Could the Kaminsky-Reinhart Model Have Predicted the 2002 Uruguayan Currency and Banking Crises?

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Abstract

Because currency and banking crises cause substantial and prolonged disruptions to an economy, economists have long sought ways to predict these events in advance. One recent theory advanced is the “leading indicators” approach of Kaminsky (1998) and Kaminsky and Reinhart (1999). Kaminsky (1998) presents four separate composite indicators, and Kaminsky and Reinhart (1999) refines the model. This paper provides one test of this theory by analyzing the currency and banking crises that arose in July 2002 in Uruguay. This study tests the efficacy of these indicators by analyzing the behavior of the indicators in the months directly preceding the Uruguayan crises. In general, three indicators performed reasonably well, while one had exceptional predictive power.

I. Introduction

Prevention of an adverse event often depends on the ability to predict the crisis in advance so that policy makers can devise strategies to avoid an economic downturn. One such catastrophe which may require policy intervention is known as a "twin crisis," which is defined as the occurrence of a currency crisis[1] and a banking crisis[2] in quick succession. These events are associated with substantial contractions in economic activity. For example, Hutchison and Noy (2005) present evidence that the cumulative output loss of such an event averages around 10% of GDP. Clearly, then, it is imperative to develop models which predict when such events are likely to occur, ideally far enough in advance that some change in macroeconomic policy can avert the crisis.

One such crisis occurred in Uruguay in July 2002. As *The Economist* reports, the Argentinean financial system's collapse in late 2001 led Argentines to withdraw deposits from Uruguay's banks ("Victim of Contagion," 2002). Fearing a freeze on deposits, Uruguayans then withdrew their money from banks, and the country was forced to abandon a currency-band scheme, resulting in a serious depreciation of its currency[3]. Since much of Uruguay's debt was dollar-denominated, the currency devaluation created serious strain in the financial system.

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[1] A currency crisis, sometimes called a balance-of-payments crisis, is informally defined as when a country experiences a precipitous depreciation of its currency, a severe depletion of its international reserves, or both of these events simultaneously.

[2] "Banking crisis" is a notoriously difficult term to define. Calomiris and Gorton (1991) discuss how much of the empirical literature on banking crisis in fact turns on the precise definition used. Generally, though, these crises feature either "runs" on banks or the closure, merger, or substantial government involvement in major financial institutions. More precise definitions of both "currency crisis" and "banking crisis," in the context of the Kaminsky-Reinhart model, will follow in section III.

[3] A currency-band system is an arrangement in which the country sets a range, or "band" of values in which the currency is allowed to trade. In practice, the arrangement is similar to a fixed exchange rate, and often has similar benefits and drawbacks.

The Uruguayan crisis was not entirely unanticipated. *The Economist* pointed out that Uruguay loosened its currency's "crawling peg" twice in the course of a year prior to the collapse[4] ("Stormy Summer," 2002). The declining currency put substantial stress on the country's debtors, and the International Monetary Fund warned that annual losses at the state-owned mortgage bank made reform "urgent." Investors' uncertainty over neighboring Brazil's presidential politics, particularly the prospect of leftist Luiz Inacio Lula da Silva's election, further weakened Latin American financial and currency systems. Finally, these events forced Uruguay to close its banks, fearing a bank run[5] ("Panic Comes Calling," 2002).

The twin crisis had a devastating effect on the Uruguay's economy. While GDP had been falling for several years, due primarily to turbulent events in Argentina and Brazil, the country's major trading partners, the events of 2002 caused a massive contraction in the economy. The *CIA World Factbook* reports that unemployment rose to nearly 20 percent, inflation skyrocketed, and the external debt burden doubled. These tremendously negative effects point out the need for effective mechanisms to predict, and then prevent, these twin crises.

One effort at constructing such a predictive model is that developed in a series of papers: Kaminsky et al. (1998); Kaminsky (1998); and Kaminsky and Reinhart (1999). The final two are the most important for this study, as they deal specifically with twin crises, where the first is concerned mostly with currency crises. Principally, Kaminsky (1998) addresses the theoretical construction of a predictive model, while Kaminsky and Reinhart (1999) refine the model by eliminating certain variables which do not seem to

[4] A crawling-peg refers to adjusting the exchange rate in small increments over time, rather than with a major devaluation or revaluation.
[5] De la Plaza and Sirtaine (2005) provide a helpful summary of activity in the banking sector.

have strong predictive power. A fuller discussion of the Kaminsky-Reinhart model can be found in section III of this paper, but a brief description of the methodology follows: First, the crisis window is set at 24 months; that is, the signals of an upcoming crisis should occur within this period. Next, a wide variety of economic data known to be related to currency and banking crises are collected, and a signal is indicated if any of the economic variables stray far from the normal values for that country. A further measure considers whether macroeconomic indicators are deteriorating continuously, as opposed to a small blip in the data. Yet another indicator adjusts these measures for noise in the data—that is, how often a signal indicates a crisis but none occurs, or when that variable fails to signal a crisis. Finally, this information is used to create a conditional probability of a currency or banking crisis occurring within a specified time window. Kaminsky (1998) and Kaminsky and Reinhart (1999) tested the model with out-of-sample data from the East Asian crises of 1997, but currency and banking crises since then, such as those of Latin America in the early 2000s, offer an opportunity to analyze the model with new data.

Indeed, one of those crises, the Argentinean crisis of 2001-2002, has already been examined using the Kaminsky-Reinhart model[6]. But, as Alvarez-Plata and Schrooten (2004) argue, the model failed to predict this crisis particularly well, as the composite indicators did not move in the desired direction. More specifically, according to the authors, indicators started to send signals too late for a successful policy intervention. Also, they find that the trend of many indicators was unclear directly before the crisis.

[6] Technically, Alvarez-Plata and Schrooten (2004) use Kaminsky et al. (1998), which is only a model predicting currency crises; however, the model is extremely similar to the one the present paper analyzes.

The present paper offers another test of the Kaminsky-Reinhart model, this time with new data from the Uruguayan crises of 2002. This study finds that the Uruguayan crisis could have been predicted reasonably well by the indicators. In particular, the first, second, and fourth composite indicators for both currency and banking crises were well above the mean for that indicator over the previous 100 months for much of the period directly preceding the crises. The third composite indicators actually achieved their maximums over the studied period in June 2002, one month before the crises, which is a very good result for the theory. The Kaminsky-Reinhart model was therefore reasonably accurate in predicting the Uruguayan twin crisis of 2002.

Section II of this paper reviews the relevant literature on currency and banking crises. Section III is divided into two subsections. The first subsection establishes a theoretical justification for the use of certain variables in the Kaminsky-Reinhart model. The second subsection describes the construction of specific indicators in Kaminsky (1998). Section IV summarizes the data used in this study. Section V analyzes the Uruguay data to establish the effectiveness of the model in signaling the onset of this particular crisis. Finally, section VI summarizes the findings and discusses the implications of this research.

II. Literature Review

Many theoretical models and empirical analyses of currency and banking crises have been created in the last quarter century. The literature on their interaction, that is, twin crises, is not as substantial, although it has been growing, especially in the past decade. There are even fewer models focusing on predicting these events in advance. The models that have been created are mostly of recent origin, so there have not been many chances to test them with out-of-sample data, since crises do not generally occur with great frequency. One influential model is the signals approach of Kaminsky (1998), and this paper tests that model with heretofore unused data, the Uruguayan crisis of 2002.

"First-generation models" of currency crises, epitomized by Krugman (1979), focus on macroeconomic fundamentals as the principal causes of currency crises. In Krugman's model, countries which attempt to peg the exchange value of their currencies find that foreign reserves are exhausted in a futile effort to defend the peg. This effort occurs primarily because countries are unwilling to let the currency appreciate due to the high cost of domestic inflation. At some point, usually far before the country's reserves would have been completely depleted, there is a speculative attack eliminating the reserves, and the country is forced to abandon the exchange rate. Kaminsky et al. (1998) emphasize variations on this model focusing on changes in economic fundamentals as the principal causes of currency crises.

So-called "second-generation models" focus instead on self-fulfilling balance-of-payments crises—in these models, there need not be any particular macroeconomic flaw that forces abandonment of an exchange-rate peg; rather, an equilibrium can arise in which individuals *think* there will be a crisis, which in fact precipitates a crisis. Obstfeld (1986) is one influential model of this kind. Building from Flood and Garber (1984), which focused on self-fulfilling attacks during a gold standard, Obstfeld argues that the economy actually possesses a continuum of equilibria, where each equilibrium corresponds to a subjective judgment of the likelihood of an exchange rate collapse. In this model, expected government actions can lead to undesired outcomes which would not emerge otherwise. Obstfeld (1996) considers this model after events in the early 1990s put great stress on the European Exchange Rate Mechanism and concludes that high unemployment may cause a crisis with self-fulfilling features, and that other "fundamentals" may have self-fulfilling components.

Ozkan and Sutherland (1995) develop a model where the abandonment of a fixed exchange rate results from an optimizing policy maker desiring to loosen monetary policy. This model has some similarities with both Krugman (1979) and Obstfeld (1986). Like Krugman, crises are triggered by a fundamental variable, though in this case it is a demand shock, rather than reserves. Likewise, there is a similarity to Obstfeld in that it is possible to have the self-fulfilling attacks and multiple equilibria that are the salient aspects of the Obstfeld model.

Frankel and Rose (1996) attempt to empirically determine the variables related to currency crises. Using annual data from over 100 countries and over two decades, they conclude that crashes usually occur when foreign direct investment inflows cease, when reserves are depleted, when the growth of domestic credit is high, when northern countries' (i.e., developed economies') interest rates rise, and when the real exchange rate is overvalued. Recessions also tend to be associated with currency crises. Though this is not an effort to generate a predictive model of currency crises, the work anticipates Kaminsky et al. (1998), Kaminsky (1998), and Kaminsky and Reinhart (1999) in that the researchers use a broad dataset to empirically estimate which factors proposed by theorists actually seem to be related to real-world events.

As Kaminsky and Reinhart (1999) point out, while many countries have experienced currency crises and major banking crises at the same time, the literature on their interactions—that is, twin crises—has been limited. Nevertheless, some studies have tried to model the twin crises phenomenon. Takeda (2004) argues that small depositors and a large trader engage in a simultaneous game. The mere presence of this trader makes small depositors more likely to withdraw money from a bank and hence precipitate a banking crisis, along with a balance-of-payments crisis. This effect becomes particularly pronounced when there is a substantial information discrepancy between the trader and the depositors. Goldfajn and Valdés (1996) also analyze the twin crisis phenomenon. In their model, movements in the real exchange rate are instrumental in correcting an "overvaluation" in a currency. These swings in the currency can cause an exaggerated business cycle, which ultimately leads to financial instability, sometimes concluding in a financial crisis. Finally, McKinnon and Pill (1996) present evidence that the currency and banking features of a twin crisis have similar causes. They argue that liberalizing countries suffer from "overborrowing," which is followed by a financial crisis. The same factors that lead to overborrowing allow greater financing from abroad, which causes a current account deficit and ultimately leads to a currency crisis.

There are two particularly interesting questions surrounding the twin crisis experience. First, there is the issue of whether the two phenomena are causally linked, as argued in Goldfajn and Valdés (1996), or whether such a connection is merely an artifact of similar macroeconomic fundamentals, as in McKinnon and Pill (1996). Several possible explanations for this link are offered. First, Stoker (1994) argues that an external shock will cause a loss of reserves but could also lead to a credit problem and finally a financial crisis. Velasco (1987) argues the opposite direction of causality, where central banks support ailing financial institutions with money creation, and the currency collapses according to Krugman's classic model. Kaminsky and Reinhart (1999) present evidence that there is indeed a vicious circle linking the events: banking crises often follow financial liberalization. A second question is whether the output losses are particularly severe for these events. This question has attracted still less study than has the existence of twin crises. Kaminsky and Reinhart (1999) demonstrate that severity of both balance-of-payments crises and banking crises are aggravated when the two events occur within a short time frame. However, this does not prove that there are particularly negative feedback effects between the two crises. Hutchison and Noy (2005) argue that while both currency and banking crises have severely negative effects on the economy, there is no conclusive evidence of any feedback or interactive elements where the two crises form a downward spiral. In other words, while a twin crisis does cause large declines in GDP, this appears to be the result of the additive effects of the two events, not a result of a vicious circle.

The literature discussed so far is concerned primarily with theoretical explanations for currency and banking crises and with empirical evidence of the features of crises. An effort at constructing a predictive model is that of Kaminsky et al. (1998); Kaminsky (1998); and Kaminsky and Reinhart (1999). Kaminsky et al. (1998) is concerned with currency crises, but Kaminsky (1998) and Kaminsky and Reinhart (1999) address the theoretical construction of a predictive model for twin crises and the selection of variables to be used in the model. Both papers tested the model with out-of-sample data from the 1997 East Asian crises.

Finally, Alvarez-Plata and Schrooten (2004) test whether the Kaminsky et al. (1998) "early warning system" could have accurately predicted the collapse of the

Argentinean peso in 2002. They find that neither the fragility index—that is, an indicator of the number of economic fundamentals signaling a crisis—nor the composite indicators accurately forecasted the Argentinean crisis. Even the signals that did correctly indicate a crisis were too late for a successful policy intervention to take place. Finally, the trend of many indicators was unclear directly before the crisis. Alvarez-Plata and Schrooten (2004) speculate that perhaps expectations might have played a role in the Argentinean crisis, and these expectations would not appear explicitly in standard macroeconomic data, or that non-economic factors such as corruption or political turmoil might be necessary to understand this crisis.

Though Alvarez-Plata and Schrooten (2004) make an important contribution to the literature, one cannot conclude that the Kaminsky-Reinhart model should be dismissed on the basis of a single failure. This paper then seeks to extend our understanding of this model by testing it with a different data set, the 2002 Uruguayan crises.

III. The Kaminsky-Reinhart Signals Approach

Defining a crisis

Before proceeding with the construction of the model, it is necessary to formally define a twin crisis, as in Kaminsky and Reinhart (1999). Currency crises are usually resolved through a devaluation of the currency, or by floating the exchange rate; however, central banks can resort to monetary policy or foreign-exchange market intervention to fight a speculative attack. In the latter cases, the currency market turbulence can be seen in increases in domestic interest rates and loss of foreign-exchange reserves. Therefore an index of currency market turbulence is created to capture these manifestations of speculative attacks[7]. A banking crisis is said to begin either when a bank run leads to the closing, merger, or public takeover of at least one financial institution, or when an important financial institution experiences closure, merging, takeover, or large-scale government assistance that marks the beginning of a string of similar outcomes for other financial institutions. Finally, a twin crisis occurs when the beginning of a banking crisis is followed by the beginning of a currency crisis within a period of 48 months.

