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SanAndrés

*Seminario del Departamento de Economía*

# "Statistical Properties of Sovereign Credit Ratings"


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Martes, 20 de marzo de 2001

First Version: Aug-03-2000
This Version: Feb-09-2001

# Statistical Properties of Sovereign Credit Ratings

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ABSTRACT

The sovereign credit rating is a key determinant of the cost and availability of international financing for an economy. This paper models ratings as a function of expected repayment capacity, derives testable hypotheses, and conducts a statistical analysis based of the ratings awarded by *Institutional Investor*. The key findings are as follows: 1) Expected rating revisions should be positive for moderately low rated countries and negative for moderately high rated countries. 2) Rating revisions are serially correlated with about one third of a country revision expected to carry-over from one semester to the next. This finding is confirmed with ratings awarded by Moody's and Standard and Poor's. 3) There are regional factors in revisions with about 17 percent of the revision to a regional portfolio expected to carry-over to each country in the region next semester. 4) The serial correlation of revisions is the highest in Emerging and Eastern European countries and the lowest among OPEC members. 5) The 1980s were surprisingly bad years for low- and middle-income country creditworthiness, while the early 1990s were surprisingly good. 6) The East Asian crisis of 1997-98 was much less significant in terms of its effect on global creditworthiness than the debt crisis of the early 1980s.

* This paper benefited greatly from the comments of my dissertation committee members: Wayne Ferson (chair), Charles Nelson, Levis Kochin, Dick Startz and Eric Zivot. I also thank Oscar Barraza and seminar participants at the wintercamp of the Latin American and Caribbean Economic Association, especially Pat Kehoe, Ricardo Caballero, Martin Uribe, and Sergio Schmukler for valuable input. All remaining errors are mine. I thank the Ford and Louisa Van Voorhis endowment at the UW for financial support. Dept. of Economics, Univ. of Washington, Seattle, WA, USA, and Univ. de San Andres. Please address correspondence to: Dept. of Economics, Univ. de San Andres, Vito Dumas 284; 1644 – Victoria; Prov. Buenos Aires; Argentina. Ph.: +5411-4725-7088. Fax: +5411-4725-7010. Email: cruces@u.washington.edu.

# 1. Introduction

It is well known that there is limited ability to enforce contracts subject to the regulatory authority of a foreign government. This is due to governments being sovereign in their territories and to having few assets beyond their borders that can be seized by foreign court order. Therefore, measures of host government sovereign risk contain critical information when contemplating international investment. This paper studies the statistical properties of the country credit ratings awarded by a pool of international bankers and published by *Institutional Investor*. The most important finding is that changes in credit ratings are to some extent predictable from their own past. Similar serial correlation is found to be present in the credit rating revisions awarded by Standard and Poor's and Moody's. Five rating forecasting models are compared and show that surprise revisions tend to be much larger in less creditworthy countries. While the early 80s showed strings of negative credit blows in less developed countries; the early 90s seem to have been surprisingly good years there. By contrast, credit surprises are relatively minuscule in developed countries.

The presence of serial correlation in credit revisions does not necessarily imply that ratings are informationally inefficient, because credit ratings forecast the probability of default during a fixed window that starts when the rating is issued. Therefore, two ratings given one year apart forecast the probability of different events. Serial correlation in revisions does imply that the standing rating is not necessarily the best forecast of the probability of future default for debt which matures beyond the credit rating window. This conclusion is interesting from several perspectives. Investors might care to know that given two long-term securities of equal rating, the one whose last revision was more favorable carries a smaller default risk. For regulators, it is important that such ratings are not statistically sufficient measures of default risk. In particular, they could be improved by accounting for the serial correlation.

Previous researchers have used rating data to explain changes in asset prices. Kaminsky and Schmukler (1999) conducted a detailed study of what triggered the 20 largest one-day changes in nine Asian countries' stock markets from January 1997 until May 1998. They meticulously scanned the press on each day of jitters for news releases regarding the state of the local economy: revisions by credit rating agencies, agreements with the IMF and the international financial community, monetary and fiscal policies, political news, etc. They used these data to explain stock returns on those days and found that credit rating revisions by international agencies had the largest impact of the eight event variables considered. On average, prices fall between 11 and 14 percent on days in which credit downgrades are announced!

Starting in 1995, a series of papers by Erb, Harvey and Viskanta (later jointly with Bekaert) used credit ratings to sort countries into portfolios of different mean rating and found that portfolios of stocks from low-rated countries outperformed portfolios from high-rated countries from 1980 until 1993.[1] Ferson and Harvey (1998) used ratings as an instrument for mispricing and for conditional risk exposure in a study of stock market returns of 20 developed countries. Cruces (2001) measures the relation between abnormal stock returns and surprise credit revisions in 39 countries from 1986 until 1999. Surprises of the magnitudes that are common in emerging markets produce equity return responses larger than the unconditional expected return. This paper complements Cruces (2001) by analyzing the credit rating data in more detail and substantiating the credit forecasting models used there. While previous researchers have analyzed the fundamental determinants of ratings, and others have used ratings to explain returns, little is known about the statistical properties of the ratings themselves. This paper intends to fill the gap.

A few stylized facts are apparent in the *Institutional Investor* ratings. The highest and lowest rated countries tend to have ratings that are relatively more stable than those of countries in the middle range. For instance, Table II.A shows that the typical country in North America and Western Europe has a rating of 81 points and a standard deviation of change in rating of 0.7 credit points per semester, just like the typical African country which, by contrast, has a rating of 23 credit points –the lowest of all regions considered.

[1] The use of *Institutional Investor* country credit ratings in an asset pricing context dates back to at least Feder and Ross (1982).

On the other hand, countries with intermediate ratings have from two to three times the volatility of revisions of African and OECD economies.[2] Table II.A also shows that mean rating revisions during five-year periods can be large in absolute magnitude and of changing signs –especially in middle income regions. For example, mean revisions were negative in all but the wealthiest three regions during the 1980s while they tended to be positive during the 1990s. If a series of positive adjustments in ratings is followed by a series of negative adjustments, are ratings reverting to some mean? If so, does this result mechanically from the fact that ratings are bounded by [0,100] or is this a consequence of the payoff structure of debt contracts? Another stylized fact is that rating revisions tend to be serially correlated in most countries with the possible exception of oil exporters (Table VII). Can a rational expectations model accommodate these stylized facts?

The paper makes the following contributions. First, it models the transition from capacity to repay to credit ratings and derives refutable propositions implied by the hypothesis that ratings are rational expectations forecasts. It shows that ratings should exhibit volatility clustering and mean reversion, and could also display non-zero expected revisions and serially correlated revisions. Second, it provides a statistical description of credit ratings across time and countries using data for all the countries for which ratings are available during 21 years --the longest period and largest cross-section of any study to date. Third, it documents that sovereign credit revisions are sticky –and more so in some countries or regions than in others.[3] Since survey data can be measured with error, the main findings are verified with sovereign ratings issued by credit rating agencies and striking similarities obtain. As a by-product, the analysis suggests a few propositions that can be tested on agencies' "under review" announcements and on bond prices. These are left for future research.

Section 2 presents the model and section 3 describes the data, reviews the history of the rating industry and briefly discusses the literature on the fundamental determinants of

[2] Perhaps, the low variance of ratings in highly rated countries makes them uninformative about conditional alpha or beta as in Ferson and Harvey (1998). Out model rationalizes why this volatility is low.
[3] Altman and Kao (1992) noticed that revision of US corporate bond ratings are also serially correlated.

credit ratings. Section 4 presents the empirical results and section 5 analyzes surprise credit revisions under different forecasting models. Section 6 concludes.

## 2. A Model of Country Credit Ratings

We study creditworthiness rather than default events for three reasons. First, only in the most extreme circumstances, do countries default in full with no possibility of future workout.[4] More commonly, the expected collection by debt-holders upon default varies greatly across time and countries. So the fact that a country entered default may not convey precise information about the magnitude of the creditor's losses. Second, countries often default informally, as reflected in a delay in payments of banking debt that may be difficult to document. Last, a given time series of default and non-default events is likely to be affected by a *peso*-like problem in that the series may not be long enough for the relative frequency of default in the sample to be an unbiased estimate of the ex-ante expectation. As a result, this paper focuses on credit ratings which explicitly measure ex-ante expectations.



According to *Institutional Investor*'s (*II*) ballot letter, "The best rating, 100, would represent the countries with the strongest debt service capacity and the least possibility of defaulting on their debt. A rating of 0, the worst rating, would represent countries with the weakest debt service capacity and the greatest possibility of default. Please use the number 0 only to indicate a ranking" (*Institutional Investor*, 1999). This wording suggests that ratings are proportional to expected collection.

Unfortunately, *II* is silent about the horizon for which creditworthiness is assessed. Perhaps, the horizon is country-specific and depends on the maturity of each bank's claims on each country. In that case, the *II* ratings and the horizon for which they are

[4] For instance, the only countries that repudiated their debts since World War II are China (1949), Cuba (1961) and North Korea (1964) (Saunders, 2000, p.331).

valid are likely to vary across countries. However, the March 1987 survey presents two tables: one table gives short-term ratings (i.e. one year into the future) while the other gives ratings for a one- to five-year time frame. Since changes with respect to adjacent semesters are reported based on the latter table, we take the ratings as representing a medium term opinion. The practice of assigning ratings for a fixed interval in the future (as opposed to a period that extends into the indefinite future) is standard in the rating industry. For instance, credit agencies assign long-term ratings for an explicit five- to ten-year horizon (Mahoney, 2000 and Cavanaugh, 2000). Therefore, we propose to define a country credit rating for a *J*-period window conditional on *t*-information, ${}_tCCR_{t+1,t+J}$, as the average of the expected collections for each period in the window,

$$(1) \qquad {}_tCCR_{t+1,t+J} \equiv \frac{1}{J}\sum_{i=1}^{J} E_t\left(C_{t+j}\right)$$

**From Capacity to Repay to Expected Collection**

The creditor's collection on a claim depends on the debtor's capacity to repay, which we postulate to be random. Assuming a statistical distribution of the latter, allows an easy solution for expected collection as a function of the moments of repayment capacity.

Suppose that capacity to repay per dollar due at $t$ is measured by a continuous random variable $(1+\phi_t)$ with support on the real line. We may think of $1+\phi$ as representing the product of ability to pay times willingness to pay. Ability to pay would be measured by the sum of net exports plus debt rollovers in the voluntary market normalized by the interest and amortizations coming due at $t$. Willingness to pay can be represented by an indicator function. When $\phi \geq 0$, the debtor pays its obligations in full, and when $-1 < \phi < 0$, there is partial default in that the debtor only pays $1+\phi$ per dollar due. When

$\phi \leq -1$, default is complete. Therefore, the collection per dollar lent, $C_t$, is related to $\phi_t$ by,

$$(2) \qquad C_t = \begin{cases} 1 & \text{if} \quad 1 \leq 1+\phi_t \\ 1+\phi_t & \text{if} \quad 0 \leq 1+\phi_t \leq 1 \\ 0 & \text{if} \quad 1+\phi_t \leq 0 \end{cases}$$

The collection of period $t$ expected as of $t$-$n$ is the probability of full payment plus the expected collection in case of default,

$$(3) \qquad E_{t-n}(C_t) = \int_0^{\infty} f_{t-n}(\phi_t)\, d\phi_t + \int_{-1}^{0} (1+\phi_t) f_{t-n}(\phi_t)\, d\phi_t$$

where $f_{t-n}$ is the density of $\phi_t$ conditional on $t$-$n$ information. For now we will assume that this density is symmetric and that it has two parameters. Figure I illustrates the various components of (3). Panel A shows different densities of $\phi_t$ conditioned on $t0$, $t1$ and $t2$ information respectively.[5] The bold sloped line is the locus of the conditional expectation of $\phi$.

The first summand in (3) is the probability of full payment and is depicted in panel B. The horizontal axis represents $E_{t-1}(\phi_t)$ and two curves are drawn for different values of $Var(\phi_t)$. The variance will not affect the probability of full payment when $E_{t-1}(\phi_t)$=0. When $E_{t-1}(\phi_t)$<0, the probability of full payment will be higher in countries with a higher variance because favorable realizations of $\phi$ will have more probability mass than if the variance were lower. When $E_{t-1}(\phi_t)$>0 the variance impacts the probability of full payment negatively because then negative states are more likely.

[5] The densities could be conditioned on time (so they pertain to one country over time) or they could be conditioned on countries (so they refer to different countries on the same date) or both. The following analysis pertains to time-conditioned distributions.

The last summand in (3) is the expected collection in case of default depicted in Panel C. This expectation is largest for debtors with $E(\phi) \in (-1,0)$ than for debtors with much higher or much lower expected repayment capacity, since for the latter the density of $\phi$ is much lower in that range. For the same reason, expected collection in the $(-1,0)$ range is larger for tighter distributions. However, for very large values of $E(\phi)$, a higher $Var(\phi)$ implies a higher expected collection in case of default than for tighter distributions, since each value of $\phi$ far from its mean will have more mass there. Similarly for very negative values of $E(\phi)$.

Having given an intuitive discussion of expected collection, we now turn to an analytic solution. Equation (3) can be rearranged as,

$$(4) \qquad E_{t-n}(C_t) = \int_{-1}^{\infty} f_{t-n}(\phi_t)\, d\phi_t + \int_{-1}^{0} \phi_t\, f_{t-n}(\phi_t)\, d\phi_t .$$

Some distributional assumption about $\phi$ needs to be made in order to solve (4) and also to conduct the simulation exercise in section 2.5 in which random draws of $\phi$ are generated. More generally, repayment capacity is the sum of net exports of numerous goods plus debt rollovers in the voluntary market normalized by the interest and amortization due within a year (these obligations are conditionally constant). "In practical terms, the Lindberg-Feller central limit theorem states that sums of random variables, regardless of their form, will tend to be normally distributed" (Greene, 1997, p.123). The shape of the logistic distribution is similar to the normal but the logistic density is more tractable. Therefore we propose to assume that $\phi$ follows a logistic distribution.

The logistic distribution has a location parameter (the mean), and a scale parameter, $\beta$, that is proportional to its variance. Assume that while the conditional mean can change over time, the conditional variance is fixed. In this case, from the logistic cdf, the first integral in (4) is

$$(5) \qquad \int_{-1}^{\infty} f_{t-n}(\phi_t)\, d\phi_t = 1 - \frac{1}{1+e^{\frac{1+E_{t-n}(\phi_t)}{\beta}}},$$

while the second integral is (see Appendix I),

$$(6) \qquad \int_{-1}^{0} \phi_t\, f_{t-n}(\phi_t)\, d\phi_t = -1 + \frac{1}{1+e^{\frac{1+E_{t-n}(\phi_t)}{\beta}}} + \beta \ln\left( \frac{1+e^{\frac{1+E_{t-n}(\phi_t)}{\beta}}}{1+e^{\frac{E_{t-n}(\phi_t)}{\beta}}} \right).$$

Adding (5) and (6), the expected collection becomes,

$$(7) \qquad E_{t-n}(C_t) = \beta \ln\left( \frac{1+e^{\frac{1+E_{t-n}(\phi_t)}{\beta}}}{1+e^{\frac{E_{t-n}(\phi_t)}{\beta}}} \right).$$

This is the key equation in this paper. It is interesting for it bridges the gap between expected repayment capacity of the debtor and expected collection by the creditor. The non-linearity results from the fact that the debtor will never pay more than what is owed and the creditor will never collect less than zero. Therefore, (7) is always positive, it asymptotes to zero for very large negative values of $E_{t-n}(\phi_t)$ and it asymptotes to one for very large positive values of $E_{t-n}(\phi_t)$. A crucial feature is that (7) is a non-linear function of $E_{t-n}(\phi_t)$ as opposed to the expectation at *t-n* of a non-linear function of $\phi_t$. This results from the fact that in order to compute $E_{t-n}(C_t)$, we use a density in (3) that depends on $E_{t-n}(\phi_t)$. Figure II shows the value of (7) for different combinations of mean and variance of repayment capacity. When there is no uncertainty about $\phi$, $E(C)$ is represented by payoff schedule (2) plotted as the solid line. As $\beta$ increases, $E(C)$ becomes smooth and piece-wise concave and convex. As $\beta \to \infty$, expected collection becomes flat at $E(C) = 0.5$. If credit ratings are proportional to $E(C)$ --as we postulate below-- then we can use (7) to derive statistical properties of ratings that can be tested on data.

### 2.1. Volatility Clustering

Naturally, expected collection increases in the conditional mean. Differentiating with respect to $E_{t-n}(\phi_t)$ gives

$$(8) \qquad \frac{\partial E_{t-n}(C_t)}{\partial E_{t-n}(\phi_t)} = \frac{e^{\frac{E_{t-n}(\phi_t)+1}{\beta}}}{1+e^{\frac{E_{t-n}(\phi_t)+1}{\beta}}} - \frac{e^{\frac{E_{t-n}(\phi_t)}{\beta}}}{1+e^{\frac{E_{t-n}(\phi_t)}{\beta}}} .$$

This is the difference between two logistic cdfs with a slight change in variables. Both cdfs are evaluated at $E_{t-n}(\phi_t)$, but each is conditioned on a different mean. The first cdf corresponds to a random variable with mean -1 while the second one corresponds to a mean zero random variable. In both cases, the scale parameter is $\beta$. With this, (8) becomes



$$(9) \qquad \frac{\partial E_{t-n}(C_t)}{\partial E_{t-n}(\phi_t)} = F_X\left[x = E_{t-n}(\phi_t) \mid E(X) = -1\right] - F_X\left[x = E_{t-n}(\phi_t) \mid E(X) = 0\right] > 0$$

Because the first cdf is centered to the left of the second one, while they are both evaluated at the same point, the partial effect is always positive. Figure III.A plots the two cdfs in (9) and their difference for illustration. Differentiating (9) gives,

$$(10) \qquad \frac{\partial^2 E_{t-n}(C_t)}{\partial E_{t-n}(\phi_t)^2} = f_X\left[x = E_{t-n}(\phi_t) \mid E(X) = -1\right] - f_X\left[x = E_{t-n}(\phi_t) \mid E(X) = 0\right] \underset{<}{\geq} 0$$

Figure III.B depicts the two densities in (10) and their difference. The first density peaks at -1 while the second one peaks at zero. From symmetry, the difference is zero at $E_{t-n}(\phi_t) = -½$, and (9) has a maximum there. At this point, the two cdfs in (9) have parallel tangents which implies that the difference between them is largest. In other words, the effect of a change in expected capacity to repay has the largest impact on expected collection there (as shown in Figure III.A). This implies that countries which are expected to pay 50 cents on the dollar should have the highest volatility of expected collection, even if shocks to the underlying repayment capacity have the same variance across all countries. If country credit ratings are a linear function of expected collection, they will inherit this relative volatility pattern.

The fact that the second derivative will also asymptote to zero as $|E(\phi)| \to \infty$ has two implications. On the one hand, as $|E(\phi)| \to \infty$, (9) will go to zero, so that expected collection is insensitive to changes in repayment capacity both when the borrower is very solvent and very insolvent. On the other hand, the fact that (7), has less curvature for extreme values of $E(\phi)$ has implications for the sign of revisions to expected collection as we shall see next.



### 2.2. Mean Reversion

The curvature of expected collection causes reversion of $E(C)$ to $E(C) = 0.5$ for initial ratings that are moderately above and moderately below this level, but not for extreme ratings. This results from the (0,1) bounds on the debt contract and from the fact that (7) is a non-linear function of expected repayment capacity as opposed to the expectation of a non-linear function of $\phi$. This is in spite of shocks to $E(\phi)$ being symmetric and mean zero. A second order Taylor expansion of $E_{t-n}(C_t)$ illustrates the point,

$$(11) \quad E_{t-n}[C_t]\big|_{E_{t-n}(\phi_t)+\Delta} - E_{t-n}[C_t]\big|_{E_{t-n}(\phi_t)} \cong \frac{\partial E_{t-n}(C_t)}{\partial E_{t-n}(\phi_t)}\Delta + \frac{1}{2}\frac{\partial^2 E_{t-n}(C_t)}{\partial E_{t-n}(\phi_t)^2}\Delta^2 \ .$$

The changing curvature of (7) causes asymmetric adjustments of expected collection through the second order term in (11). In the three regions where either $E(\phi)=-½$ or $E(\phi)\to\pm\infty$, expected collection is approximately linear, so the second order term vanishes and expected changes in expected collection are zero. However, the second summand will be negative in the range where (7) is concave and positive over the convex range.[6] Therefore, for $E(\phi)$ moderately greater than -½, the second summand will reduce the impact of positive shocks and magnify the effect of negative shocks so that the unconditional expectation of the revision is negative. Because (7) is convex for low $E_{t-n}(\phi_t)$, the reverse will happen for countries that are expected to default fully. Taking unconditional expectations of (11), shows that expected revisions should be positive for relatively insolvent countries while they should be negative for relatively solvent countries.

[6] To the left of $E_{t-n}(\phi_t)=-½$, the first density in (10) is larger than the second one and the expected collection is convex, while to the right of this point, the function is concave –in fact the concavity of $E(C)$ peaks to the right of $E(\phi)=0$ and the convexity peaks to the left of $E(\phi) = -1$. The thick line in Figure III.B shows the highly nonlinear shape of the curvature of expected collection. The analytic characterization of the points at which $E(C)$ exhibits the most curvature is not straightforward. However, a simple geometric argument delivers the intuition. The line with symbols in Figure III.B plots (10) which is the difference between the solid line and the dotted line in that graph for an arbitrary value of $\beta = ½$. Start from $E(\phi) = -½$. As we move to the right along the $E(\phi)$ axis, the density that is summing in (10) decreases and the one that is subtracting increases so that (10) becomes more negative (i.e. the concavity of expected collection rises). At $E(\phi)=0$, $f_X(x \mid EX=0)$ flattens out, so that to the right of that point both densities have negative slope. If there is a point of maximum distance between the two densities it will be where they have parallel tangents. From the bell shape of the logistic, the slope of $f_X(x \mid EX=0)$ will go from zero to very negative and then become less negative as it asymptotes towards zero. In the interval in which the density that is subtracting goes from a zero slope to a very negative slope, there will be a point at which its slope will equal that of $f_X(x \mid EX=-1)$. This will be the point of maximum concavity. As the variance of the distribution shrinks, both densities will be more peaked and the point of maximum concavity will move towards $E(\phi)=0$ (similarly the point of maximum convexity will approach $E(\phi)=-1$ from the left as $\beta \to 0$).

It is worthwhile to compare this proposition with the alternative that $E(C)$ follows a first order Markov process bounded by [0,1]. In this case, the presence of the bounds causes mean reversion when $E(C)$ is initially close to the bound. For example, if $E(C)$ is arbitrarily close to 1, it has nowhere to go but down. So the closer that $E(C)$ is to the bound, the more important the mean reversion effect. Here we make no claim of mean reversion for extremely high and extremely low $E(C)$. In fact, in such ranges (7) is approximately linear so that the second order term in (11) is negligible. In our model, the second order term is important for *moderately* high and *moderately* low $E(C)$, for which the bounded Markov process alternative does not necessarily imply mean reversion.

### 2.3. Effect of Variance of Repayment Capacity on Expected Collection

It is also of interest to analyze the effects of the variance of $\phi$ on the expected collection. Differentiating (7) with respect to $\beta$ gives (see Appendix I),

$$(12) \qquad \frac{\partial E_{t-n}(C_t)}{\partial \beta} = \frac{1}{\beta}\left\{ \underbrace{E_{t-n}(C_t) - F_X[E_{t-n}(\phi_t) \mid E(X) = -1]}_{A} \underbrace{- E_{t-n}(\phi_t)\frac{\partial E_{t-n}(C_t)}{\partial E_{t-n}(\phi_t)}}_{B} \right\}$$

When $E_{t-n}(\phi_t)$ = -½, expected collection will be unaffected by $\beta$.[7] The effect of the variance on expected collection can also be signed at two other points. When

[7] To see this, collect the terms that have the same cdfs, replace from (7) and evaluate at $E_{t-n}(\phi_t)$ = -½ to get,

$$\left.\frac{\partial E_{t-n}(C_t)}{\partial \beta}\right|_{E(\phi)=-\frac{1}{2}} = \frac{1}{\beta}\left\{ \beta \ln\left(\frac{1+e^{\frac{1}{2\beta}}}{1+e^{\frac{-1}{2\beta}}}\right) - \frac{1}{2}\left(F_X\left[-\frac{1}{2} \mid E(X) = -1\right] + F_X\left[-\frac{1}{2} \mid E(X) = 0\right]\right)\right\}$$

$E_{t-n}(\phi_t) = -1$, a higher $\beta$ increases the rating,[8] while the opposite happens at $E_{t-n}(\phi_t)$ = 0.[9]

These results are illustrated in Figure II, where for $E(\phi_t)$ < -½ a higher variance increases the expected collection, while for $E(\phi_t)$ > -½ a higher variance reduces the expected collection for a given $E(\phi_t)$. The intuition is straightforward. When borrowers are expected to pay debts in full the variance can only hurt the creditor, because while borrowers will never pay any more than what is owed, they may pay less if events are adverse. The reverse happens when borrowers are expected to default in more than one half of their obligations.

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From symmetry and the fact that both cdfs have the same scale parameter, their sum equals 1. Also, expected collection equals ½ at this point. Therefore, the effect of variance on expected collection is zero at that point.

[8] In this case, (12) reduces to,

$$\left.\frac{\partial E_{t-n}(C_t)}{\partial \beta}\right|_{E_{t-n}(\phi_t)=-1} = \frac{1}{\beta}\{\, E_{t-n}(C_t) - F_X(-1 \mid E(X)=0)\} .$$

In this case the probability of full payment, which is one component of the expected collection in (3) exactly offsets the probability that $X$ is less than –1 conditional on $E(X)=0$. This results from symmetry of the logistic distribution and from the fact that the scale parameter is the same for $\phi$ and for $X$. Then (12) is positive because the other component of $E_{t-n}(C_t)$, the expected collection in case of default, is semi-positive.

[9] In this case, only $A$ in (12) remains. In this case the probability of full payment [which is one component of $E_{t-n}(C_t)$] is ½ and is exactly offset by $F_X(-1 \mid E(X)=-1)$ [one component of $F_X(0 \mid E(X)=-1)$]. The only remaining terms are the expected collection in case of default [the second summand in (3)] and the probability that $X$ is between –1 and 0. Having the same scale parameter, the densities are the same and (12) boils down to,

$$\left.\frac{\partial E_{t-n}(C_t)}{\partial \beta}\right|_{E_{t-n}(\phi_t)=0} = \frac{1}{\beta}\int_{-1}^{0} \phi_t\, f_{t-n}(\phi_t)\, d\phi_t \qquad ,$$

which is negative since $\phi$ is always negative in this range. More generally, the last term in $B$ is always positive from (9). When the expected repayment capacity is negative, $B$ is positive. If $E_{t-n}(\phi_t)$ is sufficiently negative, $A$ is also positive, and the effect of incremental variance on expected collection is positive. Conversely, when $E_{t-n}(\phi_t)$ is large and positive, $A \to 0$ and the variance impacts expected collection negatively from $B$.

### 2.4. Non-Zero Expected Credit Revisions?

Since this paper aims to characterize surprise credit revisions, it is natural to ask if expected revisions could be different from zero and how the correlation in innovations of capacity to repay passes-through to correlations in credit revisions. We now address these issues.

To illustrate, set $J$=2 in (1) so that a rating is an average of the expected collection during two periods into the future from the time that it is issued. As time passes, the window of time for which ratings are assessed also moves. Therefore, two consecutive credit ratings are not a forecast of the same event since they pertain to periods that only partially overlap. The *partial* overlapping is crucial because it implies that expected revisions can be non-zero even if raters produce rational expectations forecasts. The increase in credit rating observed from period 0 to period 1 would be,

$$(13) \quad {}_1CCR_{2,3} - {}_0CCR_{1,2} = \frac{1}{2}[E_1(C_2) + E_1(C_3) - E_0(C_1) - E_0(C_2)] \ .$$

Assuming that credit rater's expected collections are rational in the sense of Muth (1961) they satisfy the law of iterated expectations. Then, the credit revision expected as of time zero is,

$$(14) \quad E_0\left[{}_1CCR_{2,3} - {}_0CCR_{1,2}\right] = \frac{1}{2}[E_0(C_3) - E_0(C_1)]$$

and from (7) this is,

$$E_0\left[{}_1CCR_{2,3} - {}_0CCR_{1,2}\right] = \frac{\beta}{2}\left(\ln\frac{1+e^{\frac{1+E_0(\phi_3)}{\beta}}}{1+e^{\frac{E_0(\phi_3)}{\beta}}} - \ln\frac{1+e^{\frac{1+E_0(\phi_1)}{\beta}}}{1+e^{\frac{E_0(\phi_1)}{\beta}}}\right) \tag{15}$$

So if $E_0(\phi_3) > E_0(\phi_1)$, the credit rating of this country is expected to increase over time. If changes in capacity to repay are unpredictable, $E_0(\phi_3) = E_0(\phi_1) = \phi_0$, the expected credit revision is zero and actual credit revisions should be unpredictable. However, if there are predictable changes in capacity to repay (for example, if a temporary adverse situation in period 1 is expected to go away by period 3), changes in credit ratings should be partly predictable.

