Variations in Sovereign Credit Quality Assessments across Rating Agencies

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This version 13 January 2009

Abstract

We employ sovereign ratings data for 129 countries, spanning the period 1990 to 2006, to investigate agency variation in credit quality assessment (Standard and Poor's vs. Moody's vs. Fitch). While we find that the credit rating agencies often disagree about credit quality, it is usually confined to one or two notches on the finer scale. Given we find that several variables have varying importance across agencies leads us to conclude that material heterogeneity exists between them. Also, while watch and outlook procedures are generally strong predictors of rating changes relative to other public data, additional significant variables suggest that these agency data might be augmented to provide better forecasts of rating changes.

JEL Classification: G32

Keywords: Credit rating, rating transition, prediction, information content, sovereign

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1. Introduction

A credit rating represents an assessment of the default probability of the debtor. The Basel Capital Accord has provided a renewed interest in credit ratings since it allows banks to employ these ratings to determine the default probabilities of their debtors for the purpose of calculating the capital adequate to cover their credit risks (see, inter alia, Jafry and Schuermann (2004)). To enhance decision making in this context, users will be vitally concerned about the determinants of credit ratings and the likelihood of imminent changes in credit ratings of obligors and, to this end, credit rating transition matrices have attracted increasing attention in the academic literature (e.g. see Jarrow, Lando and Turnbull, 1997). However, knowledge of credit quality is obfuscated by variation across credit rating agencies in assessments of the credit quality of the same obligor. This is manifested in the form of variations in (i) the current rating grade, (ii) the timing of changes in credit quality and (iii) the use and timing of forewarnings of changes in credit quality (i.e. credit watch and outlook status).

As investment portfolios have become increasingly diversified across national boundaries, an understanding and assessment of sovereign credit risk has become increasingly important. Brooks, Faff, Hillier and Hillier (2004), Gande and Parsley (2005) and Hill and Faff (2007) provide evidence that there are non-trivial differences in rating activity at the sovereign level across different rating agencies and Cantor and Packer (1996) show that these differences are more evident at the sovereign level than the corporate level.

The core purpose of our paper is to extend the knowledge and understanding of variations in credit related information provided by the three major rating agencies at the sovereign level. Specifically, we begin our analysis by documenting differences in sovereign rating levels and rating transitions across the three major agencies, Standard and Poor's, Moody's and Fitch. We then go on to compare the factors which determine sovereign rating levels and transitions across the three major agencies.

We deliver a range of contributions within the context of the relevant literature. First, we extend our understanding of the determinants of sovereign rating levels by employing a larger sample of sovereigns across three major agencies than previously used in existing studies. This allows us to undertake a more complete analysis of the variations in the determinants of sovereign rating levels across the three major agencies. Prior work on the determinants of sovereign rating levels has been undertaken by Cantor and Packer (1996) who examine a sample of 49 sovereigns rated by both Standard and Poor's and Moody's. Their sample was drawn up at a time when many emerging market sovereigns had yet to be rated. We extend the Cantor and Packer analysis to include Fitch Ratings and to include a considerably wider range of sovereigns (from our original sample of 129 sovereigns we have macroeconomic data for 108 sovereigns).

Second, we extend extant work to produce comparable sovereign rating migration tables for all three agencies, rather than focussing on just one agency, and we provide a more complete picture of changes in sovereign credit quality by employing a wider range of sovereigns than ever before examined (our sample consists of 129 sovereigns). Hu, Kiesel and Perraudin (2002) and Fuertes and Kalotychou (2007) have both produced rating migration matrices for sovereigns, but each of these studies is based on limited samples for one credit rating agency. We extend this work to produce comparable sovereign rating migration matrices for all three agencies for a wider range of sovereigns.

Further, there is no conclusive evidence to suggest that a within category rating change is of any less consequence than a between category change[1] and thus rating migration analyses based on broader categories potentially rely on an arbitrary subset of changes in credit quality. Accordingly, we follow Hu et al. (2002) in producing a sovereign credit migration analysis based on all credit quality changes, that is, it is based on the finer rating categories.

Third, we extend existing work at the corporate level to examine the determinants of rating migrations at the sovereign level, again with a particular focus on variations across agencies. The rating agencies provide a prediction of likely future rating outcomes in the form of rating outlooks and credit watch procedures.[2] Purda (2006) undertakes an analysis of Moody's corporate ratings outcomes employing credit watch data in addition to corporate level data. We undertake a similar analysis at the sovereign level and examine both the extent to which rating agency information captures other publicly available information likely to impact on the likelihood of a rating change, and the varying strength of these signals (i.e. watch and outlook) across agencies. We also examine whether rating agency data on outlooks and credit watch status can be augmented to provide better out-of-sample estimates of rating transition probabilities.

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[1] Although we accept that changes which cross the investment barrier would be expected to cause a greater market reaction, as regulated investors adjust their portfolios. Barron, Clare and Thomas (1997) fail to find statistical significance when examining the news content of between versus within category rating changes.

[2] An outlook takes a longer term view of the credit worthiness of a bond issuer and is typically attached to all ratings. A credit outlook typically covers a period of up to 2 years ahead. Outlooks may be either "positive" (signalling the possibility that at some stage over the two-year horizon a rating may be raised), "stable" (a rating is unlikely to be changed) or "negative" (a rating may be lowered). A credit watch is more short-term focused and is instigated where new developments become known which might affect the rating. A credit watch may be either "positive", "negative" or "developing", where this last occurs on rare occasions where "future events are so unclear" (page 1, Standard and Poor's Primer on CreditWatch and Ratings Outlooks, 08/04/2004) that either a positive or negative change is possible.

Our key findings can be summarized as follows. We find that the credit rating agencies disagree more often than they agree about the rating of a sovereign obligor, however, disagreement tends to be within one or two notches on the finer scale. Interestingly, we find considerable divergence of opinion in respect of ratings at the time of documented sovereign defaults. As expected, rating transition probabilities tend to increase as the rating level decreases across all agencies, but rating stability at lower rating levels is less for Standard and Poor's than for Fitch or Moody's.

We document that six variables are common determinants of all three agencies assessments of credit quality and a further four variables are significant for only two or less agencies. When we repeat the analysis across the subset of sovereigns which are rated by all three agencies, we confirm these differences leading us to conclude that different factors determine rating levels across agencies.

We find that sovereign rating transitions are more difficult to capture than sovereign levels. We model rating transitions via both hazard and ordered probit models and we find the same pattern of results for both models with regard to watch and outlook procedures, namely, that these events are strong predictors of rating changes relative to other public data. The exceptions are Moody's outlook status and Standard and Poor's watch positive status. The poor predictive power of these variables is not caused by their indiscriminate use but rather by their lack of use. Other variables are significant in all our rating transition models in the presence of watch and outlook data, suggesting that these agency data might be augmented to provide better forecasts of rating changes. However, out-of-sample tests based on Standard and Poor's data fail to confirm this prospect. Of the rating agency forecast data provided, we find that Standard and Poor's outlook data are by some margin the most informative predictor of rating outcomes which allows some scope for an improvement of out of sample forecasts which are based on Fitch and Moody's outlook or watch data (neither of these agencies' data were available to us for the out-of-sample period).

The remainder of our paper proceeds as follows. In Section 2 we describe our data. In Section 3 we document variations in sovereign rating levels and migrations across agencies. In Section 4 we undertake an analysis of the determinants of rating levels across the three major agencies, while in Section 5 we estimate models of rating changes, which we test both in-sample and out-of-sample. Section 6 provides a concluding discussion.

2. Data

A number of alternative ratings are issued at the sovereign level, namely, country ceilings (for domestic and foreign currency denominated debt); issuer government ratings (for domestic and foreign currency denominated debt); and individual bond issue ratings. We employ sovereign issuer ratings for foreign currency denominated debt.[3] The ratings applied by Fitch, Standard and Poor's and Moody's are shown in Table 1.[4] In Column 1

[3] Moody's only make country ceiling ratings freely available, their issuer ratings are only available via subscription. The following quote from Moody's literature illustrates the distinction between the country ceiling rating (formerly known as the sovereign ceiling rating) and a government issuer rating: "The 12 countries currently comprising the Eurozone share a common currency and so all issuers located in those countries fall under the common Aaa Eurozone ceiling. The individual governments, however, are evaluated for their own fundamental creditworthiness, with ratings on their bonds ranging from Aaa to A2" (page 4, 'Sovereign Ratings History: Special Comment', *Moody's Investors Service*, January 2002).

[4] We have Moody's sovereign issuer rating histories for all countries for which there is a rating event, but we only have sovereign ceiling histories for non-event countries. For most sovereigns, particularly those where the sovereign issuer and sovereign ceiling rating remains unchanged, the two ratings will be the same, and we therefore employ sovereign ceiling ratings as a proxy for sovereign issuer ratings for non-event countries.

of Table 1 we present a consolidated rating number for the finer rating categories employed by rating agencies, and in Column 2 we present the broader rating categories.

[Insert Table 1 about here]

Our period of analysis extends from April 1, 1990 through March 31, 2006.[5] In Table 2 we list the 129 countries for which we have rating data from at least one of the three agencies. Our sample of up to 129 sovereigns for the period 1991 through 2006 across three agencies compares very favourably with other samples employed for sovereign rating analysis (Cantor and Packer (1996) - 49 sovereigns, 1995 only, two agencies; Hu Kiesel and Perraudin (2002) - up to 62 sovereigns, 1981 through 1998, one agency; Fuertes and Kalotychou (2007) – up to 72 sovereigns, one agency, 1981 through 2004). However, relative to studies at the corporate level the sample size is small (for example, Nickell, Perraudin and Varotto (2000) employ a sample of up to 6,534 Moody's US corporate obligors for the period 1970 through 1997).

[Insert Table 2 about here]

Transition matrices are often conditioned on one or more factors. For example, Nickell et al. (2000) employ ordered probit models to condition rating transitions of Moody's upon a number of variables simultaneously (the domicile and industry of the obligor and the business cycle). At the sovereign level, data availability severely limits the possibility of conditioning each transition between ratings on a number of variables. Hu, Kiesel and Perraudin (2002), Fuertes and Kalotychou (2007) and Audzeyeva and Schenk-Hopp (2007) all examine rating migrations at the sovereign level and these

[5] It should be noted that Fitch did not rate sovereign issuers until August 10, 1994. There was very little sovereign re-rating activity prior to 1990. This lack of re-rating activity reflects the fact that sovereign ratings were only issued for a relatively select group of countries with higher credit ratings and few re-ratings were required.

papers are dominated by the common issue of coping with limited data, which they deal with by constructing rating histories to augment available data.

Hu et al. (2002) only have sovereign ratings data for one agency, Standard and Poor's, up to 1998, comprising a high proportion of sovereigns of high credit quality which have infrequent changes in rating. They therefore employ default data to determine implied historical ratings of non-rated countries, and employ predicted changes in these estimated ratings to construct a transition matrix. Fuertes and Kalotychou (2007) employ a sample of Moody's ratings for 72 countries over the period 1981-2004 and circumvent data limitations by employing bootstrap techniques to obtain sovereign transition histories. In the presence of limited data Audzeyeva and Schenk-Hoppe (2007) estimate credit rating migrations for three sovereigns[6] by employing a Bayesian estimator of rating migration probabilities in which the probability density of rating migrations is conditional on both observed transitions and a priori information, the latter being the expectation of a transition constructed from a given prior distribution.

