Modeling Country Default Risk as a Latent Variable:

A Multiple Indicators Multiple Causes (MIMIC) Approach

by

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Abstract:
We study the determinants of country default risk by applying a Multiple Indicators Multiple Causes (MIMIC) approach. This accounts for the fact that country default risk is an unobservable variable. Whereas existing (regression-based) approaches typically use only one of several possible country default risk indicators as the dependent variable, the MIMIC approach enables us to consider several indicators at once. The simultaneous consideration of sovereign yield spreads and S&P ratings may help to improve the identification of the latent country default risk. Our results confirm most of the literature's main findings regarding important determinants of country default risk, refute others and provide new evidence to controversial questions.

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JEL-Classification: F34, G15, G12
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1 Introduction

Country default risk, or sovereign risk, is an important issue in international lending – in particular in lending to developing and emerging market countries – since a country's potential inability or unwillingness to make debt servicing payments influences the lender's expected profit and, hence, its investment decision. A proper assessment of country default risk should help to reduce inefficiencies in international lending, on the one hand, by avoiding overborrowing and the evaporation of capital during financial crises and, on the other hand, by avoiding tightening of capital supply and overpricing (in terms of high interest rates). Much scientific work has thus been dedicated to the assessment of country default risk, especially its determinants. Knowing the determinants of country default risk may enable investors to assess the risk of a debt crisis and may help the governments in emerging countries to lower the risk of a debt crisis.

One major problem in the assessment of country default risk is that it is a latent variable that is, even *ex-post*, unobservable. Thus, whether a country has defaulted or not during a specific (forecast) period is observable but the probability of default is not. Robert Engle's (1993) simile that "volatility forecasting is a little like predicting whether it will rain; you can be correct in predicting the probability of rain, but still have no rain," also applies in the context of country default risk.

Because country default risk itself cannot be observed, scientific studies use several indicators for its approximation.[1] One strand considers yield spreads between default risky government bonds of the respective country and the US treasury yield curve.

[1] We review the literature in the next section in more detail, since our empirical work builds on the results of the previous literature.

Another strand applies ratings provided by major rating agencies or business journals.[2] These two types of indicators represent country risk assessments made by different agents. While bond yield spreads are determined by (a multitude of) investors in the sovereign bond market, country ratings are determined by (small groups of) experts. The latter are not directly exposed to the risk of capital losses, but paid by the rated debtor countries whereas the former face potential capital losses but gain from increasing prices.

From these considerations follows that both types of indicators may provide different assessments of country default risk. They are closely related, however, as shown in several important empirical contributions (see, for example, Cantor and Packer, 1996, Larrain et al., 1997, and Scholtens, 1999, 2002). Nevertheless, ratings do not fully explain spreads in regression models, and the relation between both indicators does change over time, as pointed out by Scholtens (2002). Thus, besides theoretical considerations also empirical findings suggest that the risk assessment of both types of indicators differs.

The existing literature identifies the determinants of country default risk by regressing one of several possible indicators, either ratings or spreads, on potential explanatory variables. In this way, the underlying causes of country risk are revealed, which improves our understanding of its nature substantially. Also, models for forecasting potential debt crises are developed which provide excellent results.

While the literature applies regression approaches with only one indicator as the dependent variable, we contribute with an approach that allows consideration of more

[2] In addition to these contemporaneously observable indicators, also dummies that rely on *ex-post* observations for whether a default has occurred or not during the period considered are used.

than one indicator.[3] Using a structural equations model, more precisely a Multiple Indicators Multiple Causes (MIMIC) model, we treat country default risk as an unobservable variable that is approximated using several observable indicators.[4] In the application of the model, we use yield spreads provided by JP Morgan's Emerging Market Bond Index (EMBI$^+$) and sovereign ratings by Standard and Poor's (S&P). Since different types of agent compile these indicators, they reflect an (at least slightly) different approximation of country default risk. Including both types of indicators, thus, considers more information and provides a better approximation of country default risk than using just one single indicator. Hence, our model may yield more precise results than alternative approaches while enabling us to verify the results of the existing literature.

We proceed as follows. Section 2 reviews the existing literature on country default and sovereign risk. Section 3 explains the MIMIC model in detail. Section 4 presents the application of the model and discusses the indicators, causal variables, and data sample. The estimation results are presented in Section 5. Section 6 concludes.

2 The Literature on Country Default Risk

Due to this paper's emphasis on empirical evidence, we focus on the empirical literature and provide a short overview of the major strands of this literature with particular respect

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[3] Some researchers are interested in the determinants of the indicator variables themselves rather than in their role as indicators for country default risk. If so, a regression using the respective variables as the dependent one is the natural choice. Since we are interested in the latent country default risk and in the role of the variables as risk indicators a MIMIC model seems to be an interesting alternative.

[4] MIMIC models have become popular in other fields dealing with latent economic phenomena such as the shadow economy (see, e.g., Dell'Anno and Schneider, 2003).

to indicator variables. Table B.1 in Appendix B shows details of the methodology, data samples, and significant variables used in this literature. We review the explaining variables separately in Section 4, where we derive our testable hypotheses based on previous results found in the literature. Before considering the empirical literature, we briefly review the theoretical literature.

2.1 Theoretical Literature

The theoretical literature is divided into two important strands. One strand focuses on a country's *ability* to meet its debt service payments, whereas the other emphasizes the importance of its *willingness* to do so. The *ability-to-pay* literature analyzes the development, sustainability, and limits of a country's indebtedness (see, for example, Domar, 1950, Avramovic, 1964, Solomon, 1977, Johnson et al., 1981, Diaz-Alejandro, 1984, and Simonsen, 1985). Whereas these papers implicitly assume that a country makes its debt service payments as long as it is able to do so, the *willingness-to-pay* literature emphasizes that a default results from a government's own decision since creditors have no means to enforce their claims against a sovereign country. A detailed discussion of this literature can be found in Eaton et al. (1986) or Eaton and Fernandez (1995).

2.2 Country Default Risk Indicators and Their Interrelations

The empirical literature on determinants and probability of country defaults can be divided into several strands according to the different indicators used to measure latent country default risk. One strand of the literature considers spreads between yields of default risky bonds of the country analyzed and risk-less interest rates of bonds with equal contractual arrangements, especially with an equal maturity. Typically, the US Treasury yield curve is used as the risk-less benchmark. It is assumed that these yield spreads largely reflect a country's default risk since it represents the discount market participants demand when buying the respective default risky security. Hence, spreads reflect market participants' assessment of country default risk in bond markets. These spreads can be further divided into primary spreads observed when bonds are issued and spreads observed on secondary markets.[5]

In addition to yield spreads, sovereign (or country) ratings can be used as indicators of country default risk. Ratings are generally a subjective and qualitative assessment by a group of experts. Several rating agencies, such as S&P, Moody's, and Fitch, provide publicly observable ratings. The Political Risk Group provides ratings focused on countries' political risk. Also business magazines like Institutional Investor[6] and Euromoney publish country ratings.

Cantor and Packer's (1996) paper is considered the "locus classicus for quantitative evidence on sovereign rating determinants" (Reisen, 2003), yet they consider not only the determinants of ratings but also the determinants of sovereign yield spreads. Cantor and Packer perform OLS cross-sectional regressions with either spreads or ratings

[5] One could also distinguish between the time periods covered. One strand of the literature considers the period prior to World War I (see, for example, Bordo and Rockoff, 1996, Obstfeld and Taylor, 2003, Meissner, 2005, and Camaron et al., 2006). Related to our data sample, we focus on the literature that considers data observed in the last decades, because the political and economic environment has changed considerably since World War I.

[6] Institutional Investor surveys experts from approximately 100 leading international banks, rather than a small group, to compile its ratings.

as the dependent variable. They use the most liquid Eurodollar bond for the respective country and ratings assigned by S&P and Moody's.

Cantor and Packer also examine the *relationship between ratings and spreads*. In a case study, they analyze the development of spreads in relation to rating changes. In considering average spreads before and after rating changes, they find that spread changes precede rating changes, but rating also affect spreads on the day the rating changes are announced. Larrain et al. (1997) conduct a similar study with even more distinct results. In addition, they test for Granger causality, which cannot be rejected in either direction. Scholtens (1999) chooses a different approach to consider the relationship between spreads and ratings. He analyzes the rank correlation between secondary market bond spreads and ratings provided by Institutional Investor and finds a highly significant correlation between the two indicators.

