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UNITED STATES OF AMERICA

STRESS TESTING

TECHNICAL NOTE

JULY 2010

INTERNATIONAL MONETARY FUND
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GLOSSARY

AIG	American Insurance Group
AFS	Available-for-sale
BHC	Bank holding company
C&I	Commercial and industrial loans
CCA	Contingent Claims Analysis
CDS	Credit default swap
CIMDO	Consistent Information Multivariate Density Optimizing
CRE	Commercial real estate
DIP	Distress Insurance Premium
DTAs	Deferred tax assets
EL	Expected losses
ES	Expected shortfall
FI	Financial institution
FSAP	Financial Sector Assessment Program
FVOAS	Fair value option adjusted spread
GFSR	Global Financial Stability Report
GSE	Government-sponsored enterprise
LGD	Loss given default
LIBOR	London Interbank Offered Rate
MBS	Mortgage-backed security
MCSR	Marginal contribution of individual firms to systemic risk
MES	Marginal Expected Shortfall
MKMV	Moody's KMV valuation model
NAIC	National Association of Insurance Commissioners
OCC	Office of the Comptroller of the Currency
OMO	Open market operations
OOM	Out-of-the-Money
OTS	Office of Thrift Supervision
PCA	Prompt corrective action
PMD	Portfolio Multivariate Density
PoD	Probability of distress
PPNR	Pre-provision pre-tax net revenue
PSPA	Preferred Stock Purchase Agreement
RBC	Risk-based capital
RND	Risk-neutral density
RNDP	Risk neutral default probability
RRE	Residential real estate loans
SCAP	Supervisory Capital Assessment Program
SES	Systemic Expected Shortfall
SMFST	Systemic macro-financial stress test

SPD	State-price density
TAC	Total adjusted capital
TARP	Troubled Asset Relief Program
UL	Unexpected losses
VaR	Value at Risk
VAR	Vector Auto-Regression
WEO	World Economic Outlook

I. Introduction and Main Findings[1]

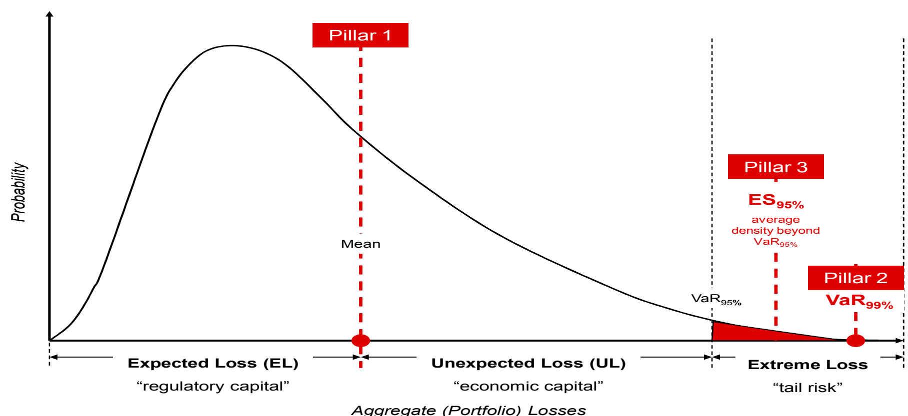
1. **The stress testing analysis in the U.S. Financial Sector Assessment Program (FSAP) consisted of three main pillars**. A wide range of approaches can be used to assess systemic resilience, and each one is subject to its own pros and cons. Mindful of this, the stress tests in this FSAP relied on a combination of tools in order to obtain a more comprehensive assessment of the strengths and vulnerabilities of the financial system than would be allowed by any single approach. In particular, each pillar examined a different aspect of financial sector soundness:

- *Balance-sheet based macroprudential stress tests* (Section II). The first pillar used publicly available financial statements and other macroeconomic data to forecasts financial firms' capital needs. Resembling in essence the authorities' Supervisory Capital Assistance Program (SCAP) methodology, but without detailed supervisory data, it modeled how macroeconomic developments may affect the health of the financial institutions, including their lending capacity to support economic growth. Unlike the other pillars in this note, however, it did not account for default dependencies across institutions, omitting the potential role of non-linearities and hence possibly underestimating tail-risk (Figure 1).
- *A macroprudential stress testing exercise with distress* (Section III). The second pillar went beyond the first pillar by accounting explicitly for distress dependencies across financial institutions. To do this, it computed various measures of probability of default using market-based credit default swap (CDS) data. This analysis added depth by providing, among others, estimates of unexpected losses, interconnectedness and spillovers. However, in an environment where few uninsured creditors bore the burden of financial distress, as was the case during the financial crisis, CDS data may not fully capture the true probability of default, at least not for all market participants and if further government bail-out expectations were wrongly priced in.
- *Estimates of government's potential contingent liabilities implied by financial market prices* (Section IV). The third pillar complemented the other pillars by using financial market prices to estimate the magnitude of risk transfer to the government and the contribution of individual institutions to this risk transfer through implicit and explicit government support. It did so by comparing implied default risk from equity and CDS prices in a high-dimensional extension of contingent claims analysis (CCA), which

[1] The work on the note was coordinated by Kal Wajid and Martin Čihák. The main authors of the note are Geoffrey N. Keim and Andrea M. Maechler (Section II); Miguel A. Segoviano and Hiroko Oura, with contributions from Ryan Scuzzarella (Section III); and Dale Gray and Andreas A. Jobst (Section IV). The note also reflects inputs from Douglas Laxton (macroeconomic scenarios), National Association of Insurance Commissioners (NAIC) staff (insurance stress testing), as well as the rest of the FSAP team. In addition, the note has benefitted from numerous discussions with staff of U.S. agencies.

captured the risk-adjusted balance sheets of individual firms and their interdependencies. By focusing on the equity market, this approach shed light on a part of the financial system that is the least likely to incorporate bail-out expectations and hence, provided an additional perspective on the resilience of the financial system. In comparison to the other two pillars, this analysis focused on the expected shortfall, namely, the average density of extreme losses beyond the 95 percent Value-at-Risk (VaR) (Figure 1).

Figure 1. Key Conceptual Differences in Loss Measurements Across Pillars



Source: IMF Staff.

2. **The stress testing analysis was based on publicly available information and on models that are subject to a considerable degree of uncertainty; this needs to be taken into account when drawing policy conclusions.** Reflecting the authorities' preference and confidentiality concerns, the analysis utilizes only publicly available data. While an impressive range of information is publicly available on U.S. financial institutions, the lack of access to more granular supervisory information was a constraint. Also, the presented findings are derived from valuation models that are subject to a considerable degree of estimation uncertainty. Reflecting data availability and data requirements of the three pillars, the three approaches analyzed slightly different samples of financial institutions (Table 1). The main limitations are acknowledged and reflected in appropriate caveats in the relevant sections of this note.

3. **The FSAP analysis included also two related components that helped further assess the financial system's shock absorbing capacity.** The two components included a survey of authorities' own stress testing practices (Appendix I) and a detailed stress test for

life insurance companies, carried out in close cooperation with the National Association of Insurance Commissioners (Appendix II).[2]

4. **Overall, the stress tests carried out by the FSAP team illustrate important vulnerabilities in the banking sector**. The system has already experienced a "tail event" and, thanks to substantive public and private capital injections, under the baseline macro scenario equity buffers appear satisfactory for the system as a whole. Nonetheless, our stress tests indicate that some individual institutions, including a few of the smaller SCAP institutions, may be less well-positioned to absorb future losses through earnings and that existing capital buffers, which have returned to historic levels, may not provide much room to meet strong credit demand as the economy recovers. Stress tests further illustrate that parts of the financial system remain vulnerable to even a modestly adverse scenario.

5. **The stress tests carried out by the FSAP team highlight the importance of macro-financial linkages and dependencies among the largest institutions**. The analysis is subject to wide confidence intervals and other caveats but suggests that in a modestly adverse scenario the banking sector could face further difficulties. It points to possible vulnerabilities among specific sets of institutions—especially the regional and smaller banks—that could be amplified by their interlinkages, including through their impact on foreclosures and real estate property prices. The analysis also suggests that, while capital injections in financial institutions substantially lowered individual financial institutions' contingent liabilities and reduced systemic tail risk, it might take time to clean up the institutions' portfolios.

6. **It is encouraging that the authorities have stated their intention to conduct periodic forward-looking scenario analyses to enhance understanding of adverse changes in the operating environment on individual firms and the system as a whole** The SCAP experience has illustrated the benefits of further building interagency and system-wide stress testing capabilities (Appendix I). The authorities are now undertaking broader and more comprehensive horizontal (cross-institution) reviews.

7. **In all the tests, a baseline and a more adverse macroeconomic scenario were considered**. The baseline was consistent with the IMF's April 2010 *World Economic Outlook* (*WEO*), while the adverse scenario was predicated on further shocks to demand and potential output, as well as the impact of market fears of an unsustainable fiscal situation and related inflationary expectations. Single factor shocks and alternative scenarios to test the sensitivity of the results were also considered. The magnitudes of the assumed shocks were consistent with historical distress episodes and with the ranges analyzed in other FSAPs.

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[2] The NAIC conducted high level stress tests for a variety of insurance sectors. A detailed stress test of the life insurance sector was conducted based on the results of the high level tests.

8. **In the first pillar, i.e., the balance sheet-based macroprudential analysis, the team stress tested a wide set of large bank holding companies (BHCs) to gauge the soundness of the banking system as a whole, and explore differences across peer groups.** The analysis projects revenues, losses, and retained earnings to assess potential capital shortfalls over a five-year period. Consideration was given to firm-specific differences in earnings and losses, based on portfolio composition and historical performance. An attempt was made to account for the impact of deleveraging, de-risking, asset on-boarding, and impaired securitization on BHC system-wide asset growth. Nonetheless, some features that could have a material impact on the results could not be accounted for in the analysis due to data and modeling constraints (e.g., purchasing accounting assumptions on acquired assets).

9. **The results of the balance-sheet based stress tests suggest that under the baseline scenario, capital would be adequate for most banks, but in the adverse scenario, almost one third of the U.S. BHCs would experience some capital shortfall**. Under the baseline, notwithstanding weak growth, high unemployment, and record high charge-off rates, the top four BHCs and the former broker dealers are expected to maintain a 6 percent Tier 1 common equity ratio over 2010–2014. However, three SCAP institutions would require US$7 billion in additional capital to maintain the same ratio and subsidiaries of foreign banks, which tend to be lightly capitalized and rely on parental support, would require an additional US$26 billion in capital if they were required to meet the same regulatory standards as their domestic peers. A number of regional banks and smaller institutions would also face capital shortfalls due to their high exposure to commercial real estate (CRE) losses. In an adverse scenario, U.S. BHCs would require a total of US$32 billion in additional capital to maintain a less stringent 4 percent Tier 1 common capital ratio until end-2014. Almost half of this shortfall (US$15 billion) would be accounted for by three SCAP institutions. The remainder by accounted for by two non-SCAP regional banks (US$2 billion) and ten smaller institutions (US$15 billion). These results assume that residential real estate and commercial real estate losses continue to rise until 2011, while losses on consumer loans start to decline from their 6.5 percent peak in the first quarter of 2010.

10. **The results illustrate the high sensitivity of BHCs' asset quality and capital positions to developments in the housing sector and the economy more broadly**. There is much uncertainty about banks' earnings outlook as well as the shape and height of their loss profiles, although they are expected to be a drag on retained earnings and credit growth for some time. Identified fragilities in regional and smaller institutions do not appear systemic but could hamper economic recovery in local communities with broader repercussions on bank loss rates. Another potential macroprudential vulnerability is the low capitalization of foreign-owned BHCs, which could result in a sharp retraction of their domestic exposures if their parents were no longer willing or able to provide adequate financial support. The results confirm that, despite strong recapitalization efforts, it will take time to clean-up banks' balance sheets.

11. **Market liquidity risks appear to have declined for the financial system as a while, although financial firms remain vulnerable to funding rollover risk.** With the infusion of short-term liquidity to the markets, financial institutions were able to improve their liquidity buffers but at the cost of shortening their funding maturity profiles. Financial firms will need to address rollover risks arising from a bunching of assets maturing in 2011–13. Although the team did not have access to supervisory data, its analysis suggests that strains on most BHCs could be exacerbated if they were unable to refinance maturing loans, as this could lead to deterioration in commercial and residential real estate losses.

12. **Analysis also suggests that the life insurance sector is relatively resilient**. Separate, but closely coordinated, stress tests focusing on the largest 30 life insurance companies (accounting for 68 percent of U.S. life insurance premium income) were carried out in cooperation with the National Association of Insurance Commissioners (NAIC). These included an adverse scenario that combines negative shocks to the companies' assets, a liability-side shock impacting variable annuity writers, and a major insurance shock (a pandemic). After the shocks, the aggregate risk-based capital (RBC) ratio would decline from 906 percent (as of end-2009) to 521 percent, with 5 out of the 30 companies having RBC below 300 percent. Companies with substantial variable annuity business would be particularly hard hit, but no company would have a negative RBC under the scenario.

13. **In the second pillar, the system was also tested for distress dependencies among major financial firms**. These interdependencies, which proved critical during the crisis, were analyzed using a forward looking, market data-based framework. It is also important to note that "interdependencies" are assessed using a statistical model that is subject to uncertainty and that relies on market-based data (rather than on direct data on the extent to which financial institutions are connected to each other through lending relationships or common exposures). The focus of attention was on losses—defined as the value of defaulted loans less recoveries—rather than capital.

14. **The results in the second pillar confirm that the U.S. financial system continues to face substantial tail vulnerabilities**. Expected losses are likely to decline from the peak observed in 2008 under both scenarios, reflecting improving macroeconomic developments. However, the tail risks appear to remain substantial under both scenarios, and systemic unexpected losses, incorporating interconnectedness among major financial institutions, is likely to remain at elevated levels in the near future.

15. **The second-pillar results also highlight considerable interconnectedness and spillovers**. The analysis suggests that the marginal contribution of an individual firm to systemic risk depends not only on size, but also on linkages to the rest of the financial system, and changes over time. The correlation between financial institutions' size (total assets) and their marginal contributions was 0.6–0.8 in 2008 and 2009. Although measures of interlinkages between banks and non-financial corporates have declined from the highest levels observed in the first quarter of 2009 (possibly due to public support), they remain

significant and appear to be increasing more recently. It is important to stress that the linkages identified in this study are the result of a statistical model and do not represent actual data on linkages through lending, counterparty exposures or other common exposures.

16. **An extension of the second-pillar analysis suggests that vulnerabilities in the global financial system have eased from recent highs, although systemic tail risk remains elevated**. The team's Banking Stability Index for the global system—a measure indicating the expected number of banks falling into distress given that at least one bank in the system becomes distressed—remains at levels similar to those observed in August 2008. The trend followed by this index is consistent with the average probabilities of default observed in each region. Also, on average, probabilities of default of U.S. banks remain higher than those of European and Asian banks. Tight interlinkages persist between U.S. and European banks, implying an ongoing risk of a cascade effect. Although these interlinkages (as measured by the conditional probabilities of distress of U.S. banks conditional on European banks, and vice-versa) have eased from their recent peaks in the first quarter of 2009, they remain significant. Indeed, the team's analysis indicates that the probability of problems at large U.S. banks spilling over to the other global banks was appreciably high as of December 2009. Moreover, some of these U.S. banks appear vulnerable to negative developments at other global banks or sovereigns.

17. **In the third pillar, the Systemic CCA framework was used to estimate the financial market's expectation of government contingent liabilities.** The analysis, based on daily data for 36 financial firms in 2007–2009, suggests that more than half of total expected losses—as indicated by lower default risk implied by CDS spread compared to equity prices—could have become public sector liabilities. Controlling for the time-varying dependence structure between sample firms, the expected market-implied joint contingent liabilities peaked at about US$140 billion at the end of March 2009, averaging US$74 billion over the sample period. Note that any market perception of implicit or explicit guarantees depresses CDS prices, which limits systemic risk measures based on CDS-implied probabilities of default to the retained risk in the financial sector.

18. **The joint tail-risk measure of contingent liabilities shows spikes in April 2008 and October 2008, indicating that the market's view of a high government exposure to financial sector distress**. If measured as the 95th percentile expected shortfall, market implied contingent liabilities from risks transferred to the government exceeded US$1 trillion and almost reached US$3 trillion in those two months, respectively. The housing government-sponsored enterprises (GSEs) were large contributors to systemic risk up to the point of conservatorship. The results are consistent with the SCAP, as BHCs that needed additional capital according to the SCAP contribute to systemic tail risk far more than the other SCAP firms after the Lehman Brothers collapse, especially if capital need is estimated jointly. Simulations indicate that capital injections into the three largest Troubled Asset Relief Program (TARP) recipients significantly lowered individual contingent liabilities and systemic tail risk.

Table 1. List of Institutions in the Three Stress Test Pillars [1/]

	Pillar 1: Balance-Sheet Based			Pillar 2: Distress-Dependency			Pillar 3: Systemic Contingent Claims		
	Number of institutions	Total assets (in billions)	In percent of sample	Number of institutions	Total assets (in billions)	In percent of sample	Number of institutions	Total assets (in billions)	In percent of sample
Total system	**54**	**16,483.9**	**100.0**	**14**	**17,406.3**	**100.0**	**36**	**20,520.8**	**100.0**
Top 4 banks	**4**	**7,702.3**	**46.7**	**4**	**7,702.3**	**44.3**	**4**	**7,702.3**	**37.5**
Bank of America Corporation	1	2,340.7	14.2	1	2,340.7	13.4	1	2,340.7	11.4
JPMorgan Chase & Co.	1	2,135.8	13.0	1	2,135.8	12.3	1	2,135.8	10.4
Citigroup Inc.	1	2,002.2	12.1	1	2,002.2	11.5	1	2,002.2	9.8
Wells Fargo & Company	1	1,223.6	7.4	1	1,223.6	7.0	1	1,223.6	6.0
Investment banks	**2**	**1,700.4**	**10.3**	**2**	**1,700.4**	**9.8**	**4**	**1,700.4**	**8.3**
Goldman Sachs Group, Inc.	1	880.7	5.3	1	880.7	5.1	1	880.7	4.3
Morgan Stanley	1	819.7	5.0	1	819.7	4.7	1	819.7	4.0
Bear Stearns	-	-	-	-	-	-	1	0.0	-
Lehman	-	-	-	-	-	-	1	0.0	-
Regional banks	**9**	**1,273.9**	**7.7**	**3**	**719.7**	**4.1**	**8**	**1,228.6**	**6.0**
PNC Financial Services Group, Inc.	1	265.4	1.6	1	265.4	1.5	1	265.4	1.3
U.S. Bancorp	1	282.4	1.7	1	282.4	1.6	1	282.4	1.4
SunTrust Banks, Inc.	1	171.8	1.0	1	171.8	1.0	1	171.8	0.8
BB&T Corporation	1	163.7	1.0	-	-	-	1	163.7	0.8
Regions Financial Corporation	1	137.3	0.8	-	-	-	1	137.3	0.7
Fifth Third Bancorp	1	112.7	0.7	-	-	-	1	112.7	0.5
KeyCorp	1	95.3	0.6	-	-	-	1	95.3	0.5
Popular, Inc.	1	33.8	0.2	-	-	-	-	-	-
W Holding Company, Inc. 2/	1	11.5	0.1	-	-	-	-	-	-
Washington Mutual	-	-	-	-	-	-	1	-	-
Processing banks	**3**	**450.2**	**2.7**	-	-	-	**3**	**450.2**	**2.2**
Bank of New York Mellon Corporation	1	221.0	1.3	-	-	-	1	221.0	1.1
State Street Corporation	1	152.9	0.9	-	-	-	1	152.9	0.7
Northern Trust Corporation	1	76.3	0.5	-	-	-	1	76.3	0.4
Consumer banks	**3**	**522.4**	**3.2**	**1**	**200.7**	**1.2**	**4**	**401.1**	**2.0**
Capital One Financial Corporation	1	200.7	1.2	1	200.7	1.2	1	200.7	1.0
American Express Company	1	142.3	0.9	-	-	-	1	142.3	0.7
Ally Financial 3/	1	179.4	1.1	-	-	-	-	-	-
CIT	-	-	-	-	-	-	1	58.1	-
Ameriprise	-	-	-	-	-	-	1	-	-
Small banks	**21**	**564.9**	**3.4**	-	-	-	-	-	-
Comerica Incorporated	1	57.2	0.3	-	-	-	-	-	-
Marshall & Ilsley Corporation	1	56.6	0.3	-	-	-	-	-	-
Zions Bancorporation	1	51.7	0.3	-	-	-	-	-	-
Huntington Bancshares Incorporated	1	51.9	0.3	-	-	-	-	-	-
Synovus Financial Corp.	1	32.4	0.2	-	-	-	-	-	-
New York Community Bancorp, Inc.	1	42.4	0.3	-	-	-	-	-	-
First Horizon National Corporation	1	25.9	0.2	-	-	-	-	-	-
BancorpSouth, Inc.	1	13.2	0.1	-	-	-	-	-	-
Associated Banc-Corp	1	23.1	0.1	-	-	-	-	-	-
BOK Financial Corporation	1	23.5	0.1	-	-	-	-	-	-
First BanCorp.	1	18.9	0.1	-	-	-	-	-	-
Webster Financial Corporation	1	18.0	0.1	-	-	-	-	-	-
Commerce Bancshares, Inc.	1	18.0	0.1	-	-	-	-	-	-
TCF Financial Corporation	1	18.2	0.1	-	-	-	-	-	-
First Citizens BancShares, Inc.	1	21.2	0.1	-	-	-	-	-	-
First National of Nebraska, Inc.	1	16.6	0.1	-	-	-	-	-	-
City National Corporation	1	20.1	0.1	-	-	-	-	-	-
Fulton Financial Corporation	1	16.4	0.1	-	-	-	-	-	-
New York Private Bank & Trust Corporation	1	13.1	0.1	-	-	-	-	-	-
Susquehanna Bancshares, Inc.	1	13.8	0.1	-	-	-	-	-	-
South Financial Group, Inc.	1	12.4	0.1	-	-	-	-	-	-
Foreign banks	**11**	**1,822.0**	**11.1**	-	-	-	-	-	-
M&T Bank Corporation	1	68.4	0.4	-	-	-	-	-	-
Harris Financial Corp.	1	65.5	0.4	-	-	-	-	-	-
BancWest Corporation	1	75.2	0.5	-	-	-	-	-	-
UnionBanCal Corporation	1	85.5	0.5	-	-	-	-	-	-
Barclays Group US Inc.	1	427.8	2.6	-	-	-	-	-	-
BBVA USA Bancshares, Inc.	1	65.2	0.4	-	-	-	-	-	-
HSBC North America Holdings Inc.	1	345.4	2.1	-	-	-	-	-	-
RBC Bancorporation (USA)	1	26.2	0.2	-	-	-	-	-	-
Taunus Corporation	1	364.1	2.2	-	-	-	-	-	-
TD Banknorth Inc.	1	154.7	0.9	-	-	-	-	-	-
Citizens Financial Group, Inc.	1	144.0	0.9	-	-	-	-	-	-
Other	**1**	**2,447.8**	**14.8**	-	-	-	-	-	-
GSEs	-	-	-	**2**	**5,654.0**	**32.5**	**3**	**5,792.7**	28.2
Fannie Mae	-	-	-	1	3,293.8	18.9	1	3,293.8	16.1
Freddie Mac	-	-	-	1	2,360.2	13.6	1	2,360.2	11.5
Sallie Mae	-	-	-	-	-	-	1	138.8	0.7
Insurance	-	-	-	**2**	**1,429.3**	**8.2**	**10**	**3,245.6**	15.8
Metlife	-	-	-	1	565.6	3.2	1	565.6	2.8
AIG	-	-	-	1	863.7	5.0	1	863.7	4.2
Prudential	-	-	-	-	-	-	1	491.9	2.4
Hartford	-	-	-	-	-	-	1	317.3	1.5
Allstate	-	-	-	-	-	-	1	132.4	0.6
Principal	-	-	-	-	-	-	1	140.8	0.7
Travelers	-	-	-	-	-	-	1	358.0	1.7
Genworth	-	-	-	-	-	-	1	109.1	0.5
Aflac	-	-	-	-	-	-	1	85.2	0.4
Lincoln	-	-	-	-	-	-	1	181.6	0.9

Source: SNL Financials.

1/ Total assets as of end-March 2010.

2/ Acquired by Banco Popular de Puerto Rico in April 2010.

3/ Opertating under the name of GMAC, Inc. prior to May 2010.

II. Balance-Sheet Based Macroprudential Stress Tests

A. Introduction

19. **To assess the resilience of the banking system to changes in the U.S. macroeconomic environment, the FSAP team conducted a forward-looking balance sheet-based analysis.** This analysis is similar to the SCAP exercise, conducted by the authorities in early 2009, in the sense that it forecasts bank's capital needs into the future based on particular macroeconomic projections.[3] In contrast to the SCAP, however, the present exercise is based entirely on publicly available information as of end-March 2010.[4] This approach is also related to the capital adequacy analysis presented in the *Global Financial Stability Report* (GFSR) with regard to aggregate loss estimates; however, it differs from the GFSR in its bank-specific "bottom-up" focus on earnings, losses, and capital positions.

20. **The exercise covers 53 BHCs, representing 85.2 percent of all BHC assets, including a number of regional and smaller banks with less widely tracked information (Table 1)**.[5] To capture differences across sizes and business strategies, the sample was grouped into 7 sub-categories, namely: the "top 4" (accounting for 46.7 percent to sample assets); the 2 former investment banks (10.3 percent of sample assets); 9 regional banks (7.7 percent of sample assets); 3 processing banks (2.7 percent of sample assets); 3 consumer banks (3.2 percent of sample assets); 21 "small" banks (3.4 percent of sample assets); and 11 foreign banks (11.1 percent of sample assets).[6] The rest of the system was grouped into a residual category, which accounted for 14.8 percent of sample assets.[7]

21. **The purpose of the stress tests is to assess the soundness of BHCs, including under "worse-than-anticipated" macroeconomic conditions**. By forecasting key elements

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[3] See Board of Governors of the Federal Reserve System (2009a, 2009b).

[4] An earlier version of this framework was used to estimate capital shortfalls in US banks in the context of the *Global Financial Stability Report* (IMF 2008a, 2008b, 2009a, 2009b) and the 2009 U.S. Article IV Consultation Report (IMF 2009c). Benefitting from constructive comments from the authorities in the context of the U.S. FSAP, the framework has been revamped to cover a wider range of institutions, better capture institution-specific idiosyncrasies, and account for various regulatory measures and other one-time events during the crisis.

[5] The institutions included in the stress tests were all operating as of end-March 2010. Since then, however, one of the regional banks (W Holding) failed, with its deposits and a portion of its assets acquired by another regional bank (Popular). No adjustment was made for this event, as it would have been difficult to assess its impact, which would depend on the terms and conditions of the take-over.

[6] The asset size of the "small" banks ranges from US$10 billion to US$60 billion and market share of assets is as of end-March 2010.

[7] Excluding BHCs with assets smaller than US$80 million, which are not reported in the bank-specific database, *SNL Financials*.

of the banks' balance sheets, the exercise captures the interactions between banks' earnings potential, their capital positions, and their ability to absorb losses. All else equal, it also provides some insights into banks' ability to support the economic recovery through lending. Lastly, the analysis can be used to explore the vulnerability of bank holding companies to a wide range of stresses, from broad macro scenarios to more targeted shocks.

22. **The results of the stress test should be interpreted with caution**. These are subject to uncertainty from a number of sources, including the specification of our statistical models, the level of bank-level detail, the possibility of even more severe and unforeseen events, and the validity of our assumptions on banks' future business practices. Many of these factors would be present under any forecasting exercise. Moreover, historical correlations that were observed in the past may not be indicative of the relationship that can be expected going forward in light of the substantial economic shock experienced during the crisis, the many and varied associated policy responses that have followed, and the more recent vulnerabilities in Europe. Thus, when interpreting the results, it is important to appreciate that the results are point estimates and there is uncertainty around them, which is not quantified. Nonetheless, where appropriate, standard tests and alternative scenarios provide some indication of the sensitivity of the results to underlying assumptions.

23. **The results contain both upside and downside risks**. The largest downside risk pertains to banks' earnings outlook, which is assumed to recover around their 1990–99 historical average, with an average annualized return on assets of 2 percent for the 2010–14 sample periods. These estimates are likely to be on the high side, as they do not incorporate the impact of the up-coming financial regulatory reforms, both domestically and internationally, banks' greater risk retention in the absence of a return to pre-crisis securitization levels, and lower credit growth in line with the relatively weak economic outlook. Another important downside risk surrounds loss estimates, particularly due to the large uncertainties regarding the new phenomenon of strategic defaults in the case of "underwater" mortgages and banks' recovery rates, given the potentially long-lasting depressed collateral values. On the upside, banks' ability to raise private capital or reduce their dividend policy could significantly strengthen their capacity to absorb losses and support economic growth when demand recovers.[8]

24. **The assessment of BHCs' capital adequacy over the forecast period employed several capital measures**. To assess the quality of capital, while allowing comparability both across countries and to the SCAP, 3 capital metrics were used; (i) the ratio of tier 1 capital to risk-weighted assets with 6 and 8 percent thresholds; (ii) the SCAP's tier 1 common

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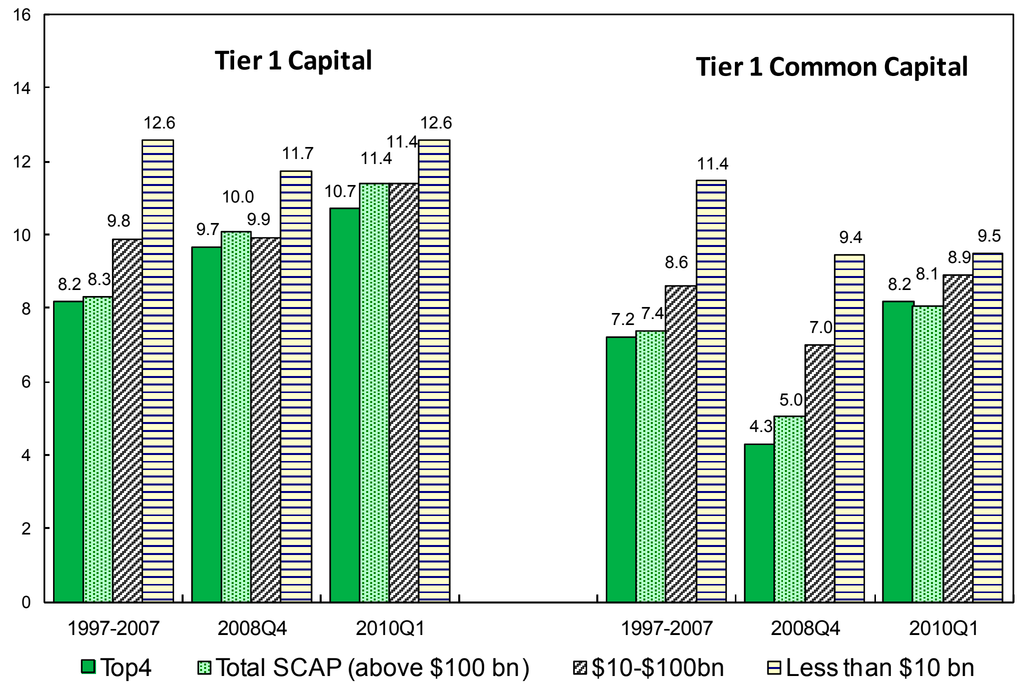
[8] We assume that banks would not raise capital over the sample horizon or that, under the baseline, profit-making financial firms would not reduce their dividends policy in anticipation of a future capital need. The latter assumption was relaxed under the adverse scenario, where banks were expected not to pay out common stock dividends, in line with the authorities' SCAP exercise.

capital/risk-weighted assets ratio with 4 and 6 percent thresholds; and (iii) a tangible common equity to tangible assets ratio with 4 and 6 percent thresholds. The thresholds were not ambitious relative to historical norms (SCAP institutions maintained an average 10 percent tier 1 capital ratio during the crisis and their tier 1 common capital ratio was on average 7.4 percent over 1997–2007) (Figure 2).[9]

Figure 2. Capital Position of BHCs, 1997–2010
(In percent of risk-weighted assets)



Source: SNL Financial.

25. **The exercise spans over a seven-year horizon**. It used realized quarterly data from end-2007 to end-March 2010 and produced quarterly forward-projections until end-2014. Most of the bank-specific data came from the publicly available Y-9C reports that bank holding companies file with the Federal Reserve and were obtained from *SNL Financial*'s database. The regulatory data was further augmented with SEC data for non-banks before their BHC conversion in 2008, *Bloomberg* for capital raising measures and securities write-downs, and the U.S. Treasury Department's website www.FinancialStability.gov for TARP repayments and dividends.

[9] Tier 1 common capital deducts all "non-common" elements from Tier 1 capital (i.e., qualifying minority interest in consolidated subsidiaries, qualifying trust preferred securities, and qualifying perpetual preferred stock).

B. Baseline Scenario

Framework

26. **The analysis projected firms' net revenues, losses, and balance sheet expansion to assess banks' potential capital shortfalls over a five-year period**. A bank's capital shortfall (if any) was computed based on its lowest capital position over the horizon. Consideration was given to firm-specific differences in earnings and losses, based on portfolio composition and historical performance. An attempt was also made to capture a number of specific post-crisis factors that would impact BHC's asset growth, including banks' efforts to deleverage and de-risk their balance sheets, the new FAS 166/167 accounting rules requiring banks to on-board certain assets previously held off-balance sheet, and greater risk retention due to impaired securitization. Moreover, the calculations also incorporated firms' ability to accumulate tax assets in loss-making quarters that could be used to offset future tax liabilities.

27. **Macro-financial linkages are built into the stress test framework**. By modeling how macroeconomic variables have influenced historically the behavior of specific financial variables, it is possible to link a particular macroeconomic path to financial sector developments and their related impact on financial firms' capital position. The nominal GDP growth forecast, for example, drives asset growth; loan loss rates reflect movements in the path for real GDP, real consumption, the unemployment rate, and the output gap. Other macroeconomic variables critical for the loss estimates, such as lending standards and house prices, are forecasted separately (Appendix III). While the link between macroeconomic variables and financial variables is the centerpiece of this exercise, it should be noted that there is no universal, consensus view as to how these variables should relate to each other and that judgmental adjustments may be needed.

28. **The Baseline Scenario was taken from the IMF's April 2010 *World Economic Outlook***. In particular, the output gap closed over the medium term from a negative level in 2009, with the unemployment rate remaining elevated (above 8 percent) until end-2011 before dropping to 5 ½ percent by end-2014. Real GDP growth was expected to peak at 3.1 percent in 2010 and to stabilize around 2.5 percent by 2012. House prices were expected to rise over the forecast horizon, albeit at a very slow pace (peaking at 4.1 percent in 2011) (Appendix III).

Underlying assumptions and forecasting methodology

29. **Five categories of loan charge-off rates were estimated on an industry-wide basis from regression analysis** (Appendix IV). These include losses on CRE loans, residential real estate (RRE) loans, commercial and industrial (C&I) loans, and consumer (CONS) loans

(Figure 3).[10] To capture historical cross-firm differences, BHC-specific charge-off rates were projected for each type of loan, given by $COR_{i,q}^{j}$, where i denotes firms (with I being the industry average), j indexes the loan type, and q denotes time. The forecasted rates were computed recursively taking as their base the previous quarter's value, to which the change in the industry-wide charge-off rate for that class of loan ($\Delta\overline{COR}_{I,q}^{j}$) was applied:

$$COR_{i,q}^{j} = COR_{i,q-1}^{j} + \Delta\overline{COR}_{I,q}^{j}$$

30. **No adjustment was made to account for much stricter underwriting standards post-2009**. In practice, stricter lending standards should help reduce future loss estimates, and particularly their sensitivity to adverse shocks. In the near term, this omission should not play a large role in the context of falling credit growth rates. For the outer years of the forecast, however, it could lead to an upward bias in the loss estimates.

31. **Only limited account was taken of the mergers and acquisitions that took place in 2008 among several large banks.** In the SCAP exercise, adjustments for losses already taken on impaired loans acquired through mergers (i.e., purchase accounting adjustments) reduced estimated losses by US$64 billion. No such adjustment was made in the current exercise, largely because of the difficulty of assessing the performance of the acquired loans relative to expectations in the absence of detailed loan-by-loan information. Furthermore, it is reasonable to assume that the impact of such purchasing accounting adjustments would diminish over time, including through amortization.