When estimating Moody's credit rating changes at the corporate level, Purda (2006) restricts the potential outcomes to upgrade, no change and downgrade. This is a useful means of modelling sovereign rating changes given sovereign data limitations – accordingly, our approach broadly follows that of Purda. On examining matrices of sovereign default probabilities we find that diagonal and immediately off diagonal elements account for about 98% of rating outcomes.[7] Immediately off diagonal elements are equivalent to a one notch rating change based on the finer rating categories employed

[6] Kadam and Lenk (2008) employ Bayesian estimation to overcome data sparseness at the corporate level.
[7] This calculation is based on Standard and Poor's sovereign issuer ratings across 32 six-month periods from April 1 1990 to March 31 2006. Of 2,071 recorded initial ratings, 1,808 remained unchanged, 227 changed by one notch, 13 by two notches, 12 by three or more notches and 11 defaulted.

by the credit rating agencies. The immediately off diagonal elements based on historical transition rates account for about 86% of rating *changes*. If we move two notches from the diagonal we capture 91% of rating changes.[8] This, however, leaves a non-trivial 9% of rating outcomes not captured by a focus on elements around the diagonal. In light of these observations, we extend Purda's model such that we capture both those changes with greatest frequency i.e. upgrades and downgrades around the diagonal and those changes with greatest significance i.e. sharp deteriorations in credit quality. By focussing on this key subset of outcomes we are able to reliably construct conditional sovereign rating transition probabilities from the data available.

3. Variations in rating levels, rating migrations and default ratings across agencies

3.1 Ratings level comparisons

In Panel A of Figure 1 we examine the relative distribution of ratings across the three agencies for 129 countries at the end of the sample period, April 1, 2006. For the sake of clarity we employ the broader rating categories identified in Table 1. The panel shows a similar distribution in ratings for Fitch and Standard and Poor's. Moody's have a lower percentage of their ratings (11% vs. approximately 20% for the others) in the sub-investment grade category Ba/BB (rating category 4) and a higher percentage of their total ratings (19% vs. approx 13%) in the investment grade category Baa/BBB (rating category 5) and (26% vs. approx 16%) in the highest category Aaa/AAA (rating category 8).

[Insert Figure 1 about here]

[8] These figures are again based on the sample referred to at Footnote 7 above. Of 263 rating changes 227 are immediately off-diagonal and 240 are changes up to 2 notches.

We examine whether these differences are explained by differences in the countries rated by the agencies, or by differences in opinion. Across rating categories 4, 5 and 8 we find only three discrepancies between Moody's and the other agencies (India: Moody's (4), Fitch/S&P (5); Jordan: S&P (4); Moody's (5); Panama: S&P (4), Fitch/Moody's (5)). Given this small divergence, the differences in (broader category) ratings are primarily caused by the countries rated rather than differences in opinion.

We also consider the extent of differences of opinion across the three rating agencies at April 1, 2006 for the finer rating categories. Of the 129 rated countries, 98 (76%) are rated by more than one agency. Discordance (59%) is more common than concordance (41%) across the three agencies but any discordance tends to be within one or two notches of the finer scale. Across agencies, the ratings accord within 1 grade (on the finer scale) for 82% of rated countries. In only two cases does the maximum number of notches of discordance between any two agencies exceed 3 notch points (on the finer scale). One of these relates to a default rating awarded to Argentina by Fitch when S&P and Moody's awarded ratings of B and B3, respectively, and the other relates to Bahrain which Moody's awarded a rating of Ba1 in early 2006 when Fitch and S&P awarded an A- rating.

In Panel B of Figure 1 we examine rating distributions across our entire sample period, with ratings measured every 6 months starting April 1, 1990 and ending March 31, 2006. Panel B will be key to understanding the results of our analysis of the determinants of rating levels across agencies and is therefore restricted to 108 countries for which we have full data on which this analysis is based. Panel B shows that across our full sample period Moody's (46% of ratings) has been more active in sub-investment grade ratings (category 4 and below) than S&P (33% of ratings) and Fitch (33% of ratings). This contrasts with the point in time distribution discussed above in which Moody's had a lower percentage of their ratings in the sub-investment grade category.

3.2 Ratings migration comparisons

We consider an N-state Markov chain where N is the number of rating bands including default and withdrawal. We calculate the transition probabilities of the Markov chain for a given time horizon in a NxN matrix, where the *ij*'th element is the probability of migrating from state *i* to state *j* in time period *t* (chosen to be one year to facilitate comparison with prior studies).

Lando and Skodeburg (2002) outline a number of advantages in using a continuous rather than discrete time assumption in calculating transition probabilities. A discrete time based matrix examines the probability of moving from the beginning to end of period rating, but ignores the transitions which occur within the discrete time period.[9] We therefore prepare continuous time based transition matrices for the 16-year period April 1, 1990 to March 31, 2006 based on the time homogenous method set out in Lando and Skodeburg. Maximum likelihood estimates of the transition probabilities from state *i* to state *j* are given by the matrix exponential of a generator matrix, with the elements of this latter matrix being given by the total transitions from state *i* to state *j* over the 16-year period divided by the total number of sovereign years spent in state *i*. Let Λ be the NxN

[9] We document further evidence in favour of employing continuous transition matrices at the sovereign level as follows: Standard and Poor's downgraded Korea between October 24 1997 and February 18 1998 from AA- to B+ in 4 stages from AA- to A+ to A- to BBB- to B+. A matrix based on, say, a discrete 6-month period from October 1 1997 to March 31 1998 would only pick up the probability of transition from AA- to B+, whereas the continuous time matrix would pick up each transitional rating state. This is a particular problem if default is a non-absorbing state, as is the case for most sovereigns, since a sovereign might move in and out of a default rating during a discrete time period without the default being noted.

generator matrix, then the matrix exponential for an arbitrary time horizon t is given by the infinite sum:

$$\exp(\Lambda t) = \sum_{n=0}^{\infty} \frac{\Lambda^n t^n}{n!}$$

Our continuous time matrix gives the (unconditional) probability of a rating change over a one-year period during the 16-year sample period.[10] Given that sovereigns emerge from default we do not assume that default is an absorbing state. Rating withdrawals are often removed from the dataset, however, since sovereign rating withdrawals may contain interesting information, we include withdrawals in preparing our matrices. Withdrawal is also assumed to be a non-absorbing state.

In Panels A to C of Table 3 we present the transition matrices for each of the three rating agencies. The diagonal elements in the matrix are shown in bold type.

[Insert Table 3 about here]

We start by discussing the Standard and Poor's matrix (Panel A) against which we then benchmark our discussion of the Moody's and Fitch matrices. The probability of a rating change tends to increase as rating levels decrease, thus for example, the probability of an AAA rating remaining the same over a one year period is 97.98% which reduces to only 4.8% for a CC rating. The probability of a rating change over a one-year period is greater than 50% at initial ratings below CCC+. It should be noted that probabilities of a change over a one-year period are non-zero for all categories other than to and from

[10] Unconditional transition matrices, in which transition probabilities are based upon historical transition rates, have been widely used for the calculation of the VaR for portfolios of bonds or loans (see, inter alia, Altman and Kao, 1992 a and b). We employ the term 'unconditional' to indicate that probabilities of transition are calculated by reference to the historic transition rates of the different rating classes and these probabilities are not conditioned upon prevailing global or obligor-specific factors.

category C (not used), but to four decimal places most probabilities round to zero. Thus, for example, the probability of default for a BBB- rating is 1.7 x 10^{-5} and this figure declines monotonically as the rating category increases to reach 1.3 x 10^{-17} for category AAA. The probability of coming out of the default category in a one-year period is 66.15%, with the most common transition being to a B- rating. At this rating the probability of going back into default over a one-year period is 6.6%.[11]

Turning to the Fitch transition matrix (Panel B of Table 3), again the probability of a rating change tends to increase as rating levels decrease and the one-year probability of remaining at an AAA rating is 99.24% which reduces to just 0.01% for a C rating. The probability of remaining at the current rating level over a one-year period is below 50% in the case of CCC+, CC and C ratings and, thus, there is a lesser tendency for ratings to change at lower rating levels for Fitch than for Standard and Poor's. In the case of Fitch the decline in default probabilities as ratings increase is non-monotonic from BBB+ (5.0 x 10^{-9}) to A- (1.4 x 10^{-8}) to A (5.7 x 10^{-7}) to A+ (1.2 x 10^{-8}). The probability of coming out of the default category in a one-year period is 38.98%, about 40% lower than Standard and Poor's. The most common transition is again to a B- rating where the probability of going back into default over a one year period is just 0.68%.

Moody's transition matrix (Panel C) is notably different from Standard and Poor's in two respects. First, the relatively low probability of remaining at an Aa1 rating over a

[11] As discussed in the introduction, data on changes in credit quality are often lost by a failure to examine the finer rating categories. Our rating matrices allow us to examine the probabilities of 'within' versus 'between' broad rating category changes. However, we acknowledge that the use of finer rating categories will affect standard error estimates. We demonstrate the potential impact of this by looking at the standard errors of rating transitions of both broad and fine scale categories from BBB for Standard and Poor's. The broad category standard errors show that the probability of upgrades to the A category and downgrades to the BB category from BBB are significant while the finer rating scale analysis fails to confirm the significance of transitions from BBB to any of the A or BB sub-categories. However, this occurs because most upgrades to A occur from the BBB+ category, while most downgrades to BB occur from the BBB- category and the probabilities of transitions from BBB+ to A- and BBB- to BB+ are highly significant.

one-year period, which is just 56.54% for Moody's but 88.22% for S&P (80.95% for Fitch). There is a roughly 25% chance over one year of being downgraded from this rating category which contrasts the less than 5% chance for a downgrade by S&P and Fitch. Second, there is a much lower probability of a rating change at lower rating categories for Moody's than for S&P. The probability of a rating change by Moody's is greater than 50% for just two categories, Caa3 and Ca. The probabilities of a one-year change are non-zero for all categories other than to and from category C (not used). Moody's did not assign a default rating to a sovereign.

Comparison of our Standard and Poor's matrix based on continuous time assumptions with the final matrix based on discrete time assumptions reported in Hu et al. (2002, p. 1399) reveals a much greater tendency towards rating stability for initial rating levels from BBB+ to B, and a greater tendency towards rating changes at initial ratings B- and below. Hu et al. did not have access to rating histories for many sovereigns with lower rating levels and constructed these data from default histories. It is perhaps not surprising, therefore, that it is among these lower rating levels that we find discrepancies.

3.3 Ratings default comparisons

It is interesting to note that the number of defaults varies across credit rating agencies. To highlight these differences, in Table 4 we present details of all sovereigns which are issued with a default rating over our sample period, and details of the ratings of other agencies around the time of default.[12]

[12] As Moody's did not assign a rating label "default" to a sovereign we obtained further information on Moody's reactions to sovereign bond defaults from a February 2003 publication "Sovereign Bond Defaults, Rating Transitions, and Recoveries (1985-2002)". In this document Moody's identify 9 sovereign defaults for the period to 2002.

[Insert Table 4 about here]

Table 4 highlights that there is some disagreement about the assignment of default ratings between Fitch and Standard and Poor's and also that Moody's do not employ "withdrawn (WR)" status to proxy for default. The defaults documented in the Moody's 2003 publication lead to Moody's downgrades around the time of default, but sometimes only invoke a limited or even no reaction from Standard and Poor's and Fitch. Conversely selective default status (SD rating) by Standard and Poor's does not invoke a similar reaction by Moody's. These points are well illustrated by the case of Venezuela in both 1998 and 2005. It would seem that the rating agencies do not agree about the timing of defaults or even existence of defaults which must bring into question some of their credit assessments at the sovereign level.

4. Modelling rating levels

In this section we determine which factors are related to sovereign credit quality and how this varies across agencies. In pursuing these aims we update/extend the much cited static model employed by Cantor and Packer (1996) to a multi-period multinomial probit model based on a considerably wider range of sovereigns. We also improve upon the OLS methodology of Cantor and Packer, and we achieve more robust estimates of the standard errors given the considerably increased sample size. In addition to updating the Cantor and Packer analysis, Purda (2007) provides two further reasons for looking at rating levels as a prelude to examining rating migrations. First, this will allow us to establish whether our selected variables are indeed related to credit ratings, and second, we employ the analysis of rating levels to calculate the extent of under or over "valuation" of a rating which provides a useful input into our prediction of rating changes.

