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FIRST: A Market-Based Approach to Evaluate Financial System Risk and Stability

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Abstract

This paper presents background work that has been the basis for the development of the *market and credit risk indicators* (MRI and CRI, respectively) as published in the IMF's *Global Financial Stability Report* (GFSR) since September 2004. The fundamental idea was to build a set of Financial Indicators on Risk and Stability (FIRST) that could reflect the market perceptions for current and future stress on financial institutions. The focus of the analysis is mainly on large, complex financial institutions (LCFIs) operating in the most advanced financial markets, MRI and CRI have also been applied to internationally active commercial banks and insurance companies.

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Glossary

CDS	Credit default swap
CRI	Credit risk indicator
DTD	Distance to default
FIRST	Financial Indicators of Risk and Stability
FOMC	Federal Open Market Committee (U.S.)
FSAP	Financial Sector Assessment Program
FSI	Financial Soundness Indicator
FTD	First to default
LCFI	Large, complex financial institution
MRI	Market risk indicator
VaR	Value-at-risk

I. INTRODUCTION

Financial system stability has become a major focus of attention in IMF surveillance, especially after the Asian crisis of the late 1990s.[2] For this reason, the IMF and World Bank have developed the Financial Sector Assessment Program (FSAP) and a set of Financial Soundness Indicators (FSI) to help in monitoring the health of financial systems in different countries. The main aim of FSI has been to extract indications of vulnerability from the analysis of the income statements and balance sheet exposures.[3] More recently, several contributions have been made to the development of structural indicators of financial stress following the Merton approach in computing distance to default (DTD).[4] The methods proposed in this paper are intended to complement the ones based on structural indicators. In fact, this paper takes a market-based approach which, following financial market practice, uses market prices instead of econometric estimations, as much as possible.

This paper presents a class of indicators called "Financial Indicators of Risk and Stability" (FIRST). The market risk indicator (MRI) and the credit risk indicator (CRI) developed here are part of this class whose main function is to account for financial stability problems, using a risk manager/investor approach.[5] From this perspective, the financial system is seen as a portfolio of exposures that supervisors need to monitor in order to understand the likely market reactions in case of stress. To this end, MRI and CRI are designed to capture the risk profiles implied by the volatility of the portfolio returns. The degree of riskiness present in the financial system is then inferred from the dynamics of the costs of the hedging strategies necessary to immunize such a portfolio. The idea is that prices of financial instruments quoted in the market and the tools used by investors to hedge their exposures directly convey crucial information concerning financial institutions' stress, in a forward-looking fashion and without the need to make the often extreme assumptions necessary to estimate a particular model.

The MRI and CRI framework allows the tracking of the risk profile of the entire portfolio of the various financial institutions that represent our financial system, as well as of subgroups within the overall portfolio or, even, individual institutions. In some cases, in fact, institutions are so big that instability in a small subset of the portfolio could be systemically relevant. For this reason, the possibility of tracking the individual institutions' risk profile and its contribution to the overall portfolio risk is crucial.

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[2] The material covered in this paper follows the outline of the author's presentation in the Monetary and Financial Systems Department (MFD) Seminar Series, May 19, 2005.

[3] IMF (2004).

[4] Merton (1974), De Nicoló, Hayward and Bhatia (2004).

[5] For further developments of the FIRST class of indicators see Avesani, Garcia Pascual, and Li (forthcoming), Avesani and Garcia Pascual (forthcoming).

Finally, this approach allows for policy analysis, and, specifically, for monitoring of the portfolio risk profile in some particular scenario and the performance of stress testing. Given the integrated nature of capital markets and the geographical reach of internationally active banks, it seems useful to have tools that allow for the evaluation of the sensitivity of these banks, as a group, to specific financial shocks. While a traditional FSAP stress test would capture the domestic dimension of the interactions among the banks of a specific country, the proposed approach brings out the effects of risk factor correlations on the risk profile of institutions belonging to different countries/areas. Therefore, it could be useful for the multilateral surveillance activities of the Fund.

The approach chosen here has a number of positive features, which will be discussed, as well as some shortcomings. In the first place, in its present form, this framework can only be used for financial institutions quoted on stock exchanges and for which a rather wide array of financial instruments are traded frequently in the markets. It is therefore appropriate only for the large, complex financial institutions (LCFIs), as defined by the Bank of England (2003), and for a broader group of internationally active, large, complex commercial banks.[6] As market-based indicators, the MRI and CRI are forward-looking in spirit because they reflect all the relevant available information, but it is clear that they cannot be expected to yield "magic predictions." In this sense, they are informative instruments, which need to be used in conjunction with other indicators. Finally, the sudden changes in market conditions frequently observed make this class of instruments vulnerable themselves to instability. Therefore, these indicators should be interpreted with care.

