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Predicting currency crisis contagion from East Asia to Russia and Brazil:
an artificial neural network approach

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Predicting currency crisis contagion from East Asia to Russia and Brazil:

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Abstract

Studies dealing with crisis prediction are often vulnerable to data mining and misspecification. This paper suggests an artificial neural network approach to crisis prediction. The properties of the multilayer perceptron are used in order to develop a method that combines daily financial data with monthly macroeconomic data. It is then tested whether the joint banking and currency crises in Russia and Brazil that occurred in 1998 and 1999 were predictable, given the then recent turmoil in East Asian countries. Both crises are found to be predictable, though the IMF plan in Brazil seems to have alleviated speculative pressures on the real.

Keywords: Artificial Neural Networks, Contagion, Crisis Prediction, Banking Crisis, Currency Crisis.

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1. Introduction

On July 2nd, 1997, the Thai baht lost 17% against the U.S. dollar after several months of speculative pressure. In a fortnight, the Philippine peso and the Malaysian ringgit were also on a float. On July 11th, the Indonesian monetary authorities widened the bands of the rupiah[1]. The Singaporean dollar, which was formally on a float, did not however come under pressure before the second week of August. The Singaporean authorities then decided not to defend the currency: it had already lost 8% against the U.S. dollar by mid-September. Both Taiwan and South Korea were spared from contagious speculative attacks during the two following months. There were not any significant speculative pressures on the Taiwanese currency until early October[2]. But they quickly compelled the Taiwanese authorities to abandon the fixed exchange rate system: they decided to let the currency float on October 20th. In Korea, a policy of gradual adjustment had allowed the won to lose only 8.4% against the U.S. dollar between July and the end of October. The won nevertheless plummeted by 25% during the sole month of November. The Korean authorities formally allowed the currency to float on December 16th. Speculative pressures on emerging markets and economies in transition did not stop. Russia was to let the ruble float on August 17th, 1998. The crawling peg of the

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[1] The Indonesian monetary authorities formally allowed the float of the rupiah on August 14th, 1997.

[2] At the same time, the Hong Kong currency suffered from speculative pressures. The float was however avoided because of the willingness of Hong Kong monetary authorities to raise short term interest rates drastically and of the existence of a currency board. Hong Kong is thus omitted from this research so as to focus on East Asian countries that had to let the exchange rate go.

Brazilian peg was abandoned on January 13th, 1999. During each of these currency crises, there were numerous bankruptcies of banking and financial institutions[3].

Studies on the joint outbreak of currency and banking crises, i.e., the "twin crises", focusing on the similarities and common occurrences between banking crises and currency crises, include Chang and Velasco (1998, 1999, 2000a, 2000b, 2001), Glick and Hutchinson (1999), Kaminsky and Reinhart (1999) and follow different paths as shown by the survey of Marion (2000). For instance Chang and Velasco (1999) extend the bank run framework of Diamond and Dybvib (1983) to account for self-fulfilling features of banking and currency crises. Some third-generation models, such as Krugman (2000) and Schneider and Tornell (2000), also study the 'balance-sheet effect'. They attempt an assessment of the influence of companies' balance sheets in determining their ability to invest, and the effects of capital flows in affecting the real exchange rate.

This paper aims at determining whether the twin crises in Russia and Brazil were predictable, given the then recent turmoil in East Asian countries. It differs from related studies such as Baig and Goldfajn (2000), Hernández and Valdés (2001), and Kaminsky and Reinhart (2000) which investigate the channels of contagion[4] from East Asia to Russia and Brazil but do not study whether the Russian and Brazilian crises could have been predicted. Our study builds upon the researches dealing with crisis prediction, which have been surveyed by Kaminsky et al. (1998) and Berg et al. (1999). They show that traditional studies on crisis prediction often fail to detect signs of speculative attacks. Therefore, another approach is needed.

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[3] See Kaminsky and Schmukler (1999), Radelet and Sachs (1998a, 1998b) and Corsetti et al. (1999a, 1999b) for differing analyses of the East Asian crisis. See Desai (2000) and Chiodo and Owyang (2002) for accounts of the Russian crisis and Franco (2000) on the Brazilian crisis.

In our opinion, four reasons justify using one of the most common ANN models, the multilayer perceptron, in order to overcome some of the problems in crisis prediction[5]. First, traditional studies on crisis prediction assume that there are linear relationships between variables, which is far from being established. Yet, nothing justifies the existence of nonlinear relations between variables. It has however been shown by Hornik et al. (1989) and Hornik (1991) that the multilayer perceptron is able to approximate any class of functions at any desired degree of accuracy. It may hence provide a linear (nonlinear) estimator if the relationships between variables are linear (nonlinear).

Second, the samples which traditional studies on crisis prediction use often range over ten years or more. Given that the fundamental determinants of crises may vary over time, relevant prediction models should however small updated data samples. Following Duin (1993, 1995, 1996), it is considered that the multilayer perceptron allows the use of samples that contain a minimum number of forty points to get a consistent and relevant estimator[6].

Third, traditional studies on crisis prediction rely on monthly, quarterly and even yearly data to predict crises. Such a method cannot assess changes in market sentiment on a

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[4] Studies on crisis contagion distinguish between political, financial and trade channels of transmission, as Dornbusch et al (2000) and De Bandt and Hartmann (2001) show in their surveys.

[5] Rosenblatt (1958, 1962) first developed the perceptron. See Anderson (1995) for a discussion on the multilayer perceptron and its properties. For a statistical perspective on ANNs, see White (1989), Ripley (1993), Cheng and Titterington (1994). See Kuan and White (1994) for an econometric perspective. Note that there are already some applications of neural networks to macroeconomics that focus on forecasting macroeconomic time series. Studies by Maasoumi et al. (1996), Stock and Watson (1996), Swanson and White (1997), Moshiri and Cameron (2000) provide mixed but promising results, even when non-linearity is not explicit

[6] This paper does not use the bootstrap method that allows estimations based on small data sets because the bootstrap does not overcome the other problems associated with currency crisis prediction. See Efron and Tishbirani (1993) on the properties of the bootstrap.

daily or a weekly basis and may therefore have limited prediction ability. Estimations should combine monthly macro-economic data with daily financial indicators so as to single out times of speculative pressures and periods of tranquility on the foreign exchange market. As shown by Schmied (2002), the multilayer perceptron allows such a combination: it requires a logarithmic transformation of monthly data.

Fourth, Berg and Patillo (1999a, 1999b, 1999c) show that studies on predicting crises that rely on cross-section models such as Bussière and Mulder (1999), Radelet and Sachs (1998a), Sachs et al. (1996) and Tornell (1999), are vulnerable to data mining and often perform poorly out of sample. The multilayer perceptron should however perform better than traditional models of crisis prediction since it requires a three-step method designed to prevent data mining. During the first step, the model is estimated with data from the four Asian countries which were hit by speculative attacks in July 1997, i.e. Thailand, The Philippines, Malaysia and Indonesia. During the second step, it is validated with data from the three East Asian countries which let their money float or let it depreciate substantially during the crisis contagion during the second semester of 1997, i.e. Singapore, Taiwan and Korea. During the third step, the model is tested on Russia and Brazil so as to determine whether the speculative attacks in these countries were predictable, given what had just happened in East Asia. As such, the model selection approach in this paper is heuristic and not theoretical, though it is in line with traditional selection models that Golden (1996) discusses.