Our dependent variable is the sovereign rating and we choose to "observe" them over a 6-monthly sampling interval i.e. ratings are measured every 6 months starting April 1, 1990 and ending March 31, 2006. We examine the relationship between the rating of a particular country and the latest macroeconomic data which pertains at the time of the rating. Given the limitations in sovereign rating data we employ the eight broader rating categories for this analysis (see Table 1). We estimate sovereign rating levels across each credit rating agency separately to fulfil our aim of comparing any differences in the determinants of rating levels across agencies.

Our variables are selected by reference to the literature provided by the credit rating agencies and to Cantor and Packer (1996).[13] This leads to the following choice of variables which represent the ability of a country to service its foreign currency debt (a full discussion of the variables is given in Cantor and Packer, 1996): (i) *GDP per capita* – in constant prices;[14] (ii) *GDP growth* – geometric average annual growth employing 3 years data; (iii) *Inflation* – geometric average annual growth in Consumer Price Index employing 3 years data; (iv) *External balance* – Current account surplus / GDP (3 year arithmetic average); (v) *Fiscal balance* – Government surplus or deficit / GDP (3 year arithmetic average); (vi) *External debt* – Foreign currency debt / Exports – latest figure;[15]

[13] Our analysis focuses on foreign currency denominated debt and this affects our variable choice. We quote from Standard and Poor's: "When assessing the default risk on foreign currency debt, Standard & Poor's places more weight on the impact… upon the balance of payments, external liquidity, and the magnitude and characteristics of the external debt burden." (page 4, Sovereign Credit Ratings: A Primer, Standard and Poor's, 3/4/2002).

[14] We test models with both the log and non-log form of GDP per capita and choose between them by minimising the Akaike Information Criterion and the Schwarz Criterion.

[15] There are no data available for external debt for sovereigns with a rating of 17 (i.e. AA-, Aa3) and above. Cantor and Packer found that the external debt balance was a significant determinant of rating levels, and changes in this variable are likely to be key determinants of rating changes. External debt balances are much less likely to be a significant cause for concern for highly-rated countries but we do not omit either this variable or highly rated countries from our analysis. To achieve this end we create a dummy variable which takes a value of 0 where the external debt variable is missing and 1 otherwise, and we

(vii) *Debt history* – this is a dummy variable which takes a value of 1 for all countries with a history of debt default or rescheduling, and 0 otherwise. We calculate this variable by reference to the sovereign rating histories produced by each agency and by reference to the data provided in Detragiache and Spilimbergo (2001) and Reinhart, Rogoff and Savastano (2003).[16]

We include two additional variables: the Institutional Investor country risk rating and the market risk premium.[17] The former of these relates to the country risk rating published every 6 months by Institutional Investor magazine which is derived from the opinions of financial experts across the globe. The latter variable represents the market risk premium and controls for changing market conditions given that our sample spans 1990 to 2006.

Examination of the mean values of variables by rating category (unreported)[18] suggests that the relationship between the credit rating and the external balance, the fiscal balance and GDP growth is unlikely to be linear. Accordingly, to capture potential non-linearities we employ quadratic terms for these variables.[19]

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employ a variable which is a product of this dummy and the external debt variable, i.e. we effectively set the external debt balance to 0 where it is missing.

[16] Cantor and Packer also include an economic development dummy in their model. The relationship between the sovereign issuer credit rating and classification as an "Advanced Country" by the IMF is likely to be endogenous and further, this variable is likely to be highly correlated with other variables such as GDP per capita. We therefore choose to omit this variable from our rating estimation.

[17] Blume, Lim and MacKinlay (1998) find that equity risk is a determinant of rating levels. Sovereign issuer ratings are connected to the sovereign stock market via the sovereign ceiling principle (albeit that some companies may pierce this ceiling), however stock market data is available for only half of our sample and we are unable to include stock market variables applicable to each sovereign.

[18] To conserve space we do not present variable statistics, but a table of the mean values of our selected variables by rating category is available from the authors on request.

[19] To deal with potential IMF restrictions in fiscal balances (the fiscal balance is low for countries with below investment grade ratings) we create a dummy variable which takes a value of 0 for below investment grade countries and 1 otherwise and we create a new variable which is a product of this dummy and the fiscal balance. This new variable (Adjusted fiscal balance) will take a value of zero where IMF restrictions are likely to apply, and otherwise will take the value of the fiscal balance.

We employ a cumulative probit model to estimate the relationship between our variables and rating levels[20] and our model predicts the probability of being in a higher rating category. The predictive power of the cumulative probit model is measured by the generalised R^2 measure proposed by Cox and Snell (1989), adjusted to have a maximum value of 1 (Nagelkerke, 1991).

The results of employing a cumulative probit model to estimate rating levels across the three credit rating agencies are shown in Panel A of Table 5. The maximum rescaled R^2 values exceed 90% for all three models indicating that they have very good predictive power. Other than the coefficient on the external balance, all other coefficients are as anticipated ex ante.

[Insert Table 5 about here]

Comparison of our findings with those of Cantor and Packer (1996) reveal some divergences. Cantor and Packer examine rating levels of Moody's and S&P and find that inflation is a significant determinant of the rating level for both agencies, that the external balance is not significant and the fiscal balance is significant for S&P only. We find that inflation is a significant determinant of the rating level for S&P only, that the external balance is significant for both Moody's and S&P rating levels and that the fiscal balance is significant only for Moody's. In addition, we find that three variables not considered by Cantor and Packer are also significant for both agencies (and for Fitch), the square of GDP growth, the institutional investor rating and the market risk premium. The external balance result may be due to sample differences but other variations are likely to be

[20] There are 14 observations across all three agencies in rating band 1 (see Table 1) and of these we have full data for 11. For all agencies we have less than 10 observations within this category, and for the purpose of estimating the cumulative probit model we are therefore obliged to combine the lower two broad rating bands, 1 and 2.

methodological (we noted earlier the discrepancies in variable selection and definition – further, Cantor and Packer employ OLS estimation of ratings at one point in time).

We now provide an analysis of the key differences in the determinants of sovereign rating levels across all three agencies. The following variables are significant determinants of the rating level across all three agencies: GDP per capita, GDP growth and its square, debt history, the institutional investor rating and the risk premium. We observe non-uniform results in relation to the external balance and external debt (significant only for Moody's and S&P), inflation (significant only for S&P) and the fiscal balance (significant only for Moody's). Recall that in Panel C of Figure 1 we examined differences in the countries rated across our sample period by the three agencies, and we indicated that 46% of Moody's ratings were based on sub-investment grade sovereigns compared with 33% for S&P and Fitch. The difference in distribution of S&P and Fitch ratings is small and thus the differences in the significance attached to the external balance, external debt and inflation are more likely to reflect these agencies differences in opinion of the weight to attach to different macroeconomic indicators. Divergence between Moody's and the other agencies might also be due to differences in the types of country rated. Thus for example, the external debt balance would be expected to be more important for countries with lower ratings.

To distinguish between these effects we re-run our regression based on the common set of 55 sovereigns rated by all three agencies. We present these results in Panel B of Table 5. These results show that Moody's and Fitch ratings are determined by the same variables but there is some disparity with Standard and Poor's. For Fitch and Moody's the fiscal balance is significant and has a quadratic relationship with the rating level, while for S&P the inflation rate and external balance are significant. As these models are based on countries rated by all three agencies, the variations in results are due to differences in agency opinion about the key factors affecting credit quality.

In Panel A of Table 5, the intercepts for the fitted regression lines relating to the broad rating categories are shown below the coefficient estimates. These intercepts are employed to calculate the probability that the dependent variable is greater than or equal to the specified rating level. The cumulative probit model output allows us to calculate, for each observation, the probability that a rating will increase, stay the same, or decrease from its current level. We therefore create a new variable "Misvaluation" equal to the conditional probability of a rating increase *less* the conditional probability of a rating decrease, which we employ in our models of rating changes.

5. Rating migration probabilities based on various conditioning factors

In this section we undertake analyses of rating migration transitions across the three agencies. Extant research has tended to make discrete time assumptions and ordered probit models have been employed to examine the impact of multiple factors on rating changes (Nickell et al., 2000, Purda 2007). Where continuous time assumptions have been employed in an analysis of rating changes, as for example, in Lando and Skodeburg (2002), the analysis has been based on a limited number of variables (just one covariate in the case of the cited paper). We employ both discrete and continuous time assumptions to examine rating changes.

The purpose of the analysis in this section is to determine the extent to which rating agency information in the form of credit watch and outlook signals captures other publicly available information likely to impact on the probability of a rating change and to comment on the varying strength of these signals across agencies. We also examine the extent to which the current rating level is a significant determinant of rating changes in the presence of other variables, and thus the effectiveness of relying on this measure to predict rating outcomes as implied by the use of rating matrices. At the end of the section, we test whether our models are able to provide better predictions of 6 month ahead rating outcomes, both in-sample and out-of sample, than agency data on rating outcomes in the form of credit watches and outlooks.

5.1 Variable selection

Rating changes represent predicted changes in default probabilities, and our models employ variables likely to affect changes in sovereign default probabilities. We begin with the two covariates which relate to information about expected rating outcomes produced by the agencies: (i) *Outlook* – the credit outlook for the agency in question which may take a value of +1 (positive), 0 (stable) or -1 (negative). No outlook is available for some sovereigns in earlier years, particularly for Moody's, and since this lack of information is neutral we employ a value of 0 in these cases. (ii) *Watch* – if a sovereign is under credit watch with the agency in question this variable takes a value of either +1 (watch positive) or -1 (watch negative). Otherwise the variable takes a value of 0.

To these two variables we add a number of others likely to be related to changes in credit quality. Most of our selected variables are given by the change in value of the variables (since the previous period) used to predict rating levels. The exception is the default history dummy which is employed again as a dummy variable. The additional variables are: (i) *Rating* – the narrower category of the credit rating (see Table 1). (ii) *Momentum* – there is evidence that rating transitions are non-Markovian. Downgrade momentum exists at both the corporate (see, inter alia, Altman and Kao, 1992; Bangia et al, 2002; Lando and Skodeberg, 2002) and sovereign (see Fuertes and Kalotychou, 2007) levels. To capture such 'momentum' effects we employ the direction of the last rating change by the same agency. We limit the memory on this variable to 30 months. (iii) *Misvaluation* – this variable is derived from our analysis into rating levels. It is given by the conditional probability of a rating upgrade (i.e. the probability of change * probability of upgrade) *less* the conditional probability of a rating downgrade. By construction, in our ratings level model, there is a zero probability of a downgrade from the lowest category and yet in reality these ratings can be downgraded. Via a dummy variable the values of this variable are set to zero for ratings in the lowest rating category. (iv) *FDI* – this variable is given by the change in foreign direct investment over a one year period as a percentage of GDP. It reflects longer term views of investment in a particular economy. (v) *Portfolio* – this variable is given by the change in portfolio investment over a one year period as a percentage of GDP. It reflects shorter term views of investment in a particular economy.

5.2 Discrete time assumption

We commence with the discrete time based model. We determine the probability of a rating change over a 6-month event period. Since we employ macroeconomic data as part of our dataset, and these data are available for all countries on an annual basis as at

December 31, to allow for a lag in the availability of national accounts data, the two 6-month periods run from April 1 (Period 1) and October 1 (Period 2) each year. Prediction is therefore made for each 6-month period from April 1 and October 31, employing national accounts data for the year ended the previous December 31. All other data are values pertaining to the beginning of the forecasting period. Where a rating is withdrawn (including default) during a 6-month period, the sovereign is removed from the dataset for that period. It rejoins the dataset for the period after which a rating is reinstated.

