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Determinants of Market-Assessed Credit Risk

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ABSTRACT

A vast body of academic literature unveils as primary determinants of sovereign credit ratings and bond yields, a number of domestic macroeconomic and financial fundamentals, as well as global factors like the international risk appetite and the global liquidity. The scope of this study is to evaluate two phenomena that have not been explored in a great extent in previous research as potential factors of sovereign ratings and rates. The first phenomenon is the shadow economy, a pervasive and widespread feature of economies throughout the world. The second one is the prevalence of information and communication technologies (ICT) that transform every aspect of social and economic life.

The study unfolds in two waves. The first wave, which corresponds to thesis' first chapter, covers the years 2001-2010 and concentrates only on ICT effects following a parametric model. More specifically, we adopt a modified random effects approach which allows us to distinguish between short and long run effects on a dataset of 65 countries for a time span of ten years. We show that ICT have a significant impact on a country's credit rating and cost of debt, regardless of the presence of other key variables proposed in the literature. The effect is stronger for non-OECD countries, indicating a pathway for developing countries to improve their access to debt markets. Our conclusions are robust to the advent of the recent financial and debt crisis.

The second wave expands in years 2001-2016, corresponding to thesis' second chapter and attempts to outline the main effects of shadow economy and ICT penetration on sovereign credit ratings and the cost of debt, along with possible second-order effects between the two variables. The chapter presents a range of machine-learning approaches, including bagging, random forests, gradient-boosting machines, and recurrent neural networks. Furthermore, following recent trends in the emerging field of interpretable ML, such as feature importance and accumulated local effects, we attempt to explain which factors drive the predictions of the so-called ML black box models. We show that policies facilitating the penetration and use of ICT and aiming to curb the shadow economy may exert an asymmetric impact on sovereign ratings and the cost of debt depending on their present magnitudes, not only independently but also in interaction.

The last chapter is a brief presentation of the time-evolving impact of the two phenomena on the Greek sovereign cost of debt through years 2001-2016. A number of local model-agnostic interpretations of predictions regarding Greece is presented in order to identify the magnitude of the attributes that shape the prediction. Policy implications drawn upon research findings and government plans and intentions are also briefly discussed.

ΠΕΡΙΛΗΨΗ

Η ύπαρξη εκτεταμένης ακαδημαϊκής βιβλιογραφίας περί των προσδιοριστικών παραγόντων της πιστοληπτικής αξιολόγησης και των επιτοκίων δανεισμού που αντιμετωπίζουν οι χώρες ανά τον πλανήτη υπογραμμίζει το ιδιαίτερο ενδιαφέρον που έχει προσελκύσει το συγκεκριμένο ζήτημα τόσο σε ακαδημαϊκό επίπεδο όσο και σε επίπεδο διαμόρφωσης κυβερνητικής πολιτικής. Η σχετική βιβλιογραφία υποδεικνύει ως κύριους προσδιοριστικούς παράγοντες την εξέλιξη των βασικών οικονομικών και δημοσιονομικών μεγεθών μιας χώρας αλλά και τη διακύμανση του παγκόσμιου οικονομικού κλίματος όπως αυτό αποτυπώνεται μέσω της επενδυτικής διάθεσης ανάληψης ρίσκου ή της επικρατούσας ρευστότητας. Στόχος της παρούσας μελέτης είναι να αναδείξει τον ρόλο που ενδεχομένως παίζουν ως προσδιοριστικοί παράγοντες της πιστοληπτικής αξιολόγησης και των επιτοκίων δανεισμού, δυο οικονομικά και κοινωνικά φαινόμενα που δεν έχουν συγκεντρώσει επαρκές έως και σήμερα ερευνητικό ενδιαφέρον ως προς την επίδρασή τους, παρότι έχουν ευρεία διάδοση στις σημερινές κοινωνίες και οικονομίες. Το πρώτο εκ των φαινομένων αυτών είναι η παραοικονομία ή μαύρη οικονομία ή παράλληλη της επίσημης οικονομία που απαντάται σε όλες τις χώρες παρόλο που διαφέρει ως προς τα ιδιαίτερα τοπικά χαρακτηριστικά ή το μέγεθος και την επιρροή. Το δεύτερο φαινόμενο είναι η διάδοση των Τεχνολογιών Πληροφοριών και Επικοινωνίας (ΤΠΕ) σε παγκόσμιο πλέον επίπεδο που αν και παρουσιάζει αρκετές διαφορές ως προς την ένταση και έκταση τόσο ανάμεσα στις ανεπτυγμένες και αναδυόμενες αγορές όσο και εντός των δύο αυτών ομάδων χωρών, έχει αναμφισβήτητα επιφέρει ευρύτατες αλλαγές σε οικονομικό και κοινωνικό επίπεδο με αποτέλεσμα να γίνεται πλέον λόγος για τη διάνυση της φάσης της ψηφιακής οικονομίας ως μια διακριτής φάση του καπιταλισμού.

Η παρούσα μελέτη ξεδιπλώνεται σε δύο φάσεις. Η πρώτη φάση, η οποία και αποτυπώνεται στο πρώτο κεφάλαιο, καλύπτει τα έτη 2001-2010 και επικεντρώνεται αποκλειστικά στις επιδράσεις των ΤΠΕ ακολουθώντας ένα παραμετρικό μοντέλο. Πιο συγκεκριμένα, υιοθετούμε ένα υβριδικό μοντέλο τυχαίων επιδράσεων που μας επιτρέπει να διακρίνουμε και να εκτιμήσουμε τις βραχυπρόθεσμες και μακροπρόθεσμες επιδράσεις ενός πλήθους προσδιοριστικών παραγόντων βασιζόμενοι σε ένα δείγμα εξήντα πέντε (65) χωρών. Η μελέτη ανιχνεύει μια σημαντική μακρόχρονη επίδραση των ΤΠΕ στο αξιόχρεο μιας χώρας, ιδιαίτερα για όσες εξ αυτών ανήκουν στις αναδυόμενες οικονομίες. Περαιτέρω, τα ευρήματα της μελέτης παρουσιάζουν συνέπεια και κατά τα έτη της παγκόσμιας οικονομικής κρίσης.

Η δεύτερη φάση της μελέτης καλύπτει μια ευρύτερη χρονική περίοδο εκτεινόμενη από το 2001 έως το 2016 και επιχειρεί να περιγράψει την επίδραση τόσο των ΤΠΕ όσο και της παραοικονομίας στην πιστοληπτική αξιολόγηση των χωρών και στη διαμόρφωση του κόστους δανεισμού όσο και να ανιχνεύσει τυχόν κοινές επιδράσεις. Κατά την δεύτερη αυτή φάση, η οποία και παρουσιάζεται στο

δεύτερο κεφάλαιο, χρησιμοποιούνται ορισμένες δημοφιλείς τεχνικές μηχανικής μάθησης όπως δένδρα απόφασης, bagging, τυχαία δάση, gradient boosting και αναδραστικά νευρωνικά δίκτυα. Περαιτέρω, ακολουθώντας τις σύγχρονες τάσεις του αναδυόμενου πεδίου της ερμηνεύσιμης μηχανικής μάθησης, γίνεται χρήση τεχνικών όπως η καθολική ερμηνεία σπουδαιότητας παραγόντων και η ανάλυση συσσωρευμένων τοπικών επιδράσεων. Η μελέτη παρουσιάζει ενδείξεις ότι πολιτικές που ευνοούν την διάχυση της χρήσης των ΤΠΕ ή σκοπούν στην περιστολή της παραοικονομίας δύναται να έχουν μη συμμετρικά αποτελέσματα αναφορικά με το αξιόχρεο των χωρών, με την επίδραση να εξαρτάται τόσο από το σύγχρονο εύρος έκτασης των φαινομένων υπό μελέτη όσο και από την συνδυαστική παρουσία τους.

Το τρίτο κεφάλαιο της παρούσας μελέτης αποτελεί μια σύντομη παρουσίαση των επιδράσεων των προαναφερθέντων φαινομένων στο κόστος δανεισμού της Ελλάδας κατά τα έτη 2001-2016. Μια σειρά τοπικών, model agnostic, μεθόδων ερμηνεύσιμης μηχανικής μάθησης μας επιτρέπουν να επιχειρήσουμε τον προσδιορισμό της χρονικής εξέλιξης των επιδράσεων των παραγόντων που σχηματίζουν τις προβλέψεις περί του κρατικού κόστους δανεισμού. Περαιτέρω, παρουσιάζεται μια συνοπτική συζήτηση περί των ευρημάτων και των βάσει αυτών ενδεδειγμένων εγχώριων πολιτικών.

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1.1 Introduction

Investment in information and communication technologies (ICT henceforth) is considered a pathway to economic development by both academics (see, for example [29]) and policy makers (e.g., [53]). ICT is viewed as a general-purpose technology (GPT) that spreads throughout the economy and significantly influences a variety of sectors enabling the creative use of labor and the restructuring of organizational assets, thus improving products and processes [28]. The presence of network externalities, production spillovers and lower information costs forces businesses to change the way they operate in order to fully realize the benefits of ICT [51].

Beginning in the mid-1990s the US economy experienced a major surge in labor productivity and grew in a surprisingly fast pace achieving at the same time low unemployment and inflation rates. This period coincided with significant investment in, and the diffusion of, ICT; US firms pumped more than $3 trillion during the1980s and 1990s into ICT investment, defined to include computer hardware, computer software and telecommunication equipment [51]. The popular view is that ICT have been the major driver and played a substantial role in explaining the sustained growth rates. The term “new or digital economy”, was coined by business press to depict a superior economic structure that arises as the joined outcome of globalization and ICT boost; signaling that the workings of the economy may have significantly changed with rules, principles, institutions that go well beyond those of traditional economy [48].

Notwithstanding, the impact of ICT is indirect and is mainly felt through the way they are used to transform the economy and enable factors that foster productivity and GDP growth (similarly to electricity). As a result, the precise measurement of the effects of ICT to the economy is a challenging task [31], a fact that explains the somewhat conflicting results presented in the extant literature. Typically, early studies, examining periods before the beginning of the 1990s report negative results while later studies tend to uncover a more positive and rather stable impact of ICT on growth [45]. Typical examples of the latter include [44] and [32], who concentrate on the USA and suggest that ICT have been the underlying factor of the US economy resurgence in the 1990s. Similarly, positive results have been reported in an international setting by studies that include

[1] A shorter version of this chapter has been published as Kotzinos A., Psychoyios, D., Vlastakis N. The impact of ICT diffusion on sovereign cost of debt. *International Journal of Banking, Accounting and Finance*. 2021, 12, 16.
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either developed countries (e.g., [42]) or both developed and developing countries (e.g., [54,45]). Conversely, other researchers report the opposite findings both in the USA [22] and on international [48] context.

In this chapter we extend the literature by considering the effects of ICT on sovereign credit ratings and cost of debt. Most of the academic research focuses on the effects of ICT to growth (usually proxied by GDP growth). A relatively smaller number of studies attempt to provide better insights on how this relationship works by examining the effect of ICT on other macroeconomic fundamentals like inflation [58], employment [14,52] and foreign direct investment (FDI) [13]. The creditworthiness and cost of debt have received very limited attention in the literature. Nevertheless, the advent of the financial crisis of 2007-2008 and the subsequent sovereign debt crisis, which resulted in several sovereigns being excluded from debt markets, underlines the importance of examining the effect that ICT has at a country level on the costs and risks of lending.

The study that is closest to ours is [11] who use an ordered response model to examine the determinants of sovereign credit ratings. They find that alongside with purely economic variables like inflation, GNP per capita, current account balance and level of foreign reserves, the diffusion of technology, proxied by the usage of mobile phones is the most significant determinant of sovereign credit ratings. Our study is different to theirs in several ways. Firstly, instead of a somewhat narrowly specified measure of technology diffusion like the use of mobile phones, we focus on the comprehensive concept of a country’s *e-readiness*, as proxied by the Networked Readiness Index (NRI). E-readiness is a relatively new concept that evolved while striving to provide a unified framework of evaluation of the rapid rate of internet penetration throughout the world, the dramatic advances in the use of ICT in business and industry as well as the depth of the digital divide between more and less developed countries [24,25]. [29] discuss the advantages of e-readiness over mobile telephony diffusion as a measure of ICT penetration. Moreover, we model the impact of ICT diffusion not only on credit ratings, but also on the cost of debt. This allows for a more robust analysis since one can generally expect a higher level of within country-year variation in the cost of debt than in credit ratings, which lends more power to our results. Finally, we follow a panel regression approach, as opposed to a cross-sectional one, with obvious advantages due to the availability of the time dimension.

We employ a dataset comprising 65 countries between the years 2001–2010. Our main hypothesis is that e-readiness will have a significant effect on credit ratings and cost of debt due to the way ICT re-shape the economy and impact growth, directly and through spillovers, as has been suggested by [32] and [44]. Our sample contains both OECD and non-OECD countries, thus we can test whether the impact of e-readiness on ratings and cost of debt is different between developed and developing countries, an issue that has been debated extensively in literature. Several studies suggest that ICT impact is stronger for developed countries since they enjoy a better telecommunication infrastructure that allow them to fully realize the benefits from ICT (see, among others, [45]). Such concerns are strengthened by the possible presence of network effects in the application of ICT [37]; massive gains from ICT can be enjoyed after a critical mass of ICT investment and usage is reached. However, other researchers (e.g., [38,49,54,55,33]) argue that ICT comprise a unique opportunity for developing countries to leapfrog to a higher level of development and experience the potential advantages of being a late comer.

The most important contributions of our study can be summarized as follows: firstly, we are the first to study the impact of e-readiness on sovereign credit ratings and cost of debt. Moreover, our dataset allows us to test the hypothesis that the effects of e-readiness on credit ratings and cost of debt are different between developed and developing countries. Finally, we examine whether this relationship has remained unchanged in the time before and after the recent financial crisis. Overall, our results confirm that e-readiness is a significant determinant of credit ratings and cost of debt, with higher e-readiness levels associated with improved credit ratings and lower cost of debt. The results also confirm that this relationship is stronger for developing countries, a fact that indicates a path for developing countries to improve their credit profile. Our results are robust to the advent of the financial crisis.

The rest of the chapter is structured as follows. The next section discusses our research hypotheses and methodology. Section 1.3 presents our data and empirical analysis and discusses the results. The final section concludes the chapter.

1.2 Research questions and methodology

1.2.1 Hypotheses formulation

The term “Information and communication technologies” refers to a variety of hardware and software combinations [58] facilitating the capturing, storing, processing and transmission of information by electronic means including mobile phones, computers and internet connectivity.

Fueled by the exponential dropping cost of microprocessors, the mass production of ICT means, led to a vivid change of how people work, communicate, learn, interact and are entertained [59], literally transforming every dimension of economic, social and cultural life. The dissemination of information linked to ICT, led theorists to frame this phase of capitalism as knowledge based or information based or network society [60,61].

The effect of ICT on economic growth is commonly studied through the lens of total factor productivity (TFP) concept. TFP or Solow residual is called by the economists and under a growth accounting framework, the unaccounted growth after considering labor and capital and is loosely designated to the contribution of technological advancements. According to a key tenet of neoclassical growth theory [49] technology is an exogenous factor of economic growth. Subsequent scholars [62,63] proposed another theory that acknowledges investment in human capital, innovation and knowledge as crucial parameters of growth, endogenously determining technological change [64]. While a cause-and effect-link between ICT and economic growth has not yet reached a unanimous acceptance among scholars [60], a considerable number of concurrent empirical studies published after the first years of the millennium or a bit later [65], concluded that the accumulation of ICT capital or capital deepening, spur economic growth through increased productivity as workers have at their disposal more and better capital equipment [51]. The dramatic decline in cost concerning computers and other ICT equipment led to an extensive substitution of labor and non-ICT capital by ICT capital in ICT using sectors. Moreover, the organizational changes in ICT producing sector, induced by the necessity to reap the obvious productivity gains of a rapidly advancing technology led also to TFP gains in the ICT sector and later to a paradigm change in business context and management processes across the economy [66]. [59] suggest that the main theoretical grounds when arguing about the positive effects of ICT on growth are the diffusion of knowledge, constant innovation, better-informed decisions of economic agents, diminishing costs of transportation and trading and the sheer increase in logistics' efficiency whereas organizational transformation is a necessary complement if ICT positive effects are to be realized [67].

Moreover, a large body of empirical literature provides evidence that the rapid growth of ICT facilitates trade and e-commerce [68] not only by creating new needs, markets and services but mainly through the dissemination of information and the enabling of almost frictionless and time-effective transportation, communication and market search. Moreover, ICT provide an enterprise with the ability to reach far-distant international audience no matter where enterprise's seat stands and to lower market entry cost barriers since ICT intensive firms need little staffing and capital investment. Furthermore, another crucial sector regarding economic growth [69][2] i.e., financial

[2] Although the late 2008 global financial and economic crisis spurred some doubts on whether this belief stands irrespective of the size of the private sector credit (%GDP) [71].

sector, benefits the most from ICT penetration. ICT completely change the entire current banking structure [71] by radically transforming through big data exploitation and digital banking, a number of crucial functions like the way banking transactions and payments are held; financial institutions and potential or current customers interact; credit worthiness analysis is conducted; appropriate financial products are constructed and provided; anti-money laundering measures are enforced. Moreover ICT enable the entry of non-traditional players (e.g. microfinance digitalization; money transfers across borders) to the market.

As we elaborated in Section 1.1, the diffusion of ICT increases efficiency and productivity and may lead to enhanced quality. More strictly, the output of a national economy is related to various production inputs such as labor, physical capital and purchased material, as well as to the level of technology. ICT is a core dimension of the current technological progress. ICT impacts the growth of productivity in three main stages. First, ICT facilitates innovation in various producing sectors of the economy. Second, the innovative outputs (products) of these sectors rapidly dominate the market resulting to a fall of their prices which permits an accumulation of them as capital in other sectors of the economy. Third, the need of the firms to incorporate in their production processes the newly accumulated capital triggers a restructuring of organizational assets that responds to these technological changes and maximizes their effectiveness [42].

Governments as well may benefit from ICT in order to minister to the needs of their citizens. Improved processes and digital connections within and between state, businesses and public [27] are the two main contribution of ICT to government functions. The digital transformation of these functions can also become a leading tool against corruption by limiting human interference and enhancing accountability and transparency.

Motivated by the positive economic effects of a country’s high level of ICT diffusion that have been discussed above, our first hypothesis is:

$H1_0$: A country’s credit rating and sovereign debt interest rates are related to its e-readiness, with higher e-readiness levels associated with improved credit ratings and lower cost of debt.

The question whether ICT contribution is a function of a country’s economic development has yet to find a definite answer (see for example [44] arguing in favor of a greater ICT impact on developed countries, [68] suggesting a greater impact on developing countries while [72] found a uniform positive among countries). The idea of higher ICT returns in developing countries is dependent on leapfrogging, meaning that this group of countries could mainly bypass spreading the internet and telephony through fixed lines with high set up cost [73], following a rather shorter pattern.

Developing countries deliver internet and telephony services mostly through mobile networks that are cheaper and easier to develop and, instead of a self-contained approach, adapt a learning by doing role, trying to attract foreign ICT investments (capital and expertise). It is indicative that concerning 2021 and according to the latest ITU estimations, mobile-cellular telephone subscriptions reached a penetration rate of 105.1% for developing countries as opposed to a rate of 134.8% for developed ones, both approaching saturation while the penetration rate of fixed-broadband subscriptions reached a 13% versus a 35.7% rate, respectively. Mobile telecommunications whether inferior in capabilities or not, brought radical changes to a wide range of crucial areas for economic growth, sometimes even with a rather unconventional usage, [74] introducing, among others, mobile platforms, mobile money, microfinance or microinsurance, m-government, m-health and boosting education and women's entrepreneurship [73].

As [54,33,55] suggest, contradicting the findings of other researchers like [45,37], ICT comprise a more important determinant of growth opportunities for developing countries. Motivated by their work we formulate our second hypothesis:

$H2_0$: The relevance of a country's e-readiness to its credit rating and sovereign debt interest rates is not the same across different stages of economic development. E-readiness has a larger impact on credit ratings and cost of debt for developing and emerging economies as compared to developed economies.

1.2.2 Methodological framework

We employ a balanced panel dataset that consists of 65 countries for a total of ten years. Let Y_{it} be the response variable, X_{it} be a vector of time-varying regressors and Z_i be a vector of another set of time-invariant regressors. Let α_i be the unknown intercept for each country that does not vary over time, representing the combined effect on Y_{it} of all unobserved variables that are constant over time and ϵ_{it} be the error term, representing the purely random variation at each point of time.

Our basic model will then be:

$$Y_{it} = \beta X_{it} + \gamma Z_i + \alpha_i + \epsilon_{it} \qquad (1)$$

These models can be tackled using pooled OLS, fixed effects or random effects. Although we assume statistical independence between α_i and ϵ_{it}, the allowance of any kind of correlation between α_i, X_{it} and Z_i will determine if we are going to use a fixed effects or a random effects approach. Following fixed effects means that we are going to allow for such correlation while random effects assume that α_i is not correlated with regressors. It would be reasonable to suggest that the unobserved time-invariant variables that have an impact on Y_{it}, given the number and the extended set of the included variables in the regression, are correlated with the vector X_{it} of time-varying regressors and therefore the use of fixed effects is appropriate and statistically sound. We also confirm this by running the fixed and random effects regressions and conducting a Hausman test which suggests that a random effects estimator would be inconsistent.

Despite the fluctuations that the economic crisis caused to credit risk ratings, agencies do not tend to change their ratings so often and so dramatically. Although consistent, fixed effects do not allow an estimation of coefficients for time-invariant variables (albeit we are still controlling them) and therefore, as [1] suggest, using fixed effects would only allow us to capture credit ratings' movements across time since the average rating would be captured by the country-specific intercept α_i. Furthermore, the literature review suggests that coefficients of time-invariant variables might be of interest. Given the limited within-country variation of credit ratings and other predictors across time, a fixed effects model could yield less efficient estimates.

As such, following [1] and [2] we opt for a hybrid random effects model that, first, allows us to estimate coefficients for both time-variant and invariant regressors and, second, eliminates the correlation between the country specific error and the time variant regressors. We assume that the country specific intercept α_i is a linear combination of time-averages of the vector X_{it} of time-varying regressors. Therefore, we formally write:

$$\alpha_i = \eta \overline{X}_i + e_i \tag{2}$$

where e_i is the random error term. Substituting equation (2) in equation (1) we obtain:

$$Y_{it} = \beta X_{it} + \gamma Z_i + \eta \overline{X}_i + e_i + \varepsilon_{it} \tag{3}$$

Adding in both sides of equation 3 the $\beta \bar{X}_i$ term, it can be written as:

$$Y_{it} = \beta\left(X_{it} - \overline{X}_i\right) + \left(\beta + \eta\right)\overline{X}_i + \gamma Z_i + e_i + \varepsilon_{it} \tag{4}$$

The within $\left(X_{it} - \overline{X}_i\right)$ and the between ($\overline{X}_i$) panel variation are now completely separated. The β coefficient can be interpreted as the short-run effect and $(\beta + \eta)$ as the long-run effect of the regressors that accounts for panel heterogeneity [4]. The model is estimated using random effects, which will allow us to estimate $(\beta + \eta)$ coefficients. Then, in order to check the validity of the results, we re-estimate the model using fixed effects, which is always consistent (although less efficient). If the coefficient estimates and their corresponding standard errors of the two models (fixed effects model and hybrid random effects model described in equation 4) are identical, both models perform equally well[3]. That is, the hybrid random effects model escapes the correlation problem we discussed earlier [4].

Both e_i and ε_{it} are assumed to be normally distributed around zero with variance σ_e^2 and σ_ε^2, respectively. The between-country error term is uncorrelated with the country mean centered covariates, since each such covariate has a mean of zero for each country [4,5]. In addition, between-country error term (e_i) is assumed to be uncorrelated with the time invariant variables, i.e.:

$$Cov\ (X_{it} - \bar{X}_i, e_i) = 0$$

$$Cov\ (\bar{X}_i, e_i) = 0$$

$$Cov\ (Z_i\ , e_i) = 0$$

The above model can be generalized to an ordered response model, which has been suggested in the literature as more appropriate to the nature of credit ratings. In order to motivate our response model and following [10] we consider a latent continuous variable which is dependent upon the same variables of equation (4). Therefore, we write:

$$Y^*_{it} = \beta\left(X_{it} - \overline{X}_i\right) + \left(\beta + \eta\right)\overline{X}_i + \gamma Z_i + e_i + \varepsilon_{it} \qquad (5)$$

Since the latent variable is unobservable and continuous, several cut off points are assumed to be employed by the agencies in order to assign the final rating in the following way:

$$Y_{it} = \begin{cases} 1\ if\ y^*_{it} < c_1 \\ 2\ if\ C_1 < y^*_{it} < C_2 \\ \\ 20\ if\ c_{19} < y^*_{it} < c_{20} \\ 21\ if\ y^*_{it} > c_{20} \end{cases}$$

where the c_1 - c_{20} are the estimated threshold parameters[5].

[3] Which is expected to a certain extent. According to [5] since the mean term $\bar{X}_i$ of each time varying variable is only associated with the across countries variance, the estimates (and standard errors) of the time-variant coefficients will be identical to those of the fixed effects estimation [43].

[4] As such, there is no need to resort to alternative methods, such as the Hausman test, to differentiate between the fixed and random effects models, since the test also takes the form of comparing the vector of coefficient estimates of the models [57].

[5] Following [1] we estimate the coefficients and cut-off points using maximum likelihood utilizing the procedure by Frechette (2001) in Stata. The random effects ordered probit estimation regards both error terms to be normally distributed.

1.3 Empirical application

1.3.1 A proxy for e-readiness

Even though the various e-readiness measures strive to approximate the same characteristic, they share limited commonality in definitions, terms and methods they use. Most of the measures have largely adopted quantitative approaches that assign numerical scores on specific components of e-readiness tools to countries and use a compound index as weighted average that aggregates the scores into a single overall value that determines the level of e-readiness of the country. Usually these results are published annually or on regular intervals allowing a country to compare itself with other countries, as well as to compare its current position with that in the past. For the purpose of our empirical analysis, we have chosen the NRI as the most suitable proxy for e-readiness (see, among others, [57,34]). The NRI (first published in 2001) was prepared by the World Economic Forum and INSEAD and it comprises of three components: the environment for IT; the readiness of the country's key stakeholders (individuals, businesses and governments) to use IT and the actual use of IT amongst these stakeholders. The final NRI score is a simple average of the three component scores.

Apart from the NRI, there are two more proxies, also popular amongst academics and practitioners, for the estimation of e-readiness (see [25] for a literature review on e-readiness assessment measures). First, the EIU E-Readiness Index (published annually since 2000), which is published and prepared from the Economist Intelligence Unit (EIU) in cooperation with the IBM Institute for Business Value. The model consists of over 100 separate quantitative and qualitative criteria. The criteria are scored by the EIU's regional analysts and editors and are organized into six primary categories with a different impact in overall score. However, the NRI is available for a broader range of countries than EIU Index, thus facilitating the compilation of a richer dataset[6]. Second, the E-Government Readiness Index (published annually since 2003), which is prepared from the United Nations Division for Public Economics and Public Administration together with the American Society for Public administration. The E-Government Readiness Index shows the level governments are aware and benefiting from ICT. As such, the E-Government Readiness Index is a 'government' specific oriented index that does not reflect the concept of e-readiness to its entirety.

[6] A correlation analysis shows a strong correlation between the two indices at the aggregate level.

1.3.2 Data and sources

Rating agencies provide scarce evidence of the actual importance they allocate [12,47] to each of the numerous economic, social and political factors they suggest as determinants of a country's evaluation. Their methodology is a blend of quantitative analysis and subjective judgments [8] but the ultimate decision for each country is always taken by the ratings committee, a small group of senior analysts and experts and remains a black box. Therefore, a large body of empirical literature focuses on successfully modelling sovereign ratings[7].

Macroeconomic fundamentals associated with solvency, liquidity and economic or political stability have been widely proposed and acknowledged in literature as the driving factors behind sovereign ratings and cost of debt [3]. Variables like growth of GDP [39], per capita income [40], external debt to GDP ratio [12,46], government budget surplus or deficit to GDP ratio [6] can be grouped as solvency variables since they show the government's ability to meet its debt service requirements. Liquidity variables illustrate the ability of a government to deal with fluctuations to foreign exchange receipts without delaying or rescheduling accrued debt payments in foreign currency [18]. Usually, they are represented in literature by the current account balance [3] and the ratio of reserves to imports [15]. Economic and political stability are proxied by indices that measure the corruption, the human development and the protection of property rights [40;9]. They reflect the quality of the government and the risk of expropriation [15]. Moreover, annual rate of inflation is employed as a sign of prudent economic management [26,11]. Other factors that empirical literature has revealed as crucial factors behind credit ratings include, but not limit to, unemployment rate [11], exchange rates volatility [40,9], public debt [47] and capacity to acquire taxes [36].

Following the literature presented above, we employ a wide collection of time variant and invariant economic, financial and other variables for 65 countries, sampled in an annual frequency between 2001 and 2010. Table 1.1 shows the variables used throughout the chapter, together with a brief description of them, the sources we used to collect them, and a sign of the presumed effect each variable is likely to have on credit rating risk and cost of debt based on previous findings. In addition, we use a set of dummy time-invariant variables to indicate: first, the eurozone membership, which in most of the years under scrutiny should be considered as providing profound economic advantages to member states but in late years (2009–2010) could have a more ambiguous role since weakest members proved vulnerable to liquidity crises [47][8].

[7] An extended depiction of the related literature can be found in Table 4.1 of the Appendix.

[8] Since European debt crisis had not yet taken place or would be still in its infancy.

Table 1.1. Variables abbreviations, short descriptions and presumed impact. A positive sign (+) suggests that the variable is expected to have a positive impact on cost of debt and credit risk ranking while a negative sign (-) suggest a negative impact according to literature and empirical findings.

Variable	Description	Source	Effect
RTGSP, RTGM, RTGF	Sovereign credit ratings assigned by S&P, Moody's and Fitch accordingly. The qualitative letter rating is transformed linearly to numerical equivalents with number 1 representing the highest score (AAA for S&P and Fitch, Aaa for Moody's) and number 21 the lowest (D for S&P and Fitch, C for Moody's), see also Table 2	S&P, Moody's, Fitch	
YTM/-EBR	The yield to maturity of a 10-year zero coupon benchmark bond multiplied by 100. If none available, then JP Morgan Emerging Markets Bond Index (Global) was used.	DataStream	
NRI	Networked Readiness Index: It is published annually by World Economic Forum and INSEAD and ranges from 1 to 10 with higher values indicating a higher diffusion and use of ICT's.	The Global Information Reports	?
EIU INDEX	Economist Intelligence Unit E-Readiness Index: It is published annually by Economist and IBM and ranges from 1 to 10 with higher values indicating a higher diffusion and use of ICT's.	Economist	?
EGOV INDEX	E – Government Development Index. It is published irregularly by the United Nations and ranges from 0 to 1 with higher values indicating a higher diffusion and use of ICT's. Data are available for 2004, 2005, 2008, and 2010.	United Nations	?
BLNC	Current Account balance: The sum of trade balance (goods and services exports less imports), net income from abroad and net current transfers. A positive current account balance reflects a country's net investment abroad while a negative current account balance reflects the foreign net investment to the country. Expressed as a fraction of GDP.	World Bank	(+/-)
CRED	Domestic credit to private sector: Refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of non-equity securities, and trade credits and other accounts receivable, that establish a claim for repayment. Expressed as a fraction of GDP.	World Bank	(+/-)
CRPT	Corruption Perception Index: The CPI scores and ranks countries based on how corrupt a country's public sector is perceived to be. It is a composite index, a combination of surveys and assessments of corruption and is published annually, ranging from zero (highly corrupt) to ten (highly clean).	Transparency International	(-)
DFCT	Cash Surplus or deficit: Revenue (including grants) minus expense, minus net acquisition of nonfinancial assets. Expressed as a fraction of GDP.	World Bank, DataStream	(-)
DFLT75/DFLT95	The two dummy variables correspond to a default to any of the three types of default identified by S&P, local currency debt, foreign currency bond debt and foreign currency bank debt. If any of these kinds of default took place during 1975-2010 then the dummy variable DFLT75 takes the value of one while if it took place during 1995 – 2010 then the dummy variable DFLT95 takes the value of one.	S&P	(+)
EURO/OECD	The two dummy variables correspond to a membership to Eurozone and OECD respectively; a value of one means that a country is a member of the Eurozone or OECD.	Eurozone, OECD	(-)
FDGDP	Foreign Government Debt: The portion of a government's debt that was borrowed from foreign lenders including commercial banks, governments or international financial institutions. Expressed as a fraction of GDP.	Euromonitor, Own calculations	(+)
FRDM	Index of Economic Freedom: It's a composite index that mainly reflects the level of enforcement of the rights of individuals to accumulate private property, to start, operate and close a business and to transfer capital resources through a country's border. The Index takes values from 1 -100 with higher values indicating a higher rank of economic freedom.	The Heritage Foundation	(-)
GNI	Gross National Income: It is the aggregate value of the gross balances of primary incomes for all sectors and is defined as GDP plus compensation of employees' receivable from abroad plus property income receivable from abroad plus taxes less subsidies on production receivable from abroad less compensation of employees payable abroad less property income payable abroad and less taxes plus subsidies on production payable abroad. Expressed in constant US$ (2013). Natural log transformed.	World Bank	(-)
GDPG	Gross Domestic Product Growth: GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is expressed as a percentage that shows the rate of change in a country's GDP from one year to the next.	World Bank	(-)
HDI	United Nation's Human Development Index: It is a composite statistic of life expectancy, education and standard of living published annually. It can take any value from 0 (least developed) to 1 (most developed).	United Nations	(-)
INFL	Inflation: As measured by the consumer price index.	World Bank	(+)
INTUSRS	Internet Users Per Inhabitant. Number of internet users as a fraction of a country's population	International Telecommunications Union	?
LGL (`x')	The five dummy variables show the origin of the legal system. LGLFRC, LGLGRM, LGLSKN, LGLSOC and LGLUK stand for a legal system that originates from France, Germany, Scandinavia, Socialist States and United Kingdom.	La Porta et.al., (1999)	(+/-)
LPROD	Labor Productivity: As measured by the output per worker expressed in constant 2010 US$. Log transformed.	International Labor Organization	(-)
PDGDP	Public Debt: Total debt owned by any level of the Government. It consists of all liabilities that require payment or payments of interest and/or principal by the debtor to the creditor at a date or dates in the future. Expressed as a fraction of GDP.	IMF	(+)
PTNTS	Patents per Inhabitant. Sum of patents granted to each country by the European Patent Office and the United States Patent Office. Expressed as a fraction of the population.	USPTO/EPO	(-)
REV	Government Revenues: A sum of taxes, subsidies, social contributions, grants receivable and other current and capital transfers. Expressed as a fraction of GDP.	IMF	(-)
TAX	Tax revenues: It refers to compulsory transfers to the central government for public purposes. Certain compulsory transfers such as fines, penalties, and most social security contributions are excluded. Expressed as a fraction of GDP.	World Bank, DataStream	(+/-)
UNPL	Unemployment: Refers to the share of the labor force that is without work but available for and seeking employment. Expressed as a fraction of total labor force.	World Bank	(+)

Second, the membership of OECD as a measure of development adopted by [19]. Third, the history of defaults, whether the more (1975–2010) or the less (1995–2010) distant in time, acts as a measure of country's willingness to repay its debt [47,15]. Finally, the origin of a sovereign's legal system as a measure of the available legal remedies against sovereign debtors in default.

Our sample of countries is grouped in two major clusters: the OECD group consists of 28 countries, namely Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, South Korea, Spain, Sweden, Switzerland, Turkey, the UK and the USA. The non-OECD group consists of 37 countries, namely Azerbaijan, Brazil, Bulgaria, Colombia, Costa Rica, Croatia, Dominican Republic, Egypt, El Salvador, Estonia, Ghana, Hong Kong, India, Indonesia, Israel, Jamaica, Jordan, Kazakhstan, Latvia, Lithuania, Malaysia, Moldova, Morocco, Nicaragua, Pakistan, Peru, the Philippines, Qatar, Romania, Russia, Singapore, Slovenia, South Africa, Sri Lanka, Thailand, Trinidad and Tobago and Tunisia[9].

The dependent variables aim to capture sovereign credit risk and cost of debt. Three different proxies of sovereign credit risk are employed, namely the credit ratings reported by the three major American agencies, Standard and Poor's (S&P), Moody's and Fitch. Following standard practice in the literature (e.g., [10,12]), the qualitative letter ratings are linearly transformed to numerical equivalents with number 1 representing the highest score (AAA for S&P and Fitch, Aaa for Moody's) and number 21 the lowest (D for S&P and Fitch, C for Moody's). The transformation is straightforward and is presented in Table 1.2. Nevertheless, unlike other empirical studies that employ the attributed sovereign rating on the 31st of December of each year, we construct a weighted average rating, which assumes a fiscal year of 360 days, multiplies every assigned rating during the specific year by the days that this rating did not change, sums the products and then divides the sum by 360. Finally, the result is rounded to the closest integer. The idea behind the constructed rating is that a single rating at just one point in time cannot comprise a satisfactory proxy of sovereign credit risk, since it disregards any upgrades or downgrades that took place during each year.

The sovereign cost of debt is proxied by the yield to maturity (YTM) of the ten-year zero-coupon sovereign benchmark bond.

[9] During 2010, Estonia, Israel and Slovenia signed the Convention on the Organization for Economic Co-operation and Development and became full members.

Table 1.2. Linear transformation of assigned ratings by S&P, Moody’s and Fitch, adopted from [1] and modified accordingly by authors.

	Characterization of issuer and debt **by Moody's**	**S&P**	**Moody's**	**Fitch**	**Numerical Transformation**		**Average Marginal Effects Transformation**
		RATING					
INVESTING GRADE	Highest Quality/Prime	AAA	Aaa	AAA	1	1	1
	High Quality/High Grade	AA+	Aa1	AA+	2	2	2
		AA	Aa2	AA	3	3	
		AA-	Aa3	AA-	4	4	
	Strong Payment Capacity/Upper Medium Grade	A+	A1	A+	5	5	3
		A	A2	A	6	6	
		A-	A3	A-	7	7	
	Adequate Payment Capacity/Lower Medium Grade	BBB+	Baa1	BBB+	8	8	4
		BBB	Baa2	BBB	9	9	
		BBB-	Baa3	BBB-	10	10	
SPECULATIVE GRADE	Likely to fulfil obligations, uncertainty/Non-investment Grade, Speculative	BB+	Ba1	BB+	11	11	5
		BB	Ba2	BB	12	12	
		BB-	Ba3	BB-	13	13	
	High Credit Risk/High Speculative	B+	B1	B+	14	14	6
		B	B2	B	15	15	
		B-	B3	B-	16	16	
	Very High Credit Risk/Substantial Risks	CCC+	Caa1	CCC+	17	17	7
		CCC	Caa2	CCC		18	
		CCC-	Caa3	CCC-		19	
	Near Default/Extremely Speculative	CC & C	Ca	CC & C		20	
	Default/In Default with little prospect of recovery	SD & D	C	RD & D & DD & DDD	21	21	

If not available, then the closest maturity is selected. We were able to obtain comparable bonds only for 36 out of the 65 countries of our sample, so our empirical analysis for YTMs will be confined to them[10].

In order to obtain an ‘expanded’ proxy of the sovereign cost of debt for more countries (expanded cost of debt-exCoD), we also use the JP Morgan Emerging Markets Bond Global Indices’ stripped yield (EMBI), in the cases where no data for YTMs of sovereign benchmark bonds are available. The index tracks the total returns of external debt instruments, and it has been proposed in the literature as an alternative measure of cost of debt [9]. As such, data for fifteen

[10] The 36 countries under considerations are: Australia, Austria, Belgium, Bulgaria, Canada, Colombia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Ireland, Israel, Italy, Japan, Lithuania, Malaysia, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Singapore, South Korea, Spain, Sweden, Switzerland, Thailand, United Kingdom and United States.

additional countries has been added to the existing dataset of YTMs of the 36 countries[11].

1.3.3 Descriptive statistics

Summary statistics of the main variables for each country under study can be obtained in Table 1.3. The credit ratings and the YTM exhibit a wide variability. Yields to maturity range from 1.382 (Japan) to 11.318 (Colombia).

Concerning the NRI, USA seize the first place with a mean of 5.595, followed by Singapore, with an average of 5.567 while the third place is occupied by Sweden with an average of 5.556. The index presents very similar variability for both OECD and non-OECD members (sd: 0.592 and 0.615 respectively). However, OECD members score about a unit higher with an average of 4.8576, compared to an average of 3.8032 for non-OECD countries.

Table 1.4 presents all averages per variable and year for both OECD and non-OECD countries and the aggregate average for all years under study. The last two columns of Table 1.4 depict the percentage change between average values for 2001 and 2010 per variable and group of countries and the p-values of the Satterthwaite-Welch t-test between averages of variables across all years for OECD and non-OECD countries. Table 1.4 shows that credit risk ratings have deteriorated for OECD countries between 2001 and 2010 as far as S&P (–14.4%) and Fitch (–4.74%) is concerned, while Moody's remained more optimistic (+2.81%). All agencies upgraded, on average, non-OECD countries, with Moody's improving its assigned credit ratings to non-OECD countries by 10.12%. The actual cost of debt has fallen sharply by 23.08% for OECD countries and 37.69% for non-OECD ones. The average assigned NRI score for OECD countries was lowered by 3.97% while it grew by 9.26% for non-OECD countries, always comparing 2001 and 2010 average values. The results shown in Table 1.4 also suggest a general deterioration of OECD countries macroeconomic fundamentals, like the current account balance (BLNC = –44.56%), the foreign government debt (FDGDP = 58.78%), the public debt (PDGDP = 22.58%) and the unemployment (UNPL = 35.59%). The latter results illustrate the economic turmoil and the interventionist efforts of the respective governments caused by the financial crisis of 2007, which originated in USA and was transmitted rapidly through financial channels, thus striking first the advanced economies, which also recovered last [16]. On the other hand, non-OECD countries escape much of the crisis backwash and present rapid improvements concerning their macroeconomic fundamentals; BLNC (294.88%), FDGDP (–36.81%), PDGDP (–21.21%) and

[11] The additional countries are Brazil, Costa Rica, Croatia, Dominican Republic, Egypt, El Salvador, Kazakhstan, Morocco, Pakistan, Peru, Romania, South Africa, Trinidad and Tobago, Tunisia, and Turkey

UNPL (–13.48%). Moreover, in order to test the equality of variable means between the two set of countries, we employ a Satterthwaite-Welch t-test which cannot reject the null hypothesis of equality only for BLNC, DFCT, and FDGDP. Overall this means that our sample consists of two well defined set of countries. On the other hand, the failure to reject the equality of means for these variables illustrates, once more, the severe effects of the economic crisis faced by those countries with stronger linkages to the international financial system, i.e., OECD countries [7]. Table 1.5 presents the Pearson correlation coefficients between the variables approximating sovereign credit risk and cost of debt and the NRI, respectively. As expected, the assigned ratings of the three main agencies are highly interdependent. Cost of debt (YTM) also exhibits a strong and stable correlation with credit ratings across agencies. The NRI is very strongly and negatively correlated with credit ratings and still strongly but more loosely with YTM. The later result can be regarded as an indication that our first hypothesis holds. Furthermore, and concerning the way NRI is linked with the rest of the variables, NRI is detected to be strongly and positively correlated to the corruption index[12].

Corruption perceptions (CRPT), and economic freedom (FRDM) are also found to be highly correlated with credit ratings and YTM. It is also striking to note that FDGDP and PDGDP are, as expected, positively correlated with credit risk ratings, albeit weakly but possess the opposite sign of correlation concerning the YTM (although for FDGDP the correlation is statistically insignificant). A possible explanation is that markets will keep financing a country's debt as long as a country remains solvent and keeps deficits under control (DFCT presents statistically significant correlation with all dependent variables).

In order to have a better insight of the way the explanatory variables correlate with response variables we break the correlation analysis in two parts, one for each set of countries and we apply a Fisher z-transformation to Pearson correlation coefficients in order to assess the significance of the difference between the two coefficients (see Table 1.6). The correlation between credit risk ratings and YTM is found to be much stronger for non-OECD countries (the difference is statistically significant for S&P), possibly because investors and debt holders have (or think they have) a much clearer picture of OECD economies.

[12] We compute the variance inflation factors of the regressors suspect to potential collinearity. The variance inflation factor of the corruption index exceeds the value of ten, which suggests further investigation. Since a high degree of collinearity destabilizes the estimated coefficients and inflates the standard errors, we re-estimate the models excluding the corruption index. The results, in general, are not supportive toward the existence of severe collinearity. Regardless the inclusion of the corruption, the standard error of the short run NRI's coefficient does not change. The standard error of the long run NRI's coefficient slightly decreases, which does not impose any econometric problem, although collinearity is probably present. Finally, the corresponding coefficients of the NRI are almost unaffected.

Table 1.3. Country-wise statistics of the main variables.

