Why didn't the Global Financial Crisis hit Latin America?

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Abstract

Latin America has a rich history of financial crises. However, it was relatively unharmed by the 2007–2009 Global Financial Crisis (GFC). This paper investigates why, and in particular the role of commodity prices and its institutional framework—in line with the fourth generation financial crisis model. We set up Early Warning Systems (EWS) for Argentina, Brazil and Mexico. These consist of an ordered logit model for currency crises for the period 1990–2007 with a dynamic factor model to deal with the large number of explanatory variables. We present forecasts for the period 2008–2009.

We find that international indicators play an important role in explaining currency crises in Mexico, while banking indicators and commodities explain the currency crisis in Argentina and Brazil. Furthermore, debt and domestic economy indicators are relevant for Argentina and Mexico. Finally, we observe that currency crises in all three countries are related to institutional indicators. For none of the countries the Early Warning System would have issued an early warning for the GFC.

Keywords: financial crises, Early Warning Systems, Latin America, dynamic factor models, ordered logit model
JEL-code: C25, G01, N26

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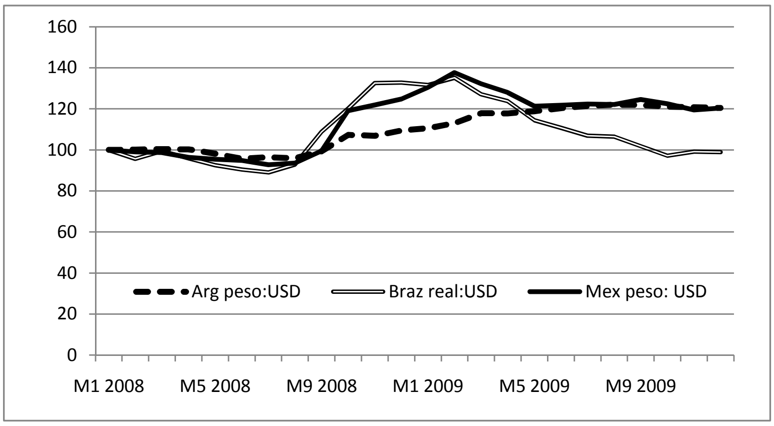
1 Introduction

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

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



Would an Early Warning System have sent a warning? We address the question whether the countries have learned from their past experiences, which makes this study also relevant for other regions. Although the countries in the region have many similarities, there are also differences. One example is the policy regime. On one side of the spectrum we can observe populist governments (Venezuela, Bolivia, Ecuador, Argentina) and on the other

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

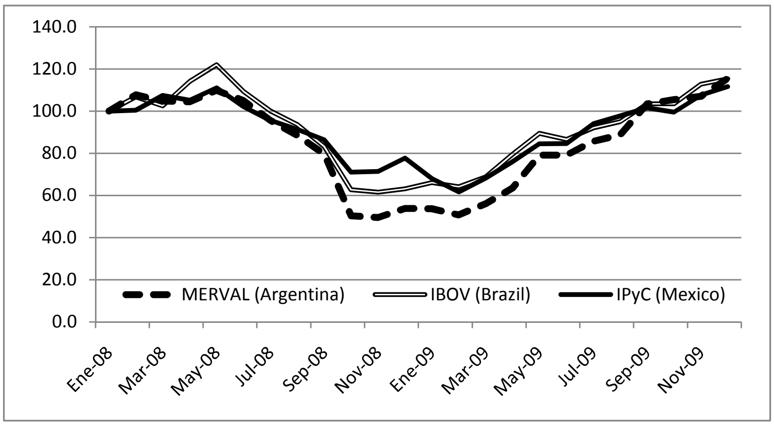
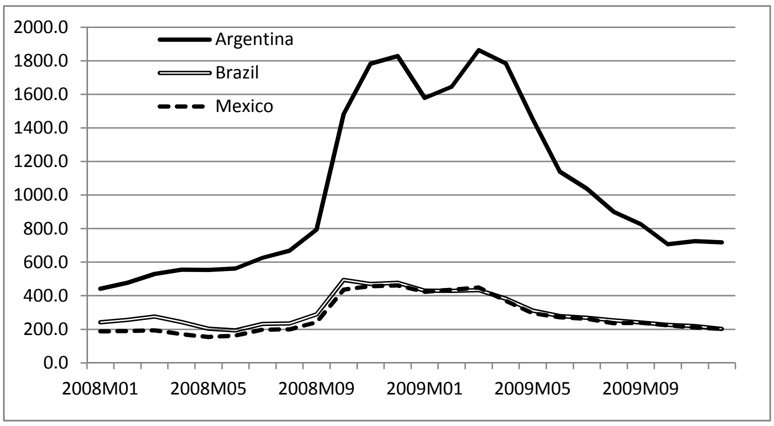


Figure 3: Sovereign bond interest rate spread for the period 2008-2009 for Mexico, Argentina and Brazil; basis points over US Treasuries



side more market oriented governments (Chile, Brazil, Colombia, Mexico, Peru, Uruguay). Over time, various countries have experienced strong institutional changes in the form of structural reforms, or changes in political power (e.g. Mexico that saw PAN took over the presidency in 2000 after 70 years of continuous PRI governments).

We confine attention in this paper on 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 essentially different characteristics than the 1970s and 1980s (hyperinflation, 1980s debt crisis, political system) and because of data availability. In addition, we only consider currency crises, and abstract from banking crises and debt crises.

Dating currency crises is not straightforward. We choose to measure currency crises as an ordered variable with responses ranging from 0 (for tranquil or non-crisis periods) to 3 (indicating a very deep crisis). We extend the crisis period by assigning the same value for both the month of crisis *and* the preceding six months. This has been done by e.g. Kaminsky (2006) and is justified since for the construction of early warning systems the run-up to the crisis is as important as the crisis itself.

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. They use the dynamic factor model of Stock and Watson (2002), and determine the number of factors and the number of lags on the basis of the information criteria of Bai and Ng (2002). We adopt the two-step framework of Doz, Giannone and Reichlin (2011), and use the criterion of Otter, Jacobs and den Reijer (2011) to determine the number of factors.

As explanatory variables we will use monthly series from 1990 to 2007 to analyze the three Latin American countries. Apart from the "usual suspects"—the common macroeconomic and financial variables—we also include institutional variables and commodity-

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

related indicators. Details on the explanatory variables are in Appendix A. We estimate the ordered logit models up to and including 2007, and forecast for 2008-2009.

We find that currency crises in Mexico are driven by international indicators, and to a lesser extent debt, by domestic economy and institutional indicators. Crises in Argentina are mainly related to banking and commodities, and to domestic economy and institutional indicators. Banking and commodities indicators dominate in the explanation of currency in Brazil; institutional indicators play a less important role. The fact that for all countries the institutional factors play a significant role supports the fourth generation financial crisis model. It also confirms previous work in which political indicators play a significant role in crisis forecasting (e.g. Bussière and Mulder 2000). For none of the three countries the Early Warning Systems would have issued a warning for the GFC.

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 crisis (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 won't 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 (see 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 behaviour leads to an excessive build-up of external private debt followed by a collapse (see 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 (see 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 still under way. 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 the 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 and 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 Factor models

In factor models an observable set of n variables is expressed as the sum of mutually orthogonal unobservable components: the unobservable common component (factors) and the unobservable idiosyncratic component. The constructed factors are independent from each other, which means maximum information with a minimum number of factors in the model. The primary reason for the popularity of factor models is that one can include a large number of variables and let the model reduce this into a much smaller number of factors ($n >> r$). This is a desirable feature since more data have become available for policy makers and researchers at a more disaggregated level. The drawback of using factor models to explain the occurrence of financial crises is the difficulty of interpretation—and sometimes unexpected signs—that can be placed upon the factors that explain financial crises.

