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What drives differences of opinion in sovereign ratings? The roles of information disclosure and political risk

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Abstract

This paper investigates the causes of split sovereign ratings across S&P, Moody's and Fitch for 64 countries from 1997 to 2011. We identify that split sovereign ratings are not symmetric, with S&P tending to be the most conservative agency. We find that opaque sovereigns are more likely to receive split ratings. Political risk plays a highly significant role in explaining split ratings and dominates economic and financial indicators. Out-of-sample model performance is enhanced by capturing political risk. Government information disclosure affects split ratings between Moody's and Fitch in emerging countries. The study implies an incentive for governments to reduce political uncertainty and to enhance transparency.

JEL classification: G15; G24; G28

Keywords: Sovereign split ratings; Opacity; Political risk; Information disclosure; Out-of-sample performance.

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1. Introduction

Amid persistent concerns surrounding the international economic outlook in the aftermath of the global financial crisis, credit rating agencies (CRAs) have attracted a higher profile. In Europe, there was a strong wave of negative sovereign rating actions which resulted in split ratings for many high-rated countries in this region. Split ratings arise when different CRAs assign unequal ratings to the same issuer at the same time (e.g. Livingston and Zhou, 2010). They may be temporary due to the CRAs' asynchronous actions or may become persistent if the disparity in ratings continues over time.

During recent years, split sovereign ratings no longer prevail solely within low-rated sovereigns in emerging countries as documented by Cantor and Packer (1996a), but are evident across different levels of economic development. Yet, there is very little evidence on the causes of split sovereign ratings. Cantor and Packer (1996a) attribute split ratings to the CRAs' lack of experience in rating sovereign default risk, but they provide little empirical evidence on this. Hill et al. (2010) report differences in the credit rating models across the largest CRAs, but they do not relate this to split sovereign ratings. Alsakka and ap Gwilym (2012) analyse macroeconomic factors, low creditworthiness and home bias as potential causes of split sovereign ratings, yet their research is focused only on emerging countries.

We hypothesize that split sovereign ratings arise due to information opacity rather than random errors by the CRAs.[1] The information opacity hypothesis for split ratings has been tested for corporate issuers and across industries. Morgan (2002) finds that split ratings occur more often in banks and insurance companies because their assets are more opaque. Livingston et al. (2007) and Hyytinen and Pajarinen (2008) evaluate corporate opacity by considering firm age, intangible assets, and other observables. We contribute to previous

[1] Ederington (1986) concludes that corporate bond split ratings result from random rating errors, which suggests that split ratings are symmetric between any pair of CRAs. See Section 3 for more details on the random error versus the information opacity hypotheses of split ratings.

literature by providing new evidence on the information opacity hypothesis for sovereign issuers. We contend that opacity arises when CRAs rely, to a great extent, on subjective evaluations of sovereign risk. We focus on two key sources of opacity in assessing sovereign ratings: *the quality of information disclosure by governments* and *political risk*.

We firstly consider split sovereign ratings in the light of governments' information quality and transparency. This approach is original because we focus on the openness and willingness of the government to release information in the public domain. Information from transparent sovereigns is richer, more accessible and updated more frequently than from opaque sovereigns. Split sovereign ratings could arise when CRAs have limited access to high-quality data with which to base their credit assessments. Quality of information is central to the quality of credit ratings. Recent developments in the regulatory sphere suggest that CRAs should be held accountable for taking appropriate measures to make use of all the available information from credible sources (European Commission, 2009). Policy makers also call on the CRAs and governments to be more transparent in terms of information disclosure (House of Lords, 2011). Therefore, material changes in the quality of the data utilised by the rating analysts must be signalled to the users. While regulators are interested in the transparency of the CRAs, we emphasize the potential benefits from governments' transparency.

Among the determinants of sovereign ratings, we focus on the importance of political risk (see Butler and Fauver, 2006; Mellios and Paget-Blanc, 2006; Afonso et al., 2011). In contrast with corporates, sovereign credit ratings consider the governments' capacity and willingness to repay. The latter factor is affected by political concerns. Political risk represents the soundness and stability of the legal and institutional systems of a country. From the perspective of financial market participants, it commands a significant risk premium and raises stocks' correlations and volatilities, particularly in weak economic conditions (Pástor and Veronesi, 2013). Recently, political risk has attracted considerable attention, not only in emerging markets, which are commonly characterised by a lack of political stability, but also in European countries. Europe is facing a confluence of serious political challenges. The impact of challenging political dynamics has been particularly evident in Greece, as well as the rise of new anti-reform political parties in some countries (e.g. Portugal and Spain) and disagreements within governments (e.g. France) reduce the governments' willingness to embark on structural reforms and fiscal consolidation.[2] However, the assessment of political issues usually involves subjectivity and ambiguity. Therefore, we expect that political risk triggers greater differences of opinions and interpretation by CRAs than do the quantitative indicators (typically used for economic and financial risks). By addressing political risk, this study is clearly differentiated from literature on split corporate ratings and from the very limited prior work on split sovereign ratings.

We investigate the determinants of split sovereign ratings from the three largest CRAs (S&P, Fitch and Moody's) using ratings, outlook and watch information from 1997 to 2011. Our data allow for consideration of split sovereign ratings in many developed countries, including a focus on the European dimension. Further, prior studies on split ratings only consider the rating notations, while outlook and watch are ignored.[3] In fact, outlook and watch signals can be at least as important as rating changes in their impact on financial markets (e.g. Sy, 2004; Kim and Wu, 2011; Afonso et al., 2012). A CRA's complete opinion on an issuer consists of a credit rating and a rating outlook/watch status, so split ratings in our paper are expressed based on all these elements.

[2] A recent example of such political influence on ratings is S&P's downgrade of Poland in January 2016, which was stated to be driven by concerns regarding radical policies implemented by its new conservative government, e.g. steps taken by the new government to seize control of Poland's public media and to challenge the independence of its constitutional court.

[3] Outlook changes indicate the changes between four statuses: positive, negative, stable and developing (or evolving by Fitch). Watch changes indicate the changes between watch for possible upgrade, watch for possible downgrade, watch with uncertain direction and no watch assignment.

Our empirical analysis supports the opacity hypothesis in explaining split sovereign ratings. We show that split sovereign ratings are lopsided rather than symmetric, with S&P tending to be the most conservative. We identify the importance of opacity inherent in political risk, particularly in countries outside Europe. We use six Worldwide Governance Indicators (WGI) published by the World Bank as the political risk proxy variables, and find that they are significant explanatory factors. Out-of-sample model performance is enhanced by capturing political risk. We highlight that rating splits that involve Fitch (vs. Moody's or S&P) are more prone to the political factor. This may imply a more political risk-focused approach to assess sovereign risk by Fitch relative to the other two CRAs. Further, we assess the information disclosure quality by whether (and for how long) a Freedom of Information Act has been in place. Our findings reveal that an incentive exists for non-European emerging countries to provide the CRAs with updated, credible information, but the evidence is only linked to Moody's vs. Fitch ratings.

We make several important contributions to the literature. First, we provide evidence that opacity is highly relevant to split ratings of sovereign issuers. Second, we distinguish our study from the literature on split corporate ratings by introducing a political risk factor to represent the "willingness to pay" element of sovereign ratings. Third, we introduce an approach to analysing the link between split ratings and quality of information disclosure by governments. Fourth, we identify that these effects differ between European countries and emerging markets in the rest of the world. Finally, the prior credit rating literature has defined split ratings using only the rating notations; this paper is the first to define split ratings that also incorporate the differences in outlook and watch statuses between two CRAs.

The remainder of the paper is structured as follows: section 2 reviews related literature, section 3 states our proposed hypotheses on split sovereign ratings, section 4 describes the data and the methodology, section 5 discusses the empirical results, and section 6 concludes.

2. Literature Review

Prompted by the increased demand for external borrowing by central governments, the sovereign rating market has grown sharply over the past two decades. Recently, there have been complaints from governments about the CRAs exacerbating market panic during crisis times with excessive downgrades on sovereign ratings and changes in CRA regulation are in progress around the world. There have been numerous papers dealing with sovereign ratings from different angles, which can be grouped into three main strands of literature.

The first strand aims to identify the determinants of sovereign credit rating levels. Several studies suggest that ratings can be predicted with relatively few quantitative economic indicators such as GDP per capita, GDP growth, inflation, external debt, the level of economic development and default history (e.g. Cantor and Packer, 1996b). Some studies report the political and/or institutional environment to be significant for sovereign ratings (e.g. Butler and Fauver, 2006). Some economic and financial determinants affect ratings in the short run, while others impact ratings in the long run (Afonso et al., 2011). However, these determinants do not carry the same degree of importance through time, across the CRAs, and between developed and developing countries (Bissoondoyal-Bheenick, 2005; Hill et al., 2010). The second strand of the literature focuses on modelling the probability of sovereign credit rating migration. Fuertes and Kalotychou (2007) and Hill et al. (2010) document evidence that forecasts of potential rating changes can be improved with information from rating outlook, watch, rating momentum and duration.