Scholtens (2002) confirms this close relationship by regressing ratings on spreads. In several specifications he obtains R^2 values between 0.81 and 0.95, whereas Cantor and Packer (1996) report an $R^2$of 0.92. Although both types of indicators are closely related, ratings cannot fully explain spreads. Thus, differences in the risk assessments from ratings and spreads still exist. Moreover, Scholtens (2002) – in applying the Chow breakpoint estimation test for stability of regression coefficients obtained by estimations for different time spans – points out that the connection between the two indicators changes over time. Indeed, the test indicates significant differences for different sub-samples. Since these findings indicate that differences between country default risk assessment of ratings and spreads exist, considering both types of indicators should improve the approximation of country default risk.

2.3. Literature on the Determinants of Ratings

In addition to papers that examine the relationship between ratings and spreads, a number of papers use regression models to identify the determinants of ratings. Based on cross-section OLS regressions, Afonso (2002) uses ratings of S&P and Moody's. He applies both a linear and a logistic transformation to convert ratings into numerical values. Rowland (2004) also employs a cross-country OLS regression. He considers S&P, Moody's and Institutional Investor ratings. In contrast to Cantor and Packer (1996) and Afonso (2002), the analysis is restricted to emerging market countries and excludes developed countries. He also considers a broader set of explanatory variables than the other studies.

Contrary to the studies on ratings mentioned so far, Mulder and Perrelli (2001) consider both cross-sectional and time series information. They use ratings from S&P and Moody's as indicators and perform regressions based on pooled data (OLS and Feasible Generalized Least Squares). Rowland and Torres (2004) perform a random effects GLS panel regression with the Institutional Investor rating as the dependent variable.

2.4 Literature on the Determinants of Sovereign Yield Spreads

Edwards (1984) is widely recognized as the first to use *sovereign yield spreads* to determine the causes of country default risk. He analyzes primary spreads of bank credits. In a later paper, Edwards (1986) also includes bond contracts in the analysis and regresses several economic variables assumed to influence country default risk on (logged) spreads. Min (1998) applies a similar approach using more recent bond data.

Eichengreen and Mody (1998) find that, in addition to observable fundamental data, expectations and market sentiments strongly influence observed sovereign yield spreads. They, too, consider primary spreads as indicators. Kamin and von Kleist (1999) confirm this finding using both primary and secondary market spreads as the dependent variable. Considering secondary market spreads avoids the problem of the issuance or selection bias,[7] pointed out already by Eichengreen and Mody (1998).

Secondary market spreads are also used as dependent variable in Arora and Cerisola (2001). They run individual regressions for eleven countries. Some papers, such as Nogués and Grandes (2001), who consider Argentina, and Rojas and Jaque (2003), who focus on Chile, conduct single-country studies based on secondary market spreads. Rowland and Torres (2004), by contrast, use a panel data framework to analyze sixteen emerging market economies.

2.5 Literature Employing Default Dummies

Ratings and spreads applied as risk indicators in the studies considered so far are immediately observable. By looking at *ex-post* observable, historical data, one can specify another type of indicator: default dummies that indicate whether a default has occurred or not during a specific period of time. Contrary to the rain (probability) predictions mentioned in the introduction, the identification of a default is not easy, even *ex-post*. The literature discusses and uses several approaches to (properly) identify defaults: different measures of arrears on debt service payments, disbursement of large IMF loans, or even (default) ratings. For the specification of dummies based on default ratings, only default and non-default ratings are distinguished whereas the studies above consider all rating categories. This points to one of the drawbacks of the dummy

[7] The conditions for issuance of emerging market bonds change over time. In times of high yield spreads, when the cost of raising capital is high, risky issuers will withdraw from the market, thus creating a bias.

approach: using a dichotomous indicator wastes potentially valuable information. Still, these papers can be helpful in identifying (possible) determinants of country default risk. We therefore include their results in the specification of potential causal variables for our model.

Studies that use default dummies as the indicator developed in the 1960s. Saini and Bates (1984) provide a comprehensive overview of the literature up to the early ’80s. While some of the early work (see, for example, Frank and Cline, 1971, Sargen, 1977, and Saini and Bates, 1978) is based on discriminant analysis, later research relies on logit and probit models (first examples are Feder and Just, 1977, and Mayo and Barrett, 1977). Early studies rely mostly on small data samples, whereas most of the later studies consider a broader data sample, especially with longer time series (see, for example, Detragiache and Spilimbergo, 2001, and Manasse, Roubini and Schimmelpfennig, 2003). The more recent papers also use a broader set of explanatory variables. The determinants of country risk are discussed in more detail in Section 4. The next section describes the MIMIC model in detail.

3 Methodology

The MIMIC model explains how observable causal variables determine the level of a latent phenomenon like country default risk, which is then approximated by several observable indicators. Thus, it allows us to deal with the multiple causes and the multiple effects of country default risk.[8] Formally, the MIMIC model consists of two parts: the structural equation model and the measurement model. The structural equation model is given by:

[8] Structural equation models were first introduced into economics by Jöreskog (1970).

$$\eta = \boldsymbol{\gamma}'\mathbf{x} + \varsigma \ , \tag{1}$$

where $\mathbf{x}' = (x_1, x_2, \ldots, x_q)$ is a $(1 \times q)$ vector and each x_i, $i = 1, \ldots, q$ is a potential cause of the latent variable η, and $\boldsymbol{\gamma}' = (\gamma_1, \gamma_2, \ldots, \gamma_q)$ is a $(1 \times q)$ vector of coefficients describing the relationships between the latent variable and its causes. Thus, the latent variable η is determined by a set of exogenous causes. Since these causes only partially explain the latent variable η, the error term ς represents the unexplained component. The variance of ς is denoted by ψ. $\mathbf{\Phi}$ is the $(q \times q)$ covariance matrix of the causes x.

The measurement model represents the link between the latent variable and its indicators, i.e. the latent variable determines its indicators. The measurement model is specified by:

$$\mathbf{y} = \boldsymbol{\lambda}\eta + \varepsilon \ , \tag{2}$$

where $\mathbf{y}' = (y_1, y_2, \ldots, y_p)$ is a $(1 \times p)$ vector of several indicator variables, $\boldsymbol{\lambda}$ is the vector of regression coefficients, and $\boldsymbol{\varepsilon}'$ is a $(1 \times p)$ vector of white noise disturbances. Their $(p \times p)$ covariance matrix is given by $\mathbf{\Theta}_{\boldsymbol{\varepsilon}}$. Figure 1 shows the structure of the MIMIC model using a path diagram.

[Insert Figure 1 about here]

Using Equation (1) in Equation (2) yields a reduced form multivariate regression model where the endogenous variables y_j, $j = 1, \ldots, p$ are the latent variable η's indicators and the exogenous variables x_i, $i = 1, \ldots, q$ its causes. This model is given by:

$$\mathbf{y} = \mathbf{\Pi}\mathbf{x} + \mathbf{z} \ , \tag{3}$$

where $\mathbf{\Pi} = \boldsymbol{\lambda}\boldsymbol{\gamma}'$ is a matrix with rank equal to 1 and $\mathbf{z} = \boldsymbol{\lambda}\zeta + \boldsymbol{\varepsilon}$. The error term $\mathbf{z}$ in Equation (3) is a $(p \times 1)$ vector of linear combinations of the white noise error terms ς and $\boldsymbol{\varepsilon}$ from the structural equation and the measurement model, i.e., $\mathbf{z} \sim (\mathbf{0}, \mathbf{\Omega})$. The covariance matrix $\mathbf{\Omega}$ is given by $\mathbf{Cov}(\mathbf{z}) = \mathbf{E}[(\boldsymbol{\lambda}\varsigma + \boldsymbol{\varepsilon})(\boldsymbol{\lambda}\varsigma + \boldsymbol{\varepsilon})'] = \boldsymbol{\lambda}\boldsymbol{\lambda}'\psi + \mathbf{\Theta}_{\boldsymbol{\varepsilon}}$ and is constrained similar to $\mathbf{\Pi}$. The estimation of the model therefore requires the normalization of one of the elements of the vector $\boldsymbol{\lambda}$ to an *a priori* value (Bollen, 1989). From Equation (1) and (2) we can derive the MIMIC model's covariance matrix $\mathbf{\Sigma}(\boldsymbol{\theta})$ (see Appendix A). This matrix describes the relationship between the observed variables in terms of their covariances. Decomposing the matrix yields the structure between the observed variables and the latent variable. This covariance matrix is given by:

