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Matthieu Bussiere[†] and Annukka Ristiniemi[‡]

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Abstract:
This paper analyses the role of credit rating agencies in sovereign debt crises. Using a panel of 53 emerging and developing countries with annual data going back to 1977, the paper shows that credit ratings are not very good predictors of debt distress events once tested against a simple benchmark model with standard macroeconomic variables. Next, the paper turns to higher frequency data for a subset of countries to analyze the link between credit ratings and bond spreads. The results indicate that bond spreads react strongly to credit ratings, especially to downgrades in the non-investment grade category. The results are robust to a variety of additional tests.

Keywords: Credit rating agencies, debt crises, fiscal policy, emerging market economies, developing countries, panel estimation.

JEL Classification: E60, C33, C35

Résumé :
Ce papier analyse le rôle des agences de notation dans les crises de la dette souveraine. Utilisant un panel de 53 pays émergents et en voie de développement avec des données annuelles depuis 1977, le papier montre que les notations de crédit ne sont pas de bons prédicteurs des événements de crédit lorsqu'on les compare à un simple modèle de référence comprenant des variables macroéconomiques usuelles. Dans un second temps, le papier utilise des données à plus haute fréquence pour un sous-ensemble de pays afin d'analyser le lien entre notations de crédit et spreads. Les résultats indiquent que les spreads réagissent fortement aux changements de notation, surtout lorsqu'elles ont lieu à la baisse et dans la catégorie « non-investissement ». Les résultats restent valides lorsqu'on les soumet à un ensemble de tests supplémentaires.

Mots-clés : agences de notation, crises de la dette, politique budgétaire, marchés émergents, pays en voie de développement, économétrie des panels.

Codes JEL : E60, C33, C35

Following the 2008 financial crisis, the role of credit rating agencies has come under scrutiny again. Credit rating agencies have been unable to detect the vulnerabilities attached to mortgage backed securities and to a variety of other new financial products[1]. They were accused of failing to anticipate fiscal distress in several advanced and emerging market economies, while at the same time, observers accused them of unduly worsening the situation by downgrading countries' debt when there was no clear deterioration in fundamentals.[2] More recently, the decision by the credit rating agency Standard and Poor's to downgrade the debt of the United States on August 5, 2011, triggered market upheavals with the S&P 500 index dropping over 150 points within days. The move was also sharply criticized by the US authorities and outside observers[3].

Such accusations are actually not new: already in the wake of the Asian crisis, at the end of the 1990s, credit rating agencies have been under pressure for their lack of foresight (Reinhart (2002a); Reinhart et al. (2000); Bussiere and Mulder (1999)). The link between credit rating agencies and debt crises is of paramount importance for crisis prevention and resolution, given the role of credit ratings for regulatory purposes and for the conduct of monetary policy[4].

This paper provides an assessment of the role of credit rating agencies in debt crises. It first provides key stylized facts on credit ratings. Among the most noteworthy findings, the paper shows that credit ratings are very correlated across agencies, although S&P tends to change its ratings more frequently than the other two agencies, especially for downgrades. Next, the paper turns to formal econometric analysis and proceeds in two steps. Firstly, the paper aims to quantify the predictive power of credit ratings: can ratings predict debt crises and is this predictive power higher than that of a simple model with standard macroeconomic variables? We find that the predictive power of ratings is low, as they do not outperform fundamentals (we compare the predictive power of ratings

[1]See for example U.S. Permanent Subcommittee on Investigations (2010): "We used as case histories the two biggest credit rating agencies in the United States, Moodys and Standard & Poors, and the ratings they gave to the key financial instruments that fueled the financial crisis – residential mortgage backed securities, or RMBS, and collateralized debt obligations, or CDOs. The Subcommittee on investigations found that those credit rating agencies allowed Wall Street to impact their analysis, their independence, and their reputation for reliability. And they did it for the money."

[2]See for example Nicolas Sarkozy and Angela Merkel in a joint letter demanding a review at how rating agencies evaluate government debt (FT 2010). Jean-Claude Trichet (FT 2007) warned that "world financial systems have been weakened by the lack of choice between global rating agencies". Also the European Commission (BBC 2011) said the timing of the [Portuguese] downgrade was questionable and raised the issue of appropriate behaviour of the agencies in general.

[3]Paul Krugman declared on the same day that: "It's hard to think of anyone less qualified to pass judgment on America than the rating agencies".

[4]The ECB for example only accepts investment grade rated debt as collateral in Eurosystem operations (ECB 2008). For more information about credit ratings in Fed's regulation see Board of Governors of the Federal Reserve System (2011).

with that of the fundamentals from the logit model of Cohen and Valadier (2011)). In fact ratings seem to react rather late into the events based on event case analysis. One would then assume that rating changes would not have an effect on the markets, given that investors following the efficient market hypothesis would simply ignore the lagging information of the ratings. We test for this in the second part of the paper using high frequency sovereign bond spread data. We find that markets do react to ratings: in case of downgrades, spreads increase by 13% on average. In the event studies section we also take outlook assignments into account and find that watch negative outlook assignments by S&P to investment grade rated bonds cause on average sovereign spreads to double. Therefore, it seems that instead of providing leading signals of distress to the investors, the ratings might end up only exacerbating the crises.

The first part of the paper, which assesses the predictive power of ratings, uses a discrete choice (logit) model for a panel of 53 emerging market economies and developing countries, with annual data starting in 1977. We focus on emerging market economies because there are far more examples of debt distress events in those countries than in advanced economies.[5] The dependent variable indicates that there is a crisis in a given year if the country has either run into substantial arrears, receives Paris Club debt relief or obtains balance-of-payments support from the IMF for more than 50% of its quota. The definition of the debt distress variable goes back to McFadden et al. (1985) and was further refined by Kraay and Nehru (2006) and by Cohen and Valadier (2011). We use the version of the latter.

The main result that stands out of the logit regressions is that credit ratings of Fitch and Moody's do have predictive power two years before debt distress events. However, when regressed together with the fundamentals, the coefficient of ratings cannot be distinguished from zero, indicating that the ratings do not have any additional information that helps predict these events. S&P ratings are not significant when regressed either alone or with the fundamentals. The comparison becomes slightly less favorable for the model with fundamentals than for the model with credit ratings at a one year horizon, but even so the performance of the model in terms of goodness of fit is better for the former. These results can be interpreted in various ways. One potential reason for the low predictive power could be that credit rating agencies are conservative and fail to predict crises for fear of sending too many false alarms. The noise-to-signal ratios in section 2.1 show however that this is not the case. Ratings correctly call less crises compared to fundamentals,

[5]Therefore, it should be emphasised that our results apply to emerging countries only and should not be extrapolated to advanced economies.

while also sending more false alarms.[6] Another potential explanation would be that governments react to rating changes. To check this, we regressed the World Bank's policy and institutional quality (CPIA) index[7] on lagged ratings: the effect is not significant. Hence, at least based on regressions using this variable, which is available across a large number of countries, it does not seem that governments improve their policies to avoid crises following downgrades.

In the second step of the analysis we investigate whether markets react to ratings using a subsample of 33 countries, for which higher frequency data on sovereign spreads are available. The regression is in first differences in order to capture the dynamic impact of rating changes on markets. On average, we find that a rating change by one notch has an impact of about 4-6% on spreads. IMF (2010) suggests that rating changes cause *"cliff effects"* in the markets, which are sudden and large increases in spreads. Our dynamic model is well suited to study this, and we do find support for cliff effects especially with rating downgrades. On average, the reaction of bond spreads to downgrades is more than 13% (while to upgrades it is only around 3%).

This dichotomy between downgrades and upgrades is confirmed by event studies, which look at the behaviour of spreads within a +/- 10 day window around rating changes. The event studies allow us to take into account the watch negative announcements in particular, which usually precede actual rating changes. The results show that there is virtually no reaction to positive outlook announcements, while the spreads rise considerably following watch negative outlook assignments. This confirms the dichotomous response between upgrades and downgrades. One possible reason for this is that in case of downgrades, there are both regulatory constraints as well as internal controls that forbid investors from investing in assets of certain rating class, which may cause investors to sell assets automatically.[8] This is not the case for upgrades.

Given the importance of the topic, several papers have looked at the predictive power of ratings: Reinhart (2002a) tests whether credit ratings predict currency and banking crises while Bussiere and Mulder (1999) focus on currency crises only. Reinhart (2002b) assesses whether ratings predict currency crises and defaults. Regressing ratings alone without fundamentals, she finds that ratings do not predict debt crises. Sy (2003) finds

[6]Credit ratings alone predict between 57-60% of the debt distress events, while 90-94% of the signals are false alarms. The fundamentals by comparison, correctly predict 72% of crises while sending 87% of false alarms.

[7]The CPIA (The Country Policy and Institutional Assessment) is used by the World Bank as a lending criteria.

[8]Downgrades also may trigger sell offs in private capital markets due to the sovereign ceiling rule - all ratings of various entities in a country are generally lower than the sovereign ratings. For a study of their importance, see Cowan et al. (2007).

that for the period 1994-2002, ratings do not predict currency crises and that the causality is the other way, currency crises predict ratings, hence agencies are too late to downgrade. He also finds that currency crises are not correlated with debt crises in that period and that ratings have some - albeit weak - prediction power of debt distress events. However, his definition of debt distress is 'spreads over 1000 basis points', so rather than predict debt crises, the variable of interest predicts market reaction, which is what our paper studies in section 3.1. Flandreau et al. (2011) look at the history of foreign ratings, whether a superior forecasting ability explains the growing importance of the agencies and finds that it does not. Carlson and Hale (2005) build a global games model to show how rating changes can have an independent effect on yields even if the agencies are late to react to the changes in fundamentals, given that the investors would have already reacted instantaneously. The additional effect is from investors revising their expectations regarding what other investors will do.[9]

This paper is the first that is able to compare ratings to an alternative, benchmark model in order to assess how good the prediction power is. Also, rather than look at defaults, we use *debt distress events*, which occur more often since a country can avert a default by turning to IMF for balance of payments support. Defaults often occur several months/years after a country has entered into debt distress and hence assessing predictive power of ratings one year ahead of a default would only capture information about an imminent default that is already public knowledge.