Selecting variables

In this section, the "signals" approach to predicting twin crises is described. This paper focuses initially on Kaminsky and Reinhart (1999), as the theory describing which variables should be used is most fully developed in this paper. Kaminsky and Reinhart (1999) survey the literature to find which economic variables might be associated with twin crises. Since their interest is in predicting these events, not constructing a theory to explain twin crises, they do not concern themselves with the fact that some of the theories behind selecting certain variables may not necessarily agree. All chosen variables, however, are believed to exhibit anomalous behavior in the periods preceding a twin crisis. When variables exceed a threshold, this is a "signal" that a crisis might occur within a specified time window, in this case, 24 months. Thresholds are selected on an

[7] Formally, the index, denoted by I, is a weighted average of the rate of change of the exchange rate, Δ_e / e, and of reserves, Δ_R / R, weighted such that the two components have equal sample volatilities. Therefore, $I = \frac{\Delta_e}{e} - \frac{\sigma_e}{\sigma_R} \cdot \frac{\Delta_R}{R}$, where σ_e is the standard deviation of the rate of change of the exchange rate and σ_R is the standard deviation of the rate of change of reserves. When the value of I is three standard deviations or more above the mean, the event is classified as a crisis.

indicator-by-indicator basis by finding the value that minimizes the noise-to-signal ratio. Either the upper or lower tail of the distribution is used for each indicator depending on the particular theoretical characteristics of the variable. Kaminsky and Reinhart (1999) divide 16 variables into four sectors: the financial sector, the external sector, the real sector and the fiscal sector. These are summarized in table 1.

In the financial sector, seven variables are used. First, the M2 multiplier[8] and the ratio of domestic credit to GDP are selected because of McKinnon and Pill's (1996) "boom-bust cycle" theory that twin crises are linked to rapid growth in credit and the monetary aggregates. The real interest rate and ratio of commercial lending to bank deposits ("lending-deposit ratio") are used because of their clear relationship with banking crises—financial deregulation, which indicates risk-taking, is associated with increased interest rates. Likewise, Kaminsky and Reinhart (1999) point out that an increase in the lending-deposit rate ratio often indicates a decline in loan quality. The effect on the currency is uncertain—first, high interest rates might reflect a risk premium associated with fears of a currency crisis; however, low interest rates might indicate a "loose" monetary policy, which Krugman (1979) hypothesizes as a cause of currency crises. Likewise, another variable used is excess M1 reserves, which is an indication of loose monetary policy, as demonstrated by Krugman (1979). The ratio of M2 to reserves is chosen due to Calvo and Mendoza's (1996) demonstration of aberrant behavior of this variable preceding the 1994 collapse of the Mexican peso. Finally, bank deposits are chosen because Goldfajn and Valdés (1995) point out that capital flight and domestic bank runs precede twin crises.

[8] That is, the ratio of M2 to base money

The six external values under consideration are divided into those related to the current account and those concerning the capital account. Measures of exports, terms of trade, and the real exchange rate are all chosen because overvaluations of the real exchange rate are central to a currency crisis and place strain on the financial sector—a decline in competitiveness and external markets leads to recession, business failures, and a decline in the quality of loans. Also, imports are selected as a variable, although it is uncertain where the rejection region should be placed—rapid import growth could indicate a booming economy, or it might indicate an overvaluation of the currency. Accordingly, both positive and negative shocks are explored. The variables concerning the capital account are reserves and real interest-rate differential, for the same reasons as bank deposits and real interest rates.

Real sector variables under consideration are output and stock prices. Their inclusion is justified by Calomiris and Gorton's (1991) demonstration that recessions and steep declines in asset prices precede financial crises. Finally, the only fiscal sector variable used is the ratio of budget deficit to GDP. This is because of Krugman's (1979) theory that loose financial policy is financed by the central bank.

Table 1

Variables used in Kaminsky and Reinhart (1999)

Financial sector	*External sector*	*Real sector*	*Fiscal sector*
M2 multiplier Domestic credit/GDP Real interest rate Lending-deposit credit ratio Excess M1 balances M2/reserves Bank deposits	Exports Terms of trade Real exchange rate Imports Reserves Real interest-rate differential	Output Stock prices	Deficit/GDP

Source: Kaminsky and Reinhart (1999)

Constructing the model

The most obvious way to capture the fragility of an economy is simply to add the number of signals of distress—presumably, the greater the number of different sectors for which variables exceed their respective thresholds, the higher the odds of a crisis.[9] Let X be a vector of n indicators, so in any particular period, there may be anywhere from zero to n signals. Therefore, the first composite indicator, I_t^1, is as follows:

(1) $$I_t^1 = \sum_{j=1}^{n} S_t^j$$

[9] The following presentation is drawn largely from Kaminsky (1998); for readability, the citations are dropped for the remainder of this section. The present author added some elaboration and numerical examples.

where $S_t^j = 1$ if the value of variable j (X_t^j) crosses its threshold ($\overline{X}^j$) in period t, and zero otherwise[10]. Note that I_t^1 can take integer values between zero and n, since the indicator is a sum of n numbers which equal either one or zero.

Simply summing the number of signals, however, does not discriminate between mildly abnormal behavior and extreme aberrations. To account for this, the second composite indicator uses two separate thresholds for each variable: $\overline{X}_m^j$, the mild threshold, and $\overline{X}_e^j$, the extreme threshold. For example, suppose the critical region for the ratio of deficit to GDP is the top 20 percent of the frequency distribution. An extreme signal is one in the top half of this region, so any value from the eightieth to the ninetieth percentile is classified as a mild signal, while one in the top decile is an extreme signal. More formally, X_t^j issues a mild signal in period t, that is, $SM_t^j = 1$ when $\left|\overline{X}_m^j\right| < \left|X_t^j\right| < \left|\overline{X}_e^j\right|$ and zero otherwise. Likewise, an extreme signal is indicated when the variable crosses the extreme threshold, or $SE_t^j = 1$ when $\left|\overline{X}_e^j\right| < \left|X_t^j\right|$ and zero otherwise. Therefore, the second composite indicator, I_t^2, is defined as:

(2) $$I_t^2 = \sum_{j=1}^{n} (SM_t^j + 2 \cdot SE_t^j)$$

It is immediately apparent that extreme signals have twice the weight of a mild signal, because of the arbitrary selection to multiply SE_t^j by 2. The index can therefore take integer values between 0 and 2n.

[10] Thresholds are set to minimize the noise-to-signal ratio. The present study uses the empirical noise-to-signal ratios from Kaminsky (1998) for every variable except the budget deficit-GDP ratio, for which Kaminsky and Reinhart (1999) is used.

However, an economy may be vulnerable without many of the indicators jointly signaling a crisis every month. For example, suppose the stock market in a country plunges in January, the real interest rate skyrockets in February, and bank deposits collapse in March. It would make little sense to assert that at the end of March the only sign of a crisis was the fall in bank deposits. Clearly this economy has serious problems, yet neither I_t^1 nor I_t^2 captures this ongoing deterioration in fundamentals. To address this shortcoming, let $S_{t-s,t}^j = 1$ if the variable *j* has signaled once either in period *t* or in any of the previous *s* periods, and zero otherwise. In this model, *s* is arbitrarily set equal to eight; however, the exact number matters little—in fact, there is evidence that the average number of signals in the last six months of the crisis window differs little from the average of the first six months. The third composite indicator, I_t^3, is therefore:

(3) $$I_t^3 = \sum_{j=1}^{n} S_{t-s,t}^j$$

This indicator can also take values from zero to *n*, as it is a sum of *n* numbers equaling either zero or one.

These three composite indicators, however, do not account for the different forecasting ability of each variable. Therefore, ω is defined as the noise-to-signal ratio. More precisely, ω is the following:

(4) $$\omega = \frac{\beta}{1 - \alpha}$$

where α is the size of the type I error (rejecting the null hypothesis of crisis when in fact there is a crisis) and β is the size of type II error (accepting the null hypothesis of crisis when in fact there is none). More precisely, α and β are functions of the threshold $\overline{X}^j$, with $\alpha'(\left|\overline{X}^j\right|) > 0$ and $\beta'(\left|\overline{X}^j\right|) < 0$. The fourth composite indicator, I_t^4, can therefore be constructed by weighting the signals by the inverse of their noise-to-signal ratio as follows:

$$(5) \qquad I_t^4 = \sum_{j=1}^{n} \frac{S_t^j}{\omega^j}$$

where ω^j is the noise-to-signal ratio of variable *j*. For example, suppose that variable *j* had a noise-to-signal ratio equaling two, or $\omega^j = 2$. Then if $S_t^j = 1$, I_t^4 is increased by $\frac{1}{2} = 0.5$ on account of variable *j*. In principle, this indicator can take on any rational value from zero to infinity[11].

By using the empirical joint distribution of the indicators and the empirical distribution of crises, the author constructs a sample-based vector of conditional probabilities for both banking and currency crises for each composite indicator by the following:

$$(6) \qquad P(C_{t,t+h} \mid I_i^k < I_t^k < I_j^k) = \frac{\textit{Months with } I_i^k < I_t^k < I_j^k \textit{ and a crisis within h months}}{\textit{Months with } I_i^k < I_t^k < I_j^k}$$

where P denotes probability, $C_{t,t+h}$ is the occurrence of a crisis in the interval [t, t + h], and k = 1, 2, 3, 4. For example, suppose that one wanted to find out the probability of a crisis in the next eight months when indicator I_t^3 has a value between 10 and 12. This can

[11] In fact, if β equals zero, $\omega = \frac{\beta}{1-\alpha} = \frac{0}{1-\alpha} = 0$, making it impossible to calculate the indicator, since doing so would involve dividing by zero. In practice, however, the rejection range is not set so high that there are no false alarms; and, of course, if such a perfectly-predicting variable existed, then this model would be superfluous—one could just use that variable to predict crises.

be done by summing the number of months where I_t^3 was between 10 and 12 *and* a crisis occurred within eight months, and dividing this by the *total* number of months where I_t^3 was between 10 and 12.

Two tests are implemented to evaluate the accuracy of the composite indicators. Both of these methods evaluate the average closeness of predicted probabilities to observed realizations. The first test is the quadratic probability score, which calculates the difference between the probability and a dummy equaling one for crisis periods and zero otherwise, and then squares this result, so that any difference is positive[12]. The other scoring rule is the log probability score, which depends on the natural logarithm of the probability forecast and therefore punishes large mistakes more than the quadratic probability score.

Regardless of the actual test used, composite indicator 4, which adjusts for the noise-to-signal ratio of the variables, performs the best; that is, it makes fewer forecasting errors than the other indicators. As such, Kaminsky (1998) gives conditional probabilities of currency and banking crises based on this indicator. These results are given in table 2. With one aberration—that a value of 1-2 indicates a slightly higher probability of a currency crisis than values from 2-4—the empirical data support the theory: In general, the higher the value of indicators, the higher the conditional probability of a crisis.

The present paper's research tests whether the indicators were high in the case of Uruguay—that is, whether the 2002 Uruguayan crisis was accurately predicted by the model. As is clear from the mathematical construction of the model, all of the composite indicators should be high when a crisis is likely to occur, so there is a clearly testable

[12] A complete mathematical description of these two measures can be found in Kaminsky (1998). For brevity, I only give a brief outline of the methodology and the results of these tests.

prediction—these composite indicators should be very high in the months preceding the crisis.

Table 2

Conditional probabilities of financial crises using composite indicator 4

Value of indicator 4	*Probability of currency crisis*
0-1	0.10
1-2	0.22
2-3	0.18
3-4	0.21
4-5	0.27
5-7	0.33
7-9	0.46
9-12	0.65
12-15	0.74
Over 15	0.96

Value of indicator 4	*Probability of banking crisis*
0-1	0.03
1-2	0.05
2-3	0.06
3-4	0.09
4-5	0.12
5-7	0.13
7-9	0.16
9-12	0.27
Over 12	0.37

Source: Kaminsky (1998)

IV. Data

Most of the data for this study come from *International Financial Statistics*, an IMF database, while the remainder is in *World Development Indicators*, a World Bank project[13]. All of the data necessary for Uruguay can be found in these two sources with the exception of a stock market index. Such an index did not exist during Uruguay's previous twin crises, and the present author's search indicates that none has been created.

The theory is not dependent on any one indicator being available, so while it is obviously desirable to have all 16, the fact that there is not a stock market index is not a fatal flaw—it should still be clear whether the composite indicators were signaling a crisis. Some time series differ from those used by Kaminsky and Reinhart (1999) when more accurate data are available.

As previously noted, Kaminsky and Reinhart (1999) select thresholds in order to minimize the noise-to-signal ratio. Table 3 summarizes their results. The values refer to the probability distributions of a variable for a particular period. For example, if the table says that for currency crises the threshold for exports is <0.10, then any value in the bottom decile of the distribution would trigger the signal. Note that different thresholds exist for currency crises and banking crises, so each aspect of a twin crisis must be analyzed independently.

[13] Helpfully, Kaminsky and Reinhart (1999) have a data appendix listing explicitly where the desired macroeconomic data can be found.

Table 3

Threshold values for signaling crises

Variable	*Currency threshold*	*Banking threshold*
M2 multiplier	>0.86	>0.90
Domestic credit/GDP	>0.90	>0.95
Real interest rates	>0.88	>0.80
Lending-deposit rate ratio	>0.80	>0.87
Excess M1 balances	>0.94	>0.91
M2/reserves	>0.87	>0.90
Bank deposits	<0.10	<0.16
Exports	<0.10	<0.10
Imports	>0.90	>0.80
Terms of trade	<0.16	<0.19
Real exchange rate	<0.10	<0.10
Reserves	<0.15	<0.28
Real interest-rate differential	>0.89	>0.81
Output	<0.11	<0.14
Stock returns	<0.11	<0.10
GDP	>0.86	>0.86

Source: Kaminsky and Reinhart (1999)[14]

Individual variables

All time series end in July 2002, since that is the beginning date for both the currency and the banking crisis, as shown in section V[15]. IFS and World Bank series begin at different times, though this study will limit the beginning date of series to January 1970 for two reasons: first, minute variations in the variable lead to extreme percentage changes at the beginning of many series, due to the very low numerical value of the measurements, and second, January 1970 is the earliest date for which the present

[14] Kaminsky and Reinhart (1999) actually have a less than symbol for real interest-rate differential for the currency crises; however, comparison with data in Kaminsky (1998) makes it clear that this is a typographical error.

