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Abstract

Changes in sovereign ratings are strongly asymmetric, as downgrades tend to be deeper and faster than upgrades. In other words, once a country loses its initial status it takes a long time to recover it. Using S&P data, we characterise "rating cycles" in terms of their duration and amplitude. We then study whether the agency reaction to new economic and financial domestic information also differs during upgrade and downgrade phases. Our results indicate that favourable fundamentals could be helpful for smoothing and slowing down the path of downgrades, whereas favourable fundamentals do not seem to accelerate the rating recovery.

Keywords: sovereign credit ratings, rating cycle, emerging countries, panel data model.

JEL classification: G24, C33.

Resumen

La evolución de los *ratings* soberanos es profundamente asimétrica, ya que las fases de bajadas de la calificación crediticia suelen ser más bruscas y de mayor intensidad que las de subidas. Dicho de otro modo, una vez que un país pierde su calificación inicial, transcurre un período prolongado hasta que logra recuperarla, si es que lo consigue. En este artículo se utilizan las calificaciones soberanas de Standard and Poor's para caracterizar la duración y la amplitud de los «ciclos de *rating*». Posteriormente, se analiza si la forma en que esta agencia incorpora la nueva información económica y financiera es distinta en los períodos de rebajas del *rating* y respecto de los de incrementos. Los resultados muestran que, mientras que la mejoría de los fundamentos económicos puede contribuir a suavizar y reducir la velocidad de las bajadas de calificación, dicha recuperación no parece acelerar la senda de subidas.

Palabras clave: *ratings* soberanos, ciclos de *rating,* economías con mercados emergentes, modelos de datos de panel.

Códigos JEL: G24, C33.

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. Upgrade moves result from favorable signals in the credit outlook, whereas downgrades stem from unfavorable indicators. This permanent updating of the credit ratings is precisely one of the reasons why financial markets rely on agencies (Cantor and Packer, 1994). 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.

Despite their importance, the agencies do not provide enough detail neither on the ratings determinants nor on their rating procedure (Mora, 2006), although some recent regulatory initiatives are trying to enhance the agencies' transparency.[1] In this article we focus on Standard & Poors (S&P onwards) rating decisions and analyze how this agency updates 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.

[1] In this sense, the EU Commission launched a regulatory reform of rating agencies on January 2013. While the EU regulatory framework for credit ratings already contains measures on disclosure and transparency, further measures such as the access to more comprehensive information on the data and the reasons underlying rating variations are needed. Although from 2013 on rating agencies are providing more methodological information (for instance, S&P, 2013), the final decision on rating variations is not exclusively linked to those models. The own rating agencies admit this fact (S&P, 2013): "These criteria represent the specific application of fundamental principles that define credit risk and ratings opinions. Their use is determined by issuer or issue-specific attributes as well as S&P's Ratings Services' assessment of the credit and, if applicable, structural risks for a given issuer or issue rating".

[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".

The number of countries that have already completed a rating cycle is rather small, and they are basically emerging countries (EMEs onwards).[3]

Rating cycles are characterized by their strong asymmetries, as their 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 periods tend to be shorter 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 described by the so-called financial cycle (see, for instance, Aizenman et al, 2013).

Given the above mentioned asymmetries in the ratings evolution, one possible interpretation could be that those signals that the agencies use to update 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?[4] There is some empirical evidence that, broadly speaking, has concluded two different results. On the one hand, the less extended view supports the adequacy of 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.

On the other hand, most 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 deduce that rating agencies, which previously failed to predict the arrival of the

[3]Our country classification between developed and emerging countries is in line with that of MSCI. We classify Korea, Latvia and the Czech Republic as EMEs, although the IMF does not consider these countries as EMEs. In our analysis, high income countries like Bermuda, Oman or Qatar are also EMEs. Our classification does not change throughout the sample period.

[4]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 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.

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, so that ratings are adjusted only when there is a sufficiently large divergence of predicted ratings from assigned ratings. 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 between accuracy and stability faced by the agencies (Cantor and Mann, 2006).[5] 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).

Most of the empirical literature on the adjustment of credit ratings to fundamentals focuses on financial crisis periods, 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 smoothed and, as in downgrade periods, are adjusted with a certain lag (Kiff et al., 2013).

The main objective of this paper is twofold. First, we describe the S&P ratings' evolution for a broad sample of countries to confirm the presence of asymmetries in the cycle, that is, if downgrade phases are faster and shorter than recovery periods. Second, once we confirm this evidence empirically, we try to disentangle the determinants of this different behavior of

[5]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).

S&P ratings in both upgrade and downgrade periods by means of a sample of 67 countries, where 43 of them are EMEs. 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 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 path.[6] Our findings are relevant to enhance the understanding of the performance of rating agencies and the interpretation of their signals to the markets. This kind of analysis could also be useful to infer some lessons about how future ratings recovery in the European peripheral countries would be 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 S&P assigns a sovereign debt rating. Throughout the paper, we are going to use exclusively the ratings of this agency so as to not mix the data sources that could lead to measurement errors. This is a non-trivial issue as, despite the interdependence of rating actions of the three major agencies, their credit rating models are different (Hill et al., 2010).[7] In particular, S&P tends to be less dependent on other agencies and it provides the lowest and more volatile ratings among the three major ones (Alsakka and ap Gwilym, 2010). The choice of S&P is also based on the data availability for a higher number of countries and a larger period, which in our data description runs from January 1975 to May 2013.[8] From 1975 the number of rated countries has gradually increased from two countries, namely the US and Canada,

[6] Our results are in line with the theoretical papers by Bar-Isaac and Shapiro (2013) and Opp et al. (2013), who state that agencies tighten their ratings standards and accuracy during economic downturns.

[7] Besides, Cantor and Packer (1996) conclude that sovereign ratings exhibit more discrepancies between agencies than corporate ratings.

[8] See S&P (2013) for a detailed description of the methodology used by this agency.

to 127 economies in 2013, 100 EMEs and 27 developed ones (see Figure 1, right-hand plot). Throughout this section we describe S&P sovereign ratings on a daily basis from 1975 and for the whole set of rated countries. The complete country sample is enumerated in the Appendix A.

From 1975 to 1988 the sample was dominated by AAA rated developed countries.[9] From that year onwards EMEs were gradually evaluated, which explains the higher range of ratings since that date (see Figure 1, left-hand plot). Thus, whereas in 1990 rating categories from AA- to AAA accounted for 67.7% of the total sample, in 2013 this percentage diminished to 24.4% as a result of the rating evaluation of EMEs and the downgrade of several developed countries. On the contrary, during this period the percentage of EMEs rated above AA- also diminished (from 22% in 1990 to 12% in 2013). Finally, also confirming the higher spectrum of rating categories towards lower ratings, the countries rated above BBB-, the category who marks the investment grade status, decreased from 97% in 1990 to 54% in 2013. In the same line, Kernel estimations for the complete rating range (Figure 2) also pointed to a change in the probability density functions throughout time, as in 2013 ratings were more concentrated in intermediate categories (from BB- to BBB+) than in 1995 or 2000,[10] due to an increase in rated EMEs,[11] and to a increase of density mass below AA- in developed economies. That is, former safest assets scaled back, as illustrated by the fact that from 2005 to 2013 the median rating fell from BBB+ to BBB-, as developed and EMEs sovereign assets became more risky (from AAA to AA+ and from BB+ to BB respectively).