Different types of factor models are distinguished: exact and approximate, static and dynamic. When the factors and the idiosyncratic components are uncorrelated and i.i.d., then the model is *static, exact*, or *strict*. Exact factor models can be consistently estimated by maximum likelihood. However the restrictions on the model are often not met in empirical applications. When the number of variables goes to infinity, the correlation restrictions of the exact factor model can be relaxed and one can use the approximate factor model. In the *static, approximate* factor model the idiosyncratic components are (weakly) correlated, which covers cross-correlation and heteroskedasticity between the idiosyncratic errors and correlation between the common components and the idiosyncratic components (see e.g. Barhoumi, Darné and Ferrara 2010).

Whereas static factor models only consider cross-sectional relations, the *dynamic* factor model also takes into account lags and leads. Most dynamic factor models are approximate. The dynamic factor model has the advantage that it takes into account both current and temporal relationships, which makes it—in theory—superior to the static model. However, empirical evidence is mixed. Barhoumi et al. (2010) for example conclude that dynamic factor models with a large number of variables do not necessarily produce better forecasting results of French GDP than static models with a small number of variables. Schumacher (2007) also mentions a number of studies with mixed empirical success for the dynamic factor model.

Static factor models

The static factor model has the following form:

$$X_{i,t} = \lambda_{i,1} f_{1,t} + \lambda_{i,2} f_{2,t} + ... + \lambda_{i,r} f_{r,t} + u_{i,t} = \Lambda f_t + u_t, \tag{1}$$

where Λ is an $(n \times r)$ matrix of factor loadings, f_t is an $(r \times 1)$ vector of factors in period t, $i = 1, \dots, n$ and $t = 1, \dots, T$. The assumptions for the *exact* static factor model are: $\mathrm{E}(u_t) = 0$, $\mathrm{E}(u_t u_t^{'}) = \Sigma = \mathrm{diag}(\sigma_1^2, \sigma_2^2, \dots, \sigma_N^2)$, $\mathrm{E}(F_t u_t^{'}) = 0$ and for the factors: $\mathrm{E}(f_t) = 0$, $E(f_t f_t^{'}) = \Omega_f$.

The principal components method is used to estimate the factors. The principal components of X_t are the factors:

$$F_t = S' X_t = (S_1 S_2 \dots S_r)' X_t, \tag{2}$$

where the factor estimates F_t are the first r principal components of X_t, and S_j, $j = 1, \dots, r$, are the eigenvectors that correspond to the r largest eigenvalues.

Dynamic factor models

The dynamic factor model extends the static factor model by also taking into account correlations over time

$$X_t = A_0 f_t + A_1 f_{t-1} + \ldots + A_p f_{t-p} + \epsilon_t, \tag{3}$$

where x_t is the $N \times 1$ vector of observations of explanatory variables in period t. The variables are stationary, demeaned and standardize; f_t is the $r \times 1$ vector of common components or factors. 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) and a *pseudo DFM* by Kapetanios and Marcellino (2009)

$$X_t = AF_t + \epsilon_t, \tag{4}$$

where $A \equiv [A_0 \; A_1 \; \ldots A_p]$ and $F_t \equiv [f_t' \ldots f_{t-p}']'$. 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

$$F_t = \Gamma(L) f_t + \nu_t, \tag{5}$$

where $\Gamma(L) f_t = \Gamma_1 f_{t-1} + \ldots + \Gamma_m f_{t-m}$ and $\nu_t \sim N(0, \Sigma_\nu)$.

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 a principal components analysis. In the second step the factors are updated via the Kalman smoother. 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 equation

$$X_t = \begin{pmatrix} A_0 & 0 & \dots 0 \end{pmatrix} \begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-p+1} \end{pmatrix} + \epsilon_t$$

$$\begin{pmatrix} f_t \\ f_{t-1} \\ \vdots \\ f_{t-p+1} \end{pmatrix} = \begin{pmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I_r & 0 & \dots & 0 & 0 \\ 0 & I_r & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \\ 0 & 0 & \dots & I_r & 0 \end{pmatrix} \begin{pmatrix} f_{t-1} \\ f_{t-2} \\ \vdots \\ f_{t-p} \end{pmatrix} + \begin{pmatrix} I_r \\ 0 \\ \vdots \\ 0 \end{pmatrix} \nu_t.$$

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), which is associated with Onatski's (2009) test statistic, and is 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).[2]

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 unexpected results.

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 Eichengreen, Rose and Wyplosz (1995). In this approach we distinguish events

[2]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.

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 as a crisis. Also the set of events does not include the set of 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.

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. Periods with hyperinflation are excluded from the periods without hyperinflation: for each subcategory an index is constructed and threshold exceedances determined. 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 maintain this definition to identify "very deep" crises. Following Cerro and Iajya (2009) we extend the definition of crises by introducing "deep" crises (two adjacent months with exceedance between 2 and 3 times the standard deviation) and "mild" crises (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 entry. In case a crisis follows within six months upon a crisis, then the second crisis is considered a continuation and is 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 $N+1$ possible outcomes, then

$$y = \begin{cases} 0 \ \text{ if } \ y^* \leq \mu_1, \\ 1 \ \text{ if } \ \mu_1 < y^* \leq \mu_2, \\ 2 \ \text{ if } \ \mu_2 < y^* \leq \mu_3 \\ \vdots \\ N \ \text{ if } \ \mu_N < y^*, \end{cases} \tag{6}$$

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

$$y^* = Z = \alpha + \beta X. \tag{7}$$

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:

$$
\begin{aligned}
P(y=0) &= \frac{1}{1+e^{-(Z-\mu_1)}}, \\
P(y=1) &= \frac{1}{1+e^{-(Z-\mu_2)}} - \frac{1}{1+e^{-(Z-\mu_1)}}, \\
&\vdots \\
P(y=N) &= 1 - \frac{1}{1+e^{-(Z-\mu_N)}}.
\end{aligned} \tag{8}
$$

Interpretation of the parameters in an ordered choice model is not trivial (see Kennedy, 2008, pp.258–259 and the references therein). Kennedy suggests to omit the intercept α to facilitate interpretation. One way to interpret the outcomes is by calculating the ratio of two parameter estimates, i.e, the relative change in one explanatory variable to compensate for a change in another explanatory variable.

4 Data

Our sample starts in the early 1990s, when the effects of last spillovers of the 1980s Latin American debt crisis faded away. 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.

To identify currency crises we follow the EMPI definition of Kaminsky (2006), but take into account the severity of the crisis. We categorize the severity of crises as mild, deep and very deep. 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). Figures 4, 5 and 6 show the crisis observations.

Figure 4: Actual crisis dates for Argentina for the period 1991-2007

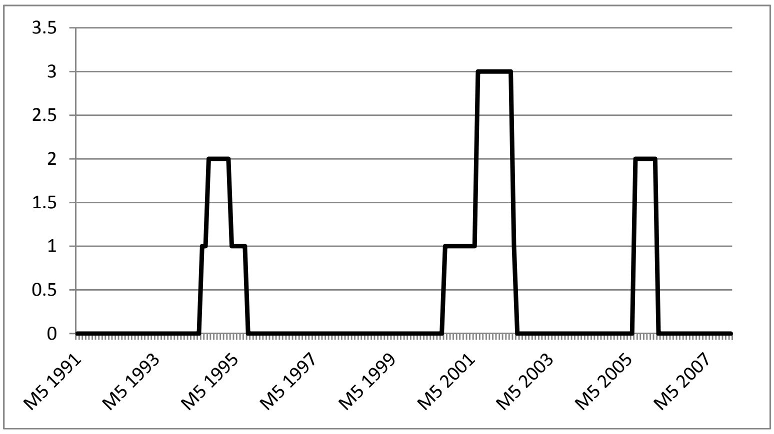
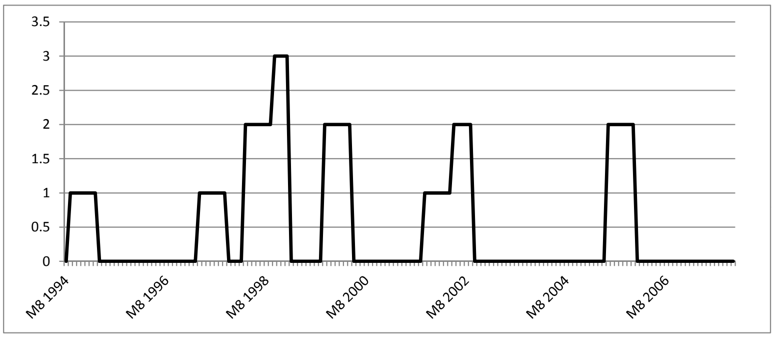