The third strand of literature relates sovereign credit signals such as sovereign rating changes, outlook and watch changes directly to the financial markets. Rating signals are treated as events which trigger responses from market participants. Sovereign credit signals have an effect on various asset classes including credit derivatives, bonds, equity and foreign exchange. Many studies detect significant market reactions to negative signals, while the reactions to positive signals are either muted or negligible (e.g. Sy, 2004; Afonso et al., 2012). The information value of CRAs' credit opinions is significant even after controlling for sovereign credit spreads and country fundamentals (Cavallo et al., 2013). In addition, the effect of sovereign rating events is transferred from country to country due to strengthening global market linkages (Gande and Parsley, 2005; Ferreira and Gama, 2007), as well as from sovereign issuers to sub-sovereign issuers due to the sovereign ceiling effect (e.g. Williams et al., 2013). Sovereign credit signals also affect the international bank flows to emerging countries and the stock and bond market correlations with their respective regional markets (Kim and Wu, 2011; Christopher et al., 2012).

Although the above research on sovereign credit ratings has developed over some time, there is very little evidence on split sovereign ratings. Split ratings arise from multiple credit ratings, a situation in which one bond issuer is assigned ratings by at least two CRAs. Prior studies on multiple ratings are mainly conducted in the context of corporate ratings. From the perspective of bond issuers, Mählmann (2009) and Bongaerts et al. (2012) investigate the issuers' incentives for purchasing multiple credit ratings. From the bond-holders' perspective, researchers investigate how bond valuation is adjusted to split ratings (e.g. Jewell and Livingston, 1998; Livingston and Zhou, 2010; Livingston et al., 2010) and the relationship between split ratings and rating migration (e.g. Livingston et al., 2008).

Researchers have attempted to explain split corporate ratings. Pottier and Sommer (1999) reject that splits are random in favour of a view that they arise from discrepancies in the models applied by different CRAs, i.e. split corporate ratings arise from the fact that CRAs apply different models and consider the factors with different levels of importance. Morgan (2002) reports that financial intermediaries are more susceptible to split ratings than industrials and utilities, and attributes this to a higher degree of opacity. Banks' information opacity is reflected by their asset mix, including loans and trading assets. Iannotta (2006) and

Flannery et al. (2004) also provide evidence on the relevance of banks' asset opacity. Livingston et al. (2007) and Hyytinen and Parajinen (2008) examine the opacity of non-financial firms and they find similar results. Livingston et al. (2007) claim that firms' opacity is not only reflected by their internal accounting data but also by external factors such as the number of equity analysts and the standard deviation of analysts' earnings forecasts. Bowe and Larik (2014) show that the split corporate ratings assigned by Moody's and S&P can be predicted with firm-specific financial and governance characteristics such as size, profitability and percentage of independent directors.

In contrast with split corporate ratings, very few papers exist on the determinants of split sovereign ratings. Cantor and Packer (1996a) emphasize the prevalence of split sovereign ratings, but they do not investigate the causes. Alsakka and ap Gwilym (2012) examine some possible causes of split sovereign ratings, but are restricted to emerging markets. They find that CRAs use different quantitative factors and place different weights on these factors. CRAs disagree more on speculative-grade rated sovereigns, and smaller CRAs tend to rate issuers in their "home region" more favourably.

In this paper, we use a richer dataset comprising both developed and developing countries. We are the first to examine the relevance of the information opacity hypothesis in explaining split sovereign ratings, considering two key sources of opacity, namely: *quality of information disclosure by governments* and *political risk*. Further, we evaluate split sovereign ratings in a different way than prior literature. We consider the extent to which a rating difference between two CRAs varies within a year, captured by the annual standard deviation of daily rating differences (*sd.split*).

3. Hypotheses

To explore the drivers of split sovereign ratings, we examine the following hypotheses:

Null hypothesis H_0 - 'Random error hypothesis': Split sovereign credit ratings between CRAs occur randomly due to the complicated, subjective nature of sovereign credit risk assessments.

Alternative hypothesis H_1 - 'Opacity hypothesis': Split sovereign ratings are a consequence of sovereign information opacity.

We use two proxies of opacity: information disclosure and political risk, and therefore test the following hypotheses:

H_2 - 'Information disclosure hypothesis': Split sovereign ratings are influenced by the quality of information disclosure by governments on both political and financial/economic aspects.

H_3 - 'Political risk hypothesis': Split sovereign ratings are a consequence of political risk, which is a significant element of sovereign credit risk assessment, but is difficult to observe and measure in an objective manner.

Ederington (1986) tests the 'random error hypothesis' through a set of tests on the alternative hypothesis that Moody's and S&P adopt different rating standards and/or attach different weights to a common set of quantitative determinants of corporate default risk. Ederington (1986) shows that CRAs assign similar weights to the commonly used factors, e.g. firm size and leverage ratio, in estimating the credit risks. Ederington (1986) asserts that split corporate ratings arise randomly because rating is a subjective and difficult task. This implies that split ratings are symmetric between any pair of CRAs, and thus we should not observe a persistent trend of either higher ratings or lower ratings from a particular CRA.

We apply a similar approach to Ederington (1986) and Livingston et al (2007) by setting up tests on the alternative hypotheses. Rejection of the 'opacity hypothesis' implies support for the validity of the 'random error hypothesis'. The literature suggests a significant linkage between information opacity and split ratings for banks and corporates (e.g. Morgan, 2002; Livingston et al., 2007; Hyytinen and Parajinen, 2008). We contribute to prior literature by testing the information opacity hypothesis (H_1) for sovereign issuers.

In sovereign credit risk assessments, CRAs encounter opacity when information disclosure is poor or important input data are difficult to measure. Regarding the first proxy of opacity (under H_2), we claim that rating assessments depend on the sovereigns' information transparency. Government agencies are usually responsible for compiling and releasing information about their activities, policies, intentions and other capabilities. Macroeconomic statistics are also under the control of governments. Government transparency is reflected by the *"legal, political and institutional structures that make the information about the internal characteristics of a government and society available to actors both inside and outside of the domestic political system…"* (Finel and Lord, 1999). Gelos and Wei (2005) document two aspects of government transparency, namely: the macroeconomic policy transparency and the data transparency. We adopt the second aspect of transparency from Gelos and Wei (2005) which refers to the timeliness and frequency with which a government releases macroeconomic data. We extend this to cover all the information about the government's characteristics, activities and intentions that are needed for rating sovereign creditworthiness. The 'information disclosure hypothesis' (H_2) is tested using a proxy variable (Freedom of Information Act (*FOIA*), see Section 4.2.1).

With regards to the second aspect of opacity (H_3), we draw from the CRAs' rating methodologies. CRAs explicitly state the key factors considered in rating sovereign creditworthiness. These comprise different quantitative and qualitative variables, with typical categories being: macroeconomic development, public finance, external finance, the soundness of the financial systems, political risk, and others. Unlike the other commonly used credit risk determinants, political risk poses a difficulty due to the lack of consistently observable and unbiased measures. Hence, H_3 tests whether political risk is a substantial component of information opacity through which split sovereign ratings arise. We test H_3 using a proxy variable (the Worldwide Governance Indicators (*WGI*), see Section 4.2.2) to measure the degree of sovereigns' political risk.

In examining H_1, we particularly focus on two groups of countries. The first group is European countries, where split ratings have become more common (primarily driven by the recent sovereign debt crisis), yet they display relatively low political risk.[4] In addition, our sample period coincides with the evolution and expansion of the European Union which is believed to reinforce government transparency among its member states. Further, the credit standing of European governments can be affected by their strong regional, trade and financial links and the high degree of integration as well as joint economic and monetary policy among the Eurozone member states. Therefore, we expect the determinants of split ratings for European countries to have some unique characteristics.

The second group includes non-European countries (the rest of the world (ROTW) group), which mainly constitutes emerging countries[5], which are characterised by a relative lack of political stability, lack of market regulation and transparency, and a higher degree of volatility and uncertainty. Many rating actions in emerging countries are driven by political events, e.g. the downgrades of Egypt, Bahrain and Tunisia in the wake of the 'Arab spring' in

[4] However, political risk is high on the recent European agenda. CRAs have warned of negative rating actions on European sovereigns as a result of heightened political uncertainty. This is driven by, for example, the ongoing migration crisis, the risk of the UK leaving the EU leading to credit market volatility, an escalation in extreme and nationalistic views and the rise of anti-reform political parties, which challenge Europe's fragile growth and financial stability (Moody's, 2015; S&P, 2015; Fitch, 2016).

[5] Around three-quarters of the observed split sovereign ratings in the ROTW group are related to emerging countries (according to the World Bank definition). We also present results based on emerging countries outside Europe (See Table 7 and Section 5.2).

2011, and the downgrade of Brazil to speculative-grade by S&P and Moody's in February 2016 caused by political turmoil hampering efforts to make fiscal adjustments.