As a first evidence of the presence of asymmetries in the upward and downward rating paths, Table 1 presents the rating variations from 1975 to 2013. Given the evolution of developed countries, where downgrades represent 74% of total variations, the total country sample exhibits a higher number of downgrades than that of upgrades (53.1%). In EMEs, upgrades predominated by a narrow margin (52.3% of total changes). Most rating variations of developed countries are clustered between AAA and AA, whereas in EMEs most changes take place around B to BB. Finally, rating changes of more than three notches in a unique announcement are practically

[9]In the 70s the rating scale did not include rating modifiers.

[10]BBB- is the rating that signals the investment grade status. Most investment funds and pension funds are not allowed to invest in asset rated below this category, so that falling below investment grade could trigger huge movements in its the price and interest rate.

[11]Note that the most frequent initial assigned rating, for developed economies is AAA (68.3%), where the range of first ratings is relatively narrow (from BBB (Greece) to AAA), whereas for EMEs it is B+ (19.2%) with a range that comprises all rating categories (from SD (Ecuador in July 2000) to AAA (Venezuela in October 1977).

non-existent. These severe rating variations usually correspond to countries that fall to the category of default from already low ratings, and are massively upgraded once the default is solved.

Next, we characterize the main features of what we denominate “rating cycle”. As for most economic variables, rating cycles can also be described in terms of their duration and amplitude. For illustrative purposes, Figure 3 represents both measures for a hypothetical country X. In this framework, the duration is the number of days from peak to trough and from trough to peak, that is, the downgrade and the upgrade phase, respectively, whereas the amplitude is the number of notches in both periods. We consider that both measures run from the day of the first increase (or decrease) of the rating to the day of the last increase (or decrease). The evolution of the rating of country X represents our a priori assumptions on asymmetries in line with the previous empirical literature. Thus, regarding duration, downgrade periods would be shorter than upgrade periods, which indicates how long does it take to recover the rating. With respect to amplitude asymmetries, at the end of the cycle the rating does not necessarily reach its initial level.

To check if S&P ratings fulfill country X rating pattern, Table 2 reports some summary statistics of the rating cycles for a selected country sample, namely the G-20, which represents around 75% of world GDP, as well as a sample of additional developed countries and EMEs. Several conclusions can be raised from this table. First, the countries with at least one complete cycle—that is, from trough to peak and from peak to trough—mainly correspond to EMEs and non-core euro economies, like Spain, Portugal or Greece. Figure 4, which represents the weighted rating averages for the complete sample of EMEs and developed countries, evidences the presence of at least a complete cycle in most EMEs, whereas developed countries are still on average amid the downward phase (although at a different stage depending on the country). Besides, the low number of upgrade and downgrade periods illustrates the strong correlation of ratings, that is, downgrades tend to be followed by downgrades and vice versa. To put it another way, sovereign ratings exhibit a strong inertia (Mora, 2006).

Second, Table 2 also shows that in those countries with at least one complete cycle, its duration is strongly asymmetric, as the length during recoveries is much longer than during rating falls, with very few exceptions. In other words, once a country loses their rating level it takes a long period to recover it. Besides, amplitudes are also asymmetric, as the number of notches from peak to trough tends to be higher than in the recovery phase for most countries.

The agency changes ratings more frequently once the country has been downgraded for the first time. Indeed,very few countries have been able to recover their previous status after a downgrade phase, that is, the difference in amplitudes between downward and upward periods is positive in most countries. To illustrate this point, 40% of the rated countries had, at the end of May 2013, a lower sovereign rating than the initially assigned by the agency, whereas only 29% improved their first qualification. Besides, of those economies that started being evaluated above investment grade (BBB-) and fell below it, only Russia and Colombia recovered this status even improved this qualification.[12]

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

What drives this asymmetric ratings path? As described in the introduction, one interpretation is that sovereign ratings do not immediately react to an improvement of economic fundamentals. In this section we develop a panel data model to analyze the main determinants of the rating cycle and to try to capture the apparent asymmetry of their reaction to fundamentals.

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).[13] 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,

[12] Of those countries that lost their investment grade status, Uruguay reach again the BBB-, whereas India, Korea and Latvia were able to recover the investment grade status although they never recovered their previous maximum previous rating.

[13] 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.

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, 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.[14], [15] 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.[16] See Appendix B 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.[17]

3.2 Determinants of sovereign rating 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 t 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,

$$DRATING\_n_{it} = \begin{cases} 1 & \text{if} \qquad RATING_{it} - RATING_{it-1} = -1 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

and

[14] 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.

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

[16] 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.

[17] 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.

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

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, the rating agency might try to overreact once the downgrading phase has begun.

Figure 5 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 5 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, in EMEs upgrades dominate 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 rating changes, either upgrades or downgrades, have become more frequent as time goes by. For example in the 90s the the average rating variations were 12 changes per year, and this figure increased to 31 changes per year in 2000-2009 and to 40 per year in 2010-2013.[18]

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), Mora (2006) or Afonso et al. (2011). The whole set of control variables, which is relatively standard, can be classified in

[18] There are alternative variable definitions to show previous sovereign upgrades and downgrades. For instance, in preliminary versions of our analysis we used dummies that were 1 if the country were downgraded or upgraded in the previous year to measure a ratings variation trend. Nevertheless, the results, which are available upon request, do not show significant differences with the present version. We have not considered either rating changes greater than one notch.

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 balance on GDP and (8) public debt on GDP, which proxy the solvency of the economy as it allows to evaluate the countrys 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 and the public debt, where a negative sign is expected.

Second, we also use three 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,[19] 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 is 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).

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 C for further details). A negative coefficient would indicate that the presence of such programs constitutes a negative signal for investors.[20]

[19] For instance, Koopman et al. (2009) use a set of variables related to bank lending conditions to analyze corporate ratings in the US. Aktug et al. (2013), employ alternative banking sector characteristics, such as banking sector size and concentration or liquidity of bank assets, to fit an ordered probit model for the S&P sovereign ratings.

[20] Given their complexity , we do not take into account the outlook and watch signals as additional explanatory

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.[21] 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.[22]

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+ are much different 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

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variables, although these are strong predictors of rating changes (Hill et al., 2010). These variables act as early warnings of upgrades and downgrades and are more frequent than rating changes. For the sake of the dataset simplicity, we have disregarded domestic financial variables related to banking sector characteristics, such as banking sector size and concentration or liquidity of bank assets.

[21] 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).

[22] 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.

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,

$$f(RATING_{it}) = \frac{1}{1 + e^{-RATING_{it}}} \qquad (3)$$

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 6 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. Finally, Table 3 shows the pairwise correlations of the nonlinear transformation of the sovereign rating and the complete set of explanatory variables of our analysis.

