Sovereign Default Risk Assessment
From The Bottom-Up

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Abstract

In 2010, the world's focus on the global financial crisis shifted from financial markets and institutions to sovereign debt, especially in Europe. This has motivated a re-examination of techniques and traditional indicators to assess the health of individual countries. Since the potential financial and economic implosion of several European countries seemed to erupt fairly quickly, one might conclude that the existing scholarly and practitioner methods were not adequate. We believe that one can learn a great deal about sovereign risk by, in addition to observing traditional macroeconomic measures of performance, to also carefully assess the health and aggregate default risk of a nation's private corporate sector - - a type of "bottom-up" analysis. Models such as Altman's original Z-Score technique and more recently, the Z-Metrics' risk system, can provide important early warning measures of sovereign vulnerability. This study does just that by analyzing the Z-Metrics' median probability of default (PD) of nine European countries and the USA from two time periods prior to the clear recognition of serious financial difficulties in the Eurosector. Our measures of PDs are also compared to the implied probability of default from a prominent market indicator, the credit default swap market, with both general confirmation and some surprising results.

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Key Words: Sovereign Risk, Financial Crisis, Default Probability, Z-Metrics

1. Introduction

Periodically, sovereign economic conditions spiral out of control and require a massive debt restructuring and/or bailout accompanied by painful austerity programs in order for the country to function again in world commerce and financial markets. Recent instances have involved several Latin American countries in the 1980s, Southeast Asian nations in the late 1990s, Russia in 1998 and Argentina in 2000. These are examples of situations when a nation's severe problems not only impacted their own people and markets but created seismic financial tremors which extended beyond their borders. In 2010, we are experiencing this with the situation in Greece and several of its southern European neighbors.

The dire condition of these nations usually first manifests as a surprise to most, including the agencies that rate the default risk of sovereigns and the companies that reside in these suddenly threatened nations. It was not long ago that Greek debt was investment grade and Spain was Aaa (June 2010)[1]. In 1996, South Korea was considered one of the so-called "Asian Tigers" with an AA- rating, one of the best credit ratings possible. Within one year, South Korea was downgraded to BB-, one of the so-called "junk" rating categories, and would have defaulted if not for a $50 billion bailout from the IMF.

Academics and market practitioners have not had an impressive record of predicting serious sovereign financial downturns or of providing adequate early warnings of impending economic and financial problems. These analysts generally use the traditional macroeconomic indicators, such as GDP growth, debt levels relative to GDP, trade and financial deficits,

[1] On April 27, 2010, Standard & Poor's Ratings Services lowered its long- and short-term credit ratings on the Hellenic Republic (Greece) to non-investment grade BB+ and B, respectively and on June 14, 2010, Moody's downgraded Greece debt to Ba1 from A2 (4 notches), while Spain was still Aaa and Portugal was A1. Both of the latter were recently downgraded. S&P gave similar ratings.

unemployment, productivity, etc. to assess sovereign health. While no absolute guarantee of providing the magic formula for early warning transparency of impending doom, we believe that one can learn a great deal about sovereign risk by analyzing the health and aggregate default risk of a nation's private corporate sector - a type of "bottom-up" analysis. Models such as my established Z-Score technique (1968), and more recently (2010) Risk Metrics' Z-Metrics™ system, can provide an important additional measure of sovereign vulnerability. We will investigate the latter system with respect to the current European Union sovereign debt crisis.

The ensuing discussion is organized as follows. Section 2 will briefly document the modern history of sovereign financial crises. Section 3 will explore the extensive academic and practitioner literature on sovereign risk, with an emphasis on those empirical studies that assess the ability to predict and explain sovereign defaults and crises. Section 4 will explain our new Z-Metrics system for individual, non-financial firm probability of default estimation, leading to its application in Section 5 to the current European Union's debt crisis. Section 6 will explore our findings and implications for bailout strategies and future research.

2. Modern History Sovereign Crises

It is fair to say that sovereign debt crises occur frequently and are not restricted to emerging market countries. Figure 1 shows a partial list of "advanced" countries' dates of financial crises (first year of the crisis). If we had included a number of currently sophisticated Asian countries as advanced countries, the period 1997-1999 would be prominent. Overall, Latin America seems to have had more recent bond and loan defaults than any other region of the world (see Figure 2).

Figure 1

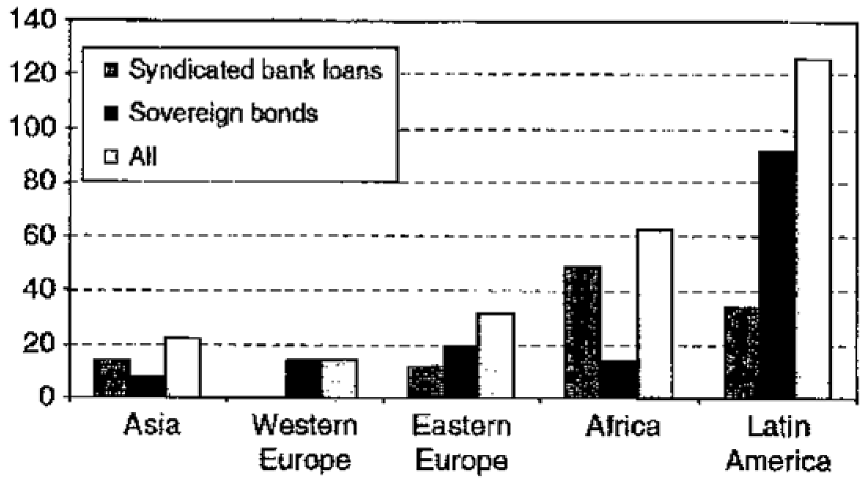
Financial Crises, Advanced Countries 1870-2010

