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Master Thesis:

Determinants of Sovereign Ratings A Re-Assessment of Countries' Credit Risk

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List of Abbreviations

AIC	Akaike's Information Criteria
AME	Average Marginal Effect
AR(p)	Autoregressive Process of Order p
BIC	Bayesian Information Criteria
CRA	Credit Rating Agencies
EAC	East Asian Crisis
EU	European Union
GDF	Global Financial Development
GDP	Gross Domestic Product
GLS	Generalized Least Squares
GMM	Generalized Methods of Moments
HAC	Heteroskedasticity- and Autocorrelation-Consistent
IMF	International Monetary Fund
LAC	Latin America and Caribbean
LR	Long Run
ME	Marginal Effect
MER	Marginal Effect at Representative Value
MEM	Marginal Effect at Mean
MLE	Maximum Likelihood Estimator
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
RMSE	Root Mean Squared Error
SR	Short Run
WEO	World Economic Outlook
2SLS	2 Stage Least Squares

1 Introduction

Credit rating agencies (CRA) affirm that their ratings aim to estimate the probability of a default, that is the inability of a debtor to service financial obligations in full and on time. Through the far-reaching consequences of this probability-estimate, sovereign ratings have attracted attention that goes beyond that of financial markets and policymakers. For instance, Vernazza and Nielsen (2015) estimate that over USD 50,000 billions of worldwide savings are invested in sovereign bonds which are directly impacted by the assessments of CRA. Furthermore, sovereign ratings are related to sovereign yields: regulatory requirements allow certain institutional investors to hold only sovereign debt that is rated at investment-grade rate or higher. Another aspect that causes ratings to affect the macro-economy is known as the principle of sovereign ceiling. According to this principle, country ratings do not only concern the creditworthiness of the respective country, but also influence the rating of all companies located there. Through the structural strength and the improved economic diversification of the state, ratings of corporate bonds are generally noticeably worse than that of the surrounding government (D'Agostino and Lennkh (2016)). Moreover, Alsakka and Gwilym (2010) argue that the impact of globalization and the growing number of debt issuers has made CRA even more influential in the recent past. The availability of the relevant data and the associated possibility to estimate sovereign ratings using macroeconomic and institutional fundamentals has furthermore attracted the attention of the research community. The wish for a transparent and trackable estimation procedure of sovereign ratings has been especially high in the aftermath of sovereign crises like the East Asian Crisis (1997-1999) or the Financial Crisis (2007-2008) which revealed the agencies' inability to foresee such events. Literature that is concerned with the estimation of sovereign ratings and their accuracy is presented in the literature review in chapter 2.2.

This thesis investigates the relationship between the sovereign ratings of the three major CRA (Moody's, S&P and Fitch) and a set of macroeconomic and institutional explanatory variables for a cross-section of 116 countries, observed over a time-span of 29 years. Thereby, I contribute to the existing literature and use a similar set of variables that has also been employed in related papers. Thus, my analytical perspective aims to balance different styles of estimation and to identify the optimal model for the present data instead of looking for a new set of explanatory variables.

The rest of this thesis is organized as follows: Chapter 2 provides a brief overview of the sovereign rating methodologies for the three analyzed CRA as well as a literature review. Subchapter 2.3 discusses the market structure and adverse incentives of the market for sovereign ratings. This consideration is important as despite its systemic importance, the market for sovereign ratings is far from perfect competition. Instead, the three major CRA are profit maximizing firms that have the luxury to operate in an oligopolistic market structure which makes the scrutiny of their performance and behavior even more urgent. Chapter 3 begins with a description of the data set, introducing the explanatory variables and testing their differences for countries with and without an investment grade rating. The conditional mean-comparison exhibits significant variations in the explanatory variables and substantiates the feasibility of explaining sovereign ratings with the help of the selected variables. In chapters 3.2 and 3.3, I formally introduce the static and dynamic panel data models. In order to utilize the random effects estimator, I model the country-specific error by a linear combination of the long-run means of the time-varying covariates as proposed by Mundlak (1978). Subsequently, this transformed expression is further used as the latent equation of the ordered probit model which is estimated twice: the ordinary model does not take the panel structure into account, whereas the random effects ordered probit model places additional assumptions on the data-generating process and is able to realize both dimensions of the data set. While the application of linear and ordered response models to sovereign ratings represents no novelty, to the best of my knowledge this is the first study to employ the generalized methods of moments-technique to estimate sovereign ratings dynamically. Moreover, I investigate the statistical properties of the presented models in a Monte-Carlo study that concludes chapter 3. Chapter 4 is concerned with the empirical application of the presented models to the data at hand. Assessing different model requirements, I identify the most promising static and dynamic models before I evaluate their ability to predict sovereign ratings as well as respective rating-changes in chapter 4.3. The final subchapter of the empirical analysis (4.4) elaborates on marginal effects of non-linear static models and thus tries to explain the most pronounced rating changes for six selected countries. Given the fact that the assigned ratings of the three CRA show strong similarities, it is no surprise that the effects of significant explanatory variables broadly agree across agencies. Moreover, the inclusion of the lagged dependent variable causes some variables to lose their significance and the fitted values tend to overlook up- and downward movements of ratings more often. All in all, the dynamic models are able to explain the overall rating level much more accurately, yet it turns out that a pure random walk does not perform noticeably worse. Finally, chapter 5 summarizes the main findings of the thesis.

2 Rating Methodology and Related Literature

2.1 Credit Rating Agencies' Rating Methodology

Before literature that is related to the scientific question of this thesis is presented, it is important to understand how the three market-dominating CRA form their rating decisions. Sovereign credit ratings are defined as *'the sovereign's ability and willingness to service financial obligations to nonofficial (commercial) creditors in full and on time'*, where a sovereign is *'a state that administers its own government and is not subject to or dependent on another sovereign for all or most prerogatives'*" (Standard and Poor's (2017)). Even though the exact choice of words is not the same for all CRA, all ratings aim to reflect the ability and willingness of a sovereign to service public debt. Likewise, the methodological approaches, qualitative and quantitative factors, as well as assigned factor weights differ across agencies. The main determinants of the ratings are nevertheless akin to each other and can be summarized as follows:

Table 2.1.1: Summarized Sovereign Rating Methodologies

Moody's (2019)	**Fitch (2019)**	**S&P (2017)**
Economic Strength	Macroeconomic Performance, Policies and Prospects	Economic Assessment
Institutions and Governance Strength	Structural Features	Institutional Assessment
Fiscal Strength	Public Finances	External Assessment
Susceptibility to Event Risk	External Finances	Fiscal Assessment
		Monetary Assessment

Source: Methodologies as published by Moody's (2019b), FitchRatings (2019) and Standard and Poor's (2017).

There are some aspects worth noting: First of all, all CRA have measurements for economic strength, public finances and political as well as institutional performance in common. Secondly, CRA publish sovereign ratings in domestic and foreign currencies. In my analysis, I will focus on long-term foreign-currency ratings exclusively, as many bonds (especially in emerging markets) are not issued in local currencies (Bartels (2015)). Moreover, ratings are not determined by an explicit formula. The CRA publish their methodological approaches in detail but argue that adjustments and judgements of the rating committee impact the final rating as well.[1] In this context, D'Agostino and Lennkh (2016) suggest that the overall rating can be partitioned into a fundamental component (based on the published methodology) and a subjective component that is unpublished and unknown to the public. Finally, in response to erroneous assessments of credit risk, CRA have adjusted their determinants and corresponding weights in the past but the main characteristics remained unchanged. For these reasons, the model-based assessment of sovereign ratings that I follow in this work has limitations

[1]For example, Moody's (2019b) explains that they *'adjust certain factor or sub-factor scores to incorporate considerations that may not be fully reflected in the scorecard metrics [...].'*

and rather pursues a statistical attempt: Instead of trying to rebuild the exact rating process of the CRA, I opt for an optimal econometric model to explain the present data.

2.2 Literature Review

Sovereign ratings and their systemic importance are frequently mentioned in the same breath. The growing importance of an assessment of the relative probability of default is thus directly linked to a vast amount of rating-related literature. Roughly speaking, there are two branches of literature that are related to this thesis. The first field elaborates on the estimation of sovereign ratings and applies a variety of techniques with different degrees of complexity. Another approach is more concerned with the actual rating decision and puts more emphasis on the methodological theory of the agencies. Instead of attempting an all-embracing overview of the existing literature, I primarily present literature that was most influential for my thesis, specifically papers which examine different estimation-methods. Literature that is more concerned with the microeconomic structure of the rating market is briefly discussed in chapter 2.3.

The first systematic analysis of the determinants of sovereign ratings was conducted by Cantor and Packer (1996). The authors transformed the latter-based ratings of Moody's and S&P on a numeric and equidistant scale of 1 to 16. Using a cross section of 49 countries, Cantor and Packer performed an ordinary linear regression where the following explanatory variables turned out to predict sovereign ratings: per capita income, GDP growth, inflation, external debt, level of economic development, and default history. They found that their model was able to predict 70% of all ratings correctly but confessed that the specification had little to say about small differences in ratings. Furthermore, the scholars investigated the relationship between ratings and sovereign yields and found a strong negative correlation. Moreover, they attributed sovereign ratings to provide additional information beyond that already contained in market yields.

Ferri et al. (1999) were the first researchers to carry out an investigation of sovereign risk that utilized a panel data structure. In response to the East Asian Crisis (EAC), the scholars re-estimated the ratings for 17 countries from 1989 to 1998. Similar to Cantor and Packer, they translated the ratings on a numeric scale of equal distances but estimated the linear model with a nonlinear conversion too. Ferri et. al. assumed that sovereign ratings are derived by a weighted average of two components: a quantitative rating that reflects the country's economic fundamentals and a rating that is generated by the CRA' qualitative judgements. The authors applied a random effect estimation methodology and identified the following variables as significant: real GDP growth, budget deficit, current account balances, a development indicator, and external

debt. Differences between their estimated ratings and the actual ratings were interpreted as the idiosyncratic judgement of the CRA. Before the EAC, the actual ratings assigned to Indonesia, Korea, Malaysia and Thailand were consistently higher than the estimated ratings by the authors, while after the crisis, the opposite was true. This lead to the argumentation that CRA behave in a manner that generates pro-cyclical sovereign ratings because they attach higher weights to economic fundamentals, both in the pre- and the post-crisis period. They concluded by arguing that this behavior might have exacerbated the EAC by further deteriorating the economic fundamentals.
The paper by Mora (2006) was also concerned with the analysis of the EAC but suggests a more cautious view. The scholar argued that the work by Ferri et. al. was flawed by virtue of technical limitations. Besides enumerating shortcomings like mismeasurement of fundamentals, data-timing problems and time-varying weights, Mora argued that the random effects estimation of Ferri et. al. was unsuitable as the implied assumption of no correlation between the country effect and the explanatory variables is hard to justify. Consequently, she employed an ordered response model without country-fixed effects but a similar set of explanatory variables and found that ratings are rather sticky than procyclical. Like Cantor and Packer, she observed that prior to the EAC, estimated ratings were lower than assigned ratings. However, she did not find opposing evidence after the crisis and that predicted ratings mostly matched actual ratings during the crisis which contradicts the observation by Ferri, Liu and Stiglitz. Mora concluded by questioning the statement of Ferri et. al. that ratings would have led to a deterioration of the boom-bust cycle of the EAC as according to her findings, they simply reacted to news related to the economy.
Among the regression-based papers, the work by Afonso et al. (2007) has hitherto been the most elaborated. Though the scholars published further related articles in 2009 and 2011 (Afonso et al. (2009), Afonso et al. (2011)), the academic contribution of 2007 is the most detailed. By employing a panel data set with 130 countries observed from 1995 until 2005, they tried to maximize the number of observations. Similar to previous publications, they translated the ratings on a numeric scale and used essentially the same set of variables as the authors of the already summarized papers. Supported by the Hausman-test, they followed Mundlaks approach to estimate sovereign ratings by a linear random effects model. Moreover, they applied ordered response models like the ordered probit and logit as well as the random effects ordered probit. As the latter takes the existence of an additional normally distributed cross-sectional error into account, it is expected to outperform the former models. They compared the predictive accuracy of the different models and found that the best static model was able to predict 70% of all ratings correctly, over 95% of the fitted values lay within 1 notch. In the outlook of their paper, the scholars noted that the expectations of rating agencies should not be overlooked in ongoing empirical work since they strongly impact

the derivation of future ratings. As I consider the work of Afonso et. al. highly valid, I will apply their proposals to some extent to my data in chapter 3.2 when analyzing static panel data models to re-assess sovereign ratings.

Mellios and Paget-Blanc (2006) pursued a more sophisticated approach to identify the determinants of sovereign ratings. Instead of simply employing a similar set of variables as their colleagues, they opted for a principal component analysis (PCA). More specifically, they collected a total of 48 economic, political and social indicators for the 86 panel units. By solving the eigenvalue-problem of the standard PCA practice, they found 13 factors to satisfy Kaiser's rule which requires only to retain those components that explain more variation of the dependent variable than the average component. After the identification of the parameters, the effect of each factor on the ratings assigned by the agencies is obtained by applying linear and logistic regressions with the 13 factors as explanatory variables. The scholars found R^2's above 0.95 and 9 respectively 11 significant explanatory factors for the logistic and the linear approach. However, the parameter-significance is likely to be overestimated as Mellios and Paget-Blanc ignored the panel-structure of the data and instead applied pooled estimation techniques. Interestingly, the crucial factors have a similar interpretation as the variables that were employed in earlier publications. Furthermore, the substantial importance of the default history of a sovereign was pointed out which induced me to also include this information in my analysis.

More recently, Brůha et al. (2017) investigated the relation between the sovereign ratings of 7 euro area countries and macroeconomic fundamentals. In contrast to the earlier contributions, their work introduced some novelties: Firstly, while other researchers maximized the scale of the cross section, Bruha et. al. included only a subgroup of euro area countries. This translated into a reduced heterogeneity and spared the scholars from criticism related to country-dependent weights by ratings agencies to economic and political indicators. More importantly, they estimated the ordered panel probit model using Bayesian methods and included the lagged dependent variable on the right-hand site of the latent regression equation. Imposing adequate restrictions on the prior distributions, like the assumption of a stationary process in the latent model, helps to identify the model's parameters. Furthermore, they used quarterly data which may prevent the delayed observation of movements in the data. However, given the relative inertia in sovereign ratings, the choice for quarterly data could also depict an attempt to artificially inflate the sample size and technically converts their data set into a macropanel. Yet the results suggest that sovereign ratings can be explained by a small number of institutional and macroeconomic variables. In addition, evidence for a structural break after the sovereign debt crisis was found as ratings seem less sticky and more responsive to the explanatory variables after 2010. Regarding the criticism by Ferri et. al., the scholars contradicted the allegation by concluding that for most of the considered countries, the rating downgrades were roughly in line with the deterioration of the covariates.

