WP/13/88

IMF Working Paper

Market-Based Structural Top-Down Stress Tests of the Banking System

Jorge A. Chan-Lau

INTERNATIONAL MONETARY FUND

WP/13/88

IMF Working Paper

Monetary and Capital Markets Department

Market-Based Structural Top-Down Macro Stress Tests of the Banking System*

Prepared by Jorge A. Chan-Lau

Authorized for distribution by Dimitri Demekas

April 2013

Abstract

Despite increased need for top-down stress tests of financial institutions, performing them is challenging owing to the absence of granular information on banks' trading and loan portfolios. To deal with these data shortcomings, this paper presents a market-based structural top-down stress testing methodology that relies in market-based measures of a bank's probability of default and structural models of default risk to infer the capital losses they could experience in stress scenarios. As an illustration, the methodology is applied to a set of banks in an advanced emerging market economy.

JEL Classification Numbers: G32, G21, G17, G18

Keywords: Stress tests, banks, default risk, systemic risk, structural models, market prices

Author's E-Mail Address:jchanlau@imf.org

* The paper benefitted from comments by Karl Driessen, Luc Everaert, Heedon Kang, Rishi Ramchand, and Andre O. Santos. Any errors or omissions are the author's sole responsibility.

Contents Page

I. The Need for Market-Based Top-Down Stress Tests

The global financial crisis experienced in 2008-9 and its severe aftermath prompted a major shift in the conduction of financial surveillance and regulation. Rather than focusing exclusively on the risks financial institutions faced in isolation, market analysts and authorities have expanded the financial surveillance framework to assess systemic risk. In this framework, the focus is placed on the potential realization of simultaneous defaults in the financial sector and their repercussion on the real economy.

With the emphasis on systemic risk assessments, top-down macro stress tests have gained in importance (IMF, 2012). However, the data requirements for conducting standard top-down stress tests can be onerous. As an alternative, this paper proposes a simple methodology for conducting structural market-based top-down macro stress tests and illustrates it using bank data for an advanced emerging market economy. The methodology uses market estimates of a bank's probability of default to calculate how its capital structure, especifically its capital-to-asset ratio, behaves under different macro-stress test scenarios.

Before presenting the methodology standard top-down stress tests and market-based stress tests are discussed briefly below.

A. Standard Top-Down Stress Tests

Top-down stress tests specify one or more severe macroeconomic scenarios that affect all banks in a jurisdiction. In consequence, systemic risk is primarily driven by common economic shocks affecting banks. Typically, in the tests the effects run only in one direction, with the banking sector affected by shocks to the real economy but not the other way around. However, some of the most sophisticated stress testing frameworks, like the RAMSI model of the Bank of England, allow for two-way feedback between the real economy and the banking sector (Alessandri et al, 2009; Burrows, Learmonth, and McKeown, 2012).

The use of top-down macro stress tests is not a recent development. For instance, the International Monetary Fund (IMF) and the World Bank have used stress tests as an integral component of the Financial Sector Assessment Program (FSAP) since 1999. Several central banks now use stress tests to asssess the soundness of domestic banking systems to adverse shocks and to guide policy decisions concerning bank recapitalization decisions. In several countries, the results of the stress tests are reported periodically in the financial stability reports published by their central banks.

When used properly, top down macro stress tests could help restore confidence by releasing information related to the resilience of banks' balance sheets and net income under adverse shocks. For instance, the U.S. Federal Reserve conducted the 2009 Supervisory Capital Assessment Program (SCAP) to assess the capital adequacy, losses, revenues, and reserve needs of nineteen U.S. financial organizations under two different macro scenarios (Table 1). The banks' projections under the program were validated and cross-checked with supervisory models.

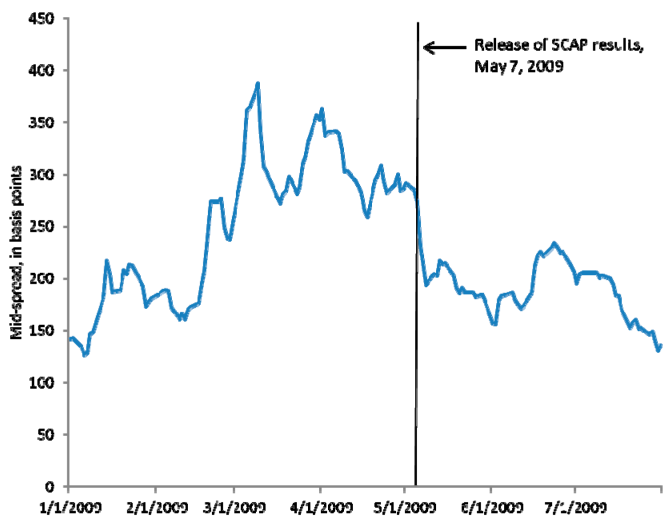
Table 1. 2009 SCAP: selected macroeconomic variables

Macroeconomic variables	Baseline		Adverse	
	2009	2010	2009	2010
Real GDP, annual percent change	-2.0	2.1	-3.3	0.5
Unemployment, in percent	8.4	8.8	8.9	10.3
Case Shiller House prices, yoy change in the fourth quarter	-14.0	-4.0	-22.0	-7.0

Source: U.S. Federal Reserve

The 2009 SCAP contributed to reduce concerns about U.S. banks, as evident in the compression of credit default swap spreads following the release of the results in early May 2009 (Figure 1). More recently, as part of the Dodd-Frank Wall Street Reform and Consumer Protection Act, the Federal Reserve has been conducting annual stress tests within the context of the Comprehensive Capital Analysis and Review (CCAR). The CCAR is used to evaluate and approve capital plans banks submit to the Federal Reserve, and includes supervisory top down stress tests to ensure financial institutions have robust, forward-loking capital planning processes.