	RTGM		YTM		NRI		BLNC		CRED		DFCT		INFL		PDGDP		REV		TAX		UNPL	
Country	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Australia	1.4	0.843	5.457	0.644	5.112	0.146	-0.049	0.016	1.110	0.155	0.002	0.020	3.006	0.849	0.137	0.036	0.351	0.016	0.237	0.013	0.054	0.008
Austria	1.0	0.000	4.172	0.612	5.002	0.234	0.025	0.015	1.137	0.081	-0.021	0.012	1.934	0.747	0.655	0.033	0.488	0.011	0.201	0.010	0.044	0.005
Azerbaijan	11.8	0.919			3.545	0.231	0.060	0.235	0.120	0.046	-0.029	0.023	7.577	6.596	0.151	0.064	0.318	0.103	0.160	0.016	0.072	0.011
Belgium	2.0	0.000	4.193	0.623	4.770	0.211	0.018	0.020	0.828	0.104	-0.013	0.018	2.082	1.135	0.947	0.069	0.491	0.008	0.255	0.008	0.078	0.007
Brazil	12.9	1.792	8.560	3.839	3.879	0.194	-0.006	0.020	0.400	0.113	-0.024	0.011	6.688	3.166	0.692	0.050	0.344	0.006	0.159	0.007	0.085	0.010
Bulgaria	11.5	1.900	5.931	1.306	3.478	0.279	-0.109	0.089	0.466	0.231	0.011	0.022	5.992	3.137	0.326	0.189	0.365	0.017	0.204	0.025	0.112	0.048
Canada	1.1	0.316	4.299	0.824	5.273	0.140	0.006	0.020	1.576	0.259	0.007	0.014	2.020	0.673	0.760	0.065	0.404	0.010	0.134	0.008	0.071	0.008
Colombia	11.7	0.483	11.318	3.084	3.559	0.256	-0.018	0.008	0.323	0.070	-0.047	0.023	5.572	1.685	0.385	0.048	0.259	0.010	0.117	0.011	0.124	0.014
Costa Rica	11.0	0.000	7.065	1.153	3.727	0.264	-0.049	0.019	0.384	0.083	-0.011	0.016	10.371	2.554	0.340	0.063	0.142	0.008	0.093	0.065	0.063	0.010
Croatia	10.0	0.000	4.971	0.748	3.773	0.250	-0.055	0.021	0.549	0.111	-0.027	0.012	2.815	1.424	0.356	0.034	0.391	0.006	0.202	0.009	0.126	0.036
Czech	5.6	1.265	4.532	1.072	4.248	0.226	-0.038	0.017	0.408	0.093	-0.039	0.016	2.553	1.824	0.294	0.038	0.398	0.014	0.145	0.008	0.070	0.013
Denmark	1.0	0.000	4.156	0.672	5.516	0.238	0.031	0.011	1.814	0.316	0.018	0.030	2.046	0.635	0.473	0.087	0.555	0.012	0.322	0.024	0.049	0.012
Dominican Rep.	14.5	1.434	9.467	4.007	3.472	0.241	-0.030	0.048	0.256	0.063	-0.017	0.013	12.934	15.287	0.272	0.061	0.148	0.014	0.138	0.012	0.160	0.014
Egypt	11.0	0.000	5.067	1.886	3.490	0.260	0.010	0.025	0.475	0.080	-0.064	0.009	8.396	4.998	0.875	0.127	0.264	0.014	0.144	0.010	0.099	0.009
El Salvador	10.1	0.316	7.369	1.347	3.470	0.221	-0.038	0.019	0.420	0.011	-0.029	0.021	3.444	1.827	0.402	0.052	0.158	0.010	0.124	0.014	0.068	0.006
Estonia	5.6	1.265			4.793	0.268	-0.083	0.068	0.741	0.245	0.009	0.017	4.207	2.905	0.052	0.011	0.382	0.040	0.161	0.006	0.097	0.039
Finland	1.0	0.000	4.069	0.654	5.521	0.232	0.048	0.028	0.756	0.139	0.030	0.029	1.541	1.229	0.415	0.044	0.530	0.003	0.217	0.013	0.082	0.010
France	1.0	0.000	4.088	0.610	4.911	0.190	-0.003	0.012	0.984	0.107	-0.037	0.019	1.713	0.693	0.669	0.081	0.498	0.005	0.219	0.009	0.087	0.006
Germany	1.0	0.000	3.983	0.659	5.111	0.137	0.046	0.024	1.123	0.045	-0.018	0.009	1.562	0.657	0.676	0.067	0.442	0.006	0.112	0.004	0.088	0.014
Ghana	14.1	0.316			3.300	0.149	-0.067	0.040	0.138	0.018	-0.046	0.020	17.027	7.418	0.550	0.264	0.166	0.015	0.163	0.035	0.122	0.012
Greece	5.6	1.265	4.676	0.745	3.903	0.112	-0.096	0.034	0.820	0.188	-0.077	0.035	3.314	0.922	1.104	0.151	0.396	0.010	0.205	0.008	0.098	0.013
Hong Kong	4.9	1.663	3.717	1.263	5.163	0.228	0.097	0.028	1.507	0.146	-0.002	0.048	0.452	2.348	0.311	0.032	0.185	0.034	0.120	0.019	0.055	0.014
Hungary	6.0	1.247	7.864	0.723	4.104	0.206	-0.058	0.034	0.534	0.140	-0.058	0.019	5.637	1.836	0.655	0.098	0.440	0.017	0.217	0.014	0.075	0.018
Iceland	3.3	3.234			5.413	0.306	-0.120	0.088	1.677	0.791	-0.018	0.065	6.260	3.498	0.499	0.248	0.447	0.024	0.249	0.024	0.038	0.019
India	10.5	0.850	6.922	1.086	3.892	0.268	-0.007	0.015	0.400	0.080	-0.035	0.014	6.363	3.071	0.780	0.052	0.191	0.014	0.098	0.012	0.070	0.022
Indonesia	14.4	1.430			3.494	0.251	0.021	0.016	0.251	0.028	-0.009	0.005	8.590	3.075	0.473	0.180	0.189	0.015	0.121	0.006	0.091	0.012
Ireland	1.2	0.632	4.254	0.594	4.849	0.165	-0.023	0.022	1.673	0.491	-0.045	0.107	2.508	3.020	0.406	0.218	0.342	0.015	0.237	0.017	0.061	0.035
Israel	5.7	0.483	6.623	2.556	4.904	0.229	0.017	0.021	0.908	0.055	-0.046	0.021	2.163	1.926	0.871	0.093	0.440	0.028	0.265	0.017	0.086	0.016
Italy	3.1	0.316	4.375	0.560	4.180	0.278	-0.018	0.011	0.948	0.148	-0.030	0.010	2.170	0.727	1.076	0.054	0.450	0.011	0.223	0.006	0.079	0.011
Jamaica	14.2	0.789			3.709	0.305	-0.104	0.046	0.218	0.054	-0.035	0.024	11.540	4.584	1.231	0.111	0.262	0.013	0.254	0.008	0.117	0.018
Japan	1.6	0.699	1.382	0.227	5.026	0.154	0.034	0.007	1.819	0.066	-0.044	0.020	-0.263	0.759	1.841	0.191	0.298	0.012	0.094	0.009	0.047	0.005
Jordan	12.3	0.483			3.812	0.281	-0.051	0.095	0.795	0.081	-0.038	0.024	4.299	4.274	0.814	0.151	0.311	0.036	0.200	0.034	0.134	0.017
Kazakhstan	9.9	1.287	8.134	4.865	3.610	0.137	-0.020	0.038	0.365	0.151	0.007	0.019	8.602	3.301	0.110	0.044	0.257	0.025	0.123	0.028	0.079	0.014

Table 1.3. Country-wise statistics of the main variables.

	RTGM		YTM		NRI		BLNC		CRED		DFCT		INFL		PDGDP		REV		TAX		UNPL	
Country	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Latvia	7.3	1.703			3.878	0.194	-0.094	0.099	0.689	0.292	-0.022	0.025	5.477	4.691	0.176	0.104	0.349	0.015	0.143	0.010	0.112	0.043
Lithuania	7.8	1.814	6.250	3.040	3.989	0.312	-0.064	0.060	0.429	0.214	-0.027	0.030	3.052	3.441	0.221	0.068	0.329	0.015	0.163	0.017	0.110	0.048
Luxembourg	1.0	0.000			4.830	0.200	0.090	0.022	1.467	0.366	0.012	0.022	2.253	0.771	0.092	0.048	0.417	0.015	0.246	0.007	0.041	0.011
Malaysia	7.6	0.843	4.092	0.489	4.512	0.323	0.132	0.037	1.138	0.084	-0.044	0.010	2.207	1.439	0.446	0.042	0.247	0.010	0.156	0.011	0.034	0.002
Moldova	17.1	0.568			3.110	0.233	-0.078	0.053	0.267	0.084	-0.003	0.024	9.638	4.262	0.411	0.212	0.366	0.044	0.171	0.030	0.068	0.013
Morocco	11.0	0.000	5.737	1.375	3.460	0.158	0.002	0.037	0.523	0.103	-0.010	0.023	1.808	1.093	0.588	0.077	0.267	0.033	0.224	0.027	0.106	0.011
Netherlands	1.0	0.000	4.095	0.608	5.268	0.288	0.057	0.023	1.710	0.267	-0.014	0.020	2.021	1.016	0.532	0.057	0.451	0.009	0.226	0.006	0.035	0.009
New Zealand	1.4	0.843	5.951	0.557	4.893	0.208	-0.054	0.026	1.266	0.176	0.022	0.023	2.574	0.766	0.245	0.049	0.322	0.014	0.302	0.016	0.048	0.010
Nicaragua	16.4	0.843			2.753	0.307	-0.175	0.036	0.284	0.090	-0.018	0.015	8.234	4.803	1.299	0.495	0.299	0.034	0.157	0.031	0.067	0.021
Norway	1.0	0.000	4.723	0.953	5.238	0.251	0.143	0.022	0.835	0.095	0.138	0.040	2.016	1.021	0.487	0.081	0.568	0.011	0.278	0.011	0.036	0.007
Pakistan	15.5	0.850	9.321	5.649	3.280	0.187	-0.016	0.047	0.259	0.036	-0.040	0.015	8.920	5.599	0.676	0.108	0.150	0.009	0.099	0.004	0.065	0.011
Peru	12.4	1.075	7.087	1.601	3.278	0.238	-0.005	0.022	0.211	0.029	-0.003	0.016	2.374	1.503	0.355	0.083	0.190	0.014	0.139	0.013	0.087	0.018
Philippines	12.8	1.398	9.856	3.420	3.427	0.179	0.023	0.025	0.312	0.031	-0.031	0.014	4.636	1.854	0.543	0.098	0.179	0.007	0.126	0.007	0.091	0.020
Poland	6.4	0.843	6.074	1.054	3.695	0.206	-0.041	0.015	0.365	0.105	-0.044	0.015	2.825	1.478	0.465	0.046	0.388	0.012	0.169	0.009	0.143	0.052
Portugal	3.1	0.316	4.281	0.581	4.387	0.230	-0.098	0.017	1.547	0.224	-0.046	0.026	2.457	1.406	0.660	0.135	0.404	0.010	0.206	0.007	0.073	0.020
Qatar	5.5	2.224			4.270	0.313	0.206	0.078	0.372	0.074	0.123	0.047	5.295	6.963	0.283	0.166	0.371	0.043	0.214	0.041	0.014	0.012
Romania	12.1	2.424	6.009	2.406	3.570	0.411	-0.076	0.035	0.268	0.155	-0.031	0.026	12.410	9.474	0.212	0.067	0.310	0.013	0.135	0.026	0.070	0.007
Russia	10.3	2.312	8.334	1.488	3.437	0.267	0.079	0.026	0.312	0.112	0.045	0.045	12.578	4.088	0.203	0.144	0.377	0.020	0.146	0.016	0.076	0.009
Singapore	1.1	0.316	2.923	0.585	5.567	0.118	0.202	0.054	1.007	0.104	0.059	0.028	1.624	1.947	0.953	0.057	0.217	0.027	0.132	0.012	0.046	0.009
Slovenia	4.0	1.155			4.304	0.204	-0.019	0.023	0.639	0.226	-0.019	0.020	4.196	2.494	0.285	0.050	0.411	0.005	0.197	0.013	0.060	0.008
South Africa	8.4	0.843	5.728	1.162	3.931	0.155	-0.033	0.028	1.403	0.153	-0.015	0.020	6.018	2.909	0.343	0.047	0.269	0.020	0.262	0.018	0.257	0.024
South Korea	6.8	1.033	5.250	0.881	5.036	0.301	0.023	0.012	0.943	0.095	0.016	0.011	3.185	0.759	0.271	0.058	0.225	0.010	0.152	0.008	0.035	0.003
Spain	1.2	0.632	4.200	0.587	4.382	0.217	-0.061	0.026	1.574	0.450	-0.009	0.035	2.799	1.239	0.478	0.081	0.382	0.019	0.123	0.020	0.120	0.039
Sri Lanka	13.6	0.516			3.435	0.277	-0.031	0.028	0.295	0.031	-0.074	0.010	10.735	5.610	0.923	0.092	0.160	0.008	0.136	0.007	0.070	0.014
Sweden	1.1	0.316	4.040	0.885	5.556	0.232	0.072	0.015	1.140	0.152	0.009	0.016	1.499	1.163	0.460	0.060	0.518	0.010	0.217	0.009	0.066	0.012
Switzerland	1.0	0.000	2.535	0.589	5.327	0.213	0.108	0.044	1.635	0.100	0.013	0.026	0.868	0.711	0.600	0.082	0.349	0.012	0.102	0.004	0.038	0.006
Thailand	8.6	0.966	4.446	0.928	3.978	0.234	0.029	0.034	1.057	0.082	0.007	0.016	2.620	1.930	0.466	0.068	0.213	0.013	0.160	0.007	0.015	0.005
Trin.& Tobago	9.1	0.994	8.493	1.635	3.542	0.143	0.173	0.121	0.371	0.041	0.007	0.033	6.987	2.825	0.396	0.132	0.312	0.050	0.251	0.033	0.075	0.024
Tunisia	9.2	0.422	4.702	1.491	4.150	0.196	-0.028	0.012	0.608	0.033	-0.020	0.007	3.384	1.025	0.529	0.106	0.279	0.014	0.194	0.007	0.142	0.007
Turkey	13.4	0.699	7.413	2.050	3.717	0.199	-0.035	0.028	0.253	0.103	-0.047	0.057	18.991	17.120	0.547	0.143	0.314	0.015	0.195	0.006	0.108	0.014
Unit. Kingdom	1.0	0.000	4.446	0.503	5.191	0.238	-0.023	0.007	1.715	0.307	-0.042	0.036	2.097	0.842	0.478	0.133	0.369	0.007	0.273	0.009	0.055	0.012
United States	1.0	0.000	4.168	0.811	5.595	0.239	-0.046	0.011	1.935	0.145	-0.042	0.035	2.395	1.204	0.707	0.140	0.325	0.012	0.106	0.012	0.061	0.018

Table 1.4. Average values per year for OECD (upper line) and non-OECD (bottom line) countries.

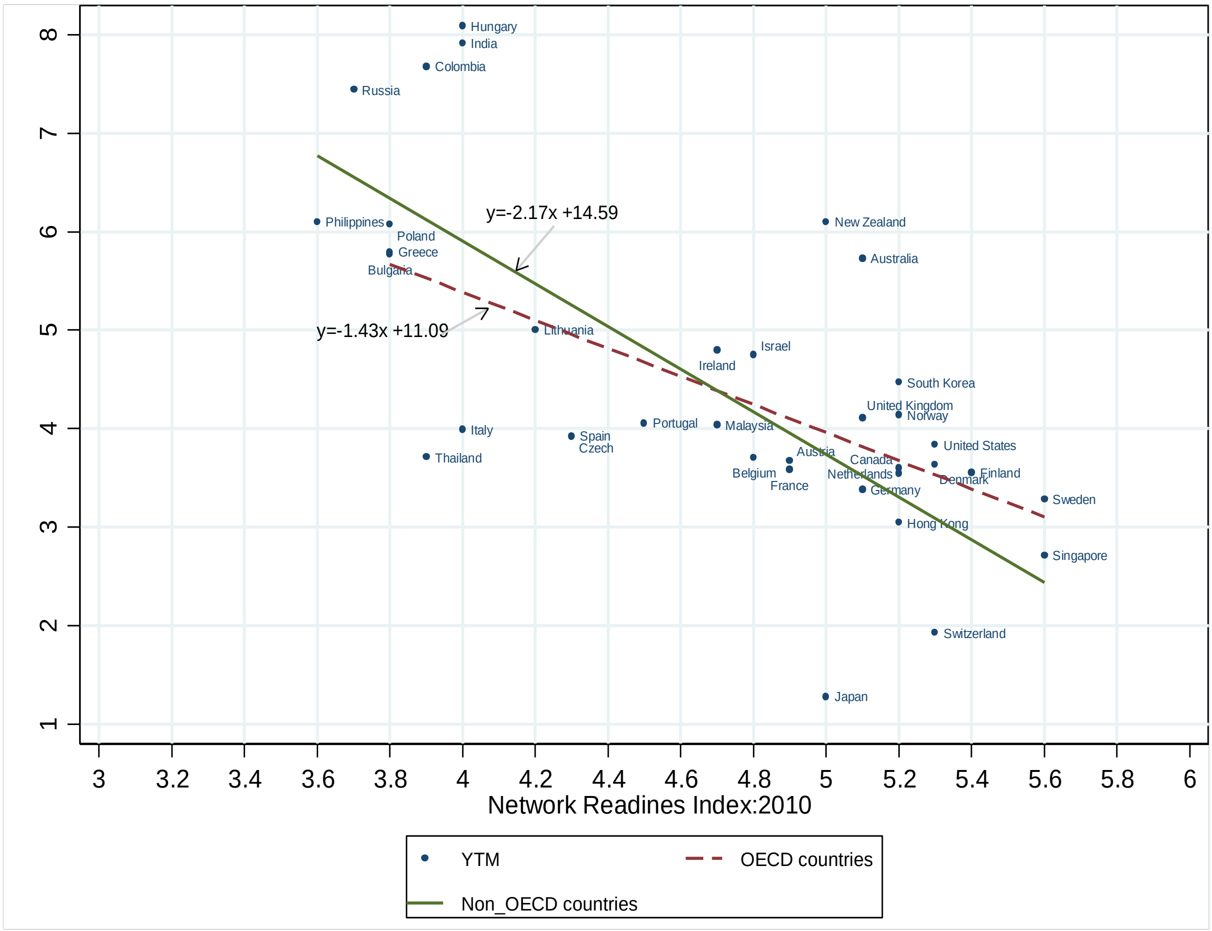
	2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**Average 2001-10**	**%change 2001-10**	**Pr(|T|>|t|)[a]**
RTGSP	3.250	3.214	3.071	3.000	3.000	2.964	3.000	3.071	3.357	3.710	3.164	-14.14	**0.000**
	11.41	11.30	10.89	10.76	10.41	10.11	9.81	9.84	10.11	10.53	10.52	7.68	
RTGM	3.286	2.929	2.500	2.464	2.464	2.429	2.464	2.500	2.786	3.194	2.702	2.81	**0.000**
	11.49	11.22	10.81	10.62	10.41	10.22	9.97	9.81	9.92	10.32	10.48	10.12	
RTGF	3.357	3.286	3.214	2.964	2.929	2.857	2.893	2.893	3.107	3.516	3.102	-4.74	**0.000**
	11.30	11.22	10.92	10.81	10.30	10.08	9.76	9.68	10.14	10.47	10.47	7.32	
YTM	5.448	5.246	4.531	4.479	4.053	3.792	4.334	4.613	3.842	4.191	4.453	-23.08	**0.000**
	8.573	7.583	6.917	6.644	5.714	5.414	5.728	6.184	5.966	5.342	6.406	-37.69	
NRI	5.005	4.907	4.554	4.600	4.839	4.982	4.982	5.039	4.861	4.807	4.858	-3.97	**0.000**
	3.596	3.649	3.537	3.662	3.778	3.905	4.005	4.043	3.927	3.929	3.803	9.26	
BLNC	0.006	0.007	0.004	0.004	-0.001	-0.007	-0.011	-0.021	-0.004	0.003	-0.002	-44.56	0.579
	-0.005	-0.007	0.002	-0.007	-0.006	-0.002	-0.021	-0.028	0.007	0.010	-0.006	294.88	
CRED	1.007	1.002	1.043	1.085	1.189	1.289	1.323	1.323	1.375	1.324	1.196	31.52	**0.000**
	0.438	0.435	0.450	0.465	0.497	0.526	0.573	0.584	0.607	0.572	0.515	30.54	
CRPT	7.200	7.200	7.300	7.300	7.400	7.400	7.400	7.300	7.300	7.100	7.290	-1.39	**0.000**
	4.100	4.100	4.000	4.000	4.100	4.100	4.100	4.100	4.100	4.000	4.070	-2.44	
DFCT	-0.003	-0.013	-0.016	-0.012	-0.004	0.006	0.008	-0.008	-0.045	-0.046	-0.013	-1355.41	0.781
	-0.018	-0.018	-0.016	-0.012	-0.006	-0.005	0.001	-0.010	-0.035	-0.029	-0.015	-57.58	
FDGDP	0.186	0.206	0.216	0.226	0.231	0.234	0.234	0.273	0.308	0.296	0.241	58.78	0.324
	0.305	0.295	0.288	0.261	0.218	0.190	0.165	0.155	0.186	0.193	0.226	-36.81	
FRDM	70.00	70.20	70.10	69.80	69.80	71.10	71.30	72.10	72.20	71.90	70.85	2.71	**0.000**
	62.20	62.20	62.60	62.20	61.80	62.20	62.00	62.60	63.00	62.80	62.42	0.96	
GNI	26.30	26.39	26.59	26.74	26.82	26.89	27.03	27.09	26.97	26.80	26.76	1.93	**0.000**
	24.18	24.24	24.37	24.52	24.67	24.85	25.04	25.20	25.14	25.29	24.75	4.61	
HDI	0.911	0.917	0.924	0.928	0.934	0.938	0.943	0.874	0.875	0.876	0.912	-3.84	**0.000**
	0.752	0.757	0.762	0.769	0.779	0.783	0.789	0.712	0.713	0.702	0.752	-6.65	
INFL	5.101	3.903	2.884	2.433	2.482	2.703	2.731	4.230	1.289	2.292	3.005	-55.07	**0.000**
	6.806	5.136	5.752	6.944	6.324	6.446	6.757	11.270	4.343	5.087	6.487	-25.25	
PDGDP	0.564	0.568	0.572	0.573	0.567	0.561	0.541	0.595	0.677	0.691	0.591	22.58	**0.000**
	0.590	0.593	0.586	0.533	0.493	0.442	0.405	0.395	0.451	0.465	0.495	-21.21	
REV	0.415	0.410	0.412	0.410	0.416	0.419	0.419	0.415	0.408	0.408	0.413	-1.68	**0.000**
	0.257	0.257	0.262	0.268	0.272	0.280	0.285	0.289	0.276	0.263	0.271	2.28	
TAX	0.205	0.201	0.200	0.200	0.206	0.208	0.209	0.205	0.194	0.195	0.202	-5.07	**0.000**
	0.153	0.153	0.157	0.161	0.171	0.173	0.175	0.174	0.161	0.155	0.163	0.87	
UNPL	0.062	0.066	0.069	0.070	0.068	0.063	0.057	0.057	0.077	0.084	0.067	35.59	**0.000**
	0.103	0.102	0.099	0.095	0.089	0.083	0.076	0.074	0.087	0.089	0.090	-13.48	

Notes: [a]P-values of the Satterthwaite-Welch t-test that allows for unequal variances formatted in italics, depict statistically significant difference between averages of variables across all years for OECD (upper line) and non-OECD (bottom line) countries.

Regarding the fundamental macroeconomic factors, OECD countries' credit risk ratings and YTM are mainly correlated with the gross national income (GNI), the inflation (INFL) and the BLNC, while tax revenues (TAX) are interpreted rather differently by agencies and markets.

More specifically TAX is negatively correlated to credit risk, but positively related to YTM. A possible explanation is that markets interpret an increase in tax revenues as a clear sign of economic distress, while agencies interpret it as an indication of adequate debt service ability. Concerning non-OECD countries, credit risk ratings and YTM are largely correlated with BLNC, DFCT and FDGDP (which in this case present a more anticipated behavior, being positively correlated to YTM). Tax revenues are negatively correlated to both ratings and YTM (though insignificant).

Figure 1.1. Scatterplot between YTM and NRI (2010) and bivariate regression line by OECD membership.



Finally, as shown in Table 1.6, the NRI is negatively correlated with all response variables for both sets of countries and exhibits a much stronger correlation for non-OECD countries presenting a first indication that our second hypothesis holds as well. Graphical depictions of these correlations are shown in Figure 1.1, along with overlaying bivariate regressions lines, one for each group of countries. A much steeper slope is discernible for non-OECD countries, suggesting a larger impact of NRI in this group of countries.

Table 1.5. Correlation Analysis

	RTGSP	RTGM	RTGF	YTM	NRI
RTGM	0.9831 *				
RTGF	0.9928 *	0.9858 *			
YTM	0.6309 *	0.6331 *	0.6436 *		
NRI	-0.8672 *	-0.8677 *	-0.8738 *	-0.5620 *	
BLNC	-0.3027 *	-0.2572 *	-0.2973 *	-0.2383 *	0.2848 *
CRED	-0.7507 *	-0.7674 *	-0.7657 *	-0.5743 *	0.7597 *
CRPT	-0.8814 *	-0.8806 *	-0.8790 *	-0.5160 *	0.8993 *
DFCT	-0.2652 *	-0.2203 *	-0.2475 *	-0.1291 *	0.2534 *
FDGDP	0.1921 *	0.1781 *	0.1874 *	-0.0121	-0.2499 *
FRDM	-0.6997 *	-0.6961 *	-0.6969 *	-0.4311 *	0.7344 *
GNI	-0.5594 *	-0.5496 *	-0.5784 *	-0.3424 *	0.5237 *
HDI	-0.8235 *	-0.8293 *	-0.8235 *	-0.4749 *	0.7450 *
INFL	0.5380 *	0.5189 *	0.5306 *	0.5760 *	-0.4317 *
PDGDP	0.0384	0.0048	0.0194	-0.2918 *	-0.0015
REV	-0.6340 *	-0.6372 *	-0.6269 *	-0.1988 *	0.5389 *
TAX	-0.3423 *	-0.3356 *	-0.3289 *	-0.0394	0.3013 *
UNPL	0.3774 *	0.3663 *	0.3801 *	0.3726 *	-0.4139 *

Note: *denotes statistically significant values at the 5% level using a two-tailed test.

1.3.4 Is a country's e-readiness inversely associated with its credit rating and cost of debt?

In light of the methodological considerations above, our discussion will be focused on the random effects estimation that appears in Table 1.7. We employ a backward selection stepwise procedure with a 0.05 significance level for removal from the model. We then rerun the model including only the regressors that our selection strategy suggested as having a statistically significant impact.

As we already explained we estimate an ordered probit random effects model for credit ratings and since it is hard to directly grasp how large the effects of regressors through the ordered probit coefficients, we compute the average marginal effects and a panel linear random effects model for the cost of debt (YTM). In order to check the validity of the results of our model, we compare them with the corresponding results of the fixed effects model. Given the limited within-country variation of credit ratings, we added estimates only for the case of the cost of debt. According to the results, both models produce similar within panel effects and standard errors. Any discrepancies are mainly due to the inclusion of time invariant regressors. As such, we can assume that both models will perform equally well. In order to gain more insight on the interpretation of independent variables when computing marginal effects[13], ratings

[13] In order to preserve coherence we do not present marginal effects estimations, but calculations are available in Table 4.2 & Table 4.3 & Table 4.4 of the Appendix. An estimation of marginal effects on the subsamples is not attempted due to limited variation.

are merged following the characterization of debt as shown in Table 1.2.

Table 1.6. Correlation analysis for OECD (upper line) and non-OECD (bottom line) countries

	RTGSP	RTGM	RTGF	YTM	NRI
RTGM	**0.9569***				
	0.9708*				
RTGF	0.9829*	**0.9627***			
	0.9866*	**0.9729***			
YTM	**0.4307***	0.4934*	0.5078*		
	0.6293*	0.5835*	0.6087*		
NRI	**-0.6755***	**-0.6505***	**-0.6784***	**-0.3399***	
	-0.8070*	**-0.8193***	**-0.8239***	**-0.5866***	
BLNC	-0.3976*	-0.3102*	-0.3996*	-0.3506*	0.3985*
	-0.4267*	-0.3905*	-0.4303*	-0.3818*	0.3475*
CRED	-0.5456*	-0.6030*	-0.5817*	-0.4984*	**0.5553***
	-0.6372*	-0.6455*	-0.6501*	-0.6153*	**0.6889***
CRPT	-0.7708*	-0.7674*	-0.7475*	**-0.2967***	0.8147*
	-0.7843*	-0.7846*	-0.7877*	**-0.5052***	0.8289*
DFCT	-0.3762*	-0.3227*	-0.3614*	**-0.0043**	**0.4293***
	-0.3791*	-0.3353*	-0.3604*	**-0.3659***	**0.2340***
FDGDP	**0.0512**	**0.015**	**0.0272**	**-0.004**	**-0.2526***
	0.4603*	**0.4623***	**0.4785***	**0.4541***	**-0.4328***
FRDM	-0.6084*	-0.6001*	-0.5916*	**-0.1689***	0.6618*
	-0.5903*	-0.5943*	-0.5967*	**-0.4769***	0.6373*
GNI	-0.2427*	-0.1866*	-0.2627*	**-0.4590***	**0.1540***
	-0.2783*	-0.2535*	-0.3047*	**0.0270**	**0.3147***
HDI	**-0.7449***	**-0.7600***	**-0.7321***	-0.3450*	0.5711*
	-0.6380*	**-0.6285***	**-0.6333***	-0.2884*	0.5513*
INFL	**0.5833***	**0.5833***	**0.5805***	**0.6421***	-0.3019*
	0.4257*	**0.3983***	**0.4167***	**0.4616***	-0.3332*
PDGDP	**0.1006**	**0.0256**	**0.0712**	**-0.4409***	-0.1307*
	0.2804*	**0.2680***	**0.2684***	**-0.0971**	-0.1211*
REV	-0.3548*	-0.3635*	-0.3320*	0.0131	0.2327*
	-0.3091*	-0.2821*	-0.2809*	0.1232	0.1915*
TAX	-0.1262*	-0.1189*	-0.0893	**0.3347***	0.1009
	-0.1941*	-0.1660*	-0.1772*	**-0.1344**	0.1408*
UNPL	**0.3877***	**0.3935***	**0.4013***	**0.1580***	**-0.5607***
	0.2405*	**0.2184***	**0.2414***	**0.5556***	**-0.2259***

Notes: A star denotes statistically significant values at the 5 percent level using a two-tailed test Values formatted in bold depict statistically significant difference at the 5 percent level between the two correlation coefficients (Fisher Z's transformation).

As we explained earlier, the rating scale, running from a high of Aaa to a low of D, comprises 21 notches and it is divided into nine sections, from 'highest quality' to 'default' (see the columns 1 and 2 of Table 1.2). Sections are mapped into numerical values from 1 to 7 (see the last column of Table 1.2), which correspond to sections from highest (highest quality) to lowest (sections 'very high credit risk', 'near default', and 'default' are merged to a common section), respectively.

Overall, our results confirm our first hypothesis that a country's relative technological advancement on the field of information and communication, as proxied by NRI is inversely associated with credit risk ratings (as categorized above) and cost of debt (as measured from both YTM and exCoD), meaning that countries that score higher in NRI index, perform better on credit ratings and can borrow from financial markets at a lower cost. As we can see in Table 1.7, NRI seems to have only a long-run effect since all short-run coefficients regarding all regressions are insignificant. In the long run a marginal increase in NRI increases the probability of a debt characterization of one (highest quality) by 0.049 for S&P and by 0.035 for Fitch while reduces the probability of six (very high credit risk) by 0.022 for S&P and by 0.023 for Fitch. Moody's seems to place much more weight on technological diffusion since a marginal improvement in NRI would increase the probability of a debt being accredited as one of the highest quality by 0.115 and reduces the probability of six (very high credit risk) by 0.112. With respect to the cost of debt a point increase in NRI reduces the cost of debt by around one percentage point (p.p.)[14].

Concerning the macroeconomic fundamentals increased GNI drives ratings and cost of debt down mainly in the short-run, except S&P where both short and long-run coefficients are significant. Marginal effects suggest that for a marginal increase in GNI natural log, the probability of a debt characterization of one (highest quality) increases by 0.05 for S&P and by 0.75 for Moody's and Fitch, while the probability of a characterization of six (very high credit risk) falls by 0.025 for S&P, by 0.072 for Moody's and by 0.049 for Fitch. In the short run a 5% increase in GNI would improve YTM by 0.104 percentage points.

Domestic credit to private sector is found to be significant, in the long run, across both rating agencies and debt markets. The findings suggest that an increase to CRED (credit to private sector) improves both ratings and cost of debt. This benign effect can be justified by arguing that the higher the credit to private sector is, the more the financial resources for the private sector, which translates to higher financial development.

A growing inflation drives upwards ratings and yields to maturity in the short and in the long run with agencies weighing more a persisting inflation. More specifically a marginal increase in

[14] The last two columns of Table 1.7 report estimations with the exCoD as the proxy of the cost of debt. As in the case of the YTM, the results support our first hypothesis. The only differences are: First, the deficit is no longer statistically significant, and second, the E.U. membership or the legal background do not seem to be appraised by the markets. Although results could be seen as a robustness check to our findings, they should be interpreted with caution due to the incongruity of the regressant.

inflation in the long run reduces the probability of a debt characterization of one (highest quality) by 0.014 while only by 0.003 for a short-run marginal increase. The change in probability for Moody’s and Fitch is 0.01 and 0.002 respectively. In the long run a one percentage point increase of inflation would increase YTM by 0.5255 p.p. while in the short run the magnitude would be smaller and YTM would be increased by 0.2623 p.p.

Unemployment does not seem to have a significant impact on cost of debt (both YTM and exCoD), nevertheless, findings on the regressor provide us with interesting insights concerning ratings. In the short run, the coefficients are all positive and statistically significant, i.e., an increase in the unemployment rate deteriorates the creditworthiness of the borrower. In the long run the results are mixed. In the cases Moody’s and Fitch, the coefficients are negative and statistically significant, while in the case of S&P the coefficient is positive and statistically insignificant.

Regarding the governmental variables, tax revenues level does not seem to have a significant impact on cost of debt although all agencies evaluate excess taxation in the long run as an anguished effort to fulfil a country’s obligations by choking the real economy. On the other hand, an improvement on public revenues in the long run has a positive impact on ratings while markets seem to penalize it by 0.06 percentage points for one p.p. increase in public revenues. Public debt also seems to be perceived differently by debt markets and rating agencies. An increase in the regressor deteriorates S&P ratings, both in the short and long-run. In contrast, as we comment in Section 1.3, debt markets do not seem alerted by such an increase. They interpret it as a sign of indefinite sustainability and of a sovereign in good standing that is being able to refinance its debt [30].

Of course, public debt is closely connected with deficit, which agencies and markets in the short and long-run penalize as a clear sign of economic distress that hinders government’s ability to finance public debt and meet payment obligations. A one percentage point decrease in deficit would drive yields down by 0.16 p.p. in the long-run and by 0.1 p.p. in the short-run while a marginal decrease in the same regressor would increase the probability of a debt characterization of one (highest quality) by 0.45 for Moody’s and by 0.42 for Fitch.

Turning to the external variables, current account balance has an inverse impact on credit ratings in the long run across all agencies. A marginal improvement in current account balance in the long run increases the probability of a debt characterization of one (highest quality) by 0.54 for S&P and by 0.5 for Fitch while reduces the probability of a debt characterization of six (very high credit risk) by 0.24 and 0.33 respectively.

Table 1.7. Baseline Regression for all countries

	RTGSP Random Effects	RTGM Random Effects	RTGF Random Effects	YTM Random Effects	YTM Fixed Effects	exCoD Random Effects	exCoD Fixed Effects
NRI_AVG	-0.9493**	-1.6672**	-0.7406**	-1.0705*(*0.5241*)		-1.5178*(*0.7227*)	
NRI_DIFF/*NRI*	-0.0160	0.2149	0.0590	0.2961(*0.3048*)	0.3007(*0.2959*)	0.6291(*0.4119*)	0.6381(*0.4131*)
BLNC_AVG	-12.9623**	-3.3343*	-14.5711**				
BLNC_DIFF	0.3008	1.0677	1.3501				
CRED_AVG	-2.0741**	-2.0491**	-1.0924**	-1.8406**(*0.3964*)		-1.8618**(*0.7009*)	
CRED_DIFF/*CRED*	0.0234	-1.3390**	0.1967	0.3398(*0.4520*)	0.3345(*0.4388*)	0.4049(*0.6147*)	0.4175(*0.6168*)
CRPT_AVG	-0.9312**		-0.8924**				
CRPT_DIFF	-0.4555**		-0.3482*				
DFCT_AVG		-19.5601**	-17.7894**	-16.2059**(*3.9191*)		-9.4161(*7.0489*)	
DFCT_DIFF/*DFCT*		-3.7224	-8.5438**	-10.2233**(*3.0797*)	-10.3019**(*2.9890*)	-4.4077(*3.6796*)	-4.2857 (*3.6988*)
FDGDP_AVG	-2.3531**	0.8733*	3.8813**				
FDGDP_DIFF	0.4605	0.8507	1.3456*				
FRDM_AVG	-0.0060	-0.0350*	-0.0136	0.0932** (*0.0322*)		0.0680(*0.0447*)	
FRDM_DIFF/*FRDM*	-0.0672**	-0.0769**	-0.0864**	0.1091**(*0.0333*)	0.1086**(*0.0323*)	0.1693**(*0.0365*)	0.1710** (*0.0366*)
GNI_AVG	-0.5035**	0.0631	-0.0113	-0.0016(*0.1484*)		0.3937(*0.2350*)	
GNI_DIFF/*GNI*	-0.8471**	-1.5426**	-1.6311**	-2.1414**(*0.2580*)	-2.1448**(*0.2504*)	-1.7193**(*0.3278*)	-1.7456**(*0.3290*)
HDI_AVG		-6.1846**					
HDI_DIFF		-7.9324**					
INFL_AVG	0.2821**	0.2189**	0.3686**	0.5255**(*0.0843*)		0.0916(*0.0686*)	
INFL_DIFF/*INFL*	0.0476**	0.0182	0.0255*	0.2623**(*0.0377*)	0.2620**(*0.0366*)	0.1441**(*0.0200*)	0.1444** (*0.0200*)
PDGDP_AVG	4.5108**			-1.3147**(*0.4055*)		-1.9539* (*0.8188*)	
PDGDP_DIFF/*PDGDP*	2.2909**			-0.4818(*0.7956*)	-0.4782(*0.7724*)	0.7208 (*1.0611*)	0.6889 (*1.0646*)
REV_AVG	-14.2792**	-11.5038**	-13.2808**	5.9895*(*2.8614*)		4.1422(*4.8096*)	
REV_DIFF/*REV*	-1.9599	5.8054*	4.0767	8.9694(*5.6733*)	9.1622(*5.5043*)	9.4170 (*6.9471*)	11.4848 (*7.1120*)
TAX_AVG	5.5140**	12.1787**	11.5739**	2.2177(*3.0742*)		2.1716 (*5.5996*)	
TAX_DIFF/*TAX*	-1.6330	0.3424	-0.3119	-6.7262 (*7.1180*)	-6.5601(*6.9087*)	-7.5004 (*7.7395*)	-10.6957 (*8.2582*)
UNPL_AVG	2.1679	-5.5566**	-8.3161**	10.6447(*5.8985*)		-0.6510 (*5.5072*)	
UNPL_DIFF/UNPL	19.6414**	11.8290**	14.9329**	1.8043(*3.7385*)	1.8509(*3.6295*)	-1.4145 (*5.0297*)	-1.7243 (*5.0500*)
DFLT75		0.7604**					
DFLT95		-0.0266					
EURO	-1.0514**	-2.2684**	-3.7601**	-2.0932**(*0.3580*)		-0.9302 (*0.6788*)	
OECD	-1.8628**	-2.3598**	-2.4738**	-0.3571(*0.4024*)		-0.8044 (*0.6905*)	
LGLGRM	-0.3240	0.6872	-0.1900				
LGLSKN	2.0081**	-1.2656*		-0.7012(*0.5837*)		0.1034 (*1.1334*)	
LGLSOC				-3.7988**(*0.5445*)		-1.5210 (*0.8040*)	
LGLUK	-1.1076**	-0.9494**	-1.5279**	-0.9725**(*0.3600*)		-0.2561 (*0.5729*)	
_CONS				3.1581(*4.1059*)	49.9523**(*6.5306*)	-1.2251 (*6.9911*)	33.8872** (*8.1979*)
LogLik	-675.045**	-695.93**	-683.23**				
R-squared				0.7394	0.0635	0.5109	0.0023
Rho[a]	0.7954	0.7801	0.7723	0.1663	0.8939	0.3321	0.8075
N. Obs	650	650	650	360	360	496	496

Notes: In order for our maximum-likelihood estimation to converge, we merged S&P ratings between 17–20 to 17 (four changes made), Moody's ratings between 17–18 to 17 (two changes made) and Fitch ratings between 17-21 to 17 (one change made). The coefficient with the variable followed by_AVG denotes the long-run coefficient while the coefficient with the variable followed by _DIFF denotes the short-run coefficient. Errors are standard. (*) and (**) denotes statistical significance at 5% and 1%. Errors in parentheses provided for comparison reasons between fixed and random effects. According to the results, both models produce similar within panel effects and standard errors. Any discrepancies are mainly due to the inclusion of time invariant regressors. Therefore, it can be assumed that the correlation between the country specific error and the regressors is removed. Variables in italics represent the non-transformed initial variables used in fixed effects models.

[a]Fraction of variance that occurs at country level or the intraclass correlation.

Foreign debt as a fraction of GDP appears to worsen ratings for Moody's and Fitch in the long run. Notwithstanding, the effect is reversed when considering S&P ratings, a fact that at first glance appears puzzling. Further insight can be gained if one examines Table 1.8 and Table 1.9, which present results by country group. It can be easily seen that the effect is present for all rating agencies in the OECD group (Table 1.8), whereas for non-OECD countries the effect is reversed, and the coefficient signs are as one would expect (Table 1.9). The difference can be attributed to the fact that emerging markets are able to sustain less debt without driving up default risk, which is reflected in ratings. OECD countries on the other hand can sustain much higher levels of debt without prompting a deterioration of their creditworthiness due to accrued trust by global investors. Therefore, the puzzling results on Table 1.7 are a mix of these two effects and the weighting differences between the agencies in the determination of ratings.

Concerning the rest of the variables under study, history of defaults seems to be penalized only by Moody's; a eurozone membership is positively viewed across all agencies while markets decrease yields by 2.1 p.p., reflecting the widespread perception that currency unification would lead to a unification of credit risk for the country members (a perception that proved to be false). Being a member of OECD also leads to lower credit risk rating albeit markets do not seem to regard this membership as a significant determinant of the cost of debt.

The index of human development is significant for Moody's since a marginal improvement in HDI would increase the probability of a debt characterization of one (highest quality) by 0.68 in the long-run and by 0.42 in the short-run. Corruption and business freedom have also a significant impact on ratings in the long and the short run. A marginal improvement in corruption index in the long run where the magnitude is larger would increase the probability of a debt characterization of one (highest quality) by 0.067 for S&P and by 0.051 for Fitch while the probability of a debt characterization of 7 (near default or default) would fall by 0.023 for S&P and by 0.01 for Fitch. On the other hand, a marginal improvement in Business Freedom Index would increase the probability of debt characterization of one (highest quality) by 0.003 for S&P, by 0.006 for Moody's and by 0.004 for Fitch. Markets also seem to appraise changes towards a more liberal business environment positively, mainly in the short-run since a one-point increase in Business Freedom Index would reduce the cost of debt by 0.11 p.p.

A country's legal system that originates from UK seems to be evaluated as a safety valve by all agencies (always in comparison to the French legal system which is our base) and leads to one percentage point drop in the cost of debt, confirming that it is perceived as the safest legal system by investors. Scandinavian legal system origination seems to be evaluated differently by S&P (riskier than French) and Moody's (safer than French) while markets seem to place their trust, not only on Anglo-Saxon legal systems, but also upon countries that their legal system has a socialistic background.

1.3.5 Does a country's e-readiness have a different level of impact on its credit ratings and cost of debt depending on its development stage?

Following the same econometric procedure[15] we turn to our second set of hypotheses, which suggest that while NRI is inversely associated with credit ratings (as re-coded numerically) and cost of debt for the entirety of countries, it will have a much more severe impact on non-OECD countries' ratings and yields. Table 1.8 and Table 1.9 present the regression analysis for OECD and non-OECD countries, respectively.

Overall, the results seem to lend support to our second hypothesis. Short and long-run NRI coefficients are not statistically significant for OECD countries (except for Moody's were NRI enters the regression with the opposite sign in the short-run) while on the contrary, long-run NRI coefficients concerning the non-OECD countries are statistically significant across all agencies, presenting an inverse correlation with credit ratings.

Additionally, debt markets seem to put also emphasis to the technological performance of a non-OECD country by reducing their cost of debt by 1.1 percentage points for every additional point in the NRI they manage to reach. The findings allow us to suggest that concerning the non-OECD countries, agencies and markets distinguish the continuing and long-lasting efforts a country makes to advance its technological status, as an important determinant of its ability to service its debt in the future.