Among the contributions that focus on the derivation of sovereign ratings, the paper by D'Agostino and Lennkh (2016) is most noteworthy. Analogously to other rating-related work, the researchers disentangled sovereign ratings into two parts: the fundamental and subjective component. The former was expected to be solely based on the published methodology, the subjective component explained the unknown judgement of the agency and constituted the objective of investigation of their paper. Based on an exact imitation of Moody's methodology, the deviation from the fundamental rating was derived and explained by a dynamic OLS regression. Firstly, their result suggests that the subjective component is applied to varying degrees, both between and within countries. Furthermore, the regression results indicate that the 10-year government yield spread to the Bund as well as the lagged rating are significant explanatory variables for the subjective component. D'Agostino and Lennkh concluded by demanding CRA to publish two ratings for each issuer, namely the quantifiable and replicable fundamental rating and the final rating that includes the subjective judgement.

Another publication which is not primarily concerned with the estimation of ratings is the paper by Gaillard (2014). In response to the European sovereign debt crisis, this research aimed to measure the sovereign ratings accuracy for 8 sovereigns and a time period lasting from 2001 to 2013. According to Gaillard, accuracy of ratings can be measured by studying ratings prior to default, computing cumulative default rates or by computing accuracy ratios. Regarding the ratings prior to defaults, the scholar found that S&P seemed to be slightly more accurate than Moody's and Fitch. He admitted, however, that the results may be skewed as rating scales are distinct and because the rating by Moody's, for example, is intended to reflect both a probability of default as well as an expected recovery in case of a default. The average cumulative default rate considers the likelihood of a default for each rating category and agency and averages the relative frequency of defaults. The results indicate that the performance of the CRA varied under different time periods and that the rating of Greece had been overly optimistic prior to the crisis. Finally, the accuracy ratio which compares for each issuer the percentage of defaults among sovereigns with the same or lower ratings to the percentages of all sovereigns with the same or lower rating suggests all ratings became less accurate after the default of Greece. The author concluded by pleading for a reduced reliance on ratings and an investor-developed assessment for credit risk as CRA repeatedly missed the opportunity to foresee a sovereign crisis.

2.3 A Brief Excursion into Market Design

The following analysis will primarily be concerned with the statistical examination of sovereign ratings. This section pursues a different viewpoint. In a first step, I describe the oligopolistic market structure of the rating market and discuss possible adverse effects on the rating quality. A brief discussion on the "Issuer-pays" model and the resulting incentive schemes concludes this excursion.

The imperfect market structure of CRA has been entrenched from the very beginning of the history of ratings. Founded in 1909, Moody's was the first company to sell bond ratings, followed by Poor's in 1916, Standard in 1922, and Fitch in the year 1924. Although many other agencies attempted to join the market, the above-named firms evolved over time and merged with potential competitors which eventually led to the so-called "Big-Three" that hold a collective global market share of roughly 95% (White (2010) and Bartels (2015)). White (2010) describes two potential barriers to enter the market as the root of this market concentration. First and most importantly, the rating market is prone to economies of scale and advantages of experience. For an established agency, the marginal costs of assessing an additional sovereign or firm are likely to be lower than the costs of an unexperienced rating firm as methodological frameworks can be transferred to any customer. Moreover, the brand name reputation is considered an important factor. CRA necessarily need to maintain their good reputation for correctly assessing the credit risk of their customers. Also investors rely on consistent ratings and thus favor agencies that have proven to provide the market with reliable information. Since newcomers have virtually no chance of building reputation before entering the market, becoming competitive is a challenging target. Surprisingly, some scholars argue that the lack of competition is related to higher rating quality. Bolton et al. (2012) model the commercial relationship between CRA, lenders and borrowers as a principal-agent model with the credit rating agency being the party that sends its private information (condensed as the rating) as a signal to issuers and investors. The microeconomists compare the statics of a game where two agencies compete for the issuer to the scenario, where only one firm sells a rating that can either be bought or be declined by the lender. As a duopoly provides more possibilities for issuers to "shop" for the most appealing rating, according to the model by Bolton et al. (2012), a more efficient market outcome is obtained under a monopolistic market structure. Then, conditional on the assumption of the same informational regime, the cumulated market surplus of the monopoly is larger than the overall surplus of the duopoly.[2] This result has been confirmed by numerous studies.

Another point of critique for which agencies are frequently criticized is the "Issuer-

[2]An informational regime of the same kind means that all firms either report the true rating or inflate it. As expected, a monopoly that inflates ratings does not dominate a truth telling duopoly in terms of efficiency.

pays" model. Prior to 1970, investors had to pay for the informational service of the CRA. Although the reasons for this change are not entirely established, White (2010) lists, inter alia, the following aspects. High-speed photocopy devices allowed investors to distribute ratings at lower costs which led to free riding behavior as investors started to share ratings among each other. Furthermore, agencies operate in an information industry that involves two market sides, and payments can possibly come from both market participants. In this context, Bartels (2015) argues that agencies might have idiosyncratically shifted the payment scheme since they feared the investors' declining willingness to pay for ratings. However, the transformation towards the "Issuer-pays" model gave rise to another conflict of interest. In praxis, an issuer only has to pay for a rating if the rating is publicly revealed by the agency. Remarkably, if a sovereign or a firm does not agree with the rating, it is free to engage another agency and the initial rating remains unpublished. Bolton et al. (2012) incorporate this particularity in their theoretical model and show that depending on the fee that is paid for the rating and the expected reputation costs for the agency resulting from inflated assessments of credit risk, agencies only have an incentive to send a truthful signal if they benefit from it. Thus, the authors conclude that ratings inflation is higher in times of economic prosperity, as investors are more trusting and punish agencies less severely if they report overly optimistic ratings.

3 Data and Methodology

The starting point of the analysis is the construction of a panel data set that consists of 116 cross-sectional units which are observed over a time span of 29 years, starting in 1990 and lasting until 2018. The use of a panel (or longitudinal) data structure is advantageous compared to a data set consisting of a single cross-section of observations for various reasons: First of all, the issue of unobserved heterogeneity is pervasive in applied econometrics. While potential solutions are rather limited in a cross-sectional setting, further possibilities like the fixed effects estimation arise if a longitudinal data structure is available. Secondly, parameters of interest can be estimated with higher precision because the sample size increases in a panel of observations. Last but not least, scientific insights of the analysis of time series data can be applied to observe the dynamic behavior of the variables. These benefits do not come without costs: To ensure a valid inference, the researcher has to control for the likely correlation of the error terms over time. Otherwise, the precision gains are typically overstated as standard errors are underestimated. Moreover, under a fixed effects estimation, partial effects can only be estimated for time-varying variables. As will be seen, ratings typically do not move much over time which causes problems under a fixed effects estimation, even though ratings constitute the dependent variable. Furthermore, when asymptotic properties are applied to panel data methods, it is convenient to assume that the time dimension T is sufficiently small relative to the scale of the cross section N. If so, it is reasonable to assume rough independence in the cross- section and the ordinary asymptotic analysis should be appropriate. Otherwise, the specific nature of the time series has to be taken into account and for $T > N$, the research quest technically turns into a multivariate time series analysis (see Wooldridge (2002) and Cameron and Trivedi (2005), Afonso et al. (2011)). For these reasons, I decided to gather information on a large amount of countries, yet this translates into an increased cross-sectional variation. Before the different panel data models are presented, the data set is briefly introduced as this makes the methods more comprehensible.

3.1 Data Description

The data set is a strongly balanced panel consisting of $3,364$ total observations distributed over 116 countries and 29 years of observation. The country-rating of a particular year is the long-term foreign currency rating that was attributed on December, 31^{st} of the given year as published by the CRA.[3] All in all, there are 93 countries having received a rating of each CRA. Moody's and S&P assessed 109 countries, Fitch rated a total of 99 countries with an average of roughly 20 years of observation per rating agency. The ratings of the three CRA are remarkably similar, indicated by pairwise correlation coefficients of over 0.97 between all agencies. Differences between ratings could depict the fact that CRA are giving varying weights to different factors or might simply reflect the idiosyncratic component when assessing default risk (see Afonso et al. (2007)). It is also worth noting that the number of rated countries experienced a significant increase in the period under consideration (see figures A.2.1 - A.2.3): In 1990, Moody's, S&P and Fitch rated 34, 29 and zero countries, respectively. By the end of 2018, however, these numbers have risen to 109, 109 and 99. This is mainly due to the fact that more developing economies gained access to ratings and is reflected by the share of non-investment grade ratings which also increased sharply (e.g., for Moodys from 0.12 in 1990 to 0.47 in 2018). As already suggested, changes in ratings do not occur frequently. For instance, among all 99 countries rated by Fitch, 77.95% of the ratings did not change from one period to the next.[4] Therefore, besides predicting the actual rating properly, one goal of the upcoming analysis will be to correctly predict the rare changes in the ratings, defined as the difference between a rating and its lagged value. Within the set of complete observations, there are 69, 66 and 92 downgrades and 87, 103 and 116 upgrades for Moody's, S&P and Fitch, respectively. Hence, when

[3] Ratings are made publicly available on the CRA' websites and a variety of websites condense this information. I rely on the following two domains: www.worldgovernmentbonds.com and www.countryeconomy.com.

[4] Similar numbers are observed for Moody's and S&P: 80.89% and 76.10%, respectively.

assessing the model performance in terms of correctly predicted rating changes, these numbers will serve as the baseline comparison.
In a first step, similar to Afonso et al. (2011) and their earlier publications in 2009 and 2007, I translate the latter-based ratings into a numeric, linear scale of 1 to 17, with 17 indicating the best and 1 the worst rating. By doing so, observations below $B3$ ($B-$) are clustered into one group as there are too few countries with a rating of such inferior quality.[5] The exact recoding is presented in table A.1.1 in the appendix of this thesis.

Table 3.1.1: Summary Statistics of Transformed Ratings

Credit Rating Agency	**Splitting**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs.**
Moody's	overall	9.6	5.14	1	17	$N = 2474$
	between		4.83	1	17	$n = 109$
	within		1.71	1.08	14.29	$\overline{T} = 22.7$
S&P	overall	9.81	5.12	1	17	$N = 2360$
	between		4.87	1.9	17	$n = 109$
	within		1.54	0.53	15.16	$\overline{T} = 21.65$
Fitch	overall	9.94	4.97	1	17	$N = 1928$
	between		4.81	2	17	$n = 99$
	within		1.53	2.35	15.23	$\overline{T} = 19.47$

As can be seen in the above-mentioned table, Moody's, S&P and Fitch exhibit grand mean ratings of 9.6, 9.81 and 9.94 after this transformation which constitutes an investment grade rating between $Baa2$ and $Baa1$ (BBB and $BBB+$). Table 3.1.1 reveals also that the variability in sovereign ratings is mostly across individuals (between) rather than over time (within), an information that has to be taken into consideration when seeking for appropriate panel data models to predict ratings and their changes.

3.1.1 Explanatory Variables

Building on the existing literature, I use a set of institutional and macroeconomic variables that have proven to determine sovereign ratings in past research. All these variables are made publicly available either by the IMF's World Economic Outlook (WEO), by the World Bank's Worldwide Government Indicators (WGI) and the Global Financial Development (GDF) Database or by the CRA. The variables, their adjustments, and their suggested effects are broadly in line with the proposals made by Afonso et al. (2007), Afonso et al. (2009), Afonso et al. (2011), Cantor and Packer (1996) and Brůha et al. (2017).
World Government Indicator: The only institutional variable is the annual average of the World Bank's WGI: Voice and Accountability, Political Stability and Lack of

[5] Even after this adjustment, among all 2,993 ratings, in only 20 occasions a rating of 1 is observed.

Violence, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption. All these sub-indicators range from -2.5 to 2.5, where 2.5 indicates the best possible value of each category. After this mean-transformation, the WGI-variable ranges from -1.66 (Angola) to 1.97 (Finland). Since this variable measures the overall quality of a government, it is assumed to be positively related to high ratings.

Real GDP per Capita: This variable is taken from the IMF WEO and is originally measured in current prices in US dollars. It is log-transformed to make the partial effect easier to interpret. This variable measures the financial wealth of a country. As richer economies should be more likely to serve their financial obligations, economies with higher values of real GDP per Capita should have better ratings.

Real GDP Growth: Taken from the IMF WEO and transformed into a three-year moving average to mimic the agencies' approach of omitting business cycle effects when assessing the credit risk of a sovereign. The effect of this variable is ambiguous: On the one hand, high real GDP growth should strengthen the government's ability to repay its financial debts. On the other hand, it is easier to achieve high growth rates of real GPD if the absolute value of real GDP is small.

Unemployment Rate, Inflation, and Current Account: Taken from the IMF WEO and also transformed into a three-year moving average. Unemployment, measured as the share of unemployed of the total labor force, is likely to be negatively related to high ratings as high unemployment diminishes the revenue of labor taxation and increases the financial burden of unemployment benefits. Furthermore, high unemployment indicates ineffective labor markets. Inflation is defined as the percentage change in average consumer prices. The current account balance enters the data set as a percentage of GDP. The effect of inflation and the current account balance is again ambiguous. High inflation is an indication of structural problems in the sovereign's finances but ceteris paribus, it reduces the government debt in domestic currency and therefore strengthens the sovereign's ability to cover debt obligations. A high current account surplus could reflect a country's difficulties to ensure foreign investment but is also an indicator for independence of a country with respect to foreign creditors.

Government Debt: The general government net debt, measured as percentage of GDP is available at the IMF WEO. Higher debt shares imply a higher interest burden and therefore a higher risk of credit default.

External Debt: This variable is taken from the GDF database and is measured as percentage of the gross national income. It is only available for non-industrial countries. Like Afonso et al. (2011), I attribute a value of zero for industrialized countries, which translates the external debt variable into a multiplicative dummy. High external indebtedness is also likely to negatively impact the sovereign rating because a high foreign currency debt relative to foreign currency earnings increases the risk of a default.

Regional Dummies: Two regional dummies are included. The EU-dummy informs about membership in the European Union, the LAC-dummy indicates whether a country belongs to Latin America and the Caribbean countries as specified by the World Bank. The EU-dummy should have a positive effect on the rating because EU-countries are monitored and supported by other member states. Since many Latin American and Caribbean countries exhibit high credit risk, this dummy should have a negative partial effect.

Default History: This dummy variable equals 1 if a sovereign defaulted in given year on a Moody's-rated sovereign bond according to Moody's (2019a). Here, I chose Moody's as this agency rated the most sovereigns in the period under consideration and because I did not encounter a country for which the default history for different agencies disagreed. Clearly, a past sovereign default will negatively influence future ratings. However, it is also possible that the effects of the regional dummies as well as of the default dummy are to some extent captured by the other explanatory variables.

