Sovereign debt defaults and currency crises in Latin America

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Chapter 4

Sovereign Debt Crises in Latin America: A Market Pressure Approach*

4.1 Introduction

In the sovereign debt crisis literature the traditional crisis indicator is a binary variable to distinguish default (crisis) periods from non-default (non-crisis) periods—see Section 1.2.3. This indicator is limited, because it only distinguishes two possible states: default or no default. De Paiva Abreu (2006) mentions that this zero-one approach does not take into account the reduction of the original obligations (for instance debt renegotiations). In reality there is a more subtle range. We present two cases that would not be captured well in the binary variable. The first example is related to the end of the default period. In general it takes a long time to renegotiate and restructure debt after a default. This process is often depends on political and legal issues, and does not reflect debt servicing difficulties. It can happen that a country that is still in default has access to the international capital markets. The second example is related to the run-up to the default period. It is possible that a default is unavoidable due to the high debt level and

* This chapter is based upon Boonman, Jacobs and Kuper (2015).

increasing interest rates, but the government refuses to default for fear of electoral losses.

The analysis of sovereign debt defaults (crises) is limited by this binary crisis indicator. To overcome this limitation we construct a continuous index for sovereign debt crises. A continuous index has two advantages. First, a continuous index is more informative. It makes it possible to compare the relative size of different debt crises, to identify near-default periods, and to perform for instance Granger causality tests with the business cycle or economic growth. Second, a sovereign debt crisis index reflects debt servicing difficulties—also if these do not end in a default. We call this sovereign debt crisis index a market pressure index. The construction of a Debt Market Pressure Index (DMPI) is our main contribution to the literature.

To construct a continuous index we combine indicators that show different patterns in times of a debt crisis compared to normal times for Argentina, Brazil, Chile and Mexico in the period 1870–2012. These countries cover roughly 70% of Latin Americas GDP (Aiolfi et al., 2011), and have a long history of sovereign debt crises.

Our crisis identification procedure is based on the idea underlying the Exchange Market Pressure Index (EMPI), which was inspired by Girton and Roper (1977), and used by Eichengreen et al. (1995) to identify currency crises. The EMPI not only captures significant currency depreciation, but also periods where the exchange rate is under pressure, and defended by depleting foreign reserves and/or increasing interest rates. Similarly, we extend the traditional focus on sovereign debt defaults to sovereign debt crises by including periods of debt servicing difficulties which puts a pressure on the market for sovereign debt.

We select indicators that could possibly be related to debt crises. The selection is based on stylized facts of sovereign debt crises in emerging economies and on the theoretical literature on sovereign debt crises, notably Arellano's (2008) incarnation of the sovereign default model of Eaton and Gersovitz (1981), and the sudden-stop model of Calvo (1998, 2003), which are explained in detail in Section 2.3. Based on the performance as a measure for debt servicing difficulties we select the best combination which consists of the debt-to-GDP ratio, the external interest rate spread and the exports-to-imports ratio. These three indicators fit well with previous studies. Empirical research on sovereign debt suggests that the debt-to-GDP ratio is a strong indicator of sovereign defaults in emerging economies (Manasse and Roubini, 2009; Furceri and Zdzienicki, 2012; Catão and Milesi-Ferretti, 2014). Reinhart and Rogoff (2011) observe that the debt-to-GDP ratio continues to rise after defaults, as debts increase through accumulated arrears, and GDP contracts. This debt overhang will remain high until the debt is restructured, which is typically defined as the end of the debt default period. Borensztein and Panizza (2009) observe that credit ratings and external interest rate spreads surge in the first years of a debt default. The current account typically reverses in times of a debt crisis (Aguiar and Gopinath, 2006; Catão and Milesi-Ferretti, 2014). This also holds for sovereign debt crises that are related to sudden stops. Agosin and Huaitu (2011) find that the higher the current account deficit, the higher the probability of a sudden stop in capital flows. And when capital flows reverse, the current account deficit decreases.