### 2.5. From Serial Correlation in Repayment Capacity Innovations to Serial Correlation in Credit Revisions

Suppose that repayment capacity innovations follow an AR(1) process,

$$\phi_t - \phi_{t-1} = \rho(\phi_{t-1} - \phi_{t-2}) + \varepsilon_t \tag{16}$$

with $|\rho| < 1$ and $\varepsilon_t \sim \text{i.i.d.}(0, \sigma^2)$. Suppose that repayment capacity has been constant for a while, and that call the time zero shock $\Delta\phi_0$. Then (15) can be written as,

$$E_0\left[{}_1CCR_{2,3} - {}_0CCR_{1,2}\right] = \frac{\beta}{2}\left(\ln\frac{1+e^{\frac{1+\phi_0+(\rho+\rho^2+\rho^3)\Delta\phi_0}{\beta}}}{1+e^{\frac{\phi_0+(\rho+\rho^2+\rho^3)\Delta\phi_0}{\beta}}} - \ln\frac{1+e^{\frac{1+\phi_0+\rho\Delta\phi_0}{\beta}}}{1+e^{\frac{\phi_0+\rho\Delta\phi_0}{\beta}}}\right) \tag{17}$$

This confirms that if $\rho = 0$, expected revisions should also be zero. It is of interest to study how would the presence of serial correlation in innovations to repayment capacity translate into correlation of credit revisions. The covariance conditional on $t$=0 information of the revisions to take place at $t$=1 and at $t$=2 is,

$$Cov_0\{({}_1CCR_{2,3} - {}_0CCR_{1,2}), ({}_2CCR_{3,4} - {}_1CCR_{2,3})\} = \tag{18}$$

$$= \frac{\beta^2}{4} Cov_0 \left( \ln \frac{\dfrac{1+e^{\frac{1+E_1(\phi_3)}{\beta}}}{1+e^{\frac{E_1(\phi_3)}{\beta}}}}{\dfrac{1+e^{\frac{1+E_0(\phi_1)}{\beta}}}{1+e^{\frac{E_0(\phi_1)}{\beta}}}} \;,\; \ln \frac{\dfrac{1+e^{\frac{1+E_2(\phi_4)}{\beta}}}{1+e^{\frac{E_2(\phi_4)}{\beta}}}}{\dfrac{1+e^{\frac{1+E_1(\phi_2)}{\beta}}}{1+e^{\frac{E_1(\phi_2)}{\beta}}}} \right)$$

which from (16) is

$$= \frac{\beta^2}{4} Cov_0 \left( \ln \frac{\dfrac{1+e^{\frac{1+\phi_0+(\rho+\rho^2+\rho^3)\Delta\phi_0+(1+\rho+\rho^2)\varepsilon_1}{\beta}}}{1+e^{\frac{\phi_0+(\rho+\rho^2+\rho^3)\Delta\phi_0+(1+\rho+\rho^2)\varepsilon_1}{\beta}}}}{\dfrac{1+e^{\frac{1+\phi_0+\rho\Delta\phi_0}{\beta}}}{1+e^{\frac{\phi_0+\rho\Delta\phi_0}{\beta}}}} , \ln \frac{\dfrac{1+e^{\frac{1+\phi_0+(\rho+\rho^2+\rho^3+\rho^4)\Delta\phi_0+(1+\rho+\rho^2+\rho^3)\varepsilon_1+(1+\rho+\rho^2)\varepsilon_2}{\beta}}}{1+e^{\frac{\phi_0+(\rho+\rho^2+\rho^3+\rho^4)\Delta\phi_0+(1+\rho+\rho^2+\rho^3)\varepsilon_1+(1+\rho+\rho^2)\varepsilon_2}{\beta}}}}{\dfrac{1+e^{\frac{1+\phi_0+(\rho+\rho^2)\Delta\phi_0+(1+\rho)\varepsilon_1}{\beta}}}{1+e^{\frac{\phi_0+(\rho+\rho^2)\Delta\phi_0+(1+\rho)\varepsilon_1}{\beta}}}} \right) \tag{19}$$

Conditional on $t$=0 information, the random variables in this expression are $\varepsilon_1$ and $\varepsilon_2$. The coefficient in a first order autoregression of credit revisions will result from dividing (19) by the variance of the first-period revision. The ultimate object of interest is actually more complicated than (19) since the rating window can be up to ten semesters long

($J$=10). Given the difficulty in obtaining an analytical solution for this equation, we performed a simulation exercise. The results are presented in Table I and Figure IV. The result in each cell of Table I is the corresponding statistic over 100 simulations of each situation. The parameters for each situation are the autocorrelation of capacity to pay innovations and the number of periods assumed to comprise the credit rating window.

For each situation, three sequences of 1000 shocks (corresponding to the $t$=0, 1 and 2 shocks) are generated from a logistic distribution with mean zero and $\beta$=0.01.[10] Also, $\phi_{-1}$ is randomly chosen for each of the 1000 observations so that the starting expected collection per dollar due in the first period has a uniform distribution between 0.8 and 1.[11] The autocorrelation of innovations in capacity to repay varies between 0.9 and –0.9 by increments of 0.15. Based on the specified parameters in each case, the credit rating at $t$=0, 1 and 2 are computed from (16), (7) and (1). The rating increase during the second period is then regressed on the increase during the first period, and the autocorrelation coefficient and its $t$-ratio are computed. The point slope estimate is saved to compute the mean estimated coefficient and the $t$-ratios greater than 1.95 in absolute value are saved to compute the number significantly different from zero in each situation.[12] The r-squared of each regression is also saved to compute the mean r-squared. Three rating window widths are considered: two periods, six periods and ten periods. Since *Institutional Investor* ratings are published twice a year, a ten-period long horizon would correspond to five years, which seem a reasonable upper bound for the horizon of these ratings.

The results show that the serial correlation of capacity to pay innovations $(\rho_{\Delta\phi})$ are partly inherited by the serial correlation of credit revisions $(\rho_{\Delta CCR})$. If $\rho_{\Delta\phi} = 0.75$ the mean

[10] This value was chosen arbitrarily. Since it affects the scale of both the regressor and regressand, it should not affect the serial correlation parameter.

[11] These bounds are suggested by the fact that interest rates above five times LIBOR are rarely observed on international loans. If default risk is diversifiable, then the expected return should be the same for a borrower who is expected to default and one who is not. Call $p$ the expected collection, then $p(1+5r) = 1+r$, which for LIBOR at 6 percent implies $p$=0.82. As an approximation, we assumed that one-period expected collection for countries in the sample varies uniformly between 0.8 and 1.

[12] When the regressors are well behaved, the asymptotic normality of the $t$-ratios results from the Central Limit Theorem and not from the assumed distribution of the disturbances (Greene, 1997, p.277). Given that each sample has 1000 observations, the assumption of asymptotic normality does not seem crucial.

$\rho_{\Delta CCR}$ is 0.26 if the rating window is two-periods long, 0.16 if it is six-periods long and 0.13 if it is 10-periods long. This larger dampening in proportion to the width of the credit rating window occurs for $\rho_{\Delta\phi}$ greater than 0.3 in absolute value. For the range of $0<\rho_{\Delta\phi}<1$ there is a monotonically increasing relationship between $\rho_{\Delta\phi}$ and $\rho_{\Delta CCR}$ for a given window width.

The columns that report the number of significant coefficients in each case agree with intuition. When $\rho_{\Delta\phi}$ = 0.9, all the 100 estimated coefficients are positive when the window is two or six periods long and only 85 of them are positive and statistically significant when the window is 10 periods long. As $\rho_{\Delta\phi}$ approaches zero, the number significantly positive decreases for a given window width as expected. When $\rho_{\Delta\phi}<0$, $\rho_{\Delta CCR}$ is still significantly positive for a large fraction of observations. This happens because subsequent credit revisions take into account the predictability of the underlying process. However, $\rho_{\Delta CCR}$ is smaller when $\rho_{\Delta\phi}$ is negative than when it is positive (for a given absolute value of $\rho_{\Delta\phi}$). This could occur because when $\rho_{\Delta\phi}$ is negative, its powers will alternate in sign in (17) and expected revisions are smaller.[13] Last, the average r-squared statistics for each situation are in proportion to the number of coefficients significantly different from zero as is obvious in univariate regression. Based on these results it seems reasonable to conjecture that a $\rho_{\Delta\phi} \approx 0.5$ will be associated with a $\rho_{\Delta CCR} \approx 0.1$. Higher values of $\rho_{\Delta\phi}$ can give values of $\rho_{\Delta CCR}$ from 0.2 to 0.35.

In sum, the assumption that credit ratings are rational expectations forecasts does not imply that expected credit revisions should be zero. Instead the expected revisions will depend on the expected changes in the underlying capacity to pay. To the extent that changes in the latter are predictable, so should changes in the former. Moreover, the serial correlation in capacity to repay innovations partly passes through to the serial correlation of credit revisions and lower absolute serial correlation in capacity to pay innovations should be associated with lower absolute correlation of credit revisions. These conclusions result from the fact that *CCR* measures creditworthiness during a window that moves as time passes.

# 3. Data Sources, Summary of the Credit Rating Industry, and Fundamental Determinants of Ratings

## 3.1. Credit Ratings from *Institutional Investor* and from Other Sources

Most leading international banks have credit analysis teams whose job is to appraise the probability of default of the bank's borrowers. *II* surveys 75 to 100 of these banks asking them to grade each country as a function of the perceived creditworthiness of each government. Banks are not permitted to rate their home countries. The individual responses are weighted by *II* giving more importance to responses from banks with greater worldwide exposure and more sophisticated country analysis systems. Only the weighted-average response for each country is reported and no information is given about either the identity of respondents or the weights used.[14] Bankers are surveyed during a two month window that ends about 45 days before the actual publication of the ratings -- November-January for the March issue and during May-July for the September issue (Ferrer, 2000).[15]

There are also other sources of sovereign rating data. The foremost commercial providers are the credit rating agencies of which there are currently three: Moody's,

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[13] The simulation also shows a modest size distortion and positive bias when $\rho_{\Delta\phi}=0$ and the window width is beyond 6 periods. Analysis of the corrections for this bias in the sample autocorrelation coefficient (e.g. Bartlett's) are left for future research.

[14] In late 1999, *Institutional Investor* began adding mutual fund managers and independent economists to its list of respondents. No information is given regarding the weights assigned to these responses.

[15] For example, while Russia defaulted on some of its government debt in mid-August 1998, its rating sequence was 31.2 (March 1998), 30.2 (September 1998) and 20.0 (March 1999).

Standard and Poor's and Fitch.[16] Credit agencies more narrowly define the ratings' meaning: "A country or 'sovereign' credit rating is a forward looking measure of the ability and willingness of a country's central bank to make available foreign currency to service debt, including that of the central government itself. It follows that this rating is not directly an evaluation of the creditworthiness of the government, but rather it relates to the total foreign debt of the country, including both public and private sector borrowers" (Moody's, 1994, p.145). In general, sovereign ratings are not associated to a particular bond issue but provide a benchmark for all debts issued by agents domiciled in a given country.

Moody's and Standard and Poor's have each made over 400 long-term foreign currency sovereign rating decision announcements involving 111 and 81 countries (Moody's and S&P respectively) from January 1975 until June 2000. The agency ratings were obtained from S&P (2000) and from Mahoney (2000). These data have the virtue of revealing the announcement day and the identity of the agency making it. By contrast, they cover a smaller number of countries than *II* and they are unequally spaced over time (e.g. Standard and Poor's made five announcements about South Korea between August 6 and December 22, 1997, while it took ten years to make the previous five announcements). While this paper focuses on the *Institutional Investor* ratings, some key properties are checked with those from Standard and Poor's and Moody's.

There are three other major providers of ratings. *Euromoney* has been publishing ratings since 1979 but their criteria changed halfway through the sample. The International Country Risk Guide began awarding ratings in 1984 and *The Economist Intelligence Unit*

[16] While these agencies rate a variety of issuers and securities, other agencies are more specialized: Thomson Bankwatch focuses on financial institutions (though it began rating sovereigns in 1994) while A.M. Best concentrates on insurance companies. Other rating agencies in Japan and Canada focus on their home markets. The sovereign rating activity depends on the amount of bonds that governments issue. While bond financing was important until the great depression, a majority of net borrower countries reverted to loans from other governments or from international organizations for several decades thereafter. In the 1970s, banks became active players in sovereign financing. After the debt crisis of the early 80s and the Brady plan in its aftermath, governments reverted back to bonds as their major financing source. Consequently the sovereign rating activity (which was important in the 1930s) only picked up in the late 1980s. For example, Moody's assigned 15 ratings in the period 1975-1985, 37 in 1986-1990, 59 in 1991-1995 and 290 in 1996-2000.

*in* 1989. The *II* ratings have the advantage of covering more countries (93 in the first survey and 145 currently) than any other source and of providing observations for all countries covered at equally spaced intervals for almost 5000 observations. The countries currently surveyed comprise over 98 percent of the world GDP as recorded by World Bank (2000). All rating data ever published by *II* are included in this study.

**3.2. The Credit Rating Industry**

The precursors of rating agencies were the mercantile credit agencies, which rated merchants' ability to pay their financial obligations and were first established in the United States after the financial crisis of 1837. The expansion of the ratings business to securities ratings began in 1909 when John Moody started to rate U.S. railroad bonds (Cantor and Packer, 1994). After World War I Moody's started rating sovereigns (Mahoney, 2000). Poor's publishing company issued its first ratings in 1916, Standard Statistics Company in 1922, and the Fitch Publishing Company in 1924. The first two companies merged into Standard and Poor's in 1941 (Cantor and Packer, 1994). Fitch merged with IBCA (a British agency focused on financial institutions) in 1997, and Fitch IBCA bought Duff and Phelps (which itself had entered the market in 1982) in 2000.

The rating categories provide a ranking of the relative chance of default of the issuers (Cantor and Packer, 1994). Until recently, the sovereign rating established a ceiling for all debt issued by entities domiciled in the country. This principle was partly amended by S&P's decision to allow a number of corporations to surpass their government's ratings.[17] The ceiling concept reflects the government's wide range of powers and resources that render its credit standing superior to any other debtor in that nation. Rating agencies are repeated players in a market for default forecasts and therefore have an incentive to impound all available information and to internalize the long-term effects of their decisions. Regulators in the U.S. set limits on the amount of assets in each rating category

[17] Moody's has been more reluctant to follow this path. Durbin and Ng (1999) find that bond yields do not strictly reflect the sovereign ceiling.

that different financial institutions may hold, and investors rely on them for independent information on the quality of each issuer. Therefore, the grades reflect the borrowing cost of the issuer.

S&P's and Moody's data list the long-term foreign currency rating for all sovereigns rated since 1975. The data cover actual rating changes (e.g. from A+ to AA-), "outlook" statements (i.e. positive, stable, and negative), and announcements that a given sovereign has been put "under review for upgrade" or "under review for downgrade" (Moody's) recorded on the day that they were made.[18] Following a long tradition in the literature (beginning with Horrigan, 1966, and continuing through Cantor and Packer, 1996), we assign numerical values to Moody's and S&P's ratings making each credit notch equivalent to one unit (starting with AAA = Aaa = 20, AA+ = Aa1 = 19, etc.). Mahoney (2000) suggests that "under review" announcements contained more information than outlook statements, so "Outlook" announcements were given one-fourth of one point and "under review" and "credit watch" announcements were given one-half of one point. While this conversion is *ad hoc*, it merely extends the standard practice in the literature to a finer scale.[19] When the outlook or under review announcement was later reversed (for example, if a country went from "under review for upgrade" to "rating confirmed") then the half point that had been added was taken off. The Moody's (S&P) data has 209 (218) observations on 58 (48) countries which had two or more revisions since January 1, 1975 until June 22, 2000 (June 7, 2000). The agency ratings will be used at the end of section 4 when checking if the serial correlation of *II* credit revisions could be due to biases induced by the surveying and aggregation processes.

[18] S&P has a slightly different categorization of the latter –it states that a country has been put under credit watch (specifying whether it is positive, developing, or negative). This indicates an increase in uncertainty which raises the chances of a rating move in the indicated direction. Credit watch – developing, does not imply any direction for the possible revision.

[19] The sensitivity of default bond yield spreads to "outlook" and "under review" announcements would provide an independent gauge of the market's assessment of these news relative to actual re-grades by one or more credit notches. The literature uses the one-rating-notch equals one-point conversion in spite of the strong evidence of the non-linearity of spreads as a function of ratings (see Cantor and Packer, 1996, Chart 1). Since we only use the agencies' data for one robustness check we follow the standard practice, though a more careful conversion should rely on market prices.

### 3.3. Fundamental Determinants of Country Credit Ratings

Shapiro (1994) summarizes the factors that bankers surveyed by *II* reported to have used in formulating the country grades in 1994 and how they thought the same factors might have affected credit grades in 1979 when the survey started.

PRIORITY GIVEN BY BANKERS IN EVALUATING SOVEREIGN CREDIT RATING TO SELECTED COUNTRY ATTRIBUTES

| Variable | Countries | | | | | |
|---|---|---|---|---|---|---|
| | OECD | | Emerging | | Rest of World | |
| | 1994 | 1979 | 1994 | 1979 | 1994 | 1979 |
| - Debt Service | 2 | 5 | 1 | 1 | 1 | 1 |
| - Political Outlook | 5 | 3 | 2 | 3 | 2 | 2 |
| - Economic Outlook | 1 | 1 | 3 | 2 | 3 | 4 |
| - Financial Reserves and Curr. Acct. | 3 | 2 | 4 | 4 | 4 | 3 |
| - Trade Balance | 7 | 4 | 5 | 5 | 5 | 5 |
| - Foreign Direct Investment | 9 | 8 | 6 | 6 | 9 | 7 |
| - Fiscal Policy | 4 | 9 | 7 | 9 | 6 | 6 |
| - Inflow of Portfolio Investments | 8 | 7 | 8 | 8 | 7 | 8 |
| - Acess to Capital Markets | 6 | 6 | 9 | 7 | 8 | 9 |
| Correlation between columns | 0.58 | | 0.92 | | 0.93 | |

Although there is some disparity in the importance of the different variables across time and type of countries their ranking seems stable --the cross-correlations being bounded by the correlation within each group of countries reported at the bottom of the table.

Some ranking differences have straightforward economic interpretations. For instance, given their history of high inflation, most non-OECD countries are usually unable to borrow in their home currencies. Developed countries, however, usually borrow in their own currencies and have used surprise inflation as the means for *de facto* defaults (albeit relatively small ones). It is then natural that the order of Economic Outlook (which we interpret to mean prospects for inflation and output) and Debt Service is reversed between these two groups of countries.[20]

[20] The *II* ratings are not necessarily limited to foreign currency denominated debt.

Some authors attempted to uncover the fundamental determinants of credit ratings. Feder and Uy (1984) and Lee (1993) use *II* data, Ul-Haque, Kumar, Mark and Mathieson (1996) use *II*, *Euromoney* and *The Economist Intelligence Unit* data, and Cantor and Packer (1996) use Moody's and S&P ratings as the dependent variable.

A recent comprehensive study, Ul-Haque, Kumar, Mark and Mathieson (1996), analyzes the correlation of ratings with variables that are presumed to affect country risk according to the sovereign risk literature. Their sample consists of over 60 developing countries observed from 1980 until 1993. They regress the level of *CCR* on the lagged values of exports growth, current account balance, international reserves, GDP growth, inflation, terms of trade, US Treasury Bill return, the lagged level of *CCR*, etc. They report three main findings. The most important domestic determinants of creditworthiness are the country's foreign reserves holdings, output growth and the current account balance in the year before the rating was published. Second, a worsening of the international scenario diminishes credit ratings by a sizable amount above and beyond its effect on local fundamentals. Third, the lagged dependent variable enters significantly with a coefficient of about 0.94.[21]

As reflected in the table above, the weights given by credit graders to the different factors probably vary as the score goes from zero to 100. This would imply that a regression on fundamentals should have coefficients that are somehow conditioned on the ratings themselves. The simplest form of conditioning is to limit the analysis to a subset of countries in the same rating range and this is what various authors have done: Ul Haque et al. focus on countries with ratings in the 20-65 range while Lee (1993) studies the determinants of 40 less developed countries' creditworthiness. Moreover, Ul Haque et al. allow the effect of inflation and debt burden on ratings to vary depending on whether countries score low or high on each of these fundamentals. Our analysis below is unaffected by the varying importance attached to various fundamental determinants of

[21] The authors ran a similar model using the first difference of *CCR* as the dependent variable. The broad results are similar to the levels specification but they do not use the lagged change in *CCR* as explanatory variable. In the specifications below, using only the lagged credit revision on the right-hand side, we attain an even higher r-squared than they did in the first-difference specification.

creditworthiness since the only assumption is that bankers make the best use of whatever data is more informative about expected collection at each level of ratings.

Ul-Haque et al. omit discussing the potential endogeneity bias in the regressions. This casts doubt on any causal interpretation of the coefficients on local variables–especially in light of their finding of high persistence in rating levels.[22] Does a country enjoy a high *CCR* because its growth rate is high or is its growth high because its credit rating is good and external financing is forthcoming? This problem pervades the literature on the fundamental determinants of credit ratings. This paper avoids the potential endogeneity problem by focusing on the time series properties of revisions –a topic yet unexplored by the literature.

## 4. Empirical Results

### 4.1. Data Description



The number of countries included in the *II* survey ranged from 90 in 1979 to 145 currently.[23] In order to summarize the data description, countries were grouped into portfolios based on geographical location and other special characteristics. The geographical portfolios partition the set of countries into eight mutually exclusive and exhaustive categories. Where notorious differences in economic characteristics of the countries within a continent are apparent, a further disagregation was carried out based on them. The geographical portfolios are: Africa, Middle East, Asia-Oceania-Low Income, Asia-Oceania-High Income, Latin America, Eastern Europe, Western Europe-Low

[22] Moreover, Ul Haque et al. use the *II* ratings published in March as the dependent variable. The survey for the March issue is actually conducted during November-December of the previous year, and therefore overlaps with the period during which the explanatory variables are measured.
[23] Three countries changed status during the period and in some cases the ratings of the predecessors were appended to those of their successors. The ratings for Russia were appended to those of the U.S.S.R. while the rating for East Germany was discontinued in March 1991. The last rating for Czechoslovakia was 46.1 in September 1992, while the first rating for Czech republic was 44.6 and that for Slovakia was 31 in March 1993. Czechoslovakia was appended to Czech republic while Slovakia started fresh in 1993.

Income and North America-Western Europe.[24] A few countries were also clustered in three topical portfolios: those belonging to the Organization of Petroleum Exporting Countries (OPEC), the members of the Group of Seven industrialized nations (G7), and those frequently labeled as "Emerging" countries in the recent literature.[25] The latter group is the same as the Emerging group in Cruces (2001) to facilitate comparison.

The portfolio *CCR* is the expected collection averaged across the countries in the portfolio. For completeness, three different set of portfolio weights are used: equal weights, GDP weights and principal component weights. The GDP weights are proportional to 1998 purchasing power adjusted GDP as reported in World Bank (2000). This source omits 23 small countries for which data are taken from Central Intelligence Agency (2000). The principal component weights (subsequently PC weights) are proportional to the first eigenvector of the covariance matrix of the change in credit rating of the countries in the portfolio. This will give more weight to countries that have highest covariance with the other countries in the portfolio (Johnson and Wichern, 1982), so the portfolio statistics will be a measure of the non-diversifiable credit movements within the countries in a portfolio.[26] Appendix II lists the members of each portfolio and the 1998 GDP and the principal component weights.

Fig. V shows the credit rating levels for each portfolio (V.A uses equal weights, V.B uses GDP and V.C uses PC). The big picture is that 1980s were difficult years for world creditworthiness while credit confidence was rebuilt during the 1990s. Moreover, the portfolio aggregation does a reasonable job of segmenting countries into leagues of different credit quality. While North America-Western Europe and Asia Oceania-High Income never dipped below 72 credit points (85 for G7), none of the other seven

[24] Western Europe-Low Income includes only Portugal, Greece and Turkey, which are all members of the Emerging portfolio. It seemed inconvenient for analytical purposes to cluster these countries with the richer nations of North America and Western Europe.
[25] The latter is a set of 20 middle and lower income countries for which the longest series of stock market data are available from the Emerging Markets Data Base of the World Bank. They have recently been studied in Harvey, 1995, Bekaert and Harvey, 1995, etc.
[26] Only countries with full time series are used in the PC portfolios. Kuwait, Iran, Iraq and Lebanon underwent war or internal strife during the period that did not seem representative of the rest of the countries in the respective portfolios, so they were excluded from the principal component portfolios. All countries are included in the equally weighted and all those with GDP data on the GDP-weights portfolios.

portfolios ever surpassed 61 credit points. The segmentation is even more striking when using GDP weights and about the same using PC weights. The fact that the first sample point occurred during the oil crisis of 1979, helps understand the secular slide of OPEC ratings, with humps around events (such as the Iraq-Kuwait war) which temporarily increased the price of oil. The Emerging country portfolio seems to have suffered much more from the debt crisis of the early 1980s than from the East Asian crisis of 1997-98. The PC weights downscale the latter and highlight the former in the Emerging portfolio.

Table II summarizes the distribution of credit rating levels and their changes for the complete sample and for five-year sub-periods for the ten portfolios. The third line of the table reports how many mean *CCR* points does each portfolio obtain for one standard deviation of *CCR*. This measures how volatile is the mean rating of the countries in a portfolio as time passes. It ranges from a high of about 40-50 for the G7 to a low of about 3.7 for Eastern Europe and Latin America. Not only is the probability of getting your money back lower in middle and lower income countries, but the change over time in this probability is much higher.

The middle panel of Table II reveals that the mean credit change from 1979 until 2000 was negative in most countries, with the richer countries having had the less serious blows. The volatility of changes in CCR shows a hump around ratings in the middle range of the scale. This agrees with the shape of equation (9) and Fig. III.A and will be tested more formally below. The bottom panel of Table II shows the mean change in credit rating. The statistics are reported by five-year sub-periods and show that while the mean 21-year revisions may have been negative, their distribution was quite heterogeneous over time. For example, Latin America's credit rating fell by over 2 points per semester from 1980 until 1985. Using the March 2000 survey results, this is like going from the expected collection of Israel to that of Sri Lanka over a five-year period. By contrast, the 1990s were much better years for the creditworthiness of low and middle income countries as can be seen by noting that most of the positive signs of mean proportional credit changes occurred during the 1990s.

The breakdown by five-year periods provides additional evidence on the higher volatility of ratings in middle-rating countries. Mean proportional credit revisions never surpassed 0.85 points (equal weights) in Asia-Oceania-High Income, North America-Western Europe and Africa. In the rest of the world however, credit revisions are much more sizable. This is confirmed by Figure VI, which depicts the credit revisions by portfolio for each semester in the sample. This figure also shows a close association between U.S. recessions (early 1980s and early 1990s) and the credit ratings of North America-Western Europe and the G7.

Table III reports the correlation coefficients between the change in ratings of each portfolio. With a few exceptions, the correlation coefficients are all positive with the lowest estimate at 0.14.[27] The positive correlation of G7 with most portfolios reflects that when output and inflation deteriorate in the leading countries, the rest of the world can expect a worsening of their terms of credit. This is consistent with the evidence in Ul-Haque et al. (1996) that world conditions affect small country ratings above and beyond their effect on local conditions. It also agrees with the argument in Calvo, Leiderman, and Reinhart (1993) and Bekaert, Harvey and Lumsdaine (1999) that capital flows to less developed countries increase when the interest rate falls in the U.S. The correlation coefficients suggest that the countries in Eastern Europe and Latin America are the most likely to suffer, should there be a credit crunch in North America-Western Europe. The lowest correlation of G7 is with OPEC showing the conflict of interest between them around the price of oil.[28] We now test a few refutable propositions arising from the model in section 2.

[27] The few negative correlations arise in the PC-weighed portfolios between Western Europe Low Income and most other portfolios and between Asia-Low Income and G7 and North America-Western Europe. Western Europe-Low Income comprises Greece, Portugal and Turkey and the covariance matrix is dominated by the latter. Greece and Portugal each have a GDP of about one third of that of Turkey. Further, Turkey experienced a severe debt crises in 1978, with default and recovery leading that of many other countries.

[28] Testing for Granger causality of credit revisions across regional or special characteristic portfolios is an interesting research avenue. This work should connect to the extensive literature on international transmission of business cycles and financial crises. In a VAR the arrangement of the subjects results from assumptions about whether shocks to one subject have contemporaneous effects on the others or not. With eight regional portfolios and no obvious priors on the right arrangement, there are 8! = 40,320 possible orderings so this extends beyond the scope of this paper. This research may shed light on the international spillover of crises using survey forecast data.

### 4.2. Tests of Refutable Propositions

**Proposition**: Absolute changes in *CCR* should describe a bell shape centered around the point where expected collection is 50 cents per dollar due [equation (9) and Fig. III.A].

In order to test this, we regressed the absolute change in *CCR* on a set of 20 dummies related to the lagged level of *CCR*,

$$
\text{(20)} \qquad
\begin{aligned}
&\left|\Delta CCR_t^i\right| = \sum_{j=0}^{19} \alpha_j I_j\left(CCR_{t-1}^i\right) + e_t^i \\
&I_j\left(CCR_{t-1}^i\right) = \begin{cases} 1 & \text{if} \quad 5j \leq CCR_{t-1}^i < 5(j+1) \\ 0 & \text{otherwise} \end{cases} \\
&i = 1,\ldots,N; \;\; t = t_i,\ldots,T_i
\end{aligned}
$$

The model is estimated by generalized least squares. We use the same error structure and estimation technique for all regressions below unless otherwise noted. The error for each country is assumed to be decomposed in a regional component and an idiosyncratic country-specific part,

$$
\text{(21)} \qquad e_t^i = u_t^s + v_t^i
$$

where $u_t^s \sim \text{iid}(0, \sigma_s^2)$ affects all countries in region $s$ to which $i$ belongs, and $v_t^i \sim \text{iid}(0, \sigma^2)$ is a country specific shock. This allows contemporaneous correlation of the errors within a region and different variances across the regions.[29] The regions correspond to the eight geographical portfolios presented in the previous section. The panel is unbalanced because over the years, *II* added about 50 countries to the 90 reported

[29] I assume zero correlation across regions. There would be 36 distinct parameters in the error covariance matrix if we allowed for cross-regional correlation.

in the original survey. Estimation is based on the 137 countries that had two or more revisions during the sample period, for a total of 4674 observations.

The coefficient on each dummy closely approximates the mean absolute rating change for countries with starting *CCR* in the respective range. Figure VII.A shows the estimated coefficient on each dummy together with a 90 percent confidence interval while the actual estimates are reported in Table IV. The highest absolute revisions occur for base ratings between 35 and 40 credit points, with those countries typically experiencing a credit revision of 1.6 credit points per semester. A country in the 15-20 and 70-75 range typically experiences a revision of about one credit point per semester, while countries in the 0-5 and 95-100 range have mean absolute revisions of about one half a credit point per semester. This behavior closely resembles that predicted by equation (9) and Fig. III.A.

**Proposition**: Mean credit revisions should be zero when expected repayment capacity is either very high or very low and when countries are expected to pay 50 cents per dollar due. For countries with expected collections moderately above (below) this threshold expected revisions should be negative (positive) [equation (11) and Fig. III.B].

Given the strong evidence of serial correlation in credit revisions to be discussed below, we use an autoregressive term to proxy for the expected revision and let intercept dummies capture the effects of shocks to $E(\phi)$ in (11).[30] The estimating model was,

$$\Delta CCR_t^i = \sum_{j=0}^{9} \alpha_j \, I_j\left(CCR_{t-1}^i\right) + \rho \; \Delta CCR_{t-1}^i + e_t^i$$

$$(22) \qquad I_j\left(CCR_{t-1}^i\right) = \begin{cases} 1 & \text{if} \quad 10j \le CCR_{t-1}^i < 10(j+1) \\ 0 & \text{otherwise} \end{cases}$$

$$i = 1,\ldots,N; \;\; t = t_i,\ldots,T_i$$

[30] We show below that the presence of mean reversion for moderate ranges is robust to more sophisticated models of the expected revision (e.g. Table VIII).

The results are reported in Table V and Figure VII.B. For ratings in the 0-30 range, future ratings are expected to rise by about 0.17 credit points per semester regardless of the magnitude of the last revision. For ratings in the 30-60 range, the lagged *CCR* level contains no information about subsequent adjustments. For ratings in the 60-70 and 90-100 range, future ratings are expected to fall by about 0.24 credit points per semester. This pattern generally agrees with the model's prediction, with some qualifications and one exception.