The remainder of the paper is as follows. Section 2 describes the model. Section 3 presents the data. Section 4 describes the empirical analysis. Section 5 concludes.

2. The model

This paper develops an ANN model of crisis prediction that builds upon the multilayer perceptron with two hidden layers. It has the same approximation capabilities as a multilayer perceptron with one hidden layer but better captures nonlinear relationships between variables

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with a reduced number of neurons, thus speeding computations. With three or four hidden layers, the estimator would not be really be consistent because the degree of freedom would be too important relatively to the number of data.

The multilayer perceptron with two hidden layers that is described in Figure 1 provides estimators for crisis prediction. It has p×T input units that represent p×T variables $\{X_t^1, X_{t-1}^1, ..., X_{t-T}^1, X_t^2 ..., X_{t-T}^p\}$ with p the number of parameters and T the number of lags. There are respectively n and m neurons on the first and the second hidden layers and one output unit Y. A threshold neuron which has a constant input that is equal to 1, is also defined.

[Insert Figure 1 Here]

It is assumed that the multilayer perceptron's output Y is a scalar. In that case, the multilayer perceptron has the following form

$$Y_t = \psi_3\left(\sum_{j=1}^{m}\alpha_j\psi_2\left(\sum_{k=1}^{n}\beta_{kj}\psi_1\left(\sum_{l=1}^{p}\sum_{i=1}^{T}\eta_{likj}X_{t-i}^l + \eta_{0kj}\right) + \beta_{0j}\right) + \alpha_0\right) \tag{1}$$

where $\left(\alpha_j\right)_{j\in\{1...m\}}$, α_0, $\left(\beta_{kj}\right)_{k\in\{1...n\},j\in\{1...m\}}$, $\left(\beta_{0j}\right)_{j\in\{1...m\}}$, $\left(\eta_{likj}\right)_{l\in\{1...T\},i\in\{1...p\},k\in\{1...n\},j\in\{1...m\}}$, and $\left(\eta_{0kj}\right)_{k\in\{1...n\},j\in\{1...m\}}$ are the coefficients of the model, with

$$\left\{\left(\alpha_j\right)_{j\in\{1...m\}},\left(\beta_{kj}\right)_{k\in\{1...n\},j\in\{1...m\}},\left(\eta_{likj}\right)_{l\in\{1...T\},i\in\{1...p\},k\in\{1...n\},j\in\{1...m\}},\alpha_0,\left(\beta_{0j}\right)_{j\in\{1...m\}},\left(\eta_{0kj}\right)_{k\in\{1...n\},j\in\{1...m\}}\right\}\in\Re^{m^5\times n^3\times T\times p}$$

and where ψ_1, ψ_2, ψ_3 are the activation functions of the model with

- $\psi_1 : \Re \to \Re$ is such that

$$\forall x\in\Re,\ \psi_1(x)=\tanh(x) \tag{2}$$

with $\tanh(x)=\dfrac{e^x - e^{-x}}{e^x + e^{-x}}$

- $\psi_2 : \Re \to \Re$ is the logistic function such that

$$\forall x\in\Re,\ \psi_2(x)=\dfrac{1}{1+e^{-x}} \tag{3}$$

- $\psi_3 : \Re \to \Re$ is a linear transfer function used to obtain the scalar Y such that

$$\forall\, x \in \Re, \; \psi_3(x) = x \tag{4}$$

In this model, the variable Y takes the following values

- if Y=0, there are no speculative pressures on the foreign exchange market;

- if Y=1, there are speculative pressures on the foreign exchange market.

This model may be seen as a sort of "ANN logit model". The problems associated with crisis prediction that were discussed in the Introduction, and that are meant to be overcome by the multilayer perceptron, however prevent a comparison between our model and a logit model.

3. The data

3.1 The data sets

Two data sets are used in this study: daily financial data and monthly macroeconomic data. For each country, financial data include exchange rates between each emerging country and the U.S. dollar, stock price indexes, interbank and deposit rates. Macroeconomic variables consist of data about international liquidity, international transactions and the national account. Following Schmied (2002), these monthly macroeconomic data are transformed in logarithm in order to diminish their variations and to fit them with the daily financial data. The list of data is given in Appendix A.

Note that most of these domestic data are originally expressed in their national currency. But artificial neural networks require data to be expressed in the same currency in order to provide a consistent analysis. This paper uses the U.S dollar as its benchmark currency. No bias is introduced when all data are converted in U.S dollar becauses no major exchange rate variation obviously occurs before a currency crisis.

3.2 Country classification

Before Russia and Brazil gave up on their crawling peg, Thailand, The Philippines, Malaysia, Indonesia, Singapore, Taiwan and Korea also had to let their exchange rate go. The problem lies in choosing which countries are to be included in the learning sample and which should be included in the validation sample.

In order to choose the content of the learning and validation samples, it seems natural to follow a chronological order. The first four countries which gave up on a fixed exchange rate system or widened their currency's floating bands, i.e. Indonesia, Malaysia, the Philippines and Thailand, are included in the learning sample. The three East Asian countries that subsequently suffered from speculative attacks, i.e. Singapore, Taiwan and Korea, are comprised in the validation sample.

3.3 Sub-period classification

The tranquility and speculative pressure periods are now distinguished. We justify the use of a smaller learning sample than in the traditional studies on crisis prediction on economic grounds: it is unlikely that the European Monetary System (EMS) crises which occurred in 1992 and 1993 influence the fall of the ruble and of the real. We cannot therefore use crisis-dating schemes which distinguish speculative periods over long-time periods by identifying sharp changes in the exchange rate à la Frankel and Rose (1996), by computing a weighted average of exchange rates and reserves à la Kaminsky et al. (1998), or a weighted average of exchange rate, reserves and interest à la Eichengreen et al. (1996a, 1996b).

This paper actually follows Baig and Goldfajn (1999, 2000) in identifying a priori the speculative pressure periods: these are the three- and five-month periods before the fall in the exchange rate. This choice is motivated on two grounds. On the one hand, a three-month data sample at least comprises forty points. Following Duin (1993, 1995, 1996), this is the smallest sample that may be used if a consistent ANN model is to be estimated. On the other hand,

economic reasons justify the use of a five-month sample. From all accounts on the East Asian crisis, the speculative pressures in Thailand started in February 1997, i.e. five months before the fall of the baht. If a bigger sample is used, the analysis may not be grounded anymore.

The tranquility periods, which are used in this study as a benchmark, must be identified. It is decided that the tranquility periods are within the one-year period prior to the beginning of speculative pressures.

The tests on the Russian and Brazilian data both begin on January 1st, 1998 and respectively end on August 14th, 1998 and on January 11th, 1999, even though the devaluations occurred on August 17th, 1998 and on January 13th, 1999[7]. If this study took into account the last days before the crises, the ANN estimator would unmistakably detect the devaluations. This would jeopardize the test and it is therefore better not to include the last days before the fall of the pegs in the data.