When the DMPI is used as a crisis index, it has to be combined with a decision rule—a crisis is signaled when the index exceeds a threshold—and compared to a benchmark crisis series. For the benchmark we follow the definition of Manasse et al. (2003), who define sovereign debt crises as episodes of either an outright default or a near-default. Near-default episodes are periods of large IMF assistance (access in excess of 100 percent of quota) to avoid a possible default. Debt defaults are thus a subset of debt crises. The threshold is determined by the trade-off between missed crises and false alarms, each having its own cost. We apply the Receiver Operating Characteristic (ROC) curve to find simultaneously the optimal set of indicators and the value of the threshold. The ROC curve was first developed by electrical engineers and radar engineers during World War II for detecting enemy objects in battlefields and was soon introduced to psychology to account for perceptual detection of stimuli. Recently, the ROC methodology has been applied in different fields of economics. Berge and Jordá (2011) apply ROC curves to evaluate the performance of their business cycle index. They write that "A major advantage of the ROC curve is that it is not tied to a specific loss function as it itself is a map of the entire space of trade-offs for a given classification problem. [...] The ROC curve can be estimated non-parametrically and ROC-based summary statistics have large sample Gaussian distributions that make formal inference convenient." (Berge and Jordá, 2011, page 249). Other applications are Jordá, Schularick and Taylor (2011) to signal banking crises, and Catão and Milesi-Ferretti (2014) to signal external debt crises. The latter use a multivariate probit model to determine which index best signals sovereign debt defaults. Our work is fundamentally different since we construct a crisis index that reflects stress on the sovereign debt position, while they set up an Early Warning System to determine which indicators have the highest predicting power for external debt crises. Also, we take into account the entire sovereign debt crisis episode while they focus only on the first year of the external debt crisis. Furthermore, whereas Catão and Milesi-Ferreti (2014) implicitly assume that missed crises are as costly as false alarms, the utility function criterion we adopt allows us to choose the optimal index under different combinations of penalties for missed crises compared to false alarms. Bussiere and Fratzscher (2006) mention two arguments for the relative importance of missed crises versus false alarms. First, false alarms are less costly from a welfare perspective than unpredicted or missed crises. Second, false alarms may have been caused by appropriate policy initiatives that were taken when the fundamentals were so weak that a crisis was predicted. The choice for the threshold depends on the perspective. A policy maker will prefer a lower threshold, hence giving a relatively large weight to avoid missed alarms, and to accept more false alarms.

The remainder of this chapter is structured as follows. Section 4.2 describes the design of our new crisis index, the weights and the threshold used. The data are presented in Section 4.3, followed by the results in Section 4.4. We apply our crisis index to analyze the relation between sovereign debt crises and business cycle turning points in a formal way in Section 4.5.

Section 4.6 concludes.

4.2 Methodology

To build a debt market pressure index (DMPI) we need to select indicators, weights and thresholds similar to the construction of an exchange market pressure index for currency crises (cf. Eichengreen et al., 1995) or a money market pressure index for banking crises (see Von Hagen and Ho, 2007).

4.2.1 Construction of the DMPI

We construct different debt crisis indices, with different combinations of indicators suggested by the literature. All indicators are transformed when required to avoid non-stationarity, and standardized per country.

We define $DMPI_t^i$ as a weighted average of three variables $X_{1,t}^i$, $X_{2,t}^i$ and $X_{3,t}^i$ say, with standard deviations $\sigma_{X_1^i}$, $\sigma_{X_2^i}$ and $\sigma_{X_3^i}$ respectively. Index i refers to the country (1 = Argentina, 2 = Brazil, 3 = Chile, 4 = Mexico), and t refers to the observation ($t = 1, \ldots, T$). The standard deviations are calculated for each variable and for each country separately. For the weights we follow Eichengreen et al. (1995) by taking inverted standard deviations, such that all underlying variables contribute equally.

$$DMPI_t^i \equiv \frac{X_{1,t}^i}{\sigma_{X_1^i}} + \frac{X_{2,t}^i}{\sigma_{X_2^i}} + \frac{X_{3,t}^i}{\sigma_{X_3^i}}. \tag{4.1}$$

4.2.2 The DMPI as a crisis index

The DMPI identifies periods with increased pressure on debt servicing. However, we have no similar benchmark that captures debt servicing difficulties, only a binary benchmark variable. Therefore, to evaluate the effectiveness of the continuous index as a crisis index we convert the index into a binary variable such that we can compare our index with a benchmark. If the index exceeds a pre-established threshold, then a crises is signaled and the value of 1 is assigned to the binary variable, and zero otherwise. The higher the threshold, the less exceedences are to be expected. This will result in less false alarms (type I error), but also in more missed crises (type II error). The optimal threshold depends on the relative costs of the two error types. To determine the optimal threshold we do a grid search and compare the crisis signals to a published benchmark crisis series. For the grid search it is important that the interval is big enough to plot a curve from one extreme (all false alarms, no missed crises) to the other extreme (no false alarms, all missed crises). For our data this implies the interval of [-2.5; 2.5] in steps of 0.1 times the standard deviation of the DMPI. For each country and each period the constructed crisis signal dummy is compared with the benchmark crisis dummy. For each threshold we construct a contingency table as in Table 4.1.

Table 4.1. Contingency table of crisis realizations and signals.

	Realization	
Index	Crisis	No crisis
Crisis	n_1 (TP)	n_2 (FP)
No crisis	n_3 (FN)	n_4 (TN)

Notes:
n_1 is the number of observations in which the model signals a crisis that actually took place: correct crisis signals (TP: True Positive); n_2 is the number of observations in which the model signals a crisis that did not take place: false alarms (FP: False Positive); n_3 is the number of observations in which the model does not signal a crisis that actually took place: missed crises (FN: False Negative); n_4 is the number of observations in which the model does not signal a crisis that did not take place: correct non-crisis signals (TN: True Negative).

4.2.3 The ROC curve

In signal detection theory a Receiver Operating Characteristic (ROC) curve is a graphical illustration of the performance of a binary classifier system as its discrimination threshold is varied. We apply the method to calibrate our crisis index and the threshold in the decision rule.