4. Data and Methodology

4.1. The sovereign credit rating data

The sovereign credit rating dataset is collected directly from CRAs' publications. It includes daily observations of long-term foreign currency issuer ratings, outlook and watch for 64 sovereigns jointly rated by at least two of the largest CRAs, namely S&P, Moody's and Fitch. Due to availability of information on the explanatory variables, the data spans from 1st January 1997 to 30th September 2011 for joint ratings by S&P-Moody's, and from 1st January 1998 to 30th September 2011 for joint ratings by Fitch-S&P and Fitch-Moody's.

We convert the sovereign rating letter grades into a 58-point numerical rating scale (see Sy, 2004). Adjacent notches on the 20-notch rating scale differ by 3 points on the 58-point scale (AAA/Aaa = 58, AA+/Aa1 = 55 … CCC-/Caa3 = 4, CC/Ca to C/SD/D = 1). We then adjust the ratings either upward or downward by one (two) point(s) if outlook (watch) is assigned respectively with either positive or negative indication. We refer to these adjusted ratings as comprehensive credit ratings (CCR). We define daily rating differences as the daily differences in CCR between two CRAs. Non-zero differences indicate daily split ratings. A split by three-CCR points is equivalent to a one-notch split, while a split by one (two)-CCR(s) is equivalent to a split by an outlook (watch) status. This method enables us to evaluate not only the notch differences but also the outlook and watch differences. This has not been previously implemented in the split ratings literature. For the remainder of this paper, the term 'ratings' refers to comprehensive credit ratings (CCR) and the term 'rating differences' refers to the differences in CCR.

Table 1 details the data summary of daily split sovereign ratings. There are 61, 54 and 52 sovereigns with joint ratings assigned by S&P versus Moody's, S&P versus Fitch, and Moody's versus Fitch. In line with Cantor and Packer (1996a) and Alsakka and ap Gwilym (2012), split ratings are very common in the samples. The proportions of the split ratings range from 53.3% to 67.3%. S&P and Fitch disagree less often than they do with Moody's, and the magnitude of their average rating differences is slightly smaller.

Figure 1 presents the distributions of daily split sovereign ratings. Most of the daily rating disagreements range between 1-CCR to 6-CCR points, which is consistent with Hill et al. (2010) who report that sovereign ratings usually differ by one or two notches on the 20-notch rating scale. Split ratings of 3-CCR points or below account for around 45% of observations. Large splits of >3 CCR-points are more common in the case of the S&P-Moody's sample, with S&P being the more conservative CRA. Similarly, S&P tends to assign lower ratings than Fitch, though the magnitudes of the splits are more concentrated at ≤ 3-CCR points.

Table 1 and Figure 1 show that the split sovereign ratings are not symmetric between any pair of CRAs, but instead the differences are more lopsided, with S&P tending to be on the downside. This pattern suggests that split sovereign ratings are not caused by random errors. It is also consistent with the findings of Morgan (2002) and Livingston et al. (2007) that split corporate ratings are lopsided, and thus is consistent with the opacity hypothesis. However, for corporate ratings Moody's typically assigns the lower ratings.

Our sample comprises 26 countries in Europe[6] and 38 countries outside this region. Table 1 shows that rating differences across the three CRAs are dispersed widely both inside and outside Europe. However, the average daily rating differences are larger in Europe than in the rest of the world (ROTW), implying harsher split ratings between CRAs in Europe. This is partly attributable to multiple-notch rating downgrades, especially during the

[6] The European country selection is initially based on the World Bank's 'Europe and Central Asia' region, and the final qualifying countries include 24 countries in Europe plus Kazakhstan and Russia.

sovereign debt crisis. Moody's disagrees on the credit quality of European countries with S&P and Fitch less often than they do on sovereigns in the rest of the world. Yet, for joint ratings by S&P and Fitch, European countries have more split ratings. Fitch tends to be more generous than Moody's in European countries, while slightly harsher in ROTW countries.[7]

In studying split ratings, it is important to consider time variation arising due to different frequencies and timing of rating actions across CRAs. Observing split ratings at specific points in time (e.g. debt issuance) fails to pick this up. In order to retain the benefits of a rich dataset, we calculate the annual standard deviation of (daily values of) rating differences between two CRAs (*sd.split*). This measure captures well the degree to which CRAs' opinions divide on sovereign credit quality. It also circumvents the problems encountered by other split measures such as the annual average of daily rating differences, for which positive and negative observations can cancel out. By using standard deviation, we give added weight to large and volatile split ratings.

Table 2 reports the summary statistics of annual *sd.split*. A similar picture to daily split ratings reported in Table 1 emerges. The average levels of dispersion of daily rating differences across the years fall between 0.5-CCR and 0.6-CCR points. S&P vs. Fitch presents a slightly lower degree of dispersion than the other two pairs. Approximately 60% of S&P vs. Fitch *sd.split* observations are non zero, compared with 55% (58%) for Moody's vs. Fitch (S&P). Disagreements between CRAs vary greatly, whereby *sd.split* reaches a maximum of 7-CCR points. We find that daily splits between CRAs are more stable (lower average *sd.split* and lower percentage of non-zero *sd.split*) in Europe than in ROTW.

[7] This is an interesting observation because Fitch has dual headquarters (US and Europe), while Moody's and S&P have headquarters in the US only. Alsakka and ap Gwilym (2012) document a 'home bias effect' by smaller CRAs.

4.2. Opacity variables

4.2.1. Quality of *information disclosure by governments*

The first variable that we use to evaluate sovereign opacity is the Freedom of Information Act (*FOIA*). An *FOIA* is often established to promote the free flow of information from governmental bodies to the public domain. It contains provisions for the government's responsibility to compile, release and update information regularly or at the request of individuals and institutions. *FOIA* reflects an important part of the legal mechanism to facilitate ease of access to government information. Although *FOIA*s might differ in content and scope from country to country, most of them reflect a government's commitment to guarantee and improve transparency. Therefore, we contend that *FOIAs* are a good signal of government transparency and effectively capture the concept of government information disclosure (see Section 3 - H_2).

We obtain information on *FOIA* from the report named "Overview of all FOI laws" in Vleugels (2011). For the purpose of this research, the countries either without FOI law or which have introduced but not yet passed the law are categorized as "not having *FOIA*". We define the countries where the law has been passed as "having *FOIA*". However, the "having *FOIA*" status does not imply that all the countries in this category have the same level of government transparency, as the content and implementation of the laws will vary across countries. We do not have information on the content of *FOIA* in each country, so we rely on the length of time the law has been enacted to evaluate government transparency for the countries in this category. We claim that there is a variation in information transparency between the countries where *FOIA* has been in place for some time and the countries where the law is new. The mere recent introduction of *FOIA* into a nation's legal framework does not assure its citizens of immediate free access to information from public agencies. Government transparency takes time to improve as effective implementation is not immediate after the law has been passed. Therefore, we define *FOIA* as a discrete variable with six ordered outcomes. It takes the value of 1 if the sovereign is "not having *FOIA*", 2 if the sovereign has adopted *FOIA* for less than five years, 3 if for more than five years and less than 10 years, 4 if for more than 10 years and less than 15 years, 5 if for more than 15 years and less than 20 years, and 6 if for more than 20 years.[8] We argue that information disclosure improves sovereign transparency, mitigates the opacity problem, and reduces the variation in daily split ratings. Therefore, we expect FOIA score to be negatively correlated with the split ratings.

Table 3 presents the summary statistics. The overall average *FOIA* is 2.2, equivalent to one to five years' experience in implementing the FOI laws. There are a few exceptional cases including Denmark, Finland, Sweden and the United States where the *FOIA* has been adopted for over 20 years prior to the start of the sample period. Among the 64 countries in the sample, 21 do not have legislation on access to information for the entire sample period.

4.2.2. Political risk

The second variable that we use to evaluate sovereign opacity is political risk. Unlike macroeconomic and public finance indicators, there is not a standard method to quantify political risk, therefore assessment is mostly opinion-based. To test H_3, we use six Worldwide Governance Indicators (WGI) estimated by the World Bank as proxy variables for political risk. Each indicator corresponds to one of six different aspects of governance, which are control of corruption, political stability and absence of violence, government effectiveness, voice and accountability, regulatory quality, and rule of law. Higher governance scores imply lower political risk. The extent to which CRAs align their sovereign rating actions with changes in political risk reflect their differing rating approaches, hence split ratings occur.

[8] The results are not sensitive to alternative definitions of *FOIA* using other time thresholds.

Whenever political risk is more complicated to evaluate, the harder it is for CRAs to estimate default probability. Therefore, we expect a negative correlation between WGI and the variation of daily split ratings.