Regarding OECD countries, all agencies seem to consider mainly the current account balance in the long run. It is worth mentioning that in the short-run, Moody's appraise a decrease in deficit as a sign of economic distress and as an effort to cut down consumption. It is also interesting that for this group of countries and in the long-run, increases on average foreign debt signal a growing trust by the investors and drive credit ratings downwards while the short-run deviation from the average enters positively and significantly the S&P model, indicating the difference between long-run trust and short-run increased indebtedness.

[15] The last two columns of Table 1.7 report estimations with the exCoD as the proxy of the cost of debt. As in the case of the YTM, the results support our first hypothesis. The only differences are: First, the deficit is no longer statistically significant, and second, the E.U. membership or the legal background do not seem to be appraised by the markets. Although results could be seen as a robustness check to our findings, they should be interpreted with caution due to the incongruity of the regressant.

Table 1.8. Regressions for OECD countries

	RTGSP	RTGM	RTGF	YTM		exCoD	
	Random Effects	**Random Effects**	**Random Effects**	**Random Effects**	**Fixed Effects**	**Random Effects**	**Fixed Effects**
NRI_AVG	1.9970	-1.2055					
NRI_DIFF/ NRI	-0.3246	1.2638*					
BLNC_AVG	-45.1795**	-7.6187	-34.5925**				
BLNC_DIFF/*BLNC*	6.5342	25.1513**	8.0091				
CRED_AVG	-7.9416**	-3.4561**	-9.4273**	-0.4535(*0.2601*)		-0.1874(*0.4343*)	
CRED_DIFF/*CRED*	0.1472	-2.6696**	2.6770**	0.6297*(*0.2443*)	0.6294*(*0.2442*)	0.5767*(*0.2532*)	0.5765*(*0.2535*)
CRPT_AVG	-0.5485	-0.8984	-3.8723**				
CRPT_DIFF/*CRPT*	-1.6664**	-1.0718**	-1.4402**				
DFCT_AVG		-9.7951	-19.0273				
DFCT_DIFF/*DFCT*		-35.9636**	-7.5810				
FDGDP_AVG	-13.2815**		-23.0815**	0.8190(*1.0631*)		3.6116*(*1.5836*)	
FDGDP_DIFF/*FDGDP*	4.1157*		2.8425	0.7792 (*0.7635*)	0.7807 (*0.7631*)	0.3372(*0.7841*)	0.3383 (*0.7848*)
FRDM_AVG	-0.3188**	-0.2434*	0.1035				
FRDM_DIFF/*FRDM*	-0.1671*	-0.0114	-0.0666				
GNI_AVG			-3.5061**	0.0857(*0.0831*)		0.1029(*0.1402*)	
GNI_DIFF/*GNI*			-4.3677**	-1.7971** (*0.1882*)	-1.8002**(*0.1884*)	-1.6841**(*0.1926*)	-1.6865**(*0.1930*)
HDI_AVG			-30.2879				
HDI_DIFF/*HDI*			13.5892*				
INFL_AVG	1.8734**	0.6579**	1.5154**	0.7522**(*0.1066*)		0.1994**(*0.0453*)	
INFL_DIFF/*INFL*	0.3332**	0.5171**	0.2264*	0.1752**(*0.0349*)	0.1750** (*0.0349*)	0.0759**(*0.0120*)	0.0758**(*0.0121*)
PDGDP_AVG	10.3598**		10.8257**	-0.5811 (*0.3362*)		-1.3941**(*0.5040*)	
PDGDP_DIFF/*PDGDP*	9.0164**		14.9529**	0.5367 (*0.5426*)	0.5462(*0.5431*)	0.2394(*0.5578*)	0.2470 (*0.5588*)
REV_AVG	-31.9096**	-11.6464*	10.4693				
REV_DIFF/*REV*	9.6996	24.7771	15.3047				
TAX_AVG	22.8588**	2.5516	-4.2216	5.4154** (*1.8429*)		5.9048(*3.1526*)	
TAX_DIFF/*TAX*	1.0132	5.7536	0.2887	-2.6294(*3.4093*)	-2.4872 (*3.4360*)	-2.6414(*3.5067*)	-2.5258 (*3.5262*)
UNPL_AVG	34.1301	-6.8458	24.4086	6.3743 (*4.1697*)		5.5550(*7.0680*)	
UNPL_DIFF/*UNPL*	23.2029**	11.4162	-7.0706	-4.4668 (2.5749)	-4.4366 (*2.5754*)	-6.0340*(*2.5796*)	-6.0075*(*2.5832*)
DFLT75	0.9245	-0.0520	2.3060				
EURO	-1.2525	-4.0779**	-7.5500**	-0.4282 (*0.3056*)		-0.7703(*0.5123*)	
LGLGRM				0.4599(*0.2847*)		0.5611(*0.4865*)	
LGLSOC		-3.1069*	-16.4932**	0.3480 (*0.4161*)		1.5694**(*0.5880*)	
LGLUK	-5.1251**	-0.2477	-1.6057	0.3941 (*0.2208*)		0.7507*(*0.3541*)	
_CONS				-0.4144(*2.4612*)	52.2135**(*5.0817*)	-0.3058(*4.1762*)	49.9208** (*5.2293*)
LogLik	-129.879**	-142.723**	-105.669**				
R-squared				0.8162	0.1817	0.7815	0.1825
Rho[a]	0.9697	0.6785	0.2349	0.23179	0.9247	0.4985	0.9123
N. Obs	283	283	283	251	251	261	261

Notes: The coefficient with the variable followed by _AVG denotes the long-run coefficient while the coefficient with the variable followed by _DIFF denotes the short-run coefficient. Errors are standard. (*) and (**) denotes statistical significance at 5% and 1%. In order for our maximum-likelihood estimation to converge, we merged S&P ratings between (9–10 to 10, 12–13 to 13, 14–16 to 16) (four changes made); Moody's ratings between (8–10 to 8, 12–13 to 13) (four changes made) and Fitch ratings between (14–16 to 14, 11–13 to 11, 9–10 to 9) (eight changes made). Errors in parentheses provided for comparison reasons between fixed and random effects. According to the results, both models produce similar within panel effects and standard errors. Any discrepancies are mainly due to the inclusion of time invariant regressors. Therefore, it can be assumed that the correlation between the country specific error and the regressors is removed. Variables in italics represent the non-transformed initial variables used in fixed effects models.

[a]Fraction of variance that occurs at country level or the intraclass correlation.

On the other hand, public debt in the short and the long-run leads to a deterioration of ratings for S&P and Moody's. Inflation also leads to a deterioration of credit ratings on both short and long-run and across all agencies while unemployment's short-run deviation from the average enters positively and significantly only the S&P estimation. Eurozone membership and legal system originating from UK or having a socialistic background seem to have a significant inverse impact on ratings driving them downwards. On the other hand, debt markets seem to employ a rather limited number of determinants concerning the OECD cluster of countries and penalize a short-run expansionary credit policy, a short and long-run raise in inflation and a long-run raise in tax revenues considering such a raise as signal of unnecessary growth of public expenses that need to be financed and abstract resources from the real economy.

When attributing ratings to non-OECD countries, agencies, except NRI, seem to put emphasis on average current account balance and long-run fiscal balance (DFCT). In contrast to OECD countries, average foreign debt in non-OECD countries is a predictor of rating deterioration. Inflation in the long run and unemployment in the short run are also significant determinants of non-OECD credit risk ratings.

Concerning the cost of debt of non-OECD countries, in the case of the YTMs, no significant random effects were found to exist, probably because of the small sample that we had in our disposal and therefore no panel random effects analysis was performed. Instead, we carried out a pooled panel regression without breaking our variables in averages and deviations from the average. In the case of the exCoD, where we incorporate data from the JP Morgan Index, the results fail to lend support to our second hypothesis and NRI fails to enter the regression. The random effects specification cannot be considered as successful since none of the mean group centered variables enter the regression (see the 5th column of Table 1.9).

The findings suggest that apart from NRI, current account and fiscal balance, along with inflation, taxation and public debt are the main predictors of the cost of debt that non-OECD countries face. It is worth mentioning that taxation enters the cost of debt model with a negative sign meaning that for this group of countries markets consider increased taxes as a reassuring sign that the country will continue to meet its debt obligations. Moreover, and contrary to the findings concerning the OECD cluster of countries, increased public debt to GDP ratio impels a rise of interest rates. Prior default is also penalized by markets while a socialistic or an Anglo-Saxon background of the country's legal system enhances investor's trust to a country's creditworthiness.

Table 1.9. Regressions for non - OECD countries

	RTGSP	**RTGM**	**RTGF**	**YTM[a]**	**exCoD**	
	Random Effects	**Random Effects**	**Random Effects**	**OLS**	**Random Effects**	**Fixed Effects**
NRI_AVG	-0.7213*	-2.1971**	-2.0276**	-1.1046*	-1.1537 (*1.2058*)	
NRI_DIFF/*NRI*	0.2943	0.1813	0.4763		0.9711*(0.7850)*	1.0113 (*0.7749*)
BLNC_AVG	-11.4006**	-14.5229**	-6.0306**	-10.2203**	3.3979 (*7.2341*)	
BLNC_DIFF/*BLNC*	1.9284	1.9258	3.2939**		-13.9690***(4.4313*)	-14.5024** (*4.4444)*
CRED_AVG	-0.0362	-1.2085**	-1.6554**			
CRED_DIFF/*CRED*	-0.5611	-1.2824	0.7721			
CRPT_AVG	-1.4742**	-0.9524**	-1.1602**			
CRPT_DIFF/*CRPT*	-0.0507	-0.3091	-0.1939			
DFCT_AVG	-12.6801**	-12.8392**	-23.5866**	-29.8458**	-13.5030 (*14.8025*)	
DFCT_DIFF/*DFCT*	-2.4567	0.6823	-2.2534		-24.9572** (*8.1901)*	-23.3627***(8.1288)*
FDGDP_AVG	1.7713*	2.0171**	2.0624**			
FDGDP_DIFF/*FDGDP*	0.0353	-0.8175	-0.6669			
FRDM_AVG	0.0250	0.0373*	0.0164			
FRDM_DIFF/*FRDM*	-0.0731**	-0.1152**	-0.0877**			
GNI_AVG	-0.0881	0.1008	0.0884			
GNI_DIFF/*GNI*	-1.6114**	-1.6426**	-2.1620**			
HDI_AVG				13.8186**	0.4985 (*6.7467)*	
HDI_DIFF/*HDI*					3.0608 (*5.1786)*	3.3062*(5.1079)*
INFL_AVG	0.2147**	0.0525*	0.2048**	0.3334**	0.1892 (*0.1103)*	
INFL_DIFF/*INFL*	0.0364*	0.0197	0.0262		0.2171** (*0.0353*)	0.2169** (*0.0348)*
PDGDP_AVG	2.0969**			3.6511**	0.0812 (*1.9672)*	
PDGDP_DIFF/*PDGP*	0.1273				9.7197***(2.3009)*	9.4570** (*2.2810)*
REV_AVG	-7.6366**					
REV_DIFF/*REV*	-1.2424					
TAX_AVG				-14.6369**	-3.7755*(7.8559*)	
TAX_DIFF/*TAX*					6.1981 (*11.2446*)	-0.9853 (*12.0495)*
UNPL_AVG	2.7448	-2.4317	4.8072*			
UNPL_DIFF/*UNPL*	18.7531**	10.9957**	19.0432**			
DFLT95				2.7126*	-0.2993 (*0.8882)*	
EURO		-1.1997	-3.7517**			
LGLSOC				-3.4939**	-1.3015*(1.0429)*	
LGLUK	-0.8137**			-3.0371**	-1.7210 (*1.1446)*	
_CONS				1.4380	11.0552** (*3.8769)*	-5.5544 (*5.6985)*
LogLik	-464.119**	-487.904**	-465.914**			
R-squared				0.7699	0.3975	0.0333
Rho[b]	0.7063	0.7957	0.2349		0.2357	0.6493
N. Obs	367	367	367	109	235	235

Notes: The coefficient with the variable followed by _AVG denotes the long-run coefficient while the coefficient with the variable followed by _DIFF denotes the short-run coefficient. Errors are standard, (*) and (**) denotes statistical significance at 5% and 1%. In order our maximum-likelihood estimation to converge, we merged S&P ratings between (2–3 to 3, 17–20 to 17) (six changes made); Moody's ratings between (2–3 to 3) (one change made) and Fitch ratings between (2–3 to 3, 17–21 to 17) (three changes made). Errors in parentheses provided for comparison reasons between fixed and random effects. According to the results, both models produce similar within panel effects and standard errors. Any discrepancies are mainly due to the inclusion of time invariant regressors. Therefore, it can be assumed that the correlation between the country specific error and the regressors is removed. Variables in italics represent the non-transformed initial variables used in fixed effects models.

[a]The estimation for YTM is a robust standard error pooled panel regression without breaking the variables to averages and deviations from the average.

[b]Fraction of variance that occurs at country level or the intraclass correlation.

1.3.6 Robustness tests

1.3.6.1 Years of crisis

The burst of the economic crisis towards the end of 2007 and the deterioration of ratings and sharp increases in cost of debt that followed, necessitate the investigation of the stability of our estimated models before and after the beginning of the economic crisis. Both Chow test and the corresponding regressions of 2001–2006 and 2007–2010 can be obtained in Table1.10. Our null hypothesis, that our coefficients are constant across the two periods is strongly rejected for all our response variables indicating a possible break in time, around 2007 which coincides with the burst of the economic crisis.

In order to take a closer look since Chow test suggests a break, we re-estimate our models separately for the two periods. Interestingly, NRI in the long run is a significant predictor during the crisis years (2007–2010) for Moody's and Fitch, while for S&P the coefficient is very similar to this of the antecedent period albeit no longer significant. So, our findings suggest that our first hypothesis is quite robust despite time breaks and that NRI is an important predictor of credit ratings before and after the beginning of the economic crisis that could possibly have altered the determinants.

Concerning the other variables, it is striking that in relation to the current account balance and the crisis years, the long-run coefficients enter the models with a negative sign and the short-run with the opposite, indicating that for the period 2007–2010, agencies prize economic policies that aim in reducing deficits or enlarging surpluses but in the short-run consider balance deficit shortenings not a result of economic growth but as a result of economic distress that cuts down consumption. Other important differences that can be spotted between the two periods is the positive appraisal by agencies of the domestic credit to the private sector during crisis years probably as a reaction to recession and the significant effect of unemployment during 2007–2010 not only in the long but also in the short run. Regarding the debt markets, there is no evidence that a discernible changing context of determinants exist before and after the time break and NRI fails to enter the estimation model as a significant predictor in both periods.

1.3.6.2 Other measures of ICT diffusion

In order to check the validity of our results in case of alternative measures of ICT diffusion, we employ as regressors and alternative proxies of the e-readiness concept the EIU E-Readiness Index and the E-Government Readiness Index. We re-estimate equations (4) and (5) using the

Table1.10. Regressions 2001-2006 & 2007-2010. Robustness Check.

	RTGSP (Random Effects)		RTGM (Random Effects)		RTGF (Random Effects)		YTM (Random Effects)		exCoD (Random Effects)	
	2001-2006	2007-2010	2001-2006	2007-2010	2001-2006	2007-2010	2001-2006	2007-2010	2001-2006	2007-2010
NRI_AVG	-1.1246*	-1.4189	-2.2933**	-3.5412**	-1.1801**	-2.4594**	-1.2130	-0.3235	-1.5424	-0.4924
NRI_DIFF	-0.4644	1.7753	-0.0797	-1.3905	-0.2657	-0.8975	0.2480	0.8009	0.4075	-0.4786
BLNC_AVG	-20.0806**	-35.7416**	-7.0230**	-8.3607*	-2.2536	-21.9490**				
BLNC_DIFF	0.9820	10.7241**	1.0566	4.0135	1.8724	13.5271**				
CRED_AVG	-2.0009**	0.2328	-1.3376**	-0.9794	-0.5884	0.1156	-1.8433*	-1.2489*	-1.8958*	-1.0921
CRED_DIFF	0.2558	-6.1946**	-2.0847*	-5.9749**	0.7913	-4.6014**	-0.3233	0.3162	1.2091	0.7109
CRPT_AVG	-2.1804**	-4.2568**			-2.0490**	-2.5713**				
CRPT_DIFF	-0.4298	-1.5708**			-0.8126**	-1.2875**				
DFCT_AVG			-17.2623**	-51.9223**	-30.8700**	-65.1731**	-21.8161**	-11.6111*	-15.2995*	-5.1023
DFCT_DIFF			7.5653	9.6595*	4.2288	-12.3667**	-21.4751**	-4.9363	-4.6617	0.5892
FDGDP_AVG	-1.8166*	4.1952*	2.2424**	8.6832**	2.5374**	13.4406**				
FDGDP_DIFF	1.5802	-3.8567	-1.5892	4.8870*	0.2329	0.7233				
FRDM_AVG	0.0038	-0.0961*	-0.0099	-0.2288**	0.0086	-0.1387**	0.1145	0.0386	0.0931	0.0146
FRDM_DIFF	-0.1611**	-0.3176**	-0.1687**	-0.1134	-0.2308**	-0.1705**	0.1368**	-0.0590	0.1213**	-0.0130
GNI_AVG	-0.2080*	-2.7144**	0.5135**	-0.8148**	-0.2014*	-1.8940**	0.0186	-0.1194	0.5188*	0.0590
GNI_DIFF	-3.2423**	-0.5133	-2.6137**	-4.8249**	-4.0011**	-2.3393*	-2.4919**	1.9706	-3.0313**	-0.4553
HDI_AVG			-13.6316**	-16.7984**						
HDI_DIFF			-16.7481**	-7.0468*						
INFL_AVG	0.3792**	1.0128**	0.3229**	0.3995**	0.4823**	0.5706**	0.6184**	0.4526**	0.0637	0.4067**
INFL_DIFF	0.0534**	0.0088	0.0184	0.0040	0.0172	0.0273	0.2382**	0.1659**	0.0655**	0.4900**
PDGDP_AVG	4.1680**	10.0445**					-1.3363	-0.9074	-2.2244*	-2.0016*
PDGDP_DIFF	-0.3610	17.1438**					-1.3862	1.0592	1.1020	3.4871
REV_AVG	-21.0933**	-42.2974**	-10.6641**	-16.2706**	-15.1178**	-29.2464**	5.9783	4.5683	6.6803	-3.1940
REV_DIFF	-0.6190	-0.8925	5.8951	-2.4201	6.4834	-4.1452	18.5957*	8.8984	8.0605	-14.7761
TAX_AVG	17.8363**	21.5214**	10.8177**	4.4088	26.8880**	21.8595**	1.3922	2.9643	3.4743	2.5561
TAX_DIFF	2.8250	12.8688	0.9814	2.3078	-6.6258	12.1185	-10.4151	12.5373	-9.0952	15.8758
UNPL_AVG	2.5203	4.7304	-4.6412	-5.1004	-8.6640**	-10.2051*	10.5000	12.2188	0.4199	-2.5484
UNPL_DIFF	14.2640**	47.0723**	4.3369	22.9106**	1.7039	52.1652**	17.8124**	2.0151	8.0306	3.3600
DFLT75			1.0827**	1.0928*						
DFLT95			-1.3866**	-0.0721						
EURO	-4.2226**	-9.1480**	-4.2516**	-5.9915**	-7.1404**	-11.5476**	-2.1562**	-1.4238**	-1.4322	-0.0304
OECD	-3.2810**	-0.6369	-4.8434**	-3.2704**	-4.0773**	-2.9337**	-0.3486	0.2308	-1.0727	0.1989
LGLGRM	0.1056	-4.2086*	0.3076	-0.5696	-0.2589	-0.7651				
LGLSKN	5.9371**	5.4184**	-2.0400*	-1.0919			-0.1322	-1.0310	-0.2389	0.0379
LGLSOC							-4.7862**	-2.1552**	-2.6459**	-0.2143
LGLUK	-0.4447	-5.0808**	-2.4269**	-2.5724**	-3.4062**	-3.9920**	-0.9040	-0.4852	-0.7207	-0.9617
_CONS							1.6546	4.2392	-6.7170	6.5758
LogLik	-357.335**	-162.862**	-391.717**	-207.886**	-347.323**	-181.335**				
R-squared							0.7954	0.7591	0.6314	0.5762
Rho[a]	0.8434	0.9619	0.8993	0.9425	0.8917	0.9514	0.5774	0.2486	0.5218	0.2586
N.obs	390	260	390	260	390	260	216	144	299	197
Chow Test[b]	3.89**		2.87**		4.666**		3.08**		4.64**	

Notes: The coefficient with the variable followed by _AVG denotes the long-run coefficient while the coefficient with the variable followed by _DIFF denotes the short-run coefficient. Errors are standard. (*), (**) denotes statistical significance at 5 %t, 1 %. [a]Fraction of variance that occurs at country level or the intraclass correlation.

[b]The formula for the Chow test is: $\frac{\frac{ess_c-(ess_1+ess_2)}{k}}{\frac{ess_1+ess_2}{N_1+N_2-2*k}}$ and the resulting test statistic is distributed F(k, N_1+N_2-2*k). Our null hypothesis is that coefficients are constant across the two periods.

same set of control variables across all regression in Table 1.7. The results are presented in Table 1.11. Both the EIU E-Readiness Index (EIU INDEX) and the E-Government Readiness Index (E-GOV INDEX) are insignificant at the 5% statistical significance level, except the cases of RTGM and YTM, where the E-Government Readiness Index is significant at 5% and 1%, respectively.

The estimations using the EIU E-Readiness Index, and the E-Government Readiness Index are similar to the equivalent estimations using NRI. The only exception is the case of the E-Government Readiness Index, where in one case its regression coefficient has the opposite sign than that expected from our baseline regressions findings. Up to our knowledge, there are two potential explanations of the above finding. First, E-Government Readiness Index shows the level governments are aware and benefiting from ICT, and as such it does not reflect the concept of e-readiness to its entirety. Second, data for the index under consideration are available only for 2003, 2004, 2005, 2008, and 2010, i.e., half of our sample size.

1.3.6.3 Other overall measures of technology

In the current section, we test if alternative overall measures of technology provide some more insights than the e-readiness concept proxied by the NRI. Toward this end, we construct two such measures namely: patents per inhabitant (PTNTS) and internet users per inhabitant (INTUSRS). The first is constructed by adding the patents granted to each country by the European Patent Office and the United States Patent Office and dividing the sum by the country's population. The second is constructed by dividing each country's internet users again by its population. We test the NRI performance, after explicitly controlling for technological diffusion, by adding both variables as additional regressors in our baseline regressions. The results are reported in Table 1.12.

In the case of credit ratings, NRI remains statistically significant with comparable to the baseline regressions effects (Table 1.7) independent to the introduction of either PTNTS or INTUSRS. Instead, in the case of the cost of debt, NRI is no longer significant, although both the sign and the effect remain almost the same compared to those of the baseline regression (see Table 1.7). Moreover, if we substitute the regressant with the second measure of the cost of debt (exCoD) the NRI becomes again statistically significant with the correct sign when introduced in the regression together with PTNTS. Patents per inhabitant is insignificant in all cases but internet users per inhabitant can be seen as being interpreted similarly to NRI by the markets (but not agencies) because when introduced to the regressions, NRI becomes insignificant while

Table 1.11. Regressions with alternative proxies of e-readiness, total sample

	RTGSP (Random Effects)		RTGM (Random Effects)		RTGF (Random Effects)		YTM (Random Effects)		exCoD (Random Effects)	
EIU INDEX_AVG	0.0756		-0.3551		-0.3932		-0.7095		-1.0798*	
EIU INDEX_DIFF	-0.0793		-0.3151		0.2928		-0.2707		0.4907	
EGOV INDEX_AVG		0.0769		1.2474**		0.0913		-0.255		0.1441
EGOV INDEX_DIFF		0.143		0.083		0.0767		0.4340*		0.2677
BLNC_AVG	-21.3781**	-11.2316**	-8.1999**	-12.5804**	-5.6874**	-7.9844**				
BLNC_DIFF	5.1079**	-1.4827	4.8266**	3.4095*	5.3476**	1.2488				
CRED_AVG	-1.4199**	-1.8785**	-2.0396**	-2.3019**	-2.6436**	-0.9356	-1.8552**	-1.5333*	-1.8597**	-1.8988**
CRED_DIFF	0.3805	-0.2005	0.2822	-1.7271*	0.3085	-0.4738	0.3428	0.727	0.5981	-0.076
CRPT_AVG	-2.1486**	-1.4003**			-1.1144**	-1.4058**				
CRPT_DIFF	-0.8390**	-0.7500**			-0.6842**	-0.5292*				
DFCT_AVG			-28.6743**	-2.1532	-19.4839**	-15.2249**	-15.0591**	-14.8670*	-9.6251	-9.2703
DFCT_DIFF			6.4961*	-6.0094	-3.6556	-15.3080**	-10.6288**	-5.7945	-4.3464	-7.3563
FDGDP_AVG	-2.8024**	-2.8794**	2.4349**	0.5337	6.0862**	3.1809**				
FDGDP_DIFF	7.8812**	0.7017	5.9935**	2.5778*	8.3386**	1.1153				
FRDM_AVG	0.0048	-0.1408**	-0.0339	-0.3379**	-0.0615*	-0.1508**	0.1214*	0.0779	0.1037	0.0095
FRDM_DIFF	-0.0501	-0.0355	-0.0623*	-0.0423	-0.0696*	-0.0322	0.1196**	0.0737	0.1698**	0.1568*
GNI_AVG	-0.6543**	-0.9453**	-0.0113	-0.7818**	-0.1113	-0.8723**	0.0573	-0.025	0.4333	0.1362
GNI_DIFF	-1.3295**	-0.4661	-2.2102**	-1.3997**	-2.5637**	-1.5213**	-1.9254**	-2.1586**	-1.9400**	-0.4218
HDI_AVG			-7.2897**	-26.0877**						
HDI_DIFF			-9.6077**	-11.7332**						
INFL_AVG	0.4271**	0.2853**	0.4305**	0.2066**	0.1984**	0.2673**	0.5054**	0.6151**	0.0063	0.1842*
INFL_DIFF	0.0710**	0.0338	0.0229	0.0256	0.019	0.0267	0.2763**	0.3639**	0.1592**	0.2027**
PDGDP_AVG	5.7893**	5.0940**					-1.3152**	-1.5386*	-2.0030*	-1.9163*
PDGDP_DIFF	3.3664**	3.0471**					-0.6244	1.9429	-0.0595	1.9079
REV_AVG	-27.4883**	-23.8383**	-18.2798**	-14.3671**	-18.2013**	-16.3598**	6.4451	3.0877	5.9016	-3.4063
REV_DIFF	-6.6482*	-1.4823	2.5782	-1.6382	3.0967	0.7942	11.2746	-5.355	14.9208	-2.6734
TAX_AVG	13.1445**	12.6820**	3.9869	11.9538**	9.8890**	15.3338**	4.758	4.9987	5.7957	3.8368
TAX_DIFF	-3.7567	-2.599	-13.6511*	1.595	-6.8992	2.4957	-6.2944	-7.0685	-14.7519	12.4545
UNPL_AVG	15.0102**	13.6229**	1.5712	-22.3987**	22.9896**	-2.9153	14.4326*	14.0502	1.8062	1.6713
UNPL_DIFF	6.9450	23.9304**	3.1431	15.5387**	7.0609	17.4340**	1.234	-7.9154	-1.5318	-10.3711
DFLT75			1.7705**	2.2268**						
DFLT95			-0.8798**	-1.2830**						
EURO	-1.2289**	-1.5018**	-2.9056**	-0.4082	-4.6373**	-4.4391**	-2.0334**	-1.9049**	-1.1368	-0.2408
OECD	-1.3772**	-0.4447	-3.4959**	-1.4065**	-1.5374**	-0.0184	-0.1322	-0.1766	-0.5455	-0.4593
LGLGRM	-0.0421	-0.1645	-1.3138*	0.0082	0.521	0.0254				
LGLSKN	5.7561**	3.0595**	-1.3755	-2.5701**			-1.1393	-0.779	-0.8109	0.1221
LGLSOC							-3.9525**	-3.0599**	-1.9804*	-0.6457
LGLUK	-2.6457**	-1.6721**	-2.9786**	-1.6311**	-1.0852**	-1.0471**	-1.2400**	-1.3055*	-0.9219	-0.3666
_CONS							-1.2054	1.2552	-5.1552	3.069
Loglik	-416.13	-332.18	-416.58	-543.70	-414.09	-348.23				
R-squared							0.7425	0.7427	0.5283	0.5158
Rho[a]	0.8683	0.7806	0.7987	0.8478	0.8597	0.757	0.2635	0.4222	0.3224	0.3515
N. Obs	502	320	472	320	492	320	357	175	438	462

Notes: The coefficient with the variable followed by_AVG denotes the long-run coefficient while the coefficient with the variable followed by _DIFF denotes the short-run coefficient. Errors are standard. (*), (**) denotes statistical significance at 5% and 1%. [a] Fraction of variance that occurs at country level or the intraclass correlation.

INTUSRS exhibits statistical significance and the expected sign.

1.3.6.4 Channels of ICT impact

In order to further investigate the channels through which ICT affects the cost and rating of sovereign debt, we introduce in our model additional economic variables, such as the GDP growth (GDPG) and the natural log of the output per worker according to International Labor Office estimates (LPROD). The variables allow us to explicitly control for the effect of economic growth and labor productivity, respectively. The results are shown in Table 1.13.

In the short-term, GDP growth negatively affects both the credit ratings and the cost of debt (YTM and exCoD). In the long-term, the effect of GDP growth is still negative in all cases except the ratings published by S&P. The effect is statistically significant in the short-term (long-term) in the case of the credit ratings (cost of debt). The latter indicates that markets focus more on the long run growth (see [1], for similar results). Regarding the productivity growth as proxied by the labor production, the results indicate that it has a long-term effect [17]. In the short-term, its effect is statistical insignificant in almost all cases. In the long run, the effect is negative in all cases and statistically significant in most of them.

The NRI variable is statistically insignificant, as expected, in all cases but Moody's. The indirect nature of the e-readiness effect on ratings and debt, controlling for labor productivity and GDP growth forces NRI variable to become statistically insignificant. Otherwise it should be presumed that ICT have an impact on both cost of debt and ratings, through additional channels that have not been addressed in the current study. It is interesting though that in the only regression that GDP growth fails to enter as a significant regressant, i.e., Moody's, NRI remains statistically significant. Thus, ICT may have a more direct impact on ratings probably as a predictor of future growth, making concurrent growth rates less relevant to the assigned ratings. Overall though, findings lend support to the conjecture that the main channels through ICT impacts debt markets are labor productivity and growth.

1.4 Conclusions

In this chapter, we investigate the role played by ICT technologies in the assigning process of credit risk ratings by the three market dominating agencies (S&P, Moody's and Fitch) and the way debt markets appraise a country's level of ICT diffusion. In order to test our hypotheses, we use ratings and yields to maturity of ten-year zero-coupon sovereign benchmark bonds along

Table 1.12. Introducing number of patents or internet users in baseline regressions as a robustness check.

	RTGSP (Random Effects)		RTGM (Random Effects)		RTGF[16] (Random Effects)	YTM (Random Effects)		exCoD (Random Effects)	
NRI_AVG	-0.7152*	-0.7829**	-2.0419**	-1.9878**	-0.8398**	-0.9989	-1.0379	-1.7962*	-1.2660
NRI_DIFF	0.1109	0.0261	0.6664*	0.2276	-0.0157	0.2583	0.2346	0.4725	0.5097
PTNTS_AVG	-3.1767		-4.4085			-0.6349		0.5568	
PTNTS_DIFF	-9.1030*		1.812			-1.3747		-2.855	
INTUSRS_AVG		-1.6639*		1.2788	-1.2752		-0.1069		-1.5293
INTUSRS_DIFF		0.6995		1.8388*	2.5633**		-2.6015**		-7.0400**
BLNC_AVG	-8.5969**	-13.1163**	-14.3804**	-3.1830**	-10.6329**				
BLNC_DIFF	0.7785	-0.4070	0.9323	0.6215	0.9641				
CRED_AVG	-0.7947**	-1.2406**	-2.4674**	-1.8487**	-1.5046**	-1.8671**	-1.8360**	-1.9462**	-1.8800**
CRED_DIFF	0.3648	-0.3759	-1.3210**	-1.9599**	-0.5028	0.2118	0.6979	0.3516	1.3313*
CRPT_AVG	-1.5190**	-1.2838**			-1.1717**				
CRPT_DIFF	-0.5630**	-0.5027**			-0.3728*				
DFCT_AVG			-7.5424*	-19.9207**	-15.5727**	-17.2228**	-16.0318**	-9.4692	-8.1883
DFCT_DIFF			-0.2904	-1.4402	-4.9662*	-9.8400**	-8.9087**	-4.474	-3.2247
FDGDP_AVG	1.4521	-0.4892	2.0346**	1.7106**	4.0869**				
FDGDP_DIFF	5.5114**	1.7677	5.4005**	2.0087**	2.8446**				
FRDM_AVG	-0.0071	-0.0098	-0.0236	-0.0721**	0.0083	0.0980*	0.0923**	0.0704	0.0693
FRDM_DIFF	-0.0643*	-0.0856**	-0.0947**	-0.0950**	-0.1004**	0.1118**	0.1312**	0.1871**	0.1951**
GNI_AVG	-0.4129**	-0.2878**	0.0613	0.1138	-0.1932**	0.0297	-0.0103	0.4472	0.3782
GNI_DIFF	-1.0783**	-0.7392*	-2.0444**	-1.7438**	-2.0014**	-2.0308**	-1.3183**	-1.6621**	0.3679
HDI_AVG			-16.8709**	-3.8655**					
HDI_DIFF			-10.6222**	-7.1571**					
INFL_AVG	0.4546**	0.3123**	0.2449**	0.2858**	0.3427**	0.5155**	0.5272**	0.0632	0.0795
INFL_DIFF	0.0850**	0.0457**	0.0269	0.0185	0.0251*	0.2568**	0.2512**	0.1497**	0.1484**
PDGDP_AVG	2.4803**	3.0067**				-1.3381*	-1.3143**	-1.9725*	-2.0240*
PDGDP_DIFF	5.4276**	4.2142**				-0.4069	0.6084	0.3337	3.1429**
REV_AVG	-20.6497**	-15.4432**	-8.2587**	-11.2448**	-9.2871**	6.1604	5.9102*	5.2743	4.4948
REV_DIFF	-10.6892*	-3.8457	-1.6055	4.9805	2.2381	9.0643	7.3674	15.7345*	6.1358
TAX_AVG	6.9118**	7.6845**	1.1169	8.5064**	9.9127**	2.116	2.1666	2.5143	1.8649
TAX_DIFF	2.8854	-3.6267	-1.5574	-3.2721	-2.8883	-6.9574	-8.9627	-13.1004	-10.3927
UNPL_AVG	3.2864	-4.4886*	-21.1388**	-4.3963*	-5.4851**	10.2275	10.8215	-2.7914	-0.9388
UNPL_DIFF	11.0483**	20.4904**	7.6330*	13.0458**	17.4193**	2.6761	0.7777	0.298	-2.7079
DFLT75			1.9075**	0.5785**					
DFLT95			-2.0464**	-0.9841**					
EURO	-3.0787**	-2.1396**	-1.9597**	-2.5813**	-4.3686**	-2.1276**	-2.1032**	-0.9256	-1.0653
OECD	-1.2276**	-2.2256**	-1.3512**	-2.9103**	-1.5390**	-0.5489	-0.2965	-0.8745	-0.4374
LGLGRM	-0.1057	-1.2571*	1.2587*	0.4668	-1.6663**				
LGLSKN	2.0796**	2.5492**	0.5425	-0.0575		-0.6707	-0.7067	0.1116	0.0456
LGLSOC						-3.8028**	-3.7994**	-1.3695	-1.5004
LGLUK	-2.4889**	-1.6598**	-1.0965**	-1.1393**	-1.2017**	-1.1378*	-0.9674*	0.0117	-0.2586
_CONS						1.9785	3.3335	-1.7712	-1.4567
Loglik	-485.10	-623.10	-527.80	-673.42	-643.52				
R-squared						0.7417	0.7437	0.5158	0.5375
Rho[a]	0.8656	0.8181	0.8724	0.8229	0.7916	0.3823	0.1759	0.3515	0.3559
N. Obs	557	646	557	646	646	354	360	462	496

Notes: The coefficient with the variable followed by_AVG denotes the long-run coefficient while the coefficient with the variable followed by _DIFF denotes the short-run coefficient. Errors are standard. (*), (**) denotes statistical significance at 5% and 1%.

[a] Fraction of variance that occurs at country level or the intraclass correlation.

[16] We do not provide estimates for Fitch concerning PTNTS because our maximum-likelihood estimation did not converge.

with a balanced panel dataset of economic, financial and qualitative regressors, suggested by previous literature. Overall, our results confirm our first hypothesis that a country's e-readiness status in significantly associated with credit risk ratings and cost of debt. The findings corroborate the view that ICT, of which e-readiness is a metric of usage and diffusion have a long-run impact on important determinants of economic and financial policies like cost of debt and credit ratings that can possibly hinder or foster a country's prosperity. Based on our robustness checks, it could be suggested that since the NRI variable loses significance when economic growth and labor productivity enter the model, these are the main channels through which ICT impacts debt markets. Moreover, the results lend support to our second hypothesis as well, indicating that in developing countries, ICT play a much more crucial role in the assignment of credit rating and the cost of debt.

In line with the findings of [54,33,55] suggesting that ICT continue to expand their contribution to developing countries growth, our results provide an indirect indication that by putting more emphasis on e-readiness, developing countries can improve their prospects with rating agencies and debt markets.

Our findings also suggest that in the short run the most important determinants of credit risk ratings and cost of debt are GNI and unemployment while in the long run domestic credit to private sector, current account balance, public revenues and taxation seem to play a more important role. Inflation, budget deficit or surplus and public debt have an impact on the response variables in the short and the long run. Being a member of eurozone, a legal system that originates from Anglo-Saxon or socialistic legal traditions and no history of default are also found to be appraised positively by agencies and markets. The rest of the robustness checks suggest that e-readiness keeps on having a significant impact on ratings before and during crisis years.

A straightforward policy implication can be derived from our findings; investing in ICTs and their diffusion will not only contribute to growth directly and through spillovers but will ease, especially for non-OECD countries, access to debt markets.

One limitation of our research is that ICT may be an endogenous variable, because shocks to the cost of public debt may imply less public and private investment in ICT. Towards this end, additional research is needed to address the theoretical underpinnings of the link between ICT, sovereign ratings and cost of debt. Understanding the economic channels through these effects are running, may lead to a more comprehensive random effects econometric model, which deals with endogeneity issues. Finally, it should be acknowledged that we only provide a brief discussion on other metrics of ICT diffusion and mainly in a robustness context.

Table 1.13. Controlling for labor productiveness and growth, total sample.

	RTGSP (Random Effects)	RTGM (Random Effects)	RTGF (Random Effects)	YTM (Random Effects)	exCoD [b] (Random Effects)
NRI_AVG	-0.0876	-1.6920**	0.2459	0.0244	-1.0325
NRI_DIFF	0.0213	0.2012	0.0001	0.1864	0.3739
BLNC_AVG	-9.0355**	-0.743	-4.2766**		
BLNC_DIFF	0.678	1.3116	1.087		
CRED_AVG	-1.2338**	-1.6742**	-0.3074	-2.3418**	-1.4018
CRED_DIFF	-0.1593	-1.3364**	-0.0311	0.2904	-1.0616
CRPT_AVG	-1.3031**		-1.3877**		
CRPT_DIFF	-0.4424**		-0.3717*		
DFCT_AVG		-22.9847**	-24.5198**	-11.1986**	-6.2814
DFCT_DIFF		-2.7691	-5.9231**	-7.9223*	-0.5594
FDGDP_AVG	-4.8389**	0.8721*	3.7634**		
FDGDP_DIFF	0.2306	0.8535	1.1677		
FRDM_AVG	0.0450**	-0.0548**	-0.0264	0.0822**	0.0657
FRDM_DIFF	-0.0779**	-0.0776**	-0.0947**	0.1050**	0.1355**
GDPG_AVG	3.0755	-4.7191	-4.9139	-55.6289**	-0.4582
GDPG_DIFF	-4.3926**	-0.775	-4.4976**	-4.1456	-7.0129*
GNI_AVG	-0.3112**	0.1542*	-0.4366**	-0.1173	
GNI_DIFF	-0.4682	-1.3932**	-1.5288**	-2.3802**	
HDI_AVG		2.3165			
HDI_DIFF		-7.7415**			
INFL_AVG	0.3974**	0.2920**	0.3983**	0.5800**	0.1358
INFL_DIFF	0.0519**	0.0188	0.0274*	0.2519**	0.1488**
LPROD_AVG	-1.0922**	-0.8597**	-0.0804	-0.7548**	-0.5326
LPROD_DIFF	-2.1500*	-0.6373	-0.3307	1.4126	-2.7421*
PDGDP_AVG	4.4134**			-1.2004**	-1.6567
PDGDP_DIFF	2.4736**			-0.3895	1.5976
REV_AVG	-12.1798**	-10.5006**	-11.0002**	2.6087	9.0046
REV_DIFF	-1.0561	5.7291*	2.6431	6.5397	5.158
TAX_AVG	15.8569**	10.6704**	8.4098**	2.3078	-2.0125
TAX_DIFF	0.9084	0.681	0.9132	-6.2384	-1.981
UNPL_AVG	-1.4327	2.0566	-3.5243*	17.2574**	0.8622
UNPL_DIFF	20.0805**	12.3087**	15.5823**	1.0247	4.1917
DFLT75		0.7987**			
DFLT95		-0.7359**			
EURO	-0.4846	-2.0955**	-3.6932**	-1.8591**	-1.1133
OECD	-2.0211**	-2.8058**	-1.7975**	-0.3546	-0.3051
LGLGRM	-2.4228**	0.8053*	-0.4061		
LGLSKN	0.9796*	0.9675		-0.9417	-0.8909
LGLSOC				-3.3001**	-1.8886*
LGLUK	-2.8726**	-0.9841**	-1.4033**	-0.5633	-0.1938
_CONS				12.4686**	10.8841**
Loglik	-653.44	-689.61	-674.41		
R-squared				0.7587	0.4932
Rho[a]	0.8305	0.8020	0.7556	0.0734	0.3266
N. Obs	650	650	650	360	496

Notes: The coefficient with the variable followed by_AVG denotes the long-run coefficient while the coefficient with the variable followed by_DIFF denotes the short-run coefficient. Errors are standard. (*), (**) denotes statistical significance at 5% and 1%.
[a] Fraction of variance that occurs at country level or the intraclass correlation. GNI is dropped due to multicollinearity.

Therefore, in order to gain additional insights much further work should be done exploring the impact of other such measures on debt markets and credit ratings.

1.5 References of Chapter 1.

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2 CHAPTER 2[17].

2.1 Introduction

The primary factors that influence sovereign bond yields are typically domestic macroeconomic and financial fundamentals, as well as global factors such as international risk appetite and global liquidity [1], as indicated by a substantial body of literature (see, among others, [2,3]). Credit ratings are widely regarded as a standard mean of measuring a country's financial risk and play a critical role in assessing its overall risk profile [4]. Furthermore, international investors seeking to realize higher returns inevitably face higher risk and volatility and scarce relevant information when focusing on emerging markets [5]. As a result, they turn to credit ratings as valuable indicators of a country's capacity or willingness to meet its financial obligations. Hence, credit ratings can also be seen, as [8] suggest, as a reflection or proxy of domestic macroeconomic and financial indicators. If a financial market is fully efficient (in the strong sense) and there are no delays in the dissemination of information, rational market participants (as suggested by [1,2]) would have already factored in any changes in a country's fundamentals since the information is considered to be available to participants at the time of the credit issuance. Nevertheless, especially concerning emerging markets, information, in reality, is scarce, and as literature suggests [6], credit ratings convey some kind of extra information to markets and do have an effect on spreads [7]. Multiple studies [1,8] have yielded consistent results indicating that yield changes are more strongly impacted by negative rate changes, particularly shifts from investment grade to speculative grade, as opposed to upgrades. It should not be forgotten, though, that there is also a regulatory (Basel III Accord) reliance on credit ratings or sometimes an internal corporate policy that forces institutional investors, such as retirement and insurance funds [1], to invest exclusively in securities that enjoy an investment grade. The objective of this study is to evaluate two complex economic and social phenomena that have not been adequately explored in previous research as potential influences of sovereign credit ratings and bond yields. The two phenomena under consideration are the prevalence of information and communication technologies and the market-driven economic changes arising from the existence of a shadow economy. The motivation for this study should be attributed to the work of [9] concerning the shadow economy and [10] regarding ICT, which, to the best of our knowledge, first introduced the two phenomena in the

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relative literature.

[9] (see also [11]) provided empirical evidence that economies with large informal sectors have a greater propensity to default. Inevitably, diminished public revenues lead to fiscal deficits that a government has three ways to finance: increase tax rates, posing the risk of prompting more businesses to shift to the shadow economy, resulting in reduced overall revenues; cutting down on public expenditures, running the risk of compromising the quality and range of public goods and services offered to citizens; and issue and sell more debt, risking an increase in its cost [12].

