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Characterizing the rating cycles in emerging countries: How do the agencies adapt new information?

Carmen Broto and Luis Molina [1]

VERY PRELIMINARY DRAFT: PLEASE DO NOT CITE OR QUOTE WITHOUT AUTHORS' PERMISSION

Abstract

Using S&P sovereign ratings from 1994 to 2013 we describe the main characteristics of the rating cycles of those countries that have already experienced downgrade and upgrade periods, which are mostly emerging economies. Downgrades tend to be deeper and faster than upgrades. In other words, once a country loses its initial status it takes a long period to recover it. After characterizing rating cycles in terms of their duration and amplitude, we try to disentangle how the decisions of the rating agencies respond to changes in the countries' fundamentals and financial market conditions. In particular, we study if there is some kind of asymmetry so that the way in which rating agencies reflect new economic and financial domestic information in their ratings is different during upgrade and downgrade phases. To this purpose, we estimate a panel data model. Our results indicate that favorable fundamentals could be helpful to smooth and slow down the path of downgrades, whereas this stylized fact does not hold during upgrade periods. That is, in general, an improve in fundamentals seems not to accelerate the rating recovery. Our results could be helpful to infer some lessons about how would be the current rating cycle in the European peripheral countries once the sovereign debt crisis will be overcome.

Keywords: Credit ratings; rating cycle; emerging countries; panel data model.

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[1] Contact authors: carmen.broto@bde.es, lmolina@bde.es. We thank Enrique Alberola and Ignacio Hernando for their helpful comments. The opinions expressed in this document are solely responsibility of the authors and do not represent the views of the Banco de España.

1 Introduction

Rating agencies have played a prominent role during the ongoing financial crisis. Agencies assign a credit rating to sovereign and private sector borrowers that indicates the probability of not fulfilling their obligations in their debt issues. In this paper we focus on sovereign credit ratings. Understanding their dynamics is relevant given their implications for capital flows and their strong link with private ratings, either from banks and non financial corporations, in the sense that sovereign ratings represent a ceiling for corporate ratings (Alsakka and ap Gwilym, 2009; BIS, 2011). Besides, sovereign ratings are a main driver of sovereign bond spreads (see, for instance, Cantor and Packer, 1996), which in turn determine the financing costs of the public sector.

Upgrade moves result from favorable signals in the credit outlook, whereas downgrades stem from unfavorable signals in the credit outlook. This permanent updating of the credit ratings is precisely one of the reasons why financial markets rely on rating agencies (Cantor and Packer, 1994). However, rating agencies do not detail sufficiently neither the determinants of ratings nor their rating procedure (Mora, 2006). This article analyzes how the agencies update sovereign ratings throughout time. In other words, we study sovereign rating cycles. Probably, in our setting the term “cycle” can be a misnomer as it suggests certain periodicity, but in the case of credit ratings such periodicity has not to be necessarily linked to the business cycle, as shown later on. Indeed, the term “rating cycle” has hardly been used in the literature.[2] In our setting, a complete credit cycle comprises a downgrade phase, when the rating goes from peak to trough, and an upgrade phase, when the rating improves, but not necessarily to reach its initial status. The number of countries that have already completed a rating cycle is very small, and they are basically emerging countries (EMEs onwards).

Rating cycles are characterized by their strong asymmetries, as the length and depth (duration and amplitude) have a very different behavior in the upgrade and in the downgrade phases. In this sense, a remarkable stylized fact is that downgrade paths tend to be faster than those of upgrade, as rating increases tend to be slower than decreases, which are more abrupt. In other words, once a country loses their rating level it takes a long period to recover it. For instance, Koopman et al. (2008) find out asymmetric effects across rating grades by means of a duration model with multiple states. These strong asymmetric dynamics are not only typical of ratings, but also of most financial variables that can be characterized by the so-called financial cycle (see, for instance, Aizenman et al, 2013).

Given the above mentioned asymmetries in the ratings behavior, one possible interpretation could be that those signals that the agencies use to modify the ratings also exhibit asymmetries in the recession and recovery periods. But, how do the rating agencies really adjust to changes in the countries’ fundamentals and financial market conditions?[3] There is some empirical evidence that, broadly speaking, has concluded

[2] As far as we know, Sy (2002) and Koopman et al. (2009) are among the few works that specifically use the term “rating cycle”.

[3] On the contrary, there is also a broad literature that analyzed the impact of rating changes on the financial and economic variables. See, for instance, Ferri et al. (1999) for an application for the East Asian crisis, or Alsakkasa and Gwilym (2013) for the European debt crisis. Larrain et

two different results. On the one hand, some papers state that rating agencies do not adjust in an accurate way to the domestic indicators. For instance, some authors conclude that the agencies respond with certain lag to the domestic indicators. Along this line, Ferri et al (1999) analyze the East Asian crisis and they obtain that rating agencies, which previously failed to predict the arrival of the crisis, had reputational incentives to downgrade these countries more than fundamentals would justify in subsequent periods, which, in turn, contributed to amplify the crisis. In other words, during downgrade phases, rating agencies would be excessively sensitive to fundamentals, so that sovereign ratings would have a procyclical nature. Monfort and Mulder (2000) also conclude the procyclycal nature of rating movements. On the contrary, Mora (2006), who also analyzes the Asian crisis, states that ratings are sticky rather than procyclical, as assigned ratings mostly match predicted ratings during crisis periods, whereas after the crisis ratings did not increase by the amount suggested by forecasts.

A widely accepted explanation for this sometimes inadequate timeliness of rating variations is the through-the-cycle methodology that agencies are supposed to apply in their rating assignments that leads to more stable ratings but less accurate (see, for instance, Löffler, 2004; Altman and Rijken, 2005; Kiff et al., 2013). This evolution of ratings comes as a result of the dilemma faced by the agencies between accuracy and stability (Cantor and Mann, 2006).[4] Thus, despite the initial ratings' stability, ratings would be more prone to sudden reversals in downgrade phases that may result in market disruption and forced selling. Besides, the through-the-cycle strategy can be an explanation of the sudden drop of ratings during downgrade periods (Ferri et al., 1999; Kiff et al., 2013) and the low power of ratings to predict future defaults (Löffler, 2004; Kiff et al., 2013).

On the other hand, other authors conclude the adequacy of the actual ratings to their models based on the countries' fundamentals. This is the case of Hu et al. (2002), who propose an ordered probit model to obtain estimates of the transition matrices. This brand of the literature would be implicitly supporting the use of a point-in-time strategy by rating agencies, so that they adapt to the borrower countries' current conditions in an updated manner.

In any case, most of the empirical literature on the adjustment of credit ratings to fundamentals focuses on their role during financial crisis, and less attention has been paid to their characterization during upgrade phases. Although there are several empirical papers analyzing the procyclical nature of corporate ratings and testing the hypothesis of rating through the cycle (see for instance Amato and Furfine, 2004), those empirical papers that have tried to characterize the dynamics of sovereign ratings and their link with the complete business cycle are scarce. In particular, those authors that analyze rating through-the-cycle conclude that in the recovery phase ratings are typically

al. (1997) and Reisen and von Maltzan (1998) also study this causal relation for emerging countries. In all these papers the authors demonstrate that the credit ratings amplified the boom-bust cycles.

4 The through-the-cycle methodology entails a focus on the permanent credit risk component that makes the agencies disregard short-term fluctuations and a prudent policy regarding rating changes (Altman and Rijken, 2005).

smoothed and, as in the case of the downgrade periods, are adjusted with a certain lag (Kiff et al., 2013).

The main objective of this paper is twofold. First, we characterize the rating cycle of a broad sample of countries to confirm the presence of asymmetries, that is, if the phase of downgrade is faster and shorter than that of the recovery period. Second, once we confirm empirically this evidence, we try to disentangle the determinants of this different behavior in both upgrade and downgrade periods by means of a sample of 67 countries, where 43 of them are EMEs that have already experienced at least a complete rating cycle. As far as we know, this is the first empirical paper that tries to characterize the link between domestic variables and the ratings' evolution distinguishing upgrade and downgrade periods. Our sample comprises both EMEs and developed countries, although we will analyze the former in more detail, as EMEs have experienced complete rating cycles to a greater extent.

Our results indicate that improving domestic fundamentals could be helpful to smooth the path of downgrades, whereas this stylized fact does not hold during upgrade phases. That is, once the initial rating of a country is lost, it takes a long time to recover it, and even with a favorable economic and financial performance the country would not accelerate the upgrade period. Our findings are relevant to enhance the understanding the role of rating agencies and the interpretation of their signals to the markets. Besides, this kind of analysis could be useful to infer some lessons about how would be future upgrade period in the European peripheral countries once the sovereign debt crisis will be overcome.

The remainder of this paper is organized as follows. Section 2 introduces our data on rating cycles and Section 3 describes our set of explanatory variables. In turn, Section 4 presents the methodological approach used in this paper. Finally, Section 5 summarizes the main results of our empirical analysis and Section 6 concludes.

2 How do rating cycles look like?

Next, we analyze the characteristics of the credit cycle for the complete sample of countries for which Standard & Poor's (S&P onwards) assigns a sovereign rating. Throughout the paper we use the ratings of a unique agency, namely S&P, so as not to mix the data sources that could lead to measurement errors. This issue is not trivial as, despite the interdependence of rating actions of major agencies, they exhibited a differential behavior.[5] For instance, S&P tends to be less dependent on other agencies, providing the lowest and more volatile ratings among the three major agencies (Alsakka and ap Gwilym, 2010). The choice of S&P is based on the availability of a higher number of countries for the larger sample period, running from January 1975 to May 2013[6]. From 1975 onwards the number of countries rated by S&P increases gradually from two countries, namely the US and Canada, to our complete country sample of 127 countries, 100 EMEs and 27 developed ones (see Figure 1, right-hand plot). From 1975

[5] For instance, Cantor and Packer (1996) conclude that sovereign ratings exhibit more discrepancies than corporate ratings.

[6] See XXX for the ranking and methodology used by this agency.

to 1988 the sample was dominated by developed countries rated with AAA. From that year onwards EMEs were rated gradually, which explains the higher range of ratings from that date onwards (see Figure 1, left-hand plot).

Figure 2 presents the distribution of frequencies of the different rating categories from 1990 onwards. Highest ranked categories (from AA- to AAA) have diminished from 67.7% of total sample in 1990 to 24.4% in 2013, due not only to an increase in rated EMEs but also to the downgrade of some developed countries. In the latter group, the percentage of countries rated above AA- fell from 89.3% in 2005 to 67.9% in 2013,. Those *fallen angels* have swelled the "trigger point" category, that is, the group of countries rated from BBB- (the category who marks the investment grade status) to BBB+[7], which increased from 9.7% to 19.7% of the whole sample (0% to 17.9% in the case of developed countries). Meanwhile the percentage of EMEs rated in the highest category doubled from 2005 to 2013.

Kernel estimations for the rating categories (Figure 3) pointed also to a change in the distribution of probability from 1990 onwards, as density is now more concentrated in intermediate categories (from BB- to BBB+) than in 1995 or 2000, due to an increase in rated EMEs but also to a increase of density in below AA- categories for the developed economies. The median rating for the whole sample has fallen from BBB+ in 2005 to BBB- in 2013, as developed sovereign assets has become more risky (from AAA to AA+) as well as EMEs median country (from BB+ to BB). Looking at weighted rating averages the picture looks the same (Figure 4): the World has become less safe as the average risk for developed country seems to have increased since 1976, and the EMEs average risk decreased, as one could expect as these countries increase their GDP per capita and their financial deepening.

Finally it is worth to note that the most frequent "entry point" (first rate assigned) for a developed economy is AAA (68.3% of ratings assigned to a developed economy for the first time were AAA) and the range is relatively narrow (from BBB (Greece) to AAA), especially in comparison with the range in May 2013 (from CCC (Cyprus) to AAA). For an EME, the most frequent entry point is B+ (19.2%) and the dispersion is so high that the range of the entry point comprises all the categories (from SD (Ecuador in July 2000) to AAA (Venezuela in October 1977)).