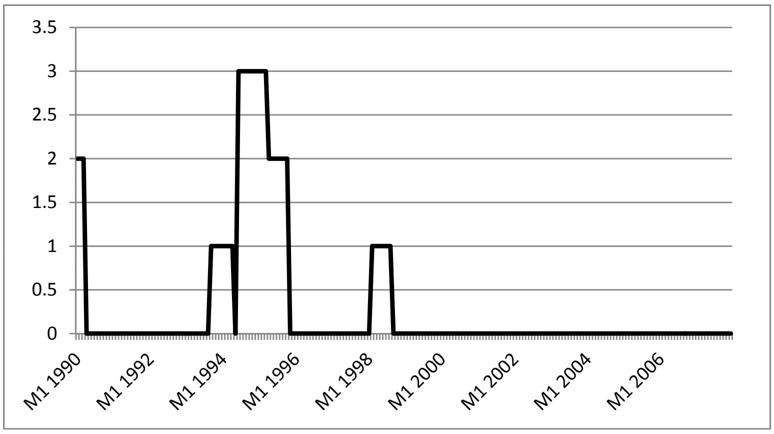
Figure 5: Actual crisis dates for Brazil for the period 1994-2007



For the explanatory variables we select series based on three 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. Another challenge is the mixed frequency of the time series. The selected series can be classified into separate categories:

- 13 external economic indicators, among which the deviation from the trend of the

Figure 6: Actual crisis dates for Mexico for the period 1990-2007



real exchange rate, exchange rate volatility, growth of exports, imports and foreign reserves, import cover, ratio of M2 to foreign reserves. Source: IFS (IMF).

- 16 domestic economic indicators, among which domestic real interest rate, inflation, M2 multiplier, industrial production. Source: IFS.

- 16 institutional indicators, among which election dates, Herfindahl indices, political stability, corruption. Sources: ICRG, DPI.

- 10 debt indicators, among which total debt, short term debt, debt service, arrears. Sources: WDI/GDF (World Bank).

- 25 banking sector indicators for Argentina (14 for Brazil and Mexico), among which credit to public sector, to private sector, ROE, deposits. Sources: Financial Structure (World Bank), WDI/GDF, IFS.

- 7 global and financial markets indicators, among which economic growth in world, US yield, share market index returns, bond yield country spread. Sources: IFS, GEM (World Bank), Economatica.

- 12 commodity related indicators, among which prices of oil, metals, agricultural products, exports and imports of fuel, agricultural products, food and metals. Sources: IFS, WDI/GDF.

For a complete overview, including definitions and transformations, we refer to Appendix A.

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 correlations with individual indicators, and the estimation results for the ordered logit models.[3]

5.1 Argentina

The criterion of Otter, Jacobs and Den Reijer (2011) suggests 11 factors for Argentina. When focusing on the variables with the largest correlation (positive or negative) we can label each factor.[4] Here we give special emphasis to institutional and commodity-related indicators:

- Factor 1 is strongly correlated with **banking and commodity indicators**. The banking indicators consist of credit granting and profitability variables and are pos-

[3]For all three countries we also employed static factors as regressors in the ordered logit models and found that differences were marginal. See Appendix C.

[4]The complete list of factors with the ten indicators with highest correlation can be found in Appendix B.

itively and negatively correlated with this factor. The commodity indicators are primarily related to agriculture and food exports; all are negatively correlated with the factor, which implies that an increase in commodity exports leads to a lower factor.

- Factor 2 is dominated by **domestic economic indicators**. Economic growth and savings are negatively correlated with the factor, the real interest rate and the M2 multiplier are positively correlated with the factor.

- Factor 3 is a **mixed factor** as it does not have any dominating category. Some indicators stand out for their high correlation with the factor. This applies to the T-bill and the return in the US market.

- Factor 4 The factor is dominated by **banking and debt indicators** and complemented by institutional indicators (bureaucratic quality and government stability—these enter with opposite signs into the factor).

- Factor 5 can be labelled the **institutional factor**. These indicators are negatively correlated with the factor.

- Factor 6 is strongly correlated with **banking and external economic indicators**. The banking indicators are mainly credit granting variables while the external economic indicators are related to imports.

- Factor 7 is—like factors 1 and 4—associated with **banking indicators**.

- Factor 8 is a **mixed factor** as it does not have any dominating category.

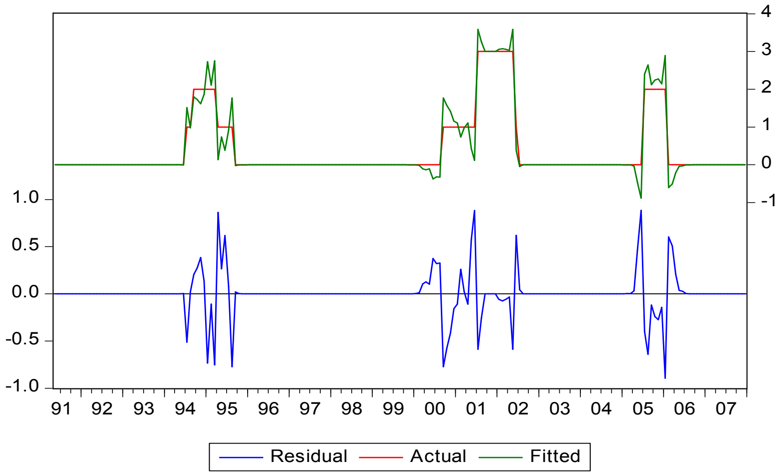
- Factor 9 is influenced mainly by **commodity and debt indicators**. The commodity indicators are related to imports and are negatively correlated with the factor.

- Factors 10 and 11 are very diverse. The variables have low correlations with the factor.

Estimation results

The dynamic factor combination which yields the best fit in the ordered logit model has 4 dynamic factors and 2 lags. Appendix C shows that factors 4, 6 and 8 are not significant at a 5% significant level. Factors 2 and 9 increase the probability of a crisis. The adjusted pseudo R^2 is 0.705 and the fit is shown graphically for the in-sample period 1991-M5 to 2007-M12 in Figure 7.

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



Interpreting the outcomes in terms of the underlying indicators is not trivial, as we argued above. Nevertheless, it can be seen that banking indicators and, to a lesser extent, debt and domestic economy indicators play an important role in the explanation of currency crises. In the following, we focus on commodities prices (factors 1 and 9) and institutions (mainly factor 5) only.

Factors 1 and 9 have opposite signs in the ordered logit model. Although this may seem contradictory at first sight, this is not so if we realize what each factor contains:

factor 1 consists of commodities *exports* indicators (negative correlation), while factor 9 consists of commodities *imports* indicators (negative correlation). Increasing exports lead to a decrease in factor 1 which is associated with a higher probability of a currency crisis. Increasing imports lead to a decrease in factor 9 which is associated with a lower probability of a currency crisis. In other words, in the run-up to the crisis the exports of commodities increase and the imports of commodities decrease. A plausible explanation is the need for foreign currency to relieve the pressure on the exchange rate to depreciate.

With respect to the role of institutions we arrive at the unlikely conclusion that better institutions (negatively correlated with factor 5) increase the probability of a crisis (negative sign in the ordered logit model). To identify the importance of the institutional indicators we re-estimated the model without institutional variables. The results, reported in Appendix C, show that the fit worsens; the adjusted pseudo R^2 decreases from 0.70 to 0.47. In addition, the re-estimated model overestimates the crises probabilities: mild and deep crises come out as deep and very deep crises, respectively.