The link between the transformation of economies to economies of knowledge through ICT was intuitively recognized by [10], who claimed that given that the diffusion of ICT (the informational technological capacity was proxied by the use of mobile phones) shapes the future, the assessment of future creditworthiness should be determined to a certain degree by the level of ICT use. In this line, although no direct effect was found, [13] proposed that ICT is an important indirect driver of sovereign ratings and interest rates by facilitating economic growth and improving labor productivity, while the indirect effect seems to be larger for the leapfrogging developing countries.

Interestingly, some researchers [14,15] have shown academic interest in the link between internet penetration (which forms a significant aspect of the ICT revolution) and the size of the shadow economy. Their research has revealed a negative correlation that is particularly pronounced in the developing stage (as indicated by GDP per capita). In this chapter, we undertake a comprehensive examination, for the first time, of the relationship between ICT and the shadow economy with respect to both sovereign ratings and the cost of debt, both separately and in conjunction. We attempt to form an understanding of the links through a series of non-parametric and parametric machine-learning approaches. Machine learning algorithms, while an established workhorse (along with logistic regression) method concerning financial institution decision processes have not seen a proportional spread in academic literature related to the sovereign cost of debt. This happens mainly because the focus of this literature is on comprehending the underlying mechanism rather than solely on prediction. Most machine learning algorithms have long been considered “black boxes” [16] and therefore unsuitable for providing information on the structure of the relationship between dependent and independent variables. The evolution of model intrinsic and model agnostic interpretability methods [17] allows the shedding of light on the underlying mechanism of machine learning algorithmic predictions.

Our analysis offers a continuation of the current empirical literature by providing additional insights into the significance of ICT diffusion and the size of the informal economy as factors influencing ratings and rates. Furthermore, it is the first to explicitly examine the potential additional impacts of these two variables while considering their primary effects. Secondly, our study suggests the utilization of recurrent neural networks, which are highly flexible, able to approximate non-linear relationships and deliver very promising results. Thirdly, we utilize state-of-the-art methods that make the behavior of the machine learning models somewhat explainable, enabling us to describe and quantify the effects being studied. Fourthly, this research adds to the crucial discussion regarding the significant role that ICT and the informal economy play in contemporary societies.

The rest of the chapter is organized as follows: Section 2.2 reviews the literature, focusing especially on the economic repercussions of the two phenomena that rating agencies and markets might take into consideration. Section 2.3 presents the empirical analysis. Section 2.4 provides some discussion on findings and policy implications, and finally, Section 2.5 concludes.

2.2 Related Literature[18]

2.2.1 Shadow Economy: Definition, Causes, and Effects

The traditional view of the shadow economy as a parasitic phenomenon [18] plagued with meager wages and poor working conditions [19] undoubtedly remains dominant among scholars and policymakers. A considerable amount of literature extensively discusses the negative impacts of the informal economy. One of the apparent consequences of this type of economy is the reduction of a government's capability to generate revenue through taxation. Since the primary focus of the informal sector is to avoid paying taxes, a large informal sector severely limits government revenues [20]. The impact of the shadow economy extends beyond just reduced public revenues; it also distorts important economic indicators, which can hamper the effectiveness of macroeconomic policies, as stated in previous literature [21]. Additionally, informal firms face limitations in accessing funding due to their hidden nature and avoidance of accumulating physical capital to avoid detection by tax authorities, which reduces their ability to operate on a larger scale and adopt technological innovations [22]. Therefore, because shadow activities tend to be concentrated in sectors of the economy that involve small-scale labor-intensive production with short cycles, the employment of low-skilled and less-experienced workers becomes unavoidable. Such sectors are usually agriculture, trade, construction, and low-added-value services. Therefore, it should be expected that in countries with large shadow economies, the above segments would become rather inflated, composing a large part of national output.

Furthermore, there is a body of literature that challenges the conventional notion that the shadow economy has only negative impacts on economic growth. Instead, some studies suggest

[18] A much more detailed depiction of the related literature can be found in Table 4.1 of the Appendix.

that, under certain circumstances, the shadow economy can have positive effects. One significant effect of the shadow economy is its potential to create employment opportunities [23] and ‘protect’ household incomes. According to [24], there is also evidence to suggest that in developing countries, there is a negative relationship between the informal economy and income inequality. Moreover, a large part of shadow activity earnings is eventually spent in the official sector [21,25], providing a significant positive stimulus effect on the formal economy and tax revenues [23]. It has also been proposed [26,27] that the informal sector may act as a buffer over business cycles since total employment, formal and informal, as a sum, is less volatile than each of them separately. Interestingly, while informal output seems to behave pro-cyclically and in tandem with official output, informal employment seems, in broad terms, to behave acyclically, meaning that it probably adjusts to economic cycles through changes in the level of wages and working hours and not in the number of employed [22]. From a neoclassical perspective [19], the informal economy is considered the optimal solution for fulfilling the demand for small-scale goods and personal or household services that maximize consumers’ utility. Thus, individuals who are willing to take higher risks and offer goods and services in the shadow economy are likely to have an entrepreneurial mindset, which can boost economic growth by increasing overall competitiveness, according to [21]. This may also compel firms operating in the formal sector to improve their productivity or exit the market [26].

2.2.2 Diffusion of ICT and Transformations of the Economy

Although scholars do not fully agree on the causal relationship between ICT and economic growth [28], a significant body of empirical research published since the early 2000s suggests that the accumulation of ICT capital, or capital deepening, promotes economic growth by increasing productivity. This is due to the availability of more and better capital equipment for workers [29]. The substantial drop in the cost of ICT equipment has resulted in two significant changes. Firstly, it led to the replacement of labor and non-ICT capital with ICT capital in ICT-using sectors. Secondly, changes in the organization of the ICT-producing sector have led to total factor productivity (TFP) gains across the industry [30]. According to [31], the theoretical bases for the positive impact of ICT on economic growth are the diffusion of knowledge, constant innovation, better-informed decision-making by economic agents, reduced costs of transportation, communication, and trading, and increased efficiency in logistics. However, to fully realize the positive effects of ICT, organizational transformation is also necessary.

The benefits of ICT are not limited to advanced economies. Developing nations provide internet and telephone services primarily through inexpensive and easy-to-implement mobile networks. Rather than using a closed-off approach, they focus on learning through experience and aim to entice foreign ICT investments, including capital and expertise. It is indicative that, concerning 2021 and according to the latest ITU estimations, mobile-cellular telephone subscriptions reached a penetration rate of 105.1% (it is remarkable that, as the World Bank (World Development Report, 2016) [32] highlights, in developing countries, more households possess a cellphone than have access to electricity or clean water) for developing countries as opposed to a rate of 134.8% for developed ones, both approaching saturation, while the penetration rate of fixed-broadband subscriptions reached 13% versus a 35.7% rate, respectively. Mobile telecommunications brought radical changes to a wide range of crucial areas for economic growth, introducing mobile platforms, mobile money, microfinance or microinsurance, m-government, m-health, and boosting education and women's entrepreneurship. The above functions affect economic development in several ways. Naming a few, digital ID alleviates severe weaknesses in civil registration systems that left millions of people without official registration documents, depriving them of opening bank accounts, registering property, or receiving social benefits [32]. Moreover, the implementation of a digital ID system permits the removal from the government payroll of "ghost" civil servants and strengthens electoral integrity. Mobile money, which started as an exchange of airtime credit, evolved in order to store credit on the SIM card [32] and became the most influential ICT enabler of financial inclusion [33] for millions of unbankable people. Such schemes made possible safe, low-cost transfers of small amounts of money to or from tiny or informal enterprises and women entrepreneurs with limited mobility due to cultural, religious, or practical reasons. M-health by providing disease surveillance and telemedicine; m-education by facilitating text message exchange between teacher and students or dispatching class tips to young and inexperienced teachers in rural areas; and m-platforms concerning the primary sector by providing information on prices, crop diseases, and potential buyers enable governments to provide innovative, low-cost solutions to long-standing deficiencies that undermine growth potential.

Conversely, there are worries about the negative consequences of ICT, particularly in terms of widening the digital gap between workers, which can negatively impact social unity and economic progress. Specifically, the increased use of ICT can lead to the replacement of unskilled labor with ICT capital and automation, which is likely to result in lower wages and job insecurity for low-skilled, low-paying, and less-educated workers [28]. As a result, opportunities for these individuals and their families are expected to diminish, leading to a reduction in social mobility.

2.2.3 ICT impact on shadow economy and possible interactions' effects

A relationship that has not been fully explored is the connection between the spread of ICT and the prevalence of the underground economy at a macro level [34]. This link has only recently been examined in academia, as seen in works such as [9,15,35]. The literature is still inconclusive about how different types of ICT interact with the underground economy, how their effects vary across different regions of the world, and also about the direction of Granger causality between ICT and the underground economy. [36] suggests that the Granger causality is bidirectional for both high- and low-income countries.

[34,35] argue that cell phones rather exacerbate the shadow economy, particularly in developing countries where broadband access is still scarce. On the contrary, high-speed internet connections seem to deter the phenomenon by enabling re-entry into formality through a greater positive productivity effect. The dual role that ICTs might play in the shadow economy also emanates from a sequence of other research papers [15] that provide mixed evidence.

Despite the potential risks associated with the underground economy, ICT presents clear opportunities for governments worldwide to combat the various factors that contribute to it. Governments can leverage ICT to reduce regulatory hurdles, enhance tax administration by adopting a more client-focused approach toward taxpayers, identify tax evasion schemes, and streamline the process of formalizing employment [37]. There is an abundance of such successful governmental policy measures; in Georgia tax reforms accompanied by a new electronic tax filing system led to an impressive 2.5 percent of GDP a year gain on tax revenues [38]; in Costa Rica, the digitization of tax registration records and company books was followed by a considerable decrease in informal employment and estimated informal output [26]; in Brazil, Peru and Estonia initiatives to enable the electronic registration of workers and the unification of data declarations to internal revenue service and ministry of labor were accompanied by increased registrations of first time workers and improved labor tax collections. In Section 2.2, we discussed how ICT can facilitate financial inclusion. As the financial sector continues to evolve and more intermediaries enter the market, the cost of credit will decrease. This, in turn, increases the opportunity cost for businesses that operate underground and are therefore excluded from official credit. Additionally, in the absence of access to formal banks, microfinance through mobile "accounts" can provide legitimate credit and security to those who have been excluded from traditional banking systems. Consequently, the financial development enabled by ICT can reduce barriers in obtaining credit and help transition informal businesses towards legitimacy [39].

Furthermore, ICT can promote transparency in government action in various ways. Firstly, internet-enabled technologies have allowed individuals to become providers of news and information, transforming the way information is consumed, created, and distributed, which enables whistleblowing and independent exposure to corruption incidents. Secondly, open government data have the potential, although not yet fully explored, to encourage collaboration between the government and stakeholders (citizens and businesses) to extract value from their use.

Table 2.1. Sampled Countries by development stage and region indicator.

Development Stage	West	Latin_Carribean	East Europe	Asia Pacific	Africa Middle-East
Developing		Brazil Colombia Costa Rica Dominican Republic El Salvador Jamaica Nicaragua Peru Trinidad and Tobago	Bulgaria Croatia Hungary Latvia Lithuania Moldova Poland Romania Russia	Azerbaijan India Indonesia Kazakhstan Malaysia Pakistan Philippines Sri Lanka Thailand	Egypt Ghana Jordan Morocco Qatar South Africa Tunisia Turkey
Advanced	Australia Austria Belgium Canada Denmark Finland France Germany Greece Iceland Ireland Italy Luxembourg The Netherlands New Zealand Norway Portugal Spain Sweden Switzerland United Kingdom United States		Czech Republic Estonia Slovenia	Hong Kong Japan Singapore South Korea	Israel

Note: Australia, New Zealand, Canada, the US, the UK, and the rest of the Western European countries, although not necessarily sharing geographic proximity, carry strong cultural and economic ties that permit financial spillovers and are grouped under the “West” label.

Thirdly, technologies such as blockchain, which are tamper-evident and tamper-resistant by definition, are suitable for secure document handling and identity management, which are crucial for reliable access to government e-services. Improved transparency in public administration, enabled by technological advancements, is a key factor in enhancing overall governance quality. Evidence shows that improving governance quality may help reduce the growth of the underground economy [18,36].

2.3 Empirical Application-Data and Sources

Our credit risk sample consists of 1029 (there are 11 country-year credit ratings missing, more specifically ratings concerning Moldova and Nicaragua and years 2011–2016). If no missing ratings existed in the sample, observations would amount to 1040 annual (end of the calendar year) observations of long-term foreign currency credit ratings of sovereign bonds assigned by Standards and Poor's rating of sixty-five countries (countries comprising our sample classified by region and development stage can be found in Table 2.1) for a time period of 16 years (2001–2016). Qualitative letter ratings are linearly transformed to numerical equivalents, with 1 representing the highest score (triple A) and 21 the lowest (default). As a result, a rise in the rating indicates a country's downgrading. We opt for Standard and Poor's rating among the major three rating agencies that dominate the market (the others are Fitch and Moody's) since there is some evidence in the literature [40] that S&P acted as a rating setter during the recent crisis and that downgrade announcements of the specific agency carry increased importance for markets. In any case, we do not expect our findings to be driven by the agency choice due to the close correspondence of the three agencies [41] and the extremely high pairwise correlation coefficients found in our sample concerning them (over 0.970 in all cases).

The sovereign cost of debt is proxied by the yield to maturity of the ten-year zero-coupon sovereign benchmark bonds; if this is not available, the closest maturity is chosen. If such data were completely unavailable, we filled, wherever possible, the dataset using the JP Morgan Chase Emerging Markets Bond Index Global (EMBI Global), which tracks total returns for traded external debt instruments in emerging markets. The cost of debt sample comprises 862 observations of sixty-one countries for a time span of 2001–2016 (on this occasion, there are 114 missing county-year observations).

The independent variables, and the focus of interest in this study, are ICT penetration and the extent of the shadow economy across countries. ICT penetration and usage among countries are measured by the NRI composite index (network readiness index). The index was not published for years 2017 and 2018 and was redesigned in 2019 by the Portulans Institute, losing its consistency. It was first published in 2002 (involving the year 2001) and aims to measure the multitude of ICT aspects that have an impact on economic development and society by assigning a score on a scale from 1 to 10, with the latter being the best possible grade. The index was, until 2016, published by the World Economic Forum, Cornell University, and INSEAD (The NRI, 2022), and therefore, despite some minor reviews, retained its consistency and suitability for use in a time-series framework.

Table 2.2. Definitions of (numeric) explanatory variables, data source, and expected sign.

Variable abbreviation/ Variable name	Definition	Source	Expected impact
nri/ Network Readiness Index	Published annually by World Economic Forum and INSEAD and ranges from 1 to 10 with higher values indicating a higher diffusion and use of ICT's.	The Global Information Reports	(-)
infrm/ Shadow economy	Shadow economy estimates across countries/years. (% GDP)	Medina and Schneider (2019)	(+)
blnc/ Current Account Balance	The sum of trade balance (goods and services exports less imports), net income from abroad and net current transfers. A positive current account balance reflects a country's net investment abroad while a negative current account balance reflects the foreign net investment to the country. (% GDP)	World Bank	(+/-)
exrate/Exchange Rates	Exchange rates as units of the local currency per US dollar	DataStream	
cred/Domestic credit to private sector	Refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of non-equity securities, and trade credits and other accounts receivable, that establish a claim for repayment. (% GDP)	World Bank	(+/-)
crpt/ Corruption perception index	The CPI scores and ranks countries based on how corrupt a country's public sector is perceived to be. It is a composite index, a combination of surveys and assessments of corruption and is published annually, ranging from zero (highly corrupt) to ten (highly clean). Scale has been reversed to avoid usual misconception that higher scores correspond to higher corruption.	Transparency International	(-)
lend/ Net lending or borrowing	Refers to government surplus/deficit under Excessive Deficit Procedure, which is net lending (+)/net borrowing (-) of general government (as defined in ESA95), plus net streams of interest payments resulting from swaps arrangements and forward rate agreements. (% GDP)	World Bank/ DataStream	(+/-)
resgdp/ Total reserves	Total reserves comprise holdings of monetary gold, special drawing rights, reserves of IMF members held by the IMF, and holdings of foreign exchange under the control of monetary authorities. The gold component of these reserves is valued at year-end (December 31) London prices. (% GDP)	World Bank/ Own calculations	(+/-)
gdpg/Gross Domestic Product annual growth	GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is expressed as a percentage that shows the rate of change from one year to the next.	World Bank	(-)
infl/inflation	As measured by the consumer price index. (%)	World Bank	(+)
pdgdp/ Public debt	Total debt owned by any level of the Government. It consists of all liabilities that require payment or payments of interest and/or principal by the debtor to the creditor at a date or dates in the future. (% GDP)	IMF	(+)
tax/ Tax revenues	Refers to compulsory transfers to the central government for public purposes. Certain compulsory transfers such as fines, penalties, and most social security contributions are excluded. (% GDP)	World Bank/ DataStream	(+/-)
unmpl/Unemployment	Refers to the share of the labor force that is without work but available for and seeking employment. (% of total labor force)	World Bank	(+)
trade/Aggregate trade	Refers to the sum of imports and exports of goods and services. (% of GDP)	World Bank/ Own calculations	(+/-)
lgopw/output per worker (log)	As measured by the output per worker expressed in constant 2010 US$. Natural log transformed.	International Labor Organization	(-)
vix/VIX index	Adjusted closing prices, year average. Natural log transformed. A benchmark index measuring market's expectation of future volatility. Sometimes called the investor fear gauge because it tends to rise during periods of increased anxiety in financial markets and of steep market falls.	Yahoo finance	(+)
risk_free/US short term yield curve. *(included only in YTM models)	Three months US yield curve. The three-month U.S. Treasury bill is a useful proxy because the market considers there is virtually no chance of the U.S. government defaulting on its obligations.	US-Department of Treasury/Own calculations	(+)

It should be noted, though, that concerning the year 2015, no assigned scores were published, and therefore we interpolated the missing values by using the inverse distance weighted method of non-missing values, with weights being reciprocals of the squared distance between values (since NRI scores do not change dramatically from year to year, this method allows for assigning more weight to the closest non-missing values). We expect higher values of the index to be associated with lower yields and better (lower) ratings.

The shadow economy estimates (% GDP) are those [25]. (To the best of our knowledge, these are the latest and most updated estimates up to 2017). In conjunction with the last consistent, in a time-series framework, publication of the NRI index (2016), the years under study cannot be significantly expanded. We expect higher values to be associated with increased yields and higher (or worse) credit ratings. Moreover, considering, on the one hand, the plethora of means that ICT delivers to the governments of developing countries to provide basic services and digitize parts of a fragile and vulnerable to corruption public sector and, on the other hand, the inverse relationship between ICT and shadow economies that is found in the literature [14], we expect that improvements on ICT diffusion will alleviate the positive (increasing) effects of large shadow economies on sovereign ratings and debt rates.

Furthermore, we employ a set of key economic variables that have been spotted in relative literature [8,42,43] as determining the capacity and willingness of borrowers to service their debt [44] along with factors capturing global conditions such as risk sentiment (VIX) and liquidity (risk-free U.S. rate). We include the specific variable only in bond yield models because it is not commonly included in modeling sovereign ratings in the relative literature.

Moreover, we use a set of dummy variables (mostly time-invariant) in order to capture a country's classification as an advanced or developing economy (*advanced*) (a definition taken by the Country Composition of World Economic Outlook Groups in 2012), eurozone membership (*eurozone*), a default after 1995 (*dflt95*), or common or civil origin of law (*lgluk*) (an abbreviation of the corresponding proxy binary variable). Countries with common law origin take the value of 1, zero otherwise, and regional effects (*West/Latin-Carribean/East Europe/Asia-Pacific/Africa/Middle East*) (binary indicators for region indicator). Additionally, a dummy variable proxies the period of extreme stress in global financial markets between 2007–2010. Definitions of numeric explanatory variables, sources, and expected impact signs are shown in Table 2.2, and overall descriptive statistics are shown in Table 2.3 and Table 2.4.

When assessing the determinants of the cost of debt, we employ ratings as an independent variable (in this case, we prefer a synthetic proxy constructed as the simple average of the assigned ratings of S&P, Moody's, and Fitch because there is no reason to believe that investors will not take under consideration, in a distinct but unknown to us ratio, all available information and therefore all assigned sovereign credit ratings by the three agencies, if of course available) driven by the “extra” information they might convey beyond economic fundamentals. Table 2.5 gives the Pearson correlation coefficients of dependent and explanatory variables. Notably, yields are mainly correlated (negatively) to ICT penetration and labor productivity and positively to assigned ratings, inflation, shadow economy and corruption. On the other hand, S&P ratings (and the synthetic metric based on the average ratings of S&P, Moody’s, and Fitch) are strongly (negatively) correlated to ICT penetration, labor productivity, and credit to the private sector, while positively correlated to corruption, the informal economy, and inflation.

Table 2.3 Summary statistics.

	Numeric Variables					**Binary Variables**							
	Obs	**Mean**	**Std Dev**	**Min**	**Max**			**Freq.**	**Percent**			**Freq.**	**Percent**
ytm	836	5.489	3.655	−0.362	23.490	Advance	0	560	53.85	asia_pacific	0	832	80
nri	1040	4.383	0.807	2.100	6.050	d	1	480	46.15		1	208	20
blnc	1040	−0.111	7.827	−29.824	38.304								
exrate	1040	235.598	1285.728	0.481	13,389.410			Freq.	Percent			Freq.	Percent
cred	1040	76.344	49.311	0.000	308.978	eurozone	0	827	79.52	africa_east	0	896	86.15
crpt	1040	4.489	2.238	0.100	8.200		1	213	20.48		1	144	13.85
infrm	1040	23.529	11.806	5.100	59.900								
lend	1040	−1.956	4.678	−32.076	21.764			Freq.	Percent			Freq.	Percent
resgdp	1040	17.793	18.061	0.343	120.840	West	0	688	66.15	dflt95	0	771	74.13
gdpg	1040	3.398	3.871	−14.839	34.466		1	352	33.85		1	269	25.87
infl	1040	4.246	4.878	−4.876	54.246								
pdgdp	1040	54.383	35.604	0.059	236.394			Freq.	Percent			Freq.	Percent
tax	1040	17.864	5.884	0.000	37.934	latin_carr	0	896	86.15	lgluk	0	801	77.02
unmpl	1040	8.003	4.538	0.150	27.800	ibean	1	144	13.85		1	239	22.98
trade	1040	94.667	68.091	19.798	442.620								
lgopw	1040	10.339	1.136	7.778	12.477			Freq.	Percent			Freq.	Percent
vix	1040	20.203	6.131	12.550	31.793	east_eur	0	848	81.54	gl_crisis	0	780	75
risk_free	1040	1.400	1.632	0.033	4.852		1	192	18.46		1	260	25

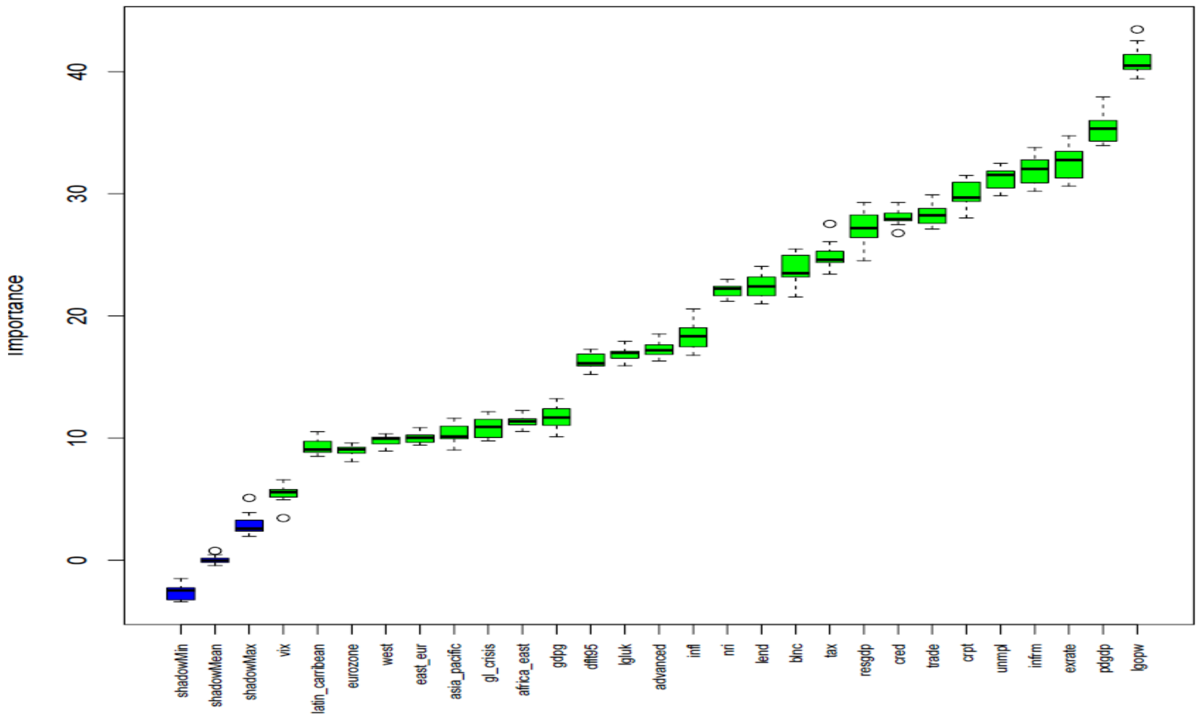
Table 2.4. Descriptive statistics.

	Numeric Variables					**Binary Variables**							
	Obs	**Mean**	**Std Dev**	**Min**	**Max**			**Freq.**	**Percent**			Freq.	Percent
ytm	836	5.489	3.655	−0.362	23.490	advanced	0	560	53.85	asia_pacific	0	832	80
nri	1040	4.383	0.807	2.100	6.050		1	480	46.15		1	208	20
blnc	1040	−0.111	7.827	−29.824	38.304								
exrate	1040	235.598	1285.728	0.481	13,389.410			Freq.	Percent			Freq.	Percent
cred	1040	76.344	49.311	0.000	308.978	eurozone	0	827	79.52	africa_east	0	896	86.15
crpt	1040	4.489	2.238	0.100	8.200		1	213	20.48		1	144	13.85
infrm	1040	23.529	11.806	5.100	59.900								
lend	1040	−1.956	4.678	−32.076	21.764			Freq.	Percent			Freq.	Percent
resgdp	1040	17.793	18.061	0.343	120.840	West	0	688	66.15	dflt95	0	771	74.13
gdpg	1040	3.398	3.871	−14.839	34.466		1	352	33.85		1	269	25.87
infl	1040	4.246	4.878	−4.876	54.246								
pdgdp	1040	54.383	35.604	0.059	236.394			Freq.	Percent			Freq.	Percent
tax	1040	17.864	5.884	0.000	37.934	latin_carribean	0	896	86.15	lgluk	0	801	77.02
unmpl	1040	8.003	4.538	0.150	27.800		1	144	13.85		1	239	22.98
trade	1040	94.667	68.091	19.798	442.620								
lgopw	1040	10.339	1.136	7.778	12.477			Freq.	Percent			Freq.	Percent
vix	1040	20.203	6.131	12.550	31.793	east_eur	0	848	81.54	gl_crisis	0	780	75
risk_free	1040	1.400	1.632	0.033	4.852		1	192	18.46		1	260	25

ICT penetration is strongly (positively) correlated to credit to the private sector and labor productivity and negatively to corruption and informality, which are also strongly and positively correlated between them.

Before proceeding with the main analysis and in order to secure the robustness of our models, we attempt to discard, if any, features[19] that are irrelevant or of little power. Thus, we employ a feature selection algorithm, Boruta[20], that adds randomness to the sample by duplicating the dataset and shuffling the values in each column, creating shadow features. Afterwards, the algorithm trains a random forest classifier in the extended data and checks if real features have higher importance than shadow ones. Nevertheless, in our case all the proposed features turn important without any ambiguity and therefore all the explanatory variables are included in our models. By far, the algorithm suggests as the most important determinant of credit ratings the labor productivity, followed by the ratio of public debt relative to GDP. The ratio of informal economy towards GDP seems to belong to a group of smaller importance along with unemployment, corruption, trade openness, credit to private sector and reserves to GDP rate while ICT penetration seems to belong to a third group of even lesser importance together with tax revenues to GDP ratio, current account balance and budget deficit.

Figure 2.1 Boruta selection algorithm. Important and unimportant features.



[19] Explanatory variables

[20] All models run on R and Rstudio platform.

We also test if the set of employed independent variables (including ratings; here we employ the average of the assigned ratings by the three agencies since this piece of information is also available to market participants) can discern between groups of countries of different creditworthiness or if we encounter an omitted-variable bias. For that purpose, we employ hierarchical clustering, an alternative to the k-means clustering approach that has the advantage of not needing a pre-specification of the number of clusters. Before applying the approach, all numeric variables are collapsed to their country means and scaled. Binary factor variables are set to their modes. The algorithm works in a bottom-up manner (agglomerative clustering), meaning that each country is considered a leaf (a distinct cluster), and at every next step, the pair of clusters with the minimum between-cluster distance are merged (Ward's method) until we end up with only one cluster (the root).

The dissimilarity between any two observations is measured by the parametric correlation distance, which is defined by subtracting the correlation coefficient from 1 and takes the following form:

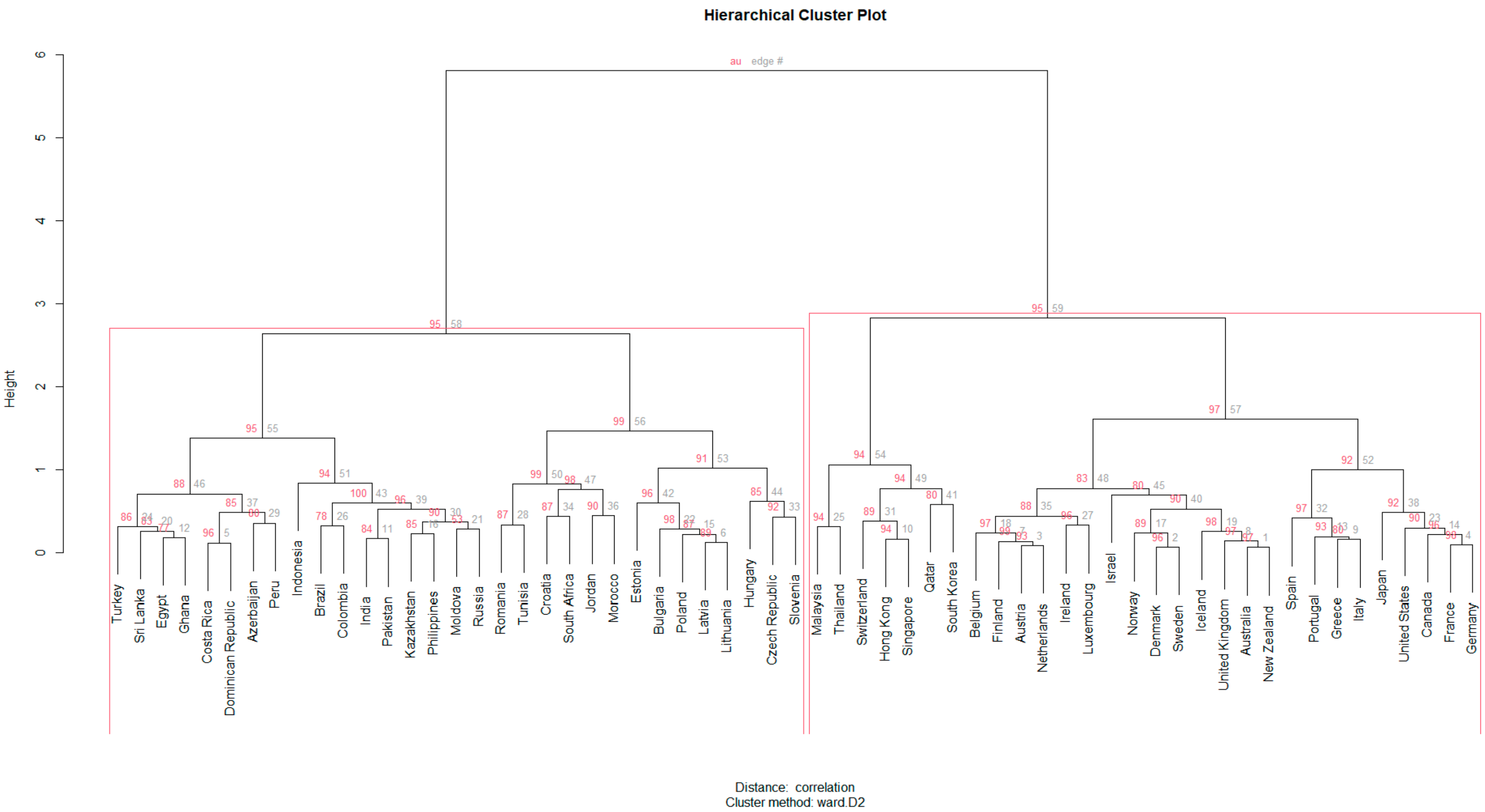
$$d_{cor(x,y)} = 1 - \frac{\sum_{t=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{t=1}^{n}(x_i - \bar{x})^2 \sum_{t=1}^{n}(y_i - \bar{y})^2}}$$

The distances are squared before cluster updating [45]. The cluster dendrogram generated along with approximately unbiased "*p*-values" of clusters support, calculated by multiscale bootstrap resampling, can be seen in Figure 2.2.

The two large groups (no. 56 and 57), generally corresponding to developing and developed countries, can be easily discerned and are strongly supported by the data (au >95%). However, this clustering is not very helpful in order to correctly identify the average expected cost of debt that a country will cope with, depending on its specific characteristics. Nevertheless, it can also be observed that with adequate confidence (au >= 94%), four distinct groups (no. 54, 55, 56, and 57) may be formed to provide us with quite a satisfactory clustering:

- *Cluster 57:* Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, United Kingdom, United States.
- *Cluster 54:* Hong-Kong, Malaysia, Qatar, Singapore, South Korea, Switzerland, and Thailand.
- *Cluster 56:* Slovenia, Czech Republic, Estonia, South Africa, Croatia, Poland, Latvia, Hungary, Lithuania, Romania, Bulgaria, Tunisia, Jordan, and Morocco.
- *Cluster 55:* Azerbaijan, Brazil, Colombia, Costa Rica, Dominican Republic, Egypt,

Figure 2.2 Hierarchical cluster dendrogram.



Notes: Values in red depict the approximately unbiased "*p*-values" calculated by multiscale bootstrap resampling. Cluster numbers in grey. Rectangles in red indicate the two main clusters supported by data (au > 95%). Conclusions about the proximity of two observations can be drawn only based on the height at which branches containing those two observations are first blended (bottom-up).

- Ghana, India, Indonesia, Kazakhstan, Moldova, Pakistan, Peru, the Philippines, Russia, Sri Lanka, and Turkey.

As we can see, the first group refers to countries that are considered to belong to the "West" or have successfully adopted Western-type institutions (e.g., Japan, and Israel). The second cluster comprises highly dynamic Asian economies with skilled labor and semi-democratic institutions, along with Switzerland and Qatar.

These two clusters are expected to be able to borrow with ease when needed. The third cluster consists mainly of ex-communist European countries rising rapidly along with African or Middle Eastern countries (South Africa, Tunisia, Jordan, and Morocco) that are more developed relative to their neighbors. This group is expected to attract investors through increased yields since it carries a higher risk than previous clusters. The last group is a mixture of South American, Eastern European, African, Asian, and Middle Eastern sovereigns that have a history of severe economic turbulence or defaults, and an unstable political environment and are obliged to cope with increased borrowing costs. Overall, the determinants seem to be able to distinguish, at least in broad terms, the different levels of credit risk depending on countries' specific traits and permit us to consider the choice of independent variables as adequate.

2.3.1 Non-Parametric Analysis of Sovereign Credit Risk

When we have a dataset and need to answer questions using machine learning techniques, it is typical to use multiple approaches and evaluate their effectiveness, according to [45]. A possible convergence of findings among different algorithms could lend us some confidence in our outcomes. Machine learning approaches are especially appropriate when dealing with complex situations [11] that lack a sound economic theory. The study (concerning empirical methods applied) that is closer to ours is that of [44] (see also [46]) that applies several artificial neural networks on a 16-point (classes) scale of 1383 annual observations assigned by eleven rating agencies; they manage to achieve a correct classification rate of 42.4% or 67.3% if predictions within one notch of the true rating are taken as correct. We employ these rates as the benchmark for our models since other similar studies have artificially limited the number of classes and therefore are not comparable to the present study.

2.3.2 Classification Trees and Bagging on Credit Ratings

Classification trees partition a dataset through an iterative process that splits the data into

Table 2.5.Pairwise correlation analysis among variables.

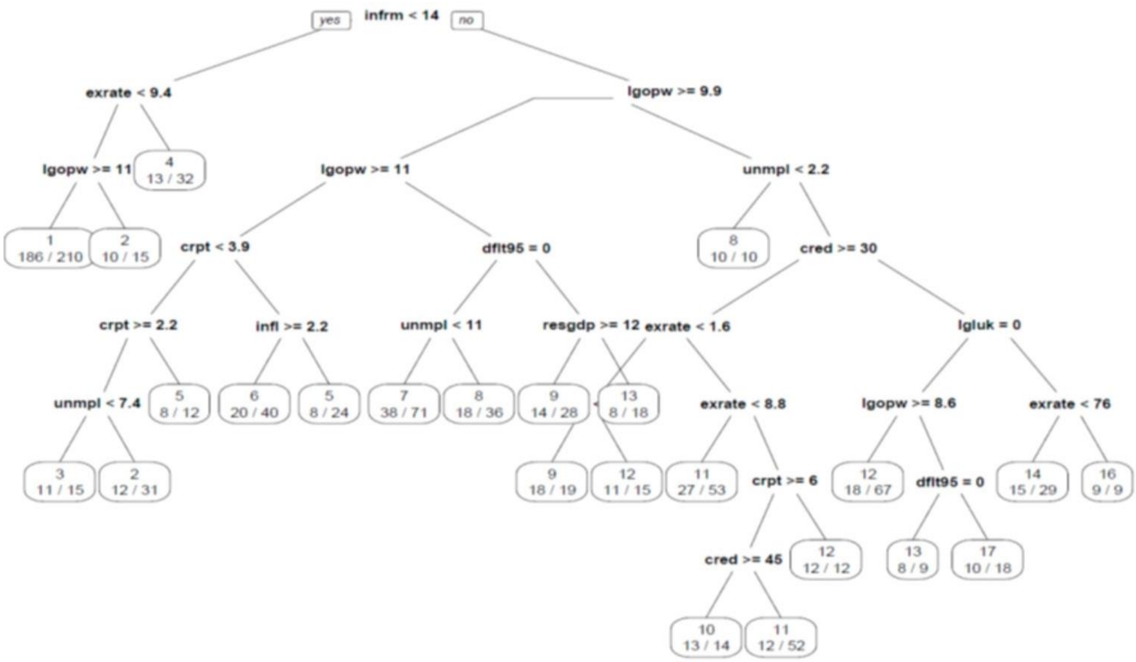
	ytm	avg_rtg	rtg_s&p	nri	blnc	exrate	cred	crpt	infrm	lend	resgdp	gdpg	infl	pdgdp	tax	unmpl	trade	lgopw	vix
ytm																			
avg_rtg	0.6918 *																		
rtg_S&P	0.6940 *	0.9933 *																	
nri	−0.6384 *	−0.8076 *	−0.8137 *																
blnc	−0.3131 *	−0.3412 *	−0.3532 *	0.4032 *															
exrate	0.1668 *	0.1851 *	0.1964 *	−0.1633 *	−0.0193														
cred	−0.4482 *	−0.5698 *	−0.5706 *	0.6415 *	0.1475 *	−0.1696 *													
crpt	0.5641 *	0.8439 *	0.8485 *	−0.8831 *	−0.3330 *	0.2133 *	−0.6209 *												
infrm	0.5795 *	0.7559 *	0.7606 *	−0.7978 *	−0.2087 *	0.0693 *	−0.5381 *	0.8409 *											
lend	−0.2293 *	−0.3154 *	−0.3134 *	0.2722 *	0.4328 *	0.0312	0.0606	−0.2587 *	−0.0836 *										
resgdp	−0.1399 *	0.0547	0.0406	0.0524	0.3575 *	−0.0414	0.1323 *	0.0215	0.0883 *	0.1920 *									
gdpg	0.0637	0.1882 *	0.1952 *	−0.2326 *	−0.049	0.1081 *	−0.2918 *	0.2335 *	0.2528 *	0.2693 *	0.1294 *								
infl	0.6615 *	0.4932 *	0.5014 *	−0.4831 *	−0.3033 *	0.1421 *	−0.3669 *	0.4841 *	0.4662 *	−0.0386	−0.0473	0.2048 *							
pdgdp	−0.1196 *	0.0083	0.0021	0.1300 *	0.0522	−0.1089 *	0.1547 *	−0.0945 *	−0.2055 *	−0.3962 *	−0.1284 *	−0.2705 *	−0.2486 *						
tax	−0.1674 *	−0.2741 *	−0.2761 *	0.2433 *	−0.1083 *	−0.1831 *	0.2326 *	−0.3854 *	−0.2824 *	0.1714 *	−0.2511 *	−0.1568 *	−0.1876 *	−0.0903 *					
unmpl	0.3072 *	0.4093 *	0.4027 *	−0.3837 *	−0.3131 *	−0.0033	−0.1450 *	0.3122 *	0.1898 *	−0.3441 *	−0.2232 *	−0.1528 *	0.0337	0.1498 *	0.1300 *				
trade	−0.2814 *	−0.2346 *	−0.2571 *	0.2785 *	0.4178 *	−0.1117 *	0.1470 *	−0.2893 *	−0.2080 *	0.2455 *	0.6177 *	0.0951 *	−0.1677 *	−0.1684 *	0.0553	−0.2294 *			
lgopw	−0.6083 *	−0.8273 *	−0.8334 *	0.8111 *	0.3048 *	−0.2351 *	0.5766 *	−0.8416 *	−0.8041 *	0.2353 *	−0.1327 *	−0.3393 *	−0.5178 *	0.1945 *	0.4126 *	−0.1428 *	0.2319 *		
vix	0.1481 *	−0.0487	−0.0512	−0.0296	−0.0464	−0.0212	0.034	−0.0143	0.0005	−0.1623 *	−0.0054	−0.3351 *	0.1311 *	−0.0461	−0.0069	−0.002	−0.013	0.0122	
risk_free	0.0562	−0.1260 *	−0.1213 *	−0.0177	−0.0690 *	−0.01	0.0246	−0.0624	0.0006	0.2601 *	−0.0816 *	0.2882 *	0.1106 *	−0.1447 *	0.0950 *	−0.0938 *	0.0139	0.0264	−0.1854 *

Note: *writing denotes statistically significant values at the 5 percent level (two-tailed tests). Listwise deletion when handling missing values.

homogeneous subgroups and then splits those subgroups (or branches) further until a certain criterion is met, a procedure known as binary recursive partitioning. Splitting the data randomly when constructing the train and the test set may cause data leakage since the time dimension would be ignored and we would try to forecast the past while we stand in the future, achieving an inflated rate of correct/near correct predictions. Therefore, we split our sample into two sequential periods: the first consists of years 2001–2013 (81.5% of total observations) and forms the training and validation set, and the second of years 2014–2016 (19.4% of total observations) and forms the testing set. Following a CART approach (classification and regression tree, developed by [47]), and after conducting a grid search in order to optimize the model's parameters, we set the minimum number of observations that must exist in a node in order for a split to be attempted to 25, the maximum depth of any node to 9 (the root node counted as 0), and define that any split that does not improve fit by 0.01 will be pruned.

Figure 2.3 visualizes the generated classification tree that uses 24 final nodes and a depth of eight levels to achieve a 55.54% (computed as relative error*Root node error) correct classification rate concerning

Figure 2.3 S&P rating classification using a CART decision tree. The tree considers all available ratings.



Notes: Numbers in nodes display the correct classification rate (correct classifications per number of observations in the node).