[15] The precise dating of the currency crisis involves constructing the index of currency market turbulence shown in footnote 7. The banking crisis is dated from the most significant government involvement in the banking sector, as shown in de la Plaza and Sirtaine (2005).

author has reliable information of the dates of previous crises, which are necessary when constructing the fourth composite indicator.

M2 Multiplier

The M2 multiplier was created by dividing M2 by base money[16]. Twelve month percentage changes are used, so the first month for which a value can be determined is December 1973[17]. The series consists of 335 measurements[18] (there are 8 months which have no value because of missing data). The variable is rising in the months before the crises. The evolution of this variable in the years preceding the crises is given in figure 1.

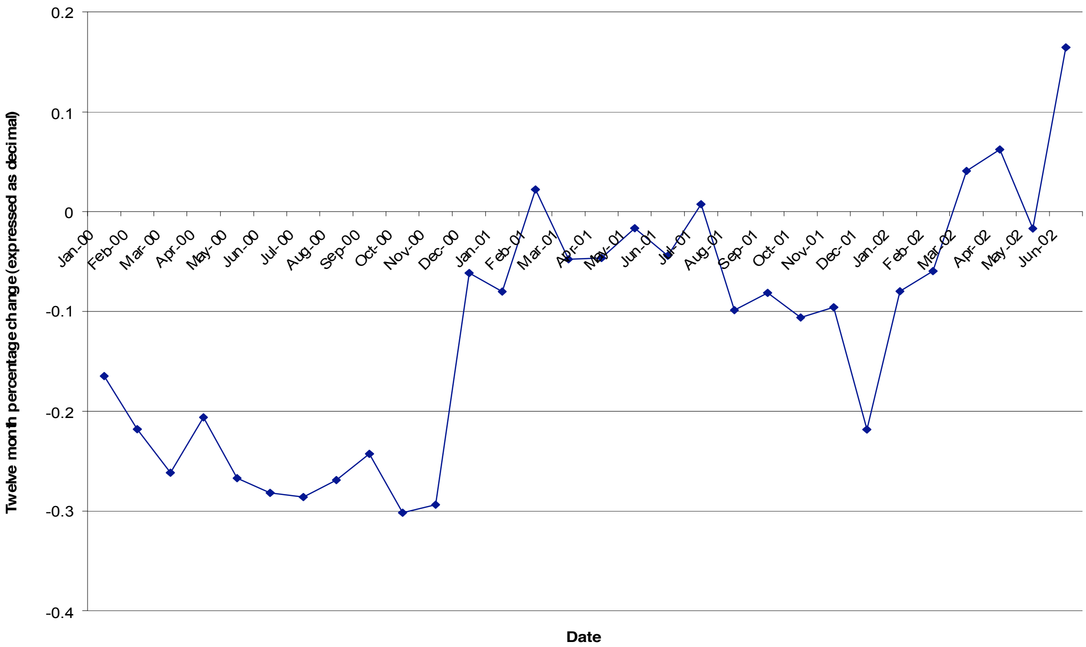
[16] M2 is IFS line 29859MB.ZF..., a monthly series beginning in December 1972. Reserve money is IFS line 29814...ZF..., a monthly series beginning in June 1965. All series are for Uruguay unless stated otherwise.

[17] The twelve month percentage change works as follows: If one wants to find the percent change for January 1991, then one takes the natural logarithm of the January 1991 value and subtracts the natural logarithm of the January 1990 value. It is then clear why one cannot use the first data point in the time series. In theory, this could result in a change of more than -100 percent even for series consisting entirely of positive numbers. This does not affect the results, since only the relative positions of the values are of interest, i.e., whether the values do or do not exceed a given threshold, defined by *percentile*.

[18] As mentioned in the introduction, the currency and banking crises arose in July 2002; therefore, time series stop in June 2002. A more complete explanation for the crisis date is given in section V.

Figure 1

M2 multiplier in Uruguay, January 2000-June 2002



Source: International Financial Statistics

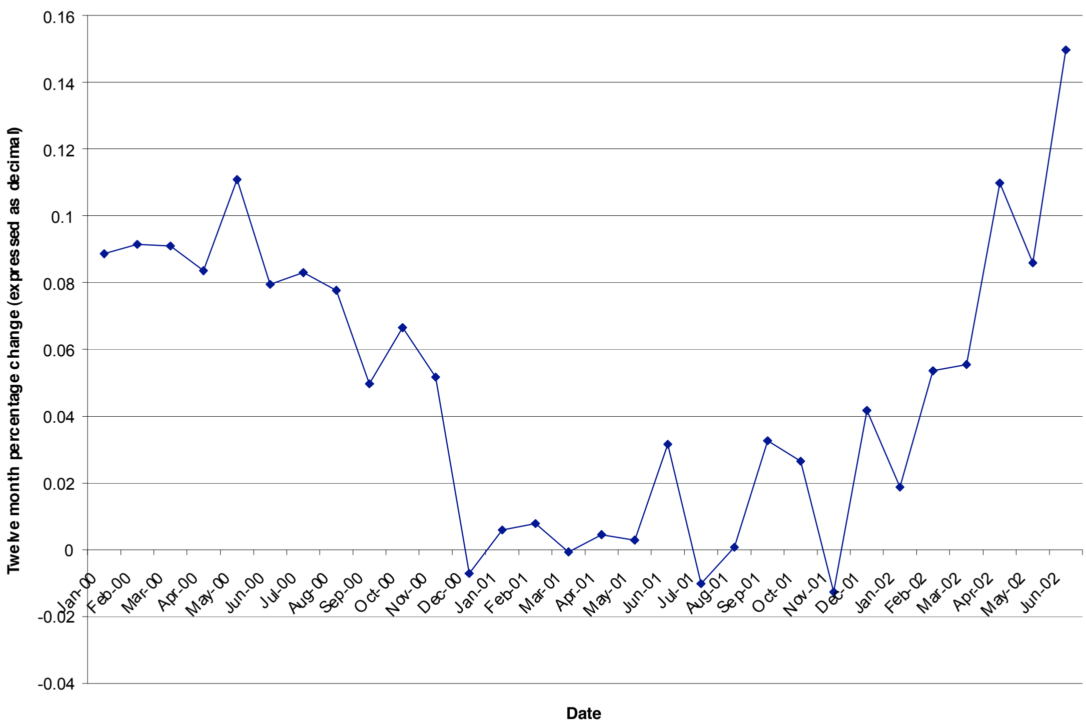
Domestic credit-GDP ratio

The ratio of domestic credit to GDP requires first interpolating monthly real GDP, since IFS only has annual, nominal GDP data for Uruguay. This is done by taking nominal GDP for a year, and assuming that that number is the value for July of that year[19]. By adding one-twelfth of the difference between that measurement and the next year's measurement each month, an interpolated nominal GDP is found. This is then divided by consumer prices to obtain real GDP[20]. The ratio of domestic credit to GDP is then constructed by dividing deflated domestic credit by this interpolated real GDP[21]. This series is twelve month percentage changes, beginning in January 1970, so there are 368 measurements (22 months cannot be measured due to missing data). This variable was rising to extremely high levels in credit in the months before the crises. The evolution of this variable in the years preceding the crises is given in figure 2.

[19] Nominal GDP is IFS line 29899B..ZF..., an annual series beginning in 1955.
[20] The consumer price index is IFS line 29864...ZF..., a monthly series beginning in January 1957.
[21] Deflated domestic credit is IFS line 29832...ZF..., a monthly series beginning in September 1965, divided by consumer prices.

Figure 2

Domestic credit-GDP ratio in Uruguay, January 2000-June 2002



Source: International Financial Statistics

Real interest rate

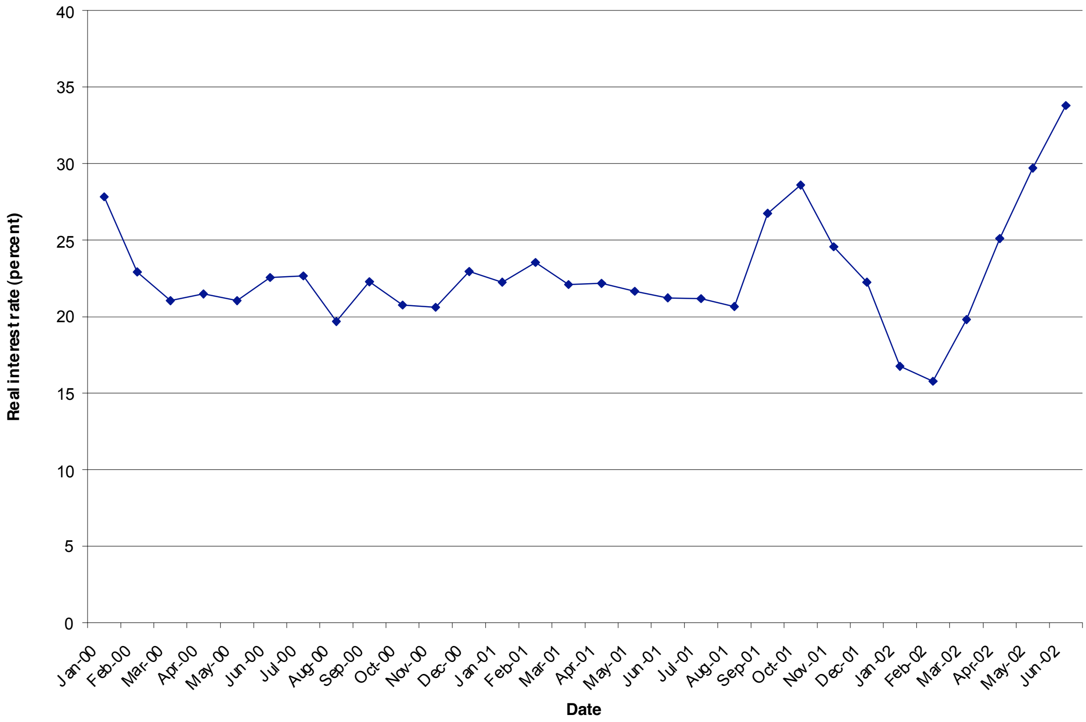
The real interest rate is constructed from the discount rate and the consumer price index[22]. Since the rate is expressed in an annual rate, but actually represents a six-month rate, the six-month interest rate was calculated as $R_{6,t} = \sqrt{1+R_{12,t}} - 1$, where $R_{6,t}$ is the interest rate over six months, and $R_{12,t}$ is the interest rate calculated as an annual rate[23]. This interest rate is then converted into net decimal form by dividing by 100. *Ex post* inflation is derived by $1+\pi_t = \dfrac{CPI_{t+6} - CPI_t}{CPI_t}$, where $1+\pi_t$ is the inflation in period *t*, expressed in gross decimal form, CPI_t is the consumer price index in period *t*, and CPI_{t+6} is the consumer price index in period *t+6*. Net real interest rates, in percentage terms, are then found from the Fisher equation: $r_t = (\dfrac{1+R_{6,t}}{1+\pi_t} - 1)\cdot 100$, where r_t is the real interest rate in period *t*. This series begins in April 1981 and has 255 measurements. The real interest rate rose in the months immediately before the crises. The evolution of this variable in the years preceding the crises is given in figure 3.

[22] The discount rate is IFS line 29860...ZF..., a monthly series beginning in April 1981.

[23] This formula is derived from the fact that $(1+R_{12,t}) = (1+R_{6,t})^2$

Figure 3

Real interest rate in Uruguay, January 2000-June 2002



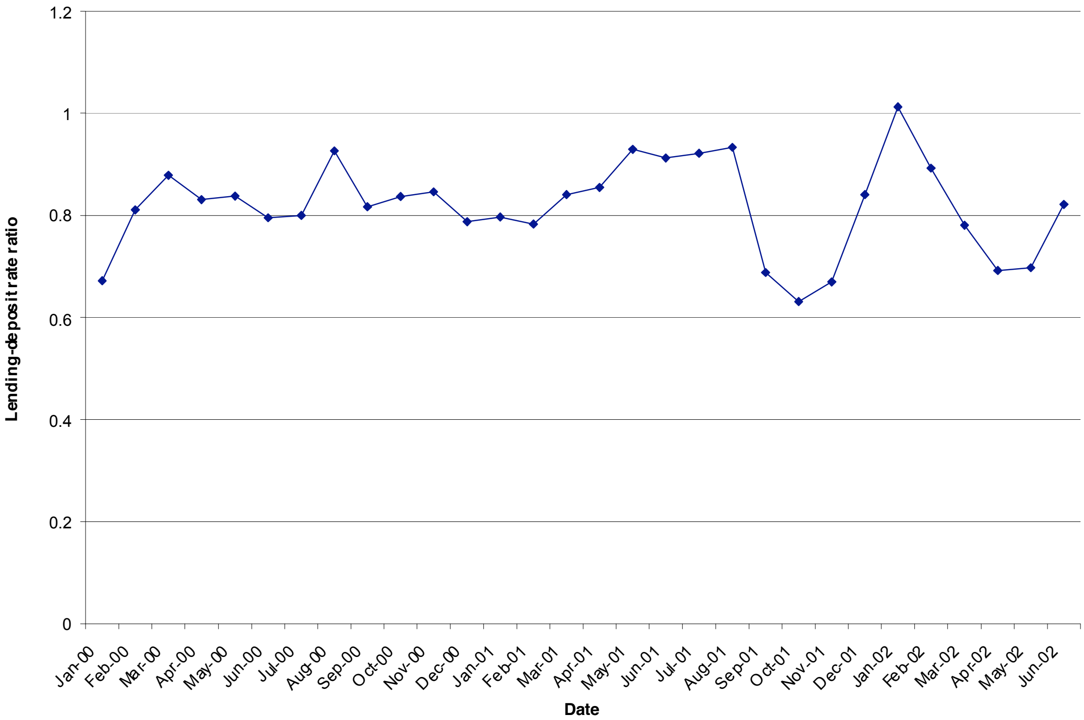
Source: International Financial Statistics

Lending-deposit credit ratio

The lending-deposit rate ratio is obtained by dividing the ordinary lending rate by the discount rate[24]. This series begins in April 1981 and has 255 measurements. Unlike the previous three variables shown, this variable has no apparent trend. The evolution of this variable in the years preceding the crises is given in figure 4.

Figure 4

Lending-deposit rate ratio in Uruguay, January 2000-June 2002



Source: International Financial Statistics

[24] The lending rate is IFS line 29860P..ZF..., a monthly series beginning in July 1976.

Excess M1 balances

Calculating the value of the excess M1 balances variable requires constructing an estimated demand for money. This is done by estimating the equation $\frac{M_t}{P_t} = \beta_0 + \beta_1 GDP_t + \beta_2 R_t + \beta_3 T_t + \varepsilon_t$. Ordinary least squares regression is used. M_t represents M1 in period *t*, P_t is the price level, GDP_t is interpolated real GDP, R_t is the nominal interest rate, and T_t is a linear time trend[25]. The "excess" balances are then the error term in this regression. The results of this regression are given in table 4.