The Total Positive Rate (TPR) or $R(c)$ is defined as $n_1/(n_1 + n_3)$, i.e. the percentage of correct crisis signals relative to the total number of crises. The TPR depends on the threshold c. A high TPR means that the index picks up the crises well, while a low TPR implies that the index misses crises. TPR is also known as the *sensitivity* or recall rate, the power of the test, or 1 minus the Type II error.

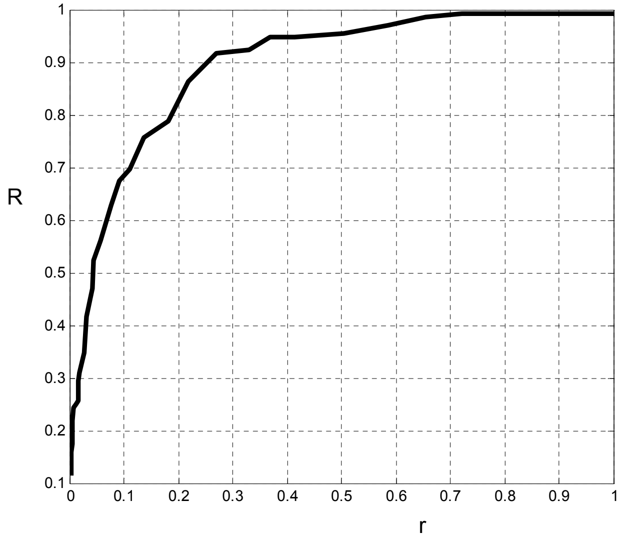
The other principal statistic is the False Positive Rate (FPR), or $r(c)$, which is defined as the percentage of false alarms relative to the total number of non-crisis years: $n_2/(n_2 + n_4)$. FPR equals 1 minus the *specificity*, or the Type I error, the size of the test. A high FPR means that the index signals crises that do not take place, and a low FPR implies that the index correctly does not signal a lot of crises. In the remainder of this chapter we use R and r to indicate the Total Positive Rate and the False Positive Rate, respectively.

Figure 4.1 displays a ROC curve for our index. A completely random guess gives a point along a diagonal line from the left bottom to the top right corner (the so-called line of no-discrimination). Points above the diagonal represent good classification results (better than random), points below the line poor results (worse than random). The perfect classifier system has a TPR of 1 and a FPR of 0. This means that the index shows 100% sensitivity (no missed crises) and 100% specificity (no false alarms).

Utility

To determine the combination of indicators and the threshold that generate the best possible outcome we employ a utility function approach. Alternatives to evaluate the signals of binary variables are the Area under the Curve, and as a special case the Youden index (Youden, 1950). However, these methods do not make a distinction between false alarms and missed crises, because all events have the same weight. We employ the utility function approach, because the cost of a missed crisis is not necessarily the same as the cost of a false alarm. This method was first introduced by Peirce in

Figure 4.1. Illustration of the Receiver Operating Characteristic (ROC) curve. r is a measure for the false alarms, where a higher value represents more false alarms. R is a measure for missed crises, where a higher value represents less missed crises.



1884 (Baker and Kramer, 2007). After assigning utility values we calculate the overall utility of the classification

$$U(r) = U_{11}R(r)\pi + U_{01}(1 - R(r))\pi + U_{10}r(1 - \pi) + U_{00}(1 - r)(1 - \pi) \quad (4.2)$$

where U_{ij} is the utility associated with signal i, given the true state j; U_{11} is the utility of a correctly signaled crisis; U_{01} is the utility of a missed crisis; U_{10} is the utility of a false alarm; and U_{00} is the utility of a correctly signaled non-crisis episode; and π is the unconditional probability of observing a crisis. R is not independent from r and vice versa. In ROC curves, it is more convenient to view R as a function from r, which is written as $R(r)$ (Baker and Kramer, 2007).

The utility is maximized by taking the first derivative of the utility function with respect to r, the false positive rate. After rearranging we obtain

$$s = \frac{dR(r)}{dr} = \frac{U_{00} - U_{10}}{U_{11} - U_{01}} \frac{1 - \pi}{\pi}. \tag{4.3}$$

So, the optimum is the point where the slope of the ROC curve equals the expected marginal rate of substitution between the net utility of accurate non-crisis and crisis signals. If the ROC curve is continuous and concave, the optimum is the point where the slope of the ROC curve equals s (Baker and Kramer, 2007).

If the loss-to-profit ratio $(U_{00} - U_{10})/(U_{11} - U_{01})$ is large or the outcome rare (π small), the slope will be steep and the optimal operating point will occur at a small value of FPR. This is the case when false alarms are relatively 'expensive' compared to missed crises. If the loss-to-profit ratio is smaller or the outcome is more common, the slope will be less steep and the optimal operating point will occur at a larger FPR value. This is the case when missed crises are relatively 'expensive' compared to false alarms.