4.2 Empirical model

All in all, the baseline model is,

$$Y_{it} = \eta_i + \alpha_t + \sum_j \beta_j X_{j,it-1} + \sum_k \beta_k Z_{k,it-1} + \varepsilon_{it}, \qquad (4)$$

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,

$$Y_{it} = \eta_i + \alpha_t + \sum_j \beta_j X_{j,it-1} + \sum_j \beta_j^n DRATING\_n_{it-1} X_{j,it-1} + \sum_k \beta_k Z_{k,it-1} + \varepsilon_{it}, \qquad (5)$$

and

$$Y_{it} = \eta_i + \alpha_t + \sum_j \beta_j X_{j,it-1} + \sum_j \beta_j^p DRATING\_p_{it-1} X_{j,it-1} + \sum_k \beta_k Z_{k,it-1} + \varepsilon_{it} \qquad (6)$$

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,

$$\begin{aligned} Y_{it} &= \eta_i + \alpha_t + \sum_j \beta_j X_{j,it-1} + \\ &\sum_j \beta_j^n DRATING\_n_{it-1} X_{j,it-1} + \sum_j \beta_j^p DRATING\_p_{it-1} X_{j,it-1} + \sum_k \beta_k Z_{k,it-1} + \varepsilon_{it}. \end{aligned} \tag{7}$$

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,

$$H_0 : \beta_j^n = \beta_j^p \tag{8}$$

Note that in most of these model specifications 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 baseline model: Some preliminary results

Table 4 reports the estimates of the basic model for the total sample, as well as for the pre-crisis and post-crisis period. We date the beginning of the crisis in 2008:Q3.[23] One aspect that

[23]We consider the pre-crisis and post-crisis period in reference to the ongoing global crisis, which blown up on 2008:Q3, and not to the idiosyncratic crisis in several EMEs such as the Asian or the Russian crisis. During the present crisis around 40% of the rated countries were downgraded, which represents a higher proportion than that of any other idiosyncratic crisis. For instance, only 20% of the economies were downgraded during the Asian crisis.

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 or non-significant. This result is in line with the S&P ratings' characterization 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, which can lead to crisis amplification. On the contrary, this result does not hold for upgrades, as past upgrades incentive future upgrades to a lesser extent. One possible explanation 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.[24]

Table 4 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. Once we check the similarity of both estimates for the baseline model, we discard the ordered logit procedure in the next steps of the analysis. The reason for this is that the use of interactions among explanatory variables in the following specifications leads to several identification problems that prevents the use of an ordered logit model. This problem comes a a result of the 21 different categories of the rating in the ordered logit estimation.

Table 4 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 less relevant than other macroeconomic indicators, in line with Mora (2006) or Cantor and Packer (1996). On the contrary, the high and significant coefficients of the expected GDP (GDP_f) underline the importance of this type of leading indicators for S&P. Surprisingly, this explanatory variable has been barely used in the literature,[25] probably as some authors conclude that rating agencies do not react to expected changes in

[24] As a robustness check we have also considered an alternative definition of DRATING_n and DRATING_p in which the variables are 1 if the country was downgraded or upgraded, respectively, during de previous year. The main results are quite similar and are available upon request.

[25] As far as we know, growth expectations have been used as explanatory variable in S&P internal models but not in the other two major agencies.

observed variables (Monfort and Mulder, 2000). However, 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 post-crisis sample is significant. However, as in our subsequent analysis, global variables will only play a minor role as time controls. Finally, categorical variables estimates are also rather similar following both methods. The coefficient of the dummy variable for emerging countries (EME) is negative 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.[26]

The sings of the explanatory variables are as expected with few exceptions. For instance, the estimated coefficient for the current account on 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), which in principle is also expected to be positive, in some cases becomes negative. 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 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, RES and REER 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 S&P seems 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 5 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

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

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 or the stock of reserves 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 6 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 6 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 6 onwards we only report the estimates obtained by the pooled OLS model.[27] 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, it can be interpreted that 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 GDP_growth and GDP_pc.[28] 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

[27] 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.

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

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.[29] 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 negative estimate of PD*DRATING_n for the total sample indicate that higher debt accelerated downgrades, particularly in the post-crisis period. 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, our findings related to the existence of previous downgrades by S&P 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 turbulence (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 7 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 7 is that, in opposition to the previous exercise for DRATING_n in Table 6, interactions with DRATING_p are almost non-significant. For instance,

[29]Specifically, the coefficient for CA for the total sample of non-previously downgraded countries would be -0.08, whereas that of the previously downgraded is 0.03.

almost 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 S&P 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 (2009).

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). 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.

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

Table 8 reports the estimates of model (8) 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 (pre-crisis and total sample of EMEs) 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 for the total sample. 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 debt on GDP also matters, which signals the importance of a healthy fiscal balance to smooth the rating downgrade path. Finally, the current account balance on GDP seems to have also a significatively different impact in upgrade and downgrade periods.

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 S&P decisions 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 the rating agency 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, although they experience a dramatic recovery.

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 the agency to the macroeconomic developments is 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, which has strong implications as the sovereign rating determines the financing costs and the sustainability of the public debt paths.

Appendix A: Country sample of Section 2

Abu Dabi, Albania, Andorra, Angola, Argentina, Aruba, Australia, Austria, Azerbaijan, The Bahamas, Bahrein, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bermuda, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Fasso, Cambodia, Cameroon, Canada, Cape Verde, Chile, China, Colombia, Cook Island, Costa Rica, Croatia, Curaçao, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Fiji, Finland, France, Gabon, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Honduras, Hong Kong SAR, China, Hungary, Iceland, India, Indonesia, Ireland, Isle of Man, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea, Kuwait, Latvia, Lebanon, Liechtenstein, Lithuania, Luxembourg, FYR Macedonia, Malaysia, Malta, Mexico, Mongolia, Montenegro, Montserrat, Morocco, Mozambique, Netherlands, New Zealand, Nigeria, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Dubai, Romania, Russian Federation, Rwanda, Saudi Arabia, Senegal, Serbia, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Suriname, Sweden, Switzerland, Taiwan, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, United Kingdom, United States, Uruguay, Venezuela, Vietnam, Zambia.

Appendix B: Country sample of the panel data model

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

Appendix C: Definition of variables and data sources

- Ratings: Standard & 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: GDP growth rate. Source: IMF. Due to the lack of data for Oman, Pakistan and Qatar, we use industrial production for those countries instead.

• GDP_f: Forecasted GDP. Source: IMF. Average in each quarter of IMF's growth forecast for the next three or five years.

• GDP_pc: GDP per capita. Source: Oxford Economics, World Bank and National Statistics Offices. GDP per capita in PPP terms, billion USD.

• INFL: Inflation. Source: IMF and National Statistics Offices. CPI y-o-y change.

• CA: Current account on GDP. Source: IMF and National Statistics Offices.

• PB: Public balance on GDP. Source: Oxford Economics, EIU and National Statistics Offices.