Table 4

Estimated real money demand for Uruguay

Real balances	*Coefficient*	*Standard error*	*T*	*p>|t|*	*95% confidence interval*
GDP_t	0.0515735	0.0061834	8.34	0.000	(0.039396, 0.063751)
R_t	-0.2060226	0.0155863	-13.22	0.000	(-0.236719, -0.175326)
T_t	-0.1169035	0.0213389	-5.48	0.000	(-0.158930, -0.074878)
Constant	48.78834	11.18752	4.36	0.000	(26.7550, 70.8217)

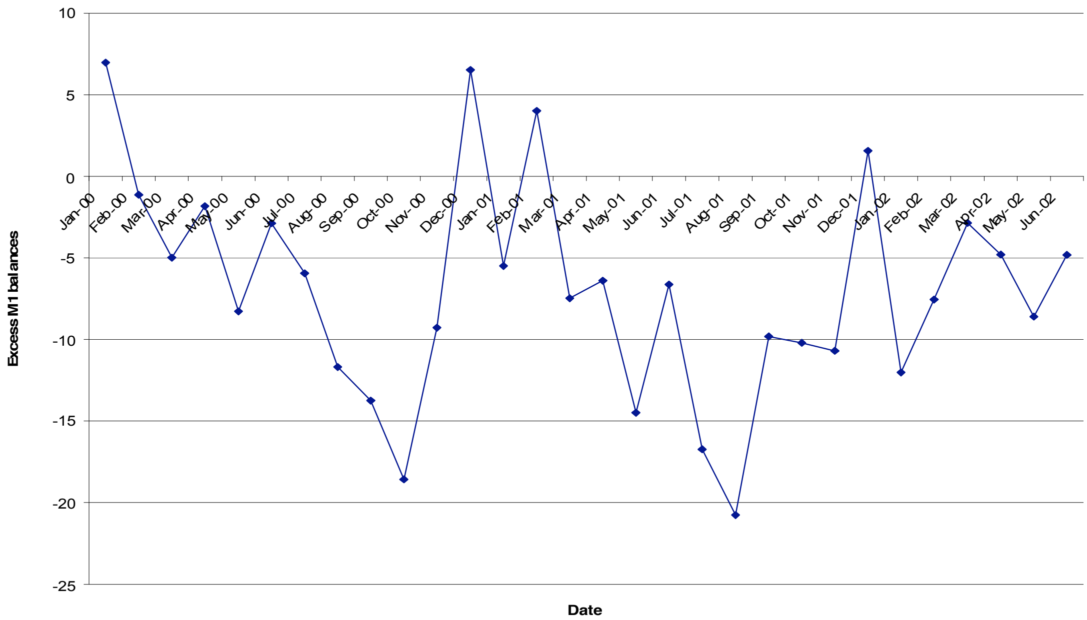
First, it must be noted that the numbers do not represent actual money supply in pesos or dollars, since GDP is scaled by a consumer price index. The most important results are that the coefficient for GDP is positive and the coefficient for interest rates is negative. This conforms with expectations—wealthier people would generally want to hold more money, and since interest rates represent the opportunity cost of holding

[25] Kaminsky and Reinhart (1999) use inflation as a proxy for nominal interest rates due to the limited availability of interest rate data; however, since there were interest rate data for Uruguay, this study uses interest rates. The time trend is a proxy for financial innovation or currency substitution.

money[26], a higher interest rate should make money less desirable. The regression has an R-squared of 0.4615 and an adjusted R-squared of 0.4551, demonstrating that it has fair predictive power. The error term represents "excess" M1 balances, and is calculated by the difference between actual M1 (deflated by consumer prices) and the estimated M1. This series begins in April 1981 and has 255 measurements. This variable shows no trend in the months before the crises. The evolution of this variable in the years preceding the crises is shown in figure 5.

Figure 5

Excess M1 balances in Uruguay, April 1981-June 2002



Source: International Financial Statistics

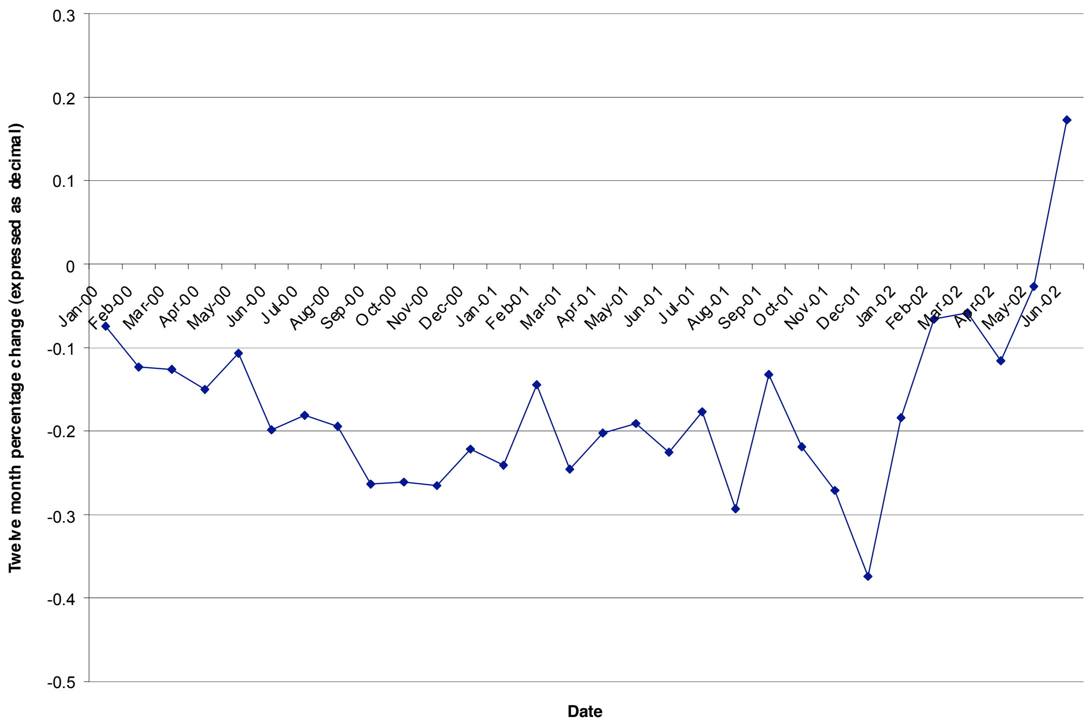
[26] Assuming that the asset has a reasonably low risk of default

M2-reserves ratio

The ratio of M2 to reserves is derived by dividing M2 by the spot exchange rate of Uruguayan pesos to U.S. dollars to obtain M2 in dollars, then dividing that by reserves[27]. This series begins in December 1973, and consists of the twelve month percentage changes of this ratio. There are 343 measurements in this series, and the variable rose dramatically in the months before the crises. The evolution of this variable in the years preceding the crises is shown in figure 6.

Figure 6

M2-reserves ratio in Uruguay, January 2000-June 2002



Source: International Financial Statistics

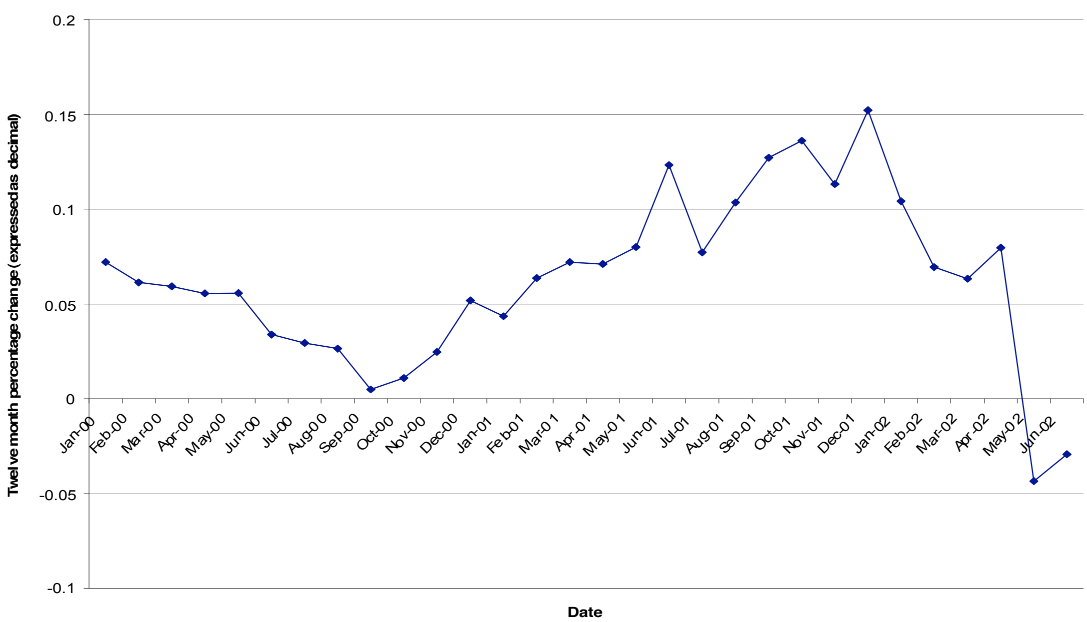
[27] The spot exchange rate is IFS line 298..AE.ZF..., a monthly series beginning in January 1964. Reserves (in dollars) are IFS line 298.1L.DZF..., a monthly series beginning in January 1958.

Bank deposits

Bank deposits are demand deposits plus time, savings, and foreign currency deposits, divided by the consumer price index[28]. Twelve month percentage changes are used for this series, and the series consists of measurements beginning in January 1970, with a total of 390 measurements. This variable was falling in the months before the crises; however, it should be noted that the variable was still positive for much of this period—the twelve month percentage change was greater than zero, so deposits were still rising compared to the previous year, albeit at lessened rates. The evolution of this variable in the years preceding the crises is shown in figure 7.

Figure 7

Bank deposits in Uruguay, January 2000-June 2002



Source: International Financial Statistics

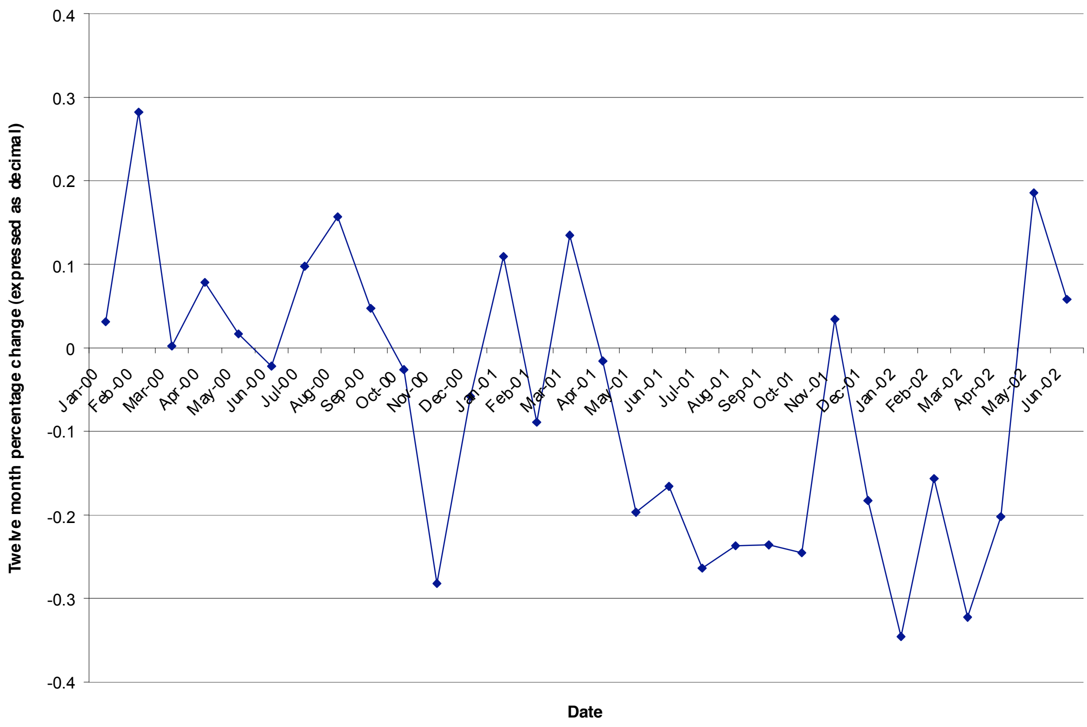
[28] Demand deposits are IFS line 29824...ZF..., a monthly series beginning in June 1965. Time, savings, and foreign currency deposits are IFS line 29825...ZF..., a monthly series beginning in December 1965.

Exports

Exports are simply twelve month percentage changes of the relevant IFS time series[29]. There are 390 measurements, beginning with January 1970. Exports were generally low in the months before the crises; however, this may be the result of the general recession in Uruguay and not evidence of balance of payments or banking pressures. The evolution of this variable in the years preceding the crises is shown in figure 8.

Figure 8

Exports in Uruguay, January 2000-June 2002



Source: International Financial Statistics

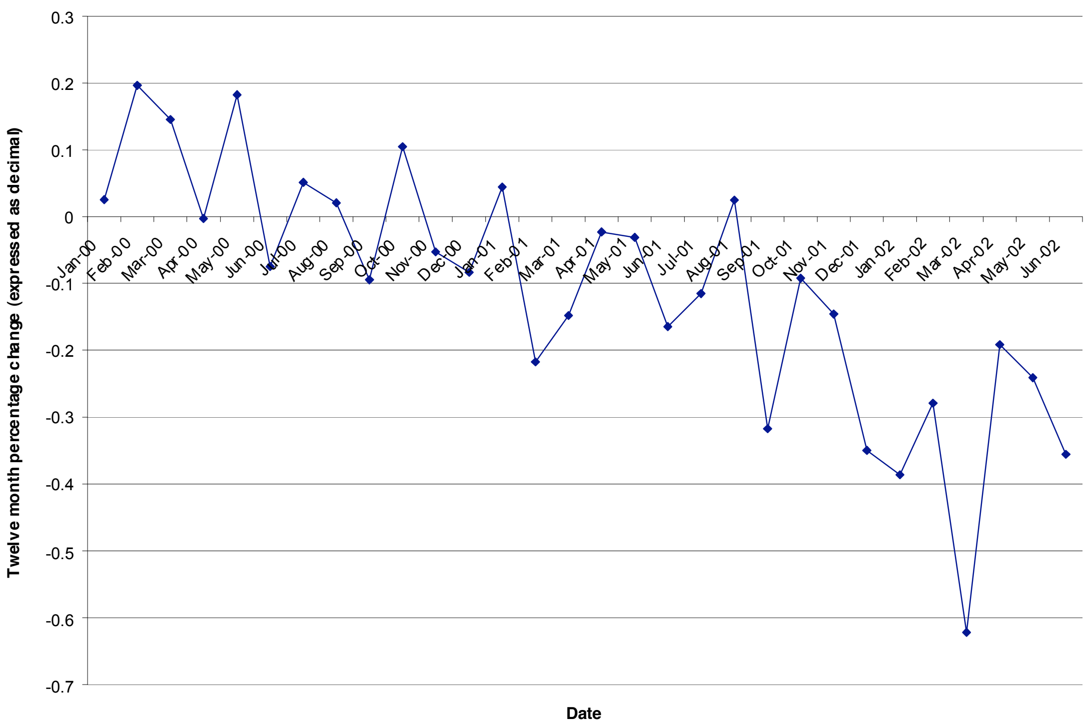
[29] Exports are IFS line 29870..DZF..., a monthly series beginning in January 1957.