We conclude that both commodities and institutional indicators play an important role in many of the factors, and by this have an impact on crisis probabilities. Furthermore, banking sector and, to a lesser extent, debt and domestic economy indicators play important roles in the explanation of currency crises.

5.2 Brazil

The criterion of Otter et al. (2011) suggests 9 factors for Brazil. The complete list of factors and the ten indicators with strongest correlations can be found in Appendix B.

- Factor 1 consists of a wide range of indicators, without any dominating category.
- Factor 2 is dominated by **banking indicators**, primarily related to credit granting. All indicators are negatively correlated with the factor, so an increase in the indicator

leads to a lower value of the factor.

- Factor 3 consists of a wide range of indicators, without any dominating category.

- Factor 4 is associated with **commodities and global indicators**. Commodities primarily contain commodities imports (negative correlation) and global indicators are associated with global economic growth (negative correlation).

- Factor 5 is dominated by **institutional and commodities indicators**. Two of the three institutional indicators are negatively correlated with the factor. Agriculture is strongly, negatively correlated with this factor, implying that an increase in the value added by agriculture sector implies a decrease in the factor.

- Factor 6 is dominated by **commodities and institutional indicators**. While agriculture imports and the petroleum price are positively correlated wit the factor, fuel exports are negatively correlated. The institutional indicators are related to the economic and investment state. Both institutional indicators are negatively correlated with the factor.

- Factor 7 is related to **institutional and external economic indicators**. The external economic indicators are all related to the foreign reserves. The institutional factors have a political character. More concentrated government (higher Herfindahl index) and a more disperse opposition are related to a higher factor, while improved law and order leads to a lower factor.

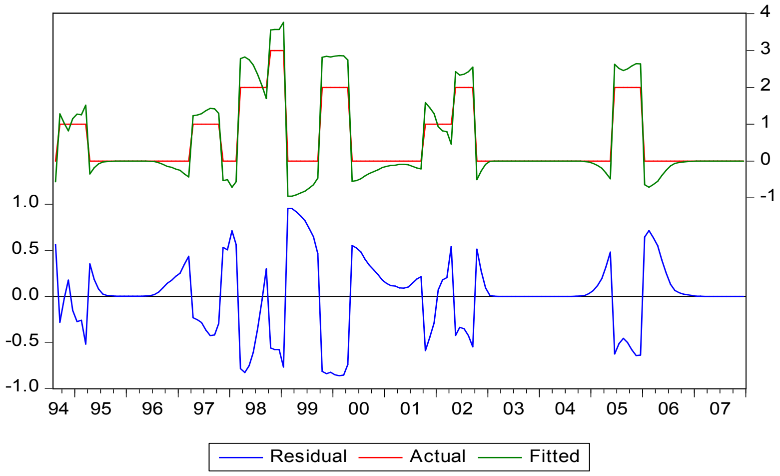
- Factor 8 is dominated by **bank indicators**.

- Factor 9 is mixed. The correlations with the factor are very low.

Estimation results

The combination of 3 dynamic factors and 2 lags yields the best fit in the ordered logit model for Brazil. We add two dummy variables: to identify an election year (elections for the executive power) and contagion (a currency crisis in one of the other two countries). The ordered logit results are presented in Appendix C. Factors 1, and 7 are not significant at the 5% significant level. Also the dummy variables are not significant. Factors 4 and 6 lower the probability of a crisis. The adjusted pseudo R^2 for the DFM is 0.225 and the fit is shown graphically for the in-sample period 1994-M8 to 2007-M12 in Figure 8. We can observe in the graph that the model overestimates crises events and underestimates crisis recovery periods, which explains the relatively low adjusted pseudo R^2. Since we are interested in crisis events, the over- and underestimation is not much of a worry—we care more about a correct timing.

Figure 8: Actual and fitted data, and the residuals form the ordered logit model for Brazil for the period 1994-2007



Banking sector indicators enter all factors. This shows the importance of the sector for the occurrence of currency crises. Domestic economic factors seem to play a minor role.

Factors 4, 5, and 6 (related to commodity prices) show ambiguous signs in the ordered logit model. Factor 4 consists of commodities imports indicators. An increase in commodities imports is associated with a higher probability of a currency crisis. From factor 5 we can derive that with increasing food exports and increasing value added by the agriculture sector the probability of a crisis decreases. Combining the effect, we can observe that in the run-up to a crisis commodities imports increase and food exports decrease. Under a fixed exchange rate regime where prices are not adjusted through the exchange rate, the imports become relatively cheap and exports relatively expensive. This situation is not sustainable and will culminate into a devaluation of the currency. Factor 6 has opposite signs and does not fit in this mechanism.

The institutional factors show a mixed picture: an improvement in bureaucratic quality, democratic accountability and internal conflict is associated with a lower probability of a crisis. However, this relation is not followed in improvements in the law and order situation and in the non-political institutional indicators (socio-economic circumstances, investment profile). The Herfindahl indices seem to indicate that governments which consist of less political parties have a higher probability of crises.

We conclude that the probability of a currency crisis in Brazil is mainly influenced by commodities, banking and institutional indicators. In contrast with Argentina and Mexico, the important categories in Brazil are limited to these three categories only.

5.3 Mexico

According to the criterion of Otter et al. (2011) the number of factors for Mexico is 7. The complete list of factors with the ten indicators which have the strongest correlation can be found in Appendix B.

- Factor 1 is dominated by **commodities indicators** and to a lesser extent by banking and external economic indicators. The commodities consist of both exports and imports, yet all indicators have the same negative correlation in this factor.

- Factor 2 is strongest correlated with **debt and economic domestic indicators**. All debt indicators are negatively correlated with the factor. The two commodities indicators are exports related to agriculture and food; both show a negative correlation with the factor.

- Factor 3 is a mixed factor and consists of banking, domestic economic and institutional indicators. Both institutional indicators are negatively correlated with the factor. The other categories have positive and negative correlations with the factor.

- Factor 4 consists of **external economic and global indicators** and is complemented by institutional indicators. The indicators are related to imports, economic growth in the USA and interest rates in the USA. Given the fact that Mexico's largest trading partner is the USA, this strong correlation should not come as a surprise. The institutional indicators show positive and negative correlations with the factor.

- Factor 5 consists of a wide range of indicators, without any dominating category.

- Factor 6 is dominated by **banking indicators**, which all show the same (negative) correlation with the factor.

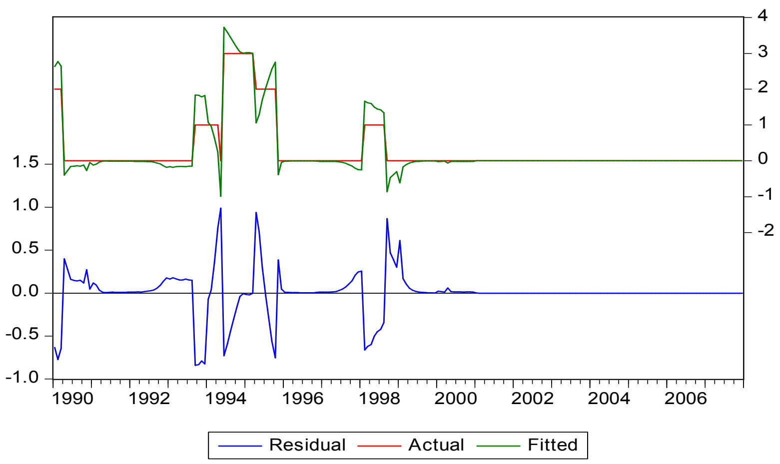
- Factor 7 has low correlations with the factor and should therefore be interpreted with caution. The categories that dominate are **external economic and global indicators**.

Estimation results

The combination of 3 dynamic factors and 2 lags yields the best fit in the ordered logit model for Mexico. As in the model for Brazil we add two dummy variables to identify an election year and to include contagion. Appendix C presents the estimation results.

Factors 1, 5 and 6 are not significant at the 5% significant level; factors 2 and 3 lower the probability of a crisis. The contagion dummy variable is not significant. The adjusted pseudo R^2 is 0.558 and the fit is shown graphically for the in-sample period 1990-M1 to 2007-M12 in Figure 9.