Table 3 presents the summary statistics. The overall means of the six political variables vary from 0.13 to 0.5 with standard deviations in the range of 0.86 to 1.02. In terms of rule of law, the top sovereigns are Finland, New Zealand, Germany, Japan and Singapore. In contrast, Cameroon, Belarus, Guatemala, Paraguay and Ecuador have the lowest scores. We also calculate a composite of all the six different aspects of governance (*Ave WGI*). Finland, Denmark, Iceland, Germany and Ireland are the sovereigns with top *Ave WGI* scores, while Belarus, Pakistan, Cameroon, Paraguay and Ecuador score the lowest *Ave WGI.*

4.3. Empirical model

We estimate the following panel data regression model with fixed-effects for the three pairs of CRAs separately, for the full sample as well as for two subsamples (Europe and ROTW countries):

$$\begin{aligned} sd.split_{i,t} = {} & \alpha_{it} + \beta_1 FOIA_{it} + \beta_2 WGI_{it-1} + \beta_3 Default\ \ Dummy_i + \\ & \beta_4 Domestic\ Credit / GDP_i + \beta_5 Reserves / Imports_i + \beta_6 GDP\ Growth_i + \\ & \beta_7 Inflation_i + \beta_8 CA\ Balance / GDP_i + \beta_9 Fiscal\ Balance / GDP_i + \\ & \beta_{10} GovernmentDebt / GDP_i + \beta_{11} Specgrade\_dum_{it} + \gamma\, Co_i + \varphi Yr_t + \varepsilon_{it} \end{aligned} \tag{1}$$

$sd.split_{it}$: the standard deviation of daily split ratings of sovereign *i* during year *t*.

$FOIA_{it:}$ the proxy of the government's quality of information disclosure for sovereign *i* at year *t*. *FOIA* is defined as a discrete variable with six ordered outcomes (see Section 4.2.1).

WGI_{it-1}: the political risk (Worldwide Governance Indicator) score of sovereign *i* at year *t-1* (see Section 4.2.2).

Default dummy: a binary variable that equals 1 if the sovereign has experienced sovereign defaults or debt restructuring, and zero otherwise.

Domestic credit/GDP: annual loans to the private sector as a proportion of GDP.

Reserves/imports: the annual dollar amount of foreign exchange reserves relative to payments for imports.

GDP growth: the 3-year average real growth in Gross Domestic Product.

Inflation: the 3-year average rate of general price appreciation.

CA balance/GDP: the 3-year average of current account balance as a proportion of GDP.

Fiscal balance/GDP: the 3-year average of the fiscal balance as a percentage of GDP.

Government debt/GDP: the gross government debt in US dollar as a percentage of GDP.

These eight economic and financial indicators are used to control for the differences in the CRAs' rating methodologies.[9] The inference for these variables helps uncover discrepancies in sovereign credit rating models across the CRAs. We select these variables by reference to CRAs' publications on credit rating models, and published research on the determinants of sovereign credit ratings (e.g. Cantor and Packer, 1996b; Bissoondoyal-Bheenick, 2005; Afonso et al., 2011). We lag these variables by one year, except for *GDP growth*, *Inflation*, *Current Account Balance/GDP* and *Fiscal Balance/GDP* which are averaged over three previous years to account for the economic cycle.

$Specgrade\_dum_{it}$: a dummy variable that takes the value of 1 if the average annual rating assigned by two CRAs for sovereign i at year t is at speculative-grade (BB+/Ba1 and lower). This controls for the different characteristics that speculative-grade vs. investment-grade rating categories may have, and hence examines whether split ratings are more common among low-rated countries than high-rated countries.

We apply Huber-White robust standard errors to obtain robust estimators to any potential heteroscedasticity and/or autocorrelation in the residuals. Following Arellano's

[9] These macroeconomic and financial fundamentals are obtained from Datastream. The sources are IMF International Financial Statistics, IMF World Economic Outlook, and Oxford Economics. See Table 3 for the summary statistics.

(1993) approach, we perform a heteroscedasticity robust-form of Hausman test (unreported) on imposing random effects vs. fixed effects on our model and the test results support fixed-effects models. The fixed-effects are captured by a series of country dummy variables Co_i and year dummy variables Yr_t.[10]

5. Empirical Results

5.1. The full sample

Table 4 presents the results of Eq. (1). We examine each pair of CRAs with separate estimations. WGI indicators are strongly positively correlated to each other (Kaufmann et al., 2010). The correlation matrix (unreported) shows that the average correlation between two WGI is 0.815. Therefore, we repeat each regression six times with six different WGI, and the results are relatively consistent across the six versions, as would be expected. Therefore, we choose "Rule of Law" to present political risk in Tables 4 - 8.[11] In addition, we estimate Eq. (1) using the average of these six WGI (following Butler and Fauver, 2006).[12]

Table 4 also reports the results of a base, simple model that only includes sovereign fundamentals, while excluding the opacity proxies (*FOIA* and *WGI*). The purpose of fitting the base model and the full model (Eq. 1) is to unravel the economic significance of sovereign opacity in explaining why split ratings occur. The base model is also relevant later in Section 5.3.

Among the macroeconomic variables, split ratings are mostly influenced by changes in the public finance variable (*Government Debt/GDP*). Specifically, a one percentage point

[10] We have tested whether *WGI* and *FOIA* are endogenous variables using 'difference-in-Hansen' tests (Hansen, 1982). The tests confirm exogeneity in all estimations.

[11] We observe that statistical inferences for most individual coefficients and the models' overall significance do not vary substantially across the six choices of WGI. The result tables when using the other five WGI are available on request from the authors.

[12] The correlation matrix has been considered and VIF tests have been conducted, and we find no evidence of multicollinearity for other explanatory variables.

increase in the ratio of government debt over GDP increases the variation of splits by 0.01-CCR-point. Table 4 also highlights that the total *Domestic Credit* is a statistically significant factor in explaining split sovereign ratings, but the magnitude of the impact is relatively small in economic terms. Consistent with Livingston et al. (2007), we find that split ratings between S&P and Fitch are more likely for speculative-grade than for investment-grade rated sovereigns.

In contrast with most of the economic variables, opacity variables are statistically and economically significant in explaining the split sovereign ratings. We find that political risk (WGI) is more influential than information transparency (*FOIA*).[13] *WGI* is the most important factor for split ratings. For all three pairs of CRAs, a unit decrease in political score increases the *sd.split* between the two CRAs by 0.5-CCR to 0.6-CCR point. Split sovereign ratings between Moody's and Fitch are slightly more affected by opaque sovereigns (with higher degree of political risk) than the split ratings between the other pairs. We find a slightly stronger impact of political risk when using the average of six WGI scores as the proxy for political risk than when using an individual indicator (rule of law). Further, the R-squared values are larger for the estimations that include FOIA and WGI than those without opacity indicators. The results support H_1 (and H_3 in particular) that split ratings are more prevalent when opacity arises, especially with regard to political risk.

5.2. Regional analysis: Europe and the rest of the world.

In this section, we conduct further analysis of the causes of split sovereign ratings for countries in and outside the European region. Specifically, the objective is to unravel the potential differences in the determinants of split sovereign ratings between countries in Europe and the rest of the world (ROTW). Persistent split ratings have become common, particularly in many high-income countries affected by the recent European sovereign debt

[13] We do not find evidence supporting the information disclosure hypothesis (H_2) in the full sample.

crisis. Further, for the ROTW group, we estimate Eq. (1) for a sub-group consisting of emerging countries only. Table 5 presents the results for European countries, Table 6 for ROTW countries, and Table 7 for the ROTW-emerging countries sub-group.

The effects of political risk on split sovereign ratings are concentrated in ROTW countries where WGI governance scores are lower. Table 6 shows that a one unit decrease in WGI (rule of law) increases the *sd.split* by 0.70, 0.96 and 1.07 CCR-point in the case of Moody's-S&P, S&P-Fitch and Moody's-Fitch, respectively. The coefficient estimates are larger (0.79, 1.31 and 1.35 CCR-point) when we use the composite governance score (average of the six WGI). Table 5 shows that the effects of political risk on split ratings are muted in Europe.[14] The political uncertainty in Europe has become a more important factor in the post-2010 period, and therefore is not apparent during most of our sample period. Table 5 also shows that split sovereign ratings increase if a government fails to meet its financial obligations in full and on time.

We find a strong and significant effect of political risk on split ratings in ROTW countries. However, the evidence for FOIA is still absent. We run Eq. (1) using a sub-set of the group ROTW excluding developed countries and present the results in Table 7. The results continue to support our hypothesis of sovereign opacity with regards to political risk (H_3). We also find significant coefficients on the FOIA variable in the case of Moody's vs. Fitch. Longer establishment of a Freedom of Information Act in emerging countries decreases split ratings between Moody's and Fitch. The *sd.split* falls by 0.2-CCR point for sovereigns that have adopted *FOIA* for up to five years compared with sovereigns that have no *FOIA* in place.

[14] In unreported results, we find that the 'political stability' WGI indicator in the case of S&P-Moody's, and 'control for corruption' and 'government effectiveness' WGI indicators in the case of S&P-Fitch have significant impact on split ratings in the anticipated direction.

To sum up, there is evidence supporting sovereign opacity in determining split sovereign ratings (H_1), and we reject the null hypothesis that split sovereign ratings occur randomly. Our results are in line with the literature on split corporate ratings (Livingston et al., 2007) and split bank ratings (Morgan, 2002). We evaluate sovereign opacity from the perspective of both political risk and the quality of information disclosure by governments. Sovereign opacity exaggerates the division of credit opinions between CRAs, and political risk is an important factor behind this, particularly in countries outside Europe, providing evidence to support H_3. Lack of good quality data in emerging countries is encountered by rating analysts when the country of interest does not have legislation to support the disclosure of information about the government. In that circumstance, it is hard for CRAs to form credit opinions and split ratings are more likely to occur. Our empirical analysis supports this argument, and hence H_2, in the case of split sovereign ratings between Moody's and Fitch in emerging countries outside Europe.