$$\mathbf{\Sigma}(\boldsymbol{\theta}) = \begin{pmatrix} \boldsymbol{\lambda}(\boldsymbol{\gamma}'\mathbf{\Phi}\boldsymbol{\gamma} + \psi) + \mathbf{\Theta}_{\boldsymbol{\varepsilon}} & \boldsymbol{\lambda}\boldsymbol{\gamma}'\mathbf{\Phi} \\ \mathbf{\Phi}\boldsymbol{\gamma}\boldsymbol{\lambda}' & \mathbf{\Phi} \end{pmatrix}, \tag{4}$$

where $\mathbf{\Sigma}(\boldsymbol{\theta})$ is a function of the parameters $\boldsymbol{\lambda}$ and $\boldsymbol{\gamma}$ and of the covariances contained in $\mathbf{\Phi}$, $\mathbf{\Theta}_{\boldsymbol{\varepsilon}}$, and ψ. Since the latent variable is not observable, its size is unknown and the parameters of the model must be estimated using the links between the observed variables’ variances and covariances. Thus, the goal of the estimation procedure is to find values for the parameters and covariances that produce an estimate for $\mathbf{\Sigma}(\boldsymbol{\theta})$, $\hat{\mathbf{\Sigma}} = \mathbf{\Sigma}(\hat{\boldsymbol{\theta}})$ that is as close as possible to the sample covariance matrix of the observed causes and indicators. As a result, the hypothesized relationships between the latent variable and its causes and indicators are identified and the corresponding coefficients are estimated.

4 Empirical Analysis

4.1 Indicators of Country Default Risk

In general, two types of indicators, which provide instant assessment,[9] are used to identify the unobservable variable country default risk: market data, as yield spreads of sovereign bonds issued by the observed countries, and ratings assigned to those countries. As already mentioned, previous studies use either market information or expert ratings, but not both. We use a prominent example for each type of indicator and thus derive a broader assessment of country default risk. Like many other studies, we use ratings assigned by S&P, one of the major rating agencies. For sovereign yield spreads, we consider data from the Emerging Market Bond Index^{+} (EMBI^{+}) provided by JP Morgan for the first trading day of every year.

Data on S&P ratings are obtained from "Sovereign Ratings History Since 1975," provided at S&P's website.[10] This document provides information on rating changes for each sovereign borrower for which a rating is assigned. We consider the long-term rating for foreign currency debt valid at the beginning of each year. For the quantitative analysis we transform the ratings into numerical values. To be as precise as possible we assign a different numerical value for each rating grade as displayed in Table B.2 in Appendix B. In addition, we assign different numerical values for different statements in the outlook, i.e., negative, stable or positive. As a result, there are several numbers for each rating grade. In addition to this (regular) outlook, S&P occasionally states that it will consider a

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[9] Default dummies, by contrast, give no instant indication of the risk of default. They only provide an *ex-post* assessment of whether a default has occurred or not. They cannot be used as risk indicators for investors trying to measure the country default risk on their investment.

[10] See http://www2.standardandpoors.com.

particular borrower for a possible rating change (i.e., put it on a “watch list”) in the near future. We include this information by adding or subtracting 0.5 from the integer value corresponding to the current rating. Since we assume a nonlinear relationship between country default risk and ratings, we calculate the natural log of the resulting numerical values, as done in other studies.

We employ secondary market spreads rather than issuing spreads for several reasons. First, it avoids disturbances resulting from the issuance bias explained in Section 2.4. Second, prices and the corresponding spreads of secondary markets result from the processing of information by a number of market participants and from their interaction. Primary spreads, by contrast, are determined by issuers and banks who execute the issuing process and may deviate from the market price. Finally, including secondary market spreads widens the pool of opinions from a small group of experts at a rating agency to the multitude of participants in financial markets.

The data from JP Morgan’s $EMBI^+$ used in our analysis is the average of data from the most liquid bonds. Using these averaged numbers rather than data from single issues curbs the influence of potential price distortions concerning single issues. We consider so-called stripped spreads, which are derived from adjusted prices that result by subtracting collaterals from the observed prices.[11]

[11] Both Eurobond and Brady bond data are included in the calculation of the $EMBI^+$. Brady bonds are typically collateralized. Thus, stripped spreads (where the collateral is subtracted from the observed prices) reflect country default risk better than “raw” blended spreads.

4.2 Potential Determinants of Country Default Risk

In the following, we discuss the causal variables used in the application of the MIMIC model, which describe potential determinants of latent country default risk. In specifying these variables we use the results of the literature discussed in Section 2. A great number of different variables were found to be significant in other papers, which are presented in Table B.1 Panel A and B in the Appendix B. In considering these results, we cannot identify variables or groups of variables that are specifically related to either spreads or ratings. For both types of indicators, more or less the same variables were found to have explanatory power. Nevertheless, the results between papers differ – even for papers that use the same type of indicator. The literature often approximates the same causes for country default risk with slightly different variables (resulting from slightly different definitions or different numerators). It follows that a large number of (slightly) different variables is used in the literature. Including all of these variables simultaneously would be problematic due to multi-collinearity. Thus, we choose the most popular variables for our analysis.

The explanatory variables found in the literature can be divided into several groups. One important group comprises rather general measures of the country's current economic state of development and its future prospects. While GDP per capita reflects a country's current situation, its investment ratio is related to its future development since investment fosters economic growth. Keeping in line with the literature, we expect these variables to have a negative influence on country default risk, i.e., higher values of the explanatory variables correspond to lower country default risk.

A second group of variables is concerned with the external sector of the economy. An important variable is the ratio of the sum of exports and imports to GDP, a measure of a country's *openness*. According to the theoretical literature focusing on a country's *(un)willingness to pay* as a major cause of debt crises (see Section 2), more open countries are less willing to default on their debt than less open countries as the costs of trade disturbances – typically associated with a default – are higher. Consequently, more open countries' default risk is lower, i.e., the expected sign of openness is negative.

Other variables related to the external sector reveal whether a country is able to accumulate foreign exchange for the purpose of debt servicing. Of course the existing foreign exchange reserves itself are important in this respect. We use reserves to imports and reserve growth in our analysis since these variables were frequently found to be significantly (negatively) correlated with country default risk in the literature. Besides the existing foreign exchange reserves also foreign exchange inflows caused by international trade are important. Thus, we include the trade balance and the growth rate of exports in our analysis. Better terms of trade are important as well because they increase a country's ability to accumulate resources for debt servicing.

In addition to the ability to provide funds for debt servicing, *the payment requirements resulting from outstanding debt* are also found to be significant in the literature. Thus, we include total debt to GDP in our analysis. This variable rather measures possible solvency problems, whereas we additionally want to consider liquidity issues. Thus, we use the debt service ratio, i.e., short-term debt payment requirements to exports, as many other studies do. The more recent literature emphasizes that not only the amount of debt but also its composition is critical. Here, especially, the ratio of short-term to total debt (or to long-term debt) plays a decisive role, whereby the higher the ratio, the higher the country default risk. Thus, we expect a positive sign for the variables measuring the level of debt and the fraction of short-term to total debt.

The last group of country-specific determinants of country default risk is related to the monetary situation. Several studies consider these indicators as the monetary sector influences the economic performance and, hence, the ability to service debt. We use inflation and changes in the money supply in our analysis, which are found to be positively correlated with country default risk in the literature.

Besides these country-specific variables, the US interest rate as an indicator of changing lending conditions in the world economy is analyzed in several studies. The literature is divided over the influence of the US interest rate: some studies find it to be significant while other do not.[12]

5. Results

In the application of the MIMIC model, we consider annual data from 31 countries from 1994 to 2006. The sample is determined by the availability of data on EMBI$^+$ spreads and ratings. This implies also that the time series for some countries start after 1994. We consider annual data for two reasons: first, we are interested in the long-term rather than short-term determinants of default risk; and, second, many of the economic variables are not available at a higher frequency.