• PD: Public debt on GDP. Source: IMF and National Statistics Offices.

• RES: Reserves on GDP. Source: IMF and National Central Banks. International Reserves (gold and Foreign Exchange) as a percentage of GDP

Financial domestic variables:

• REER: Real effective exchange rate. Source: JP Morgan and National Central Banks. Real Effective Exchange Rate, CPI-based, wide basket.

• CR: 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.

• US3M: 3-months US interest rate: Source. Datastream.

• WG: 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: 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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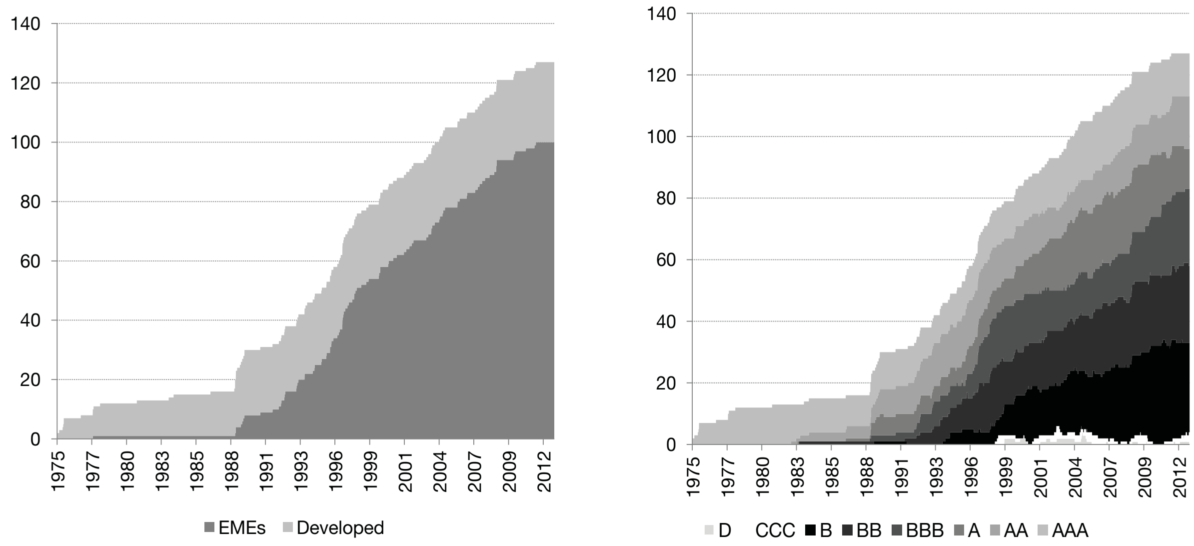
Figure 1: Number of countries rated by S&P by type (EMEs or developed countries)—left-hand plot— and by rating (right-hand plot)



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

Figure 2: Kernel density estimates for sovereign ratings.

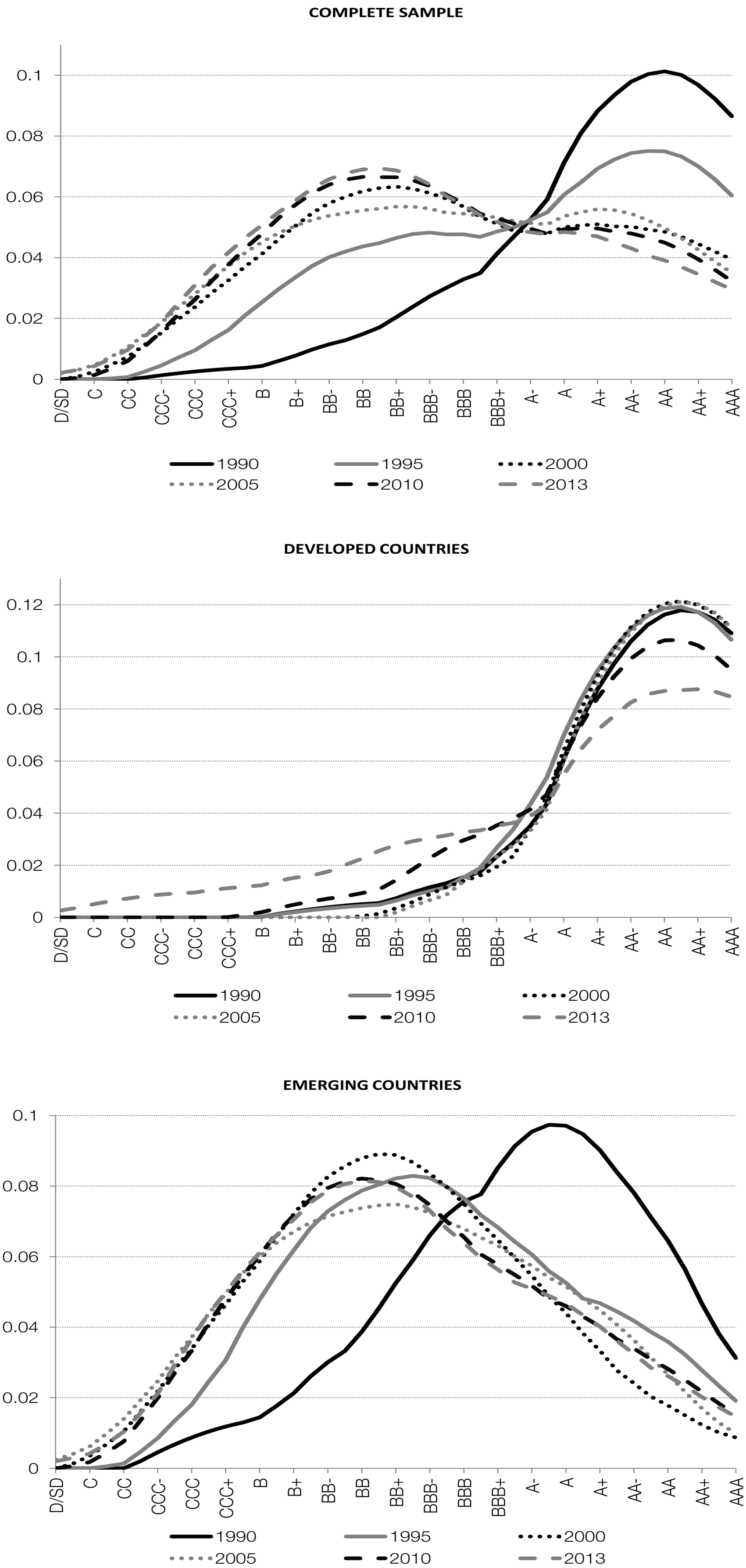


Figure 3: Rating cycle of “country X”.