We are not the first to examine the link between ratings and spreads, but the paper tackles it from a different angle, by looking at the actual dynamic impact of rating changes on markets. Previous papers such as Jaramillo and Tejada (2011); Reisen and von Maltzan (1998) have generally regressed sovereign ratings and spreads in levels, whereas we use a first differenced model given that we focus on the dynamics. Kaminsky and Schmukler (2001) used a differenced data in panel, but the data was of daily frequency, while Larrain et al. (1997) did Granger causality tests on annual data. The first differenced model is better suited for capturing the short term impact of rating changes given how rarely ratings change and how much spreads fluctuate. We use monthly data in order to strike a balance between capturing market reaction, which is generally swift and acknowledging that rating changes can be anticipated and hence markets have often reacted already before the actual change[10].

[9]For papers showing determinants of sovereign ratings, see Afonso (2002) and Cantor and Packer (1996).

[10]The paper also relates to a wider literature that looks at the impact of rating changes on bond spreads and stock prices, see for instance Dichev (2001); Hand et al. (1992); Micu et al. (2006); Amato and Furfine (2003); Jorion and Zhang (2007)

Ferri et al. (1999) were the first to propose that credit ratings are *procyclical*, they tend to be excessively downgraded compared to what fundamentals would suggest during economic downturns while being upgraded much after fundamentals have improved in booms. Reisen and von Maltzan (1998, 1999) as well as Kaminsky and Schmukler (2001) confirm this procyclicality in their empirical papers, while Gaillard (2009) disagrees. Still related to this issue, Bar-Isaac and Shapiro (2010) find that a credit rating agency is more likely to issue less accurate corporate ratings in boom times than during recessionary periods. We find that changes in ratings have the largest effects on markets when the rating change is a downgrade. Upgrades are generally not significant in the investment grade category.

The rest of the paper is organized as follows. Section 1 presents the data and stylised facts about ratings and spreads, section 2 assesses the predictive power of credit ratings using a logit model. Section 2.1 presents the main results, while section 2.2 shows robustness checks. Section 3 looks at market reactions from rating changes: section 3.1 regresses spreads on ratings to analyse the impact on markets with monthly data and section 3.2 outlines event studies with daily frequency data. Section 4 concludes.

1 Data and stylised facts

1.1 Data

Two different datasets are used in this paper. The first dataset covers 53 developing and emerging countries, and runs on annual frequency from 1977 to 2007. The countries and years are listed in appendix A. This dataset is used in section 2.1 showing logit regressions that analyse the predictive power of credit ratings against fundamentals.

The second dataset, which is used to study the effect of rating changes on markets (section 3.1), includes the JP Morgan EMBI Global index of spreads of sovereign bond yields over a benchmark bond. It covers 40 countries although only 33 are rated by all agencies and hence included in the study. The bonds used for the EMBI index by JP Morgan include US dollar-denominated bonds such as Brady bonds, Eurobonds, and traded loans issued by sovereigns and quasi-sovereigns, while the benchmark bonds are US treasury bonds. The spreads are "stripped spreads", which are homogenised for comparability across countries and maturity structures. The index is available on Datastream. This second dataset will be used at monthly frequency in section 3.1 in the panel regressions and in daily frequency in the event studies, section 3.2.

The key variable in section 2.1 (logit regressions) is a definition of debt distress events.

A country is said to be in debt distress when *one of the following three* conditions holds:

- The sum of the interest and principal arrears on long-term debt outstanding to all creditors is larger than 5% of the total debt outstanding.
- The country receives debt relief from the Paris Club.
- The country receives substantial balance-of-payments support from the IMF in the form of StandBy Agreements and Extended Fund Facility. We consider the support as substantial when the country uses more than 50% of its quota in one year.

This debt distress variable allows us to select 18 different crisis events, which are listed in table 1. The table shows the distress year, distressed country, the reason for distress (IMF, arrears or Paris Club), ratings by all agencies one year before the distress as well as the date of default when applicable. The distress data is structured so that if a datapoint is listed either as a crisis time, or a normal time, then it must be preceded by three years without a distress event, otherwise the datapoint is excluded from the observations. This ensures that when regressing the distress variable at t, the time points $t-2$ or $t-1$ are always normal times. The reason we do not use a default classification by S&P's for example is that defaults are often recorded fairly late, only when they actually take place, which is usually several months and in many cases years after the negotiations have started and when it has already become obvious to everyone that a default is going to take place. As shown in table 1, Argentina for example only defaulted the year after the distress event. Using arrears instead of defaults allows us to capture the *beginning* of debt distress events and therefore ensures that the dependent variables are measured in normal times rather than during ongoing distress events. In addition, often a country does not need to run into severe arrears if it obtains balance of payments support from the IMF or seeks debt rescheduling or reduction from the Paris Club, hence we have included those possibilities also in the definition of debt distress, as have others before us.[11]

The fundamentals the ratings are regressed against include external debt/GDP, GDP per capita, interest payments on external debt over exports, inflation and CPIA. CPIA, the "Country Policy and Institutional Assessment" index is a an indicator that the World Bank uses in its international development aid allocation decisions. All the variables are from the World Bank Data Catalog and from the Penn World Tables and are publicly

[11] Like any formal and quantitative definition, our criteria select events that do not necessarily include all cases commonly regarded as debt distress events or defaults. For a discussion of debt defaults and debt restructuring see for instance Erce and Diaz-Cassou (2011) and Erce (2012). We tested the validity of the results presented in Section 2 to the inclusion of cases not identified by our definition as debt distress events and found that the results were largely unaffected.

Table 1: Distress events

		Reason for distress			Rating one year before			Date of
Year	**Country**	**IMF**	**ParisCl**	**Arrears**	**S&P**	**Fitch**	**Moodys**	**Default**
2000	Argentina	x			BB S	BB	Ba3, RUR-	6-Nov-01
2004	Bolivia	x			B+ N		B1 S	
1998	Brazil	x			B+ P	B+	B1 - RUR+	
2005	Cameroon			x	B S	B S		
2000	Ecuador		x				B3 S	29-Jul-00
2007	Gambia, The		x			CCC S		
2006	Grenada		x		SD			
2004	Honduras		x				B2	
1997	Indonesia	x			BBB S		Baa3	
1998	Kazakhstan	x			BB- S	BB-	Ba3	
2007	Latvia	x			A- S	A- S	A2 S	
2003	Moldova			x			Caa1	
1999	Pakistan		x		B+ S		B2 S	29-Jan-99
1997	Thailand	x			A S		A2	
1995	Turkey	x			BBB N		Baa3 - RUR-	
2000	Turkey	x			B P	B+	B1 P	
1998	Uruguay	x			BB+ S	BB+	Ba1	
2002	Uruguay	x			BBB- S	BBB- S	Baa3	16-May-03

Notes: Columns 3-5 list reasons for distress: substantial balance of payments support from the IMF, Paris Club rescheduling and/or substantial arrears. Columns 6-8 show the rating and outlook one year before the distress event. The last column lists the date of default assigned by S&P when applicable.

available, except for the CPIA which is only publicly available from 2005 onwards. We have obtained the whole CPIA series from 1978-2007 directly from the World Bank.

Table 2: Ratings scale

Investment grade			**Non-investment grade**		
Code	SP, Fitch	Moody's	Code	SP, Fitch	Moody's
22	AAA	Aaa	12	BB+	Ba1
21	AA+	Aa1	11	BB	Ba2
20	AA	Aa2	10	BB-	Ba3
19	AA-	Aa3	9	B+	B1
18	A+	A1	8	B	B2
17	A	A2	7	B-	B3
16	A-	A3	6	CCC+	Caa1
15	BBB+	Baa1	5	CCC	Caa2
14	BBB	Baa2	4	CCC-	Caa3
13	BBB-	Baa3	3	CC	Ca
			2	C	C
			1	SD, RD, DDD, DD, D	

For the ratings, only the foreign currency ratings on long term debt are used, since both datasets only include developing or emerging countries that are usually not able to borrow in their own currency (Eichengreen and Hausmann (1999)). The ratings are transformed using a linear scale, which is the most common transformation used in credit rating research. We test the robustness of our results by running the regressions on different scalings, for example by using an investment grade dummy and by extending the scale to include changes in outlook. The change of scaling did not change the results qualitatively, in fact the model with the investment grade dummy performed even worse.

The numerical code corresponding to the linear scale is displayed in table 2. The ratings from 13-22 are investment grade while ratings from 1-12 are non-investment grade. S&P and Fitch assign several categories of default of which D, DD and DDD represent outright default and RD and SD indicate selective default. Since only SD and RD are usually used, we list all of them under the same category, they all are assigned a numerical rating of 1.

1.2 Stylised facts

This section presents descriptive statistics on credit ratings. It reports, for each of the three main credit rating agencies, the probabilities of rating changes, overall and conditional on whether the rating change was an upgrade or downgrade and whether the bond was rated non-investment or investment grade. The section also provides evidence of lead and lag relationships between ratings by the three agencies by computing the share of rating changes that followed a rating change by one of the other two agencies.

Firstly, table 3 shows that the ratings between the agencies are very similar, the correlation between S&P and Fitch ratings being slightly higher than with Moody's.[12] In table 4, the mean ratings of S&P are the lowest while Moody's are the highest, but the differences are very small. This suggests that there may be little value added in cross-checking the information provided by the three agencies, given that they are so tightly correlated.

Table 3: Correlations

	S&P	Moodys	Fitch
S&P	1.000		
Moodys	0.979	1.000	
Fitch	0.984	0.979	1.000

Table 4: Descriptive statistics

	Mean	StDev
S&P	15.83	5.04
Moody's	15.97	5.02
Fitch	15.86	4.99

Table 5 presents the probabilities of rating changes. The top section has the probabilities for all agencies and all ratings classes, while the middle and bottom sections show

[12]The high correlations hold also for cross-sections, on monthly basis.

probabilities for investment grade and non-investment grade bonds respectively. The data is of monthly frequency and ratings are the last rating of the month, including outlook changes. There are altogether 12872 observations of ratings, of which 70% are in the investment grade category. The sample only includes those observations for which there exists a rating by all agencies, as otherwise the samples would differ quite substantially. For example, the sample for Moody's begins already in February 1949 with an AAA rating assigned to the US, while S&P assigned its first rating in 1975 to Canada, and Fitch emerged only in 1994 with a simultaneous rating given to several large European economies as well as to the US and Canada. Furthermore, Moody's has remained more concentrated in the developed economies, while S&P and Fitch rate more new entrants to the global capital markets. For this reason, while comparing the behaviour of the rating agencies, it is important to restrict the sample to those countries and times for which there exists a rating by all three agencies.