Crisis events (first year)							
Austria	**1893,**	**1989**					
Brazil	**1898,**	**1902,**	**1914,**	**1931,**	**1939**		
Canada	**1873,**	**1906,**	**1923,**	**1983**			
Czechoslovakia	**1870,**	**1910,**	**1931,**	**2008**			
China	**1921,**	**1939**					
Denmark	**1877,**	**1885,**	**1902,**	**1907,**	**1921,**	**1931,**	**1987**
DEU	**1880,**	**1891,**	**1901,**	**1931,**	**2008**		
GBR	**1890,**	**1974,**	**1984,**	**1991,**	**2007**		
Greece	**1870,**	**1894,**	**1932,**	**2009**			
Italy	**1887,**	**1891,**	**1907,**	**1931,**	**1930,**	**1935,**	**1990**
Japan	**1942**						
Netherlands	**1897,**	**1921,**	**1939**				
Norway	**1899,**	**1921,**	**1931,**	**1988**			
Russia	**1918,**	**1998**					
Spain	**1920,**	**1924,**	**1931,**	**1978,**	**2008**		
Sweden	**1876,**	**1897,**	**1907,**	**1922,**	**1931,**	**1991**	
USA	**1873,**	**1884,**	**1893,**	**1907,**	**1929,**	**1984,**	**2008**

Source: IMF Global Financial Stability Report (2010), Reinhart and Rogoff (2010), and various other sources, such as S&P's economic reports.

FIGURE 2

Number of Sovereign "Defaults" 1824 - 2004



Source: Compilation by I. Walter, NYU Stern School of Business.

In this paper, we will concentrate on public corporate data in 2010 for a group of eight European countries to illustrate our main points about assessing sovereign health going forward. In doing so, we will refer to difficult sanctions to governments, such as Greece and Ireland, in order for them to qualify for bailouts and subsidies. The implication from our analysis is that we should be careful to promote, not destroy, private enterprise valuations.

3. Literature Review

The sovereign risk and related default probability literature is extensive with a fairly continuous supply of both academic and practitioner studies. Excellent primers on assessing sovereign risk can be found in Babbel (1996) [2], Chambers (1997), Beers, et al (2002) - the latter two from S&P - Smith and Walter (2003), and Frenkel, Karmann and Scholtens (2004). A number of studies have attempted to predict sovereign defaults or rescheduling, starting from Frank and Cline's (1971) classic study and they include statistical classification and predicting methods like discriminant analysis (e.g., Frank and Cline (1991), Grinols (1976), Sargen (1977), and Morgan (1986); logit analysis (e.g., Feder and Just (1977), Feder, Just and Ross (1981), Cline (1983), Schmidt (1984), and Morgan (1986) with a number of similar econometric techniques also having been applied, and finally the use of contingent claim analysis by Gray, Merton and Bodie (2006, 2007). The latter studies proposed a new approach to measure, analyze and manage sovereign risk based on Merton's classic "structural" approach (1974) adapted to sovereign balance sheets. It attempts to forecast credit spreads and to evaluate the impact of market risks and risks transferred from other sectors. Relying on market indicators of sovereign

[2] Babbel's (1996) study includes an excellent annotated bibliography by S. Bertozzi on external debt capacity which describes many of these studies. Babbel lists 69 potentially helpful explanatory factors for assessing sovereign risk, all dealing with either economic, financial, political, or social variables. Except for the political and social variables, all others are macroeconomic data and this has been the standard until the last few years.

health, this approach benefits and at the same time is subject to wide swings in risk assessment due to market volatility.

A number of recent studies have analyzed how a global or regional common risk factor largely determines the level of sovereign risk in the world, or in a region, such as Europe. Examples of these are Baek, Bandopadhyaya and Chan (2005) who showed that both an individual sovereign's risk factor and a common time-varying global factor affects market repricing of sovereign risk. Gerlach, Schulz and Wolff (2010) observe that aggregate risk factors drive banking and sovereign market risk spreads in the Euro area. Related to this, Sgherri and Zoli (2009) suggest that Euro area sovereign risk premium differentials tend to co-move over time and are mainly driven by a common time-varying factor. Finally, Longstaff, Pan, Pedersen and Singleton (2007) showed that sovereign credit spreads are surprisingly more related to such aggregate market indexes, such as the U.S. stock and high-yield bond markets and global capital flows, than they are to their own local economic measures. Their theme and that of the structural approach discussed earlier, is similar to Oshino and Saruwatari's paper (2005) which proposed a new approach to quantify sovereign risk using the stock market price index as a proxy for the equity value of the country. Our approach, discussed shortly, certainly utilizes stock market prices of individual companies, as well as a number of fundamental variables, in our assessment of corporate risk. We also observe the impact of the overall stock market performance in a country and its relationship with its private sovereign risk measure. This is particularly relevant in comparing our results in 2009 vs. 2010.

Several very recent papers focus on sovereign risk premiums and spreads. These include Haugh, Ollivaud and Turner's (2009) discussion of the importance of debt service relative to tax receipts in the Euro area; Hilscher and Nobusch (2010) emphasis on the volatility of terms of trade; and Segoviano, Caceres and Guzzo's (2010) analysis of debt sustainability and the management of a sovereign's balance sheet.

Some research do endorse the information content from published credit ratings and related market statistics. Indeed, Remolona, Scatigna and Wu (2008) utilize sovereign credit ratings and historical default rates provided by rating agencies to construct a measure of ratings implied expected loss. The authors conclude that sovereign ratings, especially in emerging markets, provide an improved understanding of country risks for investment analytics.

Despite these efforts and information content from published ratings, the recent crisis amongst European countries, like Greece and Spain, occurred when all rating agencies and models that I am aware of classified the countries as investment grade[3].

Chambers of S&P (1997) does mention the notion of a "bottom-up" approach but not to the assessment of sovereign risk, but to a corporate issuer located in a particular country. He advocates first an evaluation of an issuer's underlying creditworthiness to arrive at its credit rating and then considers the economic, business and social environment in which the entity operates. These latter factors, such as the size and growth and the volatility of the economy, exchange rates, inflation, regulatory environment, taxation, infrastructure and labor market conditions are factored in on top of the micro variables to arrive at a final rating of the issuer.