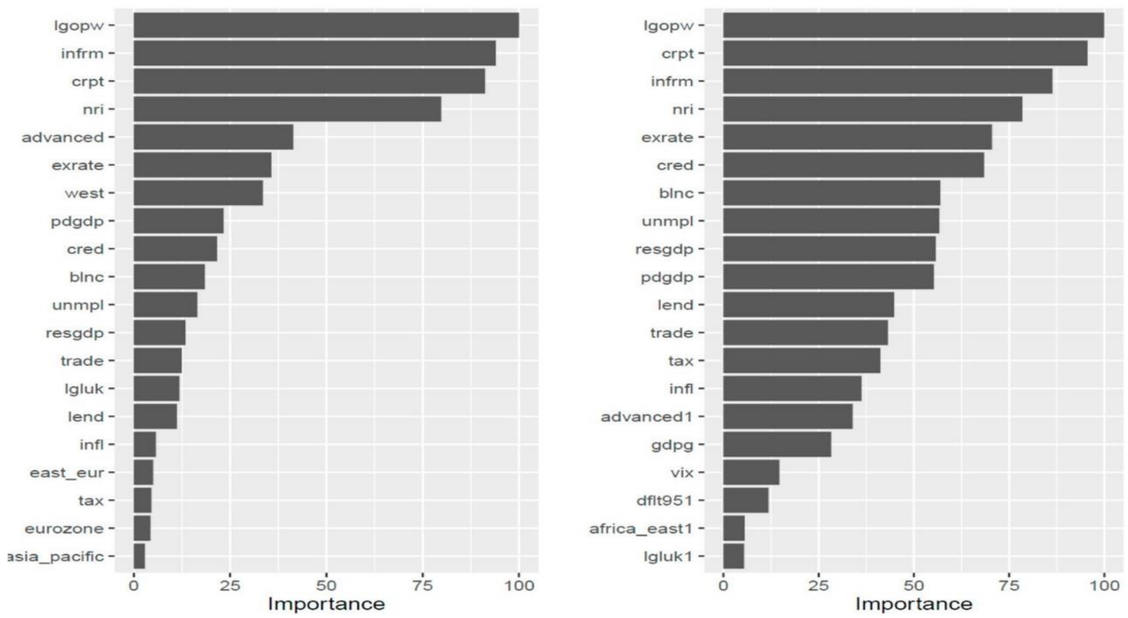
the training set and a rate of 48.2% on the testing set, which is quite satisfactory.

The default splitting criterion is the Gini index. (Alternatively, information gain can be used as the splitting criterion, but the classification rate does not improve substantially.) This is calculated by subtracting the sum of the squared probabilities of each class from one; therefore, it is defined as $Gini = 1 - \sum_{i=1}^{C} (p_i)^2$ and equals zero in the case of perfect classification.

As we can see in Figure 2, the size of the shadow economy (<14% of GDP) is the chosen feature basis of the root node. Given that a country confines the informal sector below 14% of GDP, if the local currency exchange rate to one US dollar is above 9.4 local units, the most probable anticipated assigned rate would be (AA-).

If, on the other hand, the local currency is stronger and, concurrently, output per worker equals or surpasses 59,784.14 constant 2010 USD per annum, the model predicts an AAA rating, otherwise an AA+. All branches of the presented tree can be read in the same way. Additionally, to gain a deeper understanding of the factors influencing a model's prediction (we note that a variable may score high without necessarily appearing in the tree [48]), we can measure the importance of the explanatory

Figure 2.4 Explanatory variables relative importance of S$P ratings single optimal classification tree (**left**) and bagging (**right**).



variables by summing the squared improvements across all internal nodes of the tree where each feature was selected as the partitioning variable, according to [45]. To gain a deeper understanding of the factors influencing a model's prediction, we can measure the importance of the explanatory variables by summing the squared improvements across all internal nodes of the tree where each feature was selected as the partitioning variable, according to [45]. The relative importance of the explanatory variables of our tree classification model is shown in Figure 2.4. While the classification rate of our optimal classification tree is quite satisfactory for a classification problem concerning 20 classes, single-tree models are notorious for suffering from high variance, i.e., small changes in the training set might cause great alterations to the model.

It has been proposed in the literature [49] that one way to overcome this deficiency is to average the outcomes of multiple models. Therefore, we use the proposed by [49] bagging (bagging stands for bootstrap aggregating) approach, which ultimately creates m bootstrap samples from the training set, and for each sample, a single, unpruned tree is trained while separate predictions from each tree are averaged in order to provide the finite predicted value.

This time, we repeat 10-fold cross-validation ten times in order to improve the estimation of the performance of our model. Following relative literature, the model’s performance improves significantly, not only concerning the cross-validation set, reaching a 70% correct classification rate, but more importantly, on the test set, achieving a rate of accuracy equal to 53.16%.

Relatively, the most important factors do not change dramatically, but we can discern that the CART method puts more emphasis on whether a country is considered advanced and whether it is a member of the “West”, while bagging relies more upon economic fundamentals.

Interestingly, ICT penetration and the size of the shadow economy are among the first four more important factors, with the most important being the workers’ productivity.

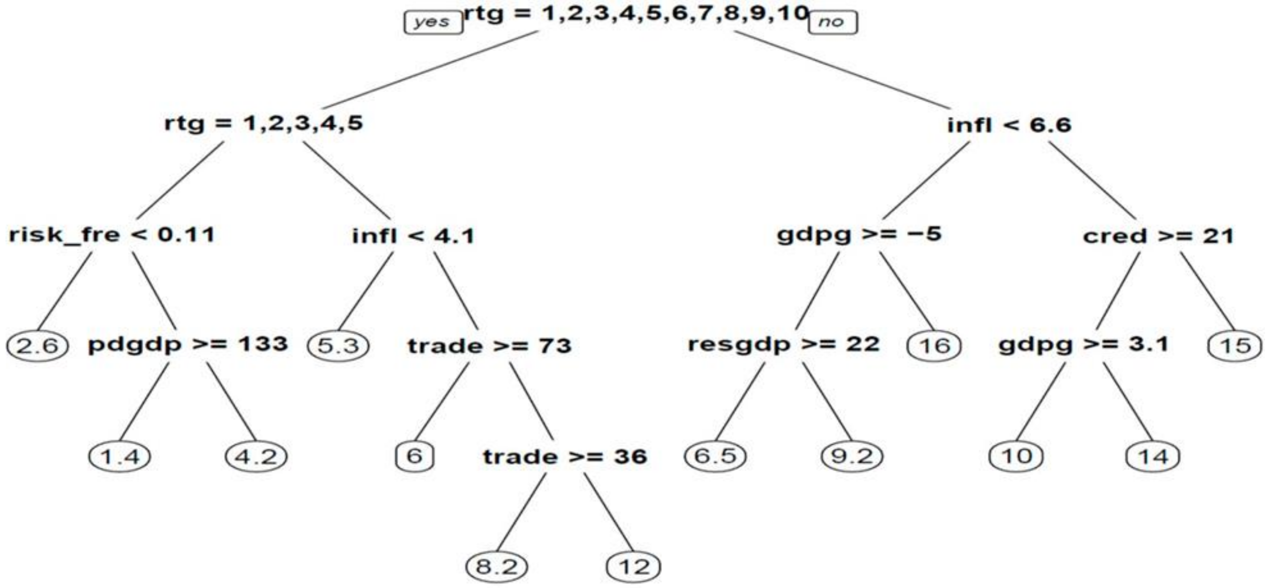
2.3.3 Classification Trees and Bagging on Bond Yields

Following the aforementioned methods, we split our sample into two sequential periods: the first consists of years 2001–2013 (78.8% of total observations) and forms the training and validating set, and the second of years 2014–2016 (21.2% of total observations) and forms the testing set. A ten-fold validation strategy is also implemented. A CART regression approach is similarly followed. After conducting a grid search in order to optimize the model’s parameters, we set the minimum number of observations that must exist in a node for a split to be attempted to 16, the maximum depth of any node to 12 (the root node counted as 0) and defined that any split that does not improve fit (overall R^2) by 0.01 should be pruned. Figure 2.5 visualizes the classification tree that uses 12 nodes and a depth of three levels to achieve a training error of 2.44 (computed as relative error*Root node error) and a testing error of 2.824. The optimizing criterion is a reduction in the sum of the squares of the residuals (SSE).

As we can see in the graph, the credit rating is the chosen feature basis of the root node, and countries that are assigned a rating between AAA and A+ while at the same time, the global risk-free rate is lower than 0.11% should expect, on average, a yield of 2.6%. If the risk-free rate is equal to or exceeds 0.11%, then the yield also depends on the public debt-to-GDP ratio.

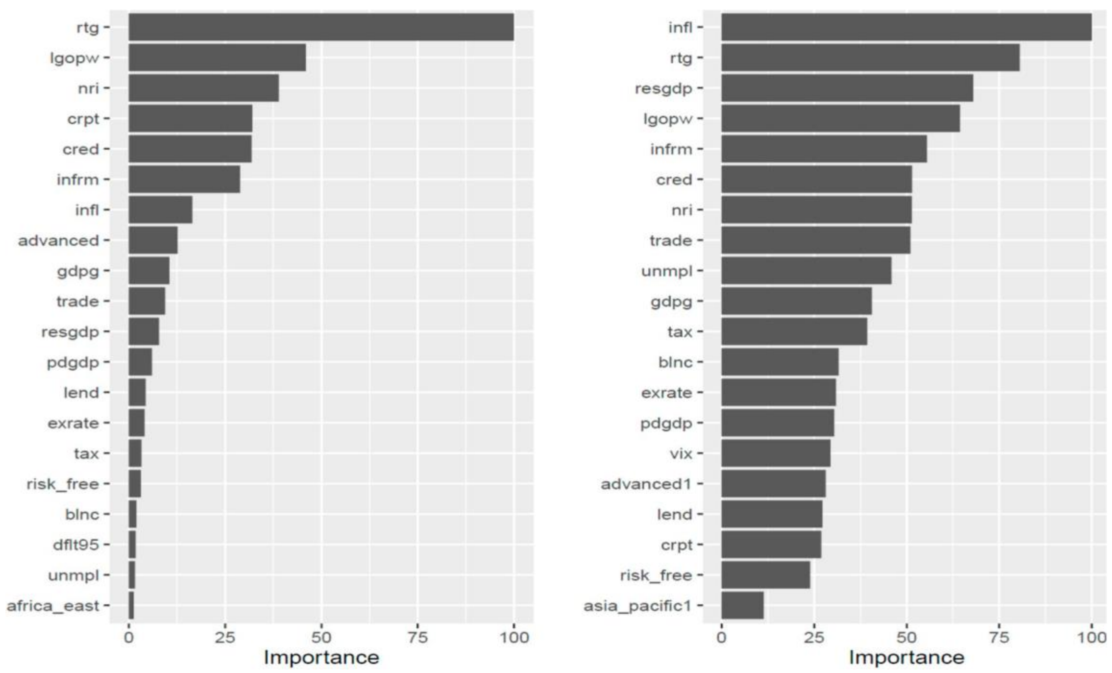
If the assigned credit rating is between A and BBB-, i.e., still in investment grade with strong or adequate payment capacity, the predictions are further split based on inflation and the country's openness to trade. On the other hand, if a country is assigned a non-investment grade, the predictions are split based on GDP growth and reserves to GDP or credit to the private sector and GDP growth.

Figure 2.5. Constructing a regression tree using the CART method concerning bond yields.



The relative importance of the explanatory variables of our tree regression model is shown in Figure 2.6, along with a similar bagging model.

Figure 2.6. Explanatory variable relative importance plot. Single optimal regression tree (**left**) and bagging (**right**) on bond yields.



As it is shown, the obvious most important feature (as expected) concerning the cart method is the assigned credit rating, followed by productivity per worker, ICT penetration, corruption, credit to the private sector, the magnitude of the informal economy, and inflation. The most noticeable difference between the two methods is that inflation and reserves relative to GDP are gaining importance with the bagging method. ICT diffusion and the informal sector are still important drivers of sovereign yields in the bagging model. It can also be seen that the stage of development and the period of crisis (2007–2010) are not playing an important role in determining yields. We should note here that our bagging model fails to improve the test data error rate, which remains unchanged at 2.85.

2.3.4 Random Forests on Credit Ratings

According to [45], although bagging regression trees can be seen as an improvement over a single tree model, which tends to have high variance, they still have the issue of tree correlation. A modification and remedy to this problem is the random forest method, which seeks to de-correlate the m-bootstrap sample trees by injecting randomness into the tree-growing process by limiting the candidate for split variables to a random subset. Furthermore, random forest models provide a method to approximate the test error without the need to withhold training data for validation purposes by utilizing the left-out data from the m-bootstrap samples, which are known as out of the bag (OOB) samples. Before running the model, a handful of tuning parameters was set through an extensive grid search. Concerning the number of variables randomly sampled as candidates at each split, the optimal number was set to 4, the number of trees to grow to 500, and the complexity of the trees, which is adjusted through the size of the nodes, to 1 (the smaller, the deeper); the OOB error rate for these parameters amounted to 27.29%. The accuracy rate of our model on the unseen (test) data increased slightly relative to the bagging model and reached a more than satisfactory 57.89% with a rather remarkable accuracy within one notch of 84.21%.

Clearly, the model finds difficulties in the area around the boundary of investing vs. non-investing grade predicting investing grade rating (BBB/9) for eight non-investing grade observations (see Table 2.6). An explanation could be that on this boundary, the assignment decision becomes even more subjective due to the profound implications.

For verification reasons, we present two plots of the variables' importance (Figure 2.7) the one (left) based on the impurity measure, which is actually the Gini index for classification, and the permutation, which breaks any association between the variable of interest and the outcome by permuting the values of all observations concerning the specific variable, computes again the accuracy and then calculates the difference. The calculation is repeated for all the random forest model trees and averaged. It seems that the importance of the workers' productivity is confirmed by the random forest model as well as the size of the informal sector and corruption. ICT penetration appears to hold a moderate but still important place as a potential driver of credit ratings.

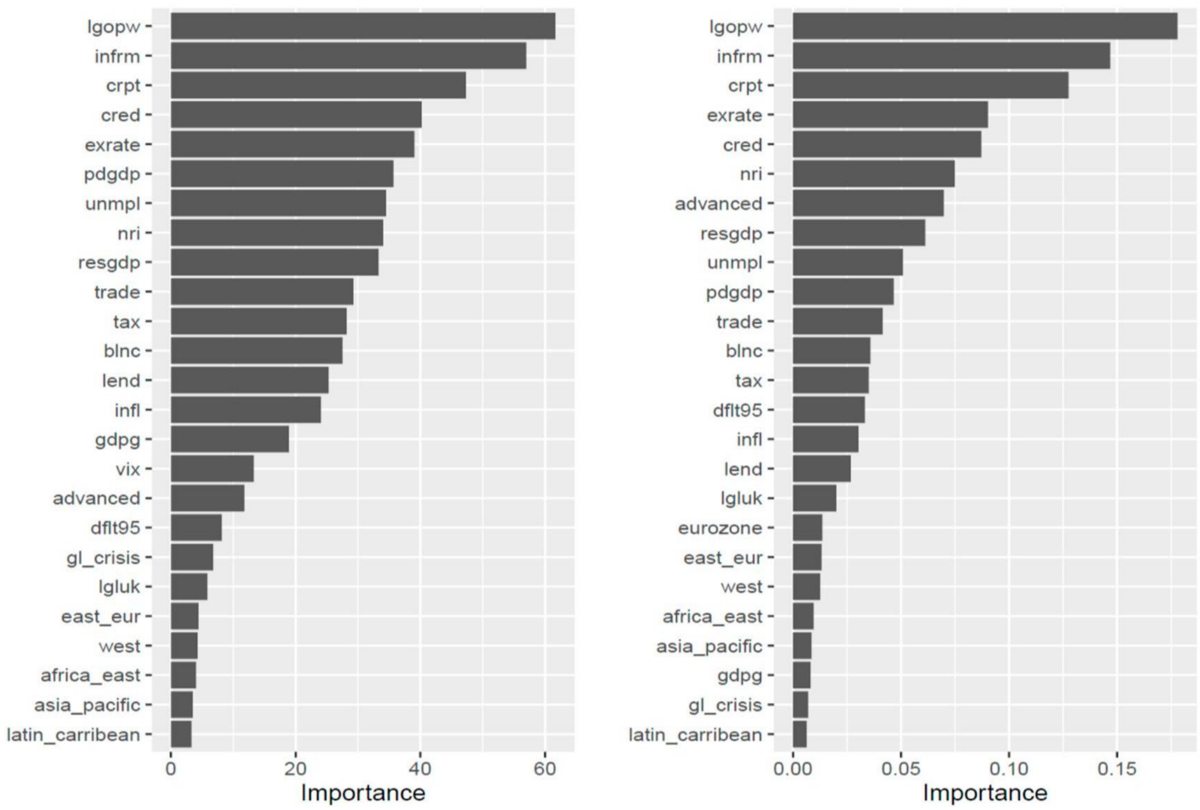
Table 2.6 Confusion matrix of random forest model

		Actual Rating									Ratings: 1 = (AAA) - 20 (CC and C)											
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**Accuracy**
Predicted rating	1	34	7	1	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	75.56%
	2	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00%
	3	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.00%
	4	0	0	0	7	2	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	58.33%
	5	0	0	2	1	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	57.14%
	6	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	66.67%
	7	0	0	0	0	0	0	8	1	0	2	0	0	0	0	0	0	0	0	0	0	72.73%
	8	0	0	0	0	0	1	2	5	1	1	0	0	0	0	0	0	0	0	0	0	50.00%
	9	0	0	0	0	0	0	1	0	3	8	6	2	0	0	0	0	0	0	0	0	15.00%
	10	0	0	0	0	0	0	0	2	5	9	1	0	0	0	0	0	0	0	0	0	52.94%
	11	0	0	0	0	0	0	0	2	0	1	5	3	0	0	0	1	0	0	0	0	41.67%
	12	0	0	0	0	0	0	0	0	0	1	3	4	3	0	0	0	0	0	0	0	36.36%
	13	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	33.33%
	14	0	0	0	0	0	0	0	0	0	0	0	0	1	4	0	0	0	0	0	0	80.00%
	15	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	3	0	0	0	0	42.86%
	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	7	1	0	0	0	58.33%
	17	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0.00%
	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

Overall accuracy rate = 110/190 = 0.5789)
Overall within one notch accuracy rate = 150/190 = 0.8421)

Notes: Ocher for correct classification, yellow for within one notch correct classification, red for prediction of investing grade but actual junk bond grade, green for non-investing predictions but actual investing grade. Blue for the significant failure of prediction: Iceland 2016, probably due to a sharp increase in public surplus/deficit from −0.792 to 12.429% that caused a one-notch upgrade and not eight as predicted.

Figure 2.7. Variable importance measures for the optimal random forest model based on impurity (**left**) and permutation (**right**).

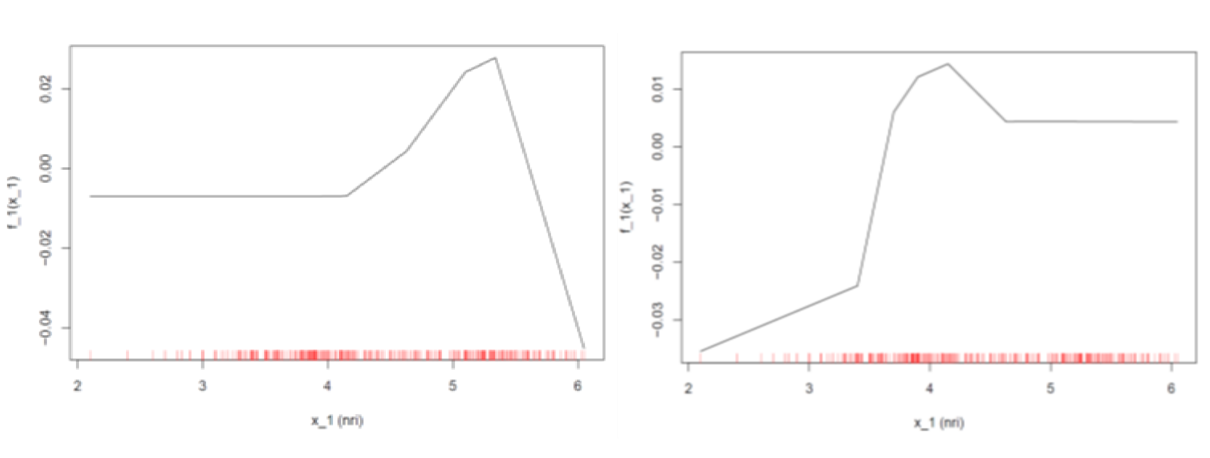


In order to shed some light on the behavior of the ICT penetration and of the size of the informal sector, we plot their accumulated local effects (ALE) plots, which describe how features influence the predicted outcome on average [50]. The output here should be interpreted as the vector of the change of predicted probabilities, as the variable of interest varies, one for each response class (20 rating classes in our case).

Therefore, we choose to present the plots only for the assigned ratings equal to (AAA) and (BB+) (first non-investment grade) in order to check the impact of the two predictors at the crucial points when a sovereign spares no effort to be assigned the covetable triple (A) or to avoid being degraded to a non-investment grade (or the contrary).

Concerning the case of the assigned rating is equal to AAA (left plot in Figure 2.8), we can see that when the ICT value is below 4.5, a mild negative constant effect equal to 0.005 decreases the probability of being assigned the specific rating, while an improvement of ICT penetration beyond this value raises the probability of being assigned a rating of AAA by about 0.02 with a diminishing trend after the ICT penetration index value surpasses 5.5. Similarly, when the assigned rating equals BB+ (right plot in Figure 2.8) and the value of the ICT index is below 4, the effect is negative but diminishes as ICT penetration rises to a magnitude of about 0.01–0.03, and as soon as the index breaches the above limit, the effect becomes positive, reaching a maximum of 0.01 and then falling again.

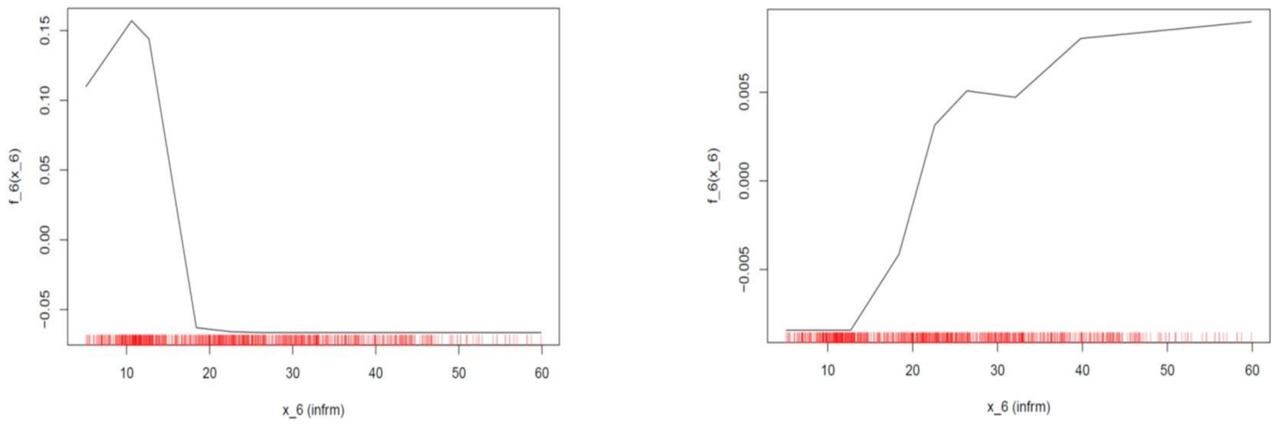
Figure 2.8. ALE plots of ICT diffusion when ratings equal AAA (**left**) and BB+ (**right**) (random forest model).



Note: The distribution of the independent determinant is depicted in red. If observations concerning specific areas of the model are limited, conclusions should be drawn with caution.

Similarly, concerning the impact of the size of the informal sector when the assigned rating equals AAA (left plot in Figure 2.9), we can discern that while the size of the informal sector remains under 10%, it has a positive impact of 0.1 to 0.15 on the probability of being assigned a rating of AAA, but as soon as the size exceeds that limit, the positive impact sharply decreases, and finally, after exceeding the ratio of 15% to GDP, the impact becomes negative.

Figure 2.9. ALE plots of the informal economy when ratings equal AAA (**left**) and BB+ (**right**) (random forest model).

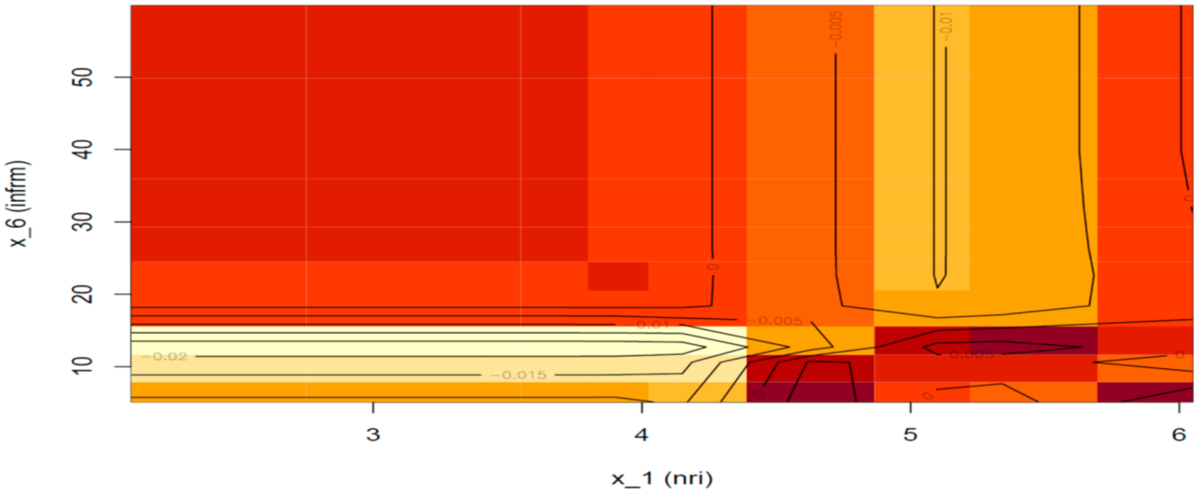


On the other hand, when the assigned rating equals BB+, the plot (Figure 2.9) shows that for the area between values 10–22% of the shadow economy, the impact is slightly negative (0.005–0.00), but when this limit is surpassed, the impact on the probability of being assigned a BB+ rating steadily increases (0.00–0.01).

Next, we consider the second-order effect of ICT penetration and the shadow economy (if any) on the prediction (Figure 2.10). The area of the plot that is formed when the ICT index is below 4.5 and the informal sector is under 10% will not be considered since the area is far from the data distribution; however, we can see that if the informal sector index ranges between 15–18%, a negative effect of magnitude 0.01–0.02 can be detected, while if the informal sector exceeds 20%, no additional effect is found. Moreover, we can see that if the ICT index is above 4.5 and at the same time the informal sector is confined below 15%, then the interaction of the two determinants adds another 0.005 to the probability of a sovereign being assigned a rating of AAA (lower right part of the plot). Nevertheless, if the informal sector exceeds 15% and the ICT index is larger than 4.5, the additional effect turns negative, with a magnitude ranging from 0.005 to 0.01.

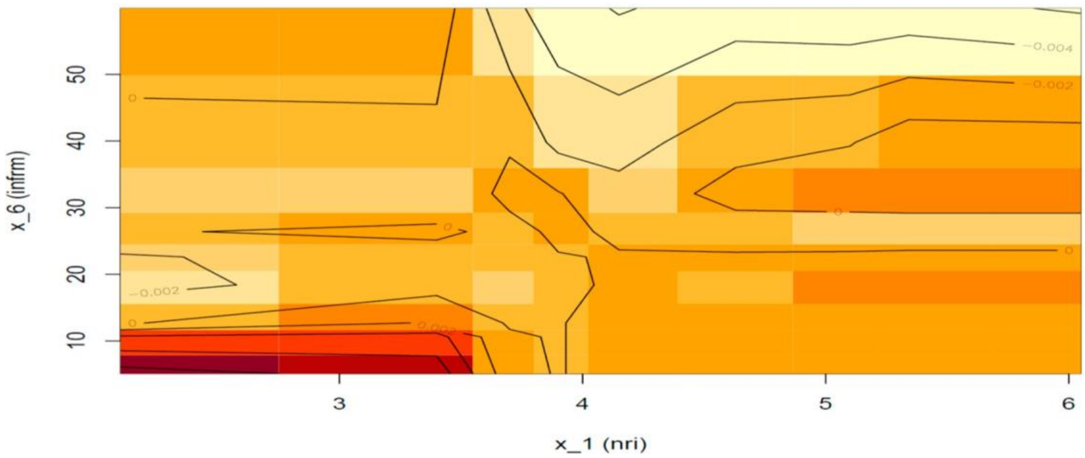
Figure 2.11 shows the additional net effect of the interaction of the two features when the assigned ratings are equal (BB+) but fails to detect any. Similar to the above, we will abstain from any conclusion driven not only from the red area of the plot but also from the top right area (yellow) because both areas are far from the data distribution.

Figure 2.10. ALE plot for the 2nd order effect of ICT penetration and informal sector random forest predictions when rating equals AAA.



Note: Red stands for positive effects (the darker, the stronger), and yellow for negative (the lighter, the stronger). In this plot, because impacts are mild, the red color on the left part of the graph stands for null.

Figure 2.11 ALE plot for the 2nd-order effect of ICT penetration and informal sector random forest predictions when rating equals BB+.



Note: Red stands for positive effects (the darker, the stronger) and yellow for negative (the lighter, the stronger).

2.3.5 Random Forests on Bond Yields

First, we tune several hyperparameters in order to adjust them until the validation error stops improving by a certain ratio. Concerning the number of variables randomly sampled as candidates at each split, the optimal number is set to 9 and the number of trees grown to 300; too many trees may lead to overfitting. Our random forest models succeed in reducing the validation error to 2.27 and the testing error to 2.57 (RMSE), while a pseudo-R-squared metric, {1-mse/Var(ytm)} indicates that the variance explained equals 79.03%. In Figure 2.12 we provide two measures of variable importance after recording the prediction error for each tree: the average difference, normalized by the standard deviation of the differences, between the mean squared error of every validation set with each predictor being permuted and the average total decrease in node impurities from splitting on each variable.

It can be observed that the random forest model considers a larger number of determinants in relation to the previous models and considers especially the risk-free rate, credit ratings, trade openness, and inflation. Concerning ICT penetration and the size of the informal economy, they seem to play a modest but considerable role. The accumulated local effects (ALE) plots (Figure 2.13) based on the random forest model show that a low rate of ICT penetration (between 3 and 3.5) increases the sovereign yields by around 0.1-0.8 p.p., but with a sharp declining rate and after the variable takes a value of 4.0, no particular effect can be detected on the average prediction. When the variable exceeds the value of 5, then ICT penetration has a negative (decreasing) effect on yields by about 0.2 p.p. On the other hand, a small size of the informal sector has a negative effect on yields of around 0.2 p.p., but a larger informal sector that surpasses a ratio of 20% to GDP has a positive (increasing) impact on yields of about 0.2 p.p. to 0.4 p.p.

Figure 2.12 Variable importance measures for the random forest optimal model.

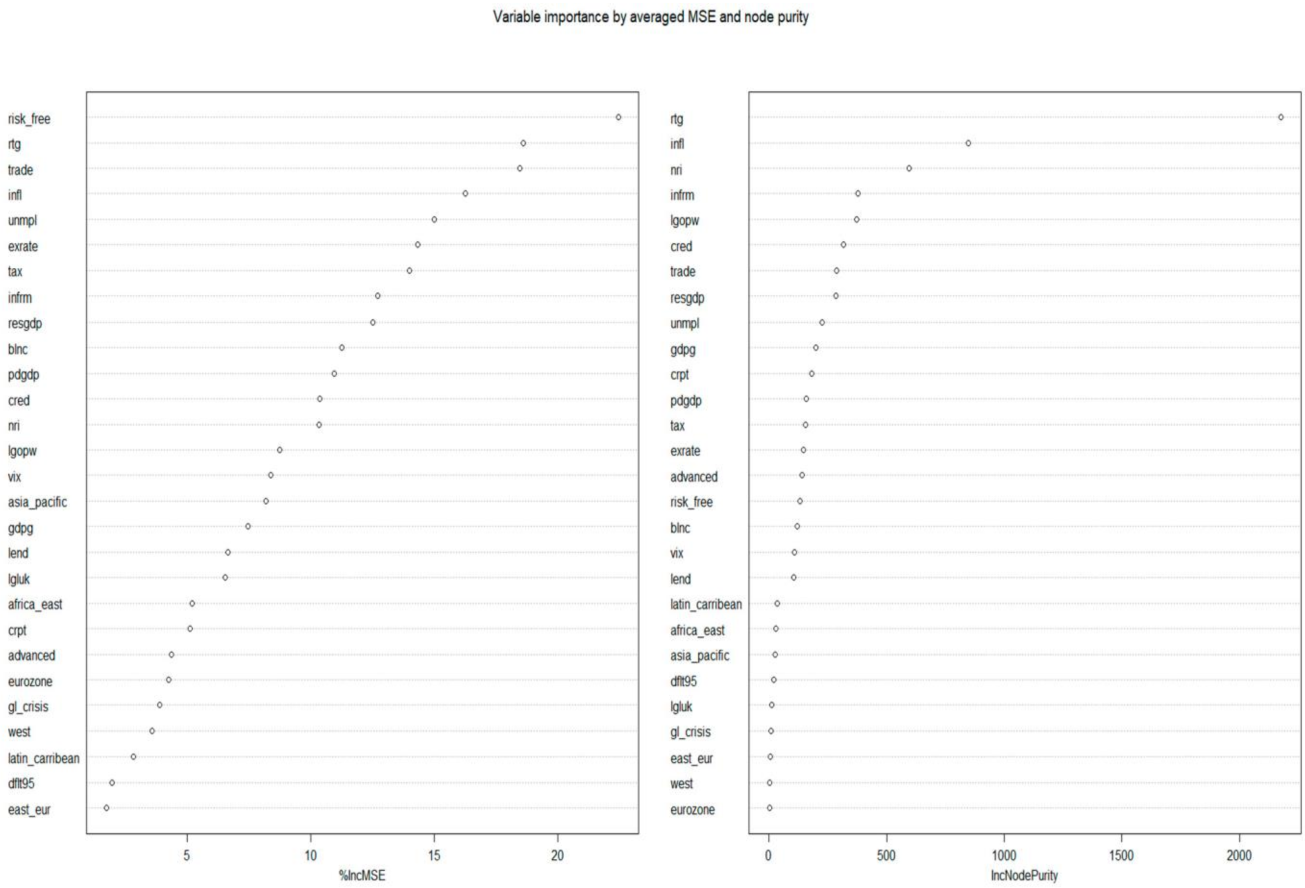
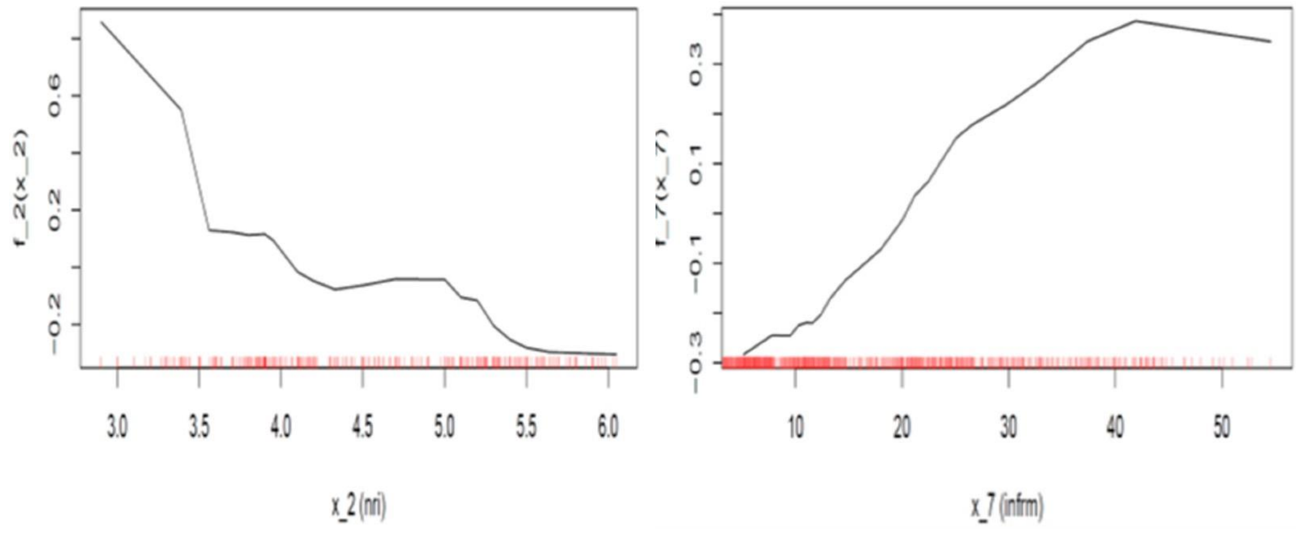


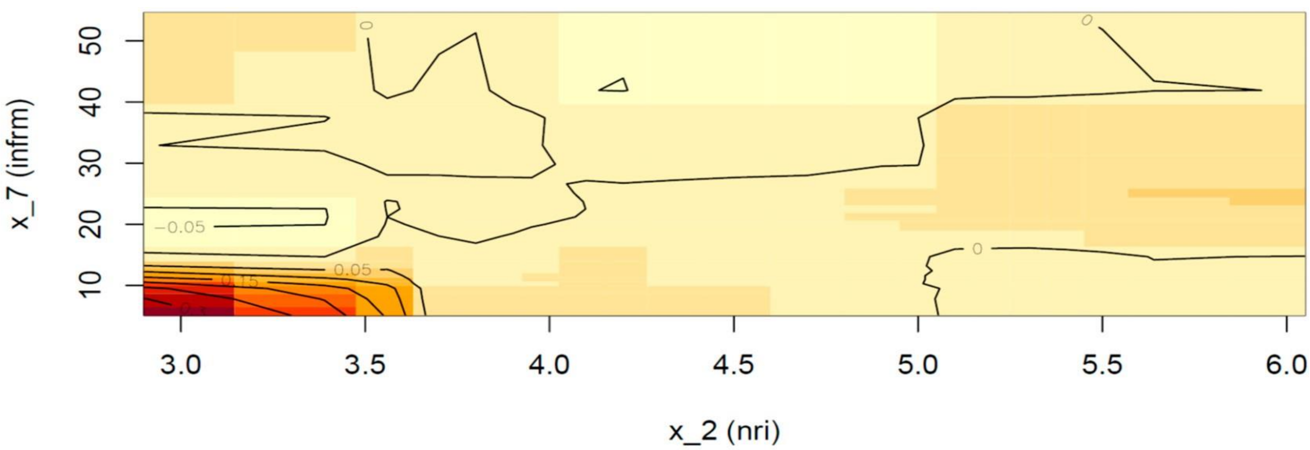
Figure 2.13. ALE plots of ICT diffusion (**left**) and informal sector (**right**) (random forest model).



Note: The distribution of the independent determinant is depicted in red. If observations concerning specific areas of the model are limited, conclusions should be drawn with caution.

Similarly, the accumulation effect plot (Figure 2.14) on the interaction of the ICT penetration and the size of the informal sector shows that an additional negative (decreasing) effect of a magnitude of 0.05 p.p. occurs when ICT penetration is very limited and the informal sector is medium-sized or when the informal sector skyrockets and the ICT penetration is mid-scaled (4.0–5.0). No other additional effect is found, while the positive (increasing) effects of the low left part of the plot are not considered since the area is far from the data distribution area.

Figure 2.14. ALE plot for the 2nd-order effect of ICT penetration and informal sector on random forest model predictions.



2.3.6 Gradient Boosting[21]

Instead of creating an ensemble of de-correlated trees such as random forests, gradient boosting builds, in an iterative fashion, an ensemble of shallow and weak trees. A weak classifier (tree) is one whose error is only slightly better than random guessing [51]. Usually, shallow trees are built with only 1–6 splits [45], with each tree being an improvement of the previous since in every iteration the new base-learner is trained on the error learned so far [45]. The gradient boosting model is tuned by trial and error (a full grid search is computationally expensive in the case of a gradient boosting machine). The learning rate is set to 0.01, the number of iterations to 1040, the tree depth to 15, the minimum number of observations required in each terminal node to 9, the percent of training data to sample for each tree, and the percent of columns to sample for each tree to 80%.

The model further reduces the validation error relating to the previously presented models to 1.38 (RMSE), while the testing error drops as well to 2.41 (RMSE) with an $R^2 = 0.73$. The variable importance plot Figure 2.15 verifies that ICT penetration and the size of the informal sector are important drivers of the predictions of the gradient boosting model as well. By far, the model places a heavy weight on the assigned credit ratings. Measures of importance are computed based on the fractional contribution of each feature to the model based on the total gain of the corresponding feature's splits. The ALE plots depicted in Figure 2.16 further refines our conclusions. The positive effect of ICT penetration (or better, its lack), when ranging between 3.2 and 3.5, declines rapidly and becomes negative (about 0.2 p.p.) as soon as the feature's value exceeds 3.5. The plot detects turbulence in the range of 3.5 to 4 since the negative effect is not stable and quickly consolidates around zero until the ICT penetration value exceeds 5. Then the negative effect sharply reaches 0.2 p.p. and seems to stabilize. On the other hand, the negative (decreasing) effect of a very confined informal sector vanishes as soon as the ratio exceeds 20%, corroborating previous results. The effect becomes positive, and afterward, as the slow rate rises slowly, it increases rapidly and stabilizes around 1 p.p.

The accumulation effect plot (Figure 2.17) on the interaction of ICT penetration and the size of the informal sector is in line with previous findings and shows that an additional negative (decreasing) effect of a magnitude of 0.25 p.p. occurs when ICT penetration is very low and a medium informal sector accounting for 20-35% is present.

Moreover, a negative effect of the same magnitude (0.25 p.p.) can be seen for levels of ICT penetration between 3.5 and 5.5 in conjunction with a skyrocketing informal sector with a ratio over 40%. The area in red is, again, not considered.

[21] We do not present the gradient boosting model for sovereign ratings because the model failed to deliver a superior classification rate in relation to the random forest model.

Figure 2.15 Explanatory variable relative importance of the gradient boosting model concerning bond yields.

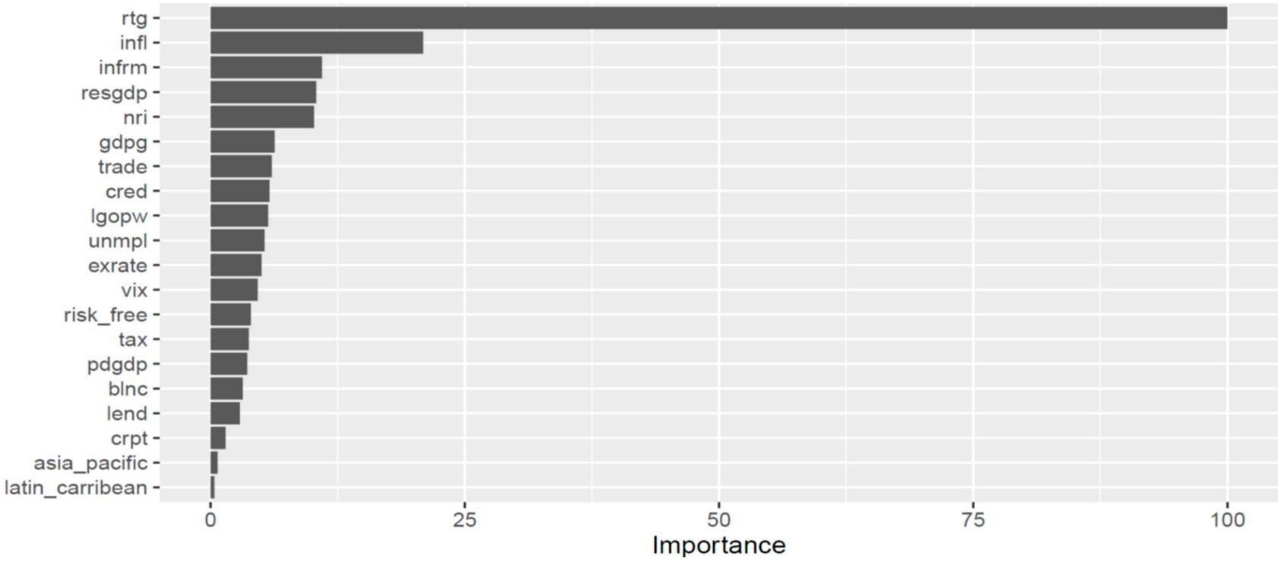
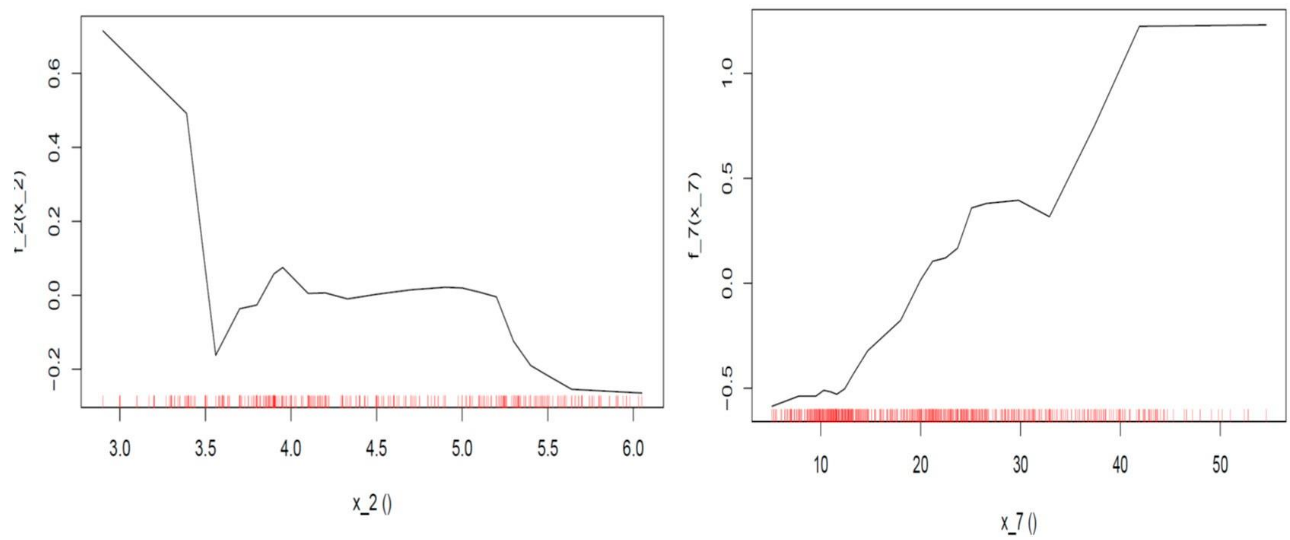
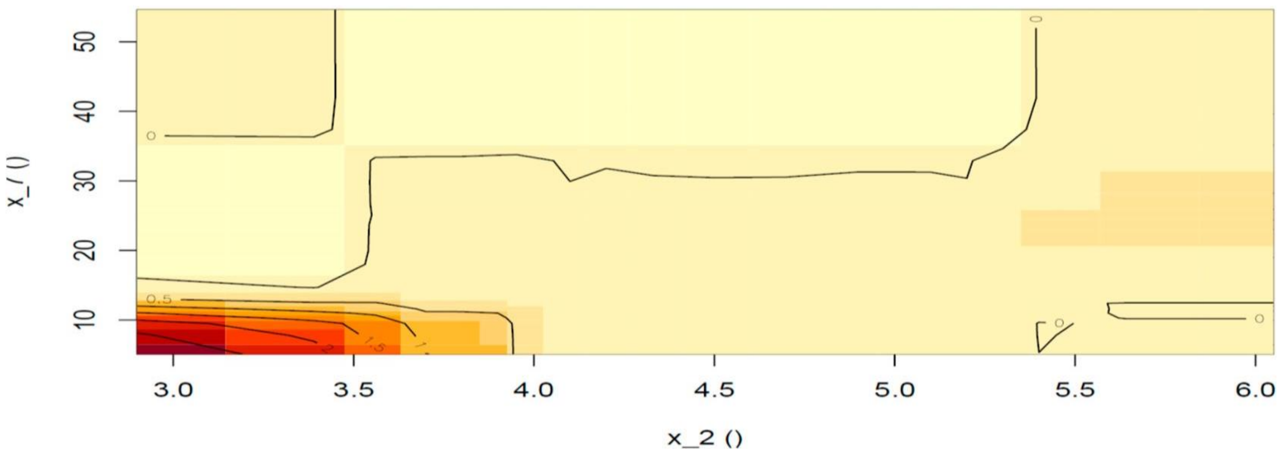


Figure 2.16 ALE plots of ICT diffusion (**left**) and informal sector (**right**) (gradient boosting model).