32. **Minor adjustments were made for the investment banks that converted to bank holding companies in late 2008.** Because of their recent conversion, focusing on historical prudential data would have put an unreasonably large weight on their (poor) performance during the crisis. In the case of Morgan Stanley, the calculations omit the company's abnormally high loan loss rates during the fourth quarter of 2008 from the moving average used to forecast its future losses. The company's earnings path was raised by adjusting it to the estimated average of the fixed-effects of the top six firms (Figure 4).[11]

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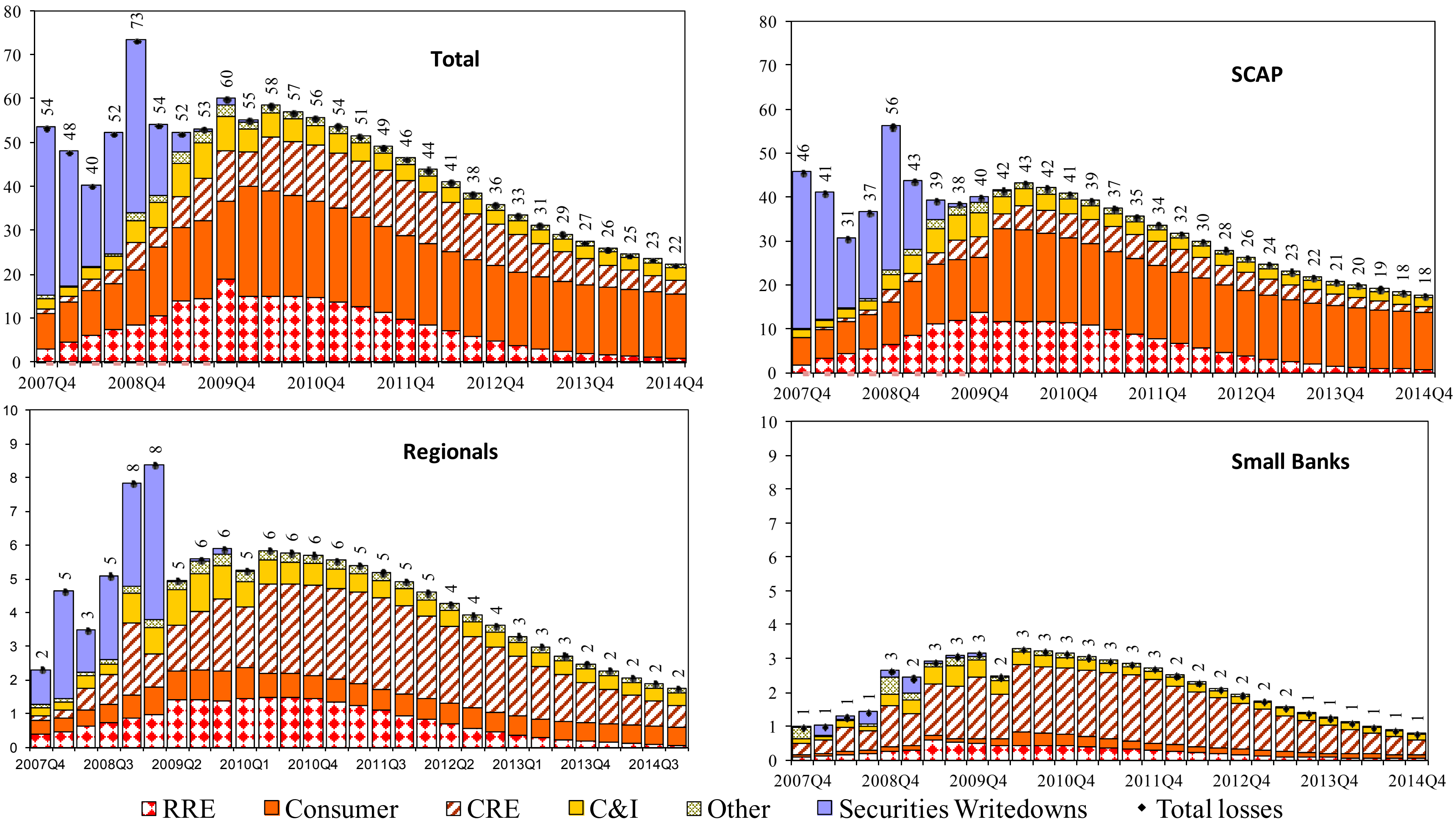
[10] We also computed a charge-off rate for "other" loans as a simple average of the other four categories.
[11] The bank-specific fixed effects were obtained from regression analysis, as detailed below.

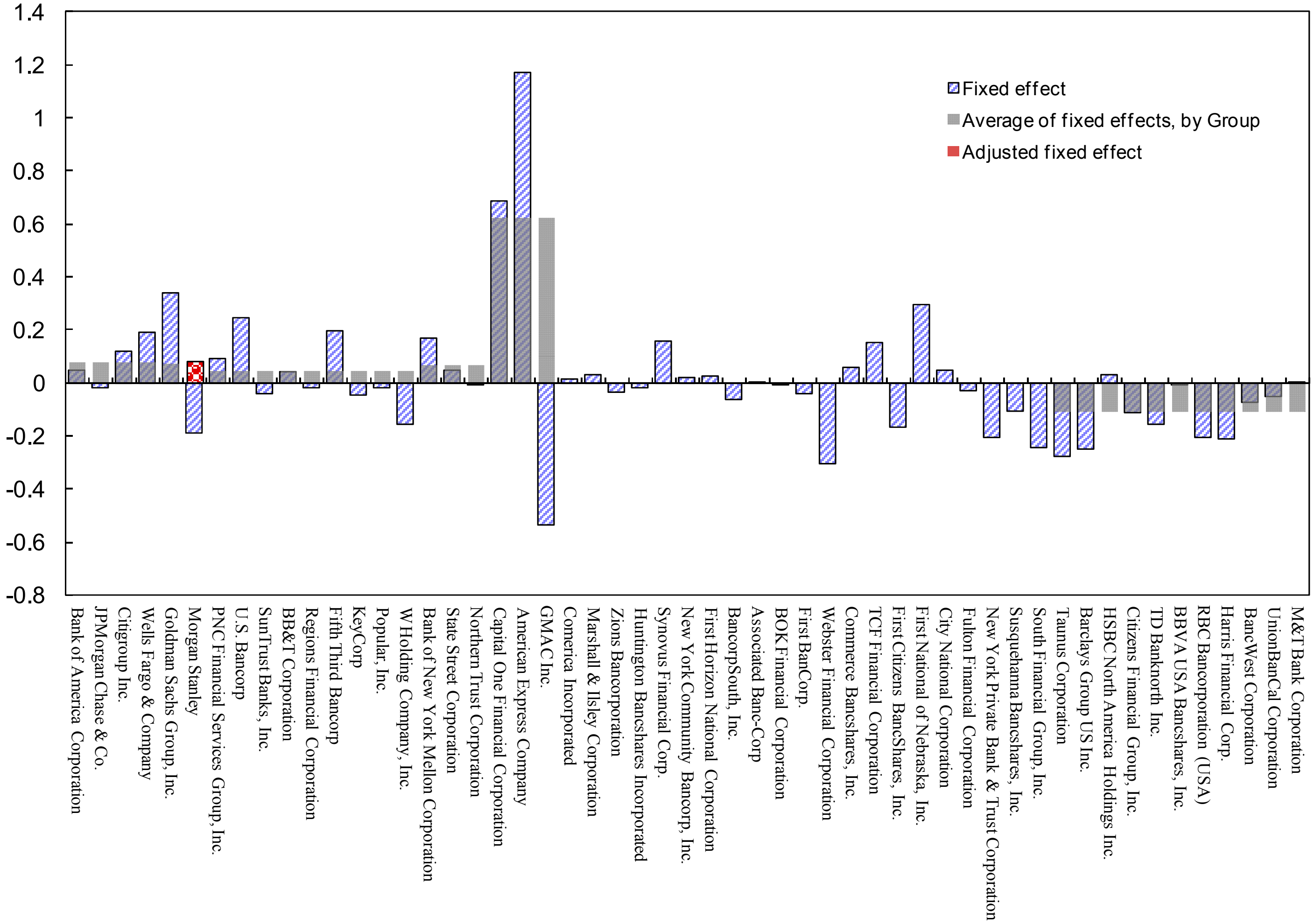
Figure 3. Baseline Scenario: Quarterly Loss Profiles, 2007–14

(In billions of dollars)



Sources: SNL Financials and IMF staff estimates.

Figure 4. Estimated Bank-Specific Effects and Group Averages in Return on Asset Regressions



Source: IMF staff estimates.

33. **The results suggest that credit risk is likely to remain a source of concern for some time, with some loss rates not peaking before mid-2011 (Table 2).** Some of the highest loss rates may have already peaked, such as consumer loans, which reached 6.5 percent at end-January 2010, and residential real estate, which rose to 2.7 percent at end-2009. Losses on commercial real estate loans, however, are expected to continue to rise until mid-2011, as they are generally expected to peak later than in the residential real estate sector. The high loss rate on consumer credit reflects partly the aggressive charge-off policy of the consumer banks in an effort to clean their balance sheets, possibly in anticipation of a pick-up in demand following the sharp credit line contractions since 2008. The relatively low commercial and industrial loans (C&I) loss rate, which peaked at 2.6 percent at end-September 2009, reflects the relatively healthy financial position of the corporate sector, which was able to either use its cash buffers to pay down debt or benefit from advantageous refinancing terms in the corporate bond market.

Table 2. Peaks for Loan Loss Charge-Off Rates, 2009-14 (Percent)

	Baseline scenario		Adverse Scenario		Alternative Scenario	
	Max.	Period	Max.	Period	Max.	Period
RRE	2.7	2009Q4	3.4	2011Q4	3.5	2012Q1
Cons	6.5	2010Q1	6.5	2010Q1	6.5	2010Q1
CRE	3.4	2011Q2	4.6	2011Q3	5.1	2011Q4
C&I	2.6	2009Q3	2.6	2009Q3	2.6	2009Q3
Other	3.4	2009Q4	3.8	2011Q2	3.6	2011Q3

Sources: SNL Financials, Bloomberg, and Fund staff estimates.

34. **While showing signs of stabilization, losses on commercial real estate loans are projected to remain high over the forecast horizon**. Unless commercial property prices start recovering from their 30 percent fall since mid-2006, banks are likely to face heavy losses, given the large volume of underwater mortgage borrowers and up-coming adjustable rate mortgage resets. Furthermore, the weak economy continues to hammer rents and occupancy rates in many markets, with negative consequences for defaults, foreclosures, and losses. The Congressional Oversight Panel (2010), for example, estimated that about US$1.4 trillion in loans will mature in 2010–14, nearly half of which are already seriously delinquent (90 days or more past due) or “underwater” (with a loan value exceeding the property value).

35. **Real estate loan quality is vulnerable to downside risks.** Although the loss rate on residential real estate loans is expected to decline going forward, the rising gap between delinquencies and foreclosures suggests a large volume of pent-up supply of houses for sale through foreclosures, which could put further downward pressure on house prices and exacerbate strategic defaults for some time to come. As of end-March 2010, seriously delinquent loans (90-days or more overdue) accounted for 5 percent of total mortgages, in contrast to actual foreclosures, which accounted for only 1.25 percent of total loans. Loan modifications could help mitigate the risk of a pick-up in foreclosures; however, re-default may be high, in which case modifications could simply postpone losses further into the future.

36. **In the baseline, total cumulative loan losses are expected to reach US$802 billion by end-2014** ($592 billion for SCAP firms). This represents a 6.5 percent cumulative loss for 2010–11 (12.3 percent for 2010–14) (Table 3). Although the two-year loss rates are below the 9.1 percent 2009-2010 loss rate assumed in the SCAP stress test, they amount to an annual average of 3.3 percent for 2010–11 and 2.5 percent for 2010–14. Consumer banks face the largest two-year loss rate, followed by the top four banks. Small and regional banks face lower but still material loss rates (9.7 and 9.4 percent, respectively), reflecting their heavy exposure concentration to commercial real estate.

Securities write-downs

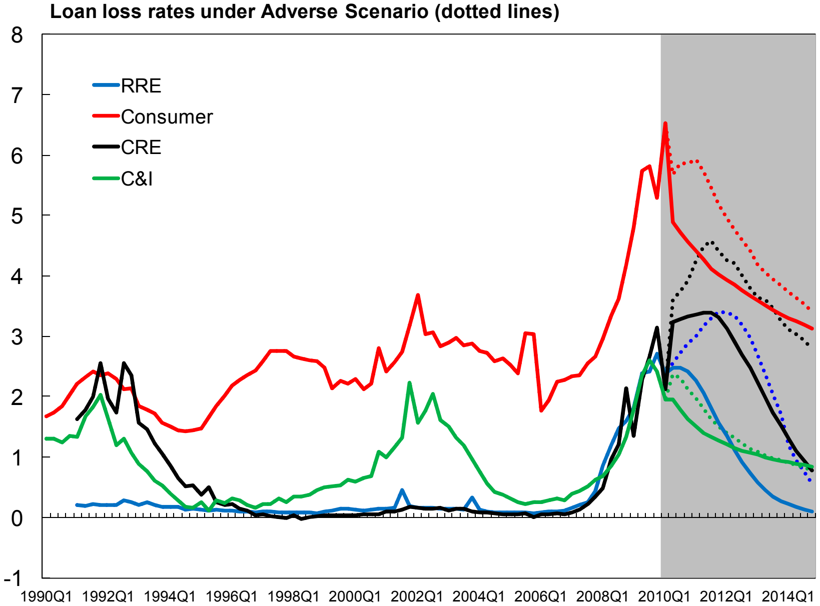
37. **Write-downs on securities were measured as declines in market valuations based on the methodology developed and updated in recent *Global Financial Stability Reports*.**[12] Under the baseline, no additional securities write-down on available-for-sale (AFS) securities was expected, and the framework did not envisage any shocks to marked-to-market trading account securities (Table 4). Since the beginning of the crisis in end-2007, BHCs reported a cumulative US$385 billion of realized marked-to-market securities write-downs (not shown), relative to the US$296 billion of write-downs estimated by the model. To be on the conservative side, no allowance was made for write-ups to banks' securities holdings.

[12] See IMF (2008a, 2008b) for a description of the methodology used for U.S. securities. This methodology was further revised to better capture losses in non-US countries, particularly Europe and Asia.

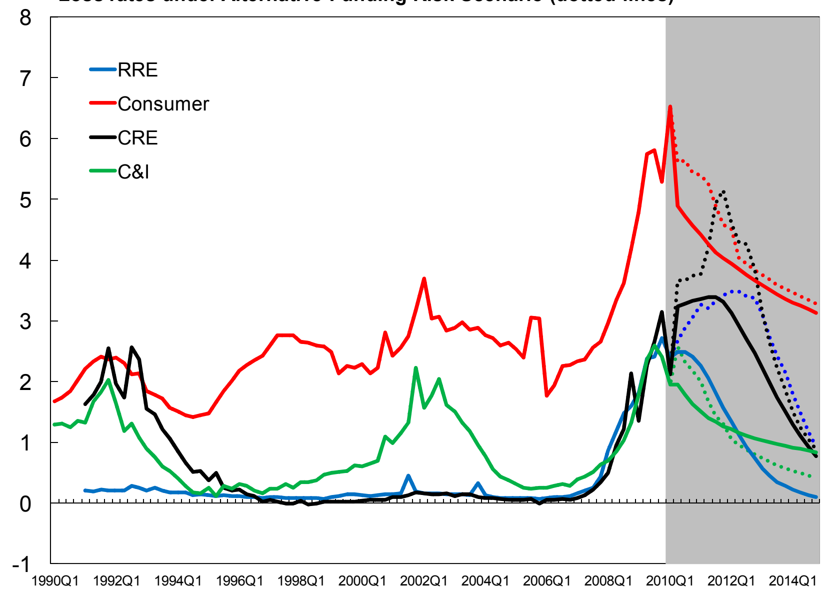
Table 3. Cumulative Loss Rates, 2010-2014 (In percent)

	Baseline				Adverse Scenario				Alternative Scenario			
	Loan losses		Total losses		Loan losses		Total losses		Loan losses		Total losses	
	2010-11	2010-14	2010-11	2010-14	2010-11	2010-14	2010-11	2010-14	2010-11	2010-14	2010-11	2010-14
Total	6.4	12.1	6.4	12.1	7.7	15.9	8.7	17.4	7.6	15.2	8.2	15.8
Top 4	8.1	15.3	8.1	15.3	9.8	19.8	10.8	21.3	9.7	19.5	10.3	20.2
Regional bank	5.1	9.4	5.1	9.4	6.3	13.4	7.0	14.5	6.3	12.4	6.7	12.8
Consumer banks	8.9	18.7	8.9	18.7	10.7	22.2	11.5	23.4	10.2	20.3	10.6	20.8
Small bank	5.5	9.7	5.5	9.7	6.5	13.3	7.0	14.1	6.5	12.0	6.8	12.3
Foreign banks	6.3	10.9	6.3	10.9	7.7	15.3	8.7	16.7	7.6	14.8	8.2	15.4
Annual average	3.2	2.4	3.2	2.4	3.8	3.2	4.4	3.5	3.8	3.0	4.1	3.2

Loan loss rates under Adverse Scenario (dotted lines)



Loss rates under Alternative Funding Risk Scenario (dotted lines)



Source: IMF staff estimates

Table 4. Securities Write-Down Projections

	Estimated Holdings	January Cumulative Losses 2010	January 2010 Cumulative Loss Rate (Percent)	Share of Total (Percent)
Residential Mortgage	1,472	166	11.3	56.2
Agency (Prime Conforming)	492	0	0.0	0.0
ABS(Home and Multifamily)	980	166	17.0	56.2
of which: Non-agency Prime MBS	530	0	0.0	0.0
of which: ABS(CDOs, other MBS)	450	166	37.0	56.2
Consumer	142	0	0.0	0.0
Commercial Mortgage	196	48	24.5	16.3
Corporate	1,115	17	1.5	5.6
Governments	580	0	0.0	0.0
Foreign	975	66	6.7	22.2
Total for Securities	**6,932**	**296**	**6.6**	**100.0**

Sources: Bloomberg and IMF staff estimates.

Earnings profiles

38. **One of the most challenging elements of this exercise was to forecast banks' earnings.** The analysis focused on pre-provision, pre-tax, and pre-dividend net revenues as a percentage of total assets, henceforth referred to as return on assets (ROA). The ultimate regression, which covers 53 BHCs, was run using a fixed-effects panel specification. It included a vector X_t of three macroeconomic variables (real GDP quarterly growth rate, output gap, and lagged quarterly unemployment growth rate), one bank-specific variable y_{it-1} (the lagged loan-to-asset ratio) to capture banks' different business strategies, and one financial market variable, z_{it} (the spread between the three-month Libor and the treasury bill of similar maturity) as a proxy for financial market conditions; u_{it} is the unit-specific residual and ε_{it} is the usual residual:

$$ROA_{it} = \alpha + \beta X_t + \delta y_{it-1} + \lambda z_{it} + u_i + \varepsilon_{it}\,.$$

39. **The model was estimated using quarterly frequency data from 1990Q1–20010Q1**. The macroeconomic variables were seasonally adjusted, whereas the bank-specific and financial variables were not. For the forecast period, the estimated coefficients were applied to the forecasted explanatory variables, allowing the resulting retained earnings to feed back into total assets each quarter. No attempt was made to model sub-groups of institutions, although the fixed effect from the panel regression allowed introducing bank-specific differences (Figure 4). Key results are shown in Table 5. The final model specification is highlighted in Column (4). The results for the macroeconomic regressions are presented in Columns (1) and (2); whereas the fixed effects regressions are presented in

Columns (3) to (5) and those for the single and multi-level mixed effects regressions are presented in Columns (6) and (7).

Table 5. Summary Results for Return on Asset Regressions

	Macro data		Fixed effects panel			Mixed effects panel	
						Bank- and group-level	Bank-level
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Loan-to-asset (lagged)	0.584***	1.792***	0.276*	0.307**	0.292*	0.324***	0.317***
	-1.06E-04	*-8.83E-08*	*-0.0714*	*-0.0433*	*-0.0508*	*0.00E+00*	*0.00E+00*
Log of total assets (lagged)	-	0.0684***	-1.65E-02	-	-	-	-
	-	*-6.07E-06*	*-0.138*	-	-	-	-
Real GDP quarterly growth	2.432	2.704**	1.363**	1.687**	1.356**	1.690***	1.708***
	-0.15	*-0.0363*	*-0.0471*	*-0.014*	*-0.0449*	*-0.00238*	*-0.00213*
3-m Libor to 3-m TBill	-0.201***	-0.188***	-0.151***	-0.150***	-0.103***	-0.150***	-0.150***
	-7.42E-08	*-4.54E-07*	*-1.28E-09*	*-1.15E-09*	*-1.28E-05*	*0.00E+00*	*0.00E+00*
Output gap	0.0129*	-0.0104	0.0240***	0.0197***	0.0204***	0.0196***	0.0194***
	-0.051	*-0.225*	*-0.000185*	*-0.00332*	*-0.00232*	*-1.24E-10*	*-1.65E-10*
Unemployment quarterly growth (lagged)	0.296	0.0319	0.138	0.0205	0.0262	0.0215	0.0225
	-0.101	*-0.848*	*-0.153*	*-0.857*	*-0.817*	*-0.805*	*-0.795*
Dummy for 2007-2008	-	-	-	-	-0.0929***	-	-
	-	-	-	-	*-0.000193*	-	-
Constant	0.269***	-1.925***	0.698***	0.393***	0.389***	0.447***	0.396***
	-2.08E-04	*-9.85E-05*	*-0.00199*	*-1.64E-04*	*-1.63E-04*	*-1.24E-10*	*0.00E+00*
Number of observations	79	79	3,401	3,401	3,401	3,401	3,401
Number of banks	-	-	53	53	53	-	-
R-squared	0.650	0.736	-	-	-	-	-
Adj R-square	0.626	0.714	0.136	0.132	0.139	-	-
Within R-square	-	-	0.138	0.134	0.140	-	-
Standard deviation residual error (*e_it)*	-	-	0.176	0.176	0.176	-	-
Number of groups	-	-	-	-	-	7	53
Random effect at bank-level	-	-	-	-	-	-1.613***	-1.478***
	-	-	-	-	-	*0.00E+00*	*0.00E+00*
Random effect at group-level	-	-	-	-	-	-1.948***	
	-	-	-	-	-	*-1.90E-05*	
Standard deviation of overall error term	-	-	-	-	-	-1.734***	-1.734***
	-	-	-	-	-	*0.00E+00*	*0.00E+00*

Notes: Independent variable is return on assets. Robust p-values indicated in italic below coefficient: *** p<0.01, ** p<0.05, * p<0.1

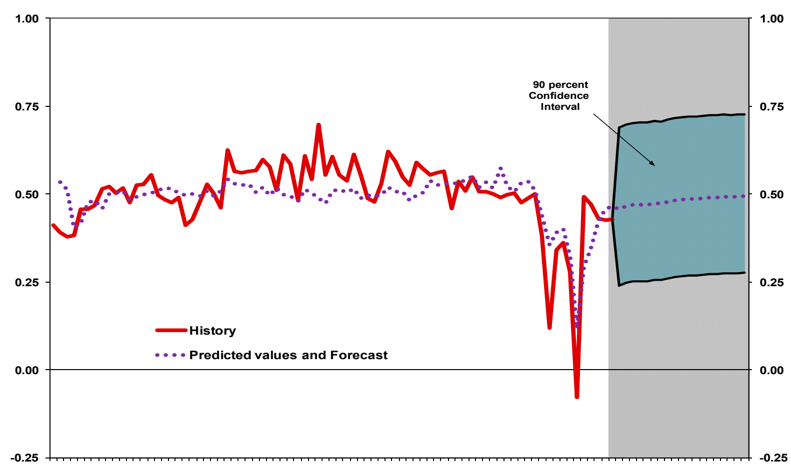
Source: IMF staff estimates.

40. **A wide range of model specifications were tested to estimate earnings, including macroeconomic (industry-wide) models and different bank-specific panel models.** Given the objective of linking the earnings forecast to various macroeconomic scenarios, the choice of explanatory variables was restricted to those that could be directly linked to the macroeconomic model used for our scenario analysis (e.g., GDP, output gap, unemployment, real consumption) or for which there was an in-house forecasting model (e.g., house prices, yields on the London Interbank Offered Rate (LIBOR) or treasury bills) that could be linked to our scenario analysis. Real personal consumption expenditures growth and house prices (both on an unadjusted and detrended basis) were found to be statistically insignificant. The lagged log of total assets (*L.lnta*), which was used to capture differences associated with size, was not found statistically significant. The inclusion of different financial market variables

yielded limited differences if using different spreads, including a 10-year high yield bond spread to 10-year treasuries and a 10-year to 3-month term structure. The three-month Libor to treasury bill spread was chosen for convenience, as these variables were part of our macroeconomic modeling forecast.

41. **Given the macro-prudential focus of the exercise, model specifications do not claim to be a definitive in forecasting bank earnings. Instead, the analysis is** designed to capture the sensitivity of banks' earnings to changes in the macroeconomic variables used in our stress scenarios. Our estimates would not be appropriate for forecasting earnings of individual institutions or group of institutions, given that no attempt was made to model different business lines. It is possible that the crisis and the subsequent changes in the financial landscape (e.g., new patterns of competition, impact of regulatory reform or limited securitization) have changed the underlying relationships between banks' earnings and their determinants. Not surprisingly, there are uncertainties over the earnings outlook over the forecast period, with signi*ficant*ly reduced accuracy of the estimates in the outer years (Figure 5).[13] Thus, parameter estimates may not be applicable and the forecasts would contain a bias. Nonetheless, the estimates provide some indication of the earnings capacity of the system as a whole (with group-specific variances) and the sensitivity of these earnings to various shocks.

Figure 5. Return on Assets, Historical and Model Forecast, 1990–2014



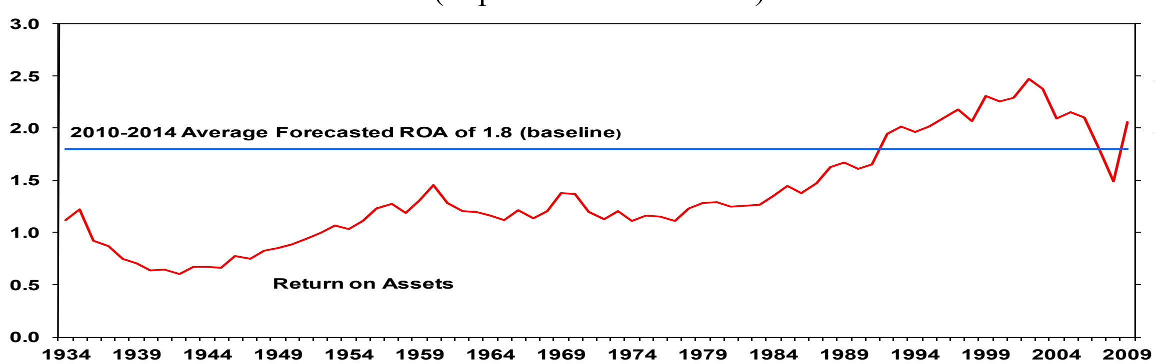
Sources: SNL Financials and IMF staff estimates.

[13] A 90 percent confidence interval could yield quarterly return on asset estimates anywhere between 0.25-0.75 percent.

42. **A range of common statistical tests were used to select the final model specification.** In particular, the Akaike and Bayesian Information Criteria were helpful in narrowing down the choice of explanatory variables, while the Hausman specification test and likelihood-ratio test were used to differentiate across model specifications. According to both the Durbin-Watson d-statistic and the Breusch-Godfrey Lagrangian multiplier test for autocorrelation, serial correlation would disappear with the inclusion of bank-specific variables. Furthermore, the random effects model was consistently rejected based on the Breusch and Pagan Lagrangian multiplier test as an appropriate model specification. Multi-level mixed effects panel models were also run. Dummies were introduced to account for the dramatic downturn in 2007 and 2008. They were not included in the final specification, as they did not help improve the model as the effects of the crisis would be captured through real GDP.

43. **According to our baseline, industry-wide bank earnings would remain modest, closer to mid-1990s levels, with large variations across sub-groups (Figure 6).** Return on asset is expected to average 1.96 percent on an annualized basis over the forecast horizon. This is substantially higher than the SCAP exercise, which assumed that banks' return on assets would remain almost 15 percent below the past twenty-year average for 2009–10, or around 1.6 percent on an annualized basis.

Figure 6. Pre-Tax, Pre-Provision Net Revenue of Commercial Banks, 1984–2009
(In percent of total assets)

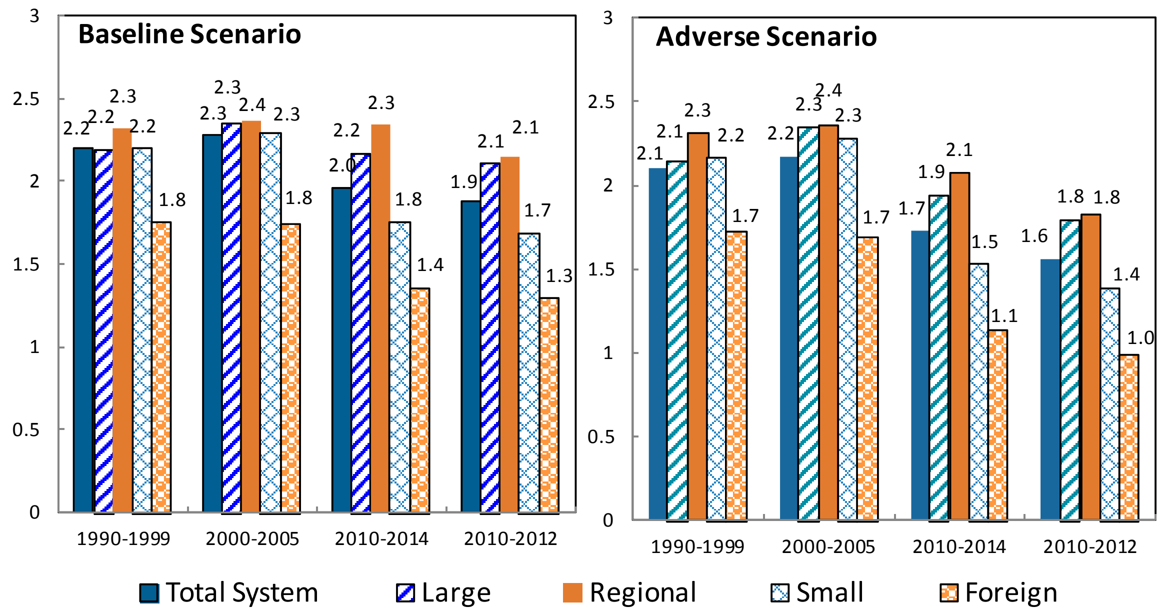


Sources: SNL Financials and IMF staff estimates.

44. **The larger banks are expected to yield larger-than-average earnings, in line with historical experience**. By category, the projected ROA for the top 4 bank holding companies is expected to average an annualized 2.17 percent over the forecast horizon, or around its 1990-99 historical average of 2.2 percent. By comparison, the average ROA forecast is 2.33 percent for regional banks, 1.75 percent for small banks, and 1.36 percent for foreign banks (Figure 7). As with the larger banks, earnings are well below the levels observed in the years immediately preceding the crisis, which were 2.37 percent for regional banks, 2.26 percent for small banks, and 1.70 percent for foreign banks. The projected ROA is slightly

lower over the next two years, or 1.9 percent for the system relative to 2 percent over 2010–14. In the adverse scenario, the system is expected to average an annualized 1.6 percent until end-2012 or 1.7 percent over the forecast horizon.

Figure 7. Baseline and Adverse Scenarios: Annualized Return on Asset, by Sub-Groups, 1990–2014[1]



Sources: SNL Financials and IMF staff estimates.
1/ Pre-tax, pre-provision, pre-dividend net revenues to total assets.

Retained earnings

45. **To estimate retained earnings, close attention was paid to firms' tax profiles, including their ability to defer tax assets in loss-making periods**.[14] Broadly, the framework applied a simple 30 percent flat tax rate on banks' corporate income. In addition, it accounted for banks' ability to accumulate deferred tax assets (DTAs), which could later be used to pay for future tax liabilities.[15] In particular, when a BHC would make losses following periods when it had taxable income, it would be allowed to carry back operating losses for two years to recover income taxes previously paid and accumulate tax benefits against future (positive) income going forward. These carry-backs are referred to as "deferred tax assets" (DTAs) as they could be used to pay down future tax liabilities. A fraction of these DTAs would qualify as tier 1 capital (we assumed up to 10 percent of Tier 1

[14] Retained earnings, which are defined as the pre-provision net revenue minus loan charge-offs, write-downs on securities, taxes, and dividends, can be thought of the net profits that are returned to capital at the end of each quarter.

[15] For details on the regulatory treatment of deferred tax assets, see Schedules HC-R and HC-F of the FR Y-9C financial statements.

capital).[16] When the institution would make profits again, it would draw down its accumulated DTAs to pay for its tax liabilities, thereby boosting retained earnings and hence organic capital growth.

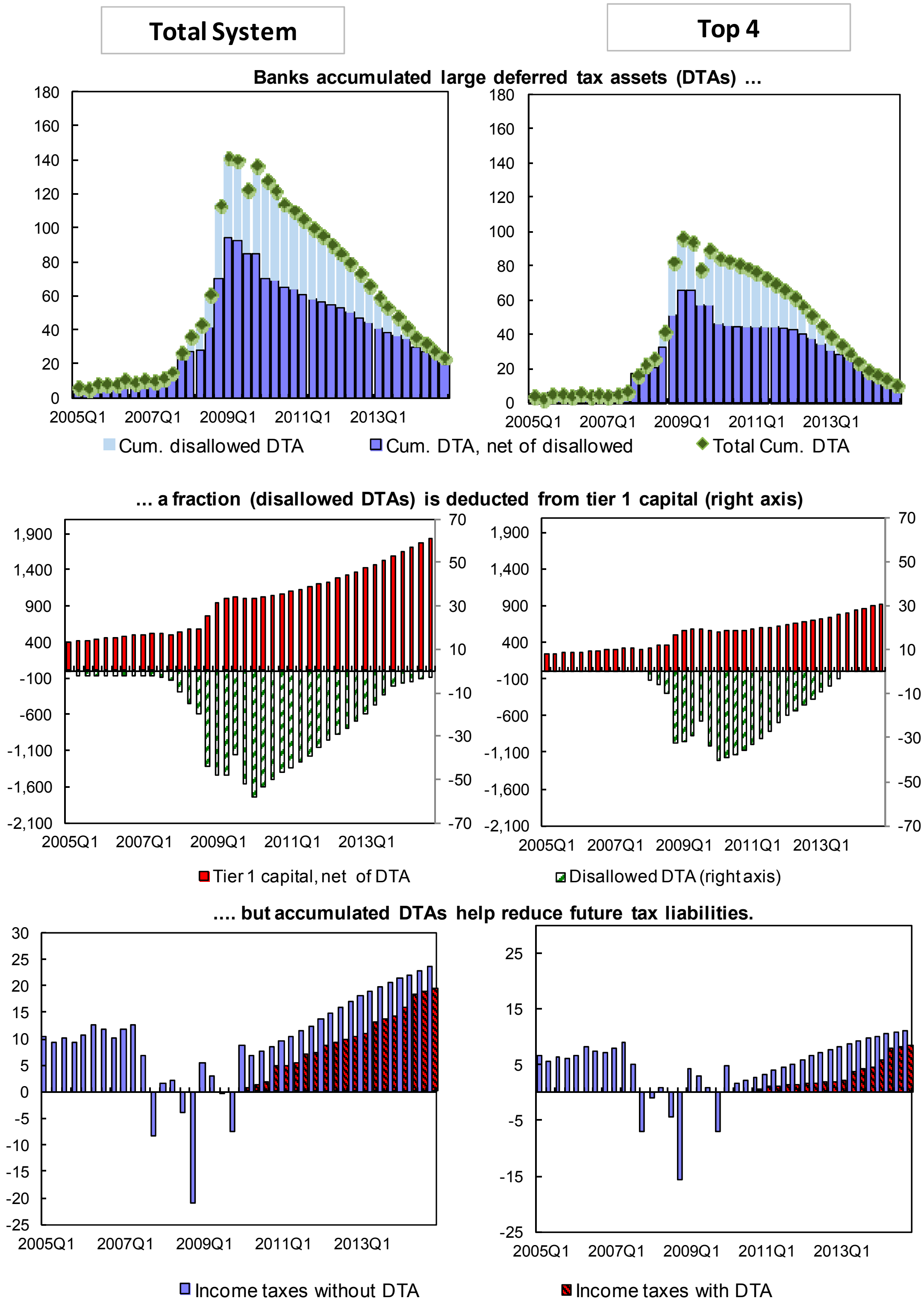
46. **According to our baseline results, the large institutions would benefit materially from DTAs over the forecast horizon.** Cumulative DTAs peaked at end-March 2009 at US$143 billion for the system, 68 percent of which was accounted for by the top 4 institutions (Figure 8). By end-2014, DTAs would help reduce future tax liabilities by 82 percent. In the baseline, 21 institutions would not have to pay income tax over the sample horizon, including one of the top 4 institutions and 5 regional banks (in the adverse scenario, the number of firms would rise to 31 institutions, including 3 of the top 4 institutions).

47. **A straightforward dividend rule was applied to all financial firms in the baseline**. In particular, when net after-tax income was positive, the calculations assumed a 5 percent annualized dividend rate for TARP preferred shares, 8 percent for other preferred shares (relative to an average of 5 percent over 1990–99), and 15 percent for common equity (relative to an average of 22 percent over 1990–99). This resulted in an 11.6 percent annualized average dividend rate for common equity and 2.6 percent annualized average dividend rate for preferred shares (Figure 9). This is significantly lower than historical dividend rates. In the downside risk scenarios, however, banks were not expected to pay out dividends on their common shares, in line with the assumption underlying the authorities' SCAP exercise.

48. **Under the baseline, banks' retained earnings would be sufficient to cover losses over the forecast period**. For the industry as a whole, retained earnings (defined as pre-provision pre-tax net revenue (PPNR), minus loan charge-offs, securities write-downs, taxes, and dividends) would remain positive, although low (slightly above $20 billion on average) until end-2011, at which point they would start rising (Figure 10). Regional banks follow a similar pattern (with average quarterly retained earnings of less than US$1 billion until end-2011), while small banks face negative retained earnings until the first quarter of 2012. Over the full 2010–14 forecast horizon, retained earnings for the system would average US$43 billion on a quarterly basis ($34 billion for SCAP firms, US$4 billion for regional banks, and less than US$1 billion for small banks).

[16] According to U.S. BHC prudential requirements, "allowed DTAs" are to be equal to the lesser of 10 percent of tier 1 capital (before DTA adjustments) or the amount of DTAs expected to be realized within one year, based on the BHC's projection of future taxable income.