Table 5: Probabilities of rating changes

All changes							
	Obs	Obs(change)	P(change)	Obs(up)	P(up)	Obs(down)	P(down)
SP	12872	620	4.8%	356	2.8%	264	2.1%
Moody's	12872	506	3.9%	321	2.5%	185	1.4%
Fitch	12872	520	4.0%	313	2.4%	207	1.6%
Investment grade							
	Obs	Obs(change)	P(change)	Obs(up)	P(up)	Obs(down)	P(down)
SP	9099	300	3.3%	171	1.9%	129	1.4%
Moody's	9248	276	3.0%	175	1.9%	101	1.1%
Fitch	9063	267	2.9%	159	1.8%	108	1.2%
Noninvestment grade							
	Obs	Obs(change)	P(change)	Obs(up)	P(up)	Obs(down)	P(down)
SP	3773	320	8.5%	185	4.9%	135	3.6%
Moody's	3624	230	6.3%	146	4.0%	84	2.3%
Fitch	3809	253	6.6%	154	4.0%	99	2.6%

The probabilities of rating changes in table 5 are very similar for Fitch and Moody's, while S&P changes its ratings slightly more frequently. Overall the probability of a rating change by Moody's is 3.9%, while for S&P it is 4.8%. The probability of an upgrade is larger than the probability of a downgrade for all agencies. For example, for Moody's the probability of an upgrade is 2.5% while the probability of a downgrade is only 1.4%.[13]

The results are similar for both investment and non-investment grade bonds: upgrades are more likely than downgrades. However, the probability of facing a rating change

[13] Gaillard (2009) finds that Moody's is the most reluctant of all agencies to change the ratings.

is more than twice as large in the non-investment grade than in the investment grade category. In the non-investment grade category, S&P changes its ratings most often, the probability of a rating change by S&P is about 2 percentage points higher than by Fitch or Moody's.

Turning to table 6, we can observe conditional probabilities of rating changes. S&P, which has the highest probability of changing its ratings, also seems to be the first mover out of the three. The table lists the percentages of all rating changes by each agency that were followed by a rating change by the same (diagonals) or another agency (off-diagonals). The columns represent rating changes in one of the previous two months and rows represent rating changes in the current month. For example the 23.9% of row 2, column 1 is the percentage of all Moody's rating changes that took place after there has been a rating change by S&P in one of the two previous months as a share of all changes by Moody's. This is more than 10 percentage points higher than the 14.9% in row 1, column 2, which is the percentage of S&P rating changes that followed a change by Moody's as a percentage of all S&P changes. Since the (off-diagonal) percentages in column 1 are significantly higher than in the other columns, we conclude that Moody's and Fitch tend to change their ratings more often following S&P than S&P following Moody's and Fitch.[14]

Table 6: Conditional probabilities between ratings

All	Rating change at (t-1) or (t-2)		
change at t	S&P	Moody's	Fitch
S&P	8.8%	14.9%	17.4%
Moody's	23.9%	14.0%	18.4%
Fitch	23.0%	16.5%	10.5%
Upgrades	Rating change at (t-1) or (t-2)		
change at t	S&P	Moody's	Fitch
S&P	1.7%	11.5%	14.3%
Moody's	16.5%	7.2%	13.4%
Fitch	16.3%	14.7%	5.8%
Downgrades	Rating change at (t-1) or (t-2)		
change at t	S&P	Moody's	Fitch
S&P	15.2%	16.7%	18.9%
Moody's	32.4%	15.7%	23.2%
Fitch	30.4%	17.9%	14.5%

For downgrades the differences are larger, over 30% of Moody's and Fitch downgrades

[14]This however partly reflects the fact that S&P makes more changes than the other two agencies as reported in Table 5.

took place after an S&P downgrade in the previous two months, while S&P downgrades only followed Moody's in 17% of the cases and Fitch 19%. Upgrades are not as clustered as downgrades, the probabilities of subsequent rating changes in each cell are lower. In addition, the differences between the agencies are not as significant in the upgrades category. Our results can be related to those of Alsakka and ap Gwilym (2010) who also find evidence of interdependence in rating actions. Furthermore, their results also suggest that S&P tends to lead the other agencies with downgrades and demonstrate the least dependence on other agencies. In contrast to us, they find that Moody's tends to be the first mover in upgrades. This can be due to the shorter sample used, a different methodology (ordered probit) as well as a different time frame; they consider subsequent rating changes up to a year later whereas we only consider two months.

The diagonal elements of table 6 show that there is some clustering of ratings by the same agencies. The probability of any rating change by Moody's given that there was a rating change by Moody's in the past two months is 14%. The figures are similar albeit slightly lower for Fitch and S&P. The clustering is more prominent in the downgrade-category, there is a 15% probability to observe consecutive S&P downgrades at most 3 months apart. On the other hand, there is only a 1.7% probability to observe consecutive upgrades by S&P. This is perhaps explained by dynamics developing far more rapidly in busts than booms.

2 Predictive power of credit ratings

2.1 Logit model

In this section, we implement a panel logit, which measures the ratings ability to predict debt distress events and assess them against a few fundamentals, which are known from the literature to predict sovereign debt distress events fairly well. We perform three logit regressions: (i) with fundamentals only, (ii) with ratings only, and (iii) with both ratings and fundamentals in the same regression to see whether the ratings provide any additional information over that provided by the fundamentals.

The logit regression is as follows:

$$y*_{it} = \beta_0 + \beta_1 Debt/GDP_{i,t-2} + \beta_2 ln(GDPp.c.)_{i,t-2} + \beta_3 InterestPaym/Exports_{i,t-2} + \\ + \beta_4 Inflation_{i,t-2} + \beta_5 CPIA_{i,t-2} + \beta_6 Rating_{i,t-2} + \epsilon_{it} \quad (1)$$

$$y_{it} = \mathbb{1}[y^*_{it} > 0]$$

$$Prob[y_{it} = 1 | X_{it} = x_{it}] = \frac{exp(x'_{it}\beta)}{1 + exp(x'_{it}\beta)}$$

where X_{it} is a vector of fundamentals: external debt/GDP, log of GDP per capita, interest payments on external debt over exports, inflation, CPIA and ratings. The last explanatory variable is *ratings*, which is the average rating of all three rating agencies for each datapoint for which at least one of the ratings exists[15]. We also check the predictive power of each rating agency separately. All the coefficients are initially lagged two years as in Cohen and Valadier (2011). This way we can be sure that the variables are actually predicting a crisis rather than a response to one. Also, we use long term ratings, which are supposed to predict events on three to five year horizon, so two years should certainly be long enough for the ratings. We also check results with one year lags later on.[16]

The results are reported below in table 7. The baseline regression includes only the fundamentals as regressors for the sample for which there exists a rating by at least one of the agencies. All the coefficients of the fundamentals except for GDP per capita are significant. They predict debt crises well two years ahead of the event. CPIA is no longer significant in these regressions even though it has been in previous work by for example Kraay and Nehru (2006); Cohen and Valadier (2011)[17].

In column 2, we add the average of the three agency ratings into the regression and in columns 3 to 5 we report the ratings of each agency separately along with the fundamentals. None of the coefficients are significant. Hence ratings do not seem to add any information over and above that provided by the fundamentals.

Since the ratings themselves should be determined by the fundamentals[18], we should be able to observe some predictive power when the other explanatory variables are excluded from the regression. This is the case indeed as is seen in table 8 below, except for S&P whose ratings are still not significant. Hence, in contrast to Reinhart (2002b) we find that ratings do predict debt crises, though they do not outperform the simple model with fundamentals.

Since with a logistic model it is not possible to compare whether ratings or funda-

[15]All ratings in this section are the average rating of the year.

[16]It is worth noting at this stage that sovereign credit ratings are *opinions* on credit risk of sovereign bonds. The credit rating agencies emphasize the word 'opinion' so that they cannot be held liable for investor losses based on investment decisions on ratings. However ratings are often interpreted as an indication of the risk of a particular asset.

[17]We also tested GDP growth, current account deficit and government deficit among other variables, but none of those were consistently significant.

[18]We checked this. The R^2 is approximately 50% when ratings are regressed against fundamentals for all three agencies.

Table 7: Logit regressions

Distress	Baseline	Ratings	S&P	Fitch	Moodys
DebtGDPlag2	4.41***	4.08***	2.77*	5.61***	2.96**
	(3.63)	(3.21)	(1.80)	(2.76)	(1.96)
lnGDPpclag2	-0.10	-0.04	0.45	1.39	-0.68
	(-0.22)	(-0.08)	(0.75)	(1.34)	(-1.03)
InterestPaym./EXPlag2	0.21***	0.21***	0.20***	0.23***	0.22***
	(3.56)	(3.56)	(3.37)	(2.87)	(3.44)
Inflationlag2	0.03**	0.03**	0.02*	0.03*	0.02**
	(2.36)	(2.32)	(1.83)	(1.82)	(2.12)
CPIAlag2	0.27	0.55	-0.02	0.25	0.52
	(0.47)	(0.83)	(-0.02)	(0.23)	(0.75)
AvgRatinglag2		-0.13			
		(-0.87)			
SPlag2			0.09		
			(0.58)		
Fitchlag2				-0.39	
				(-1.45)	
Moodyslag2					-0.04
					(-0.29)
_cons	-7.20*	-7.16*	-11.13**	-16.56*	-1.92
	(-1.81)	(-1.77)	(-2.15)	(-1.87)	(-0.36)
N	334.00	334.00	294.00	210.00	275.00

t-statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Panel logit ratings only

Distress	Avg rating	S&P	Fitch	Moody's
Avgratinglag2	-0.22**			
	(-2.29)			
SPlag2		-0.05		
		(-0.45)		
Fitchlag2			-0.36**	
			(-2.46)	
Moodyslag2				-0.19*
				(-1.92)
_cons	-0.45	-2.47**	0.93	-0.69
	(-0.44)	(-2.07)	(0.62)	(-0.63)
N	334.00	294.00	210.00	275.00

t-statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

mentals do better at predicting crises, we use noise to signal ratios. These allow us to compute the percentage of crises these two models predict, as well as the number of false alarms. The results are displayed in table 9.