Table 1 present the dynamics of our sample from 1975 to 2013. First, note that changes seem to be slightly asymmetric, that is, there are more downgrades (53.1% of total changes) than upgrades, and this is due to the evolvement of developed countries, a group in which downgrades are overwhelmingly higher (74% of total changes). In EMEs, upgrades predominated by a narrow margin (52.3% of total changes). The more frequent movement for the developed countries is a downgrade from AAA to some AA+ to AA- category, and in the case of EMEs the majority of changes are concentrated around BB- to BB+ category, both upgrades to BBB- to BBB+ category or downgrades to B- to B+ category. Finally it is worth to mention that extreme changes (more than

[7] BBB- is the rating that marks the investment grade status. A plenty of investment funds and pension funds are not allowed to invest in assets rated below this category, so a fell below investment grade could trigger huge movements in prices and interest rates

three notches) are practically null, and countries tend to fall to default category (D) from already low ratings, and are massively rated as B- to B+ after the default is solved.

Figure 5 presents the upgrades and downgrades for the whole sample and the above mentioned subgroups since 1975. Note that upgrades dominates downgrades until 2007, with the exception of 1998 (the year of the Asian and Russian crisis), and from 2008 downgrades are by far more frequent, especially in 2011 (30% of rated countries were downgraded during that year). Precisely in 2011 almost 70% of rated developed countries were downgraded by the agency, meanwhile from 2007 onwards upgrades clearly predominate in the EMEs subsample. Finally it is worth to mention that changes, be they upgrades or downgrades, have become more frequent as time passes by, so for example in the 90s the agency changes an average of 12 changes per year, and this ratio increased to 31 changes per year in 2000-2009 and to 40 per year in 2010-2013.

Now we characterize the main features of credit ratings cycles. As in the classical approach to describe cycles in economic variables—typically the GDP—, a rating cycle can be described by its duration and amplitude. In our context, the duration is the number of days from peak to trough and then from trough to peak (from the day of the first increase (or decrease) of the rating to the day of the last increase (or decrease)). The amplitude is the number of notches from peak to trough and vice versa. Figure 6 shows the scheme we use to define a rating cycle in this paper.

Table 2 displays these characteristics of rating cycles for a reduced sample of countries, namely those belonging to G-20, which comprises around 75% of World GDP. Several conclusions can be reached from this table. First, countries with at least one bullish and one bearish cycle are mainly EMEs and non-core euro economies, like Spain, Portugal or Greece. Of those with at least one cycle in each direction, we observe that the duration of the cycle is strongly asymmetric, as the length of recoveries is much longer than that of contractions, with very few exceptions. In other words, once a country loses their rating level it takes a long period to recover it. Besides, these asymmetries are also present in the amplitudes, as the number of notches from peak to trough is higher than in the recovery phase for the majority of countries. The low number of movements from peak to though and from though to peak indicates the strong presence of momentum in ratings, that is, downgrades tend to be followed by downgrades and vice versa. Finally, the last column calculates the number of days between each rating change for bullish and bearish cycles as defined above. With the exception of Indonesia and Hungary, the rest of countries present a lower ratio in the case of bearish cycles, that is, in a cycle of downgrades the agency changes more frequently the rating than in a cycle of upgrades. The poster child case is Korea, which register an upgrade of the sovereign rating every 529 days in positive cycles but a downgrade every 6 days in the case of a negative cycle.

The results by country groups reassert the results obtained above: the length of negative cycles is shorter than the length of positive cycles even for developed countries; the amplitude is also higher for negative cycles; and finally the agency changes the rating more frequently when the mood is negative.

Moreover, another feature of our sample is that very few countries have been able to recover their previous status after a downgrade cycle, and of those which start above the investment grade mark (BBB-) and fell below it, only 2 (Russia and Colombia) recovered their investment grade status and improve their previous rating;, only 1 (Uruguay) recovered the BBB-; and another 3 (India, Korea and Latvia) were able to recover the investment grade status although they never recovered the maximum previous rating. And all of them surpassed the IG mark after a very long period of time. This feature is especially relevant in recent times when sovereign ratings of some euro area countries have sunk below or close to the above mentioned mark, and taking into account the close relation between the cost of funds and sovereign ratings. Figure 7 presents the evolvement of sovereign ratings for some relevant countries of our sample: changes in ratings during upgrade phases are less frequent than during downgrading phases, so the recovery of the previous status is delayed in time and in most cases is never reached. Finally, it is worth noting that 40% of the countries included in the sample have, at the end of May 2013, a sovereign rating lower than the initially assigned by the agency, and that only 29% improved their first qualification.

So if sovereign ratings depend basically on fundamentals, is it the case that the worsening of them is also faster and more profound than their recovery? As it seems not to be the case (Figure X), in the next sections we develop a panel data model to analyze the main determinants of the rating cycle and to try to capture the apparent asymmetry and of their reaction to fundamentals and stickiness during upgrades paths

3 Disentangling the determinants of the sovereign ratings cycles with a panel data model: The data

3.1 Sovereign ratings dataset

The dependent variable of the panel model is the sovereign credit rating by S&P, which we call RATING. To that purpose we transform the daily ratings described in the previous section in a suitable format for a panel data framework. Thus, the 22 alphabetical categories of the ratings have been transformed to numerical groups that run from 0 (default) to 21 (AAA).[8] We transform the ratings into quarterly observations that correspond to their numerical value at the end of each quarter. The sample period runs from 1Q 1994 to 1Q 2013, that is, T=77. Its beginning has been chosen so as to achieve a good balance between EMEs and developed countries, as from 1975 to 1988 the countries rated by S&P were basically developed ones, whereas from that date onwards EMEs were rated gradually (see Figure 1). Besides, the choice of 1Q 1994 as starting period allows to evaluate the evolution of ratings during several financial crises,

[8] In preliminary versions of the paper we have also considered a linear numerical transformation into eight groups, following, for instance, Koopman et al. (2008). The purpose of this transformation was to avoid possible identification problems in the estimation process of ordered logit models, but finally those identification problems were not evident and with the transformation in eight categories we were loosing precision in the analysis. In any case, those results are available upon request.

namely the Mexican crisis of 1995, the East Asian and Russian crises of 1997-1998, as well as the last global financial crisis that began in 2007.

To achieve a balanced panel the selected country sample consist of the 46 countries rated in 1Q 1994, specifically 22 EMEs and 24 developed countries.[9][10] We also consider 21 more EMEs whose ratings were launched by S&P from 1994 to 1997 given their economic relevance or the high volatility of their ratings, which will be useful in the estimation process.[11] See Appendix A for the complete sample of 67 countries. The final country sample is quite representative, as these economies stand for the 93% of world GDP. Besides, 51 out of the 67 countries are along the 60 bigger countries in the world in GDP terms.[12]

3.2 Determinants of sovereign ratings cycles

The main explanatory variables of interest of this paper are build from the own ratings and they will be useful to analyze the impact on past rating variations. Thus, we construct two variables from the first difference of the rating in its linear scale —that is, from 0 to 21—, named as DRATING_n_t and DRATING_p_t. DRATING_n_t is a binary variable that is one if the country has been downgraded in a certain period and zero otherwise, whereas the second variable one is one if the country has been upgraded in *t*. That is, for all *i=1,…,N* and *t=1,…,T*, DRATING_n_t and DRATING_p_t are as follows,

$$DRATING\_n_{it} = \begin{cases} 1 & if \quad RATING_{it} - RATING_{it-1} < 0 \\ 0 & otherwise \end{cases}, \tag{1}$$

and

$$DRATING\_p_{it} = \begin{cases} 1 & if \quad RATING_{it} - RATING_{it-1} > 0 \\ 0 & otherwise \end{cases}. \tag{2}$$

Note that we focus on the fact of being downgraded (or upgraded), but not the intensity of the movement, that is, the number of notches that the country qualification has varied. A higher significance of DRATING_n compared to that of DRATING_p could be interpreted as a higher influence of downgrades to determine future rating movements, in line with the results by Ferri et al (1999). That result could imply hat, due to reputational reasons, rating agencies might try to overreact once the downgrading phase has begun.

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[9] S&P has rated Taiwan since April 1989. However, as it cannot be considered a fully independent country it lacks several domestic explanatory variables that would be used in the panel data model, we have drop it from the country sample.

[10] The sample of developed countries consist of 23 countries that where rated in 1Q1994 and Luxembourg, whose rating starts on April 1994.

[11] The sample of 21 additional EMEs consist of Bermuda, Bolivia, Brazil, Bulgaria, Czech Republic, Egypt, Estonia, Jordan, Kazakhstan, Latvia, Lithuania, Oman, Pakistan, Paraguay, Peru, Qatar, Romania, Russia, Slovenia, South Africa and Trinidad and Tobago

[12] These comparisons have been performed considering the GDP in 2011 denominated in current US dollars as published in the World Economic Indicators of the World Bank.

Figures 2 and 3 report the number of upgrades and downgrades in the panel data sample, that is, they represent the aggregation across countries of $DRATING\_n_t$ and $DRATING\_p_t$. In line with previous sections, Figure 2 shows that in EMEs there is a relatively balanced sample of upgrades and downgrades throughout the sample period, whereas in developed countries rating variations are much more scarce and clearly differentiated across time: until the onset of the financial crisis there were few upgrades and then the crisis exacerbated downgrades in several countries. In line with the outcomes in Section 2, Figure 3, that decomposes the rating movements by the number of upgrades and downgrades, signals the importance of EMEs in the study of upgrades, whereas for the analysis of downgrades both developed and EMEs are relevant although the latter are present in the complete sample period.

Apart from using these two variables to analyze the rating cycle and for the sake of robustness of our results, in line with previous empirical papers we use several variables that will serve as controls. Basically we take as reference the works by Cantor and Packer, 1996; Haque et al., 1996; Ferri et al., 1999; Hu et al., 2002; Monfort and Mulder, 2000, and Mora, 2006. The whole set of control variables, which is relatively standard, can be classified in three broad groups. First, we consider domestic macroeconomic indicators. Specifically we use (1) GDP growth; (2) Expected GDP, as forecasted by the IMF. This variable is relatively new in this type of analysis; (3) GDP per capita; (4) Consumer price inflation rate. Note that the four later macroeconomic indicators reflect the long-run prospects of the country providing an assessment of its economic performance.; (5) External balance proxied by the current account surplus to GDP; (6) Stock of reserves to GDP, which is used as an additional external indicator; (7) Public deficit on GDP, that is a variable that proxies the solvency of the economy as it allows to evaluate the country's medium to long-term ability to service its debt (Hu et al. 2002). The expected sign of the estimates of these economic variables is positive, but for the inflation, where a negative sign is expected.

Second, we also use two domestic financial variables: (1) The REER (real exchange rate), that it is also an external indicator but also signals a general picture of the tendencies of capital flows from/towards the country; (2) Credit on GDP. Variables related to the developments in the banking sector have not been much employed in the empirical literature,[13] but they can be a good leading indicator of possible future sovereign crisis to be used by rating agencies;

Besides, we use a third set of variables, which are common to all countries. This kind of drivers are helpful to control for the variability across time in the panel data. Specifically we consider, (1) the VIX index, which is frequently used as a proxy of global risk aversion in the markets; (2) the three-month interest rate in the US; (3) the world growth. These global variables can also be interpreted as possible external shocks that the economies face (Hu et al. 2002).

[13] For instance, Koopman et al. (2009)use a set of variables related to bank lending conditions to analyze corporate ratings in the US.

Finally, we also consider several dummies that will be helpful to disentangle further results in the panel analysis. Namely, we employ a binary variable to distinguish EMEs and developed countries, in the case of emerging countries we also construct another one to differentiate the region and, to conclude, a dummy that is one if the country belongs to the euro area and zero otherwise. Finally, we also construct an ordinal categorical variable that captures the fact of having an IMF program (see appendix B for further details).

4 Empirical model and econometric issues

4.1 The dependent variable

The dependent variable of the panel data model, the rating assigned by S&P, is a discrete variable with 21 categories where each rating follows a meaningful sequential order (for instance, a default is associated to 0 whereas AAA is 21). In this setting an ordered logit model is a sensible choice. Ordered logit models have been broadly used in the literature on ratings, although the first papers analyzing their determinants tended to use linear models.[14] Hu et al. (2002) is the first empirical paper that uses an ordered probit model to fit sovereign ratings. Specifically, they use it to estimate the rating transition matrices. See Hu et al. (2002) for the specific analytical form of ordered logit models applied to rating models. Using the same methodology, Bissondoyal-Bheenick (2005) concludes that domestic economic and financial indicators play a minor role.[15]

The main advantage of ordered logit models in comparison with linear models is that the later are implicitly assuming that the dependent variable has been categorized into equally spaced discrete intervals. However, this is not a sensible approach to fit ratings as there are categories whose distance between each other can be rather different. For instance, the economic implications of losing one notch from AAA to AA+ than losing the investment grade category and going from BBB to BB. To overcome this drawback of linear models in the study of ratings, Ferry et al. (1999) proposes a non-linear transformation of the rating scale. Nevertheless, ordered logit models also entail problems, as the higher the number of categories —such as in our case with 22 categories—, the higher the probability of having identification problems as this kind of model is multivariate.