3.1.2 Comparison of Investment and Non-investment Grade Ratings

In the previous sub-chapter, I made assumptions about the possible effects of the independent variables on the sovereign rating. Before these hypotheses are verified with appropriate panel data models, I want to compare basic summary statistics of the covariates for investment grade and non-investment grade ratings. As can be seen in table A.1.1, ratings below $Baa3$ ($BBB-$) are considered non-investment or speculative grade ratings. For Moody's, S&P and Fitch, among all rated countries, 37.15%, 38.35%, and 35.68% received such a rating. According to Ferri et al. (1999), a rating below investment grade aggravates a country's financial situation notably as it increases the '*cost of borrowing abroad and causes the supply of international capital to them to evaporate*'. Table A.1.2 in the appendix of this thesis summarizes the mean values as well as the standard error for the explanatory variables, distinguishing between investment grade and non-investment grade ratings. Based on this descriptive information, the assumptions from the previous section and the specific size ratio of the mean values for the two groups can be examined. This is done by applying a simple mean-comparison test which tests the null hypothesis of equal means within the investment grade and the non-investment grade group. A classical t-test assumes equal variances between the two groups. Consequently, such a test manages to derive the test statistic with two estimated parameters only, namely the variance and the difference between the two means. In this application, however, it is more reasonable to expect unequal variances: For instance, countries with non-investment grade ratings are likely to have more volatile inflation and unemployment rates because the overall economy is less stable. In Stata, a mean comparison test with unequal variances uses the Welch–Satterthwaite equation to derive the distribution of the test statistic that depends on the two unknown population variances. Thus, the test distribution has fewer degrees of freedom and

the resulting p-values are slightly more parsimonious compared to the corresponding p-values obtained under the assumption of equal variances (see Acock (2018) for more details).
In this application, the test verifies the suggested effects for most of the variables, indicated by one-sided p-values far below the 5-% significance level for all CRA. Here, for positive partial effects, verification means that the mean value of a variable is significantly larger for the group with investment grade ratings and vice versa for a negative effect. Considering inflation and the current account balance whose effects were supposed to be ambiguous, the test highlights that inflation is larger and that the current account balance is smaller in countries with non-investment grade ratings. Both one-sided p-values are below the 1%-level for all CRA. For real GDP growth, the inferences differ across the rating agencies. Focusing on Moody's, the test is not able to reject the null hypothesis of equal growth rates for investment and non-investment grade ratings. For S&P and Fitch, the test suggests smaller growth rates for countries with an investment grade rating at a significance level of respectively 6.06% and 0.05%. For the remaining seven variables, the mean-comparison test is in accordance with the presumed effects. This descriptive analysis shows that there is a significant difference between the explanatory variables for countries with different ratings. Therefore, they should be able to explain part of the variation in the ratings between countries and across time. In the next chapter, I will theoretically introduce the employed models before I evaluate their performance in the empirical application in chapter 4.

3.2 Static Panel Data Models

Static panel data models are the benchmark-estimation of this thesis. Compared to dynamic models, they are fairly easy to derive and instead of investing considerable expenditures into the consistent estimation of the parameters, non-linear models can be examined without serious estimation difficulties. Furthermore, static specifications are less affected by the frequently criticized inertia in sovereign ratings which enables them to detect rating movements more accurately. The following two subchapters present the static linear and ordered response models.

3.2.1 Linear Regression Analysis

Consider estimating a model of the form

$$Y_{it} = X_{it}^{'}\beta + Z_{i}^{'}\gamma + \alpha_i + \mu_{it}, \tag{3.1}$$

where the index $i = 1, ..., N$ denotes the country and $t = 1, ..., T$ describes the observation period. Y_{it} constitutes the rating of country i in year t that has been derived by the linear transformation as described before. The vector X_{it} contains variables that vary over time and between countries like the real GDP per Capita. Z_i contains the regional dummies as these vary only between countries but not over time. Here, it is assumed that membership in the EU and the LAC did not change since the first observation period. Likewise, the country-specific error term α_i is constant over time for any particular i. μ_{it} represents the idiosyncratic error term that is assumed to have the usual and desirable properties of a static panel data model: $\mu_{it} \overset{iid}{\sim} N(0, \sigma^2)$. In general, there are three types of linear methods which tradeoff efficiency and robustness to estimate this linear regression equation. These are the pooled OLS, the fixed and the random effects estimation. The fundamental issue to deal with in order to select the right model is the relation between the country-specific error α_i and the regressors X_{it} and Z_i, expressed as the conditional mean $E(\alpha_i|X_{it}, Z_i)$.

The fixed effects or within estimator is obtained by the subtraction of the time-averaged model. Since the country-specific effect as well as the regressors Z_i are assumed to be time-invariant, they are eliminated after this transformation. The FE-estimator is considered most robust since it can deal with arbitrary relations between α_i and the regressors as α_i is eliminated anyway. The partial effects are estimated by applying the well-known OLS-formula to the transformed model. However, the robustness of this estimator does not come without costs: Besides being unable to estimate partial effects of time-invariant covariates, the FE-estimator can be very imprecise if most of the variation in a covariate is cross-sectional because this variation is "averaged-away" when for each individual i the time-averaged model is subtracted. Examining the between (cross-sectional) and within (over time) variation of the explanatory variables, it becomes evident that most of the variables will cause difficulties under the FE-estimation: Except for the growth rate of real GDP, inflation and the dummy indicating the default history, all variables vary predominantly between countries rather than within. The regional dummies constitute the extreme cases as they do not change over time. Furthermore, when predicting sovereign creditworthiness, ratings inertia over time causes another difficulty to arise: Under a FE-estimation, country dummies would capture the average rating of a country, while the remaining, time-variant variables will only explain the rare deviations from the time-average rating (see Cameron and Trivedi (2005), Afonso et al. (2007)). In this context, Afonso et al. (2007) record '*although statistically correct, a regression by fixed effects would be seriously striped of meaning.*' This claim will be verified in chapter 4.

The above discussed arguments state that the FE-approach might be inapplicable for the research question of this thesis. However, the random effects[6] as well as the pooled OLS-estimator can only be applied if certain assumptions are met: First of

[6] More specifically, the terminology should be random intercept model as only the intercept coefficient is assumed to be random.

all, the unobserved country-effect has to be independent of the explanatory variables: $E(\alpha_i|X_{it}, Z_i) = 0 \; \forall \; i, t$. Additionally, the country-specific effect of a given i must not be correlated with the idiosyncratic component or with the country- specific effect of another country: $E(\alpha_i \mu_{it}) = 0 \; \forall \; i, t$ and $E(\alpha_i \alpha_j) = 0 \; \forall \; i \neq j$. Moreover, assume for simplicity that $\alpha_i \sim N(0, \sigma_\alpha^2)$ and $\mu_i \overset{iid}{\sim} N(0, \sigma_\mu^2)$. If these conditions are satisfied, the RE-estimation will always be preferable to the FE and the pooled OLS technique, whereas the FE-estimation is superior to the RE-estimation if α_i is endogenous. Applying a Breusch-pagan test, it will be shown that σ_α^2 is significantly different from zero. Therefore, pooled OLS will always be dominated and is not worth elaborating on. Under the above mentioned conditions, the variance-covariance matrix Σ of equation (3.1) should be equi-correlated and block-diagonal, with σ_α^2 on the off-diagonal and $\sigma_\alpha^2 + \sigma_\mu^2$ on the main-diagonal elements and have the dimension $NT \times NT$. A RE-estimator based on the GLS-technique utilizes this knowledge by including Σ^{-1} in the estimation of the relevant parameters and is therefore considered to be the best linear unbiased estimator (see Baltagi (2005)).

In the setting of this thesis however, country-specific effects are likely to be correlated with the regressors. For instance, even though the WGI-variable aims to measure the overall quality of a sovereign, the unobserved country-effect will still capture the individual ability of a government to some extent and therefore be correlated with part of the macroeconomic variables. In the ongoing analysis, this claim will be verified with specification tests like the Hausman and the Hausman-Wu test. For these reasons, neither the FE nor the RE-estimation seems appropriate and richer models for RE are required. The first scholar who proposed an alternative specification that aims to model the unobserved heterogeneity was Mundlak (1978). He relaxed the assumption that α_i is distributed independently of the regressors by assuming that α_i can be modelled as a linear function of the within-group averages: $\alpha_i = \bar{X}_i' \gamma + \epsilon_i$, with ϵ_i being a white noise error. Including this first step regression into equation (3.1) generates a model of a hierarchical type:

$$Y_{it} = (X_{it}' - \bar{X}_i')\beta + \bar{X}_i'\psi + Z_i'\gamma + \epsilon_i + \mu_{it}, \tag{3.2}$$

where $\psi = \gamma + \beta$ and ϵ_i constitutes a random, country-specific intercept. If the non-random unobserved heterogeneity α_i has been modelled correctly, model (3.2) is a RE-model that can be consistently estimated via GLS. Besides solving the problem of non-random heterogeneity, Mundlak's model is able to distinguish between short- and long-run effects. ψ can be interpreted as the long-run effect of the explanatory variables, e.g., what effect a lasting high unemployment rate has on the sovereign rating. In contrast, β measures the effect of deviations from the long-run mean of a covariate, e.g., what will be the effect of a reduced real GDP growth in a given year (see Baltagi

(2005), Afonso et al. (2007)). A drawback of Mundlak's model is the assumption that all covariates are related to α_i. Even richer models like the model proposed by Hausman and Taylor (1981) splits the set of X_{it} and Z_i into two subsets. One is assumed to be exogenous, the other one to be endogenous and correlated with α_i. The two slope parameters of X_{it} can be consistently estimated via FE, the two effects of Z_i are time-invariant, however, and cannot be obtained by the FE-estimation. Subsequently, a hybrid of the FE and RE model is employed: In a 2SLS-procedure, the residuals of the FE-estimation are regressed on the two subsets of Z_i, where the endogenous subset is instrumentalized by, e.g., the exogenous subset of X_{it}. These two regressions are used to obtain within and overall residuals which are the requisite ingredients for the variance components used to perform the GLS transformation. Amemiya and MaCurdy (1986) provide an even richer estimator by employing instruments from time periods other than the current. In this setting, however, Mundlak's approach solves the endogeneity problem sufficiently well and is used for simplicity.

3.2.2 Ordered Response Framework

Sovereign ratings are no continuous variables but possess a categorical nature. Therefore, under a linear regression framework, many relevant and important questions remain unacknowledged. Firstly, how should fitted values below 1 or above 17 be dealt with? Secondly, is it reasonable to assume that the difference between any two ratings is always the same? For some ratings this assumption seems to be justifiable, but not for all: For instance, given that the distinction between investment and non-investment grade ratings has far-reaching consequences, one should consider a model that does not assume equal distances ex ante, but one that is flexible enough to let the data solve this issue ex post. A more natural approach to the estimation of ratings is thus the ordered response framework. Such models are employed if the relationship between an ordinal dependent variable and a set of independent variables is to be estimated. The country rating is an ordinal variable because it is both categorical and ordered. The two most prominent ordered response models are the ordered probit and the ordered logit model. Roughly speaking, they differ only by the assumption they place on the distribution of the idiosyncratic error term: standard normal versus logistic, respectively. Since I already assumed the error term to follow a standard normal distribution, I will focus on the ordered probit exclusively and follow thereby the majority of the existing literature. In this model, a latent and underlying score is estimated as a linear function of the independent variables:

$$Y_{it}^* = (X_{it}' - \bar{X}_i')\beta + \bar{X}_i'\psi + Z_i'\gamma + \epsilon_i + \mu_{it}. \tag{3.3}$$

Subsequently, the actual rating is given by a function of this score and the cutoffs $(\kappa_1, \kappa_2, ..., \kappa_{16})$ that are to be estimated as well:

$$Y_{it} = \begin{cases} Aaa\ (AAA) & \text{if } Y^*_{it} \geq \kappa_{16} \\ Aa1\ (AA+) & \text{if } \kappa_{16} > Y^*_{it} > \kappa_{15} \\ ... & \\ Caa1\ (CCC+)\ or\ worse & \text{if } \kappa_1 \leq Y^*_{it}. \end{cases} \tag{3.4}$$

If μ_{it} is assumed to be standard normal, the conditional distribution of Y_{it} given the covariates can simply be computed. For instance, a rating of $Aa1$ $(AA+)$ is attributed if Y_{it} lies between κ_{16} and κ_{15} which occurs with the following probability: $\Phi(\kappa_{16} - Y^*_{it}) - \Phi(\kappa_{15} - Y^*_{it})$. It is worth noting that Y^*_{it} is not allowed to contain an intercept. The intercept is absorbed into the cut-points which ensures the conditional distribution of Y_{it} to sum up to unity. The parameters of equation (3.4), namely β, ψ, γ and $(\kappa_1, \kappa_2, ..., \kappa_{16})$ are estimated by the maximum likelihood technique. However, the computational complexity depends crucially on the assumption placed on the composed error term $\epsilon_i + \mu_{it}$ (see for example Wooldridge (2002)).

One possibility to fit equation (3.4) is to assume that there is only the country-specific error ϵ_i and to apply the standard ordered probit model. This model can be interpreted as the ordinal counterpart of the pooled OLS model because it does not utilize the panel structure of the data. Applying a robust variance-covariance matrix estimation, which takes the possible serial correlation of the error term into account, would allow to estimate (3.4) consistently. Following the argumentation of chapter 3.2.1, it is preferable to use a RE ordered probit model that considers both error components, the country-specific error ϵ_i and the white noise error term μ_{it}. Additionally, it advisable to perform a likelihood ratio test to compare the RE ordered probit with the simple ordered probit model. Under the null, the proportion of the panel-level variance component of the total residual variance $(\sigma^2_\epsilon/(\sigma^2_\epsilon + \sigma^2_\mu))$ equals zero and the RE ordered probit represents no improvement on the ordinary ordered probit model (Alsakka and Gwilym (2010)). As will be seen in the empirical application, according to the likelihood ratio test, model (3.4) is a RE ordered probit model.

In the cross-section case, the conditional probability of Y_i depends only on the distribution of μ_i. The computation of the likelihood is straightforward as described above. The generalization to the panel data setting implies, however, that the likelihood of Y_{it} is determined by the joint probability of all T error terms $(\mu_{i1}, \mu_{i2}, ..., \mu_{iT})$[7] for country i. The integration of this joint density is generally infeasible and numeri-

[7]As the panel is strongly balanced, each i is observed exactly T times and no further decomposition into T_i is needed.

cal integration methods like the Gauss–Hermite quadrature are required. Before this, the RE-property of the latent model is taken advantage of: Since the country-specific heterogeneity ϵ_i is random, without loss of generality, the joint density of μ_{it} can be obtained by integrating out this random component:

$$\begin{aligned} f(\mu_{i1}, \mu_{i2}, ..., \mu_{iT}) &= \int_{-\infty}^{+\infty} f(\mu_{i1}, \mu_{i2}, ..., \mu_{iT}|\ \epsilon_i) \cdot f(\epsilon_i) d\epsilon_i \\ &= \int_{-\infty}^{+\infty} \prod_{t=1}^{T} f(\mu_{it}|\ \epsilon_i) \cdot f(\epsilon_i) d\epsilon_i. \end{aligned}$$

As can be seen in the second line, conditioned on ϵ_i, the μ_i's are independent of each other and their joint density appears as the product of the T individual densities. This simplifies the integration considerably because instead of one T-dimensional integral, T one-dimensional integrals are to be solved. Given that the distribution of μ_{it} is known, the panel-level likelihood l_i is given by

$$l_i(\beta, \psi, \gamma, \kappa, \epsilon_i) = \int_{-\infty}^{+\infty} \left[\prod_{t=1}^{T} \left(\int_{1}^{17} f(\mu_{it}|\ \epsilon_i) d\mu_{it} \right) \right] f(\epsilon_i) d\epsilon_i.$$

The Gauss-Hermite quadrature approximates this integral by a weighted sum of the function values. Finally, the log-likelihood is derived by again applying quadrature to compute the derivatives (see Miranda and Fackler (2002), Greene (2012), StataCorp. (2013)).