Figure 1. US banks, 5-year CDS index



Source: CMA.

B. Market-based Top-Down Stress Tests

Market-based top-down stress tests can complement the standard stress tests described above. The latter build on detailed and granular information on the sources of income of a bank, and its loan and trading books. In contrast, market-based tests use market information on the default risk of a bank to assess the impact of different stress scenarios on its solvency. This type of tests rely on market participants' views on the soundness of a bank. Since banks are vulnerable to self-fulfilling runs, which do not need be triggered by weak fundamentals but rather by market perceptions, the use of market data in stress tests is justified. As is the case with any market-based methodology some caution is needed when interpreting results. Market prices may overestimate or underestimate risks since default risk premium is timevarying. Illiquid secondary markets could also reduce the reliability of information gathered from security prices.

Moody's Analytics' Stressed EDF is an examle of market-based top down stress test. The rating agency calculates stressed probability of defaults for individual firms for baseline and alternative economic scenarios combining its Expected Default Frequency (EDF) model and its macroeconomic modeling approach.[1] The calculation of the stressed EDFs requires estimating an econometric model linking changes in a default risk measure, the distance-to-default, and the behavior of macroeconomic variables and industry factors.[2]

Figure 2. A Taxonomy of top-down stress tests

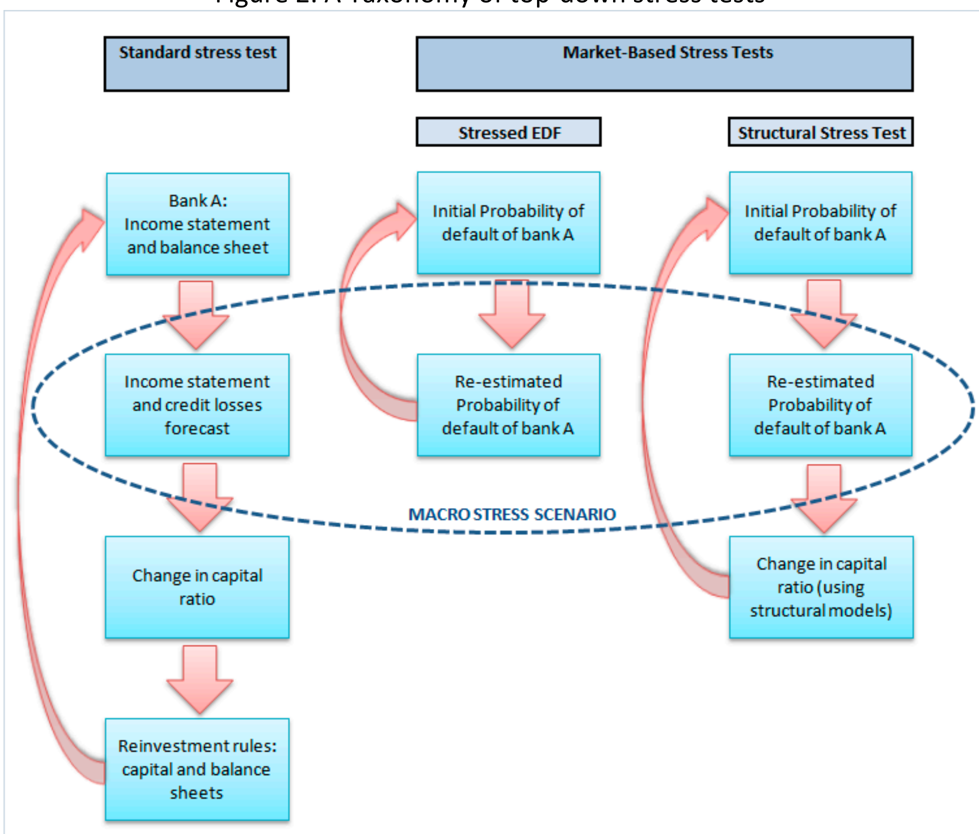


Figure 2, at the risk of oversimplification, illustrates the taxonomy and conceptual differences between standard and market-based top-down stress tests, including the structural stress test introduced here. In a standard stress test, it is necessary to forecast the income statement, including profits and loss from the trading book, and the credit losses in the macro stress scenario. Forecasting these variables requires data on the trading and banking book exposures, including the underlying credit quality of the assets.

---

[1] On the EDF model, see Bohn and Crosbie (2003); on the macroeconomic modeling approach, Zandi (2011), and on the Stressed EDF methodology, Ferry, Hughes and Ding (2012a). For applications, see Ferry, Hughes and Ding (2012a, 2012b).

[2] Wilson (1997a, b) represent earlier work on linking default rates to macroeconomic factors.

Market-based stress tests require a smaller set of data inputs. Specifically, in the stressed EDF test, the main inputs are the EDF (or probability of default) of the bank and an econometric model to link its behavior to the macro stress scenario. In the structural stress test, in addition to the probabilities of default of the bank, it is necessary to specify a structural model to link changes in the probability of default to changes in the capital structure of the bank. The calibration of the structural model requires additional data inputs which can be gathered from market prices.

The importance of translating the stress scenario into changes of capital related ratios cannot be overestimated. Since banks tend to play a systemic role in the financial system national authorities usually take a number of statutory actions, such as prompt corrective action, well ahead of the default of a bank (Chan-Lau and Sy, 2007). These actions are generally triggered by the failure of a bank's capital ratios to meet pre-established minimum levels.