All in all, we fit three different model specifications. First, in line with Mora (2006), we estimate the baseline model with both an ordered logit model where the dependent variable is the linear scale of the ratings, and with a pooled OLS using as dependent variable a non-linear transformation of the linear scale of ratings. In particular, we transform the linear scale from 0 to 21 with the logistic function. The logistic function is the following,

[14] For instance, this is the case of Cantor and Packer (1996), Haque et al. (1996), Ferry et al. (1999), Momfort and Mulder (2000) or Mora (2006).

[15] See Mora (2006) or Afonso et al. (2009) for additional papers with empirical applications that fit credit ratings by means of ordered probit/logit models.

$$f(RATING) = \frac{1}{1+e^{-RATING}} \,,$$

(3)

where rating goes from 0 to 21. As the range of the logistic function goes from 0 to 1, we conveniently rescale the resulting transformation into a scale from 0 to 21, which allows the direct comparability with the results obtained by the ordered logit model. Figure 8 represents the linear and the logistic based scale. Note that, in line with the previously suggested intuition, the slope of the logistic function is higher in the intermediate ratings as, intuitively, the step from investment grade to speculative grade have more relevant implications that other rating variations.

4.2 Empirical model

All in all, the baseline model is,

$$Y_{it} = \eta_i + \alpha_t + \sum_j \beta_j X_{j,it-1} + \sum_k \beta_k Z_{k,t-1} + \varepsilon_{it}$$

(4)

Where, for all *i=1,…,N* and *t=1,…, T*, the dependent variable Y_t is the logistic transformation of RATING for the case of the pooled OLS estimates, and RATING in its ordinal scale from 0 (default) to 21 (AAA) in the ordered logit model fit. Apart from the time and country dummies, we use as explanatory variables X_{it} the set of economic and financial domestic variables introduced in previous section and the global variables Z_t. Note that all the explanatory variables have one period lag to deal with possible endogeneity problems.

Second, we also fit the baseline model in (4) incorporating the interactions of the domestic variables with the fact of having been upgraded or downgraded, that is, we interact domestic variables with DRATING_n_t and DRATING_p_t. The model specification of these models are given by,

$$Y_{it} = \eta_i + \alpha_t + \sum_j \beta_j X_{j,it-1} + \sum_j \beta_j^n DRATING\_n_{it-1} X_{j,it-1} + \sum_k \beta_k Z_{k,t-1} + \varepsilon_{it} \;,$$

(5)

and

$$Y_{it} = \eta_i + \alpha_t + \sum_j \beta_j X_{j,it-1} + \sum_j \beta_j^p DRATING\_p_{it-1} X_{j,it-1} + \sum_k \beta_k Z_{k,t-1} + \varepsilon_{it} \;,$$

(6)

where the coefficients β^n and β^p indicate if the domestic variables can have an influence to smoothen or deepening the downgrading and upgrading path, respectively.

Finally, to allow for some statistical inference regarding the presence of asymmetries in the influence of domestic variables during the upgrading and downgrading periods we also fit the model with both the interactions with DRATING_n_t and DRATING_p_t that is given by,

$$Y_{it} = \eta_i + \alpha_t$$
$$+\sum_j \beta_j X_{j,it-1} + \sum_j \beta_j^n DRATING\_n_{it-1} X_{j,it-1} + \sum_j \beta_j^p DRATING\_p_{it-1} X_{j,it-1} + \sum_k \beta_k Z_{k,t-1} + \varepsilon_{it} \cdot$$

(7)

This specification allows to tests formally for the null hypothesis that domestic variables do have the same influence during a downgrade and an upgrade phase. That is, for all the domestic variables *j* it is possible to test for the following null,

$$H_0 : \beta_j^n = \beta_j^p$$

(8)

Note that in most of these model specifications the estimates country fixed effect dummies are not going to be estimated as there are dummy variables, basically EME and ZE, that are time-invariant throughout the sample period, so that country fixed effects would translate to the intercept. However, our broad set of control variables would allow us to control for the unobserved heterogeneity across countries. Another technical difficulty of the analysis is the possibility of endogeneity biases as a result of reverse causality and omitted variables. In our case domestic drivers—both economic and financial—are useful throughout the estimation process as they allow to identify possible omitted variable biases and are helpful to control for the unobserved heterogeneity across countries.

5 Empirical results

5.1 The basic model: Some preliminary results

Table 3 reports the estimates of the basic model for the total sample, as well as for the pre-crisis and post-crisis period. One aspect that particularly calls the attention is that previous rating downgrades have a negative influence on the future ratings, as signaled by the negative and significant estimates of DRATING_n. On the contrary, the coefficients for DRATING_p are smaller than those of DRATING_n and non-significant. This result would be in line with the descriptive aspects illustrated in Section 2, as downgrade periods are deeper and faster than those of upgrade phases, so that the probability of a future downgrade given a past downgrade is higher than that of a future upgrade given a past upgrade. According to the results in Ferri et al. (1999) for the Asian crisis, previous downgrades do influence on subsequent movements of the rating, as the rating agencies are conservative and tend to downgrade relatively late. However, once downgrades start, the agencies tend to overreact and downgrade the countries in excess, which can generate crisis amplification. On the contrary, this result does not hold for upgrades, as past upgrades do not incentivize future upgrades. One possible explanation to this fact is that of Mora (2006), who states that ratings are sticky after crisis periods as they do not increase by the amount suggested by forecasts.

Table 3 reports both the pooled OLS and the ordered logit based estimates. As already mentioned, the model is fitted by these two methodologies as a robustness test so as to check the accuracy of discarding the ordered logit estimates in the next steps of the analysis. The reason to prefer pooled OLS to ordered logit based estimates is that the use of interactions among explanatory variables leads to several identification problems in the following models taking into account the 21 different categories of the rating in the ordered logit estimation.

Table 3 suggests that, effectively, the estimates obtained by both procedures are quite similar, and the main differences are relatively minor. In both cases the domestic macroeconomic variables as well as the domestic financial variables seem to be relevant for the rating determination. Nevertheless, GDP_growth is not as relevant as other macroeconomic indicators, in line with Mora (2006) or Cantor and Packer (1996). On the contrary, the higher coefficients among the macroeconomic variables correspond to the expected GDP (GDP_f), which underlines the importance of this type of leading indicators for rating agencies[16]. Surprisingly, this explanatory variable has been barely used in the literature, [17] probably as some authors conclude that rating agencies do not react to expected changes in observed variables (Monfort and Mulder, 2000). Nevertheless, estimates for global variables are not significant in the ordered logit case, whereas for the pooled OLS estimates only the short term rate in the US for the total sample is significant. However, as in our subsequent analysis global variables will only play a minor role as time controls, this lack of significance of global variables does not represent a problem in the forthcoming phases of the analysis. Finally, categorical variables' estimates are also rather similar following both methods. The dummy variable for emerging countries (EME) is negative for the pre-crisis period but these results should be qualified by the variable REGION, which might be indirectly approximating their history of defaults, lowering the rating of Latin America and favoring that of Asia.[18]

The signs of the explanatory variables are as expected with few exceptions. For instance, the estimated coefficient for the current account over GDP (CA) is negative, although it was expected to be positive. That is, current account deficits would be associated with better ratings. Ferri et al. (1999) or Mora (2006) also obtain this result and the later interprets that better rated countries are able to run current account deficits and borrow more easily from abroad, so that this current account deficit would turn into a sign of strength of the country. The sign of the public balance on GDP (PB_GDP), which in principle is also expected to be positive, in some cases becomes negative—for instance in the post-crisis period estimated with the pooled OLS model—. This result is contrary to that of Cantor and Packer (1996), Ferri et al. (1999) or Mora (2006). Nevertheless, these authors do not consider the global financial crisis in their empirical exercise, which can influence in our different results. A complementary

16 Multicolineality between these two variables could also play a role in the non significance of GDP growth.

17 As far as we know, growth expectations have only been used as explanatory variable in the internal models of S&P.

18 Haque et al., (1996) and Mora (2006), among others directly include in their analysis an explanatory variable for past defaults.

interpretation, in line with that of CA, is that in the last part of the sample those countries with higher fiscal deficits were associated with higher ratings as markets interpret in some cases that these economies are sound enough to allow themselves a fiscal deficit.

Besides, in the post-crisis period, the ratings were less influenced by economic and domestic indicators than in the pre-crisis period. For instance, INFL and RES lose their significance. One possible interpretation of this result is that during acute crisis periods some variables lose their importance in favor of other variables, so that during the last crisis rating agencies seem to have been influenced to a greater extent by other economic indicators, such as the GDP forecast or financial variables such as the total credit on GDP.

Analogously, Table 4 reports the estimates of the basic model distinguishing the sample of EMEs, which in most cases have experienced a complete rating cycle, and developed countries. The table also reports the pooled OLS and the ordered logit based estimates. Economic and financial variables seem to influence in a different way in rating variations in both country groups. For instance, the expected GDP, the inflation rate, the current account on GDP, the stock of reserves or the exchange rate seem to play a role in EMEs, whereas this fact does not hold for developed countries. On the contrary, the public balance on GDP is relevant to explain ratings in developed countries but not in EMEs, which seems a sensible result given the developments during the last crisis— although in OLS and in ordered logit estimates the estimator sign is not robust—. In the next subsections we will perform a deeper analysis considering the interaction of domestic variables with previous downgrades and upgrades.

5.2 Can domestic variables influence on the ratings' path…?

5.2.1 …during downgrade phases?

Table 5 shows the estimates of model (5) that includes interactions of the domestic variables, both economic and financial, with DRATING_n. These interactions indicate the capacity of domestic fundamentals to smoothen or exacerbate downgrade phases. The estimates in Table 5 consist of those for the total sample and for the EMEs, as well as for the total sample period, and the pre-crisis and post-crisis period.

Given the robustness of the procedure, from Table 5 onwards we only report the estimates obtained by the pooled OLS model.[19] What first draws attention is that the interactions of the domestic variables with the fact of having experienced a downgrade for all the estimates are significant in few cases. Nevertheless, from these estimates, some interesting conclusions can be inferred. Thus, once we interact DRATING_n with some of the domestic variables, some of them seem to be useful to soften the downgrading path. On the contrary, other variables seem to exacerbate the path. For instance, the fact of having a good economic performance seems to smooth the downgrade phase, as evidenced by the positive sign of the interactions with

[19] The results for the estimates obtained by means of an ordered logit for the remaining models are also available upon request. However, as already mentioned, depending on the model specification and the specific sample (developed or EMEs, pre-crisis or post-crisis period) the ordered logit model entails identification problems considering the 22 different rating categories.

GDP_growth and GDP_pc.[20] On the contrary, regarding GDP_f, that is, the forecasted GDP, the sign of the estimated interaction is negative, which implies that the country needs more favorable leading indicators than countries that have not being downgraded to overcome the negative signal that the downgrade transmits to the markets—as indicated by the sum of the coefficient of the variable and its interaction—.

Apart from those variables related to growth, there are other significant interactions. For instance, that of CA, the current account on GDP, for the total sample becomes positive and significant. Note that for those countries without a downgrade the coefficient would be negative and bigger.[21] That is, highly rated countries can afford current account deficits, but once the country is downgraded markets do not permit those deficits in the same manner. The positive estimate of PB_GDP*DRATING_n for EMEs would have a similar interpretation. That is, in tranquil periods a given country can allow a fiscal deficit, but once the country is downgraded a healthy fiscal balance is helpful for them to smooth downgrades. Finally, RES* DRATING_n is positive for the pre-crisis sample of EMEs, which confirms the importance of the stock of reserves as a buffer to protect the country during the crisis.

All in all, the findings related to the existence of previous downgrades are in line with the results of Ferri et al. (1999), among others, according to which rating agencies might have an excess sensitivity to fundamentals. Thus, rating agencies can overreact to their evolution under turbulences (as is the case of GDP_f), what can lead to steep downgrade phases that can even exacerbate the own downward business cycle. As already stated, this outcome coincides in its spirit with those papers that have previously focused on the analysis of rating cycles during crisis periods that conclude that rating cycles have a procyclical nature with respect to economic fundamentals.

5.2.2 …during upgrade phases?