Table 1 sums up the country and sub-period classifications.

[Insert Table 1 Here]

4. Estimation procedure

The estimation procedure is a three-step process that is carried out with the Neural Network Toolbox of MATLAB. Models are first trained and selected. Simulation is then carried out on the validation sample. Finally, the estimators are tested on the Brazilian data sample.

4.1 Training and model selection

This sub-section aims at finding different specifications of the model which fit the data in the learning sample. It thus seeks the correct number of neurons on each layer of the ANN

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[7] The 14th and 17th August 1998 were a Friday and a Monday. The 11th and 13th January 1999 were a Monday and a Wednesday.

system so as to obtain a good interpolator. Indeed, if the number of selected neurons is too small, the ANN model does not learn anything. If the number of selected neurons is too big, there is overfitting: the ANN model is completely adapted to the learning data set and it cannot be used on out-of-sample data. Besides, we estimate models where the validation sample is also part of the learning data so as to obtain additional benchmarks on the relevance of the estimators.

As discussed in Section 3, this study distinguishes between a five-month and a three-month sample. However, the size of the samples prevents the estimators to be trained with algorithms that require an accurate computation of the gradient. The backpropagation algorithm, developed by Rumelhart et al. (1986), is employed because it avoids an accurate computation of the gradient[8]. This algorithm may be presented as follows.

Let ψ_i the activation function of unit i. Let $U_i = \sum_l \theta_{li} X_l$ be the sum of units prior to

unit i and $X_i = \psi_i(U_i)$. Let Y_{ip} and $\hat{Y}_{ip}$ be the ith components of the observed output and the computed output of the network that correspond to an entry p that is presented to the unit at each time period. The adaptation formulas of a connection that links unit k to unit i are

$$\Delta \theta_{ki} = \eta \delta_i X_k \tag{5}$$

where η is a strictly positive real number and

$$\delta_i = \left(Y_{ip} - \hat{Y}_{ip}\right) \psi_i'(U_i) \tag{6}$$

if unit i belongs to the output layer or

$$\delta_i = \left(\sum_{j=1}^{J} \delta_j \theta_{ij}\right) \psi_i'(U_i) \tag{7}$$

if unit i belongs to the other layers.

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[8] See Luenberger (1984) on gradient-based algorithms.

For each estimator, the optimal number of neurons on each layer is searched for. Our model selection criterion is the mean square error (MSE). Estimators must arbitrarily minimize the MSE that is arbitrarily set equal to 0.001.

Table 2 gives the results of the training process for the various specifications[9]. Their relevance must now be tested with out-of sample data.

[Insert Table 2 here]

4.2 Validation

The validation phase of the estimation procedure aims at assessing the accuracy and the fitness of the ANN estimators with out-of-sample data.

The out-of sample data consist of Singapore, Taiwan and Korea. Figure 2 shows the tranquility and speculative periods for the validation sample. If the models estimated during the training phase are relevant, the simulation on the out-of-sample data should provide a graphic similar to Figure 2.

[Insert Figure 2 here]

Table 3 sums up the results of the validation procedure.

[Insert Table 3 here]

Unsurprisingly, models whose learning data also include the validation sample perform well. Those that do not perform poorly, whatever the number of nets and the size of the samples. Figure 3 shows the results which are obtained with an estimator trained on the five-month sample.

[Insert Figure 3 here]

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[9] From Table 2, it may seem that the estimators have too many parameters. However, when estimators with fewer neurons are trained, the residual is far from 0.001, i.e. models with few parameters are not helpful when it comes to our data sets.

From Figure 3, it seems that the Korean won was under speculative pressures between June and November 1997, when the float took place. But from all accounts on the East Asian crisis, there were not any speculative attacks on Korea before October.

The ANN estimators' lack of performance does not necessarily stem from flaws in ANNs. It may result from economic causes: the specification that is used in this paper assumes that the Singaporean, Taiwanese and Korean crises are similar to those that occurred in Thailand, Indonesia, Malaysia and Philippines. But Singapore and Taiwan had relatively sound fundamentals before their currencies came under speculative pressure. What actually triggered market participants to launch attacks is their noticing that the Singaporean and Taiwanese currencies had become overvalued following the float of their main commercial partners' currencies. The situation was different in Korea which had been going through a severe economic crisis since the second semester of 1996. The Russian and Brazilian economies also suffered from macroeconomic and financial difficulties before July 1997. Moreover, the outbreak of the East Asian crisis surely increased the speculative pressures on the ruble and the real. It may then have been possible to predict the crises in these two countries.

4.3 Test

In this sub-section, the ANN estimators are tested on the Russian and Brazilian data. Table 4 sums up the test results.

[Insert Table 4 here]

No estimator with a three-month data sample is able to identify speculative pressures in the wake of the ruble's or the real's float. With a five-month data sample, the model in which the validation data are included in learning sample badly performs for Russia: it provides crisis signals between March 6th and April 14th, 1998, but neither before nor after these dates, which is hard to justify on economic grounds. It however starts giving crisis

signals for Brazil in the end of August 1998, i.e. more than four months before the fall of the real.

Explanations for this failure and the failing of the ANN estimators during the validation process studied in the previous sub-section are similar. This failure may stem from a lack of significant variables and/or from economic causes. Indeed, East Asian countries had relatively low deficits but their financial institutions and corporations were heavily indebted. However, both Brazil and Russia were running important budgetary deficits.

The only specification that actually provides interesting results for both countries is the model where the validation data sample is not included in the training process. Figure 4 provides the "raw" results of the test.

[Insert Figure 4 here]

Except for an abnormal point that appears in July 1998, it seems that Russia was undergoing a period of speculative pressure from January 1st, 1998 until the fall of the ruble. There was not however any significant attack on the Brazilian crawling peg until the end of April 1998. And strangely enough, the Brazilian economy seems to be out of dire straits in early November. Without taking into account abnormal points in Figure 4, it is found that there were speculative pressures only from 6th April to 4th November 1998. This may be related to the launch of an IMF-supported plan to prevent the real from floating. This is confirmed by Figure 5 which shows the results of the test when a test-customized threshold function[10] is applied on the "raw" outcomes.

[Insert Figure 5 here]

Such results imply that the Russian crisis resulted from deteriorated fundamentals. They also suggest that the Brazilian macroeconomic situation was not so desperate when the government gave up on the real's crawling peg in January 1999. The fall of the real must

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[10] This threshold function is programmed under MATLAB. The program is available upon request to the authors.

therefore be attributed to the speculators' self-fulfilling expectations. But the blame also rests on the joint inability of the IMF and of the Brazilian government to convince speculators that the peg was sustainable.

Needless to say, these results rest on the quality of our ANN estimators. To assess their relevance, we provide in Appendix B an out-of-sample test on Argentina and Chile, i.e. two countries that did not have to let their exchange rate go between July 1997 and January 1999. The quality of the results obtained from these out-of-sample tests is mixed. Hence, during the propagation of the East Asian crisis, it may not always have been possible to predict which countries were to be hit by speculative attacks.