The fundamentals call 72% of the crises correctly, while the ratings call 57-60% of

Table 9: Noise to signal ratios

Fundamentals				**S&P**			
	signal				signal		
distress	0	1	**Total**	distress	0	1	**Total**
0	229	87	**316**	0	145	135	**280**
1	5	13	**18**	1	6	8	**14**
Total	**234**	**100**	**334**	**Total**	**151**	**143**	**294**
% of obs. correctly called			72.5%	% of obs. correctly called			52.0%
% of crises correctly called			72.2%	% of crises correctly called			57.1%
% of false alarms of total alarms			87.0%	% of false alarms of total alarms			94.4%
% prob. of crisis given an alarm			13.0%	% prob. of crisis given an alarm			5.6%
% prob. of crisis given no alarm			2.1%	% prob. of crisis given no alarm			4.0%

Fitch				**Moody's**			
	signal				signal		
distress	0	1	**Total**	distress	0	1	**Total**
0	145	55	**200**	0	170	90	**260**
1	4	6	**10**	1	6	9	**15**
Total	**149**	**61**	**210**	**Total**	**176**	**99**	**275**
% of obs. correctly called			71.9%	% of obs. correctly called			65.1%
% of crises correctly called			60.0%	% of crises correctly called			60.0%
% of false alarms of total alarms			90.2%	% of false alarms of total alarms			90.9%
% prob. of crisis given an alarm			9.8%	% prob. of crisis given an alarm			9.1%
% prob. of crisis given no alarm			2.7%	% prob. of crisis given no alarm			3.4%

the crises correctly, more than 10 percentage points less. This could be due to rating agencies being conservative, only prepared to downgrade once the situation leaves no ambiguity. However, looking at the number of false alarms the ratings send, this does not seem to be the case. The ratings send more false alarms than fundamentals even though their prediction power is low. Fundamentals send 87% false alarms which in itself is fairly high already, while ratings send 90-94% false alarms. Hence, compared to the fundamentals, ratings do not perform as well at predicting debt distress events and if investors should choose one to base their analysis on, it seems that relying on a few straightforward fundamentals would provide more reliable information.[19]

Finally, we take the ratings and fundamentals at $(t-1)$ and see whether *one year before the distress event* the ratings have started having predictive power. Ratings on

[19]Here we have used the mean default probability as a threshold for choosing when to send a signal. A policymaker can change the threshold depending on the relative importance of false alarms vs. missed crises. See Bussiere and Fratzscher (2008).

average (column 1) do become significant at this point, although from the individual regressions, only S&P and Fitch are significant and only at the 10% level. Moody's is still not predicting debt distress events. The noise to signal ratios are displayed in appendix B. One can see that even though the ratings seem to bring additional information to fundamentals at $t-1$, they still do not outperform them. The fundamentals call correctly 77% of the crises while ratings call 64-67% of the crises. Ratings still also send more false alarms at 89-93% compared to 85% by the fundamentals. Furthermore, the ratings are supposed to predict crises at 3-5 year horizon[20] and therefore it is not clear what would be the value of having significant predictive power at $t-1$, which could just reflect large rating changes at the very end of the year.

The results of this section support the conclusions of Reinhart (2002a) that ratings are rather late in their reaction to crisis events. She looked specifically at the East Asian crisis, which was when rating agencies were criticised for downgrading too late when their information was no longer useful and instead of predicting the events ended up exacerbating the problems.

Overall our results contradict those of IMF (2010) who report that given that credit ratings are only supposed to convey ordinal ranking of creditworthiness rather than to correspond to actual default probabilities, the ratings have not fared too badly. The report states: (IMF, 2010, pg.1) *"Tested against this objective, the chapter finds that the CRAs discriminatory power of sovereign default risk is validated to some extent. For example, all sovereigns that defaulted since 1975 had non-investment grade ratings one year ahead of their default."* However, S&P records defaults only when they actually take place, which tends to be a long time after a country has already started default negotiations and at which point they are usually already in severe debt distress (see table 1). Hence, the fact that a country has a non-investment grade rating at that time would not be a leading signal of a default. Furthermore, our robustness checks show that having a non-investment grade rating is not a good predictor of debt distress.

We tested the threshold rating at which the ratings become significant predictors of debt distress events two years ahead of the event in the logit regression, by constructing a threshold dummy which is one, when the rating is below a threshold. We started from an investment grade threshold with a dummy that is one when a rating is non-investment grade. We regressed the logit again with the fundamentals and the rating dummy. None of the coefficients of the agencies were significant. We reduced the threshold one by one

[20]See House of Lords (2011). We actually ran the same regressions with a longer lag corresponding to a 3 to 5 year horizon but the results were not more favourable to ratings. Ratings were not significant, while the fundamentals retained their significance.

Table 10: Panel logit at $t-1$

Distress	Baseline	Ratings	SP	Fitch	Moodys
DebtGDPlag1	4.14***	2.84**	1.31	3.26	2.55
	(3.31)	(2.07)	(0.77)	(1.42)	(1.57)
lnGDPpclag1	-0.37	-0.24	0.16	0.46	-0.81
	(-0.74)	(-0.46)	(0.25)	(0.43)	(-1.09)
InterestPaym./EXPlag1	0.18***	0.19***	0.19***	0.24***	0.19***
	(3.36)	(3.40)	(3.31)	(3.07)	(3.20)
Inflationlag1	0.02*	0.02*	0.02	0.02	0.02*
	(1.94)	(1.94)	(1.48)	(1.20)	(1.96)
CPIAlag1	0.07	1.00	0.54	-0.46	0.74
	(0.11)	(1.38)	(0.71)	(-0.46)	(0.98)
AvgRatinglag1		-0.40***			
		(-2.98)			
SPlag1			-0.26*		
			(-1.91)		
Fitchlag1				-0.47*	
				(-1.83)	
Moodyslag1					-0.25
					(-1.52)
_cons	-3.62	-3.39	-5.79	-4.07	1.03
	(-0.90)	(-0.77)	(-1.12)	(-0.44)	(0.17)
N	305.00	305.00	272.00	201.00	258.00

t-statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

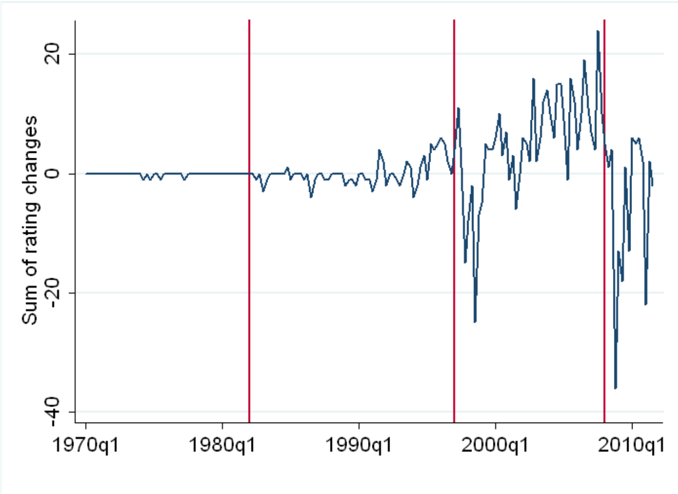
for each agency and found that the first agency to start predicting debt distress events was Fitch with a threshold of BB-: if a country's rating is BB- or below, then the country can be predicted to be in debt distress within two years. For Moody's, the threshold was B+, any rating above it will not predict debt distress events. The coefficient of ratings by S&P did not become significant at any point in the sample. Its ratings were so high in each case of debt distress events in the sample that they did not have any predictive power according to the regression results[21].

The lagging nature of rating changes is further evidenced in figure 1, which shows the sum of all rating changes by all agencies for each quarter. Upgrades are denoted +1 and downgrades -1 and all rating changes are then summed at each quarter to show the cyclicality of rating agencies behaviour. The vertical bars represent the crisis years of 1982, 1997 and 2008. It is clear from the figure that the agencies reacted late with massive downgrades at the onset of each crisis year.

Figures (2 - 5) provide event studies of rating changes for a selection of distress events,

[21]Note that the rating used here is the average rating of the year $t-2$.