Analogously, Table 6 reports the estimates of the model with interactions of the domestic variables with the existence of upgrades. That is, we combine domestic variables with DRATING_p for the total sample and for the EMEs. There are two reasons why this exercise is of particular interest. First, the upgrade periods have been less studied in the empirical literature than downgrade phases, and second, this kind of analysis can be useful to infer conclusions on the dynamics of rating upgrades for EMEs that could serve as lessons for the developed countries that were downgraded during the last financial crisis.

The most relevant outcome in Table 6 is that, in opposition to the previous exercise for DRATING_n in Table 5, interactions with DRATING_p are much less significant. For instance, none of these interactions with the variables related with economic growth — namely, GDP_growth, GDP_f and GDP_pc— are significant. That is, a positive economic performance given a prior upgrade is not a sufficient stimulus for the rating

[20] The main exception is the negative estimate for GDP_growth considering the sample of EMEs in the post-crisis period.

[21] Specifically, the coefficient for CA for the total sample of non-previously downgraded countries would be -0.10, whereas that of the previously downgraded is -0.02.

agencies to accelerate the upgrading process. In other words, the recovery to the initial rating status cannot be enhanced by the own economic and financial indicators. This result emphasizes the lack of capability of domestic authorities to speed up future upgrades under a good economic performance. However, during downgrade periods favorable economic fundamentals do play a role to smoothen the path. In summary, during upgrade periods ratings seem stickier than in downgrade periods, which is bad news for those developed economies that have lost their rating status during the crisis. This outcome is linked to that of Mora (2006).

However, there are a few significant interactions, although most of them can be directly related to the evolution of EMEs. This is the case of the stock of reserves (RES) or the real exchange rate (REER). Again, having a large stock of reserves could speed up upgrades. In a complementary manner, the exchange rate evolution is a key variable for EMEs during financial crisis. Thus, a real effective exchange rate appreciation serves as an indicator of capital inflows that, in turn, could contribute to the reserve accumulation. EMEs can take advantage of this exchange rate evolution to accelerate upgrades. Finally, the interaction with the credit on GDP is also significant for the total country sample in the post-crisis period, which is directly related to developed countries. One possible interpretation is that lower credit exposure is required to accelerate upgrades once an upgrade has taken place.

5.3 Is the role of domestic variables really different during upgrade and downgrade periods?

Table 7 reports the estimates of model (7) where the basic model is generalized with the interactions of the domestic variables, both economic and financial, with DRATING_n and DRATING_p. By means of these estimates we formally test for the null hypothesis that domestic variables do have the same influence during downgrade and upgrade phases. The table also reports the p-values of the Wald type tests of the null hypothesis in (8) for all the domestic variables.

In line with the previous results, for the total sample of countries, both EMEs and developed countries, there are few significant interactions, so that we can reject the null hypothesis in relatively few cases. However, there are some relevant cases where the null is rejected. For instance, regarding domestic growth, the tests confirm that the economic performance is an element that can smooth the downgrading path, as indicated by the tests for GDP_growth (post-crisis) and for the GDP_pc. However, in upgrade periods a good economic performance plays no differential role. Besides, growth perspectives do not have the same influence in upgrade and in downgrade phases. We find this outcome in the total sample as well as for the EMEs. Thus, whereas the country has to overcome a previous downgrade with higher expected growth than countries without downgrades, during upgrades the expected growth, whether favorable or unfavorable, plays no role to alter the rating path.

Unsurprisingly, the public balance on GDP also matters, but apparently only in the upgrade phases for the total sample and in the downgrade phase for the EMEs. In both cases the interaction coefficient is positive, which signals the importance of a healthy fiscal balance to favor the rating recovery. Finally, the current account balance on GDP seems to have also a different impact in upgrade and downgrade periods as a result of the opposite sign of interactions with DRATING_n and DRATING_p for the total sample.

The results for the total sample and for the EMEs are quite similar, but with slight differences. As already mentioned, the dynamics of rating cycles are different in EMEs, as many of these countries have already experienced complete rating cycles with deep downgrades and their subsequent gradual upgrade. The variable that seems to make a biggest difference between the total sample and the EMEs is RES. Thus, a big stock of foreign reserves on GDP does make a difference during downgrade periods in EMEs as it indicates the existence of a buffer to the rating agency that can smooth downgrades. However, the presence of this cushion would not be influential during upgrades.

6 Conclusions and policy implications

In this paper, we describe the main characteristics of the rating cycles of those countries that have already experienced downgrade and upgrade periods. Using S&P ratings, and in line with other authors, we observe that downgrade phases tend to be deeper and faster than those of upgrades. In other words, once a country loses their initial status it takes a long period to recover it.

After characterizing the ratings' evolution during downgrades and upgrades, we try to disentangle how the decisions of the rating agencies respond to changes in the countries' fundamentals and financial market conditions distinguishing downgrade and upgrade periods. To this purpose, we estimate a panel data model for 67 countries, both developed and EMEs. Our results indicate that domestic variables could be helpful to smooth the path of downgrades, whereas this outcome does not hold during upgrade phases. In other words, having healthy domestic fundamentals can influence on rating agencies to alter the downgrade path, so that national authorities have an instrument to smooth downgrades. However, the nature of upgrades is rather different, so that countries previously downgraded have little capacity to accelerate future upgrades through improving fundamentals.

That said, what would be our view regarding the debate about the procyclical or sticky nature of ratings? Our conclusions are mixed and depend on the position throughout the rating cycle, as the reaction of rating agencies to the macroeconomic developments are noticeably different during downgrade and upgrade periods. Downgrade phases would have a procyclycal character, although lagged, whereas upgrade periods would tend to be sticky. Our results could be useful to infer some lessons about how would be the current rating cycle in the European peripheral countries once the sovereign debt crisis will be overcome.

Appendix A: Country sample

Argentina	Hungary	Paraguay
Australia	Iceland	Peru
Austria	India	Philippines
Belgium	Indonesia	Poland
Bermuda	Ireland	Portugal
Bolivia	Israel	Qatar
Brazil	Italy	Romania
Bulgaria	Japan	Russian Federation
Canada	Jordan	Singapore
Colombia	Kazakhstan	Slovak Republic
Croatia	Korea, Rep.	Slovenia
Cyprus	Latvia	South Africa
Czech Republic	Lithuania	Spain
Chile	Luxembourg	Sweden
China	Malaysia	Switzerland
Denmark	Malta	Thailand
Egypt, Arab Rep.	Mexico	Trinidad and Tobago
Estonia	Netherlands	Turkey
Finland	New Zealand	United Kingdom
France	Norway	United States
Germany	Oman	Uruguay
Greece	Pakistan	Venezuela, RB
Hong Kong SAR, China		

Appendix B: Definition of variables and data sources

- Ratings: Standard and Poor's classification, running from AAA (higher rating) to D/SD (default or selective default). Investment grade category is BBB-

Macroeconomic domestic variables:

- GDP growth rate: Source: IMF. Due to the lack of data for Oman, Pakistan and Qatar, we use industrial production for those countries instead.
- Forecasted GDP: Source: IMF. Average in each quarter of IMF's growth forecast for the next three or five years.
- GDP per capita: Source: Oxford Economics, World Bank and National Statistics Offices. GDP per capita in PPP terms
- Inflation: Source: IMF and National Statistics Offices. CPI y-o-y change.
- Current account-to-GDP: Source: IMF and National Statistics Offices..
- Reserves on GDP: Source: IMF and National Central Banks. International Reserves (gold and Foreign Exchange) as a percentage of GDP
- Public deficit on GDP: Source: Oxford Economics, EIU and National Statistics Offices

Financial domestic variables:

- REER: Source: JP Morgan and National Central Banks. Real Effective Exchange Rate, CPI-based, wide basket
- Total credit on GDP: Source: IMF and National Central Banks. Total credit (to the private and public sectors) over GDP

Global variables:

- VIX: Source: Datastream.
- 3-months US interest rate: Source: Datastream.World growth: Source: Datastream.

Categorical variables:

- ZE: Dummy variable that is 1 if the country belongs to the Euro zone and zero otherwise.
- EME: Dummy variable that is 1 if the country is and emerging one and zero otherwise.
- Region: Nominal categorical variable that is 0 if the country is a developed one, and 1, 2, 3 and 4 if the country is an emerging economy that belongs to Latin America, Eastern Europe, Asia and Africa, respectively.
- IMF program: Ordinal categorical variable that is 0 if the country has no IMF finance program; 1 if the country has an FCL (Flexible Credit Line)—namely, Colombia, Mexico and Poland—, which implies a precautionary arrangement; 2 under a IMF agreement without disbursement; 3 under an IMF agreement with disbursement.

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TABLES

Table 1: Event counts

TOTAL

From…	To… AAA	AA	A	BBB	BB	B	CCC	D
AAA	---	15	0	0	0	0	0	0
AA	9	---	10	0	0	0	0	0
A	0	13	---	18	1	0	0	0
BBB	0	0	16	---	17	1	0	0
BB	0	0	0	22	---	25	0	0
B	0	0	0	0	25	---	22	6
CCC	0	0	0	0	0	10	---	15
D	0	0	0	0	0	14	6	---

DEVELOPED COUNTRIES

From…	To… AAA	AA	A	BBB	BB	B	CCC	D
AAA	---	13	0	0	0	0	0	0
AA	7	---	7	0	0	0	0	0
A	0	3	---	8	0	0	0	0
BBB	0	0	1	---	3	0	0	0
BB	0	0	0	0	---	2	0	0
B	0	0	0	0	0	---	2	0
CCC	0	0	0	0	0	0	---	2
D	0	0	0	0	0	1	1	---

EMERGING COUNTRIES

From…	To… AAA	AA	A	BBB	BB	B	CCC	D
AAA	---	2	0	0	0	0	0	0
AA	2	---	3	0	0	0	0	0
A	0	10	---	10	1	0	0	0
BBB	0	0	15	---	14	1	0	0
BB	0	0	0	22	---	23	0	0
B	0	0	0	0	25	---	20	6
CCC	0	0	0	0	0	10	---	13
D	0	0	0	0	0	13	5	---

Table 2: rating cycles

	Mean duration (days)		Mean amplitude (notches)		Number of cycles		Days between changes	
	Trough-Peak	Peak-Trough	Trough-Peak	Peak-Trough	Bullish	Bearish	Bullish	Bearish
G-20:								
Argentina	489	**221**	**8**	-6	1	2	61	**37**
Australia	1375	**1058**	2	-2	1	1	688	**529**
Brazil	1622	---	4	---	2	0	463	---
Canada	---	---	---	---	0	0	---	---
China	2494	---	5	---	1	0	499	---
France	---	---	---	---	0	0	---	---
Germany	---	---	---	---	0	0	---	---
India	**728**	2787	2	**-3**	1	1	**364**	929
Indonesia	3009	**631**	**11**	-10	1	2	274	**66**
Italy	---	6892	---	-6	0	1	---	1149
Japan	---	418	---	-3	0	1	---	139
South Korea	5322	**60**	9	**-10**	1	1	591	**6**
Mexico	2769	---	4	---	1	0	692	---
Russia	2097	**233**	**14**	-9	1	1	150	**26**
Saudi Arabia	3609	---	2	---	1	0	1805	---
South Africa	3545	---	4	---	1	0	886	---
Turkey	3533	**376**	**5**	-4	1	2	707	**94**
United Kingdom	---	---	---	---	---	---	---	---
United States	---	---	---	---	0	0	---	---
Other relevant countries:								
Greece	**2076**	2659	5	**-17**	1	1	415	**156**
Ireland	4375	**735**	4	**-7**	1	1	1094	**105**
Portugal	2609	**2394**	3	**-9**	1	1	870	**266**
Spain	2075	**1363**	2	**-9**	1	1	1038	**151**
Cyprus	---	625	---	-8	0	2	---	83
Hungary	**1516**	2354	4	**-5**	1	1	**379**	471
Uruguay	3231	**457**	**12**	**-12**	1	1	269	**38**
Colombia	2245	**246**	**3**	-2	1	1	748	**123**
Venezuela	**920**	1387	4	**-6**	1	3	230	**219**
EMEs	1865	**876**	4	**-5**	62	47	436	**169**
- Latam	2150	**955**	5	**-6**	16	19	405	**158**
- Eastern Europe	1310	**713**	**4**	-4	21	11	328	**191**
- Developing Asia	1593	**636**	4	**-5**	14	11	384	**117**
- Rest of EMEs	2856	**1365**	3	**-5**	11	6	827	**303**
Developed countries	2386	**1873**	3	**-6**	9	15	859	**319**
- Euro Area	2602	**2230**	3	**-7**	5	10	765	**310**

Table 3: Estimates of the basic model for the total sample and for the pre-crisis and post-crisis period.