The next section presents the methodology used for the definition of MRI and CRI. Section III and IV define respectively the MRI, CRI, and present some of the applications and interpretation issues that may arise. Finally, in Section V, some concluding remarks are provided as well as indications for further extensions.

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[6] The definition of LCFIs is the same as applied by the Bank of England (2003) and comprises: ABN Amro; Bank of America; Barclays; BNP Paribas; Citigroup; Credit Suisse; Deutsche Bank; Goldman Sachs; HSBC Holdings; JP Morgan Chase; Lehman Brothers; Merrill Lynch; Morgan Stanley; Société Generale; and UBS. In addition, to the LCFIs, the commercial banks selected for our portfolio are: Australia and New Zealand Banking Group; Banca Intesa; Banco Bilbao Vizcaya Argentaria; Bank of East Asia; Bank of Nova Scotia; CIBC, Commerzbank; Credit Agricole; Development Bank of Singapore; HBOS; HVB Group; Mitsubishi Tokyo Financial; Mizuho Financial; National Australia Bank; Nordea; Royal Bank of Canada; Royal Bank of Scotland; Sanpaolo IMI; Santander Central Hispano Group; Skandinaviska Enskilda Banken; Sumitomo Mitsui Financial; Svenska Handelsbanken; Toronto Dominion; UFJ Holdings; Unicredito; Wachovia; and Westpac Banking Corp.

II. Methodology

In order to present a more comprehensive analysis of the stability issues faced by financial institutions, we need to understand how markets perceive both their market and credit risks. For the market risk, the MRI, we propose a 10-day, 95 percent confidence level value-at-risk (VaR) on the portfolio, which includes the quoted equity prices of each of the institutions defined above (see Box 1).

Box 1. Value-at-Risk

Value-at-risk (VaR) is the maximum value an investor is likely to lose on her/his assets with a certain probability over a given period of time. In an intuitive way, VaR tells the investor how bad things can go for her/his portfolio. This measure was developed as a practical way to communicate to top management of a financial institution, in a single number, the level of risk to which the institution is exposed. The need for such a simplifying tool is easily understood if one looks at the situation in many financial firms, where thousands of positions are exposed daily to different market factors and the top management needs to quickly decide whether, given market conditions, such positions need to be maintained, reduced, or increased. Given its wide use by the main financial institutions, the Basel Committee in 1996, adopted VaR as the measure on which the capital adequacy for market risk of a financial institution should be based. VaR is defined as:

$$VaR = PortfolioValue * \sigma * \alpha * \sqrt{\delta t}$$

where σ is the daily volatility of the Portfolio Value, α is the confidence level at which we want to evaluate the possibility of a loss, $\sqrt{\delta t}$ is the time interval measured in days over which we evaluate the losses.

For credit risk, the CRI reflects the default probabilities implied by a n^{th} to default basket of credit default swaps, CDSs (see Box 2).

Box 2. Credit Default Swap and Credit Default Basket

A CDS is a financial contract whereby an investor (the protection seller) is supposed to make a payment to a counterpart (the protection buyer) if a certain credit event (i.e., default, downgrade) happens to a third party, the reference entity. In exchange for such a contingent payment, the protection seller would receive periodically (quarterly, semi-annually, or annually) a fee expressed in basis points.

The n^{th} to default basket of CDSs is another financial contract which requires a protection seller to provide protection through a lump-sum payment against a credit event on a portfolio of CDSs to a protection buyer. Also, in this case, the protection buyer pays periodically a fee in basis points to the protection seller. The contract is terminated and the contingent payment has to take place when the *first*, *second,* or n^{th} name in the portfolio is hit by the specified credit event.

As is the case for the information content of the VaR, the fees paid periodically (spread) by the protection buyer and the default probabilities implied by such spreads are powerful indicators of the risk that markets assign to these portfolios.

These two indicators can be viewed as two different perspectives from which to analyze the same phenomenon. They are also connected at the theoretical level: asset volatility (and therefore equity volatility) is a fundamental determinant of the default risk embodied in credit spreads.[7] We should therefore expect these two measures to be highly and increasingly correlated as market participants become more focused in arbitraging away possible misalignments between equity prices and the corresponding default probabilities.