In order to determine the optimal set of indicators and the threshold we assign values to the utilities U_{ij} of signal i given the true state j in Equation (4.2). We use $U_{11} = 1$, $U_{00} = 1$, $U_{10} = -1$, and apply a range of $-1, -2, -3, \ldots, -10$ for U_{01} . The motivation behind this non-symmetric treatment is that we assume that missed crises are more costly than false alarms. The costs of a false alarm are the costs of taking preventive actions, the risk of a self-fulfilling prophecy and the loss of trust in the policy makers when false alarms become frequent. However, policy makers and practitioners will prefer to be 'safe than sorry'. For them missed crises are far more important than false alarms. Jing, De Haan, Jacobs and Yang (2015) consider the cost of missed banking crises with a factor 5 or 10 higher than the cost of false alarms for banking crises. The more negative U_{01}, the more a missed crisis is penalized compared to false alarms.

4.3 Data description

We use an unbalanced panel consisting of four large Latin American economies (Argentina, Brazil, Chile and Mexico) for the period 1870 (for Mexico the starting year is 1895), up to and including 2012. Based on stylized facts and theoretical models of sovereign debt crises in emerging economies, as well as data availability, we select the following variables as potential crisis indicators: total (external and domestic) central government debt as a percentage of GDP (from Reinhart and Rogoff, 2011), external interest rate spread, inflation, changes in government expenditure, fiscal budget, domestic nominal interest rate, terms of trade, and the ratio of exports to imports (all from Aiolfi et al., 2011), and polity2, a dummy variable that captures the political system on a scale of +10 (full democracy) to -10 (autocracy) drawn from Polity IV, Center for Systemic Peace. We updated data from Aiolfi et al. (2011) from 2005 to 2012. All series are standardized as mentioned above. Appendix F contains further details on definitions and sources.

The external spread series is incomplete, with missing observations for Argentina 1961–1992, Chile 1957–1999, Mexico 1895–1995. We replace missing data by inflation as suggested by Manasse and Roubini (2009) and Reinhart and Rogoff (2009) especially for emerging markets. Visual inspection of the combined series (standardized external spread and standardized inflation) shows no signs of structural breaks. Correlation coefficients between inflation and external spread in years that both series are available are equal to 0.85 for Mexico (1996–2012), 0.65 for Argentina (1993–2012) and 0.33 for Chile (1870–1956). The debt-to-GDP ratio is based on total gross central government debt, which consists of both external and domestic debt.

To determine the accuracy of the DMPI we compare the crisis signals with reported benchmark crisis dummies that consist of the debt defaults according to Standard and Poor's, as reported in Borensztein and Panizza (2009), complemented with IMF large financial assistance packages (Manasse and Roubini, 2009) (see column (3) in Table 4.2). Following Reinhart and Rogoff (2009) we use an exclusion window of two years, which implies that debt crises with two years intervals or shorter are considered the same crisis.

Table 4.2. Sovereign debt crisis episodes for Argentina, Brazil, Chile and Mexico, 1870–2012. The last column combines the sovereign debt defaults with the years of IMF financial assistance. We use a window exclusion period of 2 years.

	Standard & Poor's (Borensztein and Panizza, 2009)	Manasse and Roubini (2009)	Combined
	Sovereign debt defaults	IMF financial assistance	Sovereign debt crises
Argentina	1890-1893, 1982-1993, 2001-2005	1995	1890-1893, 1982-1995, 2001-2005
Brazil	1898-1901, 1902-1910, 1914-1919, 1931-1933, 1937-1943, 1983-1994	1998-1999, 2001-2002	1898-1910, 1914-1919, 1931-1933, 1937-1943, 1983-1994, 1998-2002
Chile	1880-1883, 1931-1947, 1983-1990	-	1880-1883, 1931-1947, 1983-1990
Mexico	1866-1885, 1914-1922, 1928-1942, 1982-1990	1995	1914-1922, 1928-1942, 1982-1990, 1995

4.4 Empirical results

Based on the theoretical models, we select the debt-to-GDP as the indicator that has to be included. Then, we try all possible combinations with two or more indicators, and find that the optimal set of indicators consists of the debt-to-GDP ratio, the external interest spread and the ratio of exports to imports. This combination yields the highest utility scores for different values of the cost of a missed crisis (the only parameter that is allowed to vary). The second best combination consists of two variables, the debt-to-GDP ratio and the ratio of exports and imports.

The selected indicators are in line with the sovereign debt default model of Arellano (2008). A high debt-to-GDP ratio makes a country vulnerable to debt crises, because the probability of a debt crisis increases. The high probability causes external spreads to increase, and when a crisis unfolds the current account deficit reduces sharply. The crisis can also be caused by a sudden stop in capital inflows (Calvo, 2003). Government expenditures, the fiscal budget, the terms of trade, and (changes in) the political system do not contribute to a higher utility.

Figure 4.2. DMPI and benchmark debt crisis periods for Argentina, Brazil, Chile and Mexico, 1870–2012. DMPI: solid line; benchmark debt crisis periods: shaded areas. The benchmark for debt crises is the combination of defaults as reported by Standard and Poor's (Borensztein and Panizza, 2009) and IMF assistance as reported by Manasse and Roubini (2009), with a window exclusion period of 2 years—as shown in the last column of Table 4.2.