Note: The distribution of the independent determinant is depicted in red. If observations concerning specific areas of the model are limited, conclusions should be drawn with caution.

Figure 2.17 ALE plot for the 2nd-order effect of ICT penetration and the informal sector on gradient boosting model predictions.



2.3.7 Robustness Test

Rating agencies have often been accused of a pro-cyclical policy (meaning that rating standards are not consistent over the expansion and recession periods), responding with a considerable lag to shifts in sovereign credibility and therefore not acting as early warning systems to market participants as expected. Moreover, they are allegedly overreacting with abrupt downgrades in times of recession, exacerbating debt crises, remaining very cautious, or underreacting concerning upgrades during recovery phases or even for longer periods. In any case, the strong persistence and high level of inertia that sovereign ratings usually exhibit, come as no surprise. The reason for this phenomenon can be traced back to an agency's reputation mechanism [52], which seeks to restore their lost reputation due to warning failures by pushing them to excessive conservatism during and after crises. Stickiness may also exist, as it has been argued by agencies [53] because countries' economic behavior during crises reveals new (negative) information that was not available beforehand. The conventional econometric approach, when analyzing panel data (datasets where the behavior of entities -countries in the particular study- is observed across time -years in this study-), is to apply fixed or random effects or a complete pooling modeling approach. Nonetheless, given the persistency of sovereign credit ratings, a growing trend in the relative literature is to account for this persistency by applying dynamic panel models [54], including in the set of independent variables the lags of the dependent. In the models presented in this study so far, we have not accounted for the time-series nature of our data nor for the persistence our dependent variables exhibit.

Considering the above, a machine learning approach, which is gaining recognition lately for efficient handling of such time-dynamic behavior based on recurrent artificial neural networks, is examined further down in this study in order to address the robustness of our findings when tackling these aspects. Moreover, in order to account for any possible irregularities arising from modeling the proxy of sovereign ratings by the standalone S&P ratings, we use as a dependent variable the synthetic measure of the simple average of the three most prominent agencies (S&P, Moody's, and Fitch). As a further check for validity, we exclude the synthetic measure of ratings from the set of independent variables of bond yield determinants that are fed to the first layer of the recurrent network to detect the behavior of the remaining features in the absence of a catch-all proxy as ratings.

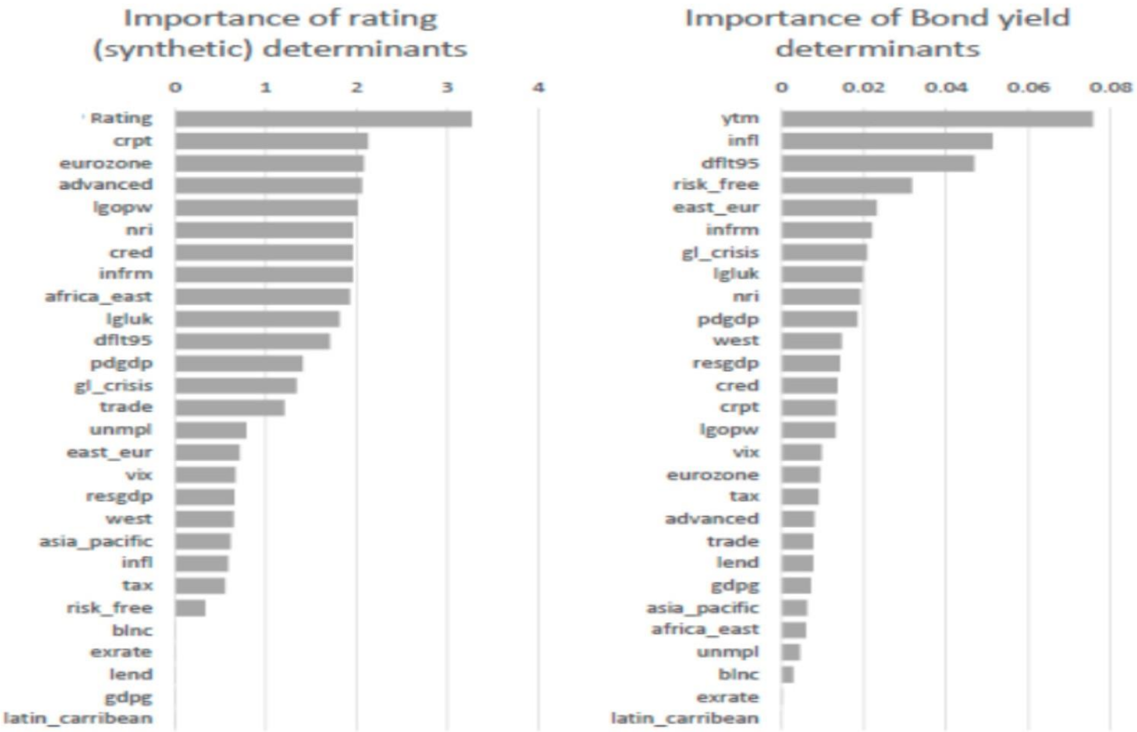
An artificial neural network (ANN) is a nonlinear model that closely resembles the structure of a biological neural network. Artificial neural networks are made up of layers of nodes, each of which is connected to the others by nonlinear activation functions. Usually, the first layer of an artificial neural network is made up of explanatory variables. The explanatory variables in the middle layer undergo intermediate transformations. The nodes in the final layer are responsible for predicting the dependent variable. Each function is associated with a set of appropriate parameters called weights and biases. Training the neural net entails the optimization of these parameter values by minimizing a loss function that depends on the predicted dependent variable and its true values.

Recurrent neural networks (RNN) [55,56] are a special class of neural networks that are utilized in problems where input can be modeled as a temporal sequence. The main purpose of RNNs is to exploit the temporal relationship between input and output in order to improve their prediction accuracy. They have gained popularity in the domain of natural language, audio, or video processing and the demand for financial market predictions [55,57]. RRNs architecture evolved through the years so as to be able to overcome its initial limitations, such as being able to retain past events in memory for an extended time. Thus, new RNN architectures such as LSTM (long-short-term memory) and GRU (gated recurrent units) are proficient at modeling long-term sequence dependencies. LSTMs sophisticated cell units can recognize, "store and preserve" an important input in a long-term state. GRU units accomplish the same performance as the LSTM units but are, in general, faster to train.

In this study, a GRU recurrent neural network architecture has been put to the test with two appropriately prepared datasets. The first dataset consists of 28 features, including all the features plus one (risk-free rate) as well as the synthetic measure of credit ratings for 65 countries over a period of 16 years. Since in all our models we had excluded the risk-free rate as a determinant of the assigned credit ratings, in order to check for potential omitting bias, we included the specific feature in the set of independent variables when feeding the first layer of RNN. Nevertheless, the risk-free rate turns out to be the least important feature with negligible impact (Figure 2.18) and therefore the omission of the variable does not insert any bias into our previous models. The dataset was utilized to create a recurrent neural network that predicts the S&P credit ratings based on longitudinal data. Similarly, the second dataset consists of 28 features, including all but one of the features used in the previous methods (S&P ratings) as well as the bond yield values for 58 countries over periods from 6 to 16 years. We exclude S&P ratings for the reasons mentioned earlier in the section. The specific dataset has been utilized to create a recurrent neural network that predicts bond yields by exploring past patterns. The two datasets have been appropriately preprocessed. Regarding the credit ratings dataset, each of the 65 countries' records has been broken into rolling 8-year windows, looking back 7 years to predict the year ahead. Similarly, the dataset concerning bond yields has been broken into rolling 6-year windows. Moreover, the datasets have been further split into training and testing datasets by country to avoid data leakage. The GRU architecture consists of a dense input layer followed by a gated recurrent unit layer, a dropout layer, and a final dense layer. The GRU neural network has been implemented utilizing the APIs of Keras, Tensorflow, and the R language. Thus, all hyperparameters have also been tuned with the assistance of Keras Tuner for R. For the credit ratings dataset, the hyperparameters of GRU units, the

GRU activation function, the GRU recurrent dropout, the dropout layer rate, and the optimizer learning rate were optimized using Adam, maximizing the accuracy metric (categorical cross entropy) on the validation set utilizing a random search algorithm. For the GRU network used in the bond yield dataset, the same scheme has been used; however, the Adam optimizer has been set to minimize the mean squared error on the validation set.

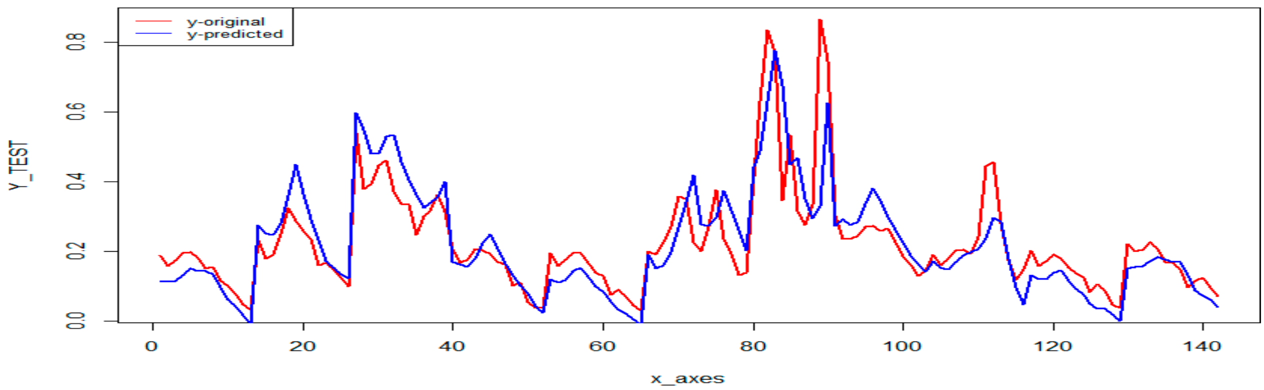
Figure 2.18 Explanatory variables of relative importance for the GRU in credit ratings (**left**) and bond yields (**right**).



After hyper tuning the RNN, the two models have been updated with the new hyper-parameter values and then applied to the two datasets. For the bond yield dataset, the RNN performed exceptionally well, presenting an RMSE of 0.0601 on the test set. Figure 18 presents the original values versus the predicted values by the RNN on the test set. For the credit ratings dataset, the RNN produces a model achieving a more than satisfactory 52.99% accuracy rate on average, which is similar to the best accuracies achieved by our previous models, or 81% if classifying as correct, predictions within one notch of real values. This specification of correct classification has been widely used in the empirical literature due to the difficulty that neural networks present in determining the correct rating in adjacent categories [58].

Moreover, as [44] have suggested, the method is equivalent to artificially creating meta-classes of evenly distributed observations by limiting the number of classification categories, a method that has also been extensively used in the literature (e.g., [11]).

Figure 2.19 Plot of GRU neural network performance over Bond yield test dataset.



In order to measure the importance of the features for both RNN models development, a permutation feature importance technique [59] has been applied to the test data sets. Next, each variable at a time is shuffled, and the model is utilized again to make new predictions. Afterwards, the root mean square difference between the original prediction and the prediction of the perturbed dataset is calculated. The process is repeated multiple times due to the stochastic nature of the methodologies used. The results of the permutation feature importance technique, presented in Figure 2.18, suggest that the ICT penetration rate and the size of the informal sector indeed play a considerable role in predicting risk ratings and sovereign debt rates, despite including lags of the dependent variables in our models or using a different metric as a proxy for the assigned ratings.

2.4 Discussion

Table 2.7 presents a summary of the 20 most significant variables obtained by employing different models on credit ratings. We first discuss the variable importance of models that exclude lags in ratings. The three models have a common set of variables in their top rankings, such as worker productivity, the size of the informal sector, and the level of corruption. ICT penetration is also considered important and is ranked sixth by the random forest model after the exchange rate and credit to the private sector. The ratings are expected to be affected by macroeconomic news, which is also observed in the analysis [60].

The importance of lagged values in our RNN model appears to indicate persistence in credit ratings, as their score is twice as high as that of any other variable. (Figure 2.18). Nevertheless, we cannot officially confirm inertia as conventionally done in the literature by testing if coefficients of lagged variables approach unity [61].

Table 2.7 Variable importance by models employed predicting S&P ratings or average ratings of S&P, Moody's, and Fitch.

	CART	**Bagging**	**Random Forest (Permutation)**	**RNN**
Rank	Determinant	Determinant	Determinant	Determinant
1	lgopw	lgopw	Lgopw	rating $_{(t-n)}$**
2	infrm	crpt	Infrm	crpt
3	crpt	infrm	Crpt	eurozone
4	nri	nri	exrate	advanced
5	advanced	exrate	cred	lgopw
6	exrate	cred	nri	nri
7	west	blnc	advanced	cred
8	pdgdp	unmpl	resgdp	infrm
9	cred	resgdp	unmpl	africa_east
10	blnc	pdgdp	pdgdp	lguk
11	unmpl	lend	trade	dflt95
12	resgdp	trade	blnc	pdgdp
13	trade	tax	tax	gl_crisis
14	lgluk	infl	dflt95	trade
15	lend	advanced	infl	unmpl
16	infl	gdpg	lend	east_eur
17	east_eur	vix	lgluk	vix
18	tax	dflt95	eurozone	resgdp
19	eurozone	africa_east	east_eur	west
20	asia_pacific	lguk	west	asia_pacific

***(t-n) refers to 7 years backward looking in order to predict the year ahead*

The levels of perceived corruption and productivity per worker continue to play an important role, along with credit to the private sector, the size of the informal sector, and ICT penetration, which comprise the top-scoring variables. The obvious difference in the RNN model compared to the other three is the high importance of being a member of the eurozone or considered an advanced country, suggesting that these properties are valued by credit agencies beyond the usual information conveyed by the economic fundamentals.

As we have already seen in Section 2.3 through ALE plots, when ICT exceeds a value of 4.5, it begins to exert a moderate impact towards a better rating, while when ranging below 4.0, it exhibits an adverse effect.

The plots involving the size of the informal sector suggest that if the ratio ranges between 5 and 15%, the probability of a country attaining the characterization of a high-quality issuer increases significantly by 0.1. Nevertheless, as soon as the size exceeds the critical value of 15%, the effect becomes negative (degrading). The second-order effects detection plots suggest there is an additional small effect of about 0.005 in the probability of being assigned a top rating when the informal sector is detained below 15% and ICT penetration exceeds 4.5. Nevertheless, if, in this case, the shadow economy exceeds 15%, the interaction with a larger informal sector seems to have an adverse effect of around 0.01. Contrary to what was expected, we find no evidence that a larger ICT penetration (meaning above a certain rate) may deter the adverse effects of an expanded shadow economy on ratings.

Concerning yields, a comparison of the variable importance of the different models can be found in Table 2.8. The first three models that lack dependent variables lag, identify rather different sets;

however, the ratings seem to be appraised by markets as a premium source of information since they are rated as one of the most important determinants after controlling for the economic fundamentals. Moreover, inflation seems to also play the role of an economic indicator and scores systematically high. Furthermore, findings confirm that, apart from country-specific fundamentals, global factors such as the VIX and the U.S. risk-free rate influence debt rates. The informal sector and ICT usage are quite important factors across models, with the size of the shadow economy ranking a bit higher.

Table 2.8 Variable importance by models employed predicting sovereign bond yields.

	CART	**Bagging**	**Random Forest (Permutation)**	**Gradient Boosting**	**RNN**
Ranking	Determinant	Determinant	Determinant	Determinant	Determinant
1	rtg (synthetic)	Infl	risk_free	rtg (synthetic)	ytm $_{(t-n)**}$
2	Lgopw	rtg (synthetic)	rtg (synthetic)	infl	infl
3	Nri	resgdp	trade	infrm	dflt95
4	Crpt	lgopw	infl	resgdp	risk_free
5	Cred	infrm	unmpl	nri	east_eur
6	Infrm	cred	exrate	gdpg	infrm
7	Infl	Nri	tax	trade	gl_crisis
8	Advanced	trade	infrm	cred	lgluk
9	Gdpg	unmpl	resgdp	lgopw	nri
10	Trade	gdpg	blnc	unmpl	pdgdp
11	Resgdp	Tax	pdgdp	exrate	west
12	Pdgdp	blnc	cred	vix	resgdp
13	Lend	exrate	nri	risk_free	cred
14	Exrate	pdgdp	lgopw	tax	crpt
15	Tax	Vix	vix	pdgdp	lgopw
16	risk_free	advanced	asia_pacific	blnc	vix
17	Blnc	lend	gdpg	lend	eurozone
18	dflt95	crpt	lend	crpt	tax
19	Unmpl	risk_free	lgluk	asia_pacific	advanced
20	africa_east	asia_pacific	africa_east	latin_carribean	trade

***(t-n) refers to 5 years backward looking in order to predict the year ahead*

The RNN model suggests that, as the most important variable, the lags of the dependent variables have an importance factor that almost doubles relative to any other factor, showing that they also exhibit a rather sticky behavior. The role of inflation and the U.S. risk-free rate seem to be confirmed by the RNN model as well, while some other variables such as the history of defaults, the period of turbulence and economic crisis (2007–2010), and the origin of the law (common law considered safer for investors) seem to gain some importance.

The impact of ICT penetration and the size of the shadow economy are validated by our robustness model but in a more modest direction. The quantification of their impact through ALE plots is quite straightforward since all our models exhibit similar patterns.

When the ICT index ranges between 3.0 and 3.5, the effect is positive and varies from 0.2 to 0.4 p.p., indicating that technological laggards pay a premium. When ICT penetration is moderate (3.5–5), no effect may be discerned, and when referring to ICT pioneers (>5), the negative effect amounts to around 0.2 p.p.

Considering the informal sector when its size does not exceed 20%, a negative (decreasing) effect of around 0.1 to 0.3 p.p. is presented, while when the sector expands, the effect rapidly becomes positive, and when considering skyrocketing (>40%) shadow economies, the effect stabilizes to a rather considerable amount of 1.0 p.p. Concerning the second-order effects, an additional negative (decreasing) effect of a magnitude of 0.25 p.p. occurs when ICT penetration is substantially low (<3.5) in interaction with a medium informal sector accounting for 20–35%. Moreover, a negative effect of the same magnitude (0.25 p.p.) can be seen for a moderate ICT penetration (3.5–5.5) in interaction with a skyrocketing informal sector of a size above 40%. These findings are somewhat in line with our expectations but in a much more intuitive way. It seems that when referring to absolute laggards concerning ICT where governments fail to deliver even the basic services, a medium-sized shadow sector provides some prospects of employment [23] and income. On the other hand, moderate or even promising ICT penetration in interaction with a large informal sector seems to have a negative impact of about 0.25 p.p. on yields, probably signaling the appraisal of the investors to a government policy that strives to provide its people with all the benefits that a digital economy brings and motivate its citizens to return to (or enter) formality.

2.5 Conclusions and Policy Implications

The determinants of sovereign credit ratings and the rates paid on sovereign debt are still the subjects of much academic discussion. While economic fundamentals clearly play a significant role, additional factors have been proposed in the literature that could contribute to our understanding of the underlying mechanism. In this study, we introduce two factors that have received less attention but may have a significant impact on the economy and society: ICT penetration as a proxy for digital transformation and the informal sector, which remains part of every economy despite policies designed to eliminate it. In addition, to examine their effect on ratings and the cost of debt, as well as their possible combined effect, we use a series of machine learning techniques and employ state-of-the-art model-agnostic methods such as feature importance and accumulated local effects to better understand the relationships under scrutiny.

Our findings suggest that there is a clear, modest negative effect of ICT diffusion and usage on ratings and rates, with technological laggards paying a premium of 0.2 to 0.4 p.p. and pioneers paying a discount of about 0.2 p.p. Countries with modest ICT penetration do not enjoy any apparent direct effect; nevertheless, if they suffer from a high rate of the shadow economy, their commitment to digitization seems to be appraised by markets at a 0.25 p.p. discount.

In contrast, we discovered a positive relationship between the size of the informal economy and ratings as well as yields. Our research indicates that there is a threshold of approximately 15–20% level that is deemed acceptable by both investors and agencies. Countries that manage to keep their shadow economies below this level increase their chances of obtaining a top rating by roughly 0.1. However, if this threshold is exceeded, the informal sector can have an adverse impact. Large shadow economies may be charged a premium of up to 1 percentage point by the markets. Notably, in the presence of poor ICT performance, a medium-sized shadow economy appears to be perceived by investors as a temporary economic safety valve.

Our results are consistent with some studies that suggest that ICT can be a significant determinant of ratings and the cost of debt [13]. However, we do not find evidence that ICT is the most important factor, as proposed by [10]. In addition, we confirmed that a shadow economy can have negative effects on sovereign risk when it exceeds a certain size, around 15–20%, which is in line with the findings of [11], who suggested a similar threshold of 18%. Additionally, by presenting evidence that the informal sector of ICT laggards should not be eliminated before advancements in ICT take place, we indirectly support the findings of [62], who suggest that in some cases the underground economy presents a positive economic impact in African countries with low ICT penetration, and therefore a consolidation of ICT infrastructure in these countries could help curb the informal economy by eliciting similar positive economic effects (absorption of unemployed workers, enhancement of entrepreneurial spirit, etc.).

The preceding discussion leads to a few policy implications. Firstly, countries can greatly benefit by keeping their shadow economies below 15–20%, which is the threshold for acceptable rates of informality set by both markets and agencies. Secondly, to take advantage of digitally transformed and interconnected economies, countries must invest heavily in ICT. Finally, if a country has a medium-sized shadow economy and low ICT penetration, it should prioritize improving its digital infrastructure before taking more aggressive measures to tackle the informal sector.

2.6 References of Chapter 2.

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3 CHAPTER 3.

3.1 Policies facilitating the ICT penetration in Greece.

One of the major concomitants of the Coronavirus pandemic that came into the foreground in a rather dramatic way was the necessity that a multitude of economic transactions and basic public services had to get digitized in order the economy and the state to remain functional while employees and generally citizens would remain safely at home.

The Greek minister of Digital Governance just after the burst of the pandemic expeditiously provided through a government's web portal (gov.gr), the ability to citizens to validate digitally solemn declarations or written authorization. Moreover, and not much later, on the 28th of March 2020, an electronic prescribing system was introduced; a crucial novelty since the Greek population is rather aged and more vulnerable to the corona virus. Since then, many more services were gradually integrated to the government portal, (e.g. vaccination against pandemic) and many more procedures aiming to relieve firms hit severely by the pandemic, were carried exclusively digitally utilizing some of the tools of the Tax Administration already in place, although designed for totally different scope.

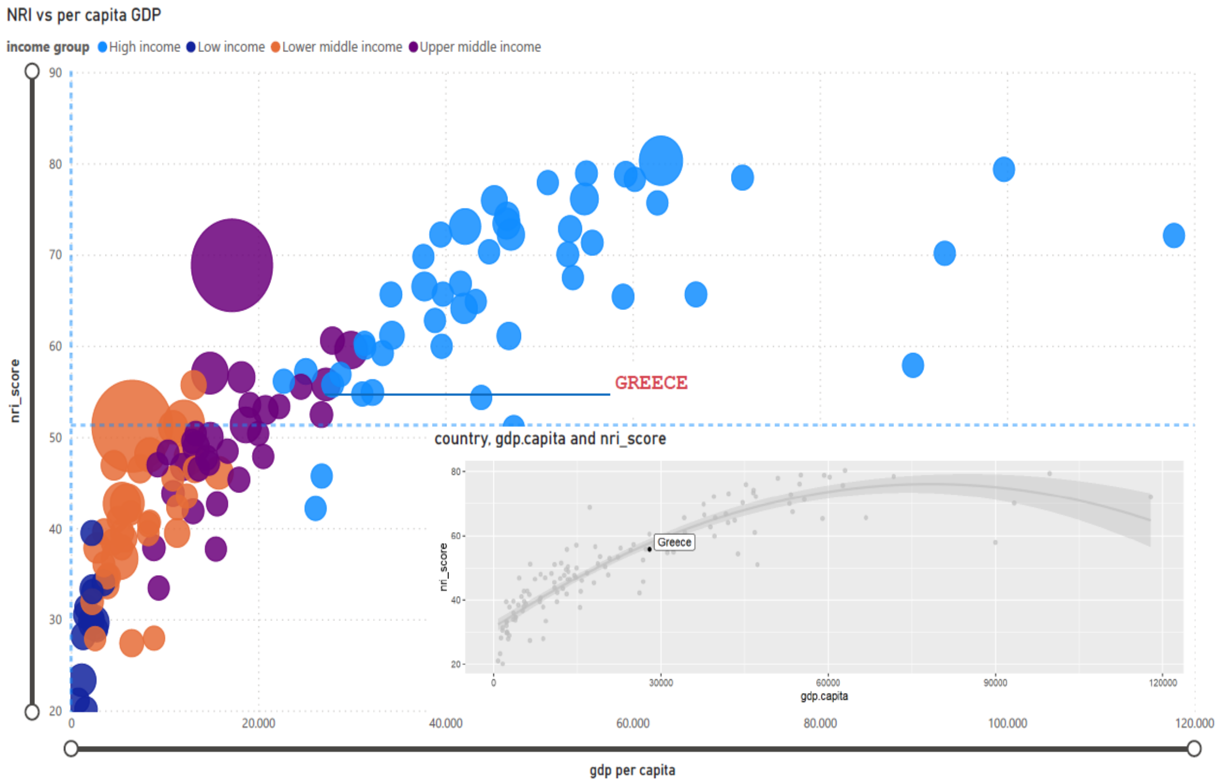
The Government has declared officially that the digital transformation of the public sector and the roll-out of advanced 5G network are of primal importance for the administration and the country. Nevertheless, the country continues to be steadily a laggard concerning the Digital Economy and Society Index (DESI), a composite index on Europe's digital performance that tracks the progress of EU countries on ICT penetration. According to the latest DESI data release concerning 2021, Greece still ranks 25th out of the 27th EU country-members, along with Bulgaria and Romania that had to undergo the undeniably painful transition from communism to capitalism and joined EU much later than Greece. Greece scored as high as 38.9 in contrast to an EU average value of 52.3. This comes as no surprise since Greece had been steadily occupying the 26th place above only Romania till last year.

DESI comprises four pillars, namely, connectivity, human capital, integration of digital technology and digital public services and tracks the evolution of EU members towards them. Regarding connectivity, Greece has made a remarkable progress since from being the slacker in years 2017-2021, now takes the 22nd place mainly due to significant progress made on very high-capacity network and 5G coverage. Concerning digital skills and human capital, Greece is catching up with the EU average while the prospects are rather promising since the country is well ahead the EU average regarding the young population. Greece scores very low in the integration of digital technologies by the small and medium sized enterprises; an alarming finding since SME comprise the backbone of the country's economy.

Nevertheless, a plan of supporting the digital transformation of SME is on the way, mainly through funds secured through the Recovery and Resilience Plan (RRP). Greece continuous to show a strong commitment in offering more digital public services to citizens and businesses but has still a long way to go in order to catch up.

The extensive use of the ICT and their convergence has fed at large innovation and productivity in sectors like logistics, public and private health, e-commerce, e-banking, e-payments, teleworking, distance learning, big data analytics but also severely affected every aspect of public governance. Naturally, every country is following its own unique path towards digital transformation sometimes successfully, sometimes not. Although there is a consensus that there is no single recipe for success, it is commonplace that the digitally advanced countries spare no effort towards digitizing public services, promoting exploitation of open public data, improving infrastructure and networks and facilitating a more favorable regulatory framework concerning adoption of digital technologies in business.

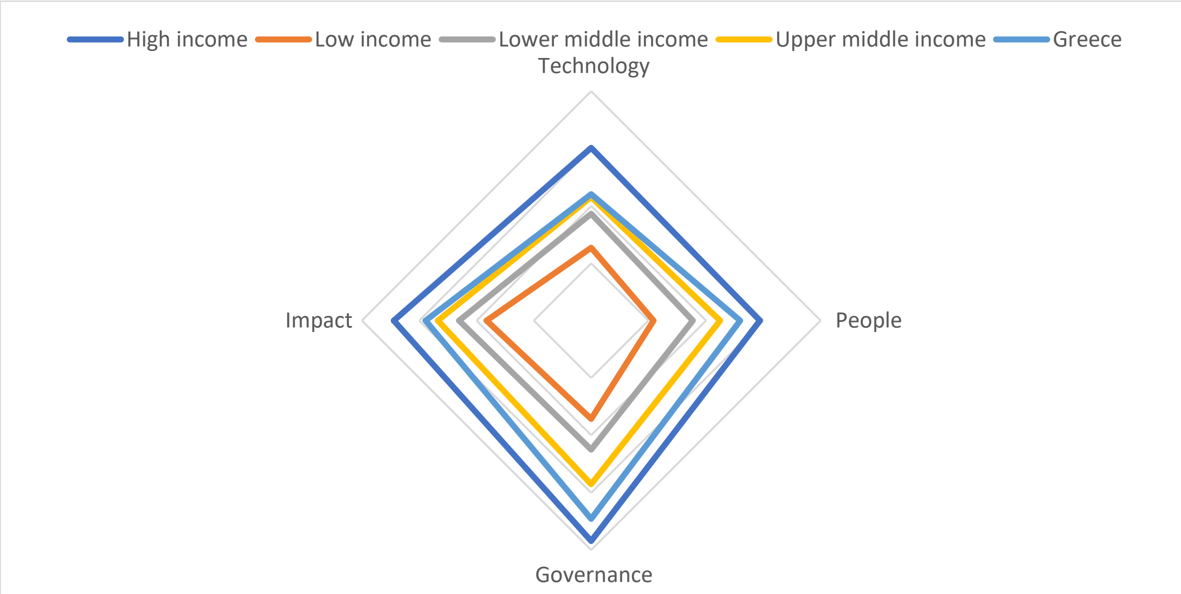
Figure 3.1. Digital Maturity and per Capita GDP. Dot size corresponds to population size.



In case we would like to check where Greece stands vis-à-vis the rest of the world, another index, alike DESI, may be used, namely Network Readiness Index (NRI). The index which has a more global orientation compared to DESI was first published in 2002 by the World Economic Forum, Cornell Greece by demonstrating such a low performance in almost all aspects of digital economy and governance is liable to endanger its already deficient competitiveness against the other member states since the locally confined lower labor cost will play a lesser role in the context of a digital economy without frontiers.

In case we would like to check where Greece stands vis-à-vis the rest of the world, another index, alike DESI, may be used, namely Network Readiness Index (NRI). The index which has a more global orientation compared to DESI was first published in 2002 by the World Economic Forum, Cornell University, and INSEAD. Today, it is being published by the Portulans Institute in a redesigned form. In its latest edition, Greece among 131 countries is on the not so enviable 49th place, two places ahead of Bulgaria and three above Romania, one behind Turkey but more than 24 units below the digital world leader, United States. Figure 3.1 depicts Greece's ranking concerning the NRI index in combination to the GDP at purchasing power parity (PPP) per capita in US$. Moreover, since World Bank classifies economies into four income groups, low, lower-middle, upper-middle, and high income, these groups are displayed in different colors. Obviously, high income countries score better in digital maturity but there is some overlapping mainly between lower and upper middle-income countries. Greece, just above the average, although considered a high-income country is in broad terms closer to the performance of countries leading the upper middle-income group as can be seen in Figure 3.1. Moreover, as shown in the subgraph of Figure 3.1, Greece is positioned below the trend line and should be expected to deliver a better performance according to the per capital income.

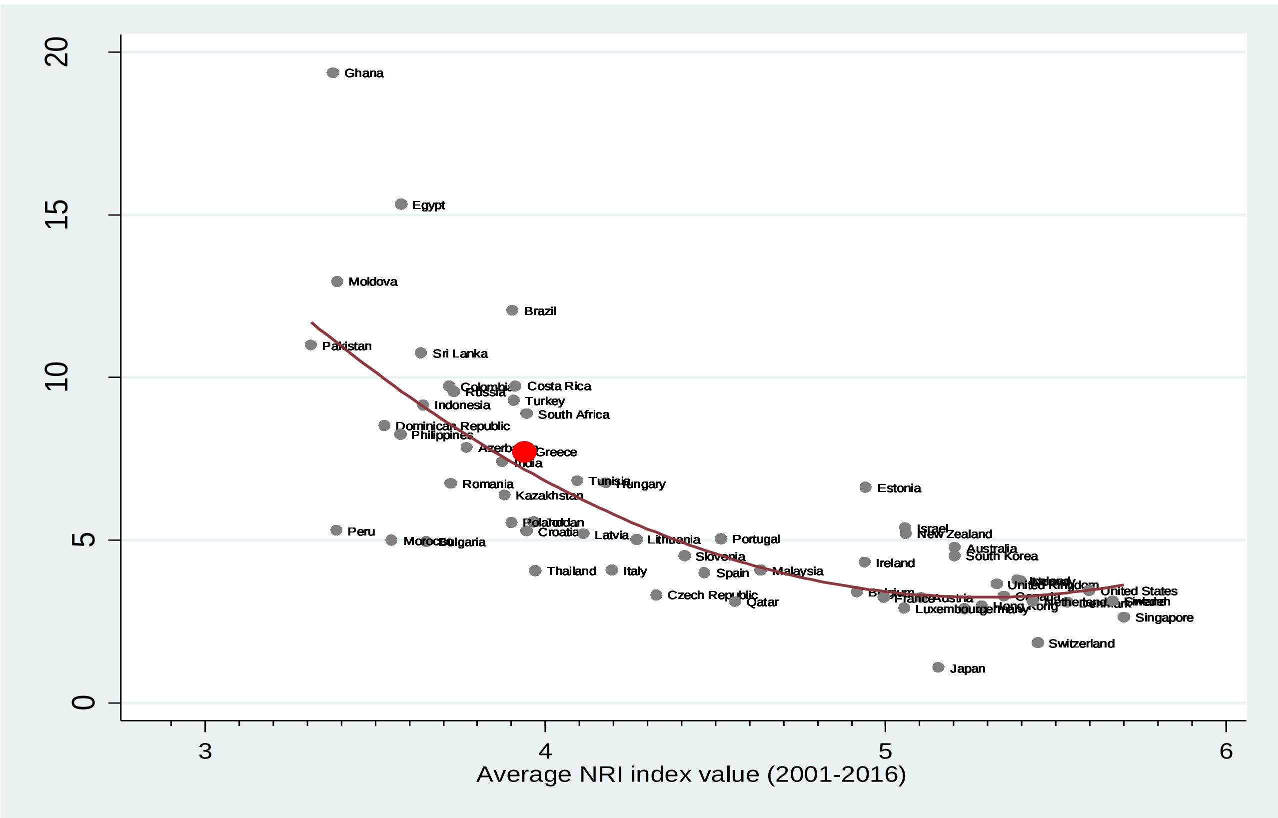
Figure 3.2. Greece performance towards the four pillars comprising the NRI index versus income groups' averages (2022).



It is interesting to check Greece's performance on the four pillars of the NRI index, especially against different income groups' averages or against countries that follow closely certain country's characteristics like population size, geographical proximity and stage of economic development. The country’s performance and the groups’ averages can be seen in Figure 3.2.

It should be noted that the technology pillar assesses the level of available technology in terms of coverage and sophistication; the people pillar measures the accessibility to technology and the skills possessed by the population or organizations in order to take advantage of the available technology; the governance pillar evaluates the safety provided to individuals and firms when using digital technology in the context of regulation and inclusion and the impact pillar weighs the overall effect of information and communication technology to the improvement and the acceleration of growth. Examining Figure 3.2 reveals that Greece scores in technology and impact as high as an average upper-middle country and performs better in people and governance but in any case, below the average score of the high-income countries. A closer look suggests that Greece performs extremely poor in sub pillars like accessibility driven mainly by a very low FTTH penetration rate (2.5%), adoption of future technologies due to a low rate of investment in such technologies and gig economy. On the other hand Greece performs quite well concerning individuals’ skills outperforming high income countries and Europe’s average.

Figure 3.3. Scatterplot between average NRI index (2001-2016) and average YTM (2001-2016).



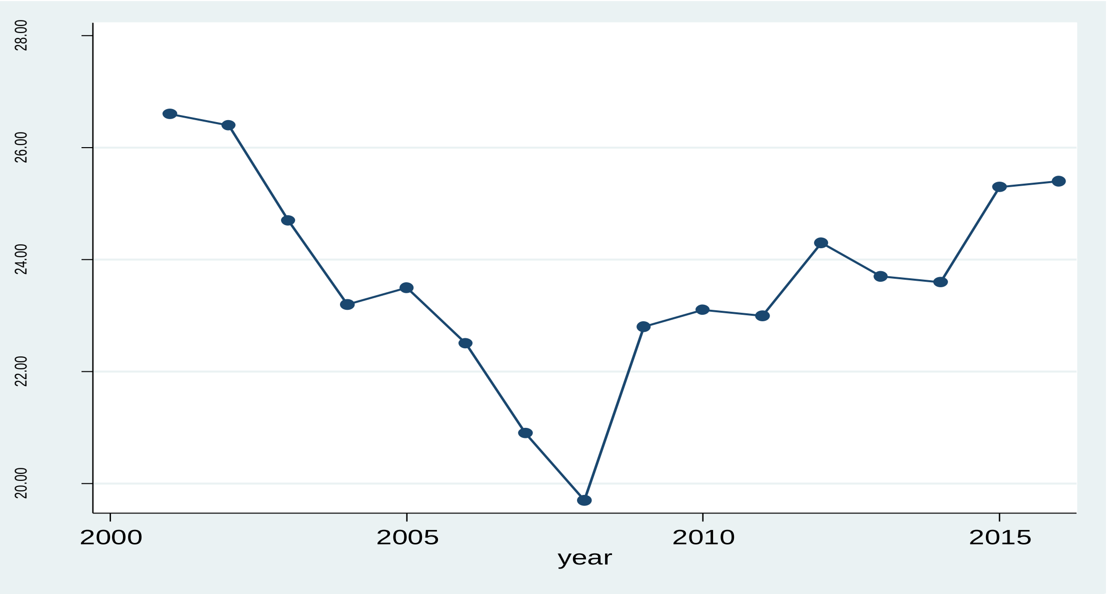
In Figure 3.3 we can see that Greece on average faced a cost of debt of 7.714%, very close to countries like Azerbaijan and India. Its network readiness reached an index score of 3.937 like countries like Kazakhstan, Croatia or Thailand that delt with a much lower cost of debt and South Africa, Turkey and

Costa Rica that faced a higher cost. Overall, Greece's cost of debt was very close to the one expected considering her network readiness. It should not escape our notice that Greece defaulted in 2010 and consequently faced increased yields while during the previous decade enjoyed much lower interest rates, than those expected if borrowed as a standalone country, as a member of Eurozone. According to our findings of the first chapter, a Eurozone membership could lead to a decrease in interest rates of about 2.1 percentage points, concerning the 2001-2010 period.

3.2 The transition from an underground to an official economy.

Greece is notorious for the size of its shadow economy, holding the supremacy even among the infamous PIGS (Portugal, Italy, Greece, Spain). Their economies were allegedly severely hit by the European debt crisis due to, among other factors, the large scale of underground activity, inefficiencies of the public sector and corruption. The evolution of the Greek shadow economy according to estimates of [1] is depicted in Figure 3.4. It is worth noting that the economic recession was so deep that even underground income was repressed [2]. Nevertheless, the trend seems to have been reversed and concerning the last available estimate of the year 2016, the size of the Greek shadow economy reaches again a daunting 26% of GDP, an extraordinary size for a member of OECD and a developed economy.

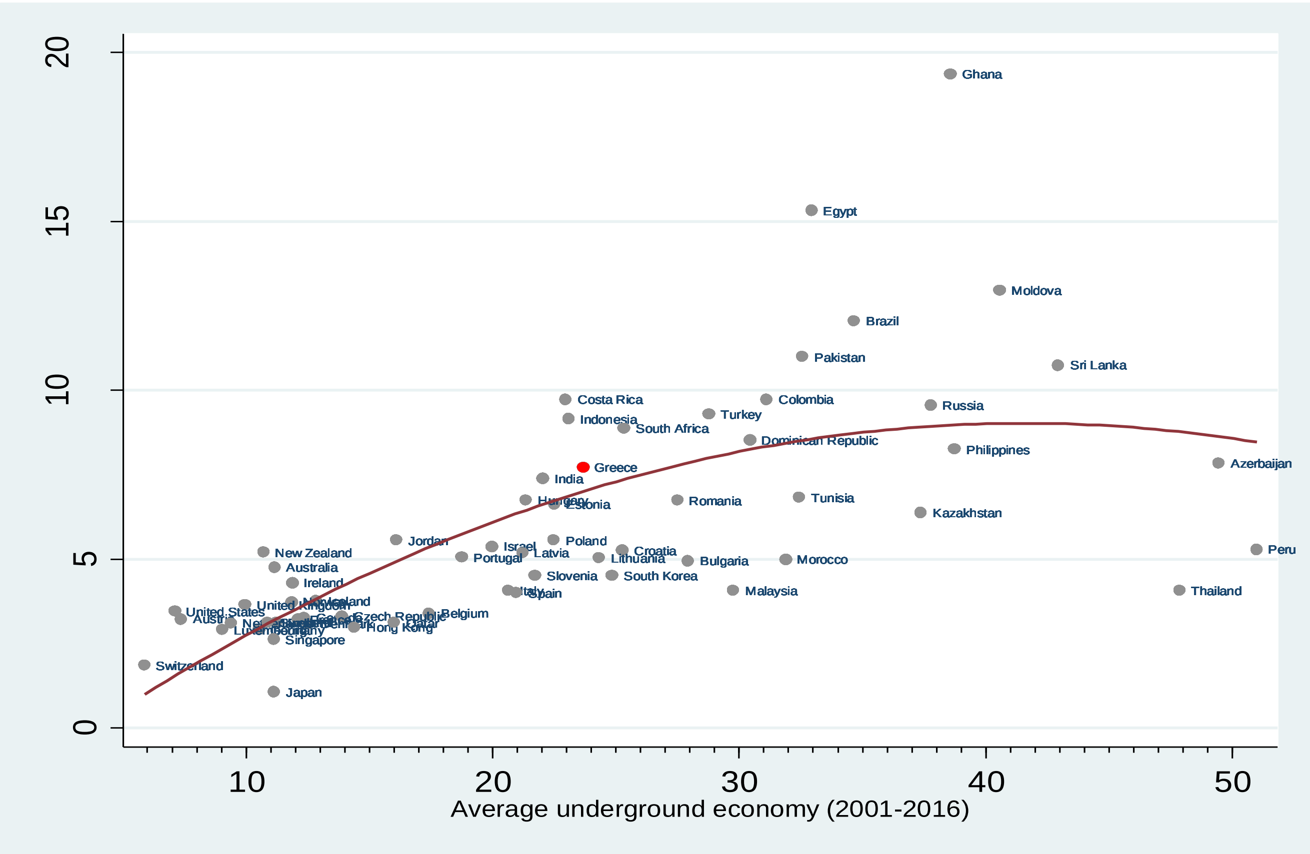
Figure 3.4. Estimates' evolution of Greek shadow economy (2001-2016) according to [1].