		OLS			Ordered logit		
		Total sample	Pre-crisis	Post-crisis	Total sample	Pre-crisis	Post-crisis
	DRATING_n	-1.03***	-0.49**	-0.98***	-2.04***	-0.99***	-2.02***
	DRATING_p	-0.22	0.04	-0.22	0.13	0.28	0.49
Domestic economic	GDP_growth	0.01	-0.06***	0.05**	0.00	-0.06**	0.01
	GDP_f	0.35***	0.28***	0.44**	0.54***	0.46***	0.59**
	GDP_pc	0.00***	0.00***	0.00***	0.00***	0.00***	0.01***
	INFL	-0.06***	-0.05***	0.07*	-0.04***	-0.02*	-0.07
	CA	-0.10***	-0.11***	-0.11***	-0.10***	-0.10***	-0.16***
	PB_GDP	-0.02	0.03	-0.11***	0.17***	0.02	-0.07
	RES	0.01***	0.04***	0.00	0.00*	0.04***	0.00
Domestic financial	REER	0.05***	0.06***	0.00	0.06***	0.07***	0.00
	CR	-0.01***	-0.01***	-0.03***	-0.01**	-0.01*	-0.02**
Global	VIX	0.01	0.01	0.02	-0.07	-0.17	-0.09
	US3M	0.17*	0.03	-0.11	3.20	-0.29	4.36
	WG	-0.03	0.05	-0.07	-0.41	-0.43	-0.57
Categorical	ZE	2.44***	-11.39***	25.35***	6.54***	-4.61	20.46***
	REGION	1.85***	2.11***	6.48***	1.23***	0.02	2.66***
	EME	-9.39***	-17.44***	24.41***	-8.61***	-31.39***	5.22
	IMF	-1.08***	-0.48***	-1.17***	-0.81***	-0.39***	-2.08***
N		3318	2171	1147	3318	2171	1147
R2		0.91	0.95	0.93	0.59	0.71	0.65

*p < 0.05; **p < 0.01; ***p < 0.001; Pooled OLS and ordered logit estimations. Dependent variable: nonlinear transformation of RATING (logistic function once the scale of rating is transformed from 0 to 1) —pooled OLS—, and RATING in its ordinal scale from 0 (default) to 21 (AAA)—ordered logit—; All the explanatory variables (except the categorical variables) are lagged by one period; DRATING_n: binary dummy, DRATING_n = 1 if the country has been downgraded and zero otherwise, DRATING_p = 1 if the country has been upgraded and zero otherwise, The remaining explanatory variables are: (1) GDP_growth: GDP growth in annual rate; (2) GDP_f: Forecasted GDP; (3) GDP_pc: GDP per capita; (4) INFL: Inflation rate; (5) CA: Current account as percentage of GDP; (6) PB_GDP: Public balance on GDP; (7) RES: Foreign reserves over GDP; (8):REER: Real effective exchange rate; (9) CR: Total credit on GDP; (10) VIX: VIX index; (11) US3M: US three-month interest rate; (12) WG: World growth; (13) ZE dummy variable. ZE =1 if the country belongs to the Euro zone; (14) Region: Nominal categorical variable that goes from 0 to 4; (15) EME: Dummy variable. EME=1 if the country is an emerging one; (16) IMF: Presence of IMF program; See Appendix B for further details on the definitions of the variables; Intercept and time controls included but not reported; We date the beginning of the crisis in 2008:Q3 The R^2 is a pseudo- R^2 for the ordered logit estimates.

Table 4: Estimates of the basic model for the sample of emerging and developed countries.

		OLS		Ordered logit	
		EMEs	Developed	EMEs	Developed
	DRATING_n	-0.82**	-1.04**	-1.64***	-1.70***
	DRATING_p	-0.03	-1.19	0.24	0.63
Domestic economic	GDP_growth	-0.04*	0.13***	-0.03*	0.07
	GDP_f	0.40***	-0.04	0.64***	0.44***
	GDP_pc	0.00***	0.00***	0.00***	0.01***
	INFL	-0.06***	0.07	-0.04***	0.07
	CA	-0.14***	-0.02	-0.14***	0.06
	PB_GDP	0.04	-0.13***	0.05	0.10**
	RES	0.01***	0.00	0.01**	0.00
Domestic financial	REER	0.06***	-0.01	0.05***	0.06***
	CR	-0.01	0.00	-0.02**	-0.01
Global	VIX	0.01	0.00	0.04	-0.46
	US3M	0.04	0.23**	1.98	8.80
	WG	0.07	-0.25**	-0.41	-1.84
Categorical	ZE	12.08***	-3.85**	14.83***	12.89***
	REGION	2.17***	(omitted)	1.10***	(omitted)
	IMF	-0.69***	-2.41***	-0.45***	-3.33***
N		2025	1293	2025	1293
R2		0.90	0.78	0.55	0.67

*p < 0.05; **p < 0.01; ***p < 0.001; Pooled OLS and ordered logit estimations. Dependent variable: nonlinear transformation of RATING (logistic function once the scale of rating is transformed from 0 to 1) —pooled OLS—, and RATING in its ordinal scale from 0 (default) to 21 (AAA)—ordered logit—; All the explanatory variables (except the categorical variables) are lagged by one period; DRATING_n: binary dummy, DRATING_n = 1 if the country has been downgraded and zero otherwise, DRATING_p = 1 if the country has been upgraded and zero otherwise, The remaining explanatory variables are: (1) GDP_growth: GDP growth in annual rate; (2) GDP_f: Forecasted GDP; (3) GDP_pc: GDP per capita; (4) INFL: Inflation rate; (5) CA: Current account as percentage of GDP; (6) PB_GDP: Public balance on GDP; (7) RES: Foreign reserves over GDP; (8):REER: Real effective exchange rate; (9) CR: Total credit on GDP; (10) VIX: VIX index; (11) US3M: US three-month interest rate; (12) WG: World growth; (13) ZE dummy variable. ZE =1 if the country belongs to the Euro zone; (14) Region: Nominal categorical variable that goes from 0 to 4; (15) EME: Dummy variable. EME=1 if the country is an emerging one; (16) IMF: Presence of IMF program; See Appendix B for further details on the definitions of the variables; Intercept and time controls included but not reported; We date the beginning of the crisis in 2008:Q3 The R^2 is a pseudo- R^2 for the ordered logit estimates.

Table 5: Estimates of the model with interactions of the domestic variables with DRATING_n, which is 1 if the country registers a downgrade and 0 otherwise, for the total sample and for the EMEs.

		Total sample			EMEs		
		Total sample	Pre-crisis	Post-crisis	Total sample	Pre-crisis	Post-crisis
	DRATING_n	-0.14	-1.30	-2.00	1.59	-0.19	-12.67
	DRATING_p	-0.19	0.05	-0.27	0.01	0.09	0.52*
Domestic	GDP_growth	-0.01	-0.08***	0.03	-0.05**	-0.09***	0.00
	GDP_f	0.41***	0.31***	0.57***	0.45***	0.30***	0.74***
	GDP_pc	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	INFL	-0.07***	-0.06***	0.04	-0.06***	-0.05***	0.07
	CA	-0.10***	-0.11***	-0.09***	-0.14***	-0.15***	-0.05**
	PB_GDP	0.00	0.04*	-0.12***	0.03	0.02	0.05
	RES	0.01***	0.04***	0.00	0.01***	0.04***	0.00
	REER	0.05***	0.06***	0.00	0.06***	0.07***	0.01
	CR	-0.01**	-0.01***	-0.03***	0.00	0.00	-0.01
Domestic * DRATING_n	GDP_growth	0.17***	0.07	0.11*	0.10*	0.01	-0.26*
	GDP_f	-0.43***	-0.30**	-0.43	-0.23*	-0.30**	2.29
	GDP_pc	0.00**	0.00	0.00**	0.00	0.00	0.00*
	INFL	0.00	0.01	-0.02	0.01	0.01	0.20
	CA	0.08***	0.04	-0.01	0.03	-0.03	0.06
	PB_GDP	0.01	-0.03	0.03	0.29**	0.06	0.38
	RES	0.01	0.03	0.00	-0.01	0.03*	0.00
	REER	0.00	-0.01	0.01	-0.01	-0.01	-0.01
	CR	-0.01	0.00	-0.01	-0.01	-0.01	0.00
Global	VIX	0.01	0.02	0.02	0.00	0.02	0.01
	US3M	0.14	0.02	-0.07	0.00	-0.07	-0.36*
	WG	-0.02	0.05	-0.04	0.06	0.23	0.02
Categorical	ZE	2.18***	-11.38***	27.11***	12.07***	4.54***	18.50***
	REGION	1.93***	2.03***	6.39***	2.31***	-1.74**	2.37*
	EME	-9.82***	-17.12***	23.36***	(omitted)	(omitted)	(omitted)
	IMF	-1.02***	-0.45***	-1.15***	-0.66***	-0.31***	-0.41**
N		3318	2171	1147	2025	1299	726
R2		0.92	0.95	0.94	0.91	0.94	0.95

*p < 0.05; **p < 0.01; ***p < 0.001; Pooled OLS estimations. Dependent variable: nonlinear transformation of RATING (logistic function once the scale of rating is transformed from 0 to 1); All the explanatory variables (except the categorical variables) are lagged by one period; DRATING_n: binary dummy, DRATING_n = 1 if the country has been downgraded and zero otherwise, DRATING_p = 1 if the country has been upgraded and zero otherwise, The remaining explanatory variables are: (1) GDP_growth: GDP growth in annual rate; (2) GDP_f: Forecasted GDP; (3) GDP_pc: GDP per capita; (4) INFL: Inflation rate; (5) CA: Current account as percentage of GDP; (6) PB_GDP: Public balance on GDP; (7) RES: Foreign reserves over GDP; (8):REER: Real effective exchange rate; (9) CR: Total credit on GDP; (10) VIX: VIX index; (11) US3M: US three-month interest rate; (12) WG: World growth; (13) ZE dummy variable. ZE =1 if the country belongs to the Euro zone; (14) Region: Nominal categorical variable that goes from 0 to 4; (15) EME: Dummy variable. EME=1 if the country is an emerging one; (16) IMF: Presence of IMF program; See Appendix B for further details on the definitions of the variables; Intercept and time controls included but not reported; We date the beginning of the crisis in 2008:Q3

Table 6: Estimates of the model with interactions of the domestic variables with DRATING_p, which is 1 if the country registers an upgrade and 0 otherwise, for the total sample and for the EMEs.

		Total sample			**EMEs**		
		Total sample	Pre-crisis	Post-crisis	Total sample	Pre-crisis	Post-crisis
	DRATING_n	-1.10***	-0.49*	-1.15***	-0.81**	-0.55*	-1.72***
	DRATING_p	-0.64	-0.78	0.02	-0.37	-0.81	2.26
Domestic	GDP_growth	0.01	-0.06***	0.04**	-0.04*	-0.07**	-0.01
	GDP_f	0.35***	0.28***	0.53***	0.40***	0.25***	0.80***
	GDP_pc	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	INFL	-0.07***	-0.05***	0.06*	-0.06***	-0.04***	0.08*
	CA	-0.09***	-0.10***	-0.09***	-0.13***	-0.15***	-0.06***
	PB_GDP	-0.01	0.03	-0.10***	0.04	0.02	0.07
	RES	0.01***	0.04***	0.00	0.01***	0.04***	0.00
	REER	0.05***	0.06***	0.00	0.06***	0.07***	0.01
	CR	-0.01***	-0.01***	-0.03***	-0.01	0.00	-0.01
Domestic * DRATING_p	GDP_growth	0.07	-0.01	-0.04	0.01	-0.01	-0.09
	GDP_f	0.07	0.13	0.05	0.07	0.15	-0.07
	GDP_pc	0.00	0.00	0.00	0.00	0.00	0.00
	INFL	-0.02	-0.03	0.08	-0.03	-0.03	0.04
	CA	-0.05*	-0.04	-0.05	-0.03	-0.03	-0.03
	PB_GDP	0.12**	0.05	0.06	0.02	0.03	-0.02
	RES	0.01*	0.00	0.01***	0.00	0.00	0.00
	REER	0.00	0.01	0.01	0.01	0.01*	0.00
	CR	-0.01	0.00	-0.01*	0.00	0.00	0.00
Global	VIX	0.01	0.01	0.02	0.01	0.01	0.01
	US3M	0.14	0.04	-0.09	0.02	-0.03	-0.39*
	WG	-0.02	0.04	-0.07	0.06	0.22	-0.03
Categorical	ZE	2.21***	-11.26***	26.19***	11.99***	5.07***	16.43***
	REGION	1.96***	2.11***	6.43***	2.16***	-1.69**	1.46
	EME	-9.97***	-17.52***	22.86***	(omitted)	(omitted)	(omitted)
	IMF	-1.04***	-0.44***	-1.14***	-0.68***	-0.32***	-0.37*
N		3318	2171	1147	2025	1299	726
R2		0.91	0.95	0.93	0.90	0.94	0.94