Our method of predicting rating outcomes involves a set of models (one for each agency) in the cumulative probit setting based on four potential outcomes: (i) upgrade (ii) no change (iii) downgrade of one or two notches (iv) credit crisis (a downgrade of 3 or more notches, or default).[21] Our rating outcomes are in all cases designed to allow a minimum number of 10 observations.[22]

We report the results of the parsimonious models obtained by employing the cumulative probit model to estimate rating changes across the three credit rating agencies in Table 6. The maximum rescaled R^2 values are between 20% and 30%, which while less impressive than our models for rating levels, compare favourably with the counterpart values for the three category ordered probit models employed by Purda (2007) to predict US corporate rating changes (Purda reports a maximum pseudo R^2 value of 18%).

[21] We also experimented with a second set of models, estimated in two stages. In stage one we estimate the probability of a credit change conditional upon factors pertaining at the beginning of the period. In stage two, conditional upon a change being predicted, we estimate the probability that the change will be an upgrade, downgrade of one or two notches, or a credit crisis. Since we find that our two stage model does not perform well, we only report the cumulative probit model results.

[22] The number of two notch downgrades for each of our rating agencies is 6 (Fitch and Standard and Poor's) and 12 (Moody's), which is why we do not include two notch downgrades as a separate category.

We find that the beginning of period watch status is a significant predictor of rating outcomes for all three agencies, but outlook status is only significant for Fitch and Standard and Poor's. This is perhaps not surprising given that Moody's introduced outlook status for sovereigns at a later date than Standard and Poor's and Fitch. We find that other variables are significant predictors of rating outcomes suggesting that the credit rating agency watch and outlook status do not capture all publicly available information. We find that changes in GDP growth (*ΔGDP growth*), the direction of the last rating change (*Momentum*) and the probabilities derived from the rating levels equation (*Misvaluation*) are all significant, for all three rating agencies. For Standard and Poor's the change in the Institutional Investor rating and the market risk premium, for Moody's, the change in GDP per capita, and for Fitch the change in external debt are also significant. All coefficients on these variables have the expected signs. These results further demonstrate that differences occur in the critical information which rating agencies use to evaluate sovereign issuers.

We find that the beginning of period rating fails to be a significant determinant of the end of period rating across all agencies. This must bring into doubt the usefulness of producing rating transition matrices based on beginning and end of period rating values to determine likely future outcomes, even where these are conditioned on a number of variables.

[Insert Table 6 about here]

5.3 Continuous time assumption

We also provide estimates of the hazard of a rating change under continuous time assumptions where at each event time, the likelihood that a rating change occurred to sovereign *i* relative to all sovereigns at risk of a rating change is calculated employing the most up to date data for each sovereign. The proportional hazards regression function is given by:

$$h(t, \mathbf{x}(t), \boldsymbol{\beta}) = h_0(t) \exp[\mathbf{x}'(t)\, \boldsymbol{\beta}]$$

where the hazard of a rating change is a function of $h_0(t)$, the baseline hazard; $\mathbf{x}'(\mathbf{t})$, a matrix of time varying covariates; and $\boldsymbol{\beta}$**,** a vector of coefficients. We restrict outcomes (events) to “transition from the current rating”. Following Lando and Skodeburg (2003) we model the hazard of transition via a downgrade and upgrade separately, that is we treat upgrades and downgrades as competing risks, and as such we assume that the probability of upgrade and downgrade are parallel processes dependent on the covariates and not on each other. An upgrade (downgrade) is treated as a censoring action for the downgrade (upgrade) process i.e. once an upgrade has taken place a sovereign is not at risk of a transition from the same state via a downgrade. Other censoring events are default and withdrawal.

Our covariates are as defined for the ordered probit model with the exception that we assume a positive (negative) watch or outlook status is informative for upgrades (downgrades) and these variables take a value of one for upgrades (downgrades) only and zero otherwise. We employ time varying covariates and as such the macroeconomic variables are updated every 1st April, the risk premium and Institutional Investor ratings are updated every 6 months and the watch and outlook status are updated daily at random intervals. The variables *Rating*, *Momentum* and *Debt History* are fixed for each sovereign for its duration in a particular rating band.

Under the discrete time case we examined the extent to which the credit watch and outlook status at the beginning of the period allowed us to predict events over the next 6 month period, relative to other publicly available data. With the hazard model we discover the extent to which the hazard of a rating change is affected, given that a particular sovereign had an informative watch or outlook status at the time of the change, relative to the latest values of other variables at the time of the change. The denominator of the likelihood function is affected if sovereigns are left on watch or outlook status longer than is necessary or if these signals of rating changes are used indiscriminately, both of which will result in a lower hazard ratio (for a more general coverage of hazard models see, for example, Andersen, Borgan, Gill and Keiding, 1993; or Hosmer, Lemeshow and May, 2008).

Since there are repeated events (upgrade or downgrade) for many sovereigns, after a transition away from a rating category each sovereign then becomes at risk anew for a transition from the new rating category. We employ the robust variance estimator of Lin and Wei (1989) to deal with dependence between observations given repeated events for each sovereign.[23] Since the hazard of an upgrade from an AAA rating is zero these ratings are not employed in the upgrades hazard model. We employ a semi-parametric proportional hazards[24] model in which the dependence of the hazard on time is left

[23] The structure of the data makes fixed effects unsuitable. Problems include only one rating change for some sovereigns, sovereigns with exactly two rating changes for which the second censored duration is shorter and greater across sovereign than within sovereign variation for many variables.

[24] We apply the term proportional hazards to describe our method since this is the common terminology but we acknowledge that the time dependent covariates change at different rates for different sovereigns such that the ratios of sovereigns' hazards of a rating change will not be constant.

unspecified. We employ the Efron approximation to deal with tied data which gives a good approximation to the exact partial likelihood in the presence of tied data (though tied data are infrequent in our sample).

As stated above, our models include time varying covariates, thus at any point in time the partial likelihood of the hazard of an event for country *i* relative to other countries is calculated by reference to the latest data for all countries at that point in time. Some countries had ratings prior to our sample start (April 1, 1990) and data for such sovereigns are left censored. We deal with this left censoring by taking the first observation from the date of the first rating change in our sample period, i.e. we omit all periods which are truncated by such left censoring. Right censoring occurs at March 31, 2006 for all sovereigns. We present the results of our proportional hazards analysis in Panels A (Downgrades) and B (Upgrades) of Table 7.

Despite the fact that the hazard of upgrade and downgrade are estimated separately there is greater variation across agencies in the factors which contribute to the hazard of a rating change than in the ordered probit model. The same pattern as we observed in the ordered probit analysis is observed with regard to the watch and outlook variables. The watch status is a significant determinant of the hazard of a rating change other than for S&P upgrades, where no watch procedures occur, and the outlook status is a significant determinant of the hazard of a rating upgrade and downgrade for Standard & Poor's and Fitch, but not for Moody's. The hazard ratio is given by e^{β}, and across all six regressions the value of β for the variable watch ranges from 3.1347 for Fitch downgrades to 4.4618 for S&P downgrades and the value of β for the variable outlook ranges from 1.4914 for S&P upgrades to 3.0373 for S&P downgrades. These figures translate into the hazard of a rating change for a sovereign on credit watch as being between 22.98 and 86.64 times greater than a sovereign not on credit watch, and the hazard of rating change of a sovereign with a non-neutral (i.e. positive or negative) outlook being between 4.44 and 20.85 times greater than a sovereign with a neutral outlook. The size of the coefficients for the watch and outlook variables are considerably larger than those of most other variables and suggest that an informative watch or outlook status strongly increases the hazard of a rating change relative to sovereigns without this status (after controlling for other covariates).

Apart from credit watch status, the change in per capita GDP is the only other significant univariate determinant (unreported) of the hazard of a rating downgrade across all three agencies, but this variable does not make it into the reported parsimonious S&P and Fitch models. Given that both the Standard and Poor's and Fitch models include both outlook and watch variables we can conclude that these variables seem to pick up different factors in each case. For the Standard and Poor's model the role of the change in GDP growth and the debt history are not picked up by the watch and outlook variables and are significant determinants of the hazard of a rating downgrade in the presence of watch and outlook status variables. The coefficients on these variables suggest that a sovereign with a history of debt problems has a hazard of a downgrade of about 1.7 times that of a sovereign without a debt history and that a 1% increase in GDP growth reduces the hazard of a rating downgrade by about 92%.[25] In the case of Fitch the impact of the change in the external debt (increase equals an increased hazard), the initial rating (increase equals a decreased hazard) and rating momentum (increase equals a decreased

[25] The estimated percentage change in the hazard due to a one unit increase in a non-dichotomous variable is given by $100(e^{\beta} - 1)$.

hazard) are not captured by the watch and outlook variables and are significant determinants of the hazard of a rating downgrade in the presence of watch and outlook status variables. In the case of Moody's the change in per capita GDP (increase equals decreased hazard), the change in the fiscal balance (increase equals decreased hazard), the debt history (increase equals increased hazard), and rating momentum (increase equals decreased hazard) are all significant determinants of the hazard of a rating downgrade in the presence of the watch status variable.

Turning to rating upgrades (Panel B), as stated above, the parsimonious Fitch model includes both watch and outlook data, the S&P model only outlook data and the Moody's model only watch data. The variable *Misvaluation* is the only significant determinant of the hazard of a rating upgrade across all three agencies. In the case of Fitch the change in GDP growth and the misvaluation variable (for both, increase equals increased hazard) are significant determinants of the hazard of a rating upgrade in the presence of watch and outlook status variables. In the case of Standard and Poor's the change in GDP per capita (increase equals increased hazard), the change in the external balance (increase equals increased hazard), the change in the risk premium (increase equals decreased hazard), the initial rating (increase equals decreased hazard), rating momentum (increase equals increased hazard) and misvaluation (increase equals increased hazard) are all significant determinants of the hazard of a rating upgrade in the presence of the outlook status variable. This long list of significant variables suggests that the watch status contains much publicly available information. In the case of Moody's the change in per capita GDP (increase equals increased hazard), the initial rating (increase equals decreased hazard), rating momentum, misvaluation and the change in foreign direct investment (for all three, increase equals increased hazard) are all significant determinants of the hazard of a rating upgrade in the presence of the watch status variable. *This* long list of significant variables suggests that the outlook status contains much publicly available information.

We find that the rating level has a significant impact on the hazard of a downgrade by Fitch and of an upgrade by Moody's and Standard and Poor's. This contrasts with the ordered probit results where the beginning of period rating failed to be a significant determinant of the end of period rating across all agencies. However, the fact that the initial rating variable is not significant in all hazard models still leads to some doubt over the usefulness of determining sovereign rating change probabilities by reference to the current rating.

The ordered probit (OP) analysis employs data for 6-month periods for each sovereign whereas the hazard analysis employs data for each duration (at a particular rating level) for each sovereign. A country enters the dataset for the OP model at the start of the next 6 month period (April 1 and October 1) after which it is first rated, whereas a country enters the dataset for the hazard model from the date of the first rating. This difference means that rating changes which occur shortly after the first rating are missed from the ordered probit model, and this is a non-trivial subset of all ratings. Since this might account for the difference in the results of the ordered probit and hazard analyses, as a robustness check we repeat the hazard analysis employing the assumption that the first duration of all sovereigns is discounted where the rating change (or final period censoring at April 31, 2006) occurs before the start date of the next 6 month period. In unreported results we confirm that the hazard results are qualitatively similar for all agencies with these excluded durations.

In summary, our hazard analysis, as with the OP analysis, suggests that rating agency data in the form of watch and outlook status are significant predictors of rating outcomes, with the exception of Moody's outlook status and Standard and Poor's watch positive status. As with the ordered probit analysis, there is some variation across agencies in terms of the publicly available data captured by the watch and outlook status. Moreover, there is evidence across all three agencies that rating agency outlook and watch data fail to capture all publicly available information which suggests that forecasts of rating outcomes based on rating agency data might be augmented by publicly available information, which is a matter to which we now turn. We perform this analysis both in-sample and out-of-sample.