5.1 Causal Variables

We consider the standardized coefficients to examine the relative effects of the causes on the dependent, latent variable. The standardized coefficients indicate the response of the

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[12] As shown in table B1, Eichgreen and Mody (1998) and Arora and Cerisola (2001) find significant influence of the risk-less US interest rate, whereas Min (1998) and Kamin and von Kleist (1999) find the US rate to be insignificant.

latent variable, ceteris paribus, for a one standard deviation-change in an explanatory, causal variable (Bollen, 1989).[13]

Figure 2 presents the concrete path diagram for our benchmark model, which includes at least one important variable from each group.

[Insert Figure 2 about here]

Clearly, most variables belonging to the same group are highly correlated, which hampers the analysis of significant influence. Thus, we run several regressions where we exchange a causal variable for a different variable from the same group.[14] Column 1 of Table 1 presents the results for the benchmark model, and columns 2 thru 7 the results for the alternative models.[15]

[Insert Table 1 about here]

[13] The standardized coefficients are calculated as $\hat{\gamma}_{ji}^{s} = \hat{\gamma}_{ji}\sqrt{\hat{\sigma}_{ii} / \hat{\sigma}_{jj}}$, where the subscript *s* indicates the standardized coefficient, *i* denotes the causal and *j* the latent variable, and $\hat{\sigma}_{ii}$ and $\hat{\sigma}_{jj}$ are the predicted variances of the *ith* and *jth* variable, respectively.

[14] As in the regression models typically used in the literature, the time series in MIMIC models are assumed to be stationary. We test this hypothesis and find all variables used in the estimations to be stationary. Results are available upon request.

[15] All calculations have been carried out using LISREL® 8.80.

The benchmark model reveals that openness is the most important variable to explain country default risk, followed by GDP per capita and the inflation rate. The corresponding standardized coefficients are -0.37, -0.28, and 0.26, respectively. Total debt to GDP is also significant. Overall, the importance of these variables is robust across all estimated model specifications.

Our analysis confirms most of the literature's results with respect to significant explanatory variables. GDP per capita and the investment ratio are significant with the expected negative sign for all specifications. The same holds true for openness of the economy and total debt (to GDP). The debt service ratio is significant with the expected positive sign for all specifications with the exception of model 3.

In model 2 we exclude the debt service ratio from the benchmark model specification to test the influence of the ratio of short-term to total debt, for which we do not find significant influence. The fact that – in contrast to composition of debt – the other debt figures are significant indicates that indebtedness influences country default risk, regardless of whether solvency or liquidity aspects are considered.

We do not find significant influence for the terms of trade or for trade balance to reserves (tested in model 5), which is in line with the findings of some other papers. Still, the significantly (negative) influence of export growth (as shown by model 3) indicates that the external sector and a country's ability to acquire foreign exchange through trade does influence country default risk. High existing reserves reduce country default risk significantly as well since reserve growth (at least for some specifications) and reserves to imports (model 4) show significant influence.

The monetary variables are also significantly related to country default risk, regardless of whether we consider the inflation rate or changes in money supply (model

6). Higher measures of both variables increase country default risk. The US interest rate is, by contrast, not found to be significant (model 7). Thus, our results contribute to the debate in the literature on whether the US rate is important to country default risk or not by providing evidence that this is not the case.

5.2 Indicators

As explained in Section 3, estimation of a MIMIC model requires the normalization of one indicator for the latent variable. Moreover, latent variables have no inherent units of measurement. Typically, researchers assign units of measurement and set the coefficient of one indicator variable to non-zero. The metric scale of the latent variable then corresponds to that of the selected indicator. If no consensus about the measurement of the latent variable exists, the indicator selected to fix the scale is arbitrary and does not affect the estimation results (Bollen, 1989).

In our MIMIC model, we fix the coefficient of the S&P ratings to 1. We choose to set the rating as the fixed indicator because if a country defaults the rating agencies assign a "default" rating, i.e., every country that defaults receives the same rating and, thus, the same index value.[16] Observed spreads, on the other hand, differ widely between different defaulted countries (although they are very high for every defaulted country).[17]

Turning to the interpretation of the indicators, we see that they are consistent for

[16] To be precise, in the case of S&P there are two possible default ratings: 'D' for default and 'SD' for selected default. The two ratings are nevertheless much more alike than observed spreads within default countries.

[17] Even defaulted bonds are not completely worthless after a default since the bond holder can expect a certain non-zero recovery rate. Since these expected recovery rates differ across countries, the spreads of defaulted bonds differ widely.

all estimated specifications. As expected, we always find a strong, significant, positive relationship between country default risk and $EMBI^+$ spreads, which confirms the findings of the existing literature. Both $EMBI^+$ spreads and ratings appear to be reliable indicators of country default risk. The slight difference between the standardized coefficients for both variables leads us to the conclusion that (under the assumptions of the MIMIC approach) the S&P ratings do a slightly better job of indicating country default risk than the $EMBI^+$ spreads.

5.3 Examining the Models' Fits

A variety of overall fit measures are available to examine the validity and reliability of MIMIC models. They range from absolute fit indices, which directly assess how well the predicted covariances reproduce the sample covariances, to information criteria, which are comparative in nature. Table 1 reports the main goodness-of-fit statistics, such as the chi-square statistics and the goodness-of-fit index (GFI), together with the degrees of freedom. All other statistics are presented in Table B.4 in Appendix B.

The absolute fit measures of the benchmark model, i.e., the GFI and the adjusted goodness-of-fit index (AGFI), produce values larger than 0.90. This reflects a good fit of the model. With a value significantly higher than 0.50, the parsimony goodness-of-fit index (PGFI) confirms the model's good performance (Mulaik et al., 1989). The chi-square statistic tests whether the model fits the data perfectly, i.e. $\Sigma = \Sigma(\theta)$.[18] The root

[18] The chi-square statistic tests the specification of the model against the alternative hypothesis that the covariance matrix of the observed variables is unconstrained. Here, smaller values indicate a better fit, i.e., a smaller chi-square does not reject the null hypothesis that the model reproduces the sample covariance matrix of causes and indicators.

mean squared error of approximation (RMSEA) shows how well the model would fit the population covariance matrix if the optimal but unknown parameter values were available.[19] A value below 0.05 indicates a good fit (Browne and Cudeck, 1993). This is the case for all estimated model specifications.

Another useful indicator for the evaluation of a model's overall fit is the expected cross validation index (ECVI), which measures the discrepancy between the fitted covariance matrix and the expected covariance matrix in another sample of equivalent size. Thus, the ECVI assesses how likely a model is to cross-validate across samples.[20] As the ECVI is below the ECVI of both the independent and saturated models, the model's fit is acceptable (Byrne, 1998).

The comparative information criteria examine a model's fit while taking its parsimony into account. A widely used comparative information criterion is the Akaike information criterion (AIC). A model fits the data well if its AIC is smaller than the AIC of the independent and saturated models. This is the case for the benchmark model as well as for all other estimated MIMIC model specifications.

Based on all goodness-of-fit statistics, we conclude that the benchmark model fits the data reasonably well and is sufficiently parsimonious. This result is also robust across all estimated MIMIC model specifications except for specification 3 where the AIC indicates a slightly less favorable fit.

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[19] In other words, the RMSEA measures the model's fit based on the difference between the estimated and the actual covariance matrix.

[20] The ECVI must be compared to the ECVIs of the independence and the saturated models. The former model is a model of complete independence between the variables while the number of parameters in the latter model is equal to the number of variances and covariances among the observable variables.

6 Conclusion

In this paper, we examine the determinants of country default risk using a MIMIC model. This approach accounts for the fact that country default risk – even *ex-post* – is an unobservable quantity that can be only approximated with observable indicators. Contrary to regression models typically used in the literature, where one single indicator is used to identify country risk, the MIMIC approach enables us to consider more than one indicator to identify the latent country default risk. We employ country default risk assessments based on two types of indicators: bond spreads, provided by JP Morgan's Emerging Market Bond Index[+], and ratings, provided by Standard and Poor's. Since the use of more than one indicator likely improves the approximation of the latent variable, we may be able to yield more precise results and, thus, verify the results of the literature with respect to our research question: what are the main determinants of country default risk.