*p < 0.05; **p < 0.01; ***p < 0.001; Pooled OLS estimations. Dependent variable: nonlinear transformation of RATING (logistic function once the scale of rating is transformed from 0 to 1); All the explanatory variables (except the categorical variables) are lagged by one period; DRATING_n: binary dummy, DRATING_n = 1 if the country has been downgraded and zero otherwise, DRATING_p = 1 if the country has been upgraded and zero otherwise, The remaining explanatory variables are: (1) GDP_growth: GDP growth in annual rate; (2) GDP_f: Forecasted GDP; (3) GDP_pc: GDP per capita; (4) INFL: Inflation rate; (5) CA: Current account as percentage of GDP; (6) PB_GDP: Public balance on GDP; (7) RES: Foreign reserves over GDP; (8):REER: Real effective exchange rate; (9) CR: Total credit on GDP; (10) VIX: VIX index; (11) US3M: US three-month interest rate; (12) WG: World growth; (13) ZE dummy variable. ZE =1 if the country belongs to the Euro zone; (14) Region: Nominal categorical variable that goes from 0 to 4; (15) EME: Dummy variable. EME=1 if the country is an emerging one; (16) IMF: Presence of IMF program; See Appendix B for further details on the definitions of the variables; Intercept and time controls included but not reported; We date the beginning of the crisis in 2008:Q3

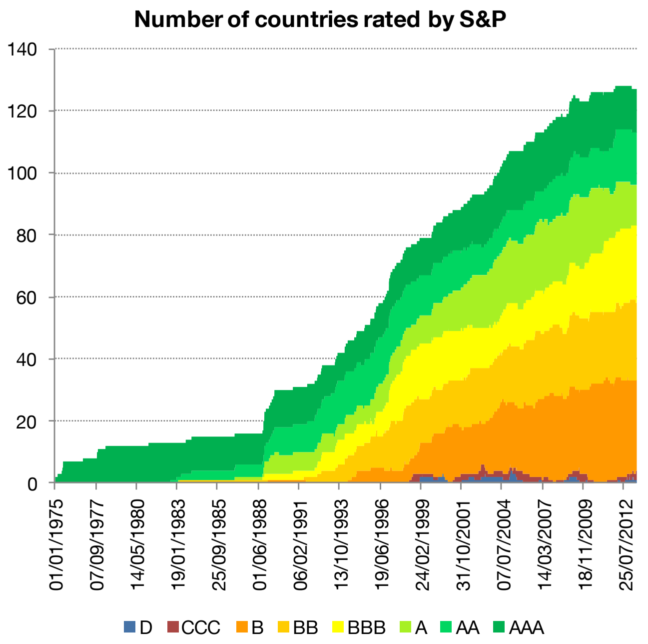
Table 7: Estimates of the model with interactions of the domestic variables with DRATING_n and DRATING_p for the total sample and for the EMEs.

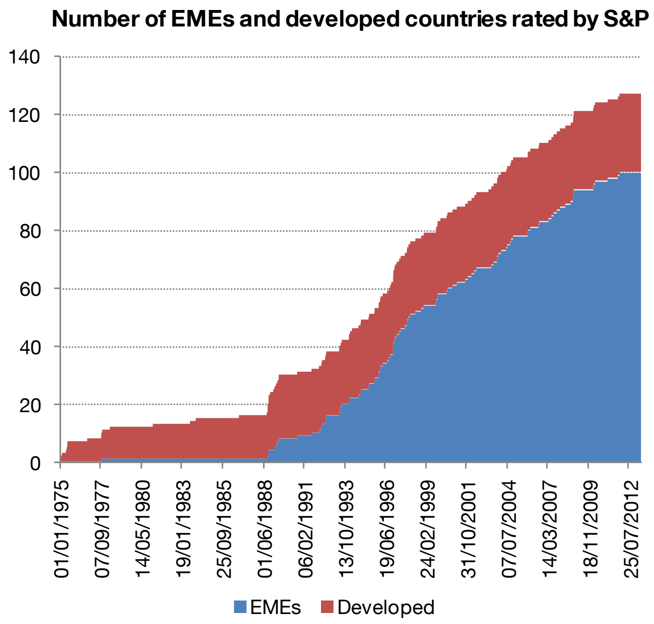
		Total sample			**EMEs**		
		Total sample	Pre-crisis	Post-crisis	Total sample	Pre-crisis	Post-crisis
	DRATING_n	-0.14	-1.31	-2.25	1.57	-0.23	-12.54
	DRATING_p	-0.60	-0.80	-0.11	-0.33	-0.81	2.03
Domestic	GDP_growth	-0.02	-0.08***	0.02	-0.05**	-0.09***	0.00
	GDP_f	0.41***	0.31***	0.60***	0.44***	0.29***	0.78***
	GDP_pc	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	INFL	-0.07***	-0.06***	0.04	-0.06***	-0.05***	0.06
	CA	-0.10***	-0.10***	-0.09***	-0.13***	-0.15***	-0.05**
	PB_GDP	-0.01	0.03	-0.11***	0.03	0.02	0.05
	RES	0.01***	0.04***	0.00	0.01***	0.04***	0.00
	REER	0.05***	0.06***	0.00	0.06***	0.07***	0.01
	CR	-0.00**	-0.01***	-0.03***	0.00	0.00	0.00
Domestic * DRATING_n	GDP_growth	0.18***	0.08	0.12*	0.11*	0.02	-0.26*
	GDP_f	-0.45***	-0.31**	-0.43	-0.23*	-0.30**	2.27
	GDP_pc	0.00**	0.00	0.00**	0.00	0.00	0.00*
	INFL	0.00	0.01	-0.02	0.01	0.01	0.20
	CA	0.08**	0.04	-0.01	0.03	-0.03	0.07
	PB_GDP	0.02	-0.03	0.04	0.29**	0.07	0.38
	RES	0.01	0.03	0.00	-0.01	0.03*	0.00
	REER	0.00	0.00	0.01	0.00	0.00	-0.01
	CR	-0.01	0.00	-0.01	-0.01	-0.01	0.00
Domestic * DRATING_p	GDP_growth	0.09	0.00	-0.04	0.02	0.00	-0.09
	GDP_f	0.04	0.10	0.04	0.06	0.13	-0.06
	GDP_pc	0.00	0.00	0.00	0.00	0.00	0.00
	INFL	-0.02	-0.03	0.10	-0.03	-0.03	0.06
	CA	-0.05*	-0.04	-0.05	-0.03	-0.03	-0.03
	PB_GDP	0.12**	0.05	0.05	0.03	0.03	-0.02
	RES	0.01*	0.00	0.01***	0.00	0.01	0.00
	REER	0.00	0.01*	0.01	0.01	0.01*	0.00
	CR	-0.01	0.00	-0.01**	0.00	0.00	0.00
H0: α(DRATING_n)=α(DRATING_p)	GDP_growth	0.114	0.283	0.049**	0.119	0.816	0.205
	GDP_f	0.002***	0.004***	0.159	0.024**	0.002***	0.171
	GDP_pc	0.004***	0.076*	0.003***	0.545	0.511	0.030**
	INFL	0.611	0.270	0.361	0.254	0.248	0.487
	CA	0.000***	0.053*	0.496	0.115	0.963	0.546
	PB_GDP	0.060**	0.394	0.843	0.023**	0.711	0.072*
	RES	0.845	0.107	0.481	0.228	0.087*	0.794
	REER	0.327	0.248	0.669	0.180	0.276	0.410
	CR	0.800	0.671	0.490	0.829	0.692	0.628
N		3318	2171	1147	2025	1299	726
R2		0.92	0.95	0.94	0.91	0.94	0.95

*p < 0.05; **p < 0.01; ***p < 0.001 for the estimates of the model. Pooled OLS estimations. Dependent variable: nonlinear transformation of RATING (logistic function once the scale of rating is transformed from 0 to 1); All the explanatory variables (except the categorical variables) are lagged by one period; DRATING_n: binary dummy, DRATING_n = 1 if the country has been downgraded and zero otherwise, DRATING_p = 1 if the country has been upgraded and zero otherwise, The remaining explanatory variables are: (1) GDP_growth: GDP growth in annual rate; (2) GDP_f: Forecasted GDP; (3) GDP_pc: GDP per capita; (4) INFL: Inflation rate; (5) CA: Current account as percentage of GDP; (6) PB_GDP: Public balance on GDP; (7) RES: Foreign reserves over GDP; (8):REER: Real effective exchange rate; (9) CR: Total credit on GDP; See Appendix B for further details on the definitions of the variables; Global and categorical variables, as well as intercept and time controls included but not reported; We date the beginning of the crisis in 2008:Q3. The hypothesis tests in H0 indicate the p-value of the Wald type test of the corresponding linear restriction and refer to significance at 1%, 5% and 10% level.

FIGURES

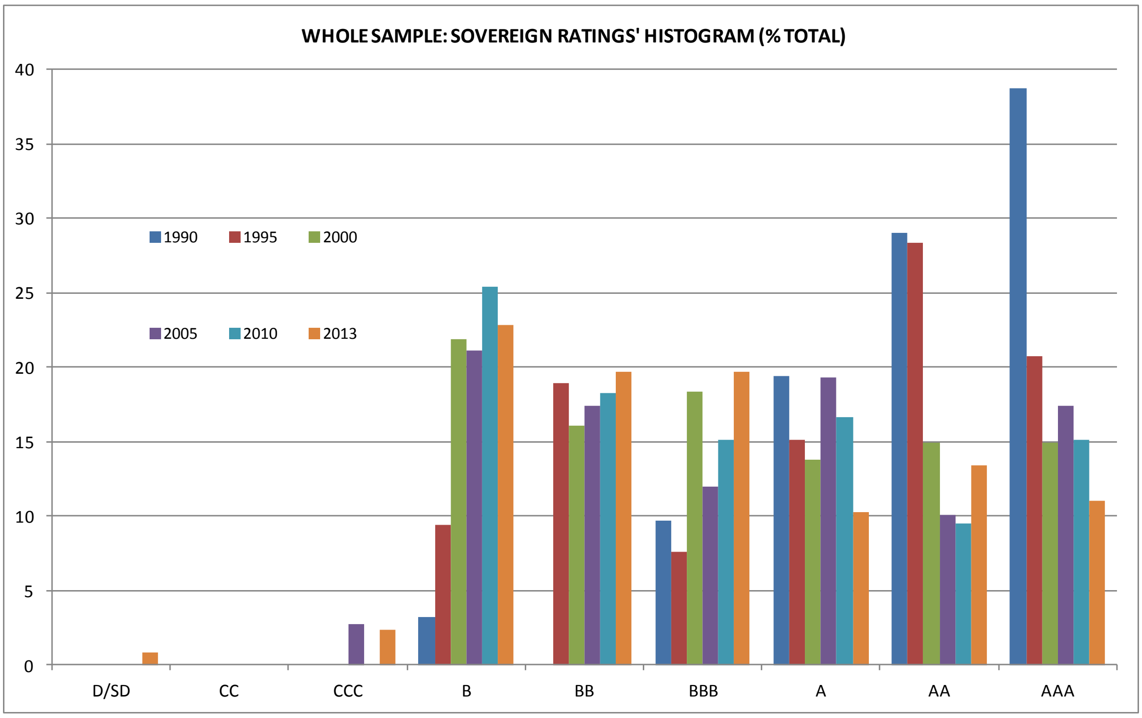
Figure 1: Number of countries rated by S&P by rating and by type (EMEs or developed countries).