Our approach advocates going in the other direction, factoring in the health of the private sector - a different type of "bottom-up" analysis - on the vulnerability of the sovereign. The idea for doing this was actually first observed in the works of Pomerleano of the World Bank (1998)

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[3] To be fair, S&P in a *Reuter's* article, dated January 14, 2009, warned Greece, Spain and Ireland that their ratings could be downgraded further as economic conditions deteriorated. At that time, Greece was rated A1 by Moody's and A- by S&P. Interestingly, it was almost a full year later on December 22, 2009 that Greece was actually downgraded by Moody's to A2 (still highly rated), followed by further downgrades on April 23, 2010 (to A3) and finally to "junk" status (Ba1) on June 14, 2010. As noted earlier, S&P downgraded Greece to "junk" status about three months earlier.

in his study of the East Asian crisis of 1997.[4] Among other factors, the author observed the average Z-Score (Altman, 1968) as a measure of “financial fragility” of eight Asian countries and, for comparison purposes, three developed countries and Latin America. Surprising to many observers, the Asian country with the highest fragility to financial distress based on the average Z-Score of listed, non-financial companies, as of the end of 1996, was South Korea, followed by Thailand and Japan and Indonesia. As noted earlier, Korea’s sovereign bond rating at that time was AA- (S&P) but within less than one year its rating plummeted to BB- and if not for the IMF bailout of $50 billion, it is likely that Korea would have defaulted on its external, non-local currency debt. And, South Korea had been growing at double-digits rates for about a decade just prior to its demise. So, a traditional macroeconomic measure like GDP growth was misleading at the time. The World Bank concluded that its findings supported the view by Krugman (1998), and others, that crony capitalism and the associated strategy and policies of implicit guarantees coupled with poor banking regulation were the ingredients for an impending crisis to the nation’s banking system and its economy.[5]

Almost all of the studies cited above were fairly optimistic as to the conceptual and practical benefits of an early warning system for sovereign crisis prevention. Sadly, they have either been ignored or have proven ineffective in forecasting most economic and financial crises and we still regularly observe these events (see our listing earlier).

[4] Pomerleano’s “Note” is based on a longer article by the author (1997).

[5] The excesses of corporate leverage and permissive banking were addressed successfully in the case of Korea and its economy was effectively restructured after the bailout.

4. The Z-Metrics™ Approach[6]

To address the assessment of credit risk of companies, we partnered with the *RiskMetrics Group* in 2009, resulting in our new Z-Metrics approach. Our methodology is what might be called a new generation of the original Z-Score model (1968). Our objective was to assess the credit risk of non-financial enterprises by developing up-to-date credit scoring and probability of default metrics for enterprises both public and private, large and small, on a global basis. Starting with a large sample of non-financial sector firm data over the period 1989-2008, involving more than 250,000 quarterly and annual firm financial statements and associated market prices and macroeconomic data observations, we utilized a multivariate logistic regression structure to construct our models. We used the criterion of a "credit event," which is defined here to be either a formal default or bankruptcy legal event, whichever comes first, to segregate firms into cohorts. Those firms which have had a credit event within a given timeframe (i.e., 1 year or 5 years) were assigned to the "distressed" or "credit event" group; those that did not incur a credit event were assigned to the non-distressed group. It is based on these cohorts that we have built our model to predict performance.

We emphasize that our results will be applicable across the complete spectrum of credit quality and ratings from the lowest to the highest default risk categories. The result is a robust model with high default/non-default classification and predicted accuracy. Whenever possible, we compare our output with publicly available credit ratings and existing models. The accuracy ratios and observed results on samples of individual defaulting firms using our new approach clearly outperform existing methodologies, including the Z-Score model.

[6] For more details, see Altman, et al, 2010 "The Z-Metrics™ Methodology for Estimating Company Credit Ratings and Default Risk Probabilities," *RiskMetrics Group*, continuously updated, available from http://riskmetrics.com/Z-Metrics.

Objectives of our Z-Metrics™ Models

- To construct an accurate, logical and robust credit-scoring model based on large and representative samples of non-financial companies that have either suffered a serious negative credit event or have remained healthy.

- To assign a point in time probability of default (PD) over one-year and five-year horizons based on a firm's credit score.

- To assign a unique Z-Metrics credit rating, given the PD, to each firm representing the full spectrum of creditworthiness; one that is easily mapped to familiar credit terminology.

- To provide stressed PDs and ratings under various scenarios.

The credit scores, Z-Metrics credit ratings and probabilities of default will be available for the following populations:

- Large (greater than $50 million in sales) publicly-held firms in the U.S. and Canada

- Large, privately-held firms in the U.S. and Canada (based on data availability)

- Small publicly-held firms in the U.S. and Canada

- Soon to be developed, large and small firms outside the U.S. and Canada in four distinct regions (U.K., Western Developed Countries, Emerging Market Countries and Japan)

We expect, however, that our U.S. model will also be immediately available to publicly-held firms in most other developed nations. Indeed, we utilize the large publicly-held firm U. S. model to evaluate the default risk of European companies in our analysis.

Variables Assessed

- We analyzed over 50 fundamental financial statement variables covering such performance characteristics at solvency, leverage, size, profitability, interest coverage, liquidity, asset quality, investment, dividend payout, and financing results.

- In addition to point-in-time measures, we analyzed the trends in many of the variables mentioned above.

- We also included equity market price and return variables and their volatility patterns, adjusted for market movements. These variables have typically been used in structural, distance-to-default measures, such as the KMV (Crosbie, KMV, 1999) model (now Moody's KMV) - - as noted earlier, Gray, et. al. (2007) adapted this analysis for sovereigns.

- Macro-economic variables are included to capture the time-series variation of default probabilities over time. Since most firms have a higher probability of default in stressed periods, e.g., at the end of 2008, we wanted to capture heightened or lower probabilities by examining such variables as GDP growth, unemployment, credit spreads, inflation, among others. As such, our model has explicitly evaluated some of the traditional sovereign risk variables in our assessment of private firm creditworthiness.

- In all cases, we carefully examined the complete distribution of variable values, especially in the credit-event sample. This enabled us to devise transformations on the variables to either capture the nature of their distributions or to reduce the influence of outliers. These transformations included logarithmic functions, first differences and dummy variables if the trends or levels of the absolute measures were positive/negative.

- The final model included 13 fundamental, market value and macroeconomic variables.

Sample Characteristics

- Our first model's original sample consisted of over 1,000 U.S. or Canadian non-financial firms that suffered a credit event ("credit event sample") and a control sample of thousands of firms that did not suffer a credit event, roughly a ratio of 1:15. After removing those firms with insufficient data, the credit event sample was reduced to 638 firms for our public firm sample and 802 observations for our private firm sample.