Figure 1: Sum of rating changes by all agencies



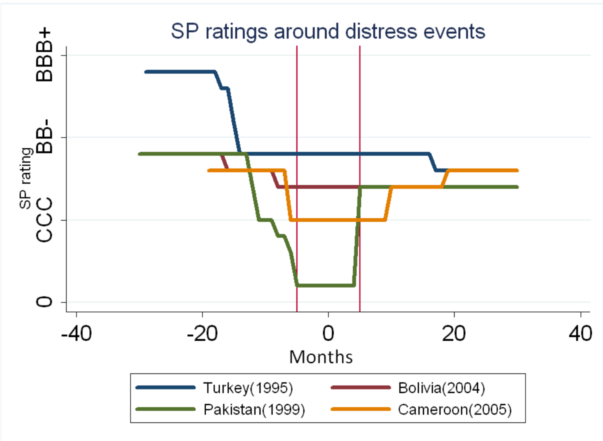


Figure 2: S&P ratings - earliest reaction

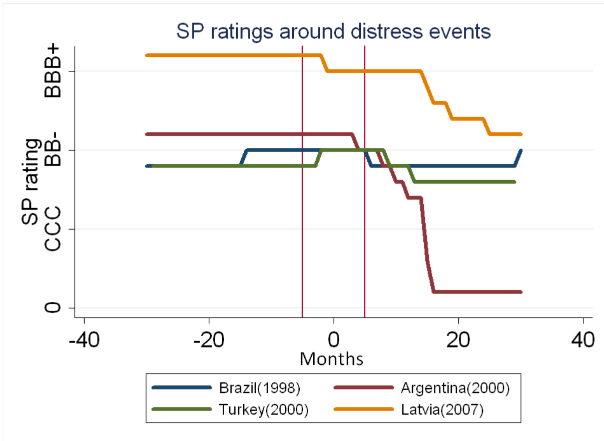


Figure 3: S&P ratings - latest reaction

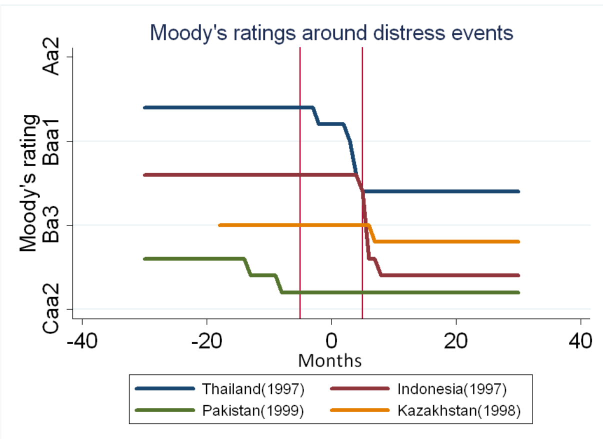


Figure 4: Moody's East Asia

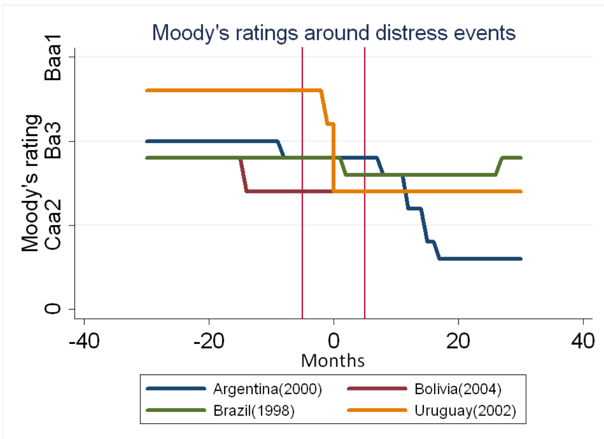


Figure 5: Moody's Latin America

where one can see the actual timing of rating changes at monthly frequency. The vertical bars correspond to the first and the last month of the event year, while the timing on the horizontal scale is so that 0's correspond to June and July of the event year and -5 and 5 respectively to the January and December of the event year. In figure (2) are the earliest S&P reactions found in the data. For example, S&P's reaction to the crisis in Turkey in 1995 was the earliest reaction out of all the distress events. S&P reacted a full 12 months before the crisis. The reaction to Bolivia's crisis in 2004 was the second earliest one with S&P downgrading Bolivia 8 months before the event year.

In figure (4) are displayed reactions by Moody's to the East Asian crisis. The figure confirms that the agency was rather late in its reaction to the events. Most countries did not get downgraded until the last quarter of the year, except for Pakistan, which was downgraded 8 months before the event year. Thailand for example lost its investment grade status only in December 1997 having turned to the IMF in August 1997.

Lastly, figure (5) shows the reactions by Moody's to the Latin American events. All four graphs show further evidence that rating agencies are rather late in their reaction to the events and seem to try to catch up fast with several subsequent downgrades.

All the distress events used in the logit model are listed in table 1. Ratings one year before the event (on January 1st of that year) are in columns 6-8. One can see that almost none of the countries had a negative outlook at that time[22], although Grenada was still rated to be in previous selective default by S&P. Moody's had put Argentina's and Turkey's ratings under negative review, while Brazil in 1997 was under review for a positive rating change. S&P had assigned only Bolivia and Turkey a negative outlook while Brazil again had a positive outlook. Indonesia, Latvia, Thailand, Turkey and Uruguay were all rated investment grade and only Gambia had a rating in the CCC category.

The last column of table 1 lists the dates of default as registered by S&P. Argentina for example defaulted a year after the distress indicator shows that Argentina was in debt distress. Hence, a year before default would be November 2000, at which point Argentina had already received substantial balance of payments support from the IMF. This shows why it is important to use an indicator that captures the distress events already before the actual default. Otherwise any predictive power captured in the ratings would reflect a response to events rather than a prediction of them.

[22]Outlook assignments are indicated after the rating with S (Stable), N (Negative) and P (Positive) where they are given. Some of Moody's outlook assignments reflecting impending rating changes are RUR- (On review for downgrade) RUR+ (On review for upgrade). A below investment grade rating is BB+ / Ba1 or less.

2.2 Robustness checks

Taking expectations into account, we could also interpret the results of the logit model, so that ratings do in fact perform well as a check on government spending if governments take lower rating signals seriously and change their policy as a result to avert crises. In that case the predictive power of ratings would be low. We test this hypothesis by regressing the change in CPIA (the World Bank's institutional and policy quality indicator) against the change in ratings at $(t-2)$ to see whether countries change their policies following rating changes.[23] The results are displayed in table (11).

Table 11: Ratings effect on policy

D.CPIA	SP	SPgrowth	Fitch	Moodys
D.SPlag2	-0.02**	-0.01		
	(-2.03)	(-1.21)		
GDPgrowth		0.01***		
		(3.39)		
GDPgrowthlag1		0.00		
		(1.05)		
GDPgrowthlag2		-0.01*		
		(-1.73)		
D.Fitchlag2			-0.01	
			(-0.80)	
D.Moodyslag2				-0.01
				(-0.51)
_cons	0.04***	0.00	0.06***	0.05***
	(3.39)	(0.05)	(4.07)	(3.88)
N	355.00	355.00	239.00	363.00

t-statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
D. signifies change.

The first column of the results shows that changes in S&P ratings at $(t-2)$ do cause a change in policies at t. However, the results could be due to rating agencies being late in their reaction so that by time t, the crisis is passing already and the CPIA increases due to that. We control for that by adding GDP growth and two of its lags to the regression. The results are reported in column 2. The S&P rating coefficient is no longer significant, however the GDP growth in t is, hence the change in the CPIA index was due to GDP growth picking up and not due to S&P rating change. The last two columns of the table show the results for Fitch and Moody's. A change in neither agency's ratings is shown

[23] The World Bank computes the CPIA index for its use in the IDA allocation process. The index covers 16 criteria which are grouped into four clusters: economic management, structural policies, policies for social inclusion and equity and public sector management and institutions. The scoring runs from 0.0-6.0.

to cause a change in government policies. As a result, there is not much evidence that countries change their policies as a result of rating changes, and that this mechanism is behind the low predictive power found in the logit regressions.[24]

As an other robustness test, we ran the logit regressions again using the same sample in all regressions. The sample sizes were allowed to vary in the previous section, mainly because Fitch rates fewer countries than the other two agencies and restricting the sample would have led us to discard a significant amount of data. Using the same sample for all regressions, restricts the sample to 7 crises (against 18 in the unrestricted sample) but does not affect the conclusions. In fact, the comparison of ratings with fundamentals is even less favourable to ratings. Ratings were not significant in the logit regressions on their own or with the fundamentals at $t-2$ or $t-1$. They all predicted 4 out of 7 crises, while fundamentals predicted 6 out of 7 crises. Ratings also sent about 10% more false alarms than fundamentals.

3 The effect of ratings on markets

3.1 Panel regressions

This section analyses the relationship between ratings and spreads. The key result from the section is that the rating changes can have very large effects on markets, particularly in case of downgrades.

The primary interest is on the dynamic response of *changes* in ratings to *changes* in spreads and hence we use a first differenced model that also has the advantage of fixed effects dropping out. This is preferable to levels, as ratings are changed so infrequently that it would be difficult to distinguish the rating changes from the fixed effects. Also, it is the only way to capture the dynamic impact of rating changes when ratings change rarely and spreads very often. Spreads are in logs as is standard in finance literature, so that the dependent variable is a percentage change in spreads.

$$\Delta\ln(\mathrm{sp})_{i,t} = \beta_1\Delta\ln(\mathrm{sp})_{i,t-1} + \beta_2\Delta R_{i,t} + \beta_3\Delta\mathrm{VIX}_t + \beta_4\Delta\mathrm{FFR}_t + \Delta\epsilon_{i,t} \quad (2)$$

We choose a lag length of one for the spreads because they seem to follow an AR(1) process. This creates an endogeneity such that $E[(\Delta ln(sp)_{t-1})'\Delta e_t]$ is not zero since $\Delta ln(sp)_{t-1} = ln(sp)_{t-1} - ln(sp)_{t-2}$ and $\Delta e_t = e_t - e_{t-1}$ are correlated because $ln(sp)_{t-1}$

[24]Future research may consider other policy indicators than CPIA for this exercise. One key challenge in this respect will be to find indicators that are available and comparable across all countries in our sample of emerging market and developing economies.

is determined by e_{t-1}: $ln(sp)_{t-1} = ln(sp)_{t-2} + x'\beta + e_{t-1}$. Hence to avoid bias in the results, we use 2SLS to instrument the lagged dependent variable by its own lag following Arellano and Bond (1991).

The exogenous variables used in equation 2 are the VIX, the index of US stock market volatility proxying risk appetite of investors and the Fed funds rate (FFR) which proxies global liquidity conditions. Both are shown to be important determinants of EMBI spreads.[25]

The data on spreads is from the second dataset described in the data section 1.1. It is of monthly frequency and contains stripped spreads from the JP Morgan EMBI Global Index. The monthly frequency is optimal for our purposes as it is short enough to capture the dynamics but long enough to avoid the error driven daily volatility and to account for cases where rating changes are well anticipated.

We test for serial correlation by regressing the predicted errors on their own lags ($\epsilon_{i,t} = \rho\epsilon_{i,t-1} + v_{i,t}$) and find that ρ is significant.[26] Instead of adding more lags to get rid of the serial correlation, we retain the model suggested number of lags and use HAC standard errors in all regressions to correct for both heteroskedasticity and autocorrelation.

The results of the regressions are reported in table 12. Since the dependent variable (the spread) is in logs, the marginal effects reported in all regressions in this section represent percentages.

In the first column of table 12 are the results with all rating agencies in the same regression. In columns 2-4 each agency (S&P, Moody's and Fitch respectively) is assessed individually to avoid collinearity. The coefficients of all rating changes are significantly different from zero at the 1% confidence level and are similar in magnitude, ranging from 4.5% (S&P) to above 6% (Moody's). Also, VIX and the fed funds rate are very good predictors of changes in spreads. Regressing with HAC standard errors, we do not get a R^2, but repeating the regression with a pooled OLS estimation with clustered standard errors, the predictive power is around 30% in all regressions. In the individual regressions all the coefficients of rating changes are significant and approximately of the same size. On average a one notch rating change has an impact of about 4-6 % impact on spreads.