Figure 9: Actual and fitted data, and the residuals form the ordered logit model for Mexico for the period 1990-2007



The categories that dominate the factors are external economy and global indicators. Other important categories are the banking sector, domestic economy indicators and institutional indicators.

Commodities are mainly represented in factor 1, and to a lesser extent in factor 2. Factor 1 is not significant at the 5% level. The interpretation of this estimate would have been hard because the correlations of all indicators with the factor is negative while we expect to see a difference between exports and imports. The two commodity indicators in factor 2 are related to exports and are negatively correlated with the factor. This implies that an increase in the commodities exports will decrease factor 2, which will increase the probability of a crisis. In other words, in the run-up to a crisis the exports of commodities increase. A plausible explanation is the need for foreign currency to relieve the pressure on the exchange rate to depreciate.

Institutional indicators do not dominate any factor, but are present in factors 3, 4, 6 and 7. The relations with factors and crises are ambiguous.

We conclude that the probability of a currency crisis in Mexico is mainly influenced by external economy and global indicators, which confirms the importance of international trade, in particular with its main trade partner, the USA. Domestic economy, debt and institutional indicators are less important in the explanation of currency crises. Contrary to Argentina and Brazil, neither commodities nor banking indicators play an important role in the explanation of currency crises in Mexico.

6 Out of sample performance

In this section we test the performance of the estimated model out of sample. We extrapolate the dynamic factors, with simple ARMA processes, and forecast the probabilities of a mild, deep and very deep crisis in the period 2008–2009.

Argentina

The forecasts under the dynamic factor model extrapolation results in a 100.0% probability that no crisis will take place in any of the months in 2008 and 2009. The ordered logit model does not pick up the mild currency crisis in October 2008.

Brazil

Table 1 shows crises forecasts for Brazil. Crisis probabilities differ from zero, but are fairly low. The probability of a mild crisis is equal to around 6 per cent at the end of 2008, the beginning of 2009. Brazil experienced a mild currency crisis in September-November 2008, which is not picked up by the EWS.

Table 1: Forecasts for Brazil for 2008-2009, for a mild, deep and very deep crisis

period	P (no crisis)	P (mild crisis)	P (deep crisis)	P (v. deep crisis)
2008M01	99.80%	0.13%	0.07%	0.00%
2008M02	99.67%	0.22%	0.11%	0.01%
2008M03	99.43%	0.37%	0.19%	0.01%
2008M04	98.99%	0.65%	0.34%	0.02%
2008M05	98.40%	1.03%	0.54%	0.03%
2008M06	97.50%	1.61%	0.85%	0.05%
2008M07	96.49%	2.25%	1.20%	0.06%
2008M08	95.31%	2.99%	1.61%	0.09%
2008M09	94.04%	3.78%	2.06%	0.11%
2008M10	92.93%	4.47%	2.47%	0.13%
2008M11	91.48%	5.35%	3.01%	0.17%
2008M12	90.64%	5.86%	3.32%	0.18%
2009M01	90.21%	6.12%	3.48%	0.19%
2009M02	90.16%	6.15%	3.50%	0.19%
2009M03	90.47%	5.96%	3.38%	0.19%
2009M04	91.07%	5.60%	3.16%	0.17%
2009M05	91.85%	5.13%	2.87%	0.16%
2009M06	92.73%	4.59%	2.54%	0.14%
2009M07	93.63%	4.04%	2.22%	0.12%
2009M08	94.49%	3.50%	1.90%	0.10%
2009M09	95.28%	3.01%	1.62%	0.09%
2009M10	95.97%	2.58%	1.38%	0.07%
2009M11	96.56%	2.21%	1.17%	0.06%
2009M12	97.05%	1.89%	1.00%	0.05%

Mexico

Table 2 shows crises probability forecasts for Mexico. Crises probabilities are close to zero. Mexico experienced a very deep currency crisis in October 2008. This is not forecast by the ordered logit model.

Table 2: Forecasts for Mexico for 2008-2009, for a mild, deep and very deep crisis

Period	P (no crisis)	P (mild crisis)	P (deep crisis)	P (v. deep crisis)
2008M01	99.99%	0.01%	0.00%	0.00%
2008M02	99.99%	0.01%	0.00%	0.00%
2008M03	99.99%	0.01%	0.00%	0.00%
2008M04	99.99%	0.01%	0.00%	0.00%
2008M05	99.99%	0.01%	0.00%	0.00%
2008M06	99.99%	0.01%	0.00%	0.00%
2008M07	99.99%	0.01%	0.00%	0.00%
2008M08	99.99%	0.01%	0.00%	0.00%
2008M09	99.98%	0.01%	0.00%	0.00%
2008M10	99.98%	0.02%	0.00%	0.00%
2008M11	99.97%	0.02%	0.00%	0.00%
2008M12	99.96%	0.03%	0.01%	0.00%
2009M01	99.94%	0.05%	0.01%	0.00%
2009M02	99.92%	0.07%	0.01%	0.00%
2009M03	99.90%	0.08%	0.01%	0.00%
2009M04	99.88%	0.11%	0.02%	0.00%
2009M05	99.85%	0.13%	0.02%	0.00%
2009M06	99.83%	0.15%	0.02%	0.00%
2009M07	99.81%	0.17%	0.03%	0.00%
2009M08	99.79%	0.18%	0.03%	0.00%
2009M09	99.77%	0.20%	0.03%	0.00%
2009M10	99.76%	0.21%	0.03%	0.00%
2009M11	99.76%	0.21%	0.03%	0.00%
2009M12	99.75%	0.22%	0.03%	0.00%

In the late Fall of October 2008 all three countries experienced a currency crisis (Argentina and Brazil: mild; Mexico: very deep). Based on information up to and including 2007, our ordered logit models did not pick up this crisis. Forecasts of the indicators that played an important role in earlier crises did not indicate a crisis.

It should be realized that the forecasts we present here are based solely on the information that is available in December 2007. For the years 2008 and 2009 the factors are extrapolated using time series models. So the global shock caused by the fall of Lehman Brothers in the USA in September 2008 is not taken into account. Using the realizations of the indicators we should be able to more precisely forecast crises. This could be done either by using the estimates from the factor models until 2007, or by re-estimating the factor models using the values of the indicators until and including the year 2009.

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, trade or financing balances 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 hoover 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 in Argentina and Brazil are driven by banking and commodities indicators, while international indicators matter most in Mexico. Furthermore, we see that in all three Latin American countries institutional indicators play a role. This result supports the fourth generation model in which institutional factors are important. It also confirms previous work in which political indicators play a significant role in crisis forecasting

With an improved institutional framework, a healthier financial system (better regulation, higher profitability margins, lower non-performing loans) and lower debt levels the countries have created a better environment than in the 1990s. This however does not mean that these 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 the characteristics were very distinct from previous crises.

Future research will include: (i) using data with mixed frequencies (monthly, quarterly, annual) and incomplete series as in Aruoba, Diebold and Scotti (2009), which allows the inclusion of a wide range of indicators, particularly institutional indicators; (ii) adding banking crises and debt crises, in order to distinguish between currency crises which remain isolated as opposed to currency crises that are accompanied by other crises and generally have a stronger impact on the economy and a longer recovery period; and (iii) carrying out a real-time analysis.