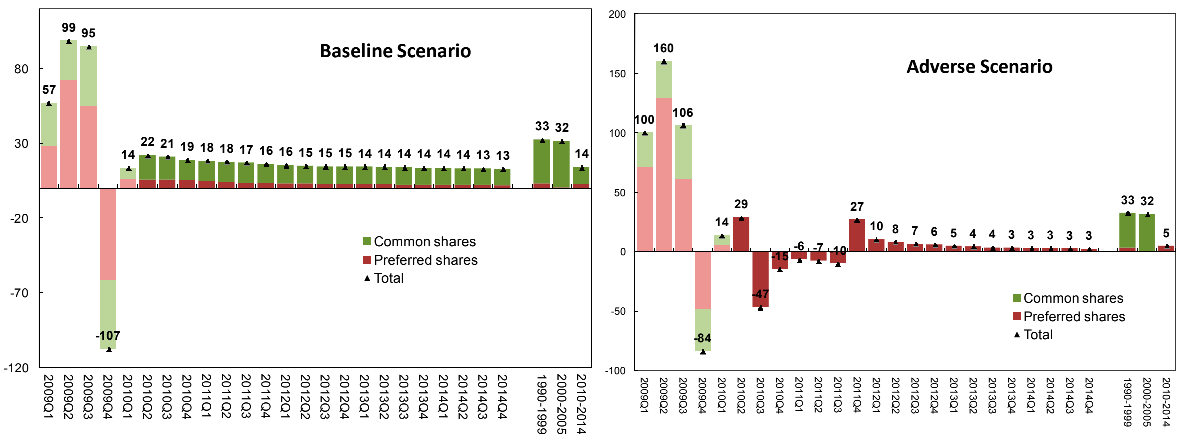
Figure 8. Baseline Scenario: Impact of Deferred Tax Assets, 2005–2014



Sources: SNL Financials and IMF staff estimates.

Figure 9. Baseline and Adverse Scenarios: Historical and Projected Dividends, 1990–2014

(In percent of pre-tax income)



Sources: SNL Financials and IMF staff estimates.

Balance sheet expansion

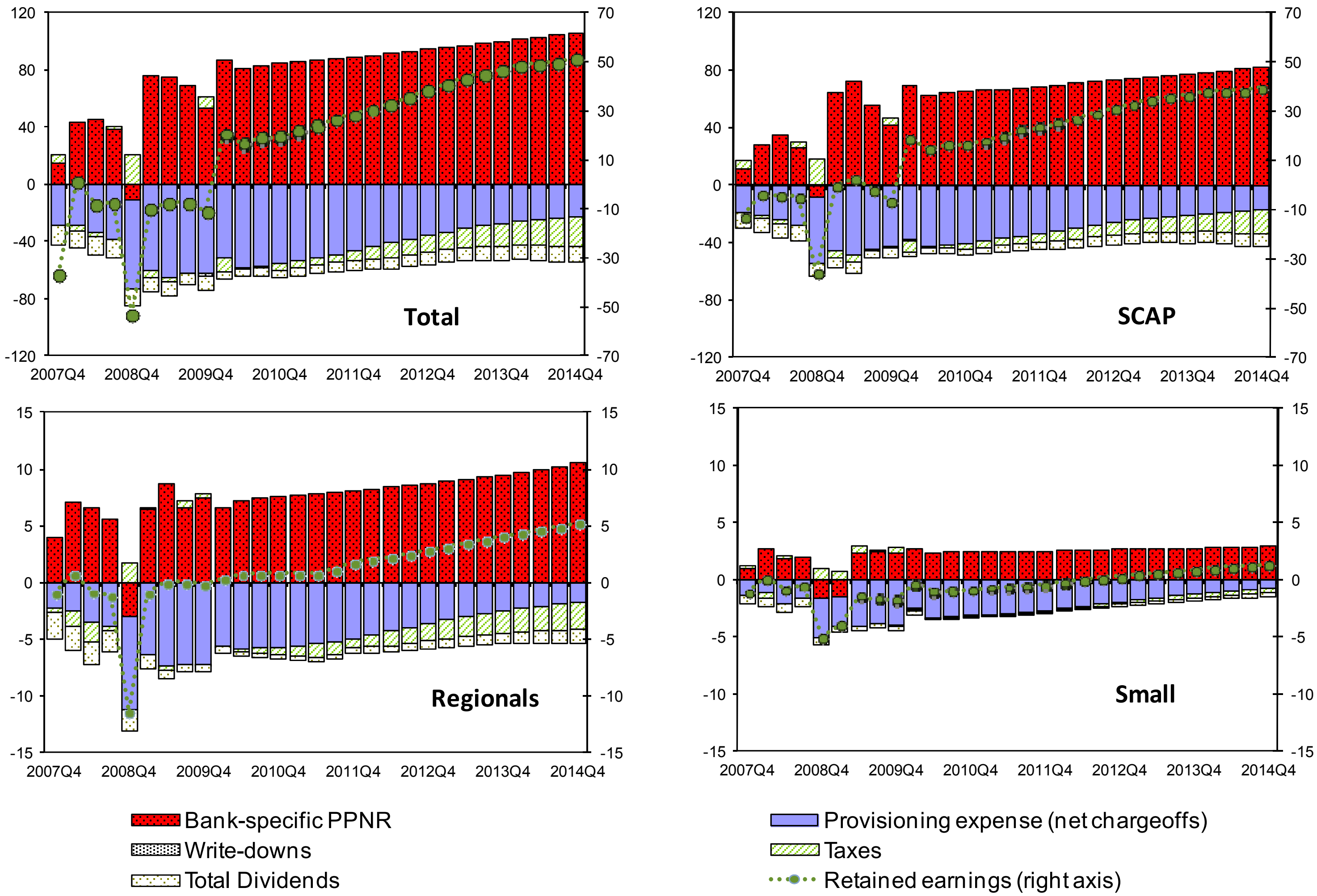
49. **Over the 2010–2014 horizon, asset growth is slightly weaker than nominal GDP growth due to deleveraging** (Figure 11). The calculations control for a number of factors that affect balance sheet expansion. In particular, weak securitization markets, which could lead banks to retain a larger than ordinary share of assets on their balance sheets are predicted to add US$195 billion to total system assets. The introduction of the FAS 166/167 accounting rules in 2010, which require banks to bring on balance sheet a significant amount of assets previously held off-balance sheet, are also assumed to expand banks' balance sheets by US$375 billion. Furthermore, retained earnings were added back into total assets, adding US$670 billion to banks' balance sheet over the sample horizon (64 percent of which generated by the top 6 firms). Factors tempering growth of total system asset included asset sales, which subtracted US$375 billion and asset maturities without rollovers, which reduced assets by US$496 billion. Except for retained earnings, which were estimated on a bank-by-bank basis, the balance sheet expansion factors were distributed across firms according to their share of total system assets. Total assets can be decomposed as follows:

$$TA_{it} = \left(rgdp\_qg * TA_{t-1}\right) + \left(\frac{TA_{it-1}}{TA_{It-1}}\right) * BSE_{It} + RE_{it} - co_{it} - wd_{it}$$

where TA_{it} is total assets for bank i at time t (I refers to the BHC sample); *rgdp_gq* the quarterly growth rate of real GDP; BSE_{it} and RE_{it} are, respectively, the projected balance sheet expansion and the estimated retained earnings; and co_{it} and wd_{it} are, respectively, the estimated loan charge-offs and securities write-downs.

Figure 10. Baseline Scenario: Retained Earnings, 2007–14

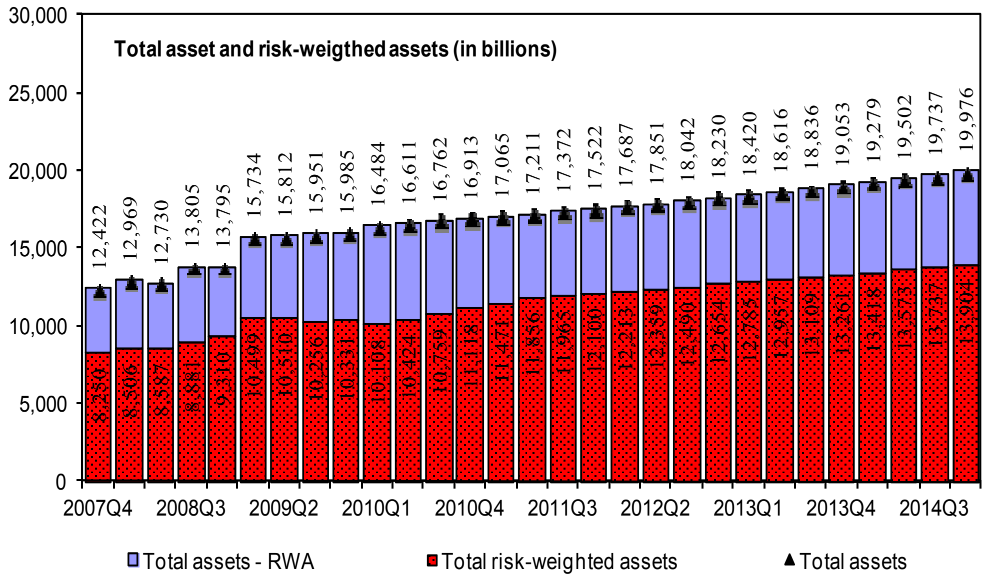
(In billions of dollars)

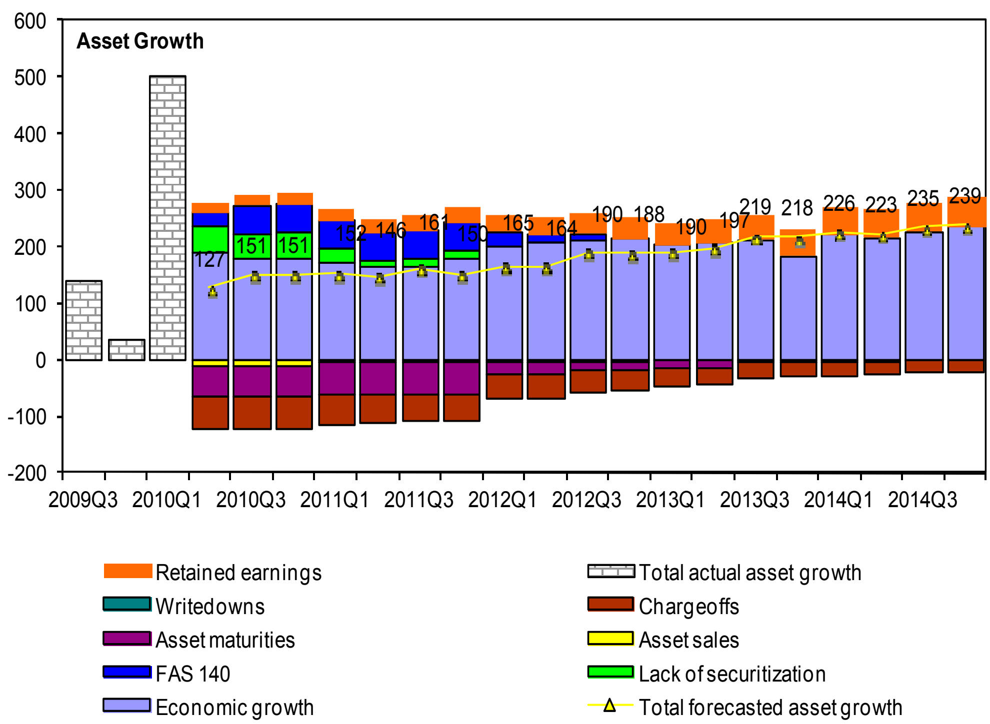


Sources: SNL Financials and IMF staff estimates.

Figure 11. Balance Sheet Expansion

(In billions of dollars)





Source: SNL Financials and staff estimates.

50. **The path for risk-weighted assets was also modeled carefully.** Since end-2007, the ratio of risk-weighted assets to total assets had fallen by over 5 percentage points to 61 percent, the lowest point recorded since the introduction of risk-weighted assets (Figure 12). This falling trend reflects banks' substantial efforts to "de-risk" their balance sheets since the onset of the crisis. However, it would not be likely for banks to maintain such a low ratio, especially as they expand their lending activities. Thus, it was assumed that, under the baseline, banks' risk-weighted to total asset ratios would return progressively back to their 2000–2005 average by mid-2011 (the adverse scenarios assumed that the ratio would remain constant at the low end-March 2010 level).

51. **Furthermore, the composition of BHC's balance sheets was allowed to adjust to ensure maximum room for credit expansion**. Broadly, the framework allowed banks' loan portfolios to grow in proportion to their asset growth, assuming a constant loan-to-asset ratio. However, this could have materially under-estimated credit growth, given banks' record low loan-to-asset ratio at end-March 2010. Instead, BHCs were also allowed to expand their loan portfolios by drawing down up to 5 percent of their "other assets" for 8 consecutive quarters (or until "other assets" reached 20 percent of total assets). As a result, the loan-to-asset ratio was raised by 7 percentage points to 50 percent by the end of the forecast horizon, although still well below historical averages. The path for total loans can be decomposed as follows:

$$TL_{it} = \left(rgdp\_qg * TL_{t-1}\right) + \left(\frac{TL_{it-1}}{TL_{It-1}}\right) * BSE_{It} + \left(\frac{TL_{it-1}}{TA_{It-1}}\right) RE_{it} - co_{it} - wd_{it} + \alpha_i \left(\frac{OA_{it-1}}{TA_{it-1}}\right)$$

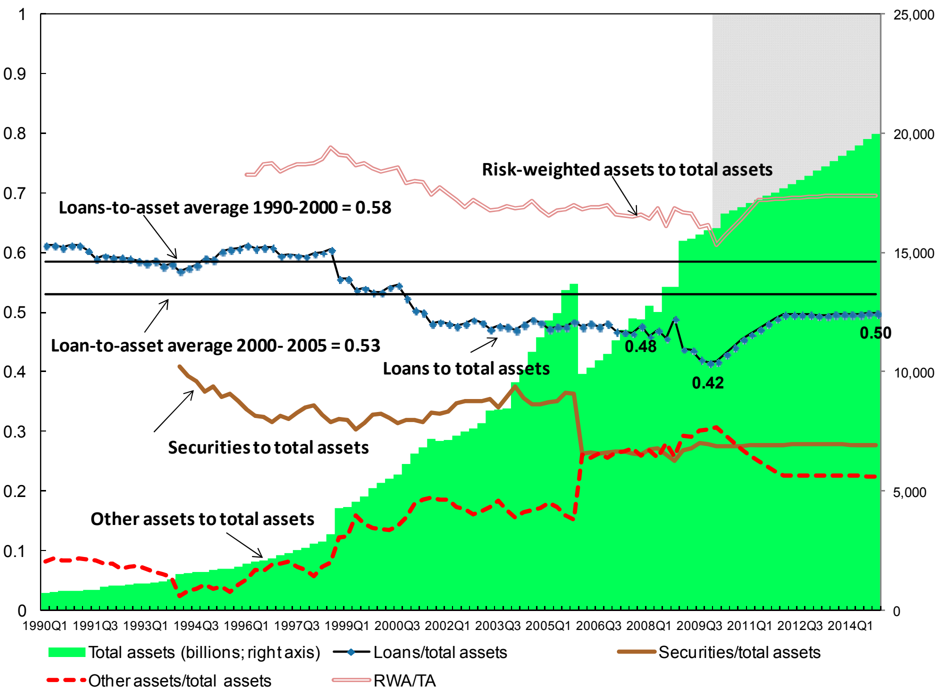
where TL_{it} stands for total loans, OA_{it} for other (non-loan non-security) assets, and α for the fraction by which securities can be substituted for loans.

Capital shortfall estimates

52. **Under the baseline scenario, bank capital would be adequate on an industry-wide basis**. Notwithstanding weak growth, high unemployment, and record high charge-off rates, the top 4 BHCs and the former broker dealers are expected to maintain a 6 percent Tier 1 common equity ratio over 2010–2014 (bottom panel in Table 5). However, three SCAP institutions would require an addition of US$7.4 billion in capital to maintain the same ratio. Due to high CRE exposure, four regional banks (including two SCAP institutions) may require US$1.3 billion in additional capital, while seven smaller institutions would likely require an additional US$6.3 billion. Subsidiaries of foreign banks, which tend to be lightly capitalized and rely on parental support, may require up to US$26.3 billion. Overall, the system would require US$40.5 billion in additional capital. The top 4 institutions would need to raise US$40.4 billion in additional capital if required to maintain a 5.9 percent tangible common equity to tangible assets ratio (or 17 times leverage).

Figure 12. Baseline Scenario: BHC Asset Composition, 1990–2014

(In percent)



Sources: SNL Financials and IMF staff estimates.

53. **Our results suggest that weak financial institutions should be encouraged to raise capital as current conditions do not allow them to grow out of their problems.** The picture of capital shortfall does not change materially when focusing on a shorter two-year forecast horizon (upper panel in Table 6). Overall, the capital shortfalls would affect the same institutions. This suggests that weak institutions are not able to rely on organic growth to improve their financial condition. The system as a whole could require as much as US$33.6 billion in additional capital to maintain a 6 percent tier 1 common capital ratio, most of which borne by the foreign banks (US$26.3 billion).

54. **The estimated capital shortfall of foreign banks is difficult to interpret.** The current exercise stresses foreign institutions in the same way as it does domestic ones as a way of assessing the broader shock absorption capacity of the U.S. banking system. In normal times, foreign holding companies tend to operate with lower capital buffers than their domestic peers, as they are not required to comply with the U.S. regulatory capital requirements, provided their parents are deemed well-capitalized and well-managed. Under a global adverse shock, however, it could be particularly difficult for regulators to require higher capital buffers when parent banks could be equally strained. Although the resulting retrenchment or closure of foreign banks would likely not have systemic consequences from

Table 6. Baseline Scenario: BHC Capital Needs, 2010–14

(In billions of dollars; unless otherwise noted)

	Top four	Investment	Regional	Processing	Consumer	Small	Foreign	Other	Total	**U.S. Only**
20010:Q2-2011:Q4 (cumulative)										
Pre-tax, pre-provision net revenue	351.0	97.6	68.1	21.3	38.8	22.4	45.9	92.2	737.3	691.4
Loan losses	276.6	0.2	51.2	0.9	26.4	27.7	40.3	62.3	485.5	445.2
Securities losses	1.51	0.06	0.19	0.00	0.00	0.13	0.00	0.0	1.9	1.9
Taxes	2.16	16.84	5.00	5.97	0.61	0.41	-0.80	0.8	31.0	31.8
Dividends	18.9	13.7	4.2	2.1	3.8	1.2	2.3	9.8	56.0	53.7
Addition to retained earnings	53.3	66.4	7.6	12.1	6.3	-6.9	4.5	23.5	166.8	162.3
Capital injection end-2011 to reach										
Tier 1 capital/risk-weighted assets ratio										
6 percent	0.0	0.0	0.0	0.0	0.0	1.6	26.6	0.0	28.2	1.6
8 percent	0.0	0.0	0.0	0.0	0.0	2.6	37.8	0.0	40.4	2.6
Number of banks requiring injection										
6 percent	0	0	0	0	0	3	4	n.a.	7	3
8 percent	0	0	0	0	0	3	4	n.a.	7	3
Tier 1 common capital/risk-weighted assets ratio 1/										
Capital injection end-2011 to reach										
4 percent	0.0	0.0	0.0	0.0	0.0	2.7	15.8	0.0	18.5	2.7
6 percent	0.0	0.0	0.5	0.0	2.2	4.5	26.3	0.0	33.6	7.2
Number of banks requiring injection										
4 percent	0	0	1	0	0	4	4	n.a.	9	5
6 percent	0	0	4	0	1	7	4	n.a.	16	12
Tangible common equity/tangible assets ratio										
Capital injection end-2011 to reach										
4 percent (25 times leverage)	0.0	2.7	0.4	0.0	2.9	3.4	32.2	0.0	41.6	9.5
5.9 percent (17 times leverage)	40.4	18.3	4.4	3.2	7.0	6.9	53.4	0.0	133.4	80.0
Number of banks requiring injection										
4 percent (25 times leverage)	0	1	2	0	1	5	4	n.a.	13	9
5.9 percent (17 times leverage)	2	1	5	1	2	11	6	n.a.	28	22
20010:Q2-2014:Q4 (cumulative)										
Pre-tax, pre-provision net revenue	895.0	262.5	179.7	56.7	99.5	55.2	121.6	244.0	1914.3	1792.6
Loan losses	496.3	0.3	87.2	1.5	51.4	46.2	66.0	111.9	860.9	794.9
Securities losses	1.5	0.1	0.2	0.0	0.0	0.1	0.0	0.0	1.9	1.9
Taxes	43.8	66.3	26.3	15.5	12.4	3.5	6.9	30.6	205.4	198.5
Dividends	68.5	34.3	14.6	5.9	8.0	4.1	8.8	23.8	168.2	159.4
Addition to retained earnings	286.2	161.1	51.5	33.6	25.9	1.3	40.3	81.8	681.8	641.5
Capital injection at lowest point for										
Tier 1 capital/risk-weighted assets ratio										
6 percent	0.0	0.0	0.0	0.0	0.0	2.8	26.6	0	29.5	2.8
8 percent	0.0	0.0	0.0	0.0	0.0	3.8	37.8	0	41.6	3.8
Number of banks requiring injection										
6 percent	0	0	0	0	0	3	4	n.a.	7	3
8 percent	0	0	0	0	0	3	4	n.a.	7	3
Tier 1 common capital/risk-weighted assets ratio 1/										
4 percent	0.0	0.0	0.0	0.0	3.8	4.1	15.8	0.0	23.7	7.9
6 percent	0.0	0.0	1.3	0.0	6.6	6.3	26.3	0.0	40.5	14.2
Number of banks requiring injection										
4 percent	0	0	1	0	1	4	4	n.a.	10	6
6 percent	0	0	4	0	1	7	4	n.a.	16	12
Tangible common equity/tangible assets ratio										
4 percent (25 times leverage)	0.0	2.7	0.6	0.0	7.7	4.8	32.2	0.0	47.9	15.7
5.9 percent (17 times leverage)	40.4	18.3	5.3	3.2	12.1	9.0	53.5	0.0	141.6	88.2
Number of banks requiring injection										
4 percent (25 times leverage)	0	1	2	0	1	5	4	n.a.	13	9
5.9 percent (17 times leverage)	2	1	5	1	2	11	6	n.a.	28	22
Memo:										
Percent of total system assets	46.5	10.4	8.0	2.8	2.9	3.5	11.3	14.6	100.0	88.7

Sources: SNL Financials and IMF staff estimates.

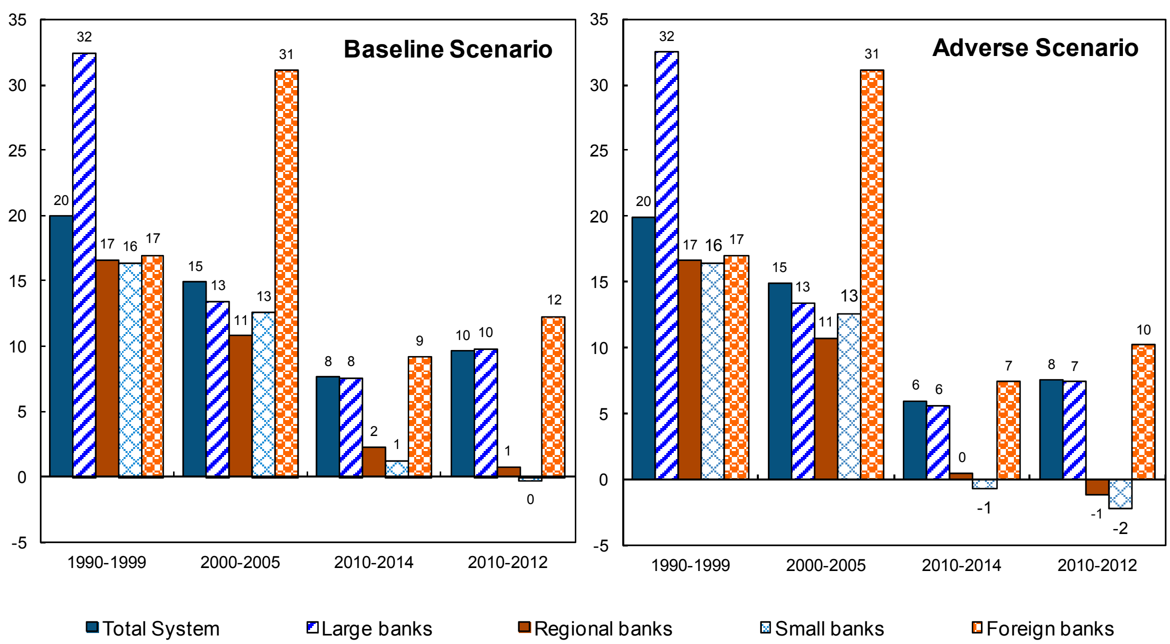
1/ Tier 1 common capital deducts all "non-common" elements of Tier 1 capital (i.e., qualifying minority interest in consolidated subsidiaries, qualifying trust preferred securities, and qualifying perpetual preferred stock).

a financial stability perspective, it may have broader macro-prudential implications depending on the operations of the affected institutions.[17] Since end-2007, foreign BHCs reduced their loan market share by 5 percentage points to 9 percent.

55. **Credit growth could remain limited for some time** (Figure 13). Although the financial system appears stable from a financial stability perspective, its relatively low level of retained earnings, combined with banks' recent efforts to deleverage and de-risk their balance sheets, may result in limited credit expansion, even after accounting for internal asset substitution away from cash and other assets into loans. Our results suggest that, in the absence of additional capital injections, credit growth could average around 8 percent for 2010–2014, which is substantially lower than historical levels. For example, credit growth rates averaged around 16.1 percent in 1993–1996 (following the S&L crisis) and 16.8 percent in 2004–07 (after the 2002–03 recession). In the adverse scenario, the average credit growth could fall by another 2 percentage points for the forecast horizon. In reality, banks will have various ways to meet credit demand, including by raising new capital, curbing dividend rates, or managing to generate higher retained earnings than anticipated.

Figure 13. Baseline and Adverse Scenarios: Credit Growth, 1990–2014

(Year-on-year in percent)



Sources: SNL Financials and IMF staff estimates.

[17] The possible retrenchment of foreign banks following a shock in the home country is well-documented in the literature, including in Peek and Rosengren (1996) regarding the behavior of Japanese banks after the stock market shock in Japan in the early 1990s and in Martinez Peria and Vladkova-Hollar (2005) regarding foreign banks in Latin America.

C. Alternative Scenarios

56. **To test banks' shock absorption capacity under worse-than-anticipated macroeconomic conditions, downside risk scenarios were considered**. These included an adverse macroeconomic scenario and an alternative funding risk scenario. The assumed values were consistent with historical distress episodes and the magnitudes of the shocks are broadly in the ranges analyzed in other FSAPs (details on the alternative scenario are presented in Appendix III). These scenarios also help demonstrate the sensitivity of the baseline results to underlying assumptions.

Adverse scenario

57. **Under the adverse scenario, loan losses continue increasing appreciably**. Residential and commercial real estate loan losses continue to rise until 2011 (peaking at 3.4 percent and 4.6 percent, respectively), while losses on consumer and C&I loans rise further, without reaching their earlier peaks (Table 1). Cumulative loan losses are expected to reach US$1.1 trillion for the system as a whole by end-2014, representing a 7.7 percent cumulative loss rate for 2010–11 (15.9 percent for 2010–14). In addition, the institutions with securities portfolios are also expected to write-down US$100 billion of marked-to-market securities, resulting in a total cumulative loss rate of 17.4 percent for 2010–14 (8.7 percent for 2010–11).

58. **On aggregate, BHCs would no longer be able to absorb their losses through earnings in the near term**. Retained earnings would remain negative until 2012 for the system as a whole and until 2014 for the smaller banks. The SCAP firms would fare slightly better with retained earnings turning positive by end-2011. Retained earnings for the system would record an average quarterly loss of US$2.4 billion for 2010–2011 US$1.2 billion for the regional banks and US$1.8 billion for the small institutions).

59. **Almost half of the U.S. BHCs would experience some capital shortfall under the Adverse Scenario** (Table 7). U.S. BHCs would require a total of US$31.8 billion capital to maintain a 4 percent Tier 1 common capital ratio until end-2014 (US$53.6 billion including the foreign BHCs). In particular, 4 regional banks would require US$8.1 billion, 10 smaller institutions another US$14.9 billion. Three SCAP banks would face a shortfall of US$14.5 billion. One of the top 4 institutions would need to raise US$15.2 billion to maintain a 4 percent tangible common equity to tangible assets ratio by end-2014. Over the 2010–11 horizon, 10 U.S. BHCs (including two SCAP institutions) would be expected to face a US$8.9 billion of capital shortfall to maintain a 4 percent tier 1 common capital ratio.

Table 7. Adverse Scenario: BHC Capital Needs, 2010–14

(In billions of dollars; unless otherwise noted)

	Top four	Investment	Regional	Processing	Consumer	Small	Foreign	Other	Total	**U.S. Only**
2010:Q2-2011:Q4 (cumulative)										
Pre-tax, pre-provision net revenue	307.5	88.2	60.7	18.6	35.5	19.3	36.0	80.5	646.3	610.3
Loan losses	327.2	0.2	60.9	1.1	31.1	32.2	48.5	69.5	570.6	522.2
Securities losses	32.70	0.17	6.47	4.05	2.03	2.47	5.32	16.5	69.7	64.4
Taxes	-2.18	13.98	1.20	6.89	0.46	0.00	-1.73	0.4	19.1	20.8
Dividends	5.9	3.6	1.8	0.4	1.5	0.7	0.3	3.8	18.0	17.7
Addition to retained earnings	-54.8	69.8	-9.6	6.1	-1.2	-16.0	-16.0	-8.5	-30.2	-14.2
Capital injection end-2011 to reach										
Tier 1 capital/risk-weighted assets ratio										
6 percent	0.0	0.0	0.3	0.0	0.0	2.8	19.4	0.0	22.5	3.1
8 percent	0.0	0.0	0.9	0.0	0.0	4.6	28.9	0.0	34.3	5.5
Number of banks requiring injection										
6 percent	0	0	1	0	0	4	4	n.a.	9	5
8 percent	0	0	2	0	0	5	5	n.a.	12	7
Tier 1 common capital/risk-weighted assets ratio 1/										
Capital injection end-2011 to reach										
4 percent	0.0	0.0	1.5	0.0	2.2	5.2	14.6	0.0	23.5	8.9
6 percent	0.0	0.0	5.5	0.0	5.2	9.5	24.4	0.0	44.6	20.2
Number of banks requiring injection										
4 percent	0	0	3	0	1	6	4	n.a.	14	10
6 percent	0	0	5	0	1	11	5	n.a.	22	17
Tangible common equity/tangible assets ratio										
Capital injection end-2011 to reach										
4 percent (25 times leverage)	8.6	2.3	3.2	0.7	4.5	6.9	36.5	0.0	62.8	26.2
5.9 percent (17 times leverage)	106.3	17.9	10.9	4.6	8.8	12.6	62.7	0.0	223.8	161.1
Number of banks requiring injection										
4 percent (25 times leverage)	1	1	4	1	1	11	5	n.a.	24	19
5.9 percent (17 times leverage)	4	1	7	1	2	12	7	n.a.	34	27
2010:Q2-2014:Q4 (cumulative)										
Pre-tax, pre-provision net revenue	770.8	238.9	156.1	49.5	89.6	46.3	94.9	208.7	1654.8	1559.8
Loan losses	633.3	0.4	121.4	2.2	60.5	61.5	90.8	143.2	1113.4	1022.6
Securities losses	47.2	0.2	9.4	5.9	3.0	3.6	7.8	24.1	101.1	93.3
Taxes	6.3	59.1	10.1	13.4	7.0	1.4	0.8	3.0	101.2	100.4
Dividends	12.6	7.6	3.6	0.4	1.5	0.9	0.4	7.5	34.4	34.0
Addition to retained earnings	72.8	171.1	11.8	27.4	15.9	-21.0	-4.4	32.1	305.7	310.1
Capital injection at lowest point for										
Tier 1 capital/risk-weighted assets ratio										
6 percent	0.0	0.0	2.8	0.0	0.0	9.1	25.5	0	37.4	11.9
8 percent	0.0	0.0	6.4	0.0	0.6	12.9	37.7	0	57.5	19.9
Number of banks requiring injection										
6 percent	0	0	3	0	0	6	6	n.a.	15	9
8 percent	0	0	4	0	1	10	7	n.a.	22	15
Tier 1 common capital/risk-weighted assets ratio 1/										
4 percent	0.0	0.0	8.1	0.0	8.8	14.9	21.8	0.0	53.6	31.8
6 percent	0.0	0.0	12.8	0.0	12.1	19.7	31.7	0.0	76.4	44.6
Number of banks requiring injection										
4 percent	0	0	4	0	1	10	4	n.a.	19	15
6 percent	0	0	5	0	1	11	6	n.a.	23	17
Tangible common equity/tangible assets ratio										
4 percent (25 times leverage)	15.2	2.3	9.8	0.7	11.2	16.4	43.4	0.0	99.1	55.7
5.9 percent (17 times leverage)	119.1	17.9	18.4	4.6	15.7	22.5	72.0	0.0	270.3	198.2
Number of banks requiring injection										
4 percent (25 times leverage)	1	1	4	1	1	11	5	n.a.	24	19
5.9 percent (17 times leverage)	4	1	7	1	2	13	8	n.a.	36	28
Memo:										
Percent of total system assets	46.5	10.4	8.0	2.8	2.9	3.5	11.3	14.6	100.0	88.7

Sources: SNL Financials and IMF staff estimates.

1/ Tier 1 common capital deducts all "non-common" elements of Tier 1 capital (i.e., qualifying minority interest in consolidated subsidiaries, qualifying trust preferred securities, and qualifying perpetual preferred stock).

Alternative scenario

60. **Rollover risk warrants careful surveillance.** Market liquidity risks appear to have declined, thanks to effective and powerful policy response by the authorities during the crisis. Financial institutions (FIs), however, remain vulnerable to the potential risk posed by the large volume of commercial real estate loans that are expected to mature between 2010 and 2014 (many of which with negative equity) when real estate prices may not have yet recovered, together with the rising stock of seriously delinquent mortgages on banks' balance sheets.

61. **The alternative scenario tests the sensitivity of banks' capital shortfall estimates to a further small deterioration in the commercial real estate sectors in 2010–11**. Under this scenario, the macroeconomic conditions are broadly similar to those in the Adverse Scenario for the first two years, but return faster to the baseline beyond 2011 (Appendix III) . Commercial real estate prices are expected to fall by another 8 percent by end-2012 (as opposed to 3.3 percent in the Adverse), while house prices are expected to fall by 4.1 percent in 2010 and another 2.6 percent in 2011. Banks' assumed difficulty in rolling over maturing debt leads to higher losses on commercial real estate loans, which peak at 5.1 percent at end-2011.

62. **Our results suggest that, except for banks already heavily exposed to commercial real estate (CRE), macroeconomic conditions are currently the key determinant to banks' financial soundness.** Broadly, our results under the Alternative Scenario (Table 8) are not materially different from those in the Adverse Scenario. Overall, 14 U.S. BHCs would require US$20.5 billion capital to maintain a 4 percent tier 1 common capital ratio over the 2010–14 (US$7.4 billion over the 2010–11 period). This suggests that banks that are heavily exposed to the CRE losses will find it difficult to earn their way out of their problems under worse-than-expected macroeconomic conditions but this result is not highly sensitive to a further small deterioration in real estate prices or recovery rates on delinquent real estate loans. Clearly, a broader shock to banks' funding conditions that leads, for example, to a substantive rise in short-term spreads would likely have a more dramatic impact on banks' earnings and hence on their ability to absorb losses.

D. Balance-Sheet Based Macroprudential Stress Tests: Conclusions

63. **The results confirm that BHCs' asset quality and capital positions are closely interlinked with developments in the housing sector and the broader macro economy.** There is much uncertainty about the shape and height of the loss profiles, although they are expected to be a drag on retained earnings and credit growth. Identified fragilities in regional and smaller institutions do not appear systemic but could hamper economic recovery in local communities with broader repercussions on bank loss rates. To mitigate this risk, the authorities intend to allocate US$30 billion of TARP money to community banks. Another potential vulnerability is the low capitalization of foreign-owned BHCs.