Our results confirm most of the literature's findings refute others, and provide new evidence for issues still being debated. We find that the most important determinants of country default risk are openness, GDP per capita, and inflation. The investment ratio, foreign exchange reserves, changes in the money supply, total debt to GDP, and the debt service ratio are also significant. Contrary to some previous papers, we do not find significant influence for the composition of debt, i.e., the ratio of short-term to total debt. With respect to the controversially discussed US interest rate, our results support the strand of the literature that objects a significant influence of this variable on country default risk.

The overall fit is quite good for every specification and both types of indicators approximate the latent country default risk nearly equally well. All in all, the MIMIC approach yields plausible and interesting results that confirm most previous findings. Additionally, it enables a more accurate risk approximation by including more than one indicator.

References

Afonso, A. (2002) Understanding the Determinants of Government Debt Ratings: Evidence for the Two Leading Agencies, Department of Economics at the School of Economics and Management (ISEG), Technical University of Lisbon, Working Papers 2002/02.

Arora, V. and Cerisola, M. (2001) How Does U.S. Monetary Policy Influence Sovereign Bond Spreads in Emerging Markets?, *IMF-Staff Papers*, **48**, 474-98.

Avramovic, D. (1964) Economic Growth and External Debt, John Hopkins Press, Baltimore.

Bordo, M.D. and Rockoff, H. (1996) The Gold Standard as a `Good Housekeeping Seal of Approval', *Journal of Economic History*, **56**, 389-428.

Bollen, K.A. (1989) Structural equations with latent variables, Wiley.

Browne, M.W. and Cudeck, R. (1993) Alternative ways of assessing model fit, in *Testing structural equation models* (Eds.) K.A. Bollen and J.S. Long, Sage, Newbury Park CA, pp. 445-55.

Byrne, B.M. (1998) Structural equation modelling with LISREL, PRELIS and SIMPLIS: Basic Concepts, Applications and Programming, Mahwah, NJ: Lawrence Erlbaum Associates.

Cameron, G., Gai, P. and Tan, K.Y. (2006) Sovereign Risk in the Classical Gold Standard Era, Australian National University, Centre for Applied Macroeconomic Analysis, CAMA Working Papers 2006-11.

Cantor, R. and Packer, F. (1996) Determinants and Impact of Sovereign Credit Ratings, *FRBNY Economic Policy Review*, **2**, 37-54.

Dell'Anno, R. and Schneider, F. (2003) The shadow economy of Italy and other OECD countries: What do we know?, *Journal of Public Finance and Public Choice*, **21**, 97-120.

Detragiache, E. and Spilimbergo, A. (2001) Crises and Liquidity – Evidence and Interpretation, IMF-Working Papers 01/02.

Diaz-Alejandro, C.F. (1984) Latin American Debt: I Don't Think We Are in Kansas Anymore, *Brookings Papers on Economic Activity*, **2**, 335-403.

Domar, E. (1950) The Effect of Foreign Investment on the Balance of Payments, *American Economic Review*, **40**, 805-26.

Eaton, J. and Fernandez, R. (1995) Sovereign Debt, NBER Working Paper 5131.

Eaton, J., Gersovitz, M. and Stiglitz, J.E. (1986) The Pure Theory of Country Risk, *European Economic Review*, **30**, 481-513.

Edwards, S. (1984) LDC Foreign Borrowing and Default Risk: An Empirical Investigation, *American Economic Review*, **74**, 726-34.

Edwards, S. (1986) The Pricing of Bonds and Bank Loans in International Markets, *European Economic Review*, **30**, 565-89.

Eichengreen, B. and Mody, A. (1998) What Explains Changing Spreads on Emerging Market Debt: Fundamentals or Market Sentiment?, NBER Working Paper 6408.

Engle, R. (1993) Statistical Models for Financial Volatility, *Financial Analysts Journal*, January/February, 72-8.

Feder, G. and Just, R. (1977) A Study of Debt Servicing Capacity Applying Logit-Analysis, *Journal of Development Economics*, **4**, 25-38.

Frank, Ch. and Cline, W.R. (1971) Measurement of Debt Servicing Capacity: An Application of Discriminant Analysis, *Journal of International Economics*, **1**, 327-44.

Herz, B. and Tong, H. (2003) The interactions between debt and currency crises – common causes or contagion?, University of Bayreuth Discussion Papers in Economics No. 17-03.

Johnson, G.G., Keller, P., Baumgartner, U., Kincaid, G.R., Tyler, M., Williams, R.C., Nowzad, B., Dillon, K.B., and Reichmann, T. (1981) External Indebtedness of Developing Countries, IMF Occasional Paper 3.

Jöreskog, K.G. (1970) A general method for analysis of covariance structures, *Biometrika*, **57**, 239-51.

Kamin, S.B. and von Kleist, K. (1999) The Evolution and Determinants of Emerging Market Credit Spreads in the 1990s, BIS Working Paper 68.

Larrain, G., Reisen, H. and von Maltzan, J. (1997) Emerging Market Risk and Sovereign Credit Ratings, OECD Development Centre Working Paper 124.

Manasse, P., Roubini, N. and Schimmelpfennig, A. (2003), Predicting Sovereign Debt Crises, IMF-Working Paper 03/221.

Mayo, A. L. and Barrett, A.G. (1977) An Early Warning Model for Assessing Developing Country Debt, in *Financing and Risk in Developing Countries* (Ed.) S. H. Goodman, Praeger, New York, pp. 81-7.

Meissner, Ch.M. (2005), A New World Order: Explaining the International diffusion of the Gold Standard, *Journal of International Economics*, **66**, 385-406.

Min, H. G. (1998) Determinants of Emerging Market Bond Spread: Do Economic Fundamentals Matter?, World Bank Policy Research Working Paper 1899.

Mulaik, S.A., James, L.R., Van Alstine, J., Bennett, N., Lind, S., and Stilwell, C.D. (1989) Evaluation of goodness-of-fit indices for structural equation models, *Psychological Bulletin*, **105**, 430-45.

Mulder, Ch. and Perrelli, R. (2001) Foreign Currency Credit Ratings for Emerging Market Economies, IMF Working Paper No 01/191.

Nogués, J. and Grandes, M. (2001) Country Risk: Economic Policy, Contagion Effect or Political Noise?, *Journal of Applied Economics*, **0**, 125-62.

Obstfeld, M. and Taylor, A.M. (2003) Sovereign Risk, Credibility and the Gold Standard: 1870-1913 versus 1925-31, *Economic Journal*, **113**, 241-75.

Reinhart, C.M. (2002) Default, currency crises, and sovereign credit ratings, *World Bank Economic Review*, **16**, 151-70.

Rojas, A. and Jaque, F. (2003) Determinants of the Chilean Sovereign Spread: Is It Purely Fundamentals?. Documentos de Trabajo – Banco Central de Chile.

Rowland, P. and Torres, J.L. (2004) Determinants of Spread and Creditworthiness for Emerging Market Debt: A Panel Data Study, Banco de la Republica de Colombia – Borradores de Economia 00295.

Rowland, P. (2004) Determinants of Spread, Credit Ratings and Creditworthiness for Emerging Market Sovereign Debt: A Follow-Up Study Using Pooled Data Analysis, Banco de la Republica de Colombia – Borradores de Economia 002336.

Saini, K. G. and Bates, P.S. (1978) Statistical Techniques for Determining Debt-Servicing Capacity for Developing Countries: Analytical Review of the Literature and Further Empirical Results, Federal Reserve Bank of New York – Working Paper 7818.

Saini, K.G. and Bates, P.S. (1984) A Survey of the Quantitative Approaches to Country Risk Analysis,. *Journal of Banking and Finance*, **8**, 341-56.

Sargen, N. (1977) Economic Indicators and Country Risk Appraisal, Federal Reserve Bank of San Francisco – Economic Review.

Scholtens, B. (1999) On the Comovement of Bond Yield Spreads and Country Risk Ratings, *Journal of Fixed Income*, **8**, 99-103.