First, the model predicts that for extreme (positive or negative) repayment capacities, we should observe no effect of lagged *CCR* on future adjustments. In the data, lagged *CCR* decile dummies are significant for ratings from the beginning of the *CCR* scale until 30 credit points. This could be due to the fact that countries surveyed lie in a truncated region of expected repayment capacity shown in Fig. III.A (e.g. only countries with $E(\phi) \geq -1$ make it into the survey). If this were the case and a rating near zero implies that $E(\phi) \approx -1$, then the significance of lagged *CCR* in explaining future revisions for low *CCR* levels is consistent with the model.

Second, the asymmetry in the 90-100 and the lack thereof in the 70-90 range differs from the predicted behavior. We could surmise that ratings above 70 (which roughly correspond to a Standard and Poor's rating of AA or better) are associated with such a high repayment capacity that there should be no asymmetric effect in this region (see Fig. III.B). But if this is the case, it remains to be explained why the coefficient on the 90-100 dummy is again negative and significant. This finding stands in contrast with the model's prediction.

Third, the model predicts that the point about which the asymmetric adjustment should change signs and the point about which one should observe the largest absolute changes of *CCR* is when the country is expected to pay 50 cents per dollar due. While we have found in the data a pattern that is similar to that predicted by the model for ratings in the high 30s, it is not obvious that a credit rating in this range is associated with an expected collection of 50 cents on the dollar. While such *II* ratings roughly correspond to the junk bond categories of ratings assigned by credit agencies, (in the range of B- to BBB-), it is unclear that an investor in such securities only expects the issuer to pay half of its obligations.

**Proposition**: The serial correlation of credit revisions should be proportional to the absolute value of the serial correlation in underlying repayment capacity.

Given that expected repayment capacity is unobserved, testing this proposition is not straightforward.[31] We first study the serial correlation of credit revisions for the whole sample, for subperiods and for subsets of countries. We then discuss the limitations on actual tests of this proposition and present the results of one test.

### 4.3. Are the Signs of *Institutional Investor* Revisions Sticky?

Table VI.A reports the observed relative frequency distribution of one semester's revision sign conditional on the sign of the previous semester revision. In the sample period, 66 percent of credit upgrades were followed by another upgrade while 61 percent of downgrades were followed by another downgrade. Similar patterns are present when the sample is broken by sub-periods. While the top-left and bottom-right corners in each panel provide measures of persistence in revisions, the other two corners provide preliminary indication of changing credit situations. For example, during 1980-1985, 44 percent of the positive revisions were followed by negative revisions, while only 23 percent of negative revisions were followed by positive revisions, for a tendency towards deterioration. The reverse happened during the nineties. This is consistent with the evidence in Figure VI that ratings bottomed out near the late eighties.

[31] The same caveat extends to testing the differential effect of the variance of repayment capacity on expected collection for low and high levels of expected collection analyzed in Section 2.3.

If we ignore the absolute magnitude of revisions and categorize them as either upgrades or downgrades, a credit revision is a random variable from a Bernoulli distribution with parameter $p$ and the sum of $N$ independent revisions follows a Binomial($N$, $p$). We can use this distribution to test for the null hypothesis that the probability of a second change, given a first is 0.5 in either direction as in Altman and Kao (1992, see ft.9). The last column of Table VI.A reports the $p$-value of such tests, conducted separately for positive and for negative current revisions. For the whole sample period, there is overwhelming statistical evidence against the null. When the sample is broken by five-year periods, a similar result obtains in five out of eight cases. The important exceptions are during the 1990s, when negative revisions were about equally likely to be followed by revisions of either sign. This preliminary indication of serial correlation in revisions agrees with the finding of Altman and Kao (1992) who studied U.S. corporate bond ratings drift.

### 4.4. Autocorrelation in *Institutional Investor* Credit Revisions

Section 2 showed that under rational expectations, the difference between expected collection during non-overlapping periods generates non-zero expected credit revisions and serial correlation. The autocorrelation of innovations in repayment capacity may have commonalties across countries with similar characteristics (e.g. if a given good is a significant component of the foreign trade of a group of countries) or over certain time periods (e.g. if the whole world underwent periods of high uncertainty followed by periods of more predictable behavior). We now analyze the serial correlation in revisions where the autoregressive coefficient is conditioned on various characteristics that may be common across subsets of countries or time periods. Box-Jenkins analysis suggests that credit revisions may be well described by an AR(1) or AR(2) process. The general estimating equation is,

$$\Delta CCR_t^i = \alpha^i + \rho_1 \ \Delta CCR_{t-1}^i + \rho_2 \ \Delta CCR_{t-2}^i + \sum_j \beta^j D^{i,j} \Delta CCR_{t-1}^i + e_t^i, \quad (23)$$
$$i = 1,..,N, t = t_i,...,T_i$$

where $\Delta CCR_t^i = CCR_t^i - CCR_{t-1}^i$. The dummy $D^{i,j}$ is one when country $i$ at time $t$-1 shares the characteristic of group $j$ being analyzed. The coefficient on each dummy modifies the general slope $(\rho_1)$ for the group under consideration.

The literature on estimation of dynamic panels finds sizable biases in the autoregressive coefficient when $T$ is small (2 or 3) and $N$ is large which is typical in many labor panels (Hsiao, 1986). Here $T$=40 for at least 90 countries in the sample. As noted by Hsiao (p.75-7) the model with country-specific intercepts will underestimate the true autoregressive coefficient when $\rho > 0$ while the model without them will overestimate it. We present the biased-down results in Table VII.A and the biased-up results in Table VII.B. The minor differences between them suggest that there would be modest gains from correcting this bias (e.g. as in Kiviet, 1995).

We shall report results in pairs, the first one from Table VII.A and the second one from VII.B. In the most basic specification (column 1), between 37 and 42 percent of one semester's revision is expected to carry over to the next one. When a second lag is added, an extra 9-11 percent independently carries over for two semesters. If a country has undergone a string of positive revisions, then future revisions are also expected to be positive, suggesting that the expected collection during any five-year window is expected to diminish as the starting date of that window moves further into the future. If a country has undergone a series of negative revisions, then expected collection is expected to be shrink as time passes.

Conditional on the model in section 2, this finding indicates that there are important serial correlations in innovations to repayment capacity. The absolute magnitude of the first order serial correlation, on the order of 39, percent should be compared with the simulation results in Table I. This suggests that either the credit rating window is two semesters long and $\rho_{\Delta\phi} \approx 0.9$ or that our model only partly explains the serial correlation of revisions found in the data.

Figure VI suggests that, perhaps, there is asymmetry in the correlation of credit revisions with sharp downward adjustments in times of crises followed by prolonged periods of slow recoveries. This is tested by computing the coefficient on a dummy that turns on when the lagged revision for a country is negative. This dummy multiplies the lagged change in rating so that the coefficient on the product of the two variables indicates how different is the autocorrelation following a negative revision from that following an up revision. If downward adjustments are indeed more brisk than upward ones, then serial correlation should be closer to zero following downward revisions. The point estimate is –0.01 (insignificant) in the model with country-specific intercepts and –0.06 (marginally significant) in the model without intercept. Overall, there seems to be modest evidence of asymmetric correlation in adjustments.

A few outliers that took place during a sub-period characterized by a string of highly correlated revisions could affect the serial correlation estimate. The next regression checks whether serial correlation is specific to any one five-year sub-period during the sample –using 1996-2000 as benchmark. No sub-period dummy is statistically significant indicating that serial correlation was a generalized phenomenon during the sample. The negative point estimate for 1991-95 reinforces the evidence in Table VI that this was a turning point in global creditworthiness.

The next set of dummies addresses whether any of the regional portfolios have different serial correlation than North America-Western Europe. The regional dummy equals 1 when the observation for a lagged revision corresponds to a country in the geographical portfolio being analyzed. Again, the coefficient on the dummy indicates how different is the serial correlation of countries in that portfolio from those in the control group. The big picture from column (5) is that the highest- and lowest-income countries have the same serial correlation while middle-income countries differ.

The Middle Eastern countries stand out as having a much lower correlation coefficient than the rest of the world. Only about 12-16 percent of one semester revision carries over to the next –a similar point estimate than for the OPEC countries in the next column.[32] The finding that credit revisions are less predictable in countries where oil is an important component of net exports suggests that, perhaps, innovations in repayment capacity are less serially correlated in those countries than in others. We check below whether this is the case using a proxy variable for repayment capacity.

The other regions where serial correlation is significantly different than North America-Western Europe are Latin America and Eastern Europe and, to a lesser extent, Western Europe-Low Income. Although not statistically significant, Asia-Oceania-Low Income also has a positive point estimate. While expected collection is quite volatile in these countries (bottom panel of Table II) our model suggests that the innovations to repayment capacity must be more serially correlated in these countries than in the rest of the world. These two findings are consistent with these countries having implemented significant structural reforms during the sample period, which made the future look quite different from the present in a rather predictable way. The same argument extends to the positive slope coefficient on the Emerging portfolio slope dummy in column (7). Finally, the G7 portfolio's slope dummy does not carry a statistically significant coefficient.

Given the importance of regional factors mentioned above and the prolific recent literature on contagion (e.g. Calvo, 1999), it is of interest to test if the lagged change in the regional rating helps explain the current credit revision in a country. The lagged revision being added is that corresponding to the GDP-weighted regional portfolio of which each country is a member. Accordingly, (23) is expanded as,

$$\begin{aligned}(24)\qquad \Delta CCR_t^i &= \alpha^i + \rho_1\ \Delta CCR_{t-1}^i + \rho_2\ \Delta CCR_{t-2}^i + \sum_j \beta^j D^{i,j} \Delta CCR_{t-1}^i + \\ &+ \pi\ \Delta CCR_{t-1}^{NAWE} + \sum_s \delta^s D^{i,s}\ \Delta CCR_{t-1}^s + e_t^i, \quad i = 1,..,N, t = t_i,...,T_i\end{aligned}$$

[32] A large fraction of Middle Eastern countries are oil exporters even if they are not one of the twelve

where $\Delta CCR_{t-1}^{NAWE}$ is the lagged change in rating for the North America-Western Europe portfolio and $\Delta CCR_{t-1}^{s}$ is the lagged revision in regional portfolio $s$. The dummy $D^{i,s}$ is one when the country is a member of regional portfolio $s$.

The results reported in column (9) indicate that about thirty percent of a regional portfolio revision is expected to spill to each member country next semester. It is interesting that the country own AR coefficient in this specification (between 0.36 and 0.41) is quite similar to what it was in the previous models, indicating that the country's own lagged revision is not subsumed by that at the regional level. Since the regional portfolio uses GDP weights, whatever happens to the big countries in each region today is likely to drip over to the smaller countries as time passes. The oil pattern discussed above is again apparent with the lagged regional information. If the country is in the Middle East, the lagged regional revision contains no information for predicting individual country revisions.[33] Likewise if it is in Western Europe-Low Income.

Since one of the aims of this paper is to document the surprise credit revisions used in Cruces (2001) we next combine all the variables that the theoretical and statistical analysis suggested. This includes the 'mean reversion' of credit ratings documented in Table V, which indicated that countries with base ratings in the 0-30 range should see their ratings rise and countries in the 60-70 and 90-100 should see their ratings fall over time, regardless of their lagged revisions. Note that the dummies for *CCR* level affect the intercept of the regression [as in (22)] instead of affecting any of the serial correlation slopes. Given the small size of the dynamic panel bias and the concern for not overfitting the data, we focus on regressions that exclude the intercept.

Table VIII presents the results. The first column uncovers a few collinearities. The Middle East country slope dummy knocks out the OPEC and the Middle East lagged regional effects. Likewise, the Emerging country dummy cuts the significance of the

OPEC members.

[33] These last two results were tested in an independent unreported regression.

Latin America country dummies and Western Europe-Low Income country and regional effects.

The regression in column (2) drops all insignificant variables in (1).[34] In summary, about 33 percent of one country's credit revision is expected to carry over to the next semester and about 9 percent of it independently carries over for two semesters. If the country is in the Middle East, the serial correlation coefficient drops by one half. There are important regional effects with about 17 percent of a regional revision expected to drip to the individual countries six months later. If the country is in Eastern Europe or one of the 20 Emerging markets, then the country serial correlation is higher by between 10 and 20 percent. This finding is consistent with these countries having undergone major structural reforms during the sample period, which make the future look quite different from the present in a partially predictable way.

Dummies representing the lagged level of *CCR* are still significant with countries in the 0-30 range expected to increase their rating by about one-fifth of a credit point regardless of their lagged revision. Conversely, countries with base ratings in the 60-70 range are expected to fall by a similar amount. We noted above that the finding that countries in the 90-100 range were also expected to drop their ratings was inconsistent with our model in that the curvature of expected collection should not be so important in that range. The *p*-value on the coefficient on this dummy is 0.08, so its reduced statistical significance speaks in favor of the model in section 2.

It is noteworthy that in spite of being parsimonious, the adjusted r-squared statistic that would be obtained estimating this model by OLS is 0.30. This is higher than the 0.22 obtained by Ul-Haque et al. (1996) who use from 12 to 16 explanatory variables based on

[34] The negative revision and the Western Europe-Low Income portfolio dummies were dropped in the regression in column (2) because in addition to being borderline significant in column (1) they were also insignificant in the (unreported) regression that allows for country-specific intercepts.

country specific fundamentals but exclude the lagged change in ratings (see their Table 6.b).[35]

**Interpretation**

The basic findings from the study of serial correlation are that Eastern European and Emerging countries have higher serial correlation of revisions while oil exporting and Middle-Eastern countries have lower serial correlation than most other countries in the world. In section 2, we showed that the serial correlation in repayment capacity is partly inherited by serial correlation of credit revisions. Ideally, we would like to have an indicator for expected repayment capacity and test if its changes are more highly serially correlated in Emerging and East European countries than they are in the Middle East. Given that expected repayment capacity is unobserved such test is not straightforward.

We could use the fitted values from studies that sought to uncover the fundamental determinants of credit ratings as proxy for $\phi$ in order to test the null that high values of $\rho_{\Delta CCR}$ are associated with high values of $\rho_{\Delta\phi}$. To the extent that students of the fundamental determinants of ratings select covariates that are correlated with the ratings, the test could be biased towards finding a correspondence, so accepting the null would not be very convincing.[36] However, if we found that $\rho_{\Delta\phi}$ is no different between oil and non-oil countries, that would be significant evidence against our maintained hypothesis.[37] We used the ratio of exports to interest and dividend payments in a given year as a proxy

[35] It should be stressed that their goal is not to predict –or even explain– the changes in *CCR* but rather to study the determinants of its *level*. They present their first-difference specification in an unpublished appendix. The emphasis here is different. The point however is that lagged revisions go a long way in explaining current revisions.

[36] After all, the fitted *CCR* values result from a model that intends to mimic *CCR* as best as possible. In the limiting case where such regressions gave a perfect fit, the correspondence between $\rho_{\Delta\phi}$ and $\rho_{\Delta CCR}$ would also be perfect. The fact that the fundamental covariates are not selected in regards to each country partly mitigates this argument.

[37] We are in the process of obtaining the fitted values of $\Delta CCR$ in Ul-Haque, Kumar, Mark and Mathieson (1996) from Nelson Mark.

variable for repayment capacity in order to test this correspondence hypothesis, but the results are not conclusive.[38]

Given these limitations, we give a heuristic justification for the relative serial correlation pattern assuming that countries are always willing to repay so that only expected repayment *capacity* (as opposed to *willingness*) affects credit ratings. Emerging and East European countries implemented significant structural reforms during the sample period. Many of these reforms resulted in the installation in those countries of export-oriented projects that will gradually mature over time and thereby slowly enhance their repayment capacity (e.g. tree plantations). This will cause credit revisions to be highly serially correlated. If, on the other hand, the export structure of OPEC countries did not change as drastically over the sample period and if changes in their ratings mainly reflect variations in the price of oil (a storable commodity), it is conceivable that these be less serially correlated than the increase in export quantities of the first group of countries.



[38] On the one hand, only one of the nine oil countries considered has a significant coefficient at the 10 percent level, and the only Middle Eastern countries with significant coefficients are not oil exporters (Syria -0.44 and Israel +0.43). On the other hand, only three of the 14 Eastern European and five of the 19 Emerging Countries have a significant coefficient. In sum, it is not obvious that the serial correlation in revisions results from the serial correlation of the exports over interest and dividend payments ratio. We did the same analysis using data by semesters but this gave rise to two problems: The number of countries with data fell from 127 to 76 and a strong seasonal pattern was apparent (which likely results from the seasonal pattern in agricultural exports). For example, $\rho_{\Delta\phi}$ for India was –0.6 ($p$ value=0) using semester data while it was +0.44 ($p$ value=0.03) on a yearly basis. While the results were equally inconclusive, the yearly figure seemed a more precise measure of actual changes in repayment capacity. The data for this test are taken from the balance of payments figures published by the International Financial Statistics of the IMF. Exports include both goods and services. The data for interest payments are presented in the Income-Debit line bundled with dividends accrued to non-residents from direct and portfolio investment. Unfortunately, these data do not include a separate line for debt amortizations but instead these are bunched with new debt placements under Portfolio Investments – Liabilities. So if this line reads 100 during a given year, we do not know if the increase in liabilities resulted from paying 100 due of amortization and issuing 200 of new debt, or if there was no amortization and 100 new debt were placed). Given these constraints, we proxied repayment capacity by taking the ratio of yearly exports to yearly Income-debit. While these data are disseminated by the IMF, they are compiled by each country, which raises a concern over the possible use of different measurement techniques across countries. For this reason we did not carry out panel tests as those in equation (23) in which the ratings to different countries are assigned by the same group of bankers. We computed the first order serial correlation of changes in this proxy for repayment capacity on a country by country basis.

### 4.5. Robustness checks

### Survey-Induced Biases

Can the averaging of individual opinions in the *II* survey importantly bias our findings? For example, if some bankers update their priors about a country based on the gap between the increase they gave to that country last time and the increase that other bankers awarded to it then, this may induce serial correlation in revisions. Also, could the veil on the identity of respondents and their answers induce strategic behavior in filling the survey? For instance, some bankers may hike countries in which they are heavily exposed so that the published rating will be high and other bankers will lend to it allowing the first group to collect (Heffernan, 1986, pp.31-2). Without the individual banker data, such possibilities may not be ruled out so they are potential caveats to the findings above. We assess the importance of this caveat in two ways.

First, there was an active literature in the 70s and 80s that tested whether surveys of experts' forecasts complied with the rational expectations hypothesis. When only the mean response was available, authors used this as the testing benchmark and ignored aggregation biases.[39] Friedman (1980) notes that if all individual surveyed subjects produce rational expectations forecasts, a linear combination thereof should also comply with rational expectations. Zarnowitz (1984) compared individual and mean group forecasts and found that, to the extent that agents have partially idiosyncratic information sets, the cross-sectional mean forecast typically outperformed individual forecasts over time. So the pooling of individual forecasts may actually improve the quality of the forecast.

[39] Friedman, (1980) studied the mean interest rate forecasts of 50 professionals published by the Goldsmish-Nagan Bond and Money Market Letter. Nordhaus (1987) tested the forecasting efficiency of the Eggert Consensus of real GNP growth, which is an average of 30 individual forecasters' opinions. Nelson and Peck (1985) studied the North American Electric Reliability Council's summary forecast of energy demand, which is an aggregation of forecasts, produced by individual utilities. In a study of the response of interest rates to money announcements, Roley (1983) used the median of about 60 responses to a Money Market Services Inc.'s survey as a proxy for market expectations.

Treating Standard and Poor's and Moody's ratings as those issued by an individual banker, we can test whether survey-induced biases are responsible for our findings. It is important to emphasize that these data are immune from the criticisms that could be cast on the survey data. The potential serial correlation in revisions that could arise if bankers update their priors when they see the published survey results should not be present if the raters discuss their views before the rating committee reaches a conclusion, so that the decision is based on a common information set. Although bankers could exploit the anonymity and play games in filling the survey, agencies are repeated players whose future income hinges on the reputation of their forecasts. Finally, whereas *II* surveys are taken over a two-month window and published 45 days after data collection, agency revisions are recorded on the day of the announcement. In spite of these differences, it will be shown below that the serial correlation estimates are almost identical.

**Sign Correlation in Agency Revisions**

Tables VI.B and VI.C show that the pattern of agency revisions closely resembles that of *II*. A positive revision was followed by another positive revision in 68 and 79 out of 100 cases (S&P and Moody's respectively). Also, a negative revision was followed by another negative revision in 64 and 68 out of 100 cases (S&P and Moody's respectively). This compares with 66 percent for up revisions and 61 percent for down-revisions for *II*. The binomial tests provide even more striking evidence than those based on the *II* data against the null of equal probability of up and down moves following a given revision. In summary, the conditional probabilities seem quite similar whether a survey of bankers or credit agency data are used.

**Serial Correlation in Agency Revisions**

One problem in estimating the serial correlation in agency revisions is that they are unequally spaced over time. Therefore, the correlation between two subsequent revisions for the same country will depend on the time lag between them and the variance of the error will also depend on the lag. Assume that the unobserved daily credit revisions follow an AR(1) process,

$$(25) \quad CCR(t+1) - CCR(t) = \rho \; \left(CCR(t) - CCR(t-1)\right) + v(t+1) \,,$$

where, $v(t) \sim \text{i.i.d.}(0, \sigma^2)$. Substituting recursively implies that two credit revisions spaced $n$ days apart are related by,

$$(26) \quad CCR(t+n) - CCR(t+n-1) = \rho^n \; \left(CCR(t) - CCR(t-1)\right) + \sum_{s=1}^{n} \rho^{n-s} \, v(t+s)$$

Because credit revisions take place when agencies see fit, the lag between subsequent revisions changes with each country-revision. The median interval was 8.5 months for Moody's and about 13 months for S&P. The minimum interval between revisions was four days while 90 percent of revisions took place within 3.07 years (S&P) and 4.25 years (Moody's) of the previous one. Assuming that a given rating stays fixed during $n$-1 periods, so that $CCR(t+n-1) = CCR(t)$, we can emphasize these facts by rewriting (26) as,

$$(27) \quad CCR^i(t_j) - CCR^i(t_{j-1}) = \rho^{\,(t_j - t_{j-1})} \left(CCR^i(t_{j-1}) - CCR^i(t_{j-2})\right) + e^i(t_j - t_{j-1}) \,,$$

where $CCR^i(t_j)$ is the rating on country $i$ awarded at time $t_j$, $i = 1,\ldots,N$, $j = 1,\ldots,J_i$, where each $t_j$ indicates each date at which the rating on country $i$ was changed (either by a regrade, an announcement of under review for regrade, or an outlook announcement). The $i$ subscript on $J$ indicates that the number of credit revisions is country-specific and the exponent on the serial correlation coefficient indicates that $\rho$ is the expected correlation between two revisions that are one unit of time apart. Measuring time in days allows for a an exact solution for $\mathrm{Var}\left(e^{i}(t_j - t_{j-1})\right)$. Suppose that two credit revisions for the same country are spaced $T$ days apart, so that $t_j - t_{j-1} = T$. Then,

$$(28) \qquad e\left(t_j - t_{j-1}\right) = \rho^{T-1} v_1 + \rho^{T-2} v_2 + \ldots + \rho v_{T-1} + v_T$$

and $\mathrm{Var}\left(e(t_j - t_{j-1})\right) = \sigma^2 \dfrac{1-\rho^{2T}}{1-\rho^2}$.

Estimation is done in two steps pooling together observations for all countries and assuming cross-sectional homoskedasticity. The first step estimates (27) by non-linear least squares ignoring the lag-heteroskedasticity. The estimates are consistent under standard assumptions. The estimated $\rho$ together with the time lag between subsequent credit revisions is used to measure the error variance for each observation. The second step uses the reciprocal of these standard deviations to weight each observation in estimating (27) again.

Table IX presents the results expressed in semester units (the semester AR coefficient is the daily coefficient to the 180$^{th}$). The semester serial correlation estimates are 0.37 for Moody's and 0.30 for S&P ($R^2$ around 0.25 in first-pass regressions) and are quite close to the semester autoregression coefficients based on the *II* data. So, if Moody's just upgraded a country by one notch, the best guess of the status of that country a year hence is that it will be put under review for another upgrade at that time ($0.37^2$+0.37=0.51).

In summary, agency ratings are much higher quality data than *II*, in that the identity of the issuer is known, revisions are recorded on the day that they are made and agencies are repeated players in a market for forecasts. In spite of these differences, the serial correlation estimates are quite similar to those based on *II* data. We conclude that the surveying process itself can not be responsible for the finding of serial correlation of revisions.

## 5. Analysis of Surprise Revisions

Given the predictability of credit revisions documented above and the wide spread of the variance of revisions across portfolios, it is of interest to study if some portfolios or time periods are characterized by greater surprises. Since surprises are unobserved, measured surprises are conditional on a forecasting model. Five forecasting models are used and the resulting surprises are analyzed.

The first model assumes that *CCR* changes are unpredictable so the full *CCR* revision is assumed to be the surprise. The other forecasting models use some autoregressive representation for credit revisions. The second model is the last equation presented in Table VIII and its parameters are estimated using the full panel of revisions from March 1980 until March 2000. The remaining models are constructed in real time. Models three and four use a recursive panel sample, which starts in 1980 and ends at the time that the forecast has to be made. The autoregressive parameters are assumed to be common across countries. Model three is again the last equation in Table VIII but now estimated in real time as opposed to forecast model two. When estimated on a recursive sample not all the explanatory variables are significant at each point in time. Only those variables with absolute $t$-ratios greater than 1.95 were included each semester. For example, the emerging country slope dummy does not become statistically significant until March 1989 so it is only included from then on.[40] While the asymmetric revisions for low rated countries are significant since early in the sample, the asymmetry for highly rated countries only becomes significant in Sep-97 (seventh decile) and Sep-98 (tenth decile). Model four is a plain AR(2) that ignores asymmetry and regional or lagged portfolio effects. It is estimated on a recursive sample with common slopes for all countries. Model five differs from four in that it is estimated by country using no more than the last ten

[40] Note that around this time, many Emerging countries began implementing large-scale structural reforms. This suggests that expected collection for distant periods in the future became higher than for near periods. Therefore, we should expect a string of positive –and highly serially correlated– revisions.

semesters of data available at each point in time. Unlike the previous forecasting models, model five allows for an intercept in the estimating equation.

The forecast errors are computed by country and aggregated into portfolios using GDP weights. Statistics of the forecast errors (i.e. surprises) expressed in credit rating units are presented in Table X, while plots of the five sets of surprises for each portfolio are included in Appendix III. The top panel shows mean surprises and root mean squared surprises for the period 1982-2000.[41] The rolling window, country-specific model produces the largest squared surprises in 9 of the 11 portfolios, followed by the random walk model. Models 2-4 deliver the smallest mean squared forecast errors –and these are within the same order of magnitude across these models. This agrees with Cruces (2001) who used stock market data and found that the panel recursive and whole sample models captured market surprises better than both the rolling window and the random walk models.

The evidence suggests that root mean squared surprises were much larger outside the Group of Seven and Asia-Oceania-High Income. These surprises would be even larger if expressed in proportion to the starting rating for each portfolio. From Table II, the rating level of low income countries is between one half and one third of that of high-income countries.

The bottom panels of Table X present the mean portfolio surprises by five-year period conditional on the two recursive models. They confirm that surprises tend to be relatively small in G7, North America-West Europe and Asia-Oceania-High Income. By contrast, surprises are much larger and their signs change by sub-period in Asia-Oceania-Low Income, Latin America and Eastern Europe. Both models indicate that Latin America and Emerging countries suffered unexpected credit downgrades in the early 1980s while Eastern Europe suffered from the transition from 1986 until 1995. By contrast, the early 1990s were a particularly benign period in developing countries. Likewise, the fact that

[41] The first forecast figure available from model five is for March 1982, so surprises from the other models starting at this time are used in comparing the models.

the beginning of the sample coincides with the peak of oil prices helps explain why OPEC had negative mean surprises during the four sub-periods.

## 6. Conclusions and Directions for Future Research

This paper set to analyze the statistical properties of sovereign credit ratings awarded by a pool of about 100 international bankers. This is the largest consistent data set on sovereign ratings available, both in terms of the number of countries covered, the years for which it is available and the uniformity of the criteria used over time in awarding ratings.

A credit rating is an average of expected collection per period during a fixed window of time from the moment that it is issued. We solve for expected collection as a function of expected repayment capacity during each period. The solution explains how the volatility of ratings should change with the rating level and why ratings in some range should be expected to fall (and other to rise) regardless of their previous movements. Two credit ratings given one year apart pertain to expected collection during periods that only partly overlap. The non-overlapping periods allow for non-zero expected credit revisions –even if raters produce rational expectations forecasts. Likewise, the autocorrelation in repayment capacity innovations is expected to pass through to the serial correlation in credit revisions. The evidence is broadly consistent with the model's refutable propositions.

The main findings are that ratings effectively display mild mean reversion over moderate rating ranges and that region and other characteristics capture common movements in the ratings. Ratings are much more stable in very high- and very low-rated countries as suggested by the model. The sovereign ratings are much higher and much less volatile in developed countries. Changes in ratings have interesting serial correlation properties. A positive revision has a probability of two-thirds of being followed by another positive revision six months later. Autoregression analysis indicates that about a third of one semester's revision for a country is expected to carry over to the next semester. There are also important regional components in credit revisions. About 17 percent of the revision of a GDP-weighted portfolio of countries in a given region is expected to carry over to the individual countries six months later (above and beyond the own country effect). Surprises are larger in all but the wealthiest countries, and they can be consistently positive or negative during periods of up to five years.

The predictability of credit revisions could be spuriously caused by aggregation or by individual bankers behaving strategically in order to better themselves. The findings were checked with all the sovereign credit revisions awarded by Moody's and Standard and Poor's since 1975. The results with these other data resemble those found with the *Institutional Investor* series.

The finding of serial correlation in credit revisions awarded by major rating agencies can be extended in two directions. First, announcements that countries are put under revision for upgrade can be subject to a fixed-event test of forecast informational efficiency in the sense of Nordhaus (1987). The outcome of a revision should be unpredictable based on lagged information if the horizon to which both ratings pertain is the same.[42] Preliminary evidence suggests that this is not the case. Second, if credit revisions are serially correlated, the standing rating on a country may not be a statistically sufficient measure of default risk.[43] For instance, it could be improved by accounting for the direction of the last few revisions. Therefore, of two equally rated countries; the one whose last revision was more favorable carries a smaller default risk and should be priced accordingly.

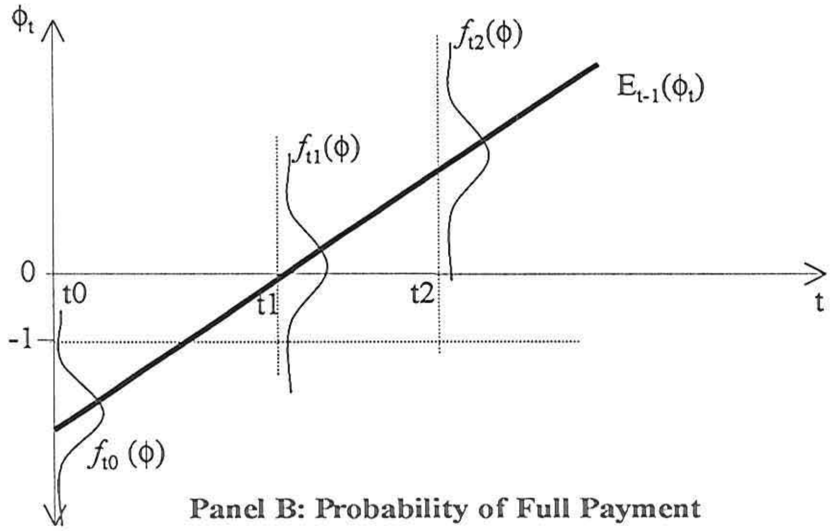
A third extension entails testing for Granger causality of credit revisions across regional or special characteristic portfolios. This research may shed light on the international spillover of crises using survey forecast data. These three lines of research are left for future work.