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: $(1+R_{nominal}) / (1+Inflation) - 1$, 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

Financial market indicators						
1	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
2	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
3	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
Institutional indicators: dummies (not included in factor model)						
1	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
2	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
3	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
4	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
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
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
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

B Correlations of factors with indicators

ARGENTINA

For each of the 11 factors: ten variables with highest correlation with the factor

Factor 1 bank & commodity

D_BANK_PRIV	0.8789	bank
D_BANK_TSFC_DEPOS	0.7811	bank
BANKROE	0.7953	bank
D_DMBANKAS	-0.8492	bank
NETINTMG	-0.7781	bank
DCREDBANK	-0.8505	bank
D_VA_AGRI	-0.8549	commodity
D_AGRI_EXP	-0.7831	commodity
D_FOOD_EXP	-0.8734	commodity
D_METAL_EXP	-0.8064	commodity

Factor 2 economy

REALINT	0.6532	Eco Dom
D_INDPROD	-0.7123	Eco Dom
M2MULT	0.7574	Eco Dom
D_RGDP	-0.6483	Eco Dom
GDSAV_GDP	-0.7204	Eco Dom
D_IMP	-0.6938	Eco Ext
ERVOL	-0.7968	Eco Ext
BANKCONC	-0.6978	bank
DCREDPUB	-0.6780	bank
ARR_TDEBT	-0.8781	debt

Factor 3

GFCAP_GDP	-0.6160	Eco Dom
HHCONS_GDP	0.6044	Eco Dom
INFLAT	0.5475	Eco Dom
TOT	-0.5990	Eco Ext
D_TBILL	-0.7488	global
D_GDPWORLD	-0.6921	global
D_BCRED_BDEP	-0.6112	bank
D_CB_BANKS	0.5518	bank
D_PR_METAL	-0.6684	commodity
D_CORRUPT	0.5951	institutional

Factor 4 bank & debt

M2MULT	0.5068	eco dom
D_FSDEPOS	-0.5708	bank
NETINTMG	-0.4619	bank
D_LIQLIAB	-0.5828	bank
D_PCRED_DMB	-0.4497	bank
D_LTPNG_DEBT	-0.5801	debt
DSERV_EXP	0.5373	debt
DSERV_RES	0.7348	debt
D_BURQUAL	-0.5885	institutional
D_GOVSTAB	0.5199	institutional

Factor 5 Institutional

D_GDPUSA	0.3864	Global
D_BANKASSET	0.5400	bank
D_BANKLIAB	0.4369	bank
D_CB_CGVT	-0.5357	bank
D_AGRI_IMP	0.3804	commodity
D_CORRUPT	-0.4420	institutional
D_INTCONFL	-0.6104	institutional
D_LAWORD	-0.4351	institutional
D_SOCIOECO	-0.4210	institutional
D_BURQUAL	-0.3749	institutional

Factor 6 Economic & bank

UNEMPL	0.4022	Eco Dom
D_IMP	0.2938	Eco Ext
M2RES	0.5223	Eco Ext
D_IMPCOV	-0.5443	Eco Ext
D_BANK_PPG	0.5365	bank
BANKROE	-0.3773	bank
D_BCRED_BDEP	-0.4395	bank
D_PCRED_GDP	-0.3933	bank
D_LTPPG_DEBT	-0.3667	debt
D_SOCIOECO	-0.5023	institutional

Factor 7 bank

D_M2	-0.5498	Eco Dom
INFLAT	0.4025	Eco Dom
D_GDPUSA	-0.4027	global
D_BANKRES	-0.4359	bank
D_BCRED_BDEP	0.3246	bank
D_FSDEPOS	-0.3851	bank
D_LIQLIAB	-0.4289	bank
D_PCRED_DMB	-0.3303	bank
STD_DEBT	0.3857	debt
D_INTCONFL	-0.3555	institutional

Factor 8 all

NETFDI_GDP	0.4135	Eco Ext
D_GDPUSA	0.2891	global
D_USYIELD	0.3807	global
D_BANKASSET	-0.2959	bank
D_CB_CGVT	-0.4553	bank
D_BANKRES	-0.3297	bank
D_PR_AGRI	0.3715	commodity
D_PR_PETROL	0.5764	commodity
DSERV_EXP	0.3828	debt
HERFGOV	-0.4756	institutional

Factor 9 commodity & debt

GOVCONS_GDP	0.2874	Eco Dom
D_RES	-0.2846	Eco Ext
D_BANKLIAB	-0.3034	bank
D_PCRED_DMB	0.2717	bank
D_FOOD_IMP	-0.5438	commodity
D_FUEL_IMP	-0.3567	commodity
D_METAL_IMP	-0.3711	commodity
D_LTPNG_DEBT	0.3432	debt
D_RES_DEBT	0.4292	debt
REDU_TDEBT	-0.3841	debt

Factor 10 all

D_EXP	0.3209	Eco Ext
D_IMPCOV	-0.2908	Eco Ext
D_USYIELD	0.2451	global
D_BANKLIAB	0.3482	bank
D_BANK_PPG	-0.3082	bank
D_LIQLIAB	-0.2477	bank
D_LTPPG_DEBT	0.4191	debt
REDU_TDEBT	0.3116	debt
STD_DEBT	-0.2971	debt
D_INVPROF	0.2992	institutional

Factor 11 all

M2RES	0.3006	Eco Ext
TOT	-0.3490	Eco Ext
D_GDPUSA	0.2690	global
D_BANK_FA_FL	0.2962	bank
D_BANK_PPG	-0.3225	bank
D_FUEL_EXP	-0.3080	bank
D_PR_AGRI	-0.2962	debt
D_LTPNG_DEBT	0.2689	debt
D_LTPPG_DEBT	-0.3998	debt
D_INVPROF	0.3288	institutional

BRAZIL

For each of the 9 factors: ten variables with highest correlation with the factor

Factor 1 debt and others

PCRED_DMB		0.7039	Bank
PCRED_OTH		0.6966	Bank
DEBT_GDP	-	0.7876	Debt
DSERV_EXP	-	0.8467	Debt
DSERV_RES	-	0.8231	Debt
GR_GCAP		0.7574	Econ.Dom.
GR_IMP		0.7055	Econ.Ext
RER_DEV	-	0.8145	Econ.Ext
METAL_EXP	-	0.7030	Commod.
HERFOPP	-	0.7522	Institut.

Factor 2 bank

BANKROE	-	0.6816	Bank
BCRED_BDEP	-	0.7015	Bank
DCREDPUB_GDP	-	0.7074	Bank
DCREDGDP	-	0.6966	Bank
ARR_TDEBT		0.6919	Debt
LTDPNG_TDEBT		0.7465	Debt
GDSAV_GDP	-	0.7005	Econ.Dom.
ERVOL	-	0.7166	Econ.Ext
BURQUAL	-	0.7420	Institut.
HERFGOV		0.7019	Institut.

Factor 3 All

BANKCONC	-	0.4857	Bank
PCRED_DMB	-	0.5874	Bank
REDU_TDEBT	-	0.6471	Debt
RES_DEBT	-	0.4807	Debt
INFLAT		0.5656	Econ.Dom.
GR_RES	-	0.5860	Econ.Ext.
RER_DEV		0.5160	Econ.Ext.
AGRI_EXP		0.5646	Commod.
FOOD_IMP		0.4667	Commod.
INTSPREAD		0.7616	Financial

Factor 4 commodities & global

DMBANKAS	-	0.6147	Bank
FSDEPOS	-	0.4936	Bank
LIQLIAB	-	0.5122	Bank
AGRI_IMP	-	0.5176	Commod.
FUEL_IMP	-	0.5355	Commod.
METAL_IMP	-	0.4799	Commod.
PETROL	-	0.4914	Commod.
GR_GDPUSA	-	0.6409	global
GDPWORLD	-	0.5367	global
SOCIOECO		0.8461	institut.

Factor 5 institut & commodities

BANKZ		0.5058	Bank
CBASSET	-	0.4014	Bank
DCREDPUB_GDP	-	0.3908	Bank
RGDPCAP_GR		0.5624	Econ.Dom.
GR_GOVREV	-	0.4146	Econ.Dom.
GR_VA_AGRI	-	0.8686	Commod.
FOOD_EXP	-	0.5284	Commod.
DEMACC	-	0.5537	institut.
INTCONFL	-	0.5194	institut.
LAWORD		0.5003	institut.