5.4 In-sample forecasts

Given a particular rating level and employing a sovereign transition matrix, the most likely outcome at most rating levels is that a sovereign issuer rating will not change (see the transition matrices produced in Table 3). This is of limited use to banks who would like to adjust their credit exposures where conditions specific to a particular sovereign suggest that in fact a rating will change. In this section we evaluate further the relative ability of the watch and outlook data provided by the agencies to determine rating outcomes and the extent to which these data might be augmented to determine changes in credit quality for each agency.

Banks and investors are interested primarily in *t*-period ahead forecasts and we therefore employ our models to calculate the risk of a rating change based on data taken every 6 months over our sample period. To produce the in-sample forecasts we employ the sample data taken every 6 months used for the ordered probit analysis, and we compare the results of our models with the actual outcomes over the next 6 month period. We employ the ordered probit models to calculate predicted probabilities of the outcomes upgrade, no change, downgrade and crisis and the proportional hazard models to calculate a risk score for the events downgrade and upgrade which we then convert to a 'net risk of downgrade' score, by subtracting the risk of upgrade from the risk of downgrade. The values of these probabilities and risk score are only meaningful relative to other sovereigns' values under the same model.[26]

We select the actual outcomes to be commensurate with our ordered probit (OP) analysis i.e. crisis, downgrade, no change, upgrade. At the beginning of each 6 month period we document (i) the watch and (ii) outlook status, (iii) the probability of the rating outcomes upgrade, no change, downgrade and crisis (discrete OP model)[27] and (iv) the net risk of downgrade (= risk of downgrade *less* risk of upgrade from the continuous hazard model) which we then compare with actual rating outcomes over each 6 month period, as outlined above. Our results are presented in Table 8. The columns headed "Watch" and "Outlook" show results for both positive and negative status with the latter

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[27] The explanatory variables are related to the inverse cumulative distribution function of the probability of the rating outcomes as shown in Table 6. The values of alpha (α) which are employed to calculate cumulative probabilities that the outcome is at each of three ordered levels (Upgrade, Same, Downgrade) are also shown in Table 6. The output from the models is converted to the standard normal cumulative distribution function at different levels of α, from which probabilities of the events (i) to (iv) are readily derived. The value of the variable *Misvaluation* is calculated from the variable values shown in Table 5. The output from the model is similarly converted to the standard normal cumulative distribution function, to allow the conditional probability of an upgrade versus a downgrade to be calculated from this model.

being in parentheses. Thus, for example, for S&P crises, watch and outlook positive status each predicted 0% of crises, watch negative predicted 9.5% and outlook negative 71.4%.

[Insert Table 8 about here]

Table 8 indicates that the mean and median predicted outcome probabilities and risk scores from our models vary in a manner expected across actual outcomes for all agencies. That said, some events are not well predicted by our models. For example, over the period October 1, 2004 to March 31, 2005, Standard and Poor's reported that Venezuela had a selective default on its foreign currency denominated debt, and yet our OP model predicts a 15% probability of an upgrade, and our hazard model gives a net risk of downgrade of 0.295, which by reference to Panel A of Table 8 both suggest that an upgrade was likely.[28] The Institutional Investor rating underwent a 15% increase in value during the same period, which is in line with our model's prediction that an upgrade was likely.

The usefulness of beginning of period watch and outlook status for predicting rating outcomes varies considerably across agencies. For S&P, 71.4% of crises and 54% [29]of all downgrades (both crisis and one or two notch) would be predicted by their outlook status at the beginning of the period versus only 10.6% of downgrades which would be anticipated by their beginning of period watch status. This can be accounted for by the fact that the credit watch is a shorter term measure.

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[28] Panel A of Table 8 suggests that upgrades have an average predicted probability of upgrade of about 20% (median 16%), against 7% (median 4%) where the rating remains the same. With regard to the hazard model, Panel A of Table 8 suggests that the mean (median) values for the net risk of a downgrade varied as follows: Crises: 4.601 (5.000); Downgrades: 4.120 (4.307); No change: 2.391 (2.315); Upgrades: 0.822 (0.847). Clearly, the Venezuelan example is an outlier.

[29] $[(0.714x21)+(0.484x64)/(21+64)]$

The above-mentioned figures can be contrasted against Moody's and Fitch. For Moody's the outlook status predicts 1.9% [30]of downgrades (both crisis and one or two notch) and 2.5% of upgrades and the watch status predicts 18.5% of all downgrades and 17.7% of upgrades. This can be explained by the fact that Moody's outlooks are only available for the later entries in our dataset and thus Moody's outlook data are less informative. For Fitch the outlook status predicts 30% of all downgrades and 23.5% of upgrades and the watch status predicts 18% of all downgrades and 5.9% of upgrades. The best prediction performance is thus provided by S&P outlook status but this comes at the cost of a higher one-period 'false' positive rate, with 11.5% of ratings with no change having a positive status and 9.4% of ratings with no change having a negative status.

5.5 Out-of-sample testing

It would seem that for banks and investors interested in one period ahead forecasts of ratings for particular sovereigns there may be some scope to improve on agency data, particularly in the case of Fitch and Moody's. To assess our models prediction accuracy we are required to select suitable cut-off points at which we deem a crisis, a downgrade or an upgrade to be likely. Since we could artificially construct these on our in-sample data to maximise prediction accuracy, instead we employ in-sample statistics to set cut-offs point which we then employ out-of-sample. We now turn therefore to out-of-sample predictions.

[30] $[(0x10)+(0.023x44)/(10+44)]$

Owing to data availability, we are obliged to confine our out-of-sample testing to Standard and Poor's ratings only.[31] Since we argue that our models are more likely to be of use in the case of Fitch and Moody's, we effectively present a "worst case scenario" regarding their out-of-sample utility. We are particularly interested in whether our models add information about future rating outcomes to the agency-based information on outlook and watch status

Given that our ordered probit model looks 6 months ahead, we select an out-of-sample test period from April 1, 2006 to September, 30 2006. We employ data at April 1, 2006 and evaluate whether our models give us better information about actual rating outcomes than rating watch or outlook data. As at April 1, 2006 Standard and Poor's rated 110 sovereign issuers,[32] and full data are available for 92 of these sovereigns. There was a rating change for 15 sovereigns during this 6-month period and we have full data for all of these cases. Thus in our sample, 16% of sovereigns underwent a rating change in the out-of-sample period, while 84% did not. Of the rating change group, 12 are upgrades and 3 are downgrades. In October 2007, i.e. just outside our sample period, two countries, Argentina and Bulgaria, were upgraded, and one country, Italy, was downgraded, and we anticipate that our model may reflect these events. Accordingly, including these rating changes, we have 14 upgrades, 4 downgrades and 74 with no change.

The watch and outlook status of the 92 sovereigns we examine at April 1, 2006 is as follows. No countries are on credit watch, 5 countries have a negative outlook and 20

[31] We are only able to undertake this analysis with respect to Standard and Poor's since at the time of writing Fitch sovereign rating histories were last updated in June 2006 and Moody's sovereign issuer ratings are not available to us post June 2006.
[32] This period was the first full 6-month period when S&P rated Georgia, Nigeria and Sri Lanka.

countries have a positive outlook. We find that 3 out of 4 countries downgraded April through October had a negative outlook and 7 out of 14 countries upgraded April through October had a positive outlook. If we were to employ rating agency data to forecast outcomes between April and October we would find that negative outlooks have a 75% successful prediction rate (3 out of 4) and a 2% 'false' positive rate[33] (2 out of 88), and positive outlooks have a 50% successful prediction rate (7 out of 14) and an 17% 'false' positive rate (13 out of 78). This is the benchmark against which we compare our ordered probit model and hazard model estimates.

Our hazard model allows us to calculate the hazard of a downgrade and upgrade separately for each sovereign. Like the outlook and watch data of the agencies this has the limitation of not allowing us to predict the possibility of a credit crisis. The ordered probit overcomes this shortcoming. Using our estimated ordered probit model, we are able to calculate the predicted out-of-sample probability of the following events: (i) upgrade; (ii) no change; (iii) one or two notch downgrade; (iv) credit crisis.

As stated above, to employ the hazard model and ordered probit (OP) model out of sample we are required to calculate cut-off points at which we deem OP probabilities or hazard risk scores translate into a rating actions. The in-sample analysis provides us with likely cut-off points for upgrades and downgrades at different prediction accuracy/false positive trade-off levels.

We employ the hazard model set out in Table 7 to calculate risk scores for each of the 92 sovereigns as at April 1, 2006. As for the in-sample estimates we calculate the risk of downgrade and upgrade separately and then calculate a net risk of downgrade score by

[33] The false positive rate is given by the number of false positives (2 out of 5 on outlook negative did not undergo a downgrade) divided by the number of sovereigns which did not undergo the event (92 – 4 = 88 sovereigns did not undergo a downgrade.

subtracting the risk of upgrade from the risk of downgrade. We find that our hazard model risk scores predict identical outcomes to the outlook status, and thus despite the in-sample result that certain macroeconomic data did improve forecasts of the hazard of a rating change, out of sample these data could not improve on forecasts employing solely agency data. Given the high in-sample prediction accuracy of S&P outlooks this is perhaps not surprising.

Turning to our ordered probit model, the results of our out-of-sample test are shown in Table 9. For the purpose of preparing this table we included the rating changes occurring in October 2007. We employ the data in Panel A of Table 8 (in addition to natural breaks in the calculated probabilities of events) to allow us to determine suitable cut-off points for making predictions based on the forecast probabilities of different events. In Panel B of Table 9 we report the observations around the two selected cut-off points one for upgrades and one for downgrades.

[Insert Table 9 about here]

We are cautious in drawing strong conclusions based on our out-of-sample forecasts given the small sample size, however, we find that our downgrades model again mirrors the results using rating agency data – the same four countries are predicted to undergo a downgrade, three of which do undergo a downgrade (75% successful prediction rate) and one of which doesn't (2% false positive rate). Again, given the high in-sample prediction accuracy of S&P *negative* outlooks these might be expected to be difficult to beat.

While our model does less well when predicting upgrades, it does however improve on the agency data prediction rate. Specifically, 57% of countries whose ratings are upgraded are predicted to upgrade, versus 50% employing only rating outlook data – but this improvement comes at the (slight) cost of a higher false positive rate: 18% of countries whose rating does not undergo an upgrade are predicted to upgrade versus 17% using solely rating outlook data.[34]

Given the time and effort involved in trying to predict 'enhanced' rating outcomes, these results suggest that banks would be better to rely on rating agency outlook and watch status data to predict Standard and Poor's sovereign rating outcomes over a 6-month ahead period. Our analyses of in-sample performance suggests that models might, however, improve considerably upon Fitch and Moody's agency outlook and watch data when attempting to predict Fitch and Moody's rating changes. If the aim is to predict sovereign rating outcomes then our analysis also suggests that the ordered probit approach, which allows the simultaneous modelling of a number of outcomes, offers advantages in terms of accuracy, in addition to the wider range of modelled events, over a hazard model in which downgrade and upgrade hazards are modelled independently.

6. Conclusion

Using sovereign ratings data for 129 countries, spanning the period 1990 to 2006, we investigate the broad question of agency variation in credit quality assessment in the sovereign context. First, we present data on differences in sovereign rating levels and rating migrations across the three major agencies: Standard and Poor's, Moody's and

[34] These results in fact relate to one additional country (additional to the S&P outlook data forecast) predicted by our model to undergo an upgrade which does and one additional country predicted by our model to undergo an upgrade which doesn't.