Under the FE-estimation of the ordered probit model in the panel data context, even more severe estimation issues occur: Whereas the panel-specific heterogeneity could be integrated out in the RE-context, this is no longer possible if these effects are non-random. The panel-specific effects of the latent model ϵ_i can only be consistently estimated if T is sufficiently large because each ϵ_i is essentially estimated with T observations. However, the estimators of β, ψ and γ are functions of the estimates for ϵ_i and an inconsistent maximum likelihood estimator of the ϵ_i's will lead to flawed estimators of β, ψ and γ, too. This statistical problem is known as the *incidental parameters problem* and was first discovered by Neyman and Scott (1948). The inconsistency is the larger the fewer time periods are available and for $T = 2$, it has even been argued that biases of up to 100% can emerge. Even though there are bias-corrected estimators, these methods are often model-specific and no unified solution to the problem exists (Cameron and Trivedi (2005)). Consequently, when estimating a panel ordered probit model, I will have to rely on the strong exogeneity assumption of the panel-specific heterogeneity to utilize the RE-methodology. Therefore, it will be important to compare its performance to the standard ordered probit model as the sophisticated RE ordered probit should only be used if it is a true improvement compared to the simpler model. Note that the incidental parameters problem does not arise for the estimation of the linear FE-model as this regression is based on the mean-deviation. Under the limited dependent variable framework with FE, each ϵ_i has to be estimated, while $\bar{Y}_i$ serves as minimal sufficient statistic for ϵ_i in the linear FE-model. Unfortunately, such a statistic is not available for the distribution of the panel ordered probit model (Greene (2002)).

3.3 Dynamic Panel Data Models

This section considers the estimation of model 3.1 (henceforth the *basic linear model*) with the complication that current rating realizations are influenced by passed ones. Intuitively this specification makes sense because the vast majority of economic relationships can be assumed to have a dynamic nature. Although CRA do not argue that past ratings impact the current assessment of countries' credit risk, it is reasonable to suppose that some connection exists. Consequently, the following section presents the two most commonly applied dynamic panel models, namely the difference- and the system-GMM model. Additionally, I examine the estimation preciseness for the presented models in a Monte-Carlo study with a sample obtained from a dynamic data-generating process.

3.3.1 Linear GMM-Based Methods

The dynamic version of the *basic linear model* (henceforth the *dynamic basic linear model*) has the following form:

$$Y_{it} = \varphi Y_{i,t-1} + X_{it}^{'}\beta + Z_i^{'}\gamma + \alpha_i + \mu_{it}. \tag{3.5}$$

In the empirical application, it will be shown that the *Mundlak*-extension of model 3.1 is a RE-model, allowing its consistent estimation via OLS, RE and FE. In the dynamic framework, however, the estimation results of 3.5 via static panel estimators are inconsistent, no matter which estimator of the previous section is chosen and despite the possibility of α_i being a random effect. This is a consequence of the fact that $Y_{i,t-1}$ represents an endogenous regressor of Y_{it} as it is correlated with the time-invariant panel heterogeneity α_i. The degree to which $Y_{i,t-1}$ and α_i vary similarly can straightforwardly be computed by repeated substitution:

$$\begin{aligned}
Cov(Y_{i,t-1}, \alpha_i + \mu_{it}) &= Cov(\varphi Y_{i,t-2} + X_{i,t-1}^{'}\beta + Z_i^{'}\gamma + \alpha_i + \mu_{i,t-1}, \alpha_i + \mu_{it}) \\
&= \sigma_{\alpha_i}^2 + \varphi \cdot Cov(Y_{i,t-2}, \alpha_i + \mu_{it}) \\
&= \sigma_{\alpha_i}^2 + \varphi\sigma_{\alpha_i}^2 + ... + \varphi^{t-2}\sigma_{\alpha_i}^2 \\
&\approx \frac{\sigma_{\alpha_i}^2}{1-\varphi}.
\end{aligned}$$

Note that this transformation depends upon a stationary process and on T being sufficiently large. In the static framework, endogeneity can be solved by the FE-estimator that subtracts the within-mean of the regression equation. In the dynamic setup, this estimator regresses $(Y_{it} - \bar{Y}_i)$ on $(Y_{i,t-1} - \bar{Y}_{i,-1})$[8] and the remaining demeaned explanatory variables. Since α_i is cancelled out, this regression has the error term $(\mu_{it} - \bar{\mu}_i)$. However, $\bar{\mu}_i$ contains $\mu_{i,t-1}$ which is also correlated with $Y_{i,t-1}$ by construction. Therefore, it also holds that $Cov(Y_{i,t-1}, \bar{\mu}_i) \neq 0$. In this context, Nickell (1981) was able to show that for a fixed T and for $N \rightarrow \infty$, the probability limit of $\hat{\varphi} - \varphi$ does not converge to zero, where $\hat{\varphi}$ indicates the FE-estimator of φ.[9] The same argumentation applies for the RE-estimator that can be shown to quasi-demean the regression equation in order to apply GLS. Thus, the correlation between $Y_{i,t-1}$ and $\mu_{i,t-1}$ will again yield inconsistent estimators. This correlation will also cause the first-difference-estimator to be inconsistent, an alternative specification to remove the endogeneity caused by α_i (see Baltagi (2005) and Greene (2012)). As a consequence, specific dynamic panel models should be taken into consideration. The theoretical properties of the static and the dynamic estimators will be examined empirically in chapter 3.3.2 in which I generate a dynamic panel data set and compare the accuracy of the different estimators. Before the dynamic models are introduced, I want to elaborate briefly on alternative approaches to deal with autocorrelation and on methods to detect it.

First of all, instead of assuming a full dynamic model as done in 3.5, one could also use a static model like 3.1 that allows the errors to follow an $AR(1)$ process of the form: $\mu_{it} = \rho\mu_{i,t-1} + \upsilon_{it}$. Such a model could be estimated following a two-step procedure: In the first step, 3.1 is estimated via FE, in the second step, the autoregressive parameter ρ is obtained by regressing the residual of the first-stage regression on its lagged value. Subsequently, model 3.1 is transformed by the subtraction of $\rho \cdot Y_{i,t-1}$ on the left-hand side and $\rho \cdot X_{i,t-1}$ on the right-hand side. Lastly, the transformed model can be estimated via the FE- or the RE-estimator, depending on the statistical properties of α_i. Alternatively, one could rewrite the static model with autocorrelated errors into a dynamic model by substituting μ_{it} by its autoregressive process and by replacing $\rho \cdot \mu_{i,t-1}$ with $\rho \cdot (Y_{i,t-1} - X'_{i,t-1}\beta - Z'_i\gamma)$. However, such a specification would place strong assumptions on the effect of $X_{i,t-1}$ on Y_{it} as its value had to be predetermined (Breitung (2019)). In this thesis, I will opt for a full dynamic approach in order to better understand how sovereign ratings were derived.

In chapter 3.2.1, I assumed an *iid*-error term that exhibits no autocorrelation per

[8] $\bar{Y}_{i,-1}$ reflects the mean of the $T-1$ observations that are available from period 1 until period $T-1$: $\bar{Y}_{i,-1} = \frac{1}{T-1}\sum_{t=2}^{T} Y_{i,t-1}$.

[9] Nickell found that the estimation bias of the autoregressive model and the model with explanatory variables coincide, given the variables in X_{it} are uncorrelated with the error term. This inconsistency takes the form $\text{plim}_{N\rightarrow\infty}(\hat{\varphi} - \varphi) = -\frac{1+\varphi}{T}$.

definition: $E(\mu_{it}\mu_{is}) = 0$ for $t \neq s$. If this is not the case, all static estimators will yield biased standard errors and inefficient estimators. Therefore, besides of having the educated guess that a dynamic model could be sensitive, one should test for serial correlation using corresponding statistical tests. One of the most prominent tests for autocorrelation in panel data is the test by Wooldridge (2002). His method utilizes the residuals of a first difference regression of 3.1 that has the following form:

$$\Delta Y_{it} = \Delta X_{it}^{'}\beta + \Delta\mu_{it}.$$

The central idea is the observation that if μ_{it} is serially uncorrelated, the correlation θ_{WD} between $\Delta\mu_{it}$ and $\Delta\mu_{i,t-1}$, obtained by a regression of $\Delta\hat{\mu}_{it}$ on $\Delta\hat{\mu}_{i,t-1}$, equals $-\frac{1}{2}$.[10] The test statistic follows the usual t statistic for the hypothesis of no autocorrelation $H_0 : \theta_{WD} = -\frac{1}{2}$ and observed values larger (smaller) than $-\frac{1}{2}$ are taken as evidence for positive (negative) autocorrelation. Drukker (2003) conducted a Monte-Carlo study and was able to show that Wooldridge's test for serial correlation has good size and power properties given that the sample is reasonably sized. Another test that is not based on first differences and therefore likely to exhibit a higher probability of rejecting the null hypothesis when the alternative hypothesis is true, is a modified Lagrange-Multiplier test proposed by Born and Breitung (2016). Their test is based on the LM-test by Baltagi and Li (1991) but has the advantage that its limiting distribution does not depend on T. The scholars consider the same regression as Baltagi and Li:

$$(\hat{\mu}_{it} - \bar{\hat{\mu}}_i) = \theta_{BB}(\hat{\mu}_{i,t-1} - \bar{\hat{\mu}}_i) + \upsilon_{it},$$

where $\bar{\hat{\mu}}_i = \frac{1}{T}\sum_{t=1}^{T}\hat{\mu}_{it}$. Unlike Baltagi and Li, Born and Breitung estimate the parameter $\hat{\theta}_{BB}$ using HAC-standard errors, as otherwise, this parameter is biased for autocorrelated innovations υ_{it}. The necessary residuals for this regression are obtained from a FE-regression of model 3.1. Under the null of no autocorrelation, θ_{BB} equals $-\frac{1}{T-1}$.[11] The corresponding t-statistic is asymptotically normally distributed yielding a LM-statistic that is asymptotically χ^2-distributed, for $N \to \infty$ and all T. Using a generated data set obtained from 10,000 Monte Carlo simulations, Born and Breitung show that the modified LM-test has superior power-properties compared to Wooldridge's test and performs similar to a modified version of the Durbin-Watson test (see Born and Breitung (2016)). As the null hypothesis of no autocorrelation is likely to be rejected for sovereign ratings, possible dynamic models are discussed subsequently.

[10] $\theta_{WD} = Corr(\Delta\mu_{it}, \Delta\mu_{i,t-1}) = \frac{E[(\mu_{it}-\mu_{i,t-1})(\mu_{i,t-1}-\mu_{i,t-2})]}{E[(\mu_{i,t-1}-\mu_{i,t-2})^2]} = \frac{-\sigma_\mu^2}{2\sigma_\mu^2} = -\frac{1}{2}$.

[11] $\theta_{BB} = Corr(\hat{\mu}_{it} - \bar{\hat{\mu}}_i, \hat{\mu}_{i,t-1} - \bar{\hat{\mu}}_i) = \frac{E\left[(\hat{\mu}_{it} - \frac{1}{T}\sum_{t=1}^{T}\hat{\mu}_{it})(\hat{\mu}_{i,t-1} - \frac{1}{T}\sum_{t=1}^{T}\hat{\mu}_{it})\right]}{E\left[(\hat{\mu}_{i,t-1} - \frac{1}{T}\sum_{t=1}^{T}\hat{\mu}_{it})^2\right]} = \frac{-(1/T)\sigma_\mu^2}{((T-1)/T)\sigma_\mu^2} = -\frac{1}{T-1}$.

The Arellano-Bond Estimator

Arellano and Bond (1991) write model 3.5 in differences:

$$Y_{it} - Y_{i,t-1} = \varphi\left(Y_{i,t-1} - Y_{i,t-2}\right) + \left(X_{it} - X_{i,t-1}\right)^{'}\beta + (\mu_{it} - \mu_{i,t-1}). \qquad (3.6)$$

The first difference removes the panel-level effects, yet it has already been discussed that the correlation between $Y_{i,t-1}$ and $\mu_{i,t-1}$ yields inconsistent results for the static estimation procedures. The instrumental-variables technique helps to overcome this endogeneity-issue if a variable is available that is relevant, i. e., related to the endogenous variable $(Y_{i,t-1} - Y_{i,t-2})$ and valid, that is not related to the error term.[12] One candidate that meets these requirements is $Y_{i,t-2}$, as proposed by Anderson and Hsiao (1981). This method requires three periods of data for each i, as $Y_{i,t-2}$ is required to predict $(Y_{it} - Y_{i,t-1})$. Note that the total number of potential instruments is a quadratic function of T: If higher lags of $Y_{i,t-2}$ are also proper instruments for $(Y_{i,t-1} - Y_{i,t-2})$, each additional time period yields another potential instrument. Consequently, a T-time period long-lasting panel data set has $1 + 2 + ... + (T - 2) = \frac{(T-2)(T-1)}{2}$ available instruments. The estimator by Arellano and Bond is more efficient than the one proposed by Anderson and Hsiao because it employs all these possible instruments. However, the number of instruments exceeds the number of regressors in 3.6 which leads to an overidentification problem that can be addressed by applying the panel GMM-technique. Under the standard OLS-setting, the GMM-estimator solves the theoretical moment condition $E(X_{it}^{'}\mu_{it}) = 0$ empirically to obtain the vector $\hat{\beta}_{GMM}$. As the number of moment conditions and the number of parameters coincide, the model is just-identified and all empirical moments can be exactly solved. Pursuing the approach of Anderson and Hsiao, the same procedure can be applied with the difference that the theoretical moment condition is based on the orthogonality condition between the instruments and the error term. Under an overidentified model, there are more moment conditions than parameters. Then, the inner product of the instruments and the errors cannot be set to zero because a system of equations with more equations than parameters usually cannot be solved (see Roodman (2009) and Cameron and Trivedi (2005)). For this reason, the theoretical moments can only be satisfied as good as possible, that is the inner product of the instruments and the errors is minimized via an objective function. This objective function takes the form of a squared gaussian norm with some weighting matrix W in between the empirical moments. Minimization of the objective function yields the corresponding GMM estimator $\theta_{GMM} = (X'ZWZ'X)^{-1}X'ZWZ'Y$, where $\theta_{GMM} = [\beta, \varphi]^{'}$, X indicates the variables that are, possibly by themselves, instrumentalized by Z, and W constitutes some weighting matrix. If there is no correlation between the instruments and the error, any W yields an estimator θ_{GMM} that converges

[12]Note that the validity-condition requires serially uncorrelated errors.

in probability to the true value θ as the sample grows larger. Comparing an GMM-estimator Θ_{GMM} that employs an arbitrary W to Θ^*_{GMM} which uses $W^* = (Z'\Omega Z)^{-1}$, it can be shown that W^* depicts the optimal weighting matrix, where $\Omega = E(\Delta\mu_i \Delta\mu_i')$. Like the GLS-estimator of the RE-model, Θ^*_{GMM} takes the autocorrelation of the lagged errors into account and is therefore more efficient than Θ_{GMM}. If μ_{it} is generated by a white-noise process, the theoretical form of Ω is known: On the main diagonal, the elements of Ω should equal $E[(\mu_t - \mu_{t-1})(\mu_t - \mu_{t-1})] = -2\sigma^2_\mu$, on the second diagonal, the elements should be $-\sigma^2_\mu$ as two white-noise errors from different time-periods are uncorrelated. For the same reason, all remaining entries of Ω should be equal to zero. It is worth noting that Ω is based on the assumption that errors are only correlated within, but not between panel-units. Therefore, it is generally considered sensitive to include time-dummies to capture time-related shocks. The one-step estimator by Arellano and Bond assumes the theoretical form of Ω, whereas the two-step estimator uses the sample covariance matrix of the estimated residuals from step one to estimate W. The two-step estimator is not only consistent but asymptotically efficient and robust to heteroscedasticity and autocorrelation, yet the one-step estimator is still frequently used in applied work. One explanation is the evidence from simulation studies that suggest modest efficiency gains from the two-step estimation (see for example Roodman (2009) and Breitung (2019)). Stata reports routinely the Arellano-Bond test for an autoregressive process of orders one and two in the first differences. As the model is specified in differences, AR(1) should be significant, the opposite is true for AR(2): If the test rejects the null hypothesis of no second order serial correlation, this indicates that some lags of the dependent variable, possibly used as instruments, are endogenous, violating the validity-condition of proper instruments. Then, only lags of order 3 and higher of Y_{it} should be used as instrument set. The above described estimator is known as the difference-GMM by virtue of the proposal to difference the dynamic model. However, if the data set is unbalanced, the first-differencing can reduce the sample size remarkably. This drawback motivates the "deviations-GMM"-transformation which subtracts the average of all future available observations and thereby reduces the data loss (Roodman (2009)). In my application, the two transformations should not change the results significantly as the panel is strongly balanced.