The taxonomy of the top-down stress models hints at the data challenges associated with their implementation. These challenges are discussed next.

II. Data challenges associated with top-down stress tests

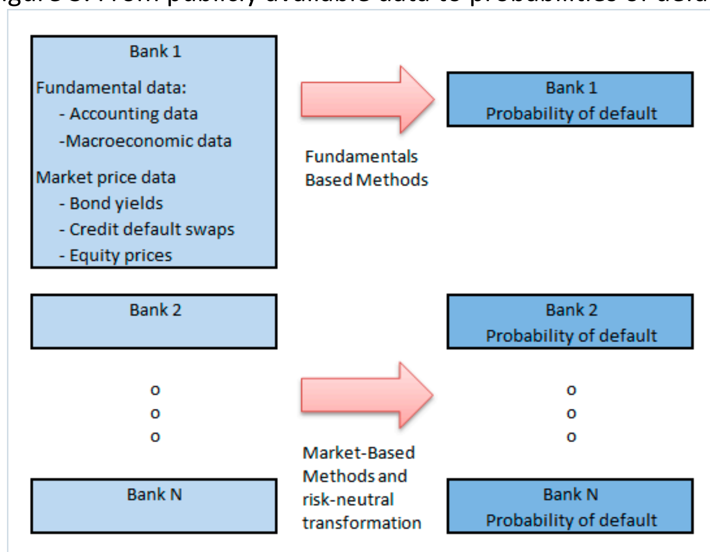
A necessary first step for performing a top-down macro stress test requires collecting the data required to evaluate how the capital buffers of banks would behave under different economic scenarios. The economic data is easy to collect since it is usually available to the public albeit with a lag. Market data, such as interest rates, bond spreads, and/or credit default swap spreads can be accessed through market data providers such as Bloomberg or Thomson Reuters Datastream. Access to financial institutions data, including banks, is more restricted since this information tends to be available mainly in restricted supervisory reports and credit registers (Canatta and Kruger, 2009).

For national central banks and domestic supervisory agencies, the conduction of supervisory top-down stress test is facilitated by the authorities' power to collect data from the institutions under their purview. The data available to the authorities could include granular information on a bank's portfolio that is not reported in regulatory filings available to the public. In the case of top-down stress tests conducted under the IMF-World Bank FSAP, the multilateral agencies tend to benefit from the close cooperation with national authorities for obtaining detailed data.

For bank analysts or country economists in the private sector accessing detailed banking data is somewhat difficult since they lack the leverage of the official sector. Performing a top-down stress test, hence, may require using data gathered from public regulatory filings and annual reports. These data can be complemented sometimes with aggregate data available from central bank and supervisory agencies, enabling the analyst to make some assumptions about the possible composition of a bank's portfolios and conduct a standard top-down stress test.

Market-based stress tests offer an alternative to the more granular approach of standard top-down stress tests. As Figure 3 indicates, different methods can be used to calculate the probability of default of a bank or other financial institutions based on accounting data and/or the prices of traded securities issued by or referencing the bank. Fundamentals-based methods, such as the Altman Z-score, credit scoring methods, or Moody's RiskCalc use financial ratios to determine the probability of default of the firm. Market-based methods reverse-engineering asset pricing models to recover probabilities of default from bond yields, credit default swap spreads, or equity prices. The resulting probabilities of default are risk-neutral since the asset pricing models weigh in the aversion of investors to adverse outcomes. But a number of different methods can be used to transform risk-neutral probabilities of default into their real-world counterparts.[3]

Figure 3. From publicly available data to probabilities of default



The next section describes in detail the methodology underlying structural market-based top-down stress tests. But before concluding this section it is important to note that assembling the required data is only the first step in a top-down stress test exercise. We will not deal in detail here on issues related to scenario design and the specification of econometric models linking economic and financial variables with the behavior of the balance sheet of financial institutions and their associated probability of default.

Instead the reader is referred to IMF and World Bank (2005) for early applications; Foglia (2009) for authorities' approaches; Quagliarello (2009) and Rosch and Scheule (2008) for comprehensive surveys of stress testing practices in the official and private sectors; IMF (2012) and Greenlaw, Kashyap, Schoenholtz, and Shin (2012) on stress testing principles; and Chan-Lau (2013) on the modeling of default risk using fundamentals and market-based data. Finally, Glasserman, Kang, and Kang (2012) offer an alternative to the standard scenario design method based on the analysis of historical episodes.

[3] For textbook treatments see Altman and Hotchkiss (2006), Bohn and Stein (2009), and Chan-Lau (2013) among others. The latter two also discuss methods for transforming risk-neutral probabilities of default into real-world probabilities of default. Lando (2004) also presents an overview of useful statistical techniques for analyzing defaults.