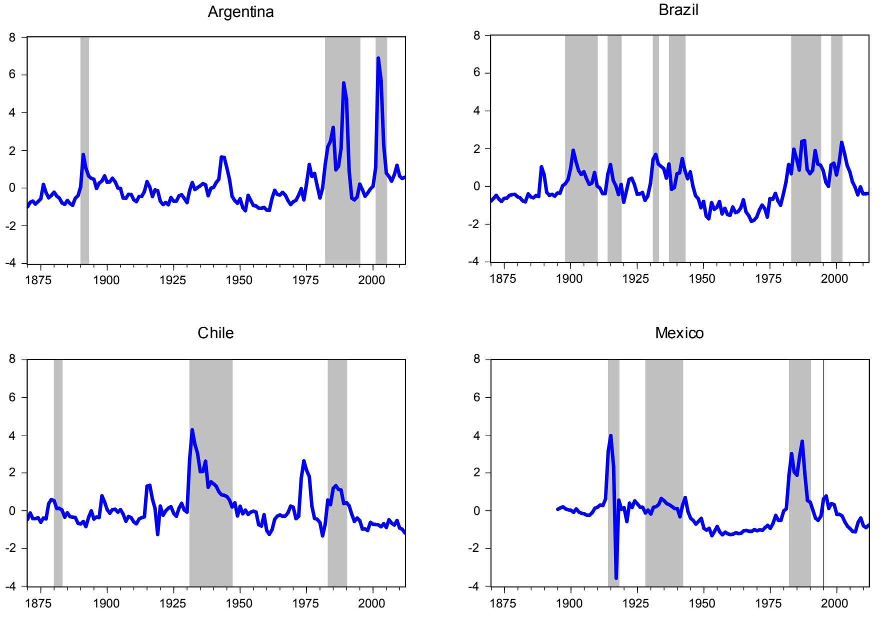
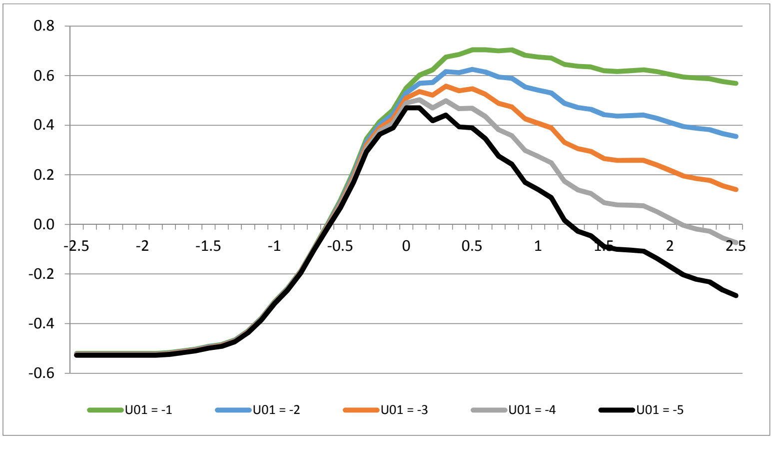


Figure 4.2 shows the DMPI and the benchmark crisis periods for the four Latin American countries. A peak in the DMPI implies increased pressure on debt servicing. We can see that our debt crisis index peaks at the time of the debt crises, except for the Mexican debt crisis in the 1930s. We also observe that our index has peaks that are not associated with debt crises,

such as for the revolutionary reforms during Peronist era in Argentina in the 1940s and for Chile in the 1970s (high inflation and political turmoil).

Figure 4.3 shows the utility values for different values of the partial utility indicator U_{01}. With a low threshold (the minimum is -2.5 times the standard deviation), there are no missed crises, but the number of false alarm is very high. The total utility score is negative, and there is no difference between different penalty values for missed crises, because with such a low threshold no crises are missed. When the threshold increases the number of false alarms will be lower and as a consequence the utility score is less negative. From a threshold of approximately -0.5 times the standard deviation and higher, we can observe an increasing difference in the lines that represent different penalties for missed crises. This means that with these thresholds our index misses some actual crises.

Figure 4.3. DMPI: utility (vertical axis) under different penalty values for missed crises, with the threshold on the horizontal axis.



The higher the threshold, the more missed crises and the less false alarms. The line with the highest penalty for a missed crisis ($U_{01} = -5$) peaks at a threshold of 0.1 times the standard deviation. With higher thresholds, the number of missed crises increases and reduces the utility score. The line with the lowest penalty for a missed crisis ($U_{01} = -1$) has a higher utility score, which does not come as a surprise, because missed crises are penalized less, while the penalty for a false alarm and the rewards for correctly predicted outcomes remain the same. The curve is also flatter and the peak comes at a higher threshold, 0.8 times the standard deviation. With even higher thresholds, the number of missed crises increases and is penalized, which reduces the utility score. The optimal threshold for this penalty is therefore 0.8 times the standard deviation.