The Arellano–Bover/Blundell–Bond Estimator

The system estimator by Arellano and Bover (1995) and Blundell and Bond (1998) presents an alternative specification to the difference-GMM estimator. This estimator is motivated by the observation that for high values of the autoregressive parameter φ, the difference-GMM technique performs poorly in finite samples because the instruments used become less informative. Consider, for instance, the extreme case of a pure random walk: Past levels virtually convey no information, making the untransformed lags poor instruments for the transformed variables. Using Monte- Carlo experiments, the scholars show that their estimator which exploits additional moment conditions outperforms the difference-GMM estimator clearly. In my application, the sample is with 29 time periods sufficiently sized, but φ is likely to be near one, which makes the consideration of the system-estimator crucial. Besides, even for the longest time period of $T = 11$ and $\varphi \geq 0.8$, the system-GMM estimator showed large efficiency gains in the simulation study of Blundell and Bond.

Instead of using levels to substitute differences, the system estimator also instruments levels with differences. By doing so, regression 3.5 remains unchanged and $Y_{i,t-1}$ is instrumented by $\Delta Y_{i,t-1}$. This approach is valid if the instruments are exogenous to the fixed effects, as these are not removed in the level regression. For serially uncorrelated errors this is the case:

$$\begin{aligned}
Cov[\Delta Y_{i,t-1}, (\epsilon_i + \mu_{it})] &= Cov[(\varphi \Delta Y_{i,t-2} + \Delta X'_{i,t-1}\beta + \Delta \mu_{i_t-1}), (\epsilon_i + \mu_{it})] \\
&= \varphi \cdot Cov[(Y_{i,t-2} - Y_{i,t-3}), (\epsilon_i + \mu_{it})] \\
&= \varphi \cdot (Cov[Y_{i,t-2}, \epsilon_i] - Cov[Y_{i,t-3}, \epsilon_i]) = 0.
\end{aligned}$$

Consequently, the validity-condition is based on the assumption that the fixed effect and the difference of the AR(1)-process offset each other in expectation. Additionally, $\Delta Y_{i,t-1}$ is a relevant instrument for $Y_{i,t-1}$ as both variables are correlated by construction (see Roodman (2009)). As it was the case for the difference-GMM estimator, also higher lags of the differenced variable are potential instruments for the variable in levels. Adding these additional instruments to the instruments of the difference-GMM estimator exploits the initial moment condition and involves the use of a greater number of instruments. This can lead to a dramatic increase in estimation precision which is particularly important when the time period is short and φ is close to 1. Similar to the difference-GMM estimator, the system-GMM estimator is obtained via the minimization of an objective function as the number of instruments outnumbers the parameters to be estimated. Again, using the residuals from a first step-regression to form the weighting matrix, the efficient two-step system-GMM estimator is derived.

Windmeijer (2005) found that the standard GMM two-step estimator (difference and system) of the estimated asymptotic standard errors is seriously downward biased in finite samples. This is because the weighting matrix used in the two-step procedure is based on consistent estimates of the first stage. Windmeijer showed that the estimated parameters of the weighting matrix are responsible for the difference between the asymptotic variance of the two-step estimator and the estimation results of the finite sample. Including a correction term that is based on a Taylor series approximation, the difference can be estimated and taken into consideration when a finite sample corrected variance-estimate is derived (see also Baltagi (2005)).

Furthermore, it is obligatory to present the results of the Sargan/Hansen specification test which examines the validity of the employed instruments. An over-identified model has the advantage that invalid moment conditions can be detected, whereas a just-identified model will simply estimate the vector of parameters such that orthogonality is guaranteed. A rejection of the null of joint instrument validity therefore indicates an incorrect specification. As the vector of empirical moment is distributed randomly around zero, the resulting test statistic is χ^2-distributed with the degrees of freedom equal to the difference between instruments and parameters, i.e., the degree of overidentification. Earlier in this chapter, I noted that the number of available instruments is a quadratic function of T which can cause problems in finite samples. If the finite sample lacks sufficient information, the estimation of the variance-matrix, itself quadratic in T, may, due to singularity, become infeasible. Even though this issue does not jeopardize consistency, it will lead to estimates dissociated from their true value. Moreover, too many instruments can compromise the Hansen-test such that p-values are obtained that are *'too good to be true'*. Different scholars were able to show that the error rate of this test increases proportionally with the number of instruments. As a rule of thumb, p-values above 0.25 should be treated with skepticism and the number of instruments should not outnumber the individual units in the panel. To reduce the number of instruments, the "xtabond2"-command offers the "collapse"-option. By applying this option, Stata collapses the available instruments such that each additional time period generates only one additional column (two additional columns) in the instrument matrix for the difference-GMM estimator (system-GMM estimator) (see Roodman (2009) and Arellano and Bond (1991).

To decide between the difference- and the system-GMM-estimator, Bond et al. (2001) propose a rule of thumb that utilizes the knowledge on alternative estimators for the autoregressive parameter. To do so, the dynamic model is in a first step estimated via pooled OLS and via fixed effects. The already discussed Nickell-bias indicates that the FE-estimate is seriously biased downwards in short panels, whereas the OLS-estimate of φ is biased upward if individual effects are positively correlated with the explanatory variables. Thus, the OLS-estimate is considered an upper-bound estimate, the FE-estimate is considered a lower-bound estimate and a consistent GMM-estimate for φ should lie in between the two bounds. The scholars state that difference-GMM estimates close to the lower bound suggest that this GMM-estimate is, due to weak instruments, downward biased and the system-GMM estimator should be employed instead. In the empirical application, I will present the results of both estimators and discuss their ability to predict the in-sample ratings in detail in chapter 4.3

3.3.2 Monte Carlo Study: Testing Theoretical Concepts

In this section, I report the results of a Monte Carlo study which aims to confirm the discussed statistical properties of the different estimators. The data generating process is a dynamic linear panel data model of the following form:

$$Y_{it} = \varphi Y_{i,t-1} + \beta X_{it} + \alpha_i + \mu_{it},$$

where different dimensions of the cross-section ($N = 150, 300, 600$) and the time-series ($T = 4, 8, 16, 32$) are examined, and φ varying from 0 to 0.95. In contrast, the partial effect of X_{it} is held constant at the value $\beta = 3$. Note that for $N = 150$ and $T = 32$, the simulation-setting depicts similarities to the estimation of sovereign ratings ($N = 116$ and $T = 29$). Thereby, I hope to receive some indications for the actual research question of this thesis. Due to computational limitation, the Monte Carlo study comprises only 500 simulations. In each simulation, α_i and μ_{it} are assumed to be drawn independently from a gaussian distribution with mean zero and variance 4: $\alpha_i, \mu_{it} \sim N(0, 4)$. As α_i is a fixed effect, it varies only between the panel-units. Further, I create correlation between X_{it} and α_i by adding $0.4 \cdot \alpha_i$ to $X_{it} \sim N(1, 6.25)$. I estimate the dynamic model with four estimation techniques: pooled OLS, FE, difference- and system-GMM.[13] Based on the aforementioned arguments, I expect the following outcomes: Due to the positive correlation between X_{it} and α_i, the OLS-estimator should significantly overestimate the partial effects $\hat{\varphi}$ and $\hat{\beta}$. As proposed by Nickell (1981), the FE-estimator will underestimate the true parameter values because $Y_{i,t-1}$ is correlated with $\bar{\mu}_i$. This bias is more severe, the shorter the time period. Given that the lagged values are informative instruments for the difference-regression, difference- and system-GMM should yield similar results. It has already been discussed that instruments lose their informational content as the data generating process approaches a random walk. I therefore expect the system-GMM technique to outperform the difference-GMM for high values of φ. Similar to Blundell and Bond (1998), I report the mean of the estimated parameters over the 500 iterations as well as the corresponding standard deviations. The results of the simulation can be found in the tables A.1.13 - A.1.16 in the appendix, where in each table and each row, the estimator closest to the true value is marked in bold type.

Born and Breitung (2016) noted that their Monte Carlo-study shows little qualitative differences for varying values of the cross-section dimension. My results support this observation, indicated by essentially no difference within estimation-techniques for different values of N. This encourages me to assume that the cross-sectional dimension

[13] The GMM estimators are estimated via the two-step procedure and with first-difference deviation. As the panel is strongly balanced, orthogonal deviations yield roughly the same result. No robust variance-covariance estimation is applied as the primary interest lies in the slope parameters.

of the application for sovereign ratings is sufficiently large to ensure independence. In the first instance, the inconsistency of the OLS-estimator is clearly observable. In each simulation, this estimator overestimated the partial effects with basically no signs of improvement for increasing values of T. The FE- and the difference-GMM-estimator outrival their competitors with tremendous explicitness: In 142 of all 144 scenarios, the most accurate estimator was either the difference-GMM or the FE. For all values of T and the highest value of φ, FE outperformed difference-GMM. In the scenarios where $T = 4$ and $T = 8$, difference-GMM was superior to FE for the remaining values of φ. For $T = 16$ and $T = 32$ the Nickell-bias vanished such that a more balanced result is obtained. Similar to the OLS-estimator, the system-GMM-estimator tends to overestimate the parameters though it is more precise. However, even for $\varphi = 0.95$ and $T = 4$, it is unable to perform better than FE or difference-GMM. Based on this empirical evidence, I will estimate the dynamic panel model of sovereign ratings via OLS, FE, difference- and system-GMM.

4 Empirical Analysis and Results

In this section, I present the estimation results of the introduced models of chapter 3. Starting with the static models, I discuss the results of the linear regression analysis and the ordered response framework. In the second sub-chapter, I elaborate on the estimation results of the dynamic models and examine which static and dynamic specification is dominating in order to predict ratings and the respective changes. Finally, I utilize the estimation results to perform a specific country analysis for selected panel units. More specifically, I compare the partial effects of the ordered response models by computing marginal effects for the binary and the continuous explanatory variables. As will be seen, the interpretation is especially involved for the latter type of covariates.

4.1 Static Panel Data Models

4.1.1 Linear Regression Analysis

The theoretical discussion on linear panel data models of chapter 3.2.1 proposed three procedures to estimate the *basic linear model*: pooled OLS, RE and FE. The estimation results for these techniques can be found in tables A.1.3 - A.1.5 in the appendix. It has been argued that all models are inadequate to estimate (3.1): pooled OLS because there are panel-specific effects, RE because these effects are non-random, and FE because both dependent and independent variables vary mostly between cross-section units which leads to imprecise FE-estimates. Using statistical tests, these hypotheses will be verified hereafter.

Breusch and Pagan (1980) developed a Lagrange multiplier test to test the existence of unobserved panel-heterogeneity. Formally stated, absence of unobserved heterogeneity is equivalent to $H_0 : \sigma_\alpha^2 = 0$. If this hypothesis is not rejected, one should conclude that the simple pooled model is adequate. Their test examines the effect on the score, i.e., the first derivative of the likelihood of imposing the null hypothesis. The rationale is that when $\sigma_\alpha^2 = 0$, the estimates under the restricted (pooled OLS) and the unrestricted (RE) model should be alike and the computed score under the null be near zero. Under H_0, the test statistic is asymptotically $\chi^2(1)$ distributed as only one restriction is in place. Therefore, the test rejects the null if the test statistic is greater than 6.63 (the corresponding value of the $\chi^2(1)$ distribution) at 1%. For all CRA, test statistics above 1000 are observed which leads to a clear rejection of the pooled OLS model. However, a rejection of the null does not imply the RE-model is correct, but only that some panel data model is required because panel-heterogeneity is present. The FE-counterpart to the Breusch-Pagan test is a simple F-test for the null hypothesis that the panel units all have a common intercept, with the degrees of freedom being equal to the number of observations minus the number of groups and the time-variant covariates. Again, a rejection of the null indicates the necessity of a panel data model which is the case for all CRA (see tables A.1.3 - A.1.5). These results come as no surprise and will be taken into account in the further analysis. The next question to answer is which linear static panel model can be used to estimate sovereign ratings. This will be done with the help of the Hausman-test.

Hausman (1978) developed a specification test that is based on the difference between the RE- (GLS) and FE-estimates to probe the consistency of the former estimates. Formally, consistency of the GLS-estimates is ensured if the requirement of orthogonality of the panel-specific effects and the regressor vector is satisfied: $H_0 : E(\alpha_i | X_{it}, Z_i) = 0$. Is this hypothesis not rejected, evidence for the RE model has been found. The Hausman-test is based on estimating a measure for the difference of the time-varying covariates of the RE- and FE-estimators. This distance measure is asymptotically $\chi^2(p)$ distributed, with p indicating the number of time varying covariates. Stata computes this difference-measure by the matrix-difference method, i.e., by calculating the variance of the difference of the coefficients: $V(\beta_{FE} - \beta_{RE})$. Generally, this matrix is assumed to be positive definite because β_{FE} is consistent in any case, but in finite samples a negative definite difference-matrix may occur. In such occasions, the Hausman test is not identified as negative χ^2 are not admissible (see Wooldridge (2002)).