The reverse of the trend is not that unexpected since the underground transactions are well rooted deeply in Greek economy and society. The corresponding academic literature [2,3,4] concerning the causes of the Greek shadow economy has highlighted a number of structural problems of Greek economy and public sector that actually impel underground economy like, among others, the consistently high unemployment rate, the excessively large number of self-employed, the low quality of public services, the weak rule of law and the consequent erosion of trust to authorities, the lack of determination of political parties in power to curb the phenomenon and the relaxation of tax controls during electoral circles.

As can be seen in Figure 3.5, Greece's average size of the shadow economy is comparable to economies in transition like India, Indonesia and Costa Rica or former Eastern European countries like Hungary and Estonia. According to [6] international debt markets may reward a one percentage point decrease concerning the size of the shadow economy with a decrease of sovereign debt interest rates up to 3.79 p.p..

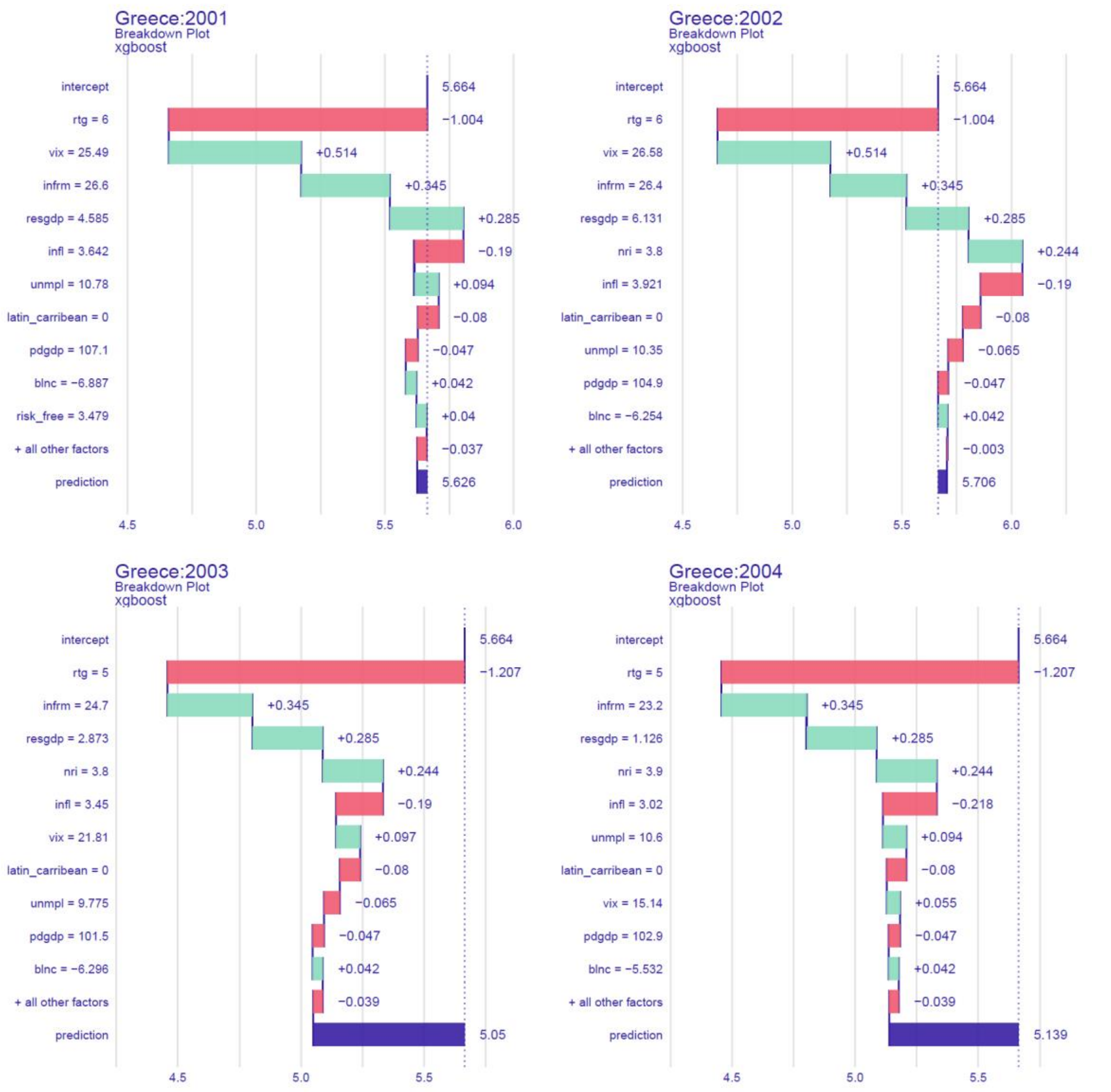
Figure 3.5.Scatterplot between average SE estimates (2001-2016) and average YTM (2001-2016).



3.3 The determinants of cost of the Greek sovereign debt

Considering our Gradient Boosting model on sovereign yields we present local model-agnostic interpretations of predictions regarding Greece in order to identify the magnitude of the attributes shaping the prediction. The procedure follows a break down approach[22] which tracks the changes of the average response model while fixing the values of consecutive factors in order to catch the contribution of each independent variable [5].

Figure 3.6. Breakdown plot of the contribution of 10 most important attributes of interest rates for years 2001-2004.



In Figure 3.6 we can see the 10 most important determinants of Greek sovereign debt interest rates that shape each year's prediction. It can be easily discerned the crucial role played by the favorable rating that Greece enjoyed along that time period as the new member of Eurozone. Concerning years 2001-2004 the size of the informal sector adds a 0.345 p.p. to interest rates while the rather disappointing network readiness of the country adds another 0.244. It is also interesting to highlight that while the ratio

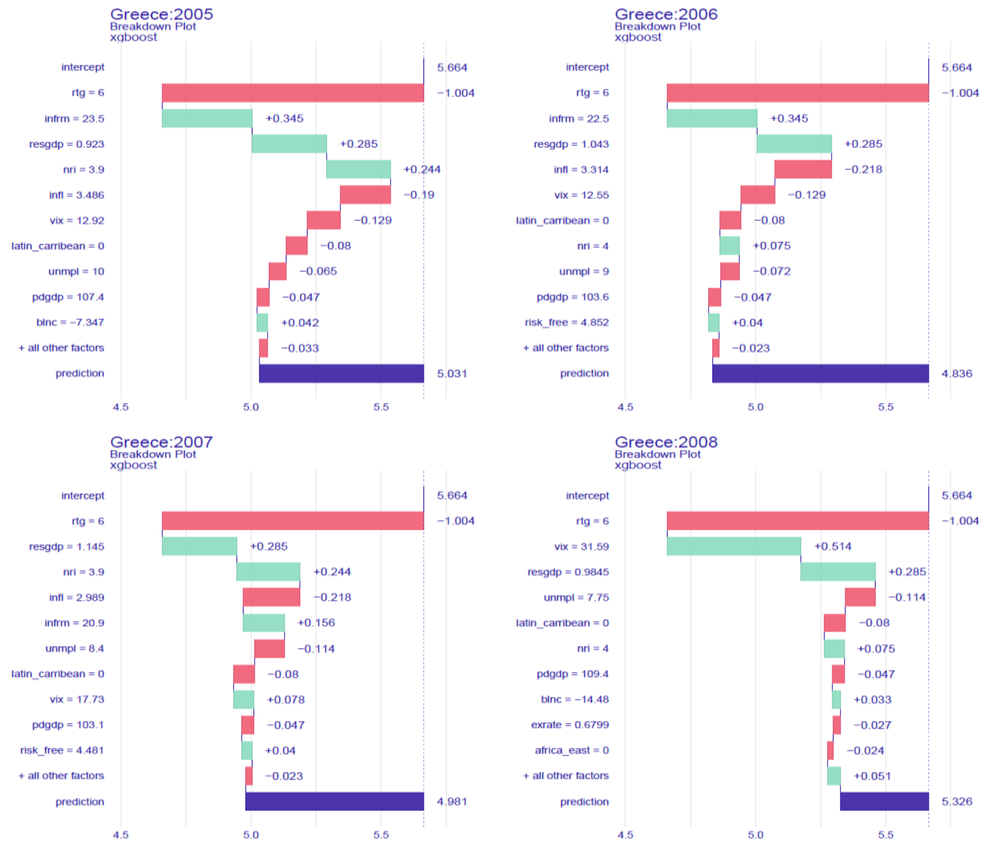
[22] We run the routine with "DALEX" package in R.

of public debt to GDP (101.5% -107.1%) is well above the Maastricht's Treaty limit of 60% of GDP, its size is treated positively by markets since it reduces interest rates by 0.047 p.p.

The same conclusions can be drawn considering years 2005-2007 as shown in Figure 3.7. Greece still scores low in digital transformation and high in shadow economy while markets gently dispraise the country's discouraging performance on both fields. Interestingly, as soon as the size of the shadow economy drops below the 20% (in 2008), its contribution is no longer amongst the most important.

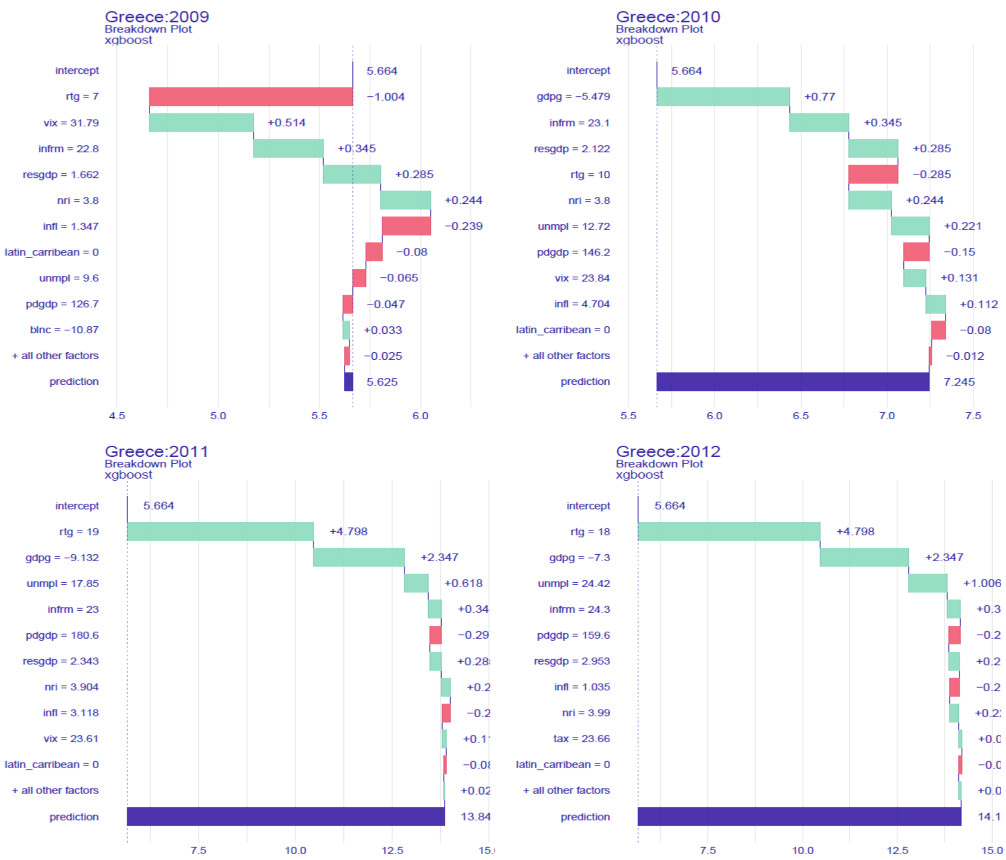
In years 2009-2012 (Figure 3.8) Greece slides to the worst economic crisis that a Western country ever faced since the Great Depression in non-war times. The rapid fall of GDP and the exacerbation of credit ratings lead the cost of debt to prohibitive limits and Greece outside of debt markets and to bailout rescue. The restored size of the shadow economy and the poor performance in the diffusion of technology have a comparable contribution to years before 2008.

Figure 3.7. Breakdown plot of the contribution of 10 most important attributes of interest rates for years 2005-2008.



In the following years, 2013-2016 (Figure 3.9) while the informal sector's contribution consolidates to a magnitude of 0.3 p.p., a slightly improved network readiness reduces the negative contribution of the specific factor. The contribution of the exploded unemployment rate to the predicted interest rates during this period should also be highlighted.

Figure 3.8. Breakdown plot of the contribution of 10 most important attributes of interest rates for years 2009-2012.

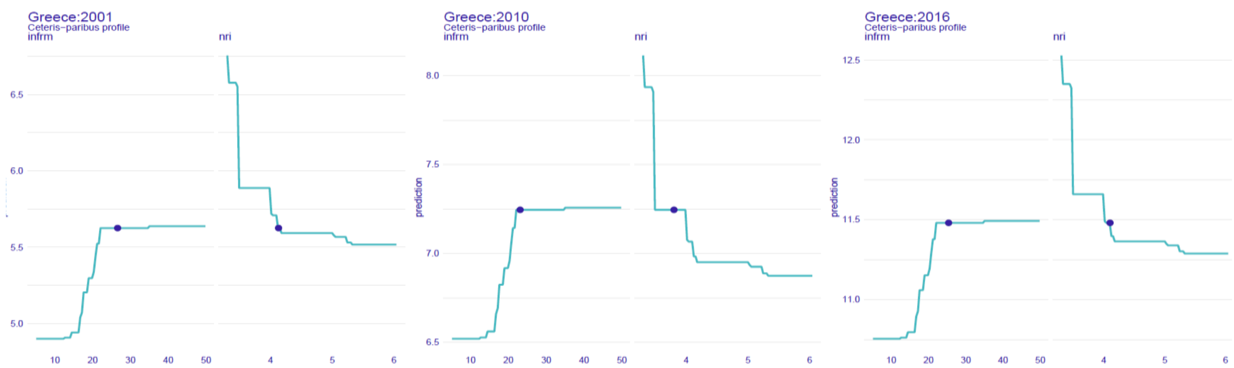


In general, the above can be encapsulated in Figure 3.10, a ceteris paribus profile plot that shows how much would the response model change for the indicative observations (Greece 2001;2010;2016) if only the size of the informal sector or the network readiness index changed. The plot shows clearly that Greece should strive to confine the informal sector below 20% of GDP and could expect an improvement of interest rates up to 0.5-0.7 p.p.. Moreover, the network readiness seems, as expected, to have a moderate impact and if an index score of more than 4.2 or 4.3 achieved, could lead to an amelioration of rates by about 0.1 to 0.3 p.p. according to the size of the improvement.

The conclusions are in broad terms in line with the findings of the previous chapter that a country that attempts to get access to cheaper market funding should curb the shadow economy to a rate below 20% of GDP and on the other hand to invest heavily in digital technologies since laggards are severely penalized by markets for poor performance on the field.

Figure 3.9. Breakdown plot of the contribution of 10 most important attributes of interest rates for years 2013-2016.

Figure 3.10. Ceteris paribus profile plots regarding years 2001, 2010 and 2016.



3.4 Policy implications for Greece.

The above findings concerning Greece could lead to certain policy implications. After decades of unacceptable for a developed country rates of shadow economy, Greece should spare no effort and mean to control and curtail the size of the shadow economy. Several measures have been proposed in literature like the restoring of trust to authorities and the reinforcement of anti-corruption policies, the provision of better-quality public goods, the reduction of the statutory tax rate and social security contributions, the reorganization of the Tax Agency and the lessen of stringent labor regulations that have partially taken place etc. Probably the most important is the governmental willpower to act regardless of any political costs.

On the other hand, Greece has made a considerable progress, especially concerning the last years, in order to prepare its state and economy for the much-needed digital transformation. Measures that have been proposed towards this direction include, among others, the investment in 5G networks, the digitization of the provision of public goods where Greece exhibits remarkable underperformance like Justice and public health especially in isolated or insular areas, the consolidation of public procurement contacts under a dedicated information system, the provision of public open data to an editable form, the creation of a lasting link between universities and markets through collaborative or industry funded doctoral studies or the facilitation of dedicated ecosystems for technological startups.

Greece has struggled for a long time in order to service a costly public debt and got even more indebted when financing got cheaper due to Eurozone membership. A sound performance in confining the shadow economy and digitally transforming the structure of the state and the economy would provide a solid expectation for a cheaper financing by international markets when needed.

3.5 References of Chapter 3.

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4 APPENDIX.

Table 4.1. Extensive literature review on the determinants of sovereign ratings and spreads along with definitions, sources and group of explanatory variables that each determinant belongs according to literature. Column one depicts the dependent variables that each determinant intended to explain.

Dependent variable	Explanatory Variable	Group of explanatory variables	Definition	Source if available	Literature
Sovereign debt ratings; Default probabilities	Dummy for default; Years since last default; Previous default	Indicators of default history; Macroeconomic Fundamentals and Fiscal strength; Financial stability and fiscal performance	Default on foreign currency debt since 1960;1970;1975;1980;1983; 1995; 3 or 5 previous years; maximum eleven (11) years; 1 for defaulted year t0 and exponentially decay at the rate of 20% till year t + 4	S&P; Moody's; Bank of Canada	Cantor and Packer, (1996); Rowland, (2005); Mellios, (2006); Mora, (2006); Amstad, (2015); Hilscher, (2010); De Moor, (2018); Vernazza, (2015); Fuchs, (2017); Afonso, (2011); Butler, (2006)
Sovereign debt ratings	Dummy for economic development; Underdevelopment index; Dummy for emerging markets	Indicators of development	IMF classification as an industrialized country; OECD membership; Underdevelopment index as the sum of the decile rankings of infant mortality, internet users per population, literacy, unemployment rate and paved airport runways; Emerging market dummy takes 1 if Morgan Stanley Capital International and the Global Stock Markets Factbook define country as such.	IMF; OECD; CIA Factbook; Morgan Stanley Capital International & Global Stock Markets Factbook	Cantor and Packer, (1996); Bennell, (2006); Mora (2006); Reusens, (2017); Vernazza, (2015); Afonso, (2011); Butler, (2006)
Sovereign debt ratings	Mobile phones; NRI or EIU index or E-Government Index; Patents; Internet users	Diffusion of technology	Users of cellular phones per 1000 people; Network Readiness Index; Economist Intelligence Unit Index; Patents per inhabitant; Internet users per inhabitant	World Economic Forum;EIU;UN; International Telecommunications Union; USPTO/EPO	Bissoondoyal-Bheenick, (2006)
Sovereign debt ratings; ΔCDS spreads; Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries	Exchange rates; Exchange rates change (%); Deviation of real exchange rate from trend (squared)	Proxies of the state of the local economy; Economic stability	Exchange rates as units of the local currency per US dollar; Long-run trend real exchange rate is the Hodrick-Prescott filtered real exchange rate index, calculated as the relative consumer prices expressed in country i’s currency.	Datastream	Longstaff et.al, (2007);Bissoondoyal-Bheenick, (2005); Mellios et.al., (2006); Peter, (2002); Baek, (2005); Powell, (2008); Afonso, (2015)

Dependent variable	Explanatory Variable	Group of explanatory variables	Definition	Source if available	Literature
Sovereign debt ratings;Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries; Cost of debt	Fiscal balance; Projected (expected) surplus/deficit to GDP;	Proxies of the state of the local economy;Indicators of debt situation; Solvency; Credit Risk; Macroeconomic Fundamentals and Fiscal strength; Government variables	Average annual government budget surplus relative to GDP 3-year basis; Annual government budget surplus relative to GDP; Projected deficit (1-year ahead) to GDP ratio	World Bank & Federal Reserve Bank; IMF; OECD; Thomson Reuters	Cantor and Packer, (1996); Maltritz (2011); Bissoondoyal-Bheenick, (2005); Bennell, (2006); Rowland, (2005); Mora (2006); Reusens, (2017), Gärtner, (2011); Baek, (2005); Powel, (2008); Bernoth, (2010); Beirne, (2013); Bastida, (2017); De Moor, (2018); Afonso, (2011); Afonso, (2015); McNamara, (2000)
Sovereign debt ratings;Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries; Institutional Investor ratingss; CDS spreads; Cost of debt	GDP growth	Proxies of the state of the local economy; Solvency; Economic progress; Domestic Economic performance	Annual real GDP growth on a year-over-year basis; Average annual GDP growth t-9 to t; Average 3-year; Squared	World Bank & Federal Reserve Bank; OECD; IMF	Cantor and Packer, (1996); Maltritz (2011); Ratha, (2011); Bennell, (2006); Rowland, (2005); Mora, (2006); Reusens, (2017); Amstad, (2015); Gärtner, (2011); Baek, (2005); Powell, (2008); Feder, (1985); Beirne, (2013); Bastida, (2017); De Moor, (2018); Vernazza, (2015); Fuchs, (2017); Afonso, (2011); McNamara, (2000)
Sovereign debt ratings; Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries; Institutional Investor ratingss	GDP/GNP/GNI;GDP/GNP per capita	Proxies of the state of the local economy;Solvency; Economic progress; Macroeconomic Fundamentals and Fiscal strength; Domestic Economic Performance	Natural logarithm of nominal GDP/GDP in constant prices of year t or PPP-adjusted exchange rates/nominal GDP divided by mid-year population/ GNP per capita	IMF; Thomson Reuters; World Bank	Bennell, (2006); Rowland, (2005); Mora, (2006); Reusens, (2017), Amstad, (2015); Gärtner, (2011); Powell, (2008); Feder, (1985); De Moor, (2018); Vernazza, (2015); Fuchs, (2017); Afonso, (2011); McNamara, (2000); Butler, (2006); Cantor and Packer, (1996), Bissoondoyal-Bheenick, (2005); Ratha, (2011)
Sovereign debt ratings; Cost of debt	Unemployment rate	Proxies of the state of the local economy; Economic progress; Macroeconomic Fundamentals and Fiscal strength	Annual; 3 year average	OECD; Moody's	Bissoondoyal-Bheenick, (2005); Powell, (2008); Bastida, (2017); De Moor, (2018); Afonso, (2011)
Sovereign debt ratings	Unit labour cost; Labour productivity	Proxies of the state of the local economy	Output per worker	OECD; International Labour Organisation	Bissoondoyal-Bheenick, (2005)

Dependent variable	Explanatory Variable	Group of explanatory variables	Definition	Source if available	Literature
Sovereign debt ratings; Default probabilities; Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries; CDS spreads; Cost of debt	Current account balance	Proxies of the state of the local economy; Solvency; Macroeconomic Fundamentals and Fiscal strength; External performance; External variables	Average annual current account surplus relative to GDP 3-year basis; Current account surplus relative to GDP	World Bank & Federal Reserve Bank; IMF; Thomson Reuters	Cantor and Packer, (1996); Bissoondoyal-Bheenick, (2005); Bennell, (2006); Rowland, (2005); Peter, (2002); Mora, (2006); Baek, 2005, Powell, (2008); Bastida, (2017); De Moor, (2018); Fuchs, (2017); Afonso, (2011); McNamara, (2000)
Sovereign debt ratings;Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries; Default probabilities; Default risk	Inflation	Proxies of the state of the local economy; Indicators of the ability to meet debt obligations; Socioeconomic enviroment; Economic stability; Economic progress; Domestic Economic Performance	Average annual consumer price inflation rate 3 -year basis; Inflation as annual change in CPI	World Bank & Federal Reserve Bank; IMF; Moody's;	Cantor and Packer, (1996); Maltritz (2011); Bissoondoyal-Bheenick, (2005); Rowland, (2005); Peter, (2002); Mora, (2006); Gärtner, (2011); Lemmen, (1999); Baek, (2005); Powell, (2008); Fuchs, (2017); Afonso, (2011); McNamara, (2000); Butler, (2006)
Sovereign debt ratings	External (foreign) debt/exports	Proxies of the state of the local economy; Debt and the external sector; External variables	Foreign currency debt relative to exports	World Bank & Federal Reserve Bank	Cantor and Packer, (1996); Powell, (2008); Afonso, (2011); McNamara, (2000)
Sovereign debt ratings; ΔCDS spreads	Foreign currency reserves	Proxies of the state of the local economy	US dollar value of sovereign foreign currency holdings	Datastream	Longstaff et.al, (2007);Bissoondoyal-Bheenick, (2005)
Sovereign debt ratings	External Debt/GDP	Proxies of the state of the local economy	Future interest to be paid to nonresidents relative to GDP; Debt a counrtry owes other as a percent of GDP	Moody's; IMF	Bissoondoyal-Bheenick, (2005)
Default probabilities	Credit to private sector/GDP	Indicators of liquidity; Solvency	Financial resources provided to the private sector	World Bank	Peter, (2002); Amstad, (2015)
Institutional Investor ratingss	Export vulnerability	Indicators of vulnerability to external shocks	Measure of the extent to which export revenues are concentrated in very few commodities for example three		Feder, (1985)
Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries; Institutional Investor ratingss	Terms of trade growth;volatility of trade growth	Indicators of the external sector	Terms of Trade Index (1990 = 100) annual growth; std of the annual percentage change over 10 years	EIU; COMTRADE; Global Financial Data	Maltritz (2011); Hilscher, (2010); Feder, (1985)
Sovereign debt ratings; Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries	Trade openness/Trade dependency/Trade	Indicators of the external sector; Macroeconomic Fundamentals and Fiscal strength; External performance	Exports plus imports over GDP annually or 3-year average	IMF; Thomson Reuters	Maltritz (2011); Bissoondoyal-Bheenick, (2006); Rowland, (2005); Mellios et.al. (2006); De Moor, (2018); Fuchs, (2017)

Dependent variable	Explanatory Variable	Group of explanatory variables	Definition	Source if available	Literature
ΔCDS spreads	U.S. stock market returns	Proxies of the state of the international economy	Montly value - weighted returns on all NYSE, AMEX and Nasdaq stocks minus the one month Treasury Bill return	Ibbotson Associates	Longstaff et.al, (2007);
Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries	Dummy variable for years of crisis	Years of crisis	Time dummy variable i) Dummy to begin in August 2007 ii) Dummy to begin in March 2009		Afonso, (2015)
Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries	Risk-less US interest rate	Indicators of global conditions; global liquidity	Bond yield from US treasury yield curve for one-year maturity; 10 year maturity rate	Datastream	Maltritz (2011); Baek, (2005); Hilscher, (2010); Powell, (2010)
Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries; CDS spreads	VIX index	Indicators of global risk aversion; International risk factor	(Log of) VIX index	Bloomberg	Hilschler, (2010); Powell, (2008); Beirne, (2013); Afonso, (2015)
Default risk	Tax raising capability	Indicator of Government finance	The difference between the highest level of government current receipts over a period minus the current receipts to GDP		Lemmen, (1999)
Sovereign Ratings; Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries	Tax revenues/GDP	Indicator of Government finance	Tax revenues as percent of GDP	World Bank	
Sovereign Ratings; Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries	Tax revenues/Total Debt	Indicator of Government finance	Tax revenues/Total Debt		Powell, (2008)
Sovereign debt ratings	Dummy for legal origin	Legal institutions' variable	Dummies for UK, Socialist, French, German & Scandinavian	La Porta, (1999) & Reynolds and Flores, (1989)	Butler, (2006)
Sovereign debt ratings	Dummy for Eurozone	Members of monetary Unions; Political and institutional performance	Dummy for Eurozone	ECB	Reusens, (2017); Gärtner, (2011); Fuchs, (2017)
Sovereign debt ratings	Corruption perception index; Corruption index	Demographics;Institutional quality		Transparency International; Heritage Foundation	Mellios et.al., (2006); Bastida, (2017)

Dependent variable	Explanatory Variable	Group of explanatory variables	Definition	Source if available	Literature
Sovereign debt ratings; Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries	Informal sector	Quality of governance and institutions	Informal sector as a percentage of GDP based on the estimates of Schneider et al. (2010) for the period 2003–2007.	Schneider, (2010)	
Sovereign debt ratings	Legal environment composite index	Legal institutions' variable	The sum of ranks of voice of the people, political stability, government effectiveness, regulatory quality, rule of law and corruption control	CIA Factbook	Butler, (2006)
Sovereign debt ratings	Rule of law; Rule of law index	Political and institutional performance	Function of various governance indicators, such as enforcement of property rights and accountability of the government	Kaufmann, Kraay, and Mastruzzi (2006); World Bank; International Country Risk Guide	Ratha, (2011); Vernazza, (2015); Fuchs, (2017)
Sovereign debt ratings; Default probabilities	Debt or external debt /exports or current account receipts	Indicators of liquidity; Solvency;External Assessment	Debt or external debt /exports or current account receipts	World Bank; External Debt Statistics; IMF	Ratha, (2011); Bennell (2006); Rowland, (2005); Peter, (2002); Mora, (2006), Amstad, (2015); Vernazza, (2015)
Sovereign debt ratings; Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries; Default probabilities; Default risk; Institutional Investor ratingss; CDS spreads	Debt to GDP/GNP or expected Debt/GDP	Indicators of debt situation; Solvency; Credit risk; Financial stability and fiscal performance; Government variables	Total government debt as percentage of GDP; Change in Debt/GDP 3-year average	IMF; Eurostat;	Maltritz (2011); Bissoondoyal-Bheenick, (2005); Rowland, (2005); Peter, (2002); Reusens, (2017); Amstad, (2015); Gärtner, (2011); Lemmen, (1999); Hilscher, (2010); Powell, (2008); Feder, (1985); Bernoth, (2010); Beirne, (2013); Vernazza, (2015); Fuchs, (2017); Afonso, (2011); Afonso (2015)
Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries; Sovereign ratings	Foreign debt/GDP	Solvency; Macroeconomic Fundamentals and Fiscal strength; External performance	Foreign currency debt relative to GDP or year average	Thomson Reuters; World Bank; Reinhart-Roggof; Political Risk Guide	Baek, (2005); Powell, (2008); De Moor, (2018); Vernazza, (2015); Fuchs, (2017); Butler, (2006)
Sovereign debt ratings; Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries; Institutional Investor ratingss	Reserves/(Imports + Short term debt) or Imports or GDP; Reserves	Indicators of liquidity; Macroeconomic Fundamentals and Fiscal strength	Log of foreign currency reserves of the government Reserves;/(Imports + Short term debt)	BIS; Thomson Reuters	Ratha, (2011); Rowland, (2005); Amstad, (2015); Baek, (2005); Hilscher, (2010); Powell, (2008); Feder, (1985); De Moor, (2018); Afonso, (2011)

Dependent variable	Explanatory Variable	Group of explanatory variables	Definition	Source if available	Literature
Bond yields or Bond yield spreads or stripped yield spreads over German sovereign bonds or US treasuries; Cost of debt	Sovereign ratings; Sovereign outlook	Sovereign ratings	Ratings assigned by Moody's or S&P, or the average of the two agencies' ratings; Average ratings or outlooks assigned by the three agencies	Moodys & S&P & Fitch	Cantor and Packer, (1996); Bastida, (2017); Afonso, (2015)

Table 4.2. Marginal effects of the independent variables of random effects ordered probit regression concerning S&P ratings. The derivative for each observation is evaluated and the average of the marginal effects is reported.

Predicted mean=1	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	0.049149	0.051092	0.96	0.336	-0.0509907	0.149288
nri_diff	-0.012051	0.017744	-0.68	0.497	-0.0468285	0.022726
blnc_avg	0.548246	0.233377	2.35	0.019	0.0908345	1.005656
blnc_diff	-0.133766	0.077088	-1.74	0.083	-0.2848562	0.017325
lglskn	-0.176507	0.076844	-2.3	0.022	-0.3271176	-0.025897
cred_avg	0.043395	0.041916	1.04	0.301	-0.0387592	0.125549
cred_diff	-0.005234	0.020532	-0.25	0.799	-0.0454763	0.035009
crpt_avg	0.067345	0.024403	2.76	0.006	0.0195157	0.115174
crpt_diff	0.022892	0.011501	1.99	0.047	0.0003506	0.045434
fdgdp_avg	0.081752	0.089382	0.91	0.36	-0.0934338	0.256939
fdgdp_diff	-0.0043	0.056106	-0.08	0.939	-0.1142663	0.105666
frdm_avg	0.00056	0.002712	0.21	0.836	-0.0047551	0.005875
frdm_diff	0.003201	0.001635	1.96	0.05	-4.54E-06	0.006406
gni_avg	0.027921	0.01032	2.71	0.007	0.0076942	0.048148
gni_diff	0.054746	0.016942	3.23	0.001	0.02154	0.087951
lgluk	0.053591	0.034421	1.56	0.119	-0.0138733	0.121055
infl_avg	-0.013788	0.004562	-3.02	0.003	-0.02273	-0.004846
infl_diff	-0.002508	0.00097	-2.59	0.01	-0.0044088	-0.000608
pdgdp_avg	-0.161345	0.052253	-3.09	0.002	-0.2637593	-0.05893
pdgdp_diff	-0.045992	0.046583	-0.99	0.323	-0.1372937	0.04531
rev_avg	0.859456	0.26229	3.28	0.001	0.3453785	1.373534
rev_diff	-0.019963	0.176081	-0.11	0.91	-0.3650746	0.325148
tax_avg	-0.362602	0.315839	-1.15	0.251	-0.9816352	0.256432
tax_diff	-0.008885	0.214105	-0.04	0.967	-0.428523	0.410754
unpl_avg	-0.142673	0.301381	-0.47	0.636	-0.7333681	0.448022
unpl_diff	-1.170696	0.33136	-3.53	0	-1.820149	-0.521243
oecd	0.047488	0.033523	1.42	0.157	-0.0182164	0.113192
euro	0.075317	0.042349	1.78	0.075	-0.0076869	0.15832
lglgrm	0.029921	0.064552	0.46	0.643	-0.0965998	0.156441

Predicted mean=2	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	-0.017739	0.020017	-0.89	0.376	-0.0569705	0.021493
nri_diff	0.00435	0.007251	0.6	0.549	-0.0098617	0.018561
blnc_avg	-0.197875	0.180394	-1.1	0.273	-0.5514405	0.155691
blnc_diff	0.048279	0.046264	1.04	0.297	-0.0423956	0.138954
lglskn	0.063706	0.059259	1.08	0.282	-0.0524391	0.17985
cred_avg	-0.015662	0.020478	-0.76	0.444	-0.0557986	0.024474
cred_diff	0.001889	0.007461	0.25	0.8	-0.0127341	0.016512
crpt_avg	-0.024306	0.02229	-1.09	0.276	-0.0679939	0.019381
crpt_diff	-0.008262	0.007598	-1.09	0.277	-0.0231545	0.00663
fdgdp_avg	-0.029506	0.034847	-0.85	0.397	-0.0978044	0.038792
fdgdp_diff	0.001552	0.020284	0.08	0.939	-0.0382043	0.041308
frdm_avg	-0.000202	0.00098	-0.21	0.837	-0.0021236	0.001719
frdm_diff	-0.001155	0.001062	-1.09	0.277	-0.0032361	0.000926
gni_avg	-0.010077	0.008064	-1.25	0.211	-0.0258832	0.005728
gni_diff	-0.019759	0.016234	-1.22	0.224	-0.0515771	0.012059
lgluk	-0.019342	0.018426	-1.05	0.294	-0.0554557	0.016771
infl_avg	0.004976	0.004064	1.22	0.221	-0.0029889	0.012942
infl_diff	0.000905	0.000772	1.17	0.241	-0.0006076	0.002418
pdgdp_avg	0.058233	0.042259	1.38	0.168	-0.024592	0.141058
pdgdp_diff	0.0166	0.021285	0.78	0.435	-0.0251172	0.058317
rev_avg	-0.310198	0.25499	-1.22	0.224	-0.8099696	0.189574
rev_diff	0.007205	0.063812	0.11	0.91	-0.1178635	0.132274
tax_avg	0.130871	0.165585	0.79	0.429	-0.1936695	0.455412
tax_diff	0.003207	0.077433	0.04	0.967	-0.14856	0.154973
unpl_avg	0.051494	0.112669	0.46	0.648	-0.1693335	0.272321
unpl_diff	0.422532	0.344305	1.23	0.22	-0.2522933	1.097356
oecd	-0.017139	0.017316	-0.99	0.322	-0.051078	0.016799
euro	-0.027184	0.028334	-0.96	0.337	-0.0827174	0.028351
lglgrm	-0.010799	0.024451	-0.44	0.659	-0.0587213	0.037123

Predicted mean=3	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	-0.003862	0.012637	-0.31	0.76	-0.0286302	0.020907
nri_diff	0.000947	0.002809	0.34	0.736	-0.0045588	0.006453
blnc_avg	-0.043076	0.111138	-0.39	0.698	-0.2609032	0.174751
blnc_diff	0.01051	0.027844	0.38	0.706	-0.0440635	0.065084
lglskn	0.013868	0.036815	0.38	0.706	-0.0582884	0.086025
cred_avg	-0.00341	0.008466	-0.4	0.687	-0.0200017	0.013183
cred_diff	0.000411	0.002013	0.2	0.838	-0.0035348	0.004357
crpt_avg	-0.005291	0.013253	-0.4	0.69	-0.0312659	0.020683
crpt_diff	-0.001799	0.004753	-0.38	0.705	-0.0111133	0.007516
fdgdp_avg	-0.006423	0.019421	-0.33	0.741	-0.0444883	0.031642
fdgdp_diff	0.000338	0.004481	0.08	0.94	-0.0084438	0.00912
frdm_avg	-0.000044	0.000245	-0.18	0.857	-0.0005244	0.000436
frdm_diff	-0.000252	0.000658	-0.38	0.702	-0.0015416	0.001039
gni_avg	-0.002194	0.005595	-0.39	0.695	-0.013159	0.008771
gni_diff	-0.004301	0.011178	-0.38	0.7	-0.0262098	0.017607
lgluk	-0.004211	0.011205	-0.38	0.707	-0.0261724	0.017751
infl_avg	0.001083	0.002834	0.38	0.702	-0.0044705	0.006637
infl_diff	0.000197	0.000516	0.38	0.702	-0.0008136	0.001208
pdgdp_avg	0.012677	0.034271	0.37	0.711	-0.0544925	0.079847
pdgdp_diff	0.003614	0.009909	0.36	0.715	-0.0158078	0.023035
rev_avg	-0.067528	0.175162	-0.39	0.7	-0.4108404	0.275784
rev_diff	0.001569	0.014325	0.11	0.913	-0.0265086	0.029646
tax_avg	0.02849	0.077123	0.37	0.712	-0.122669	0.179649
tax_diff	0.000698	0.016869	0.04	0.967	-0.0323637	0.03376
unpl_avg	0.01121	0.042124	0.27	0.79	-0.0713517	0.093772
unpl_diff	0.091983	0.239438	0.38	0.701	-0.3773071	0.561272
oecd	-0.003731	0.010482	-0.36	0.722	-0.024275	0.016813
euro	-0.005918	0.014888	-0.4	0.691	-0.0350978	0.023262
lglgrm	-0.002351	0.007656	-0.31	0.759	-0.0173556	0.012654

Predicted mean=4	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	0.023056	0.026652	0.87	0.387	-0.0291816	0.075294
nri_diff	-0.005653	0.008717	-0.65	0.517	-0.0227375	0.011431
blnc_avg	0.257188	0.123038	2.09	0.037	0.016038	0.498338
blnc_diff	-0.062751	0.042366	-1.48	0.139	-0.1457873	0.020286
lglskn	-0.082801	0.045322	-1.83	0.068	-0.17163	0.006027
cred_avg	0.020357	0.018263	1.11	0.265	-0.0154386	0.056153
cred_diff	-0.002455	0.009729	-0.25	0.801	-0.0215234	0.016613
crpt_avg	0.031592	0.017053	1.85	0.064	-0.0018317	0.065016
crpt_diff	0.010739	0.006805	1.58	0.115	-0.0025987	0.024077
fdgdp_avg	0.038351	0.041244	0.93	0.352	-0.042486	0.119188
fdgdp_diff	-0.002017	0.026228	-0.08	0.939	-0.0534225	0.049388
frdm_avg	0.000263	0.001242	0.21	0.832	-0.0021712	0.002697
frdm_diff	0.001501	0.000955	1.57	0.116	-0.0003695	0.003372
gni_avg	0.013098	0.007006	1.87	0.062	-0.0006331	0.026829
gni_diff	0.025682	0.012437	2.06	0.039	0.0013057	0.050058
lgluk	0.02514	0.01861	1.35	0.177	-0.0113338	0.061614
infl_avg	-0.006468	0.003183	-2.03	0.042	-0.0127062	-0.00023
infl_diff	-0.001177	0.000636	-1.85	0.064	-0.0024227	6.94E-05
pdgdp_avg	-0.075689	0.036041	-2.1	0.036	-0.1463271	-0.00505
pdgdp_diff	-0.021575	0.02405	-0.9	0.37	-0.0687122	0.025561
rev_avg	0.40318	0.171611	2.35	0.019	0.0668287	0.739531
rev_diff	-0.009365	0.082554	-0.11	0.91	-0.1711684	0.152439
tax_avg	-0.1701	0.159847	-1.06	0.287	-0.4833944	0.143194
tax_diff	-0.004168	0.10049	-0.04	0.967	-0.2011241	0.192788
unpl_avg	-0.066929	0.161815	-0.41	0.679	-0.3840814	0.250223
unpl_diff	-0.549186	0.254756	-2.16	0.031	-1.048498	-0.049874
oecd	0.022277	0.020438	1.09	0.276	-0.0177812	0.062335
euro	0.035332	0.023163	1.53	0.127	-0.0100677	0.080731
lglgrm	0.014036	0.029397	0.48	0.633	-0.0435812	0.071653

Predicted mean=5	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	-0.011326	0.013597	-0.83	0.405	-0.0379743	0.015323
nri_diff	0.002777	0.004685	0.59	0.553	-0.0064051	0.011959
blnc_avg	-0.126336	0.107788	-1.17	0.241	-0.3375971	0.084924
blnc_diff	0.030825	0.029811	1.03	0.301	-0.0276039	0.089253
lglskn	0.040674	0.034444	1.18	0.238	-0.0268344	0.108182
cred_avg	-0.01	0.011222	-0.89	0.373	-0.0319946	0.011995
cred_diff	0.001206	0.004885	0.25	0.805	-0.0083673	0.010779
crpt_avg	-0.015519	0.013963	-1.11	0.266	-0.0428849	0.011847
crpt_diff	-0.005275	0.005033	-1.05	0.295	-0.0151388	0.004588
fdgdp_avg	-0.018839	0.018339	-1.03	0.304	-0.0547826	0.017105
fdgdp_diff	0.000991	0.012878	0.08	0.939	-0.0242487	0.026231
frdm_avg	-0.000129	0.000621	-0.21	0.835	-0.0013466	0.001088
frdm_diff	-0.000738	0.0007	-1.05	0.292	-0.0021092	0.000634
gni_avg	-0.006434	0.005827	-1.1	0.269	-0.0178543	0.004986
gni_diff	-0.012616	0.010917	-1.16	0.248	-0.0340119	0.008781
lgluk	-0.012349	0.010842	-1.14	0.255	-0.0335998	0.008901
infl_avg	0.003177	0.002855	1.11	0.266	-0.0024192	0.008774
infl_diff	0.000578	0.000527	1.1	0.273	-0.0004552	0.001611
pdgdp_avg	0.03718	0.029645	1.25	0.21	-0.020924	0.095284
pdgdp_diff	0.010598	0.014207	0.75	0.456	-0.0172477	0.038444
rev_avg	-0.198051	0.152493	-1.3	0.194	-0.4969326	0.10083
rev_diff	0.0046	0.040697	0.11	0.91	-0.0751651	0.084366
tax_avg	0.083557	0.093188	0.9	0.37	-0.0990888	0.266203
tax_diff	0.002047	0.049303	0.04	0.967	-0.094584	0.098679
unpl_avg	0.032877	0.086799	0.38	0.705	-0.1372464	0.203001
unpl_diff	0.269773	0.225852	1.19	0.232	-0.1728889	0.712434
oecd	-0.010943	0.012738	-0.86	0.39	-0.0359095	0.014024
euro	-0.017356	0.017647	-0.98	0.325	-0.0519429	0.017231
lglgrm	-0.006895	0.014288	-0.48	0.629	-0.0348977	0.021108

Predicted mean=6	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	-0.022344	0.026286	-0.85	0.395	-0.0738626	0.029175
nri_diff	0.005479	0.008314	0.66	0.51	-0.0108167	0.021774
blnc_avg	-0.249244	0.123663	-2.02	0.044	-0.4916186	-0.00687
blnc_diff	0.060813	0.041243	1.47	0.14	-0.0200212	0.141647
lglskn	0.080244	0.040145	2	0.046	0.0015609	0.158927
cred_avg	-0.019728	0.018895	-1.04	0.296	-0.056761	0.017305
cred_diff	0.002379	0.009399	0.25	0.8	-0.0160426	0.020801
crpt_avg	-0.030616	0.014855	-2.06	0.039	-0.0597312	-0.001501
crpt_diff	-0.010407	0.006122	-1.7	0.089	-0.0224071	0.001592
fdgdp_avg	-0.037166	0.045814	-0.81	0.417	-0.1269609	0.052628
fdgdp_diff	0.001955	0.025555	0.08	0.939	-0.0481326	0.052042
frdm_avg	-0.000255	0.00122	-0.21	0.835	-0.0026451	0.002136
frdm_diff	-0.001455	0.00091	-1.6	0.11	-0.0032386	0.000329
gni_avg	-0.012694	0.006782	-1.87	0.061	-0.0259865	0.0006
gni_diff	-0.024889	0.011448	-2.17	0.03	-0.0473267	-0.00245
lgluk	-0.024364	0.021422	-1.14	0.255	-0.0663506	0.017623
infl_avg	0.006268	0.002494	2.51	0.012	0.0013809	0.011156
infl_diff	0.00114	0.000593	1.92	0.055	-0.0000228	0.002303
pdgdp_avg	0.073351	0.03642	2.01	0.044	0.0019692	0.144732
pdgdp_diff	0.020909	0.022396	0.93	0.351	-0.0229864	0.064804
rev_avg	-0.390727	0.177425	-2.2	0.028	-0.7384745	-0.04298
rev_diff	0.009076	0.08	0.11	0.91	-0.1477213	0.165873
tax_avg	0.164847	0.143927	1.15	0.252	-0.1172443	0.446937
tax_diff	0.004039	0.097427	0.04	0.967	-0.1869134	0.194992
unpl_avg	0.064862	0.134281	0.48	0.629	-0.1983234	0.328048
unpl_diff	0.532223	0.231305	2.3	0.021	0.0788742	0.985572
oecd	-0.021589	0.017313	-1.25	0.212	-0.0555209	0.012343
euro	-0.034241	0.02209	-1.55	0.121	-0.0775355	0.009055
lglgrm	-0.013603	0.030734	-0.44	0.658	-0.0738397	0.046635

Determinants of Market-Assessed Credit Risk

Predicted mean=7	dy/dx	Std. Err.	z	P>|z|	[95% Confidence	Interval]
nri_avg	-0.016935	0.016703	-1.01	0.311	-0.0496726	0.015804
nri_diff	0.004152	0.00623	0.67	0.505	-0.0080577	0.016363
blnc_avg	-0.188902	0.088647	-2.13	0.033	-0.3626459	-0.015158
blnc_diff	0.04609	0.028134	1.64	0.101	-0.0090508	0.101231
lglskn	0.060817	0.028379	2.14	0.032	0.0051951	0.116438
cred_avg	-0.014952	0.015949	-0.94	0.348	-0.0462107	0.016307
cred_diff	0.001803	0.007045	0.26	0.798	-0.0120036	0.01561
crpt_avg	-0.023204	0.010305	-2.25	0.024	-0.043402	-0.003006
crpt_diff	-0.007888	0.004455	-1.77	0.077	-0.0166188	0.000843
fdgdp_avg	-0.028168	0.03384	-0.83	0.405	-0.0944929	0.038156
fdgdp_diff	0.001482	0.019282	0.08	0.939	-0.0363104	0.039274
frdm_avg	-0.000193	0.000937	-0.21	0.837	-0.0020292	0.001643
frdm_diff	-0.001103	0.000627	-1.76	0.079	-0.0023316	0.000126
gni_avg	-0.00962	0.00518	-1.86	0.063	-0.0197735	0.000533
gni_diff	-0.018863	0.007381	-2.56	0.011	-0.0333285	-0.004398
lgluk	-0.018465	0.012038	-1.53	0.125	-0.0420594	0.005129
infl_avg	0.004751	0.002241	2.12	0.034	0.0003594	0.009142
infl_diff	0.000864	0.000361	2.4	0.017	0.000157	0.001572
pdgdp_avg	0.055593	0.026512	2.1	0.036	0.0036299	0.107555
pdgdp_diff	0.015847	0.016616	0.95	0.34	-0.0167206	0.048414
rev_avg	-0.296132	0.128816	-2.3	0.022	-0.5486069	-0.043657
rev_diff	0.006878	0.060798	0.11	0.91	-0.1122836	0.12604
tax_avg	0.124937	0.111855	1.12	0.264	-0.0942939	0.344168
tax_diff	0.003061	0.073728	0.04	0.967	-0.141442	0.147565
unpl_avg	0.049159	0.109265	0.45	0.653	-0.1649966	0.263315
unpl_diff	0.403372	0.156072	2.58	0.01	0.0974768	0.709266
oecd	-0.016362	0.012155	-1.35	0.178	-0.040185	0.007461
euro	-0.025951	0.013332	-1.95	0.052	-0.0520807	0.000179
lglgrm	-0.010309	0.022275	-0.46	0.643	-0.0539665	0.033348

Table 4.3 Marginal effects of the independent variables of random effects ordered probit regression concerning Moody's ratings. The derivative for each observation is evaluated and the average of the marginal effects is reported.