Imports

Similarly, imports are twelve month percentage changes of the IFS time series, consisting of 390 measurements beginning in January 1970[30]. The twelve month percentage change for imports was highly negative in the year before the crises. The evolution of this variable in the years preceding the crises is shown in figure 9.

Figure 9

Imports in Uruguay, January 2000-June 2002



Source: International Financial Statistics

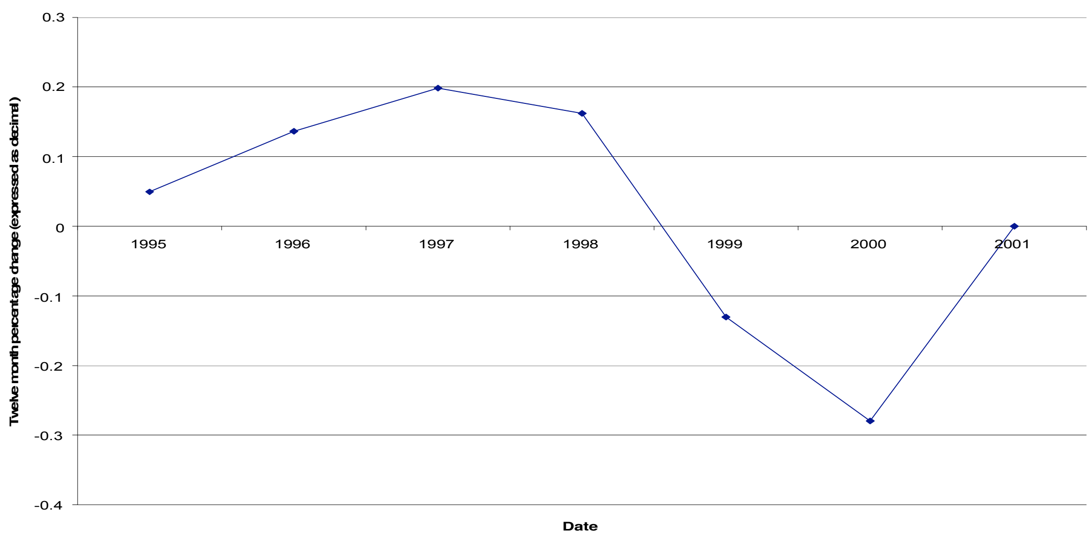
[30] Imports are IFS line 29871..DZF..., a monthly series beginning in January 1957.

Terms of trade

Unfortunately, the IMF has no monthly series for the terms of trade. The terms of trade are an annual series from the World Bank, so in each month of a year this variable sends the same signal, or lack thereof[31]. This variable is therefore a relatively noisy one. Since the 2002 data at least in part postdate the crises, the series will stop in 2001. There are 32 measurements in this series, beginning in 1970. Twelve month percentage changes are used. No trend is apparent in this variable. The evolution of this variable in the years preceding the crises is given in figure 10.

Figure 10

Terms of trade in Uruguay, 1995-2001



Source: World Bank

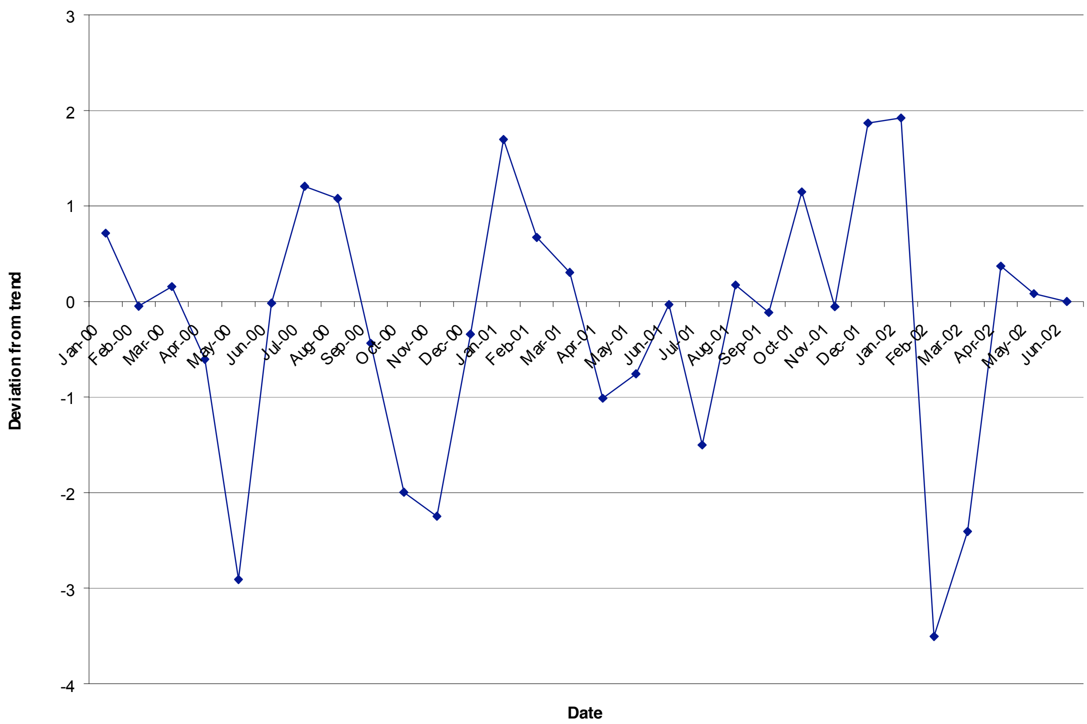
[31] The terms of trade are World Bank line NY.TTF.GNFS.KN, an annual series beginning in 1960. Note that since some of these values are negative, the logarithm estimation for percent change could not be used. Instead, the percent change is given by the present value less the past year value, divided by the past year value. In practice, this change makes no difference for this study, since the logarithm estimation is a monotonic transformation of this calculation for percent change.

Real exchange rate

The variable for real exchange rate is not the exchange rate itself, since not all real appreciations represent disequilibria. Instead, deviations from trends are used[32]. The series begins in January 1979 and has 270 measurements. There is no strong trend in the real exchange rate deviation in the months before the crises. The evolution of this variable in the years preceding the crisis is given in figure 11.

Figure 11

Real exchange rate deviation from trend in Uruguay, January 2000-June 2002



Source: International Financial Statistics

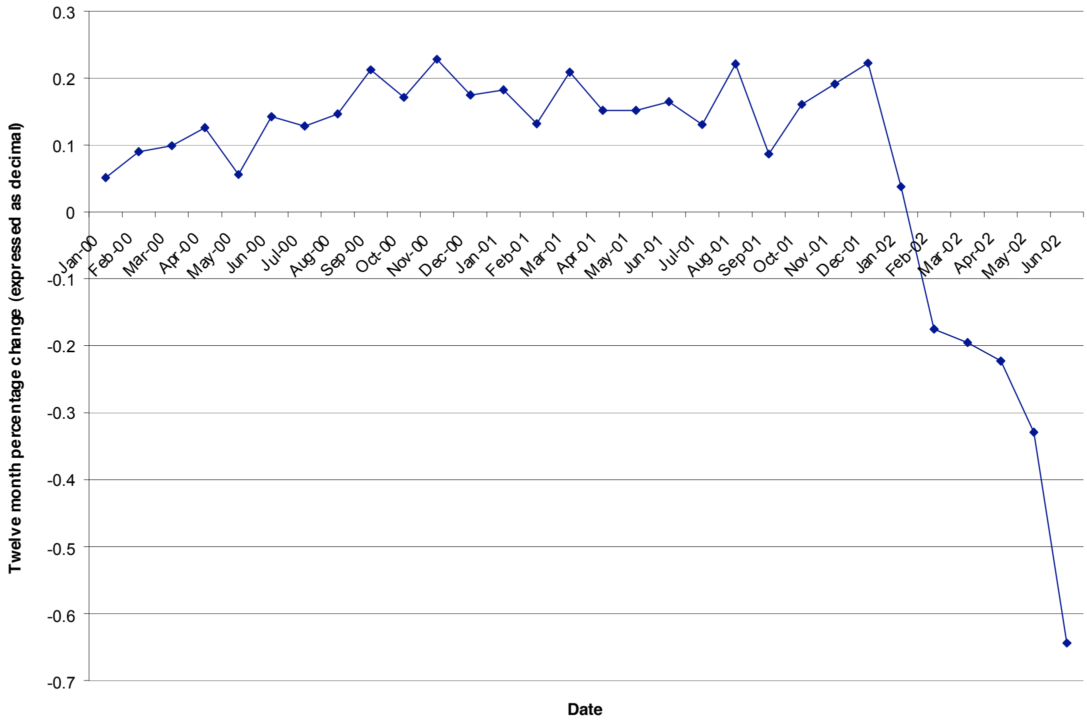
[32] The Stata smoothing command is used here.

Reserves

Reserves are given in dollars. The series begins in January 1970 and has 390 measurements. Twelve month percentage changes are used. As expected, reserves fell drastically in the months before the crises. The evolution of this variable in the years preceding the crises is described in figure 12.

Figure 12

Reserves in Uruguay, January 2000-June 2002



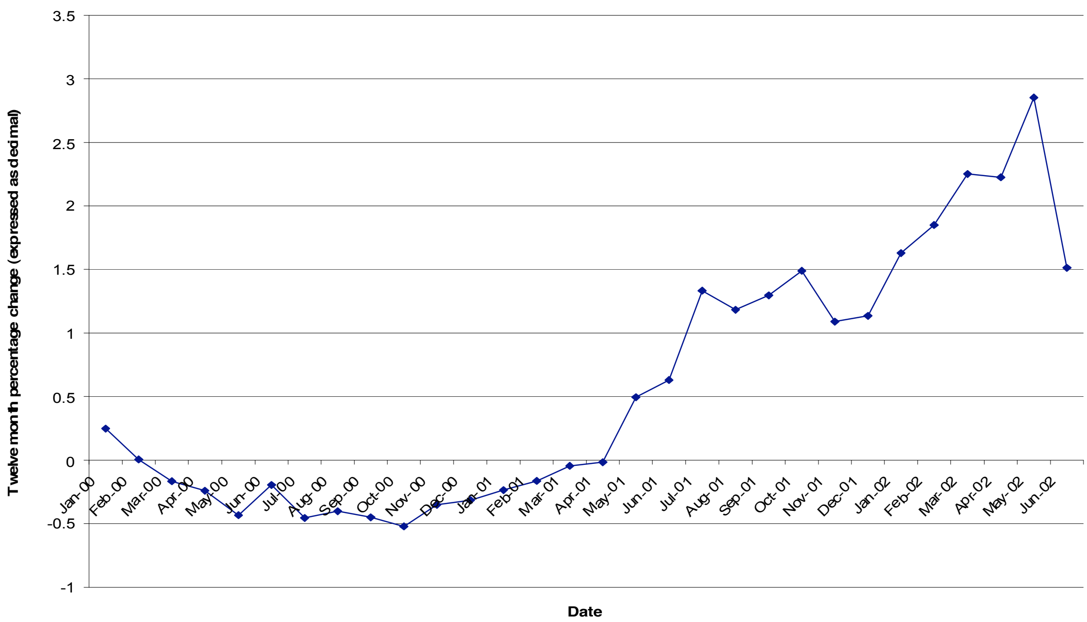
Source: International Financial Statistics

Real interest rate differential

The Uruguayan real interest rate is constructed as described in part 3 of this section. The United States real interest rate is constructed similarly, with slightly different data sets[33]. The real interest rate differential is the difference between these two rates. Twelve month percentages change are used. The series starts in June 1977, and there are 301 measurements. The real interest rate differential generally rose in the months preceding the crises. The evolution of this variable in the years preceding the crises is shown in figure 13.

Figure 13

Real interest rate differential between Uruguay and the United States, January 2000-June 2002



Source: International Financial Statistics

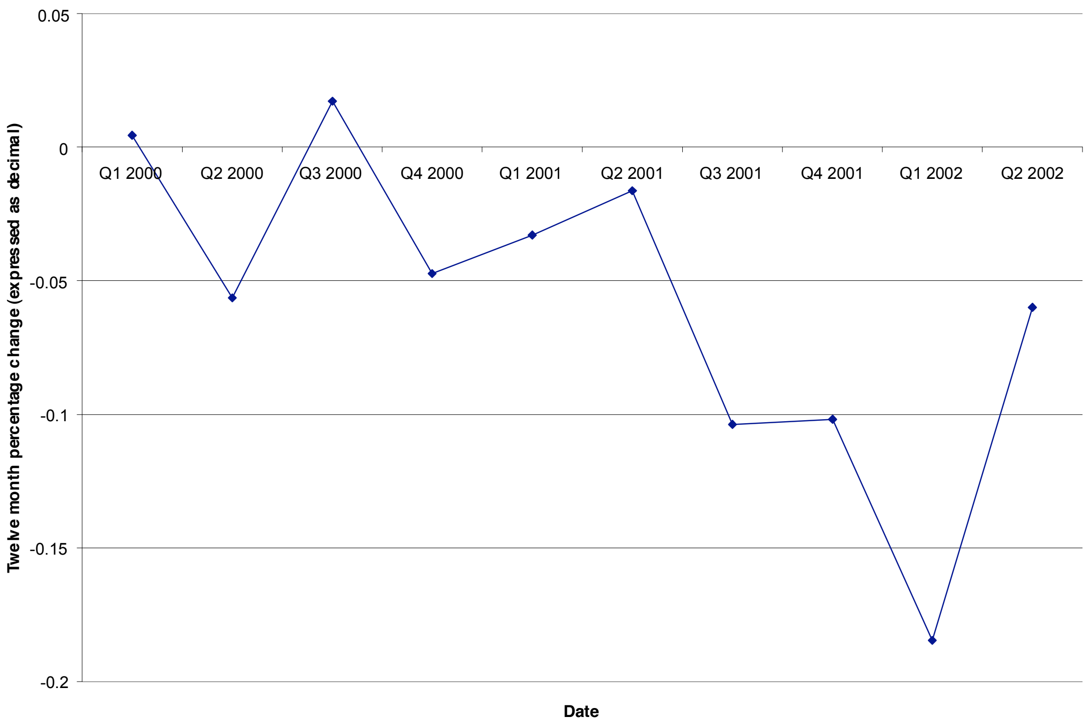
[33] The United States discount rate is IFS line 11160...ZF..., a monthly series beginning January 1964. The United States consumer price index is IFS line 11164...ZF..., a monthly series beginning January 1957.