In my application, for Moody's, S&P and Fitch, test statistics of 112.92, 56.52 and 28.5 are observed respectively, rejecting H_0 for all CRA at the common significance levels. This result indicates clearly that (3.1) is no RE-model and that further transformations like the one proposed by Mundlak are necessary if the RE-methodology wants to be adopted. Therefore, (3.1) should be estimated via FE though it entails the already discussed drawbacks. At first sight, these do not seem too severe in this setting. Besides the real GDP per Capita variable that turns out to be insignificant[14] for Moody's and S&P and the inability to measure the partial effects of the regional dummies, all variables that are significant under pooled OLS or RE also appear significant under the FE-estimation. Considering the model fit (R^2), the weakness of the FE-estimation becomes more evident: Compared to the pooled OLS and RE-model, the FE-model explains considerably less variation in the ratings within panel units and over time, the consequence of an informational loss triggered by the subtraction of the within model. Even though R^2 should not be the only measure when assessing the goodness-of-fit of a model, this quantity shows that a specification that is able to model the panel-heterogeneity is advantageous compared to a simple FE-estimation. Note that due to scale-invariance, the root mean squared error (RMSE) cannot serve as a comparison criterion for model accuracy. It is, however, included for the sake of completeness. Ceteris paribus, the RMSE will not yield the same result for argument Y_{it} as it does for the argument $c \cdot Y_{it}$, where c is some constant. As under the FE-estimation equation (3.1) is de-meaned, smaller RMSE-values are natural. I will elaborate on the model adequacy in more detail when I assess the predictive properties of the different models in chapter 4.3

Tables A.1.6 - A.1.8 present the *Mundlak model* (3.2), i.e., the model that adds the within means of the regressors as additional explanatory variables. The acronyms (LR) and (SR) outline the distinction between long-run and short-run coefficients. The *Mundlak* specification is considered successful if the coefficients of the within means are significant and if the Hausman-test delivers no evidence against the orthogonality hypothesis. First of all, the Breusch-Pagan and the F-test indicate again for all CRA that a specification by pooled OLS will yield inconsistent estimates. Examining the results of the Hausman-test, it becomes evident that the transformation of the *basic linear model* to the *Mundlak model* constitutes an improvement: For Moody's and S&P, the null hypothesis of no systematic difference in the coefficients is not rejected, indicating that RE-estimation is preferable to the FE-estimation. For Fitch, the model fails to meet the asymptotic assumptions of the Hausman-test and a negative test statistic is observed. Such a result can be interpreted as strong evidence that the null hypothesis cannot be rejected and the usage of a RE-estimator is again the preferable option (see for example StataCorp. (2013)). Additionally, for all CRA, the joint test of all long-run coefficients being equal to zero is clearly rejected. Moreover, the share of explained variation is worth elaborating: Comparing the overall R^2 for the RE-estimation of the *basic model* and the *Mundlak model*, one notices an increase of 7.1, 6.1 and 5.6 percentage points for Moody's, S&P and Fitch. The R^2 of the *Mundlak model* under FE-estimation reveals a noteworthy feature of this estimation technique, too. The long-run coefficients do not vary over time and cannot be estimated, whereby the knowledge

[14]When I talk about significance of parameters, I take the 10%-significance level as basis.

on the overall scale of these variables is lost as the short-run coefficients only contain information about deviations from the long-run means. Consequently, this model tries to explain the sovereign rating only with the help of the long-run mean-deviations. As can be seen in tables A.1.6 - A.1.8, R^2-values merely above zero result and demonstrate the importance of the within means. Based on the aforementioned discussion, it seems reasonable to opt for the *Mundlak*-augmented RE-methodology to estimate the static linear panel data model of (3.1) whose coefficients will be discussed hereafter.

The regression outputs for the three CRA reveal a more or less homogenous set of significant explanatory variables with expected signs and magnitudes and a small share of covariates that are not statistically different from zero. Among the 20 explanatory variables, four variables are found to be insignificant for Moody's[15], five for S&P[16], and four for Fitch[17]. On the real side, the Real GDP per Capita (LR) coefficients range from 0.792 to 0.911 and are the largest for Fitch. Translated into marginal effects, ceteris paribus, a 1% increase in the long-run Real GDP per Capita corresponds to a 0.009 increase in the rating by Fitch. Therefore, in order to achieve a one notch increase in the Fitch-rating by an increase in the Real GDP per Capita (LR) variable exclusively, a country would need to augment its long-run GDP per Capita by almost 300%[18]. The Real GDP per Capita (SR) coefficient is only for Fitch significant with a value of 0.303. For the growth rate of real GDP per Capita, only the short-run deviation has an impact on the rating and is largest for Moody's (0.076). Considering the fiscal area, the significant coefficients for Government Debt turn out to be negative in the short- and the long-run are again largest in absolute value for Fitch. The effect of the World Government Indicator is particularly large in the short-run, ranging from 3.747 to 4.127 among the CRA. It is largest for Moody's both in the short- and the long-run. Unemployment and inflation have a negative impact on the sovereign rating that is most pronounced in the short-run for both variables with Moody's showing the largest coefficients in absolute value (-0.207 and -0.015, respectively). On the external side, the effect of the Current Account Balance is more important in the long-run rather than in the short-run and is largest for S&P (0.045). The External Debt variable is only significant in the long-run and largest for Fitch (0.017). Surprisingly, high current account balances as well as high values of External Debt are related to better ratings. If one compares the mean values of the Current Account and the External Debt variables for investment and non-investment grade ratings as done in table A.1.2, this result appears even more debatable and could indicate inconsistent estimates for

[15] Real GDP per Capita (SR), Real GDP Growth (LR), Current Account (SR) and External Debt (LR).

[16] Real GDP per Capita (SR), Real GDP Growth (LR), Unemployment Rate (LR), External Debt (LR) and LAC.

[17] Real GDP Growth (LR), Unemployment Rate (LR), External Debt (LR) and LAC.

[18] A 1% increase in real GDP results in a $ln(1.01) \cdot 0.911 = 0.009$ increase in the rating. To ensure a rating-increase by 1, real GDP has to increase by $e^{1/0.911} = 2.9972$, i.e. almost 300%.

these two variables. Finally, the three dummy variables EU, LAC and Defaulted all have again the expected signs and magnitudes of remarkable size. For instance, holding everything else equal, according to Fitch, being a member of the EU is associated to ratings that are 1.374 notches higher compared to ratings of countries outside the EU with similar other characteristics. Also, according to S&P, countries that defaulted on sovereign debt are rated 3.317 notches below similar countries that did not default. The LAC dummy is only significant for Moody's with a coefficient of -0.724.

4.1.2 Ordered Response Framework

In chapter 3.2.2, it has been argued that the ordered response framework should be preferred over the linear approach. The two non-linear models at hand are the ordered probit and the RE ordered probit. For the latent model specification, two linear models are available: the *basic linear model* (3.1) and the *Mundlak model* (3.2). I chose the *Mundlak model* for two reasons: First of all, in the linear framework, the distinction into short- and long-run coefficients helped to generate a model that passed the Hausman test. Thus, the more efficient RE-methodology could be employed. In the non-linear framework, it is even more important to assume random panel-heterogeneity because due to the incidental parameters problem, the FE ordered probit model cannot be estimated consistently. Since the *Mundlak model* generated a linear RE-model, I also assume it to model the unobserved heterogeneity in the non-linear context sufficiently well. Second, as will be seen in the regression outputs of the non-linear models, the long-run coefficients are again mainly significant. Lastly, information criteria like Akaike's information criterion (AIC) and the Bayesian information criterion (BIC) favor Mundlak's specification as well. These criteria do not simply compare the goodness-of-fit but include a "punishment-term" that takes the total amount of regressors into account.
The estimation results for the three CRA can be found in the appendix in the tables A.1.9 - A.1.11. Considering Moody's, a large consensus between the linear RE and the ordered RE *Mundlak model* is noticeable: All variables that turned out to be insignificant under the linear model are also insignificant under the RE ordered model.[19] Furthermore, the regional dummies have no significant impact under the RE ordered probit. The ordered probit with robust standard errors is less parsimonious and finds that only the variables Real GDP Growth (SR) and (LR) as well as Current Account (SR) are insignificant, an indication that this model is overly optimistic because it does not recognize the panel structure of the data. As the ordered models employ a model of a hierarchical type, the partial effects are not given by the coefficients itself and can thus not be compared to the coefficients of the linear model. Note also that due to different cutoff values between standard and RE ordered probit, coefficients cannot di-

[19] These are Real GDP per Capita (SR), Real GDP Growth (LR), Current Account (SR) and External Debt (LR).

rectly be compared. A detailed comparison of the partial effects is performed in chapter 4.4, which discusses the contribution of the explanatory variables to the fitted values of the two ordered response models for selected countries. A similar observation applies for S&P, too. All insignificant variables of the linear RE model are also insignificant under the RE ordered probit (see footnote 16 for the variable names). Additionally, the coefficient of the Real GDP Growth (SR) is statistically not significantly different from zero. The standard ordered probit model finds five insignificant variables[20] but shows otherwise the same signs. Finally, the estimation results for Fitch reveal again that all insignificant variables of the linear RE model plus the coefficient for Inflation (LR) are insignificant under the RE ordered probit. However, for the standard ordered probit, a different set of explanatory variables has no significant impact on the rating of Fitch.[21] Considering significant variables only, the signs of the linear and the non-linear RE models coincide for Moody's, S&P and Fitch.

To decide between the standard and the RE ordered probit model, a likelihood ratio test as described in chapter 3.2.2 is applied. The null hypothesis of this test is that the panel-level variance component is statistically not different from zero. If this hypothesis is rejected, the RE ordered probit should be preferred over the standard ordered probit as the latter ignores the possible panel-level specific variance. In my application, the panel specific variance σ_ϵ^2 equals 0.697, 0.93 and 0.99 for Moody's, S&P and Fitch. Since the standard errors of these variances are sufficiently small, the H_0 is rejected for all CRA as can be seen in the last rows of tables A.1.9 - A.1.11.[22] Furthermore, the value of the log-likelihood, the two information criteria AIC and BIC and the McFadden R^2 are displayed. For all CRA, the log-likelihood of the RE ordered probit exceeds the corresponding value of the standard ordered probit. Consequently, also the two information criteria favor the RE ordered probit because these criteria translate the likelihood-value and the number of parameters into an accessible comparison-criteria. As the number of parameters coincide for the two models, larger likelihood-values automatically lead to smaller criteria-values. The same logic applies to the McFadden R^2 as this goodness-of-fit measure relates the likelihood of the restricted model (constant only) to the unrestricted model. Based on the discussed results, it seems reasonable to prefer the RE ordered probit over its ordinary counterpart. The forthcoming elaboration on the estimated cutoffs will therefore only consider the RE specification.

Figures A.2.4 and A.2.5 in the appendix of the thesis visualize the model-generated cut-

[20] These are Real GDP per Capita (SR), Real GDP Growth (SR) and (LR), Inflation (LR) and LAC.

[21] These are Real GDP per Capita (SR), Real GDP Growth (SR) and (LR), Inflation (SR) and (LR) and External Debt (LR).

[22] Notice that $\bar{\chi}^2(1)$ instead of $\chi^2(1)$ is reported by Stata. This happens if two models that are supposed to differ only with respect to the variance component are compared. As the limiting distribution of the MLE is a normal with truncation at the boundary zero, the distribution of the LR test statistic is a 50:50 mixture of a $\chi^2(0)$ and a $\chi^2(1)$. This mixture is indicated by the bar (StataCorp. (2013)).

offs and the respective differences between two adjacent cutoffs. Note that the cutoffs are shifted to the origin to facilitate the comparison. The two figures reveal that for all CRA, the linear transformation of the ratings which has been employed in chapter 4.1.1 constitutes a sound approach. Especially for S&P, the model-generated cutoffs and the linear cutoffs are astonishingly similar. For Fitch, the difference between the first and the second cutoff exceeds the value of 1 clearly, but afterwards the cutoffs show a more or less linear pattern with equal differences of size 1. Considering the associated cutoffs for Moody's, it appears like a linear transformation with a mean-distance slightly below 1 could improve results in the linear model framework. These observations are supported by mean-distances between cutoffs of 0.794, 1.024, 1.096 and for Moody's, S&P and Fitch. Furthermore, it becomes evident that non-linear transformations like the logistic are inappropriate to this application. Such a scaling would imply higher cutoff-differences near the origin and the end of the scale which constitutes, based on the model-generated cutoffs, no upgrade for either CRA. The underlying data for figures A.2.4 and A.2.5 can be found in table A.1.12. The next chapter seeks to identify an appropriate technique to estimate the dynamic linear model of chapter 3.3.

4.2 Dynamic Panel Data Models

Chapter 3.3 proposed four techniques to derive the parameters of a dynamic panel data model: FE, pooled OLS, difference and system GMM. The different estimation results will be presented in this chapter, where all estimations are conducted with robust standard errors and orthogonal deviations for the GMM-based models. First of all, applying the Wooldrige-Drucker test to the *basic linear model* yielded the expected results: F-values between 74.6 and 305.5 for the three CRA indicate a clear rejection of the null hypothesis of no serial correlation. Also the bias-corrected test for serial correlation in a FE panel setting validated this suspicion.

It has been argued that the estimated autoregressive parameter of the FE- and the pooled OLS estimation can serve as lower and upper bound of the true population parameter. Based on this argumentation, I present the corresponding regression results in tables A.1.17 - A.1.19 in the appendix of the thesis. Note that year dummies are included as control variables. Roodman (2009) argues that the inclusion of such dummies is sensitive in the estimation of the difference and the system GMM-model as the assumption of no correlation across panel units in the idiosyncratic error term is more likely to hold with time controls. Since the pooled OLS- and FE-technique serve as benchmark-estimations, the dummies should also be included in these regressions. It is well-known that the estimation of a dynamic model by pooled OLS and FE has its limitations. Nonetheless, the OLS- and FE-results of the *basic linear model* and *dynamic basic linear model* are worth elaborating on, especially if the overall goodness-of-fit and

the parameter-significance are to be compared.
Under the OLS-estimation of the *basic linear model*, among the 12 explanatory variables including the constant, one variable was insignificant for Moody's (External Debt), two for S&P (External Debt and LAC), and two for Fitch (External Debt and Default History). These variables are also found insignificant under the dynamic specification. However, for the *dynamic basic linear model*, three further variables are insignificant for Moody's (Unemployment Rate, EU, LAC) and S&P (Unemployment Rate, Inflation, EU), and two for Fitch (Unemployment Rate, LAC). This indicates that some explanatory power of significant variables under the static estimation is now captured by the lagged value of the dependent variables. All common significant covariates have the same sign under the dynamic and the static OLS-estimation procedure though their magnitudes differ clearly. As argued, the estimated partial effects of the lagged dependent variables will serve as upper bound in the upcoming analysis. They are remarkably close for the three CRA: 0.86 (Fitch), 0.87 (S&P), 0.874 (Moody's). Regarding the share of explained variation, the dynamic OLS-estimations clearly outperform their static counterparts: On average, the R^2 increased by 9.15% percentage points which is, considering the already very high values of the static specifications, an imposing improvement. The estimation results of the FE-model reveal a similar pattern: The R^2 ascended even by 28.27% percentage points on average. Also, the amount of insignificant covariates rose from two, one and one to four, four, and six for Moody's, S&P and Fitch, respectively. Again, all common significant variables have the same signs for the static and the dynamic versions. Due to the Nickell-Bias, the values of the autoregressive parameters are likely to be underestimated and serve as lower bound: 0.789 (Moody's), 0.787 (S&P) and 0.765 (Fitch).
Tables A.1.20 - A.1.22 present the estimation results of the difference-GMM technique for four different sets of instruments. In order to interpret the GMM-estimation output in a panel data setting properly, different indications should be examined. First of all, the Hansen statistic informs about the validity of the employed instruments. If the used instruments are valid, the null hypothesis of joint validity should not be rejected by the test. It has already been mentioned that the error rate of the Hansen-test increases proportionally with the number of used instruments. Therefore, a p-value of one indicates a fit that is too good to be true and the number of instruments should be reduced if such a result occurs. Consequently, I will be looking for p-values that support a rejection of the null but are sufficiently small. Secondly, as the lagged dependent variables appear on the right-hand side of the model equation, there should be first order autocorrelation by construction. Thus, the Arellano-Bond test for first order autocorrelation should not be rejected. Furthermore, the test for second order autocorrelation should be rejected as if the model is suffering from second order autocorrelation, higher lags of the dependent variable should be considered to be included.

