Why didn't the Global Financial Crisis severely affect Latin America?

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Abstract

Despite its rich history of financial crises, Latin America was relatively unharmed by the 2007–2009 Global Financial Crisis (GFC). Although currencies depreciated sharply in 2008, this did not result in a financial or economic crisis. This paper investigates the effect of the GFC on Latin American countries, focusing on the role of commodity prices and inspired by fourth generation financial crises models on institutional factors.

We develop Early Warning Systems (EWS) for Argentina, Brazil and Mexico, which consist of an ordered logit model for currency crises for the period 1990–2007. We apply dynamic factor models to deal with the large number of explanatory variables. Finally, we present out-of-sample forecasts for the period 2008–2009.

We find that currency crises in Brazil and Mexico are related to institutional variables, while commodities play an important role for Argentina and Brazil. Debt indicators are important for Argentina and Brazil. Banking variables are important for Argentina. Mexico's crises are related to domestic and international indicators.

We interpret the out-of-sample results as evidence that Brazil's fast recovery can be attributed to the improved institutional framework, while Argentina has not made sufficient improvement in institutions. We identify Mexico's strong fundamentals –including institutional indicators– as the main reason for not suffering a more severe crisis.

Keywords: Financial crises, Early Warning Systems, Latin America, Dynamic factor models, Ordered logit model

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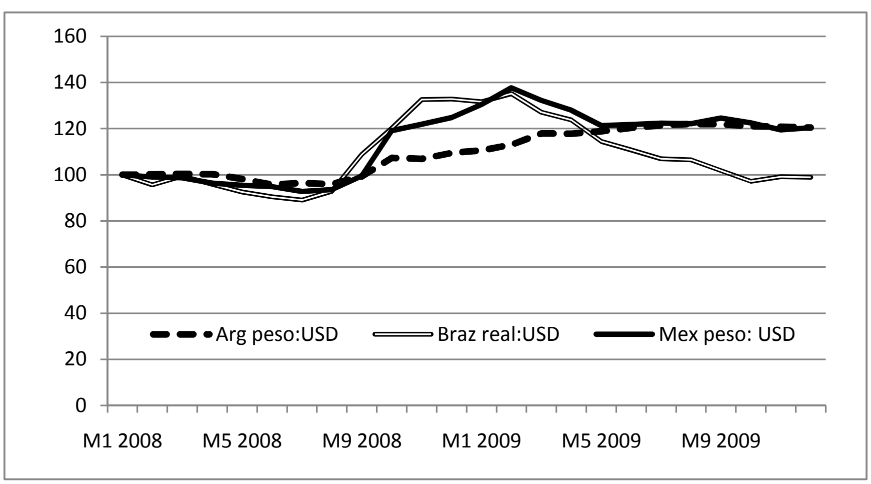
1. Introduction

The 2007–2009 Global Financial Crisis (GFC) has affected many countries including Latin America. In the fall of 2008 Latin American currencies depreciated sharply versus the US dollar. In Brazil and Mexico the local currencies depreciated by more than 40%, and the Argentine peso depreciated by 20% vis-à-vis the US dollar (see Figure 1). The stock markets plunged—in Argentina and Brazil by more than 50%— as is illustrated in Figure 2, and spreads on yields quadrupled in Argentina, and doubled in Mexico and Brazil (see Figure 3). These dramatic changes did not trigger a financial crisis. The real economy contracted in 2009 in Mexico due to the recession in the USA, the sudden-stop in international trade and the influenza A-H1N1, while Argentina and Brazil were hardly affected. The financial sector was not in danger at any time and no debt crises developed. The exchange rates returned relatively quickly to a level close to the pre-crisis situation, particularly in Brazil.

Figure 1: Nominal exchange rates indexed (2008M1 = 100) for the period 2008-2009 for Mexico, Argentina and Brazil



We address the question whether the countries have learned from their past experiences, which makes this study also relevant for other regions. In our analysis we include a particular group of variables which represent the state of the institutional framework.

Figure 2: Stock market index for the period 2008-2009 for Mexico, Argentina and Brazil; 2008M1 = 100

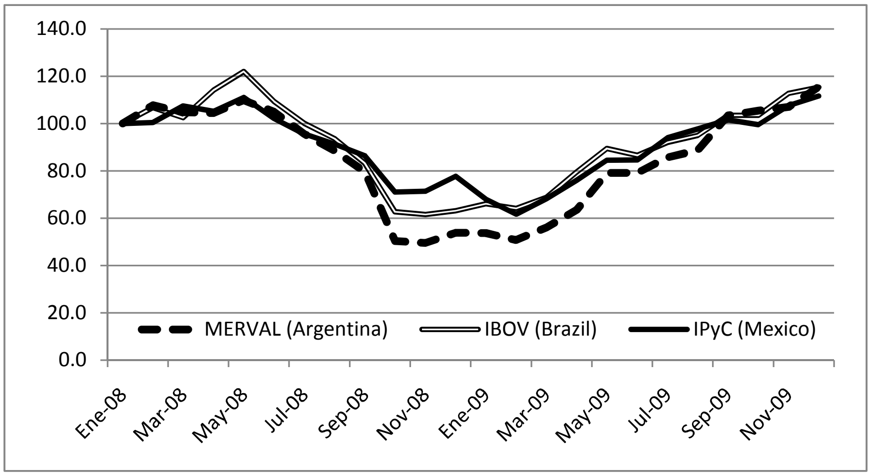
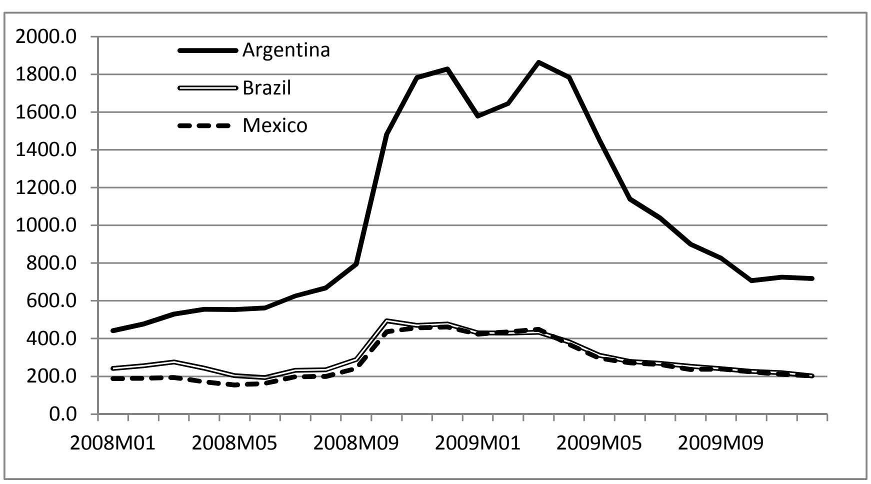


Figure 3: Sovereign bond interest rate spread for the period 2008-2009 for Mexico, Argentina and Brazil; basis points over US Treasuries



Over time, various countries have experienced strong institutional changes in the form of structural reforms, or changes in political power. For instance, in Mexico the conservative National Action Party (PAN) took over the presidency in 2000 after 70 years of Institutional Revolutionary Party (PRI) governments. We hypothesize that institutional change has made these countries less vulnerable to the current crisis. These new institutions are national institutions. These may not prevent a country being hit by a crisis emerging abroad, but these new national institutions may be geared at reducing the impact on the domestic economy. We refer to Moshirian (2011) for a discussion of cross border regulation and the emergence of new national and international institutions. Furthermore, we pay attention to commodity-related indicators. The region is a large commodity producer at the global level. The surge in demand and prices in the second half of the first decade of the 21st century may have contributed to the relative stability, healthy fiscal balances and low debt levels.

We confine attention in this paper to the three most important economies of Latin America: Argentina, Brazil and Mexico (LA-3).[1] We focus on the period 1990 to 2009 because this period has entirely different characteristics than the 1970s and 1980s (hyperinflation, 1980s debt crisis, political system) and because of data availability. In this paper, we model the probability of a currency crises in an ordered logit model.

We apply the ordered logit model using dynamic factor models to cope with the large number of crisis indicators. In that respect our paper is related to Cipollini and Kapetanios (2009), who also apply dynamic factors in their Early Warning System.[2]

As explanatory variables we will use monthly series from 1990 to 2007 for the three Latin American countries. Apart from the "usual suspects"—the common macroeconomic and

[1]The fourth economy, Chile, is not included because it has not experienced financial crises in the 1990–2009 period.

[2]An alternative is Innoue and Rossi (2008), who apply a diffusion index method as Early Warning Systems to forecast currency crises.

financial variables—we include institutional variables and commodity-related indicators. Details on the explanatory variables are given in Appendix Appendix A. We estimate the ordered logit models up to and including 2007, and present forecasts for 2008-2009.

We find that Argentina's crises are correlated most with banking, debt and global indicators, and commodities, while Brazil's crises are related to debt and banking indicators and commodities. Mexico's crises are related to domestic and international indicators (external economy and global). In Brazil and Mexico institutional indicators play an important role which supports the fourth generation financial crisis models discussed in the next section. It also confirms previous work in which political indicators play a significant role in crisis forecasting (e.g. Bussière and Mulder 2000). We interpret the results as follows: Immediately following the fall of Lehman Brothers the fundamentals in all countries considered worsened but this is not fully reflected in our forecasts because the current crises differs from earlier crises. Brazil however was affected stronger than Argentina and Mexico due to falling commodity prices in mid-2008. In the period following the events in 2008 the institutional framework in Brazil prevented the crisis from deepening, since the inclusion of institutional variables decreases the probability of a currency crisis. In the case of Mexico our out-of-sample forecast does not indicate any increase in the probability of a crisis after 2008. The insignificance of the institutional variables and the delayed increase in probability of a crisis in Argentina leads us to conclude that the crisis was not handled adequately—which may be blamed on insufficient institutional reforms.

The remainder of the paper is structured as follows. After a review of financial crises and models, early warning systems and empirical studies for Latin America in Section 2, Section 3 discusses the method. The data are presented in Section 4, followed by the empirical results in Section 5 and the analysis of out of sample performance in Section 6. Section 7 concludes.

2. Review

2.1. Four generations of crises and models

Theoretical models for currency crises have been developed since the late 1970s, based on the seminal work of Krugman (1979). The characteristics of crises have changed over time and so have the models. The literature distinguishes four generations of financial crises (models). The *first generation models* explain the crises as the result of fundamental inconsistencies in domestic policies, which at that time (1960s and 1970s) characterize the crises. The crises are preceded by a deterioration in the fundamentals, such as recurring budget deficits which are monetary financed, or persistent current account deficits which exhaust the foreign reserves.

With the crisis of the European Monetary System in 1992-1993 a *second generation crisis* appears, because the weak economic fundamentals alone could not explain such a dramatic drop in the exchange rate. Fundamentals still play a role: if these are very strong then no currency attack will take place, and if these are very weak then the government will not defend the currency. But when the fundamentals are in a "grey zone", multiple equilibria are possible. Relative small changes can have a big impact, which is known under the term "sunspot view". When speculators suspect that the government is not committed to defend the exchange rate (e.g. for restoring international competitiveness), then a massive currency attack follows which can trigger a self-fulfilling devaluation (Obstfeld, 1996).

The Asian crisis of 1997–1998, a *third generation crisis*, gave a new boost to crisis research. Banks and financial institutions expand and ease their loan granting policies prior to the crisis, because they count on a government bailout in case of solvency problems. This moral hazard behavior leads to an excessive build-up of external private debt followed by a collapse (McKinnon and Pill, 1997). A currency devaluation can trigger a banking and debt crisis when banks and government have a mismatch in the balance sheet: domestic assets financed by foreign liabilities (Chang and Velasco, 1998). Krugman (2003) adds that a combination of factors such as panics in the international investment community, policy mistakes in handling the crisis and poorly designed international rescue programs cause a financial panic which results in currency crises, runs on banks, massive bankruptcies and political turmoil.