Scholtens, B. (2002) Bond Yield Spreads and Country Risk: A Lasting Relationship, *Kredit und Kapital*, **35**, 193-215.

Simonsen, M. H. (1985) The Developing Country Debt Problem, in *International Debt and the Developing Countries* (Ed.) G.W. Smith and J. T. Cuddington, World Bank, Washington D.C., pp. 101-26.

Solomon, R. (1977) A Perspective on the Debt of Developing Countries, *Brookings Papers on Economic Activity*, **2**, 479-501.

Table 1. *Results of MIMIC Model Estimations*

Causes: ***Specification:***	1	2	3	4	5	6	7
GDP per capita	-0.28*** (-7.21)	-0.27*** (-8.63)	-0.20*** (-5.29)	-0.28*** (-7.32)	-0.30*** (-7.62)	-0.33*** (-8.76)	-0.27*** (-6.82)
Investment ratio	-0.15*** (-3.96)	-0.19*** (-5.50)	-0.09*** (-2.63)	-0.17*** (-3.93)	-0.17*** (-4.23)	-0.21*** (-5.01)	-0.14*** (-3.72)
Total debt / GDP	0.25*** (7.22)	0.28*** (7.57)	0.32*** (8.84)	0.23*** (6.88)	0.21*** (5.98)	0.21*** (6.15)	0.28*** (8.65)
Short-term debt / exports	0.10*** (3.20)		0.03 (0.89)	0.13*** (4.89)	0.12*** (3.54)	0.15*** (4.07)	0.10*** (3.13)
Short-term debt / total debt		-0.03 (-0.98)					
Reserves growth’	-0.06 (-1.47)	-0.07** (-1.98)	-0.10*** (-2.47)		-0.06 (-1.58)	0.01 (0.22)	-0.06 (-1.59)
Reserves / Imports ratio				-0.07* (-1.80)			
Trade balance / Reserves					0.03 (1.34)		
Change of the Term of trade	-0.01 (-0.24)	-0.01 (-0.16)		0.00 (0.04)		-0.01 (-0.25)	-0.02 (-0.44)
Exports growth’			-0.12*** (-2.71)				
Inflation rate	0.26*** (11.36)	0.25*** (11.14)	0.25*** (10.76)	0.26*** (11.51)	0.27*** (11.49)		0.24*** (11.05)
Change of money supply						0.18*** (5.06)	
Openness	-0.37*** (-9.38)	-0.41*** (-12.27)	-0.47*** (-12.13)	-0.36*** (-8.38)	-0.37*** (-9.48)	-0.34*** (-8.76)	-0.40*** (10.432)
US interest rate							-0.01 (-0.30)

Indicators:	***Specification:***	1	2	3	4	5	6	7
EMBI+ spreads		0.86*** (27.51)	0.88*** (28.73)	0.86*** (31.25)	0.84*** (27.23)	0.84*** (27.51)	0.80*** (23.54)	0.88*** (29.53)
S&P ratings		0.98	0.96	0.98	0.98	0.98	1.00	0.97
Goodness of Fit Indices:								
No. of observations		242	242	242	242	242	242	242
Degrees of freedom		43	43	43	43	43	43	43
Chi-square		50.05	54.84	119.53	25.20	66.20	62.83	79.48
GFI		0.96	0.95	0.91	0.98	0.95	0.95	0.96
RMSEA		0.03	0.3	0.09	0.00	0.05	0.04	0.05

Note: t-statistics in parentheses; * Significance at the 10% level, ** Significance at the 5% level, *** Significance at the 1% level.