Thirdly, the interpretation of partial effects should be limited to significant covariates only and the number of instruments should not outnumber the amount of panel-groups. Lastly, the effect of the limited dependent variable should fall into the interval of the lower and upper bound, obtained from the corresponding FE- and OLS-regressions (see for instance Breitung (2019)).

In the first columns of tables A.1.20 - A.1.22, I present the estimation results for the one-step difference-GMM estimation that utilizes all available instruments. Even though the tests for AR(1) and AR(2) support the just made argumentation for all CRA, this estimation employs far too many instruments and thus inflates the Hansen-statistic. Hence, I reduced the number of instruments by applying the collapse-option in the second columns. However, for this specification, the Hansen-test rejects the hypothesis of joint instrument-validity at the 5%-level for all CRA. Furthermore, the partial effect of the lagged dependent variable exceeds the upper bound for Moody's (0.939 vs. 0.874) and Fitch (0.994 vs. 0.86). For S&P, this value falls with 0.826 in between the bounds. Unfortunately, for this rating agency, the Hansen-test rejects the null even below the 1%-level. In the third column, I manually reduced the used lags by including the "laglimits(1 2)"-option in the "xtabond2"-command. As the difference-GMM model is used, this means that only $Y_{i,t-2}$ is used to instrument $\Delta Y_{i,t-1}$. After this adjustment, the Hansen-statistic reveals rejections of the null at 24,7%, 5.2% and 38.5% for Moody's, S&P and Fitch. With 66 used instruments, the number of groups (59 for Moody's and S&P, 55 for Fitch) falls just short of the amount of moment conditions. Apart from this issue, the estimation results for this specification look most promising. Nevertheless, it should not be concealed that the estimated effect of $Y_{i,t-1}$ lies below the lower FE-bound for Moody's and S&P. For Fitch, the parameter is virtually equivalent to the upper OLS-bound. In the last column, I present the estimation of a two-step procedure for the model with limited instruments. As expected, the Hansen-statistic remains unchanged, the slope coefficient and their significance levels change though. Except for the coefficient of the unemployment rate that is positively significant for the second specification for Moody's and the fourth for Fitch, all significant parameters have the same and expected sign across all CRA. Summarizing the results of the difference-GMM estimation, it seems like no specification is able to meet all of the aforementioned criteria. The Hansen-statistic is only for the lag-limited scenario in a satisfactory range, which might admittedly, be only due to the artificially reduced amount of moment conditions. However, in five out of six total cases with an acceptable Hansen-statistic, the partial effects of the lagged dependent variables lies outside the assumed interval. This could be a sign of inconsistent estimates resulting from the poor instrumentalization under the difference-GMM technique.

The estimation results of the system-GMM estimator can be found in tables A.1.23 - A.1.25. This technique is able to utilize the initial moment condition of the model equation which is of particular importance if this condition possesses most of the available information. Although the results of my data-generating experiments did not support the system-GMM estimator, I hope to meet the discussed requirements for panel GMM-estimators in a more satisfactory manner than the previous results did. Again, I present the estimation results for four specifications. As the system-GMM estimator uses even more instruments than the difference-GMM, I omit the results that are based on all available and uncollapsed instruments. The Hansen-statistic would again yield the unreliable result of 1. In all cases, the Arellano-Bond test for first and second order autocorrelation confirms the desired results. The first two columns show the outputs of the one- and the two-step estimation with all available and collapsed instruments. For this option, joint instrument-validity is rejected at levels between 2.7% (S&P) and 4.7% (Fitch) and the number of instruments equals the number of groups for all CRA. Furthermore, the autoregressive parameter exceeds 1 and therefore also the upper bound for every rating agency in the one-step scenario. Since it is hard to justify that rating agencies derive the sovereign ratings based on an explosive AR(1)-parameter and the Hansen-statistic expresses clear doubt about the instrument-validity, these results should be treated with skepticism. Similar to the previous results, columns three and four show the one- and two-step results that are based on instruments from the first two lags only. The Hansen-statistic is clearly inflated by the use of 89 (Moody's, Fitch) or 88 (S&P) instruments and thus yields unacceptable rejection levels over 88.6%. However, the autoregressive parameter is now closer to the OLS-benchmark for every agency.[23] To conclude, it seems like the system-technique is even less capable of dealing with the criteria-trade-off for panel GMM models. Under the difference-GMM specification, most of the parameters failed to fall in between the bounds of the FE- and OLS-regressions but otherwise fulfilled the criteria. The system-GMM estimates, on the other hand, already failed to confirm the validity of the instruments. Nonetheless, I will study their ability to predict the in-sample ratings of my data set in the next chapter. Possibly, one can de-emphasize some unmet criteria in return for a high goodness-of-fit.

4.3 Prediction Analysis

This chapter compares the ability to predict sovereign ratings in the data set for the presented methods. As indicated earlier in the thesis, predictive expressiveness is a two-fold challenge. First of all, a good model should predict a decent share of ratings correctly and hold the amount of over- and underpredicted fitted values low. Furthermore, it has been repeatedly mentioned that changes in sovereign ratings do not occur

[23]Unfortunately, also the combination of the collapse- and the laglimit-command did not improve the estimation results. Instead, explosive AR-processes with even larger parameters than in the first columns were found.

frequently. Therefore, the second assessment criterion of the presented models is their ability to predict the up- and downward movements precisely. By comparing the models based on these two criteria, some statistics like the R^2 of the basic models will be confirmed and the analysis will help to better compare models with different estimation techniques (OLS, MLE, GMM). Unfortunately, there is no unique model that beats the counterparties in both disciplines. Rather, it will be seen that the dynamic models achieve a better rate of correctly predicted ratings, while the static models possess the ability to explain movements in sovereign ratings more accurately. Moreover, the obtained results are checked against a pure random-walk model. Due to the high degree of inertia in sovereign ratings, such a model is able to predict a respectable share of ratings correctly but displays fundamental flaws when it comes to the prediction of changes.

Ability to Predict Ratings

In order to make the different estimation results comparable, I rounded the fitted values of the linear regression methods (OLS and GMM) to the nearest integer and assigned a value of 1 or 17 respectively for predictions below 1 or above 17. Regarding the ML-based models, the fitted values are translated to the initial rating scale of 1 to 17 by the help of the corresponding cutoff-estimates. Afonso et al. (2007) proposed that two predictions can be calculated for the RE-estimation of the *basic linear model* and the *Mundlak model*: With and without the country-specific effect $\hat{\epsilon}_i$, where the country-specific effect is obtained by taking the time average of the obtained residual for each country. This extra information can subsequently be used in a second step estimation to make out-of-sample and in-sample predictions. Note that this two-step procedure can only be applied to panel data models, as the overall error component cannot be predicted by models that do not take the panel structure into account. Furthermore, since the country effect is estimated by the within-mean of this error component, this additional covariate is time-invariant and useless in a FE-estimation. In the context of the ordered response models, I used the country effects of the linear RE-estimations of the *Mundlak model* as an additional regressor. Tables A.1.26 - A.1.28 summarize the overall predictive power of the presented static and dynamic models as well as a pure random walk model that simply predicts the previous rating in the current time period.

The multi-column "Deviation: $Y_{it} - \hat{Y}_{it}$" represents the deviation between the actual rating and the model prediction. Here, negative (positive) numbers indicate an overprediction (underprediction) by the respective number. Likewise, a deviation of zero constitutes a correct prediction. Observations for which the fitted value exceeds (falls below) the true rating by more (less) than two notches are clustered into the group "≤ -3" ("≥ 3"). The column "Percentage Correct" informs about the share of fitted values which are correctly predicted, correctly within one and within two notches. At first glance, it becomes obvious that the random walk predicts with 81.99%, 76.27% and 77.37% a considerable share of the sovereign ratings by Moody's, S&P and Fitch correctly.[24] One has to consider, though, that this benchmark-estimation is unsuitable to make any out-of-sample predictions as this model depends crucially on the existence of correct current ratings to predict the followings. For this purpose, a true time-series approach that employs richer models than a simple AR(1)-unit-root model could help to better understand the growth path of country ratings over time.

Considering the static models, some already discussed properties become evident. First of all, there is a clear model-hierarchy: the *basic models* are outperformed by the *Mundlak models* which are surpassed by the ordered response models, predicting between 43.95% and 46.12% of the ratings correctly. The difference between the simple and the panel ordered probit are marginal, for Moody's and Fitch the latter is more accurate while for S&P, the pooled ordered probit slightly outperforms its panel-specific counterpart. Moreover, the poor performance of the FE-models is confirmed by a tiny fraction of flawless predictions and a high number of fitted values that under- or overpredict Y_{it} by three or more notches for both the *basic* and the *Mundlak model* among all agencies. As expected, the models including the estimated country effect have an improved fit compared to the models without country effect. Afonso et al. (2007) conclude that this effect captures systematically important information like political risk and uncertainty as well as social tensions. Therefore, the inclusion of this effect corrects the models for the absence of this knowledge. Similar to the random walk model, these models are incapable of making any predictions for panel-units not included in the data set. However, if one assumes that the country effect is not too severely influenced by the inclusion of further time periods, upcoming ratings of included countries can be forecasted with these models.

The examination of the dynamic models reveals interesting findings regarding the OLS- and GMM-based models, too. First of all, with 76.87%, 75.64% and 76.53% of correct predictions, the pooled OLS model clearly outpaces the FE model (64.3%, 64.05%, 59.5%) for Moody's, S&P and Fitch. Even though the dynamic FE model improved in comparison to the static FE model, the OLS model is still able to predict significantly more ratings correctly. Regarding the GMM-based models, the relation between valid instruments and consistent estimates becomes more evident. For instance, the one- and two-step estimation of the difference-GMM model with limited lags presents an extremely poor fit for Moody's and S&P. For both applications, the autoregressive parameter falls below the discussed lower bound, though the Hansen statistics are with 0.247 (Moody's) and 0.052 (S&P) in a reasonable order. This puzzle might be

[24]In fact, for Moody's, not a single model of the discussed static and dynamic candidates is able to surpass this benchmark.

explained by the limitations of the difference-GMM estimator if the data-generating process is close to a random walk and if the relative variance of the panel specific effects is large (Blundell and Bond (1998). Moreover, the deviations-distributions are skewed in all occasions for every rating agency: The one-step, collapsed difference estimator is clearly skewed right for Moody's and S&P. In all remaining instances, the difference-GMM estimators significantly underpredict the sovereign ratings, leading to deviations-distributions with too much probability mass associated to the values $1, 2$ and ≥ 3. The system-GMM estimators constitute a considerable improvement and should be the favored candidates for the consistent estimation of the *dynamic basic linear model*. The deviations-distribution of the system-GMM estimators is clearly more centered around zero, yet it also tends to underpredict ratings. For Moody's and Fitch, the procedure that utilizes the two-step approach and instruments from the first two periods only predicts the highest share of ratings correctly. For S&P, the two-step approach combined with the "collapse"-option performs slightly better than the final specification. For all CRA, the best system-GMM model predicts roughly the same amount of ratings correctly as the random walk does. However, if one examines the proportion of ratings that are correctly predicted within one and two notches, the system-GMM models outperform the random walk. Admittedly, this observation might in part result from the high estimated autoregressive parameters which make these models quite similar to the simple random walk. This could also be an explanation for their high accuracy despite the fact that the joint instrument validity is rejected at the 5%-level for all agencies.

Ability to Predict Changes

In the next step, I investigate the models' ability to predict changes in ratings. Besides of studying current movements in the ratings, I also considered predicted movements that lead or lag the true movement. However, there is an overlapping-problem because one fitted value can both lead and lag a change if the adjacent predictions take on according values. Thus, such an assessment criterion would yield results that were hard to interpret and is therefore not presented in this thesis. The models' ability to predict sample up- and downgrades can be found in tables A.1.29 - A.1.31 in the appendix. In the second and third multi-column of the tables, I report for the up- and downgrades the respective amount of changes in the sample, the amount of predicted changes and the number of instances in which the model prediction and the sample movement coincided. The first most striking observation is that all models tend to overpredict both up- and downgrades at similar magnitudes. Also, among all CRA, the static models outperform their dynamic counterparts in predicting changes correctly with the simple ordered probit being the best model for Moody's (48 correct changes) and S&P (68) and the OLS estimation of the *Mundlak model* for Fitch (52). However, this observation also follows from the fact that the static models are more volatile and predict a larger amount of changes than the dynamic models do. Obviously, this fact makes it easier for these models to correctly predict changes and hampers a ceteris-paribus comparison between the two model-types. Regarding Moody's, the dynamic models have serious problems to correctly predict changes and achieve correct prediction rates merely above the ones of the random walk. The performance of the models with country-specific effect is similar to the simple static models, though especially the ordered response models of the former specification predict a number of changes that is closer to the true value. For S&P, the overall rate of correct predictions is higher than for Moody's and Fitch. Again, this observation is related to the increased number of changes in the sample. For this agency, the models with country effect have difficulties to realize the downgrades accurately, yet they still perform comparably to the static ordered response models. Even though the dynamic models of this agency also experience troubles to beat the prediction rate of the random walk, the difference-GMM estimations anticipate the changes better than the remaining dynamic models and are almost as precise as the static estimations. Lastly, for Fitch, all dynamic models perform on roughly the same low level and the comparison between static models with and without country effect does not differ significantly from the one discussed for S&P. Summarizing the findings from the discussed tables, the following can be assessed: Among the dynamic models, the system-GMM models are the best models to predict the sovereign rating of countries in the sample, but they demonstrate weaknesses when it comes to the anticipation of changes. For the static models, a reverse observation is made as these models are capable of detecting changes more frequently. Yet in more than 50% of the cases, they yield a wrong fitted value of the sovereign rating. All in all, the static ordered response models with country-specific effect are dominating in order to balance the trade-off between accuracy in the prediction of both ratings and changes. Nonetheless, even the best models forecasted with 30.77% for Moody's and Fitch and 32.69% for S&P less than a third of the rating changes correctly. Hence, there seems to be room for improvement regarding the prediction of changes in sovereign ratings that I tried to fill by estimating the rating difference between two adjacent time periods directly. Yet, it turned out that this estimation causes similar troubles as the FE-approach of the earlier chapters. By taking the difference between the country ratings of two time periods, the entire knowledge about the actual rating level is lost. Consider, for instance, two countries, one with a high investment grade, the other with a low speculative rating and assume that both ratings do not change much over the period under consideration. Despite the fact that these countries have vastly different characteristics (expressed by the magnitude of the explanatory variables like WGI, Real GDP per Capita, and so on), the change in the rating that is to be explained is the same for both countries. Thus, similar to the FE-estimator, a major share of the within panel knowledge is lost when estimating the difference between two ratings. As a consequence, even the most agile models predicted in over 92.82% of the cases no change in the sovereign rating and were therefore less able to anticipate rating changes than the static ordered response models.