The development of *fourth generation models* of financial crises is ongoing. Breuer (2004) refers to a model in which crises are determined by institutional factors. Poor institutional factors are the underlying cause for unsustainable policies, excessive borrowing and lending, hyperinflation, etc. Although economic factors also play a role in fourth generation models, the institutional factors set the conditions for economic outcomes. Many databases that quantify institutional factors have become available recently, enabling more research.

2.2. Early Warning Systems

Early Warning Systems (EWS) are models that send signals or warnings well ahead in time of a potential financial crisis. The dozens of EWS that have been developed differ widely in the definition of a financial crisis, the period of estimation, data frequency and the countries included in the database, the inclusion of indicators, the forecast horizon and the statistical or econometric method (Jacobs, Kuper and Lestano, 2008). For an overview see Kaminsky, Lizondo and Reinhart (1998) and Abiad (2003). Most studies use binary methods (logit or probit), the signals approach, Ordinary Least Squares, Markov Switching models, binary recursive trees, contingent claims analysis or a combination of these methods.

The typical EWS model is applied to a large number of emerging countries from all over the world—in order to obtain sufficient crisis observations. This approach has received criticism. To quote Abiad (2003): "The one-size-fits-all, panel data approach used in estimating most Early Warning Systems (EWS) might be one of the causes of their only moderate success". Kaminsky (2006) confirms this and Beckmann, Menkhoff and Sawischlewski (2006) also suggest that differences between geographical regions justify a regional approach. A growing number of studies focuses on a geographic region—particularly South East Asia, Central Europe and Latin America. Even within a region distinctions can be made. Van den Berg, Candelon and Urbain (2008) construct country clusters for six Latin American countries. In this study for the period 1985-2004, Argentina, Brazil and Peru are grouped in one cluster because of similar inflation patterns, while Mexico, Uruguay and Venezuela are grouped in the other cluster, due to important privatizations in the early 1990s.

2.3. Empirical studies for Latin America

With its rich history of financial crises (Reinhart and Rogoff 2009), Latin American countries—particularly Argentina, Brazil and Mexico—have been included in EWS models applied to emerging economies from all over the world. There are also studies with an exclusive focus on the region. Kamin and Babson (1999) use a binomial probit model with Vector AutoRegressions to distinguish between external and internal factors, to predict financial crises. They use panel data for six Latin American countries, for the period 1981–1998. Herrera and Garcia (1999) group the indicators into a composite index, to analyze the indicators jointly. As in the signals approach, they set thresholds which indicate financial crises. They apply their model to eight Latin American countries. Argentina's long history of currency and other financial crises is analyzed in studies such as Alvarez Plata and Schrooten (2004), Kaminsky, Mati and Choueiri (2009) and Cerro and Iajya (2009). Another crisis that has been researched widely is the Mexico 1994/1995 "tequila" crisis. Sachs, Tornell and Velasco (1996) focus on contagion, whereas Beziz and Petit (1997) study the use of real time data on predicting the crisis.

3. Method

We first apply dynamic factor models to extract the factors from the indicators, and then use the estimated factors as regressors in the ordered logit model, with a crisis dating dummy as dependent variable.

3.1. Dynamic factor models

Dynamic factor models exploit the idea that movements in a large number of variables are driven by a limited number of common factors, which may enter with leads and lags

$$\boldsymbol{X}_t = \boldsymbol{A}_0 \boldsymbol{f}_t + \boldsymbol{A}_1 \boldsymbol{f}_{t-1} + \ldots + \boldsymbol{A}_p \boldsymbol{f}_{t-p} + \boldsymbol{\epsilon}_t, \tag{1}$$

where $\boldsymbol{X}_t$ is the $N \times 1$ vector of observations of explanatory variables in period t, $\boldsymbol{f}_t$ is the $r \times 1$ vector of common components or factors, and $\boldsymbol{\epsilon}$ is a vector of idiosyncratic components, $\boldsymbol{\epsilon}_t \sim \mathcal{N}_N(0, \boldsymbol{\Phi})$. The variables are typically stationary, demeaned and standardized. For a review of dynamic factor models we refer to Stock and Watson (2011).

Dynamic factors can take several forms. Stock and Watson (1998) allow for time varying loadings, but do not allow for autoregressive dynamics. Forni, Hallin, Lippi and Reichlin (2005) adopt a different definition, which is christened a *static factor representation of the DFM* by Stock and Watson (2005) or a *pseudo DFM* by Kapetanios and Marcellino (2009)

$$\boldsymbol{X}_t = \boldsymbol{A}\boldsymbol{F}_t + \boldsymbol{\epsilon}_t, \tag{2}$$

where $\boldsymbol{A} \equiv [\boldsymbol{A}_0 \ \boldsymbol{A}_1 \ \ldots \boldsymbol{A}_p]$ and $\boldsymbol{F}_t \equiv [\boldsymbol{f}_t' \ldots \boldsymbol{f}_{t-p}']'$. Hence, a dynamic factor model with r common factors can be written as a static factor model with $(p+1)r$ static factors.

The dynamics of the r common factors is represented by a vector autoregressive VAR(m)

process of order m

$$\boldsymbol{F}_t = \boldsymbol{\Gamma}(L)\boldsymbol{F}_t + \boldsymbol{\nu}_t, \tag{3}$$

where $\boldsymbol{\Gamma}(L)\boldsymbol{F}_t = \boldsymbol{\Gamma}_1\boldsymbol{F}_{t-1} + \ldots + \boldsymbol{\Gamma}_m\boldsymbol{F}_{t-m}$ and $\boldsymbol{\nu}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}_\nu)$.

The factors can be estimated in the frequency domain (Forni et al., 2000, 2002), by principal components (Bai and Ng, 2002; Stock and Watson, 2002a, 2002b), or by principal components in combination with the Kalman filter (Forni et al. 2009; Doz, Giannone and Reichlin, 2011, henceforth DGR). In this paper we employ the two-step approach of DGR. In the first step preliminary estimates of the factors and estimates of the parameters of the dynamic factor models are computed by principal components. In the second step the factors are updated via the Kalman filter.[3]

Note that DGR use a slightly different version of the static factor representation of the dynamic factor model, without dynamics, in the measurement equation of their state space form, in combination with a VAR(p) for the common factors in companion form as state

[3] The Kalman filter is a forward recursion procedure. We are not using the Kalman smoother (backward recursions) because if we extend the database in our out-of-sample forecast exercise these backward recursions would change the historical values for the dynamic factors.

equation

$$\boldsymbol{X}_t = \begin{pmatrix} \boldsymbol{A}_0 & 0 & \dots & 0 \end{pmatrix} \begin{pmatrix} \boldsymbol{f}_t \\ \boldsymbol{f}_{t-1} \\ \vdots \\ \boldsymbol{f}_{t-p+1} \end{pmatrix} + \boldsymbol{\epsilon}_t$$

$$\begin{pmatrix} \boldsymbol{f}_t \\ \boldsymbol{f}_{t-1} \\ \vdots \\ \boldsymbol{f}_{t-p+1} \end{pmatrix} = \begin{pmatrix} \boldsymbol{A}_1 & \boldsymbol{A}_2 & \dots & \boldsymbol{A}_{p-1} & \boldsymbol{A}_p \\ \boldsymbol{I}_r & 0 & \dots & 0 & 0 \\ 0 & \boldsymbol{I}_r & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & \boldsymbol{I}_r & 0 \end{pmatrix} \begin{pmatrix} \boldsymbol{f}_{t-1} \\ \boldsymbol{f}_{t-2} \\ \vdots \\ \boldsymbol{f}_{t-p} \end{pmatrix} + \begin{pmatrix} \boldsymbol{I}_r \\ 0 \\ \vdots \\ 0 \end{pmatrix} \boldsymbol{\nu}_t.$$

Determination of the number of factors

One of the issues in factor analysis is the determination of the optimal number of factors. Various procedures have been proposed, e.g. the Bayesian Information Criterium, the Kaiser Criterium and Cattell's scree test. The number of factors is better overestimated than underestimated, because the factors are still estimated consistently if the number of factors is overestimated (Breitung and Eickmeier, 2006).

With the large dimensional factor models of recent years many studies have proposed solutions and consistent estimators for the number of factors using different factor model and distributional assumptions. See e.g. Bai and Ng (2002, 2007), Amengual and Watson (2007), Kapetanios (2010), Hallin and Liška (2007), Harding (2009), Jacobs and Otter (2008), and Onatski (2009). Here we employ the criterion of Otter, Jacobs and den Reijer (2011; henceforth OJdR), which is associated with Onatski's (2009) test statistic, and related to the scree test.

Interpreting the factors

Using factor models comes at a cost. Determining the economic relevance of factors and interpreting the factors in a meaningful way is problematic. The factor loadings can be used to assign a label to each of the common factors. This is a good strategy for static factors, but for dynamic factors it is cumbersome. Here we look at correlations between dynamic factors and the indicators (following e.g. Breitung and Eickmeier, 2006).[4]

3.2. Crisis dating

Identifying and dating currency crises has been debated since the mid 1990s. Two approaches can be distinguished: the *successful attack* approach and the *speculative pressure* approach. In this study, we opt for the speculative pressure approach, which was initialized by Girton and Roper (1977) and later used by Eichengreen, Rose and Wyplosz (1995) for currency crisis purposes. In this approach we distinguish events from crises to identify and date currency crises. Events consist of significant changes in exchange rate arrangements, such as official decisions to float or fix the exchange rate, to widen the fluctuation band, etc. Crises consist of periods in which the exchange rate comes under speculative attack. The set of crises periods is not a subset of the set of events. For example, when the exchange rate arrangement is not preceded by a significant exchange market pressure, then this is not considered a crisis. Also the set of events does not include all crises. For example, when a speculative attack is unsuccessful so that there is no realignment of exchange rates, then it is not an event, but it is considered a crisis. In other words, also unsuccessful attacks should be considered a crisis. A currency attack can be unsuccessful when it is successfully defended by the monetary authorities through the use of international reserves, by increasing the interest rates or by restricting transactions in foreign currency.

[4] An alternative is to place the set of variables in well-defined groups, and apply factor analysis to each of the groups. Obviously, the factors derived in this way are no longer orthogonal.

The speculative pressure index, or the Exchange Market Pressure Index (EMPI), is defined as a weighted average of exchange rate changes, changes in the international reserve and changes in the interest rates. A crisis is identified if the index exceeds an upper bound. We follow the modified definition of Kaminsky and Reinhart (1999) and Kaminsky (2006): the weighted average of exchange rate changes and reserve changes, with weights such that the two components of the index have equal conditional volatilities. To determine the crises we deviate from Kaminsky and Reinhart (1999), who identify a crisis when the observation exceeds the mean by more than three standard deviations. We use this definition to identify "very deep" crises. Similar to Cerro and Iajya (2009) we extend the definition of crises by introducing "deep" crises (which we define as two adjacent months with exceedance between 2 and 3 times the standard deviation) and "mild" crises (which we define as two adjacent months with exceedance between 1 and 2 times the standard deviation). The ordinal variable that indicates crises periods is constructed as follows: the value 0 indicates no crisis periods, the value 1 is assigned to mild crises, 2 to deep crises and 3 to very deep crises. As is common in early warning systems of currency crisis, we will use the same dummy variable for the crisis entry month and the run-up to the crisis. In this paper we choose a period of six months preceding the crisis start. In case a crisis follows within six months after a previous crisis, then the second crisis is considered a continuation of the earlier one and eliminated. If types of crises overlap we assign the highest ordinal number to that crisis.