Table 8. Alternative Scenario: BHC Capital Needs, 2010–14

(In billions of dollars; unless otherwise noted)

	Top four	Investment	Regional	Processing	Consumer	Small	Foreign	Other	Total	U.S. Only
2010:Q2-2011:Q4 (cumulative)										
Pre-tax, pre-provision net revenue	313.3	89.3	61.7	19.0	35.9	19.7	37.6	82.6	659.1	621.5
Loan losses	326.5	0.2	61.0	1.1	29.8	32.3	48.0	69.5	568.3	520.3
Securities losses	18.91	0.12	3.70	2.26	1.13	1.44	2.97	9.2	39.7	36.8
Taxes	-2.18	14.35	1.61	7.35	0.46	0.08	-1.73	0.4	20.4	22.1
Dividends	6.4	3.6	1.9	0.4	1.5	0.7	0.3	5.5	20.3	20.0
Addition to retained earnings	-35.0	70.6	-6.3	7.8	1.4	-14.7	-11.5	-0.8	11.4	22.9
Capital injection end-2011 to reach										
Tier 1 capital/risk-weighted assets ratio										
6 percent	0.0	0.0	0.2	0.0	0.0	2.5	18.4	0.0	21.1	2.7
8 percent	0.0	0.0	0.7	0.0	0.0	4.0	26.3	0.0	31.1	4.7
Number of banks requiring injection										
6 percent	0	0	1	0	0	3	4	n.a.	8	4
8 percent	0	0	2	0	0	5	5	n.a.	12	7
Tier 1 common capital/risk-weighted assets ratio 1/										
Capital injection end-2011 to reach										
4 percent	0.0	0.0	0.9	0.0	1.7	4.8	13.4	0.0	20.8	7.4
6 percent	0.0	0.0	4.3	0.0	4.7	8.4	22.0	0.0	39.4	17.4
Number of banks requiring injection										
4 percent	0	0	3	0	1	5	3	n.a.	12	9
6 percent	0	0	4	0	1	11	5	n.a.	21	16
Tangible common equity/tangible assets ratio										
Capital injection end-2011 to reach										
4 percent (25 times leverage)	0.0	2.5	2.3	0.4	3.8	5.9	34.1	0.0	49.0	14.9
5.9 percent (17 times leverage)	78.4	18.0	8.7	4.3	8.1	11.5	59.7	0.0	188.6	128.9
Number of banks requiring injection										
4 percent (25 times leverage)	0	1	3	1	1	11	5	n.a.	22	17
5.9 percent (17 times leverage)	4	1	6	1	2	12	7	n.a.	33	26
2010:Q2-2014:Q4 (cumulative)										
Pre-tax, pre-provision net revenue	812.6	247.3	163.5	52.3	92.7	49.4	106.4	223.6	1747.7	1641.4
Loan losses	625.3	0.4	112.9	2.1	55.7	56.0	88.2	128.4	1068.8	980.7
Securities losses	21.1	0.1	4.1	2.5	1.3	1.6	3.3	10.4	44.6	41.2
Taxes	8.9	61.7	14.6	15.4	9.2	2.1	3.2	16.1	131.3	128.0
Dividends	14.5	7.6	4.1	0.4	1.5	1.5	0.4	9.2	39.1	38.7
Addition to retained earnings	144.2	177.1	27.9	31.7	23.3	-11.6	11.6	60.8	464.9	453.3
Capital injection at lowest point for										
Tier 1 capital/risk-weighted assets ratio										
6 percent	0.0	0.0	0.8	0.0	0.0	5.9	21.4	0	28.1	6.7
8 percent	0.0	0.0	2.7	0.0	0.0	8.0	31.9	0	42.7	10.8
Number of banks requiring injection										
6 percent	0	0	1	0	0	5	5	n.a.	11	6
8 percent	0	0	3	0	0	7	5	n.a.	15	10
Tier 1 common capital/risk-weighted assets ratio 1/										
4 percent	0.0	0.0	4.0	0.0	6.4	10.0	17.8	0.0	38.3	20.5
6 percent	0.0	0.0	8.2	0.0	9.7	14.5	27.6	0.0	60.0	32.4
Number of banks requiring injection										
4 percent	0	0	4	0	1	9	4	n.a.	18	14
6 percent	0	0	4	0	1	11	5	n.a.	21	16
Tangible common equity/tangible assets ratio										
4 percent (25 times leverage)	0.0	2.5	5.9	0.4	9.0	11.6	39.3	0.0	68.6	29.3
5.9 percent (17 times leverage)	79.3	18.0	12.6	4.3	13.5	17.3	65.7	0.0	210.5	144.8
Number of banks requiring injection										
4 percent (25 times leverage)	0	1	4	1	1	11	5	n.a.	23	18
5.9 percent (17 times leverage)	4	1	6	1	2	12	8	n.a.	34	26
Memo:										
Percent of total system assets	46.5	10.4	8.0	2.8	2.9	3.5	11.3	14.6	100.0	88.7

Sources: SNL Financials and IMF staff estimates.

1/ Tier 1 common capital deducts all "non-common" elements of Tier 1 capital (i.e., qualifying minority interest in consolidated subsidiaries, qualifying trust preferred securities, and qualifying perpetual preferred stock).

64. **Despite the significant improvement in BHC's capital buffers, our results suggest that additional capital may be needed to create room for meaningful credit growth.** Since the crisis, BHCs have managed to almost double their holdings of "high-quality" capital. Nonetheless, the current combination of record low risk-weighted to total asset ratio, outlook for a protracted period of high loss profiles, limited risk transfer through securitization, and general recognition that financial institutions need to hold higher capital buffers than in pre-crisis, means that banks' balance sheet may not be as strong as their capital buffers would suggest.

III. Macroprudential Stress Tests with Distress Dependence

A. Introduction

65. **The recent crisis underlined the importance of distress dependence among FIs for the stability of the financial system**. The distress (i.e., large losses and possible default) of a FI can have a significant impact in other institutions in the system. FIs are usually interlinked, either directly or indirectly and, in times of distress, the fortunes of FIs decline concurrently through either contagion after idiosyncratic shocks (direct links) or through negative systemic shocks (indirect links). To assess the stability of the U.S. financial systems from a systemic perspective, the FSAP team performed a systemic macro-financial stress test (SMFST), i.e., a forward-looking assessment of systemic losses and spillovers among institutions based on a risk-based framework.[18] The SMFST framework complements standard balance-sheet stress tests (such as those presented in Section II) by taking into account distress-dependence among FIs, capturing the joint interaction of financial risk in the system, and its changes across the economic cycle. It incorporates a wide set of macroeconomic and financial risk factors, capturing risk heterogeneity across institutions and allowing to model macro-financial linkages.

66. **The SMFST framework allows for the quantification of the followings**:

- Expected losses, and extreme losses (unexpected losses), taking into account the distress-dependence among the institutions and its changes through the economic cycle.

- The marginal contribution of individual firms to systemic risk, which reflects both the level and the relative size of interconnectedness of each institution with the system.

[18] The calculations performed in this exercise were based on the joint implementation of the Consistent Information Multivariate Density Optimizing Methodology (CIMDO) presented in Segoviano (2006) and Segoviano and Padilla (2006), and the framework for estimating Banking Stability Measures presented in Segoviano and Goodhart (2009) all of them described below.

- Stability measures that analyze financial stability from three, complementary perspectives: the evolution of tail risk in the system, distress dependence among firms, and cascade effects (the impact of distress at a given firm on the other firms).

- Spillovers between major U.S. and foreign FIs, U.S. FIs and emerging market sovereigns, and U.S. financial markets and selected U.S. non-financial corporations.

67. **There are a number of caveats in interpreting the SMFST estimates**:

- The estimates are not forecasts; as in any stress test exercise, they are outcomes of "what if" calculations conducted under a baseline scenario and an adverse scenario.

- This test was performed exclusively with publicly available information. Supervisory information of banks' portfolio compositions, asset risk parameters, off-balance sheet items, counterparty risk, and interbank exposures was not available to the FSAP team. Therefore, importantly, none of the analysis that follows benefited from actual data or information on actual interconnections (lending relationships, counterparty exposures, other common exposures) among financial institutions.

- This test was performed in the middle of considerable uncertainty in the wake of the financial crisis. While the situation has stabilized and financial conditions have improved, considerable sources of uncertainty remain for the financial system.

- The main objective of the SMFST was to assess financial stability based on systemic potential (expected and unexpected) losses and spillovers among FIs. In addition, the adequacy of *existing* capital buffers to withstand unexpected losses was also assessed for illustration purposes. An alternative treatment of the evolution of buffers across time is presented in Section II.

- As noted above, because supervisory data were not available, the results depend on market expectations of distress as manifested in historical CDS prices. Conclusions about future interconnections among firms are inferred from historical co-movements in CDS market prices, not from any actual data about interconnections. Market perceptions, liquidity issues in CDS markets and a series of mergers and acquisitions in the financial sector upon the crisis could influence our estimates.

B. Methodology

68. **The system was tested from a systemic perspective using the systemic macro-financial stress test that** interprets the financial system as a portfolio of FIs.[19]

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[19] This includes the largest banks, GSEs and a large insurance company. The banks included in the exercise are Goldman Sachs (GS), Morgan Stanley (MS), Bank of America (BoA), Citigroup (C), J.P. Morgan (JPM), Wells Fargo (WFC), SunTrust (STI), U.S. Bancorp (USB), Capital One (COF), PNC, and MetLife (MET). These

(continued)

Interconnectedness, which proved critical during the crisis, were incorporated into the analysis using a forward looking risk-based framework that allows assessment of (i) systemic potential losses, (ii) the contribution of individual FIs to systemic risk, (iii) financial stability measures, and (iv) spillovers between U.S. and foreign FIs, U.S. FIs, and emerging market sovereigns, and between U.S. FIs and the U.S. corporate sector.

69. **The SMFST involved an eight-step procedure (Figure 14):**

Step 1: Definition of macroeconomic scenarios

Step 2: Conceptualization of the Financial System as a portfolio of FIs

Step 3: Inference of probabilities of distress (PoD) for each FI under analysis

Step 4: Adjustment of PoDs for risk aversion

Step 5: Modeling of PoDs as functions of macroeconomic and financial variables

Step 6: Modeling of the system's portfolio multivariate density (PMD)

Step 7: Simulation of systemic losses and contribution of individual FIs to systemic risk

Step 8: Estimation of financial stability measures and spillovers

70. **As discussed in Section I and Appendix III, baseline and adverse scenarios were considered for this test**. These macroeconomic scenarios are then mapped to the macroeconomic and financial variables used to forecast PoDs of FIs.[20] The historical distribution of major macroeconomic variables in the scenario (output gap for most of the PoD explanatory variables) is matched with those of PoD explanatory variables.

71. **There are several methods to infer the PoD of each FI.** At the level of individual firms, estimates of their probabilities of distress can be estimated from (i) detailed supervisory data or from (ii) market-based information. Supervisory data of banks' portfolio compositions, asset risk parameters (exposures to different types of assets, default probabilities, recovery rates), off-balance sheet items, counterparty risk, and interbank exposures was not available. It was thus necessary to perform the SMFST using market-based information. There are alternative approaches by which PoDs of individual FIs can be empirically estimated from market-based information. The most well known include the structural approach, PoDs derived from Credit Default Swap (CDS) spreads (CDS-PoDs), or from out-of-the-money (OOM) option prices.

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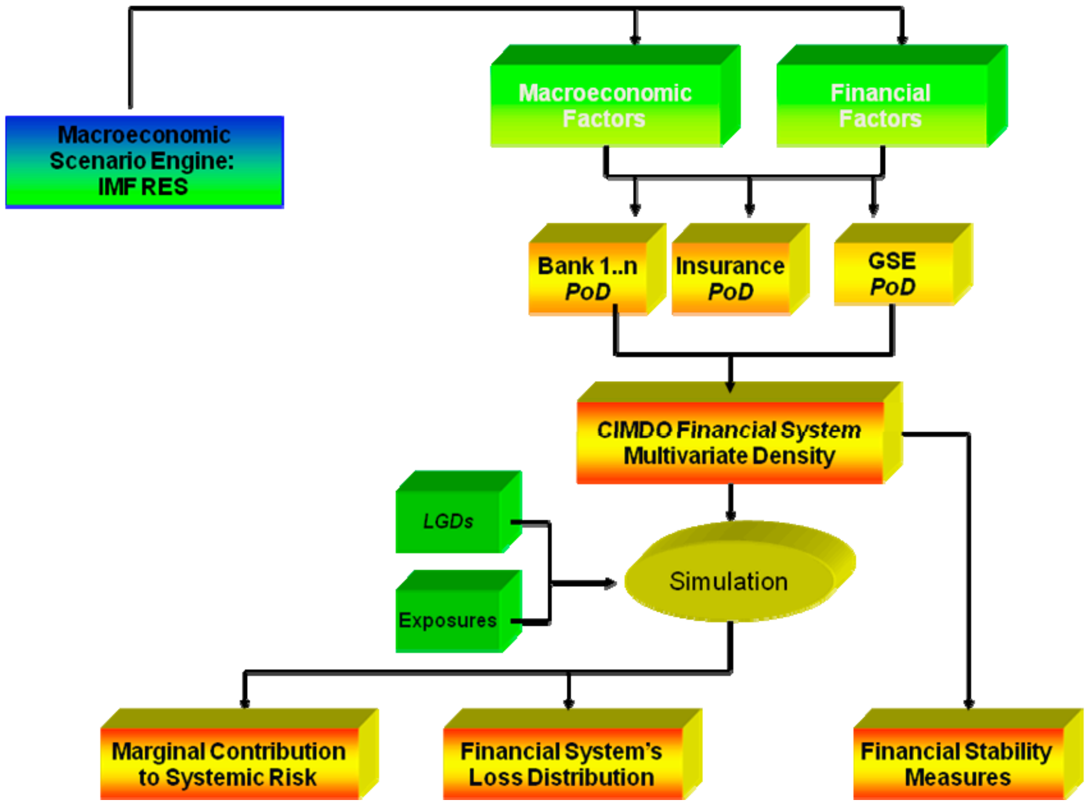
institutions cover approximately 78 percent of depository institutions' total assets in 2009Q3 (Appendix Table 1). AIG, Fannie Mae (FNM), and Freddie Mac (FRE) were also included in the exercise.

[20] Not all the explanatory variables for PoDs are given in the macroeconomic scenarios. Therefore, additional mapping exercise is necessary to interpret the scenarios.

Figure 14. The Procedure of Systemic Macro-Financial Stress Test



Source: IMF staff.

72. **These alternative approaches have advantages and disadvantages**. An extensive empirical analysis of these approaches and a discussion of their pros and cons in terms of availability of data necessary for their implementation, parameterization of quantitative techniques, and consistency of empirical estimations are presented in Athanosopoulou, Segoviano, and Tieman (2010). The structural approach presented significant difficulties for the proper parameterization of its quantitative framework. For example, it is very difficult to separate the volatility of individual FIs from the overall volatility of the market. Moreover, the information content of stock prices is questionable at a time of extreme volatility, mergers, acquisitions and policy intervention, which can highly dilute the value to stock holders. Thus, the structural approach produced estimates that appeared counterintuitive. The OOM approach suffered from similar problems as the structural approach. This is because it is necessary to measure the impact of macroeconomic shocks on PoDs, and it is essential to have proxies of PoDs for a period that covers at least one economic cycle, a period for which it was not possible to estimate PoDs from OOM.

73. **In this exercise, CDS-PoDs were chosen to perform the SMFST, although CDS-PoDs are not free of problems.** CDS spreads may exaggerate a firm's "fundamental" risk when there is lack of liquidity in a particular CDS market. Although such arguments might

be correct to some degree, lack of liquidity can become self-fulfilling if it affects the market's perception and, therefore, has a real impact on the market's willingness to fund/invest in a particular firm. Consequently, this can cause a real effect on the firm's financial health, as has been seen in the recent financial turmoil. Equivalently, assessing at what point "liquidity risk" becomes "solvency risk" is difficult, and disentangling these risks is a complex issue. Moreover, although CDS spreads may overshoot at times, they do not generally stay wrong for long. Rating agencies have documented that CDS spreads frequently anticipate rating changes. Though the magnitude of the moves may at times be unrealistic, the direction is usually a good distress signal.

74. **CDS spreads are employed to extract CDS-PoDs.** CDS spreads reflect the cost of insurance offered by a CDS contract. Events triggering the payment of a CDS contract cover not only the event of default of an underlying security but a wider set of "credit events," i.e., major downgrades, payment restructurings or any event that represents large losses to the security holder; thus, "distress risk" represents the risk of large losses and the possible default of a security issued by the FIs under analysis. For these reasons, and due to the challenges encountered with the other approaches (which the FSAP team considered more serious), in the absence of supervisory data, the team decided to use CDS-PoDs to perform the SMFST. Although CDS-PoDs represent reasonable input variables to perform the SMFST, one needs to keep in mind their potential shortcomings when drawing conclusions in the analysis. Thus, results of the SMFST provide an illustrative guideline, rather than as an accurate estimate. Moreover, the analysis showed the consistency of CDS-PoDs with other variables indicating market's perceptions of risk. Furthermore, when CDS-PoDs were employed in the SMFST (once such estimates were adjusted for risk aversion, as described below), consistency of the SMFST results with historical losses was achieved.[21]

75. **To estimate losses, PoDs derived from market-based information need to be adjusted for risk aversion.** Thus, CDS-PoDs were corrected for risk aversion before systemic losses were estimated. PoDs derived from market-based information are risk neutral; i.e., such PoDs reflect both market expectations of the assets' *actual* risk (based on the market expectations of the assets' returns) and systemic risk aversion (the price of risk, which is the price that investors are willing to pay for receiving "income" in "distressed" states of nature). Therefore, in order to estimate losses, which should be based on *actual* risk, it was necessary to strip out the effect of risk aversion from risk neutral PoDs. Such adjustment was performed following Espinoza and Segoviano (2010). See Appendix V for technical details. Figure 15 compares the mean of risk neutral PoD and the mean of adjusted PoD for the system. While an attempt was made to isolate the component of CDS PoD's that represent actual or fundamental risks, it is always difficult to disentangle actual risks from market sentiment.

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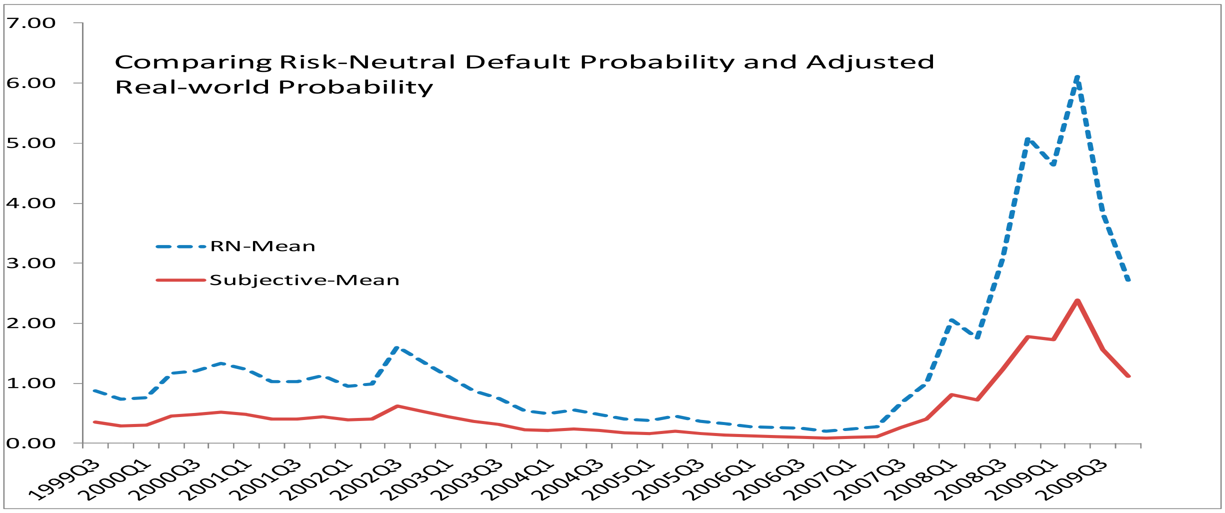
[21] Note that PoDs are exogenous variables to be used by CIMDO framework (explained below) used in the SMFST. Thus, the CIMDO methodology is not intrinsically related to CDS-PoDs, the CIMDO methodology can be implemented with any PoD estimator that is perceived to be correct.

Figure 15. Risk Neutral and Adjusted Probability of Distress



Sources: Bloomberg and IMF staff estimates.

76. **Modeling of PoDs as functions of macroeconomic and financial variables.** Factor models were run separately for the PoDs of each individual institution, to analyze heterogeneity among institutions due to differentiation in portfolio compositions, risk profiles, and business models.[22] A summary of the statistically significant variables explaining the PoD of each FI under analysis is presented in Table 9 with estimated coefficients' sign.[23]

77. **Although differences were found in (i) explanatory risk factors, (ii) the sensitivity of individual PoDs to risk factors, and (iii) lags, the factor models shows:**

- PoDs of all the FIs under analysis are highly sensitive to (i) macroeconomic conditions (unemployment and house prices); (ii) banking sector's loan activities (credit and C&I loan index); (iii) profitability and funding conditions (Libor spread); and (iv) risk measures in markets (VIX). Activity in securitization markets, especially in Mortgage Backed Securities (MBS) markets, appears to be a significant explanatory variable for the PoD of some FIs under analysis.

- Systemic risk, as measured by the interlinkage index,[24] is statistically significant explanatory factor, reflecting the fact that the sample FIs are highly interconnected via direct or indirect links.

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[22] Karim Youssef provided data to perform this analysis.

[23] Specifications were chosen based on the economic consistency of coefficients, adjusted R squared, and forecast performance (RMSE).

[24] The interlinkage index is based on the measures of distress dependence explained in Section III-D.

Table 9. Probability of Distress, Explanatory Variables

	Statistically Significant Explanatory Variables for PoDs 1/													
	BAC	COF	PNC	STI	USB	WFO	C	GS	JPM	MS	MET	FNM	FRE	AIG
	Sensitivity													
House price	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Unemployment	+		+	+	+		+	+	+	+	+	+	+	+
Credit	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C&I loan	+			+					+	+	+			+
Libor spread	+	+		+	+	+	+	+	+	+	+	+	+	
VIX	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Securitization			-	-	-	-	-			-				
MBS												-		
Interlinkage index	+	+	+	+	+	+	+	+	+	+	+	+	+	+

1/ All the variables are on monthly basis, (including interpolated variables). + (-) indicates that the estimated coefficients are positive (negative). Showing the parameter sign only for statistically significant variables.

Source: IMF staff estimates.

78. **PoDs are then used to model the PMD that characterizes the implied asset values of the FIs under analysis**. The approach used in the SMFST recovers the joint statistical distribution of the portfolio of institutions that are assumed to represent the system, termed the portfolio multivariate density, which implicitly characterizes both the individual and joint asset value movements of a chosen portfolio of FIs. The PMD is recovered using (i) the CIMDO methodology (Segoviano, 2006, and Segoviano and Padilla 2006) and (ii) the PoD for each of the FIs under analysis, which are input variables for the CIMDO methodology. In the SMFST, the estimated PoDs (under stressed macroeconomic scenarios) for each FI described above were employed. The CIMDO methodology is a non-parametric framework based on the cross-entropy approach (Kullback, 1959). This is heuristically described in Appendix VII.

79. **The PMD captures interdependence among the FIs' probabilities of distress, which captures FIs' linear (correlations) and non-linear distress dependence, and their changes throughout the economic cycle. This reflects the fact that dependence increases in periods of distress**. These are key technical improvements over traditional risk models, which usually account only for linear dependence (correlations) that are assumed to remain constant over the cycle, or over a fixed period of time. The PMD embeds the structure of linear and nonlinear default dependence among the FIs in the portfolio that is used to represent the financial system. Such dependence structure is characterized by the copula function of the PMD, i.e., the CIMDO-copula, which changes at each period of time,

consistent with changes in the empirically observed PoDs. To illustrate this point, the copula approach has been heuristically introduced to characterize dependence structures of random variables and explain the particular advantages of the CIMDO-copula in Appendix VII. For further details, see Segoviano and Goodhart (2009).

80. **The one-year *potential* losses that the financial system could experience are simulated using the PMD**. The simulation produces the distribution of systemic potential losses. Then, the expected loss (EL) is measured as 50 percentile VaR, of this loss distribution. It is estimated in line with the Basel definition as

$$ELSystem = \sum_{i=1}^{N} Exp_i x PoD_i x LGD_i$$

where Exp_i, and LGD_i are exposure and loss given default for FI i, respectively. Unexpected losses (UL) are measured as 99 percentile VaR of this loss distribution (Figure 1). Lastly, marginal contributions to systemic risk (MCSR) are built on the expected shortfall (ES) at the 95.0 percent confidence.[25]

81. **Using the PMD, financial stability and interlinkages among institutions can be analyzed from three alternative perspectives.** The PMD characterizes the probability of distress of the individual FIs included in the portfolio, their distress dependence, and changes across the economic cycle. This is a rich set of information that allows us to analyze financial stability from three different, yet complementary, perspectives. For this purpose, a set of financial stability measures is defined to quantify (i) common distress in the FIs of the system, (ii) distress between specific FIs, and (iii) distress in the system associated with a specific FI. For details of these measures see Segoviano and Goodhart (2009).

C. Main Results

82. **The stress tests were performed against the background of considerable uncertainty in the aftermath of the financial crisis.** While the situation has stabilized, loss buffers have been replenished, and pretax income and financial conditions have substantially improved in the last two quarters of 2009—thanks to unprecedented monetary, financial, and fiscal policy interventions—the supply of credit remains tight and continued household deleveraging, rising unemployment, and accelerating corporate and commercial property defaults are the sources of risk for the financial system.

83. **Macroeconomic scenarios imply that the PoDs—the key inputs in the quantification of systemic risk and loss estimates—are likely to remain at higher levels than pre-crisis levels in the near future**. Towards the end of 2009, PoDs implied by actual

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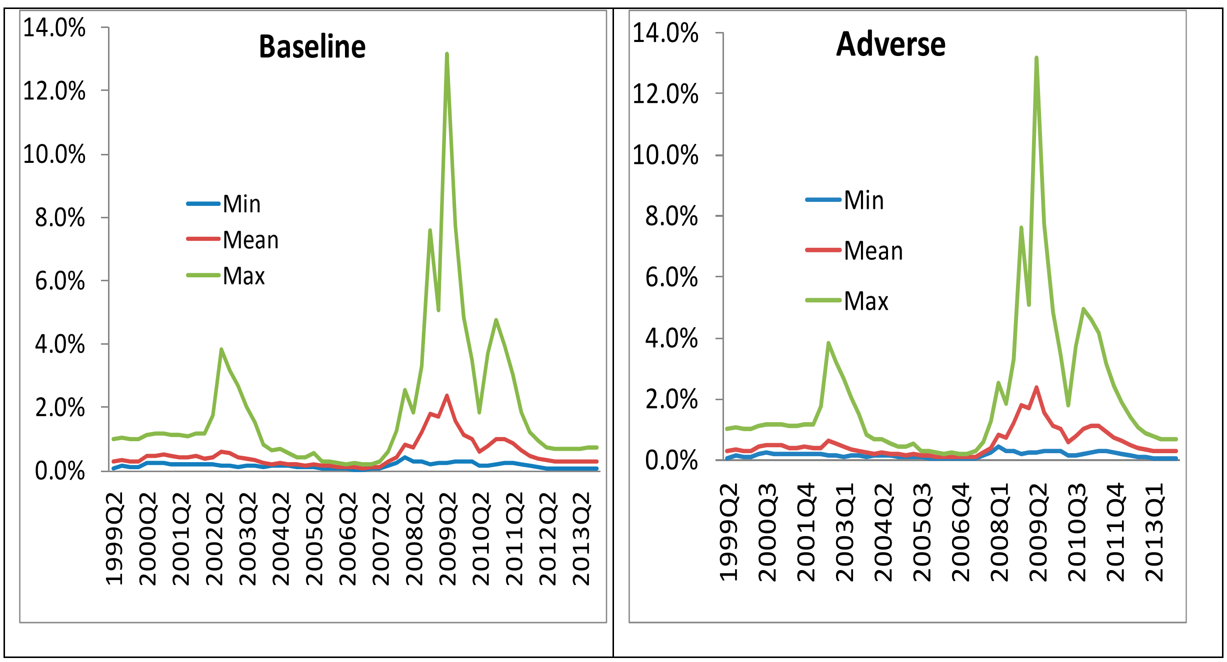
[25] The ES at 95 percent confidence level is the conditional expected loss in the worst 5 percent of the distribution. The ES provides an alternative extreme loss measure to VaR that is more sensitive to the shape of the loss distribution at its tail.

CDS spreads and other major financial market data improved sharply, despite of one of the weakest macroeconomic data in the past 50 years, possibly reflecting various extraordinary measures taken to support the financial sector.[26] On the other hand, the forecasted PoDs from 2010 on are strongly influenced by the lagged effects of the still substantial macroeconomic shocks in 2009 and 2010. From 2011 on, the projected PoDs gradually moderates in line with the improvement of macroeconomic and financial conditions implied by the scenarios (Figure 16).

84. **The SMFST shows that the tail vulnerabilities remain in the U.S. financial systems (Tables 10 and 11)**. As expected from the PoD development, ELs decline gradually in both scenarios, supported by rapid macroeconomic recovery and reach below end 2007 levels by the end of our stress testing horizon. However, the tail risks appear to remain substantial in both scenarios, as the ULs continue to remain above end-2007 levels for the whole exercise horizon. In particular, cumulative EL and UL would be substantial.

Figure 16. Probability of Distress: Minimum, Mean, and Maximum



Sources: Bloomberg and IMF staff estimates.

[26] This does not imply the out-of-sample performance of the PoD forecasting model is weak. Rather, it reflects the challenges linking macroeconomic development into the progression of financial variables used in PoD forecasting models.

Table 10. Systemic Expected Losses

	Baseline			Adverse		
	Bn USD	% Assets	% GDP	Bn USD	% Assets	% GDP
2007	28	0.2	0.2	28	0.2	0.2
2008	125	1.0	0.9	125	1.0	0.9
2009	82	0.6	0.6	82	0.6	0.6
2010	75	0.6	0.5	77	0.6	0.5
2011	34	0.3	0.2	56	0.4	0.4
2012	20	0.2	0.1	24	0.2	0.1
2013	21	0.2	0.1	20	0.2	0.1

Sources: Bloomberg, SNL, and IMF staff estimates.

Table 11. Systemic Extreme Losses

	Baseline VaR 99%			Adverse VaR 99%		
	Bn USD	% Assets	% GDP	Bn USD	% Assets	% GDP
2007	182	1.5	1.3	182	1.5	1.3
2008	427	3.3	3.0	427	3.3	3.0
2009	330	2.5	2.3	330	2.5	2.3
2010	326	2.5	2.2	331	2.6	2.2
2011	224	1.7	1.5	280	2.2	1.8
2012	191	1.5	1.2	204	1.6	1.3
2013	192	1.5	1.1	192	1.5	1.1
Memo item						
2009 total equity	1,020	7.9	7.2			

Sources: Bloomberg, SNL, and IMF staff estimates.

85. **Contribution from GSEs to systemic unexpected losses (UL) appears to be substantial, owing to GSEs' (i) large (individual) ULs and (ii) their interconnectedness to the system.** The share of GSEs' total assets in the system is about 13 percent. However, GSE's share of systemic extreme losses (99 percent VaR) is about 20 percent in 2008 and 2009 (not shown), indicating that distress dependence between GSEs and the system is sizeable. The distress in GSEs seems to be causing considerable distress in the system owing to their interconnectedness, despite of various policy measures to support them directly.

86. **Potential losses in the system could be compared to the buffers that may be able to absorb those losses—capital.** From a risk-based perspective, loan loss reserves represent

the buffer to absorb expected losses, while capital represents the buffer available to absorb unexpected losses. Table 12 shows these buffers in dollar amounts and as a percentage of the sum of total assets of the sample. The largest cumulative losses from 2007 to 2009 were experienced by Citigroup, AIG, Fannie Mae, and Freddie Mac.

Table 12. Provisions and Capital

	2007		2008		2009	
	Bn USD	% Assets	Bn USD	% Assets	Bn USD	% Assets
Loan loss reserves[1]	52	0.42	117	0.91	162	1.25
Pretax income[2]	95	0.78	-225	-1.75	-57	-0.44
Total risk-based capital[3]	805	6.60	914	7.13	1,058	8.16
Total equity	803	6.58	849	6.62	1,020	7.86

Source: SNL Financial and staff calculations

[1] 2009 AIG estimated from Q3 YTD provision expense; 2007-2008 data unavailable for GS, MS - not included in numerator, but included in denominator

[2] AIG,FRE,FNM negative pretax income

[3] 2007-2008 GS, MS & 2007-2009 AIG, FNM, FRE substitute total equity for risk-based capital

87. **To assess the *capacity of existing capital buffers* to withstand ULs, the capital gap is measured as follows**:[27]

$$CapitalGap = \frac{Systemic \quad total \quad equity}{Systemic \quad total \quad assets} - \frac{ULs}{Systemic \quad total \quad assets}$$

88. **In line with the projected trends in ULs, capital gap continues improve in both scenarios throughout the exercise horizon, exceeding the 2007 levels already in end-2009 (Table 13).**

Table 13. Capital Gap

	Baseline			Adverse		
	VaR 99%			VaR 99%		
	Bn USD	% Assets	% GDP	Bn USD	% Assets	% GDP
2007	620	5.09	4.41	620	5.09	4.41
2008	422	3.29	2.92	422	3.29	2.92
2009	689	5.31	4.84	689	5.31	4.84
2010	693	5.35	4.70	688	5.31	4.66
2011	795	6.13	5.18	740	5.70	4.81
2012	829	6.39	5.17	816	6.29	5.09
2013	827	6.38	4.95	827	6.38	4.95

Sources: Bloomberg, SNL, and IMF staff estimates.

[27] Although alternative measures of capital are presented in Table 11; only total equity and common equity are available for all the institutions considered in this analysis. This is due to the fact that some of the institutions under analysis are not BHCs. End-2009 total equity and assets data are used for 2010 on as well.

89. **However it should be noted that it is difficult to formulate reasonable assumptions about loss buffers given the amount of uncertainty in the current environment**. Assuming that current capital levels (in percent of total asset) remain constant through the exercise horizon might look unrealistic. The system has experienced severe stress, which has provoked both extreme losses in some institutions and unprecedented policy intervention. While our approach might only allow us to analyze heuristically the *capacity of existing capital* to withstand extreme losses, it can avoid contaminating estimates with erroneous forecasts of capital buffers.

90. **The MCSR is measured using ES**. ES built on our simulated loss distribution accounts for the tail distress dependence among the 14 FIs in the system. Then, ES for sub-portfolios of 13 institutions is calculated by subtracting one institution from the entire portfolio at a time. The MCSR of a FI *i* is defined as the difference between the ES with all 14 institutions and the ES with 13 institutions excluding the FI *i*.[28]

91. **Results show that interconnectedness of a FI contributes noticiable to the FI's MCSR in addition to its mere size, and the MCSR changes over time**. The correlation betweeen financial institution's asset size and their MCSR decreased to 0.6 in 2008 and increased to 0.8 in 2009. Equivalently, the relationship between asset size and the MCSR for our sample FIs decreased considerably in 2008. For some institutions, the MCSR was comparatively larger than their relative asset size in the system, while for some others, the MCSR was comparatively smaller than their relative size in the system. The MCSR of FIs changes reflecting the changes of their PoDs, which in turn had an effect on the stress caused by such FIs in the system. In 2008, some institutions' PoDs increased more than proportionally than others' thus the negative spillover effects caused by such institutions in the system increased more than proportionally. Therefore their MCSR increased relative to their asset size. While the MCSR of others decreased relative to their asset size. Thus, the correlation between FIs' asset size and MCSR decreased in 2008. (Figure 17).

D. Spillovers and Interconnectedness[29]

92. **A sample of large U.S., European, and Asian banks was analyzed to assess spillover risks from the U.S. financial system to other financial systems**.[30] The analysis suggests that vulnerabilities in the global financial system have eased from the highest levels

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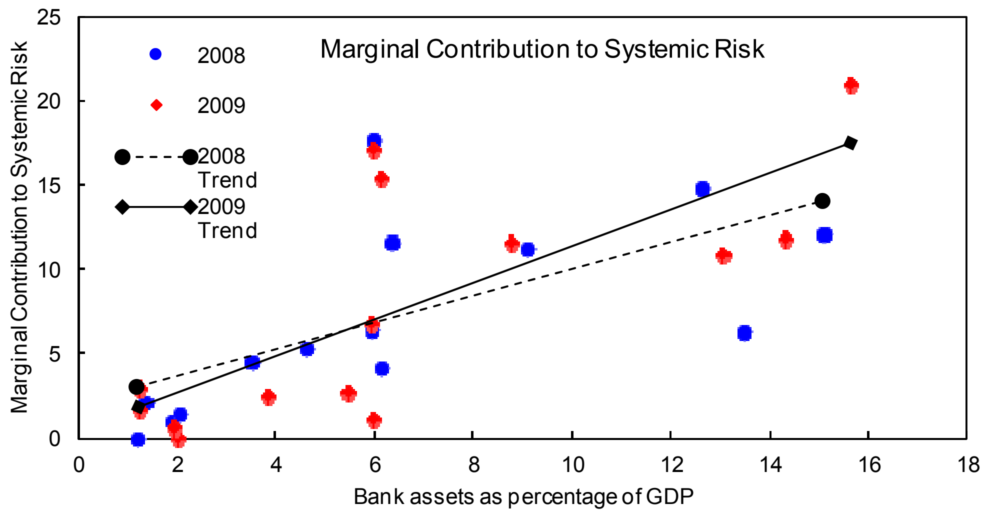
[28] Alternative measures are presented in Segoviano and Goodhart (2010).

[29] The financial stability indicators employed in this section to do the analysis; i.e., (i) the banking stability index, (ii) conditional probabilities of distress, and (iii) the probability of cascade effects are defined in Segoviano and Goodhart (2009). A detailed explanation of the methodology to define these indicators is also presented in this paper.

[30] These included Citigroup, Bank of America, J.P Morgan, Wachovia, Merrill Lynch, Morgan Stanley, Goldman Sachs, HSBC, RBS, UBS, Deutsche Bank, IB of Korea, ANZ, Mitsubishi UFJ, and Bank of China. The estimates were performed for data from January 2005 up to December 2009.