Factor 6 commod & institutional

DCREDPUB_GDP	-	0.3684	Bank
PCRED_DMB	-	0.4172	Bank
IMF_GDP		0.4253	Debt
ERVOL		0.3756	Econ.Ext.
AGRI_IMP		0.5827	Commod.
FUEL_EXP	-	0.5469	Commod.
PETROL		0.3916	Commod.
GR_GDPUSA		0.3748	Global
INVPROF	-	0.7557	institut.
SOCIOECO	-	0.5621	institut.

Factor 7 Econ.Ext & institutional

BANKCONC	-	0.3844	Bank
LTDPPG_TDEBT		0.5213	Debt
GR_M2		0.3778	Econ.Dom.
GR_RES	-	0.5761	Econ.Ext.
M2RES		0.3762	Econ.Ext.
IMPCOV	-	0.5767	Econ.Ext.
FOOD_IMP	-	0.5306	Commod.
HERFGOV		0.4058	institut.
HERFOPP	-	0.4110	institut.
LAWORD		0.5088	institut.

Factor 8 bank

BANKCONC	-	0.3333	Bank
CBASSET	-	0.6482	Bank
DCREDPUB_GDP	-	0.3647	Bank
NETINTMG	-	0.4587	Bank
STD_DEBT		0.3313	Debt
INDPROD		0.3354	Econ.Dom.
GR_UNEMPL		0.4188	Econ.Dom.
ERVOL		0.4491	Econ.Ext.
AGRI_IMP		0.3317	Commod.
BURQUAL		0.5127	institut.

Factor 9

BANKZ	-	0.6375	Bank
CBASSET		0.2946	Bank
LTDPNG_TDEBT		0.2888	Debt
RGDPGR	-	0.2946	Econ.Dom.
GR_GCAP	-	0.4027	Econ.Dom.
FA_GDP	-	0.3342	Econ.Ext.
METAL_IMP	-	0.3279	Commod.
GR_GDPUSA		0.3037	Global
GOVSTAB	-	0.4054	institut.
INVPROF	-	0.2914	institut.

MEXICO

For each of the 7 factors: ten variables with highest correlation

Factor 1 Commodities, bank

BANKCONC	0.7472	bank
D_FSDEPOS	0.6907	bank
D_LIQLIAB	0.6972	bank
D_LTPPG_DEBT	0.6865	debt
RER_DEV	- 0.8636	ext eco
CA_GDP	- 0.7453	ext eco
D_AGRI_IMP	- 0.7558	comm
D_FUEL_EXP	- 0.6946	comm
D_METAL_EXP	- 0.7417	comm
D_METAL_IMP	- 0.7948	comm

Factor 2 debt

DCREDBANK	-0.7681	bank
DEBT_GDP	-0.8818	debt
IMF_GDP	-0.9061	debt
STD_DEBT	-0.5993	debt
INFLAT	-0.9472	dom eco
GFCAP_GDP	0.6923	dom eco
D_TRD_OPEN	-0.5842	ext eco
D_AGRI_EXP	-0.7492	comm
D_FOOD_EXP	-0.7013	comm
D_SOCIOECO	0.6267	instit

Factor 3 All

D_BCRED_BDEP	-0.5435	bank
D_DMBANKAS	-0.5725	bank
DCREDPUB	0.7434	bank
D_RES_DEBT	0.6375	debt
REALINT	-0.7373	dom eco
GDSAV_GDP	0.6997	dom eco
GR_RES	0.5996	ext eco
D_CETES	-0.5522	fin
D_BURQUAL	-0.7458	instit
D_INTCONFL	-0.6049	instit

Factor 4 External economic / global

INDPROD	0.5558	dom eco
DSERV_RES	0.5174	debt
GR_IMP	0.4673	ext eco
IMPCOV	-0.4970	ext eco
D_GDPUSA	0.4992	global
USYIELD	0.4810	global
TBILL	0.4749	global
D_CORRUPT	-0.5330	instit
D_GOVSTAB	0.4555	instit
D_INVPROF	0.4635	instit

Factor 5 all

BANKROE	-0.5144	bank
D_PCRED_DMB	-0.4602	bank
D_PCRED_OTH	-0.4381	bank
ARR_TDEBT	-0.4122	debt
REDU_TDEBT	0.5016	debt
M2MULT	0.5794	dom eco
INVCHG_GDP	-0.4446	dom eco
TOT	-0.5492	ext eco
NETFDI_GDP	0.4498	ext eco
D_GDPWORLD	-0.4678	global

Factor 6 bank

D_DMBANKAS	-0.6643	bank
D_FSDEPOS	-0.4292	bank
D_LIQLIAB	-0.4885	bank
D_PCRED_DMB	-0.5294	bank
D_PCRED_OTH	-0.5339	bank
D_LTPNG_DEBT	0.7329	debt
D_LTPPG_DEBT	-0.3978	debt
D_FOOD_IMP	0.5013	comm
D_GOVSTAB	-0.5828	instit
HERFOPP	0.4384	instit

Factor 7 Institutional and external economic

ARR_TDEBT	0.3411	debt
INDPROD	-0.3972	dom eco
GOVBAL_GDP	-0.3858	dom eco
GR_IMP	-0.4727	ext eco
FA_GDP	-0.3411	ext eco
NETPI_GDP	-0.5651	ext eco
D_CETES	0.2992	instit
D_GDPWORLD	-0.2998	instit
D_LAWORD	0.3505	instit
D_SOCIOECO	0.5133	instit

C Ordered Logit estimation results

Argentina

Static Factor Model

Variable	**Coefficient**	**Std. Error**	**Prob.**
SF1	-3.8583	0.9363	0.0000
SF2	6.0855	1.3795	0.0000
SF3	-8.8692	2.0522	0.0000
SF4	1.9512	0.5782	0.0007
SF5	-2.1185	0.7584	0.0052
SF6	0.7558	0.7446	0.3101
SF7	-5.3066	1.3505	0.0001
SF8	-1.5626	0.5041	0.0019
SF9	1.7025	0.7712	0.0273
SF10	-5.4003	1.3482	0.0001
SF11	2.4378	1.0833	0.0244
	Limit Points		
LIMIT_1:C(12)	24.31531	5.205633	0
LIMIT_2:C(13)	27.75734	5.67798	0
LIMIT_3:C(14)	32.33869	6.319964	0

Pseudo R-squared		0.7454
Schwarz criterion		0.7540
Hannan-Quinn criter.		0.6165
LR statistic		224.3511
Prob(LR statistic)		-
Akaike info criterion		0.5231
Log likelihood	-	38.3070
Restr. log likelihood	-	150.4825
Avg. log likelihood	-	0.1915
Adjusted Pseudo R2		0.6723

Dynamic Factor Model (q 4, p 2)

Variable	**Coefficient**	**Std. Error**	**Prob.**
DF1	-16.9394	4.4928	0.0002
DF2	15.7001	3.5181	0.0000
DF3	-33.7729	8.0580	0.0000
DF4	1.9719	1.3834	0.1540
DF5	-15.3724	6.6354	0.0205
DF6	5.2748	3.0599	0.0847
DF7	-14.7328	3.3648	0.0000
DF8	0.3376	2.2714	0.8818
DF9	5.5524	2.4638	0.0242
DF10	-17.1661	4.1700	0.0000
DF11	-16.0372	6.3991	0.0122
	Limit Points		
LIMIT_1:C(12)	78.66688	23.41531	0.0008
LIMIT_2:C(13)	82.99804	23.82539	0.0005
LIMIT_3:C(14)	87.19589	24.18201	0.0003

Pseudo R-squared		0.7783
Schwarz criterion		0.7045
Hannan-Quinn criter.		0.5671
LR statistic		234.2336
Prob(LR statistic)		-
Akaike info criterion		0.4737
Log likelihood	-	33.3657
Restr. log likelihood	-	150.4825
Avg. log likelihood	-	0.1668
Adjusted Pseudo R2		0.7052