Fitch. Our transition matrices are based on the finer rating categories and constructed under continuous time assumptions. Second, we examine differences in the determinants of sovereign rating levels and changes across the three agencies via two approaches: ordered probit and hazard model regressions. We follow Purda (2006) by restricting the number of rating transitions considered which allows us to condition credit rating changes on a much larger number of factors. Our analyses allow us to comment on the extent to which each agency's outlook and watch information captures publicly available information and to examine whether rating agency data on outlooks and credit watch status can be augmented to provide better out-of-sample estimates of rating transition probabilities.

Our key findings are readily summarized. First, while we find that the credit rating agencies often disagree, it is usually confined to one or two notches on the finer scale. Second, rating transition probabilities tend to increase as the rating level decreases across all agencies, but rating stability at lower rating levels is less for Standard and Poor's than for Fitch or Moody's. Third, we document that six variables are common determinants of all three agencies assessments of credit quality. However, given that a further four variables have varying importance across agencies leads us to conclude that material heterogeneity exists between them. Fourth, our hazard and ordered probit models both suggest that watch and outlook procedures are generally strong predictors of rating changes relative to other public data. Standard and Poor's outlook data provide the strongest in-sample prediction performance of any agency based rating forecast, but Moody's and Fitch watch data outperform the prediction performance of Standard and Poor's watch data.

Notably, other variables are significant in all our rating transition models in the presence of watch and outlook data, suggesting that these agency data might be augmented to provide better forecasts of rating changes. Out-of-sample tests fail to confirm this prospect for Standard and Poor's ratings and suggest that those interested in predicting outcomes for Standard and Poor's ratings would be unlikely to much improve on agency outlook status data. However, since in-sample Standard and Poor's outlook status has a particularly high prediction accuracy relative to Fitch and Moody's watch and outlook data, those interested in predicting rating outcomes for Fitch and Moody's might usefully augment watch and outlook data with a range of publicly available variables to improve prediction accuracy.

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Table 1
A Comparison of Rating Agencies Credit Rating Measures

This table summarizes the credit rating measures applied by the three leading agencies; Standard and Poor's (S&P), Moody's and Fitch. In the first column a consolidated rating number is presented relating to the finer rating categories and in Column 2 a consolidated rating number is presented relating to the broader rating categories.

Rating Number (Fine)	Rating No. (Broad)	S&P	Moody's	Fitch
21 (Highest credit rating)	8	AAA	Aaa	AAA
20	7	AA+	Aa1	AA+
19	7	AA	Aa2	AA
18	7	AA-	Aa3	AA-
17	6	A+	A1	A+
16	6	A	A2	A
15	6	A-	A3	A-
14	5	BBB+	Baa1	BBB+
13	5	BBB	Baa2	BBB
12	5	BBB-	Baa3	BBB-
11	4	BB+	Ba1	BB+
10	4	BB	Ba2	BB
9	4	BB-	Ba3	BB-
8	3	B+	B1	B+
7	3	B	B2	B
6	3	B-	B3	B-
5	2	CCC+	Caa1	CCC+
4	2	CCC	Caa2	CCC
3	2	CCC-	Caa3	CCC-
2	1	CC	Ca	CC
1	1	C	C	C
Default	Default	SD/D		DDD/DD/D

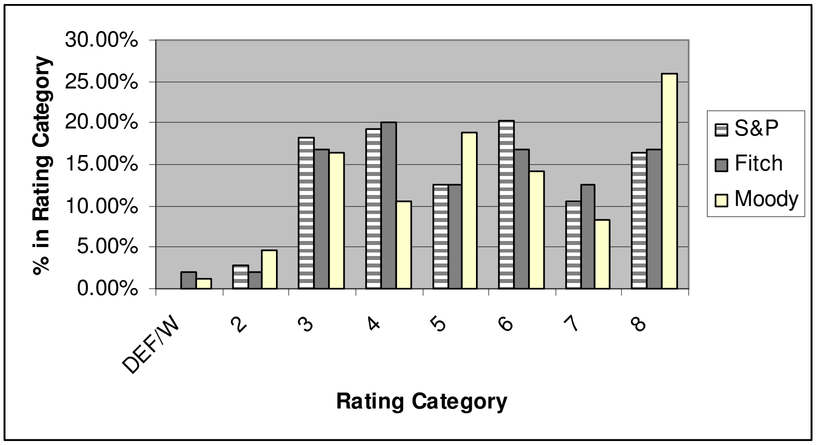
Table 2
Sample Countries and Year of First Rating

Country	*1st Rated*	*Country*	*1st Rated*	*Country*	*1st Rated*
Andorra	2003	Greece	1988	Mozambique	2003
Argentina	1986	Grenada	2002	Netherlands	1989
Aruba	2002	Guatemala	2001	New Zealand	1965
Australia	1975	Guernsey	1997	Nicaragua	1998
Austria	1975	Honduras	1998	Norway	1975
Azerbaijan	2000	Hong Kong	1988	Oman	1996
Bahamas	2003	Hungary	1992	Pakistan	1994
Bahrain	2000	Iceland	1989	Panama	1958
Barbados	1994	India	1990	Papua New Guinea	1999
Belgium	1988	Indonesia	1992	Paraguay	1995
Belize	1999	Iran	1999	Peru	1997
Benin	2003	Ireland	1987	Philippines	1993
Bermuda	1994	Isle of Man	2000	Poland	1995
Bolivia	1998	Israel	1988	Portugal	1986
Botswana	2001	Italy	1986	Qatar	1996
Brazil	1986	Jamaica	1998	Romania	1996
Bulgaria	1996	Japan	1975	Russia	1996
Burkina Faso	2004	Jersey	1997	San Marino	2001
Cameroon	2003	Jordan	1995	Sark	1997
Canada	1951	Kazakhstan	1996	Saudi Arabia	1999
Cape Verde	2003	Korea	1988	Senegal	2000
Cayman Islands	1997	Kuwait	1995	Serbia	2004
Chile	1992	Latvia	1997	Singapore	1989
China	1988	Lebanon	1997	Slovak Republic	1994
Colombia	1993	Lesotho	2002	Slovenia	1996
Cook Islands	1998	Liechtenstein	1996	South Africa	1994
Costa Rica	1997	Lithuania	1996	Spain	1988
Croatia	1997	Luxembourg	1994	Suriname	1999
Cuba	1999	Macau	1997	Sweden	1977
Cyprus	1994	Macedonia	2004	Switzerland	1988
Czech Republic	1993	Madagascar	2004	Taiwan	1989
Denmark	1981	Malawi	2003	Thailand	1989
Dominican Republic	1997	Malaysia	1986	Trinidad & Tobago	1993
Ecuador	1997	Mali	2004	Tunisia	1995
Egypt	1997	Malta	1994	Turkey	1992
El Salvador	1996	Mauritius	1996	Turkmenistan	1998
Estonia	1997	Mexico	1990	Ukraine	1999
Finland	1977	Moldova	1997	United Kingdom	1978
France	1975	Monaco	1997	USA	1941
Gambia	2002	Mongolia	1999	Uruguay	1993
Germany	1983	Montenegro	2004	Venezuela	1976
Ghana	2003	Montserrat	2004	Vietnam	2002
Gibraltar	1997	Morocco	1998	Uganda	2005

Figure 1
Sovereign Rating Distribution

Panel A: As at April 1, 2006

The *x* axis shows the consolidated rating number as set out for the broader rating categories in Table 1. The *y* axis shows the % of the countries within a particular rating band for each agency at April 1, 2006.



Panel B: At 6 month periods

The *x* axis shows the consolidated rating number as set out for the broader rating categories in Table 1. The *y* axis shows the % of the countries within a particular rating band for each agency for the period April 1, 1990 to March 31, 2006, across sovereigns for which we have full data only.

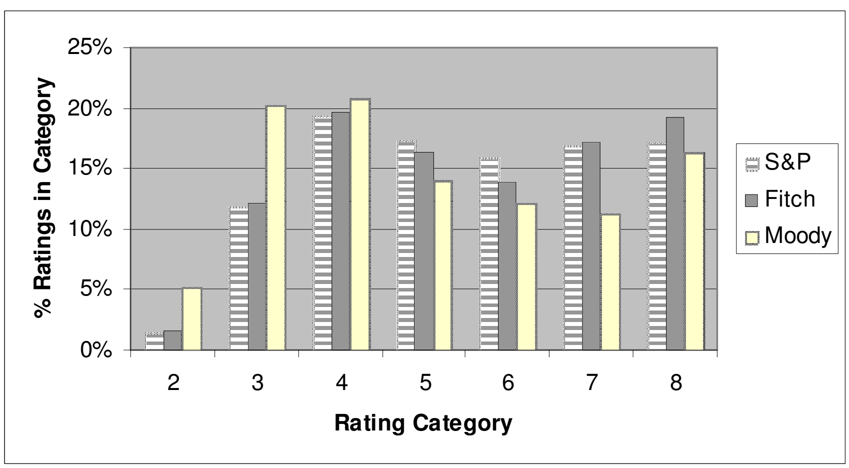


Table 3
Sovereign Rating One-Year Transition Matrices

These matrices are the matrix exponential of a maximum likelihood generator matrix based upon continuous-time data over the period April 1, 1990 to March 31, 2006. The final column shows the number of sovereign years spent in each rating category.

Panel A: Standard and Poor's

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	SD	Years
AAA	**0.9789**	0.0207	0.0003	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	179.8
AA+	0.0795	**0.8822**	0.0279	0.0102	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	93.5
AA	0.0049	0.1091	**0.8179**	0.0664	0.0016	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	62.2
AA-	0.0002	0.0080	0.1220	**0.8274**	0.0391	0.0027	0.0006	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	40.3
A+	0.0000	0.0003	0.0079	0.1047	**0.7566**	0.1067	0.0229	0.0005	0.0002	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	37.6
A	0.0000	0.0000	0.0004	0.0077	0.1140	**0.8399**	0.0368	0.0008	0.0003	0.0003	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	69.6
A-	0.0000	0.0000	0.0001	0.0012	0.0197	0.1137	**0.8047**	0.0344	0.0129	0.0128	0.0004	0.0001	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	65.5
BBB+	0.0000	0.0000	0.0000	0.0002	0.0046	0.0416	0.2638	**0.6402**	0.0243	0.0242	0.0009	0.0002	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	32.6
BBB	0.0000	0.0000	0.0000	0.0000	0.0006	0.0062	0.0525	0.1997	**0.6709**	0.0667	0.0024	0.0005	0.0001	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	55.5
BBB-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0043	0.0222	0.1503	**0.7464**	0.0536	0.0111	0.0019	0.0081	0.0013	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	84.1
BB+	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0015	0.0149	0.1443	**0.7455**	0.0616	0.0146	0.0038	0.0123	0.0010	0.0001	0.0001	0.0000	0.0000	0.0000	0.0001	61.8
BB	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0020	0.0236	0.1211	**0.7461**	0.0712	0.0191	0.0145	0.0016	0.0001	0.0001	0.0000	0.0000	0.0000	0.0002	62.1
BB-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0037	0.0327	0.0969	**0.6931**	0.1386	0.0262	0.0072	0.0004	0.0003	0.0001	0.0001	0.0000	0.0004	60.2
B+	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0016	0.0158	0.0229	0.1546	**0.6033**	0.1295	0.0589	0.0048	0.0030	0.0010	0.0007	0.0000	0.0037	57.5
B	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0016	0.0021	0.0175	0.1410	**0.6915**	0.1053	0.0095	0.0089	0.0039	0.0025	0.0000	0.0160	58.2
B-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0002	0.0015	0.0185	0.1722	**0.5725**	0.0942	0.0388	0.0208	0.0151	0.0000	0.0660	32.9
CCC+	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0035	0.0491	0.2426	**0.4649**	0.0339	0.0175	0.0314	0.0000	0.1568	8.3
CCC	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0048	0.0667	0.2283	0.0491	**0.0756**	0.1540	0.0850	0.0000	0.3361	2.6
CCC-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0044	0.0626	0.1754	0.0494	0.0072	**0.2260**	0.0846	0.0000	0.3901	1.3
CC	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0006	0.0091	0.1098	0.2901	0.0833	0.0135	0.0041	**0.0480**	0.0000	0.4415	1.3
C	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**	0.0000	0.0
SD	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0012	0.0153	0.1489	0.3560	0.1055	0.0196	0.0072	0.0075	0.0000	**0.3385**	10.2

Table 3 (cont.)