Figure 17. Marginal Contribution to Systemic Risk and Financial Institutions' Assets



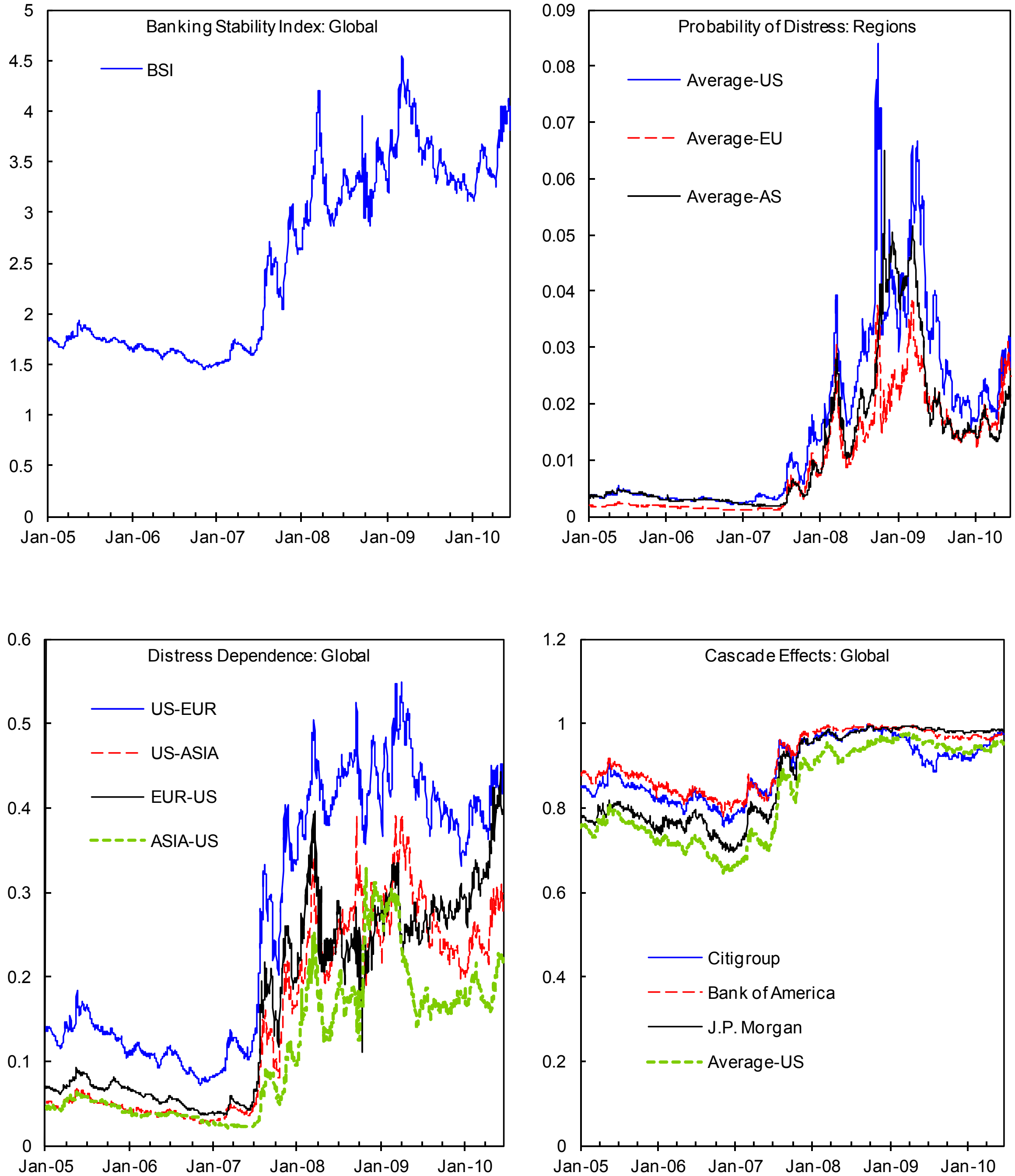
Sources: Bloomberg, SNL, and IMF staff estimates.

observed by the end of the first quarter in 2009. However, tail systemic risk, measured by the global banking stability index—the expected number of banks falling in distress given that at least one bank in the system becomes distressed—remains at similar levels than the ones observed during August 2008 (Figure 18, upper left) for global financial systems. Similar trends appear with average PoDs in each region. Note also that on average, PoDs of U.S. banks remain higher than European and Asian banks (Figure 18, upper right). These indicators show that the global risk remains elevated although it has come down from its highest levels observed in March 2009.

93. **Tight inter-linkages persist between U.S. and European banks (Figure 18)**. Although this inter-dependence—measured by the probabilities of distress of U.S. banks conditional on distress in European Union banks, and vice-versa—has eased from its recent peak in early 2009, it continues to be higher than pre-crisis level. By mid-2010, this interdependence was rising again, possibly reflecting instability in the euro area. For example, as of June 2010, if all the US (European) banks in the sample were to fall into distress, there would be a 40 percent chance that this distress would spill over to European (US) banks (lower left panel in Figure 18).

94. **The probability of cascade effects in the global system provoked by distress in U.S. banks remains significantly high.** Cascade effects are measured by the probability of at least one bank in the system going into distress conditional on the distress of a specific FI. Distress of Citigroup, Bank of America, or J.P Morgan would raise the chances of distress of other global banks above 90 percent since 2007 (Figure 18, lower right).

Figure 18. Global Financial Stability Measures



Source: IMF staff estimates
Sample includes US FIs (Citigroup, Bank of America, J.P Morgan , Wachovia, Merril Lynch, Morgan Stanley, Goldman Sachs), European FIs (HSBC, RBS, UBS, Deutsche Bank) and Asian FIs(Industrial Bank of Korea, ANZ, Mitsubishi UFJ, Bank of China).
Banking stability index is the expected number of FIs becoming distressed given that at least one bank becomes distressed.
Distress dependence (group A-group B) shows the probability that all members in group A become distressed conditionial on all members in group B becoming distressed.
Cascade effect is the probability that at least one FI becomes distressed given that a specific FI becomes distressed.

95. **In addition, some of the institutions that could potentially provoke large systemic risks in the global system appear vulnerable to negative developments in other global FIs and emerging market sovereigns (Figure 19)**. The PoD of Bank of America, J.P Morgan, and Citigroup conditional on other global banks becoming distressed decreased (from the highest levels observed during 2009) towards the end of 2009 (Figure 19, top), implying their vulnerabilities against shocks to other part of global financial system has been mitigated somewhat. Nonetheless, the level of the PoD of Citigroup conditional on global FIs' distress remains significantly higher than the pre-crisis level. Moreover the PoD of Citigroup conditional on the distress among major emerging market sovereigns around the world remains at a high level (Figure 19, bottom three panels). Thus, it is important to follow closely the developments in other countries and consider potential spillover effects from the rest of the world to major U.S. FIs in order to assess the stability of the U.S. financial systems in a comprehensive manner.

96. **Spillovers between banks and corporates appear to be increasing as well.**[31] The analysis suggests that although in recent months interlinkages (as measured by the PoDs of bank distress conditional on corporate distress and the PoDs of corporate conditional on bank distress) have eased from the highest levels observed in the first quarter of 2009 (possibly due to public support), they remain high, and appear to be increasing towards the end of 2009 (Figure 20, top).

97. **Banks' distress given corporate distress is higher than corporates' distress conditional on banks' distress**. This likely reflects the current vulnerable state of the banking system and that risk in the banking system appears to be larger than in the corporate sector. However, spillovers appear to be rising in the corporate sector, which show spillovers of the banking crisis into the real economy (Figure 20, bottom).

E. Macroprudential Stress Tests with Distress Dependence: Conclusions

98. **The macroprudential stress tests with distress dependence suggest that vulnerabilities remain in the U.S. financial system.** Losses would increase in 2010 and 2011. Under the baseline scenario, ELs would have an appreciable increase in 2010; however, to levels below ELs in 2008, and ULs would increase to similar levels than ULs in 2008. Under the adverse scenario, ELs and ULs would remain at higher levels than the baseline scenario for a prolonged period of time.

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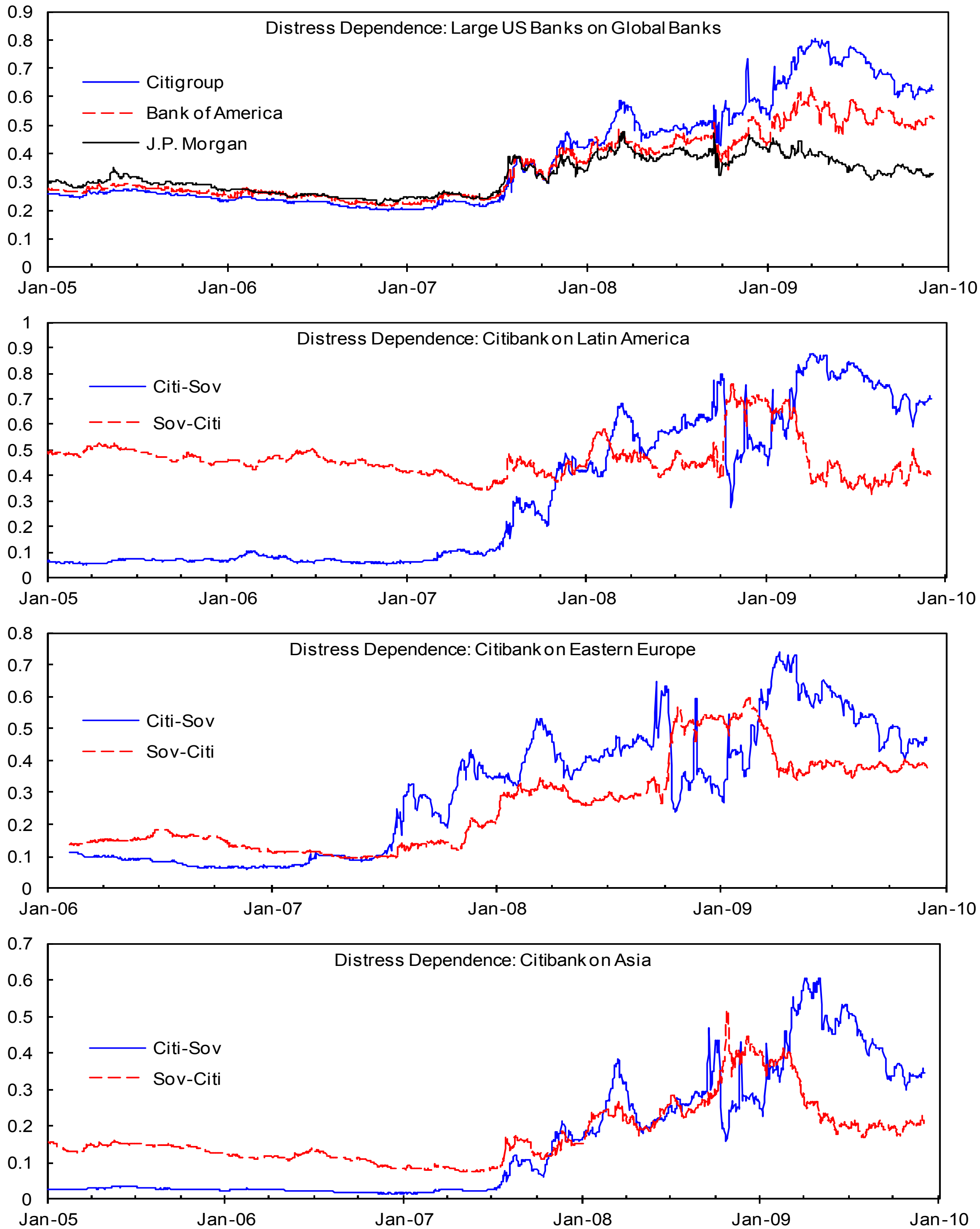
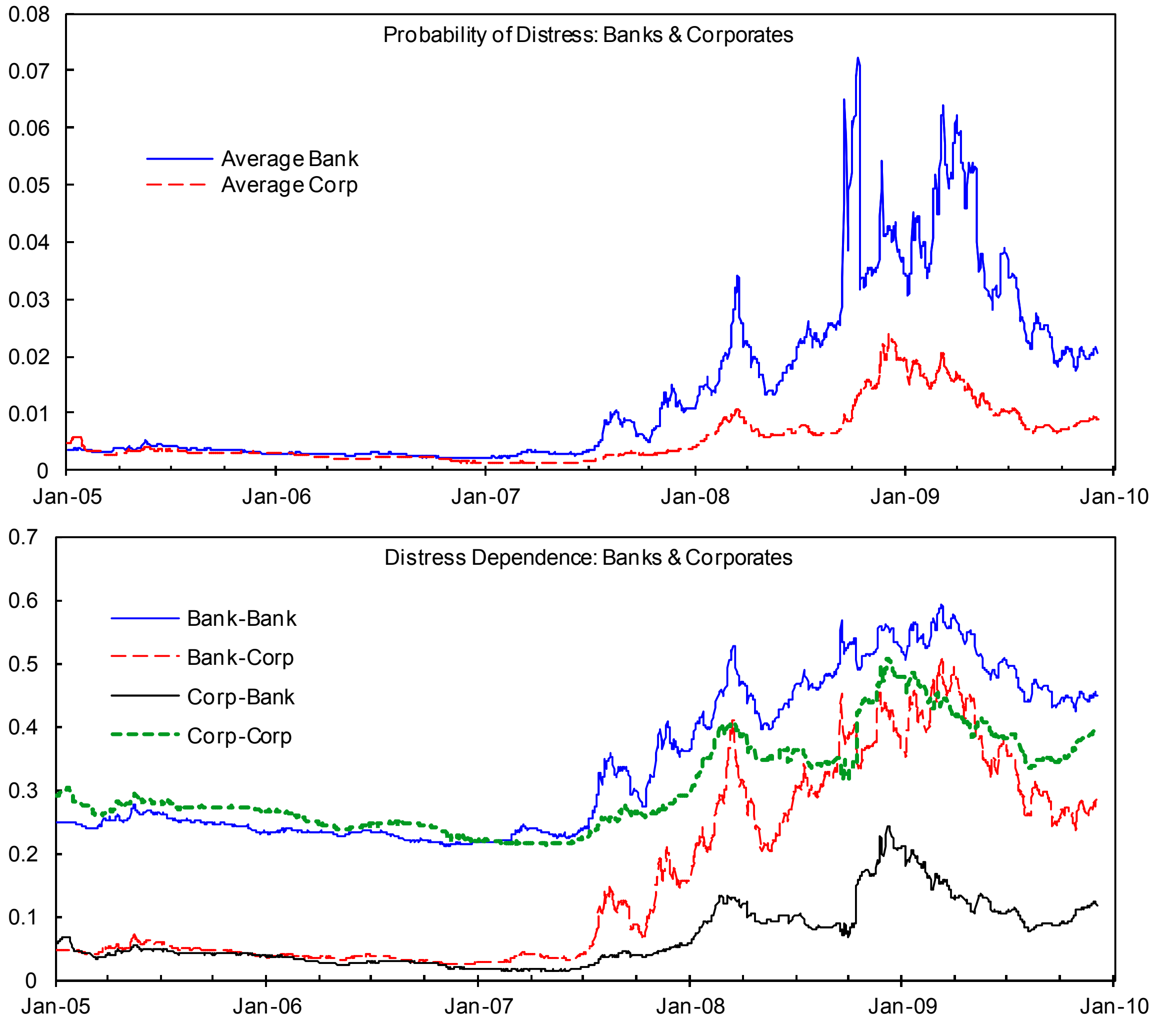
[31] The firms included in this analysis comprise Bank of America, Citigroup, J.P Morgan, Wells Fargo, Goldman Sachs, and Morgan Stanley (banks), Boeing, AT&T, Johnson and Johnson, IBM, Wal-Mart, and Chevron (corporates). The sample of corporates is narrow, and therefore the analysis should be considered only as illustrative.

Figure 19. Distress Dependence: U.S. Banks and Emerging Market Sovereign



Source: IMF staff calculations
Distress dependence (group A-group B) shows the probability that all members in group A become distressed conditionial on all members in group B becoming distressed.

Figure 20. Spillovers between U.S. Banks and Corporates



Source: IMF staff calculations
Distress dependence (group A-group B) shows the probability that all members in group A become distressed conditionial on all members in group B becoming distressed.
Sample includes major US Banks (Bank of America, Citigroup, J.P. Morgan, Wells Fargo, Goldman Sachs, and Morgan Stanley) and major US corporates (Boeing, AT&T, Johnson and Johnson, IBM, Walmart, and Chevron).

99. **The analysis also leads to important conclusions about the interlinkages of the U.S. financial institutions with the rest of the world and other sectors.** In particular, global tail systemic risk has eased from the highest levels observed in early 2009 but remains significantly higher than pre-crisis levels. Close interlinkages remain between U.S. and European FIs. The probability of cascade effects provoked by the distress of U.S. banks remains high. The analysis also points to increasing interlinkages between the U.S. financial and non-financial sectors.

IV. Government's Market-Implied Contingent Liabilities

A. Introduction

100. **The focus of this section is on market-implied estimates of the government's liabilities from potential expected losses in the financial sector**. Since October 2008, unprecedented and sweeping government interventions appear to have stabilized the U.S. financial sector, but the potential of a resumption of credit problems and the unresolved moral hazard problem of large and complex financial institutions results in large contingent liabilities for the public sector being implied by financial asset prices. Such market-implied contingent liabilities may imperil fiscal sustainability as they increase the susceptibility of public finances to the potential impact of systemic distress ("tail risk") and the future performance of the U.S. financial sector. While Section III ("second pillar" of the analysis) dealt with expected losses retained by the banks, this section focuses on the financial market's assessment of expected losses that could possibly become contingent liabilities to the public sector.

101. **To quantify systemic risk of contingent liabilities from the financial sector, the so-called *Systemic CCA* framework is applied**. This framework combines financial market data and accounting information to infer the risk-adjusted balance sheets for individual financial institutions and the dependence between them in order to estimate the joint market-implied contingent liabilities. The framework uses daily data on 36 institutions (Appendix Table 1) from January 1, 2007 through end-January 2010 in order to derive expected losses implied by equity prices after controlling for residual risk that is captured by CDS spreads on the same reference entity. This model-based approach helps quantify the potential magnitude of risk transfer to the government, subject to inherent estimation uncertainties (and the breakdown of efficient asset pricing in situations of illiquidity) related to unprecedented market disruptions, the capital structure impact of crisis interventions, and the contribution of individual institutions to such market-implied contingent liabilities over time depending on their size and asset price co-movement. These risk-adjusted balance sheets facilitate simulations and stress testing to evaluate the potential impact of policies to manage systemic risk (Gray et al., 2008).

102. **Systemic CCA relies on the conceptual underpinnings of the CCA methodology to determine expected loss**. Since CCA stems from option pricing theory pioneered by Black-Scholes (1973) and Merton (1973), this approach is forward-looking by construction, providing a consistent framework based on current market conditions rather than on historical experience.[32] When applied to the analysis and measurement of credit risk, CCA is commonly called the Merton Model (Appendix VIII), which is predicated on three principles: (i) the values of liabilities (equity and debt) are derived from assets; (ii) liabilities

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[32] Although market prices are subject to market conditions not formally captured in this approach, they endogenize the capital structure impact of government interventions.

have different priority (namely, senior, and junior claims); and, (iii) assets follow a stochastic process. Assets (present value of income flows, proceeds from assets sales, etc.) are stochastic and over a certain time horizon may be above or below promised payments on debt, which constitute a default barrier. When there is a chance of default, the repayment of debt is considered "risky," to the extent that it is not guaranteed in the event of default (risky debt= risk-free debt minus explicit (and/or implicit) guarantee against default).

103. **The CCA model assumes that the total market value of assets, *A*, at any time, *t*, is equal to the sum of its equity market value, *E*, and its risky debt, *D*, maturing at time *T*.** Asset value is stochastic and may fall below the value of outstanding liabilities, which constitute the bankruptcy level ("default threshold" or "distress barrier") *B*.[33] *B* is defined as the present value of promised payments on debt discounted at the risk-free rate. The value of risky debt is equal to default-free debt minus the present value of expected loss due to default. The firm's outstanding liabilities constitute the bankruptcy level, whose standard normal density defines the "distance to default" relative to the firm value. Default occurs when the asset value is insufficient to meet the amount of debt owed to creditors at maturity, i.e., $A<B$. Equity value is the value of an implicit call option on the assets, with an exercise price equal to default barrier. It can be computed as the value of a call option. The expected potential loss due to default can be calculated as the value of a put option, *P*, on the assets with an exercise price equal to B. The equity value can be computed as the value of a call option:

$$E(t) = A(t)N(d_1) - Be^{-rT}N(d_2)$$

$$d_1 = \frac{\ln\left(\frac{A}{B}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \text{ and } d_2 = \frac{\ln\left(\frac{A}{B}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

where *r* is the risk-free rate, σ is the asset return volatility, and *N*(*d*) is the cumulative probability of the standard normal density function below *d*. In its basic concept, the model assumes that the implicit options are of the European variety, and set the time until expiry, T equal to the time horizon of interest, usually between one and five years.

104. **The present value of market-implied expected losses associated with outstanding liabilities can be valued as an implicit put option, which is calculated with the default threshold *B* as strike price on the asset value *A* of each institution.** Thus, the present value of market-implied expected loss can be computed as follows:

$$P_E(t) = Be^{-rT}N(-d_2) - A(t)N(-d_1)$$

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[33] MKMV defines this barrier equal to total short-term debt plus one-half of long-term debt.

105. **Several widely-used techniques have been developed to calibrate the CCA models using a combination of balance sheet information and forward-looking information from equity markets**. The market value of assets of corporations and financial institutions cannot be observed directly but it can be implied using financial asset prices. From the observed prices and volatilities of market-traded securities, one can estimate the implied values and volatilities of the underlying assets in financial institutions, which accounts for increasing sensitivity of asset values to changes in market capitalization as a firm approaches a distress situation.[34] Also, in some cases asset and asset volatility can be estimated directly and can be used to calibrate risk-adjusted balance sheet models. In the traditional Merton (1973) model, the calibration requires knowledge about value of equity, *E*, the volatility of equity, σ_E, and the distress barrier as inputs into equations $E = A_0 N(d_1) - Be^{-rT} N(d_2)$ and $E\sigma_E = A\sigma_A N(d_1)$ in order to calculate the implied asset value *A* and implied asset volatility σ_A.[35]

106. **In this case, the so-called *state-price density* (SPD) of implied asset values is derived from equity option prices.** This requires the estimation of the risk-neutral density (RND) function of the underlying asset price using the parameters of a mixture of log-normal densities to match the observed option prices (Melick and Thomas, 1997) and nonparametric regression (Aït-Sahalia and Lo, 1998).[36] Once the asset value and asset volatility are known, together with the default barrier, time horizon, and the discount rate *r*, the values of the implicit put option, $P_E(t)$, can be calculated. Since the implicit put option $P_E(t)$ can be decomposed into the default probability and LGD.

$$P_E = N(-d_2)\underbrace{\left(1 - \frac{N(-d_1)}{N(-d_2)}\frac{A}{Be^{-rT}}\right)}_{LGD} Be^{-rT}$$

There is no need to introduce potential inaccuracy of assuming a certain LGD. Alternatively, it is possible to directly use the following relation between the implicit put option and some debt spread *s*.

$$s = -T^{-1}\ln\left(1 - P_E(t)/Be^{-rT}\right)$$

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[34]An implied value refers to an estimate derived from other observed data. Techniques for using implied values are widely used in options pricing and financial engineering applications (Bodie, Merton, and Cleeton (2009).

[35] See Merton (1974, 1977, 1992), Gray, Merton, and Bodie (2008), as well as Gray and Malone (2008).

[36] Note that all input variables are calculated from market prices, with the exception of the default barrier, which is derived from discounting the so-called "adjusted liabilities" (i.e., short-term debt plus half of long-term debt) provided by Moody's KMV for each sample firm.

Note that this specification does not incorporate skewness, kurtosis, and stochastic volatility, which can account for implied volatility smiles and skews of equity prices, in order to maintain an analytical form. For robustness,[37] however, the calculations also employ the closed-form Gram-Charlier model in Backus, *et al*. (2004), which allows for kurtosis and skewness in returns and does not require market option prices to implement, but is constructed using the same diffusion process for stock prices as the Merton model.[38]

107. **The calibrated CCA model also informs scenario analysis and stress testing.** Based on a bootstrap procedure that simulates the counterfactual change of all major input variables of CCA, it is possible to determine the likely effect of capital injections that are higher and lower than the ones provided as part of TARP. Moreover, a macro-financial stress testing framework is defined to estimate the future systemic risk from market-implied expected losses and contingent liabilities under both the baseline and adverse scenarios as described in Appendix III. From 2010 Q1 to 2014 Q4, the framework provides quarterly estimates of all 28 "surviving" sample banks and insurance companies beyond the historical sample end point (January 2010). The necessary macro-financial linkages underpinning the forecast are derived from the historical sensitivity of monthly market-implied expected losses for each institution to selected macro variables using a multivariate dynamic factor model over the entire sample time period.

B. Measuring Market-Implied Contingent Liabilities

108. **The implicit put option calculated for each financial institution from equity market and balance sheet information using CCA can be combined with information from CDS markets to construct a market-implied estimate the market-implied contingent liabilities**. If guarantees do not affect equity values in a major way (especially when the asset value is close to the default barrier), CDS spreads should capture only the expected loss *retained* by the bank—and borne by unsecured senior creditors—after accounting for the implicit guarantee. Hence, the scope of the government guarantee is defined as difference between the total expected loss (i.e., the value of a put option $P_E(t)$ derived from the bank's equity price) associated with default net of any financial guarantees,

[37] These results, not reported here for brevity, can be provided upon request.

[38] Further refinements of this model would include various simulation approaches at the expense of losing analytical tractability. The ad-hoc model of Dumas, Fleming, and Whaley (1998) is designed to accommodate the implied volatility smile and is easy to implement, but requires a large number of market option prices. The Heston (1993) and Heston and Nandi (2000) models allow for stochastic volatility, but the parameters driving these models can be difficult to estimate. Many other models have been proposed, to incorporate stochastic volatility, jumps, and stochastic interest rates. Introducing jumps in asset prices leads to small improvements in the accuracy of option prices. Other option pricing models include those based on copulas, Levy processes, neural networks, GARCH models, and non-parametric methods. Finally, the binomial tree proposed by Cox, Ross, and Rubinstein (CRR) (1979) spurned the development of lattices, which are discrete-time models that can be used to price any type of option—European or American, plain-vanilla, or exotic.

i.e., residual default risk on unsecured senior debt and the value of an implicit put option derived from the bank's CDS spread.[39]

$$P_{CDS}(t) = \left(1-\exp\left(-\left(s_{CDS}/10,000\right)\frac{RFV}{RMV}T\right)\right)Be^{-rT}$$

with the ratio between recovery at *face* value (RFV) and recovery at *market* value (RMV) as adjustment factor, which decreases (increases) the CDS spread *s* (in basis points) in the case of a positive (negative) difference ("basis") with the corresponding bond spread. Using this relation, it can be seen that

$$\alpha(t) = 1 - P_{CDS}(t)/P_E(t)$$

where $P_{CDS}(t)$ determines the fraction α of total potential loss due to default, $P_E(t)$, covered by implicit guarantees that depress the CDS spread below the level that would otherwise be warranted for the option-implied default risk. Thus, this definition, if applied to daily data, allows us to measure the time pattern of the government's contingent liability and the retained risk in the financial sector.

109. **While this definition of market-implied contingent liabilities provides a useful indication of possible sovereign risk transfer, the estimation of the alpha value depends on a variety of assumptions that influence the assessment of the likelihood of government support, especially at times of extreme stress during the credit crisis**. The extent to which the put option values of the Merton model differ from the one implied by CDS spreads, however, might also reflect distortions stemming from the modeling choice (and the breakdown of efficient asset pricing in situations of illiquidity), changes in market conditions, and the capital structure impact of crisis interventions, such as equity dilution in the wake of capital injections by the government, beyond the influence of explicit or implicit guarantees. The following discusses some caveats of the analysis:

- *The option pricing model might generate biased estimators of expected losses but will not undermine the validity of the alpha value.*

  Such an effect washes out since both model-implied put values (via equity prices) and market-implied put values (via CDS spreads) are derived from the same valuation method. Moreover, higher alpha values are not attributable to the choice of the option

[39] We approximate the change in recovery value based on the stochastic difference between the standardized values of the fair value CDS (FVCDS) spread and the fair value option adjusted spread (FVOAS) reported by Moody's KMV (MKMV). Both FVOAS (FVCDS) are credit spreads (in basis points) over LIBOR for the bond (CDS) of a particular company, calculated by the MKMV valuation model based on duration (term) of t years (where *t*=1 to 10 in one-year increments). Both spreads imply a LGD determined by the industry category. In practice, this adjustment factor is very close to unity for most of the cases, with a few cases where the factor is within a 10 percent range (0.9 to 1.1).

pricing model. Even though the Merton model contains simplifying assumptions, such as constant volatility[40] and a lognormal asset process, its empirical irregularities are more pronounced the lower the intrinsic value of the put option (and the further away asset values are from the default barrier). In other words, alternative (and more accurate) option pricing methods would generate expected losses similar to the ones under the Merton model (and, thus, would leave the alpha-value unchanged) in distress situations while differences would emerge as distress abates. So during the credit crisis, the current specification of contingent liabilities is conservative.[41]

- *Equity prices might have declined below the level warranted by fundamental values but this decline was not the only explanation for higher alpha values.*

  During the credit crisis rapid declines in market capitalization of financial firms were not only a signal about future solvency risk, but also reflected a "flight to quality" motive that was largely unrelated to expectations about future firm earnings. Assuming that CDS pricing was efficient, the definition of alpha would erroneously flag implicit government support due to extremely low equity valuations but not as a result of depressed CDS spreads (in expectation of possible guarantee to short-term creditors). However, empirical evidence, at least in the case of the United States, does not support this "denominator effect" of equity prices. For the given sample, a high cointegration and weaker negative dependence between equity prices and CDS spreads during stress periods suggest consistent co-movement but lower sensitivity of CDS spreads to changes in default risk over time.

- *The equality condition of default probabilities derived from equity prices and from CDS spreads eliminate the possibility of positive alpha values only in absence of market distress.*

  Carr and Wu (2007) and Zou (2003) show that for many corporations the put option values from equity options and CDS are closely related.[42] Arbitrage trading between both price shows in the synthetic replication of credit protection on guaranteed bonds using equity (i.e., a long position in an equity option "straddle" combined with a short

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[40] Bakshi, *et al*. (1997) suggest that most of the improvement over the Merton model comes from introducing stochastic volatility.

[41] An ex post adjustment of the exogenous default barrier does not influence this consideration, because it would influence both put option values. Moreover, it is unnecessary given that most support measures via capital injections do not change the liability structure but increase the total asset value and reduce the expected losses (implicit put option) as a result.

[42] Carr and Wu (2007) find that equity options used in a modified CCA seem to produce risk-neutral default probabilities (RNDP) matching fairly closely RNDPs derived from CDS (sometimes higher, sometimes lower, and differences seem to predict future movements in both markets). Zou (2003) finds that divergences of default probabilities derived from equity options used in CCA model and CDS disappear or revert driven by capital arbitrage relationships and trading impacts. The paper by Yu (2006) uses a less sophisticated model based on *CreditGrades*, which contains some simplifying assumption that are currently being revised by *RiskMetrics*.

CDS position). However, in stress situations, the implicit put options from equity markets and CDS spreads differ in their capital structure impact and should be priced differently. Besides guarantees, there are several distortions that could set apart the CDS-implied put option and the equity put option, so that RNDP implied by the CDS spread (based on an exponential hazard rate) to be higher than the RNDP component of the equity put option value. Some of these factors include (i) the recovery-at-face value assumptions underlying CDS spreads, which results in a disproportionate spread increase amid rising default risk and (ii) different risk horizons. These issues are addressed via an adjustment for "basis risk" over the same maturity of option prices in cases when below-par bonds push up the implied recovery rate of CDS, causing a mark-up of CDS spreads.[43]

110. **Since extreme events during the credit crisis might elude valuation models driving market prices of both equity and CDS, tail risks needs to be accounted for.** During extreme conditions it might not be too unexpected to find that economic models provide less than accurate predictions. Economic models are constructed as general representations of reality in a steady-state. During the credit crisis, however, financial market behavior was characterized by rare and non-recurring events, which are not captures by the statistical apparatus underlying conventional asset pricing theory (Jobst (forthcoming)). Thus, different option pricing models are explored that account for higher moments while acknowledging the irreducible core of unpredictable outcomes defying statistical assumptions underlying valuation models.

C. The Systemic Contingent Claims Analysis Methodology

111. **Our interest in market-implied contingent liabilities from the financial sector (and the systemic risk stemming from multiple institutions with "too-big-to-fail" properties), warrants measuring the joint, or systemic, risk of the financial sector.** However, conventional CCA is predicated on the measurement of default risk of an individual firm only. To address this issue, the financial sector is viewed as a portfolio of individual risk-adjusted balance sheets (with individual risk parameters), whose joint implicit put option can be accounted for by including correlation,[44] or more precisely, dependence in a multivariate extension of CCA.

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[43] A further explanation for differences between default risk implied by equity and CDS prices could be explained by segmented markets ("preferred habitat"). CDS participants who are willing to write credit protection may be the most optimistic about future prospects and may place little weight on failure irrespective of their views of government support. Leading up to the credit crisis, this was apparent in negative basis trades when the CDS spread was below the corresponding bond spread on the same obligor. While this phenomenon was short-lived (due to the easy arbitrage of negative CDS spread bases), it might explain a precipitous increase of market-implied contingent liabilities in the early phase of the credit crisis.

[44] Conventional (bivariate) correlation is ill-suited for systemic risk analysis when extreme events occur jointly (and in a non-linear fashion).

112. **This approach generates the multivariate density of each institution's marginal distribution of market-implied contingent liabilities and their dependence structure—the *Systemic CCA* approach (Gray and Jobst (2010 and forthcoming); Gray, Jobst and Malone, (2010), see Box 1).** The marginal distributions fall within the domain of Generalized Extreme Value distribution, which identifies possible limiting laws of asymptotic tail behavior of normalized extremes in order to quantify the possibility of common extreme shocks (Pickands (1981), Coles, et al. (1999), Poon, et al. (2003), Stephenson (2003), and Jobst (2007)). The dependence function is estimated iteratively on a unit simplex that optimizes the coincidence of multiple series of cross-classified random variables.

113. **This approach can also be used to quantify the contribution of specific institutions to the dynamics of the components of systemic risk (at different levels of statistical confidence),[45] how this systemic risk affects the government's market-implied contingent liabilities, and how policy measures may influence the size and allocation of this systemic risk over time**. Since point estimates of systemic risk are derived daily from a time-varying multivariate distribution rather than a conditional metric over certain time periods in this model, it is arguably more comprehensive than the current exposition of both CoVaR (Adrian and Brunnermeier (2008)) and Marginal Expected Shortfall, MES (Acharya et al. (2009), as well as extensions thereof, such as Huang, et al. (2009)) (Appendix IX).

114. **The amount of estimated market-implied government market-implied contingent liabilities from the financial sector can be used to calculate a market-implied fair value price of a systemic risk surcharge or guarantees fee**. The fair value (in basis points) of a risk-based surcharge that would compensate for the average market-implied contingent liabilities can be written as

$$-\frac{1}{T}\ln\left(1-\frac{1}{T}\frac{VaR_{q_a,t}}{\sum_j^p B_j e^{-rT}}\right)\times 10,000 \quad ,$$

where B represents the aggregate default barrier of all n-institutions in the sample, r is the risk-free rate, T is time horizon of the surcharge, and $G^{-1}_{\mu,\sigma,\xi}(.)$ is the multivariate density function (with location, scale and shape parameters μ,σ and ξ) μ,σ and ξ of individual market-implied contingent liabilities as a time-varying fraction α of expected losses $P_{p,T}$ (equity put option).

---

[45] The contribution to systemic (joint tail risk) is derived as the partial derivative of the multivariate density relative to changes in the relative weight of the univariate marginal distribution of each bank at the specified percentile. More specifically, the total expected shortfall can be written as a linear combination of the expected shortfalls of individual contingent liabilities, where the relative weights (in the weighted sum) are given by the second order cross partial derivatives of the inverse of the joint probability density function to changes in both the dependence function and individual contingent liabilities for threshold percentile *a*.

Box 1. Systemic Contingent Claims Analysis: Calculating Systemic Risk from Contingent Liabilities and Expected Losses

It is assumed that individual implicit put options as individual estimates of expected losses (or individual implicit put options times the alpha-values as individual estimates of market-implied contingent liabilities) are represented as a random vector $\mathbf{X}_{i,j}$ of independent and identically distributed (i.i.d.) observations. Individual asymptotic tail behavior of elements in $\mathbf{X}_{i,j}$ is specified as the limiting law of a p-sequence of normalized maxima, such that each univariate marginal distribution

$$Y_j = F_j\left(X_j\right) = \left(1 + \xi_j\left(x - \mu_j\right)/\sigma_j\right)_+^{-1/\xi_j}$$

with $1 + \xi_j\left(x - \mu_j\right)/\sigma_j > 0$ is generalized extreme value. The multivariate dependence structure is defined the function $A\left(\omega_1, ..., \omega_{p-1}\right)$, which is derived non-parametrically by expanding the bivariate logistic method proposed by Pickands (1981) to the multivariate case and adjusting the margins according to Hall and Tajvidi (2000) so that

$$A(\omega) = \min\left(1, \max\left\{n\left\{\sum_{i=1}^{n} \bigwedge_{j=1}^{p} \frac{y_{ij}/\hat{y}_{\bullet j}}{\omega_j}\right\}^{-1}, \omega, 1-\omega\right\}\right)$$

where $\hat{y}_{\bullet j} = \sum_{i=1}^{n} y_{ij}/n$ and $0 \leq \max\left(\omega_1, ..., \omega_{p-1}\right) \leq A\left(\omega_j\right) \leq 1$ for all $0 \leq \omega_j \leq 1$, subject to the optimization of the *(p-1)*-dimensional unit simplex

$$S_p = \left\{\left(\omega_1, ..., \omega_{p-1}\right) \in \mathrm{R}_+^n : \omega_k \geq 0, 1 \leq k \leq p-1; \sum_{k=1}^{p-1} \omega_k \leq 1 \text{ and } \omega_p = 1 - \sum_{k=1}^{p-1} \omega_k \right\}$$

which establishes the degree of coincidence of multiple series of cross-classified random variables similar to a Chi-statistic that measures the statistical likelihood of observed values to differ from their expected distribution.