5. Conclusion

This study suggests that the fundamental determinants of the twin crises in the first four East Asian countries that were affected by speculative attacks and in the last three that subsequently had to let the exchange rate go were different. It also implies that the speculative attacks in Thailand, Malaysia, the Philippines and Indonesia bear a strong resemblance to the Russian and Brazilian crises. Nevertheless, it seems that the outbreak of the Brazilian crisis may be partly attributed to the foreign exchange market participants' self-fulfilling expectations.

This study also casts a new light on crisis prediction. Berg and Patillo (1999a) already investigated whether it was possible to predict crises and answered: "Yes, but not very well". Likewise, it appears in this paper that it was possible to predict the outbreak of the Russian and Brazilian crises using ANNs, but not very well. However, ANNs provide a promising path of research because they are able to overcome many of the problems usually associated with crisis prediction.

Appendix A

Two data sets are used in this study : daily financial data and monthly macroeconomic data. All data are converted from each national currency into U.S. dollar. This is done by using the spot exchange rate at the opening of the market for each currency to the U.S. dollar as given by the Datastream software. To convert monthly macroeconomic data into U.S. currency, the spot exchange rate at the end of each month is used.

Daily financial data are taken from the Datastream software and comprise for each country :

Stock market indexes: Dow Jones World Index, Dow Jones Bank Index, Dow Jones Basic Industries Index, Dow Jones Financial Institutions Index, Dow Jones Telecom Index and Dow Jones Utilities Index are used for all countries except for Russia where A& KM indexes are used. A& KM indexes are similar to Dow Jones indexes.

Interbank rate: Overnight rate.

Deposit rates: 90-day deposit rate, 180-day deposit rate.

Monthly macroeconomic data are taken from the IMF International Financial Statistics (IFS) for all countries except for Taiwan where data from the Taiwanese Central Bank (available at www.stat.gov.tw/main.htm) are used. Monthly macroeconomic data are the following :

International liquidity: Total reserves minus Gold (IFS row 1l.d), Reserve Position in the Fund (IFS row 1c.d), Deposit money bank : Assets (IFS row 7a.d), Deposit money bank : Liabilities (IFS row 7b.d), Other Banking Institutions: Assets (IFS row 7e.d), Other Banking Institutions : Liabilities (IFS row 7f.d).

International transactions: Exports (IFS row 70.d), Imports, c.i.f. (IFS row 71.d)

National account: Deficit (-) or surplus (IFS row 80), Total Debt by Residence (IFS row 88).

Note that in order to account the influence of deposit money banks and other banking institutions in each country, rows 7a.d and 7e.d on the one hand and rows 7b.d and 7f.d have been coalesced in this study.

Appendix B

To assess the relevance of the ANN estimators, we test them on countries that did not have to adopt a flexible exchange rate system immediately in the wake of the East crisis. We choose to test the estimators on Argentina and Chile. The choice of these countries is not fortuitous. While Chile has so far withstood speculative attacks, Argentina forsook its currency board in early January 2002, although it seemed in a better situation than Brazil in January 1999.

We choose to analyze these estimators from January 1st, 1998 to 30 January 1999. We do not carry on the estimations after January 1999 since the time lag between the training period for the estimators (July 1997 to November 1998) and the test period would be too important: this would cast doubt on the pertinence of the analyzes. Table 5 details the results of these out-of sample tests.

[Insert Table 5 Here]

Both three-month estimators give positive results for Argentina, i.e. they do not provide crisis signals. The three-month estimator where the training sample is not included in the learning sample also performs well over Chile. However, the three-month estimator where the training sample is not included gives a crisis signal from 27 August 1998 to 11 September 1998. Such a signal is however likely to be false all the more so as none of the three-month estimators performed well over Brazil and Russia.

The five-month estimator with the training sample included in the learning sample gives crisis signals for Argentina from beginning to end of the sample, but does not give any for Chile. The results obtained with five-month estimator where the training sample is not

included in the learning sample are graphed in Figure 6. This estimator provides crisis signals for several periods, all of them in the wake of the Russian crisis. This may indicate that the Russian crisis, not the East Asian crisis, weighted on the stability of the Argentinean currency board. However, this estimator does not provide a clear signal for Chile, but only very brief periods with and without speculative pressures, which are impossible to interpret.

[Insert Figure 6]

All in all, the quality of the results obtained from these out-of-sample tests is mixed. Some estimators perform rather well on one country, but never on both of them.

References

Anderson, J.A., 1995. An introduction to neural networks, MIT Press, Cambridge, MA.

Baig, T., Goldfajn, I., 1999. Financial market contagion in the Asian crisis, International Monetary Fund Staff Papers 46 (2), 167-195.

Baig, T., Goldfajn, I., 2000. The Russian default and the contagion to Brazil, IMF Working Paper n°00/160, International Monetary Fund, Washington DC.

Berg, A., Borensztein, E., Milesi-Feretti, G.M., Patillo, C., 1999. Anticipating balance-of-payments crises: the role of early warning systems, IMF Occasional Paper, International Monetary Fund, Washington DC.

Berg, A., Patillo, C. 1999a. Are currency crises predictable?, a test, IMF Staff Papers 46 (2), 107-38.

Berg, A., Patillo, C. 1999b. Predicting currency crises: the indicators approach and an alternative, Journal of International Money and Finance 18 (4), 561-586.

Berg, A., Patillo, C. 1999c. What caused the Asian crises: an early warning system approach, Economic Notes 28 (3), 285-334.

Bussière, M., Mulder C., 1999. Political instability and economic vulnerability, IMF Working Paper n°99/46, International Monetary Fund, Washington DC.

Chang, R., and A. Velasco (1998), Financial fragility and the exchange rate regime, National Bureau of Economic Research Working Paper, 6469, Cambridge, MA: National Bureau of Economic Research.

Chang, R., and A. Velasco (1999), Liquidity crises in emerging markets : theory and policy, National Bureau of Economic Research Working Paper, 7272, Cambridge, MA: National Bureau of Economic Research.

Chang, R., and A. Velasco (2000a), Financial crisis in emerging markets : a canonical model, Journal of Economic Theory, 90 (2), 1-34.

Chang, R., and A. Velasco (2000b), Banks, debt maturity and financial crises, Journal of International Economics, 51, 169-194.

Chang, R., and A. Velasco (2001), 'A Model of Financial Crises in Emerging Markets', Quarterly Journal of Economics, 116 (2001), 489-517.

Cheng, B., Titterington, D.M., 1994. Neural networks: a review from a statistical perspective, Statistical Science, 9 (1), 2-54.

Chiodo, A.J., Owyang, M.T., 2002, A case study of the currency crisis: the Russian default of 1998, Federal Reserve Bank of St. Louis 84 (6), 7-17.

Corsetti, G., Pesenti, P., Roubini, N., 1999a. Paper tigers? a model of the Asian crisis, European Economic Review, 43 (7), 1211-1236.

Corsetti, G., Pesenti, P., Roubini, N., 1999b. What caused the Asian currency and financial crisis?, Japan and the World Economy, 11 (3), 305-373.