3.3. Ordered logit model

As our dependent variable can only take four values (0=no crisis; 1=mild crisis; 2=deep crisis, and 3=very deep crisis), we employ an ordered choice model, which extends the binary choice model, allowing for a natural ordering in the outcomes y. Assume that there are $K+1$ possible outcomes, then

$$y = \begin{cases} 0 \ \text{ if } \ y^* \leq \mu_1, \\ 1 \ \text{ if } \ \mu_1 < y^* \leq \mu_2, \\ 2 \ \text{ if } \ \mu_2 < y^* \leq \mu_3 \\ \vdots \\ K \ \text{ if } \ \mu_K < y^*, \end{cases} \tag{4}$$

where y is the observed ordinal variable, and y^* is the continuous latent variable that is equal to

$$y^* = Z = \alpha + \beta X. \tag{5}$$

The limits μ_i separate the various outcomes, and are estimated simultaneously with the parameters α and β.

We use the ordered logit model, because the logistic distribution (logit model) has wider tails than the normal distribution (probit model). This is preferable if an event has a very low frequency, as is the case in financial crises (Manasse, Roubini and Schimmelpfennig 2003). The probabilities for each of the outcomes are:

$$\begin{aligned} P(y=0) &= \frac{1}{1+e^{-(Z-\mu_1)}}, \\ P(y=1) &= \frac{1}{1+e^{-(Z-\mu_2)}} - \frac{1}{1+e^{-(Z-\mu_1)}}, \\ &\vdots \\ P(y=K) &= 1 - \frac{1}{1+e^{-(Z-\mu_K)}}. \end{aligned} \tag{6}$$

Interpreting estimation results using factors as dependent variables needs to be done with great care. Most indicators feature in more than one factor, so focusing on a single factor only partially explains the full impact of an indicator on the probability of a crisis, and may even lead to counterintuitive results. So, interpretation of the parameters in an ordered choice model is not trivial (Kennedy, 2008, pp.258–259 and the references therein).

For each country we will estimate two versions of the ordered logit model. The first uses dynamics factors calculated from the data set, excluding institutional variables for reasons discussed below. The second model adds (a subset of) institutional variables to the dynamic factors as separate regressors. These models are estimated using data until and including 2007.

4. Data

Our sample starts in the early 1990s, when the effects of spillovers of the 1980s Latin American debt crisis were gone. The analysis for Argentina starts after the introduction of the Convertibility Plan (April 1991) and for Brazil after the introduction of the Real Plan (July 1994), which both can be regarded as a structural break with the hyperinflation periods. Mexico did not experience any period of hyperinflation in the 1990s.

As explained above, we distinguish mild, deep and very deep crises. Very deep crises are rare; each of the countries under investigation experienced only one very deep crisis in the in-sample period: Mexico (December 1994), Brazil (January 1999) and Argentina (January 2002). We estimated the EMPI based on the period up to 2007M12, and extended this to 2009M12 using the same weights (standard deviations) as in the in-sample period. These periods coincide with Figures 4, 5 and 6 show the crisis observations.

For the explanatory variables we select series based on two criteria: (i) series have to be complete, i.e. no missing observations; and (ii) series have to be used in the literature. There are however some data limitations. Not all time series are sufficiently long which limits the selection of explanatory variables.

Figure 4: Actual crisis dates for Argentina for the period 1991-2009

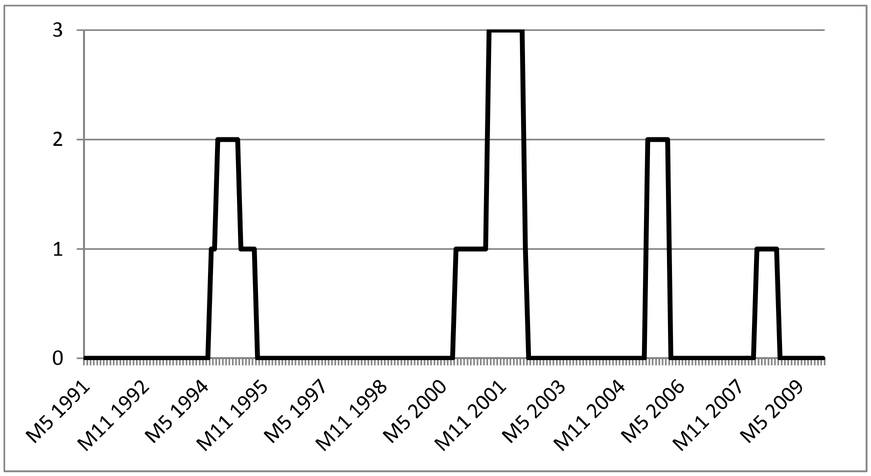


Figure 5: Actual crisis dates for Brazil for the period 1994-2009

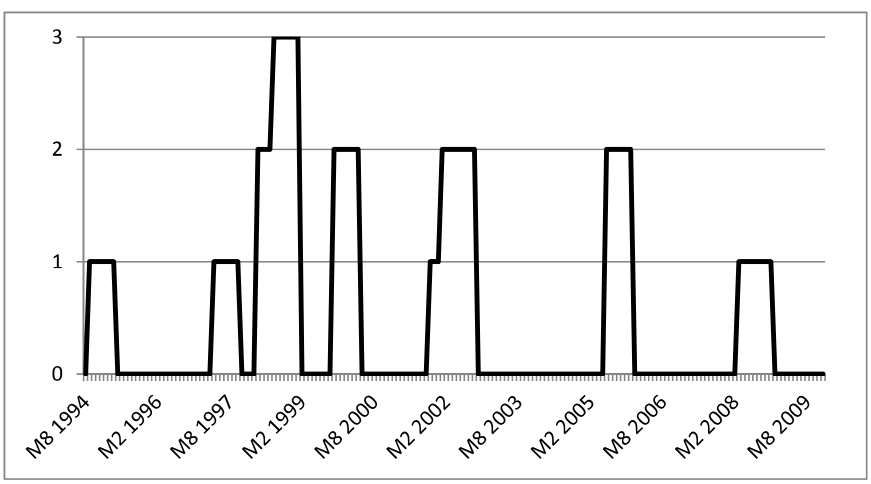
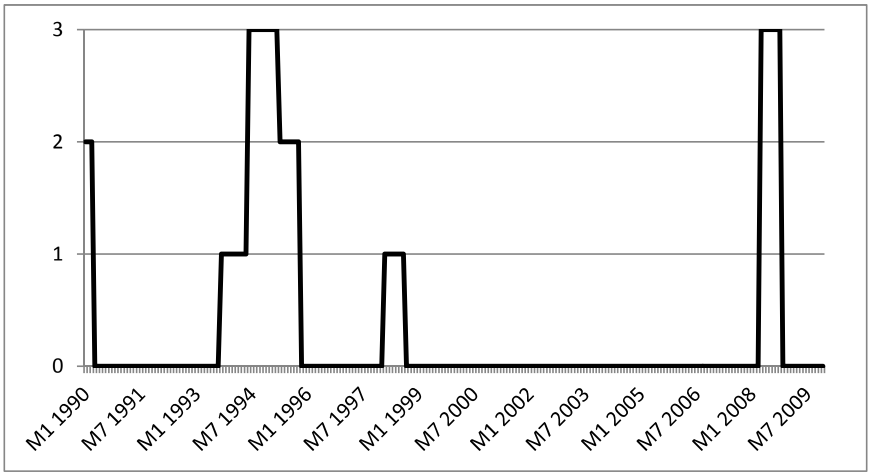


Figure 6: Actual crisis dates for Mexico for the period 1990-2009



The selected series can be classified into separate categories:[5]

- 13 external economic indicators, among which the real exchange rate, exchange rate volatility, growth of exports, imports and foreign reserves, import cover, ratio of M2 to foreign reserves.

- 19 domestic economic indicators, among which domestic real interest rate, inflation, M2 multiplier, industrial production, share market index return, country spread.

- 14 institutional indicators, among which election dates, Herfindahl indices, political stability, corruption, investment profile, internal conflict.

- 10 debt indicators, among which total debt, short term debt, debt service, arrears.

- 25 banking sector indicators for Argentina (14 for Brazil and Mexico), among which credit to public sector, to private sector, ROE, deposits.

- 5 global and regional indicators, among which economic growth in world, US yield,

[5]For a complete overview, including definitions, transformations, and sources we refer to Appendix Appendix A.

contagion dummy.

- 12 commodity related indicators, among which prices of oil, metals, agricultural products, exports and imports of fuel, agricultural products, food and metals.

The series have been tested for non-stationarity (using Augmented Dickey-Fuller tests) and visually inspected for seasonal effects. Where necessary a transformation was made to render them stationary. To deal with mixed frequencies in series, we apply simple quadratic interpolations. All series are normalized, i.e. demeaned and divided by its sample standard deviation.

5. Empirical results

We estimate the ordered logit model for Argentina, Brazil and Mexico for the period up to and including 2007, and we forecast for the 2008–2009 period. In this section we discuss both the dynamic factor model outcomes, and the estimation results for the ordered logit models. We do not include institutional variables in the model, because these cause quasi complete separation due to their low variation. We introduce a second model in which a subset of the institutional variables are added to the dynamic factors in the ordered logit model. The extended model allows us to test whether the institutional variables contain additional information that is significant for currency crisis periods.[6]

5.1. Argentina

The OJdR criterion (Otter et al. (2011)) suggests 10 factors for Argentina. When focusing on the variables with the largest correlation (either positive or negative) we can label each factor. Factors 1 and 5 are dominated by bank indicators, while factors 2, 4, 7,

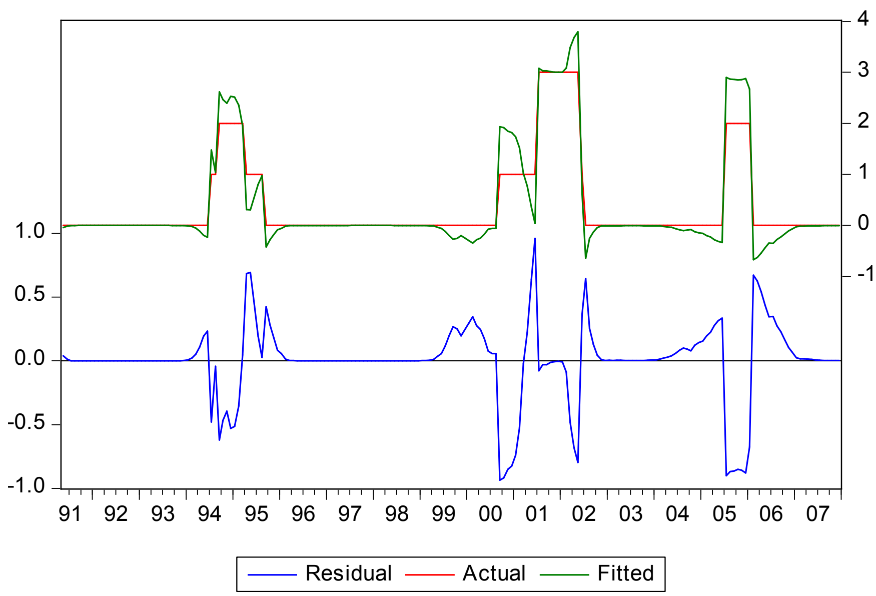
[6] For all three countries we also employed static factors as regressors in the ordered logit models. These results are not reported here, but the differences are marginal.

9, and 10 are labeled as debt factors. We label factor 3 as a global factor, and factor 6 as an external economic factor. Finally, factor 8 is driven by commodities.[7]

Estimation results

The dynamic factor combination which yields the best fit in the ordered logit model has 4 dynamic factors and 2 lags. Table Appendix C.1 in Appendix Appendix C shows that all factors, except 9 and 10, are significant at a 5% significant level. Factors 2, 3, 6 and 8 increase the probability of a crisis. The pseudo R^2 is 0.530 and the fit is illustrated for the period 1991-M5 to 2007-M12 in Figure 7.