5.3. Economic significance of sovereign opacity

5.3.1. Likelihood ratio test

We perform a test on the collective explanatory power of opacity variables (FOIA and WGI) in explaining split ratings. The test is based on a Likelihood Ratio (LR) test statistic with two restrictions on FOIA and WGI. The LR statistic is given by '*-2 ln (L0/L1)*' where *L1* is the value of the likelihood function for the un-nested full model that includes all the variables with unconstrained coefficients (see Eq. 1) and *L0* is the value of the likelihood function for the nested model in which coefficients on FOIA and WGI are restricted to zero. The LR statistic follows a Chi-square distribution with degrees of freedom equal to two (the number of constraints imposed).[15] The results are presented in Panel A of Table 8.

[15] The estimation of LR is based on a maximum likelihood (ML). The coefficient estimates and inference on the explanatory variables of Eq. (1) in Tables 4-7 are unchanged when using ML.

We find that opacity variables significantly improve the fit of the model. The LR statistics are more significant in the cases of S&P/Moody's vs. Fitch than for S&P vs. Moody's. Unlike for ROTW countries, opacity variables do not help in improving the explanatory power of the model for European countries.[16] For a sub-group of ROTW-emerging countries, where our empirical results highlight a significant role of FOIA, we also find support from the LR test.

5.3.2. Out-of-sample prediction analysis

This section presents an out-of-sample prediction analysis. We compare the predictive power of a full model (Eq. 1) incorporating two opacity variables (WGI and FOIA) and a restricted base model without opacity variables (and only including macroeconomic and financial indicators). The purpose of such analysis is to unravel the importance of opacity in improving the performance of an empirical model of split sovereign ratings. We estimate the base model (without WGI and FOIA) and the full model (including WGI and FOIA) using a data sample from 1997 to 2006, and use 2007 to 2011 as the hold-out period. The forecast of *sd.split* is produced for the hold-out period using coefficients estimated from the estimation period. The mean absolute and mean squared errors (deviations of actual values from their forecast values) are compared between the base and full models, and the results are presented in Panel B of Table 8. We find that the full model in which opacity variables are included outperforms the base model for the three pairs of CRAs, particularly in the cases of sub-sample analyses. The evidence is more robust in the case of Moody's vs. Fitch.

[16] Unreported results show significant LR statistics for three WGIs: control of corruption, government effectiveness, and political stability (see footnote 14).

6. Conclusions

The paper examines the causes of split sovereign ratings using a large dataset of ratings, outlook and watch assignments by S&P, Moody's and Fitch for 64 sovereigns during the period 1997-2011. To best of our knowledge, this is the first paper that relates opacity to split ratings for sovereign issuers. Prior literature documents that opacity raises the probability of split corporate and bank ratings (Morgan, 2002; Iannotta, 2006, Livingston et al., 2007). We focus on two key sources of opacity in assessing sovereign credit ratings: *the quality of information disclosure by governments* (proxied by Freedom of Information Acts (*FOIA*)) and *political risk* (proxied by Worldwide Governance Indicators (*WGI*)).

We find that more opaque sovereigns are more likely to have split ratings. Split sovereign ratings are not symmetric for CRA pairs, with S&P tending to be the most conservative. This suggests that split sovereign ratings are not attributable to random errors, thus supporting the opacity hypothesis. We also highlight that opacity variables significantly improve the fit of the model and increase its out-of-sample predictive power.

We find that political risk plays a highly significant role in explaining split sovereign ratings. Compared with economic variables, political risk has a much stronger impact on split sovereign ratings. The three CRAs are affected by political risk, though Fitch appears to be more influenced by this factor relative to the other CRAs. Sovereigns with higher political risk are more likely to have split ratings, particularly in countries outside Europe. Political uncertainty in Europe is a major current issue but only came to the fore after our sample period.

We also show that lack of government transparency in emerging countries outside Europe increases split sovereign ratings between Moody's and Fitch. We do not find similar effects of information disclosure in European countries, where the right to access information has long been ensured by legislation on freedom of information. Enhancing the quantity and quality of data for credit assessment purposes can help mitigate the opacity problem, and thus reduce split ratings in emerging countries. In this respect, our study does not only support the recent proposals (e.g. House of Lords, 2011) encouraging the engagement of government authorities with the CRAs, but also calls for establishing legal and institutional frameworks that promote credible and timely information disclosure to improve ratings quality.

The study will be of interest to many sovereign borrowers and bond investors since it provides clear insights on rating differences across the three largest CRAs. There are also considerable benefits and economic significance for countries to undertake reforms to reduce political uncertainty. Further, our study emphasizes the importance of enhancing the quality of data for political as well as financial and economic aspects about the country. Our findings are consistent with the recent evidence on the pricing of split-rated bonds (e.g. Livingston and Zhou, 2010; Livingston et al., 2010; Vu et al. 2015), therefore sovereign issuers should be more open and willing to share information with the CRAs since the reward for this is lower borrowing costs.

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Table 1. Summary statistics and distributions of daily rating differences

	No of obs.	Countries	Mean	S.D.	Min	Max	<= -1 CCR (%)	0 CCR (%)	>= 1 CCR (%)
Panel A. S&P versus Moody's									
Full sample	213,182	61	-0.66	3.12	-20	11	40.11	32.73	27.16
Europe	92,996	26	-1.27	3.20	-20	10	45.94	35.44	18.62
ROTW	120,186	35	-0.19	2.98	-15	11	35.59	30.64	33.77
Panel B. S&P versus Fitch									
Full sample	188,303	54	-0.24	2.40	-15	18	31.56	46.69	21.75
Europe	89,653	24	-0.37	2.18	-15	6	33.62	43.65	22.73
ROTW	98,650	30	-0.12	2.58	-15	18	29.69	49.45	20.85
Panel C. Moody’s versus Fitch									
Full sample	183,390	52	0.56	3.03	-12	17	25.30	40.47	34.22
Europe	89,949	24	0.96	2.80	-10	15	15.62	47.36	37.01
ROTW	93,441	28	0.17	3.19	-12	17	34.62	33.84	31.54

This table presents the descriptive statistics and distribution of daily split sovereign ratings between S&P, Moody's and Fitch for the full sample and subsamples of European countries (‘Europe’) and the rest of the world (‘ROTW’); see footnote #6 for the definition of countries. We compute the daily differences using the 58-point comprehensive credit ratings (CCR) between two credit rating agencies (CRA) for each sovereign on each business day. Rating differences are observed over a period from Jan 1997 to Sep 2011 for joint ratings by Moody’s and S&P and from Jan 1998 to Sep 2011 for joint ratings by Fitch and S&P/Moody’s. Panel A reports ratings by S&P minus ratings by Moody’s. Panel B (C) reports ratings by S&P (Moody’s) minus ratings by Fitch. Columns ‘<=1 CCR (%)’ and ‘>=1 CCR (%)’ are the proportions of lower and higher, respectively, sovereign ratings by the first CRA than the second CRA to the total number of daily observations on the same row. Column ‘0 CCR (%)’ reports the proportion of equal ratings (i.e. non-split ratings) by both CRAs to the total number of observations. ‘Mean’ and ‘S.D.’ indicate the overall sample averages and standard deviations of daily split sovereign ratings. ‘Min’, ‘Max’ state the smallest and largest CCR differences.

Table 2. Summary statistics and distributions of the annual standard deviation of daily rating differences (*sd.split*)

	No. of obs.	Mean	S.D.	Min	Max	%>0
Panel A. S&P versus Moody's						
Full sample	834	0.62	0.87	0	7.12	58.75
Europe	367	0.59	0.82	0	5.47	54.49
ROTW	467	0.64	0.91	0	7.12	62.09
Panel B. S&P versus Fitch						
Full sample	686	0.56	0.75	0	6.62	59.91
Europe	320	0.54	0.64	0	3.81	58.43
ROTW	366	0.58	0.84	0	6.62	61.20
Panel C. Moody's versus Fitch						
Full sample	666	0.60	0.86	0	7.51	55.41
Europe	320	0.59	0.85	0	5.72	50.63
ROTW	346	0.61	0.86	0	7.51	59.82

This table presents the descriptive statistics and the distribution of annual standard deviations of daily rating differences (*sd.split*) between each pair of CRAs for the full sample and subsamples of European countries ('Europe') and the rest of the world ('ROTW'). We compute the differences using the 58-point comprehensive credit ratings (CCR) between two credit rating agencies (CRA) for each sovereign on each business day. The standard deviations of daily CCR differences (*sd.split*) are calculated for each sovereign in each calendar year. Rating differences are observed over a period from Jan 1997 to Sep 2011 for joint ratings by Moody's and S&P and from Jan 1998 to Sep 2011 for joint ratings by Fitch and S&P/Moody's. The numbers of countries are the same as reported in Table 1. Column '%> 0' reports the proportion of non-zero *sd.split* to the total number of annual observations.