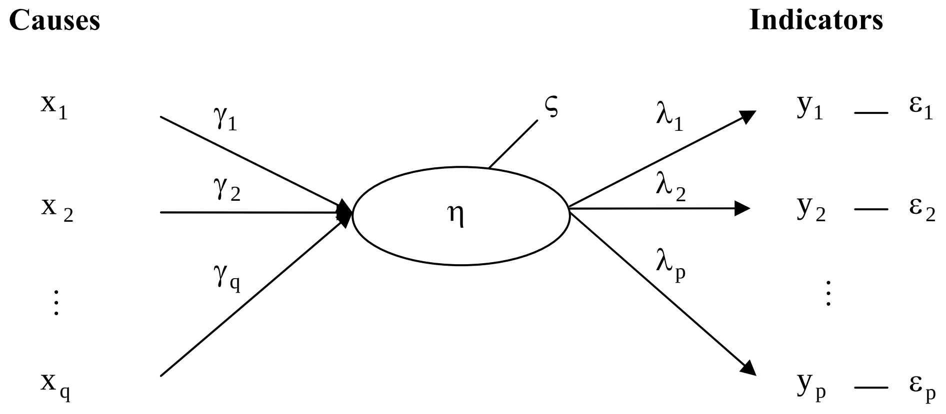

Figure 1. *Structure of a MIMIC Model*

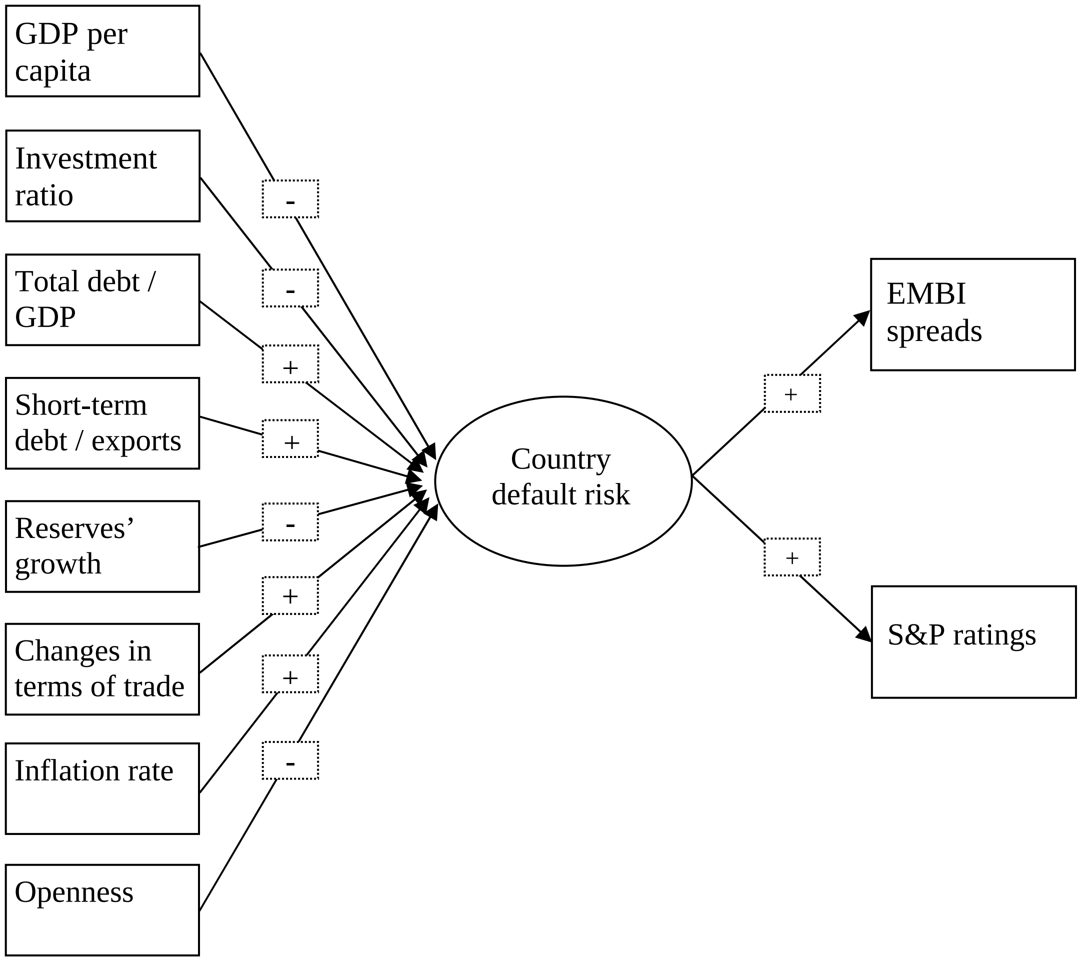

Figure 2. *Path diagram of benchmark model 1*

Appendix A: Deriving the MIMIC Model's Covariance Matrix

The MIMIC model's structural and measurement equations are $\eta = \boldsymbol{\gamma}'\mathbf{x} + \varsigma$ and $\mathbf{y} = \boldsymbol{\lambda}\eta + \boldsymbol{\varepsilon}$, respectively. It assumes that the variables are measured as standardized deviations from their mean and that the error term does not correlate to the causes, i.e. $\mathbf{E}(\eta) = \mathbf{E}(\mathbf{x}) = \mathbf{E}(\varsigma) = 0$ and $\mathbf{E}(\mathbf{x}\varsigma') = \mathbf{E}(\varsigma\mathbf{x}') = 0$. The indicators are also standardized deviations from their mean, i.e. $\mathbf{E}(\mathbf{y}) = \mathbf{E}(\boldsymbol{\varepsilon}) = 0$, and the error terms in the measurement model do not correlate either to the causes $\mathbf{x}$ or to the latent variable η. Hence, $\mathbf{E}(\mathbf{x}\boldsymbol{\varepsilon}') = \mathbf{E}(\boldsymbol{\varepsilon}\mathbf{x}') = 0$ and $\mathbf{E}(\eta\boldsymbol{\varepsilon}') = \mathbf{E}(\boldsymbol{\varepsilon}\eta') = 0$. A final assumption is that the $\boldsymbol{\varepsilon}$´s do not correlate to ζ, i.e. $\mathbf{E}(\boldsymbol{\varepsilon}\varsigma') = \mathbf{E}(\varsigma\boldsymbol{\varepsilon}') = 0$. Expressing the MIMIC model in terms of covariances gives:

$$\boldsymbol{\Sigma}(\boldsymbol{\theta}) = \begin{pmatrix} \mathbf{Var}(\mathbf{y}) & \mathbf{Cov}(\mathbf{y},\mathbf{x}) \\ \mathbf{Cov}(\mathbf{x},\mathbf{y}) & \mathbf{Var}(\mathbf{x}) \end{pmatrix} = \mathbf{E}\left(\begin{bmatrix} \mathbf{y} \\ \hline \mathbf{x} \end{bmatrix} \begin{bmatrix} \mathbf{y} \\ \hline \mathbf{x} \end{bmatrix}' \right).$$

After taking the transposes, multiplications, and making use of the assumptions that:

1. the variables are measured as deviations from mean, i.e. $\mathbf{E}(\eta) = \mathbf{E}(\mathbf{x}) = \mathbf{E}(\varsigma) = \mathbf{E}(\mathbf{y}) = \mathbf{E}(\boldsymbol{\varepsilon}) = 0$;
2. the error terms do not correlate to the causes, i.e. $\mathbf{E}(\mathbf{x}\varsigma') = \mathbf{E}(\varsigma\mathbf{x}') = 0$ and $\mathbf{E}(\mathbf{x}\boldsymbol{\varepsilon}') = \mathrm{E}(\boldsymbol{\varepsilon}\mathbf{x}') = 0$;
3. the error terms do not correlate across equations, $\mathbf{E}(\boldsymbol{\varepsilon}\varsigma') = \mathbf{E}(\varsigma\boldsymbol{\varepsilon}') = 0$; and,
4. the errors of the measurement model do not correlate to the latent variable, i.e. $\mathbf{E}(\eta\boldsymbol{\varepsilon}') = \mathbf{E}(\boldsymbol{\varepsilon}\eta') = 0$;

we distribute the expectation operator and can thus derive both the variance and covariance between the observable variables. By doing this, it follows that:

$$
\begin{aligned}
\mathbf{E}(\mathbf{yy}') &= \mathbf{E}\left[(\boldsymbol{\lambda}\eta+\boldsymbol{\varepsilon})(\boldsymbol{\lambda}\eta+\boldsymbol{\varepsilon})'\right] \\
&= \mathbf{E}(\boldsymbol{\lambda}\eta\eta'\boldsymbol{\lambda}'+\boldsymbol{\lambda}\eta\boldsymbol{\varepsilon}'+\boldsymbol{\varepsilon}\eta'\boldsymbol{\lambda}'+\boldsymbol{\varepsilon\varepsilon}') \\
&= \boldsymbol{\lambda}\mathbf{E}(\eta\eta')\boldsymbol{\lambda}'+\boldsymbol{\Theta}_{\boldsymbol{\varepsilon}} \\
&= \boldsymbol{\lambda}\mathbf{E}\left[(\boldsymbol{\gamma}'\mathbf{x}+\varsigma)(\boldsymbol{\gamma}'\mathbf{x}+\varsigma)'\right]\boldsymbol{\lambda}'+\boldsymbol{\Theta}_{\boldsymbol{\varepsilon}} \\
&= \boldsymbol{\lambda}\mathbf{E}(\boldsymbol{\gamma}'\mathbf{xx}'\boldsymbol{\gamma}+\boldsymbol{\gamma}'\mathbf{x}\varsigma'+\varsigma\mathbf{x}'\boldsymbol{\gamma}+\varsigma\varsigma')\boldsymbol{\lambda}'+\boldsymbol{\Theta}_{\boldsymbol{\varepsilon}} \\
&= \boldsymbol{\lambda}(\boldsymbol{\gamma}'\boldsymbol{\Phi}\boldsymbol{\gamma}+\psi)\boldsymbol{\lambda}'+\boldsymbol{\Theta}_{\boldsymbol{\varepsilon}}
\end{aligned},
$$

$$
\begin{aligned}
\mathbf{E}(\mathbf{xy}') &= \mathbf{E}\left[\mathbf{x}(\boldsymbol{\lambda}\eta+\boldsymbol{\varepsilon})'\right] \\
&= \mathbf{E}(\mathbf{x}\eta'\boldsymbol{\lambda}'+\mathbf{x}\boldsymbol{\varepsilon}'+\boldsymbol{\varepsilon}\eta'\boldsymbol{\lambda}'+\boldsymbol{\varepsilon\varepsilon}') \\
&= \mathbf{E}(\mathbf{x}\eta')\boldsymbol{\lambda}' \\
&= \mathbf{E}\left[(\mathbf{x})(\boldsymbol{\gamma}'\mathbf{x}+\varsigma)'\right]\boldsymbol{\lambda}' \\
&= \mathbf{E}(\mathbf{xx}'\boldsymbol{\gamma}+\mathbf{x}\varsigma')\boldsymbol{\lambda}' \\
&= \boldsymbol{\Phi}\boldsymbol{\gamma}\boldsymbol{\lambda}'
\end{aligned},
$$

$$
\begin{aligned}
\mathbf{E}(\mathbf{yx}') &= (\boldsymbol{\Phi}\boldsymbol{\gamma}\boldsymbol{\lambda}')' \\
&= \boldsymbol{\lambda}\boldsymbol{\gamma}'\boldsymbol{\Phi}
\end{aligned},
$$

$$
\mathbf{E}(\mathbf{xx}') = \boldsymbol{\Phi}.
$$

Thus, $\boldsymbol{\Theta}_{\boldsymbol{\varepsilon}}$ is the covariance matrix of the error terms in the measurement model; ψ is the variance of the error term in the structural equation; and, $\boldsymbol{\Phi}$ is the covariance matrix of the causes. Finally, the covariance matrix of the MIMIC model is:

$$
\boldsymbol{\Sigma}(\boldsymbol{\theta}) = \begin{pmatrix} \boldsymbol{\lambda}(\boldsymbol{\gamma}'\boldsymbol{\Phi}\boldsymbol{\gamma}+\psi)\boldsymbol{\lambda}'+\boldsymbol{\Theta}_{\boldsymbol{\varepsilon}} & \boldsymbol{\lambda}\boldsymbol{\gamma}'\boldsymbol{\Phi}) \\ \boldsymbol{\Phi}\boldsymbol{\gamma}\boldsymbol{\lambda}' & \boldsymbol{\Phi} \end{pmatrix}.
$$