Finally, using maximum likelihood estimation, both the marginal distribution and the dependence structure can be estimated recursively or based on a rolling window with periodic updating, so that one obtains the following point estimate of the complete multivariate density $G_{\hat{\xi},\hat{\mu},\hat{\sigma}}^{-1}(.)$ at quantile *q=1-a* at any point in time *t* (and estimation period τ).

$$\hat{x}_{a,p,t} = G_{\hat{\xi},\hat{\mu},\hat{\sigma}}^{-1}\left(a\right) = \hat{\mu}_j + \hat{\sigma}_j/\hat{\xi}_j\left(\left(-\frac{\ln\left(a\right)}{A\left(\omega\right)}\right)^{-\hat{\xi}_j} - 1\right)$$

The next step is to obtain the expected shortfall (or *conditional* Value-at-Risk (VaR)), reflecting the probability-weighted residual risk beyond a pre-specified threshold probability *a* (say, 95th percentile level for *a*=0.05) of maximum losses. The average daily ES for a total sample of p institutions can then be written as

$$ES_{a,t} = -\mathrm{E}\left[P_{p,t} \middle| P_{p,t} \geq G_{t,\mu,\sigma,\xi}^{-1}\left(a\right) = Va\mathrm{R}_{q_a,t}\right]$$

for threshold quantile

$$Va\mathrm{R}_{q_a,t} = \sup\left\{G_{t,\mu,\sigma,\xi}^{-1}\left(\bullet\right) \middle| \Pr\left[P_{p,t} > G_{t,\mu,\sigma,\xi}^{-1}\left(\bullet\right)\right] \leq a = 0.05\right\}.$$

D. Market-Implied Expected Losses and Contingent Liabilities for Major U.S. Financial Institutions

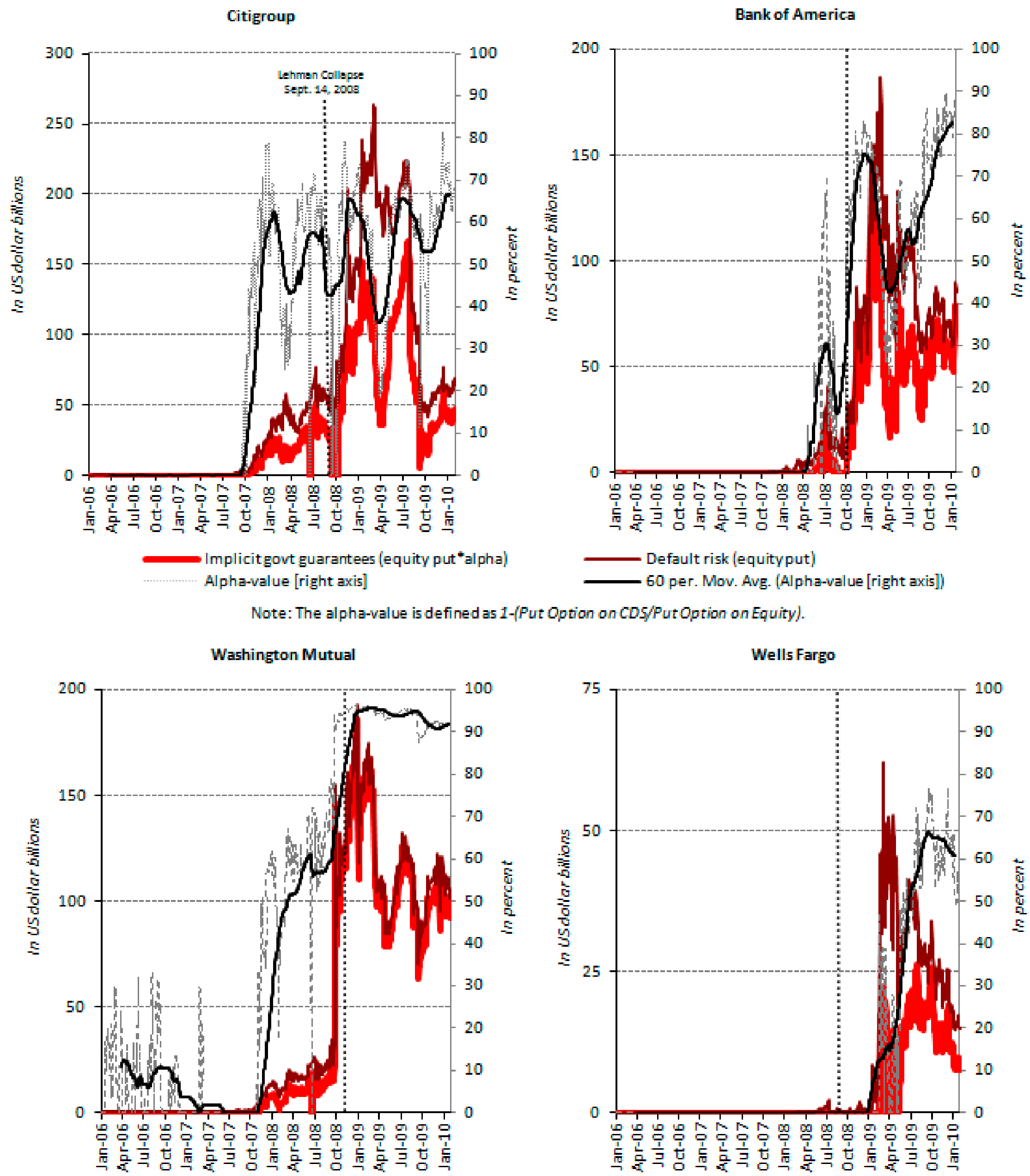
115. **This section describes results obtained from the historical estimation of market-implied expected losses and contingent liabilities from the pre-crisis period to early 2010**. The institutions covered are 17 SCAP BHCs, 8 other banks (processing and consumer finance) and the major broker dealers, GSEs (Fannie Mae and Freddie Mac, until conservatorship on September 8, 2008), AIG, and 8 other insurance groups, for a total of 36 institutions.[46] The analysis was based on daily data January 3, 2007 to January 29, 2009. Key inputs used were daily market capitalization of each firm (from Bloomberg), the default barrier estimated for each firm from Moody's KMV *CreditEdge* based on quarterly financial accounts, risk-free rate of interest, a one-year time horizon, and CDS spreads from *MarkIt*. Outputs were the market-implied expected losses (implicit put option values over a one year horizon) and the market-implied contingent liabilities (alpha*implicit put options). Figure 21 shows the univariate results for the expected losses and contingent liabilities of four sample banks that have either been subject to direct government support (Citigroup and Bank of America) or private sector resolution via mergers and acquisitions (Wells Fargo and Washington Mutual).

116. **The pre-crisis alpha (i.e., the share of risk taken by the government) was very low**. As an example for one bank, $\alpha(t)$ was near zero up to October 2007, then increased to between 50 and 68 percent, the market-implied expected loss, $P_E(t)$, increased to US$150 to 220 billion between October 2008 and August 2009 and the market-implied contingent liability estimate, $\alpha(t)P_E(t)$, the thick red line, ranged from US$ 50 to 150 billion. The alpha-value for corporates and most financials is near zero pre-2008 as shown in Figure 22 with Ford and GE as examples.

117. **Following the categorization of the banking sector in section II ("sub-groups"), the summary of individual CCA estimates by groups suggests that average market-implied expected losses and contingent liabilities were the highest for investment banks and GSEs and the lowest for regional, consumer, and processing banks**. The 36 FIs are the top 4 banks and investment banks, GSEs, insurance, failed banks and others (regional, processing, and consumer banks). The graphs show the median value (dark line) within the range between the 25th percent quartile and the 75th percent quartile. For the top 4 banks and investment banks the median market-implied expected loss was in the US$ 75 to 100 billion range from November 2008 to March 2009 (Figure 23). For the same period median market-

[46] Sample institutions are: Bank of America-Merrill Lynch, Citibank, Wells Fargo, Regions, Suntrust, Keycorp, Morgan Stanley, Fifth Third, PNC, American Express, Bank of New York Mellon, BB&T, Capital One, J.P. Morgan, State Street, US Bancorp, Goldman Sachs, Washington Mutual, Ameriprise, Northern Trust, CIT, Lincoln, Lehman Brothers, Bear Stearns, AIG, Metlife, Prudential, Hartford, Allstate, Principal, Travelers, Genworth, Aflac, Sallie Mae, Freddie Mac, and Fannie Mae.

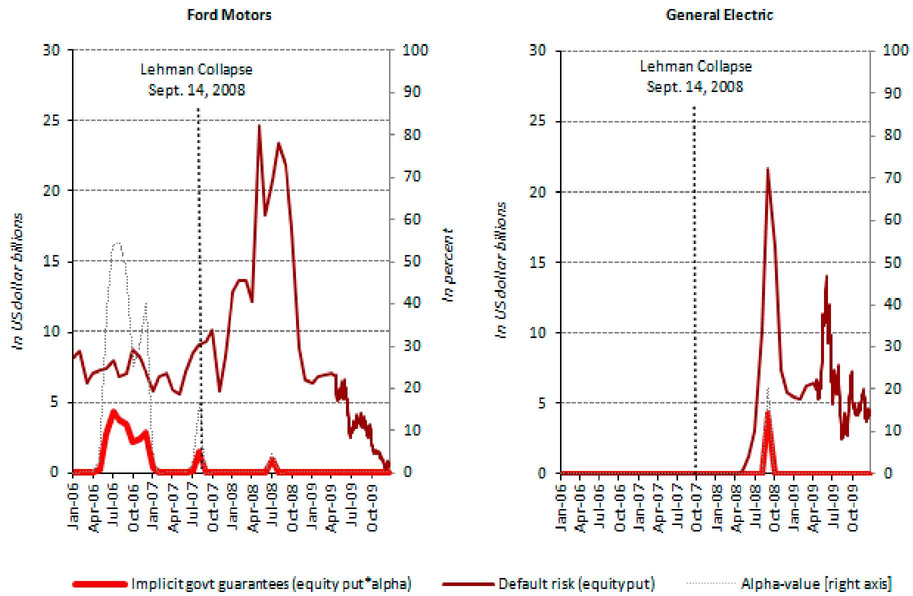
Figure 21. Market-Implied Expected Losses, Alpha Factor, and Market-Implied Contingent Liabilities for Selected Sample Banks (One-Year Risk Horizon)



Note: The alpha-value is defined as *1-(Put Option on CDS/Put Option on Equity)*.

Source: IMF staff estimates.

Figure 22. Market-Implied Expected Losses, Alpha Factor, and Market-Implied Contingent Liabilities for Selected Non-Financial Corporates (One-Year Risk Horizon)



Note: The alpha-value is defined as *1-(Put Option on CDS/Put Option on Equity)*. As opposed to all calculations for financial institutions, this example of CCA of non-financial corporates uses monthly data up to April 2008 after which daily data are available.

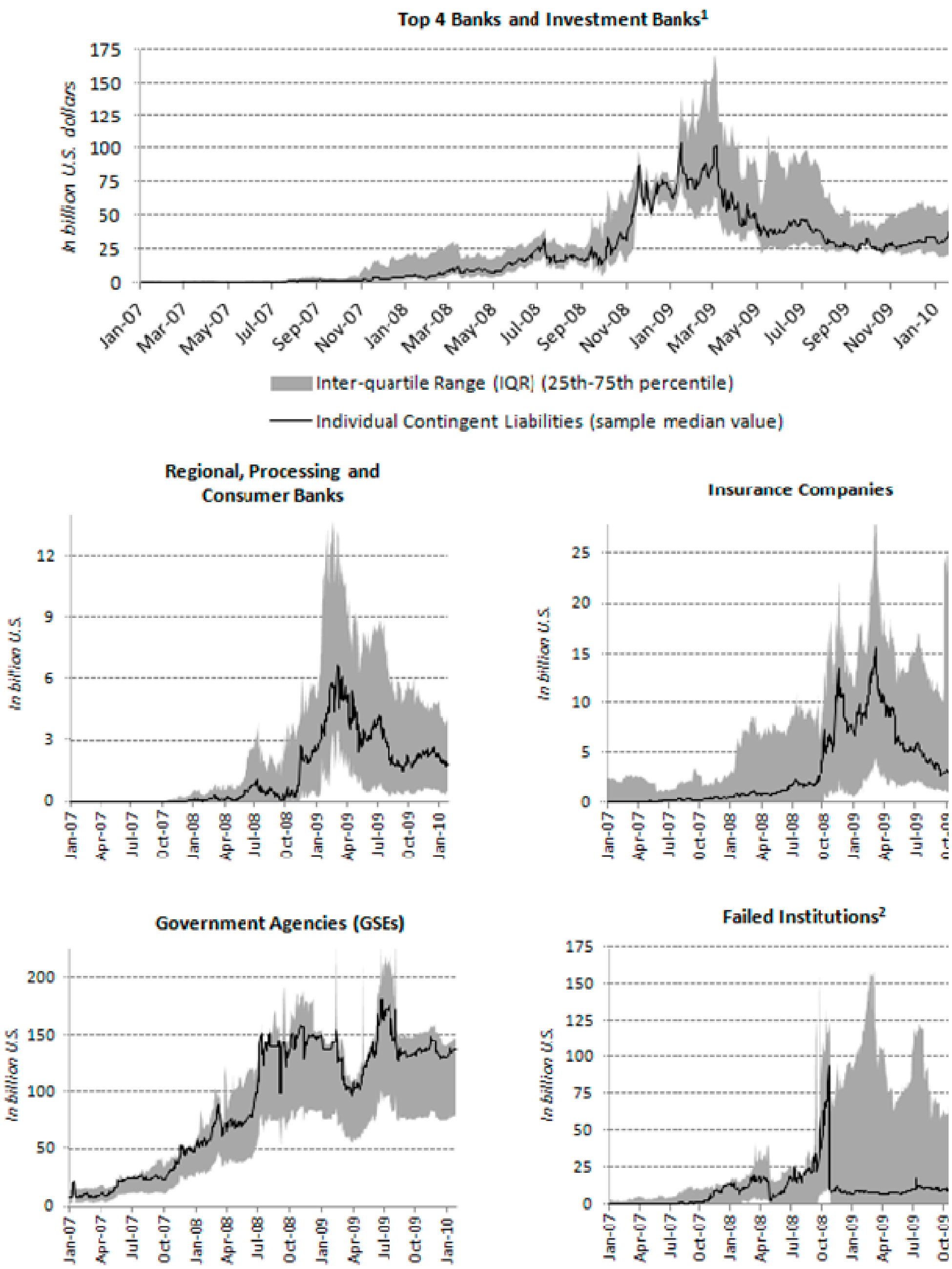
Source: IMF staff estimates.

implied expected losses for regional, processing and consumer banks was US$3 to 6 billion, and for insurance companies was US$ 8 to 15 billion. Median market-implied expected losses for the GSEs reach US$ 150 billion in mid-2008 and up to the conservatorship similarly to results in Gapen (2009). Data after the conservatorship, which are likely distorted due to the conservatorship, show high market-implied contingent liabilities for the GSEs For the top 4 banks and investment banks the median market-implied contingent liabilities were in the US$ 30 to 60 billion range from November 2008, to March 2009 (Figure 24).

118. **The simple sum of the market-implied expected losses (line) and market-implied contingent liabilities (area) are highest between the periods just after Lehman collapse and end August 2009 (Figure 25).** Freddie Mac and Fannie Mae entered conservatorship September 7, 2008 and were subsequently taken out of the sample—this date is marked by the sharp drop in the line and a little more than a week later Lehman declared bankruptcy). The analysis suggests that the portion of total market-implied expected losses transferred to the government was 50–75 percent.

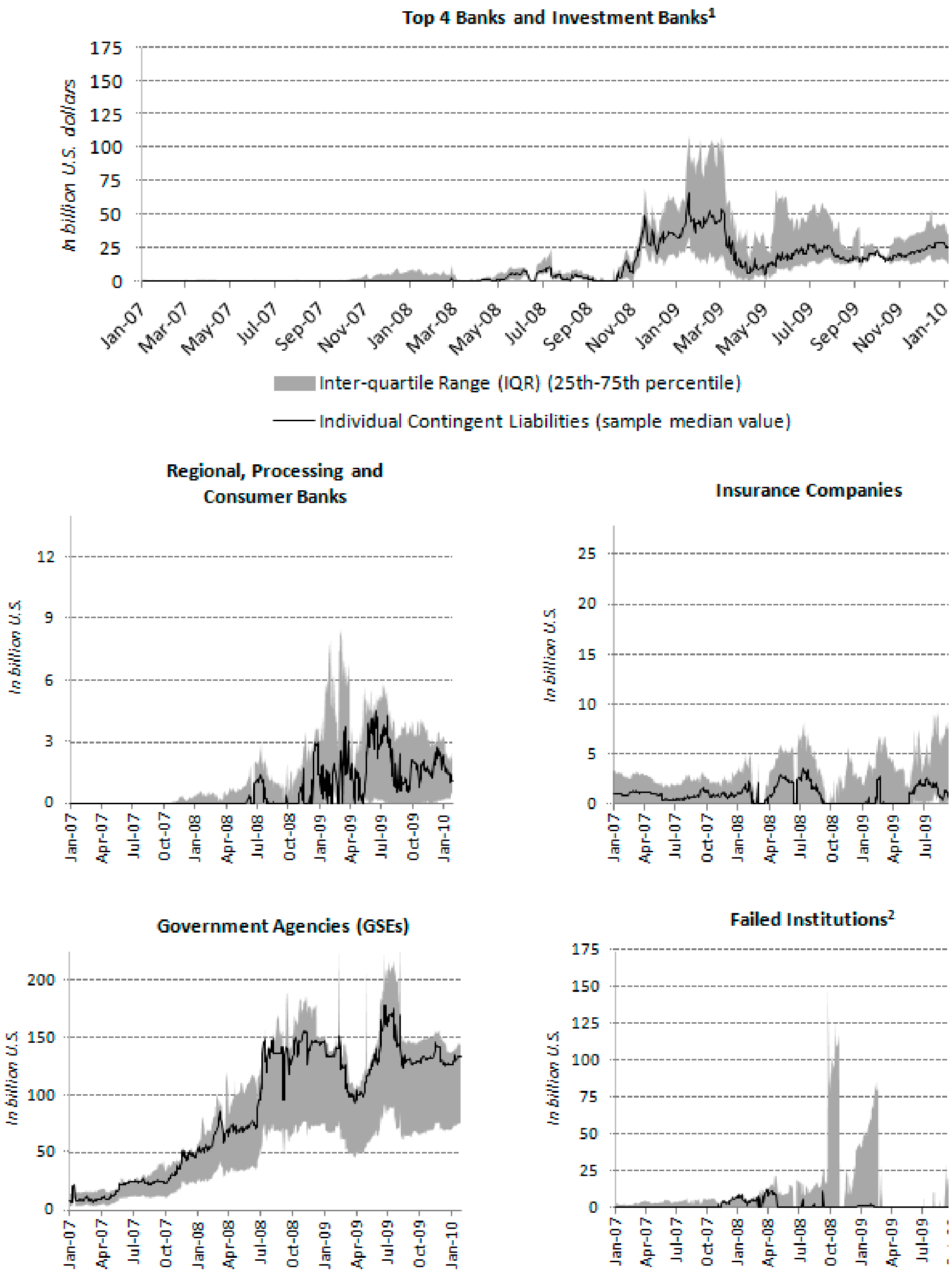
119. **The median of the joint distribution is much lower than the simple summation of individual market-implied contingent liabilities, which underscores the importance of the dependence structure.** A simple summation of individual CCA market-implied expected losses and market-implied contingent liabilities implies a correlation of one and

Figure 23. Summary of Market-Implied Expected Losses by Group, 2007–10



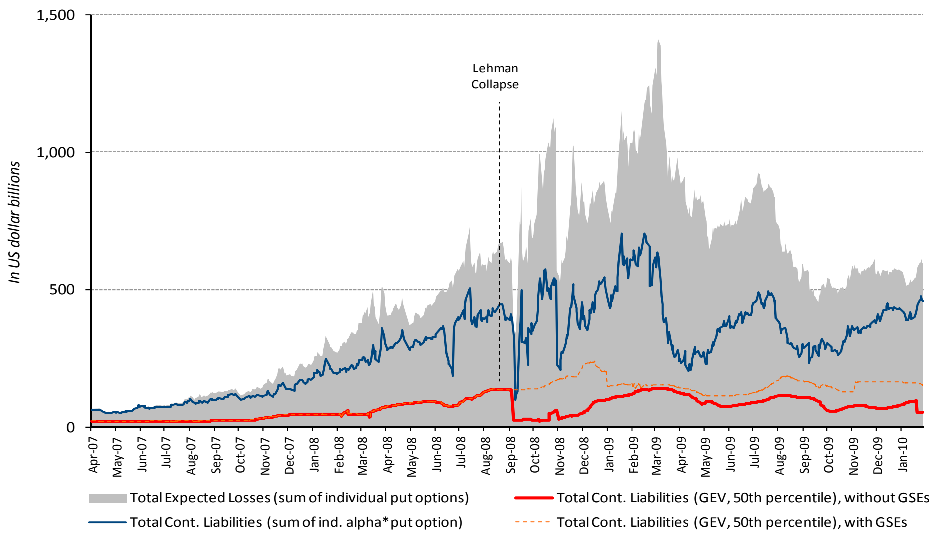
Sample period: 01/03/2007-01/29/2010 (743 obs.) of individual put option values of sample banks. 1/ Top 4 Banks are Bank of America, Citigroup, J.P. Morgan Chase, and Wells Fargo. Investment banks are Morgan Stanley and Goldman Sachs. 2/ Failed institutions are Bear Sterns, CIT, Lehman Brothers, and Washington Mutual. Source: IMF staff estimates, Bloomberg, Markit, Moody's KMV Creditedge.

Figure 24. Group-Wise Summary of Market-Implied Contingent Liabilities, 2007–10



Sample period: 01/03/2007-01/29/2010 (743 obs.) of individual put option values of sample banks. 1/ Top 4 Banks are Bank of America, Citigroup, J.P. Morgan Chase, and Wells Fargo. Investment banks are Morgan Stanley and Goldman Sachs. 2/ Failed institutions are Bear Sterns, CIT, Lehman Brothers, and Washington Mutual. Source: IMF staff estimates, Bloomberg, MarkIt, Moody's KMV Creditedge.

Figure 25. Financial Sector—Total Market-Implied Contingent Liabilities and Multivariate Density of Market-Implied Contingent Liabilities



Source: Staff estimates.

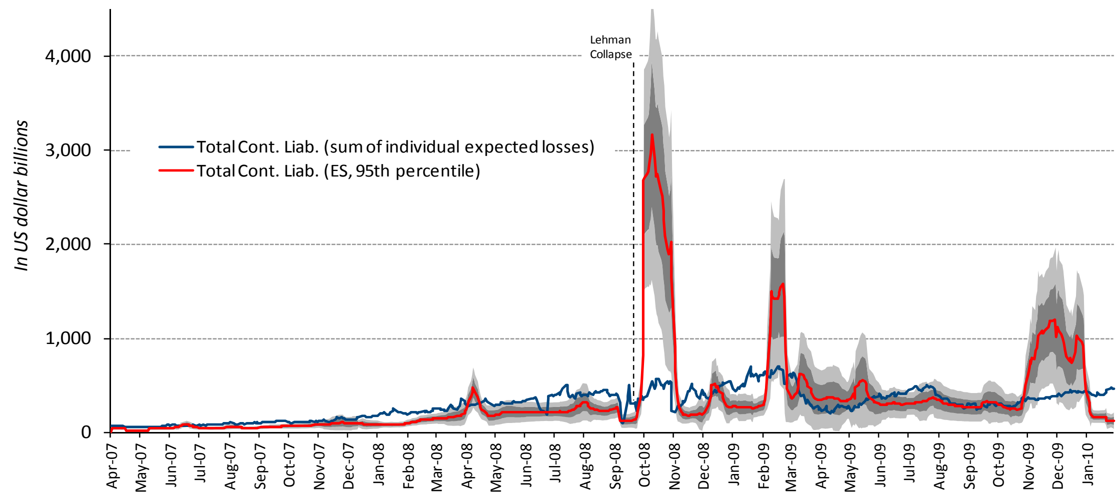
thus does not capture intertemporal changes in the dependence structure between this "portfolio" of financial institutions. With the dependence structure included, the average of the multivariate distribution (solid, 50th percentile line) is much lower, the difference being due to a "diversification effect." The expected joint market-implied contingent liabilities (solid line) peaked at about US$140 billion at the end of March 2009, averaging US$74 billion over the sample period. The second, dashed, 50th percentile line shows the case where Freddie and Fannie are left in the sample (daily equity prices were still available after the conservatorship but it can be argued that information may be much less informative following conservatorship).

120. **After the collapse of Lehman, the extreme tail risk in the system increased sharply, as measured by the 95th percentile market-implied expected shortfall**. The tail risk value skyrocked to extremely high levels in the months after the Lehman collapse (Figure 26). The shaded bands show the one and two standard deviation bands around the estimate, as a robustness check. These numbers can be interpreted to mean that in November 2008 there was a five percent chance of losses being US$3 trillion over a one-year horizon in the group of 36 financial institutions before the release of the SCAP stress test results led to a considerable decline of tail risk to around US$200 billion. Tail risks briefly flared up in November following prominent bankruptcies but stablizied to under US$100 billion as of end-January 2010.

121. **The joint tail risk measure of market-implied contingent liabilities shows spikes in April 2008 and October 2008, indicating a high government exposure to financial sector distress**. Tail risk, as measured as the 95th percentile expected shortfall of market-

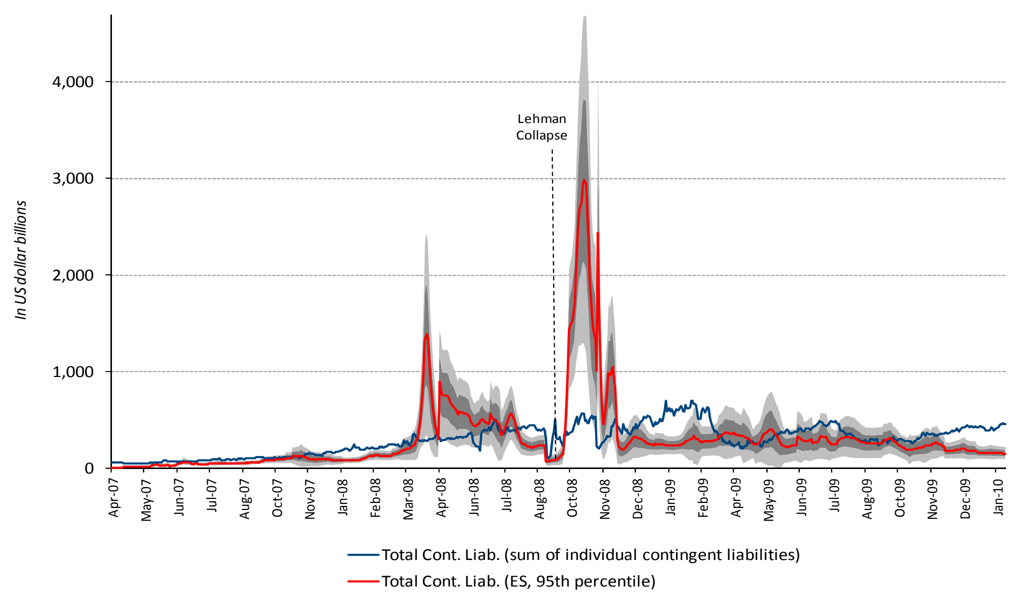
implied contingent liabilities for the entire sample exceeded US$1 trillion in April 2008 and almost reached US$3 trillion in October 2008 (Figure 27) as shown by the red line within a

Figure 26. Financial Sector—Daily Expected Shortfall Based on Multivariate Density of Market-Implied Expected Losses



Source: IMF staff estimate.

Figure 27. Financial Sector—Daily Expected Shortfall Based on Multivariate Density of Market-Implied Contingent Liabilities



Source: IMF staff estimate.

confidence band of one and two standard deviations (grey areas). Note the first spike beginning in March after the Bear Stearns rescue. The bailout of Bear Stearns led to expectations of futher public support amid high tail dependence of the market-implied contingent liabilities. This spike in April 2008 is mostly absent in the earlier chart showing market-implied expected losses (Figure 26), illustrating the sudden and highly correlated expectations of government support across numerous insitutions after the Bear Stearns bailout.

122. **The market-implied contingent liabilities were considerable during the credit crisis** (Table 14). For the whole period from April 1, 2007 to January 29, 2010, the average market-implied contingent liabilities at the 50th percentile level were US$75 billion, at the 95th percentile level were US$144 billion, and at the 95th percentile market-implied expected shortfall were US$336 billion. The average at the 50th percentile (US$74 billion) can be used with the sum of the default barriers for all institutions to calculate a price of a systemic risk surcharge or guarantees fee (Appendix X illustrates a possible calculation along these lines).

Table 14. Size of Market-Implied Contingent Liabilities for Different Time Periods and Different Percentiles

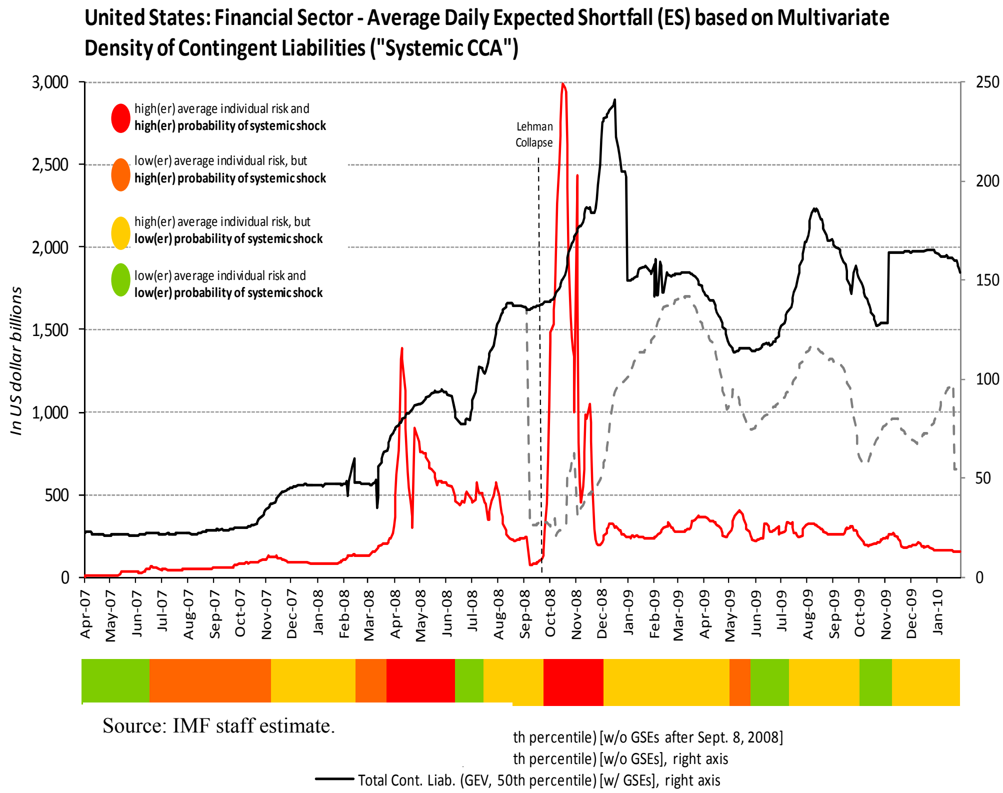
Average **Systemic CCA of Financial Sector (from Contingent Liabilities)**
(in US dollar billions unless indicated otherwise)

Estimation period	**50th percentile**	**95th percentile**	**ES (at 95%)**
April 1, 2007 - Jan. 29, 2010	75	144	336
Pre-Crisis: July 1, 2007-Sept. 15, 2008	61	92	246
Crisis Period 1: Sept. 15-Dec. 31, 2008	48	315	**932**
Crisis Period 2: Jan. 1-May 8, 2009	121	170	290
Crisis Period 3: May 11, 2009-Dec. 31, 2009	86	145	260

Source: IMF staff estimate.

123. **The Systemic CCA framework can also serve as an early warning indicator that helps pin-point periods of high systemic risk (Figure 28)**. In periods when the average risk and extreme tail risk are both high, there is a higher probability of systemic risk. Figure 28 shows the evolution of the average risk (50th percentile) of market-implied contingent liabilities if the GSEs are excluded following their entering conservatorship (dashed line, right hand side) and if they are retained in the sample (solid black line, right hand side). Comparing the solid black line to the red line representing the 95th percentile is informative about the evolution of systemic risk over time and the extent to which it is precipitated by individual risk. Periods when the average risk and the 95th percentile risk are both high (marked in red) reflect *high individual risk* and *high probability of systemic risk*.

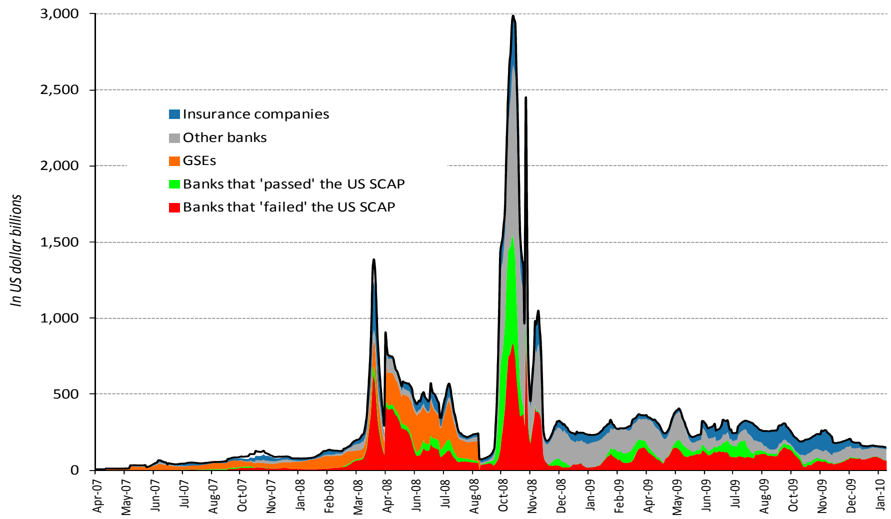
Figure 28. Market-Implied Expected Shortfall as Early Warning Indicator for Systemic Risk



Source: IMF staff estimate.

124. **The housing GSEs were large contributors to systemic risk up to the point when they were taken into conservatorship and then after the Lehman Brothers collapse, BHCs that needed additional capital according to the SCAP contributed to systemic tail risk far more than the other SCAP firms.** The contributions of different groups of institutions to tail-risk of market-implied contingent liabilities (Figure 29) are consistent with the SCAP, as BHCs that needed additional capital according to the SCAP contribute to systemic tail risk (as identified by the CCA) far more than the other SCAP firms after the collapse of Lehman Brothers, especially if capital need is estimated jointly. An examination of the percentage share of systemic tail risk in different periods (Table 15) suggests that pre-crisis (up to September 14, 2008) the GSEs were the biggest contributor at 44.5 percent, while from September 15 to December 31, 2008 the banks identified (later) by SCAP in need of more capital were the biggest contributors to systemic risk at 27.4 percent.

Figure 29. Financial Sector—Decomposition of Average Daily Market-Implied Expected Shortfall Based on Multivariate Density of Market-Implied Contingent Liabilities



Source: IMF staff estimate.

Table 15. Average Contributions to Systemic Risk from Market-Implied Contingent Liabilities

United States: Contingent Liabilities - *Average* Individual Contribution to Systemic Risk from Contingent Liabilities 1
(In percent, average expected shortfall at the 95th percentile)

	Total: April 1, 2007-Jan. 29, 2010	*in U.S. dollar billions*	Pre-Crisis: July 1, 2007-Sept. 15, 2008	Crisis Period 1: Sept. 15-Dec. 31, 2008	Crisis Period 2: Jan. 1-May 8, 2009	Crisis Period 3: May 11, 2009-Dec. 31, 2009
Banks						
w/SCAP-identified capital need	**26.4**	*102.0*	**20.7**	**27.4**	**30.7**	**39.1**
w/o SCAP-identified capital need	**7.5**	*35.9*	**4.9**	**13.5**	**9.0**	**11.5**
other	**8.8**	*31.5*	**2.1**	**22.5**	**14.9**	**10.7**
failed	**14.7**	*54.4*	**10.7**	**21.7**	**31.7**	**8.7**
Government agencies (GSEs)	**23.9**	*38.2*	**44.5**	**-**	**-**	**-**
Insurance companies	**19.8**	*50.9*	**17.1**	**14.9**	**13.7**	**30.0**
			100.0	100.0	100.0	100.0

1/ Each group's percentage share aggregates each constituent institution's time-varying contribution to the multivariate density of total contringent liabilities at the 95th percentile. The multivariate probability distribution is generated from univariate marginals and a time-varying dependence structure based on generalized extreme value.

Source: IMF staff estimate.

E. Scenario Analysis and Stress Tests

125. **This section describes the counterfactual analysis of TARP-based stabilization measures and introduces a stress testing framework based on a dynamic factor model expected losses conditional on forecasted changes of macro variables**. It assesses the impact of different configurations of recapitalizations, i.e., the direct injection of capital partially or fully originating from public funds, on systemic risk and associated government market-implied contingent liabilities. More specifically, the calibrated Systemic CCA model is used to measure counterfactual impact of modifications to the system-wide recapitalization program conducted by U.S. authorities.

126. **The scenario analysis combines actual and assumed sensitivity of balance sheet identities to different forms of government interventions.** For capital injection, the calculations estimate an alternative diffusion of market capitalization, implied assets values, and asset volatility in order to generate counterfactual results for market-implied contingent liabilities. First, we determine the actual sensitivity of balance sheet identities and asset values (i.e., market capitalization, implied assets values, and asset volatility) of each firm's implicit put option value to government interventions and extrapolate the economic impact over an event window of three days around the day of announcement ("event day sensitivity"). A bootstrap procedure is then applied to simulate counterfactual asset paths of these CCA input parameters until the sample end-date based on their historical relationship (while controlling for their joint asymptotic tail dependence). For the purpose of this section, the analysis focuses on (the announcements of) capital injections on October 14 and November 23, 2008, to three major recipients of support under the Capital Purchase Program, the Targeted Investment Program, and the Systemically Significant Failing Institutions Program (in one case) sponsored by the Troubled Asset Relief Program (TARP) pursuant to the Emergency Economic Stabilization Act.[47]

127. **Simulations indicate that the capital injections lowered individual market-implied contingent liabilities and reduced systemic tail risk.** Following the sequence of steps described in Appendix VIII, the individual market-implied contingent claims of the three largest TARP fund recipients are estimated on the assumption that these institutions either did not receive any capital support or received twice the original amount of government aid during the fourth quarter of 2008 (October 28 and November 23, 2008). These estimates are then compared with the ones obtained from previous Systemic CCA results based on actual observations. The result is that the capital support helped significantly reduce systemic risk from the joint market-implied contingent liabilities. Supporting these institutions reduced their individual contribution to systemic risk, with benefits slightly outweighing cost of intervention. CCA simulations suggest that doubling the original amount of capital injected into these firms would have had little additional effect over time.