Figure 7: Actual and fitted data, and the residuals from the ordered logit model for Argentina for the period 1991-2007



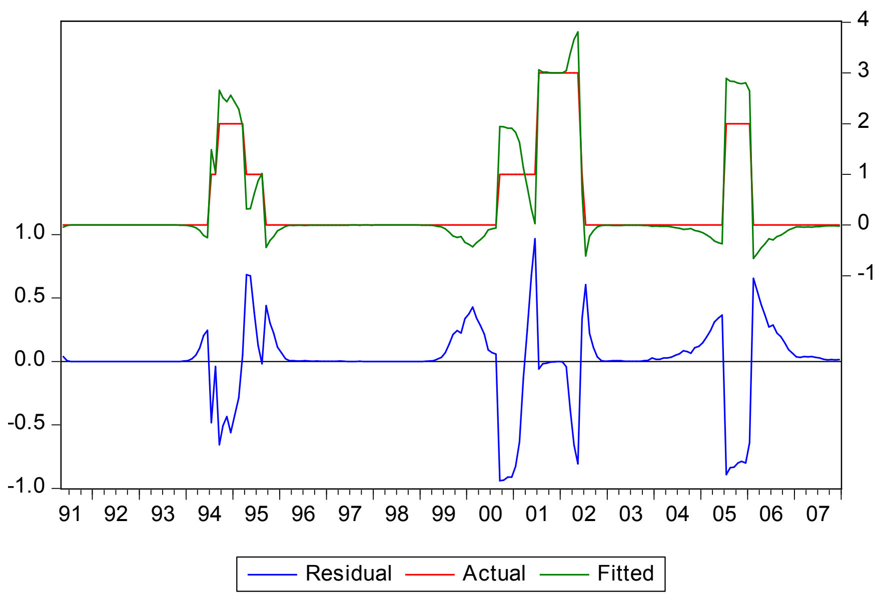
Including institutional variables

To identify the importance of the institutional indicators we add a selection of the institutional variables to the factors. The results are reported in Table Appendix C.2 in

[7]If we consider the five biggest correlations (see Appendix Appendix B) instead of the highest correlation, then factors 2, 7, and 8 are not dominated by a single category, and commodities also play a role in factors 1 and 10.

Appendix Appendix C. The institutional variables that add most information while not causing quasi complete separation are changes in law and order, investment profile and whether there is an election year or not. An additional dummy variable is also included: contagion is 1 if there is a crisis in Brazil or Mexico. The pseudo R^2 is 0.535 and the fit is illustrated for the period 1991-M5 to 2007-M12 in Figure 8.

Figure 8: Actual and fitted data, and the residuals from the ordered logit model for Argentina for the period 1991-2007; including institutional variables



The Wald test (F-value is 0.439, and the p-value equals 0.780) shows that the institutional variables do not contribute to explaining the currency crises in Argentina. So, we conclude that institutional indicators do not play an important role in the model for Argentina.

5.2. Brazil

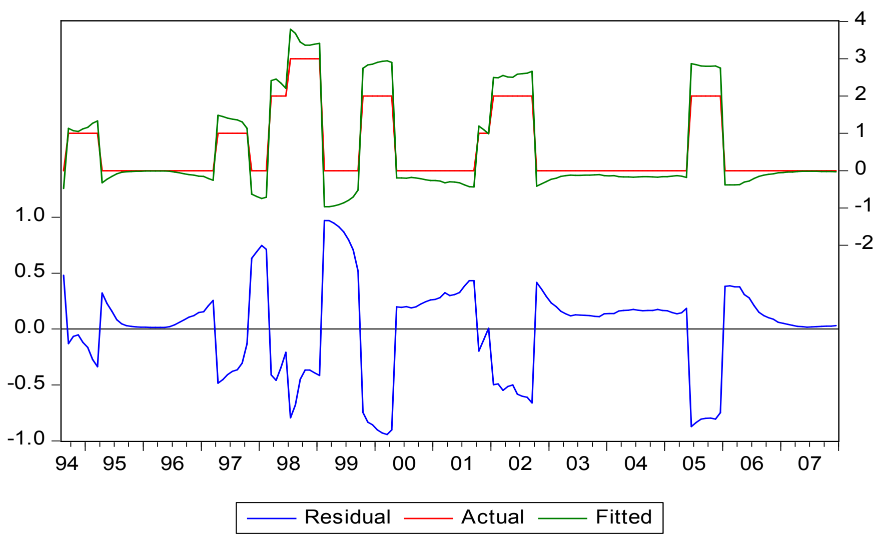
The criterion of Otter et al. (2011) suggests 8 factors for Brazil. When focusing on the variables with the largest correlation (either positive or negative) we label factors 1, 2, 3 and 6 as debt-related factors. Factors 4 and 8 are interpreted as bank factors, and factors

5 and 7 are driven by commodities.[8]

Estimation results

The combination of 4 dynamic factors and 2 lags yields the best fit in the ordered logit model for Brazil. The pseudo R^2 for the DFM is 0.200 and the fit is shown graphically for the period 1994-M8 to 2007-M12 in Figure 9. Table **??** in Appendix Appendix C shows that all factors, except 4 and 7, are significant at a 5% significant level. Except for factor 2 all factors increase the probability of a crisis.

Figure 9: Actual and fitted data, and the residuals from the ordered logit model (dynamic factors only) for Brazil for the period 1994-2007



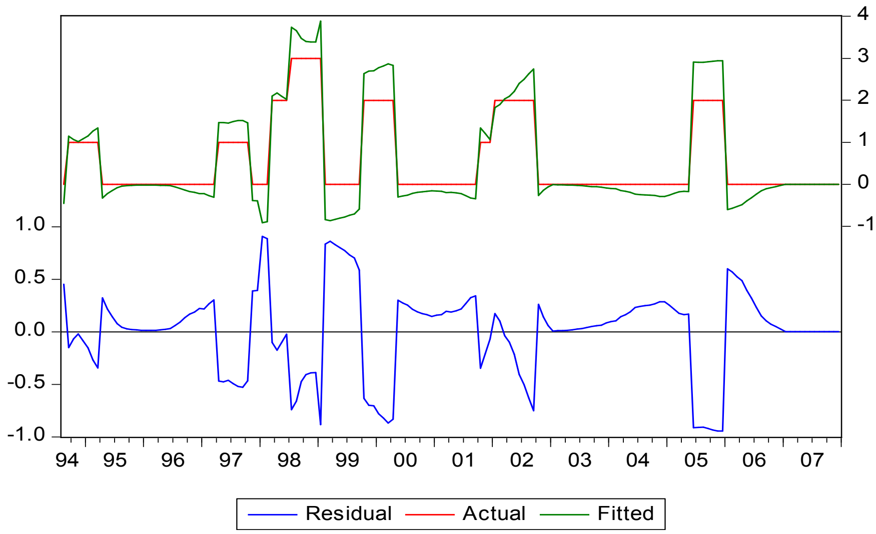
Including institutional variables

To identify the importance of the institutional indicators we add a selection of the institutional variables to the factors. The results are reported in Table Appendix C.3 in Appendix Appendix C. The institutional variables that add most information while not causing quasi complete separation are changes in government stability and corruption and

[8]When we consider the five indicators with the highest correlations (Appendix Appendix B) then factors 2, 3 and 6 are combined factors consisting of debt and to a lesser extent external economy variables.

whether there is an election year or not. The pseudo R^2 improves to 0.251 and the fit is illustrated for the period 1991-M5 to 2007-M12 in Figure 10.

Figure 10: Actual and fitted data, and the residuals from the ordered logit model for Brazil for the period 1994-2007; including institutional variables



We conclude that institutional indicators do play an important role in the model. Not only does the fit improve, the Wald test (F-value is 4.108, and the p-value equals 0.008) shows that the included institutional variables contribute to explaining the currency crisis in Brazil.

5.3. Mexico

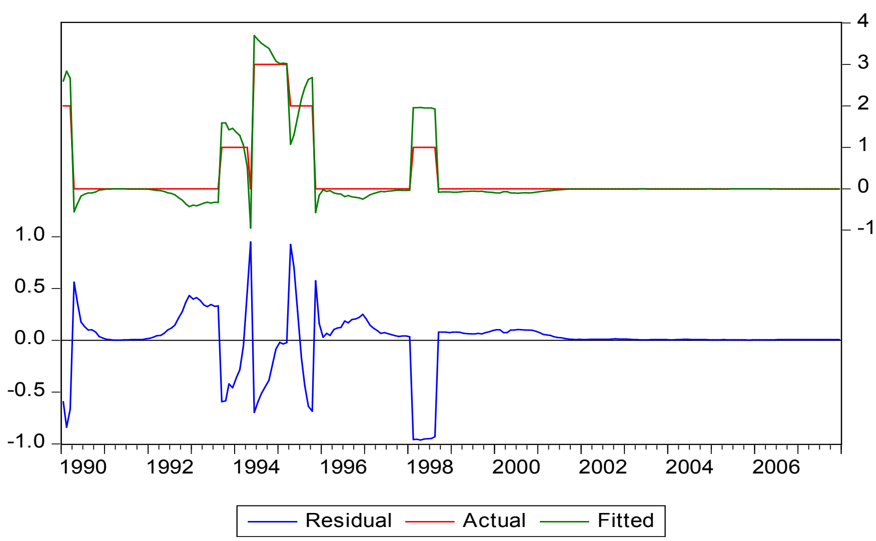
According to the OJdR criterion (Otter et al. (2011)) the number of factors for Mexico is 6. Based on the variables with the largest correlation (either positive or negative) we label factor 1 as an external economic factor. Factors 2 and 3 and related to domestic economic indicators. Factors 4 and 5 are interpreted as global factors, and factor 6 is dominated by debt indicators.[9]

[9]Based on the five biggest correlations (see Appendix Appendix B) factors 2 and 3 are related to both domestic economic and debt indicators, and factors 4 and 5 are mixed factors, with a strong correlation with global indicators.

Estimation results

The combination of 3 dynamic factors and 3 lags yields the best fit in the ordered logit model for Mexico. Table Appendix C.4 in Appendix Appendix C presents the estimation results for the period 1990-M1 to 2007-M12. The pseudo R^2 for the DFM is 0.484 and the fit is illustrated in Figure 11. Table Appendix C.4 in Appendix Appendix C shows that factors 2, 3 and 5 are significant at a 5% significant level. Factor 1 is significant at a 10% significance level. All factors increase the probability of a crisis.

Figure 11: Actual and fitted data, and the residuals from the ordered logit model (dynamic factors only) for Mexico for the period 1990-2007

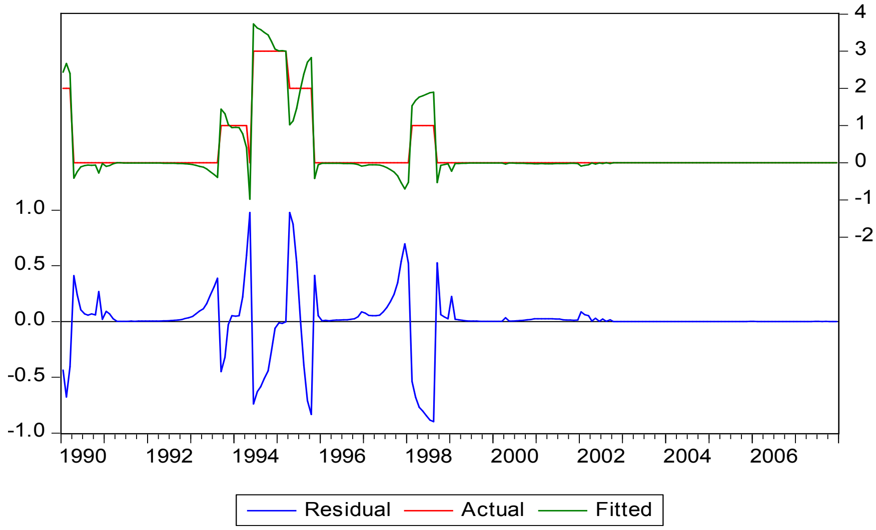


Including institutional variables

Including institutional indicators improves the R^2 to 0.604 and the fit is illustrated for the period 1990-M1 to 2007-M12 in Figure 12. The institutional variables that add most information while not causing quasi complete separation are changes in bureaucratic quality, democratic accountability and investment profile.