Appendix B: Tables

Table B.1. *Literature review on country default risk*

Panel A: Studies with bond spreads and/or ratings as a dependent variable

Study	Sample	Explanatory variables with significant influence
Edwards (1986)	1976 – 1980, 13 countries, 167 bonds.	Debt to output ratio, Gross investment ratio, Debt service ratio, Maturity.
Cantor and Packer (1996)	September, 29, 1995, 45 countries.	Ratings (S&P and Moody's), External debt, Stage of economic development (according to IMF classification), Default history.
Min (1998)	1991 – 1995, 10 countries, 482 bonds.	Debt Service Ratio, Terms of Trade, Growth rates of exports and imports, Current account balance, Ratio of debt to GDP, Ratio of reserves to GDP.
Eichengreen and Mody (1998)	1991 – 1996, 55 countries, 1033 bonds.	Ratio of debt to GDP, Debt Service Ratio, Dummy for rescheduling, (10 year) risk-less US interest rate, Private placement, Israel dummy, Supranational, Public or private issuer, Currency (DM/Yen), Latin America dummy, Ratings of Institutional Investor.
Kamin and von Kleist (1999)	1991 – 1997, 304 bonds.	Debt Service Ratio, Ratio of total debt to GDP, Ratio of reserves to imports; Ratings of S&P and Moody's, Maturity, Currency dummy (Yen, Non USD), Time dummies.
Arora and Cerisola (2001)	1994 – 1999, 11 countries.	Risk-less interest rates, Debt service ratio, Ratio of total debt to GDP, Ratio of reserves to GDP, Ratio of reserves to imports.
Afonso (2001)	June 2001, 81 countries.	GDP per capita, external debt, stage of economic development, default history, real growth rate, inflation rate.
Mulder and Perrelli (2001)	1992 -1995, 25 countries.	Debt over exports, default history, fiscal balance , output growth, log of inflation, investment ratio to GDP, external current account deficit.
Rowland (2004)	July 2003, 50 countries.	GDP per capita, the economic growth rate, the inflation rate, external debt ratio, debt-service ratio, the level of international reserves, openness of the economy.
Rowland and Torres (2004)	1998 – 2002, 16 countries.	Economic growth, Ratio of debt to exports, Ratio of debt service to GDP, Ratio of reserves to GDP.

Table B.1. *Literature review on country default risk*

Panel B: Studies with a crisis dummy as a dependent variable

Study	Sample	Explanatory variables with significant influence
Frank and Cline (1971)	1960 – 1968, 26 countries.	Debt Service Ratio, Ratio of imports to reserves, Ratio of debt repayments to total debt.
Sargen (1977)	1960 – 1976, 44 countries.	Debt service ratio, Inflation, Export growth, growth rate of money supply, Real GDP growth rate, Deviations in purchasing power parity.
Saini and Bates (1978)	1960 – 1977, 25 countries.	Growth rate of consumer prices, Growth rate of money supply, Current account balance to exports, Growth rate of reserves.
Mayo and Barrett (1977)	1960 – 1975, 45 countries.	Ratio of credits to exports, Growth rate of consumer prices, Ratio of reserves to imports, Ratio of imports to GDP, Ratio of gross capital formation to GDP, Ratio of IMF quota to imports.
Feder and Just (1977)	1965 – 1972, 30 countries.	Debt Service Ratio, Ratio of imports to reserves, Ratio of debt repayments to total debt, Per capita income, Ratio of capital inflows to debt repayments, Growth rate of real exports.
Lloyd-Ellis, McKenzie and Thomas (1989)	1977 – 1981, 27 countries.	Growth rate of exports, Ratio of long-term debt to total debt, Ratio of short-term debt to total debt of banks, Ratio of bank deposits to disbursed credits, Ratio of reserves to IMF-Quota.
Detragiache and Spilimbergo (2001)	1971 – 1998, 69 countries.	Ratio of short-term debt to total debt, Ratio of total debt to GDP, Ratio of reserves to GDP, Overvaluation of the currency, Share of credits from multilateral creditors on total debt, Openness of the economy.
Manasse, Roubini and Schimmel-pfennig (2003)	1970 – 2002, 47 countries.	Ratio of short-term debt to reserves, Ratio of debt services to reserves, Ratio of current account balance to GDP, Interest rate on US treasury bills, Growth rate of GDP, Dummy for inflation rate above 50%, Dummy for past defaults, Index of political freedom, Dummy for years with presidential election.

Table B.2. *Ratings conversion*[a]

S&P Rating	Numerical Values
AAA	1-2
AA+	3-5
AA	6-8
AA-	9-11
A+	12-14
A	15-17
A-	18-20
BBB+	21-23
BBB	24-26
BBB-	27-29
BB+	30-32
BB	33-35
BB-	36-38
B+	39-41
B	42-44
B-	45-47
CCC+	48-50
CCC	51-53
CCC-	54-56
CC	57-59
C	60-62
SD/D	63/64

a) The numerical value is specified depending on the outlook: positive is means the lowest number, stable the second lowest number and negative the highest number.

Table B.3. *Data sources and definitions*

No	Variable	Description / Source
I	$EMBI^{+}$ sovereign yield spread	The $EMBI^{+}$ spread is the average spread of several bond issues of the respective country. For a more detailed description see JP Morgan (1999). It is calculated by JP Morgan and provided by DataStream®.
II	S&P's Sovereign ratings	Numerical values calculated by taking the natural logarithm of the values numerical values corresponding to the different ratings as shown in Table 2.
1	GDP per capita (US$, thousands)	The data on GDP per capita is provided by DataStream®. The original source is the Economist Intelligence Unit.
2	Investment ratio	Describes the gross fixed investment as a percentage of GDP. Data is provided by DataStream®.
3	Total debt / GDP	Total debt describes the total external debt stock, comprising public and publicly guaranteed debt, private non-guaranteed debt, use of IMF credit and short-term debt. The data on total debt (as well as GDP) is provided by DataStream®. The original source is the Economist Intelligence Unit.
4	Debt service ratio, i.e. short-term debt payments to exports	Data on short-term debt is provided by Datastream®. The original source is Economist Intelligence Unit.
5	Short-term debt / total debt	See row 3 and 4 for the short-term and total debt, respectively.
6	Reserves growth	Foreign exchange reserves comprise foreign exchange reserves plus gold. The data is provided by DataStream®. The original source is the Economist Intelligence Unit.
7	Reserves / imports ratio	See row 6 for a description of reserves. The data on imports is provided by DataStream®. The original source is International Financial Statistics.
8	Trade balance / reserves	See row 6 for a description of reserves. Data on terms of trade is provided by DataStream®. The original source is the Economist Intelligence Unit.

9	Change of the term of trade	Describes annual changes in the terms of trade. It is calculated by the Economist Intelligence Unit. Data is provided by DataStream®.
10	Exports growth'	The Data on exports is provided by DataStream®. The original source is International Financial Statistics.
11	Inflation rate	To calculate inflation we use data on consumer price indices, which is provided by DataStream®. The original source is the Economist Intelligence Unit.
12	Money supply change	This variable describes the yearly change in the money supply (M1). The Data is provided by DataStream®. The original source is Economist Intelligence Unit.
13	Openness: (imports + exports) / GDP	See No. 3, 7 and 10 for GDP, imports and exports, respectively.
14	US interest rate	Describes the short-term (one-year) US interest rate, as specified by the OECD and provided by DataStream®.

Table B.4. *Further goodness-of-fit statistics of the MIMIC models*

Goodness-of-Fit Statistics	Specification						
	1	2	3	4	5	6	7
AGFI	0.95	0.94	0.88	0.98	0.94	0.93	0.95
PGFI	0.75	0.74	0.71	0.77	0.75	0.74	0.77
ECVI	0.31	0.33	0.60	0.28	0.37	0.36	0.44
ECVI Independence Model	3.15	1.84	3.19	3.32	3.58	2.97	0.55
ECVI Saturated Model	0.46	0.46	0.46	0.46	0.46	0.46	0.46
AIC	74.05	78.84	143.53	49.20	90.20	86.83	105.48
AIC Independence Model	757.96	442.44	813.69	798.93	862.04	760.15	843.90
AIC Saturated Model	110.00	110.00	110.00	110.00	110.00	110.00	110.00