We apply two criteria to choose the penalty for a missed crisis: (i) the threshold is positive, and (ii) the cost of a missed crisis is higher than the cost of a false alarm. We report two optimal thresholds for different penalties for a missed crisis:

1. Mild penalty for missed crises (U_{01} = -2): the optimal threshold is 0.5 times the standard deviation. The corresponding R (Total Positive Rate) is 0.704 and the r (False Positive Rate) is 0.108, and the contingency table:

	Realization	
DMPI index	Crisis	No crisis
Crisis	93 (17.0%)	45 (8.2%)
No crisis	39 (7.1%)	370 (67.6%)

2. Strong penalty for missed crises (U_{01} = -4, -5): the optimal threshold is 0.1 times the standard deviation. The corresponding R is 0.909 and r is 0.258. The results are shown in the contingency table:

	Realization	
DMPI index	Crisis	No crisis
Crisis	120 (21.9%)	107 (19.6%)
No crisis	12 (2.2%)	308 (56.3%)

Comparison of the contingency tables shows that increasing the threshold decreases the number of false alarms, but at the cost of an increase in the number of missed crises. When comparing the lower threshold (0.1) with the higher threshold (0.5) we observe that R (the True Positive Rate) increases by 0.205 and r (the False Positive Rate) increases by 0.150. By using a higher threshold the performance in terms of missed crises improves relatively more than the performance in terms of false alarms deteriorates.

The performance of DMPI against the benchmark for debt crises is shown in Table 4.3. The third column lists the identified debt crises for a high penalty for missed crises, and the last column for a mild penalty for missed crises. Which threshold to use depends on how strong the policy maker wants to penalize missed crises. In our analysis in the remainder of this section we use a threshold of 0.5 (the last column of Table 4.3). The crisis signals are to a large extent similar to the published benchmark crisis dummies (the default episodes as identified by Standard and Poor's, complemented by the episodes of substantial IMF assistance). Our index does not miss any crisis period, although in some crises our DMPI does not identify the entire debt crisis periods. Especially towards the ends of the crisis periods our index often does not identify an increased pressure on the debt position. This can be explained by the renegotiations that often depend on political and legal issues. Even when the renegotiations have not ended and therefore the crisis period continues according to the traditional binary variable definition, it is possible that the economy has recovered from the negative impact of a sovereign debt crisis and that the country can access the international capital markets. In this respect our index does precisely what it was made for: reflecting debt servicing difficulties. Our index picks up most crises in time; there are four crises that are picked up one year late, and one crisis (Mexico 1928–1942) that is picked up six years late.

The false alarms occur in periods with high volatility in the region or major political events. The sovereign debt crisis in Argentina in 1890 (Barings crisis) causes increased pressure from international investors on the entire region, in particular Brazil. In the late 1890s Brazil experiences a debt crisis

Table 4.3. Benchmark debt crises and the constructed DMPI, with thresholds of 0.1 and 0.5 standard deviation. The benchmark for debt crises is the combination of defaults as reported by Standard and Poor's (Borensztein and Panizza, 2009) and IMF assistance as reported by Manasse and Roubini (2009), with a window exclusion period of 2 years—as shown in the last column of Table 4.2.

Country	Benchmark	DMPI	
Threshold		*0.1 σ*	*0.5 σ*
Argentina	—	1876	—
Argentina	1890-1893	1891-1903	1891-1894, 1899-1902
Argentina	—	1915	—
Argentina	—	1932-1937	—
Argentina	—	1941-1946	1943-1945
Argentina	—	1975-1979	1976-1978
Argentina	1982-1995	1982-1991, 1995	1982-1991
Argentina	2001-2005	2001-2012	2001-2012
Brazil	—	1889-1890	1889-1890
Brazil	1898-1910	1898-1909	1900-1905, 1909
Brazil	1914-1919	1914-1916	1914-1915
Brazil	—	1922-1923	—
Brazil	1931-1933, 1937-1943	1930-1945	1931-1945
Brazil	1983-1994, 1998-2002	1981-2006	1982-2005
Chile	1880-1883	1878-1882	1879-1880
Chile	—	1898-1899	1898
Chile	1931-1947	1915-1950	1915-1917, 1931-1946
Chile	—	1969-1977	1973-1976
Chile	1983-1990	1983-1991	1983-1988
Mexico	—	1896-1897	—
Mexico	1914-1922	1909-1927	1913-1918, 1924
Mexico	1928-1940	1931-1943	1934-1935, 1943
Mexico	1982-1990	1982-1990	1982-1989
Mexico	1995	1995-1999	1995-1996

which affects Argentina and Chile. In Argentina a period of frauds in the 1930s is followed by revolutionary reforms in the Peronist era starting in 1943. In the mid 1970s both Argentina and Chile experience military coups, start market reforms experiments and suffer from (very) high inflation (Ocampo and Ros, 2011).