- The one-year (12 months) model is based on data from financial statements and market data approximately one year prior to the credit event and includes macroeconomic data. The five-year model includes up to five annual financial statements prior to the event, except we use quarterly data for trend variables in conjunction with market data for the same period. No macroeconomic variables are included in the five-year models.

Public and Private Firm Models

Our emphasis in this application will be on the Z-Metrics publicly-owned firm model. In addition, we construct essentially a private firm model, although the data is from publicly-held companies and we replace market value with book value of equity. The application of our privately-held firm model will be useful for analysts who are interested in non-public firms. Some practitioners will be interested in "private" leveraged buyout firms with publicly-held debt and financial statements available.

Z-Metrics Model Construction and Tests

Logit Model Estimation

- We estimate our credit scoring model based on a standard logit-regression functional form whereby:

$$CS_{i,t} = \alpha + \Sigma \mathrm{BX}_{i,t} + \mathrm{E}_{i,t} \quad (1)$$

$$CS_{i,t} = Z\text{–}Metrics\ credit\ score\ of\ company\ i\ at\ time\ t$$

$$B \quad = variable\ parameters\ (or\ weights)$$

$$X_{i,t} \quad = set\ of\ fundamentd,\ market\ based\ and\ macroeconomic\ variables\ for\ firm/quarter\ observations$$

$$\mathrm{E}_{i,t} = error\ terms\ (assumed\ to\ be\ identically\ and\ independently\ distributed$$

$$CS_{i,t}\ is\ transformed\ into\ a\ probability\ of\ default\ by\ PD_{i,t} = \frac{1}{1+\exp(CS_{i,t})}$$

- Comparisons are made with the actual issuer ratings. In order to ensure a fair comparison, credit scores are converted to agency equivalent (AE) ratings by ranking credit scores and by matching exactly the actual Agency rating distribution with the AE rating distribution at any point in time.

- We also compare our Z-Metrics results to the well established Altman Z"-score (1995) model.[7]

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[7] Altman's original Z-score model (1968) is well-known by practitioners and scholars alike and is considered by many as the traditional benchmark for bankruptcy prediction. It was built, however, over 40 years ago and is primarily applicable to publicly-held manufacturing firms. A more generally applicable Z"-score variation was popularized in 1995 as a means to assess the default risk of non-manufacturers as well as manufacturers, and was first applied to emerging market credits. Both models are discussed in Altman and Hotchkiss (2006) and will be compared in several tests to our new Z-Metrics model. The Altman Z-score models do not translate easily into a probability of default rating system, as does the Z-Metrics system.

Accuracy Ratios

One of the key success determinants of any credit risk model is how well the model classifies firms into high risk (low ratings) levels based on data from before some critical credit event takes place. In our model's estimation, the objective is to attain high levels of accuracy (low levels of errors) to classify, and ultimately to predict, firms which default on their obligations and/or go bankrupt. The standard measure for these assessments is the so-called "accuracy ratio," which measures the proportion of credit-event firms correctly predicted to go bankrupt or non-bankrupt based on different credit score cut-off levels. In essence, the objective is to maximize the Type I and Type II accuracy levels (minimize errors) for test and holdout samples of firm.

Figure 3 compares the Type I error rates for our Z-Metrics AE ratings to actual Agency ratings and Altman *Z*"-score AE ratings, for the entire sample period 1989-2008, for our 1-year and 5-year models. The results are based on the percentage Type I accuracy (predicting default when the firm defaults) using the credit score cut-offs for different AE rating classes. The various AE rating classes can also be thought of as different PD or credit score levels. Rating class 1 includes firms with a rating ≤ CCC+/Caa1, rating class 2 = B-/B3, 3 = B, 4 = B+/B1 and so on.

We see that if the cut-off score was set at the 4^{th} rating class equivalent level (B+), our (12-month) Z-Metrics model would result in about a 10% error (90% accuracy) rate for one-year predictions, compared to an 18% error rate for Agency ratings and about a 30% error for the Z"-score model. For a five-year horizon, Type I error rates are about the same for Z-Metrics models and Agency ratings. This latter result is not surprising since the Rating Agencies' through-the-cycle methodology is a longer term perspective approach as is our five-year Z-Metrics approach.

FIGURE 3

Type I error for Agency ratings Z"-score, and Z-Metrics agency equivalent (AE ratings (1989-2008): one year prediction horizon for publicly owned firms

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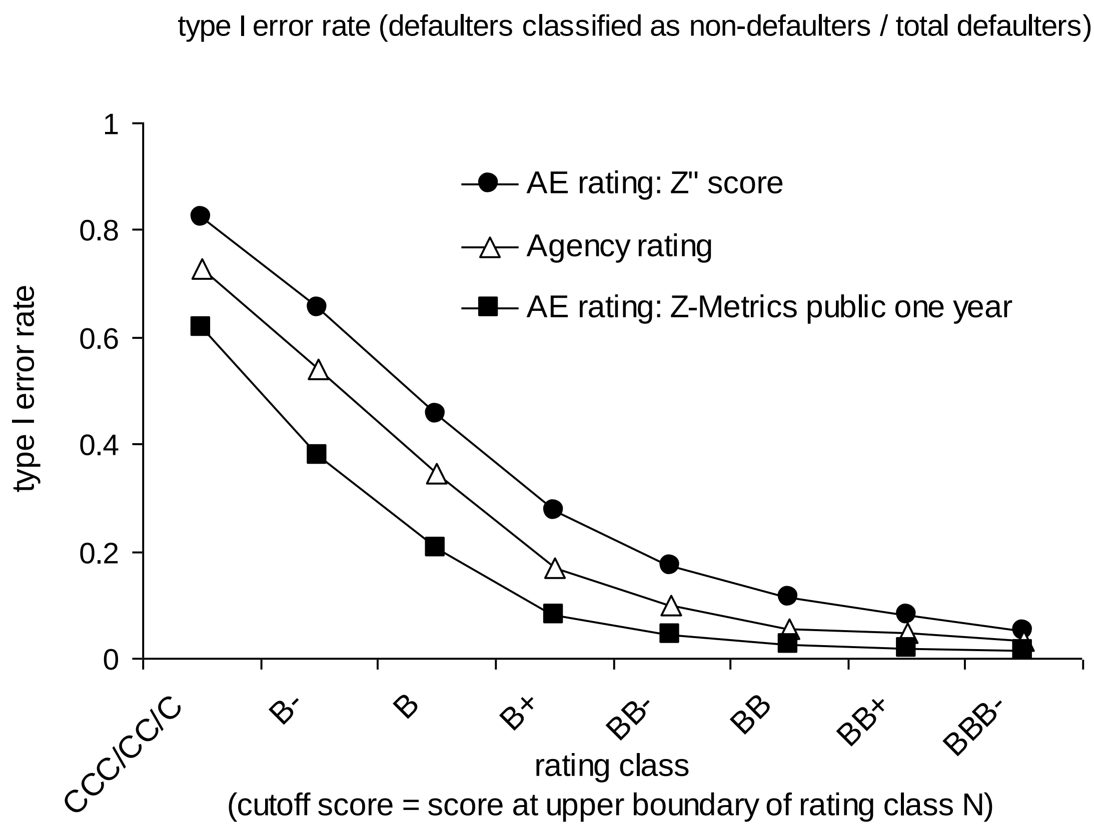