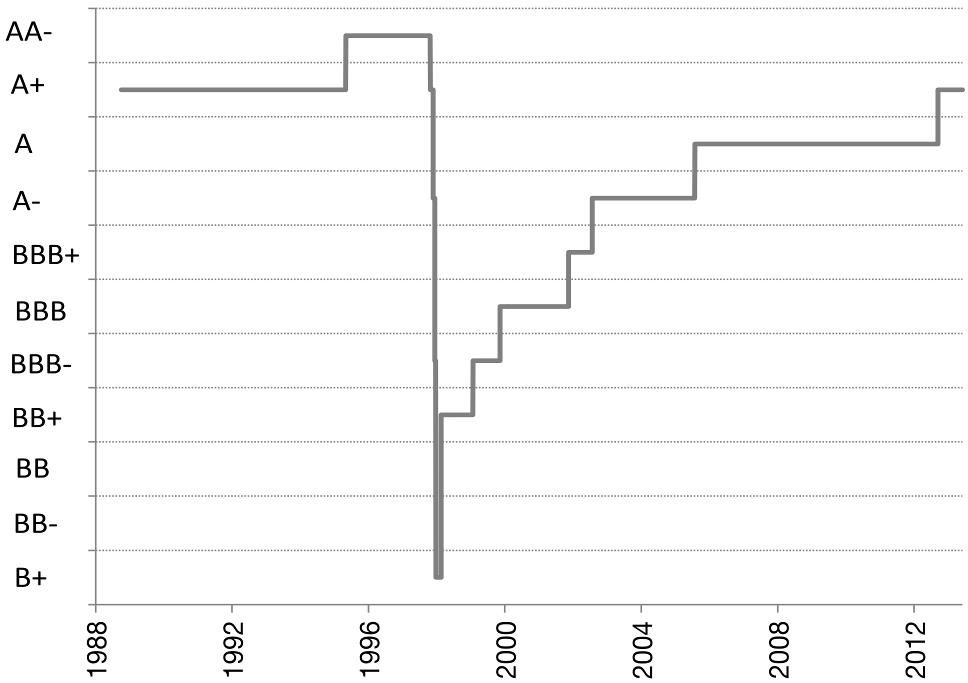


Figure 4: GDP weighted average sovereign rating.

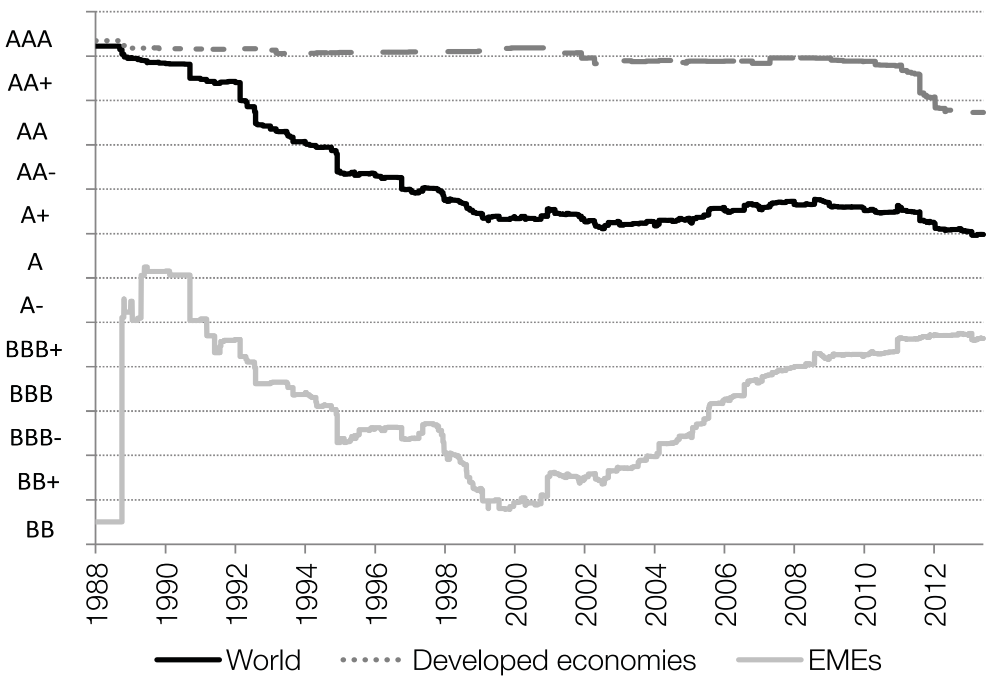


Figure 5: Number of rating upgrades and downgrades, $DRATING\_p$ and $DRATING\_n$, in EMEs and developed countries.

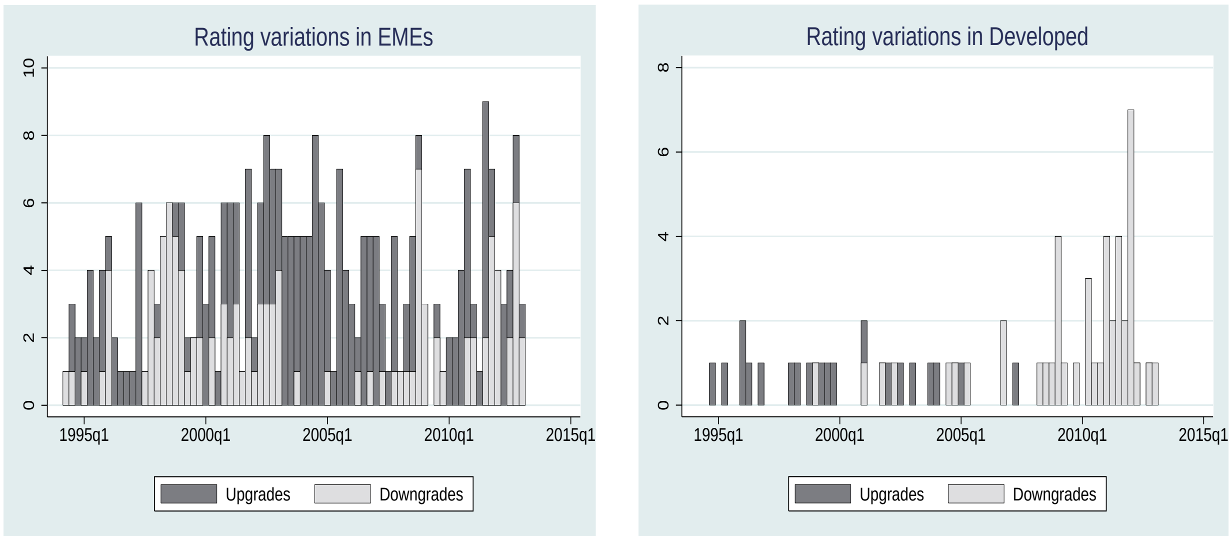


Figure 6: Linear scale of ratings and logistic transformation.