III. METHODOLOGY

Figure 2 shows that the difference between a market-based stress test and a market-based structural stress test boils down to the connection between the probability of default and the capital structure of the bank (or financial institution). This connection can be established using a structural model of default risk. Structural models build on the option-price analogy of the capital structure of the firm, first described by Black and Scholes (1973) and Merton (1974), which points to the call-option nature of the equity of a firm.[4]

We build the methodology starting from Merton (1974). In Merton's model the probability of default of a bank, p, over a time horizon T, can be associated with its capital structure by:

(1) $$p = \Phi\left(-\frac{\ln(V/D) + (\mu - \sigma^2 T/2)}{\sigma\sqrt{T}} \right),$$

where V/D is the inverse of the debt to asset ratio of the bank, μ and σ are the growth rate and volatility of the asset value of the bank. Therefore, if the probability of default is known, the debt to asset ratio can be calculated from equation (1) assuming reasonable estimates for the growth rate and the volatility of the asset value of the firm. Once the debt to asset ratio is known, the capital-to-asset ratio, K/V, follows simply from:

(2) $$K/V = 1 - D/V.$$

From equations (1) and (2), it follows that the probability of default is a monotonic decreasing function, G, of the capital-to-asset ratio if other model parameters are held constant:

(3) $$p = G(K/V), \qquad \frac{\partial}{\partial_{\mathrm{K/V}}} G < 0.$$

On the other hand, it is possible to link the probability of default to stress scenarios. Basically, it suffices to specify a model or equation, F, linking it to one or more of the economic variables, X, and market risk factors, M, specified in the scenarios:

(4) $$p_t = F(X_t, M_t).$$

Given the paths of the economic and market risk factors in a stress scenario, equation (4) determines the corresponding dynamics of the probability of default. From equations (3) and

---

[4] See Lando (2004) and Bohn and Stein (2009) for a comprehensive analysis of structural models. The complementary approach, reduced form models, is explained in Bielecki and Rutkowski (2002) and Duffie and Singleton (2003) among others.

(4), the mapping the economic variables and risk factors into the capital-to-asset ratio of the bank is given by:

$$K/V = G^{-1}\left(F(X_t, M_t)\right). \quad (5)$$

Since G is a monotonic function, there is a unique capital asset ratio corresponding to each value of the probability of default. While the methodology has been built using the Merton model, it is straightforward to extend it to other structural models such as those with stochastic interest rates, jumps in asset values, and default barriers (Lando, 2004). Following this clarification, the next section illustrates the methodology with a numerical example.

IV. A Numerical Illustration

Individual bank data for thirteen banks in an advanced emerging market economy were used to illlustrate the market-base structural top-down stress test methodology. The data comprised quarterly time-series of probabilities of default over a one-year horizon calculated by Moody's Analytics during the period 2006 Q3 to 2012 Q3. The one-year probabilities of default corresponded to Moody's one-year EDFs. The EDF is the physical, or real-world, probability of default obtained from using a structural model conceptually similar to that of Merton (1974). The EDF model combines observed equity prices, equity price volatility, and balance sheet data and is calibrated using Moody's proprietary historical default data (Bohn and Crosbie, 2003). Table 2 summarizes the descriptive statistics of the EDF for each bank.

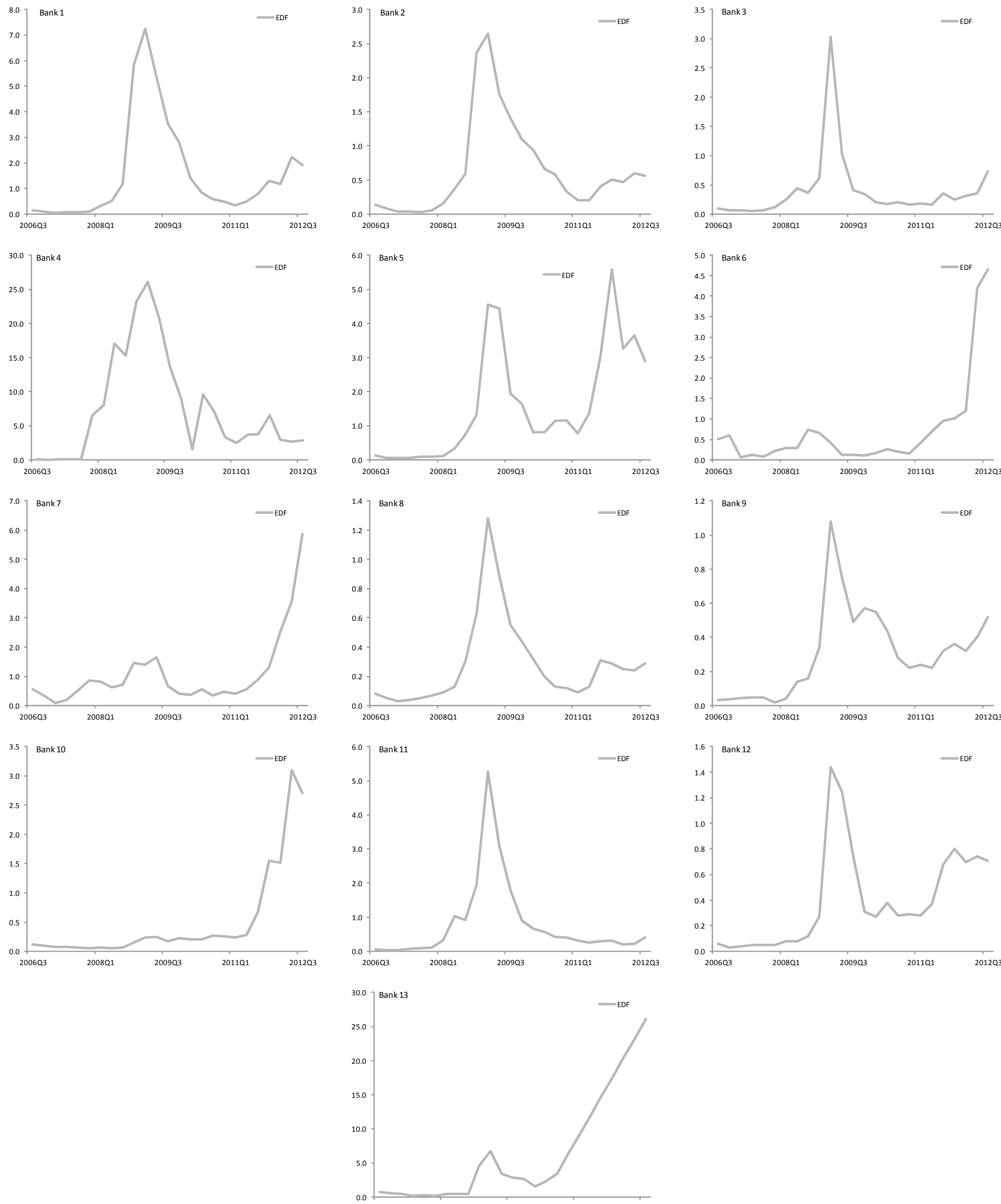
Table 2. EDF descriptive statistics, sample period 2006Q3 – 2012 Q3, in percent