Industrial output

Only quarterly data are available for industrial output[34]. Therefore, each month in a given quarter will have an equal value. This variable is therefore somewhat noisy. Twelve month percentage changes are used. There are 90 measurements in this set, which begins in the first quarter of 1980. Output was slightly lower in the quarters before the crisis. The evolution of this variable in the years preceding the crises is given in figure 14.

Figure 14

Output in Uruguay, January 2000-June 2002



Source: International Financial Statistics

[34] Industrial output is IFS line 29866EY.ZF..., an annual series beginning in 1957.

Stock market

There does not seem to be a stock market index for Uruguay.

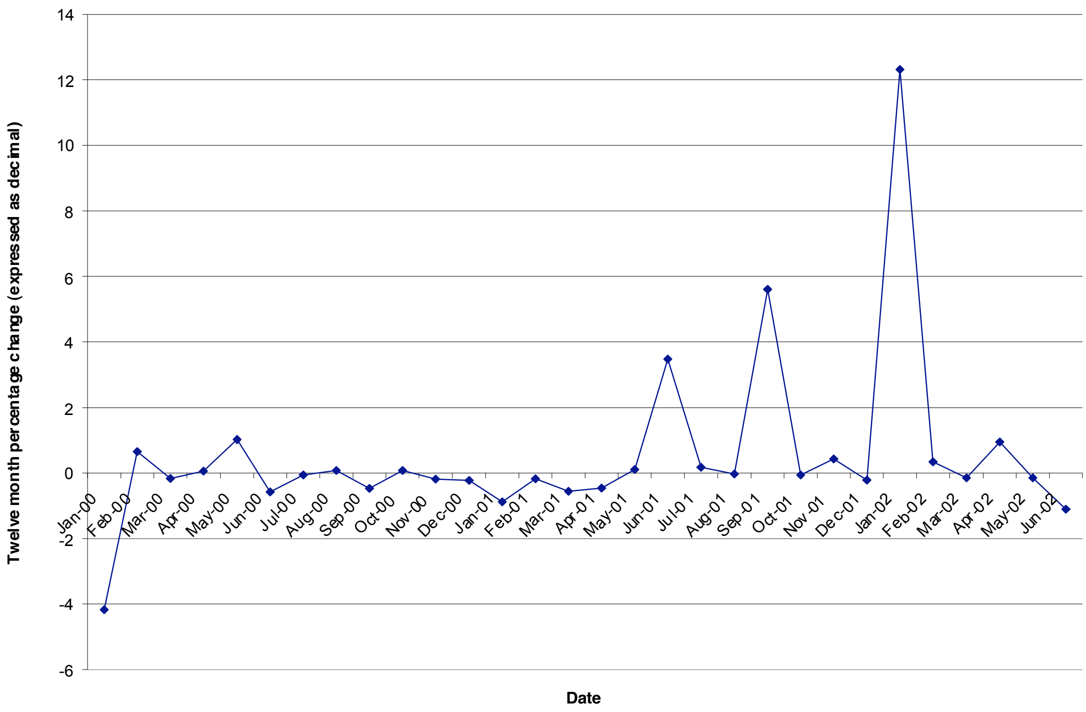
Deficit-GDP ratio

The real deficit is constructed by dividing the nominal deficit by consumer prices[35]. This is then divided by interpolated real GDP as described above to create the ratio of deficit to GDP. Twelve month percentage changes are used, and the series begins in April 1973. There are 351 measurements in the series. There is little trend in this series, although it is notable that the magnitude of the spike for January 2002 is enormous—the nominal deficit rose from 48.8 million pesos in January 2001 to 673.1 million pesos a mere year later. The evolution of this variable in the years preceding the crisis is shown in figure 15.

[35] The nominal deficit is IFS line 29880...ZF..., a monthly series beginning April 1972.

Figure 15

Budget deficit-GDP ratio in Uruguay, January 2000-June 2002



Source: International Financial Statistics

V. Uruguayan Composite Indicators

Dating the Crisis

The construction of the composite indicators necessarily requires that a specific month be named as the crisis month. For currency crises, this is done by constructing the index of currency market turbulence, or $I = \frac{\Delta_e}{e} - \frac{\sigma_e}{\sigma_R} \cdot \frac{\Delta_R}{R}$, where I represents the index of turbulence. For the variable $\frac{\Delta_e}{e}$, the percentage change in the exchange rate, the market rate of Uruguayan pesos per dollar is used[36]. For period t, the variable equals the natural logarithm of the market rate in period t, minus the natural logarithm of the market rate in period $t-1$. This time series begins in January 1964 and ends in December 2005[37]. The variable $\frac{\Delta_R}{R}$ represents the rate of change in the reserves. For this, total reserves minus gold (in dollars) are used[38]. This is a monthly time series with values beginning in January 1958. The standard deviation of the rate of change in the exchange rate, σ_e, equals 0.073791, while the standard deviation of the rate of change in the reserves, σ_R, equals 0.306635. Therefore, the index of currency market turbulence, I, can be calculated by the following equation:

$$I = \frac{\Delta_e}{e} - \frac{0.073791}{0.306635} \cdot \frac{\Delta_R}{R} \tag{7}$$

Since both devaluations of the domestic currency and decreases in reserves cause the index to rise, high values of I are considered to be a crisis—specifically, values three standard deviations or more over the mean. Since the mean for I equals 0.025529, and the standard deviation equals 0.093334, then any value greater than 0.305531 indicates a crisis. The time series for the index of currency market turbulence is given in figure 16.

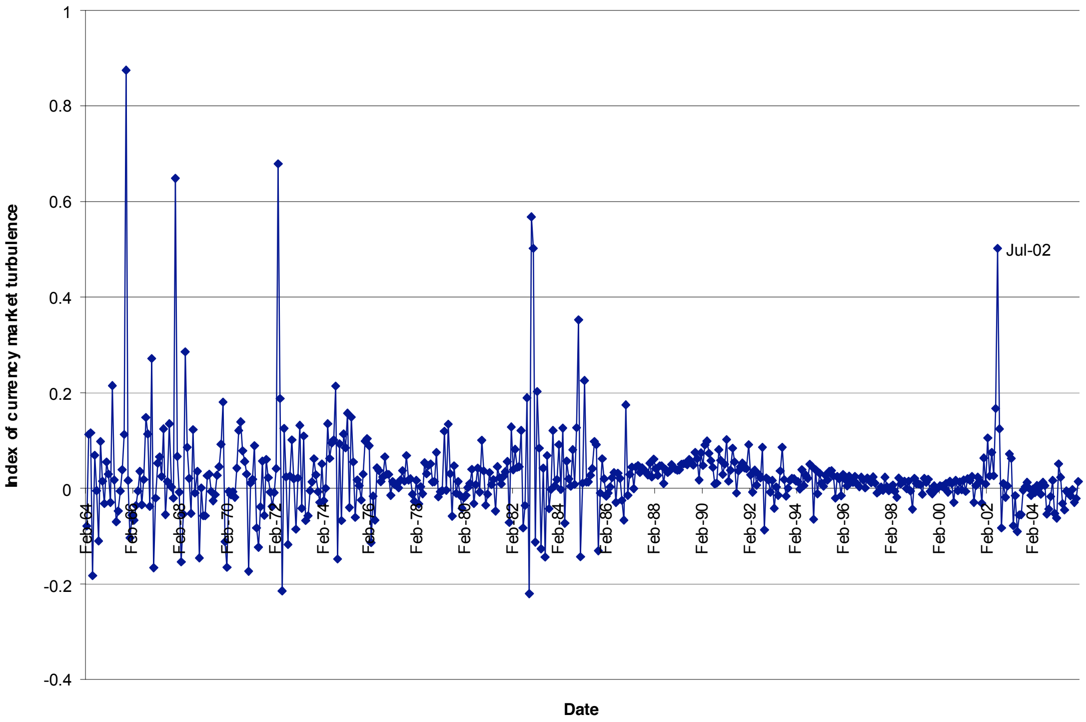
[36] This monthly series represents the *end-of-month* exchange rate. For the large devaluations associated with currency crises, it does not matter whether end-of-month rates or monthly average rates are used. In order for devaluations to enter the index as positive numbers, the inverse of the exchange rate—that is, the ratio of dollars per peso—is used. The rate is IFS line 298..AE.ZF….

[37] December 2005 is several years after the Uruguayan crisis; however, to minimize noise, one wants as large a time series as can be obtained in order to properly date the crisis.

[38] Total reserves minus gold (in dollars) is IFS line 298.1L.DZF.

Figure 16

Index of currency market turbulence in Uruguay, February 1964-December 2005



Source: International Financial Statistics

As is clear from the graph, the Uruguayan peso has a turbulent history. The month of July 2002 has a value of 0.502288, well above the threshold of three standard deviations over the mean. In this month, the spot exchange rate rose from 18.5 pesos per dollar to 25 pesos per dollar, and the level of reserves plunged from $1,451,060,000 to $628,946,000, making the selection of July 2002 as the crisis date seem even more reasonable. Therefore, the currency crisis will be dated July 2002 for this study.

The banking crisis is more difficult to date precisely. As de la Plaza and Sirtaine (2005) illustrate, events in Uruguay's banking sector deteriorated for several months, making naming an exact crisis date troublesome[39]. However, the most substantial government involvement in the crisis was the declaration of a bank holiday on July 30, 2002. Up to that point, the Uruguayan central bank had suspended operations or intervened with certain individual banks, but not the entire banking system (de la Plaza and Sirtaine 2005). Furthermore, when describing the reserves needed to service the foreign debt, de la Plaza and Sirtaine write that "the tilting point came in early July," which makes a July 2002 dating of the crisis seem even more reasonable (2005, p. 10). In this study, therefore, the banking crisis will be dated in July 2002, the same month as the currency crisis.

Testing the indicators

If the Kaminsky-Reinhart model successfully predicted the 2002 Uruguayan currency and banking crises, the four composite indicators described in section III, I_t^1, I_t^2, I_t^3, I_t^4, should rise in the months directly preceding the crises. If there is little discernable difference between "normal" values and "pre-crisis" values, then one can conclude that the Kaminsky-Reinhart model failed to predict this crisis. For this study, an indicator is termed "high" if its value exceeds one standard deviation over the mean value for the past 100 months, and "very high" if it is more than two standard deviations over the mean[40].

The theory behind calculating these indicators is established in section III. Stated more briefly, there are 16 separate variables which the model considers. These are given

[39] De la Plaza and Sirtaine's table "Chronology of the Uruguayan Banking Crisis" (2005, p. 9) is particularly useful.
[40] The selection of 100 months is arbitrary, intended to allow a comparison with recent events without excessive noise. The results are not very sensitive to different length windows. A sensitivity analysis is given in appendix A.

in table 3, though no stock market index was found for Uruguay. Most variables are reported on a monthly basis, one is quarterly, and one is annual. Twelve month percent changes are used when necessary. Then, once the distributions of the values of these variables are known, the indicators are constructed as detailed in section III.

Kaminsky (1998) finds the frequency distribution of the number of signals in both tranquil periods and crisis periods. When currency crises occur, the mean number of signals is 5.56, while in tranquil periods, the mean is only 3.28[41]. Likewise, during banking crisis periods, the mean number of signals is 7.14, but in tranquil periods, the mean is only 4.12. This illustrates two important points about these data: First, one should not expect there to be *no* signals of crisis in tranquil times; second, it is highly unlikely that all variables will simultaneously signal the 2002 Uruguayan crises, and therefore a failure for all variables to signal a crisis is not a failure of the model.

Since both the currency and the banking crises begin in July 2002, the indicators look similar for banking and currency crises, and therefore this section will be organized on an indicator-by-indicator basis. The conditional probabilities could not be determined due to the lack of a stock market index.

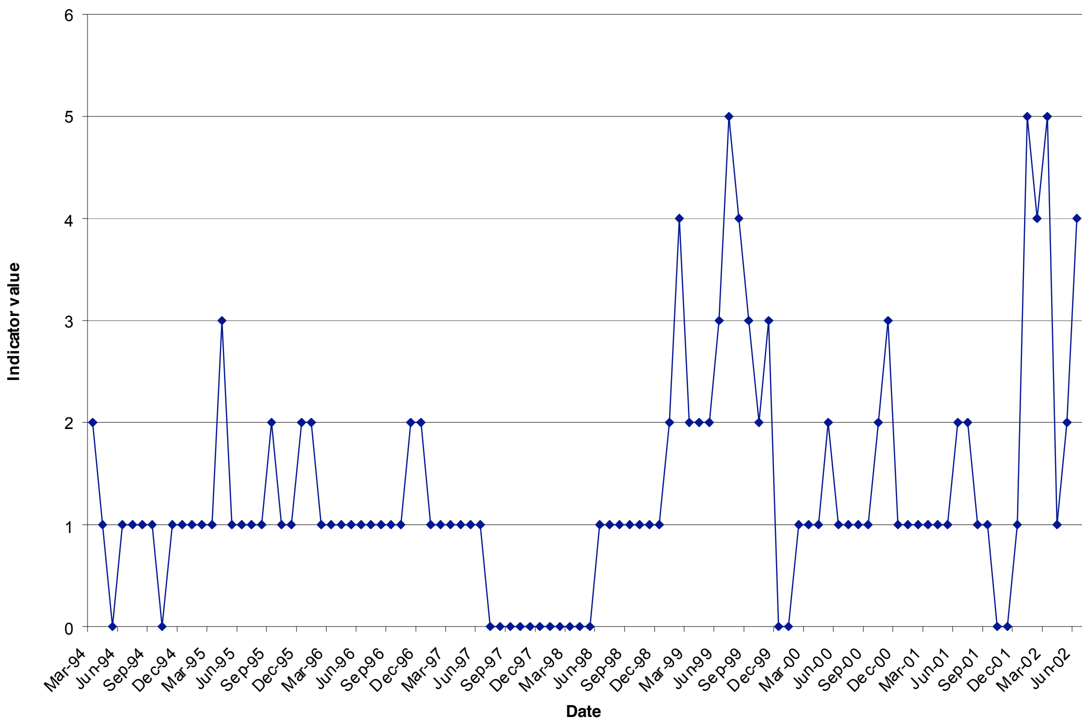
[41] These numbers simply represent the sum of signals, that is, I_t^1. Kaminsky (1998) contains more detail about the distributions of more precise measures, such as the number of extreme signals.