As mentioned, the portfolio examined here is composed of a group of the largest internationally active banks and securities firms in mature market economies. In addition to a full portfolio of these institutions, the paper looks at subportfolios, distinguished by the main activities performed by the firms (e.g., investment banking versus commercial banking). Risk analysis based on geographic location is also possible. Focusing on these subportfolios, highlights the market perception of vulnerabilities to different types of market events.

III. Market Risk Indicator

The fundamental element in the VaR computation is equity volatility. It incorporates factors that capture both market-wide and institution-specific elements. Both of these contain relevant information for monitoring activity. The first indicates the influences of general market dynamics, while the second reflects the behavior of the individual institution. Therefore the MRI is presented in two versions: the first based on the original volatility data, and the second after market-wide effects (both international and domestic) have been taken away. Following Hawkesby, Marsh, and Stevens (2005) the original volatility of each institution is purged of the world market (W) and local market (L) effects with a simple regression:

$$r_{i,t} = \alpha_i + \beta_i W_{i,t} + \gamma_i Li_{i,t} + r^*_{i,t}$$

The results of these regressions show that the local market effect is always significant. The estimated values of the γ_i indicate that the institutions in our sample are quite sensitive to local market influences.[8] World market effects, while significant for most of the institutions considered, are less relevant.

Figure 1 indicates the relative importance of institution-specific shocks (VaR-beta) relative to market-wide shocks (VaR). These measures are both relevant and have important policy implications from a market surveillance point of view. The dynamics of the two measures clearly indicate that there are events that have system-wide implications in term of increased riskiness.

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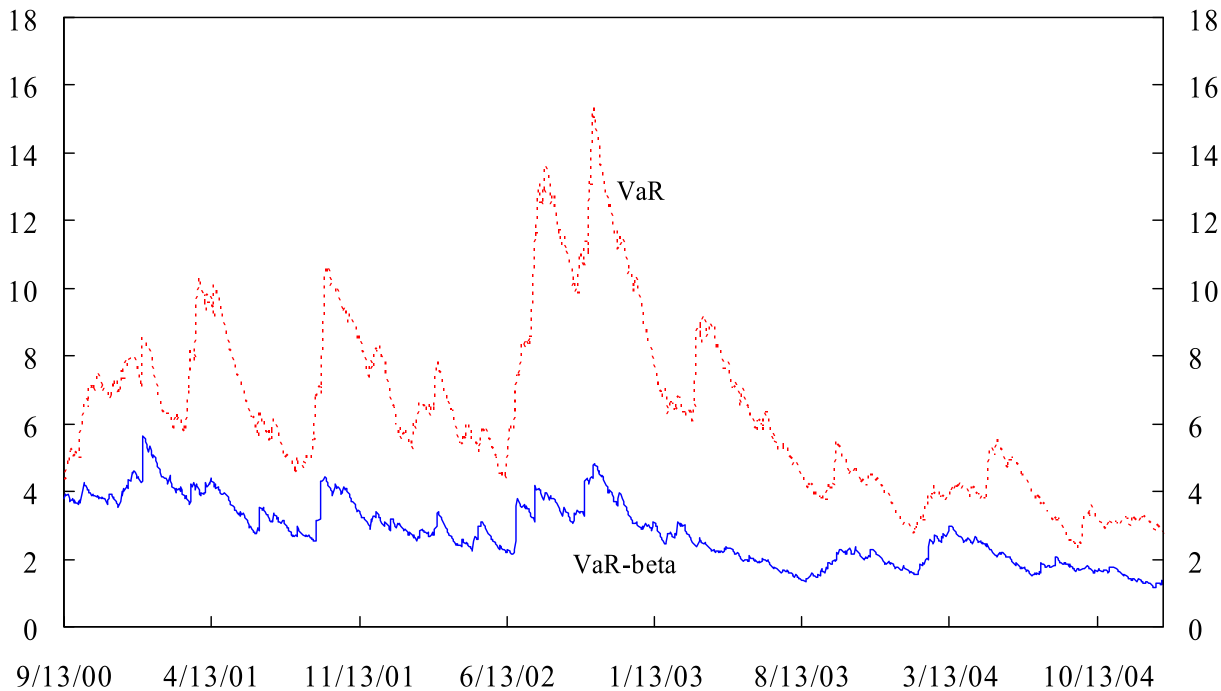
[7] Merton (1974).