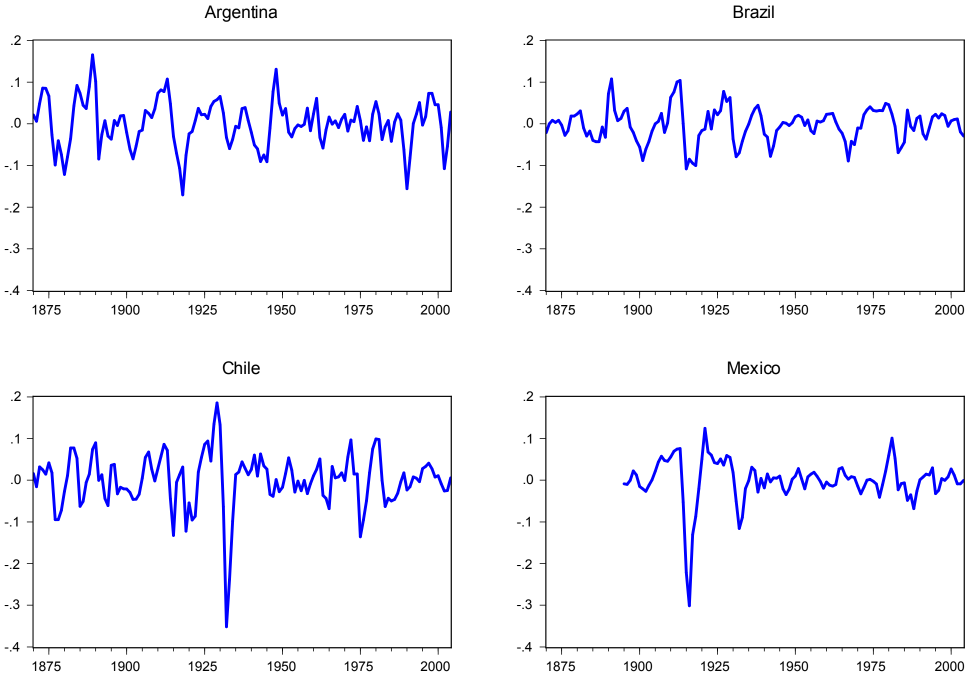
4.5 Sovereign debt crises and business cycles

An advantage of a continuous index as opposed to a binary variable is that the continuous index is more informative. This additional information can be used for a more detailed analysis, such as testing for endogeneity or causality between sovereign debt crises and economic growth and/or business cycles. Here we analyze the relation between business cycles and sovereign debt crises for four Latin American countries, and show impulse response functions based on a two-variable VAR system.

We perform an econometric analysis for the relation between debt crises and the short business cycle index of Aiolfi et al. (2011), which is shown in Figure 4.4. This index is constructed by common factor extraction with backcasting procedures to build an index from an extensive set of aggregate and sector variables, such as sector output, investments, government revenues and expenditures, money aggregates, inflation, domestic interest rate, foreign trade, wage, population and foreign capital flows, real GDP and interest rate. We do not update the index, so the comparison is for the period 1870–2004. We determine the DMPI for this shorter time horizon and find that the same combination of indicators performs best in mimicking its benchmark, the debt-to-GDP ratio, the external interest rate spread and the exports-to-imports ratio. The correlation coefficient between the business cycle index and the DMPI is -0.388. The negative sign is expected since defaults typically take place in the recession phase of the business cycle.

To gain more insight into the relationship between the debt crisis index (DMPI) and the business cycle (BCS) we build a VAR system and analyze the impulse response functions (i.e. responses to one unit reduced form in-

Figure 4.4. Business cycle indexes for Argentina, Brazil, Chile and Mexico, 1870–2004. The business cycle index is constructed by Aiolfi et al. (2011).

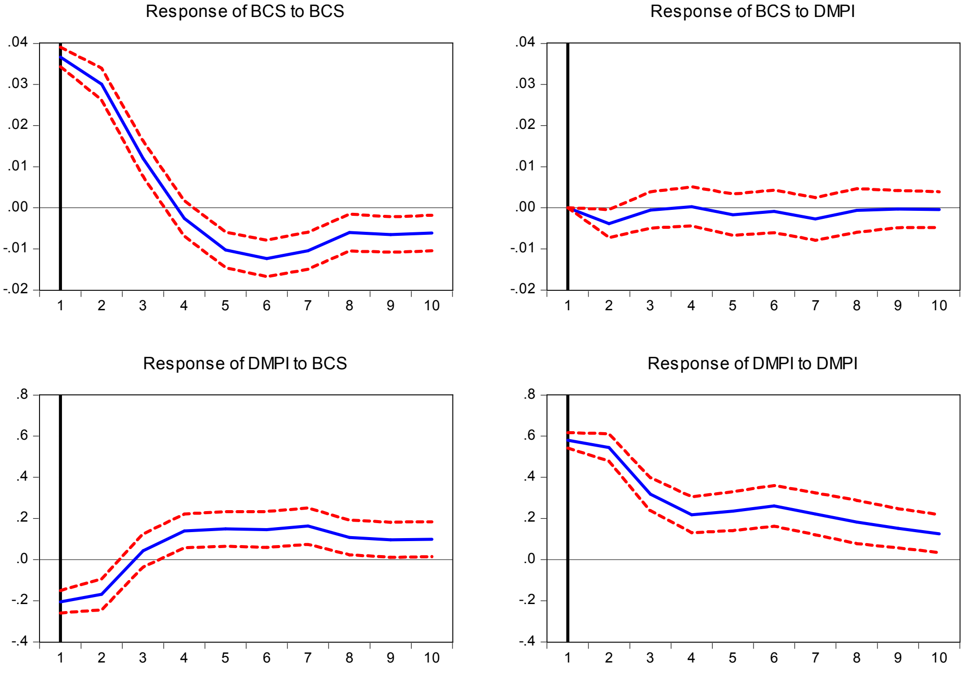


novations) derived from the moving average or Wold representation of the reduced form model. The number of lags based on the likelihood ratio test is eight, which is about the average length of a sovereign debt crisis. Experimenting with different lags, or including exogenous variables like the US long-term interest rate and US real GDP growth yields similar impulse response functions.