De Bandt, O., Hartmann, P. 2000. Systemic risk: a survey, CEPR Discussion Paper n°2634.

Desai, P., 2000. Why did the ruble collapse in August 1998 ?, AEA Papers and Proceedings 90 (2), 49-52.

Diamond, D.D.W. and P.H. Dybvig (1983), Bank runs, deposit insurance, and liquidity, Journal of Political Economy, 91, 401-419.

Dornbusch, R., Park, Y.C., Claessens., S., 2000. Contagion: how it spreads and how it can be stopped, The World Bank Research Observer 15 (2), 177-197.

Duin, R.P.W., 1993. Superlearning capabilities of neural networks?, SCIA '93, Proceedings 8th of the Scandinavian conference on image analysis 1, Tromso, 547-554.

Duin, R.P.W., 1995. Small sample-sized generalizations, SCIA '95, Proceedings of the 9th Scandinavian conference on image analysis 2, Tromso, 957-964.

Duin, R.P.W., 1996. A note of comparing classifiers, Pattern Recognition Letters 17, 5, 529-536.

Efron, B., Tishbirani, R.J., 1993. An introduction to the bootstrap, Chapman & Hall, Boca Raton, FLA.

Eichengreen, B., Rose, A.K., Wyplosz, C., 1996a. Contagious Currency Crises, CEPR Discussion Paper n°1453.

Eichengreen, B., Rose, A.K., Wyplosz, C., 1996b. Exchange market mayhem :the antecedents and aftermath of speculative attacks, Economic Policy 21, 251-312.

Franco, G.H.B., 2000. The real plan and the exchange rate, Essays in International Finance, n°217, Princeton University.

Frankel, J., Rose, A.K., 1996. Currency crashes in emerging markets : an empirical treatment, Journal of International Economics 41, 351-366.

Glick, R. and M. Hutchinson (1999), Banking and currency crises : How Common are Twins ?, Federal Reserve Bank of San Francisco Center for Pacific Basin Monetary and Economic Studies, Economic Research Department Working Paper, 99-07, San Francisco, CA: Federal Reserve Bank of San Francisco.

Golden, R., 1996. Mathematical methods for neural network analysis and design, MIT Press, Cambridge, MA.

Hernández, L.F., Valdés, R.O., 2001. What drives contagion: trade, neighborhood or financial links?, IMF Working Paper n°01/29, International Monetary Fund, Washington DC.

Hornik, K., 1991. Approximation capabilities of multilayer feedforward networks, Neural Networks 4, 251-257.

Hornik, K., Stinchombe, M., White, H., 1989. Multilayer feedforward networks are universal approximators, Neural Networks 2, 359-366.

Kaminsky, G.L., Lizondo, S., Reinhart, C.M., 1998. Leading indicators of currency crises, International Monetary Fund Staff Papers, 45, 1-48.

Kaminsky, G.L. and C.M. Reinhart (1999), The twin crises : the causes of banking and balance-of-payments problems, American Economic Review, 89 (3), 473-500.

Kaminsky, G.L., Reinhart, C.M., 2000. On crises, contagion, and confusion, Journal of International Economics 51 (1), 169-181

Kaminsky, G.L., Schmukler, S.L., 1999. What triggers market jitters? a chronicle of the Asian crisis, Journal of International Money and Finance 18, 537-560.

Krugman, P. (2000), Balance sheets, the transfer problem, and financial crises, in Peter Isard, Assaf Razin and Andrew K. Rose (eds), International Finance and Financial Crises, Essays in Honor of Robert P. Flood Jr, Boston, MA : Kluiwer Academic Publishers, 31-43.

Kuan, C.M., White, H., 1994. Artificial neural networks: an econometric perspective, Econometric Reviews 13 (1), 1-91.

Maasoumi, E., Khotanzad, A. Abaye, A., 1996, Artificial neural networks for some macroeconomic series: a first report, Econometric Reviews 13 (1), 105-22.

Marion, N.P. (2000), Some parallels between currency and banking crises, in Peter Isard, Assaf Razin and Andrew K. Rose (eds), International Finance and Financial Crises, Essays in Honor of Robert P. Flood Jr, Boston, MA: Kluiwer Academic Publishers, 1-29.

Moshiri, S., Cameron, N., 2000, Neural network versus econometric models in forecasting inflation, Journal of Forecasting, 19, 201-217.

Radelet, S., Sachs, J., 1998a. The East Asian financial crisis: diagnosis, remedies, prospects, Brookings Papers on Economic Activity 1, 1-90.

Radelet, S., Sachs, J., 1998b. The onset of the East Asian crisis, NBER Working Paper n°6680.

Ripley, B.D., 1993. Statistical aspects of neural networks. In Barndoff-Nielsen O.E., Jensen J.L., Kendall W.S. (Eds), Networks and chaos - statistical and probabilistic aspects, Chapman and Hall, London, 40-123.

Rosenblatt, F. 1958. The perceptron: a probabilistic model for information storage and organization in the brain, Psychological Review 65, 386-408.

Rosenblatt, F. 1962. Principles of neurodynamics: perceptrons and the theory of brain mechanisms, Spartan, Washington DC.

Rumelhart, D.E, Hinton, G.E., Williams, R.J., 1986. Learning internal representations by error propagation. In Rumelhart, D.E., McClelland, J.L., and the PDP Research Group (Eds.), Parallel distributed processing, Vol. I, MIT Press, Cambridge, MA, 318-362.

Sachs, J., Tornell, A., Velasco, A., 1996. Financial crises in emerging markets: the lessons from 1995, Brookings Papers on Economic Activity 1, 147-215.

Schmied, A., 2002. A note on modeling monthly and daily data in supervised learning systems, Mimeo, Université Paris-XII.

Schneider, M. and A. Tornell (2001), Boom-Bust Cycles and the Balance-Sheet Effect, Working Paper, UCLA.

Stock, J.H., Watson, M.W., 1996. Evidence on structural instability in macroeconomic time series relations, Journal of Business and Economic Statistics, 14 (1), 11-30.

Swanson, N., White, H., 1997. A model selection approach to real-time macroeconomic forecasting under linear models and artificial neural networks, The Review of Economic and Statistics, 540-550.

Tornell, A., 1999. Common fundamentals in the Tequila and Asian crises, NBER Working Paper n°7139.

White, H., 1989. Learning in artificial neural networks: a statistical perspective, Journal of the American Statistical Association 87, 1252.