FIGURE 4

Type II error rates for Agency ratings, Z”-score, and Z-Metrics agency equivalent (AE) ratings (1989-2008): one-year prediction horizon for publicly owned firms

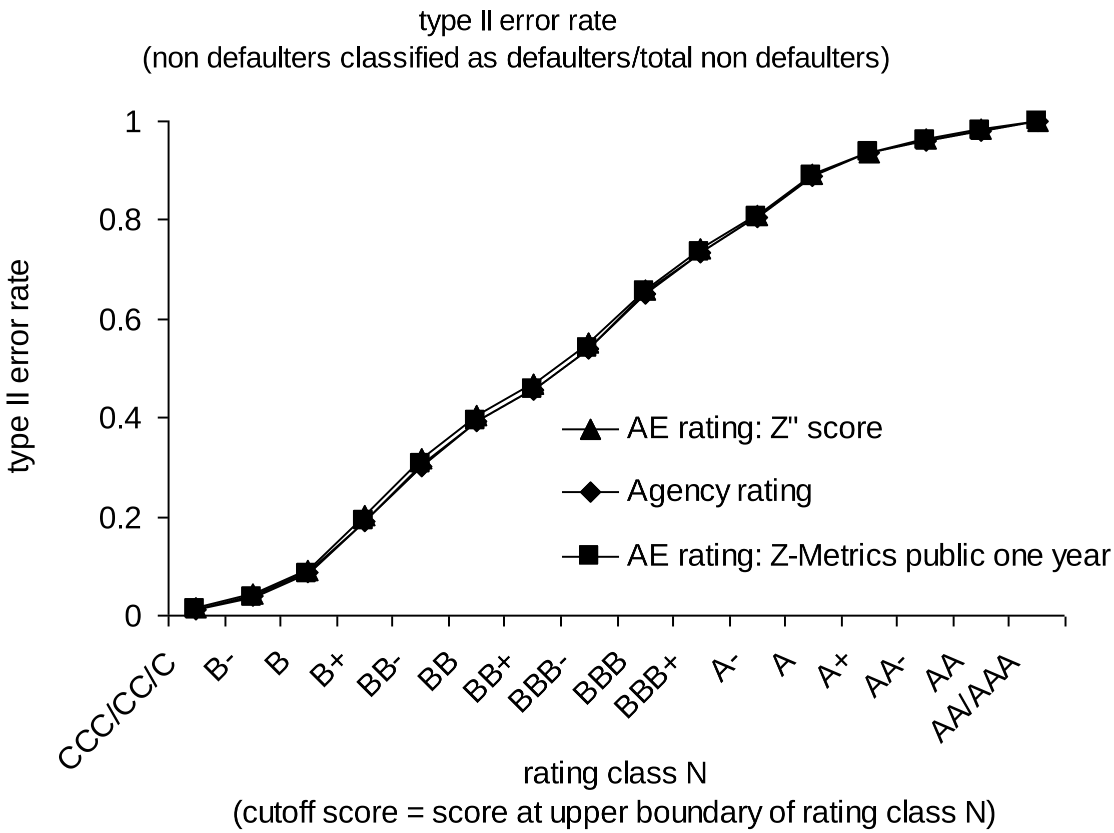


Figure 4 shows the Type II error rate (false positive prediction of default) for the three models based on a one-year prediction horizon at various rating class cut-off levels. As expected, there is very little difference between the three models at all rating class cut-off levels since the ratio of non-defaults to defaults is greater than fifteen to one over the entire 20-year sample period. At the 4^{th} rating class cut-off level, the Type II error rate is approximately 20% for all models. To conclude, the Type I and II error rates at our proposed cut-off score level (B+) results in a 10% Type I and 20% Type II error rate. These compare very favourably to Agency ratings and Z"-score models.

Figures 5 and 6 compare the Z-Metrics AE ratings with the Agency ratings over one-year and five-year horizons for two different 10-year sample periods: an in-sample 1989-1998 period (equivalent to a model construction sample) and 1999-2008 (equivalent to a holdout or out-of sample period). Note that the Z-Metrics public model is approximately 7.5% more accurate for one-year predictions in the in-sample period and a little better, about 10.0% more accurate, in the out-of-sample period. The Z-Metrics one-year public model has better accuracies for all horizon periods during the in-sample period. In the out-of-sample period test (Figure 6), the Z-Metrics one-year public model outperforms the Agency ratings for all horizon periods as well. Similar results are observed with the five-year Z-Metrics model compared to Agency ratings. The Z-Metrics private-firm models' results are not as impressive but still quite acceptable. This is mainly due to the lack of market value of equity data in the private model. Of course, most of the private firms will not, in reality, have an Agency rating.