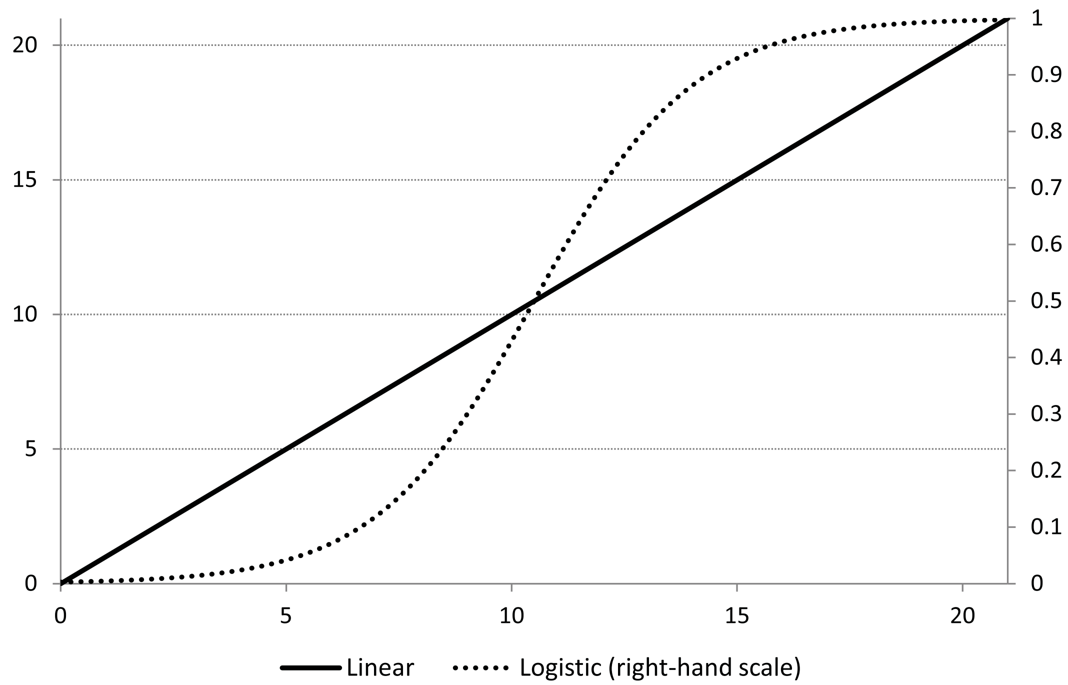


Table 1: Number of upgrades and downgrades from a rating (row) to a new one (column) over the sample period.

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

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	–

EMEs

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	–

Note: We have transformed the 22 rating categories of S&P, where the default is also included, to eight groups. D denotes default.

Table 2: Descriptive statistics of upward and downward rating phases.

	Mean duration (days)		**Mean amplitude (notches)**		**Number of cycles**	
	Trough-Peak	Peak-Trough	Trough-Peak	Peak-Trough	Up	Down
G-20:						
Argentina	489	221	8	−6	2	1
Australia	1375	1058	2	−2	1	1
Brazil	1622	–	4	–	0	2
Canada	–	–	–	–	0	0
China	2494	–	5	–	0	1
France	–	–	–	–	0	0
Germany	–	–	–	–	0	0
India	728	2787	2	−3	1	1
Indonesia	3009	631	11	−10	2	1
Italy	–	6892	–	−6	1	0
Japan	–	418	–	−3	1	0
South Korea	5322	60	9	−10	1	1
Mexico	2769	–	4	–	0	1
Russia	2097	233	14	−9	1	1
Saudi Arabia	3609	–	2	–	0	1
South Africa	3545	–	4	–	0	1
Turkey	3533	376	5	−4	2	1
United Kingdom	–	–	–	–	0	0
United States	–	–	–	–	0	0
Other countries:						
Greece	2076	2659	5	−17	1	1
Ireland	4375	735	4	−7	1	1
Portugal	2609	2394	3	−9	1	1
Spain	2075	1363	2	−9	1	1
Cyprus	–	625	–	−8	2	0
Hungary	1516	2354	4	−5	1	1
Uruguay	3231	457	12	−12	1	1
Colombia	2245	246	3	−2	1	1
Venezuela	920	1387	4	−6	3	1
EMEs	1865	876	4	−5	47	62
- LatAm	2150	955	5	−6	19	16
- Eastern Europe	1310	713	4	−4	11	21
- Developing Asia	1593	636	4	−5	11	14
- Other EMEs	2856	1365	3	−5	6	11
Developed countries	2386	1873	3	−6	15	9
- Euro Area	2602	2230	3	−7	10	5

EMEs denotes emerging countries; LatAm indicates Latin America.

Table 3: Correlation matrix.

	RATING	DRATING_n	DRATING_p	GDP_growth	GDP_f	GDP_pc	INFL	CA	PB	PD	RES	REER	CR	VIX	US3M	WG
RATING	1															
DRATING_n	−0.14*	1														
DRATING_p	−0.08*	−0.04*	1													
GDP_growth	−0.03	−0.18*	0.11*	1												
GDP_f	−0.15*	−0.13*	0.14*	0.49*	1											
GDP_pc	0.66*	−0.05*	−0.11*	−0.15*	−0.41*	1										
INFL	−0.24*	0.07*	0.03	−0.03*	0.04*	−0.09*	1									
CA	0.09*	−0.08*	0.00	0.01	0.04*	0.32*	0.01	1								
PB	0.13*	−0.13*	0.05*	0.14*	0.18*	0.21*	−0.04*	0.29*	1							
PD	0.03*	0.06*	−0.06*	−0.16*	−0.38*	0.22*	0.06*	0.06*	−0.35*	1						
RES	0.07*	−0.06*	0.01	0.12*	0.26*	0.02	−0.02	0.25*	0.10*	−0.12*	1					
REER	0.04*	0.01	0.03*	0.02	0.12*	−0.14*	−0.02	−0.19*	−0.02	−0.31*	0.05*	1				
CR	0.53*	0.09*	−0.11*	−0.14*	−0.37*	0.60*	−0.02	0.5*	−0.17*	0.29*	0.11*	−0.17*	1			
VIX	−0.03	0.09*	−0.02	−0.21*	−0.13*	0.03	−0.03*	−0.02	−0.02	−0.02	0.01	0.04*	0.03*	1		
US3M	−0.02	−0.07*	−0.00	0.20*	0.11*	−0.15*	0.09*	−0.08*	0.10*	−0.02	−0.11*	−0.20*	−0.18*	−0.31*	1	
WG	−0.01	−0.07*	0.05*	0.41*	0.15*	−0.04*	0.02	0.01	0.07*	0.00	−0.02	−0.07*	−0.06*	−0.47*	0.41*	1

* Significant pairwise correlation at 5%. RATING denotes the nonlinear transformation of the sovereign rating based on a logistic function once its scale is transformed from 0 to 1.

Table 4: Estimates of the basic model for the total sample and for the pre-crisis and post-crisis period. All the explanatory variables but the categorical ones are lagged one period.