	Minimum	Median	Mean	Maximum	Standard deviation
Bank 1	0.05	0.79	1.56	7.25	1.97
Bank 2	0.03	0.47	0.65	2.64	0.71
Bank 3	0.06	0.25	0.40	3.03	0.59
Bank 4	0.05	3.74	7.46	26.04	7.67
Bank 5	0.05	1.15	1.60	5.59	1.64
Bank 6	0.07	0.30	0.73	4.64	1.16
Bank 7	0.09	0.62	1.09	5.87	1.26
Bank 8	0.03	0.20	0.28	1.28	0.29
Bank 9	0.02	0.28	0.31	1.08	0.26
Bank 10	0.06	0.20	0.51	3.09	0.82
Bank 11	0.03	0.33	0.79	5.27	1.18
Bank 12	0.03	0.28	0.40	1.44	0.39
Bank 13	0.18	2.84	6.41	26.11	7.92

Source: Moody's Analytics.

Most of the banks in the sample experienced a sharp increase in their probabilities of default during the global financial crisis in 2008, which abated as global liquidity conditions and counterparty risk improved (Figure 4). Four banks that were somewhat insulated from the crisis started to experienced solvency problems in the second half of 2012.

Figure 4. Banks: One-year Expected Default Frequencies (in percent)



Source: Moody's Analytics and author's calculations.

Simple non-linear models were estimated to link the behavior of the EDF to year-on-year changes of real GDP using quarterly data spanning the period 2006 Q3 to 2012 Q3. Table 3 lists the non-linear models used and their estimated parameters. For some banks, models were estimated using only data for the period 2010 Q3 -2012 Q3.

Table 3. Non-linear models for banks' EDFs as a function of yoy real GDP changes

Three different models were fitted to link banks' expected defaut frequencies to year-on-year regal GDP changes: (1) a one-term exponential model, $y = \mathrm{a}e^{bx}$; (2) a rational polynomial, $y =$ (ax+b)/(x+c); and (3) a second degree polynomial, $y = \mathrm{a}x^2 + bx + c$. The 95 percent confidence levels are shown within brackets.

Exponential curves

Coefficients	a			b		
Bank 1	10.40	(6.45 ,	14.36)	-0.56	(-0.76 ,	-0.36)
Bank 2	3.19	(1.92 ,	4.45)	-0.45	(-0.62 ,	-0.27)
Bank 4	25.49	(10.39 ,	40.59)	-0.34	(-0.56 ,	-0.12)
Bank 5	5.67	(2.88 ,	8.46)	-0.33	(-0.51 ,	-0.15)
Bank 8	1.60	(1.09 ,	2.11)	-0.52	(-0.67 ,	-0.36)
Bank 9	1.24	(0.97 ,	1.51)	-0.38	(-0.46 ,	-0.29)
Bank 10	9.02	(0.64 ,	17.41)	-0.58	(-0.93 ,	-0.23)
Bank 12	1.84	(1.28 ,	2.40)	-0.42	(-0.55 ,	-0.29)
Bank 13	51.90	(15.15 ,	88.65)	-0.35	(-0.57 ,	-0.13)

Rational polynomial curve

Coefficients	Bank 6			Bank 7		
a	-53.56	(-759.41 ,	652.29)	-19.56	(-112.67 ,	73.55)
b	249.71	(-3019.78 ,	3519.21)	93.75	(-341.96 ,	529.47)
c	29.82	(-385.67 ,	445.31)	8.65	(-40.16 ,	57.4665)