Table 3. Summary statistics of explanatory variables

Variables	Mean	St. deviation	Minimum	Maximum
FOIA (1-6)	2.24	1.64	1	6
WGI (Control of Corruption)	0.36	1.02	-1.45	2.59
WGI (Government Effectiveness)	0.50	0.87	-1.17	2.37
WGI (Political Stability)	0.13	0.89	-2.70	1.66
WGI (Regulatory Quality)	0.53	0.78	-1.64	2.23
WGI (Rule of Law)	0.37	0.91	-1.30	2.01
WGI (Voice & Accountability)	0.41	0.86	-1.77	1.83
Ave WGI	0.38	0.82	-1.14	1.98
Default Dummy	-	-	0	1
Domestic Credit/GDP (%)	72.32	55.12	0.33	319.46
Reserves/Imports (%)	40.90	36.15	0.29	255.29
GDP growth (%)	3.92	2.80	-7.51	12.73
Inflation (%)	8.03	27.21	-1.06	719.22
CA Balance/GDP (%)	-1.32	6.28	-22.05	26.86
Fiscal Balance/GDP (%)	-2.06	3.46	-17.60	21.92
Government debt/GDP (%)	50.46	30.71	3.69	215.95
Speculative Grade Dummy	-	-	0	1

This table reports the statistical properties of the variables used for explaining split sovereign ratings. There are 862 annual observations of 64 sovereigns with joint rating from S&P, Moody's and Fitch over the period Jan 1997 - Sep 2011. Time series of each sovereign are set equal to the total number of years within the period Jan 1997 - Sep 2011 when the sovereign is rated by any two of the three CRAs. FOIA refers to for Freedom of Information Act. The FOIA variable takes discrete values between 1 and 6, depending on whether the sovereign has adopted legislation on access to information. A value of 1 is for the sovereigns without FOIA, value of 2 is for the sovereigns adopting the law for less than 5 years, value of 3 for between 5 and 10 years, value of 4 for between 10 and 15 years, value of 5 for between 15 and 20 years, and value of 6 for above 20 years. Worldwide Governance Indicators (WGIs) include six annual measures of governance from the World Bank, taking values from approximately -2.7 to +2.7. Ave WGI is the average of these six WGI scores. Higher values of WGIs indicate better governance. WGIs reflect the general political risk and institutional strength of the sovereigns in the sample. Default dummy is a binary variable which equals 1 if the sovereign has experienced sovereign defaults or debt restructuring, and zero otherwise. Domestic credit/GDP is the annual loans to the private sector as a proportion of GDP. Reserves/imports indicate the annual dollar amount of foreign exchange reserves relative to payments for imports. GDP growth is the 3-year average real growth in Gross Domestic Product. Inflation is the 3-year average rate of general price appreciation. CA balance/GDP is the 3-year average of current account balance as a proportion of GDP. Fiscal balance/GDP is the 3-year average of the fiscal balance as a percentage of GDP. Government debt/GDP is gross general government debt in US dollars as a percentage of GDP. Speculative grade dummy is a dummy variable that takes the value of 1 if the average annual rating assigned by two CRAs for sovereign i at year t is at speculative-grade (BB+/Ba1 and lower).

Table 4. Results of Eq. (1) – Full sample of countries

Explanatory Variables	S&P vs. Moody's			S&P vs. Fitch			Moody's vs. Fitch		
FOIA (1-6)		0.037	0.049		0.079	0.086		-0.010	0.002
		(0.56)	(0.73)		(1.10)	(1.21)		(-0.12)	(0.02)
WGI (rule of law)		-0.487**			-0.450*			-0.584**	
		(-2.21)			(-1.94)			(-2.33)	
WGI (average)			-0.626**			-0.474*			-0.593*
			(-2.30)			(-1.67)			(-1.70)
Default Dummy (0/1)	0.227	0.152	0.175	0.492	0.418	0.462	-0.164	-0.319	-0.253
	(0.58)	(0.38)	(0.44)	(1.14)	(1.01)	(1.10)	(-0.33)	(-0.67)	(-0.53)
Domestic Credit/GDP (%)	0.004**	0.005**	0.004**	0.006***	0.006***	0.006***	0.003	0.004	0.003
	(2.18)	(2.46)	(2.32)	(3.73)	(3.98)	(3.88)	(1.39)	(1.64)	(1.46)
Reserves/Imports (%)	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.09)	(0.07)	(0.08)	(-0.28)	(-0.34)	(-0.33)	(-0.67)	(-0.74)	(-0.72)
GDP Growth (%)	-0.004	-0.003	0.001	0.011	0.010	0.013	-0.016	-0.017	-0.014
	(-0.15)	(-0.12)	(0.06)	(0.53)	(0.49)	(0.63)	(-0.65)	(-0.72)	(-0.57)
Inflation (%)	0.001	0.000	0.000	0.001	0.001	0.001	0.004	0.003	0.002
	(0.95)	(0.72)	(0.50)	(0.27)	(0.29)	(0.12)	(0.56)	(0.45)	(0.30)
CA Balance/GDP (%)	-0.010	-0.010	-0.011	0.008	0.010	0.010	-0.010	-0.012	-0.012
	(-0.97)	(-0.95)	(-1.04)	(0.76)	(0.90)	(0.86)	(-0.75)	(-0.83)	(-0.85)
Fiscal Balance/GDP (%)	0.001	-0.001	0.006	0.009	0.007	0.013	-0.009	-0.012	-0.004
	(0.04)	(-0.07)	(0.31)	(0.46)	(0.35)	(0.64)	(-0.32)	(-0.43)	(-0.13)
Government debt/GDP (%)	0.011***	0.010**	0.011**	0.006	0.005	0.005	0.005	0.005	0.005
	(2.61)	(2.55)	(2.58)	(1.34)	(1.15)	(1.19)	(1.04)	(1.00)	(1.05)
Speculative grade_dum	0.025	0.025	0.027	0.239*	0.248*	0.239*	0.252	0.229	0.225
	(0.18)	(0.18)	(0.19)	(1.75)	(1.85)	(1.78)	(1.24)	(1.16)	(1.14)
Constant	0.332	0.245	0.335	0.478	0.362	0.456	1.191*	1.112*	1.218*
	(0.73)	(0.54)	(0.74)	(0.88)	(0.70)	(0.85)	(1.88)	(1.80)	(1.95)
Year and Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	834	834	834	686	686	686	666	666	666
R-squared (adjusted) %	16.7	17.1	17.2	19.6	20.2	20.0	17.5	18.1	17.8

The table presents the results of Eq. (1) using heteroscedasticity-robust standard errors. The data includes 61, 54, and 52 sovereigns with joint ratings respectively from S&P and Moody's, S&P and Fitch, and Moody's and Fitch between Jan 1997 and Sep 2011. The dependent variable is the annual standard deviation of daily rating differences (*sd.split*) using the 58-point rating scale. See Table 3 for the definitions of explanatory variables. We estimate Eq. (1) using one of the six worldwide governance indicators (WGI). The estimation results for 'rule of law' and *Ave WGI* (the average of these six WGI scores) are reported in this Table. Fixed effects are captured by a full set of country and year dummies. T-statistics are in parentheses. ***, **, and * represent significance at 1%, 5% and 10% levels.