		OLS			Ordered logit		
		Total sample	Pre-crisis	Post-crisis	Total sample	Pre-crisis	Post-crisis
	DRATING_n	−1.60***	−1.19***	−1.13**	−2.44***	−2.42***	−2.98***
	DRATING_p	0.11	0.34*	0.31	0.59***	1.03***	0.81*
Economic	GDP_growth	0.03*	−0.02	0.07***	0.02	−0.03	0.06*
	GDP_f	0.22***	0.09*	0.50**	0.52***	0.36***	0.73***
	GDP_pc	0.74***	0.37**	1.32***	3.16***	3.83***	4.04***
	INFL	−0.05***	−0.04***	0.07*	−0.06***	−0.07***	−0.10*
	CA	−0.08***	−0.09***	−0.08***	−0.07***	−0.06	−0.13***
	PB	−0.06**	0.05**	−0.15***	0.09***	0.00	−0.11**
	PD	−0.05***	−0.06***	−0.09***	−0.11***	−0.16***	−0.20***
	RES	0.01***	0.04***	0.00	0.01***	0.05***	0.01
Financial	REER	0.04***	0.04***	0.00	0.04***	0.04***	0.00
	CR	−0.01***	−0.01***	−0.03***	−0.01***	−0.02***	−0.03**
Global	VIX	0.00	0.00	0.01	−0.06	−0.18	−0.06
	US3M	0.02	−0.06	−0.56***	2.46	−0.37	5.07
	WG	−0.03	0.07	−0.05	−0.59	−0.41	−1.35
Categorical	ZE	−7.13***	12.96***	−15.19***	3.58***	−8.39***	3.72
	EME	−13.05***	3.11*	−24.43***	−16.16***	−42.73***	−29.15***
	REGION	2.32***	2.37***	5.79***	1.29***	0.28	2.55***
	IMF	−0.88***	−0.44***	−0.88***	−0.62***	−0.48***	−1.62***
N		3226	2106	1120	3226	2106	1120
R^2		0.91	0.96	0.93	0.63	0.74	0.68

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; 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. See Appendix B for a detailed description of the remaining explanatory 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 basic model for the sample of emerging and developed countries. All the explanatory variables but the categorical ones are lagged one period.

		OLS		Ordered logit	
		EMEs	Developed	EMEs	Developed
	DRATING_n	-2.08^{***}	-0.92^{*}	-2.56^{***}	-3.05^{***}
	DRATING_p	0.22	−0.52	0.67^{***}	1.37^{*}
Economic	GDP_growth	0.00	0.14^{***}	−0.02	0.07
	GDP_f	0.17^{**}	−0.03	0.60^{***}	0.41^{***}
	GDP_pc	0.72^{***}	0.52^{***}	3.07^{***}	5.08^{***}
	INFL	-0.04^{***}	0.05	-0.05^{***}	−0.10
	CA	-0.11^{***}	−0.02	-0.12^{***}	0.05
	PB	0.04	-0.15^{***}	0.02	0.05
	PD	-0.07^{***}	-0.01^{**}	-0.09^{***}	-0.10^{***}
	RES	0.01^{***}	0.00	0.01^{**}	0.00
Financial	REER	0.04^{***}	-0.01^{**}	0.04^{***}	0.04^{***}
	CR	0.00	0.00	-0.01^{*}	-0.02^{**}
Global	VIX	0.00	0.00	−0.01	−0.47
	US3M	−0.09	0.22^{**}	2.80	9.61
	WG	0.05	-0.24^{*}	−0.91	−1.96
Categorical	ZE	13.01^{***}	1.72^{***}	13.59^{***}	10.25^{***}
	REGION	2.58^{***}	–	1.03^{***}	–
	IMF	-0.47^{***}	-2.42^{***}	-0.31^{***}	-2.21^{***}
N		1934	1292	1934	1292
R^2		0.91	0.77	0.57	0.70

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; 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. See Appendix B for a detailed description of the remaining explanatory variables; Intercept and time controls included but not reported; The R^2 is a pseudo-R^2 for the ordered logit estimates.

Table 6: 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. All the explanatory variables but the categorical ones are lagged one period.

		Total sample			**EMEs**		
		Total sample	Pre-crisis	Post-crisis	Total sample	Pre-crisis	Post-crisis
	DRATING_n	0.56	−1.56	4.25	1.04	−0.41	−8.62
	DRATING_p	0.09	0.35*	0.20	0.25	0.40**	0.73**
Domestic	GDP_growth	0.01	−0.04**	0.05**	−0.01	−0.03	0.00
	GDP_f	0.26***	0.12**	0.64***	0.20**	−0.06	0.78***
	GDP_pc	0.64***	0.32**	1.16***	0.64***	0.16	0.68*
	INFL	−0.06***	−0.05***	0.05	−0.05***	−0.04**	0.04
	CA	−0.08***	−0.09***	−0.07***	−0.11***	−0.09***	−0.05***
	PB	−0.02	0.05**	−0.13***	0.03	−0.03	0.05
	PD	−0.05***	−0.06***	−0.08***	−0.07***	−0.10***	−0.07***
	RES	0.01***	0.04***	0.00	0.01***	0.04***	−0.01
	REER	0.04***	0.04***	0.00	0.04***	0.05***	0.00
	CR	−0.01***	−0.02***	−0.03***	0.00	0.01*	0.00
Domestic*DRATING_n	GDP_growth	0.24***	0.24**	0.14	0.17**	0.17	−0.11
	GDP_f	−0.41*	−0.08	−0.71	−0.15	−0.08	2.21
	GDP_pc	0.76***	0.73**	0.52*	0.44	−0.52	1.48*
	INFL	0.07**	0.09***	−0.19*	0.11***	0.13***	0.10
	CA	0.11**	0.12**	−0.06	0.11**	0.07	0.15
	PB	−0.15**	−0.07	−0.05	0.00	−0.12	0.29
	PD	−0.05***	−0.01	−0.04***	−0.06**	−0.04	−0.06
	RES	0.01	0.04*	−0.01	0.01	0.07***	0.01
	REER	−0.01	−0.03*	0.00	−0.02	−0.02	−0.02
	CR	−0.01	0.00	−0.02*	0.00	−0.01	0.00
Global	VIX	0.00	0.00	0.01	−0.01	0.00	0.00
	US3M	−0.02	−0.08	−0.53***	−0.10	−0.26**	−0.56**
	WG	−0.02	0.05	0.00	0.02	0.18	0.01
Categorical	ZE	−13.77***	12.66***	−13.66***	12.87***	6.71***	22.38***
	EME	−21.14***	2.82	−25.13***	–	–	–
	REGION	2.42***	2.24***	5.78***	2.60***	0.64	5.30***
	IMF	−0.79***	−0.37***	−0.76***	−0.40***	−0.15*	−0.23
N		3226	2106	1120	1934	1235	699
R^2		0.92	0.96	0.94	0.91	0.95	0.95

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; 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. See Appendix B for a detailed description of the remaining explanatory 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_p, which is 1 if the country registered an upgrade and 0 otherwise, for the total sample and for the EMEs. All the explanatory variables but the categorical ones are lagged one period.

