer loans		All other loans					
	Credit card	Other consumer	Leases	Other real estate	Depository institutions	Agriculture	Foreign governments	Other loans
Panel B. Consumer and all other loans								
Lagged dependent variable	0.856***	0.701***	0.635***	0.573***	0.351**	0.597***	0.574***	0.558***
	(0.0477)	(0.0993)	(0.0782)	(0.149)	(0.137)	(0.136)	(0.167)	(0.131)
Commercial property price growth (%, year-over-year)	0.701***			−0.00933*				
	(0.0993)			(0.00534)				
Commercial property price growth if negative (else zero)				−0.00365				
				(0.0150)				
Annualized change in unemployment (%)	0.359***	0.150***	0.102***		0.0510	0.0297**	0.0870	0.117***
	(0.0795)	(0.0306)	(0.0219)		(0.0411)	(0.0120)	(0.156)	(0.0407)
Time trend (annual)		0.0191**						
		(0.00862)						
Constant	0.721***	0.264***	0.172***	0.191***	0.133***	0.0834***	0.145	0.152***
	(0.221)	(0.0934)	(0.0379)	(0.0681)	(0.0446)	(0.0212)	(0.243)	(0.0463)
Observations	90	90	90	90	90	90	90	90
R^2	0.899	0.825	0.616	0.555	0.158	0.440	0.360	0.607

* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jbankfin.2015.09.021.

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