According to the block exogeneity Wald (Chi-square) test Granger causality is uni-directional from business cycles to the DMPI at a level of significance of 5%. Accordingly, we assume that contemporaneous shocks to business cycles Granger-cause debt crises. The impulse response functions are shown in Figure 4.5.

The bottom-left panel represents the response of the DMPI after a shock to the business cycle index (BCS). A one standard deviation shock to BCS lowers DMPI for two periods, which implies that the pressure on the debt

Figure 4.5. Impulse response functions for the Debt Market Pressure Index (DMPI) and the business cycle index (BCS) with 2 standard error bands about the impulse responses. Cholesky ordering: BCS−DMPI. The solid line represents the impulse response, and the dotted lines represent the 2 standard error bands about the impulse response. The graph shows the response of a variable to a shock of 1 standard deviation. The response is shown up to 10 years after the shock occurred. The Business Cycle Index is from Aiolfi et al. (2011).



market decreases, in other words, the probability of a debt crisis decreases. The DMPI increases in periods 4–7, which means that the pressure on the debt market increases 4 years after the shock. Since the model is linear, for negative shocks the signs of the responses are opposite. At continuation, we explain the graphs with an opposite impact. A negative shock to economic activity increases the probability of a debt crisis for two years. In a recession the probability of a default is higher, which explains the increased probability of a debt crisis. After four periods the debt crisis index decreases while at the same time the business cycle starts an upturn (see top-left panel in

Figure 4.5). The top-right panel represents the impact on the business cycle as a consequence of the change in the DMPI. There is no significant impact. The bottom-right panel shows the 'aftershocks' of the DMPI after a shock in the DMPI. The effect of a temporary increase in the DMPI do not fade away within 10 years after the shock.

Our approach to construct a continuous DMPI can be easily applied to other countries. In Boonman et al. (2013) we calculate the continuous sovereign debt crisis index for five European countries for the period 1992–2012. For these European countries we use the same three indicators as for the Latin American countries. However, we can not calibrate the continuous sovereign debt crisis indexes in terms of the selection of indicators and the threshold in the decision rule by maximizing utility as explained in this section, because of the low number of currency crises that have occurred in the period 1992–2012.

4.6 Conclusion

We construct a continuous sovereign debt crisis index for four large Latin American countries for the period 1870–2012. Applying the Receiver Operating Characteristic (ROC) curve we determine the optimal sovereign debt crisis index and the threshold by converting the index into a binary variable to compare it with a benchmark crisis index.

To determine the optimal sovereign debt crisis index (DMPI) we try all possible combinations of a selection of eight variables that are associated with sovereign debt crises according to empirical research and theoretical models. The combination that has the best performance in terms of highest utility value of the ROC curve consists of the debt-to-GDP ratio, the external interest rate spread, and the exports-to-imports ratio. These indicators fit within the model of Arellano (2008). In this model an increase in the probability of default leads to an increase in the interest rate spread. Additionally, default is more likely when the debt level is high ('debt overhang') and the economy experiences a recession. From stylized facts we know that the debt overhang will remain high until the debt is restructured, which marks the end of a debt default period. Also the interest rate spread remains at an elevated level during the debt crisis compared to tranquil periods. Furthermore, in a sovereign debt default capital inflows reverse, which lead to a deficit on the capital account. The reversal can occur as a consequence of the default (balance of payment crisis as in Krugman, 1979), or the reversal can cause the default (sudden stop model as in Calvo, 2003). In either case, there will be a real depreciation of the exchange rate and a slowdown in the economy, which leads to a decrease in imports and an increase in exports. The resulting surplus in the current account is necessary to finance the deficit in the capital account, when international reserves are not sufficient to finance the net capital outflows.

The benchmark for the DMPI consists of defaults according to Standard and Poor's, complemented by periods when IMF assistance was required. The optimal threshold is 0.5 times the standard deviation when missed crises have a relatively low cost (two times the costs of a false alarm), or 0.1 when missed crises have a relatively high cost (four to five times the costs of a false alarm). Using the former as threshold, the DMPI performs well in terms of missed crises: it does not miss any debt crisis period, although for various crises our constructed crisis dummy does not identify the entire debt crisis period. Our index generates many false signals, yet all these periods can be traced down to high volatility in the region (debt crises in neighboring countries), sharp drops in commodity prices or major political events (military coups).

We illustrate the potential of our debt market pressure index with an analysis of the relationship between the business cycle index and the debt crises index in a two-variable VAR model. The impulse responses show that a negative shock to economic activity increases the probability of a debt crisis for two years. Four years after the shock the probability of a debt crises drops.