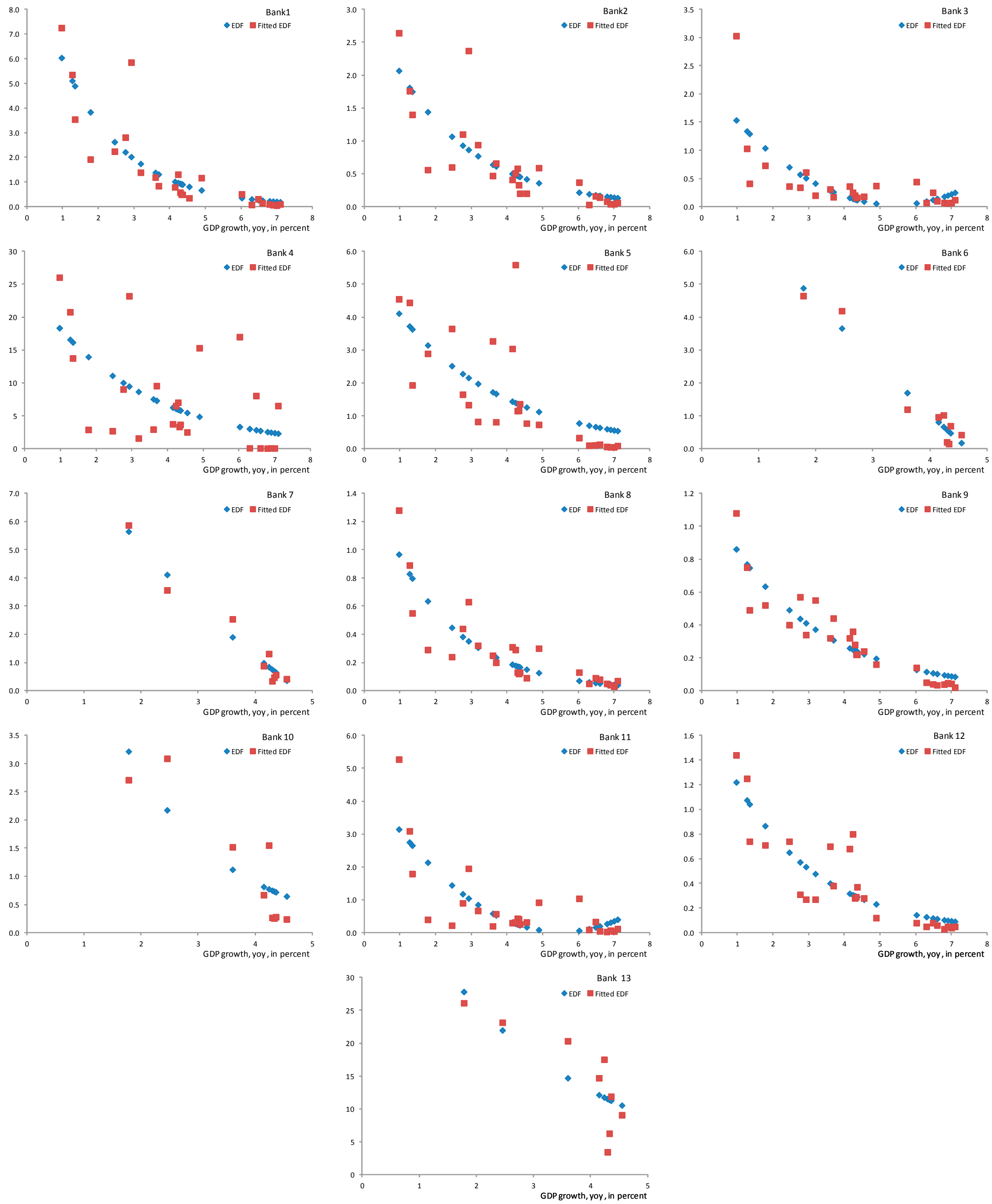
Polynomial curve

Coefficients	Bank 3			Bank 11		
a	0.08	(0.02 ,	0.13)	0.15	(0.06 ,	0.24)
b	-0.82	(-1.26 ,	-0.38)	-1.66	(-2.47 ,	-0.85)
c	2.26	(1.42 ,	3.10)	4.62	(3.06 ,	6.17)

Source: Moody's Analytics and author's calculations.

Figure 5 shows the goodness-of-fit of the non-linear models. Note also that despite the very simple non-linear model specifications used, which include only one macroeconomic explanatory variable, the fit is quite good. For two banks the goodness-of-fit was somewhat counterintuitive as the probability of default increased when growth rates exceeded 7 percent. Since these growth rates values did not realize in the macro stress scenarios it was not considered necessary to further refine the non-linear models. Indeed, the results obtained by fitting one-factor models as suggested by Hamerle, Jobst, Knapp, and Lerner (2008) were very similar to those obtained with simpler models.

Figure 5. Fitted non-linear models for banks' EDFs



Source: Moody's Analytics and author's calculations.