[8] These results are available upon request from the author.

Figure 1. Value-at-Risk (VaR) and VaR Without World Market and Local Market Effects (VaR-beta)

(In percent)



Sources: Bloomberg L.P.; IMF staff estimates.

In more stable periods, the idiosyncratic components, which reflect the risk profile of each institution, acquire greater relevance. This seems also to suggest that in the unfolding of big shocks, supervisory attention should be more focused on the overall market infrastructure, providing, where possible, tools for smoothing the impact of the events. In normal market conditions, surveillance should focus more on the individual institution's behavior because in those periods the decisions taken within each institutions matter the most.[9]

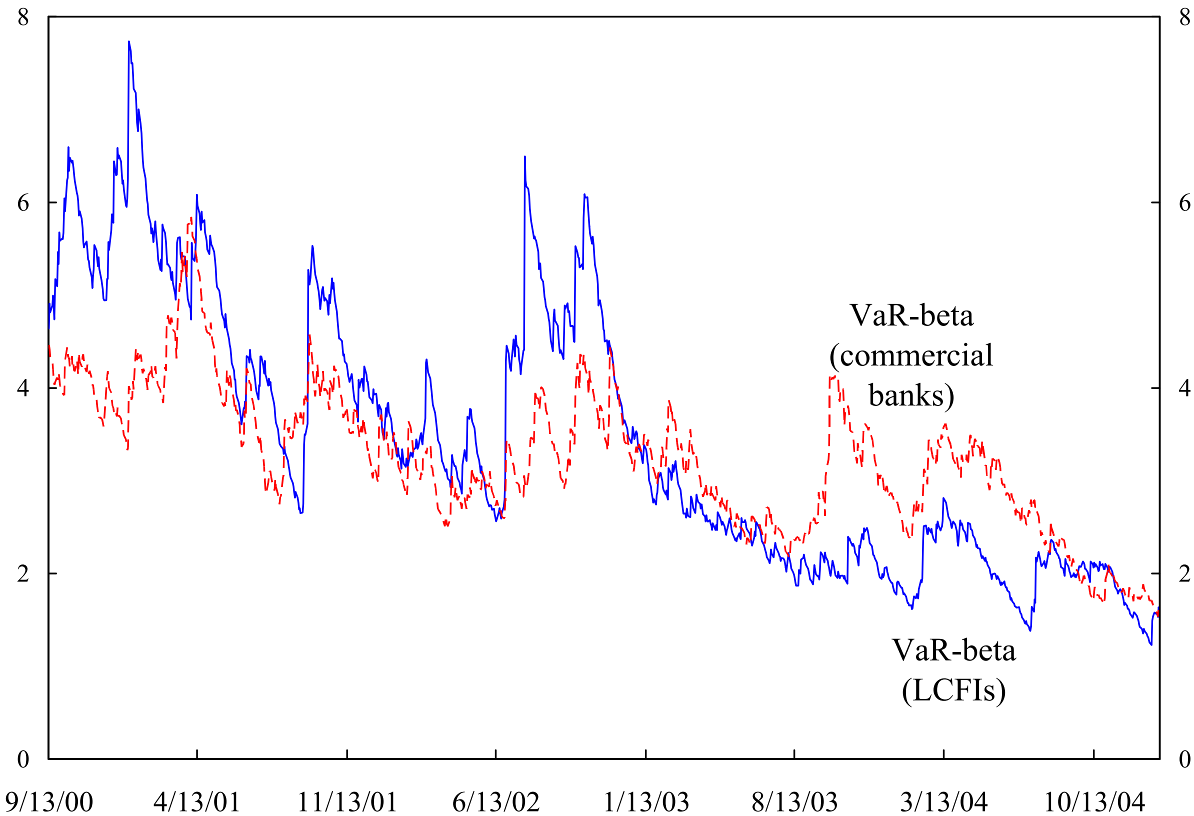
Figure 2 presents the profile of the specific VaR (i.e.,VaR-beta) for the two main groups of financial institutions that are part of the reference portfolio: commercial banks and LCFIs. The two measures, both on a downward trend over the reported period, show the different behavior of the two groups in different market events. It seems that LCFIs are more sensitive to the shocks hitting the financial system in the first half of the sample (including the stock market crash in the Spring of 2001, September 11, and the corporate scandals of 2002). From

[9] Levy-Yeyati, Martinez-Peria, and Schmukler (2005), also find that under normal market circumstances idiosyncratic behavior dictated by the fundamentals of each institutions is the driving force of their dynamics whereas, during market shocks, these lose some of their predictive power.

the second part of 2003, commercial banks appear to be more responsive to the change in the monetary policy taking place in the United States.