[25] See for example Longstaff et al. (2011) who find that sovereign credit risk is mainly determined by global factors. Gonzales-Rozada and Levy-Yeyati (2008) find that sovereign spreads are well predicted by VIX and US 10-year treasury yield in particular. On the other hand Eichengreen and Mody (2000) look at country specific determinants of spreads and do find correlation. We did test trade balance/imports, CPI and industrial production, but none of these variables were consistently significant while VIX and FFR were. For this reason, we do not include fundamentals in equation 2.

[26] See Wooldridge (2001), p. 282.

Table 12: Effect of rating changes to changes in spreads

D.ln(spread)	All	SP	Moodys	Fitch
D.ln(spread)lag1	2.19	5.16	5.10	4.55
	(0.21)	(0.49)	(0.49)	(0.44)
D.SP	-3.29***	-4.48***		
	(-3.65)	(-4.28)		
D.Moodys	-4.24***		-6.29***	
	(-4.67)		(-5.39)	
D.Fitch	-2.94***			-4.88***
	(-3.29)			(-4.27)
D.VIX	1.66***	1.68***	1.68***	1.68***
	(27.13)	(26.89)	(26.60)	(27.03)
D.FFR	-6.55***	-6.58***	-6.88***	-6.58***
	(-6.15)	(-6.09)	(-6.24)	(-5.97)
_cons	-0.39*	-0.41**	-0.42**	-0.43**
	(-1.89)	(-1.98)	(-1.98)	(-2.05)
N	4135.00	4148.00	4149.00	4139.00

t-statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Monthly data frequency, spreads from EMBI Global index. D. denotes change.

The dependent variable is change in log spreads

This shows that the rating changes do have an independent effect on spreads, in addition to the reaction that takes place at the time of the changes in fundamentals.[27]

Next, the analysis turns to the dichotomous response between upgrades and downgrades. We assign three dummies to count for upgrades, downgrades and no change in rating as follows:

$$up = \begin{cases} 1 & \text{if rating change is an upgrade} \\ 0 & \text{if rating change is a downgrade or rating does not change} \end{cases} \tag{3}$$

$$down = \begin{cases} 1 & \text{if rating change is a downgrade} \\ 0 & \text{if rating change is an upgrade or rating does not change} \end{cases} \tag{4}$$

$$no = \begin{cases} 1 & \text{if rating does not change within the month} \\ 0 & \text{if rating changes} \end{cases} \tag{5}$$

The results are reported in table 13. From now on, only the results of the dummies are reported to avoid cluttering. The full results are in Appendix C. The dichotomy between upgrades and downgrades is very clear. When a rating change is a downgrade, spreads rise by between 13 and 16 %, but when there is an upgrade, the ratings decrease by much less, only between 2 and 4%.

Table 14 narrows the analysis further by looking at upgrades and downgrades within the investment grade and non-investment grade categories respectively. The coefficients of upgrades are again much smaller than the coefficients of downgrades in both categories. Especially in the investment grade category, Moody's and S&P upgrades are not significant at all and have very small coefficients. Surprisingly though, Fitch's upgrades in the investment grade category are significant while downgrades are not. The coefficients in the non-investment grade category are more significant for both upgrades and downgrades and seem to drive the overall results.

The reason why S&P and Fitch upgrades in the non-investment grade category are significant is probably that they assign default statuses to bonds, which effectively stop many investors from investing in these assets. Therefore any upgrades from default status would likely have an impact on spreads as investors regain their right to invest in those assets.

One reason for this dichotomous response between upgrades and downgrades can be

[27]This can be due to investors revising their expectations about actions of other investors, as in Carlson and Hale (2005).

Table 13: Upgrades downgrades

D.ln(spread)	S&P	Moodys	Fitch
downSP	13.15***		
	(5.58)		
upSP	-2.40*		
	(-1.95)		
downMoodys		15.69***	
		(5.26)	
upMoodys		-3.03**	
		(-1.98)	
downFitch			13.61***
			(4.98)
upFitch			-3.85***
			(-3.79)
_cons	-0.61***	-0.56***	-0.57***
	(-3.03)	(-2.77)	(-2.70)
N	4148.00	4149.00	4139.00

t-statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Monthly data frequency, spreads from EMBI Global index

Table 14: Investment grade and non-investment grade bonds

D.ln(spread)	SPIG	SPJunk	MoodysIG	MoodysJunk	FitchIG	FitchJunk
downsp	12.48***	13.31***				
	(2.80)	(5.07)				
upsp	1.64	-4.61***				
	(0.95)	(-2.94)				
downmoodys			22.97***	14.60***		
			(3.21)	(4.56)		
upmoodys			-1.38	-4.26*		
			(-0.72)	(-1.92)		
downfitch					4.69	15.38***
					(0.99)	(5.15)
upfitch					-5.13***	-2.91**
					(-3.75)	(-2.07)
_cons	-0.28	-0.83***	-0.16	-0.86***	-0.11	-0.86***
	(-0.89)	(-3.15)	(-0.52)	(-3.17)	(-0.36)	(-3.11)
N	1664.00	2484.00	1792.00	2357.00	1635.00	2504.00

t-statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Monthly data frequency, spreads from EMBI Global index

regulatory constraints as mentioned in the introduction. When a country is downgraded, either those bonds can no longer be used as collateral at the central banks or specific clauses in private agreements are activated in both cases causing investors to flee those bonds, especially if they are too tightly leveraged. In case of upgrades, the situation is not as pertinent however, as investors can choose whether they want to invest in those assets or not, and take their time to make their decisions. This would explain why the response to downgrades is much larger than to upgrades; such argument has been made for example by Opp et al. (2012). Fitch at least also acknowledges that regulatory reasons could explain the dichotomous responses to downgrades and upgrades[28]. The rating agencies themselves are generally against ratings being mentioned in regulation[29].

Even if the large reaction from ratings to spreads shown in this section was not due to causality, but spurious correlation, at minimum it would tell us that the agencies tend to downgrade during bad times - i.e. during rising spreads, with large effects on markets but fail to symmetrically upgrade when spreads are falling. Hence, the regressions would lend support to procyclicality.

3.2 Event studies

Using higher frequency data, we confirm the results of the previous section 3.1: that downgrades have a larger impact on spreads than upgrades and the results are more pronounced in the non-investment grade category. The event studies also allow us to capture the impact of outlook changes instead of only looking at actual rating changes as we have done until now. Watch negative events are particularly interesting because they tend to have very large effects on the markets given that they are warning signals of impending downgrades. The rating agencies tend to only assign them at times of

[28]"It is the case that typically the market price of sovereign (and other) rated securities tends to react more to downgrades than upgrades. This may in part be because positive rating actions are largely priced-in in by market participants as they generally reflect sustained improvements in the sovereign credit profile, while downgrades are more often in response to material adverse news. Moreover, there is evidence that the crossing of, or approach to, particular credit rating thresholds that for regulatory purposes or for reasons of market convention have become particularly important notably the threshold between investment grade and sub-investment or speculative grade does tend to generate a more pronounced reaction in the market pricing of sovereign debt and other financial securities." House of Lords (2011)

[29]Fitch: "We believe that certain market participants have relied too heavily, or given the impression of having relied to heavily, on credit ratings, rather than conducting their own analysis. We also believe that one reason for this was the use of ratings in regulations. It follows that regulatory regimes should not rely exclusively on credit ratings." Moody's: "The priority for policymakers should therefore be to address the shortcomings in market regulation and practice which give rise to these problems without preventing market participants from continuing to use credit ratings in their credit assessment should they choose to do so. Regulators need to modify the use of ratings in regulation and to remove any inducement to react disproportionately to changes in ratings." ... "For more than 10 years we have put forward a clear argument against using ratings in regulation. We felt it would naturally lead to a situation where investors only look at the rating without trying to understand the underlying credit risk and react in a fairly mechanistic way to rating changes." House of Lords (2011). Financial Stability Board (2010) has issued principles of reducing reliance on CRA ratings.

severe distress, when the investors tend to be more reactive to signals no matter how imperfect they may be. Since the actual downgrades themselves are anticipated by the watch negative announcements, the impacts are larger for the latter.

The event studies look at a +/- 10 day window around different types of rating actions, such as upgrades and downgrades and outlook changes. In this section only S&P ratings are used, but the analysis could easily be extended to the other two agencies as well. A new database is compiled for each type of event that includes only those rating events that do not overlap with other types of events. For example if there is a positive outlook announcement and within 10 days an upgrade, both of those events would be excluded from the database.

The results of the event studies are displayed in the appendix D. All the spreads are translated into an index, which is 0 at day -10 and therefore any changes can be interpreted in percentage terms. The figures show that all the graphs evolve in the correct direction, i.e. the spreads rise with downgrades and decline with upgrades, except for positive outlook assignments, which do not seem to have much of an impact on the spreads at all. Many events seem to be well anticipated, and in many cases, most of the action happens before the actual rating event. Kaminsky and Schmukler (2001) take this as evidence of ratings being procyclical, being downgraded in bad times and upgraded in good times, but because the frequency of data is daily, a 10 day rise/fall in spreads is too short to draw conclusions about the cycle. Another reason for the early rise in spreads could be anticipation. There is in fact a study by Purda (2007) that looks at whether rating changes of corporate bonds can be anticipated. She finds that approximately 20% of the rating changes can be anticipated using publicly available data. There are no studies that look at the possibility of anticipating *sovereign* rating changes to our knowledge.

Looking at the magnitudes of changes in the event study graphs, we confirm again that the impact of downgrades is larger than the impact of upgrades. The first two graphs in appendix D display the impacts for the total sample and show a decrease in spreads of just over 4 percent in case of upgrades and an increase of about 10 percent in case of downgrades, very similar magnitudes to the results in the panel study. The results are more muted for investment grade bonds where the impact of an upgrade recovers very soon.

The effect of the watch negative announcements on spreads for the total sample is approximately 40%, and 30% for non-investment grade bonds. But for investment grade bonds it is close to 100%. There are five watch negative announcements for investment grade category countries. Of those, in Hungary and Tunisia the spreads tripled within the 21 days, and in Bulgaria they doubled. In the other two countries, Kazakhstan and Trinidad & Tobago, the spreads rose significantly as well, but not by as much. A watch negative listing of an investment grade country can therefore have a huge impact on markets.