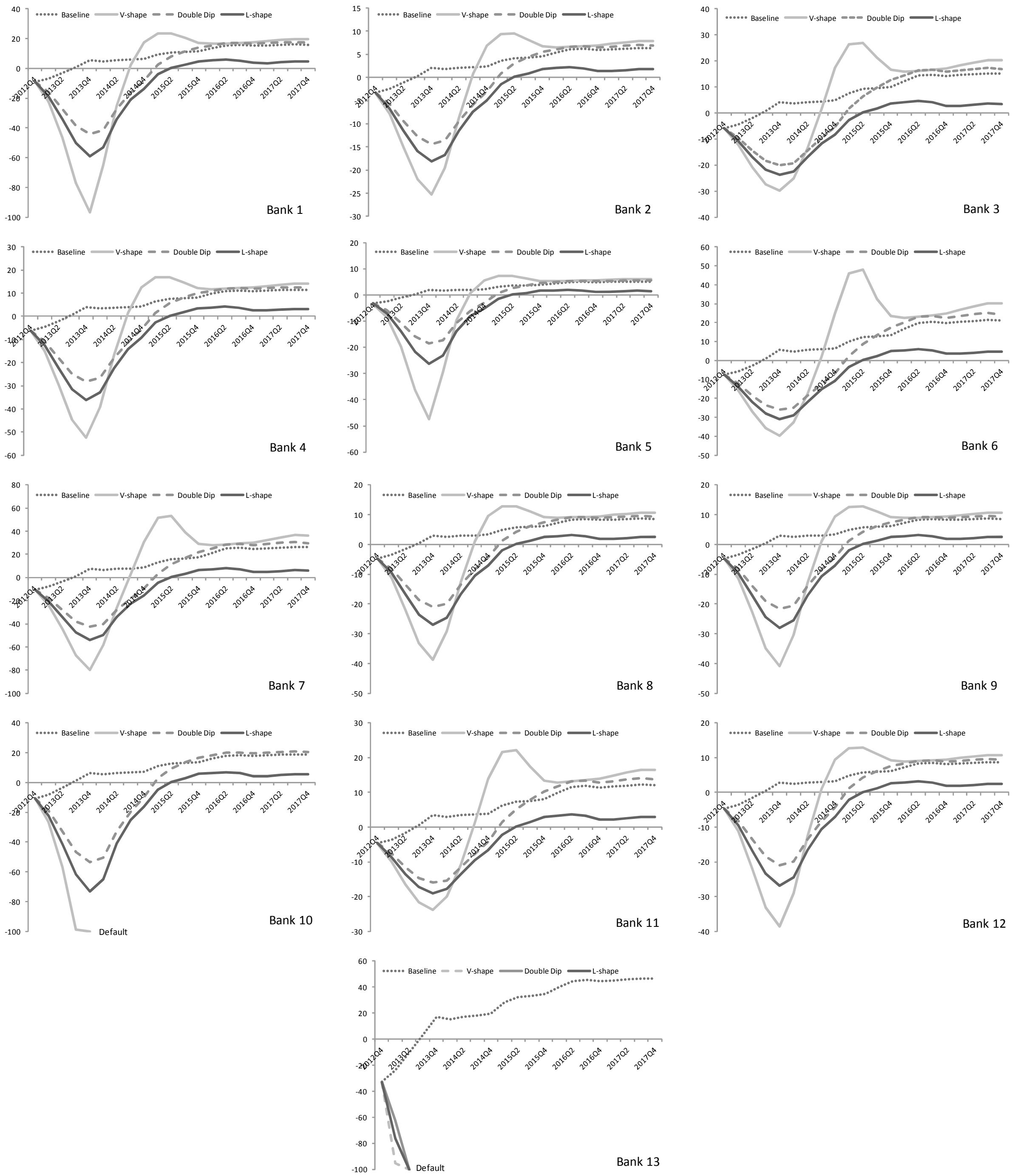
Once the non-linear models were estimated, it was possible to calculate changes in the banks' capital-to-asset ratios under different macro stress scenarios using equation (5), with structural model parameters set equal to those calculated by Moody's Analytics by end-2012. Four five-year scenarios were considered: a baseline scenario; a V-shaped recession characterized by a sharp decline in GDP followed by a strong recovery; a double-dip or two-year recession, and a L-shaped recession, characterized by a sharp drop in real GDP growth followed by lackluster growth. These scenarios are summarized in Table 4.

Table 4. Macro scenarios, GDP growth year-on-year

	Baseline	V-shaped recession	Double dip recession	L - shaped recession
2012 Q3	1.78	1.80	1.80	1.80
2012 Q4	0.94	0.94	0.96	0.95
2013 Q1	1.14	-0.14	0.36	0.14
2013 Q2	1.49	-1.78	-0.52	-1.01
2013 Q3	1.87	-3.24	-1.28	-1.99
2013 Q4	2.33	-3.89	-1.63	-2.46
2014 Q1	2.25	-2.74	-1.47	-2.14
2014 Q2	2.32	-0.36	-0.52	-1.01
2014 Q3	2.36	2.00	0.33	-0.05
2014 Q4	2.40	3.66	1.02	0.55
2015 Q1	2.72	4.35	2.03	1.43
2015 Q2	2.89	4.38	2.60	1.83
2015 Q3	2.92	3.99	2.97	2.03
2015 Q4	2.98	3.60	3.26	2.28
2016 Q1	3.20	3.54	3.42	2.33
2016 Q2	3.40	3.58	3.58	2.39
2016 Q3	3.43	3.62	3.61	2.32
2016 Q4	3.39	3.66	3.55	2.16
2017 Q1	3.42	3.76	3.59	2.15
2017 Q2	3.45	3.84	3.64	2.21
2017 Q3	3.48	3.91	3.68	2.26
2017 Q4	3.47	3.91	3.64	2.26

Figure 6 shows the changes in the capital-to-asset ratio of each bank relative to its 2012Q3 levels. In general, the capital-to-asset ratio fell during the first two years of the recession scenarios, with the decline reversed after positive growth resumed. The decline in the capital-to-asset ratio could be substantial, ranging from 20 percent to 60 percent, making impossible to rule out the possibility that some banks could default, i.e. their capital-to-asset becomes non-positive. Under the additional assumption that asset values remain constant, large capital losses could have eventually caused some banks to breach minimum regulatory capital ratios.

Figure 6. Changes in banks' capital-to-asset ratio under different macro scenarios relative to 2012 Q3 levels



Source: Moody's Analytics and author's calculations.

V. Conclusions

Top-down stress tests have increasingly become important tools for national authorities, multilateral institutions, market analysts, and country economists monitoring systemic risks and vulnerabilities in the banking sector. Standard top-down stress tests are data intensive, requiring detailed and granular information on banks' trading and loan portfolios. While authorities can gain access to these data owing to their supervisory and regulatory authority, this is not the case for most analysts, especially those in the private sector.

Absent the access to granular data, market-based top-down stress tests offer an alternative. In these tests, it suffices to use historical data on the probability of default of a bank to model its response to macroeconomic variable and market risk factors. The model, in turn, allows assessing how a bank's probability of default changes under different stress scenarios.