Figure 2. Bank and Large, Complex Financial Institutions (LCFIs) Portfolios
(Value-at-Risk (VaR) Without World Market and Local Market Effects (VaR-beta))

(In percent)



Sources: Bloomberg L.P.; IMF staff estimates.

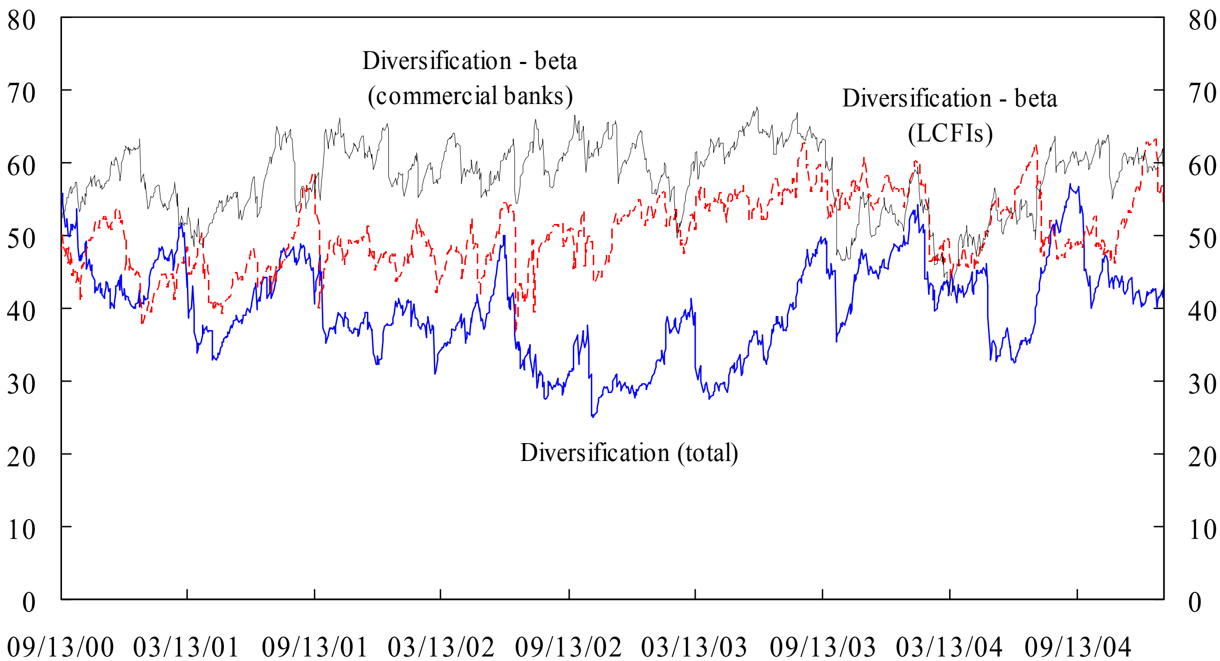
This distinct behavior highlights the fact that the market perceived the difference in the sensitivity of balance sheet compositions and therefore the economic performance of the two groups of banks with respect to the different sets of market conditions. In the first case, the shocks were affecting mainly the capital-market-sensitive components of the balance sheets, whereas, in the second, the lending operations were perceived to be more at risk.

From a financial stability perspective, the degree of correlation in the response to the shocks of the different agents of the financial sector is important. A high degree of correlation may imply an amplification of systemic volatility, particularly if it persists, and such correlation may pose severe problems in the event of an adverse shock.

I analyze the effects of correlation by comparing two different VaR measures. I use the VaR computed thus far (i.e., by taking account of correlations), and the VaR calculated as the simple sum of the individual VaRs of each institution. This second measure is called the undiversified VaR, and it is always bigger than (or at least equal to) the first. Taking the difference between these two VaR measures captures the diversification effect embedded in the portfolio. When this difference is small, it means that the equity prices are highly correlated, and therefore shocks or short-term changes in volatility are more likely to impact (with amplifying effects) the financial sector and the market as a whole.

Figure 3. Diversification Effect

(In percent)



Sources: Bloomberg L.P.; IMF staff estimates.