Composite indicator 1

Recall that the first composite indicator was simply the sum of the number of signals. The evolution of this indicator is shown in figures 17 and 18.

Figure 17

Composite indicator 1 (currency), March 1994-June 2002

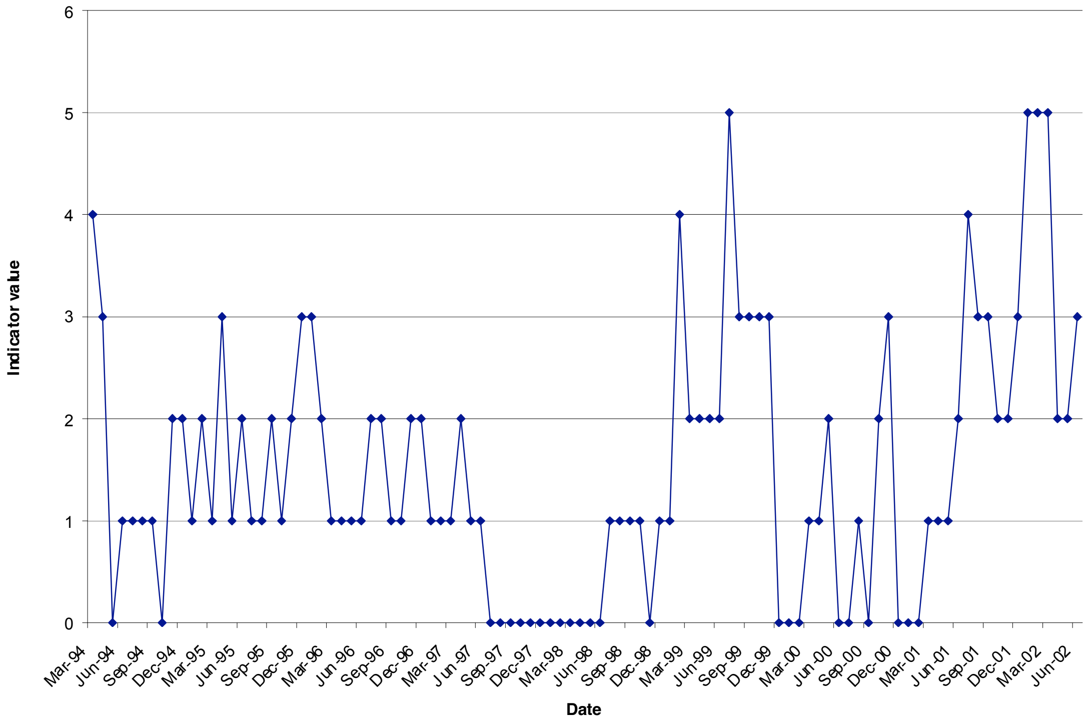


The currency indicator had a mean of 1.33 and a standard deviation of 1.128644. For four of six months preceding the currency crisis—January, February, March, and June—the indicator was very high[42]. January and March, in fact, represent the sample maximum of 5, and June was only one lower.

[42] All months given are in the year 2002 for the remainder of this section unless otherwise stated.

Figure 18

Composite indicator 1 (banking), March 1994-June 2002



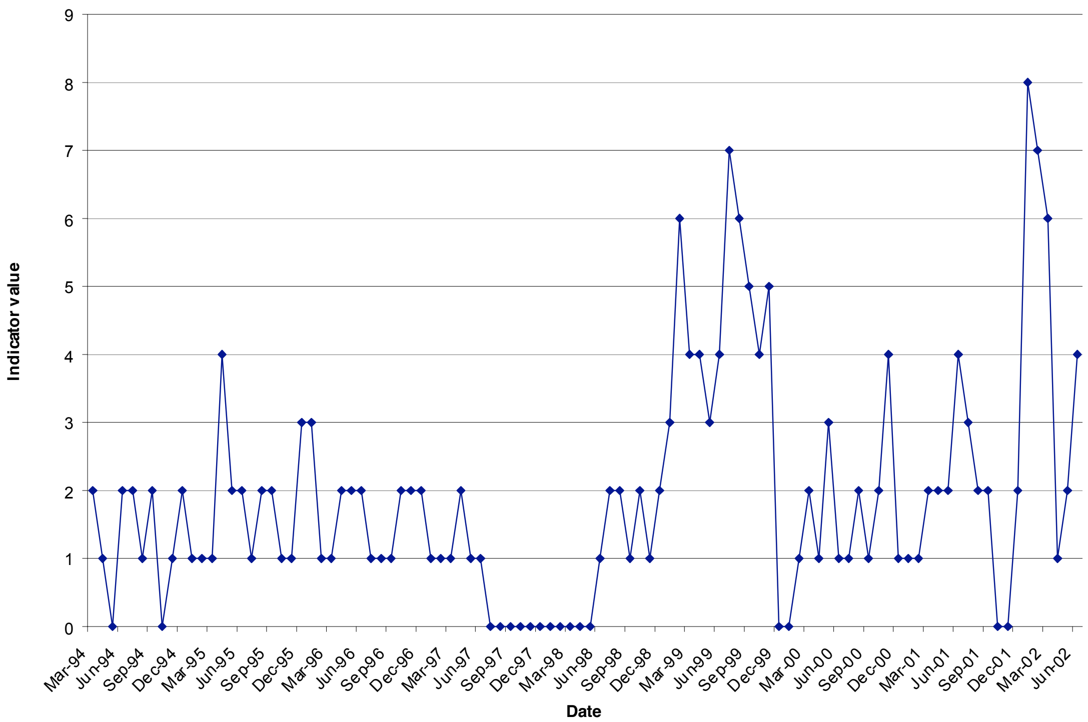
The currency indicator and the banking indicator move in similar ways, although the banking indicator exhibits somewhat more month-to-month variance in the first half of the sample. The mean of this indicator was 1.5, and the standard deviation is 1.290994. The indicator was very high in January, February, and March, and high in June, so the indicator performed reasonably well in terms of its ability to predict the crisis, although values of 2, 2, and 3 in the months directly preceding the crisis are rather low. The fact that January through March tied the sample maximum further indicates that the model had predictive power.

Composite indicator 2

The second composite indicator used extreme and mild thresholds, rather than just one threshold. The evolution of this indicator is given in figures 19 and 20.

Figure 19

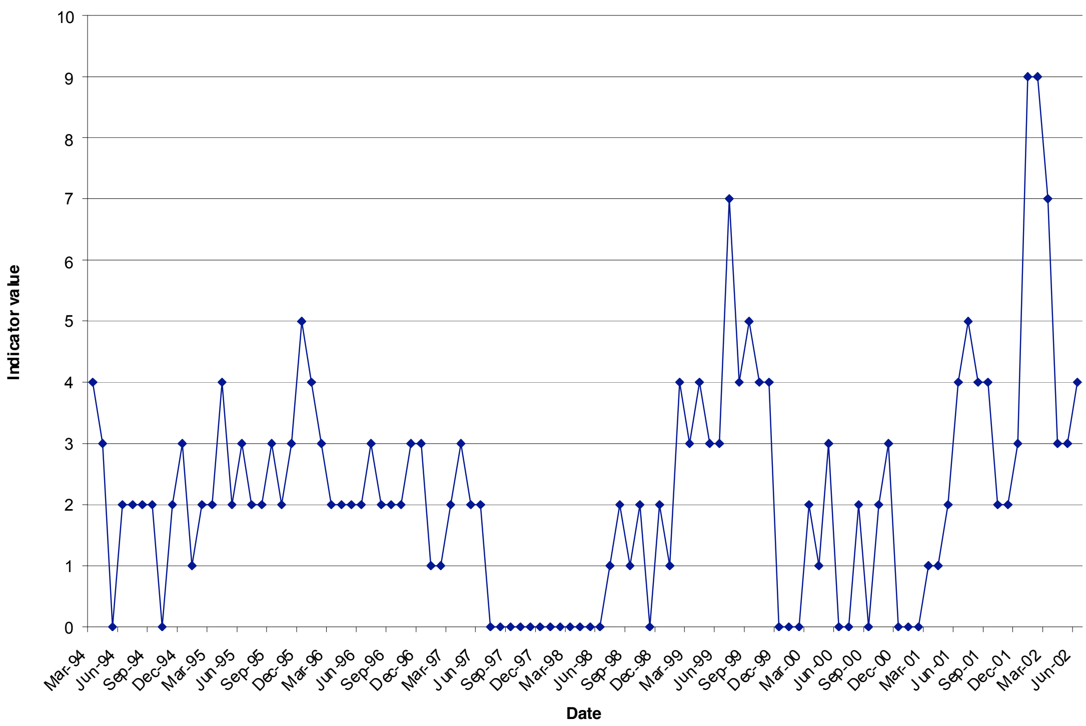
Composite indicator 2 (currency), March 1994-June 2002



The mean of this indicator was 1.91, with a standard deviation of 1.706168. The indicator was very high in January, February, and March, and it was high in June. This indicator, then, performed well. January represented the sample maximum for this indicator.

Figure 20

Composite indicator 2 (banking), March 1994-June 2002



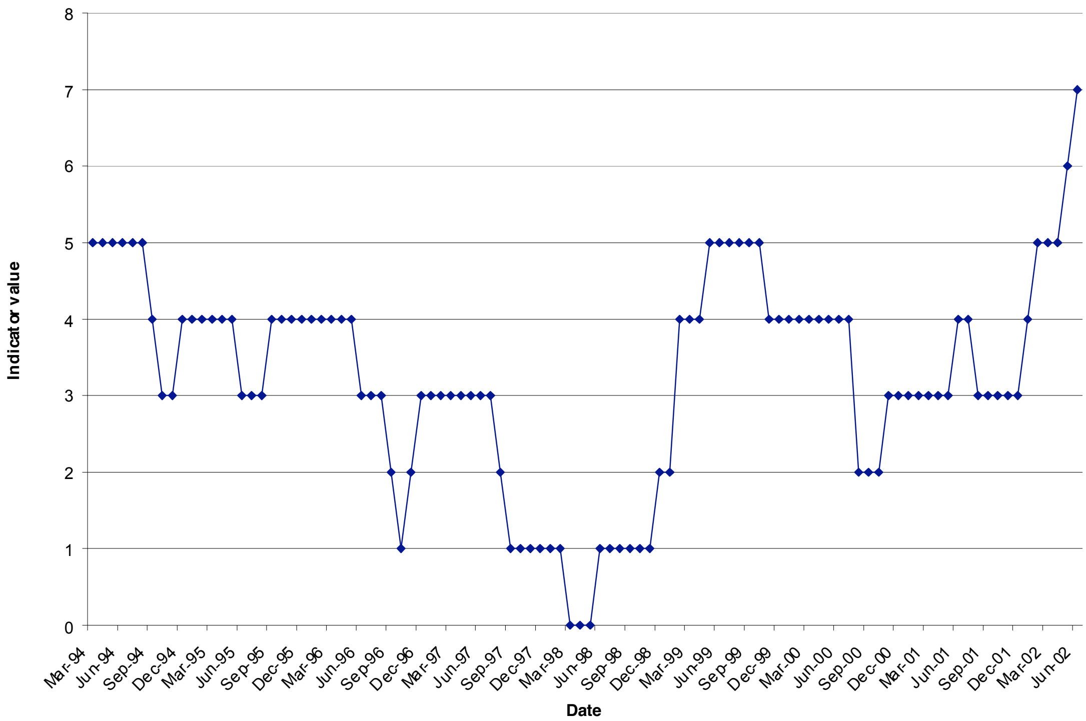
This indicator had a mean of 2.18 and a standard deviation of 1.860705. The indicator was very high in January, February, and March, and nearly reached the "high" threshold in June. This indicator, then, performed similarly to the banking crisis composite indicator 1. The sample maximum was reached in January and February.

Composite indicator 3

The third composite indicator has variables signal a crisis if the variable crossed its threshold in that month *or in any one of the eight previous months*. Since, quarterly data were used for industrial output, the output variable sends a signal if it crosses its threshold in that quarter or in any of the two previous quarters[43]. Likewise, since only annual data for terms of trade could be found, the terms of trade variable sends a signal if it crosses its threshold in that year or in the previous year. The evolution of this indicator is given in figures 21 and 22.

Figure 21

Composite indicator 3 (currency), March 1994-June 2002



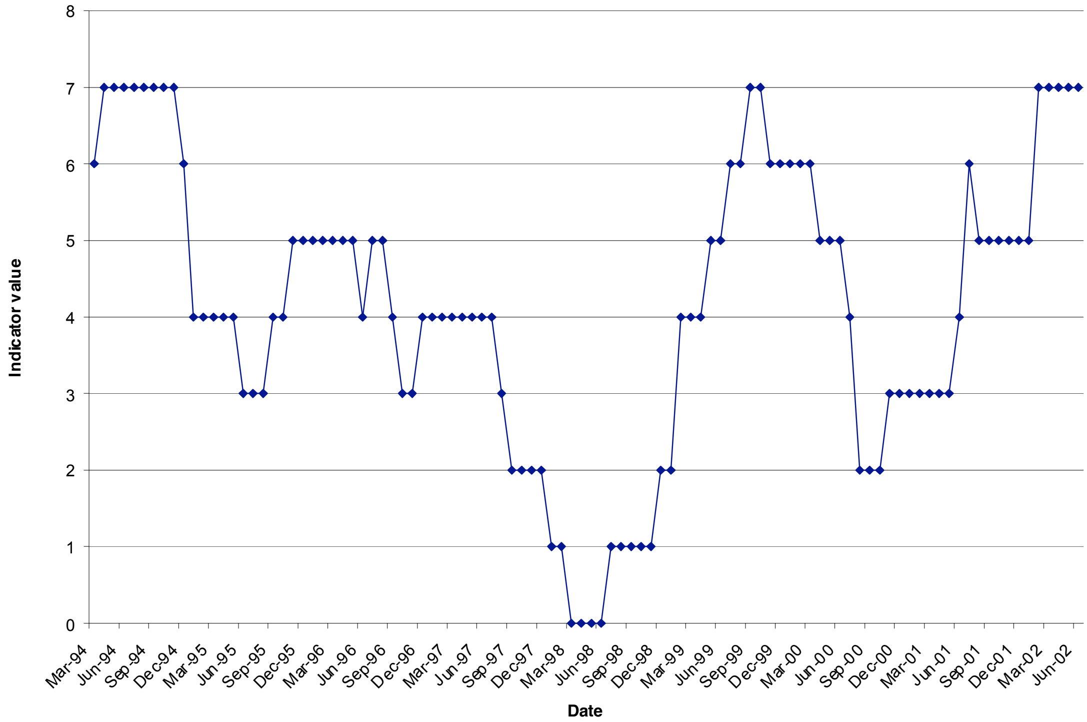
This indicator had a mean of 3.25 and a standard deviation of 1.409742. It was high in February, March, April, and May, and very high in June—in fact, June 2002 represents the sample maximum. This indicator, then, performed quite well in predicting

[43] The two previous quarters were used because this represents nine months of information—the six months represented in the previous two quarters, and the three months represented in the present quarter. This is therefore as close to the ideal eight previous months plus the present month as data limitations allow.

the currency crisis, although it must be noted that there was not a crisis in 1999, despite consistently high values for the indicator.