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[47] Note that these counterfactual results need to be taken with caution as they do not provide a comprehensive assessment of policy effectiveness. The analysis focuses on an immediate market response to individual policy announcements to extrapolate the counterfactual asset process of expected losses and contingent liabilities.

However, without capital support as a result of policy inaction, average market-implied contingent liabilities from the banking sector would have increased by more than 50 percent in 2009 (95 percent VaR) and the tail risk and average risk would have escalated substantially (Table 16).[48]

128. **The Systemic CCA framework can also be used for stress testing**. By modeling how macroeconomic conditions have influenced the changes in the financial institution's market-implied expected losses (as measured by monthly implicit put option changes), it is possible to link a particular macroeconomic path to project financial sector performance in the future. The results of this analysis, summarized in the next section, are in line with those reported in Section III.

Table 16. Financial Sector—Scenario Analysis: Scenario Analysis: Actual and Counterfactual Average Value-at-Risk Estimate of Market-Implied Contingent Liabilities

(In billions of U.S. dollars)

	95th percentile		
Estimation period	no capital injections	actual	2x capital injections
April 1, 2007 - Jan. 29, 2010	**238**	214	**197**
Pre-Crisis: July 1, 2007-Sept. 15, 2008	**91**	91	**91**
Crisis Period 1: Sept. 15-Dec. 31, 2008	**484**	479	**469**
Crisis Period 2: Jan. 1-May 8, 2009	**414**	359	**353**
Crisis Period 3: May 11, 2009-Dec. 31, 2009	**356**	227	**226**

Source: IMF staff calculations.

F. Stress Testing Systemic Contingent Claims Analysis: Dynamic Factor Model

129. **In this section, the macro-financial linkages affecting financial sector performance are considered in a forward-looking assessment of contingent liabilities**. By modeling how macroeconomic conditions have influenced the changes in the financial institution's expected losses (estimated by monthly implicit put option changes), it is possible to link a particular macroeconomic path to project financial sector performance in the future.

130. **First, the log-likelihood estimate of the joint historical sensitivity of monthly implicit put option values between 01/03/2007–01/29/2010 (93 observations) is**

[48] A fair actuarial cost-benefit trade-off would require estimating the *unconditional expectation of contingent liabilities* (i.e., average of Systemic CCA estimate). Under this measure, estimation results suggest a disproportionate change of contingent liabilities to capital support offered.

determined in a multivariate dynamic factor model. In addition to the vector autoregressive structure of unobserved factors in our specification, we include a set of macro variables as exogenous covariates in both the equations for the latent factors and the equations for observable dependent variables, whose innovations may be serially correlated. The macro variables used are the same as those used in the macro-financial group-by-group stress test presented earlier in this note: nominal and real GDP growth, real consumption, output gap, unemployment rate, housing prices, ROA in the banking sector, and the three-month-LIBOR-treasury rate spread (or in short, "TED spread").[49]

131. **Second, for each bank the baseline/adverse scenarios of implicit put option values are extrapolated based on their joint historical sensitivity derived from a dynamic factor model at statistical significance threshold of 10 percent**. The multivariate density of both expected losses and contingent liabilities is then estimated over a rolling window of 20 observations using the marginal distributions of forecasted put option values and their dependence structure for each quarter until end-2014 according to the Systemic CCA model. During the credit crisis substantial changes in the financial sector have occurred and impacted the risk profile of financial institutions after several mergers, acquisitions and government support measures.[50]

132. **The results of the analysis can be summarized as follows** (Table 16 and Figures 30–31):

Stress Test Results for Market-Implied Contingent Liabilities

For the baseline scenario, the median (50th percentile) of contingent liabilities is projected at around US$31 billion but with rising estimation uncertainty until 2014 (and a 10 percent chance of this amount doubling to over US$60 billion, based on the 90th percentile estimate). The scenario results, however, also indicate an improvement in 2012 as tail risks from

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[49] The model is estimated with a simple lag structure as a maximum-likelihood problem in accordance with the De Jong (1988) method for determining the initial values for the Kalman filter when the model is stationary and uses the De Jong (1991) diffuse Kalman filter when the model is non-stationary.

[50] While it is difficult to forecast the impact of these changes on the risk-adjusted balance sheet going forward, only 4 out of a total of 36 institutions experienced a significant re-organization and associated change in their consolidated balance sheet - Bank of America-Merrill Lynch, J.P. Morgan, Wells Fargo, and Washington Mutual (note Lehman Brothers, Bear Stearns, CIT Group, Freddie Mac and Fannie Mae have been excluded from the sample), we find that the calibration of the stress test was not influenced by these structural changes. Although implied assets and adjusted liabilities increased in response to M&A activities during the crisis, the associated impact on balance sheet size increased expected losses without changing default risk due to higher leverage. Moreover, the magnitude effect of higher expected losses occurred as a structural break over two days (out of 744 days in the estimation window from January 3, 2007 to January 29, 2009) in the estimation of the dynamic factor model. Thus, at a statistical significance threshold of 10 percent used for the calibration of historical sensitivity to macro-financial factors, the parameter coefficient estimates were well within the statistical power of the regression analysis (implying a smooth adjustment of expected losses to changes in macro-financial conditions over time).

contingent liabilities (at percentiles far removed from the median) begin to stabilize (Figure 30, lower panel). Under the adverse scenario, the median (50^{th} percentile) estimate increases by a third to around US$41 billion but with a great deal of uncertainty in 2011 (90^{th} percentile over US$120 and 95^{th} at US$240 billion). The scenario shows improvement by end-2012 and into 2013 (Figure 31, lower panel).

Stress Test Results for Market-Implied Expected Losses

Under the baseline scenario, the median of projected expected losses rises from US$56 billion to US$81 billion in 2012 Q2 and declines to little more than one half of that level by 2014 (Figure 30, top panel). Systemic tail risk (captured by expected shortfall at the 95^{th} percentile) peaks in 2012 Q2 at US$591 billion, which is almost double the amount estimated for 2010 Q2. Under the adverse scenario, median expected losses exceed US$100 billion by 2011 Q1 but then decline only slightly US$97 billion (Figure 31, top panel). From a systemic risk perspective, a normalization of financial sector to pre-crisis conditions does not occur before 2012 Q3. Under the adverse scenario, systemic tail risk is even higher than under the baseline, exceeding the US$3 trillion mark in 2011 Q4 and then declining to pre-crisis conditions in 2012 Q3 (Table 17).

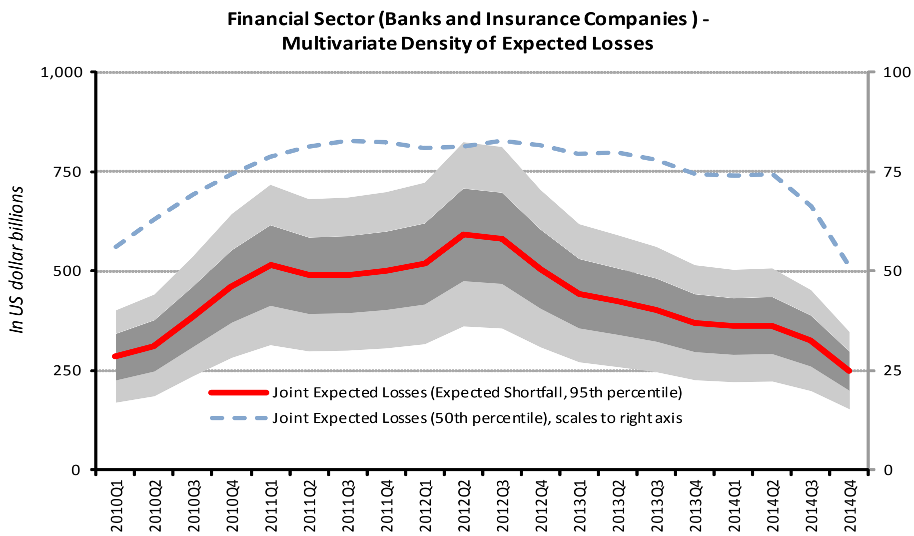
Table 17. Results of the Systemic Contingent Claims Analysis Stress Test—Baseline and Adverse Scenarios

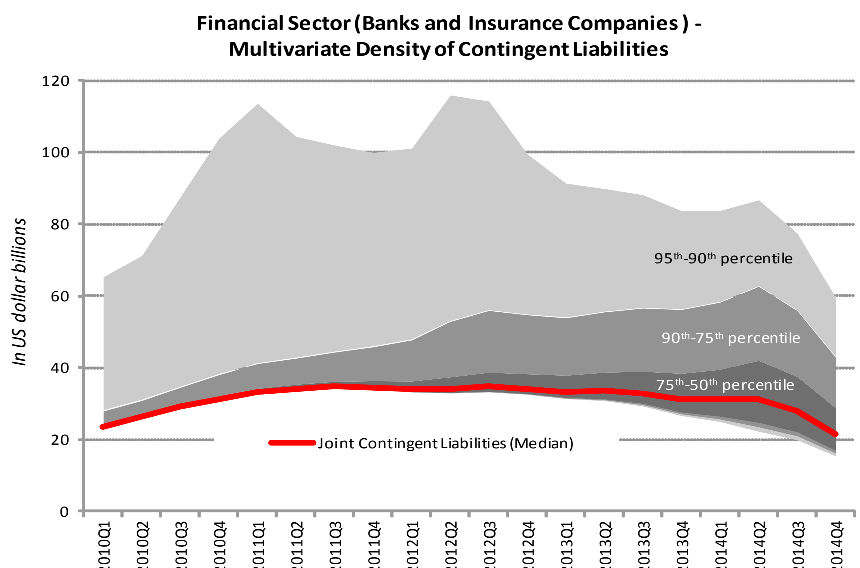
Systemic CCA of Financial Sector -
Average Systemic Risk from Expected Losses and Contingent Liabilities
(In billion US dollars unless indicated otherwise)

Forecasting Period, 2010 Q1 - 2014 Q4	50^{th} percentile	VaR (95%)	ES (95%)
Baseline Scenario			
Market-Implied Contingent Liabilities	31	92	180
Market-Implied Expected Losses	75	219	429
Adverse Scenario			
Market-Implied Contingent Liabilities	41	130	382
Market-Implied Expected Losses	97	308	910

Source: IMF staff estimate.

Figure 30. Results of the Systemic Contingent Claims Analysis Stress Test—Baseline Scenario





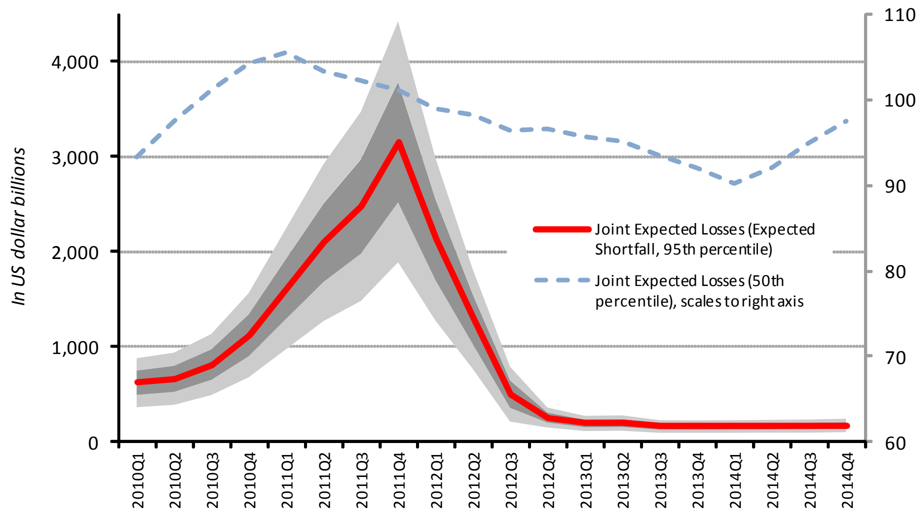
Source: IMF staff estimates.

Sample period: 2010 Q1-2014 Q4 (20 observations) of quarterly put option values of 36 sample banks and insurance companies forecasted via a multivariate dynamic factor model from monthly put option values between 01/03/2007-01/29/2010 (93 observations). In the first chart, the red line shows the ES for the entire sample at a 95th percentile threshold within a confidence band of one and two standard deviations (grey areas). In the second chart, the red line shows the median point estimate and the corresponding percentile ranges (grey areas).

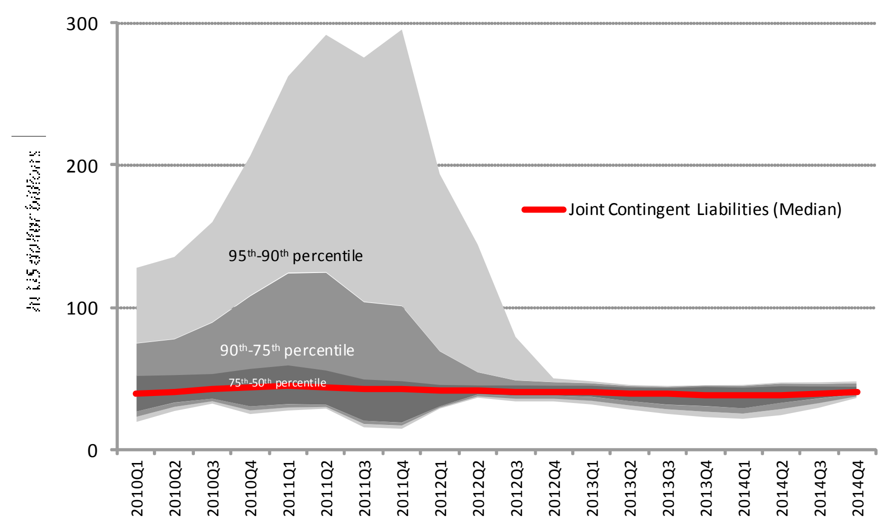
Source: IMF staff estimates, Gray and Jobst (2010).

Figure 31. Results of the Systemic Contingent Claims Analysis Stress Test—Adverse Scenario

Financial Sector (Banks and Insurance Companies) - Multivariate Density of Expected Losses



Financial Sector (Banks and Insurance Companies) - Multivariate Density of Contingent Liabilities



Source: IMF staff estimates.

Sample period: 2010 Q1–2014 Q4 (20 observations) of quarterly put option values of 36 sample banks and insurance companies forecasted via a multivariate dynamic factor model from monthly put option values between 01/03/2007–01/29/2010 (93 observations). In the first chart, the red line shows the ES for the entire sample at a 95th percentile threshold within a confidence band of one and two standard deviations (grey areas). In the second chart, the red line shows the median point estimate and the corresponding percentile ranges (grey areas).

Source: IMF staff estimates, Gray and Jobst (2010).

G. Market-Implied Contingent Liabilities: Conclusions

133. **The portion of total market-implied contingent liabilities could have amounted to more than 50 percent of expected losses**. The analysis, based on daily data for 36 financial firms from January 1, 2007 to January 31, 2009, suggests that controlling for the time-varying dependence structure between sample firms, the expected joint market-implied contingent liabilities peaked at about US$140 billion at the end of March 2009, averaging US$74 billion over the sample period.

134. **The joint tail-risk measure of market-implied contingent liabilities shows spikes in April 2008 and October 2008, indicating a high government exposure to financial sector distress**. An extreme tail risk measure (95th percentile expected shortfall) of market-implied contingent liabilities from risks transferred to the government exceeded US$1 trillion and almost reached US$3 trillion in those two months, respectively. The housing GSEs were large contributors to systemic risk up to the point when they were taken into conservatorship. After the Lehman Brothers collapse, BHCs that needed additional capital according to the SCAP contribute to systemic tail risk (as identified by the CCA) far more than the other SCAP firms. The results are consistent with the conclusions of the SCAP.

135. **Simulations indicate that the government's capital injections lowered individual market-implied contingent liabilities and systemic tail risk**. Capital support to the largest three TARP recipients helped significantly reduce systemic risk from the joint market-implied contingent liabilities. Indeed, CCA simulations suggest that doubling the original amount of capital injected into these firms would have had little additional effect over time. Conversely, in the absence of capital injections, the tail risk and average risk would have escalated substantially.

136. **This macro-financial stress test indicates lower market-implied contingent liabilities going forward, but with greater variability**. Under the baseline scenario, median (50^{th} percentile) market-implied contingent liabilities are projected at US$31 billion on average, but with considerable tail risk uncertainty in end-2012 (diminishes slowly from 2013 onwards). Under the adverse scenario, the median is US$41 billion but with a great deal of uncertainty in 2011. The results for systemic tail risk are in line with the ones obtained from other stress tests in this technical note. However, the Systemic CCA framework captures market expectations of both expected losses and contingent liabilities, whereas the analysis in Section III covers only expected losses retained in the financial sector. After adjustment for different sample sizes, the Systemic CCA framework generates worst-case market-implied loss estimates of more than US$350 billion.[51]

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[51] The sample used for the Systemic CCA estimation has US$14.9 trillion worth of on-balance liabilities for 36 sample institutions compared to US$7.4 trillion for 12 sample institutions as of end-October 2009 in Section III. For consistent comparison, we adjust the 99 percent VaR estimate in Section III by taking out the GSE from both losses and liabilities. Given that the sample of banks in Section III covers only 39 percent of the sample used for Section IV, we multiply the 95 percent ES by 0.39, which results in losses of about US$167 billion under the baseline and about $354 billion under the adverse scenario.

APPENDIX I: STRESS TESTS CARRIED OUT BY U.S. AUTHORITIES

Microprudential stress testing has long been a part of the U.S. authorities' supervisory process. Single factor exposure assessment has been the primary type of stress testing conducted in the past, which has recently evolved into more firm-wide comprehensive stress testing. In February 2009, the authorities announced an unprecedented stress test exercise known as the SCAP. The SCAP was a top-down analysis of the 19 largest U.S. BHCs, i.e., those with assets greater than US$100 billion, with total assets corresponding to roughly 2/3rds of the U.S bank holding companies.

The SCAP assessed these institutions' capital positions under a baseline and an adverse macroeconomic scenario, defined by the U.S. authorities. The participating BHCs, were asked to project losses, revenues, and loan loss reserve needs over a two-year period. The authorities set a benchmark for capital under the adverse scenario of a 4 percent Tier 1 common equity to risk-weighted assets. Tier 1 common capital deducts all "non-common" elements of Tier 1 capital (qualifying minority interest in consolidated subsidiaries, qualifying trust preferred securities, and qualifying perpetual preferred stock). Any BHC falling short of this benchmark was required to raise additional capital by November 2009, either in public markets or by issuing mandatory convertible preferred securities to the U.S. Treasury.

The stress test results suggested that 10 of the 19 participating BHCs required a combined US$185 billion of additional capital buffer. The results, published in early May 2009, bolstered confidence in the stability of major financial institutions during a period of heightened global and firm-specific uncertainty. As a result, the participating BHCs were able to take substantial actions to improve their capital position, which had fallen to record low levels.

The 10 BHCs that required additional capital increased their Tier 1 common equity by more than US$77 billion by the November deadline (with only one institution requiring an additional public capital injection). In addition, as of early February 2010, 12 of the participating BHCs fully redeemed their US$156.7 billion of preferred shares under the Treasury's Capital Purchase Program and another five have either announced or taken steps to do so in the near future.

The success of the SCAP confirmed the value of aggregation of global risks across complex financial holding companies. Drawing on the SCAP experience, the U.S. authorities have started to increase their emphasis on horizontal reviews, with focus on particular risks or activities across a group of banking organizations. Going forward, the authorities plan to conduct more frequent, broader, and more comprehensive horizontal examinations, evaluating both the overall risk profiles of institutions as well as specific risks and risk-management issues.

APPENDIX II: INSURANCE STRESS TESTING

Stress tests focusing on the largest 30 life insurance companies were carried out in cooperation with the NAIC. The companies account for 68 percent of U.S. life insurance premium income. The scenarios included an adverse scenario that combines negative shocks to the companies' assets (including their bond, stock, real estate, and loan portfolios), a liability-side shock impacting variable annuity writers, and a major insurance shock (a pandemic). The shocks were calibrated consistently with the adverse macroeconomic scenario in Appendix II; the pandemic was an additional shock with an impact equivalent to 100 percent of RBC. Based on a detailed discussion with the FSAP team on the shocks, scenario construction, and methodology, the NAIC has implemented the calculations using supervisory data. Stress testing of property and casualty insurance companies was not carried out because of the relatively limited sensitivity of the sector to macroeconomic shocks and the high degree of reinsurance cover, in markets overseas, of key catastrophe risks.

The results suggest that the life insurance sector is relatively resilient. The aggregate RBC ratio, at 906 percent as of end-2009, would decline to 521 percent after the shocks, with 5 out of the 30 companies having RBC below 300 percent. Companies with substantial variable annuity business would be particularly hard hit, but no company would have a negative RBC under the scenario.

Appendix III: Stress Test Scenarios and Shocks for the U.S. Financial Sector Assessment Program

The stress tests in the U.S. FSAPs included a baseline scenario and alternative scenarios. These included an adverse macroeconomic scenario and an alternative funding risk scenario.[52] The assumed values were consistent with historical distress episodes, and the magnitudes of the shocks are broadly in the ranges analyzed in other FSAPs.

Baseline scenario

The baseline was the scenario from the IMF's April 2010 World Economic Outlook update. The output gap closes over the medium term from a negative level in 2009, while inflation is well-anchored and stabilizes at about 2¼ percent. Ten-year government bond yields continue to rise moderately from 3.3 percent to 6.6 percent by 2015, reflecting the increasing government debt-to-GDP ratio.

Adverse scenario

The Adverse Scenario was generated using a simple closed-economy business cycle model for the United States, with standard monetary channels (Taylor rule and nominal rigidities) and fiscal channels (a fiscal rule and a link between the real interest rate and government debt).[53] The scenario was calibrated to illustrate the combined impact of four adverse shocks: (i) a sizeable and persistent shock to the growth rate of potential output, reflecting continued difficulties in the financial system and very weak investment; (ii) an additional short run demand shock, reflecting high unemployment, weak credit, and continued fall in housing prices; (iii) further near-term fiscal stimulus to support near-term growth; and (iv) rising inflation expectations, reflecting concerns over medium-term fiscal risks and renewed higher oil prices.

Reflecting this combination of shocks, the output gap falls by another 2.3 percentage points in 2011 relative to the baseline and the unemployment rate remains close to 10 percent in 2010–11. House prices fall by another 2.2 percent in 2010 and 2.1 percent in 2011, before starting a modest upward trend in 2012. Reflecting the weaker macroeconomic environment, banks' annualized return on assets falls slightly over the forecast horizon. Inflation and

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[52] In a recent speech, for example, Federal Reserve Board Vice Chairman Kohn highlighted the potential upward push on interest rates if the rising trajectory of U.S. debt to GDP is not curbed in the future, and the impact of higher interest rates on financial intermediaries ("Focusing on Bank Interest Rate Risk Exposure," January 29, 2010). Furthermore, the federal banking agencies released policy statements highlighting their expectations for sound practices in managing interest rate risk (http://www.federalreserve.gov/newsevents/press/bcreg/20100107a.htm) and funding and liquidity risk (http://www.federalreserve.gov/newsevents/press/bcreg/20100317a.htm).

[53] See M. Kumhof and D. Laxton (2007), "A Party Without a Hangover? On the Effects of U.S. Fiscal Deficits," IMF Working Paper 07/202.

government bond yields rise, and the government debt-to-GDP ratio increased by almost 10 percentage points compared to the baseline in 2013 (Table 18).

Alternative scenario

The alternative funding risk scenario was conducted to test banks' resilience to a further small deterioration in the real estate sectors, including difficulties in rolling over their commercial real estate maturing debt and continuing to accumulate seriously delinquent mortgages on their balance sheets. The fact that nearly half of the US$1.4 trillion in commercial real estate loans are expected to mature between 2010 and 2014 have negative equity (see Congressional Oversight Panel, 2010), together with the rising stock of seriously delinquent mortgages (many of which "underwater") suggests that banks could face difficulties in re-financing a large volume of loans and facing larger real estate loan losses if economic conditions do not improve and real estate prices do not rebound.

Under this scenario, the output gap falls more sharply in 2010 (3.3 percent relative to 3 percent) and the unemployment rate rise faster (10.6 percent relative to 10 percent). House prices are expected to fall by 4.1 percent in 2010 and another 2.6 percent in 2011, while commercial real estate prices fall by another 8 percent by end-2012 (as opposed to 3.3 percent in the Adverse). Short-term market spreads react slightly more than under the Adverse in 2010, but return faster to the baseline in the outer years, allowing banks to earn higher profits over the forecast horizon. Importantly, banks' assumed difficulty in rolling over maturing debt leads to higher losses on commercial real estate loans, which peak at 5.1 percent at end-2011.

Single-factor shocks

In addition to the scenarios, a range of single-factor shocks were employed to examine resilience of the financial system with respect to individual risk factors. The calibration of these shocks was based on long-term U.S. historical data as well as experience from other countries.

Table 18. Macroeconomic Assumptions

(Percent change, unless otherwise noted)

	2010		2011		2012		2013		2014	
Baseline scenario										
Real GDP	3.1		2.6		2.4		2.5		2.4	
Real personal consumption expenditures	2.4		2.1		2.0		2.0		2.0	
Nominal GDP	3.9		4.0		4.2		4.4		4.3	
Output gap (percent)	-2.0		-1.0		-0.6		-0.3		-0.1	
Unemployment rate (percent)	9.8		8.9		7.0		5.8		5.5	
Case-Shiller 10-city house prices	2.1		2.0		2.9		2.5		1.5	
Spread of 3-month LIBOR to 3-month T-Bill	0.2		0.4		0.4		0.4		0.4	
Return on assets (annualized; percent)	1.7		1.8		1.8		1.8		1.9	
Adverse										
Real GDP	2.3	-0.8	0.8	-1.7	2.6	0.2	2.6	0.1	2.2	-0.2
Real personal consumption expenditures	1.9	-0.6	0.6	-1.6	1.6	-0.4	1.5	-0.5	1.3	-0.6
Nominal GDP	3.8	-0.2	3.4	-0.7	4.1	-0.2	4.6	0.2	4.5	0.2
Output gap (percent)	-3.0	-1.0	-3.3	-2.3	-2.1	-1.5	-1.1	-0.8	-0.6	-0.4
Unemployment rate (percent)	10.0	0.2	9.9	1.0	8.9	1.9	7.7	1.9	6.9	1.5
Case-Shiller 10-city house prices	-2.2	-4.3	-2.1	-4.1	2.2	-0.7	2.5	0.0	1.8	0.2
Spread of 3-month LIBOR to 3-month T-Bill	0.3	0.1	0.6	0.3	0.7	0.3	0.6	0.2	0.6	0.2
Return on assets (annualized; percent)	1.6	-0.2	1.4	-0.5	1.5	-0.4	1.6	-0.3	1.7	-0.3
Alternative Funding Risk										
Real GDP	2.4	-0.6	0.8	-1.8	1.6	-0.8	2.5	0.0	2.4	0.0
Real personal consumption expenditures	2.3	-0.2	0.2	-1.9	0.0	-2.0	1.3	-0.7	1.7	-0.2
Nominal GDP	3.3	-0.7	1.9	-2.1	3.1	-1.1	4.4	0.0	4.4	0.1
Output gap (percent)	-3.3	-1.3	-2.6	-1.6	-0.8	-0.3	-0.3	0.0	-0.1	0.0
Unemployment rate (percent)	10.6	0.8	9.9	1.0	7.2	0.1	5.8	0.0	5.5	0.0
Case-Shiller 10-city house prices	-4.1	-6.1	-2.6	-6.7	3.1	0.3	2.4	0.0	1.5	0.0
Spread of 3-month LIBOR to 3-month T-Bill	0.4	0.1	0.5	0.1	0.5	0.1	0.4	0.0	0.4	0.0
Return on assets (annualized; percent)	1.5	-0.3	1.6	-0.3	1.7	-0.2	1.8	-0.1	1.9	-0.1

Source: IMF staff

Note. Shaded numbers denote deviations from baseline.

APPENDIX IV: INDUSTRY-WIDE LOAN LOSS PROJECTIONS FOR BHCS[54]

Charge-off rates for different loan types are modeled as dependent on a set of economic and financial variables. The general methodology was initially developed and subsequently refined in the context of the system-wide capital shortfall estimates presented in the *Global Financial Stability Report* (see IMF 2008b and 2009a for a description of the methodology).

This appendix outlines the methodology for forecasting bank charge-off rates, lending standards, and house prices.

In order to better capture future turning points in the charge-off patterns, levels and log levels (rather than growth rates) were used for the explanatory variables. Since a decline in bank lending standards indicates a slower rate of tightening, the use of cumulative net balances for lending standards was warranted (referred to as "cumulative lending standards" hereafter).

This was to reflect that, for example, charge-offs can continue to rise despite a slowdown in house price declines and a deceleration in the pace of tightening in lending standards. Similarly, to capture deterioration in economic conditions amid a slowdown in negative growth rates, we used the output gap (which can be viewed as the detrended level of real GDP), instead of GDP growth.

The underlying historical data on loan loss rates and lending standards were obtained from the Federal Reserve, while macroeconomic and financial data came from Haver Analytics. Where available, forecast data were taken from the WEO. Housing prices and lending standards were modeled separately, as shown below. The sample was comprised of quarterly data from 1991 to 2009 so as to incorporate the last two recessions.

Charge-off Rates

To deal with non-stationary in the variables, the empirical Bayesian approach was employed. The estimation was carried out by running 10,000 Markov Chain Monte Carlo simulations using the Gibbs sampler package WinBUGS (Lunn and others, 2000). Convergence was obtained within 1,000 burn-in runs. The estimated coefficients in the resented equations were statistically significant at 5 percent. Lending standards were particular to each type of loan.

Real estate charge-off rates

Charge-off rates for real estate loans followed a two-step approach. First, the percent of loans that would become delinquent was estimated. Second, the "hazard rate" or the transition rate was estimated to capture the percentage of delinquent loans that would transition into actual

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[54] This appendix was prepared jointly with Sergei Antoshin (IMF).

charge-offs. The exact specification for commercial and residential charge-off rates looked as follows:

Charge-off rates for commercial real estate (C_CRE)

$$C\_CRE_t = D\_CRE_t * T\_CRE_t$$

The first term D_CRE_t is the delinquency rate, which is modeled as a function of the cumulative lending standards LS_CRE and commercial real estate pricesCP:

$$\ln(D\_CRE_r) = 0.00131*LS\_CRE_t - 2.3137*\ln(CP_t) + 11.45$$

The second term is the transition rate, which is modeled as a function of the cumulative lending standards:

$$\ln(T\_CRE_t) = 0.00117*LS\_CRE_t + 1.37$$

Residential real estate charge-off rates

$$C\_RRE_t = D\_RRE_t * T\_RRE_t$$

The delinquency rate is a function of the cumulative lending standards and level of residential real estate prices:

$$\ln(D\_RRE_t) = 0.00308*LS\_RRE_t - 0.0025*HP_t + 0.912$$

The transition rate is a function of the cumulative lending standards and unemployment rate:

$$\ln(T\_RRE_t) = 0.00284*LS\_RRE_t + 0.12848*UR_{t+4} + 0.997$$

Consumer charge-off rate (C_CONS)

The consumer loans charge-off rate is modeled as a function of the cumulative lending standards, and the output gap:

$$\ln(C\_CL_t) = 0.00079*LS\_CL_t - 0.0925*GAP_t + 0.705$$

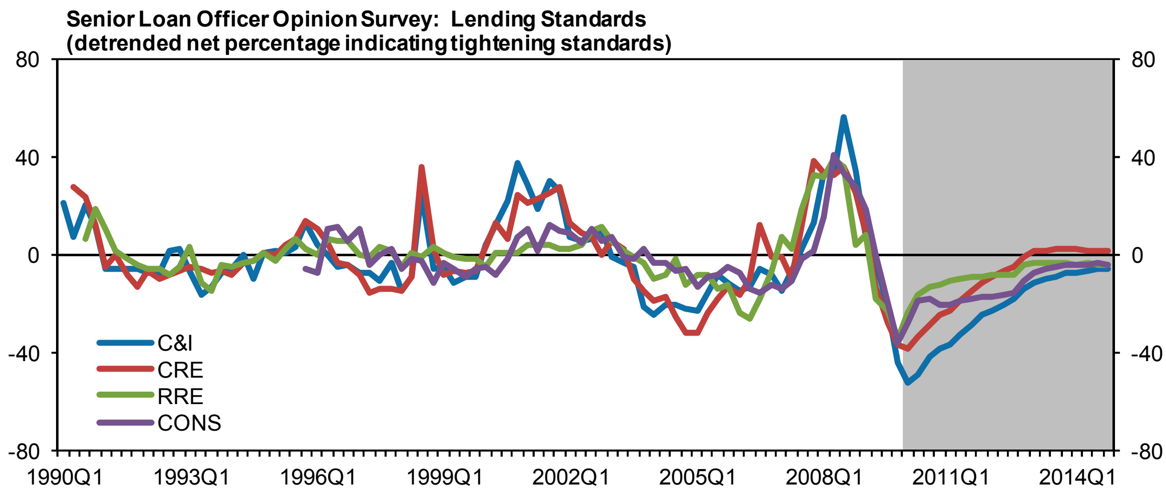
Commercial and industrial charge-off rate (C_CI)

The commercial and industrial loans charge-off rate is modeled as a function of the detrended cumulative lending standards and the output gap:

$$\ln(C\_CI_t) = 0.00341*LS\_CI\_DT_t - 0.1398*GAP_{t+1} - 0.5752$$

Lending standards

The lending standards reported in the Federal Reserve Board's Senior Loan Officer Opinion Survey of Bank Lending Practices (SLOOS) appear as an independent variable in each of the charge-off and delinquency models. The respondents to the survey, which is usually conducted quarterly, include large U.S. commercial banks and large branches and agencies of foreign banks. For each loan category, the respondents report whether over the past three months they have tightened, loosened, or maintained the criteria used to determine whether a borrower is creditworthy. The Federal Reserve Board reports these responses as the percentage of respondents indicating that their bank had tightened standards less the percentage indicating that their bank had loosened standards for a number of different kinds of loans. Whenever these measures are positive, it is generally more difficult for borrowers to obtain loans.



Source: Federal Reserve Board.

To ground forecasts of these lending standards, we estimated four vector autoregression (VAR) models. The variables in each system included real GDP growth, CPI inflation, the change in corporate bond spreads, the change in the Federal Funds Target Rate, oil prices, and the growth of total bank loans. Further, each model contained one loan category's lending standards. Since SLOOS asks banks to report on their lending standards over the previous three months, we lagged the lending standards one quarter so that the change in standards would be contemporaneous with the changes in the other variables. We obtained forecasts for each class of lending standards from the estimated systems of equations, treating the macro variables as exogenous, similar to the approach discussed by Swiston (2008).

Output from these models estimated with de-trended lending standards augurs a loosening in lending standards for all types of loans over the forecast horizon (Figure). These results are in line both with recent developments in the SLOOS as well as the baseline scenario, which calls for continued macroeconomic growth and financial stabilization. Nevertheless, to align the forecasts with the historical behavior of lending standards in previous business cycles, we adjusted model-based projections with judgmental forecasts.

House prices

Prices for residential and commercial real estate enter the equations used to forecast residential and commercial real estate loan delinquency rates. Neither the WEO nor the macro simulation models used in the scenario analysis contain a forecast for prices of housing or commercial real estate. Thus, to generate the forecasts required for the delinquency rate models, we used a model for house prices and an observation about the house prices-commercial real estate prices to generate the CRE price forecast.

We tried a number of specifications for the S&P/Case-Shiller 10-city house price index, which included variables, both considered key determinants of house prices and forecasted in the WEO and simulation models. The specification that we used in this exercise was the following:

$$\Delta^2 HP = \underset{(0.0944)^{***}}{-0.7449}*\Delta^2 HP_{t-2} + \underset{(0.2445)^{***}}{0.8184}*\Delta^2 RGDP_t + \underset{(0.2392)^{*}}{0.4605}*\Delta^2 RGDP_{t-1} - \underset{(0.0076)^{**}}{0.0154}*\Delta^2 UR_{t-1}$$

In the equation, *HP* is the 10-city S&P Case-Shiller house price index in log levels, *RGDP* is real GDP, *UR* is the unemployment rate, and Δ^2 denotes the second difference[55]. Standard errors are reported underneath the coefficient estimates, and ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively. Under the baseline scenario, using output and unemployment forecasts from WEO, house prices rise moderately but are still 24 percent below their 2006:Q2 peak by end-2014.

The calculations use the observation that developments in house prices have generally feed into commercial real estate prices with a lag when forecasting CRE prices. Consistent with the GFSR's methodology, the MIT Center for Real Estate's Transactions-Based Index of Institutional Commercial Property Investment Performance was used. Since the late-1980s, this price index has closely tracked the Case-Shiller index, with about a four-quarter lag (table). Taking this relationship into account, we took actual and forecasted growth rate for the Case-Shiller index and used it to project CRE prices for the same period in the following year. As with house prices, commercial real estate prices increase steadily, but are 39 percent off their 2007:Q2 peak and the end of the forecast period.

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[55] The second-difference was used after performing an Augmented Dickey-Fuller test on the Case-Shiller 10-city house price inflation rate series, which provided evidence of a unit root.