Stability of the Models

We assessed the stability of the Z-Metrics models by observing the accuracy ratios for our tests in the in-sample and out-of-sample periods and also by observing the size, signs and

FIGURE 5

In sample test: Relative ACR ratio values for Z-Metrics agency equivalent (AE) ratings compared to Agency ratings. Models are estimated and tested in the 1989-2008 sample for public and private firm models

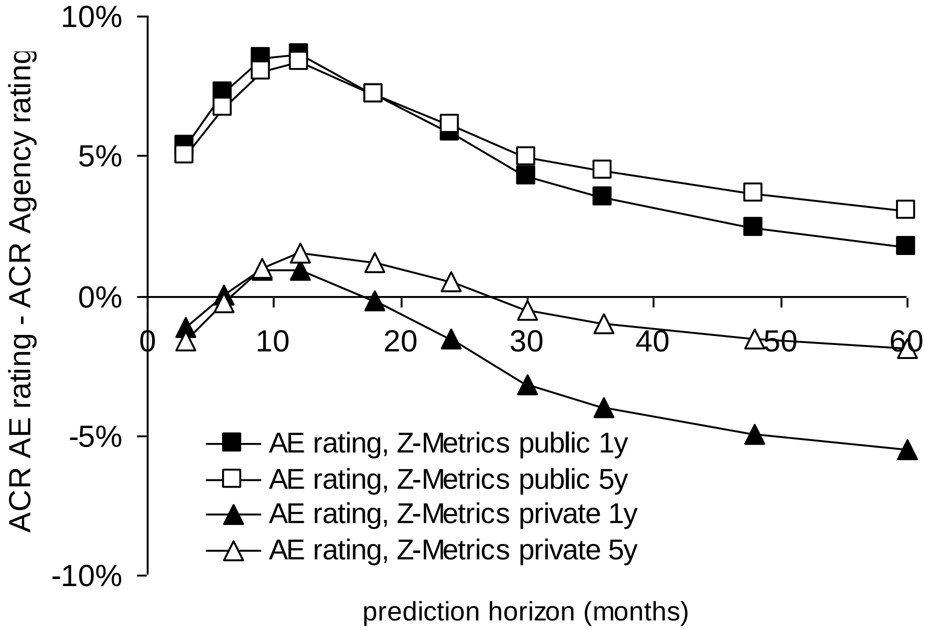
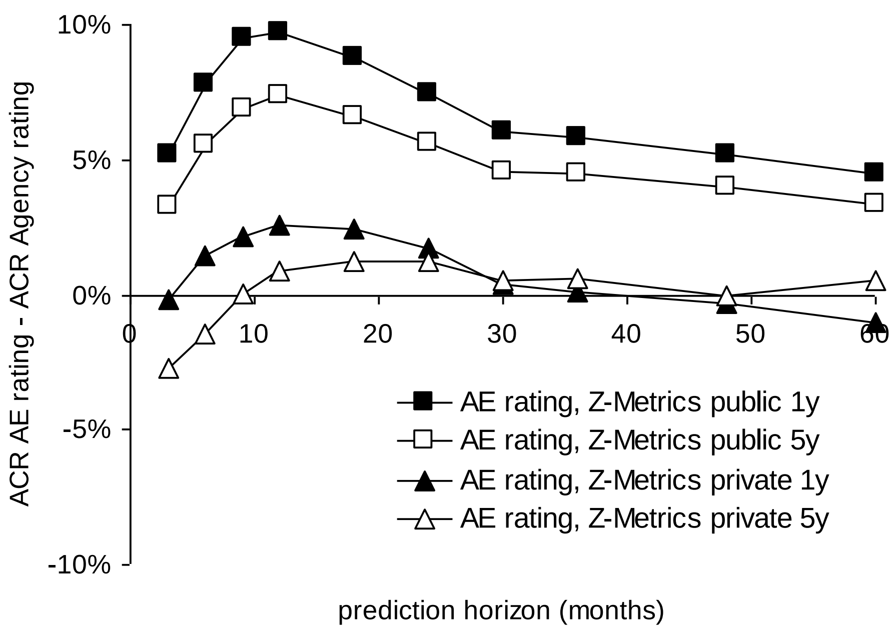


FIGURE 6

Out of sample test: Relative ACR ratio values for Z-Metrics agency equivalent (AE) ratings compared to Agency ratings, Models are estimated in a 1989-1998 sample and tested in the 1999-2008 sample



significance of the coefficients for individual variables. The accuracy ratios were very similar between the two sample periods and the coefficients and significance tests were extremely close.

The Z-Metrics™ Rating System

The Z-Metrics Rating System has 15 rating categories ranging from the most credit worthy "ZA+" rating to the lowest quality "ZF-" rating. The rating categories are based on a firm's probability of default (PD) for one- and five-year horizons for public firms, as shown in Figure 7. The PD of an entity is computed via the logit transformation of a raw score, as shown in equation 1.

For public firms, note that ratings ZA+ to ZB- (top 6 levels) all have one-year PDs of less than 0.2% and less than 4.5% for five years. We classify these firms as "high-grade." The "low-grade" levels are for one-year PDs greater than 1% and greater than 14% for five-year PDs. The "mid-grade" range is the ZC levels. We observe that within the period 1989-2008, 22.6% of the firms had one-year PDs greater than 1% and about the same percentage (22.2%) had five-year PDs above 14%. 16.9% percentage of the observations had extremely low one-year PDs of less than 6 basis points (0.06%) – our three-top ZA categories - and 18.0% had five-year PDs less than 1.75%. About 5.3% of the observations had one-year PDs of more than 10% (our bottom-three ZF ratings), and 5.4% had five-year PDs of at least 45%; 1% of the firms had five-year PDs greater than 80%.