Table 1. Country and sub-period classification

	3-month data sample		5-month data sample	
	Beginning and end dates of the tranquility period	Beginning and end dates of the speculative pressure period	Beginning and end dates of the tranquility period	Beginning and end dates of the speculative pressure period
Learning sample				
Thailand	02-Apr-1996 - 02-Apr-1996	02-Apr-1997 - 02-Jul-1997	02-Feb-1996 - 02-Apr-1996	02-Feb-1997 - 02-Jul-1997
Indonesia	11-Apr-1996 - 11-Jul-1996	11-Apr-1997 - 11-Jul-1997	11-Feb-1996 - 11-Jul-1996	11-Feb-1997 - 11-Jul-1997
The Philippines	11-Apr-1996 - 11-Jul-1996	11-Apr-1997 - 11-Jul-1997	11-Feb-1996 - 11-Jul-1996	11-Feb-1997 - 11-Jul-1997
Malaysia	12-Apr-1996 - 15-Jul-1996	14-Apr-1997 - 14-Jul-1997	12-Feb-1996 - 15-Jul-1996	14-Feb-1997 - 14-Jul-1997
Validation sample				
Singapore	10-May-1996 - 12-Aug-1996	12-May-1997 - 12-Aug-1997	12-Mar-1996 - 12-Aug-1996	12-Mar-1997 - 12-Aug-1997
Taiwan	19-Jul-1996 - 21-Oct-1996	18-Jul-1997 - 20-Oct-1997	20-May-1996 - 21-Oct-1996	20-May-1997 - 20-Oct-1997
South Korea	21-Aug-1996 - 21-Nov-1996	21-Aug-1997 - 21-Nov-1997	21-Jun-1996 - 21-Nov-1996	20-Jun-1997 - 21-Nov-1997
Test sample				
Russia	-	01-Jan-1998 - 14-Aug-1998	-	01-Jan-1998 - 14-Aug-1998
Brazil	-	01-Jan-1998 - 11-Jan-1999	-	01-Jan-1998 - 11-Jan-1999

Table 2. Training specification and results

The validation sample is included in the learning sample	Number of neurons on the first and second hidden layers	Maximum number of epochs	Step	Epoch number when the goal is reached	Mean Square Error	Gradient
3-month sample period, backpropagation training algorithm						
Error goal 0,001						
Yes	15,12	4000	1	774	0.000099451/0.001	0.0123805/1e-006
No	7,5	4000	1	729	0.000998153/0.001	0.027247/1e-006
5-month sample period, backpropagation training algorithm						
Error goal 0,001						
Yes	15,12	4000	1	1695	0.00099973/0.001	0.15253/1e-006
No	10,7	1000	1	507	0.000099455/0.001	0.0717818/1e-006

Table 3. Training specification and simulation results

The validation sample is included in the learning sample	Do the simulation results fit the validation sample data ?
3-month sample period, backpropagation training algorithm	
Goal 0,001	
Yes	Yes
No	No
5-month sample period, backpropagation training algorithm	
Goal 0,001	
Yes	Yes
No	No

Table 4. Training simulation and test results

The validation sample is included in the learning sample	Crisis Signal in Russia	Crisis Signal in Brazil
3-month sample period, backpropagation training algorithm		
Goal 0,001		
Yes	No	No
No	No	No
5-month sample period, backpropagation training algorithm		
Goal 0,001		
Yes	From 06-Mar-1998 to 14-Apr-1998	From 01-Jan-1998 to 21-Jan-1998 and from 27-Aug-1998 to 11-Jan-1999
No	From 01-Jan-1998 to 14 Aug-1998	From 06-Apr-1998 to 04-Nov-1998

Table 5. Training simulation and results on Argentinean and Chilean data

	The validation sample is included in the learning sample	Crisis Signal in Argentina	Crisis Signal in Chile
3-month sample period, backpropagation training algorithm			
Goal 0,001			
	Yes	No	No
	No	No	From 27-Aug-1998 to 11-Sep-1998
5-month sample period, backpropagation training algorithm			
Goal 0,001			
	Yes	From 01-Jan-1998 to 30-Jan-1999	No
	No	From 18-Aug-1998 to 22-Sep-1998, from 29-Sep-1998 to 9-Oct-1998, from 27-Nov-1998 to 9-Dec-1998 and from 21-Dec-1998 to 30-Jan-1999	No clear pattern

Fig. 1. The architecture of the multilayer perceptron with two hidden layers.
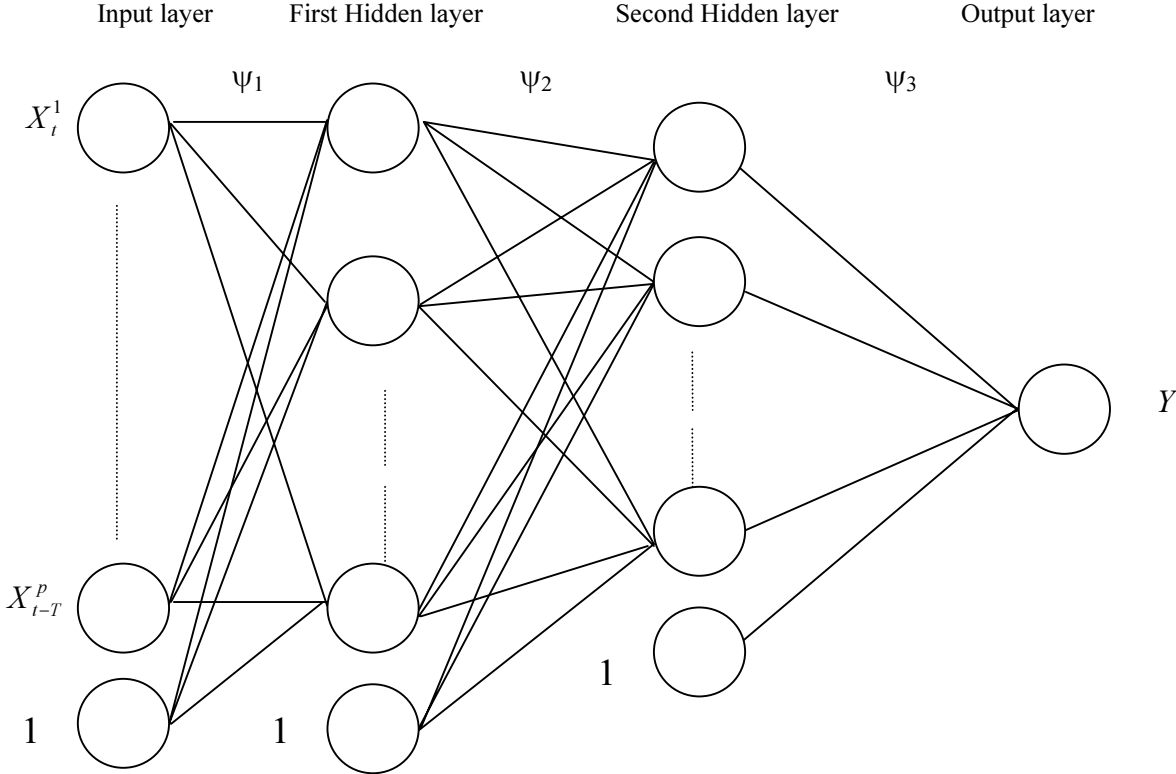
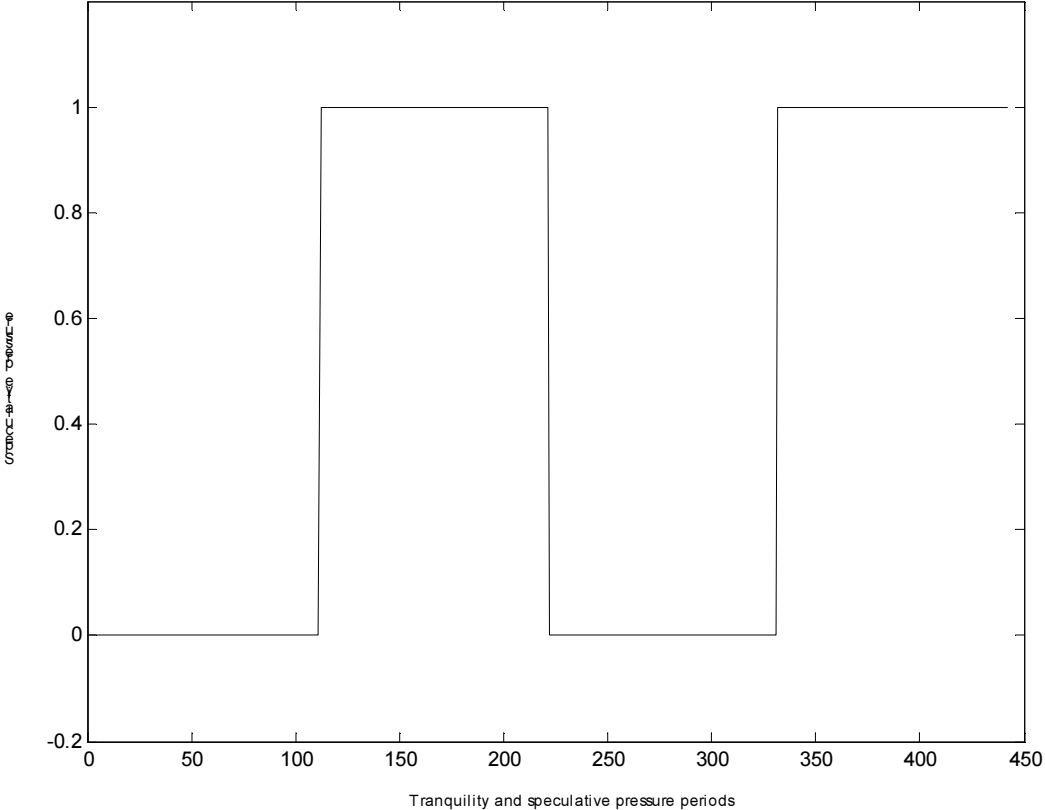Fig. 2. The absolute validation data set (five-month sample).