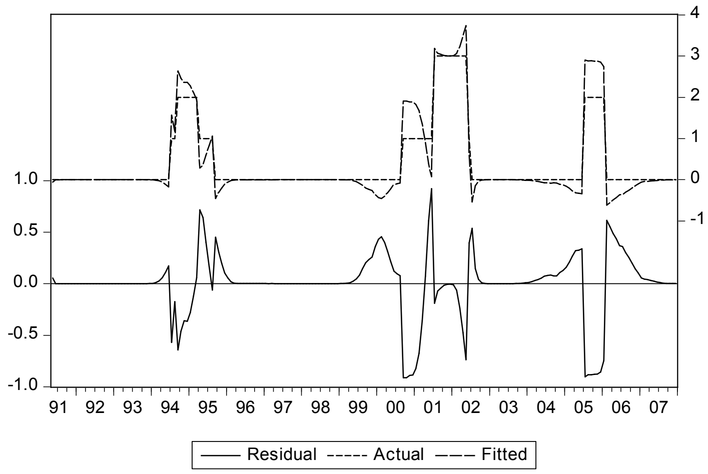
Argentina - excluding institutional indicators

Static Factor Model

Variable	Coefficient	Std. Error	Prob.
SF1	-0.8022	0.3721	0.0311
SF2	-1.1398	0.4154	0.0061
SF3	-1.6924	0.7783	0.0297
SF4	-0.7198	0.2442	0.0032
SF5	0.6460	0.4854	0.1832
SF6	-0.1896	0.3604	0.5987
SF7	1.1974	0.4509	0.0079
SF8	0.8275	0.5232	0.1137
SF9	0.6956	0.2802	0.0130
SF10	1.5930	0.5126	0.0019
Limit Points			
LIMIT_1:C(11)	5.524574	1.504236	0.0002
LIMIT_2:C(12)	7.374564	1.617115	0
LIMIT_3:C(13)	10.35381	1.993956	0
Pseudo R-squared		0.5716	
Schwarz criterion		0.9891	
Hannan-Quinn criter.		0.8615	
LR statistic		172.0237	
Prob(LR statistic)		0.0000	
Akaike info criterion		0.7747	
Log likelihood		-64.4707	
Restr. log likelihood		-150.4825	
Avg. log likelihood		-0.3224	
Adjusted Pseudo R2		0.5051	

Dynamic Factor Model (q 4, p 2)

Variable	Coefficient	Std. Error	Prob.
DF1	-0.4385	0.2701	0.1044
DF2	-0.4332	0.1442	0.0027
DF3	-0.7619	0.3372	0.0239
DF4	-0.6298	0.1953	0.0013
DF5	1.3419	0.3172	0.0000
DF6	1.0736	0.4154	0.0097
DF7	1.2530	0.3536	0.0004
DF8	0.5543	0.5599	0.3222
DF9	0.2384	0.2635	0.3657
DF10	0.0583	0.3854	0.8798
Limit Points			
LIMIT_1:C(11)	3.564912	0.748121	0
LIMIT_2:C(12)	5.227112	0.856032	0
LIMIT_3:C(13)	7.910543	1.173544	0
Pseudo R-squared		0.5398	
Schwarz criterion		1.0368	
Hannan-Quinn criter.		0.9092	
LR statistic		162.4752	
Prob(LR statistic)		0.0000	
Akaike info criterion		0.8224	
Log likelihood		-69.2449	
Restr. log likelihood		-150.4825	
Avg. log likelihood		-0.3462	
Adjusted Pseudo R2		0.4734	



Brazil

Static Factor Model

Variable	Coefficient	Std. Error	Prob.
SFM1	-0.151451	0.06051	0.0123
SFM2	0.201862	0.074308	0.0066
SFM3	0.255185	0.091236	0.0052
SFM4	-0.185297	0.093921	0.0485
SFM5	-0.220431	0.150569	0.1432
SFM6	-0.481383	0.165013	0.0035
SFM7	0.221075	0.137723	0.1084
SFM8	-0.093765	0.132033	0.4776
SFM9	0.445396	0.147062	0.0025
CONTAG	-0.038387	0.723748	0.9577
ELECEXEYEAR	0.50863	0.557482	0.3616
	Limit Points		
LIMIT_1:C(12)	1.491236	0.362886	0
LIMIT_2:C(13)	2.420088	0.387949	0
LIMIT_3:C(14)	5.223494	0.696023	0
Pseudo R-squared		0.222879	
Schwarz criterion		1.859625	
Hannan-Quinn criter.		1.700474	
LR statistic		65.4653	
Prob(LR statistic)		0	
Akaike info criterion		1.591676	
Log likelihood		-114.13	
Restr. log likelihood		-146.8626	
Avg. log likelihood		-0.708882	
Adjusted Pseudo R2		0.14798	

Dynamic Factor Model (q 3, p 2)

Variable	Coefficient	Std. Error	Prob.
DF1	-0.093127	0.079353	0.2406
DF2	0.423517	0.132326	0.0014
DF3	1.287673	0.33803	0.0001
DF4	-0.621748	0.174039	0.0004
DF5	0.728228	0.359769	0.043
DF6	-2.152564	0.555648	0.0001
DF7	0.463516	0.27275	0.0892
DF8	0.825458	0.319504	0.0098
DF9	1.801576	0.43153	0
CONTAG	-0.61224	0.797549	0.4427
ELECEXEYEAR	1.062805	0.688428	0.1226
	Limit Points		
LIMIT_1:C(12)	2.930082	0.752875	0.0001
LIMIT_2:C(13)	3.981299	0.781824	0
LIMIT_3:C(14)	7.033818	1.075833	0
Pseudo R-squared		0.299977	
Schwarz criterion		1.71897	
Hannan-Quinn criter.		1.559819	
LR statistic		88.11075	
Prob(LR statistic)		0	
Akaike info criterion		1.451021	
Log likelihood		-102.8072	
Restr. log likelihood		-146.8626	
Avg. log likelihood		-0.638554	
Adjusted Pseudo R2		0.22508	

Mexico

Static Factor Model

Variable	Coefficient	Std. Error	Prob.
SF1	-1.3022	0.5939	0.0283
SF2	-2.4353	0.9528	0.0106
SF3	-1.0909	0.2609	0.0000
SF4	1.6104	0.5572	0.0039
SF5	1.2663	0.6412	0.0483
SF6	-0.8414	0.4901	0.0860
SF7	0.7497	0.2596	0.0039
CONTAG	2.3571	1.4523	0.1046
ELECEXEYEAR	1.9721	1.1801	0.0947
	Limit Points		
LIMIT_1:C(10)	12.18136	4.419629	0.0058
LIMIT_2:C(11)	14.4149	4.508815	0.0014
LIMIT_3:C(12)	17.29079	4.621632	0.0002

Pseudo R-squared	0.63111
Schwarz criterion	0.75448
Hannan-Quinn criter.	0.64272
LR statistic	168.45610
Prob(LR statistic)	-
Akaike info criterion	0.56696
Log likelihood	- 49.23168
Restr. log likelihood	- 133.45970
Avg. log likelihood	- 0.22792
Adjusted Pseudo R2	0.56368

Dynamic Factor Model (q 3, p 2)

Variable	Coefficient	Std. Error	Prob.
DF1	0.9429	0.5497	0.0863
DF2	-1.5622	0.7622	0.0404
DF3	-0.9340	0.1889	0.0000
DF4	1.1777	0.3946	0.0028
DF5	0.5129	0.4882	0.2934
DF6	0.2829	0.5419	0.6016
DF7	0.8179	0.2106	0.0001
CONTAG	1.6256	1.0997	0.1393
ELECEXEYEAR	2.4562	1.0989	0.0254
	Limit Points		
LIMIT_1:C(10)	8.691282	3.858121	0.0243
LIMIT_2:C(11)	10.94631	3.926914	0.0053
LIMIT_3:C(12)	15.07563	4.214669	0.0003

Pseudo R-squared	0.62531
Schwarz criterion	0.76164
Hannan-Quinn criter.	0.64988
LR statistic	166.90820
Prob(LR statistic)	-
Akaike info criterion	0.57413
Log likelihood	- 50.00563
Restr. log likelihood	- 133.45970
Avg. log likelihood	- 0.23151
Adjusted Pseudo R2	0.55788

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