In addition to the rating distribution over relatively long sample periods (e.g., 20 years), our model can calculate one-year PDs as of a particular point in time. For example, as of year-end 2008, when several macro-variables and particularly our stock market measures indicated an

FIGURE 7

DEFINITION OF Z-METRICS RATINGS FOR *PUBLIC* MODELS

Z-METRICS™ RATINGS	Z-METRICS PUBLIC - 1 YEAR					Z-METRICS PUBLIC - 5 YEARS			
	ONE YEAR PD		% REPRESENTATION			FIVE YEAR PD		% REPRESENTATION	
	MIN	MAX	1989/ 2008	2008		MIN	MAX	1989/ 2008	2008
ZA+	0.00%	0.02%	3.5%	2.1%		0.00%	0.75%	3.4%	2.4%
ZA	0.02%	0.04%	5.8%	4.6%		0.75%	1.25%	7.0%	5.4%
ZA-	0.04%	0.06%	7.6%	6.1%		1.25%	1.75%	7.6%	6.4%
ZB+	0.06%	0.09%	10.6%	10.0%		1.75%	2.50%	10.6%	9.9%
ZB	0.09%	0.14%	10.9%	11.2%		2.50%	3.50%	11.1%	11.3%
ZB-	0.14%	0.20%	8.8%	9.1%		3.50%	4.50%	8.1%	8.6%
ZC+	0.20%	0.30%	9.4%	10.8%		4.50%	6.00%	8.6%	9.7%
ZC	0.30%	0.50%	10.1%	10.4%		6.00%	9.00%	11.1%	12.1%
ZC-	0.50%	1.00%	10.6%	11.4%		9.00%	14.00%	10.0%	10.3%
ZD+	1%	2%	7.6%	8.2%		14%	20%	6.3%	6.8%
ZD	2%	4%	5.2%	5.8%		20%	30%	6.0%	6.6%
ZD-	4%	10%	4.5%	4.7%		30%	45%	4.5%	4.9%
ZF+	10%	25%	2.6%	2.6%		45%	65%	3.0%	3.2%
ZF	25%	50%	1.5%	1.6%		65%	80%	1.4%	1.6%
ZF-	50%	100%	1.2%	1.3%		80%	100%	1.0%	1.0%

extremely stressed environment based on such measures as yield spreads, unemployment rates, and equity/debt ratios, the distribution of PDs shows a much smaller percentage of firms with extremely low one-year PDs (e.g., only about 8.4% of firms had PDs below 0.06% [ZA], compared to 16.9% for the entire 20-year sample period) and a higher percentage of firms with high one-year PDs (e.g., about 9.8% of firms had PDs above 10% [ZFs] and about 33.4% of firms had PDs above 1.0% [ZD + ZF], compared to respectively 5.3% and 22.6% for the entire 20-year sample period). Our five-year horizon model does not have macro-variables since we assume that such factors are not likely to affect default probabilities as far out as 3-5 years.

A one-year PD of 20 basis points (0.20%) in the Z-Metrics Rating System is equivalent to a BBB (Baa) rating and a one-year PD of about 4.0% (400 bps) is analogous to single B companies.[8] For five years, a BBB (Baa) equivalent company is comparable to a Z-Metrics PD of about 2.5%-3.5% and a B rated company would have an equivalent Z-Metrics PD of 20-30%.

Based on our Z-Metrics results, our rating system classifies firms in the high-grade range of credit risk [ZA and ZB ratings], mid-grade range [ZC ratings] or low-grade range [ZD and ZF ratings].

Prediction Results – 2009 Defaults/Bankruptcies

Perhaps the most important robustness tests of credit scoring models are how well they *predict* critical events based on samples of firms which were not used to build the model, and particularly if the events took place subsequent to the building of the model(s). An associated test is how well the model compares to other methods which are available and where the data and comparable results are transparent, again outside the test sample period. These results are

[8] Cumulative default frequencies are published regularly by the three major rating agencies and are combined and compared in Caouette, Altman, et al, (2008), p.263.

indicative of the models' predictive accuracy for both our public and private Z-Metrics models for one-year and five-year horizons and also comparative tests with Agency ratings and the Z-score and Z"-score models. Z-Metrics model results are displayed in terms of AE ratings, probabilities of default and also our own rating system. These results can be found in the Z-Metrics White Paper, mentioned in footnote #6.

5. The "Bottom-Up" Approach for Sovereign Risk Assessment

By using our Z-Metrics default probabilities for individual firms and aggregating these probabilities by country, one can compute both a median default probability and rating for each country and use these as one assessment of the overall health of the nation's private sector. The recent situation in Europe is importantly instructive.

We have selected nine key European countries to examine as of two time period intervals prior to the height of the recent European sovereign debt crisis. The periods of analysis include the first six months of 2009 and the first three months of 2010. The clear recognition of the crisis and the concern over a European Union collapse was in June 2010, when Greece's debt was downgraded to non-investment grade and both Spain and Portugal also were downgraded to a lower rating, albeit still amongst the top three rating categories. Clearly, however, the credit market recognized the Greek and Irish problems prior to June 2010 and as we will show, ascribed a high implied probability of default during the first half of 2010 and even in 2009. In order to capture the essence of our model's PD estimates, we observe the median PDs and their associated ratings based on the population of listed non-financial companies. For the sovereign

CDS spread, and our model's estimates, we observe the median level for the six-month/three-month periods.[9]

Figure 8 shows the median Z-Metrics' PD estimates for listed European stock companies for the two time periods described above and also the median implied default probability from CDS spreads. We observed these risk measures for nine European countries as well as the United States. It is of great interest to examine the differential PDs not only across different countries, but also between the two time periods. These comparisons indicate not only sovereign risks differences but also the impact of differential asset values as determined primarily by market values of the outstanding equity securities of the companies.

In the first quarter of 2010, our Z-Metrics' 5-year PDs for European corporate default risk placed Greece (10.60%) and Portugal (9.36%) in the highest risk categories (ZC-ratings), followed by Italy (7.99%), Ireland (6.45%) and Spain (6.44%), all in the ZC category, then Germany and France (both about 5.5% - ZC+), with the U.K. (3.62%) and the Netherlands (3.33%) at the lowest risk levels (ZB– and ZB). The U.S.A. compares fairly well at 3.93% (ZB-). For the most part, this risk hierarchy is logical since most analysts would place countries like Greece and Portugal amongst the most risky in Europe and France, Germany and the Netherlands amongst the least risky. There were a few surprises, with the U.K. demonstrating a fairly healthy private sector and Germany and France perhaps not as healthy as one might have thought. Perhaps the U.K.'s relative strong showing is somewhat driven by the fact that our risk measure does not include financial sector firms, which comprised about 35% of the market values of listed U.K. corporates and were in poor financial condition in recent periods. Also

[9] The median CDS spread is based on the daily observations in the six/three-month periods. The median Z-Metrics PD is based on the median company PDs each day and then we calculated the median for the period.