[42] The median lag until a review resulted in a regrade in the indicated direction was below 62 days

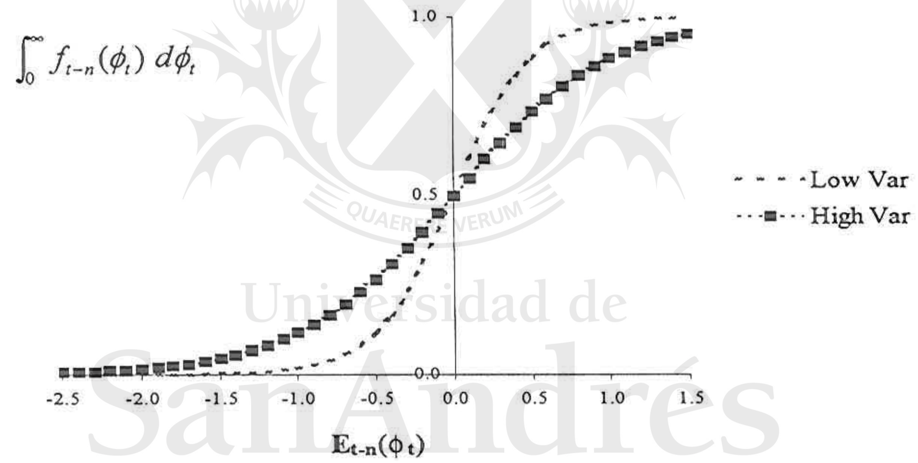
[43] If a statistic is sufficient for a given parameter and two sample points have the same value of the statistic, then any inference about the parameter should be the same whether either sample point is observed (Casella and Berger, 1990).

## Figure I

### Panel A: Conditional Distribution of $\phi_t$




### Panel B: Probability of Full Payment




### Panel C: Expected Collection in Case of Default

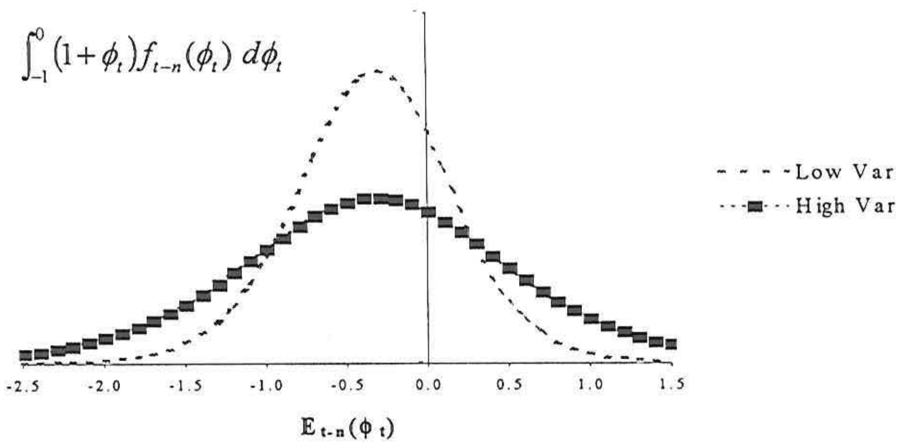
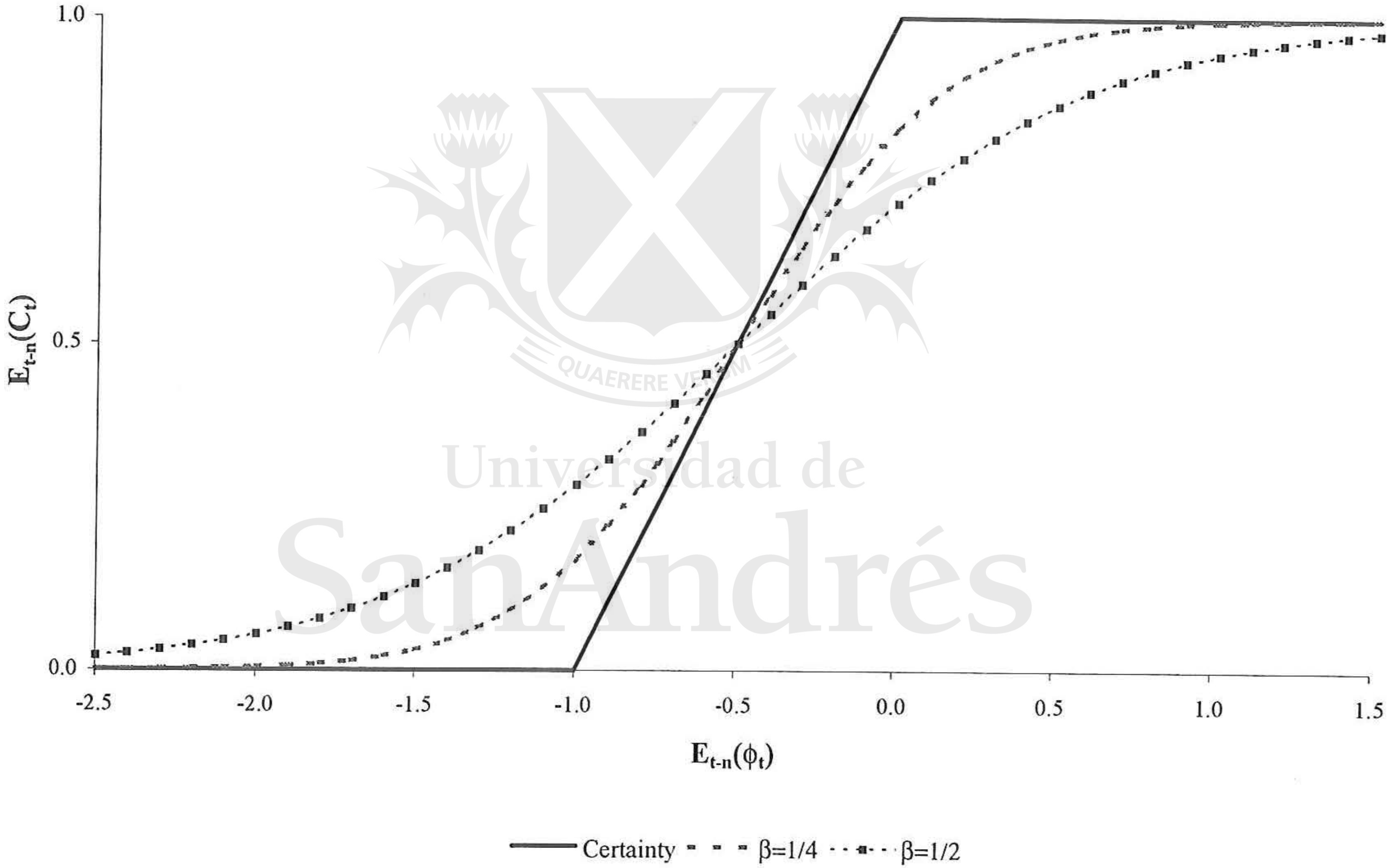
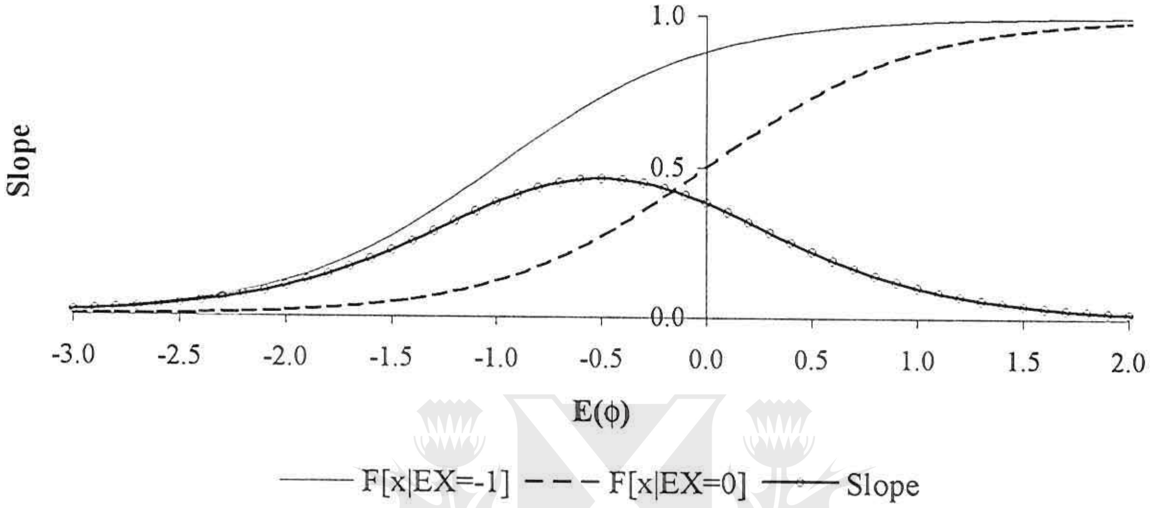


**Fig. II: Expected Collection per Dollar Due**
**as a Function of $E_{t-n}(\phi_t)$ and $Var_{t-n}(\phi_t)=\pi^2\beta^2/3$**



## Fig. III.A: Slope of Expected Collection

$$\frac{\partial E_{t-n}(C_t)}{\partial E_{t-n}(\phi_t)} = F_X\left[x = E_{t-n}(\phi_t) \mid E(X) = -1\right] - F_X\left[x = E_{t-n}(\phi_t) \mid E(X) = 0\right]$$




## Fig. III.B: Curvature of Expected Collection

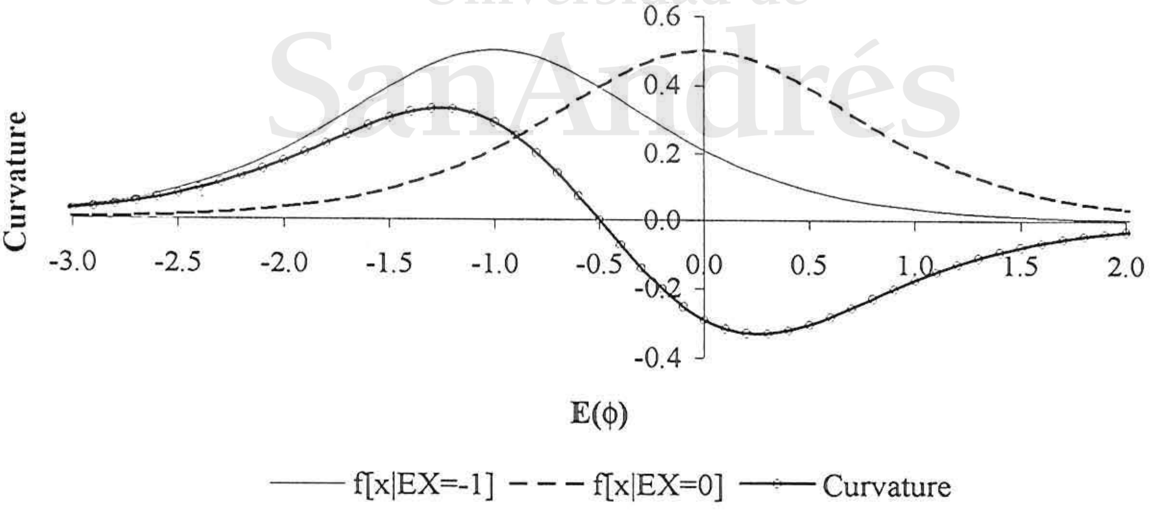
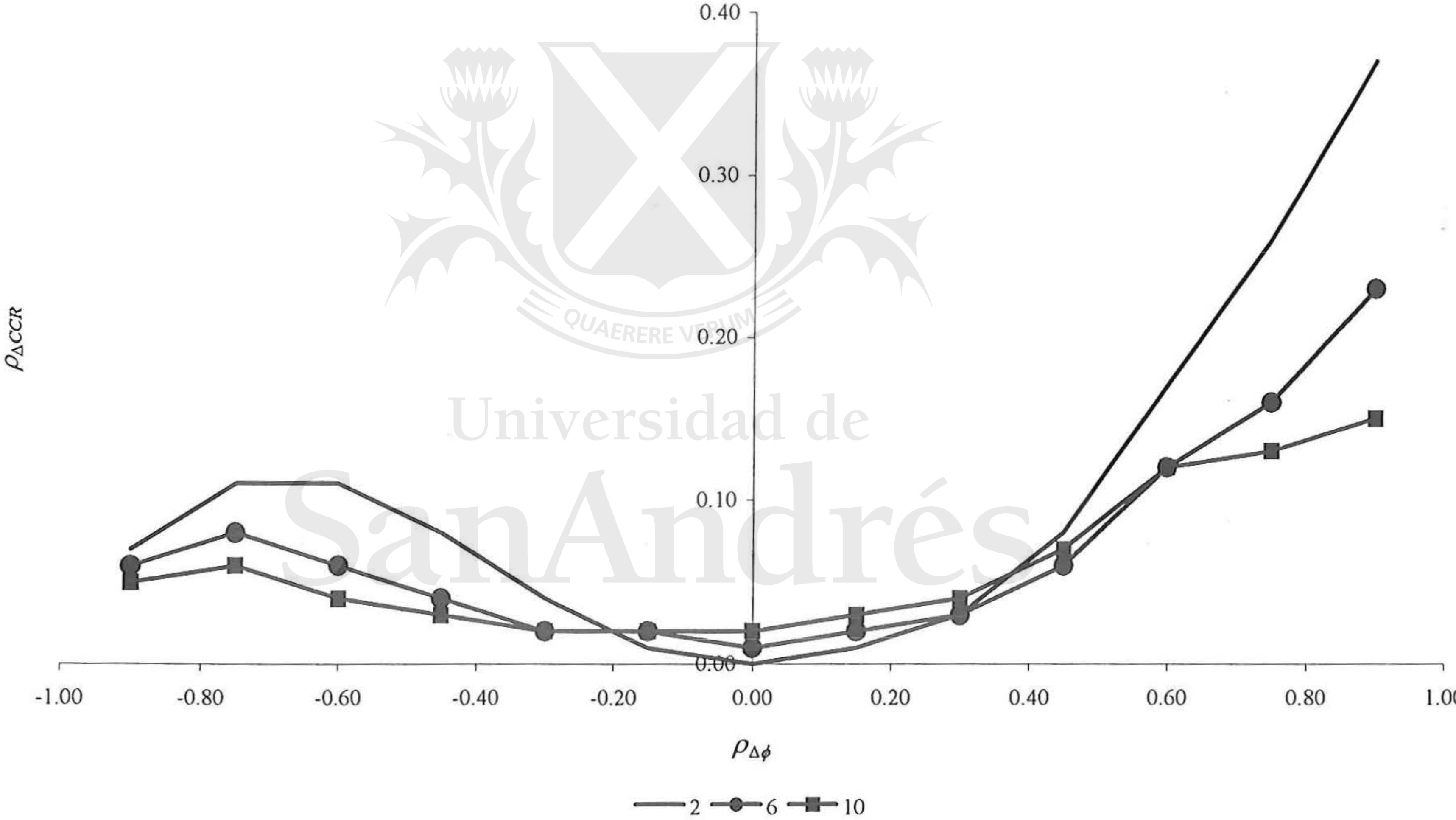
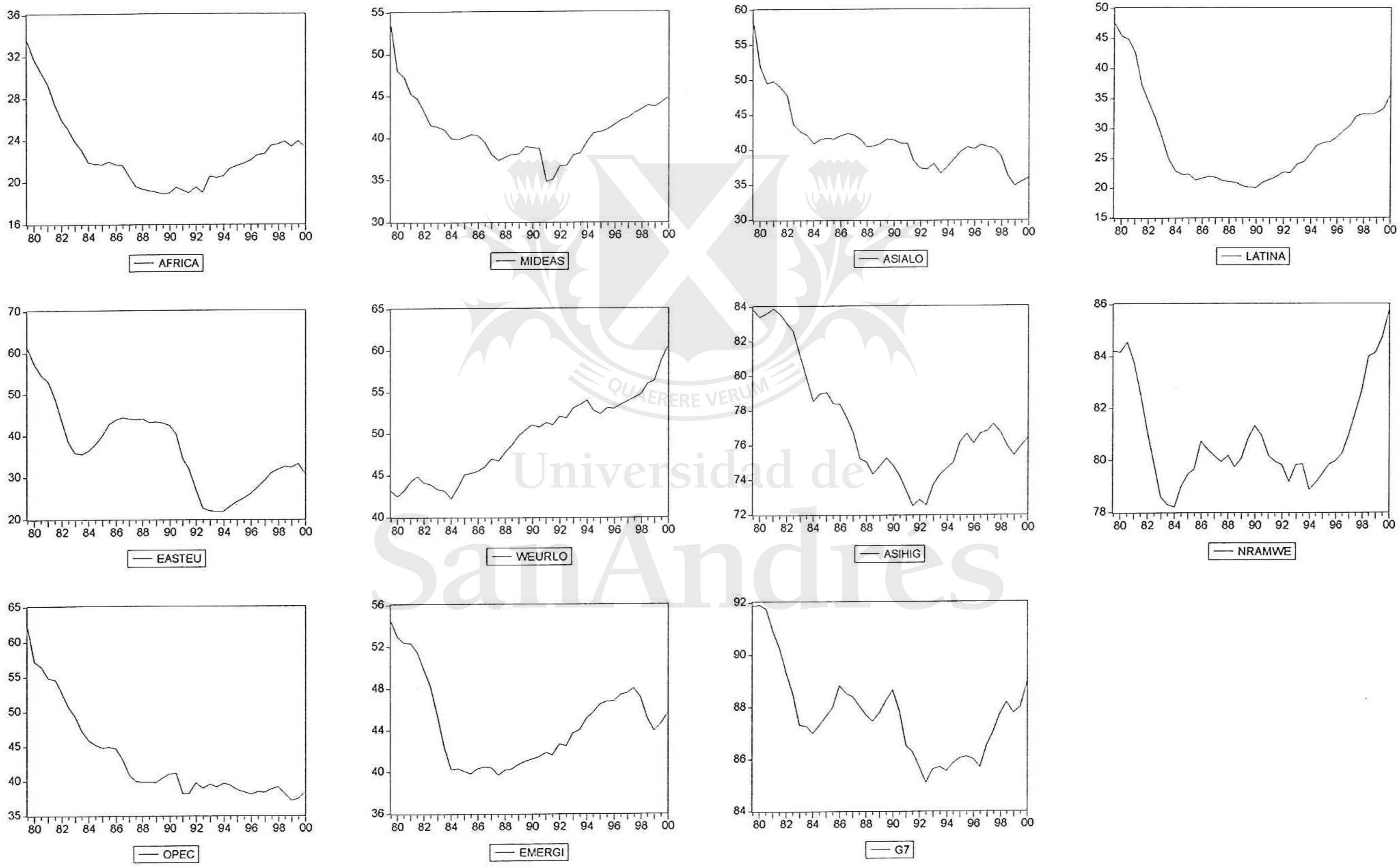


**Fig. IV: Autocorrelation in Credit Revisions Implied by Autocorrelation in Repayment Capacity Innovations**

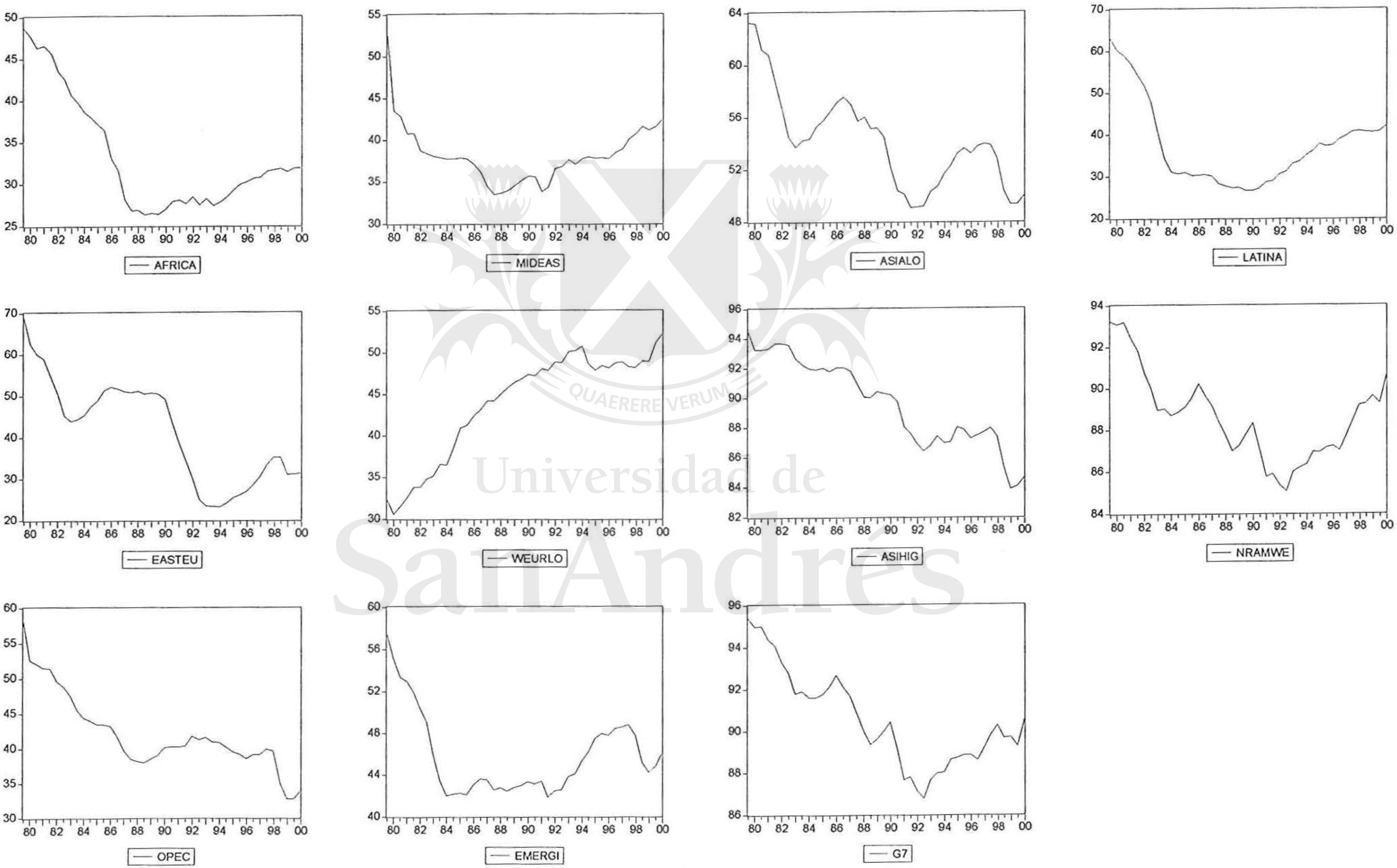
**(For Credit Rating Windows 2-, 6- and 10-Periods-Long. Mean $\rho_{\Delta CCR}$ across 100 replications)**



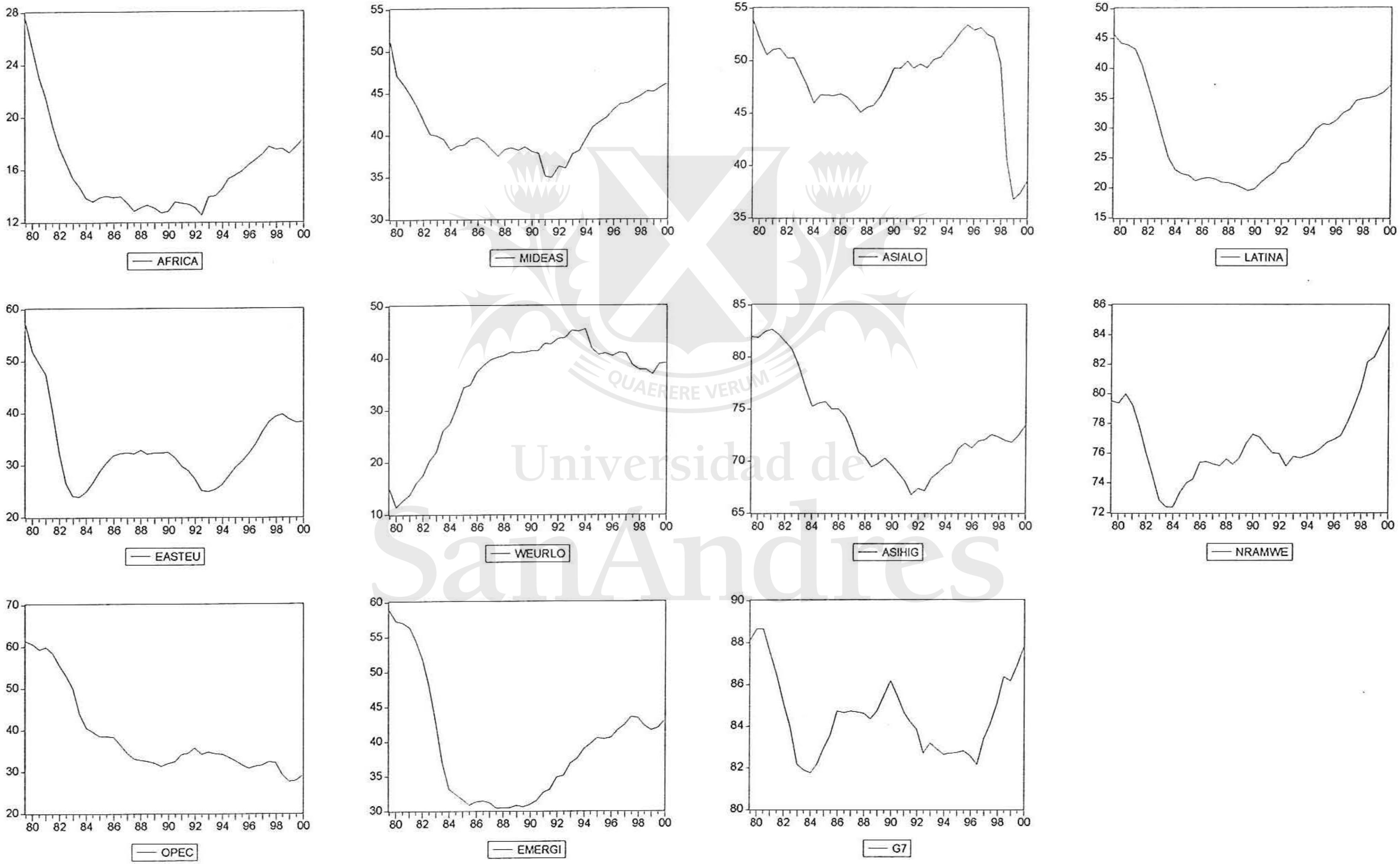
# Fig. V.A: AVERAGE RATING OF PORTFOLIOS EQUALLY WEIGHTED



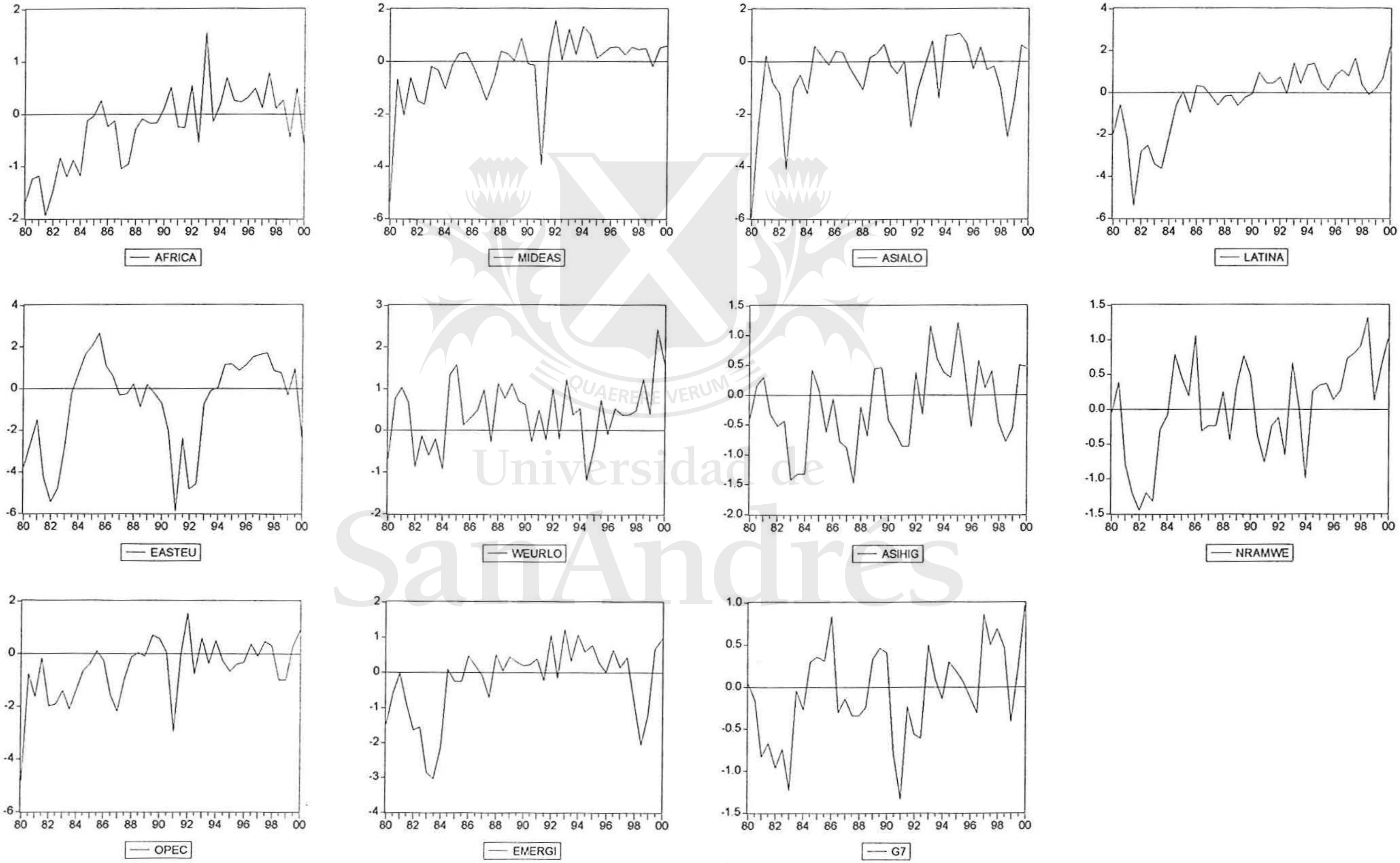
## Fig. V.B: AVERAGE RATING OF PORTFOLIOS
## GDP WEIGHTS