Table 5. Results of Eq. (1) – Europe

Explanatory Variables	S&P vs. Moody's			S&P vs. Fitch			Moody's vs. Fitch		
FOIA (1-6)		0.095	0.095		0.101	0.096		0.113	0.109
		(1.00)	(0.98)		(0.96)	(0.89)		(0.87)	(0.83)
WGI (rule of law)		0.002			0.352			0.039	
		(0.00)			(1.23)			(0.10)	
WGI (average)			-0.002			0.346			0.114
			(-0.00)			(1.05)			(0.22)
Default Dummy (0/1)	2.339**	2.446**	2.445**	0.689*	2.950***	2.793***	1.581**	2.401*	2.556
	(2.23)	(2.26)	(2.13)	(1.80)	(3.02)	(2.96)	(2.22)	(1.67)	(1.64)
Domestic Credit/GDP (%)	0.003	0.003	0.003	0.006***	0.006***	0.006***	0.003	0.003	0.003
	(1.40)	(1.40)	(1.43)	(3.71)	(3.57)	(3.76)	(1.20)	(1.18)	(1.22)
Reserves/Imports (%)	-0.003	-0.003	-0.003	-0.002	-0.002	-0.002	-0.003	-0.003	-0.003
	(-0.68)	(-0.62)	(-0.63)	(-0.70)	(-0.76)	(-0.70)	(-0.61)	(-0.61)	(-0.61)
GDP Growth (%)	0.012	0.011	0.011	0.024	0.024	0.022	-0.007	-0.008	-0.008
	(0.36)	(0.33)	(0.32)	(0.92)	(0.92)	(0.84)	(-0.20)	(-0.23)	(-0.24)
Inflation (%)	0.006	0.006	0.006	0.003	0.004	0.004	0.008	0.008	0.008
	(0.98)	(1.04)	(1.02)	(0.65)	(0.78)	(0.91)	(1.02)	(1.05)	(1.05)
CA Balance/GDP (%)	-0.025	-0.023	-0.023	-0.006	-0.005	-0.005	-0.030	-0.028	-0.028
	(-1.35)	(-1.21)	(-1.21)	(-0.40)	(-0.34)	(-0.31)	(-1.40)	(-1.29)	(-1.30)
Fiscal Balance/GDP (%)	-0.043	-0.041	-0.041	0.012	0.013	0.009	-0.057	-0.058	-0.059
	(-1.26)	(-1.24)	(-1.22)	(0.44)	(0.47)	(0.34)	(-1.47)	(-1.48)	(-1.49)
Government debt/GDP (%)	0.012	0.011	0.011	0.015*	0.014	0.014	0.009	0.007	0.007
	(1.33)	(1.21)	(1.21)	(1.81)	(1.59)	(1.59)	(0.86)	(0.66)	(0.67)
Speculative grade_dum	-0.347	-0.340	-0.340	-0.136	-0.140	-0.124	-0.422	-0.406	-0.398
	(-1.36)	(-1.32)	(-1.33)	(-0.84)	(-0.90)	(-0.78)	(-1.64)	(-1.55)	(-1.51)
Constant	-1.634*	-0.902	-0.896	0.148	-1.771**	-1.723**	0.160	-0.625	-0.746
	(-1.66)	(-1.18)	(-1.03)	(0.29)	(-2.45)	(-2.32)	(0.25)	(-0.71)	(-0.77)
Year and Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	367	367	367	320	320	320	320	320	320
R-squared (adjusted) %	22.8	22.5	22.5	26.3	26.7	26.6	26.4	26.1	26.1

The table presents the results of Eq. (1) using heteroscedasticity-robust standard errors, using a sub-sample of countries in 'Europe' that have joint ratings respectively from S&P and Moody's, S&P and Fitch, and Moody's and Fitch between Jan 1997 and Sep 2011. The dependent variable is the annual standard deviation of daily rating differences (*sd.split*) using the 58-point rating scale. See Table 3 for the definitions of explanatory variables. We estimate Eq. (1) using one of the six worldwide governance indicators (WGI). The estimation results for 'rule of law' and *Ave WGI* (the average of these six WGI scores) are reported in this Table. Fixed effects are captured by a full set of country and year dummies. T-statistics are in parentheses. ***, **, and * represent significance at 1%, 5% and 10% levels.

Table 6. Results of Eq. (1) – ROTW

Explanatory Variables	S&P vs. Moody's			S&P vs. Fitch			Moody's vs. Fitch		
FOIA (1-6)		-0.062	-0.055		-0.084	-0.081		-0.217	-0.200
		(-0.63)	(-0.57)		(-0.74)	(-0.72)		(-1.62)	(-1.51)
WGI (rule of law)		-0.699**			-0.956***			-1.068***	
		(-2.51)			(-2.95)			(-3.35)	
WGI (average)			-0.789**			-1.307***			-1.351***
			(-2.18)			(-2.81)			(-2.81)
Default Dummy (0/1)	0.105	-0.004	0.041	0.496	0.284	0.328	-0.100	-0.402	-0.343
	(0.26)	(-0.01)	(0.10)	(1.21)	(0.76)	(0.85)	(-0.20)	(-0.83)	(-0.72)
Domestic Credit/GDP (%)	0.003	0.005	0.003	0.004	0.004	0.003	0.004	0.005	0.003
	(0.62)	(0.88)	(0.60)	(0.79)	(0.97)	(0.58)	(0.62)	(0.81)	(0.43)
Reserves/Imports (%)	-0.000	-0.001	-0.001	0.001	0.000	0.001	-0.004	-0.005	-0.004
	(-0.14)	(-0.31)	(-0.23)	(0.33)	(0.13)	(0.29)	(-1.54)	(-1.60)	(-1.49)
GDP Growth (%)	-0.023	-0.021	-0.017	-0.017	-0.017	-0.013	-0.041	-0.039	-0.034
	(-0.60)	(-0.56)	(-0.45)	(-0.44)	(-0.45)	(-0.34)	(-1.07)	(-1.05)	(-0.90)
Inflation (%)	0.000	0.000	0.000	-0.000	-0.001	-0.006	-0.008	-0.011	-0.015
	(0.80)	(0.85)	(0.68)	(-0.03)	(-0.10)	(-0.38)	(-0.63)	(-0.90)	(-1.20)
CA Balance/GDP (%)	-0.003	-0.007	-0.011	0.020	0.012	0.006	0.004	-0.008	-0.014
	(-0.21)	(-0.48)	(-0.67)	(0.84)	(0.55)	(0.26)	(0.19)	(-0.33)	(-0.55)
Fiscal Balance/GDP (%)	0.030	0.031	0.040	0.049	0.046	0.069*	0.062**	0.063**	0.084***
	(1.25)	(1.29)	(1.64)	(1.43)	(1.41)	(1.94)	(2.02)	(2.10)	(2.65)
Government debt/GDP (%)	0.007	0.007	0.008	0.001	0.000	0.001	0.003	0.003	0.004
	(1.37)	(1.39)	(1.48)	(0.14)	(0.03)	(0.16)	(0.49)	(0.52)	(0.68)
speculative grade_dum	0.122	0.091	0.096	0.382**	0.353**	0.344**	0.559*	0.491*	0.489**
	(0.75)	(0.58)	(0.62)	(1.99)	(2.01)	(2.02)	(1.96)	(1.96)	(1.98)
Constant	0.793	0.580	0.684	0.683	0.528	0.694	1.377*	1.266*	1.449**
	(1.47)	(1.07)	(1.27)	(1.04)	(0.88)	(1.14)	(1.86)	(1.80)	(2.07)
Year and Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	467	467	467	366	366	366	346	346	346
R-squared (adjusted) %	15.0	15.9	15.6	17.7	20.0	20.2	14.8	18.3	18.0

The table presents the results of Eq. (1) using heteroscedasticity-robust standard errors, using a sub-sample of countries in the rest of the world ('ROTW') that have joint ratings respectively from S&P and Moody's, S&P and Fitch, and Moody's and Fitch between Jan 1997 and Sep 2011. The dependent variable is the annual standard deviation of daily rating differences (*sd.split*) using the 58-point rating scale. See Table 3 for the definitions of explanatory variables. We estimate Eq. (1) using one of the six worldwide governance indicators (WGI). The estimation results for 'rule of law' and *Ave WGI* (the average of these six WGI scores) are reported in this Table. Fixed effects are captured by a full set of country and year dummies. T-statistics are in parentheses. ***, **, and * represent significance at 1%, 5% and 10% levels.

Table 7. Results of Eq. (1) – ROTW – Emerging countries

Explanatory Variables	S&P vs. Moody's			S&P vs. Fitch			Moody's vs. Fitch		
FOIA (1-6)		-0.032	-0.038		0.109	0.094		-0.205**	-0.202*
		(-0.29)	(-0.35)		(0.92)	(0.81)		(-1.99)	(-1.81)
WGI (rule of law)		-0.659**			-0.951***			-1.047***	
		(-2.17)			(-3.16)			(-3.57)	
WGI (average)			-0.382			-0.800*			-0.686*
			(-0.96)			(-1.95)			(-1.78)
Default Dummy (0/1)	0.086	0.072	0.099	0.337	0.309	0.351	-0.343	-0.222	-0.167
	(0.17)	(0.14)	(0.19)	(0.63)	(0.56)	(0.63)	(-0.56)	(-0.31)	(-0.25)
Domestic Credit/GDP (%)	-0.001	0.001	-0.001	-0.000	0.002	0.001	0.011	0.017**	0.014*
	(-0.19)	(0.14)	(-0.10)	(-0.04)	(0.31)	(0.14)	(1.52)	(2.38)	(1.89)
Reserves/Imports (%)	0.001	-0.000	0.000	0.001	0.000	0.000	-0.009*	-0.014**	-0.013**
	(0.33)	(-0.04)	(0.08)	(0.19)	(0.01)	(0.01)	(-1.82)	(-2.59)	(-2.41)
GDP Growth (%)	-0.060	-0.051	-0.054	-0.064	-0.062	-0.060	-0.025	-0.011	-0.015
	(-1.10)	(-0.93)	(-0.96)	(-1.34)	(-1.30)	(-1.26)	(-0.60)	(-0.27)	(-0.36)
Inflation (%)	0.000	0.000	0.000	-0.007	-0.006	-0.008	-0.001	-0.003	-0.005
	(0.57)	(0.66)	(0.59)	(-0.46)	(-0.42)	(-0.55)	(-0.12)	(-0.26)	(-0.43)
CA Balance/GDP (%)	-0.016	-0.017	-0.017	0.003	0.003	0.002	0.034	0.037	0.035
	(-0.81)	(-0.86)	(-0.86)	(0.10)	(0.08)	(0.07)	(1.08)	(1.21)	(1.14)
Fiscal Balance/GDP (%)	0.036	0.039	0.042	0.113**	0.111**	0.119***	0.088*	0.095**	0.102**
	(1.23)	(1.30)	(1.38)	(2.57)	(2.58)	(2.68)	(1.91)	(2.14)	(2.18)
Government debt/GDP (%)	-0.001	-0.000	-0.001	0.002	0.002	0.002	-0.010	-0.008	-0.010
	(-0.15)	(-0.04)	(-0.10)	(0.34)	(0.34)	(0.28)	(-1.39)	(-1.25)	(-1.48)
speculative grade_dum	0.026	-0.018	0.004	0.259	0.251*	0.266*	0.402*	0.309	0.339*
	(0.18)	(-0.12)	(0.03)	(1.60)	(1.68)	(1.79)	(1.86)	(1.58)	(1.67)
Constant	1.178	0.825	0.585	1.216	1.347	1.342	1.323	1.503*	1.981**
	(1.07)	(1.12)	(0.78)	(1.16)	(1.33)	(1.30)	(1.57)	(1.96)	(2.48)
Year and Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of obs.	317	317	317	237	237	237	209	209	209
R-squared (adjusted)	12.5	12.9	12.1	20.9	23.9	22.1	19.5	24.6	20.8