Panel B: Fitch Ratings

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	D	Years
AAA	**0.9924**	0.0074	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	121.1
AA+	0.1490	**0.8095**	0.0211	0.0199	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	42.2
AA	0.0083	0.0947	**0.8676**	0.0287	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	61.9
AA-	0.0003	0.0060	0.1088	**0.8416**	0.0409	0.0022	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	39.2
A+	0.0000	0.0003	0.0086	0.1322	**0.7709**	0.0857	0.0000	0.0000	0.0002	0.0019	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	18.2
A	0.0000	0.0000	0.0005	0.0123	0.1453	**0.8002**	0.0001	0.0004	0.0047	0.0336	0.0021	0.0004	0.0000	0.0001	0.0000	0.0003	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	21.5
A-	0.0000	0.0000	0.0000	0.0005	0.0098	0.1078	**0.8516**	0.0276	0.0002	0.0023	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	53.7
BBB+	0.0000	0.0000	0.0000	0.0002	0.0040	0.0487	0.2975	**0.6485**	0.0001	0.0009	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	24.9
BBB	0.0000	0.0000	0.0000	0.0000	0.0004	0.0067	0.0572	0.1785	**0.7016**	0.0325	0.0021	0.0005	0.0027	0.0151	0.0015	0.0011	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	41.6
BBB-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0006	0.0060	0.0249	0.1911	**0.6531**	0.0860	0.0171	0.0018	0.0032	0.0016	0.0129	0.0004	0.0003	0.0007	0.0000	0.0000	0.0001	49.5
BB+	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0007	0.0030	0.0293	0.1252	**0.7594**	0.0512	0.0155	0.0120	0.0013	0.0019	0.0001	0.0000	0.0001	0.0000	0.0000	0.0002	62.0
BB	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0005	0.0058	0.0378	0.1106	**0.7618**	0.0720	0.0075	0.0014	0.0016	0.0001	0.0000	0.0001	0.0000	0.0000	0.0009	49.0
BB-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0006	0.0044	0.0267	0.1218	**0.6518**	0.1207	0.0280	0.0269	0.0015	0.0005	0.0013	0.0001	0.0000	0.0156	40.2
B+	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0005	0.0049	0.0200	0.2127	**0.5717**	0.1128	0.0635	0.0054	0.0015	0.0033	0.0003	0.0001	0.0030	36.5
B	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0032	0.0041	0.0542	0.1806	**0.5568**	0.1387	0.0391	0.0081	0.0077	0.0022	0.0005	0.0045	27.9
B-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0020	0.0234	0.0013	0.0091	0.0421	0.1394	**0.6280**	0.0400	0.0272	0.0731	0.0064	0.0008	0.0068	29.3
CCC+	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0035	0.0001	0.0008	0.0054	0.0222	0.2058	**0.4376**	0.1522	0.0108	0.0370	0.0072	0.1170	7.1
CCC	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0051	0.0002	0.0013	0.0079	0.0319	0.2801	0.0091	**0.6464**	0.0156	0.0010	0.0001	0.0008	2.2
CCC-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0002	0.0008	0.0143	0.0002	0.0001	**0.8194**	0.0767	0.0052	0.0828	5.0
CC	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0024	0.0001	0.0005	0.0035	0.0153	0.1849	0.0044	0.0026	0.0073	**0.1402**	0.0113	0.6275	1.0
C	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0050	0.0002	0.0012	0.0076	0.0313	0.2917	0.0090	0.0055	0.0152	0.0010	**0.0001**	0.6320	0.2
D	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0003	0.0056	0.0002	0.0014	0.0087	0.0349	0.3040	0.0100	0.0062	0.0171	0.0011	0.0002	**0.6102**	6.1

Table 3 (cont.)

Panel C: Moody's

	Aaa1	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa1	Caa2	Caa3	Ca	C	WR	Years
Aaa1	**0.9282**	0.0602	0.0095	0.0020	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	60.1
Aa1	0.1798	**0.5654**	0.2088	0.0438	0.0014	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	16.6
Aa2	0.0481	0.0748	**0.8390**	0.0364	0.0011	0.0006	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	46.6
Aa3	0.0299	0.0070	0.1258	**0.7582**	0.0499	0.0260	0.0014	0.0001	0.0017	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	31.6
A1	0.0017	0.0003	0.0076	0.0945	**0.7895**	0.0368	0.0333	0.0025	0.0326	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	24.7
A2	0.0005	0.0001	0.0021	0.0273	0.0707	**0.8211**	0.0258	0.0033	0.0475	0.0015	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	34.6
A3	0.0004	0.0001	0.0019	0.0248	0.0278	0.1143	**0.8041**	0.0218	0.0038	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	35.9
Baa1	0.0000	0.0000	0.0001	0.0025	0.0035	0.0414	0.1297	**0.7527**	0.0031	0.0310	0.0022	0.0007	0.0000	0.0000	0.0001	0.0011	0.0001	0.0000	0.0000	0.0000	0.0000	0.0316	24.3
Baa2	0.0000	0.0000	0.0000	0.0009	0.0017	0.0301	0.0348	0.1002	**0.7759**	0.0515	0.0016	0.0011	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0021	30.9
Baa3	0.0000	0.0000	0.0000	0.0003	0.0004	0.0037	0.0205	0.0381	0.0945	**0.7588**	0.0481	0.0316	0.0010	0.0007	0.0011	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.0008	48.8
Ba1	0.0000	0.0000	0.0000	0.0001	0.0001	0.0012	0.0042	0.0326	0.0220	0.1179	**0.7552**	0.0321	0.0141	0.0034	0.0142	0.0016	0.0006	0.0000	0.0000	0.0000	0.0000	0.0009	52.0
Ba2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0007	0.0028	0.0038	0.0495	0.0878	**0.7420**	0.0287	0.0337	0.0309	0.0155	0.0027	0.0004	0.0004	0.0001	0.0000	0.0009	52.3
Ba3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0011	0.0008	0.0068	0.0524	0.0971	**0.6316**	0.1427	0.0532	0.0101	0.0024	0.0002	0.0002	0.0001	0.0000	0.0010	29.5
B1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0014	0.0048	0.0409	0.0684	**0.7246**	0.0910	0.0536	0.0092	0.0014	0.0013	0.0004	0.0000	0.0028	40.4
B2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.0000	0.0000	0.0002	0.0020	0.0051	0.0262	0.1322	**0.6266**	0.1164	0.0548	0.0042	0.0039	0.0019	0.0000	0.0254	31.3
B3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0014	0.0000	0.0000	0.0001	0.0015	0.0013	0.0044	0.0452	0.1516	**0.5347**	0.1542	0.0321	0.0281	0.0111	0.0000	0.0342	20.5
Caa1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0002	0.0003	0.0021	0.0134	0.1117	0.1038	**0.6536**	0.0390	0.0343	0.0369	0.0000	0.0045	18.8
Caa2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001	0.0001	0.0004	0.0042	0.0232	0.1068	0.1417	**0.6124**	0.0147	0.0933	0.0000	0.0031	5.8
Caa3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0018	0.0221	0.0222	0.2634	0.0285	**0.4742**	0.1869	0.0000	0.0006	2.5
Ca	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003	0.0020	0.0230	0.0304	0.2602	0.1173	0.1018	**0.4641**	0.0000	0.0008	4.7
C	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**	0.0000	0.0
WR	0.0000	0.0000	0.0000	0.0009	0.0010	0.0045	0.0633	0.0021	0.0009	0.0047	0.0612	0.0013	0.0007	0.0018	0.0071	0.0514	0.0066	0.0013	0.0012	0.0003	0.0000	**0.7896**	12.6

Table 4
A Comparison of Rating Action across Agencies for all Countries with a Default Rating or for which a Default was Recorded

Country	Standard & Poor's	Fitch	Moody's
Argentina	Selective Default 06-Nov-01 On 01-Jun-05 new rating B-	DDD rating 03-Dec-01 On 14-Jan-05 DDD to D. On 03-Jun-05 D to DDD	Defaulted 3-Jan-2002 Downgraded from B3 to Ca between 26-Jul-01 & 20-Dec-01.
Dominican Republic	Selective Default 01-Feb-05 On 29-Jun-05 new rating B	DDD rating 05-May-05 On 19-Jul-05 new rating B-	Rating not available
Ecuador	1st rating of SD 29-Jul-00. On 28-Aug-00 rating changed to B-.	Rating not available	Defaulted 01-Oct-99. On 5-Oct-99 downgraded from Caa1 to Caa3
Grenada	Selective Default 30/12/04	Rating not available	Rating not available
Indonesia	Selective Default 30-Mar-99, 17-Apr-00, 23-Apr-02 On 05-Sep-02 new rating CCC+	Downgraded from BBB- to B- between 22-Dec-97 & 16-Mar-98. B- rating until 01-Aug-02	Downgraded from Baa3 to B3 between 21-Dec-97 & 20-Mar-98. B3 rating until 29-Sep-03
Ivory Coast	Rating not available	Rating not available	Defaulted March 2000. Rating not available
Moldova	Rating not available	DD rating 28-Jun-02 On 04-Feb-03 new rating B-	Defaulted June 2001 and 13 June 2002. Downgraded from Caa1 to Ca between 14-Jan-02 and 11-Jul-02. Ca rating until 06-May-03
Pakistan	Selective Default 29-Jan-99 On 21-Dec-99 new rating B-	Rating not available	Defaulted 1999. Downgraded from B3 to Caa1 23-Oct-98. Caa1 rating until 13-Feb-02
Paraguay	Selective Default 13-Feb-03 On 26-Jul-04 new rating B-	Rating not available	Rating not available
Peru	Watch negative 19-May-00, back to stable outlook 15-June 00. Negative outlook 19-Sep-00, downgraded BB to BB- 31-Oct-00	Watch negative 8-Nov-00. Rating downgraded BB to BB- 18-Apr-01	Defaulted 7-Sep-00 Rating lowered from Ba3 toB1 on 19-Sep-00 and back to Ba3 on 5-Oct-00.
Russia	Selective Default 27-Jan-99 On 08-Dec-00 new rating B-	Downgraded from BB+ to CCC between 07-Jun-98 & 27-Aug-98. CCC rating until 08-May-00	Defaulted 1998 Downgraded from Ba2 to Ca between 11-Mar-98 & 14 Sept -98. Ca rating until 2000.
Ukraine	Rating not available	Rating not available	Defaulted 28-Feb-00. On 05-Jan-00 downgraded from B3 to Caa1. Caa1 until 24-Jan-02.
Uruguay	Selective Default 16-May-03 On 02-Jun-03 new rating B-	DDD rating 16-May-03 On 17-Jun-03 new rating B-	Downgraded from B1 to B3 on 31-Jul-02. B3 rating until end of sample period in 2006.
Venezuela	Rating outlook changed to negative 31-Aug-1998. Rating remained at B+ until Dec 1999.	No reaction. Rating remained at BB- until 2002.	Defaulted Jul 1998. Downgraded Ba2 to B1 22-Jul-98
Venezuela	Selective Default 18-Jan-05 On 03-Mar-05 new rating B	Upgraded from B- to B+ on 20-Sep-04. Upgraded from B+ to BB- 14-Nov-05	Upgraded from Caa1 to B2 on 07-Sep-04. B2 rating until end of sample period in 2006