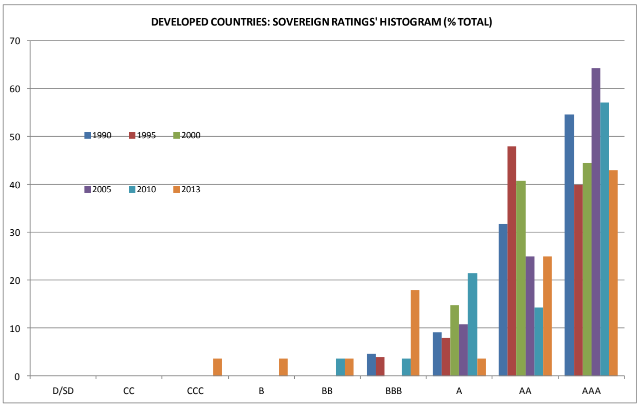




Notes: D denotes default. The 22 rating categories have been simplified to eight (including default). See Appendix B for more details.

Figure 2: Histograms of sovereign ratings





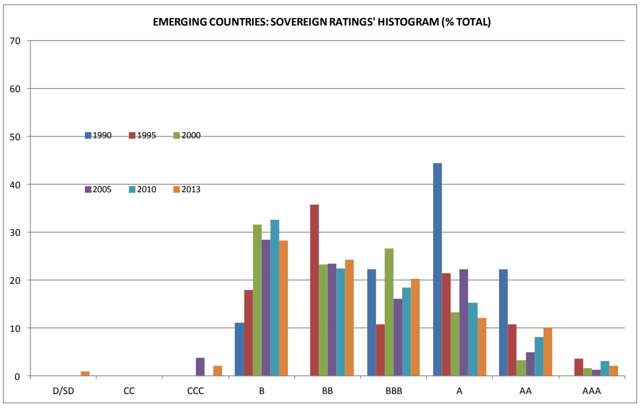
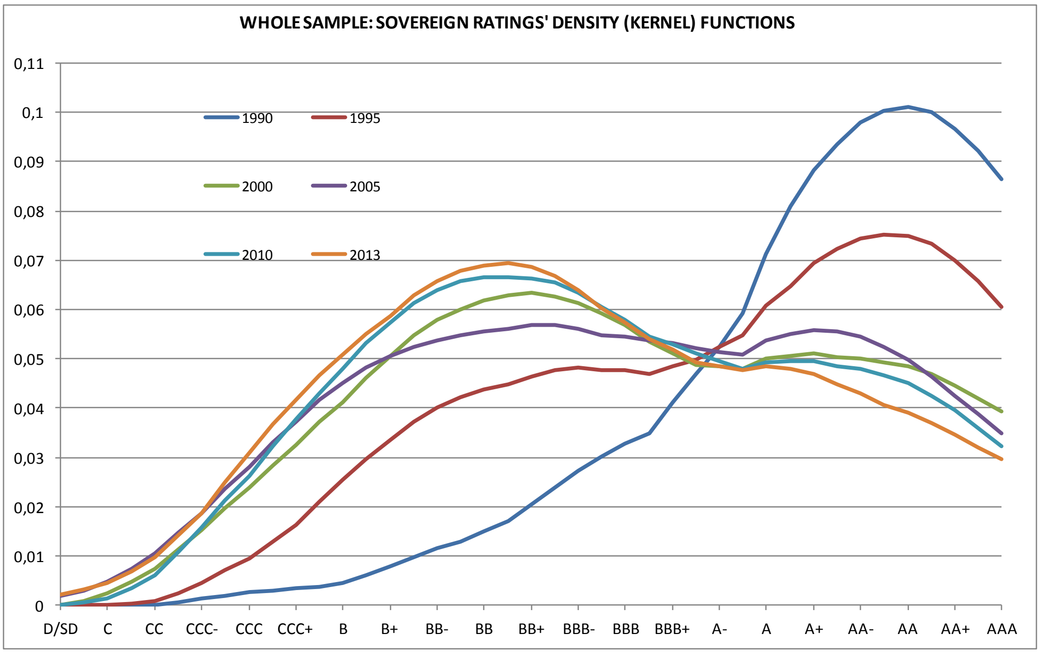
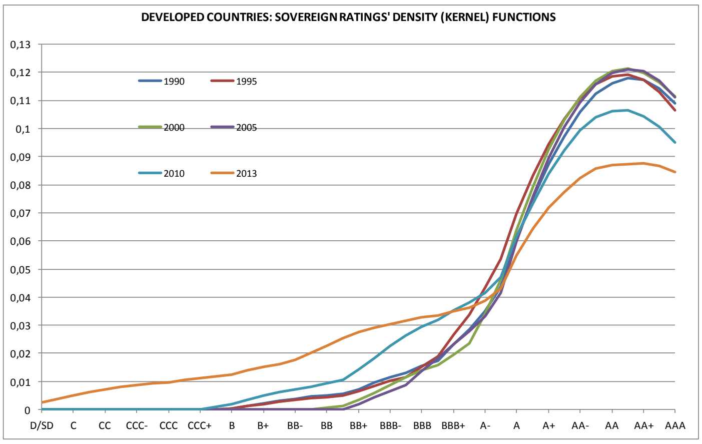
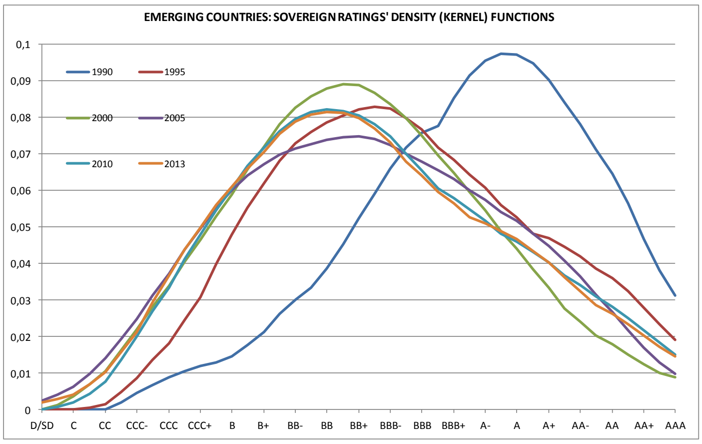


Figure 3: Kernel distributions and medians of sovereign ratings







	MEDIAN
1990	AAA
1995	AA+
2000	AA+
2005	AAA
2010	AAA
2013	AA+

	MEDIAN
1990	A-
1995	BB+
2000	BB+
2005	BB+
2010	BB+
2015	BB

Figure 4: aggregate sovereign ratings

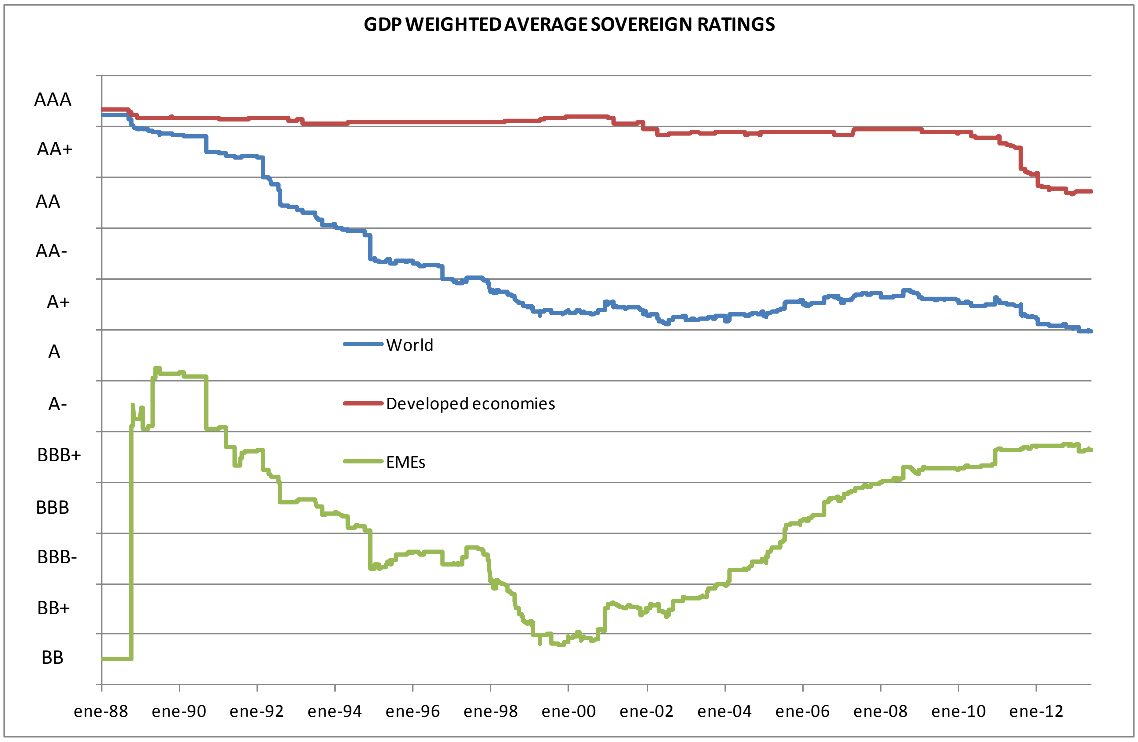
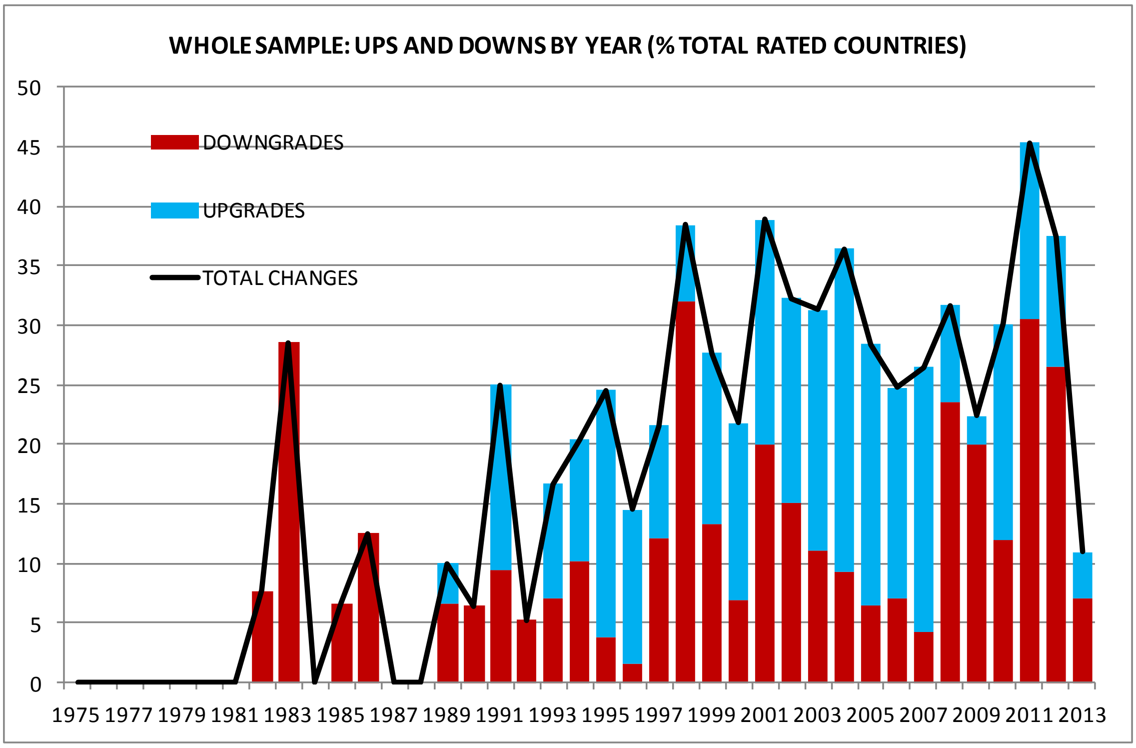
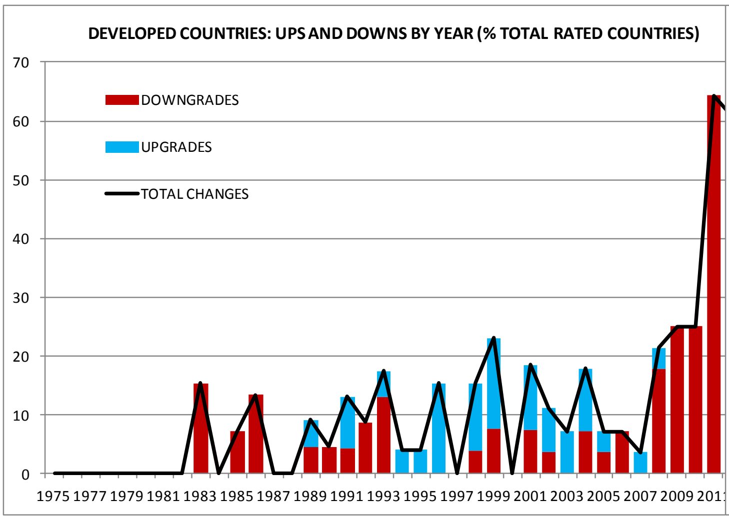