But assessing changes in the probability of default is not enough since regulatory actions are usually prescribed when minimum capital ratios are breached. The structural market-based top-down stress testing methodology presented here enables mapping the impact on the stress test scenarios to changes in the capital structure of a bank. This mapping is accomplished through the use of a structural model of default risk.

There are some caveats on using market prices as the information they contain may be affected by risk premia associated not only with default risk but also liquidity risk and even market manipulation. But it is important to highlight that market prices also react faster to new information and that a bank run could be potentially triggered by changes in market expectations rather than fundamental information. Market-based structural top-down stress tests, therefore, could complement well other standard top-down stress test methodologies, especially in instances when detailed data on a bank's portfolio is not available.

References

Alessandri, Piergiorgio, Prasanna Gai, Sujit Kapadia, Nada Mora, and Claus Puhr, 2009, "Towards a Framework for Quantifying Systemic Stability," *International Journal of Central Banking*, Vol. 5, No. 3, pp. 47–81.

Altman, Edward, and Edith Hotchkiss, 2006, *Corporate Financial Distress and Bankruptcy*, 3rd edition (Hoboken, New Jersey: John Wiley and Sons).

Bielecki, Tomasz R., and Marek Rutkowski, 2002, *Credit Risk: Modeling, Valuation and Hedging* (Berlin: Springer Verlag).

Black, Fischer, and Myron S. Scholes, 1973, "The Pricing of Options and Corporate Liabilities," *Journal of Political Economy*, Vol. 81, No. 3, pp. 637–54.

Board of Governors of the Federal Reserve Ssytem, 2009, "The Supervisory Capital Assessment Program: Design and Implementation" (Washington, D.C.)

Bohn, Jeffrey R., and Peter Crosbie, 2003, "Modeling Default Risk: Modeling Methodology," Moody's KMV.

Bohn, Jeffrey R., and Roger M. Stein, 2009, *Active Credit Portfolio Management in Practice* (Hoboken, New Jersey: John Wiley and Sons).

Burrows, Oliver, David Learmonth, and Jack McKeown, 2012, "RAMSI: A Top Down Stress Testing Model," Financial Stability Paper No. 17 (London: Bank of England).

Canatta, Francesco, and Ulrich Kruger, 2009, "Data Needs for Stress-Testing," in Mario Quagliarello, editor, *Stress Testing the Banking System: Methodologies and Applications* (Cambridge, England: Cambridge University Press).

Chan-Lau, Jorge A., 2013, *Systemic Risk Assessment and Oversight* (London: Risk Books).

Chan-Lau, Jorge A., and Amadou N.R. Sy, 2007, "Distance-to-Default in Banking: A Bridge Too Far?" *Journal of Banking Regulation*, Vol. 9, No 1, pp. 14–24.

Duffie, Darrell J., and Kenneth S. Singleton, 2003, *Credit Risk: Pricing, Measurement, and Management* (Princeton, New Jersey: Princeton University Press).

Ferry, Danielle H., Tony Hughes, and Min Ding, 2012a, "Stressed EDF™ Credit Measures," Modeling Methodology, May (Moody's Analytics).

Ferry, Danielle H., Tony Hughes, and Ming Ding, 2012b, "Stressed EDF Credit Measures for Western Europe," Modeling Methodology (Moody's Analytics).

Foglia, Antonella, 2009, "Stress Testing Credit Risk: A Survey of Authorities' Approaches," Vol. 5, No. 3, pp. 9–45.

Glasserman, Paul, Chulmin Kang, and Wanmo Kang, 2012, "Stress Scenario Selection by Empirical Likelihood," mimeo, Columbia University and Korea Advanced Institute of Science and Technology.

Greenlaw, David, Anil K. Kashyap, Kermit Schoenholtz, and Hyun Song Shin, 2012, "Stressed Out: Macroprudential Principles for Stress Testing," Chicago Booth Paper No. 12-08 (The University of Chicago, Booth School of Business).

Hamerle, Alfred, Rainer Jobst, Michael Knapp, and Matthias Lerner, 2008, "Stress-Testing Credit Value-at-Risk: A Multiyear Approach," in Daniel Rosch and Harald Scheule, editors, *Stress Testing for Financial Institutions: Applications, Regulations and Techniques* (London: Risk Books).

International Monetary Fund, 2012, "Macrofinancial Stress Testing – Principles and Practices," August 22 (Washington, D.C.).

International Monetary Fund and the World Bank, 2005, *Financial Sector Assessment: A Handbook* (Washington, D.C.).

Lando, David, 2004, *Credit Risk Modeling: Theory and Applications* (Princeton, NJ: Princeton University Press).

Merton, Robert C., 1974, "On the Pricing of Corporate Debt: the Risk Structure of Interest Rates," *Journal of Finance*, Vol. 29, No. 2, pp. 449–70.

Quagliarello, Mario, editor, 2009, *Stress Testing the Banking System:Methodologies and Applications* (Cambridge, England: Cambridge University Press).

Rosch, Daniel, and Harald Scheule, editors, 2008, *Stress Testing for Financial Institutions: Applications, Regulations and Techniques* (London: Risk Books).

Wilson, Thomas C., 1997a, "Portfolio Credit Risk I," *Risk*, Vol. 10, No. 9, pp. 111–117.

Wilson, Thomas C., 1997b, "Portfolio Credit Risk II," *Risk*, Vol. 10, No. 10, pp. 56–61.

Zandi, Mark, 2011, "The Moody's Analytics US Macroeconomic Model," (Moody's Analytics).