Table 5
Cumulative Probit Estimates of Rating Levels across Three Agencies

Variable	Moody's Estimate	Moody's Wald	Moody's $Pr > \chi^2$	S&P Estimate	S&P Wald	S&P $Pr > \chi^2$	Fitch Estimate	Fitch Wald	Fitch $Pr > \chi^2$
Panel A: Full Sample Results									
GDP per capita	$4.6\text{x}10^{-5}$	25.977	<.0001	$5.5\text{x}10^{-5}$	61.1806	<.0001	$5.6\text{x}10^{-5}$	46.16	<.0001
GDP growth	1.473	11.061	0.0009	2.077	21.474	<.0001	2.025	17.36	<.0001
$(\text{GDP growth})^2$	-9.510	18.459	<.0001	-16.331	50.567	<.0001	-15.908	49.42	<.0001
Inflation				-0.520	11.033	0.0009			
External balance	-0.017	4.842	0.0278	-0.016	6.820	0.0090			
Fiscal balance (adj.)	0.003	3.905	0.0481						
External debt	-0.103	6.823	0.0090	-0.080	7.883	0.0050			
Debt History	-0.406	12.388	0.0004	-0.859	90.104	<.0001	-1.095	118.85	<.0001
Inst. Inv. Rating	0.156	701.820	<.0001	0.161	1017.446	<.0001	0.173	808.30	<.0001
Risk Premium	-31.797	3.829	0.0504	-62.867	22.098	<.0001	-90.836	34.43	<.0001
Intercept 8	-13.393	689.454	<.0001	-14.229	1102.506	<.0001	-15.457	893.33	<.0001
Intercept 7	-10.886	663.753	<.0001	-11.301	1022.625	<.0001	-12.061	841.08	<.0001
Intercept 6	-8.697	566.601	<.0001	-8.817	828.236	<.0001	-9.339	686.88	<.0001
Intercept 5	-6.873	434.008	<.0001	-6.404	600.455	<.0001	-6.743	527.81	<.0001
Intercept 4	-4.763	263.455	<.0001	-4.161	314.527	<.0001	-4.214	294.71	<.0001
Intercept 3	-2.280	67.833	<.0001	-1.519	35.681	<.0001	-1.330	28.84	<.0001
Max-rescaled R^2	0.926			0.929			0.939		
N	1094			1662			1343		
Panel B: Reduced (Common) Sample Results									
GDP per capita	$5.2\text{x}10^{-5}$	29.395	<.0001	$4.9\text{x}10^{-5}$	39.360	<.0001	$6.0\text{x}10^{-5}$	13.853	0.0002
GDP growth	1.369	8.466	0.0036	1.5549	9.475	0.0021	1.479	5.833	0.0157
$(\text{GDP growth})^2$	-6.419	7.916	0.0049	-15.053	34.874	<.0001	-16.010	30.647	<.0001
Inflation				-0.363	5.279	0.0216			
External balance				-0.059	37.068	<.0001			
Fiscal balance (adj.)	0.024	8.6264	0.0033				0.033	8.032	0.0046
$(\text{Fiscal balance\_adj})^2$	$1.1\text{x}10^{-4}$	6.085	0.0136				$1.9\text{x}10^{-4}$	6.965	0.0083
External debt	-0.171	10.822	0.0010	-0.265	21.457	<.0001	-0.237	13.658	0.0002
Debt History	-0.587	23.587	<.0001	-0.805	52.843	<.0001	-1.225	74.652	<.0001
Inst. Inv. Rating	0.164	629.059	<.0001	0.168	708.325	<.0001	0.180	384.980	<.0001
Risk Premium	-51.076	8.154	0.0043	-87.159	28.444	<.0001	-129.3	32.732	<.0001
Max-rescaled R^2	0.931			0.934			0.939		
N	926			1155			668		

Table 6
Cumulative Probit Estimates of Rating Change Probabilities across Three Agencies

		Moody's			S&P			Fitch	
Variable	Estimate	Wald	Pr > χ^2	Estimate	Wald	Pr > χ^2	Estimate	Wald	Pr > χ^2
ΔGDP per capita	0.211	5.270	0.0217						
ΔGDP growth	1.439	9.274	0.0023	2.167	23.013	<.0001	1.224	6.932	0.0085
ΔExternal debt							-0.747	4.429	0.0353
ΔInst. Inv. Rating				3.387	19.091	<.0001			
ΔRisk Premium				-0.530	12.193	0.0005			
Outlook				0.934	137.974	<.0001	0.826	47.916	<.0001
Watch	1.848	71.917	<.0001	1.840	32.416	<.0001	1.723	55.618	<.0001
Momentum	0.367	22.305	<.0001	0.181	6.942	0.0084	0.332	18.702	<.0001
Misvaluation	0.643	16.917	<.0001	0.319	6.023	0.0141	0.796	27.628	<.0001
Intercept 1	-1.641	612.223	<.0001	-1.745	863.124	<.0001	-1.615	705.076	<.0001
Intercept 0	1.826	607.441	<.0001	1.933	808.617	<.0001	1.985	681.785	<.0001
Intercept -1	2.666	359.801	<.0001	2.746	594.460	<.0001	2.710	430.985	<.0001
Max-rescaled R^2	0.207			0.282			0.226		
N	1,094			1,661			1,343		

Table 7
Hazard Models of Rating Change Probabilities across Three Agencies

	Moody's			S&P			Fitch		
Variable	β	SE β	Pr > χ^2	β	SE β	Pr > χ^2	β	SE β	Pr > χ^2
Panel A: Downgrades									
Outlook				3.0373	0.3133	<.0001	2.0914	0.2542	<.0001
Watch	3.2273	0.3127	<.0001	4.4618	0.3434	<.0001	3.1347	0.3154	<.0001
ΔGDP per capita	-3.3992	1.1698	0.0037						
ΔGDP growth				-2.6197	0.9213	0.0045			
ΔFiscal Balance	-0.0811	0.0179	<.0001						
ΔExternal debt							1.5808	0.6094	0.0095
Debt History	0.7365	0.1894	0.0001	0.5442	0.2254	0.0157			
Rating							-0.0852	0.0384	0.0265
Momentum	-0.6548	0.1676	<.0001				-0.4452	0.1877	0.0177
Likelihood Ratio	162.578		<.0001	308.850		<.0001	190.842		<.0001
N	240			373			304		
Event	64			108			76		
Censored	176			265			228		
Panel B: Upgrades									
Outlook				1.4914	0.1716	<.0001	1.5781	0.1559	<.0001
Watch	3.3237	0.1780	<.0001				3.5763	0.3233	<.0001
ΔGDP per capita	0.3441	0.0388	<.0001	0.1974	0.0469	<.0001			
ΔGDP growth							3.6286	0.7673	<.0001
ΔExternal balance				0.1196	0.0315	0.0001			
ΔRisk Premium				-0.7664	0.3907	0.0498			
Rating	-0.0727	0.0291	0.0126	-0.1394	0.0296	<.0001			
Momentum	0.3030	0.1136	0.0076	0.6461	0.1205	<.0001			
Misvaluation	0.6437	0.3087	0.0370	0.7555	0.2202	0.0006	1.1608	0.2787	<.0001
FDI	6.4411	2.0261	0.0015						
Likelihood Ratio	168.967		<.0001	147.483		<.0001	167.651		<.0001
N	231			362			287		
Event	94			140			127		
Censored	137			222			160		

Table 8
In-Sample Aggregate Sovereign Rating Predictions

The columns headed “Watch” and “Outlook” show results for both positive and negative status with the latter being in parentheses. Thus, for example, the prediction accuracy of agency based forecasts of Standard and Poor’s “crisis” events are as follows: Watch and outlook positive status predict 0% of crises, watch negative status predicts 9.5% of crises and outlook negative status predicts 71.4% of crises.

The values of the predicted outcome probabilities and net risk of downgrade scores are only meaningful relative to other sovereigns’ probabilities and risk scores under the same model. Thus, for example, on average Standard and Poor’s “crisis” events have a predicted probability of crisis of 11.66% and net risk of downgrade score of 4.601 and these values decline monotonically as the actual outcome becomes more positive such that Standard and Poor’s upgrades have a predicted probability of crisis of 0.17% and net risk of downgrade score of 0.822.

		% Positive (Negative)		Mean (Median) Predicted Outcomes OP model				Mean (Median) Net Risk Score Hazard Models
	N	Watch	Outlook	Pr Up	Pr Same	Pr Down	Pr Crisis	Net Risk DG
Panel A: Standard and Poor’s								
CRISIS	21	0%	0%	1.19%	67.90%	19.25%	11.66%	4.601
		(9.5%)	(71.4%)	(0.07%)	(68.87%)	(21.50%)	(9.56%)	(5.000)
Downgrade	64	0%	3.1%	2.62%	77.60%	12.74%	7.05%	4.120
		(10.9%)	(48.4%)	(0.46%)	(84.04%)	(11.16%)	(2.95%)	(4.307)
No Change	1,443	0%	11.5%	7.27%	88.33%	3.50%	0.90%	2.391
		(0.3%)	(9.4%)	(4.46%)	(92.20%)	(2.13%)	(0.26%)	(2.315)
Upgrade	133	0%	45.9%	19.93%	78.90%	1.00%	0.17%	0.822
		(0%)	(0.8%)	(16.10%)	(81.71%)	(0.34%)	(0.02%)	(0.847)
Panel B: Moody’s								
CRISIS	10	0%	0%	2.39%	81.57%	9.61%	6.43%	2.477
		(10.0%)	(0%)	(2.75%)	(90.99%)	(5.37%)	(0.89%)	(2.313)
Downgrade	44	0%	0%	2.88%	80.42%	10.59%	6.10%	2.329
		(20.5%)	(2.3%)	(2.22%)	(90.17%)	(6.20%)	(1.09%)	(2.013)
No Change	961	0.1%	0.5%	6.39%	89.23%	3.62%	0.76%	1.088
		(0.9%)	(0.3%)	(5.03%)	(91.07%)	(3.01%)	(0.38%)	(1.277)
Upgrade	79	17.7%	2.5%	20.55%	77.23%	1.95%	0.27%	-0.425
		(0%)	(0%)	(9.59%)	(88.67%)	(1.40%)	(0.13%)	(0.448)
Panel C: Fitch								
CRISIS	12	0%	0%	1.51%	79.03%	12.58%	6.89%	1.129
		(16.7%)	(33.3%)	(0.41%)	(82.44%)	(12.41%)	(4.74%)	(1.660)
Downgrade	38	0%	2.6%	3.01%	84.00%	8.85%	4.13%	0.368
		(18.4%)	(28.9%)	(1.43%)	(89.52%)	(6.28%)	(1.64%)	(0.286)
No Change	1,174	0.5%	5.0%	7.96%	88.62%	2.66%	0.76%	-1.331
		(0.8%)	(4.2%)	(5.65%)	(91.82%)	(1.89%)	(0.31%)	(-1.473)
Upgrade	119	5.9%	23.5%	20.86%	77.73%	1.16%	0.25%	-2.162
		(0%)	(1.7%)	(12.44%)	(86.52%)	(0.64%)	(0.08%)	(-1.982)

Table 9
Out-of-Sample Sovereign Rating Predictions: Standard and Poor's Ratings

Panel A: Prediction Accuracy				
	N	Predicted UG	Predicted Same	Predicted DG
Upgrades	14	8 (57%)	6 (43%)	0 (0%)
No change	74	14 (19%)	59 (80%)	1 (1%)
Downgrades	4	0 (0%)	1 (25%)	3 (75%)
Panel B: Observations around Cut-off Points				
	Up	Same	Down Crisis	CRISIS
Upgrades				
Before	18.32%	81.41%	0.26%	0.02%
After	12.98%	86.48%	0.50%	0.04%
Downgrades				
Before	0.54%	86.53%	10.32%	2.60%
After	1.59%	92.13%	5.33%	0.95%