Figure 5: Number of rating upgrades and downgrades





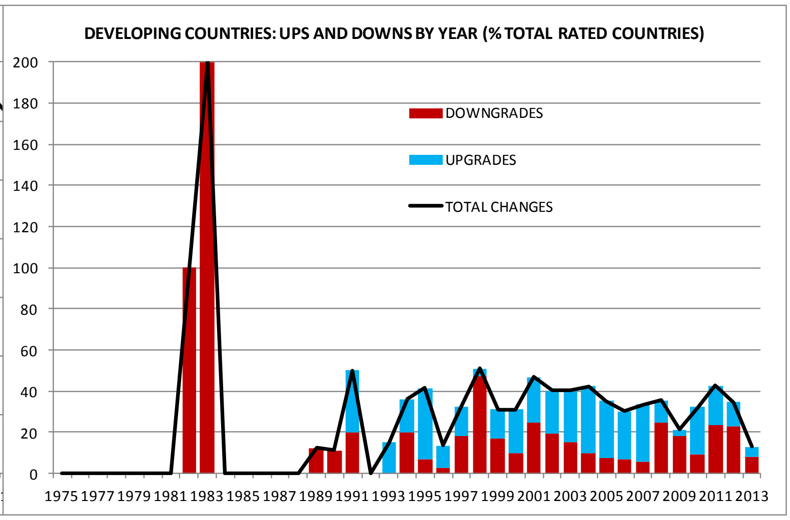


Figure 6: Characterizing rating cycles

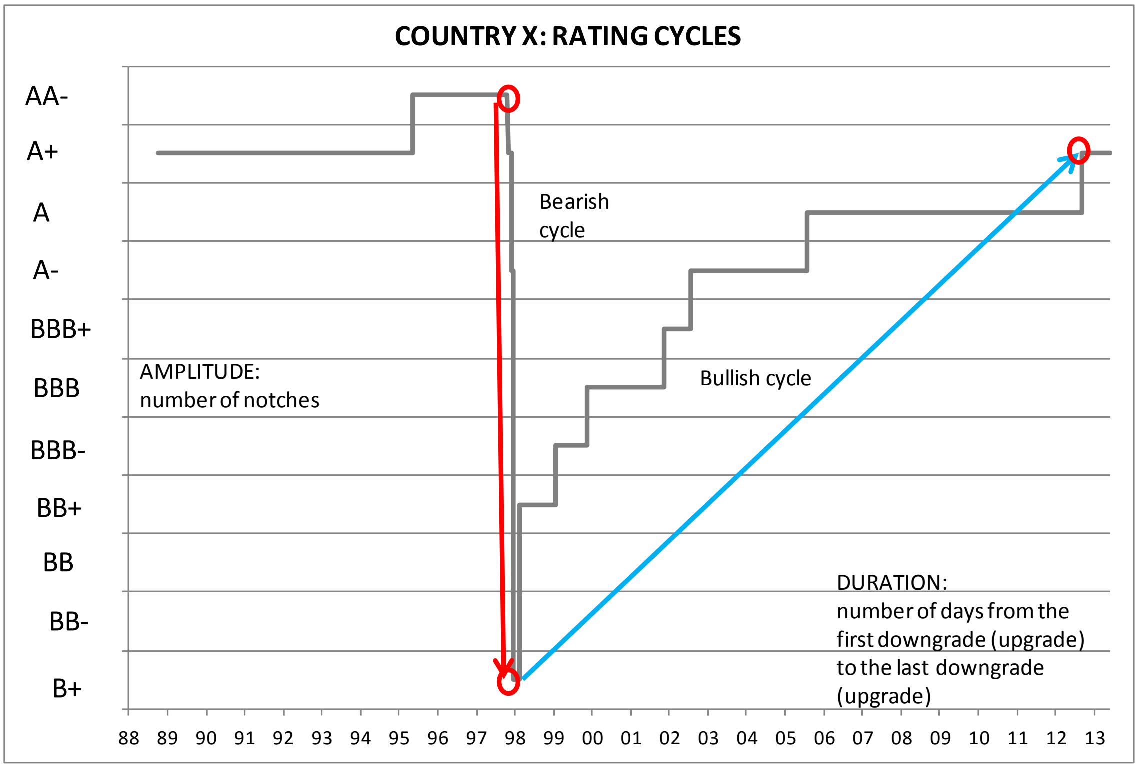


Figure 7: Rating cycles in relevant countries

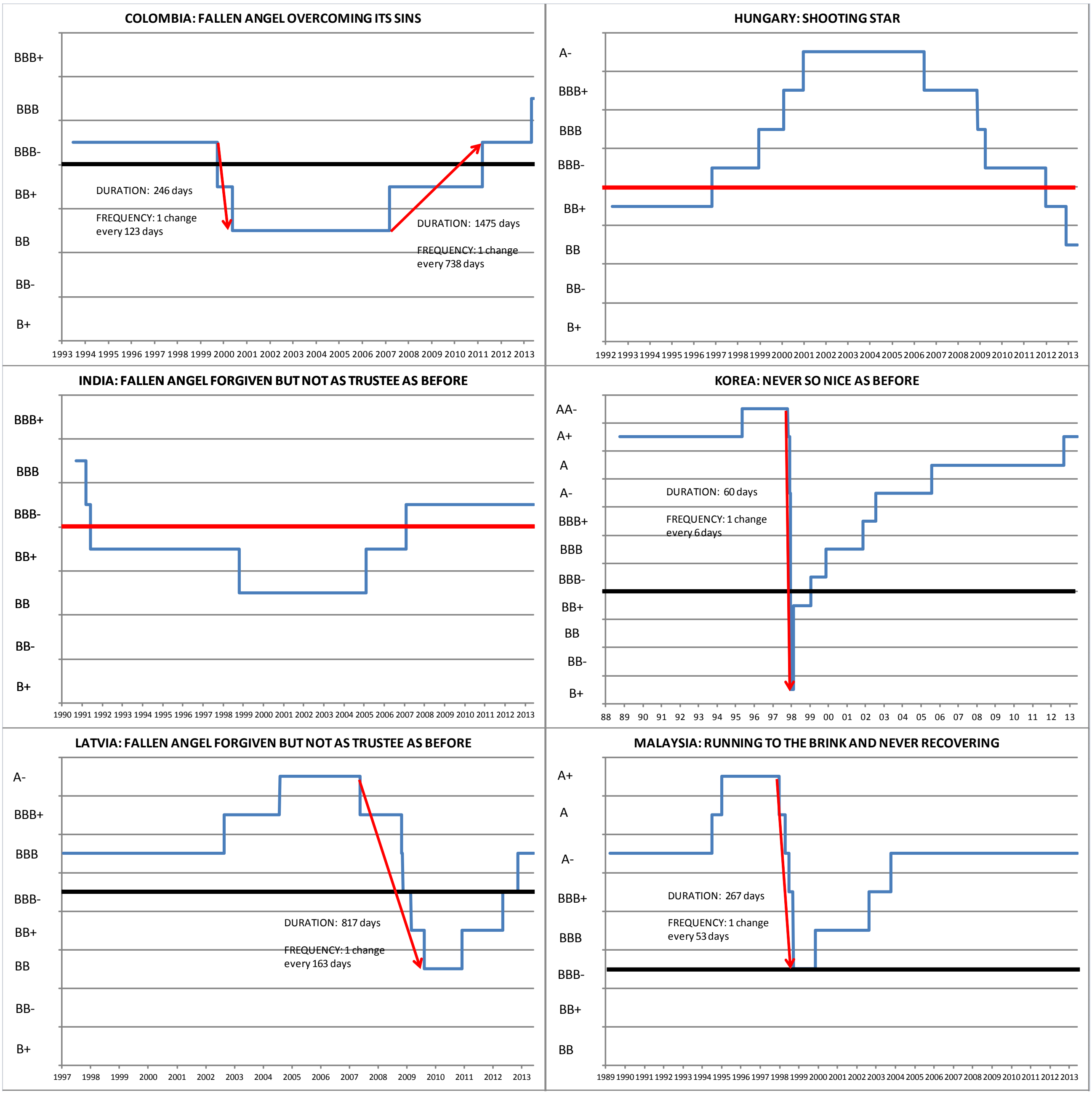


Figure 7 (contd.): Rating cycles in relevant countries

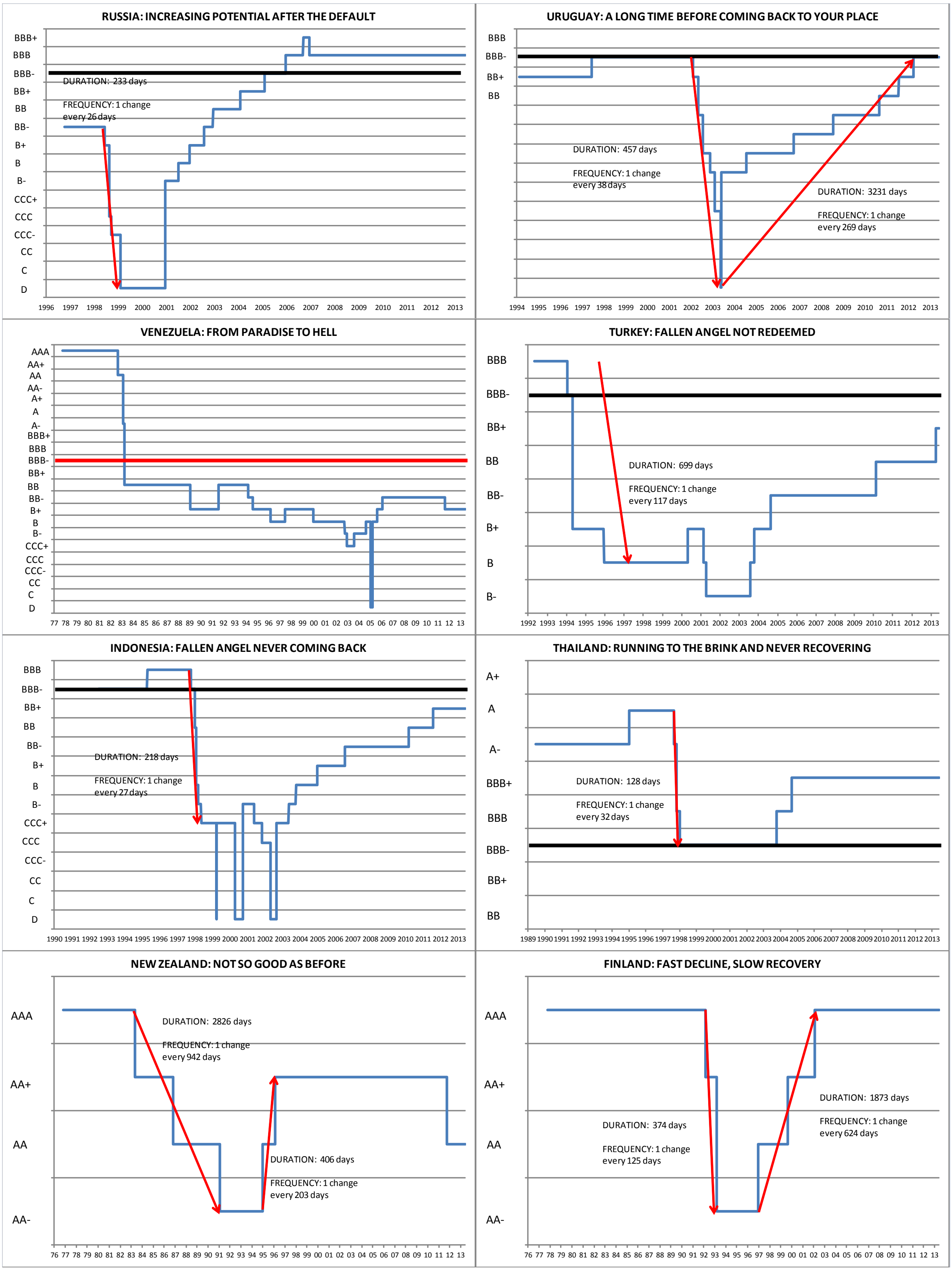


Figure 8: Linear scale of ratings and logistic transformation.