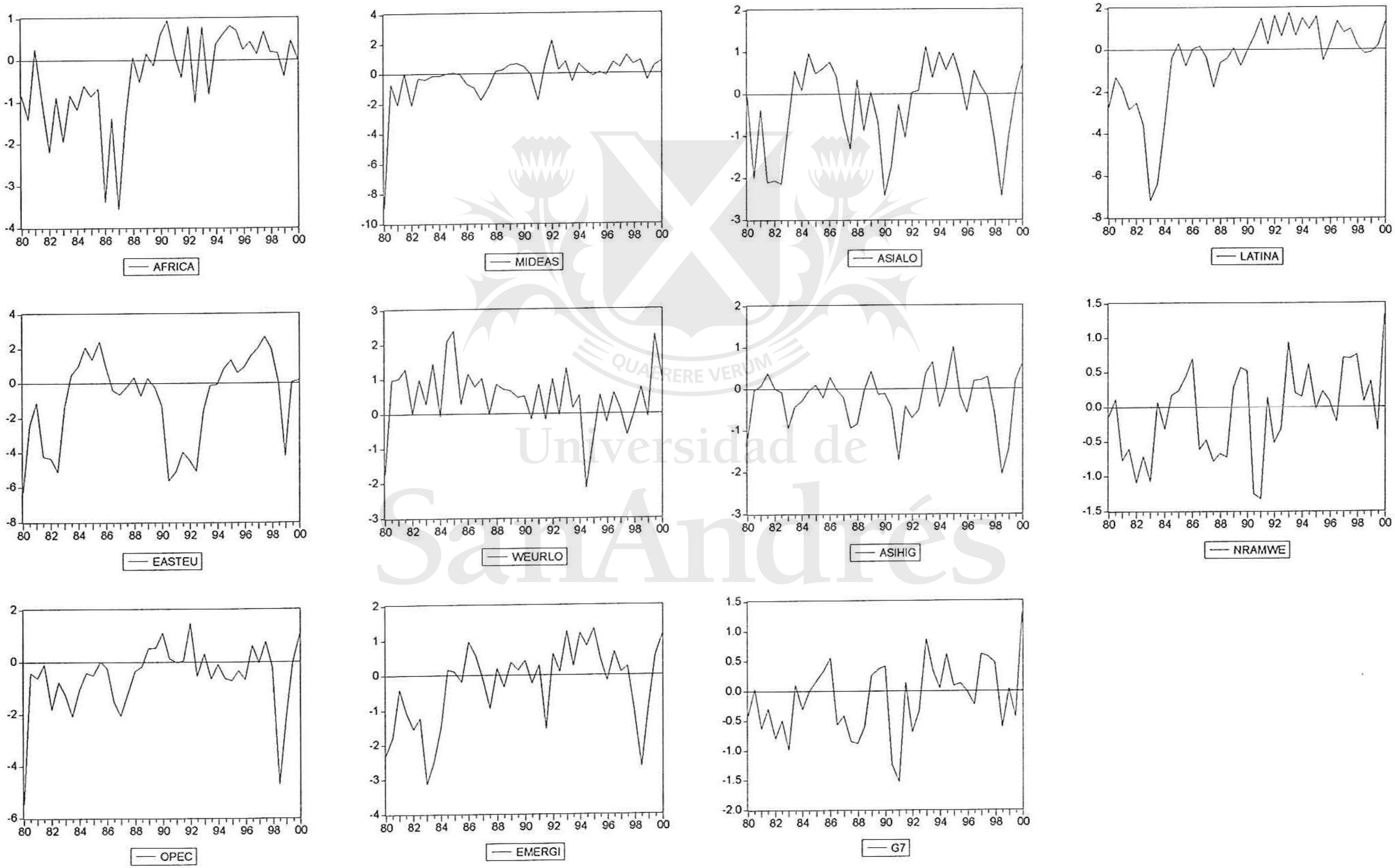
# Fig. V.C: AVERAGE RATING OF PORTFOLIOS
# PRINCIPAL COMPONENT WEIGHTS



# Fig. VI.A: CHANGE IN AVERAGE RATING OF PORTFOLIOS EQUALLY WEIGHTED



# Fig. VI.B: CHANGE IN AVERAGE RATING OF PORTFOLIOS
## GDP WEIGHTS



# Fig. VI.C: CHANGE IN AVERAGE RATING OF PORTFOLIOS
# PRINCIPAL COMPONENT WEIGHTS

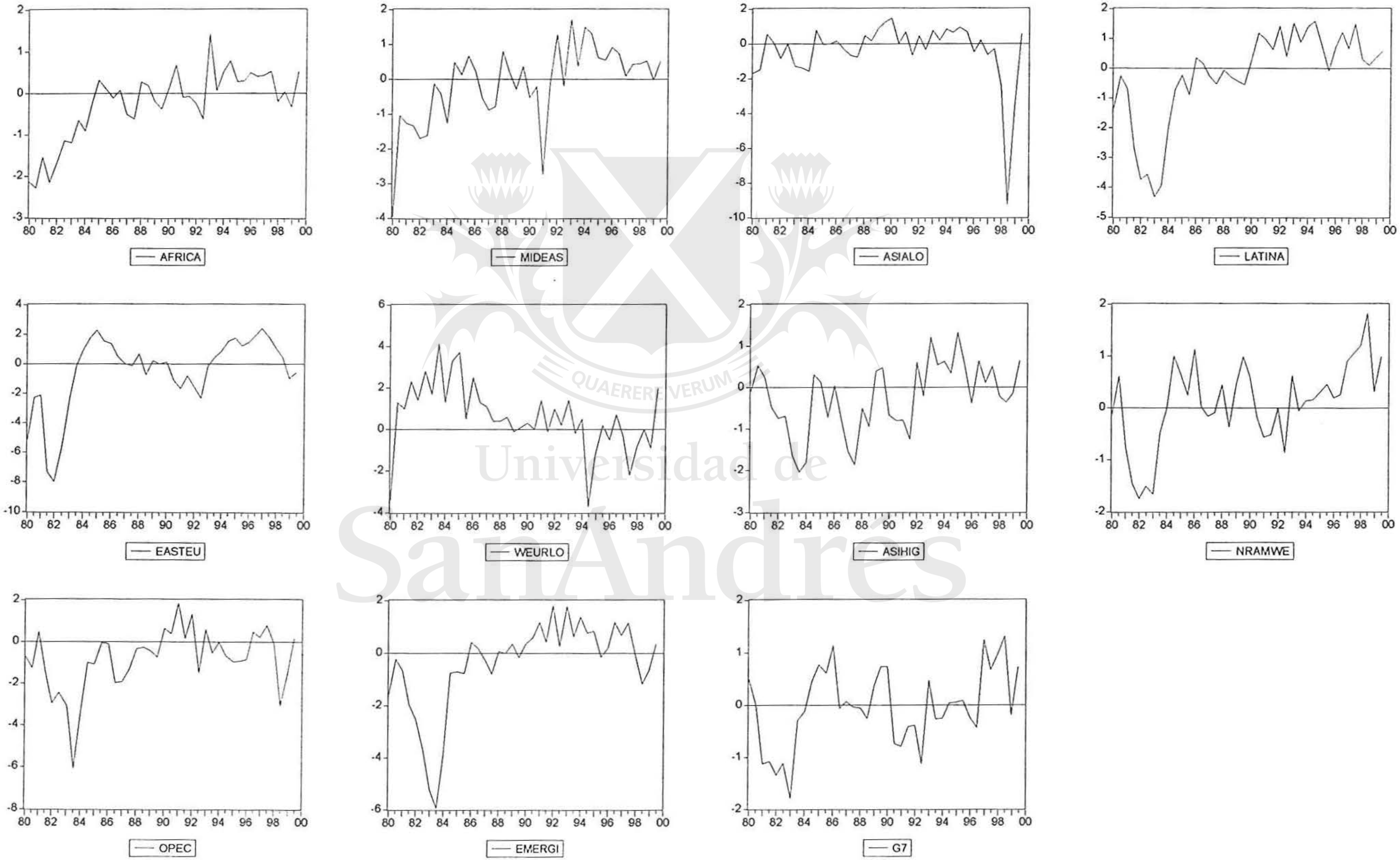


**Fig. VII.A: Mean Absolute Change *CCR* and *CCR* $_{t-1}$**
**Coefficient on Dummy and 90% Confidence Interval**

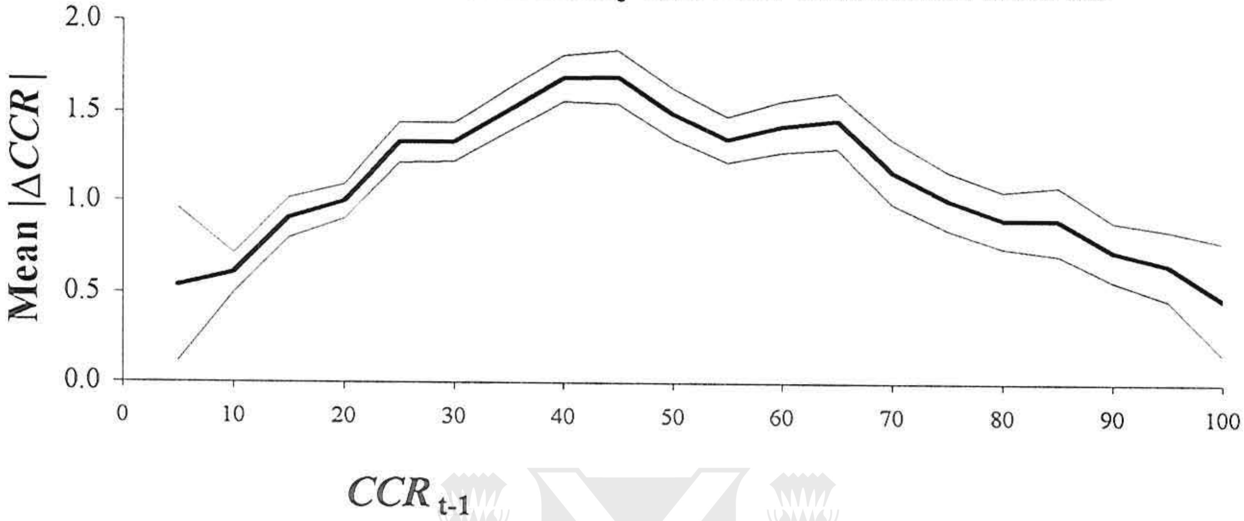
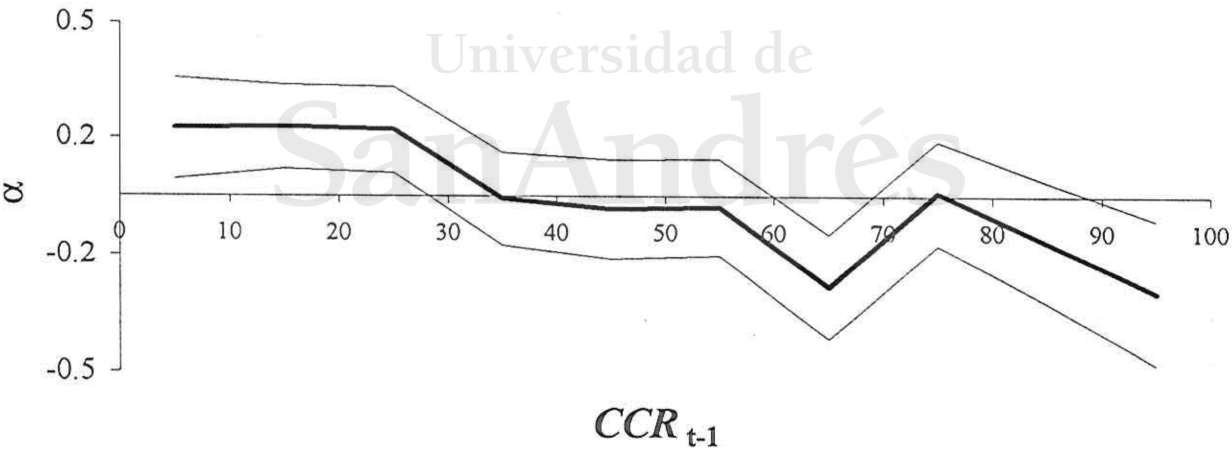



**Fig. VII.B: Asymmetry in CCR Revisions**
**Coefficient on Dummy and 90% Conf. Intervals**




$$\Delta CCR_t^i = \rho \ \Delta CCR_{t-1}^i + \sum_{j=0}^{9} \alpha_j \ I_j\left(CCR_{t-1}^i\right) + e_t^i$$

$$I_j\left(CCR_{t-1}^i\right) = \begin{cases} 1 \text{ if } & 10j \le CCR_{t-1}^i < 10(j+1) \\ 0 \text{ otherwise} \end{cases}$$

**Table I: Autocorrelation in Credit Revisions Implied by Autocorrelation of Repayment Capacity Innovations**
**Simulation Results**

| $\rho(\Delta\phi)$ | Number of Periods Assumed in Credit Rating Window | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2 | | | | 6 | | | | 10 | | | |
| | Estimated $\rho(\Delta CCR)$ | | | Mean $R^2$ | Estimated $\rho(\Delta CCR)$ | | | Mean $R^2$ | Estimated $\rho(\Delta CCR)$ | | | Mean $R^2$ |
| | Mean | # Sig. + | # Sig. - | | Mean | # Sig. + | # Sig. - | | Mean | # Sig. + | # Sig. - | |
| 0.90 | 0.37 | 100 | 0 | 0.12 | 0.23 | 100 | 0 | 0.04 | 0.15 | 85 | 0 | 0.02 |
| 0.75 | 0.26 | 100 | 0 | 0.06 | 0.16 | 91 | 0 | 0.02 | 0.13 | 82 | 0 | 0.02 |
| 0.60 | 0.17 | 100 | 0 | 0.03 | 0.12 | 81 | 0 | 0.01 | 0.12 | 72 | 0 | 0.01 |
| 0.45 | 0.08 | 68 | 0 | 0.01 | 0.06 | 44 | 2 | 0.01 | 0.07 | 51 | 4 | 0.01 |
| 0.30 | 0.03 | 24 | 1 | 0 | 0.03 | 19 | 3 | 0 | 0.04 | 32 | 4 | 0 |
| 0.15 | 0.01 | 7 | 0 | 0 | 0.02 | 17 | 8 | 0 | 0.03 | 29 | 7 | 0 |
| 0.00 | 0 | 3 | 6 | 0 | 0.01 | 16 | 8 | 0 | 0.02 | 24 | 7 | 0 |
| -0.15 | 0.01 | 5 | 1 | 0 | 0.02 | 11 | 5 | 0 | 0.02 | 21 | 5 | 0 |
| -0.30 | 0.04 | 22 | 1 | 0 | 0.02 | 18 | 4 | 0 | 0.02 | 20 | 4 | 0 |
| -0.45 | 0.08 | 68 | 0 | 0.01 | 0.04 | 27 | 1 | 0 | 0.03 | 23 | 3 | 0 |
| -0.60 | 0.11 | 88 | 0 | 0.01 | 0.06 | 50 | 1 | 0.01 | 0.04 | 38 | 2 | 0 |
| -0.75 | 0.11 | 92 | 0 | 0.01 | 0.08 | 63 | 0 | 0.01 | 0.06 | 46 | 0 | 0 |
| -0.90 | 0.07 | 55 | 0 | 0.01 | 0.06 | 45 | 0 | 0.01 | 0.05 | 40 | 0 | 0 |

(corresponding to the $t$=0, 1 and 2 shocks) are generated from a logistic distribution with mean zero and $\beta$=0.01. Also, $\phi_{-1}$ is randomly chosen for each of the 1000 observations so that the starting expected collection per dollar due has a uniform distribution between 0.8 and 1. Based on the specified parameters in each case [$\rho(\Delta\phi)$ and the number of periods assumed to be comprised in the credit rating window], the credit rating at $t$=0, 1 and 2 are computed from equation (14). The credit rating increase during the second period is then regressed on the increase during the first period, and the autocorrelation coefficient and its $t$-ratio are computed. The point slope estimate is saved to compute the mean estimated autocorrelation of credit revisions and the $t$-ratios greater than 1.95 in absolute value are saved to compute the number significantly different from zero in each situation. The r-squared of each regression is also saved to compute the mean r-squared.

## Table II.A: DISTRIBUTION OF CREDIT RATING AND ITS CHANGES BY PORTFOLIOS AND SUB-PERIODS

**EQUALLY WEIGHTED PORTFOLIOS**

**(in credit rating units)**

| Period | Statistic | Geographical Portfolios | | | | | | | | Special Characteristic Portfolios | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Africa | Middle East | Asia Low Income | Latin America | Eastern Europe | Western Europe Low Income | Asia High Inc. & Oceania | North Am. & West Europe | OPEC Countries | Emerging Countries | G7 Countries |
| | | **CREDIT RATING LEVEL** | | | | | | | | | | |
| 1979-2000 | Mean | 22.57 | 41.01 | 41.48 | 27.82 | 36.82 | 49.48 | 77.26 | 80.91 | 43.07 | 44.58 | 87.73 |
| | Std.Dev | 3.54 | 3.60 | 4.59 | 7.50 | 10.05 | 4.90 | 3.37 | 1.98 | 6.40 | 4.13 | 1.73 |
| | Mean / SD | 6.38 | 11.38 | 9.04 | 3.71 | 3.67 | 10.10 | 22.90 | 40.96 | 6.73 | 10.79 | 50.64 |
| | | **CHANGE IN CREDIT RATING** | | | | | | | | | | |
| 1980-2000 | Mean | -0.25 | -0.21 | -0.53 | -0.29 | -0.73 | 0.42 | -0.18 | 0.04 | -0.58 | -0.22 | -0.07 |
| | Std.Dev | 0.74 | 1.30 | 1.42 | 1.57 | 2.28 | 0.76 | 0.68 | 0.69 | 1.17 | 1.04 | 0.56 |
| | | **CHANGE IN CREDIT RATING BY PERIOD** | | | | | | | | | | |
| 1980-85 | Mean | -0.96 | -1.07 | -1.36 | -2.17 | -1.52 | 0.18 | -0.45 | -0.38 | -1.42 | -1.21 | -0.33 |
| 1986-90 | | -0.25 | -0.17 | -0.06 | -0.04 | -0.24 | 0.56 | -0.42 | 0.13 | -0.38 | 0.16 | -0.01 |
| 1991-95 | | 0.23 | 0.23 | -0.05 | 0.68 | -1.53 | 0.23 | 0.24 | -0.11 | -0.27 | 0.53 | -0.17 |
| 1996-00 | | 0.18 | 0.42 | -0.50 | 0.86 | 0.66 | 0.81 | -0.03 | 0.66 | 0.00 | -0.13 | 0.32 |
| Countries in Portf. # | | 28 | 14 | 14 | 23 | 12 | 3 | 5 | 18 | 15 | 20 | 7 |

# The last row reports the average number of countries in each portfolio during the sample period. The actual number of countries increased over time as *Intitutional Investor* added more countries to the survey. The simple average of the changes by period is slightly different than the average change for the whole period because the 1980-85 subperiod has two more semesters than the other subperiods.

### Table II.B: DISTRIBUTION OF CREDIT RATING AND ITS CHANGES BY PORTFOLIOS AND SUB-PERIODS

**GDP WEIGHTED PORTFOLIOS**

**(in credit rating units)**

| Period | Statistic | Geographical Portfolios | | | | | | | | Special Characteristic Portfolios | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Africa | Middle East | Asia Low Income | Latin America | Eastern Europe | Western Europe Low Income | Asia High Inc. & Oceania | North Am. & West Europe | OPEC Countries | Emerging Countries | G7 Countries |
| | | **CREDIT RATING LEVEL** | | | | | | | | | | |
| 1979-2000 | Mean | 33.26 | 38.21 | 54.15 | 37.35 | 41.45 | 43.88 | 89.62 | 88.61 | 42.05 | 45.84 | 90.52 |
| | Std.Dev | 6.84 | 3.44 | 3.70 | 9.93 | 12.44 | 6.43 | 2.94 | 2.12 | 5.49 | 3.92 | 2.26 |
| | Mean / SD | 4.86 | 11.10 | 14.64 | 3.76 | 3.33 | 6.83 | 30.44 | 41.89 | 7.66 | 11.70 | 39.97 |
| | | **CHANGE IN CREDIT RATING** | | | | | | | | | | |
| 1980-2000 | Mean | -0.41 | -0.25 | -0.32 | -0.51 | -0.92 | 0.49 | -0.24 | -0.06 | -0.59 | -0.28 | -0.12 |
| | Std.Dev | 1.06 | 1.64 | 1.03 | 2.00 | 2.52 | 0.90 | 0.63 | 0.64 | 1.33 | 1.13 | 0.60 |
| | | **CHANGE IN CREDIT RATING BY PERIOD** | | | | | | | | | | |
| 1980-85 | Mean | -1.01 | -1.22 | -0.57 | -2.72 | -1.46 | 0.75 | -0.22 | -0.31 | -1.21 | -1.28 | -0.27 |
| 1986-90 | | -0.85 | -0.22 | -0.60 | -0.30 | -0.76 | 0.59 | -0.20 | -0.25 | -0.32 | 0.11 | -0.29 |
| 1991-95 | | 0.20 | 0.23 | 0.33 | 1.00 | -1.76 | 0.12 | -0.19 | 0.01 | -0.11 | 0.48 | -0.03 |
| 1996-00 | | 0.21 | 0.51 | -0.40 | 0.54 | 0.58 | 0.42 | -0.36 | 0.39 | -0.60 | -0.22 | 0.19 |
| Countries in Portf. # | | 29 | 14 | 14 | 23 | 12 | 3 | 5 | 18 | 12 | 20 | 7 |

# GDP weights are proportional to 1998 PPP-adjusted GDP as reported in World Bank (2000) and CIA (2000). The number of countries may differ from those in Table I.A. because GDP data may not be available for a few countries. The simple average of the changes by period is slightly different than the average change for the whole period because the 1980-85 subperiod has two more semesters than the other subperiods.

## Table II.C: DISTRIBUTION OF CREDIT RATING AND ITS CHANGES BY PORTFOLIOS AND SUB-PERIODS

### PRINCIPAL COMPONENT WEIGHTED PORTFOLIOS

**(in credit rating units)**

| Period | Statistic | Geographical Portfolios | | | | | | | | Special Characteristic Portfolios | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Africa | Middle East | Asia Low Income | Latin America | Eastern Europe | Western Europe Low Income | Asia High Inc. & Oceania | North Am. & West Europe | OPEC Countries | Emerging Countries | G7 Countries |
| | | **CREDIT RATING LEVEL** | | | | | | | | | | |
| 1979-2000 | Mean | 15.87 | 40.89 | 48.36 | 28.86 | 33.21 | 34.93 | 73.33 | 76.87 | 38.25 | 39.29 | 84.51 |
| | Std.Dev | 3.40 | 3.64 | 4.12 | 7.76 | 7.57 | 10.24 | 4.71 | 2.81 | 10.00 | 8.46 | 1.90 |
| | Mean / SD | 4.66 | 11.23 | 11.73 | 3.72 | 4.38 | 3.41 | 15.56 | 27.33 | 3.82 | 4.65 | 44.38 |
| | | **CHANGE IN CREDIT RATING** | | | | | | | | | | |
| 1980-2000 | Mean | -0.22 | -0.12 | -0.37 | -0.21 | -0.46 | 0.59 | -0.21 | 0.12 | -0.79 | -0.39 | -0.01 |
| | Std.Dev | 0.84 | 1.12 | 1.77 | 1.54 | 2.42 | 1.60 | 0.85 | 0.82 | 1.49 | 1.73 | 0.75 |
| | | **CHANGE IN CREDIT RATING BY PERIOD** | | | | | | | | | | |
| 1980-85 | Mean | -1.12 | -0.96 | -0.59 | -2.03 | -2.21 | 1.67 | -0.58 | -0.44 | -1.91 | -2.33 | -0.38 |
| 1986-90 | | -0.05 | -0.17 | 0.26 | -0.02 | 0.09 | 0.66 | -0.62 | 0.28 | -0.60 | 0.07 | 0.19 |
| 1991-95 | | 0.23 | 0.43 | 0.41 | 0.95 | -0.07 | -0.05 | 0.29 | -0.04 | -0.07 | 0.88 | -0.26 |
| 1996-00 | | 0.27 | 0.45 | -1.66 | 0.73 | 0.83 | -0.21 | 0.19 | 0.87 | -0.29 | 0.29 | 0.55 |
| Countries in Portf. # | | 22 | 10 | 9 | 17 | 6 | 3 | 5 | 17 | 9 | 20 | 7 |

# Portfolio weights are proportional to the first eigenvector of the covariance matrix of the proportional change in *CCR* for the countries in each portfolio. A few countries were excluded because they dominated the principal component (Iran, Iraq, Kuwait and Lebanon were excluded from Middle East and the first three from OPEC). These countries were subject to extreme political turmoil (e.g. war) during the sample period and the movements in their credit ratings reflected country-specific shocks more than regional shocks. Because we work with the covariance matrix (instead of the correlation matrix) these outliers are very influential in the first principal component.

## Table III.A: INTERNATIONAL CORRELATION IN CREDIT REVISIONS

### EQUALLY WEIGHTED PORTFOLIOS

| | Geographical Portfolios | | | | | | | | Special Charac. Portf. | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Africa | Middle East | Asia Low Income | Latin America | Eastern Europe | Western Europe Low Inc | Asia High Inc. & Oceania | North Am. & West Europe | OPEC Countries | Emerging Countries |
| Middle East | 0.64 | 1.00 | | | | | | | | |
| Asia Low Income | 0.49 | 0.54 | 1.00 | | | | | | | |
| Latin America | 0.78 | 0.45 | 0.39 | 1.00 | | | | | | |
| Eastern Europe | 0.50 | 0.48 | 0.45 | 0.38 | 1.00 | | | | | |
| Western Europe Low Income | 0.28 | 0.28 | 0.30 | 0.29 | 0.20 | 1.00 | | | | |
| Asia High Inc. & Oceania | 0.50 | 0.38 | 0.39 | 0.47 | 0.22 | 0.43 | 1.00 | | | |
| North Am. & West Europe | 0.54 | 0.39 | 0.19 | 0.58 | 0.65 | 0.43 | 0.42 | 1.00 | | |
| OPEC | 0.63 | 0.90 | 0.54 | 0.50 | 0.35 | 0.40 | 0.47 | 0.41 | 1.00 | |
| Emerging | 0.63 | 0.38 | 0.58 | 0.75 | 0.21 | 0.44 | 0.72 | 0.34 | 0.58 | 1.00 |
| G7 | 0.44 | 0.42 | 0.22 | 0.47 | 0.66 | 0.33 | 0.44 | 0.87 | 0.43 | 0.32 |

Corelation between the changes in the average credit rating of the countries in each portfolio.

**Table III.B: INTERNATIONAL CORRELATION IN CREDIT REVISIONS**

**GDP WEIGHTED PORTFOLIOS**

| | Geographical Portfolios | | | | | | | | Special Charac. Portf. | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Africa | Middle East | Asia Low Income | Latin America | Eastern Europe | Western Europe Low Inc | Asia High Inc. & Oceania | North Am. & West Europe | OPEC Countries | Emerging Countries |
| Middle East | 0.36 | 1.00 | | | | | | | | |
| Asia Low Income | 0.14 | 0.06 | 1.00 | | | | | | | |
| Latin America | 0.47 | 0.32 | 0.32 | 1.00 | | | | | | |
| Eastern Europe | 0.10 | 0.39 | 0.49 | 0.15 | 1.00 | | | | | |
| Western Europe Low Income | -0.15 | 0.32 | 0.06 | -0.05 | 0.12 | 1.00 | | | | |
| Asia High Inc. & Oceania | 0.02 | 0.24 | 0.35 | 0.20 | 0.37 | 0.14 | 1.00 | | | |
| North Am. & West Europe | 0.22 | 0.27 | 0.36 | 0.37 | 0.52 | -0.07 | 0.34 | 1.00 | | |
| OPEC | 0.37 | 0.68 | 0.20 | 0.42 | 0.22 | 0.26 | 0.52 | 0.21 | 1.00 | |
| Emerging | 0.36 | 0.36 | 0.58 | 0.79 | 0.31 | 0.11 | 0.52 | 0.33 | 0.63 | 1.00 |
| G7 | 0.15 | 0.28 | 0.38 | 0.30 | 0.51 | -0.06 | 0.55 | 0.96 | 0.30 | 0.37 |

Corelation between the changes in the average credit rating of the countries in each portfolio.

**Table III.C: INTERNATIONAL CORRELATION IN CREDIT REVISIONS**

**PRINCIPAL COMPONENT WEIGHTED PORTFOLIOS**

| | Geographical Portfolios | | | | | | | | Special Charac. Portf. | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Africa | Middle East | Asia Low Income | Latin America | Eastern Europe | Western Europe Low Inc | Asia High Inc. & Oceania | North Am. & West Europe | OPEC Countries | Emerging Countries |
| Middle East | 0.74 | 1.00 | | | | | | | | |
| Asia Low Income | 0.21 | 0.12 | 1.00 | | | | | | | |
| Latin America | 0.70 | 0.51 | 0.17 | 1.00 | | | | | | |
| Eastern Europe | 0.74 | 0.64 | 0.07 | 0.59 | 1.00 | | | | | |
| Western Europe Low Income | -0.18 | -0.05 | 0.10 | -0.46 | -0.14 | 1.00 | | | | |
| Asia High Inc. & Oceania | 0.34 | 0.44 | 0.29 | 0.58 | 0.23 | -0.27 | 1.00 | | | |
| North Am. & West Europe | 0.54 | 0.48 | -0.17 | 0.61 | 0.72 | -0.21 | 0.48 | 1.00 | | |
| OPEC | 0.43 | 0.22 | 0.47 | 0.75 | 0.23 | -0.34 | 0.55 | 0.33 | 1.00 | |
| Emerging | 0.59 | 0.43 | 0.33 | 0.94 | 0.41 | -0.41 | 0.65 | 0.49 | 0.85 | 1.00 |
| G7 | 0.44 | 0.31 | -0.15 | 0.45 | 0.61 | -0.20 | 0.35 | 0.92 | 0.25 | 0.37 |

Corelation between the changes in the average credit rating of the countries in each portfolio.