		Total sample			**EMEs**		
		Total sample	Pre-crisis	Post-crisis	Total sample	Pre-crisis	Post-crisis
	DRATING_n	-1.70^{***}	-1.20^{***}	-1.21^{**}	-2.10^{***}	-1.70^{***}	-1.79^{***}
	DRATING_p	0.35	-0.20	0.90	-0.74	-0.03	2.46
Domestic	GDP_growth	0.03	-0.03	0.06^{***}	0.00	-0.01	0.01
	GDP_f	0.23^{***}	0.10^{*}	0.56^{***}	0.17^{**}	-0.08	0.80^{***}
	GDP_pc	0.71^{***}	0.36^{**}	1.28^{***}	0.72^{***}	0.25	0.92^{**}
	INFL	-0.06^{***}	-0.04^{***}	0.06	-0.04^{***}	-0.03^{*}	0.06
	CA	-0.08^{***}	-0.09^{***}	-0.07^{***}	-0.11^{***}	-0.10^{***}	-0.05^{***}
	PB	-0.05^{*}	0.05^{**}	-0.13^{***}	0.04	0.00	0.07
	PD	-0.05^{***}	-0.06^{***}	-0.09^{***}	-0.06^{***}	-0.09^{***}	-0.07^{***}
	RES	0.01^{***}	0.04^{***}	0.00	0.01^{***}	0.05^{***}	0.00
	REER	0.04^{***}	0.04^{***}	0.00	0.04^{***}	0.04^{***}	0.00
	CR	-0.01^{***}	-0.01^{***}	-0.03^{***}	0.00	0.01	0.00
Domestic*DRATING_p	GDP_growth	0.11	0.02	-0.05	0.03	0.02	-0.18^{*}
	GDP_f	0.02	0.05	-0.08	0.11	0.12	-0.08
	GDP_pc	0.07	-0.04	-0.30	0.01	-0.04	-0.37^{*}
	INFL	-0.03	-0.04	0.14	-0.04	-0.04	0.06
	CA	-0.04	-0.02	-0.04	-0.01	-0.02	-0.02
	PB	0.09	-0.01	0.01	0.00	-0.03	-0.01
	PD	-0.02	-0.01	-0.01	-0.01	-0.01	0.01
	RES	0.00	0.00	0.01^{*}	0.00	0.00	0.01
	REER	0.00	0.01	0.01	0.01	0.01	0.00
	CR	-0.01	0.00	-0.01	-0.01	0.00	0.00
Global	VIX	0.00	0.00	0.01	0.00	0.00	0.01
	US3M	0.03	-0.04	-0.52^{***}	-0.07	-0.17^{*}	-0.58^{**}
	WG	-0.02	0.06	-0.04	0.05	0.22^{*}	-0.02
Categorical	ZE	-7.00^{***}	13.02^{***}	-14.74^{***}	12.84^{***}	7.07^{***}	20.07^{***}
	EME	-13.14^{***}	2.94^{*}	-24.96^{***}	–	–	–
	REGION	2.29^{***}	2.36^{***}	5.87^{***}	2.56^{***}	0.47	3.45^{***}
	IMF	-0.86^{***}	-0.39^{***}	-0.82^{***}	-0.46^{***}	-0.20^{*}	-0.27
N		3226	2106	1120	1934	1235	699
R^2		0.92	0.96	0.93	0.91	0.95	0.94

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; 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. See Appendix B for a detailed description of the remaining explanatory variables; Intercept and time controls included but not reported; We date the beginning of the crisis in 2008:Q3.

Table 8: 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	0.65	−1.60	4.40	0.95	−0.40	−8.78
	DRATING_p	0.53	−0.27	0.81	−0.70	0.03	2.20
Domestic	GDP_growth	0.00	−0.05**	0.04**	−0.01	−0.03	0.01
	GDP_f	0.27***	0.12**	0.67***	0.19**	−0.06	0.76***
	GDP_pc	0.63***	0.31*	1.13***	0.65***	0.14	0.76*
	INFL	−0.06***	−0.05***	0.05	−0.05***	−0.03**	0.04
	CA	−0.08***	−0.08***	−0.07***	−0.11***	−0.09***	−0.05***
	PB	−0.02	0.05**	−0.12***	0.03	−0.03	0.05
	PD	−0.05***	−0.06***	−0.08***	−0.07***	−0.10***	−0.07***
	RES	0.01***	0.04***	0.00	0.01***	0.04***	−0.01
	REER	0.04***	0.04***	0.00	0.04***	0.04***	0.00
	CR	−0.01***	−0.01***	−0.03***	0.00	0.01*	0.00
Domestic*DRATING_n	GDP_growth	0.25***	0.24**	0.15	0.17**	0.17	−0.11
	GDP_f	−0.42*	−0.08	−0.71	−0.15	−0.08	2.24
	GDP_pc	0.77***	0.73**	0.57*	0.44	−0.55	1.49*
	INFL	0.07**	0.09***	−0.19*	0.11***	0.13***	0.11
	CA	0.11**	0.12**	−0.06	0.11**	0.06	0.16
	PB	−0.15**	−0.07	−0.06	0.00	−0.12	0.29
	PD	−0.05***	−0.01	−0.04***	−0.06**	−0.04	−0.06
	RES	0.01	0.04*	−0.01	0.01	0.07**	0.01
	REER	−0.01	−0.03*	0.00	−0.02	−0.02	−0.02
	CR	−0.01	0.00	−0.02*	0.00	−0.01	0.00
Domestic*DRATING_p	GDP_growth	0.13	0.03	−0.02	0.04	0.02	−0.18*
	GDP_f	−0.01	0.04	−0.12	0.09	0.11	−0.08
	GDP_pc	0.09	−0.04	−0.27	0.01	−0.07	−0.35*
	INFL	−0.02	−0.04	0.16	−0.03	−0.03	0.09
	CA	−0.04	−0.02	−0.04	−0.01	−0.02	−0.02
	PB	0.08	−0.01	0.02	0.01	−0.03	−0.02
	PD	−0.02	−0.01	−0.01	−0.01	−0.01	0.01
	RES	0.00	0.00	0.02**	0.00	0.00	0.01*
	REER	0.00	0.01	0.01	0.01	0.00	0.00
	CR	−0.01	0.00	−0.02	−0.01	0.00	0.00
$H_0 : \beta^n = \beta^p$	GDP_growth	0.164	0.020**	0.126	0.078*	0.140	0.629
	GDP_f	0.081*	0.454	0.256	0.236	0.361	0.109
	GDP_pc	0.001***	0.005***	0.005***	0.165	0.317	0.009***
	INFL	0.041**	0.001***	0.036**	0.001***	0.000***	0.912
	CA	0.002***	0.003***	0.770	0.009***	0.342	0.292
	PB	0.002***	0.511	0.554	0.910	0.584	0.140
	PD	0.073*	0.648	0.065*	0.016**	0.201	0.089*
	RES	0.790	0.013**	0.044**	0.464	0.002***	0.844
	REER	0.311	0.013**	0.294	0.049**	0.132	0.266
	CR	0.801	0.415	0.902	0.539	0.472	0.737
N		3226	2106	1120	1934	1235	699
R^2		0.92	0.96	0.94	0.92	0.95	0.95

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; 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. See Appendix B for a detailed description of the remaining explanatory 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. In the hypothesis tests, H_0, we report the p-value of the Wald type test of the corresponding linear restriction and refer to significance at 1%, 5% and 10% level.

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