Predicted mean=1	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	0.1154155	0.0574127	2.01	0.044	0.0028887	0.2279424
nri_diff	-0.0165215	0.0171514	-0.96	0.335	-0.0501377	0.0170947
blnc_avg	0.2793911	0.2150946	1.3	0.194	-0.1421866	0.7009687
blnc_diff	-0.0528665	0.0678219	-0.78	0.436	-0.185795	0.0800619
lglskn	-0.0208246	0.072095	-0.29	0.773	-0.1621283	0.1204791
cred_avg	0.0956751	0.0513551	1.86	0.062	-0.0049789	0.1963292
cred_diff	0.087399	0.0344744	2.54	0.011	0.0198304	0.1549676
dfct_avg	0.5837855	0.5066251	1.15	0.249	-0.4091816	1.576752
dfct_diff	0.4570804	0.177263	2.58	0.01	0.1096512	0.8045096
fdgdp_avg	-0.0299755	0.0784377	-0.38	0.702	-0.1837105	0.1237595
fdgdp_diff	-0.0399528	0.0366628	-1.09	0.276	-0.1118106	0.031905
frdm_avg	0.0024317	0.0031117	0.78	0.435	-0.0036671	0.0085305
frdm_diff	0.0059977	0.001967	3.05	0.002	0.0021424	0.009853
gni_avg	0.0132548	0.0117368	1.13	0.259	-0.0097489	0.0362585
gni_diff	0.0736855	0.0213956	3.44	0.001	0.031751	0.1156201
hdi_avg	0.6858829	0.3437519	2	0.046	0.0121415	1.359624
hdi_diff	0.4252888	0.1506761	2.82	0.005	0.1299692	0.7206085
infl_avg	-0.0100821	0.0051158	-1.97	0.049	-0.0201089	-0.0000553
infl_diff	-0.0019671	0.0009675	-2.03	0.042	-0.0038633	-0.0000709
lglgrm	-0.0204548	0.0599585	-0.34	0.733	-0.1379714	0.0970617
rev_avg	0.4786421	0.2548485	1.88	0.06	-0.0208519	0.978136
rev_diff	-0.5279353	0.2086611	-2.53	0.011	-0.9369036	-0.118967
tax_avg	-0.0914665	0.3496785	-0.26	0.794	-0.7768237	0.5938908
tax_diff	-0.1143375	0.2161647	-0.53	0.597	-0.5380125	0.3093376
unpl_avg	0.3653067	0.4121532	0.89	0.375	-0.4424988	1.173112
unpl_diff	-0.5344019	0.2456068	-2.18	0.03	-1.015782	-0.0530215
oecd	0.0451833	0.0340155	1.33	0.184	-0.0214858	0.1118525
euro	0.0572163	0.0379654	1.51	0.132	-0.0171945	0.1316272
dflt75	-0.0371933	0.0404592	-0.92	0.358	-0.1164918	0.0421052
dflt95	0.04828	0.0425629	1.13	0.257	-0.0351416	0.1317017
lgluk	0.0327758	0.044048	0.74	0.457	-0.0535567	0.1191082

Determinants of Market-Assessed Credit Risk

Predicted mean=2	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	-0.0484754	0.0378349	-1.28	0.2	-0.1226305	0.0256797
nri_diff	0.0069392	0.0083058	0.84	0.403	-0.0093398	0.0232182
blnc_avg	-0.1173463	0.0886116	-1.32	0.185	-0.2910219	0.0563292
blnc_diff	0.0222043	0.0314223	0.71	0.48	-0.0393823	0.0837909
lglskn	0.0087465	0.0295519	0.3	0.767	-0.0491741	0.0666671
cred_avg	-0.0401843	0.0343915	-1.17	0.243	-0.1075904	0.0272218
cred_diff	-0.0367082	0.026735	-1.37	0.17	-0.0891078	0.0156914
dfct_avg	-0.2451942	0.2815475	-0.87	0.384	-0.7970173	0.3066288
dfct_diff	-0.1919772	0.137421	-1.4	0.162	-0.4613175	0.0773632
fdgdp_avg	0.01259	0.0344634	0.37	0.715	-0.0549571	0.080137
fdgdp_diff	0.0167805	0.0185146	0.91	0.365	-0.0195076	0.0530685
frdm_avg	-0.0010213	0.0012662	-0.81	0.42	-0.003503	0.0014603
frdm_diff	-0.0025191	0.0017553	-1.44	0.151	-0.0059594	0.0009213
gni_avg	-0.0055671	0.0061654	-0.9	0.367	-0.0176511	0.0065169
gni_diff	-0.0309485	0.0208373	-1.49	0.137	-0.0717889	0.0098919
hdi_avg	-0.2880759	0.2431872	-1.18	0.236	-0.7647141	0.1885622
hdi_diff	-0.1786245	0.1271114	-1.41	0.16	-0.4277582	0.0705093
infl_avg	0.0042346	0.0034225	1.24	0.216	-0.0024734	0.0109425
infl_diff	0.0008262	0.0006584	1.25	0.209	-0.0004642	0.0021166
lglgrm	0.0085912	0.0250744	0.34	0.732	-0.0405537	0.0577361
rev_avg	-0.2010332	0.1379272	-1.46	0.145	-0.4713656	0.0692991
rev_diff	0.2217367	0.1604749	1.38	0.167	-0.0927882	0.5362617
tax_avg	0.0384166	0.141992	0.27	0.787	-0.2398827	0.3167159
tax_diff	0.0480226	0.0948774	0.51	0.613	-0.1379338	0.233979
unpl_avg	-0.1534315	0.1911903	-0.8	0.422	-0.5281576	0.2212945
unpl_diff	0.2244528	0.1748249	1.28	0.199	-0.1181976	0.5671032
oecd	-0.0189773	0.0184736	-1.03	0.304	-0.055185	0.0172303
euro	-0.0240313	0.0228872	-1.05	0.294	-0.0688894	0.0208268
dflt75	0.0156215	0.0194725	0.8	0.422	-0.022544	0.0537869
dflt95	-0.020278	0.0209976	-0.97	0.334	-0.0614325	0.0208766
lgluk	-0.0137661	0.0209944	-0.66	0.512	-0.0549144	0.0273822

Determinants of Market-Assessed Credit Risk

Predicted mean=3	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	0.0255906	0.0275488	0.93	0.353	-0.0284042	0.0795853
nri_diff	-0.0036632	0.0053427	-0.69	0.493	-0.0141347	0.0068082
blnc_avg	0.0619481	0.0634762	0.98	0.329	-0.0624629	0.1863592
blnc_diff	-0.0117219	0.0193216	-0.61	0.544	-0.0495915	0.0261477
lglskn	-0.0046173	0.0156167	-0.3	0.767	-0.0352255	0.0259908
cred_avg	0.0212136	0.0273496	0.78	0.438	-0.0323905	0.0748178
cred_diff	0.0193786	0.0213618	0.91	0.364	-0.0224898	0.0612469
dfct_avg	0.1294402	0.1990095	0.65	0.515	-0.2606114	0.5194917
dfct_diff	0.1013464	0.1121172	0.9	0.366	-0.1183992	0.321092
fdgdp_avg	-0.0066463	0.0205819	-0.32	0.747	-0.0469862	0.0336935
fdgdp_diff	-0.0088586	0.012376	-0.72	0.474	-0.0331151	0.015398
frdm_avg	0.0005392	0.0008561	0.63	0.529	-0.0011387	0.002217
frdm_diff	0.0013298	0.0014403	0.92	0.356	-0.0014931	0.0041528
gni_avg	0.0029389	0.0043469	0.68	0.499	-0.0055808	0.0114586
gni_diff	0.016338	0.0173743	0.94	0.347	-0.0177151	0.0503911
hdi_avg	0.1520778	0.1755351	0.87	0.386	-0.1919648	0.4961203
hdi_diff	0.0942974	0.1017652	0.93	0.354	-0.1051586	0.2937535
infl_avg	-0.0022355	0.0025713	-0.87	0.385	-0.0072752	0.0028043
infl_diff	-0.0004362	0.0005045	-0.86	0.387	-0.0014249	0.0005526
lglgrm	-0.0045354	0.0119484	-0.38	0.704	-0.0279538	0.0188831
rev_avg	0.1061272	0.1140778	0.93	0.352	-0.1174612	0.3297156
rev_diff	-0.1170568	0.1285818	-0.91	0.363	-0.3690725	0.134959
tax_avg	-0.0202805	0.0734938	-0.28	0.783	-0.1643257	0.1237647
tax_diff	-0.0253515	0.0547148	-0.46	0.643	-0.1325906	0.0818875
unpl_avg	0.0809978	0.1302759	0.62	0.534	-0.1743382	0.3363339
unpl_diff	-0.1184906	0.1323584	-0.9	0.371	-0.3779083	0.1409271
oecd	0.0100183	0.0117675	0.85	0.395	-0.0130456	0.0330822
euro	0.0126863	0.0166044	0.76	0.445	-0.0198577	0.0452303
dflt75	-0.0082467	0.011603	-0.71	0.477	-0.0309881	0.0144947
dflt95	0.0107049	0.0145704	0.73	0.463	-0.0178525	0.0392623
lgluk	0.0072672	0.0130085	0.56	0.576	-0.0182289	0.0327634

Determinants of Market-Assessed Credit Risk

Predicted mean=4	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	0.014413	0.0305738	0.47	0.637	-0.0455105	0.0743366
nri_diff	-0.0020632	0.004545	-0.45	0.65	-0.0109712	0.0068448
blnc_avg	0.0348902	0.078287	0.45	0.656	-0.1185495	0.18833
blnc_diff	-0.006602	0.015252	-0.43	0.665	-0.0364953	0.0232914
lglskn	-0.0026006	0.0107245	-0.24	0.808	-0.0236201	0.018419
cred_avg	0.0119479	0.022601	0.53	0.597	-0.0323493	0.056245
cred_diff	0.0109144	0.0216597	0.5	0.614	-0.0315379	0.0533666
dfct_avg	0.0729029	0.1271143	0.57	0.566	-0.1762366	0.3220424
dfct_diff	0.0570801	0.1134332	0.5	0.615	-0.165245	0.2794051
fdgdp_avg	-0.0037433	0.0106151	-0.35	0.724	-0.0245485	0.0170619
fdgdp_diff	-0.0049893	0.0104786	-0.48	0.634	-0.0255269	0.0155483
frdm_avg	0.0003037	0.0007793	0.39	0.697	-0.0012238	0.0018311
frdm_diff	0.000749	0.0014821	0.51	0.613	-0.0021559	0.0036539
gni_avg	0.0016553	0.0037043	0.45	0.655	-0.005605	0.0089155
gni_diff	0.0092018	0.0181397	0.51	0.612	-0.0263514	0.0447551
hdi_avg	0.0856528	0.1624809	0.53	0.598	-0.2328038	0.4041095
hdi_diff	0.0531099	0.1057711	0.5	0.616	-0.1541976	0.2604175
infl_avg	-0.001259	0.0024808	-0.51	0.612	-0.0061212	0.0036031
infl_diff	-0.0002457	0.0004891	-0.5	0.615	-0.0012042	0.0007129
lglgrm	-0.0025544	0.0100112	-0.26	0.799	-0.022176	0.0170672
rev_avg	0.0597726	0.1167437	0.51	0.609	-0.1690408	0.288586
rev_diff	-0.0659284	0.1309247	-0.5	0.615	-0.3225361	0.1906793
tax_avg	-0.0114223	0.04905	-0.23	0.816	-0.1075586	0.084714
tax_diff	-0.0142784	0.0381876	-0.37	0.708	-0.0891247	0.0605678
unpl_avg	0.0456193	0.0811989	0.56	0.574	-0.1135276	0.2047663
unpl_diff	-0.066736	0.134445	-0.5	0.62	-0.3302432	0.1967713
oecd	0.0056425	0.0125002	0.45	0.652	-0.0188575	0.0301424
euro	0.0071451	0.014722	0.49	0.627	-0.0217094	0.0359997
dflt75	-0.0046447	0.0112102	-0.41	0.679	-0.0266163	0.0173269
dflt95	0.0060292	0.0138979	0.43	0.664	-0.0212101	0.0332685
lgluk	0.004093	0.0076285	0.54	0.592	-0.0108585	0.0190446

Determinants of Market-Assessed Credit Risk

Predicted mean=5	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	0.0255	0.0416301	0.61	0.54	-0.0560936	0.1070936
nri_diff	-0.0036503	0.0069423	-0.53	0.599	-0.0172568	0.0099563
blnc_avg	0.0617289	0.1106144	0.56	0.577	-0.1550714	0.2785291
blnc_diff	-0.0116804	0.023817	-0.49	0.624	-0.0583608	0.0350001
lglskn	-0.004601	0.0185328	-0.25	0.804	-0.0409247	0.0317227
cred_avg	0.0211385	0.0372363	0.57	0.57	-0.0518432	0.0941203
cred_diff	0.01931	0.0316683	0.61	0.542	-0.0427588	0.0813788
dfct_avg	0.128982	0.2457678	0.52	0.6	-0.352714	0.610678
dfct_diff	0.1009877	0.1649544	0.61	0.54	-0.222317	0.4242923
fdgdp_avg	-0.0066228	0.0187335	-0.35	0.724	-0.0433397	0.0300941
fdgdp_diff	-0.0088272	0.0163265	-0.54	0.589	-0.0408265	0.0231721
frdm_avg	0.0005373	0.0010536	0.51	0.61	-0.0015277	0.0026022
frdm_diff	0.0013251	0.0021318	0.62	0.534	-0.0028531	0.0055033
gni_avg	0.0029285	0.0045759	0.64	0.522	-0.00604	0.0118971
gni_diff	0.0162801	0.0261088	0.62	0.533	-0.0348921	0.0674524
hdi_avg	0.1515394	0.2658305	0.57	0.569	-0.3694788	0.6725577
hdi_diff	0.0939636	0.1510689	0.62	0.534	-0.2021259	0.3900531
infl_avg	-0.0022275	0.003494	-0.64	0.524	-0.0090757	0.0046206
infl_diff	-0.0004346	0.0007147	-0.61	0.543	-0.0018354	0.0009662
lglgrm	-0.0045193	0.0136105	-0.33	0.74	-0.0311953	0.0221567
rev_avg	0.1057515	0.1939523	0.55	0.586	-0.2743879	0.485891
rev_diff	-0.1166424	0.1903498	-0.61	0.54	-0.4897212	0.2564364
tax_avg	-0.0202087	0.0883522	-0.23	0.819	-0.1933758	0.1529585
tax_diff	-0.0252618	0.0636114	-0.4	0.691	-0.1499379	0.0994143
unpl_avg	0.0807111	0.1730709	0.47	0.641	-0.2585016	0.4199239
unpl_diff	-0.1180711	0.1930908	-0.61	0.541	-0.4965221	0.2603798
oecd	0.0099828	0.0169424	0.59	0.556	-0.0232236	0.0431893
euro	0.0126414	0.020878	0.61	0.545	-0.0282788	0.0535616
dflt75	-0.0082175	0.0156179	-0.53	0.599	-0.038828	0.0223929
dflt95	0.010667	0.0190381	0.56	0.575	-0.026647	0.047981
lgluk	0.0072415	0.0173733	0.42	0.677	-0.0268096	0.0412926

Determinants of Market-Assessed Credit Risk

Predicted mean=6	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	-0.1120499	0.0566939	-1.98	0.048	-0.223168	-0.0009318
nri_diff	0.0160397	0.0169252	0.95	0.343	-0.017133	0.0492125
blnc_avg	-0.2712437	0.227201	-1.19	0.233	-0.7165496	0.1740621
blnc_diff	0.0513249	0.0663196	0.77	0.439	-0.0786591	0.1813089
lglskn	0.0202173	0.0714405	0.28	0.777	-0.1198035	0.1602382
cred_avg	-0.0928852	0.0555381	-1.67	0.094	-0.2017378	0.0159675
cred_diff	-0.0848503	0.0358947	-2.36	0.018	-0.1552027	-0.0144979
dfct_avg	-0.5667617	0.4859917	-1.17	0.244	-1.519288	0.3857645
dfct_diff	-0.4437514	0.1888126	-2.35	0.019	-0.8138173	-0.0736855
fdgdp_avg	0.0291014	0.0732361	0.4	0.691	-0.1144387	0.1726416
fdgdp_diff	0.0387877	0.0363248	1.07	0.286	-0.0324075	0.109983
frdm_avg	-0.0023608	0.0032605	-0.72	0.469	-0.0087512	0.0040296
frdm_diff	-0.0058228	0.0020371	-2.86	0.004	-0.0098154	-0.0018302
gni_avg	-0.0128683	0.0110441	-1.17	0.244	-0.0345144	0.0087779
gni_diff	-0.0715368	0.0226924	-3.15	0.002	-0.1160131	-0.0270605
hdi_avg	-0.6658819	0.3302476	-2.02	0.044	-1.313155	-0.0186084
hdi_diff	-0.412887	0.1501418	-2.75	0.006	-0.7071596	-0.1186144
infl_avg	0.0097881	0.0043311	2.26	0.024	0.0012993	0.0182769
infl_diff	0.0019097	0.000957	2	0.046	0.000034	0.0037855
lglgrm	0.0198583	0.0566146	0.35	0.726	-0.0911043	0.1308209
rev_avg	-0.4646844	0.3097416	-1.5	0.134	-1.071767	0.142398
rev_diff	0.5125401	0.2134912	2.4	0.016	0.0941051	0.9309751
tax_avg	0.0887992	0.3457048	0.26	0.797	-0.5887697	0.7663681
tax_diff	0.1110033	0.212677	0.52	0.602	-0.305836	0.5278426
unpl_avg	-0.354654	0.4022789	-0.88	0.378	-1.143106	0.4337981
unpl_diff	0.5188182	0.2380042	2.18	0.029	0.0523385	0.9852979
oecd	-0.0438657	0.0325703	-1.35	0.178	-0.1077024	0.019971
euro	-0.0555478	0.0353775	-1.57	0.116	-0.1248865	0.0137908
dflt75	0.0361087	0.0403183	0.9	0.37	-0.0429137	0.1151311
dflt95	-0.0468721	0.0446553	-1.05	0.294	-0.1343949	0.0406507
lgluk	-0.03182	0.044123	-0.72	0.471	-0.1182994	0.0546594

Determinants of Market-Assessed Credit Risk

Predicted mean=7	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	-0.0203939	0.0152736	-1.34	0.182	-0.0503296	0.0095419
nri_diff	0.0029193	0.0032594	0.9	0.37	-0.0034691	0.0093077
blnc_avg	-0.0493683	0.0513548	-0.96	0.336	-0.1500219	0.0512853
blnc_diff	0.0093415	0.0125629	0.74	0.457	-0.0152813	0.0339642
lglskn	0.0036797	0.0131633	0.28	0.78	-0.0221199	0.0294793
cred_avg	-0.0169058	0.0115663	-1.46	0.144	-0.0395752	0.0057637
cred_diff	-0.0154434	0.0092156	-1.68	0.094	-0.0335056	0.0026188
dfct_avg	-0.1031546	0.0917648	-1.12	0.261	-0.2830103	0.0767011
dfct_diff	-0.0807659	0.0477531	-1.69	0.091	-0.1743602	0.0128284
fdgdp_avg	0.0052967	0.0148996	0.36	0.722	-0.0239061	0.0344994
fdgdp_diff	0.0070596	0.0068668	1.03	0.304	-0.006399	0.0205182
frdm_avg	-0.0004297	0.0005768	-0.74	0.456	-0.0015602	0.0007008
frdm_diff	-0.0010598	0.0005875	-1.8	0.071	-0.0022112	0.0000916
gni_avg	-0.0023421	0.0021723	-1.08	0.281	-0.0065997	0.0019155
gni_diff	-0.0130202	0.0068485	-1.9	0.057	-0.0264429	0.0004025
hdi_avg	-0.1211952	0.0845792	-1.43	0.152	-0.2869674	0.0445771
hdi_diff	-0.0751483	0.0428561	-1.75	0.08	-0.1591448	0.0088482
infl_avg	0.0017815	0.001066	1.67	0.095	-0.0003079	0.0038709
infl_diff	0.0003476	0.0002198	1.58	0.114	-0.0000833	0.0007784
lglgrm	0.0036144	0.0106453	0.34	0.734	-0.01725	0.0244787
rev_avg	-0.0845758	0.0564187	-1.5	0.134	-0.1951544	0.0260027
rev_diff	0.0932859	0.0563864	1.65	0.098	-0.0172293	0.2038012
tax_avg	0.0161621	0.0613824	0.26	0.792	-0.1041451	0.1364693
tax_diff	0.0202034	0.0386445	0.52	0.601	-0.0555385	0.0959452
unpl_avg	-0.0645495	0.084805	-0.76	0.447	-0.2307642	0.1016651
unpl_diff	0.0944286	0.0614567	1.54	0.124	-0.0260244	0.2148815
oecd	-0.0079839	0.0070335	-1.14	0.256	-0.0217694	0.0058016
euro	-0.0101101	0.0085667	-1.18	0.238	-0.0269006	0.0066804
dflt75	0.006572	0.0075428	0.87	0.384	-0.0082116	0.0213556
dflt95	-0.0085311	0.0084172	-1.01	0.311	-0.0250286	0.0079664
lgluk	-0.0057915	0.0078768	-0.74	0.462	-0.0212297	0.0096468

Table 4.4 Marginal effects of the independent variables of random effects ordered probit regression concerning Fitch ratings. The derivative for each observation is evaluated and the average of the marginal effects is reported.

Predicted mean=1	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	0.0353431	0.045532	0.78	0.438	-0.053898	0.1245843
nri_diff	-0.0298252	0.0185031	-1.61	0.107	-0.0660906	0.0064403
blnc_avg	0.5078955	0.1815885	2.8	0.005	0.1519886	0.8638025
blnc_diff	-0.1483145	0.0773606	-1.92	0.055	-0.2999384	0.0033095
cred_avg	0.0379024	0.0415283	0.91	0.361	-0.0434916	0.1192964
cred_diff	-0.0052992	0.0212309	-0.25	0.803	-0.046911	0.0363126
crpt_avg	0.0510477	0.0192247	2.66	0.008	0.013368	0.0887275
crpt_diff	0.0253987	0.0112749	2.25	0.024	0.0033003	0.047497
dfct_avg	0.5713871	0.3659375	1.56	0.118	-0.1458373	1.288611
dfct_diff	0.4237011	0.1676234	2.53	0.011	0.0951653	0.752237
fdgdp_avg	-0.1437932	0.0730667	-1.97	0.049	-0.2870013	-0.000585
fdgdp_diff	-0.0365968	0.0375134	-0.98	0.329	-0.1101218	0.0369281
frdm_avg	0.003423	0.0027181	1.26	0.208	-0.0019043	0.0087503
frdm_diff	0.0036501	0.0016152	2.26	0.024	0.0004844	0.0068159
gni_avg	0.0224502	0.0115011	1.95	0.051	-0.0000915	0.0449918
gni_diff	0.0746871	0.0184346	4.05	0	0.0385559	0.1108183
lgluk	0.0563538	0.0315026	1.79	0.074	-0.0053901	0.1180976
infl_avg	-0.0122257	0.0040891	-2.99	0.003	-0.0202402	-0.0042112
infl_diff	-0.0023652	0.0009298	-2.54	0.011	-0.0041876	-0.0005428
lglgrm	0.0147273	0.050789	0.29	0.772	-0.0848173	0.1142719
rev_avg	0.717535	0.1864343	3.85	0	0.3521306	1.082939
rev_diff	-0.0549631	0.1815026	-0.3	0.762	-0.4107017	0.3007755
tax_avg	-0.5102602	0.2519752	-2.03	0.043	-1.004122	-0.0163979
tax_diff	-0.1546737	0.2206821	-0.7	0.483	-0.5872027	0.2778554
unpl_avg	0.1717767	0.2858787	0.6	0.548	-0.3885353	0.7320886
unpl_diff	-1.008206	0.2695298	-3.74	0	-1.536475	-0.4799374
oecd	0.0428477	0.0307973	1.39	0.164	-0.0175139	0.1032094
euro	0.2235019	0.0478734	4.67	0	0.1296717	0.317332

Determinants of Market-Assessed Credit Risk

Predicted mean=2	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	-0.020242	0.0247034	-0.82	0.413	-0.0686597	0.0281757
nri_diff	0.0170817	0.0117112	1.46	0.145	-0.0058717	0.0400352
blnc_avg	-0.2908863	0.127533	-2.28	0.023	-0.5408465	-0.0409262
blnc_diff	0.084944	0.052067	1.63	0.103	-0.0171055	0.1869934
cred_avg	-0.0217078	0.0255785	-0.85	0.396	-0.0718407	0.028425
cred_diff	0.003035	0.0121542	0.25	0.803	-0.0207867	0.0268567
crpt_avg	-0.0292365	0.0161098	-1.81	0.07	-0.0608112	0.0023382
crpt_diff	-0.0145466	0.0080893	-1.8	0.072	-0.0304014	0.0013082
dfct_avg	-0.3272497	0.2233127	-1.47	0.143	-0.7649346	0.1104351
dfct_diff	-0.2426658	0.1245718	-1.95	0.051	-0.486822	0.0014904
fdgdp_avg	0.0823545	0.0513251	1.6	0.109	-0.0182408	0.1829498
fdgdp_diff	0.02096	0.0225772	0.93	0.353	-0.0232905	0.0652106
frdm_avg	-0.0019605	0.0016911	-1.16	0.246	-0.005275	0.0013541
frdm_diff	-0.0020905	0.0011473	-1.82	0.068	-0.0043393	0.0001582
gni_avg	-0.0128579	0.0084166	-1.53	0.127	-0.0293541	0.0036383
gni_diff	-0.0427754	0.0172853	-2.47	0.013	-0.0766541	-0.0088968
lgluk	-0.0322754	0.0204749	-1.58	0.115	-0.0724054	0.0078546
infl_avg	0.007002	0.0031364	2.23	0.026	0.0008547	0.0131492
infl_diff	0.0013546	0.0006955	1.95	0.051	-8.46E-06	0.0027177
lglgrm	-0.0084348	0.0289159	-0.29	0.771	-0.0651088	0.0482393
rev_avg	-0.4109529	0.16407	-2.5	0.012	-0.7325241	-0.0893817
rev_diff	0.031479	0.1044667	0.3	0.763	-0.173272	0.2362299
tax_avg	0.2922406	0.1597967	1.83	0.067	-0.0209552	0.6054365
tax_diff	0.088586	0.1309156	0.68	0.499	-0.1680039	0.345176
unpl_avg	-0.0983814	0.161235	-0.61	0.542	-0.4143962	0.2176334
unpl_diff	0.5774286	0.2442733	2.36	0.018	0.0986617	1.056195
oecd	-0.0245401	0.0178504	-1.37	0.169	-0.0595262	0.0104459
euro	-0.1280059	0.0477341	-2.68	0.007	-0.2215631	-0.0344488

Determinants of Market-Assessed Credit Risk

Predicted mean=3	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	0.0111296	0.0118851	0.94	0.349	-0.0121647	0.0344239
nri_diff	-0.009392	0.0074353	-1.26	0.207	-0.023965	0.005181
blnc_avg	0.1599374	0.1057534	1.51	0.13	-0.0473355	0.3672103
blnc_diff	-0.0467046	0.0352016	-1.33	0.185	-0.1156983	0.0222892
cred_avg	0.0119356	0.0155603	0.77	0.443	-0.0185621	0.0424332
cred_diff	-0.0016687	0.0067231	-0.25	0.804	-0.0148458	0.0115083
crpt_avg	0.016075	0.0117984	1.36	0.173	-0.0070493	0.0391994
crpt_diff	0.0079981	0.0054957	1.46	0.146	-0.0027732	0.0187694
dfct_avg	0.179931	0.1500378	1.2	0.23	-0.1141376	0.4739997
dfct_diff	0.1334244	0.0897312	1.49	0.137	-0.0424456	0.3092944
fdgdp_avg	-0.0452808	0.0366605	-1.24	0.217	-0.1171341	0.0265725
fdgdp_diff	-0.0115244	0.0134147	-0.86	0.39	-0.0378167	0.0147678
frdm_avg	0.0010779	0.0010522	1.02	0.306	-0.0009844	0.0031402
frdm_diff	0.0011494	0.0007967	1.44	0.149	-0.0004121	0.0027109
gni_avg	0.0070696	0.0054076	1.31	0.191	-0.0035291	0.0176683
gni_diff	0.0235191	0.0137497	1.71	0.087	-0.0034298	0.0504681
lgluk	0.0177459	0.0146021	1.22	0.224	-0.0108736	0.0463654
infl_avg	-0.0038499	0.0022196	-1.73	0.083	-0.0082002	0.0005004
infl_diff	-0.0007448	0.0004914	-1.52	0.13	-0.0017078	0.0002182
lglgrm	0.0046377	0.016029	0.29	0.772	-0.0267785	0.0360539
rev_avg	0.2259533	0.1503453	1.5	0.133	-0.0687179	0.5206246
rev_diff	-0.017308	0.0579882	-0.3	0.765	-0.1309629	0.0963469
tax_avg	-0.160682	0.1143033	-1.41	0.16	-0.3847124	0.0633483
tax_diff	-0.0487071	0.0757526	-0.64	0.52	-0.1971794	0.0997653
unpl_avg	0.0540928	0.0981345	0.55	0.581	-0.1382472	0.2464329
unpl_diff	-0.3174863	0.1884312	-1.68	0.092	-0.6868048	0.0518321
oecd	0.0134928	0.0106002	1.27	0.203	-0.0072832	0.0342689
euro	0.0703812	0.0389084	1.81	0.07	-0.0058779	0.1466404

Determinants of Market-Assessed Credit Risk

Predicted mean=4	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	0.0171203	0.024383	0.7	0.483	-0.0306695	0.0649101
nri_diff	-0.0144474	0.0103027	-1.4	0.161	-0.0346402	0.0057455
blnc_avg	0.2460255	0.1253776	1.96	0.05	0.00029	0.491761
blnc_diff	-0.0718438	0.0411334	-1.75	0.081	-0.1524638	0.0087762
cred_avg	0.01836	0.0199025	0.92	0.356	-0.0206482	0.0573682
cred_diff	-0.0025669	0.0102873	-0.25	0.803	-0.0227297	0.0175958
crpt_avg	0.0247276	0.012854	1.92	0.054	-0.0004658	0.049921
crpt_diff	0.0123032	0.0068391	1.8	0.072	-0.0011011	0.0257075
dfct_avg	0.2767809	0.1916526	1.44	0.149	-0.0988512	0.652413
dfct_diff	0.2052416	0.1012578	2.03	0.043	0.0067799	0.4037033
fdgdp_avg	-0.0696537	0.0359698	-1.94	0.053	-0.1401532	0.0008459
fdgdp_diff	-0.0177276	0.0184671	-0.96	0.337	-0.0539224	0.0184673
frdm_avg	0.0016581	0.0012182	1.36	0.173	-0.0007295	0.0040458
frdm_diff	0.0017681	0.0009311	1.9	0.058	-0.0000567	0.003593
gni_avg	0.0108749	0.0054757	1.99	0.047	0.0001427	0.0216071
gni_diff	0.0361786	0.0136416	2.65	0.008	0.0094414	0.0629157
lgluk	0.0272979	0.0148841	1.83	0.067	-0.0018745	0.0564702
infl_avg	-0.0059221	0.002449	-2.42	0.016	-0.0107221	-0.0011222
infl_diff	-0.0011457	0.0005685	-2.02	0.044	-0.0022599	-0.0000315
lglgrm	0.0071339	0.0242023	0.29	0.768	-0.0403017	0.0545696
rev_avg	0.3475752	0.110579	3.14	0.002	0.1308444	0.564306
rev_diff	-0.0266242	0.0880245	-0.3	0.762	-0.199149	0.1459005
tax_avg	-0.2471709	0.1659996	-1.49	0.136	-0.5725243	0.0781824
tax_diff	-0.0749242	0.1094511	-0.68	0.494	-0.2894444	0.139596
unpl_avg	0.0832089	0.1331572	0.62	0.532	-0.1777743	0.3441922
unpl_diff	-0.4883768	0.2016704	-2.42	0.015	-0.8836435	-0.0931101
oecd	0.0207555	0.0179731	1.15	0.248	-0.0144711	0.0559821
euro	0.1082647	0.0437275	2.48	0.013	0.0225604	0.193969

Determinants of Market-Assessed Credit Risk

Predicted mean=5	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	-0.0130263	0.0162816	-0.8	0.424	-0.0449376	0.018885
nri_diff	0.0109926	0.0085106	1.29	0.196	-0.0056879	0.027673
blnc_avg	-0.1871934	0.1209179	-1.55	0.122	-0.424188	0.0498013
blnc_diff	0.0546638	0.0366162	1.49	0.135	-0.0171026	0.1264301
cred_avg	-0.0139696	0.0167648	-0.83	0.405	-0.046828	0.0188888
cred_diff	0.0019531	0.0079026	0.25	0.805	-0.0135357	0.0174419
crpt_avg	-0.0188145	0.0120443	-1.56	0.118	-0.0424208	0.0047918
crpt_diff	-0.0093611	0.0060214	-1.55	0.12	-0.0211628	0.0024406
dfct_avg	-0.2105942	0.1494562	-1.41	0.159	-0.503523	0.0823346
dfct_diff	-0.1561621	0.0923555	-1.69	0.091	-0.3371755	0.0248513
fdgdp_avg	0.0529974	0.0401438	1.32	0.187	-0.025683	0.1316777
fdgdp_diff	0.0134884	0.0148051	0.91	0.362	-0.015529	0.0425058
frdm_avg	-0.0012616	0.0011188	-1.13	0.259	-0.0034544	0.0009312
frdm_diff	-0.0013453	0.0008444	-1.59	0.111	-0.0030004	0.0003097
gni_avg	-0.0082744	0.0055186	-1.5	0.134	-0.0190906	0.0025418
gni_diff	-0.0275272	0.014109	-1.95	0.051	-0.0551803	0.000126
lgluk	-0.0207701	0.0098461	-2.11	0.035	-0.0400681	-0.0014721
infl_avg	0.004506	0.0024875	1.81	0.07	-0.0003695	0.0093814
infl_diff	0.0008717	0.000532	1.64	0.101	-0.0001709	0.0019144
lglgrm	-0.005428	0.0181039	-0.3	0.764	-0.040911	0.030055
rev_avg	-0.2644595	0.120264	-2.2	0.028	-0.5001725	-0.0287464
rev_diff	0.0202576	0.0671144	0.3	0.763	-0.1112843	0.1517995
tax_avg	0.1880649	0.1313485	1.43	0.152	-0.0693735	0.4455032
tax_diff	0.0570076	0.0854674	0.67	0.505	-0.1105055	0.2245206
unpl_avg	-0.0633111	0.0977591	-0.65	0.517	-0.2549154	0.1282931
unpl_diff	0.3715912	0.1919294	1.94	0.053	-0.0045835	0.7477658
oecd	-0.0157922	0.0140299	-1.13	0.26	-0.0432904	0.0117059
euro	-0.0823753	0.0414631	-1.99	0.047	-0.1636416	-0.0011091

Determinants of Market-Assessed Credit Risk

Predicted mean=6	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	-0.0232541	0.0319846	-0.73	0.467	-0.0859428	0.0394346
nri_diff	0.0196236	0.0124962	1.57	0.116	-0.0048686	0.0441157
blnc_avg	-0.3341716	0.1304062	-2.56	0.01	-0.5897631	-0.0785801
blnc_diff	0.097584	0.0515747	1.89	0.058	-0.0035005	0.1986686
cred_avg	-0.024938	0.0264837	-0.94	0.346	-0.0768452	0.0269691
cred_diff	0.0034866	0.0139457	0.25	0.803	-0.0238465	0.0308198
crpt_avg	-0.033587	0.0125997	-2.67	0.008	-0.058282	-0.0088921
crpt_diff	-0.0167112	0.0075076	-2.23	0.026	-0.0314259	-0.0019964
dfct_avg	-0.3759461	0.262426	-1.43	0.152	-0.8902915	0.1383993
dfct_diff	-0.2787756	0.1135326	-2.46	0.014	-0.5012955	-0.0562558
fdgdp_avg	0.0946092	0.0405085	2.34	0.02	0.0152139	0.1740045
fdgdp_diff	0.024079	0.0254355	0.95	0.344	-0.0257736	0.0739316
frdm_avg	-0.0022522	0.0016912	-1.33	0.183	-0.005567	0.0010626
frdm_diff	-0.0024016	0.0010766	-2.23	0.026	-0.0045118	-0.0002915
gni_avg	-0.0147712	0.006446	-2.29	0.022	-0.0274051	-0.0021372
gni_diff	-0.0491406	0.0122784	-4	0	-0.0732059	-0.0250754
lgluk	-0.0370782	0.0248607	-1.49	0.136	-0.0858043	0.011648
infl_avg	0.0080439	0.0022372	3.6	0	0.0036591	0.0124287
infl_diff	0.0015562	0.0006186	2.52	0.012	0.0003438	0.0027686
lglgrm	-0.0096899	0.0338836	-0.29	0.775	-0.0761005	0.0567207
rev_avg	-0.4721047	0.1587356	-2.97	0.003	-0.7832206	-0.1609887
rev_diff	0.0361632	0.119431	0.3	0.762	-0.1979172	0.2702436
tax_avg	0.3357275	0.1887942	1.78	0.075	-0.0343023	0.7057572
tax_diff	0.1017681	0.1462117	0.7	0.486	-0.1848017	0.3883378
unpl_avg	-0.113021	0.1998363	-0.57	0.572	-0.5046929	0.2786508
unpl_diff	0.6633527	0.1904503	3.48	0	0.2900771	1.036628
oecd	-0.0281918	0.0212968	-1.32	0.186	-0.0699327	0.0135491
euro	-0.1470538	0.037844	-3.89	0	-0.2212267	-0.072881

Determinants of Market-Assessed Credit Risk

Predicted mean=7	dy/dx	Std. Err.	z	P>|z|	[95% Confidence Interval]	
nri_avg	-0.0070706	0.0091589	-0.77	0.44	-0.0250216	0.0108804
nri_diff	0.0059667	0.0037597	1.59	0.113	-0.0014022	0.0133356
blnc_avg	-0.1016071	0.0425095	-2.39	0.017	-0.1849242	-0.01829
blnc_diff	0.0296711	0.0152714	1.94	0.052	-0.0002604	0.0596025
cred_avg	-0.0075826	0.0083856	-0.9	0.366	-0.024018	0.0088529
cred_diff	0.0010601	0.0042437	0.25	0.803	-0.0072574	0.0093777
crpt_avg	-0.0102124	0.0041137	-2.48	0.013	-0.0182751	-0.0021496
crpt_diff	-0.0050811	0.0022852	-2.22	0.026	-0.0095601	-0.0006022
dfct_avg	-0.1143089	0.0792837	-1.44	0.149	-0.269702	0.0410842
dfct_diff	-0.0847636	0.0357599	-2.37	0.018	-0.1548517	-0.0146755
fdgdp_avg	0.0287666	0.0139489	2.06	0.039	0.0014273	0.0561059
fdgdp_diff	0.0073214	0.0067112	1.09	0.275	-0.0058323	0.0204751
frdm_avg	-0.0006848	0.0005143	-1.33	0.183	-0.0016928	0.0003232
frdm_diff	-0.0007302	0.0003235	-2.26	0.024	-0.0013642	-0.0000963
gni_avg	-0.0044913	0.0020707	-2.17	0.03	-0.0085498	-0.0004327
gni_diff	-0.0149415	0.0038865	-3.84	0	-0.022559	-0.007324
lgluk	-0.0112739	0.0065823	-1.71	0.087	-0.0241749	0.0016272
infl_avg	0.0024458	0.0009317	2.63	0.009	0.0006198	0.0042718
infl_diff	0.0004732	0.0001721	2.75	0.006	0.0001358	0.0008105
lglgrm	-0.0029463	0.0101227	-0.29	0.771	-0.0227865	0.0168939
rev_avg	-0.1435466	0.0474355	-3.03	0.002	-0.2365185	-0.0505746
rev_diff	0.0109957	0.0365513	0.3	0.764	-0.0606436	0.0826349
tax_avg	0.1020802	0.0605464	1.69	0.092	-0.0165886	0.2207489
tax_diff	0.0309433	0.0438389	0.71	0.48	-0.0549794	0.1168659
unpl_avg	-0.0343648	0.0585353	-0.59	0.557	-0.1490919	0.0803623
unpl_diff	0.2016968	0.0600164	3.36	0.001	0.0840668	0.3193268
oecd	-0.0085719	0.0064314	-1.33	0.183	-0.0211772	0.0040333
euro	-0.0447127	0.0110971	-4.03	0	-0.0664625	-0.0229629