Fig. 3. Simulation on the validation sample of the estimator in which the validation data is not included in the learning process (five-month sample).
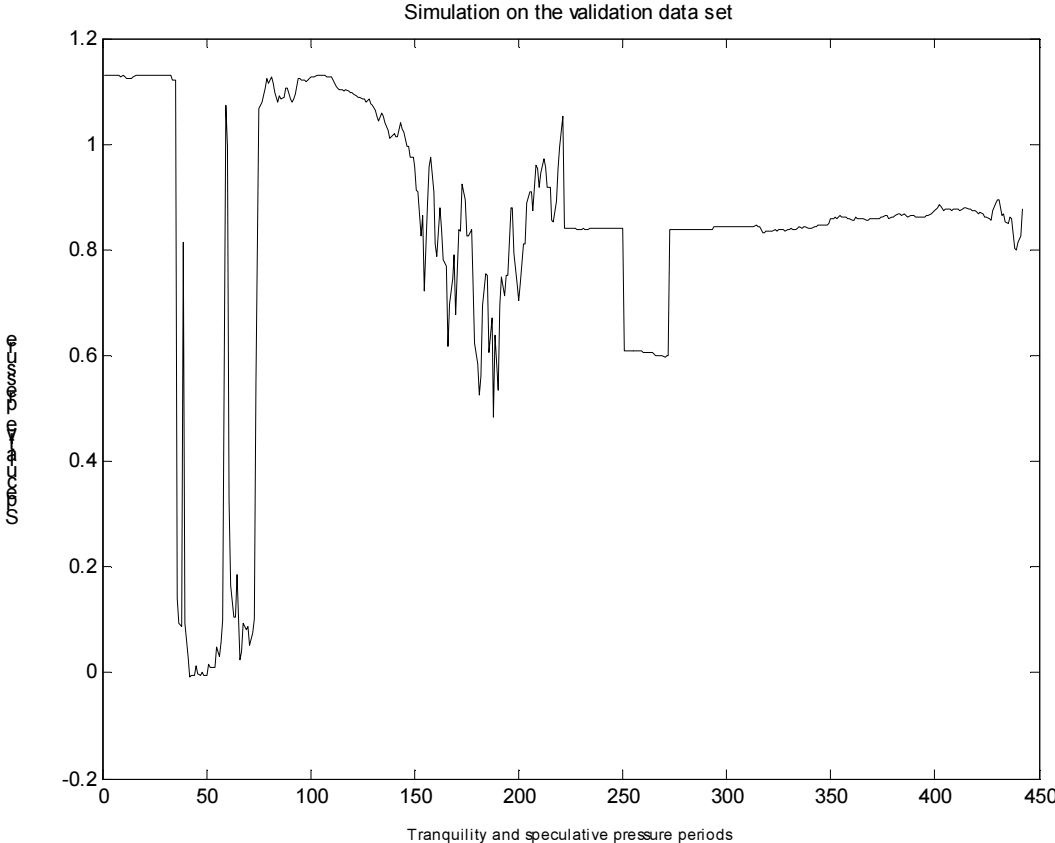
Fig. 4. Test results on Russian and Brazilian data of the estimator in which the validation

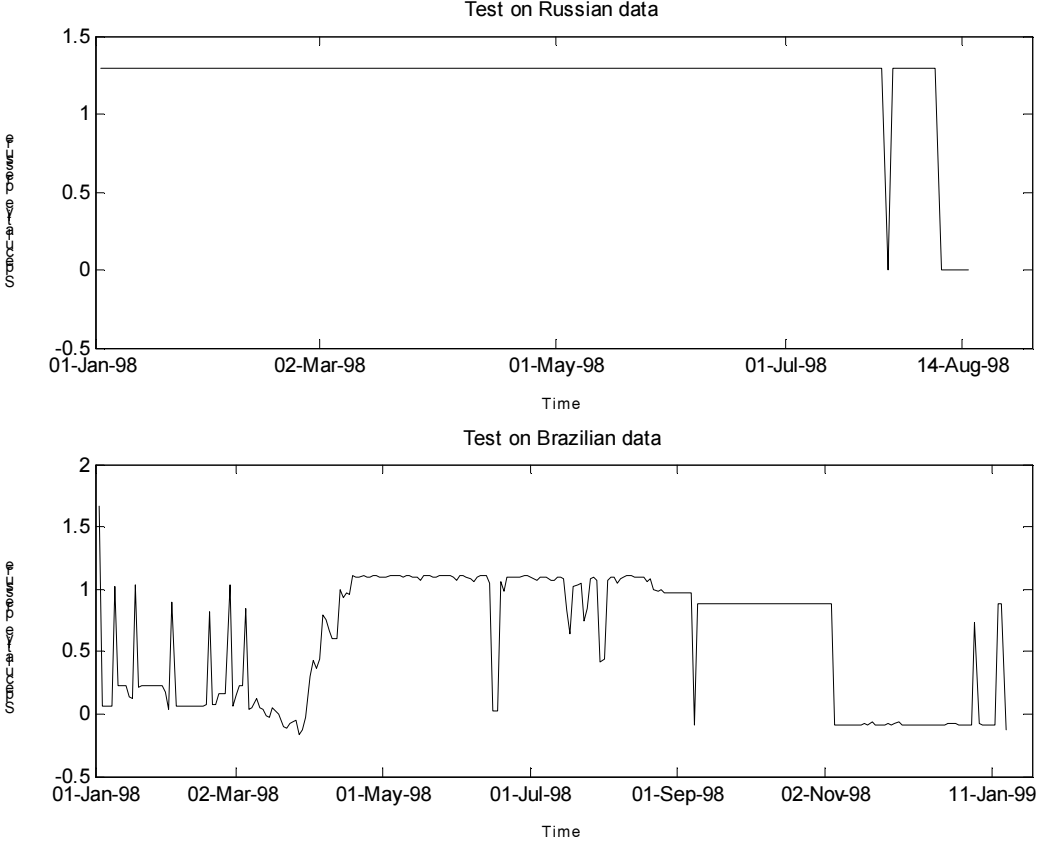sample is not included in the learning process (five-month sample).