The impact of rating changes on spreads varies significantly between different types of rating announcements and different categories of ratings. Some rating events such as positive outlook assignments, seem to be ignored by the markets, whereas surprise events such as watch negative announcements to investment graded bonds can cause severe distress and cliff effects on the markets.

4 Conclusion

This paper has presented empirical evidence on the ability of sovereign credit ratings to anticipate debt distress events using a panel of emerging and developing countries. The results indicate that credit ratings do not perform well; a parsimonious model using very standard variables similar to (Cohen and Valadier (2011)) fares better based on noise to signal ratio analysis. In addition, event case analysis reveals that credit rating agencies tend to react very late.

If the ratings are not a good predictor of debt distress events compared to a simple model based on common fundamentals, then the investors should be able to ignore them. We do not observe this however, as we show that markets do respond to rating changes, especially to downgrades in the non-investment grade category. Several factors may explain this outcome. It could be that ratings act as a signal and coordinating device for market participants. Yet, another reason for this may be that ratings are strongly connected to both regulation and to internal rules of investors. For this reason, if a country gets downgraded, the investors may have to abandon the investments, whereas if a country is upgraded, the investors gain the right, but not the obligation, to invest in the assets. This would explain why downgrades have larger effects on markets than upgrades. Further research may help distinguish these different explanations.

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A Datasets

Table 15: Countries used in the logit regressions of section 2.1

	Country	Start	End		Country	Start	End
1	Argentina	1997	2000	26	Latvia	1997	2007
2	Azerbaijan	2000	2007	27	Lesotho	2002	2007
3	Belize	1999	2007	28	Macedonia	2004	2007
4	Bolivia	2000	2004	29	Malaysia	1986	2007
5	Bosnia and Herz.	2005	2007	30	Mali	2004	2007
6	Botswana	2001	2007	31	Mauritius	1996	2007
7	Brazil	1995	1998	32	Mexico	1998	2007
8	Bulgaria	2002	2007	33	Moldova	2001	2003
9	Cameroon	2003	2005	34	Mongolia	1999	2007
10	Cape Verde	2004	2007	35	Morocco	1998	2007
11	China	1988	2007	36	Pakistan	1994	2007
12	Colombia	1993	2007	37	Panama	1997	2007
13	Costa Rica	1997	2007	38	Papua New Guinea	1998	2007
14	Ecuador	1997	2000	39	Paraguay	1996	2007
	Ecuador	2005	2007	41	Peru	1998	2007
15	Egypt	1997	2007	42	Philippines	2001	2007
16	El Salvador	1996	2007	43	Poland	1995	2007
17	Fiji	1999	2007	44	Romania	1996	2007
18	Gambia, The	2005	2007	45	Russian	2004	2007
19	Ghana	2004	2007	46	Senegal	2002	2007
20	Grenada	2003	2006	47	South Africa	1995	2007
21	Honduras	2001	2004	48	Thailand	1989	2007
22	India	1989	2007	49	Tunisia	1995	2007
23	Indonesia	1992	1997	50	Turkey	1992	2000
24	Jordan	2004	2007	51	Ukraine	2003	2007
25	Kazakhstan	1996	1998	52	Uruguay	1993	2002
	Kazakhstan	2000	2007	53	Venezuela, RB	1977	1990
					Venezuela, RB	1994	2007

Table 16: List of EMBI countries, used in section 3.1

	Country	Start	End		Country	Start	End
1	Argentina	1997m6	2011m5	17	Lebanon	1998m7	2011m5
2	Brazil	1995m1	2011m5	18	Lithuania	2010m2	2011m5
3	Bulgaria	1998m12	2011m5	19	Malaysia	1998m9	2011m5
4	Chile	1999m8	2011m5	20	Mexico	1995m9	2011m5
5	China	1998m1	2011m5	21	Panama	1998m10	2011m5
6	Colombia	1997m5	2011m5	22	Peru	1999m11	2011m5
7	Croatia	1997m2	2011m5	23	Philippines	1999m8	2011m5
8	Dominican Rep.	2003m9	2011m5	24	Poland	1995m11	2011m5
9	Ecuador	2002m12	2011m5	25	South Africa	1995m3	2011m5
10	Egypt	2001m10	2011m5	26	Sri Lanka	2010m10	2011m5
11	El Salvador	2002m7	2011m5	27	Tunisia	2002m8	2011m5
12	Georgia	2010m11	2011m5	28	Turkey	1996m9	2011m5
13	Hungary	1999m4	2011m5	29	Ukraine	2002m1	2011m5
14	Indonesia	2004m8	2011m5	30	Uruguay	2001m8	2011m5
15	Jamaica	2008m1	2011m5	31	Venezuela	1997m10	2011m5
16	Kazakhstan	2007m9	2011m5	32	Vietnam	2006m2	2011m5
				33	Russia	1998m3	2011m5

B Noise to signal ratios at $t-1$

Table 17: Noise to signal ratios $t-1$

Fundamentals				**S&P**			
	signal				signal		
distress	0	1	**Total**	distress	0	1	**Total**
0	212	76	**288**	0	159	127	**286**
1	4	13	**17**	1	5	9	**14**
Total	**216**	**89**	**305**	**Total**	**164**	**136**	**300**
% of obs. correctly called			73.8%	% of obs. correctly called			56.0%
% of crises correctly called			76.5%	% of crises correctly called			64.3%
% of false alarms of total alarms			85.4%	% of false alarms of total alarms			93.4%
% prob. of crisis given an alarm			14.6%	% prob. of crisis given an alarm			6.6%
% prob. of crisis given no alarm			1.9%	% prob. of crisis given no alarm			3.0%

Fitch				**Moody's**			
	signal				signal		
distress	0	1	**Total**	distress	0	1	**Total**
0	158	55	**213**	0	182	90	**272**
1	4	7	**11**	1	5	10	**15**
Total	**162**	**62**	**224**	**Total**	**187**	**100**	**287**
% of obs. correctly called			73.7%	% of obs. correctly called			66.9%
% of crises correctly called			63.6%	% of crises correctly called			66.7%
% of false alarms of total alarms			88.7%	% of false alarms of total alarms			90.0%
% prob. of crisis given an alarm			11.3%	% prob. of crisis given an alarm			10.0%
% prob. of crisis given no alarm			2.5%	% prob. of crisis given no alarm			2.7%

C Full results of panel regressions

Table 1: Upgrades downgrades

Dlnspread	SPUpDown	MoodysUpDown	FitchUpDown
Dlspreadhatlag1	3.86	5.58	4.93
	(0.37)	(0.53)	(0.47)
downsp	13.15***		
	(5.58)		
upsp	-2.40*		
	(-1.95)		
downmoodys		15.69***	
		(5.26)	
upmoodys		-3.03**	
		(-1.98)	
downfitch			13.61***
			(4.98)
upfitch			-3.85***
			(-3.79)
dvix	1.67***	1.68***	1.68***
	(26.90)	(26.78)	(27.16)
dffr	-6.47***	-6.80***	-6.44***
	(-5.99)	(-6.25)	(-5.89)
_cons	-0.61***	-0.56***	-0.57***
	(-3.03)	(-2.77)	(-2.70)
N	4148.00	4149.00	4139.00

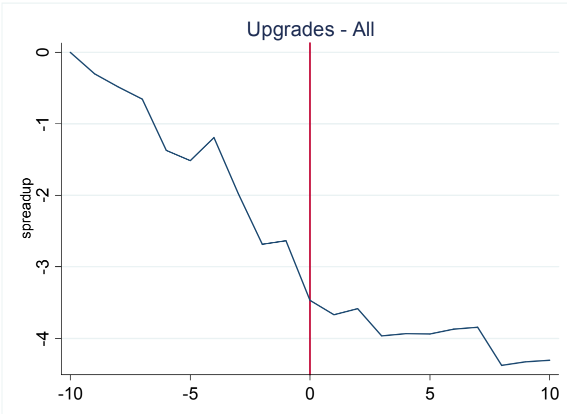
t-statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Monthly data frequency, spreads from EMBI Global index

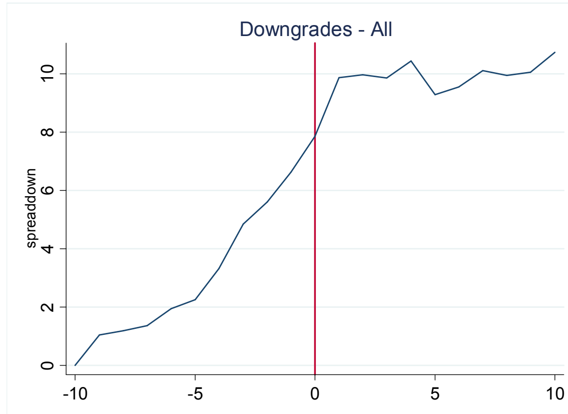
Table 2: Investment grade and junk bonds

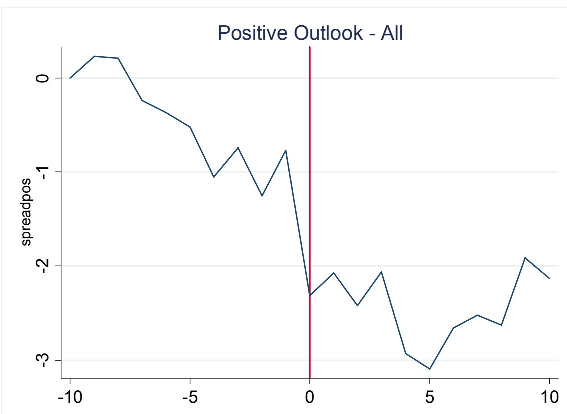
Dlnspread	SPIG	SPJunk	MoodysIG	MoodysJunk	FitchIG	FitchJunk
Dlspreadhatlag1	-7.99	11.52	-2.90	11.14	-11.16	15.08
	(-0.44)	(0.94)	(-0.16)	(0.87)	(-0.59)	(1.23)
downsp	12.48***	13.31***				
	(2.80)	(5.07)				
upsp	1.64	-4.61***				
	(0.95)	(-2.94)				
downmoodys			22.97***	14.60***		
			(3.21)	(4.56)		
upmoodys			-1.38	-4.26*		
			(-0.72)	(-1.92)		
downfitch					4.69	15.38***
					(0.99)	(5.15)
upfitch					-5.13***	-2.91**
					(-3.75)	(-2.07)
dvix	1.60***	1.72***	1.60***	1.74***	1.59***	1.75***
	(16.16)	(22.02)	(16.35)	(21.74)	(16.23)	(22.38)
dffr	-5.30***	-7.32***	-4.83***	-8.19***	-5.83***	-6.87***
	(-2.94)	(-5.47)	(-2.78)	(-5.88)	(-3.19)	(-5.05)
_cons	-0.28	-0.83***	-0.16	-0.86***	-0.11	-0.86***
	(-0.89)	(-3.15)	(-0.52)	(-3.17)	(-0.36)	(-3.11)
N	1664.00	2484.00	1792.00	2357.00	1635.00	2504.00