In our portfolio, the diversification measure does not differ much between commercial banks and LCFIs. In May 2004, the overall diversification index shows a sudden drop following the meeting of the U.S. Federal Open Market Committee (FOMC) meeting, which signaled the intention to increase short-term official rates,. Even though such a move by the U.S. Federal Reserve had been anticipated, the elimination of the residual uncertainty prompted a discrete unidirectional adjustment of positions.

IV. Credit Risk Indicator

The CRI uses the probabilities of defaults implied by a n^{th} to default basket of CDSs as a tool to represent market perception of credit risk. In recent years, the credit derivative market has grown exponentially and today, especially for large financial institutions, the CDS market is quite liquid. Therefore, the quoted CDS prices for the internationally active banks correctly reflect the market perception of those institutions' credit risk. The n^{th} to default baskets, in particular, have become a popular financial instrument in the last year due to the developments that took place in the CDSs markets.[10] This class of financial tools allows the investor to buy protection by paying periodically a fee against the possibility that any one of the CDSs in a basket (or any number of those CDSs) may default.[11] (See Box 2).

I observe that the fee paid by the protection buyer in a first to default (FTD) basket is higher than the one that would be paid for protection on the riskier names in the basket but lower than what would be paid to buy protection on all of the names in the basket. This is due to the effects of correlation among the default rates of the different names. To understand this, let us think of a concrete example in which the different names in a basket have a 100 percent default correlation. In such a case, the FTD probability would approach the default probability of the lowest-rated name, and the price of the basket would reflect the protection against the default of that name. At the other extreme, if the correlation is zero, the portfolio FTD probability would approach the cumulative default probability of all the names in the portfolio.

In this application, the default correlation is modeled as dependent on a common factor which drives the assets' dynamics.[13] The value of the assets (x_i) is determined by: $x_i = a_i m + \sqrt{1-a_i} z_i$ where x_i, m (the common factor) and z_i are mean-zero, unit variance, normally distributed random variables.[14] It is also the case that $-1 \leq a_i \leq 1$ and $a_i a_j$ represents the correlation between x_i and x_j. Default will happen when x_i goes over a certain threshold value $\bar{x}$, determined for a certain value of the default probability (q_i) through the inverse cumulative normal distribution (F): i.e., $F_i^{-1}(q_i(t))$.

This parameterization allows for an easy interpretation of the common factor and opens the way for a new approach to stress testing. In fact, *m* can be characterized as the "business

[10] See IMF (2005), p. 42. Greater liquidity was brought into the market after the development of the standardized i-Traxx and DJ Trac-x indices respectively for Europe and the United States. The availability of liquid indices for several sectors of the economy and different class of credit quality allowed market participants to rely on recognized benchmarks for price determination and hedging purposes.

[11] For 2nd, 3rd or nth to default, the protection payment is triggered respectively when the second, third or *n*th default is experienced.

[13] Hull and White (2005).

[14] In the examples reported here a_i is set to $\sqrt{0.3}$. The impact of different values of a_i is explored in Avesani, Garcia Pascual, and Li (2005).

cycle risk," since the business cycle is the main determinant of default correlations. Given that m is $N(0,1)$ distributed, one can compute the default probabilities conditional on its specific realizations at certain intervals, i.e., the 10^{th}, 50^{th}, or 90^{th} percentiles. These correspond respectively to an economic boom, trend growth, or a recession.[15] This seems to be a very promising way of bringing the macroeconomic environment to bear in a coherent way inside the risk management world.[16]

As an additional advantage, the n^{th} to default CDS represents a more flexible and easily updatable risk indicator with respect to the now widely used DTD.[17] In recent years, in fact, several supervisory institutions have produced DTD indicators that are a combination of aggregate balance sheet data (i.e., assets and debts) and market data (i.e., volatilities) of the institutions considered. These are very useful tools which may find, for the large institutions of the advanced countries, a natural complement in the risk indicators proposed here. In fact, the CRI is based on market data and therefore allows for real-time monitoring. In addition, because the CRI does not rely on balance sheet data, there is no need to face the difficulties often found in:

- combining data coming from institutions operating in different jurisdictions;
- aggregating data on debt of different maturities, embedded optionality, and seniority; and
- dealing properly with different degrees of off-balance sheet exposures and riskiness.[18]

Finally, as mentioned above, the n^{th} to default basket allows for an easy and coherent implementation of sensitivity and stress testing exercises using alternative specifications and/or values of the common factor and therefore of the correlations among the default probabilities.