Figure 8

Financial Health of the Private, Non-Financial Sector: Selected European Countries and U.S.A. in 2010/2009 (Z-Metrics PD Estimates and Implied PDs from CDS Spreads)

	No. of Listed Companies		Z-Metrics PD Estimates: Five-Year Public Model*				Five-Year Implied PD from CDS Spread	
Country	2010	2009	2010 Median PD	2009 Median PD	2010 Std. Dev.	2009 Std. Dev.	2010	2009
Netherlands	61	60	3.33%	5.62%	7.52%	9.33%	2.83%	6.06%
United Kingdom	442	433	3.62%	5.75%	11.60%	12.70%	6.52%	8.13%
U.S.A.	2226	2171	3.93%	6.97%	9.51%	15.15%	3.28%	4.47%
France	297	294	5.51%	7.22%	9.72%	12.34%	3.75%	4.05%
Germany	289	286	5.54%	7.34%	13.10%	15.16%	2.67%	3.66%
Spain	82	78	6.44%	7.39%	9.63%	11.26%	9.39%	8.07%
Ireland	28	26	6.45%	7.46%	16.29%	16.30%	12.20%	17.00%
Italy	155	154	7.99%	10.51%	10.20%	14.11%	8.69%	11.20%
Portugal	30	30	9.36%	12.07%	7.25%	12.44%	10.90%	7.39%
Greece	79	77	10.60%	11.57%	14.40%	12.99%	24.10%	13.22%

* Based on median Z-Metrics PDs from January 1 – June 30, 2009 and January 1 – April 30, 2010.
**Assuming a 40% recovery rate; based on the median CDS spread observed for first six months of 2009 and first three months of 2010.

Sources: RiskMetrics Group (MSCI), Markit, Compustat.

there are several very large, healthy multinational entities in the U.K. index. The CDS/5-year market's assessment of U.K. risk was harsher in 2010 with the median of the first-quarter days implying a 6.52% probability of default, about double our Z-Metrics median level. Greece also had a much higher CDS implied PD at 24.10% compared to 10.60% for Z-Metrics. Of course, the choice of the median Z-Metrics PD is arbitrary and there are 50% of the listed companies with higher PDs than 10.60%.

We also observe that several countries had a relatively high standard deviation of Z-Metrics PDs, indicating a longer tail of very risky companies. These countries include Ireland, Greece and, surprisingly again, Germany, based on 2010 data. So, while almost everyone considers Germany as the benchmark-low risk country in Europe (e.g., its 5-year CDS spread was just 2.67% in 2010, even lower than the Netherlands (2.83%), we are more cautious, at lease based on a broad measure of private sector corporate health.

2010 vs. 2009

In Figure 9, we can also examine how our two risk measures (Z-Metrics PDs and CDS spread implied PDs) differed between the first six months of 2009 and the first quarter of 2010. Note that in all cases, our 2009 PD estimates are uniformly higher (more risky) than early in 2010, even if the world was more focused on Europe's problems in the later year. We believe the main reason for the higher PDs was the significant impact of the stock market, which is a powerful variable in the Z-Metrics model - - and also in many other default probability models (e.g., Moody's KMV). Recall that the stock markets were at very low levels at the end of 2008 and into the early months of 2009, while there was a major recovery in early 2010.

Figure 9 shows the percent increase in median 2010 stock market index levels for our nine European countries and the USA compared to 2009 levels. Note that almost all countries enjoyed increases of greater than 20% between the first six months of each year. Only Greece had a relatively low increase (5.5%), consistent with its modest improvement in its Z-Metrics PD (-8.4%). Figure 9 also shows the sovereigns' percent improvement in PDs (lower risk) in 2010, which are, for the most part, consistent with stock market index values. It is noteworthy, however, that Ireland stands out in that while its stock market index value increased by 26.2%, its corporate sector only enjoyed a modest improvement (-7.4%) in Z-Metrics' median PD. Perhaps this was due to the earlier austerity measures taken in Ireland compared to other shaky European nations. As noted earlier, there are many other variables, mainly fundamental measures of corporate health and macroeconomic conditions, included in the Z-Metrics model which are not impacted by stock prices.

Figure 9

Median Percent Change in Various Country Stock Market Index Values and Z-Metrics' PDs Between the First Six Months of 2010 Vs. 2009

Country	Index	Median Percent Change (2010 vs. 2009)*	Median Z-Metrics Percent Change (2010 vs. 2009)
France	CAC40	24.1%	-23.6%
Germany	DAX	31.8%	-24.5%
Greece	ASE	5.5%	- 8.4%
Ireland	ISEQ	26.2%	- 7.4%
Italy	FTSEMIB	18.2%	-24.0%
Netherlands	AEX	34.4%	- 25.3%
Portugal	PSI-20	17.8%	-22.4%
Spain	IBEX35	20.9%	-12.9%
UK	FTSE100	27.8%	-37.6%
USA	S&P500	31.9%	-43.6%

***Median of the various trading day stock index values and PDs.**

Sources: Z-Metrics Model calculations from RiskMetrics (MSCI) Group, Bloomberg for stock index values.

6. Conclusion and Implications

The modern day prescription for bailouts of ailing sovereigns is a heavy dose of austerity measures to help bring the sovereign back to credibility and perceived solvency by foreign creditors. In the current case of Europe, Greece, Ireland, Spain, Portugal, Italy and the U.K., governments have already begun some of these painful measures while others, like France and Hungary, have resisted. In prescribing difficult sanctions to governments for them to qualify for bailouts and subsidies, we caution that such measures should not deteriorate or destroy private enterprise valuations. Indeed, these critical resources should be nurtured and promoted. A healthy private sector will provide critical tax revenues for the sovereign and jobs for its citizens. Certainly politicians, as well as World Bank, IMF and Central Bankers, understand these realities.

With respect to modeling sovereign risk, we propose that classical measures of macroeconomic performance be combined with more modern techniques, like contingent claims analysis and our bottom-up approach, to enhance explanatory and predictive results. This will be the theme of our future research.

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