Again, the institutional indicators do play an important role in the model; the Wald test (F-value is 5.291, and the p-value is smaller than 0.001) shows that the included

Figure 12: Actual and fitted data, and the residuals from the ordered logit model for Mexico for the period 1990-2007; including institutional variables



institutional variables contribute to explaining the currency crisis in Mexico.

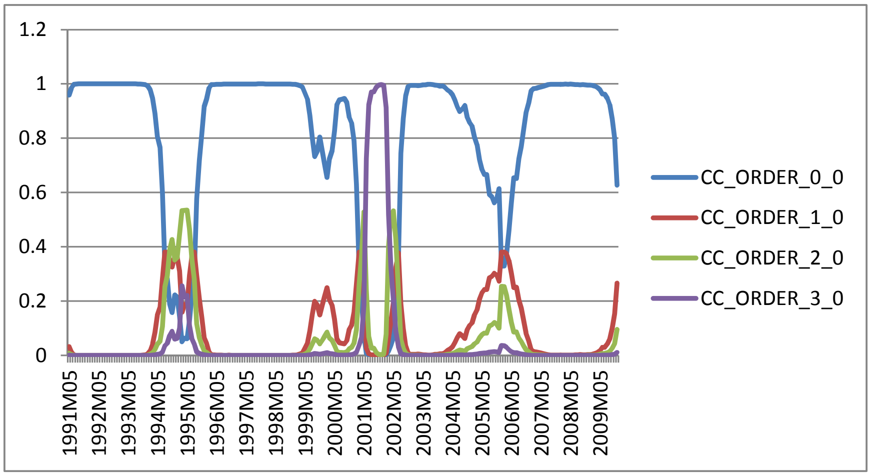
6. Out of sample performance

In this section we test the performance of the estimated model out-of-sample for the period 2008M1–2009M12. We use realized monthly data for the indicators for the years 2008 and 2009, and extrapolate the dynamic factors using the Kalman filter without re-estimating the parameters for the dynamic factor model. Next, we forecast the probabilities of a mild, deep and very deep crisis in the period 2008–2009. In the last subsection we will comment on some of the puzzling results.

Argentina

The institutional factors do not contribute to prediction a currency crisis in Argentina. So, we show only one graph (Figure 13) that gives a graphic representation of the forecast. We predict an increase in the probability of a very deep currency crisis towards the end of the sample.

Figure 13: Forecasts for Argentina for the period 1991-2009; excluding institutional variables



Brazil

Figures 14 and 15 show crises forecasts for Brazil, for the model with only dynamic factors and the model including institutional variables. We observe that the model without institutional variables shows an increase in the probability of a deep currency crisis starting already at the end of the year 2008. The model including institutional variables does not predict any crisis at all.

Figure 14: Forecasts for Brazil for the period 1994-2009; excluding institutional variables

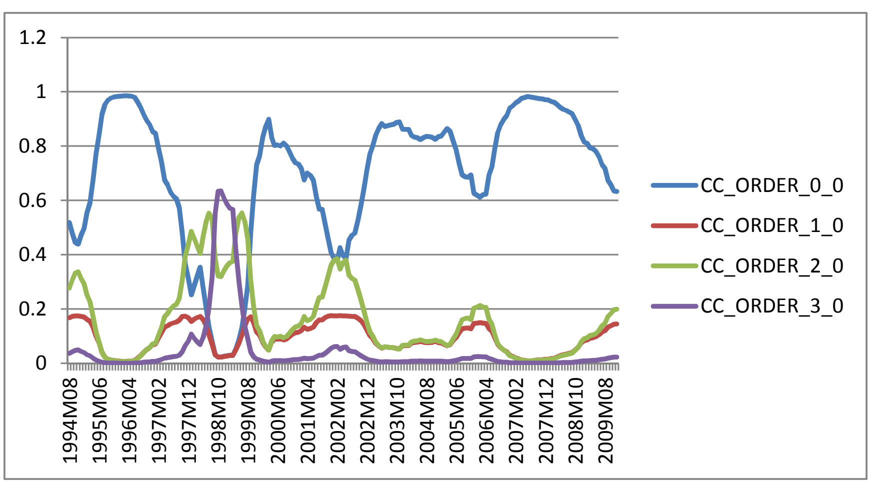
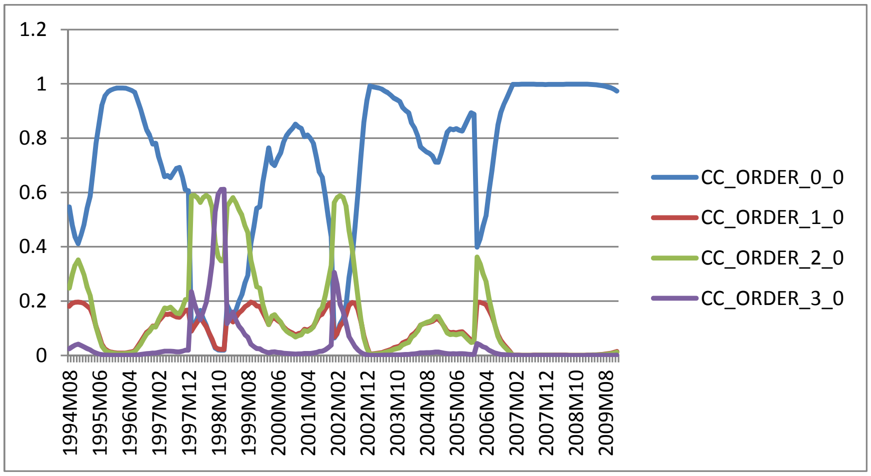


Figure 15: Forecasts for Brazil for the period 1994-2009; including selected institutional variables



Mexico

Figures 16 and 17 show crises forecasts for Mexico. The first graph is based on the model with dynamic factors only, while the second graph is based on the model including institutional variables. The graphs are almost identical. Mexico experienced a deep currency crisis in October 2008. This is not foreseen by neither version of the ordered logit model.

Figure 16: Forecasts for Mexico for the period 1990-2009; excluding institutional variables

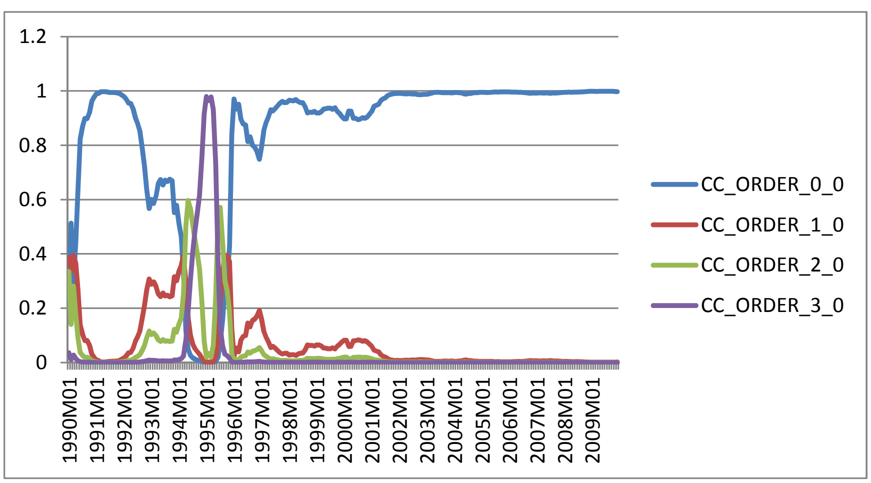
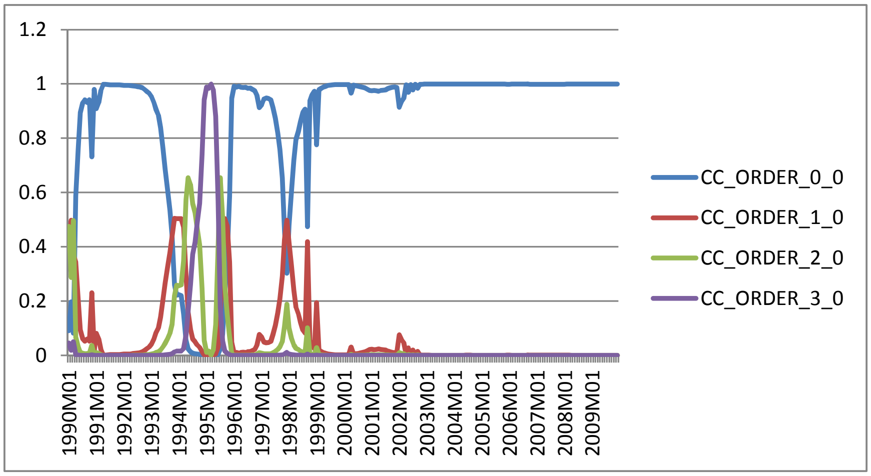


Figure 17: Forecasts for Mexico for the period 1990-2009; including selected institutional variables



Discussion

In the late Fall of 2008 all three countries experienced a currency crisis. The crisis in Argentina and Brazil was mild, but in Mexico the crisis was very deep. Based on information up to and including 2007, our ordered logit model does pick up the crisis in Argentina, but this is one year after the September 2008 event. Our model does not pick up the crisis in Mexico. The crisis in Brazil is predicted only if we not include institutional variables. With institutional variables included in the model, the probability of a crisis occurring in Brazil is greatly reduced.

For Argentina and Mexico the crisis in the second half of 2008 is not predicted by our model, possibly because the causes are very distinct when compared to earlier crises: while the GFC is an external crisis, previous crises are of a domestic nature. However, one year after the September 2008 event the probability of a crisis in Argentina increases sharply. Combining this delayed negative effect with the result that the institutional variables do not contribute in a significant way, we conclude that the handling of the crisis in Argentina has not been adequate. The elections of October 2009 were held already in June 2009 in order to deal with the GFC. However, the results of the elections made things worse for the ruling presidents party. Contrary to Argentina we observe no increase in the probability of a crisis for Mexico in the year after the September 2008 event. Our results indicate that Mexico has improved the internal economic situation. Due to its low debt level, a healthy financial sector and an improved institutional framework Mexico had stronger fundamentals. As a result the GFC did not trigger a severe financial crisis, and had the exchange rate bouncing back to almost the pre-crisis level. For Brazil our model predicts an increased probability of a crisis in 2008. When we include institutional variables the probability of a crisis decreases. The structural reforms that Brazil has adopted since the 1999 crisis seem to be picked up in our model. Our results provide support for the fourth generation crisis models.

It should be emphasized that the forecasts presented here include all available information, including the global shock caused by the fall of Lehman Brothers in the USA in September 2008. What we did not do is to re-estimate the factor models. In that respect our exercise is a true out-as-sample forecasting exercise.

7. Conclusion

The fall of Lehman Brothers in September 2008 sent a shock all over the world; emerging markets were affected severely. Exchange rates depreciated by more than 40% (Mexico, Brazil) and share prices decreased by more than 50% (Argentina, Brazil). Despite relative solid fundamentals the currencies showed a sharp depreciation, particularly countries with high trade and financial flows with the USA and countries with fiscal or trade balance deficits. International trade was also severely affected.

Given the rich history of financial crises of the three Latin American countries that we studied, it is remarkable that in none of these countries the effect spread to the banking sector or affected debt servicing. In 2009 the exchange rates, stock prices and interest spreads reversed and returned to somewhere between the pre-crisis and crisis levels.