In the present configuration, I propose the evaluation of the two-year forward (FTD) probability implied by a basket of CDSs on LCFIs and large commercial banks.[19] This

[15] Gibson (2004).

[16] In the context of IMF financial surveillance, Avesani, Garcia Pascual, and Li (2005) presents some extensions of a similar framework to perform sensitivity analysis and stress testing.

[17] The DTD indicates the number of standard deviations that the asset value of a certain institution is away from default (Duffie and Singleton, 2003; Bank of England, 2004; European Central Bank, 2004; and IMF, 2005).

[18] All of these considerations apply both to the assets side and the liabilities side of an institution's balance sheet.

approach may be useful for bank supervisors who oversee large and complex institutions in order to identify common or emerging weaknesses among a group of (similar) institutions.[20]

In our data set, which starts in July 2002, the credit outlook has improved steadily from October 2002, as the probability of observing a single default has greatly diminished. During this period, the term structure of default probabilities from the three-month to the five-year maturities has flattened, indicating that the market perceives the recent favorable credit environment as rather stable. However, expectations of aggressive interest rate policy actions from the U.S. Federal Reserve (November 2003 to June 2004) had some impact on default probabilities. Throughout this period (Figure 4), LCFIs demonstrated a higher sensitivity than the subset of commercial banks, which are used in this analysis, to the possibility of a worsening credit outlook.[21]

I also conducted a stress test to evaluate the response of default probabilities to a substantial and sudden worsening of the credit environment, i.e., a recession. To do so, as indicated above, I used the realizations of the common factor in the 90th percentile (i.e., the one corresponding to a recession), and computed the default probabilities conditional on these specific realizations. In this case (Figure 5), the probability of observing a default in the group of all financial institutions (i.e., the portfolio of large commercial banks and LCFIs) over a one-year period, in fact, rises from 7 percent to 22 percent, and on a two-year horizon, from 11 percent to 33 percent. For LCFIs, the probability of observing a default increases from 6 percent to 16 percent over a one-year horizon, while for large commercial banks the probability rises from 3 percent to 9 percent. Based on this analysis, therefore, it seems that large commercial banks and LCFIs respond in a similar way to an abrupt worsening of economic conditions.

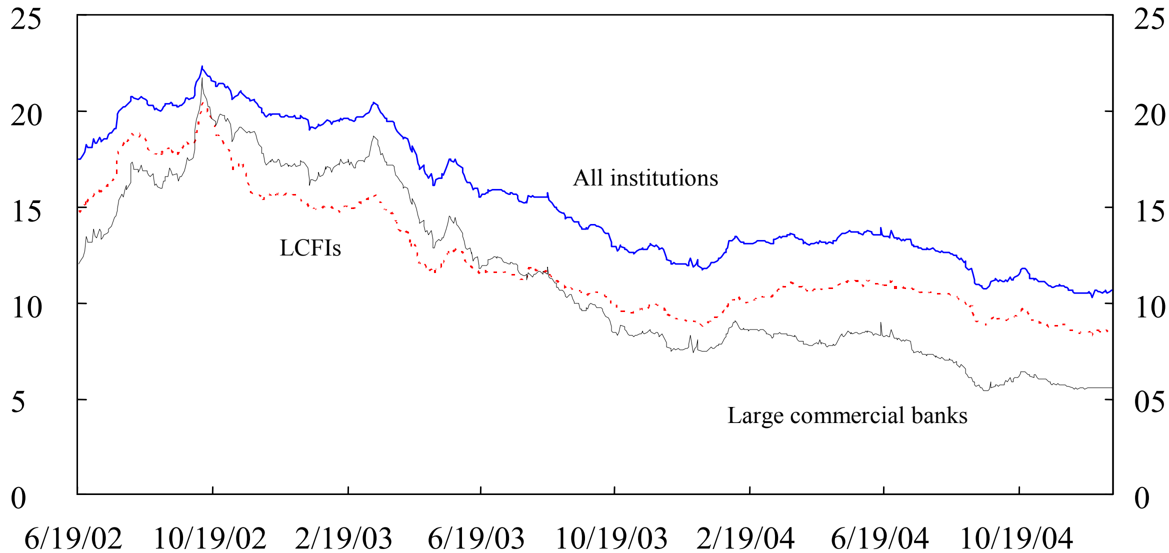
[19] The institutions analyzed include the LCFIs and 10 other large banks within our portfolio for which CDSs quotations were available: Commerzbank; Credit Agricole; HVB Group; Royal Bank of Scotland; San Paolo IMI; Santander Central Hispano Group; UFJ Holdings; UniCredito Italiano; and Wachovia.