The table presents the results of Eq. (1) using heteroscedasticity-robust standard errors, using a sub-sample of emerging countries in the rest of the world ('ROTW') that have joint ratings respectively from S&P and Moody's, S&P and Fitch, and Moody's and Fitch between Jan 1997 and Sep 2011. The dependent variable is the annual standard deviation of daily rating differences (*sd.split*) using the 58-point rating scale. See Table 3 for the definitions of explanatory variables. We estimate Eq. (1) using one of the six worldwide governance indicators (WGI). The estimation results for 'rule of law' and *Ave WGI* (the average of these six WGI scores) are reported in this Table. Fixed effects are captured by a full set of country and year dummies. T-statistics are in parentheses. ***, **, and * represent significance at 1%, 5% and 10% levels.

Table 8. Economic significance of opacity (FOIA and WGI) in explaining split sovereign ratings

	Panel A. Log likelihood ratio (LR) test		**Panel B. Out-of-sample prediction**					
			Mean absolute errors			**Mean squared errors**		
	Rule of law & FOIA	***Ave WGI & FOIA***	***Base model***	***Rule of law & FOIA***	***Ave WGI & FOIA***	***Base model***	***Rule of law & FOIA***	***Ave WGI & FOIA***
S&P vs. Moody's								
Full sample	6.25**	6.83**	0.628	0.641	0.636	0.790	0.791	0.791
Europe	1.10	1.10	0.932	**0.864**	**0.881**	1.579	**1.439**	**1.521**
ROTW	7.17**	5.60*	0.605	**0.602**	0.611	0.707	**0.674**	**0.689**
ROTW-Emerging	3.83	0.86	0.798	**0.793**	0.799	1.130	**1.046**	**1.098**
S&P vs. Fitch								
Full sample	7.16**	5.59**	0.647	0.679	0.679	0.845	0.876	0.880
Europe	4.25	3.65	0.544	0.553	**0.543**	0.695	0.707	**0.680**
ROTW	12.49***	13.31***	0.706	**0.698**	**0.686**	1.053	**0.996**	**0.978**
ROTW-Emerging	11.90***	6.08**	0.719	0.782	0.769	1.061	1.228	1.226
Moody's vs. Fitch								
Full sample	7.08**	4.74*	0.667	**0.661**	0.676	0.896	**0.884**	0.901
Europe	1.25	1.32	0.749	**0.660**	**0.679**	1.114	**0.928**	**0.962**
ROTW	16.65***	15.50***	0.742	**0.637**	**0.661**	1.116	**0.925**	**0.954**
ROTW-Emerging	16.17***	5.75*	0.615	**0.608**	**0.611**	0.709	**0.668**	**0.700**

Panel A of the table presents the results of Likelihood Ratio (LR) test statistic with two restrictions on FOIA and WGI. The LR statistic is given by '*-2 ln (L0/L1)*' where *L1* is the value of the likelihood function for the full model that includes all the variables with unconstrained coefficients (see Eq. 1) and *L0* is the value of the likelihood function for the nested model in which coefficients on FOIA and WGI are restricted to zero. The LR statistic follows a Chi-square distribution with degrees of freedom equal to two (the number of constraints imposed). ***, **, and * represent significance at 1%, 5% and 10% levels.

Panel B of the table presents the results of out-of-sample prediction analysis. We compare the predictive power of a full model incorporating two opacity variables (WGI and FOIA – Eq. 1) and a restricted base model without opacity variables (without WGI and FOIA, and only including the macroeconomic and financial indicators). We estimate the models using a data sample from 1997 to 2006, and use 2007 to 2011 as the hold-out period. The forecast of *sd.split* is produced for the hold-out period using coefficients estimated from the estimation period. Figures in bold indicate that the mean absolute and mean squared errors (deviations of actual values from their forecast values) are smaller in the full model than the base model.

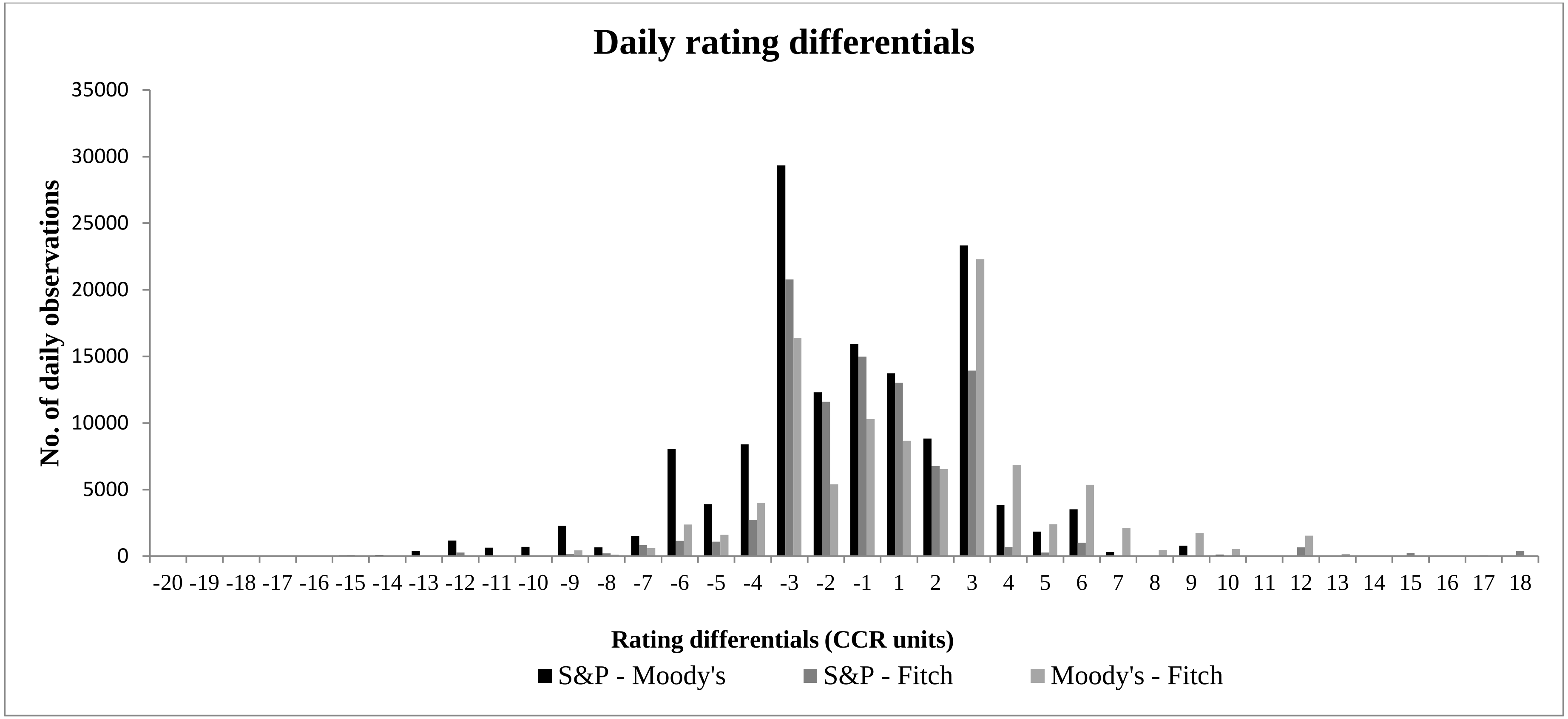

Fig. 1. The distribution of daily rating differences for 64 sovereign issuers. We transform ratings using the 58-point comprehensive credit rating scale (CCR). Rating differences equal the ratings assigned by the first CRA minus the ratings assigned by the second CRA. The time periods are 1 January 1997 to 30 September 2011 for S&P versus Moody's, and 1 January 1998 to 30 September 2011 for S&P versus Fitch and Moody's versus Fitch.