Table 19. Correlations Between Commercial and residential Real Estate Prices

(Sample: 1987:Q1 - 2009:Q4)

	Commercial real estate prices					
	t	t+1	t+2	t+3	t+4	t+5
S&P Case-Shiller house prices (10-city)						
Levels	0.92	0.94	0.95	0.96	0.96	0.95
Growth	0.43	0.33	0.31	0.41	0.49	0.34

Sources: S&P/MacroMarkets, LLC; MIT Center for Real Estate; Haver Analytics; and Fund staff estimates.

APPENDIX V: RISK AVERSION ADJUSTMENT AND THE MARKET PRICE OF RISK

CDS-PoDs, as any other PoD inferred from market prices, reflect both market expectations of the assets' *actual* risk (based on the market expectations of the assets' returns) and systemic risk aversion (the price of risk, which is the price that investors are willing to pay for receiving "income" in "distressed" states of nature). Therefore, in order to estimate losses, which should be based on *actual* risk, it is necessary to strip out the effect of risk aversion from risk neutral PoDs. The linear pricing and the risk-neutral pricing formulae (see Cochrane, 2001) state that, if $m_{t+1}(s)$ is the price of a security paying \$1 in state s, then the price of an asset paying off an uncertain stream x_{t+1} next period is:

$$P_t = \sum_s \pi_{t+1}(s) m_{t+1}(s) x_{t+1}(s) = \frac{1}{1+r_t^f} \sum \hat{\pi}_{t+1}(s) x_{t+1}(s) = \frac{\hat{E}_t[x_{t+1}]}{1+r_t^f}$$

$\pi_{t+1}(s)$ is the *actual* probability of nature that state s occurs and r_t^f is the risk-free rate. Note that: $\sum_s m_{t+1}(s) = 1/(1+r_t^f)$) and $\hat{\pi}_{t+1}(s) = (1+r_t^f)\pi_{t+1}(s) m_{t+1}(s)$ (1)

is called the *risk-neutral* probability because it is the probability measure that a risk-neutral investor would need to use, when forming her expectations and computing a NPV consistent with the market price of the asset P_t. Estimating the *actual* probability of default from a CDS spread-implied *risk-neutral* probability is equivalent to estimating the market price of risk in the state where the CDS pays off (the *distress* test). Espinoza and Segoviano (2010) use the conditional expectation formula for normal distributions to estimate

$$E_t[m_{t+1} \mid distress] = E_t[m_{t+1} \mid m_{t+1} > threshold] = E_t[m_{t+1}] + \sqrt{\operatorname{var}_t[m_{t+1}]} \frac{\varphi(\alpha_t)}{1 - \Phi^{-1}[\alpha_t]} \quad (2)$$

Where $\alpha_t = (threshold - E_t[m_{t+1}]) / \sqrt{\operatorname{var}_t[m_{t+1}]}$, φ is the normal distribution density function, and Φ^{-1} is the inverse cumulative distribution function of the normal distribution. $\sqrt{\operatorname{var}_t[m_{t+1}]}$ is deduced from the *price* of risk $\lambda_m = (1+r_t^f)\operatorname{var}(m_{t+1})$, which is an important variable in the CAPM literature. In a CAPM, excess returns are equal to the *price* of risk multiplied by the *quantity* of risk – the beta of an asset - since $E_t[r_{t+1}^i] - r_t^f = \beta_{i,m}\lambda_m$. The *price* of risk can be estimated via the Fama-MacBeth regressions. Espinoza and Segoviano (2010) suggest a calibration based on the VIX. At any single point in time, the market price of risk under stress (the conditional expectation) is re-calculated since the risk-free rate (the mean) and the price of risk (the variance) are changing. The threshold defines the scenario under which the asset is under distress. Such threshold can be defined exogenously or it can be chosen, in a more consistent way, such that the probability that the market-price of risk exceeds the threshold is equal to the actual probability of nature:

$$threshold = E[m] + \Phi^{-1}[1 - \pi_t] * \sqrt{\operatorname{var}(m)} \quad (3)$$

In that case, the non-linear equations (1), (2) and (3) have to be solved jointly. Espinoza and Segoviano (2010) show that there is a unique solution.

APPENDIX VI: THE CONSISTENT INFORMATION MULTIVARIATE DENSITY OPTIMIZING METHODOLOGY

The Consistent Information Multivariate Density Optimizing (CIMDO) methodology is based on the minimum cross-entropy approach (Kullback, 1959). Under this approach, a *posterior* multivariate distribution *p*—the CIMDO-density—is recovered using an optimization procedure by which a *prior* density *q* is updated with empirical information via a set of constraints. Thus, the *posterior* density satisfies the constraints imposed on the *prior* density. In this case, the FIs' empirically estimated PoDs represent the information used to formulate the constraint set. Accordingly the CIMDO-density—the PMD—is the *posterior* density that is closest to the *prior* distribution and that is *consistent* with the empirically estimated PoDs of the FIs making up the system. In order to formalize these ideas, we proceed by defining a financial system—portfolio of FIs—comprising two FIs; i.e., FI X and FI Y, whose logarithmic returns are characterized by the random variables x and y. Hence we define the CIMDO-objective function as: $C[p,q]=\int\int p(x,y)\ln\left[\frac{p(x,y)}{q(x,y)}\right]dxdy$, where $q(x,y)$ and $p(x,y) \in \mathbb{R}^2$. It is important to point out that the *prior* distribution follows a parametric form q that is consistent with economic intuition (e.g., default is triggered by a drop in the firm's asset value below a threshold value) and with theoretical models (i.e., the structural approach to model risk). However, the parametric density q is usually inconsistent with the empirically observed measures of distress. Hence, the information provided by the empirical measures of distress of each FI in the system is of prime importance for the recovery of the *posterior* distribution. In order to incorporate this information into the *posterior* density, we formulate consistency-constraint equations that have to be fulfilled when optimizing the CIMDO-objective function. These constraints are imposed on the marginal densities of the multivariate *posterior* density, and are of the form:

$$\int\int p(x,y)\,\chi_{\left(x_d^x,\infty\right)}dxdy = PoD_t^x, \int\int p(x,y)\,\chi_{\left(x_d^y,\infty\right)}dydx = PoD_t^y \qquad (1)$$

where $p(x,y)$ is the *posterior* multivariate distribution that represents the unknown to be solved. PoD_t^x and PoD_t^y are the empirically estimated probabilities of distress (PoDs) of each of the FIs in the system, and $\chi_{\left[x_d^x,\infty\right)}$, $\chi_{\left[x_d^y,\infty\right)}$ are indicating functions defined with the distress thresholds x_d^x, x_d^y, estimated for each FI in the portfolio. In order to ensure that the solution for $p(x,y)$ represents a valid density, the conditions that $p(x,y) \geq 0$ and the probability additivity constraint $\int\int p(x,y)dxdy = 1,$ also need to be satisfied. Once the set of constraints is defined, the CIMDO-density is recovered by minimizing the functional:

$$L[p,q] = \int\int p(x,y)\ln p(x,y)dxdy - \int\int p(x,y)\ln q(x,y)\,dxdy + \qquad (2)$$

$$\lambda_1\left[\int\int p(x,y)\,\chi_{[x_d^x,\infty)}dxdy - PoD_t^x\right] + \lambda_2\left[\int\int p(x,y)\,\chi_{[x_d^y,\infty)}dydx - PoD_t^y\right] + \mu\left[\int\int p(x,y)\,dxdy - 1\right]$$

where λ_1, λ_2 represent the Lagrange multipliers of the consistency constraints and μ represents the Lagrange multiplier of the probability additivity constraint. By using the calculus of variations, the optimization procedure can be performed. Hence, the optimal solution is represented by a *posterior* multivariate density that takes the form

$$\widehat{p(x,y)} = q(x,y)\exp\left\{-\left[1+\widehat{\mu}+(\widehat{\lambda_1}\chi_{\left[x_d^x,\infty\right)})+(\widehat{\lambda_2}\,\chi_{\left[x_d^y,\infty\right)})\right]\right\} \qquad (3)$$

Intuitively, imposing the constraint set on the objective function guarantees that the *posterior* multivariate distribution (the PMD) contains marginal densities that satisfy the PoDs observed empirically for each FI in the portfolio. CIMDO-recovered distributions outperform commonly used parametric multivariate densities in the modeling of portfolio risk under the Probability Integral Transformation criterion. When recovering multivariate distributions through the CIMDO approach, information embedded in the constraint set is used to adjust the "shape" of the PMD via the optimization procedure described above. This appears to be a more efficient manner of using the empirically observed information than under parametric approaches, which adjust the "shape" of parametric distributions via fixed sets of parameters. For detailed robustness test see Segoviano (2006).

APPENDIX VII: THE CIMDO-COPULA: INCORPORATION OF CHANGES IN DISTRESS DEPENDENCE AS PROBABILITY OF DISTRESS OF INDIVIDUAL FIS CHANGE

To provide a heuristic explanation of the CIMDO-copula, and how it incorporates changes in distress dependence "automatically" as PoDs of individual FIs change, we define a bivariate copula from a parametric distribution and the CIMDO-copula. First, Segoviano and Goodhart (2009) show that if x and y are two random variables with individual distributions $x \sim F, y \sim H$ and a joint distribution $(x, y) \sim G.$ The joint distribution contains three *types* of information. Individual (marginal) information on the variable *x*, individual (marginal) information on the variable *y* and information on the dependence between *x* and *y*. In order to model the dependence structure between the two random variables, the copula approach *sterilize*s the marginal information on *x* and *y* from their joint distribution; consequently, isolating the dependence structure. *Sterilization* of marginal information is done by transforming the distribution of *x* and *y* into a uniform distribution, **U(0,1)**, which is *uninformative*. Under this distribution the random variables have an equal probability of taking a value between 0 and 1 and a zero probability of taking a value outside [0,1]. Therefore, this distribution is typically thought of as being *uninformative*. To transform *x* and *y* into **U(0,1),** the Probability Integral Transformation is used, under which two new variables are defined as $u = F(x), v = H(y),$ both distributed as U(0,1) with joint density $c[u, v]$. Under the distribution of transformation of random variables (Cassella and Berger, 1990), the copula function $c[u, v]$ is defined as: $c[u,v] = \dfrac{g\left[F^{(-1)}(u), H^{(-1)}(v)\right]}{f\left[F^{(-1)}(u)\right]h\left[H^{(-1)}(v)\right]},$

where g, f, and h are defined densities. From this equation (1), we see that copula functions are multivariate distributions, whose marginal distributions are uniform on the interval [0,1]. Segoviano (2006) shows that the CIMDO distribution with *q*(*x*,*y*) as the prior is of the form,

$$\widehat{p(x,y)} = q(x,y)\exp\left\{-\left[1+\widehat{\mu}+(\widehat{\lambda_1}\chi_{\left[x_d^x,\infty\right)})+(\widehat{\lambda_2}\,\chi_{\left[x_d^y,\infty\right)})\right]\right\}.$$ We define

$u = F_c(x) \Leftrightarrow x = F_c^{-1}(u),$ and $v = H_c(y) \Leftrightarrow y = H_c^{-1}(v).$ Thus, the CIMDO marginal densities take the form, $f_c(x) = \int_{-\infty}^{+\infty} q(x,y)\exp\left\{-\left[1+\widehat{\mu}+(\widehat{\lambda_1}\chi_{x_d^x}(x))+(\widehat{\lambda_2}\chi_{x_d^y}(y))\right]\right\}dy,$ and

$$h_c(y) = \int_{-\infty}^{+\infty} q(x,y)\exp\left\{-\left[1+\widehat{\mu}+(\widehat{\lambda_1}\chi_{x_d^x}(x))+(\widehat{\lambda_2}\chi_{x_d^y}(y))\right]\right\}dx.$$

Substituting these into the copula definition we get, the CIMDO-copula, $c_c(u, v),$

$$c_c(u,v) = \frac{q\left[F_c^{-1}(u), H_c^{-1}(v)\right]\exp\left\{-\left[1+\widehat{\mu}\right]\right\}}{\int_{-\infty}^{+\infty} q\left[F_c^{-1}(u), y\right]\exp\left\{-\widehat{\lambda_2}\chi_{x_d^y}(y)\right\}dy\int_{-\infty}^{+\infty} q\left[x, H_c^{-1}(v)\right]\exp\left\{-\widehat{\lambda_1}\chi_{x_d^x}(x)\right\}dx}.$$

This equation shows that the CIMDO-copula is a nonlinear function of $\widehat{\mu}, \widehat{\lambda_1},$ and $\widehat{\lambda_2}$, which change as the PoDs of the FIs under analysis change. Therefore, the CIMDO-copula captures changes in PoDs, as these changes at different periods of the economic cycle.

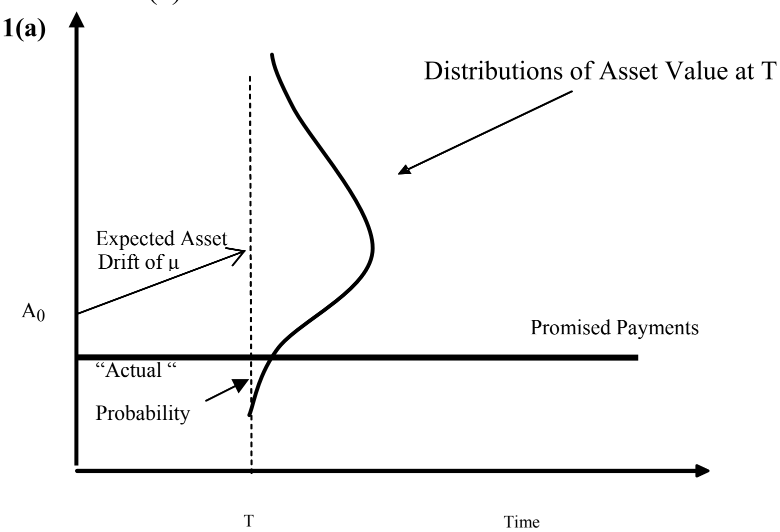
APPENDIX VIII: CONTINGENT CLAIMS ANALYSIS

Contingent Claims Analysis

Contingent claims analysis is used to construct risk-adjusted balance sheets and is based on three principles: (i) the values of liabilities (equity and debt) are derived from assets; (ii) liabilities have different priority (i.e. senior and junior claims); and, (iii) assets follow a stochastic process. Assets (present value of income flows, proceeds from assets sales, etc.) are stochastic and over a horizon period may be above or below promised payments on debt which constitute a default barrier. Uncertain changes in future asset value, relative to the default barrier, are the driver of default risk which occurs when assets decline below the barrier.

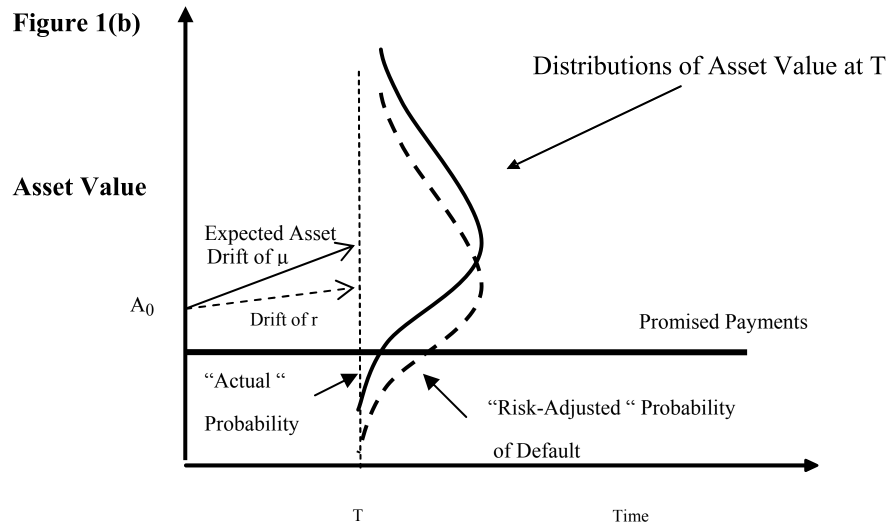
The value of assets at time t is *A(t)*. The asset return process is $dA/A = \mu_A dt + \sigma_A \varepsilon \sqrt{t}$, where μ_A is the drift rate or asset return, σ_A is equal to the standard deviation of the asset return, and ε is normally distributed, with zero mean and unit variance. The probability distribution at time *T* is shown in (a) below.

Figure 1(a)



Default occurs when assets fall to or below the promised payments, B_t. The probability of default is $A_t \le B_t$ so that $\text{Prob}(A_t \le B_t) = \text{Prob}\left(A_0 \exp\left[\left(\mu_A - \sigma_A^2/2\right)t + \sigma_A \varepsilon \sqrt{t}\right] \le B_t\right) = \text{Prob}\left(\varepsilon \le -d_{2,\mu}\right)$. Since $\varepsilon \sim N(0,1)$, the "actual" probability of default is $N(-d_{2,\mu})$, where $d_{2,\mu} = \frac{\ln\left(A_0/B_t\right) + \left(\mu_A - \sigma_A^2/2\right)t}{\sigma_A \sqrt{t}}$. Shown in (b) below is the probability distribution (dashed line) with drift of the risk-free interest rate, *r*. Risk adjusted probability of default is $N(-d_2)$.

Figure 1(b)



The area below the distribution in Figure 1(a) is the "actual" probability of default. The asset-return probability distribution used to value contingent claims is not the "actual" one but the "risk-adjusted" or "risk-neutral" probability distribution, which substitutes the risk-free interest rate for the actual expected return in the distribution. This risk-neutral distribution is the dashed line in Figure 1(b) with expected rate of return r, the risk-free rate. Thus, the "risk-adjusted" probability of default calculated using the "risk-neutral" distribution is larger than the actual probability of default for all assets which have an actual expected return (μ) greater than the risk-free rate r (that is, a positive risk premium).[56] The calculations of the "actual" probability of default is outside the CCA/Merton Model but it can be combined with an equilibrium model of underlying asset expected returns to produce estimates that are consistent for expected returns on all derivatives, conditional on the expected return on the asset. (The rationale is that one does not have to know expected returns to use the CCA/Merton models for the purpose of value or risk calculations.)

Technical description of the Systemic CCA methodology

We assume that individual implicit put options as individual estimates of expected losses (or individual implicit put options times the alpha-values as individual estimates of contingent liabilities) are represented as an independent and identically distributed (i.i.d.) random vector $\mathbf{X}_{i,j} = \left(X_{1,1},...,X_{1,p}\right),...,\left(X_{n,1},...,X_{n,p}\right)$ of multivariate observations.

We first specify individual asymptotic tail behavior of elements in $\mathbf{X}_{i,j}$ as limiting law of a p-sequence of normalized maxima, such that the probability of the order statistic

[56] See Merton (1992, pp.334-343; 448-450).

$\lim_{n\to\infty} \Pr\left(\left(X_{p:p}^{1}-b_{p}^{1}\right)/a_{p}^{1},\ldots,\left(X_{p:p}^{n}-b_{p}^{n}\right)/a_{p}^{n}\right)$ converges to the non-degenerate limit distribution $G(X)$ as $n\to\infty$ and $X\in\mathbb{R}$ (Vandewalle et al., 2004; Stephenson, 2002),[57]

$$F_n^{[t]}(X)=\lim_{n\to\infty}\Pr\left(\left(Y-b_n\right)/a_n\le y\right)=\left[F\left(a_n y+b_n\right)\right]^n\to G(x) \tag{A1}$$

for a choice of constants $a_n>0$ and b_n. If $F_n^{[a_n x+b_n]}(x)\approx G(x)$, each univariate marginal distribution $Y_j=F_j\left(X_j\right)=\left(1+\xi_j\left(x-\mu_j\right)/\sigma_j\right)_+^{-1/\xi_j}$ with $1+\xi_j\left(x-\mu_j\right)/\sigma_j>0$ is generalized extreme value and unit exponential, so that $G(x)=\exp\left(-Y_j\right)$ for p=1,…,*n* where μ_j is the location parameter, scale parameter $\sigma_j>0$, and shape parameter ξ_j. The higher the absolute value of shape parameter, the larger the weight of the tail and the slower the speed at which the tail approaches its final *y*-value of 0 (asymptotic tail behavior).[58]

As an alternative to a copula function $C\left\{F_1\left(X_1\right),\ldots,F_n\left(X_n\right)\right\}$ that links the *i*th univariate marginal distributions using only a single (and time-invariant) dependence parameter, we then specify the multivariate dependence structure in the form of function $A\left(\omega_1,\ldots,\omega_{p-1}\right)$. $A(.)$ can be derived non-parametrically by expanding the bivariate logistic method proposed by Pickands (1981)

$$A(\omega)=A\left(\omega_1,\ldots,\omega_{p-1}\right)=n\left\{\sum_{i=1}^{n}\min\left(\frac{Y_{i,1}}{\omega_1},\ldots,\frac{Y_{i,p}}{\omega_p}\right)\right\}^{-1}=n\left\{\sum_{i=1}^{n}\bigwedge\nolimits_{j=1}^{p}\frac{Y_{j,1}}{\omega_j}\right\}^{-1} \tag{A2}$$

to the multivariate case and adjusting the margins according to Hall and Tajvidi (2000) so that

$$A_n(\omega)=n\left\{\sum_{i=1}^{n}\bigwedge\nolimits_{j=1}^{p}\frac{Y_{i,j}/\hat{Y}_{\bullet j}}{\omega_j}\right\}^{-1} \tag{A3}$$

for any point in time *t* over the sample period *T*, where $\hat{Y}_{\bullet j}=\sum_{i=1}^{n}Y_{ij}/n$, subject to the optimization problem of the (*p*-1)-dimensional unit simplex

[57] The upper tails of most (conventional) limit distributions (weakly) converge to this parametric specification of asymptotic behavior, irrespective of the original distribution of observed maxima (unlike parametric VaR models).

[58] The shape parameter also indicates the number of moments of the distribution, e.g., if $\xi=2$, the first moment (mean) and the second moment (variance) exist, but higher moments have a finite value. This is of practical importance since many results in for asset pricing in finance rely on the existence of several moments.

$$S_p = \left\{ \left(\omega_1, ..., \omega_{p-1} \right) \in \mathbb{R}_+^n : \omega_k \geq 0, 1 \leq k \leq p-1; \sum_{k=1}^{p-1} \omega_k \leq 1 \text{ and } \omega_p = 1 - \sum_{k=1}^{p-1} \omega_k \right\}. \quad \text{(A4)}$$

Since the estimator $A_n(\omega)$ of $A(.)$ over p observations does not satisfy $0 \leq \max\left(\omega_1, ..., \omega_{p-1}\right) \leq A_n(\omega) \leq 1$ for all $0 \leq \omega \leq 1$, we resort to an obvious modification to derive the rationally scaled measure

$$A_n^{'}(\omega) = \min\left(1, \max\left\{A_n(\omega), \omega, 1-\omega\right\}\right) \quad \text{(A5)}$$

so that $A_n^{'}(.)$ represents a convex function on $[0,1]$ with $A_n^{'}(0) = A_n^{'}(1) = 1$, i.e. the upper and lower limits are obtained under complete dependence and mutual independence respectively. $A_n^{'}\left(\omega_1, ..., \omega_{p-1}\right) \equiv 1$ implies that each component of $\mathbf{X}_{i,j}$ is independent of all the others, while $A_n^{'}\left(\omega_1, ..., \omega_{p-1}\right) \equiv \max\left(\omega_1, ..., \omega_{p-1}\right)$ signifies that $F_1(X_1) \equiv ... \equiv F_p(X_p)$.

Finally, both the marginal distribution and the dependence structure can be estimated recursively or based on a rolling window of length τ with periodic updating, so that we obtain the point estimate

$$\hat{x}_{a,p} = G_{\hat{\xi},\hat{\mu},\hat{\sigma}}^{-1}(a) = \hat{\mu}_j + \hat{\sigma}_j \big/ \hat{\xi}_j \left(\left(-\frac{\ln(a)}{A_n^{'}(\omega)} \right)^{-\hat{\xi}_j} - 1 \right) \quad \text{(A6)}$$

of the complete multivariate density $G_{\hat{\xi},\hat{\mu},\hat{\sigma}}^{-1}(.)$ at quantile q=1-a over estimation period τ, where

$$G_{t,\mu,\sigma,\xi}(x) = \exp\left\{ -\left(\sum_{j=1}^{p} Y_{j,t} \right) A_n^{'}(\omega) \right\}_{59} \quad \text{(A7)}$$

Based on (A7) above, we obtain the ES (or *conditional* Value-at-Risk (VaR)) as the probability-weighted residual density beyond a pre-specified statistical significance of 1-q=a (say, a=0.05 for 95th percentile threshold) of maximum losses.[60] Thus, ES defines the average

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[59] Note that we do not consider notation for the estimation time period τ and drop time-dependence of the point estimate at time t for simplicity in the rest of the paper.

[60] Expected shortfall (ES) is an improvement over VaR, which, in addition to being a pure frequency measure, is "incoherent", i.e., it violates several axioms of convexity, homogeneity, and sub-additivity found in coherent risk measures. For example, sub-additivity, which is a mathematical way to say that diversification leads to less risk, is not satisfied by VaR. In contrast, ES is a coherent risk measure, but conditioning ES on the most severe outcomes for the entire sample of banks ignores the potential optionality that a wide range of underlying asset values below the ES threshold could increase the magnitude of tail events.

value of the aggregate implicit put option (or contingent liabilities if we control for the alpha-value) on days when it exceeds the statistical confidence limit of q. We can write the average daily ES for a total sample of p institutions as

$$ES_{a,t} = -\mathrm{E}\left[P_{p,t} \middle| P_{p,t} \geq G^{-1}_{t,\mu,\sigma,\xi}(a) = VaR_{q_a,t} \right] \quad \text{(A8)}$$

for every day t within the sample time period T for threshold quantile

$$VaR_{q_a,t} = \sup\left\{ G^{-1}_{t,\mu,\sigma,\xi}(\bullet) \middle| \Pr\left[P_{p,t} > G^{-1}_{t,\mu,\sigma,\xi}(\bullet) \right] \leq a = 0.05 \right\}, \quad \text{(A9)}$$

assuming a confidence level of 1-a=0.95.

Scenario Analysis Steps

We follow the following steps to estimate the impact of counterfactual policies:

Estimate the bivariate extreme value distribution (EVD) (Pickands, 1990) *between pairs of CCA input parameters* underlying the individual put option values of sample institutions (equity and implied assets as well as implied assets and asset volatility). This method is superior to the frequently used method of statistical mapping, because it matches both variables conditional on actual joint occurrence over the historical sample period (rather than similar individual probability of occurrence regardless of timing).

Let *G(.)* be the fitted bivariate distribution function with margins G_1 and G_2, such that the quantile function for the probability p is defined by

$$\hat{x}_p = G^{-1}_{\hat{\xi},\hat{\mu},\hat{\sigma}}(p) = \left\{ G_1^{-1}(p_1), G_2^{-1}(p_2) \right\}$$

where $p_{1,n} = p^{\omega / A_n^{'}(\omega)}$ and $p_{2,n} = p^{(1-\omega)/A_n^{'}(\omega)}$, with $A_n^{'}(.)$ being the estimated non-parametric dependence function defined in equation (8) above, where $\omega \in [0,1]$. The margins are estimated under convergence to the generalized extreme value distribution (Section IV).

Derive of the modified bivariate generalized extreme value by matching the first moment so that theoretical and empirical percentiles of parameter distributions are the same on the day of intervention. In this way, we control for the intertemporal change in default barrier affecting the historical relationship between CCA input parameters.

Determine the impact of one (or more) capital injection(s) on CCA input parameters (incl. default barrier) of an institution (here: Citigroup, Bank of America and AIG) over a three-day event window (including one day before and one day after the intervention) by calculating the sensitivity of both the equity price and the implied asset value of each firm to US$1 billion of capital injected.

Derive the counterfactual asset process of the CCA input parameters (Efron, 1992; Tibshirani, 1988; Efron and Tibshirani, 1986 and 1993).

- Bootstrap the sample mean (and associated confidence intervals) of the sample mean of all "shocked" CCA input parameters (see step 2 above), using a rolling estimation window starting 60 days prior to intervention, for each day after the intervention.

- Adjust estimated asset process by dilution effect on day of intervention and condition the asset process on subsequent capital injections, such as in the case of both Citigroup and Bank of America, which received US$45 billion and US$45 billion under both the Capital Purchase Program and the Targeted Investment Program (TIP).

Re-calculate the revised put option value (using the updated CCA input parameters) in order to derive both expected losses and contingent liabilities for each institution.

Re-estimate the multivariate density of all put option values using the Systemic CCA framework.

APPENDIX IX: DIFFERENT SYSTEMIC RISK MEASURES

The goal of financial systemic risk measures is to quantify the impact of the potential failure of individual financial institutions on a system as a result of the volume of financial services provided and the interlinkages between institutions, which could be exacerbated by the degree of complexity of financial institutions, leverage, and maturity mismatches. The ultimate objective is to assess how the individual contribution to systemic risk could be internalized through special taxes, risk-based surcharges, and/or insurance premiums that mitigate excessive risk-taking. Four of the main systemic risk models proposed so far are CoVaR, Systemic Expected Shortfall (SES), Distress Insurance Premium (DIP), and Systemic CCA. A short description and a comparison of several systemic risk measures is shown below and in Table 20.

CoVaR (Adrian and Brunnermeier, 2008): The CoVaR quantifies how financial difficulties of one institution can increase the tail risk of others. CoVaR for a certain institution is defined as the VaR of the whole sector conditional on a particular institution being in distress. More specifically, the CoVar of Bank X is the conditional VaR of Bank Y, after conditioning that Bank X is in difficulty (Bank X marginal contribution to systemic risk is then computed as the difference between its CoVaR and the financial system's VaR. The methodology uses quintile regression analysis to predict future CoVaR on a quarterly basis, which are then related to particular characteristics (e.g., leverage) and observed market risk factors (e.g., CDS spreads). The model relies on infrequent bank-specific VaRs and there are methodological short-comings in the estimation of system-wide VaR. The concept of "Conditional CoRisk" (Chan-Lau, 2010) is a framework similar to CoVaR, which allows the examination of defaults of pairs of institutions (based on quantile regressions of CDS spreads) without ignoring important data influencing this relation. In addition to CoVaR, this measure of bivariate dependence also conditions the sensitivity of CoVaR on the individual tail risk of one institution.

Systemic Expected Shortfall (SES) (Acharya et al., 2009) The marginal expected shortfall (MES) specifies historical expected losses, conditional on having breached some high systemic risk threshold. Adjusting MES by the degree of firm-specific leverage and capitalization yields the SES. MES measures only the average, linear, bivariate dependence. It does not consider interaction between subsets of banks and is limited to cases when the *entire* banking sector is undercapitalized.

Distress Insurance Premium (DIP) (Huang et al., 2010): This approach to measuring and stress-testing the systemic risk of a banking sector extends the approach Huang, Zhou, and Zhu (2009) to identifying various sources of financial instability and to allocating systemic risk to individual financial institutions. The systemic risk measure, called the Distress Insurance Premium is defined as the insurance cost to protect against distressed losses in a banking system, is a summary indicator of market perceived risk that reflects expected default risk of individual banks and correlation of defaults. It combines estimates of default risk backed out of CDS spreads with correlation backed out of bank equity returns.

Systemic Contingent Claims Approach (Systemic CCA) (Gray and Jobst, 2010 and forthcoming). This approach uses CCA for individual institutions and estimates a multivariate generalized extreme value distribution with a time-varying and non-linear dependence structure to measure the potential of systemic distress (measured as Expected Shortfall) under explicit tail risk assumptions. Information from equity and CDS markets is used to calculate both individual contingent liabilities and a conditional, non-linear metric of systemic contingent liabilities. By applying a multivariate set-up, it is able to quantify the marginal contribution of an individual firm, while accounting for rapidly changing market valuations of balance sheet structures. It can be adapted to value systemic risk charges/guarantees /insurance within a consistent framework for estimating potential losses based on current market conditions using forward-looking information rather than on historical experience (Khandani et al., 2009).

Table 20. Comparison of Systemic Risk Measures

	Conditional Value-at-Risk (CoVaR)	Systemic Expected Shortfall (SES)	Distress Insurance Premium (DIP)	Systemic Contingent Claims Analysis (CCA)
Dimensionality	multivariate	bivariate	bivariate	multivariate
Frequency	quarterly	quarterly	daily	daily
Conditionality	percentile of individual default risk	percentile of total default risk	percentile of total default risk	both (individual and joint default risk)
Dependence measure	linear, parametric	empirical	linear, parametric	non-linear, non-parametric
Method	panel quantile regression	empirically-derived expected shortfall	conditional correlation (DCC GARCH)	various option pricing and RND estimation methods, multivariate GEV
Data Input	asset returns	equity returns	equity returns and CDS implied default probabilities	expected losses ("implicit put option")
Macro/Micro Control Factors	macro state variables in panel estimation	leverage ratio as scaling factor of SES	n.a.	reduced-form estimation in balance sheet identities of CCA and implicit put option
Reference	*Adrian and Brunnermeier (2008)*	*Acharya, Pedersen, Philippon and Richardson (2009)*	*Huang, Zhou and Zhu (2010)*	*Gray and Jobst (2010)*

Source: IMF staff.

Discussion and comparison

CoVaR and the parametric specification of SES/MES use quarterly estimated data (due to the estimation of a leverage ratio from quarterly available data), which is insensitive to rapidly changing market valuations of balance sheet structures.

The concept of ES applied in SES and Systemic CCA is an improvement over VaR as a pure frequency measure used in CoVaR and CoRisk approaches.[61] While ES is a coherent risk measure, conditioning ES on the most severe outcomes for the entire sample of banks in SES, however, ignores the potential that a wide range of underlying asset values below the ES threshold could increase the residual risk and the magnitude of tail events. While SES explicitly controls for market conditions (similar to contingent claims analysis (CCA) where the implicit put option (either using default barrier or using default barrier plus minimum capital) is a function of market leverage (i.e., market value of asset and barrier)), it does so only after the estimation of ES, whereas Systemic CCA considers market leverage *ex ante*.

DIP has similarities to SES in the sense that correlations from equity market returns are used but default probabilities are backed out of CDS. The DIP framework has the advantage of using daily information from both equity markets and debt markets. The CDS reflects the retained risk in the banks since CDS is affected by government liability guarantees.

The Systemic CCA considers the time-variation of point estimates due to a periodic updating, as compared to alternative measurement approaches to systemic risk, such as CoVaR, CoRisk, and Systemic Expected Shortfall (SES). A multivariate density estimation like Systemic CCA, allows the determination of the marginal contribution of an individual institution to concurrent changes of both the severity of systemic risk and the dependence structure across any combination of sample institutions for any level of statistical confidence and at any given point in time. Combining individual contingent liabilities with a measure of joint contingent liabilities generates a conditional, non-linear metric of systemic risk sensitivity to individual firms. Estimating the empirical bivariate density of both vectors over the entire distribution of expected losses (rather than a *specific* quantile, like CoVaR) returns the marginal rate of substitution (MRS) between the individual and the joint impact of expected losses on contingent liabilities.

[61] ES is known to be a coherent risk measures. For example, sub-additivity, which is a mathematical way to say that diversification leads to less risk, is not satisfied by VaR.

APPENDIX X: USING CCA TO CALCULATE A POSSIBLE SYSTEMIC RISK SURCHARGE

There is an ongoing debate about the advantages and disadvantages of systemic risk surcharges or fees, risk-based premiums, taxes and where such fees should be charged ex-post or ex-ante and whether proceeds would go to special funds or to general government revenue. For more information on systemic-risk-based surcharges, including systemic capital surcharges and risk-budgeting approaches (with surcharges proportional to an institution's additional contribution to systemic risk) see Chapter 2 in IMF (2010).

The CCA estimate of government contingent liabilities from the financial sector can be used to calculate a "fair value" price of a systemic risk surcharge. To illustrate this, a fair value price for guarantees or risk surcharges can be calculated from risk indicators derived from models that quantify the magnitude of risk transfer from the financial sector to the sovereign balance sheet, such as the Systemic CCA model. More specifically, the fair value (in basis points) of a risk-based surcharge that would compensate for the average contingent liabilities can be written

$$-\frac{1}{T}\ln\left(1-\frac{\frac{1}{T}G^{-1}_{\mu,\sigma,\xi}\left(a;\alpha P_{p,T}\right)}{\sum_{j}^{p}B_{j}e^{-rT}}\right)\times 10,000$$

where B represents the aggregate default barrier of all p-institutions in the sample, r is the risk-free rate, T is time horizon of the surcharge, and $G^{-1}_{\mu,\sigma,\xi}(.)$ is the multivariate density function (with location, scale and shape parameters μ,σ and ξ (Section IV)) of individual contingent liabilities as a time-varying fraction α of expected losses $P_{p,T}$ (equity put option).

As an illustration, using the results obtained from the CCA analysis since April 1, 2007 (Section IV), the estimated average annual systemic surcharge for systemically important financial institutions would at least be 49 basis points. This reflects a fair value charge to pay back the government for the implicit and explicit liability guarantees it provided over the period of the crisis. This charge would be on debt liabilities excluding insured deposits.[62] A reasonable average systemic surcharge for systemically important financial institutions would be 39 basis points per year if based on observations between July 2007 and September 2008 before the Lehman crisis (text table below).

[62] After considering the time-variation of contingent liabilities (and their distributional behavior), it would be possible to devise a counter-cyclical surcharge by combining estimates at different percentile levels of statistical confidence.

Table 21. United States: Estimated Fair Value Surcharge for Systemic Risk Based on Total Contingent Liabilities from the Financial Sector

	Systemic Cont. Liabilities - 50th percentile		*Systemic Contingent Liabilities - 95th percentile*	
Period	US$ billion	annual fee (basis points)	*US$ billion*	*annual fee (basis points)*
April 1, 2007 - Jan. 29, 2010	74	**49**	214	142
Pre-Crisis: July 1, 2007-Sept. 15, 2008	59	39	91	60
Crisis Period 1: Sept. 15-Dec. 31, 2008	43	28	479	317
Crisis Period 2: Jan. 1-May 8, 2009	119	76	359	232
Crisis Period 3: May 11, 2009-Dec. 31, 2009	88	58	227	150

Source: IMF staff estimates.

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