[20] De Ferrari and Palmer (2001), recognize the benefits for supervisors of focusing not only on individual bank’s behavior, but also on monitoring groups of institutions which share a similar risk profile such as the large, complex banking organizations.

[21] The different result present here in comparison with the one in the VaR analysis for commercial banks and LCFIs could be explained by differences in portfolio composition.

Figure 4. Probability of Observing a Default Over a Two-year Period

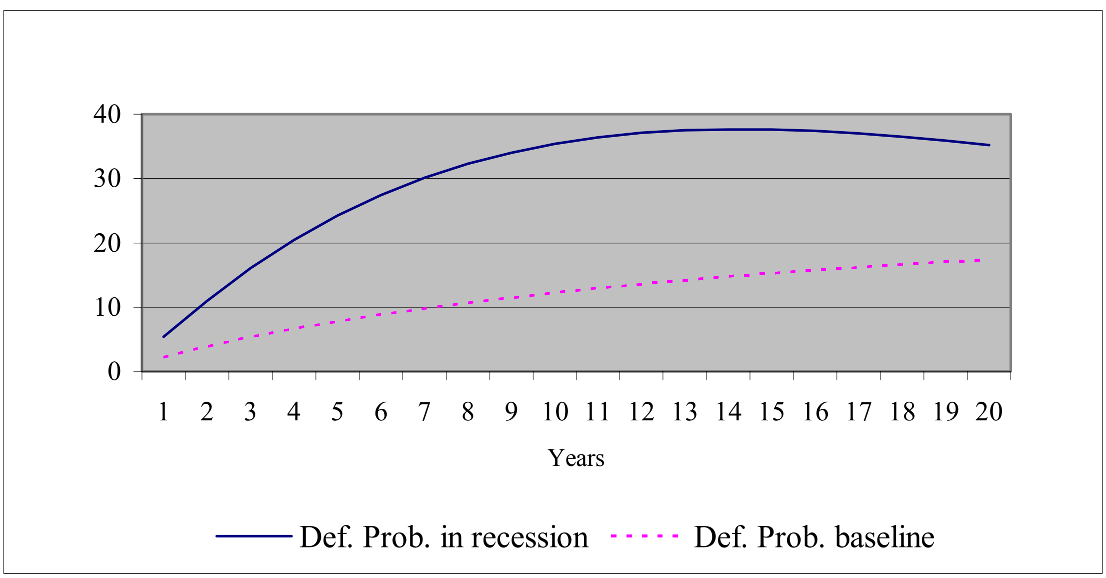
(In percent)



Sources: Bloomberg L.P.; IMF staff estimates.

Figure 5. Term Structure for Probability of One Default
(Entire Portfolio: LCFI and Commercial Banks)

(In percent)



Sources: Bloomberg L. P.; IMF staff estimates.

V. Conclusions

In this paper, I present a class of market-based financial indicators (FIRST) which look at the monitoring activities related to financial stability issues from a risk management/investor perspective. Following market practice, I relied as much as possible on market prices to extract indications of market stress. In particular, I used market instruments to determine the price and/or to assess the cost of the hedging strategies needed to cover the risk present in the financial system.

I chose a portfolio composed of the most relevant internationally active financial institutions as a reference, and then monitored MRI and CRI performance. These are institutions for which the traditional monitoring activity performed through the FSI cannot give the expected results due to the specificity of their balance sheet composition. In fact, a prominent part of their activities and risk are off-balance-sheet and change very rapidly following changes in market conditions. For these reasons, I believe that financial indicators that rely as much as possible on current market prices are more apt to capture the rapid changes in these institutions' on- and off-balance-sheet risk profiles.

The approach taken here also has the advantage of allowing for stress testing in a very natural way. For the MRI, this could take the form of the historical VaR or Monte Carlo simulations. For the CRI, the stress test could be implemented through different specifications of the common factor behavior. Further work along these lines, in particular a generalization of the pricing of a n^{th} to default basket using a multifactor structure, should provide a richer framework for evaluating the impact of the macro environment on the performance of the CRI.[22]

[22] Avesani, Garcia Pascual, and Li (2005).

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