This paper investigates why Latin America was relatively unharmed by the GFC. To that purpose we set up ordered logit models for Argentina, Brazil and Mexico, using dynamic factor models to reduce the dimension of the information set. We find that currency crises are driven by a limited number of categories: Argentina's crises are correlated most with banking, debt and global indicators, and commodities, while Brazil's crises are related to debt and banking indicators, and commodities. Mexico's crises are related to domestic and international indicators (external economy and global). In Brazil and Mexico institutional indicators play an important role. For Brazil we interpret the results as in improvement of the institutional framework. This may explain why Brazil recovered fast from the events in the fall of 2008. It is also in line with previous work in which political indicators play a significant role in crisis forecasting. Our model does not indicate any increase in probability of a crisis in Mexico: the GFC is substantially different from earlier crises in the 1990s and the economic fundamentals (debt, financial sector) are stronger, which explains why the events have not triggered a severe financial crisis. For Argentina we conclude that the handling of the crisis was not adequate. However, this does not mean that the countries "graduated from financial crises" to borrow a term from Qian, Reinhart and Rogoff (2010). The LA-3 passed a serious test with the GFC, but its characteristics were very distinct from previous crises.

Appendix A. Data

	Indicator	*Code*	*Definition and source*	*Transformation*	*Data freq*	*Countries*
Economic indicators: external sector						
1	Real Exchange Rate (RER): deviation from trend	RER_DEV	RER = e (P_f / P), with: e = nominal exchange rate Local Currency Unit per US dollar (IFS: AE.ZF) P = domestic price level: Consumer Price Index (IFS: 64..ZF) P_f = foreign price level: Consumer Price Inflation in USA (IFS 111.64..ZF)	deviation from 5 year moving average	Monthly	A, B, M
2	Exchange rate volatility	ERVOL	Monthly volatility of the nominal exchange rate (IFS: AE..ZF) in the current month and the 47 months preceding.	Standard deviation	Monthly	A, B, M
3	Export growth	D_EXP	Exports F.O.B.; in USD (IFS: 70.D..ZF)	12 months percentage change	Monthly	A, B, M
4	Import growth	D_IMP	Imports F.O.B.; in USD (IFS: 71.VD..ZF)	12 months percentage change	Monthly	A, B, M
5	Terms of Trade	TOT	ToT = exports prices / imports prices Two ways to define this: (i) Export price index (= IFS-76) / import price index (= IFS-76X) -Mex; (ii) Unit value of exports: IFS-74D ; Unit value of imports: IFS-75D - Arg & Bra	None (ratio)	Arg & Bra (series 74, 75): quarterly, Mex (series 76): monthly	A, B, M
6	Ratio of Current Account to GDP	CA_GDP	Current account, in USD: IFS-78AL (78ALDZF…) = balance on goods, services and income plus current transfers. GDP, in nominal USD: IFS 99, converted in USD by average nominal exchange rate (IFS: ..RF.ZF... for Arg & Bra, ..WF.ZF... for Mexico).	None (ratio)	Quarterly	A, B, M
7	Net Portfolio Investment / GDP	NETPI_GDP	Portfolio assets (IFS: 78BFDZF...) - portfolio liabilities (IFS: 78BGDZF...). Both in USD. GDP in USD: see CA_GDP	None (ratio)	Quarterly	A, B, M
8	Ratio FDI to GDP	NETFDI_GDP	FDI outflow = IFS series 78BDDZF… and FDI inflow = IFS series 78BEDZF… (both in USD). Arg and Bra: net FDI; Mex: FDI inflow GDP in USD: see CA_GDP	None (ratio)	Quarterly	A, B, M
9	Ratio of Financial Account to GDP	FA_GDP	Financial account = balance of all accounts: from trade to FDI and portfolio investments. Financial Account = IFS: 78BJDZF… GDP in USD: see CA_GDP.	None (ratio)	Quarterly	B, M
10	Trade openness	D_TRD_OPEN	Trade openness = sum of absolute value of exports and imports, divided by nominal GDP in USD. IFS: 78AADZF… + 78ADDZF… (= exports of goods and services) and 78ABDZF… + 78AEDZF… (= imports of goods and services) GDP in USD: see CA_GDP	12 months percentage change	Quarterly	A, B, M
11	Growth of forex reserves	D_RES	Foreign exchange reserves, excluding gold; in USD (IFS: 1.LD..DZF)	12 months percentage change	Monthly	A, B, M
12	Ratio of M2 to forex reserves	M2RES	M2: IFS series 59MB.ZF… (Arg > 2000; Bra & Mex), Central Bank Rep.Argentina (< 2000, Arg). Converted into USD with end-of-period nominal exchange rate: IFS series ..AE.ZF...; Foreign Exchange Reserves: IFS series .1L.DZF…	None (ratio)	Monthly	A, B, M
13	Import cover	D_IMPCOV	Forex Reserves excl.gold from IFS, in USD (.1L.DZF…) and imports F.O.B. from IFS, in USD (IFS: 71.VD..ZF)	12 months percentage change	Monthly	A, B, M

Economic indicators: domestic real and public sector

1	real GDP growth	D_RGDP	GDP in nominal LCU. IFS: 99B..ZF... (Arg > 1995; Bra & Mex), INDEC (Arg < 1995). Consumer Price index (IFS: 64..ZF…);	12 months percentage change	Quarterly	A, B, M
2	GDP per capita	D_RGDPCAP	GDP divided by total population; GDP: see D_RGDP; Total population: IFS-99Z.	12 months percentage change	Annual	A, B, M
3	Unemployment	D_UNEMPL	Unemployment as % of (# unemployed + # employed). IFS: 67R..ZF…	12 months percentage change	Annual < 2001, quarterly > 2001	B
4	Government consumption expenditure to GDP	GOVCONS_GDP	Gov.Cons. (in LCU): IFS 91F..ZF… GDP (in LCU): IFS 99B	None (ratio)	Quarterly	B, M
5	Household consumption expenditure (incl. NPISHS) to GDP	HHCONS_GDP	Household cons: IFS series 96F..ZF… GDP (in LCU): IFS 99B	None (ratio)	Arg < 1993: annual, > 1993 quarterly; Bra & Mex: quarterly	A, B, M
6	Ratio of government revenues to GDP	D_GOVREV	Gov't revenues: integrate two incomplete series (IFS: c1...BA… and a1...CG…). GDP (in LCU): IFS 99B	12 months percentage change	Quarterly	B, M
7	Ratio of government expenses to GDP	D_GOVEXP	Gov't expenses: integrate two incomplete series (IFS: c2...BA… and a2...CG…). GDP (in LCU): IFS 99B	12 months percentage change	Quarterly	B, M
8	fiscal balance to GDP	GOVBAL_GDP	Budget = difference between revenues (IFS: c1...BA… and a1...CG…) and expenses (IFS: c2...BA… and a2...CG…) GDP (in LCU): IFS 99B	None (ratio)	Quarterly	B, M
9	Change in inventories to GDP	INVCHG_GDP	Change in inventories (in LCU) IFS 93I.CZF... GDP (in LCU): 99B.RWF…	None (ratio)	Quarterly	M
10	Inflation (CPI)	INFLAT	Consumer Price Inflation (IFS: 64..ZF)	12 months percentage change	Monthly	A, B, M
11	Growth of industrial production	D_INDPROD	Industrial production index: Bra & Mex: IFS-66. Arg: Datastream (code AGIPTOT.G)	12 months percentage change	Monthly	A, B, M
12	Domestic Savings	GDSAV_GDP	Ratio of savings to GDP: WDI-code: NY.GDS.TOTL.ZS	None (ratio)	Annual	A, B, M
13	Gross capital formation	GFCAP_GDP	Arg & Mex: 93E.CZF... and 99B.RWF… (quarterly) Bra: WDI code: NE.GDI.TOTL.KD.ZG (annual)	12 months percentage change	Arg & Mex: quarterly, Bra: annual	A, B, M
14	Domestic real interest rate	REALINT	6 month time deposit rate deflated by CPI: $(1+R_{nominal}) / (1+\text{Inflation}) - 1$, with: 6 months time deposit rate (IFS: 60L..ZF) CPI (IFS: 64..ZF)	See formula	Monthly	A, B, M
15	M2 growth (real LCU)	D_M2	M2: see M2RES	12 months percentage change	Monthly	A, B, M
16	M2 money multiplier	M2MULT	Ratio of M2 to monetary base. M2: see M2RES Base money: IFS: 19MA.ZF…	ratio	Monthly	A, B, M

17	Sovereign Bond Interest Rate Spreads, basis points over US Treasuries	INTSPREAD	GEM: difference between local government interest rate on bonds in USD and US government on bonds in USD.	None (spread)	Monthly	B
18	J.P. Morgan Emerging Markets Bond Index (EMBI+): monthly return	EMBI_RET	GEM: index that measures the value of the bonds.	Monthly return	Monthly	B
19	Return on the major stock index	STOCKRET	Major stock index from each country (IPC for Mexico, Merval for Argentina and BOVESPA for Brazil). In own currency. Source: Economatica.	Monthly return	Monthly	A, B, M
Debt indicators						
1	Ratio total debt to GDP	DEBT_GDP	WDI code for total -external- debt (in USD): DT.DOD.DECT.CD GDP (in USD): see CA_GDP	None (ratio)	Annual	A, B , M
2	ST debt / total debt	STD_DEBT	Short term debt: (WDI code) DT.DOD.DSTC.CD Total debt: (WDI code) DT.DOD.DECT.CD	None (ratio)	Annual	A, B , M
3	Use of IMF credit to GDP	IMF_GDP	IMF credit: (WDI code) DT.DOD.DIMF.CD GDP (in USD): see CA_GDP	None (ratio)	Annual	A, B , M
4	Arrears to total debt	ARR_TDEBT	WDI code for interest arrears (USD): DT.IXA.DPPG.CD WDI code for principal arrears (USD): DT.AXA.DPPG.CD WDI code for total external debt (USD): DT.DOD.DECT.CD	None (ratio)	Annual	A, B , M
5	Debt reduction / total debt	REDU_TDEBT	Debt reduction: (WDI code) DT.DFR.DPPG.CD Total debt: (WDI code) DT.DOD.DECT.CD	None (ratio)	Annual	A, B , M
6	LT PNG debt / total debt	LTDPNG_TDEBT	LT PNG debt: (WDI code) DT.DOD.PRVS.CD Total debt: (WDI code) DT.DOD.DECT.CD	12 months percentage change.	Annual	A, B , M
7	LT PPG debt / total debt	LTDPPG_TDEBT	LT PPG debt: (WDI code) DT.DOD.PUBS.CD Total debt: (WDI code) DT.DOD.DECT.CD	12 months percentage change.	Annual	A, B , M
8	International reserves to total external debt	D_RES_DEBT	Total debt: (WDI code) DT.DOD.DECT.CD Reserves (IFS code): .1L.DZF…	12 months percentage change	Annual	A, B , M
9	Ratio of debt service to exports	DSERV_EXP	WDI code for debt service (current USD): DT.TDS.DECT.CD IFS code for exports (*millions* of current USD): 70..DZF...	None (ratio)	Annual	A, B , M
10	Ratio of debt service to reserves	DSERV_RES	Debt service (WDI code): DT.TDS.DECT.CD Reserves (IFS code): .1L.DZF…	None (ratio)	Annual	A, B , M
Bank sector indicators						
1	Ratio of domestic credit to the public sector to GDP	DCREDPUB	Domestic credit provided by banking sector (% of GDP) (WDI code = FS.AST.DOMS.GD.ZS) minus Domestic credit to private sector (% of GDP) (WDI code = FS.AST.PRVT.GD.ZS)	None (ratio)	Annual	A, M
2	Ratio of commercial bank lending to GDP	DCREDBANK	Domestic credit provided by banking sector (% of GDP). WDI code = FS.AST.DOMS.GD.ZS	None (ratio)	Annual	A, B, M