## Table IV: Mean Absolute Revisions and *CCR* Level

$$\left|\Delta CCR_t^i\right| = \sum_{j=0}^{19} \alpha_j \, I_j\left(CCR_{t-1}^i\right) + e_t^i$$

$$I_j\left(CCR_{t-1}^i\right) = \begin{cases} 1 & \text{if} \quad 5j \leq CCR_{t-1}^i < 5(j+1) \\ 0 & \text{otherwise} \end{cases}$$

| j | For $CCR_{t-1}$ From | To | $\alpha_j$ | SE($\alpha_j$) | t($\alpha_j$) |
|---|---|---|---|---|---|
| 0 | 0 | 5 | 0.55 | 0.24 | 2.33 |
| 1 | 5 | 10 | 0.57 | 0.07 | 8.47 |
| 2 | 10 | 15 | 0.80 | 0.07 | 11.51 |
| 3 | 15 | 20 | 0.94 | 0.06 | 15.21 |
| 4 | 20 | 25 | 1.22 | 0.07 | 17.30 |
| 5 | 25 | 30 | 1.28 | 0.07 | 18.92 |
| 6 | 30 | 35 | 1.45 | 0.07 | 19.56 |
| 7 | 35 | 40 | 1.57 | 0.08 | 20.27 |
| 8 | 40 | 45 | 1.42 | 0.09 | 16.03 |
| 9 | 45 | 50 | 1.29 | 0.08 | 15.30 |
| 10 | 50 | 55 | 1.18 | 0.08 | 14.95 |
| 11 | 55 | 60 | 1.20 | 0.09 | 13.81 |
| 12 | 60 | 65 | 1.31 | 0.09 | 14.54 |
| 13 | 65 | 70 | 1.03 | 0.10 | 10.19 |
| 14 | 70 | 75 | 0.97 | 0.09 | 10.69 |
| 15 | 75 | 80 | 0.89 | 0.09 | 10.26 |
| 16 | 80 | 85 | 0.91 | 0.11 | 8.65 |
| 17 | 85 | 90 | 0.73 | 0.09 | 7.95 |
| 18 | 90 | 95 | 0.66 | 0.11 | 6.25 |
| 19 | 95 | 100 | 0.46 | 0.17 | 2.66 |

## Table V: Asymmetry in *CCR* Revisions

$$\Delta CCR_t^i = \rho\ \Delta CCR_{t-1}^i + \sum_{j=0}^{9} \alpha_j\ I_j\left(CCR_{t-1}^i\right) + e_t^i$$

$$I_j\left(CCR_{t-1}^i\right) = \begin{cases} 1 \text{ if } & 10j \le CCR_{t-1}^i < 10(j+1) \\ 0 & \text{otherwise} \end{cases}$$

$$i = 1,\ldots,N;\ \ t = t_i,\ldots,T_i$$

| j | For $CCR_{t-1}$ From | To | $\alpha_j$ | $SE(\alpha_j)$ | $t(\alpha_j)$ |
|---|---|---|---|---|---|
| 0 | 0 | 10 | 0.17 | 0.08 | 2.17 |
| 1 | 10 | 20 | 0.18 | 0.07 | 2.68 |
| 2 | 20 | 30 | 0.17 | 0.07 | 2.52 |
| 3 | 30 | 40 | -0.01 | 0.07 | -0.09 |
| 4 | 40 | 50 | -0.03 | 0.08 | -0.43 |
| 5 | 50 | 60 | -0.03 | 0.08 | -0.37 |
| 6 | 60 | 70 | -0.23 | 0.08 | -2.83 |
| 7 | 70 | 80 | 0.01 | 0.08 | 0.10 |
| 8 | 80 | 90 | -0.12 | 0.09 | -1.26 |
| 9 | 90 | 100 | -0.25 | 0.11 | -2.19 |
| $\rho$ | | | 0.42 | 0.01 | 32.64 |

Estimated by GLS allowing for different variance of *CCR* across regions

**Table VI.A: Serial Correlation in the Sign of Credit Revisions**
**SOURCE: *INSTITUTIONAL INVESTOR***

$\Pr\{ sg(\Delta CCR_{t+1})=i \mid sg(\Delta CCR_t)=j \}$ $i = +, 0, -;$ $j = +, 0, -.$

**Allsample: 1980-2000**

| | | Obs 4,674 | sign($\Delta CCR_{t+1}$) + | 0 | - | P Value |
|---|---|---|---|---|---|---|
| sign($\Delta CCR_t$) | + | 2,366 | 0.66 | 0.04 | 0.30 | 0.00 |
| | 0 | 156 | 0.49 | 0.04 | 0.46 | |
| | - | 2,152 | 0.36 | 0.03 | 0.61 | 0.00 |

**Subsample: 1980-1985**

| | | Obs 1,135 | sign($\Delta CCR_{t+1}$) + | 0 | - | P Value |
|---|---|---|---|---|---|---|
| sign($\Delta CCR_t$) | + | 344 | 0.54 | 0.02 | 0.44 | 0.15 |
| | 0 | 22 | 0.27 | 0.05 | 0.68 | |
| | - | 769 | 0.23 | 0.02 | 0.75 | 0.00 |

**1986-1990**

| | | Obs 1,102 | sign($\Delta CCR_{t+1}$) + | 0 | - | P Value |
|---|---|---|---|---|---|---|
| sign($\Delta CCR_t$) | + | 541 | 0.60 | 0.05 | 0.36 | 0.00 |
| | 0 | 43 | 0.51 | 0.07 | 0.42 | |
| | - | 518 | 0.38 | 0.03 | 0.59 | 0.01 |

**1991-1995**

| | | Obs 1,220 | sign($\Delta CCR_{t+1}$) + | 0 | - | P Value |
|---|---|---|---|---|---|---|
| sign($\Delta CCR_t$) | + | 705 | 0.71 | 0.04 | 0.26 | 0.00 |
| | 0 | 47 | 0.49 | 0.06 | 0.45 | |
| | - | 468 | 0.46 | 0.04 | 0.50 | 0.45 |

**1996-2000**

| | | Obs 1,217 | sign($\Delta CCR_{t+1}$) + | 0 | - | P Value |
|---|---|---|---|---|---|---|
| sign($\Delta CCR_t$) | + | 776 | 0.73 | 0.03 | 0.24 | 0.00 |
| | 0 | 44 | 0.59 | 0.00 | 0.41 | |
| | - | 397 | 0.47 | 0.04 | 0.49 | 0.35 |

Source: *Institutional Investor*'s complete credit rating data set, 1979.2-2000.1, 147 countries (two observations lost in differencing and lagging). The last column reports the $p$-value of a test that the sign of the current revision contains no information about the sign of the next revision based on an asymptotically valid normal approximation to the Binomial distribution.

## Table VI.B: Serial Correlation in the Sign of Credit Revisions
## SOURCE: STANDARD AND POOR'S

$\Pr\{ sg(\Delta CCR_{t+1})=i \mid sg(\Delta CCR_t)=j \}$ $\quad i = +, 0, -; \quad j = +, 0, -.$

**Allsample: 1975-2000**

| | | Obs | $sign(\Delta CCR_{t1})$ | | P Value |
|---|---|---|---|---|---|
| | | 209 | + | - | |
| $sign(\Delta CCR_{t0})$ | + | 90 | 0.68 | 0.32 | 0.00 |
| | - | 119 | 0.36 | 0.64 | 0.00 |

**Subsample: 1980-1985**

| | | Obs | $sign(\Delta CCR_{t1})$ | | P Value |
|---|---|---|---|---|---|
| | | 3 | + | - | |
| $sign(\Delta CCR_{t0})$ | + | 0 | | | |
| | - | 3 | | 1.00 | |

**1986-1990**

| | | Obs | $sign(\Delta CCR_{t1})$ | | P Value |
|---|---|---|---|---|---|
| | | 12 | + | - | |
| $sign(\Delta CCR_{t0})$ | + | 1 | 1.00 | | |
| | - | 11 | 0.27 | 0.73 | 0.03 |

**1991-1995**

| | | Obs | $sign(\Delta CCR_{t1})$ | | P Value |
|---|---|---|---|---|---|
| | | 62 | + | - | |
| $sign(\Delta CCR_{t0})$ | + | 27 | 0.70 | 0.30 | 0.02 |
| | - | 35 | 0.31 | 0.69 | 0.01 |

**1996-2000**

| | | Obs | $sign(\Delta CCR_{t1})$ | | P Value |
|---|---|---|---|---|---|
| | | 130 | + | - | |
| $sign(\Delta CCR_{t0})$ | + | 60 | 0.65 | 0.35 | 0.01 |
| | - | 70 | 0.41 | 0.59 | 0.08 |

Source: Standard and Poor's complete sovereign ratings record, Jan-1-1975/June-7-2000. Forty five countries had two or more credit revisions during this period. No country had more than one credit revision between 1975 and 1979. The last column reports the *p* -value of a test that the sign of the current revision contains no information about the sign of the next revision based on an asymptotically valid normal approximation to the Binomial distribution. When only 11 revisions were done, the reported p-value corresponds to an exact binomial test.

**Table VI.C: Serial Correlation in the Sign of Credit Revisions**
**SOURCE: MOODY'S**

$\Pr\{ sg(\Delta CCR_{t+1})=i \mid sg(\Delta CCR_t)=j \}$ $\quad i = +, 0, -; \quad j = +, 0, -.$

**Allsample: 1975-2000**

| | | Obs | sign($\Delta CCR_{t1}$) | | P Value |
|---|---|---|---|---|---|
| | | 211 | + | - | |
| sign($\Delta CCR_{t0}$) | + | 100 | 0.79 | 0.21 | 0.00 |
| | - | 111 | 0.32 | 0.68 | 0.00 |

**Subsample: 1980-1985**

| | | Obs | sign($\Delta CCR_{t1}$) | | P Value |
|---|---|---|---|---|---|
| | | 0 | + | - | |
| sign($\Delta CCR_{t0}$) | + | 0 | | | |
| | - | 0 | | | |

**1986-1990**

| | | Obs | sign($\Delta CCR_{t1}$) | | P Value |
|---|---|---|---|---|---|
| | | 3 | + | - | |
| sign($\Delta CCR_{t0}$) | + | 2 | | 1.00 | |
| | - | 1 | | 1.00 | |

**1991-1995**

| | | Obs | sign($\Delta CCR_{t1}$) | | P Value |
|---|---|---|---|---|---|
| | | 27 | + | - | |
| sign($\Delta CCR_{t0}$) | + | 11 | 0.73 | 0.27 | 0.03 |
| | - | 16 | 0.38 | 0.63 | 0.11 |

**1996-2000**

| | | Obs | sign($\Delta CCR_{t1}$) | | P Value |
|---|---|---|---|---|---|
| | | 181 | + | - | |
| sign($\Delta CCR_{t0}$) | + | 87 | 0.82 | 0.18 | 0.00 |
| | - | 94 | 0.31 | 0.69 | 0.00 |

Source: Moody's complete sovereign ratings record, January-1-1975/June-22-2000. Fifty eight countries had two or more credit revisions during this period. No country had more than one credit revision between 1975 and 1985. The last column reports the $p$-value of a test that the sign of the current revision contains no information about the sign of the next revision based on an asymptotically valid normal approximation to the Binomial distribution. When less than 16 revisions were done, the reported $p$-value corresponds to an exact binomial test.

## Table VII.A: Autorregressions of Changes in Country Credit Ratings - Country-Specific Intercepts

$$\Delta CCR_t^i = \alpha^i + \rho_1\ \Delta CCR_{t-1}^i + \rho_2\ \Delta CCR_{t-2}^i + \sum_j \beta^j D^j \Delta CCR_{t-1}^i + \pi\ \ \Delta CCR_{t-1}^{NAWE} + \sum_{s=1}^{S} \delta^s\ D^s\ \Delta CCR_{t-1}^s + e_t^i\ ;$$

$$D^j = (1 \text{ if } i \in\ j,\ 0 \text{ otherwise}),\ D^s = (1 \text{ if } i \in s,\ 0 \text{ o/w});\ \ i = 1,..., N;\ s = 1,..., S;\ t = t_i,..., T_i$$

| Explanatory Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Lagged Change in *CCR*** | | | | | | | | | |
| **First Lag ($\Delta CCR_{t-1}$)** | **0.37** | **0.35** | **0.38** | **0.34** | **0.33** | **0.42** | **0.32** | **0.37** | **0.36** |
| | 27.86 *** | 23.67 *** | 12.23 *** | 11.09 *** | 5.67 *** | 28.35 *** | 20.40 *** | 27.82 *** | 26.34 *** |
| **Second Lag ($\Delta CCR_{t-2}$)** | | **0.09** | | | | | | | |
| | | 6.00 *** | | | | | | | |
| **Negative Revision Dummy** | | | **-0.01** | | | | | | |
| | | | -0.28 | | | | | | |
| **Time Dummies** | | | | | | | | | |
| **1980-1985** | | | | **0.06** | | | | | |
| | | | | 1.63 | | | | | |
| **1986-1990** | | | | **0.05** | | | | | |
| | | | | 1.04 | | | | | |
| **1991-1995** | | | | **-0.04** | | | | | |
| | | | | -0.92 | | | | | |
| **Regional Dummies** | | | | | | | | | |
| **Africa** | | | | | **-0.01** | | | | |
| | | | | | -0.08 | | | | |
| **Middle East** | | | | | **-0.22** | | | | |
| | | | | | -3.34 *** | | | | |
| **Asia - Low Income** | | | | | **0.08** | | | | |
| | | | | | 1.20 | | | | |
| **Latin America** | | | | | **0.13** | | | | |
| | | | | | 1.99 ** | | | | |
| **Western Europe - Low Income** | | | | | **0.14** | | | | |
| | | | | | 1.38 | | | | |
| **Eastern Europe** | | | | | **0.22** | | | | |
| | | | | | 3.26 *** | | | | |
| **Asia - High Income and Oceania** | | | | | **0.07** | | | | |
| | | | | | 0.64 | | | | |

Table VII.A: Autorregressions of Changes in Country Credit Ratings - Country-Specific Intercepts (continued)

| Explanatory Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Topical Portfolios** | | | | | | | | | |
| **OPEC** | | | | | | **-0.21** | | | |
| | | | | | | -6.99 *** | | | |
| **"Emerging" Countries** | | | | | | | **0.16** | | |
| | | | | | | | 5.96 *** | | |
| **G 7** | | | | | | | | **-0.12** | |
| | | | | | | | | -1.32 | |
| **Lagged Change in Regional Portfolio CCR** | | | | | | | | | **0.32** |
| | | | | | | | | | 2.21 ** |
| **Africa** | | | | | | | | | **-0.26** |
| | | | | | | | | | -1.54 |
| **Middle East** | | | | | | | | | **-0.41** |
| | | | | | | | | | -2.36 ** |
| **Asia - Low Income** | | | | | | | | | **-0.20** |
| | | | | | | | | | -1.10 |
| **Latin America** | | | | | | | | | **-0.03** |
| | | | | | | | | | -0.22 |
| **Western Europe - Low Income** | | | | | | | | | **-0.60** |
| | | | | | | | | | -3.03 *** |
| **Eastern Europe** | | | | | | | | | **-0.03** |
| | | | | | | | | | -0.21 |
| **Asia - High Income and Oceania** | | | | | | | | | **-0.32** |
| | | | | | | | | | -1.48 |
| Residual Log Likelihood | -8146 | -7808 | -8149 | -8149 | -8054 | -8124 | -8131 | -8146 | -8135 |

Estimated coefficients reported in bold, *t*-ratios below them. All included variables allow for the slope on the lagged revision to differ by the category under consideration. Country-specific intercepts allowed in all regressions. Errors allowed to be heteroskedastic by regions in all cases. Regressions use unbalanced panel based on all *CCR* revisions by *Institutional Investor* since March 1980.

## Table VII.B: Autorregressions of Changes in Country Credit Ratings - No Intercept

$$\Delta CCR_t^i = \rho_1 \ \Delta CCR_{t-1}^i + \rho_2 \ \Delta CCR_{t-2}^i + \sum_j \beta^j D^j \Delta CCR_{t-1}^i + \pi \ \ \Delta CCR_{t-1}^{NABE} + \sum_{s=1}^{S} \delta^s \ D^s \ \Delta CCR_{t-1}^s + e_t^i \ ;$$

$$D^j = (1 \text{ if } i \in j, \ 0 \text{ otherwise}); D^s = (1 \text{ if } i \in s, \ 0 \text{ o/w}); \ i = 1,\ldots,N; \ s = 1,\ldots,S; \ t = t_i,\ldots,T_i$$

| Explanatory Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Lagged Change in *CCR*** | | | | | | | | | |
| **First Lag** | **0.42** | **0.38** | **0.46** | **0.43** | **0.36** | **0.46** | **0.38** | **0.48** | **0.41** |
| | 32.52 *** | 26.48 *** | 17.23 *** | 14.32 *** | 6.29 *** | 32.33 *** | 25.12 *** | 39.47 *** | 30.76 *** |
| **Second Lag** | | **0.11** | | | | | | | |
| | | 7.96 *** | | | | | | | |
| **Negative Revision Dummy** | | | **-0.06** | | | | | | |
| | | | -1.89 * | | | | | | |
| **Time Dummies** | | | | | | | | | |
| **1980-1985** | | | | **0.00** | | | | | |
| | | | | -0.02 | | | | | |
| **1986-1990** | | | | **0.02** | | | | | |
| | | | | 0.50 | | | | | |
| **1991-1995** | | | | **-0.05** | | | | | |
| | | | | -1.26 | | | | | |
| **Regional Dummies** | | | | | | | | | |
| **Africa** | | | | | **0.03** | | | | |
| | | | | | 0.45 | | | | |
| **Middle East** | | | | | **-0.20** | | | | |
| | | | | | -3.10 *** | | | | |
| **Asia - Low Income** | | | | | **0.07** | | | | |
| | | | | | 1.06 | | | | |
| **Latin America** | | | | | **0.12** | | | | |
| | | | | | 2.00 ** | | | | |
| **Western Europe - Low Income** | | | | | **0.19** | | | | |
| | | | | | 1.85 * | | | | |
| **Eastern Europe** | | | | | **0.26** | | | | |
| | | | | | 4.02 *** | | | | |
| **Asia - High Income and Oceania** | | | | | **0.06** | | | | |
| | | | | | 0.64 | | | | |

**Table VII.B: Autorregressions of Changes in Country Credit Ratings - No Intercept (continued)**

| Explanatory Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| **Topical Portfolios** | | | | | | | | | |
| **OPEC** | | | | | | **-0.19** | | | |
| | | | | | | -6.57 *** | | | |
| **"Emerging" Countries** | | | | | | | **0.12** | | |
| | | | | | | | 4.87 *** | | |
| **G 7** | | | | | | | | **-0.12** | |
| | | | | | | | | -1.22 | |
| **Lagged Change in Regional Portfolio CCR** | | | | | | | | | **0.26** |
| | | | | | | | | | 1.82 * |
| **Africa** | | | | | | | | | **-0.19** |
| | | | | | | | | | -1.16 |
| **Middle East** | | | | | | | | | **-0.38** |
| | | | | | | | | | -2.23 ** |
| **Asia - Low Income** | | | | | | | | | **-0.15** |
| | | | | | | | | | -0.84 |
| **Latin America** | | | | | | | | | **-0.01** |
| | | | | | | | | | -0.06 |
| **Western Europe - Low Income** | | | | | | | | | **-0.37** |
| | | | | | | | | | -1.92 * |
| **Eastern Europe** | | | | | | | | | **-0.01** |
| | | | | | | | | | -0.06 |
| **Asia - High Income and Oceania** | | | | | | | | | **-0.23** |
| | | | | | | | | | -1.12 |
| Residual Log Likelihood | -8169 | -7815 | -8170 | -8174 | -8122 | -8150 | -8160 | -8169 | -8162 |

Estimated coefficients reported in bold, *t* -ratios below them. All included variables allow for the slope on the lagged revision to differ by the category under consideration. No intercepts allowed in any regression. Errors allowed to be heteroskedastic by regions in all cases. Regressions use unbalanced panel based on all *CCR* revisions by *Institutional Investor* since March 1980.

## Table VIII: Summary Autorregressions of Changes in *CCR*
## No Intercepts

| Explanatory Variables | (1) | (2) |
|---|---|---|
| Lagged Change in *CCR* | | |
| First Lag ($\Delta CCR_{t-1}$) | **0.36** | **0.33** |
| | 11.38 *** | 15.60 *** |
| Second Lag ($\Delta CCR_{t-2}$) | **0.09** | **0.09** |
| | 6.54 *** | 6.65 *** |
| Negative Revision Dummy | **-0.06** | |
| | 1.65 * | |
| Regional Dummies | | |
| Middle East | **-0.13** | **-0.17** |
| | -3.01 *** | -4.39 *** |
| Latin America | **0.03** | |
| | 0.80 | |
| Western Europe - Low Income | **0.17** | |
| | 1.73 * | |
| Eastern Europe | **0.23** | **0.22** |
| | 5.99 *** | 6.02 *** |
| Topical Portfolios | | |
| OPEC | **-0.04** | |
| | -0.98 | |
| "Emerging" Countries | **0.12** | **0.12** |
| | 3.87 *** | 4.18 *** |
| Lagged Change in Regional Portfolio CCR | **0.17** | **0.17** |
| | 4.80 *** | 4.79 *** |
| Middle East | **0.04** | |
| | 0.21 | |
| Western Europe - Low Income | **-0.43** | **-0.27** |
| | -2.83 *** | -2.02 ** |
| Dummies by level of $CCR_{t-1}$ | | |
| $CCR \in [0,10)$ | **0.23** | **0.22** |
| | 3.22 *** | 3.06 *** |
| $CCR \in [10,20)$ | **0.24** | **0.23** |
| | 4.23 *** | 4.23 *** |
| $CCR \in [20,30)$ | **0.20** | **0.21** |
| | 3.44 *** | 3.69 *** |
| $CCR \in [60,70)$ | **-0.22** | **-0.20** |
| | -2.79 *** | -2.60 *** |
| $CCR \in [90,100]$ | **-0.19** | **-0.19** |
| | -1.79 * | -1.77 * |
| Residual Log Likelihood | -7767 | -7762 |

Estimated coefficients reported in bold, t-ratios below them. All included variables allow for the slope on the lagged revision to differ by the category under consideration except for the dummies that depend on the level of $CCR_{t-1}$ which affect the intercept. No intercepts allowed in any regression. Errors allowed to be heteroskedastic by regions in all cases. Regressions use unbalanced panel based on all *CCR* revisions by Institutional Investor since March 1980.

## Table IX: Autocorrelation of Credit Revisions Announced by Major Credit Rating Agencies

$$\Delta CCR^i(t_j) = \alpha + \rho^{(t_j - t_{j-1})}\ \Delta CCR^i(t_{j-1}) + e^i(t_j - t_{j-1})\ ;\ \ i = 1,\ldots,N,\ j = 1,\ldots,J_i$$

| | Homoskedasticity Assumed | | Heteroskedasticity Controlled | |
|---|---|---|---|---|
| | S&P | Moody's | S&P | Moody's |
| **Semester Coefficients** | | | | |
| $\alpha$ | 0.08 | 0.06 | -0.05 | -0.12 |
| | 1.24 | 1.03 | -0.59 | -1.70 |
| $\rho$ | 0.37 | 0.59 | 0.30 | 0.37 |
| | 3.32*** | 6.56*** | 2.36*** | 2.40*** |
| $R^2$ | 0.25 | 0.25 | n.a. | n.a. |
| $N$ | 45 | 58 | 45 | 58 |
| $OBS$ | 209 | 211 | 209 | 211 |

$\Delta CCR^i(t_j)$ is the change in country $i$'s credit rating announced at time $t_j$. Measuring time in days allows to control for heteroskedasticity arising from unequally spaced data over time more precisely. The reported semester coefficients are based on the daily autoregression results. Asymptotic $t$-ratios reported below estimated coefficients. Analysis performed on all countries that had two or more credit revisions since Jan-1-1975 until Jun-22-2000 (Moody's) and until Jun-7-2000 (S&P). Revisions recorded on the day that they were announced by the respective agencies. Coefficients are pooled non-linear OLS regression estimates. A two-step approach was used when controlling for heteroskedasticity. The first pass computes the simple daily AR coefficient which is consistent under standard assumptions (reported in left columns). The second step uses this estimated coefficient to weight observations. The variance of the error when credit revisions are $T$ days appart is proportional to $(1-\rho^{2T}) / (1-\rho^2)$.

## Table X: Statistics of Forecast Errors By Model and Sub-Periods

### GDP weights - Results in credit points

| Mar-1982 / Mar-2000 | Geographical Portfolios | | | | | | | | Special Characteristic Portfolios | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Forecast Model** | Africa | Middle East | Asia Low Income | Latin America | Eastern Europe | Western Europe Low Inc | Asia High Inc. & Oceania | North Am. & West Europe | OPEC Countries | Emerging Countries | G7 Countries |
| | **Mean Surprise** | | | | | | | | | | |
| 1. Random Walk | -0.34 | 0.04 | -0.18 | -0.33 | -0.59 | 0.50 | -0.24 | -0.03 | -0.48 | -0.16 | -0.10 |
| 2. AR w/Dummies - Allsample | -0.21 | -0.04 | 0.03 | -0.09 | -0.04 | 0.28 | 0.06 | 0.11 | -0.25 | 0.01 | 0.10 |
| 3. AR w/Dummies - Recursive | -0.24 | -0.12 | -0.02 | -0.08 | -0.02 | 0.16 | -0.08 | 0.04 | -0.30 | -0.01 | 0.00 |
| 4. AR no Dummies - Recursive | -0.15 | 0.05 | -0.05 | -0.09 | -0.22 | 0.24 | -0.11 | 0.02 | -0.20 | -0.04 | -0.02 |
| 5. AR by Country - Roll Window | 0.04 | 0.11 | 0.23 | 1.01 | 0.19 | -0.07 | -0.14 | 0.11 | 0.62 | 0.57 | 0.07 |
| | **Root Mean Squared Surprise** | | | | | | | | | | |
| 1. Random Walk | 1.13 | 0.83 | 0.98 | 2.01 | 2.39 | 0.98 | 0.67 | 0.64 | 1.22 | 1.10 | 0.62 |
| 2. AR w/Dummies - Allsample | 0.92 | 0.78 | 0.80 | 1.22 | 1.53 | 0.89 | 0.61 | 0.61 | 1.08 | 0.87 | 0.60 |
| 3. AR w/Dummies - Recursive | 0.96 | 0.80 | 0.84 | 1.22 | 1.58 | 0.95 | 0.62 | 0.61 | 1.08 | 0.87 | 0.60 |
| 4. AR no Dummies - Recursive | 0.92 | 0.78 | 0.82 | 1.31 | 1.72 | 0.90 | 0.62 | 0.60 | 1.08 | 0.90 | 0.60 |
| 5. AR by Country - Roll Window | 1.12 | 0.77 | 1.73 | 3.56 | 2.73 | 1.20 | 0.70 | 0.66 | 5.48 | 2.22 | 0.65 |

### Mean Surprise by Sub-Period

| Period | Geographical Portfolios | | | | | | | | Special Characteristic Portfolios | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Africa | Middle East | Asia Low Income | Latin America | Eastern Europe | Western Europe Low Inc | Asia High Inc. & Oceania | North Am. & West Europe | OPEC Countries | Emerging Countries | G7 Countries |
| | **Forecast Model 3. AR w/Dummies - Recursive** | | | | | | | | | | |
| 1982-85 | -0.54 | -0.50 | 0.16 | -0.63 | 1.11 | 0.18 | -0.10 | 0.00 | -0.52 | -0.27 | -0.01 |
| 1986-90 | -0.34 | -0.37 | -0.41 | -0.18 | -0.87 | 0.17 | -0.08 | -0.17 | -0.23 | 0.05 | -0.19 |
| 1991-95 | -0.07 | 0.07 | 0.32 | 0.14 | -0.07 | 0.07 | -0.04 | 0.10 | -0.23 | 0.16 | 0.07 |
| 1996-00 | -0.05 | 0.29 | -0.13 | 0.30 | -0.02 | 0.20 | -0.12 | 0.24 | -0.25 | -0.05 | 0.14 |
| | **Forecast Model 4. AR no Dummies - Recursive** | | | | | | | | | | |
| 1982-85 | -0.56 | -0.13 | 0.09 | -1.26 | 0.24 | 0.38 | -0.14 | -0.05 | -0.44 | -0.51 | -0.06 |
| 1986-90 | -0.29 | -0.10 | -0.43 | -0.07 | -0.81 | 0.25 | -0.11 | -0.20 | -0.13 | 0.05 | -0.22 |
| 1991-95 | 0.10 | 0.12 | 0.35 | 0.44 | -0.43 | 0.08 | -0.06 | 0.08 | -0.10 | 0.28 | 0.06 |
| 1996-00 | 0.09 | 0.29 | -0.19 | 0.34 | 0.26 | 0.27 | -0.14 | 0.25 | -0.19 | -0.07 | 0.15 |

The mean surprises under the random walk model differ from the mean change in *CCR* in Table II.B because the sample here starts in March 1982 for all the forecasting models considered (some observations are lost in estimating the AR models) whereas that in Table II starts in March 1980. The surprises here are uniformly larger than those in Table II.B because 1980 and 1981 were bad years for world creditworthiness --as is obvious from Figs. V and VI.

## Appendix I

**Proof of equation (6)**

Let

(A.1) $$L = \int_{-1}^{0} \phi_t \; f_{t-n}(\phi_t)\, d\phi_t$$

where $f_{t-n}(\phi_t)$ is the logistic density conditioned on the *t-n* expectation of $\phi_t$,

(A.2) $$f_{t-n}(\phi_t) = \frac{1}{\beta} \frac{e^{-\left(\frac{\phi_t - E_{t-n}(\phi_t)}{\beta}\right)}}{\left(1 + e^{-\left(\frac{\phi_t - E_{t-n}(\phi_t)}{\beta}\right)}\right)^2} \quad .$$

To simplify notation, let $\mu_{t-n} = E_{t-n}(\phi_t)$, relabel $x_t = \phi_t$ and drop the time subscript. Also drop the limits of integration for now and let $L^*$ be the indefinite counterpart of $L$. The limits of integration will be recovered in (A.12),

(A.3) $$L^* = \int x \, \frac{1}{\beta} \frac{e^{-\left(\frac{x-\mu}{\beta}\right)}}{\left(1 + e^{-\left(\frac{x-\mu}{\beta}\right)}\right)^2} \, dx \; .$$



Integrate (A.3) by parts as in $L^* = \frac{1}{\beta} \int h(x)\, g'(x)\; dx$, where

(A.4) $$g'(x) = \frac{d}{dx} \beta \left[1 + e^{-\left(\frac{x-\mu}{\beta}\right)}\right]^{-1} = \frac{e^{-\left(\frac{x-\mu}{\beta}\right)}}{\left(1 + e^{-\left(\frac{x-\mu}{\beta}\right)}\right)^2}$$

and $h(x) = x$. This gives the solution to (A.3) as, (A.5) $L^{*} = x\left[1+e^{-\left(\frac{x-\mu}{\beta}\right)}\right]^{-1} - \int\left[1+e^{-\left(\frac{x-\mu}{\beta}\right)}\right]^{-1} dx$ .