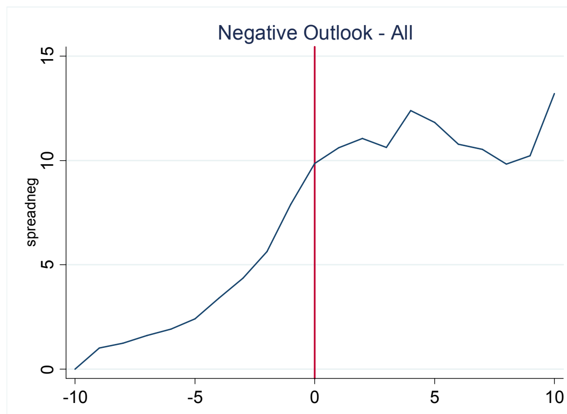
t-statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Monthly data frequency, spreads from EMBI Global index

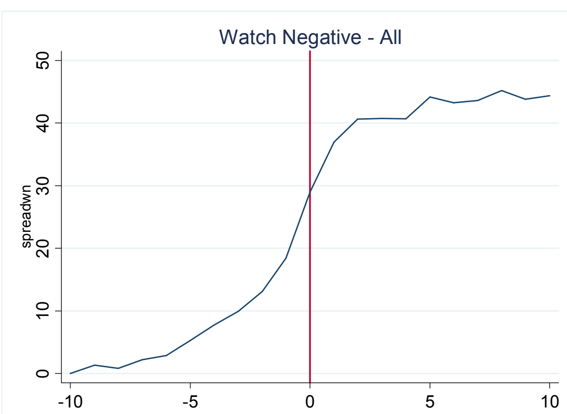
D Event studies – All



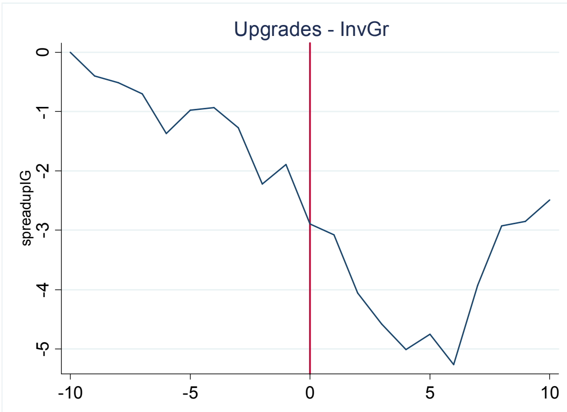


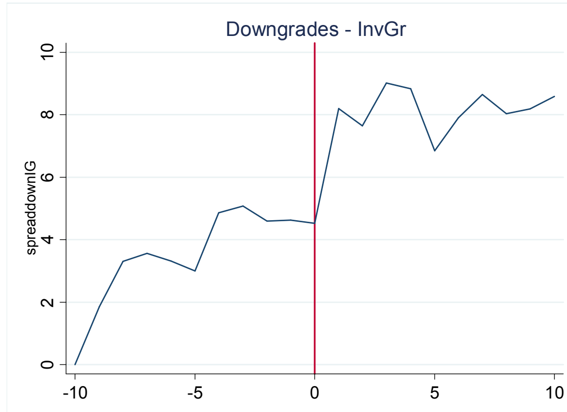


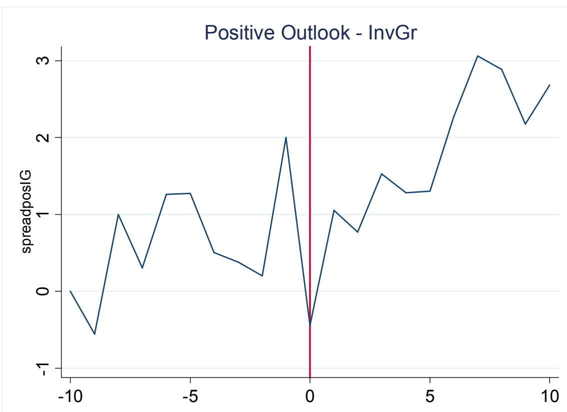


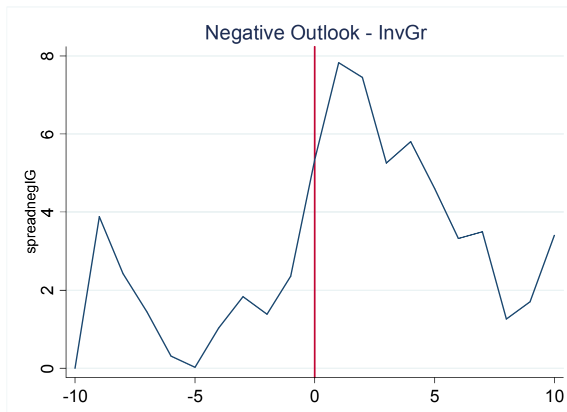


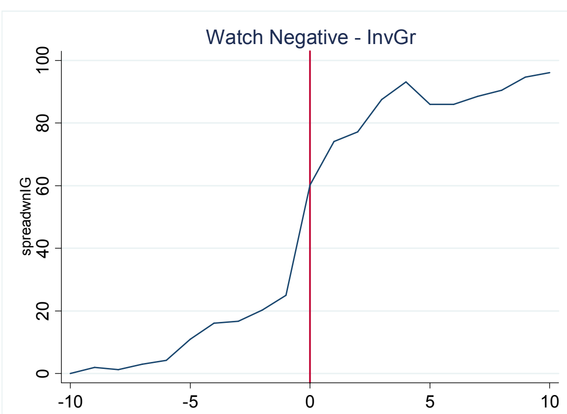
Event Studies – Investment grade











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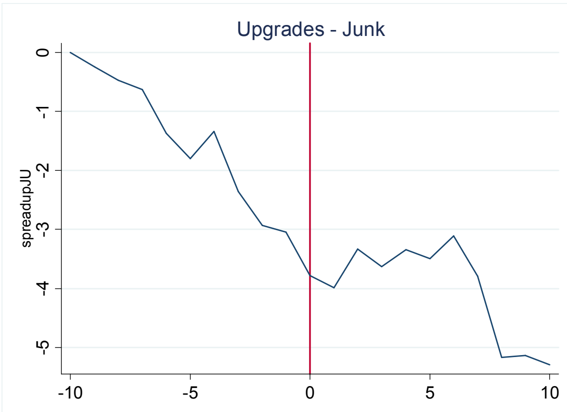

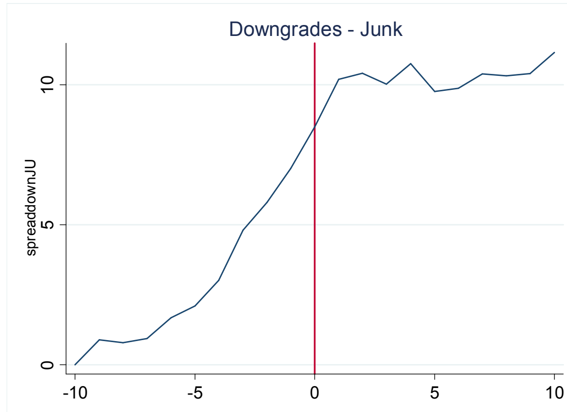

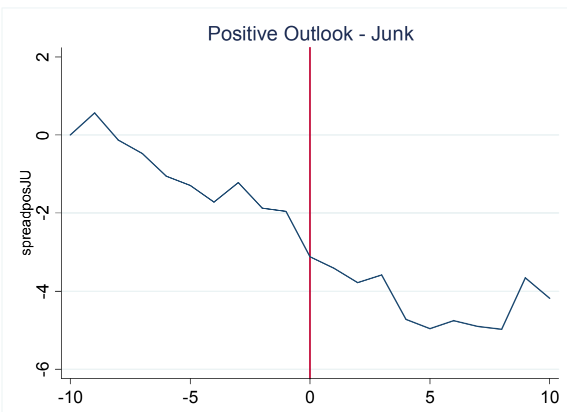

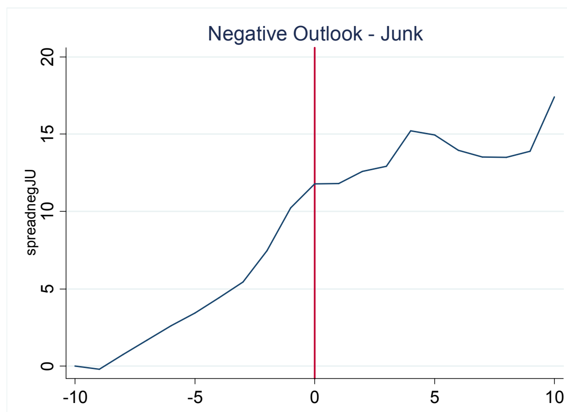

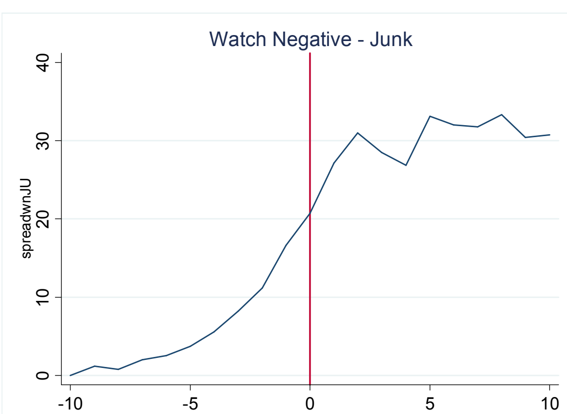

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