3	Liquid liabilities (% of GDP)	D_LIQLIAB	Code: ll_usd. Source: Financial Structure, from World Bank (FS/WB) and Beck et al. 2000, 2009	12 months percentage change	Annual	A, B, M
4	Central bank assets (% of GDP)	CBASSET	Claims on domestic real nonfinancial sector by the Central Bank as a share of GDP. FS/WB code: cbagdp	12 months percentage change	Annual	B
5	Deposit money bank assets (% of GDP)	D_DMBANKAS	Claims on domestic real nonfinancial sector by deposit money banks as a share of GDP. FS/WB code: dbagdp	12 months percentage change	Annual	A, B, M
6	Private credit by all financial institutions (% of GDP)	D_PCRED_GDP	Private credit by deposit money banks and other financial institutions to GDP. FS/WB code: pcrdbofgdp	12 months percentage change	Annual	A
7	Private credit by deposit money banks (% of GDP)	D_PCRED_DMB	Private credit by deposit money banks to GDP. FS/WB code: pcrdbgdp	12 months percentage change	Annual	A, B, M
8	Private credit by other financial institutions (% of GDP)	D_PCRED_OTH	Private credit by other financial institutions to GDP. Difference between private credit by all fin.institutions and private credit by deposit money banks. FS/WB code: pcrdbofgdp - pcrdbgdp	12 months percentage change	Annual	B, M
9	Financial system deposits (% of GDP)	D_FSDEPOS	Demand, time and saving deposits in deposit money banks and other financial institutions as a share of GDP. FS/WB code: fdgdp	12 months percentage change	Annual	A, B, M
10	Ratio Bank credit to bank deposits	D_BCRED_BDEP	Private credit by deposit money banks as a share of demand, time and saving deposits in deposit money banks. FS/WB code: bcbd	12 months percentage change	Annual	A, B, M
11	Net interest margin	NETINTMG	Accounting value of bank's net interest revenue as a share of its interest-bearing (total earning) assets. FS/WB code: netintmargin	None	Annual	A, B, M
12	Bank concentration	BANKCONC	Assets of three largest banks as a share of assets of all commercial banks. FS/WB code: concentration	None	Annual	A, B, M
13	Bank ROE	BANKROE	Average Return on Equity (Net Income/Total Equity). FS/WB code: roe	None	Annual	A, B, M
14	Bank Z-Score	BANKZ	Z = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E with: A = Working Capital/Total Assets B = Retained Earnings/Total Assets C = EBIT/Total Assets D = Market Value of Equity/Total Liab E = Sales/Total Assets	None	Annual	B
15	Deposit money banks and other banking instit: assets	D_BANKASSET	Sum of: Deposit money banks Assets (IFS: 7A.DZF…) Other banking institutions Assets (IFS: 7E.DZF…)	12 months percentage change	Monthly	A
16	Deposit money banks and other banking institutions: liabilities	D_BANKLIAB	Sum of: Deposit money banks Liabilities (IFS: 7B.DZF…) Other banking institutions Liabilities (IFS: 7F.DZF…)	12 months percentage change	Monthly	A
17	CB: foreign assets - foreign liabilities	D_CB_FA_FL	Difference between: Foreign assets (IFS: 11...ZF…) Foreign liabilities (16C..ZF…)	12 months percentage change	Monthly	A
18	CB: claims - deposits from central government	D_CB_CGVT	Difference between: Claims on central government (IFS: 12A..ZF…) Central government deposits (IFS 16D..ZF…)	12 months percentage change	Monthly	A

19	CB: claims on deposit money banks and other banking inst.	D_CB_BANKS	Sum of: Claims on Deposit Money Banks (IFS: 12E..ZF…) Claims on Other banking institutions (IFS: 12F..ZF…)	12 months percentage change	Monthly	A
20	Bank sector: reserves	D_BANKRES	Sum of: Reserves from DMB (IFS: 20...ZF…) Reserves from other banking institutions (IFS: 40...ZF…)	12 months percentage change	Monthly	A
21	Bank sector: Foreign assets - foreign liabilities	D_BANK_FA_FL	Difference between: Foreign assets from banks (IFS: 21...ZF… + 41...ZF…) Foreign liabilities from banks (IFS: 26C..ZF… + 46C..ZF…)	12 months percentage change	Monthly	A
22	Bank sector: claims on PPG	D_BANK_PPG	Claims on PPG: Claims on central govt (IFS: 22A..ZF… + 42A..ZF…) Claims on state and local government (IFS: 22B..ZF… + 42B..ZF…) Claims on official entities (IFS: 22BX.ZF… + 42BX.ZF…)	12 months percentage change	Monthly	A
23	Banks: claims on private sector	D_BANK_PRIV	Claims from DMB and other banking instit. on private sector (IFS: 22D..ZF… and 42D..ZF…)	12 months percentage change	Monthly	A
24	Banks: demand deposits	D_BANK_ DEM_DEPOS	Demand deposits in DMB (IFS: 24...ZF…)	12 months percentage change	Monthly	A
25	Banks: time, savings and foreign currency deposits	D_BANK_TSFC_DEPOS	Time, savings and foreign currency deposits (IFS: 25...ZF… + 45...ZF…)	12 months percentage change	Monthly	A

Institutional indicators: indices

1	Herfindahl Index Government	HERFGOV	DPI (World Bank / Beck et al. 2001): HERFGOV represents a measure of government coalition concentration, by squaring the percentage of parties in the government coalition. The presence of a majority party in the government coalition increases the index. Having many (small) parties in the government reduces it.	None.	Annual	A, B, M
2	Herfindahl Index Opposition	HERFOPP	DPI: herfopp. Idem herfgov, but now for government opposition.	None.	Annual	B, M
3	Political stability	D_GOVSTAB	On a scale from 0 to 12, with 12 the highest level of stability and 0 the highest level of instability. Source: ICRG	12 months percentage change.	Annual	A, B, M
4	Socioeconomic Conditions	D_SOCIOECO	On a scale from 0 to 12, with 12 the highest level of socioeconomic conditions and 0 the lowest level. Source: ICRG	12 months percentage change	Annual	A, B, M
5	Investment Profile	D_INVPROF	On a scale from 0 to 12, with 12 the best investment profile (= low risk) and 0 the worst profile. Source: ICRG	12 months percentage change	Annual	A, B, M
6	Internal Conflict	D_INTCONFL	On a scale from 0 to 12, with 12 the lowest level of internal conflict (low risk) and 0 the highest level (high risk). Source: ICRG	12 months percentage change	Annual	A, B, M
7	Democratic Accountability	D_DEMACC	On a scale from 0 to 6, with 6 the highest level of dem.accountability and 0 the lowest level. Source: ICRG	12 months percentage change	Annual	A, B, M

8	Corruption	D_CORRUPT	ICRG. Scale 6 (low corruption) to 0 (high corruption).	12 months percentage change	Annual	A, B, M
9	Law and Order	D_LAWORD	ICRG. Scale 6 (high law and order) to 0 (low law and order).	12 months percentage change	Annual	A, B, M
10	Bureaucracy Quality	D_BURQUAL	ICRG. Scale 4 (high bureaucratic quality) to 0 (low bureaucratic quality).	12 months percentage change	Annual	A, B, M
11	Party orien-tation with resp. to econ. policy	GOVT_RLC	Dummy indicates orientation of the executive power. Right (1); Left (3); Center (2); No information (0). DPI code: execrlc	None	Annual	A, B, M
12	Absolute majority in the houses	GOVT_MAJ	Dummy indicates if executive has absolute majority in the houses. 1 = yes, 0 = no. DPI code: allhouse	None	Annual	A, B, M
13	Degree of polarization	POLARIZ	Polarization is the maximum difference between the chief executive's party's value (EXECRLC) and the values of the three largest government parties and the largest opposition party. 0 = no polarization. DPI code: polariz	None	Annual	A, B, M
14	date of elections for executive power	ELECEXE	Dummy variable with value 1 in the month of elections for executive power and 0 otherwise (DPI: dateexec, exelec)	The calender year of the elections is assigned 1.	Monthly	A, B, M
Global economy indicators						
1	US long term interest rate	D_USYIELD	Yield on the 10 year US government bond (IFS: 111.61.ZF)	12 months percentage change	Monthly	USA
2	US short term interest rate	TBILL	IFS: 11160C..ZF...	None	Monthly	USA
3	US real GDP growth	D_GDPUSA	IFS series: 11199B.CZF… and 11164..ZF…	12 months percentage change	Quarterly	USA
4	GDP volume % change	D_GDPWORLD	Change (year-on-year) of the volume of the GDP growth. IFS series 00199BPXZF...	None	Annual	world
5	Contagion of crises in the region	CONTAG	Based on EMPI calculations: dummy = 1 if there is a financial crisis in one of the other LA3 countries	None	Monthly	A, B, M
Commodity indicators						
1	Agriculture, value added (% of GDP)	D_VA_AGRI	WDI code: NV.AGR.TOTL.ZS	12 months percentage change	Annual	A, B, M
2	Oil prices	D_PR_PETROL	World oil price (IFS: 00176AADZF...)	12 months percentage change	Monthly	world
3	Agricultural commodities price index	D_PR_AGRI	Global agricultural raw materials price index (IFS: 00176BXDZF)	12 months percentage change	Monthly	world
4	Metals commodities price index	D_PR_METAL	Global metals price index (IFS: 00176AYDZF)	12 months percentage change	Monthly	world

5	Agricultural raw materials exports:	D_AGRI_EXP	Agricultural raw material exports, expressed as % of GDP. Elaborated from the following series: Agricultural raw material exports, as % of merchandise exports. Source: WDI, code: TX.VAL.AGRI.ZS.UN Goods exports (BoP, current US$; Source: WDI, code: BX.GSR.MRCH.CD) GDP (current US$; Source: WDI, code: NY.GDP.MKTP.CD)	12 months percentage change	Annual	A, B, M
6	Food materials exports:	D_FOOD_EXP	Idem, but food materials exports. Source: WDI, code: TX.VAL.FOOD.ZS.UN	Idem	Annual	A, B, M
7	Fuel exports:	D_FUEL_EXP	Idem, but fuel exports. Source: WDI, code: TX.VAL.FUEL.ZS.UN	Idem	Annual	A, B, M
8	Ores and metals exports:	D_METAL_EXP	Idem but ores and metals exports. Source: WDI, code: TX.VAL.MMTL.ZS.UN	Idem	Annual	A, B, M
9	Agricultural raw materials imports:	D_AGRI_IMP	Agricultural raw material imports, expressed as % of GDP. Elaborated from the following series: Agricultural raw material imports, as % of merchandise imports. Source: WDI, code: TM.VAL.AGRI.ZS.UN Goods imports (BoP, current US$; Source: WDI, code: BM.GSR.MRCH.CD) GDP (current US$; Source: WDI, code: NY.GDP.MKTP.CD)	Idem	Annual	A, B, M
10	Food materials imports:	D_FOOD_IMP	Idem, but food materials imports. Source: WDI, code: TM.VAL.FOOD.ZS.UN	Idem	Annual	A, B, M
11	Fuel imports:	D_FUEL_IMP	Idem, but fuel imports. Source: WDI, code: TM.VAL.FUEL.ZS.UN	Idem	Annual	A, B, M
12	Ores and metals imports:	D_METAL_IMP	Idem, but ores and metals imports. Source: WDI, code: TM.VAL.MMTL.ZS.UN	Idem	Annual	A, B, M

Appendix B. Correlations of factors with indicators

Argentina: correlations between dynamic factors and (five) strongest correlated variables

DF1

D_BANK_PRIV	**bank**	**0.88894**
D_DMBANKAS	bank	-0.83652
DCREDBANK	bank	-0.85174
D_VA_AGRI	commod.	-0.84334
D_FOOD_EXP	commod.	-0.86295

DF2

M2MULT	dom.econ.	-0.75669
GDSAV_GDP	dom.econ.	0.74507
ERVOL	ext.econ.	0.80703
DCREDPUB	bank	0.70899
ARR_TDEBT	**debt**	**0.87440**

DF3

GFCAP_GDP	dom.econ.	0.61801
D_TBILL	**global**	**0.72830**
D_GDPWORLD	global	0.71135
D_BCRED_BDEP	bank	0.66312
D_PR_METAL	commod.	0.70303

DF4

D_FSDEPOS	bank	-0.58222
D_LIQLIAB	bank	-0.58677
D_LTPNG_DEBT	debt	-0.54055
DSERV_EXP	debt	0.53925
DSERV_RES	**debt**	**0.81442**