Figure 22

Composite indicator 3 (banking), March 1994-June 2002



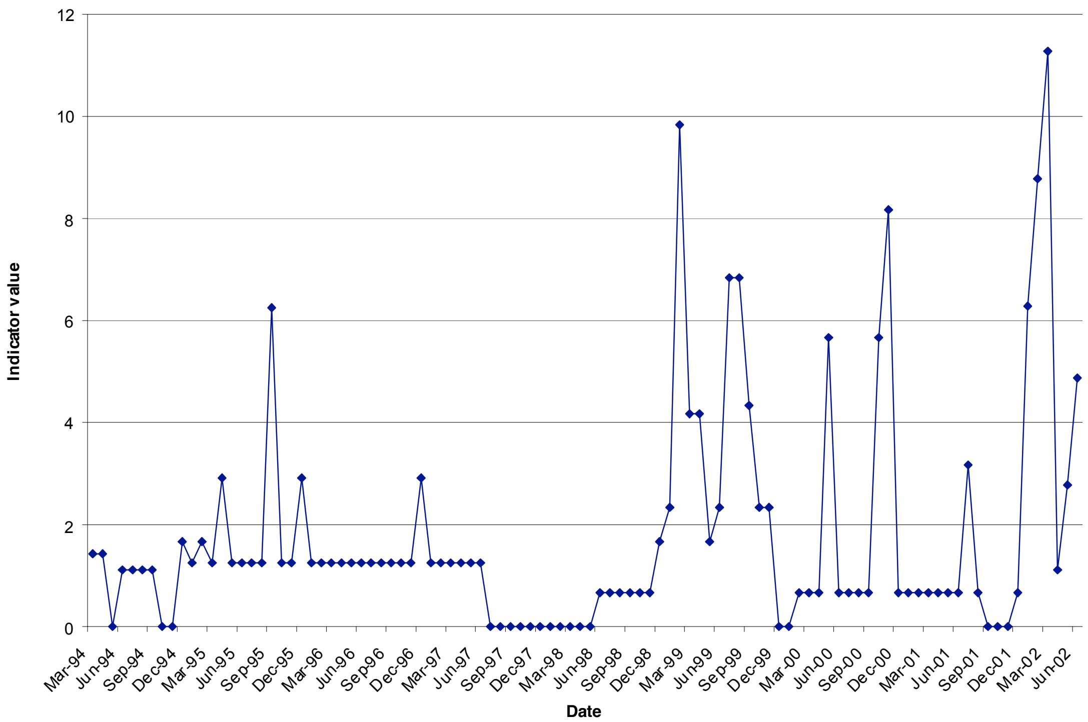
The indicator had a mean of 4.17 and a standard deviation of 1.928285. It was high in February, March, April, May, and June. Not once did the indicator cross the "very high" threshold—the variance was too high for any values two standard deviations over the mean. Nevertheless, the indicator equaled the sample maximum in the period February through June. This indicator, then, performed well, though the movement was not as obvious as that of the currency indicator.

Composite indicator 4

The fourth composite indicator adjusts these variables for the empirical noise-to-signal ratio of the variables. The evolution of this indicator is given in figures 23 and 24.

Figure 23

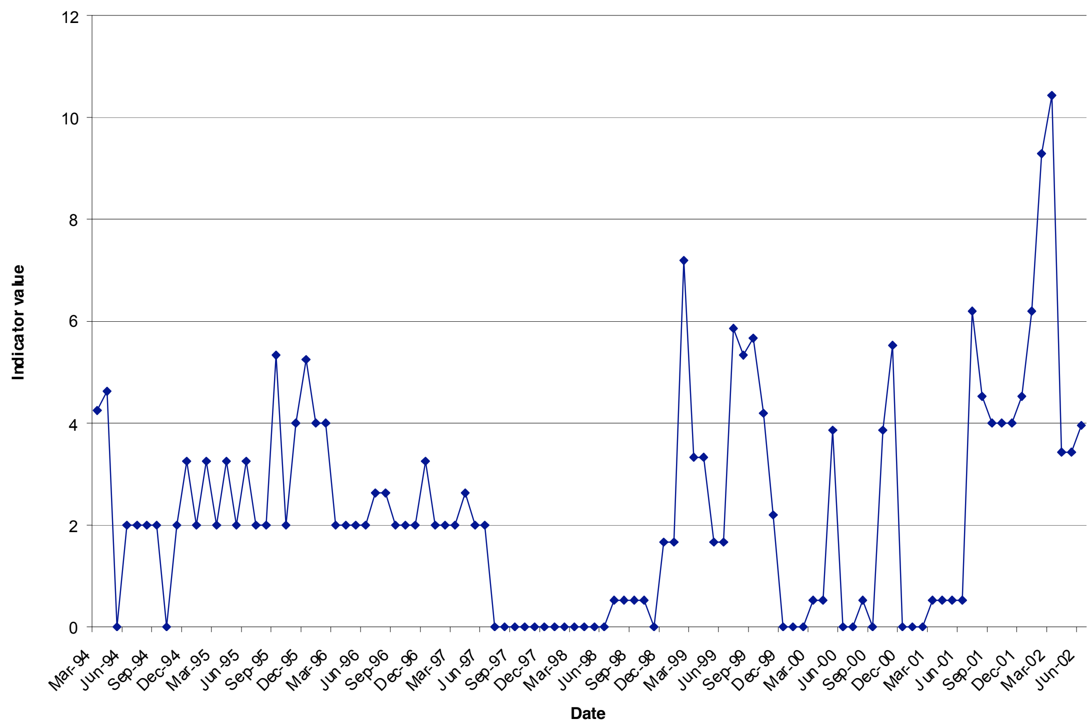
Composite indicator 4 (currency), March 1994-June 2002



The indicator had a mean of 1.781468 and a standard deviation of 2.24473. It was very high in January, February, and March—in fact, the sample maximum occurred in March—and high in June. Again, under ideal circumstances, the indicator should not have fallen directly before the crisis. Nevertheless, the indicator performed adequately.

Figure 24

Composite indicator 4 (banking), March 1994-June 2002



This indicator had a mean of 2.283578 and a standard deviation of 2.139256. It was high in December 2001 and January 2002, and very high in February and March. Unlike the other indicators, however, it rose very little directly before the crisis, so the fourth composite indicator was disappointing in this respect. This failure occurred largely because of the real exchange rate and industrial output, both of which have a low noise-to-signal ratio, not sending a signal in the period April through June. The fact that new sample maximums were set in February and March, however, somewhat offsets this failure.

VI. Summary of Results and Concluding Remarks

In predicting the currency crisis, the first, second, and fourth composite indicators were all very high three to six months before the July crisis, fell in April and May, and rose in June, although not to the levels reached in the beginning of the year. These indicators, then, performed adequately but imperfectly in predicting the currency crisis. The third composite indicator rose consistently before the crisis, reaching its sample maximum in the month directly before the crisis. This is an exceptionally good result for the Kaminsky-Reinhart model.

The banking composite indicators performed similarly to the currency indicators, with the first, second, and fourth indicators very high from February and March (the first and second were very high in January as well), falling for April and May, and finally rising again in June. The third composite indicator was again at its maximum in the months before the crisis—in fact, it was at this level for the months of February through June. The third composite indicator was therefore a very good predictor of the banking crisis. One final fact supporting the Kaminsky-Reinhart model's predictive power in the case of the Uruguayan crises of 2002 is that all eight indicators reached sample maximums in the six months preceding the crises.

Interestingly, while Kaminsky (1998) finds that the fourth composite indicator is generally the most accurate predictor of both currency and banking crises, in this study, the third indicator showed the most obvious trend. This opens a possible area for future research—testing a new indicator which accounts both for the presence of signals in previous months and adjusts the magnitude of the indicator for the noise-to-signal ratio of the variables.

The results are in stark contrast to Alvarez-Plata and Schrooten's (2004) conclusions about the Argentinean crisis, as they found that "the development of many indicators in particular could be interpreted as the beginning of a relaxing process;" i.e., the currency market pressure intrinsic to a currency crisis was diminishing (2004, p. 601). A possible conclusion, then, is that the Argentinean crisis displayed unique characteristics that made it rather unpredictable with this model, which still has useful predictive power for most other crises.

There are two important limitations to this research. First, one of the sixteen variables desired—the stock market index—was not found, one series (industrial output) was quarterly, and another (terms of trade) was annual. While these data deficiencies are not debilitating, they limit the confidence one can have in conclusions from this twin crisis. Second, and more importantly, only one crisis was analyzed. This paper, then, is something of a "case study," which adds to the weight of evidence in favor of the Kaminsky-Reinhart model, but certainly should not be conclusive in accepting it. More research, then, will be needed to more firmly accept, reject, or modify the model.

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Appendix A

The test window of 100 months was arbitrary. To see how dependent this paper's results were on this selection, alternate windows of 50 and 150 months were tested. All months are results for the first six months of 2002[44], and "sample max" denotes that the sample maximum was set or tied in the six months prior to the crises. The results of this analysis are given in tables A1 through A8

Table A1

Composite indicator 1 (currency) results using 50, 100, and 150 month windows

	50 months	*100 months*	*150 months*
"High"	Feb, Jun		
"Very high"	Jan, Mar	Jan, Feb, Mar, Jun	Jan, Feb, Mar, Jun
Sample max	yes	yes	yes
Mean	1.74	1.33	1.313333
Standard deviation	1.337222	1.128644	1.087678

[44] There is nothing special in the model about a six month window, but since the results of the paper are such that these are the most important months, these are the months considered in this sensitivity analysis.

Table A2

Composite indicator 1 (banking) results using 50, 100, and 150 month windows

	50 months	*100 months*	*150 months*
"High"		Jun	
"Very high"	Jan, Feb, Mar	Jan, Feb, Mar	Jan, Feb, Mar
Sample max	yes	yes	yes
Mean	1.78	1.5	1.786667
Standard deviation	1.502243	1.290994	1.303514

The first composite indicator for currency crises performs slightly worse with the 50 month window, as February and June are no longer very high but merely high. The 150 month window, however, performs identically to the 100 month window. For the banking indicator, the 50 and 150 month windows perform the same as the 100 month window, except June is no longer high in the 50 and 150 month windows.

Table A3

Composite indicator 2 (currency) results using 50, 100, and 150 month windows

	50 months	*100 months*	*150 months*
"High"	Mar	Jun	Jun
"Very high"	Jan, Feb	Jan, Feb, Mar	Jan, Feb, Mar
Sample max	yes	yes	yes
Mean	2.6	1.91	1.806667
Standard deviation	2.010178	1.706178	1.587268

Table A4

Composite indicator 2 (banking) results using 50, 100, and 150 month windows

	50 months	*100 months*	*150 months*
"High"	Mar		
"Very high"	Jan, Feb	Jan, Feb, Mar	Jan, Feb, Mar
Sample max	yes	yes	yes
Mean	2.52	2.18	2.42
Standard deviation	2.260937	1.860705	1.814446

For currency crises, the second composite indicator performs worse using the 50 month window, as March falls from very high to high and June falls from high. The 150 month window performs identically to the 100 month window. For banking crises, March falls from high using the 50 month window, but once again the 100 and 150 month window results were identical.

Table A5

Composite indicator 3 (currency) results using 50, 100, and 150 month windows

	50 months	*100 months*	*150 months*
"High"	Feb, Mar, Apr, May	Feb, Mar, Apr, May	May
"Very high"	Jun	Jun	Jun
Sample max	yes	yes	yes
Mean	3.4	3.25	3.553333
Standard deviation	1.470804	1.409742	1.582355

Table A6

Composite indicator 3 (banking) results using 50, 100, and 150 month windows

	50 months	*100 months*	*150 months*
"High"	Feb, Mar, Apr, May, Jun	Feb, Mar, Apr, May, Jun	Feb, Mar, Apr, May, Jun
"Very high"			
Sample max	yes	yes	No
Mean	4.16	4.17	4.793333
Standard deviation	2.063878	1.928285	1.987534

The third composite indicator for currency crises performed identically using the 50 and 100 month windows; however, when using the 150 month window, February, March, and April fell from high. The banking indicator performed identically using all three windows, except that the sample maximum was no longer reached in the six months prior to the crises.

Table A7

Composite indicator 4 (currency) results using 50, 100, and 150 month windows

	50 months	*100 months*	*150 months*
"High"	Jan	Jun	Jun
"Very high"	Feb, Mar	Jan, Feb, Mar	Jan, Feb, Mar
Sample max	yes	yes	yes
Mean	2.425238	1.781468	1.780772
Standard deviation	2.87102	2.24473	2.065393

Table A8

Composite indicator 4 (banking) results using 50, 100, and 150 month windows

	50 months	*100 months*	*150 months*
"High"	Jan	Jan	Jan
"Very high"	Feb, Mar	Feb, Mar	Feb, Mar
Sample max	yes	yes	yes
Mean	2.535489	2.283578	2.616234
Standard deviation	2.659214	2.139256	2.121136

For the fourth composite indicator for currency crises, the 50 month window caused January to fall from very high to high and June to fall from high. The 100 month window performed identically to the 150 month window. For banking crises, all three windows performed identically.

In general, there was not much difference between the 50, 100, and 150 month windows. Usually, the 100 and 150 month windows were very close, with the only exception being the third composite indicator for currency crises. This is an encouraging result, since an increase in the amount of data does not affect the conclusions strongly in any direction. In conclusion, then, the results are not very sensitive to different time windows.