Fig. 5. Test results on Russian and Brazilian data of the estimator in which the validation sample is not included in the learning process (five-month sample) and where a threshold function is applied.
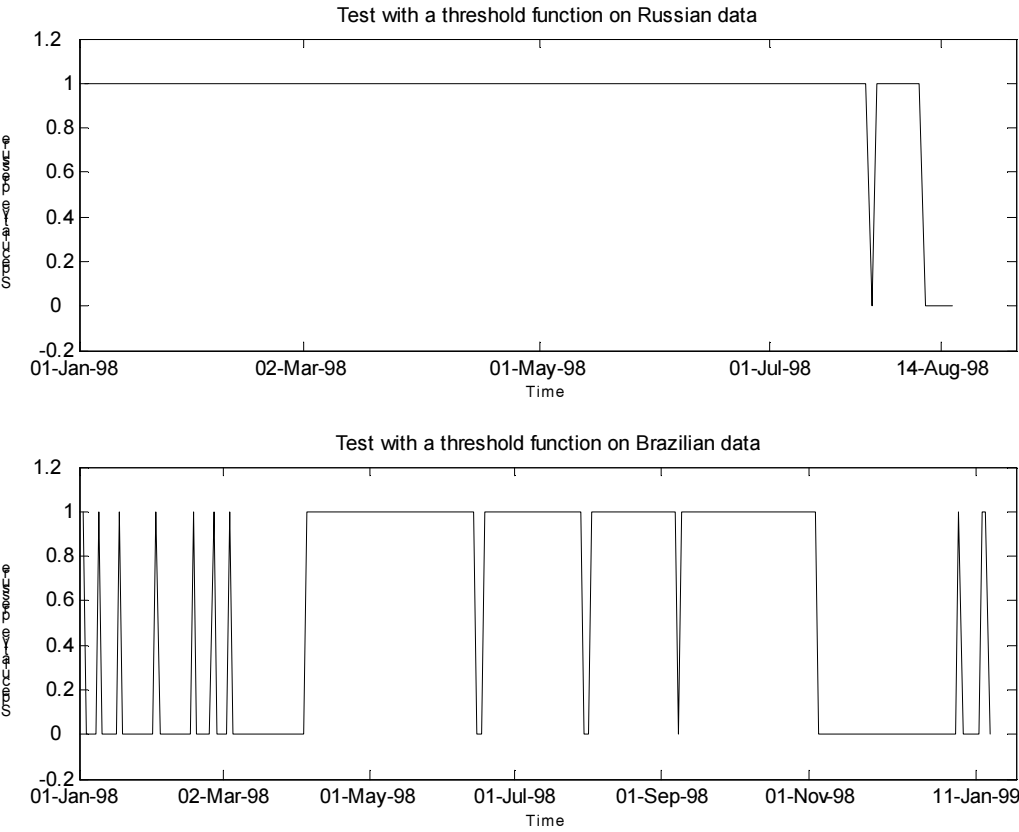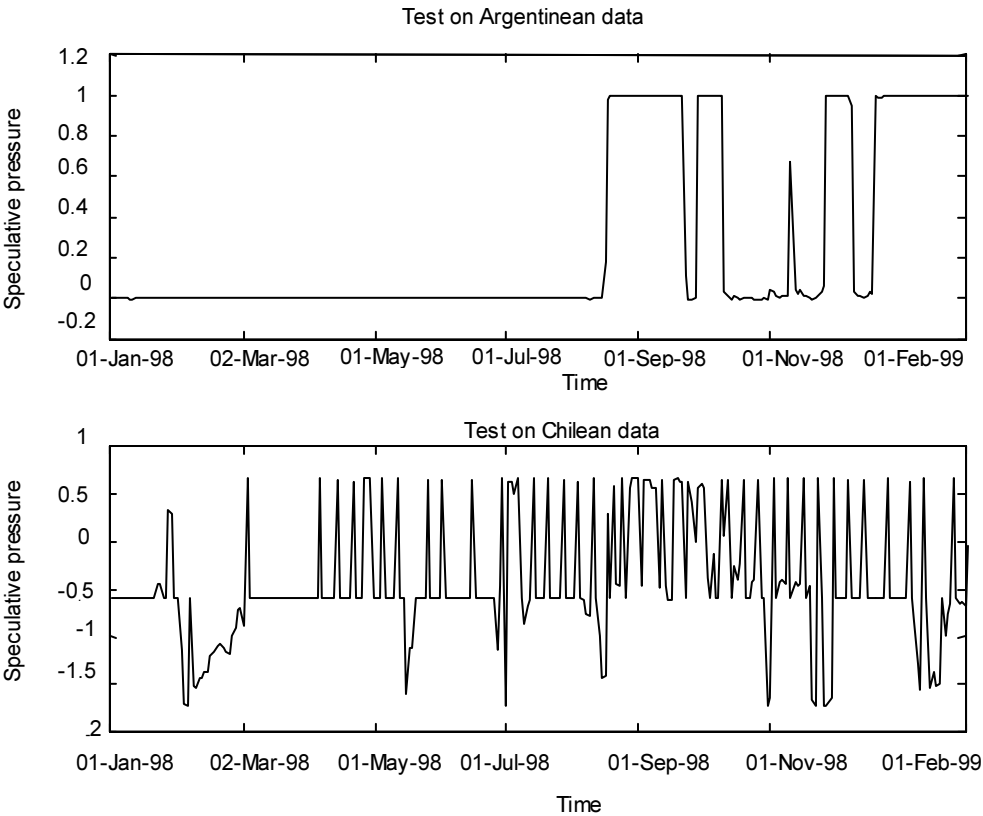
Fig. 6. Test results on Argentinean and Chilean data of the estimator in which the validation

sample is not included in the learning process (five-month sample) and where a threshold

function is applied.

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