Call $L_2^{*}$ the second summand,

(A.6) $L_2^{*} = \int\left[1+e^{-\left(\frac{x-\mu}{\beta}\right)}\right]^{-1} dx$

This part will be integrated by substitution of variables. Define

(A.7) $u(x) = 1+e^{-\left(\frac{x-\mu}{\beta}\right)}$,

which implies $\frac{d}{dx}u(x) = -\frac{1}{\beta}e^{-\left(\frac{x-\mu}{\beta}\right)}$. Therefore, we can express $dx$ as,

(A.8) $dx = -\beta\frac{1}{u-1}du$

With this substitution, rewrite (A.6) as

(A.9) $L_2^{*} = \int -\beta\frac{1}{u\ (u-1)}du$

Note that,

(A.10) $\frac{1}{u\ (u-1)} = -\frac{1}{u} + \frac{1}{u-1}$ ,

so (A.9) becomes

$$\begin{aligned} L_2^{*} &= \beta\left(\int\frac{1}{u}du - \int\frac{1}{u-1}du\right) \\ &= \beta(\ln u - \ln(u-1)) \end{aligned}$$

$$= \beta \ln\left(\frac{u}{u-1}\right)$$

(A.11)

$$= \beta \ln \frac{1+e^{-\left(\frac{x-\mu}{\beta}\right)}}{e^{-\left(\frac{x-\mu}{\beta}\right)}}$$

Plugging the solution for $L_2^*$ into (A.5) and recovering the integration limits gives,

$$\text{(A.12)} \quad L = \left( x\left[1+e^{-\left(\frac{x-\mu}{\beta}\right)}\right]^{-1} - \beta \ln \frac{1+e^{-\left(\frac{x-\mu}{\beta}\right)}}{e^{-\left(\frac{x-\mu}{\beta}\right)}} \right)\Bigg|_{-1}^{0}$$

Simplify this by rearranging the second summand as,[1]

$$\text{(A.13)} \quad L = \left( x\left[1+e^{-\left(\frac{x-\mu}{\beta}\right)}\right]^{-1} + \beta \ln \frac{1}{e^{\frac{x-\mu}{\beta}}+1} \right)\Bigg|_{-1}^{0}$$

Evaluating (A.13) at the upper limit of integration gives,

$$\text{(A.14)} \quad \beta \ln \frac{1}{e^{-\frac{\mu}{\beta}}+1}$$

while at the lower limit of integration it is,

$$\text{(A.15)} \quad -\left[1+e^{\frac{1+\mu}{\beta}}\right]^{-1} + \beta \ln \frac{1}{e^{-\left(\frac{1+\mu}{\beta}\right)}+1}$$

Subtracting (A.15) from (A.14) gives the solution to (A.4),

$$\text{(A.16)} \quad L = \beta \ln \frac{1}{1+e^{-\frac{\mu}{\beta}}} + \frac{1}{1+e^{\frac{1+\mu}{\beta}}} - \beta \ln \frac{1}{1+e^{-\left(\frac{1+\mu}{\beta}\right)}} \ ,$$

which can be rearranged as,

[1] Invert the argument of the log function, take the minus sign in front, and multiply numerator and denominator of the argument by $e^{\frac{x-\mu}{\beta}}$

$$\text{(A.17)}\quad L = \frac{1}{1+e^{\frac{1+\mu}{\beta}}} + \beta \ln \frac{1+e^{-\left(\frac{1+\mu}{\beta}\right)}}{1+e^{-\frac{\mu}{\beta}}}.$$

Multiply and divide the last ratio by $e^{\frac{\mu}{\beta}}$ to get,

$$\text{(A.18)}\quad L = \frac{1}{1+e^{\frac{1+\mu}{\beta}}} + \beta \ln \frac{e^{\frac{\mu}{\beta}} + e^{-\frac{1}{\beta}}}{e^{\frac{\mu}{\beta}}+1},$$

and factor $e^{-\frac{1}{\beta}}$ out of the numerator of this last ratio,

$$\text{(A.19)}\quad L = \frac{1}{1+e^{\frac{1+\mu}{\beta}}} + \beta \ln \frac{e^{-\frac{1}{\beta}}\left(e^{\frac{1+\mu}{\beta}}+1\right)}{e^{\frac{\mu}{\beta}}+1}.$$

Distributing the log (and reverting to $E_{t-n}(\phi_t)=\mu_t$) obtains,

$$\text{(A.20)}\quad L = \frac{1}{1+e^{\frac{1+E_{t-n}(\phi_t)}{\beta}}} - 1 + \beta \ln \frac{e^{\frac{1+E_{t-n}(\phi_t)}{\beta}}+1}{e^{\frac{E_{t-n}(\phi_t)}{\beta}}+1}.$$

which is (6) in the paper.

**Proof of equation (12)**

Rewrite (7) more conveniently as,

$$\text{(A.21)}\quad E_{t-n}(C_t) = \beta \left\{ \ln\left(1+e^{[1+E_{t-n}(\phi_t)]\beta^{-1}}\right) - \ln\left(1+e^{E_{t-n}(\phi_t)\beta^{-1}}\right) \right\}$$

Differentiating with respect to $\beta$ gives,

$$\frac{\partial E_{t-n}(C_t)}{\partial \beta} = \frac{E_{t-n}(C_t)}{\beta} + \beta \left\{ \frac{e^{[1+E_{t-n}(\phi_t)]\beta^{-1}}}{1+e^{[1+E_{t-n}(\phi_t)]\beta^{-1}}}(-1)[1+E_{t-n}(\phi_t)]\beta^{-2} - \frac{e^{E_{t-n}(\phi_t)\beta^{-1}}}{1+e^{E_{t-n}(\phi_t)\beta^{-1}}}(-1)E_{t-n}(\phi_t)\beta^{-2} \right\}$$
(A.22)

and simplify to get,

(A.23) $$\frac{\partial E_{t-n}(C_t)}{\partial \beta}=\frac{E_{t-n}(C_t)}{\beta}+\left\{\frac{e^{E_{t-n}(\phi_t)\beta^{-1}}}{1+e^{E_{t-n}(\phi_t)\beta^{-1}}}\frac{E_{t-n}(\phi_t)}{\beta}-\frac{e^{[1+E_{t-n}(\phi_t)]\beta^{-1}}}{1+e^{[1+E_{t-n}(\phi_t)]\beta^{-1}}}\frac{1+E_{t-n}(\phi_t)}{\beta}\right\}.$$

Pull $\beta$ out and take common factor inside the brackets to get,

(A.24)
$$\frac{\partial E_{t-n}(C_t)}{\partial \beta}=\frac{1}{\beta}\left\{E_{t-n}(C_t)-\frac{1}{e^{-[1+E_{t-n}(\phi_t)]\beta^{-1}}+1}+E_{t-n}(\phi_t)\left(\frac{1}{e^{-E_{t-n}(\phi_t)\beta^{-1}}+1}-\frac{1}{e^{-[1+E_{t-n}(\phi_t)]\beta^{-1}}+1}\right)\right\}$$

which using the fact $F_X(x\mid E(X)=\mu,\beta)=\left(1+e^{-\frac{x-\mu}{\beta}}\right)^{-1}$ gives,

(A.25)
$$\frac{\partial E_{t-n}(C_t)}{\partial \beta}=\frac{1}{\beta}\{E_{t-n}(C_t)-F_X(x\mid EX=-1)+E_{t-n}(\phi_t)[F_X(x\mid EX=0)-F_X(x\mid EX=-1)]\}$$

Recognizing that the term in square brackets is identical to minus equation (9) gives (12).

## Appendix II: Countries Included in Each Portfolio, Date of First *CCR* Observation, 1998 GDP and First Principal Component Weights[2]

Portfolio: Africa

| NAME | FIRSTOBS | GDP | PRINCOMP |
|---|---|---|---|
| Algeria | SEP79 | 137 | 0.03 |
| Angola | SEP79 | 12 | 0.13 |
| Benin | MAR94 | 5 | . |
| Botswana | MAR92 | 9 | . |
| Burkina Faso | SEP93 | 9 | . |
| Burundi | MAR00 | 4 | . |
| Cameroon | MAR82 | 20 | . |
| Chad | MAR00 | 6 | . |
| Congo | SEP79 | 2 | 0.11 |
| Congo Dem Rep-Zaire | SEP79 | 35 | 0.23 |
| Ivory Coast | SEP79 | 21 | 0.09 |
| Ethiopia | SEP79 | 35 | 0.21 |
| Gabon | SEP79 | 7 | -0.00 |
| Ghana | SEP92 | 32 | . |
| Guinea | SEP93 | 12 | . |
| Kenya | SEP79 | 28 | 0.16 |
| Lesotho | MAR00 | 5 | . |
| Liberia | SEP79 | 3 | 0.39 |
| Libya | SEP79 | 39 | 0.17 |
| Malawi | MAR81 | 6 | . |
| Mali | SEP93 | 7 | . |
| Mauritius | SEP81 | 10 | . |
| Morocco | SEP79 | 89 | 0.13 |
| Mozambique | MAR88 | 13 | . |
| Namibia | MAR98 | 9 | . |
| Niger | MAR00 | 7 | . |
| Nigeria | SEP79 | 89 | 0.08 |
| Senegal | SEP79 | 12 | 0.16 |
| Seychelles | SEP79 | 1 | 0.24 |
| Sierra Leone | SEP79 | 2 | 0.33 |
| South Africa | SEP79 | 343 | 0.04 |
| Sudan | SEP79 | 35 | 0.38 |
| Swaziland | MAR88 | 4 | . |
| Tanzania | SEP79 | 16 | 0.32 |
| Togo | MAR94 | 6 | . |
| Tunisia | SEP79 | 48 | 0.05 |
| Uganda | SEP79 | 22 | 0.36 |
| Zambia | SEP79 | 7 | 0.25 |
| Zimbabwe | SEP79 | 29 | 0.06 |

[2] The countries with missing Principal Component entries either lack full time series or were highly volatile and this volatility reflected mainly domestic events as opposed to regional ones (e.g. Iraq, Lebanon, etc.). The reported figures under PRINCOMP are the entries of the first eigenvector of the covariance matrix of changes in *CCR* for the countries in each portfolio. They do not add to one, because only the length of the eigenvector has to be one. The weights used in the PC portfolios are proportional to these entries.

Portfolio: Middle East

| NAME | FIRSTOBS | GDP | PRINCOMP |
|---|---|---|---|
| Bahrain | SEP79 | 9 | 0.20 |
| Cyprus | SEP79 | 10 | 0.23 |
| Egypt | SEP79 | 193 | 0.20 |
| Iran | SEP79 | 317 | . |
| Iraq | SEP79 | 60 | . |
| Israel | SEP79 | 101 | 0.46 |
| Jordan | SEP79 | 12 | 0.49 |
| Kuwait | SEP79 | 45 | . |
| Lebanon | SEP79 | 17 | . |
| Oman | SEP79 | 20 | 0.17 |
| Qatar | SEP79 | 12 | 0.23 |
| Saudi Arabia | SEP79 | 218 | 0.16 |
| Syria | SEP79 | 41 | 0.53 |
| United Arab Emirates | SEP79 | 51 | 0.19 |

Portfolio: Asia-Low Income

| NAME | FIRSTOBS | GDP | PRINCOMP |
|---|---|---|---|
| Afghanistan | SEP93 | 21 | . |
| Bangladesh | SEP82 | 177 | . |
| China | SEP79 | 3779 | -0.02 |
| India | SEP79 | 2018 | 0.10 |
| Indonesia | SEP79 | 490 | 0.78 |
| Malaysia | SEP79 | 171 | 0.24 |
| Myanmar | SEP91 | 59 | . |
| Nepal | MAR88 | 27 | . |
| North Korea | MAR80 | 23 | . |
| Pakistan | SEP79 | 217 | 0.37 |
| Papua New Guinea | SEP80 | 10 | . |
| Philippines | SEP79 | 280 | 0.16 |
| South Korea | SEP79 | 616 | 0.35 |
| Sri Lanka | SEP82 | 55 | . |
| Taiwan | SEP79 | 357 | 0.00 |
| Thailand | SEP79 | 338 | 0.19 |
| Vietnam | MAR92 | 129 | . |

Portfolio: Latin America

| NAME | FIRSTOBS | GDP | PRINCOMP |
|---|---|---|---|
| Argentina | SEP79 | 424 | 0.35 |
| Bahamas | MAR00 | 6 | . |
| Barbados | MAR84 | 3 | . |
| Bolivia | SEP79 | 18 | 0.38 |
| Brazil | SEP79 | 1070 | 0.18 |
| Chile | SEP79 | 126 | 0.23 |
| Colombia | SEP79 | 239 | 0.09 |
| Costa Rica | SEP79 | 20 | 0.41 |

| | | | |
|---|---|---|---|
| Cuba | MAR80 | 19 | . |
| Dominican Republic | SEP79 | 36 | 0.24 |
| Ecuador | SEP79 | 37 | 0.24 |
| El Salvador | MAR81 | 24 | . |
| Grenada | SEP81 | 0 | . |
| Guatemala | SEP81 | 38 | . |
| Haiti | MAR84 | 11 | . |
| Honduras | SEP81 | 14 | . |
| Jamaica | SEP79 | 9 | 0.10 |
| Mexico | SEP79 | 714 | 0.25 |
| Nicaragua | SEP79 | 9 | 0.35 |
| Panama | SEP79 | 14 | 0.15 |
| Paraguay | SEP79 | 23 | 0.10 |
| Peru | SEP79 | 104 | 0.26 |
| Trinidad & Tobago | SEP79 | 9 | 0.08 |
| Uruguay | SEP79 | 28 | 0.13 |
| Venezuela | SEP79 | 133 | 0.18 |

Portfolio: Eastern Europe

| NAME | FIRSTOBS | GDP | PRINCOMP |
|---|---|---|---|
| Albania | MAR92 | 10 | . |
| Belarus | SEP92 | 65 | . |
| Bulgaria | SEP80 | 39 | . |
| Croatia | SEP92 | 30 | . |
| Czech Republic | SEP79 | 126 | 0.14 |
| East Germany | MAR80 | 0 | . |
| Estonia | MAR92 | 11 | . |
| Georgia | SEP93 | 19 | . |
| Hungary | SEP79 | 99 | 0.09 |
| Kazakhstan | SEP92 | 67 | . |
| Kyrgyzstan | MAR00 | 11 | . |
| Latvia | MAR92 | 14 | . |
| Lithuania | MAR92 | 23 | . |
| Moldova | MAR00 | 9 | . |
| Poland | SEP79 | 292 | 0.72 |
| Romania | SEP79 | 125 | 0.56 |
| Russia | SEP79 | 907 | 0.23 |
| Slovakia | MAR93 | 52 | . |
| Slovenia | SEP92 | 29 | . |
| Tajikistan | MAR00 | 6 | . |
| Turkmenistan | MAR00 | 8 | . |
| Ukraine | SEP92 | 157 | . |
| Uzbekistan | SEP92 | 49 | . |
| Yugoslavia | SEP79 | 27 | 0.30 |



Portfolio: Western Europe - Low Income

| NAME | FIRSTOBS | GDP | PRINCOMP |
|---|---|---|---|
| Greece | SEP79 | 147 | -0.08 |
| Portugal | SEP79 | 145 | -0.10 |
| Turkey | SEP79 | 419 | 0.99 |

Portfolio: Asia - High Income

| NAME | FIRSTOBS | GDP | PRINCOMP |
|---|---|---|---|
| Australia | SEP79 | 409 | 0.64 |
| Hong Kong | SEP79 | 139 | 0.53 |
| Japan | SEP79 | 2982 | 0.09 |
| New Zealand | SEP79 | 61 | 0.52 |
| Singapore | SEP79 | 80 | 0.18 |

Portfolio: North America and Western Europe

| NAME | FIRSTOBS | GDP | PRINCOMP |
|---|---|---|---|
| Austria | SEP79 | 187 | 0.17 |
| Belgium | SEP79 | 241 | 0.31 |
| Canada | SEP79 | 691 | 0.18 |
| Denmark | SEP79 | 126 | 0.24 |
| Finland | SEP79 | 106 | 0.28 |
| France | SEP79 | 1248 | 0.26 |
| Germany | SEP79 | 1807 | 0.10 |
| Iceland | SEP79 | 6 | 0.40 |
| Ireland | SEP79 | 67 | 0.41 |
| Italy | SEP79 | 1173 | 0.26 |
| Luxembourg | SEP91 | 15 | . |
| Malta | MAR94 | 5 | . |
| Netherlands | SEP79 | 350 | 0.12 |
| Norway | SEP79 | 116 | 0.16 |
| Spain | SEP79 | 628 | 0.32 |
| Sweden | SEP79 | 176 | 0.28 |
| Switzerland | SEP79 | 191 | 0.06 |
| United Kingdom | SEP79 | 1200 | 0.06 |
| United States | SEP79 | 7904 | 0.06 |

Portfolio: OPEC

| NAME | FIRSTOBS | GDP | PRINCOMP |
|---|---|---|---|
| Algeria | SEP79 | 137 | 0.18 |
| Indonesia | SEP79 | 490 | 0.44 |
| Iran | SEP79 | 317 | . |
| Iraq | SEP79 | 60 | . |
| Kuwait | SEP79 | 45 | . |
| Libya | SEP79 | 39 | 0.36 |
| Nigeria | SEP79 | 89 | 0.52 |
| Oman | SEP79 | 20 | -0.05 |
| Qatar | SEP79 | 12 | -0.02 |
| Saudi Arabia | SEP79 | 218 | 0.07 |
| United Arab Emirates | SEP79 | 51 | -0.03 |
| Venezuela | SEP79 | 133 | 0.60 |

Portfolio: Emerging Countries

| NAME | FIRSTOBS | GDP | PRINCOMP |
|---|---|---|---|
| Argentina | SEP79 | 424 | 0.43 |
| Brazil | SEP79 | 1070 | 0.33 |
| Chile | SEP79 | 126 | 0.40 |
| Colombia | SEP79 | 239 | 0.14 |
| Greece | SEP79 | 147 | 0.07 |
| India | SEP79 | 2018 | 0.02 |
| Indonesia | SEP79 | 490 | 0.13 |
| Jordan | SEP79 | 12 | 0.04 |
| Malaysia | SEP79 | 171 | 0.07 |
| Mexico | SEP79 | 714 | 0.32 |
| Nigeria | SEP79 | 89 | 0.28 |
| Pakistan | SEP79 | 217 | 0.02 |
| Philippines | SEP79 | 280 | 0.34 |
| Portugal | SEP79 | 145 | 0.08 |
| South Korea | SEP79 | 616 | 0.04 |
| Taiwan | SEP79 | 357 | -0.01 |
| Thailand | SEP79 | 338 | 0.00 |
| Turkey | SEP79 | 419 | -0.23 |
| Venezuela | SEP79 | 133 | 0.32 |
| Zimbabwe | SEP79 | 29 | 0.19 |

Portfolio: Group of Seven Industrialized Nations

| NAME | FIRSTOBS | GDP | PRINCOMP |
|---|---|---|---|
| Canada | SEP79 | 691 | 0.45 |
| France | SEP79 | 1248 | 0.57 |
| Germany | SEP79 | 1807 | 0.26 |
| Italy | SEP79 | 1173 | 0.61 |
| Japan | SEP79 | 2982 | 0.01 |
| United Kingdom | SEP79 | 1200 | 0.11 |
| United States | SEP79 | 7904 | 0.15 |