DF5

D_INDPROD	dom.econ.	0.45406
D_BANKASSET	**bank**	**0.52320**
D_BANKLIAB	bank	0.44911
D_BANK_PPG	bank	0.44002
BANKROE	bank	-0.50929

DF6

INFLAT	dom.econ.	0.41889
M2RES	**ext.econ.**	**0.55499**
D_IMPCOV	**ext.econ.**	**-0.55403**
D_GDPUSA	global	-0.43826
D_LTPPG_DEBT	debt	-0.44617

DF7

D_USYIELD	global	-0.41145
D_BANKRES	bank	-0.32761
D_BCRED_BDEP	bank	0.39371
D_LTPNG_DEBT	debt	-0.38980
STD_DEBT	**debt**	**0.55017**

DF8

NETFDI_GDP	ext.econ.	-0.36758
TOT	ext.econ.	0.37811
D_CB_CGVT	bank	0.47227
D_BANKRES	bank	0.46042
D_PR_PETROL	**commod.**	**-0.53141**

DF9

D_EXP	ext.econ.	0.33949
D_FOOD_IMP	commod.	0.35229
D_RES_DEBT	**debt**	**-0.46442**
REDU_TDEBT	**debt**	**0.46365**
STD_DEBT	debt	-0.37425

DF10

D_M2	dom.econ.	0.32300
D_PR_AGRI	commod.	-0.35006
D_PR_PETROL	commod.	-0.36768
D_LTPPG_DEBT	**debt**	**-0.57849**
DSERV_EXP	debt	-0.33381

Brazil: correlations between dynamic factors and (five) strongest correlated variables

DF1

D_GCAP	dom.econ.	-0.77403
RER_DEV	ext.econ.	0.78696
DEBT_GDP	debt	0.73201
DSERV_EXP	**debt**	**0.85323**
DSERV_RES	debt	0.82453

DF2

GDSAV_GDP	dom.econ.	0.71148
ERVOL	ext.econ.	0.69355
CA_GDP	ext.econ.	0.69548
DCREDGDP	bank	0.69575
LTDPNG_TDEBT	**debt**	**-0.77354**

DF3

INTSPREAD	dom.econ.	0.68510
INFLAT	dom.econ.	0.58338
D_RES	ext.econ.	-0.56310
D_IMPCOV	ext.econ.	-0.52194
REDU_TDEBT	**debt**	**-0.75455**

DF4

D_GDPUSA	global	-0.51988
D_DMBANKAS	**bank**	**-0.73317**
D_FSDEPOS	bank	-0.62666
D_LIQLIAB	bank	-0.66243
D_FUEL_IMP	commod.	-0.57370

DF5

D_RGDPCAP	dom.econ.	-0.44365
D_LIQLIAB	bank	0.42425
D_FOOD_EXP	commod.	0.44482
D_VA_AGRI	**commod.**	**0.71633**
D_PR_PETROL	commod.	-0.49498

DF6

M2RES	ext.econ.	0.63281
D_IMPCOV	ext.econ.	-0.52847
LTDPPG_TDEBT	**debt**	**0.63852**
D_AGRI_IMP	commod.	-0.58794
D_FOOD_IMP	commod.	-0.55180

DF7

TOT	ext.econ.	-0.36781
D_GDPUSA	global	-0.49659
IMF_GDP	debt	-0.41437
D_AGRI_IMP	**commod.**	**-0.51435**
D_FUEL_EXP	commod.	0.48415

DF8

D_INDPROD	dom.econ.	-0.39227
D_GDPUSA	global	0.43705
CBASSET	**bank**	**0.66203**
NETINTMG	bank	0.37558
D_FUEL_EXP	commod.	-0.36863

Mexico: correlations between dynamic factors and (five) strongest correlated variables

DF1

RER_DEV	**ext.econ.**	**-0.84413**
CA_GDP	ext.econ.	-0.79731
BANKCONC	bank	0.75290
D_METAL_EXP	commod.	-0.74426
D_METAL_IMP	commod.	-0.79689

DF2

INFLAT	**dom.econ.**	**0.96288**
GFCAP_GDP	dom.econ.	-0.72317
DEBT_GDP	debt	0.90527
IMF_GDP	debt	0.91989
D_AGRI_EXP	commod.	0.73437

DF3

REALINT	**dom.econ.**	**0.79496**
D_CETES	dom.econ.	0.62781
D_RES	ext.econ.	-0.68945
D_RES_DEBT	debt	-0.66358
DCREDPUB	debt	-0.66206

DF4

GOVCONS_GDP	dom.econ.	0.51277
M2RES	ext.econ.	-0.51859
ARR_TDEBT	debt	-0.54437
REDU_TDEBT	debt	0.56130
TBILL	**global**	**-0.63038**

DF5

INDPROD	dom.econ.	0.55323
ERVOL	ext.econ.	0.53868
D_PCRED_DMB	bank	-0.46821
D_PCRED_OTH	bank	-0.47173
D_GDPUSA	**global**	**0.61625**

DF6

D_IMP	ext.econ.	-0.46380
ARR_TDEBT	debt	0.48538
D_LTPNG_DEBT	**debt**	**0.63214**
D_LTPPG_DEBT	debt	-0.54043
D_FOOD_IMP	commod.	0.47060

Appendix C. Ordered Logit estimation results

Appendix C.1. Argentina - dynamic factors only

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Q4P2_DF1	-0.736565	0.26603	-2.768731	0.0056
Q4P2_DF2	-0.466328	0.155741	-2.99425	0.0028
Q4P2_DF3	0.972162	0.365215	2.661889	0.0078
Q4P2_DF4	0.696551	0.205421	3.390849	0.0007
Q4P2_DF5	-1.386896	0.342668	-4.047345	0.0001
Q4P2_DF6	1.438906	0.391755	3.672971	0.0002
Q4P2_DF7	-1.41217	0.400708	-3.524186	0.0004
Q4P2_DF8	1.044013	0.448537	2.327596	0.0199
Q4P2_DF9	0.092885	0.268329	0.34616	0.7292
Q4P2_DF10	-0.172742	0.346464	-0.498585	0.6181
	Limit Points			
LIMIT_1:C(11)	4.026614	0.83361	4.830333	0
LIMIT_2:C(12)	5.632409	0.938146	6.003766	0
LIMIT_3:C(13)	8.022832	1.181607	6.789766	0

Pseudo R-squa	0.529866	Akaike info criterion	0.83747
Schwarz criter	1.051861	Log likelihood	-70.74702
Hannan-Quinr	0.924231	Restr. log likelihood	-150.4825
LR statistic	159.471	Avg. log likelihood	-0.353735

Appendix C.2. Argentina - dynamic factors and selected institutional indicators

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Q4P2_DF1	-0.955235	0.370379	-2.579074	0.0099
Q4P2_DF2	-0.572125	0.217262	-2.633347	0.0085
Q4P2_DF3	1.111024	0.404537	2.746411	0.006
Q4P2_DF4	0.703573	0.210835	3.337073	0.0008
Q4P2_DF5	-0.974901	0.451138	-2.160982	0.0307
Q4P2_DF6	1.458088	0.405791	3.593198	0.0003
Q4P2_DF7	-1.13265	0.411141	-2.754898	0.0059
Q4P2_DF8	1.057472	0.607734	1.740025	0.0819
Q4P2_DF9	0.446707	0.350732	1.273641	0.2028
Q4P2_DF10	-0.852142	0.751953	-1.13324	0.2571
D_LAWORD	0.266244	0.739133	0.360211	0.7187
D_INVPROF	1.466117	1.137053	1.2894	0.1973
ELECLEGYR	0.055161	0.330817	0.166742	0.8676
CONTAG	-0.012675	0.18946	-0.066901	0.9467
	Limit Points			
LIMIT_1:C(15)	3.630428	0.792575	4.580546	0
LIMIT_2:C(16)	5.287249	0.894552	5.910496	0
LIMIT_3:C(17)	7.822938	1.129809	6.924128	0

Pseudo R-squa	0.535189	Akaike info criterion	0.869459
Schwarz criter	1.149816	Log likelihood	-69.94595
Hannan-Quinn	0.982916	Restr. log likelihood	-150.4825
LR statistic	161.0732	Avg. log likelihood	-0.34973

Appendix C.3. Brazil - dynamic factors and selected institutional indicators

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Q4P2_DF1	0.225666	0.113364	1.990638	0.0465
Q4P2_DF2	-0.239119	0.081635	-2.929109	0.0034
Q4P2_DF3	0.436567	0.152632	2.860269	0.0042
Q4P2_DF4	-0.116798	0.116167	-1.005435	0.3147
Q4P2_DF5	0.33176	0.157061	2.112301	0.0347
Q4P2_DF6	0.0884	0.212394	0.416209	0.6773
Q4P2_DF7	-0.306015	0.213902	-1.430634	0.1525
Q4P2_DF8	0.098179	0.157194	0.624569	0.5323
D_GOVSTAB	-0.105386	0.46224	-0.227989	0.8197
D_CORRUPT	-0.98591	0.523766	-1.882348	0.0598
ELECLEGYR	1.088477	0.328408	3.314405	0.0009
	Limit Points			
LIMIT_1:C(12)	1.523356	0.347448	4.38441	0
LIMIT_2:C(13)	2.317928	0.379998	6.09984	0
LIMIT_3:C(14)	5.028458	0.652147	7.710618	0
Pseudo R-squa	0.25141	Akaike info criterion		1.571402
Schwarz criter	1.839351	Log likelihood		-112.4979
Hannan-Quinr	1.6802	Restr. log likelihood		-150.2797
LR statistic	75.56355	Avg. log likelihood		-0.698745

Appendix C.4. Mexico - dynamic factors only

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Q3P3_DF1	0.220944	0.121552	1.817688	0.0691
Q3P3_DF2	0.555655	0.164166	3.384702	0.0007
Q3P3_DF3	0.863321	0.124651	6.925917	0
Q3P3_DF4	-0.079747	0.144834	-0.55061	0.5819
Q3P3_DF5	0.613642	0.17202	3.567278	0.0004
Q3P3_DF6	0.35009	0.217415	1.610237	0.1073
	Limit Points			
LIMIT_1:C(7)	4.171097	0.86327	4.831743	0
LIMIT_2:C(8)	5.843001	0.967348	6.040225	0
LIMIT_3:C(9)	8.597815	1.274766	6.744623	0
Pseudo R-squ	0.483194	Akaike info criterion		0.72197
Schwarz criter	0.862606	Log likelihood		-68.97275
Hannan-Quinn	0.778787	Restr. log likelihood		-133.4597
LR statistic	128.9739	Avg. log likelihood		-0.319318

Appendix C.5. Mexico - dynamic factors and selected institutional indicators

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Q3P3_DF1	0.265619	0.289372	0.917915	0.3587
Q3P3_DF2	0.815719	0.396354	2.058056	0.0396
Q3P3_DF3	1.170627	0.315713	3.707883	0.0002
Q3P3_DF4	-0.047602	0.30493	-0.156109	0.8759
Q3P3_DF5	0.091483	0.376352	0.243077	0.8079
Q3P3_DF6	0.198642	0.278823	0.71243	0.4762
CONTAG	0.681134	0.31103	2.189934	0.0285
D_BURQUAL	1.171887	0.306974	3.817542	0.0001
D_DEMACC	0.824841	0.591296	1.394971	0.163
D_INVPROF	1.26665	0.663984	1.907652	0.0564
	Limit Points			
LIMIT_1:C(11)	5.10627	2.066697	2.47074	0.0135
LIMIT_2:C(12)	7.332222	2.136163	3.432426	0.0006
LIMIT_3:C(13)	10.46589	2.323954	4.503483	0
Pseudo R-squa	0.604377	Akaike info criterion		0.609257
Schwarz criter	0.812399	Log likelihood		-52.79978
Hannan-Quinr	0.691327	Restr. log likelihood		-133.4597
LR statistic	161.3199	Avg. log likelihood		-0.244443

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