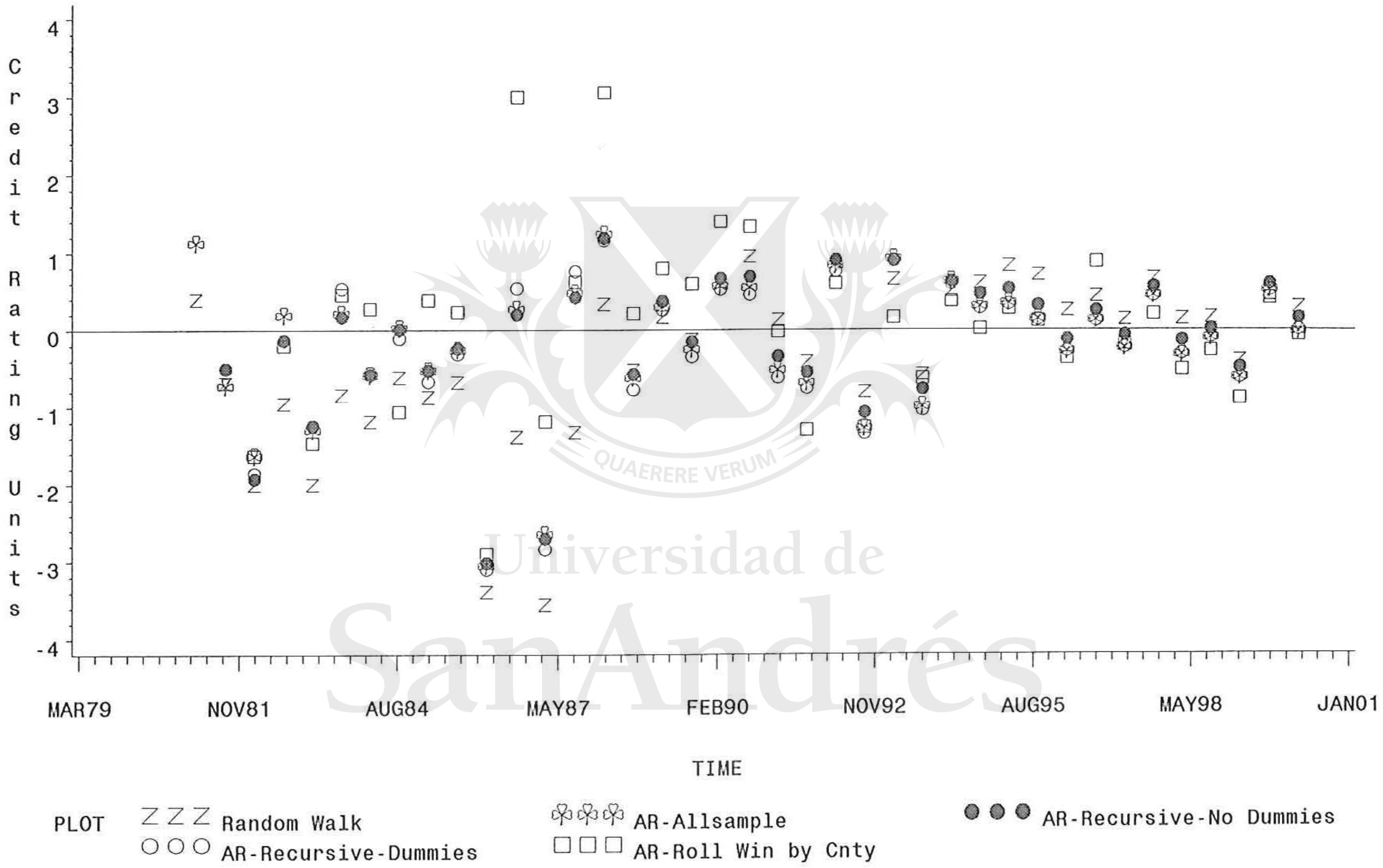
# APPENDIX III

# PLOTS OF SURPRISE CREDIT REVISIONS BY PORTFOLIOS

# FOR THE FIVE CREDIT FORECASTING MODELS

## SURPRISE CREDIT REVISIONS FROM DIFFERENT FORECASTING MODELS

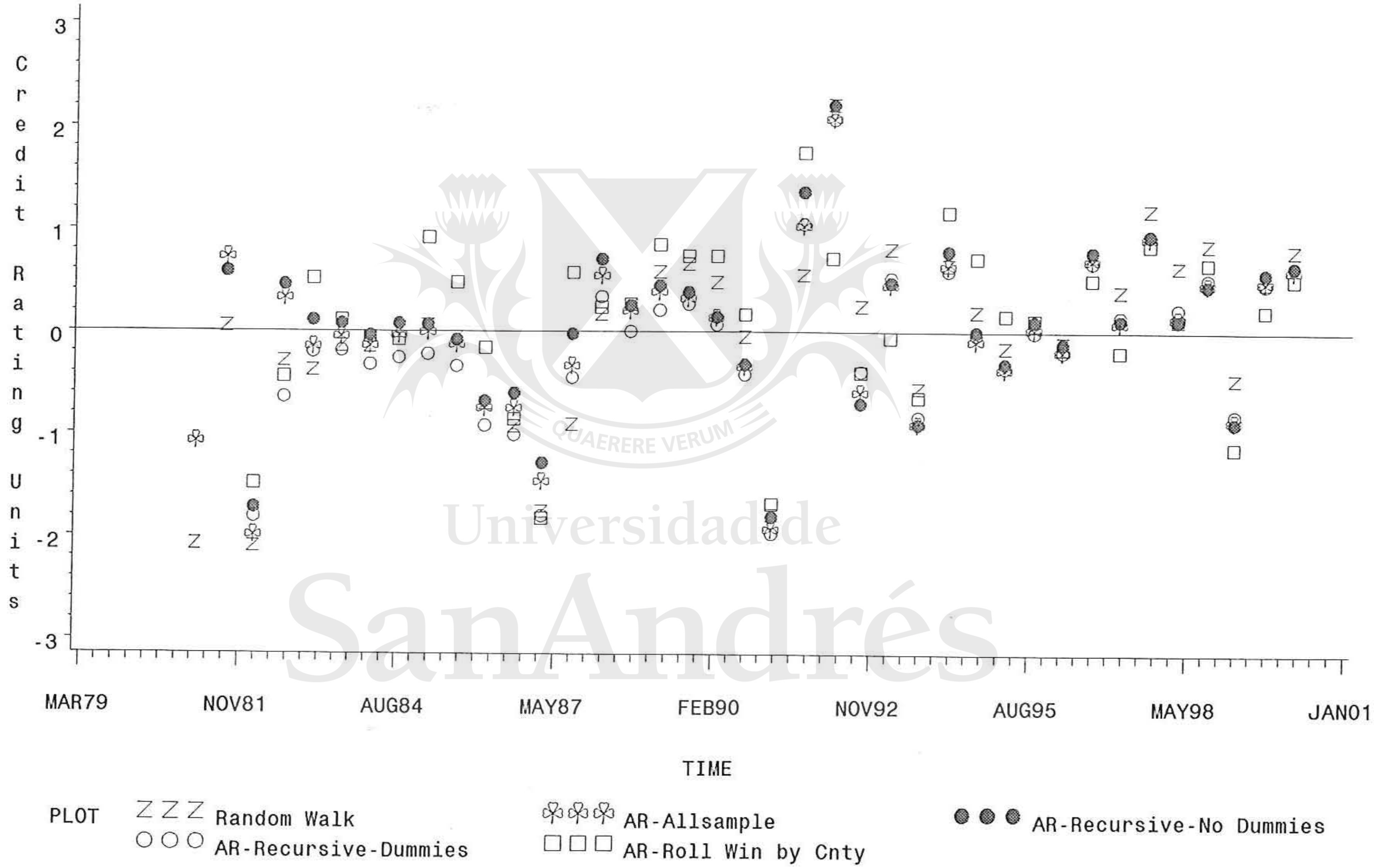
SORT=0Africa




Source: Institutional Investor, Sep – 1979/Mar – 2000

# SURPRISE CREDIT REVISIONS FROM DIFFERENT FORECASTING MODELS

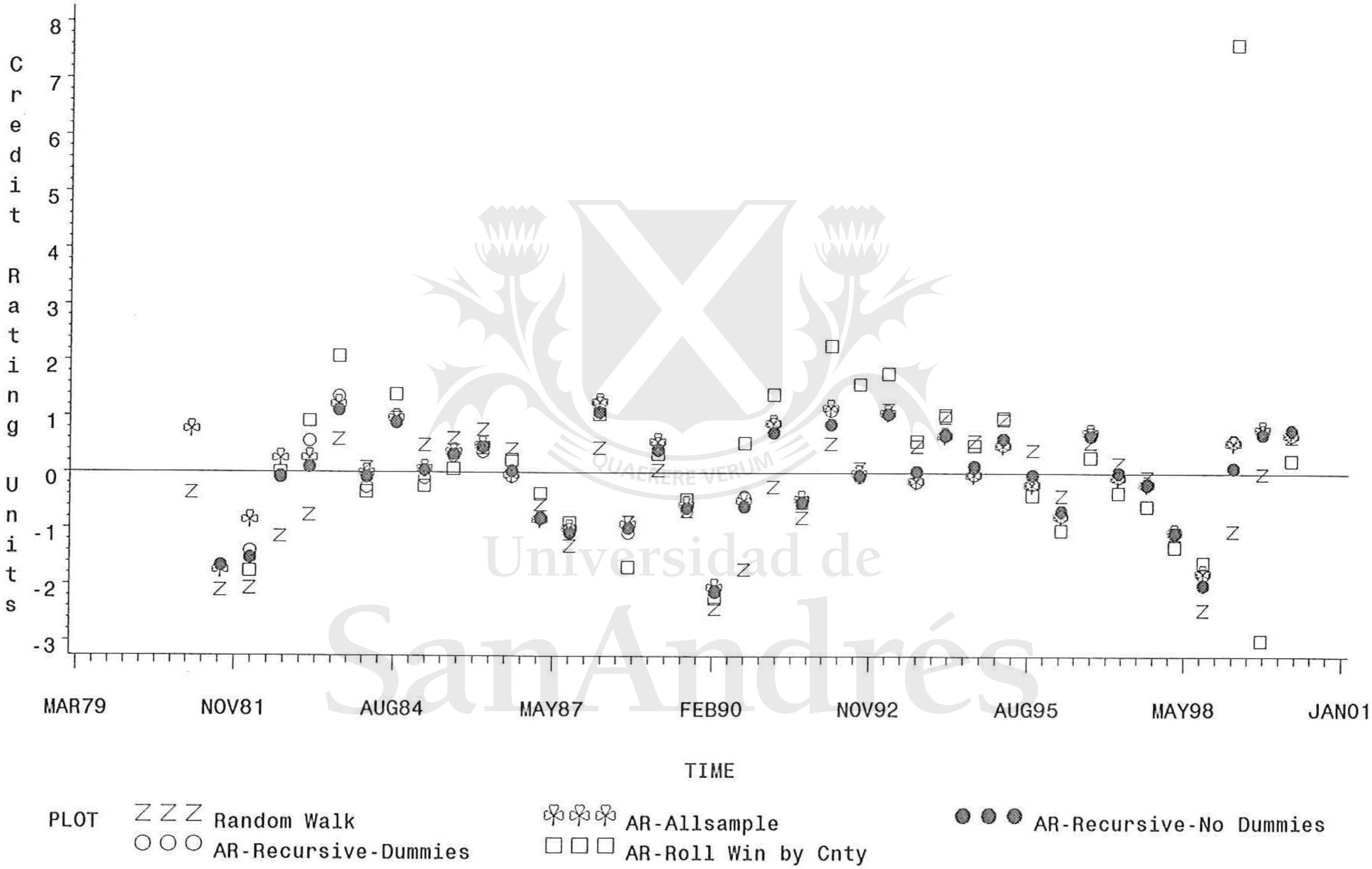
SORT=1Mideast



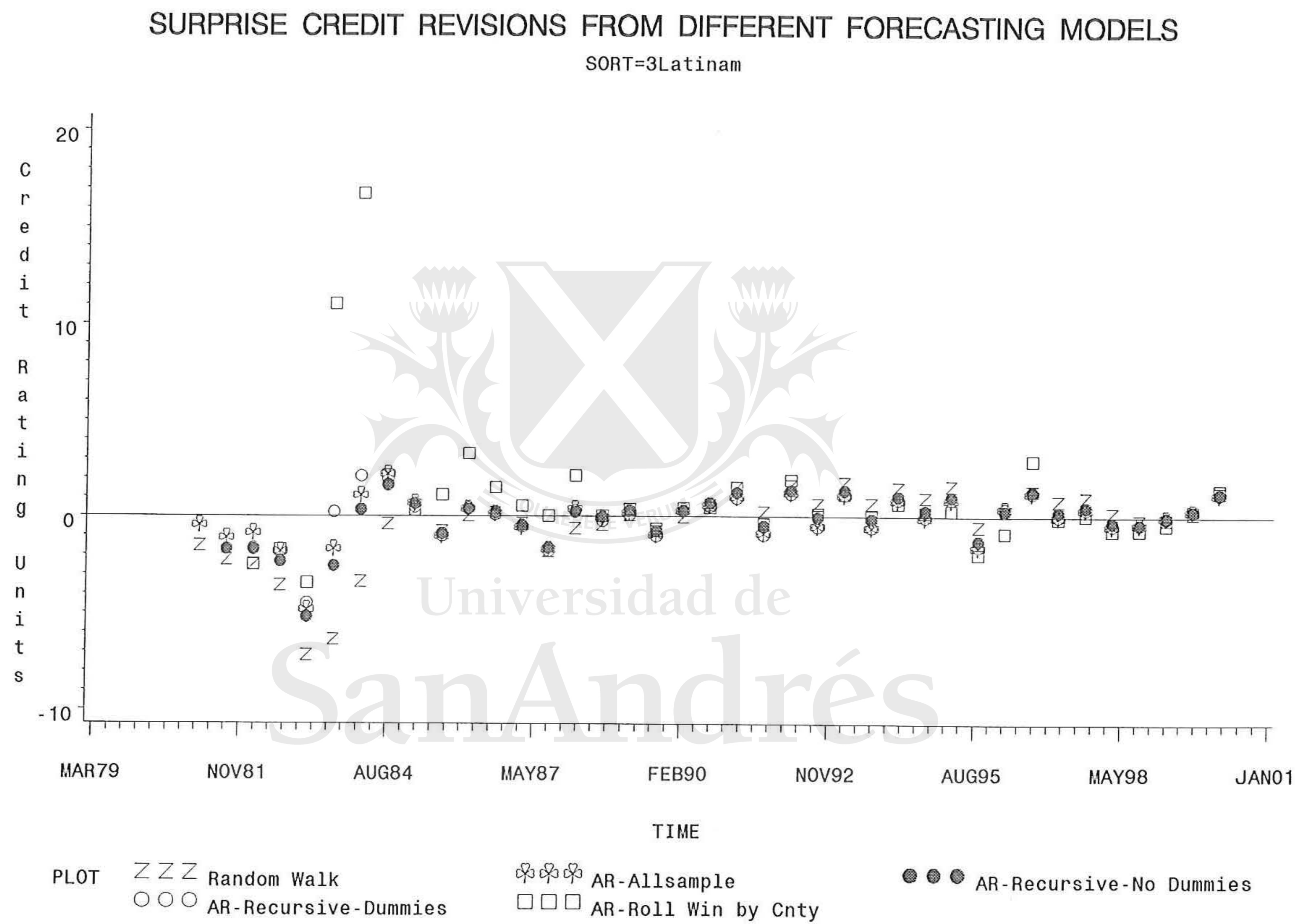

Source: Institutional Investor, Sep – 1979/Mar – 2000

# SURPRISE CREDIT REVISIONS FROM DIFFERENT FORECASTING MODELS

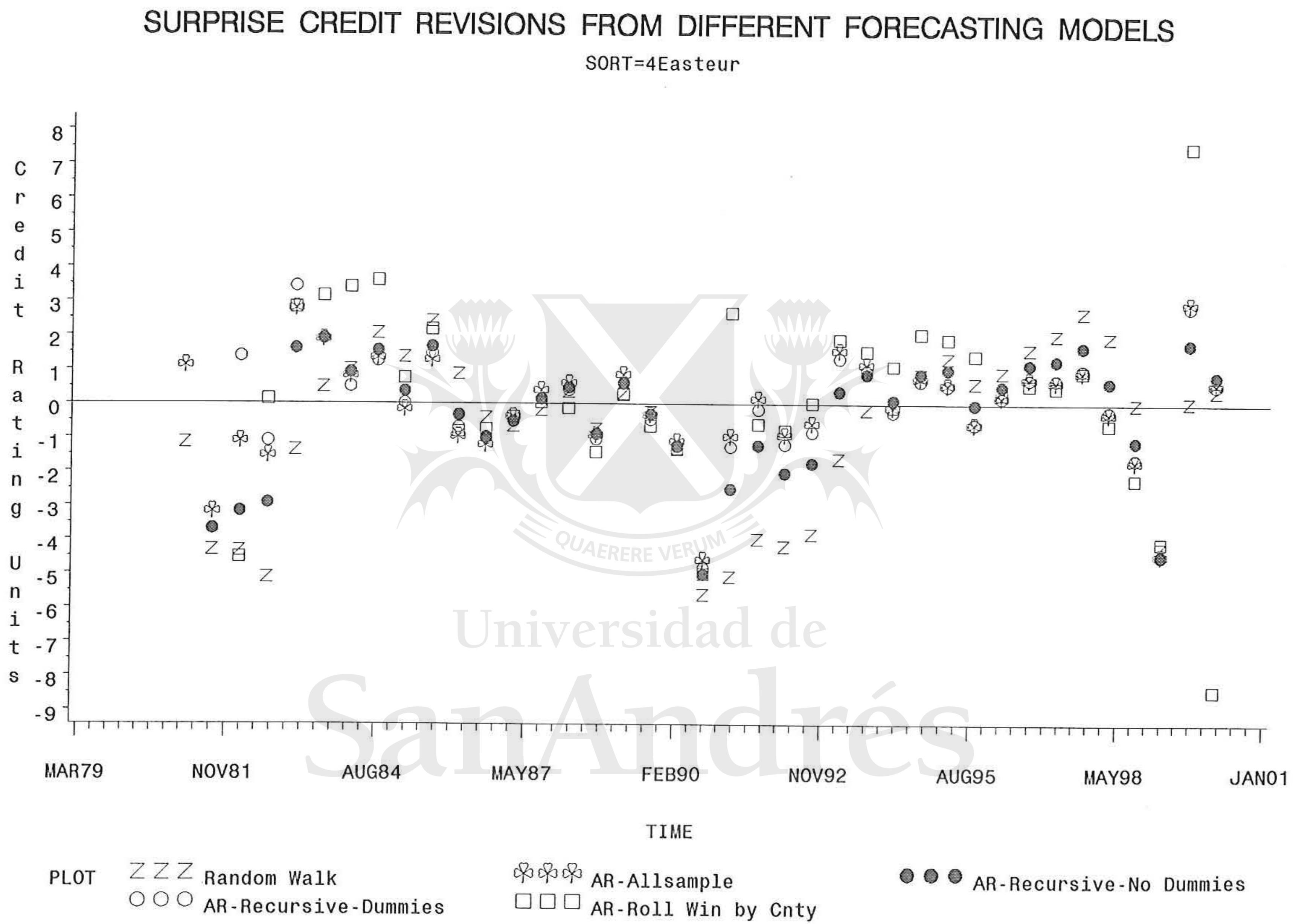
SORT=2AsiaLow




Source: Institutional Investor, Sep – 1979/Mar – 2000



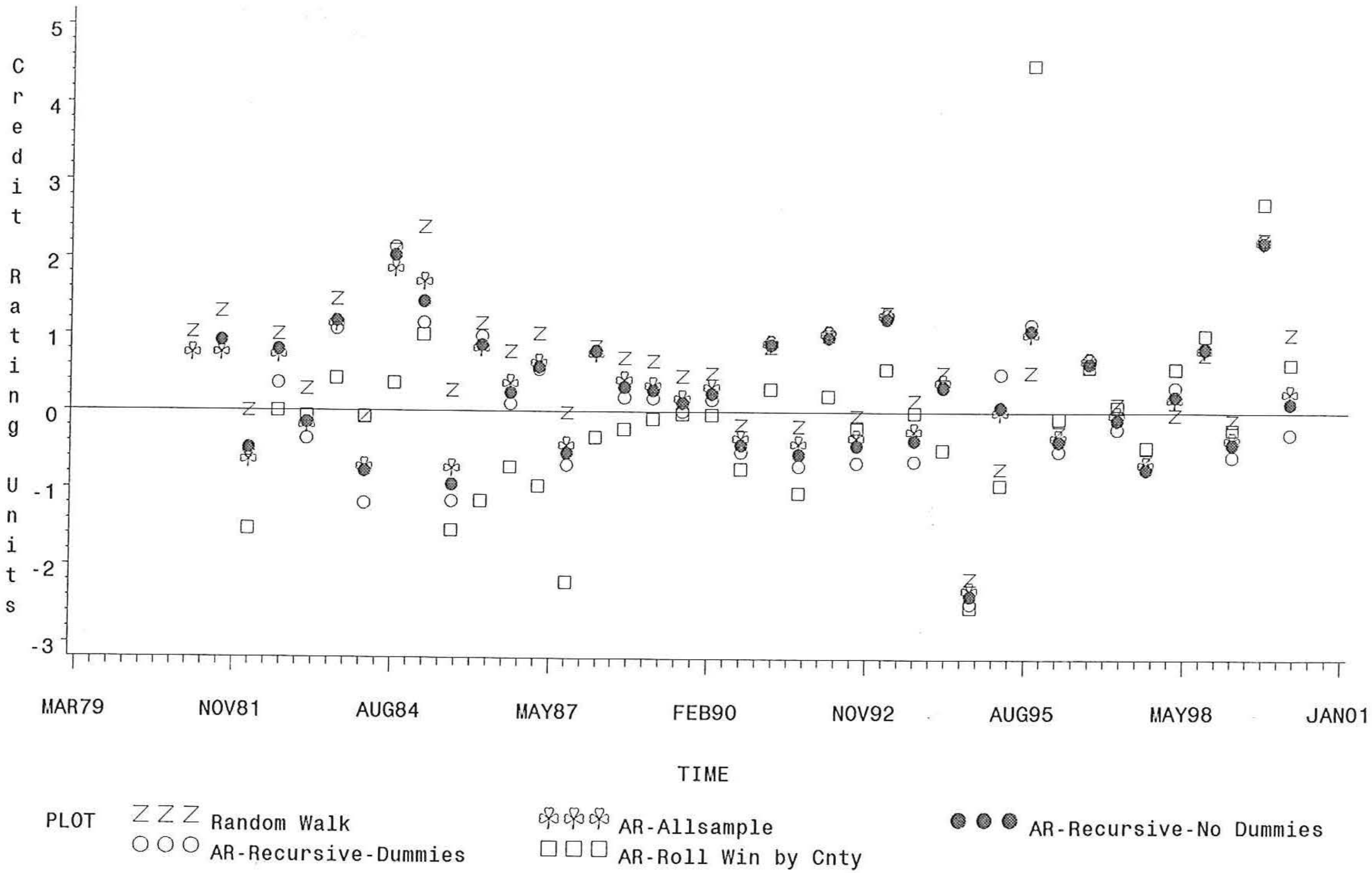

Source: Institutional Investor, Sep – 1979/Mar – 2000



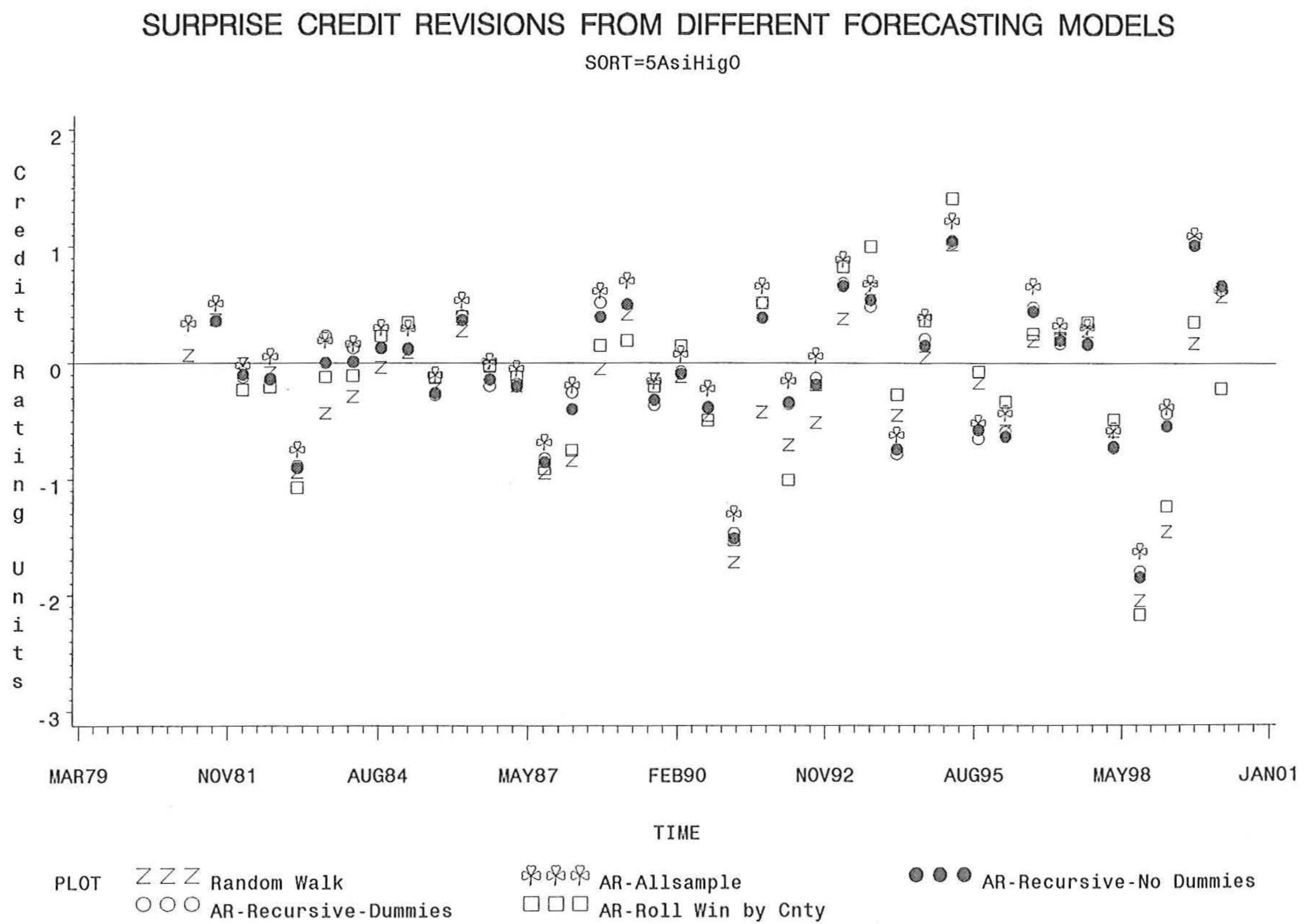

Source: Institutional Investor, Sep – 1979/Mar – 2000

# SURPRISE CREDIT REVISIONS FROM DIFFERENT FORECASTING MODELS

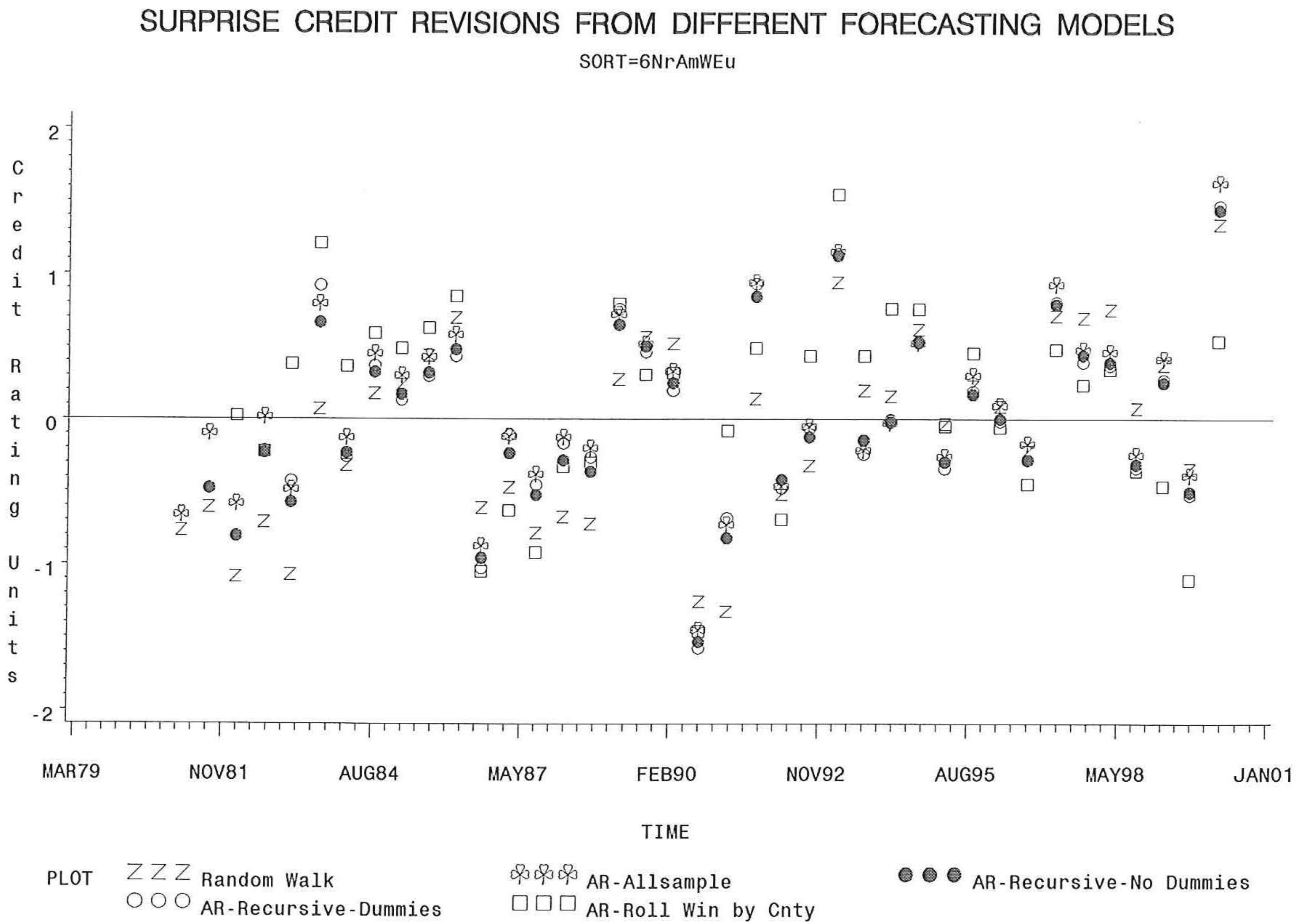
SORT=4WEurLow



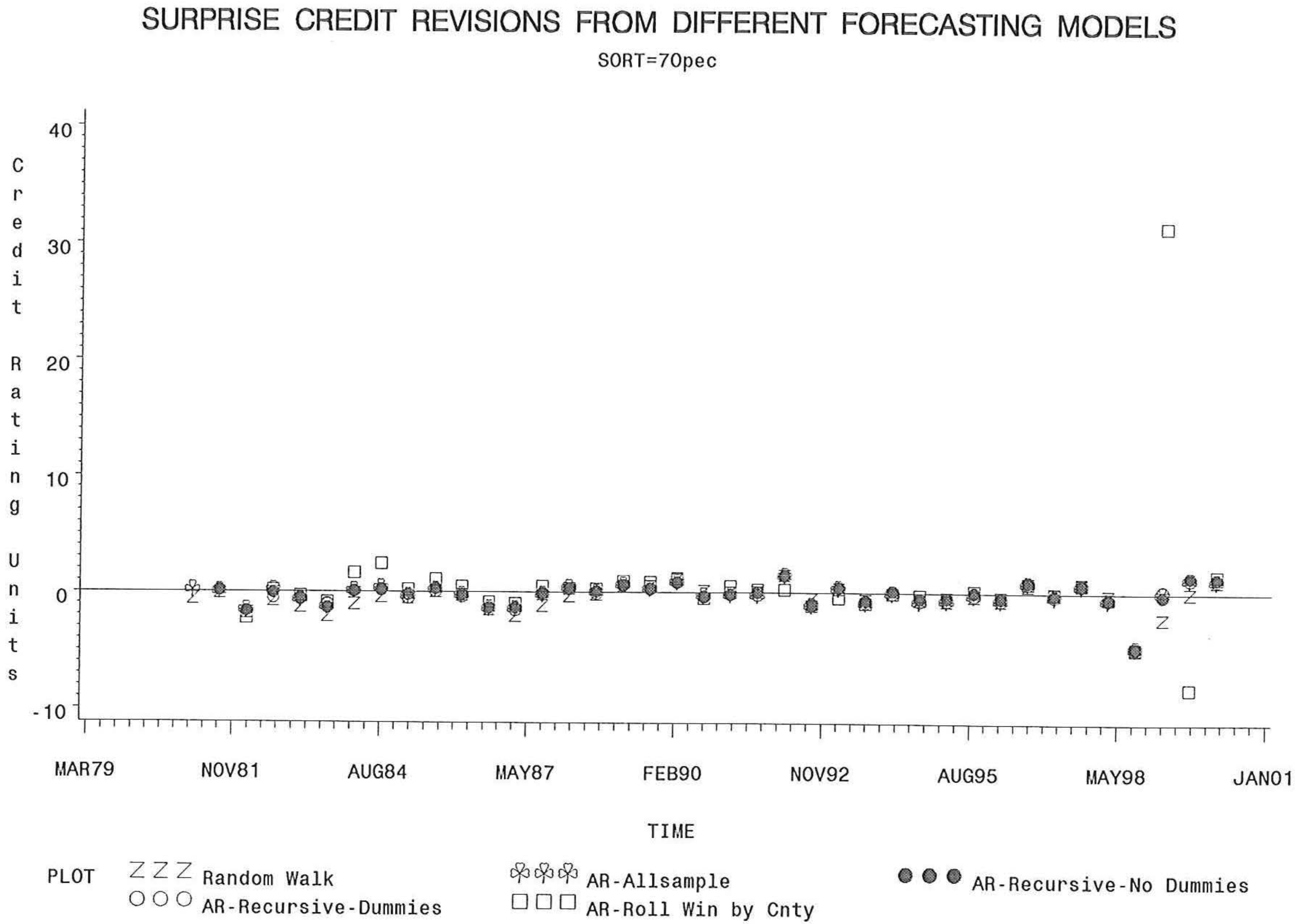

Source: Institutional Investor, Sep – 1979/Mar – 2000




Source: Institutional Investor, Sep–1979/Mar–2000



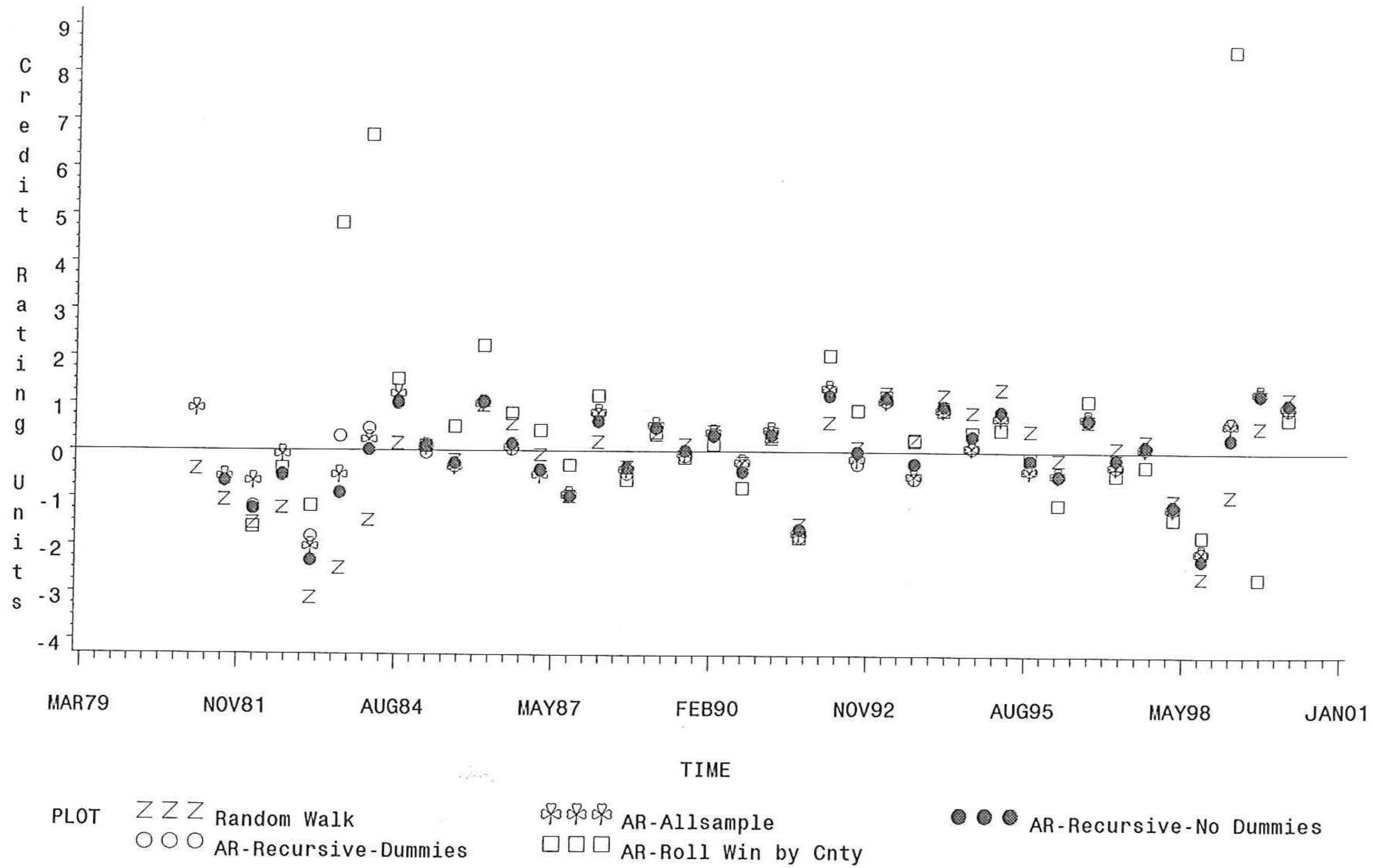

Source: Institutional Investor, Sep – 1979/Mar – 2000




Source: Institutional Investor, Sep – 1979/Mar – 2000

## SURPRISE CREDIT REVISIONS FROM DIFFERENT FORECASTING MODELS

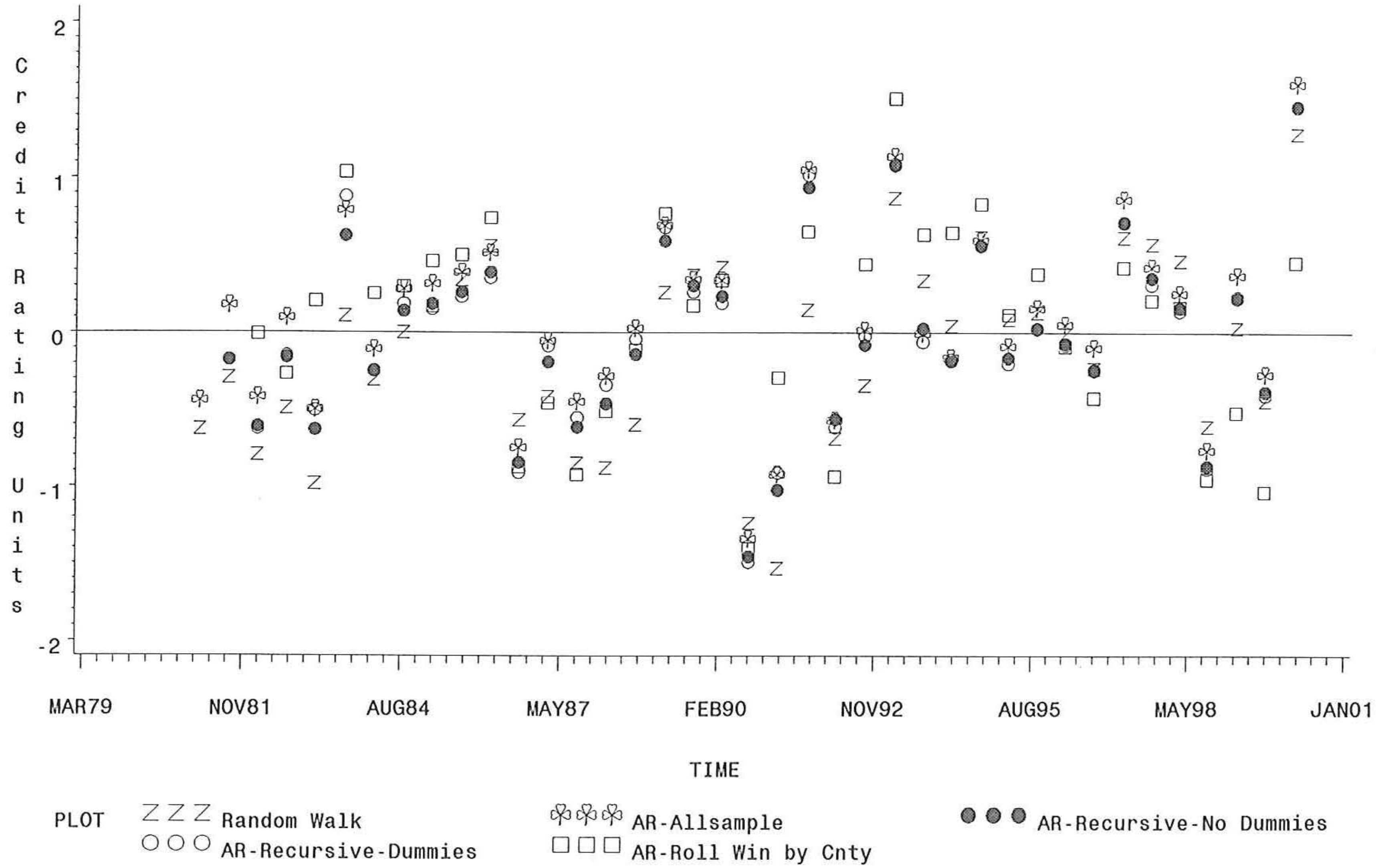
SORT=8Emergin




Source: Institutional Investor, Sep – 1979/Mar – 2000

## SURPRISE CREDIT REVISIONS FROM DIFFERENT FORECASTING MODELS

SORT=9G7




Source: Institutional Investor, Sep – 1979/Mar – 2000

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