4.4 Specific Country Analysis

In the last chapter of the empirical application, the specific country analysis contributes to the partial effects of the explanatory variables on the assigned ratings of six selected countries. To ensure that enough variation in the rating can be explained by the independent variables, I chose three countries that experienced the most significant downgrade between the years 2000 and 2018 (Greece, Barbados and Portugal) and three countries which exhibited the strongest improvement during this time period (Indonesia, Romania, Slovak Republic). I compared the ratings of 2018 to the ratings of 2000 because prior to 2000, there are many observations with missing values. The graphical illustration of the associated up- and downgrades for the selected countries is presented in figures A.2.6 and A.2.7 in the appendix. The analysis is restricted to the ratings of Moody's and to the estimation of the *Mundlak model.* As partial effects and associated ratings do not differ significantly across CRA, the analysis can easily be transferred to S&P and Fitch. In order to make the partial effects comparable, I further restricted the analysis to the simple ordered probit and the RE ordered probit model and compared the suggested marginal effects. The consideration of the dynamic models is omitted since the partial effects of the variables are strongly affected by the inclusion of the lagged dependent variable and because no decomposition into short- and long-run coefficients was performed. Moreover, as the assigned ratings are supposed to be connected to changes of the explanatory variables, I considered only the time-varying (short-run) covariates.

The ratings by Moody's, their respective fitted values for the two estimation procedures as well as the explanatory variables in levels and in short-run expressions for the years 2000 and 2018 are presented in the tables A.1.32 and A.1.33.[25] Before the fitted values can be related to respective expressions of the explanatory variables, the marginal effects of the ordered response models have to be calculated as, unlike the linear models, they are not given by the coefficients. Instead, the marginal effect (ME) varies with the point of evaluation and there are three common choices: the marginal effect at the mean (MEM), the average marginal effect (AME) and the marginal effect at a representative value (MER). As the name suggests, the MEM uses the mean values of the other variables when the ME for some variable X_{it} is computed. In the micro-econometric context, this often leads to the criticism of setting the values of the

[25] Note that for the Slovak Republic, Greece and Indonesia not all fitted values could be computed as the observations exhibit missing values.

variables to delusive levels as there is no person who is, e.g., 10% black or 48% male. The AME on the other hand, uses the actual observed values for the variables and averages over the predicted probabilities. Lastly, the MER computes the ME for some selected values of the other variables (Williams (2012)). The interpretation is further complicated because, except for the regional dummies and the default indicator, all explanatory variables are continuous in nature and the dependent variable has with 17 possible ratings too many categories. In the context of ordered response models, ME are typically interpreted with respect to the specific category of the outcome variable, e.g., how does the probability of receiving a good rating change if a covariate changes by one unit or one standard deviation. In order to make the marginal effects easier to interpret, the number of rating categories is reduced to 4 categories. Ratings of 14 or larger are grouped into the best category (good ratings), ratings greater than 7 and smaller than 14 form the second group (decent ratings) and ratings of 7 or worse but better than 1 are clustered into the group of bad ratings. Finally, the group with ratings of 1 remains unchanged (very bad ratings).

I start the analysis with the computation of the ME for the binary explanatory variables which measure discrete changes, e.g., the effect of a default on the rating. Table A.1.34 shows the estimated MEM, AME and MER of the three binary variables for the two non-linear models and the estimated coefficients for the respective model with four ratings categories. The ME for discrete explanatory variables are obtained by comparing the conditional probability of the rating category given the two levels of each variable. The stars indicate the common significance levels with standard errors obtained by the delta-method. Regarding the point of evaluation, the mean values among the six countries are chosen for the MER and the overall mean or rather the actual observed values of the other variables for the MEM and the AME. The first striking observation is that even though the two models yield different coefficients, once they are adjusted for the respective cutoffs, the marginal effects are approximately even. Secondly, the effects vary significantly with the selected values of the remaining variables which complicates the interpretation and emphasizes the difficulty of interpreting marginal effects for non-linear models. Regarding the simple ordered probit, on an all other things equal basis, member states of the EU are 0.4%-8.3% less likely to obtain a bad rating and 1.6%-15.1% more likely to receive a good rating. The LAC-dummy has, indicated by the coefficient, no significant impact on the rating. Lastly, the default-indicator has a strong impact: Sticking to the ordered probit, for defaulted sovereigns the probability of receiving a bad rating is 16.5%-84.3% higher, the likelihood of a decent rating is 7.5%-84.2% smaller. Barbados is the only country whose assigned rating is affected by the effect of a binary covariate: In 2018, the country defaulted on its sovereign debt which certainly played a decisive role for the sharp downgrade by Moody's.

For the continuous variables, the first derivative of the density function with respect to the variable of interest is required to obtain the *instantaneous rate of change*. This ME measures the effect of an infinitesimal change of the covariate on the probability of receiving a certain rating. Table A.1.35 present the MEM, AME and the MER, evaluated at the mean value of the respective covariate for the six countries.[26] The interpretation of the ME is not particularly intuitive because, due to the non-linearity, they only state that if the covariate changes by a very small amount (e.g. 0.01), the probability of falling into the associated group changes by the ME times the change (e.g. $0.01 \cdot ME$). Depending on the distributional properties of the explanatory variable and its measurement unit, the ME may, however, provide a poor approximation for, e.g., a unit change. Also, the ME is heavily influenced by the point of evaluation. Thus, in view of the mentioned difficulties, I refrain from interpreting the presented effects in greater detail. To circumvent this issue, Cameron and Trivedi (2010) proposed to compare the predicted probability at the mean of a variable with the predicted probability evaluated at the mean plus one thousandth standard deviation. Despite the difficulties of interpreting the ME, it can be stated that the effects for both models are broadly consistent. Furthermore, the contributions of the explanatory variables on the received rating can be illustrated by enumerating the variables that impacted the up- or downgrade for the selected country. For instance, for Indonesia, the enhanced levels of GDP Growth, Inflation and the WGI impacted the upgrade clearly.

5 Conclusion

This thesis was dedicated to the estimation of sovereign ratings and to the identification of relevant explanatory variables. Therefore, I constructed a panel data set consisting of 116 countries observed from 1990 until 2018 and applied elaborated static and dynamic econometric estimation techniques. Regarding the linear static models, I found that the country-specific error could be modeled effectively by the within-means of the time-varying variables. This transformation caused the Hausman-test to confirm the existence of a panel-heterogeneity that is unrelated to the explanatory variables and thus allows for the consistent estimation of the linear static model by the RE-methodology. Subsequently, I estimated the static model with the help of non-linear ordered response models. While it turned out that the set of significant explanatory variables roughly coincides with the set of the linear estimation framework, the two ordered response models significantly increased the amount of correctly predicted ratings and changes compared to the linear specifications. Specifically, the most suitable non-linear models predicted between 48.66% and 51.46% of the ratings correctly and between 81.8% and 87.02% correctly within one rating-notch (see tables A.1.26 - A.1.28). Regarding the share of accurately predicted up- and downgrades, the linear

[26]Regarding the values of the other variables, the ME are computed like those of the binary variables.

models do not come off any worse. The ratio of correctly predicted upgrades for the best static models varies between 33.33% and 37.93% and between 30.3% and 34.78% for the downgrades (see tables A.1.29 - A.1.31). However, considering the trade-off between the two criteria of prediction accuracy and the fact that the linear models tend to overestimate the overall amount of rating changes, the ordered response models seem superior. Moreover, the performance difference between the non-linear models is only marginal, and the specific country analysis additionally revealed that the partial effects hardly differ if the different cutoff-values are controlled for. The frequently raised accusation of inertia in sovereign ratings led me to the consideration of dynamic panel data models. However, the analysis disclosed the models' inability to beat the predictive accuracy of a pure random walk model and showed also that no specification was able to simultaneously meet all mentioned requirements for dynamic models estimated by the GMM-technique. To conclude the econometric analysis of sovereign ratings, it seems like there is no unique model that fulfills all criteria at the same time. Instead, if the presented models are to be used for in- and out-of-sample predictions, a mixture of methods could help to detect the maximum number of correct ratings and their respective changes. It must be conceded, however, that the data set consists of an extremely heterogenous set of countries and that CRA have adjusted their methodological approach during the 29 years of observation. Furthermore, the analysis does not consider possible effects of ratings duration or additional explanatory variables and is thus restricted by construction. Altogether, the presented models nevertheless show a decent predictive performance, both between countries and across time-periods.

Looking forward, one natural extension to the work of this thesis would be to connect the core strengths of the static and dynamic models into one estimation framework. In particular, a dynamic panel-ordered response model could be used to combine the high predictive power of the dynamic models with the increased ability to detect rating changes of the static ordered response models. Hasegawa (2009) provides a well-structured introduction into the bayesian estimation of this model that has initially been applied to sovereign ratings by Brůha et al. (2017). Instead, one could also opt for the incorporation of covariates that add new and rating-related information to the existing set of variables. One promising candidate are the published expectations of the CRA which seem to be an informative indicator for ratings changes. Another qualitative information are government bond spreads that have been successfully incorporated into the estimation of sovereign ratings by D'Agostino and Lennkh (2016). Furthermore, given the vast amount of country-related data, one could also apply data mining approaches like classification trees or random forests to the scientific quest of the thesis. Possibly, such a statistical learning technique could identify a new and yet disregarded set of variables and thereby improve the explanatory power of the employed models.

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A Appendix

A.1 Tables

Table A.1.1: Moody's, S&P and Fitch Rating System with Numeric Transformation

Rating description		Long Term Rating			Transformation
		Moody's	S&P	Fitch	Linear Scale
Prime	Investment grade	Aaa	AAA	AAA	17
High quality	Investment grade	Aa1 Aa2 Aa3	AA+ AA AA-	AA+ AA AA-	16 15 14
Upper medium grade	Investment grade	A1 A2 A3	A+ A A-	A+ A A-	13 12 11
Lower medium grade	Investment grade	Baa1 Baa2 Baa3	BBB+ BBB BBB-	BBB+ BBB BBB-	10 9 8
Non-investment grade speculative	Speculative grade	Ba1 Ba2 Ba3	BB+ BB BB-	BB+ BB BB-	7 6 5
Highly speculative	Speculative grade	B1 B2 B3	B+ B B-	B+ B B-	4 3 2
Substantial risks	Speculative grade	Caa1 Caa2 Caa3	CCC+ CCC CCC-	CCC+ CCC CCC-	1
In default, little prospect for recovery	Speculative grade	Ca	CC	CC C	1
Default	Speculative grade	C	SD D	DDD D D	1

Table A.1.2: Mean Values (Std. Err.) of Explanatory Variables by Rating Grade

Variables	**Rating Grade**	**Credit Rating Agencies**		
		Moody's	S&P	Fitch
World Government Indicator	Investment	0.81 (0.71)	0.87 (0.71)	0.84 (0.74)
	Speculative	-0.26 (0.47)	-0.27 (0.45)	-0.24 (0.48)
Real GDP per Capita	Investment	5.14 (1.81)	5.26 (1.77)	5.39 (1.77)
	Speculative	3.54 (1.50)	3.67 (1.53)	3.75 (1.45)
Real GDP Growth	Investment	3.50 (2.66)	3.49 (2.63)	3.40 (2.62)
	Speculative	3.45 (3.44)	3.69 (3.34)	3.91 (3.61)
Unemployment Rate	Investment	7.64 (4.52)	7.41 (4.39)	7.54 (4.41)
	Speculative	9.73 (4.99)	10.04 (5.00)	9.72 (4.62)
Inflation	Investment	5.10 (31.96)	3.54 (3.77)	3.50 (3.95)
	Speculative	13.01 (33.22)	14.21 (51.42)	16.50 (58.38)
Current Account	Investment	0.94 (7.50)	1.28 (7.61)	1.21 (7.46)
	Speculative	-3.67 (7.63)	-3.80 (7.47)	-3.34 (7.87)
Government Debt	Investment	33.19 (36.01)	32.55 (36.02)	34.28 (34.48)
	Speculative	49.30 (41.39)	48.06 (41.43)	42.43 (42.35)
External Debt	Investment	9.25 (21.85)	6.27 (17.25)	7.64 (18.86)
	Speculative	45.8 (35.36)	46.09 (33.78)	41.67 (32.80)
EU	Investment	0.29 (0.45)	0.31 (0.46)	0.32 (0.47)
	Speculative	0.04 (0.19)	0.03 (0.16)	0.04 (0.19)
LAC	Investment	0.10 (0.30)	0.08 (0.27)	0.08 (0.26)
	Speculative	0.44 (0.50)	0.36 (0.48)	0.37 (0.48)
Default History	Investment	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	Speculative	0.04 (0.19)	0.03 (0.16)	0.03 (0.17)

Table A.1.3: Linear Estimation Results for Moodys (*basic linear model*)

	Pooled OLS (robust)	**Random Effects**	**Fixed Effects**
Constant	5.479***	7.611***	12.214***
	(0.328)	(0.544)	(0.78)
World Government Indicator	3.926***	4.273***	4.207***
	(0.115)	(0.192)	(0.379)
Real GDP per Capita	0.863***	0.6***	-0.113
	(0.036)	(0.071)	(0.114)
Real GDP Growth	0.137***	0.108***	0.074***
	(0.03)	(0.021)	(0.02)
Unemployment Rate	-0.108***	-0.17***	-0.206***
	(0.012)	(0.018)	(0.021)
Inflation	-0.023**	-0.01***	-0.013***
	(0.011)	(0.003)	(0.003)
Current Account	0.034***	0.004	-0.002
	(0.01)	(0.011)	(0.011)
Government Debt	-0.023***	-0.042***	-0.054***
	(0.002)	(0.003)	(0.003)
External Debt	0.002	0.014***	0.022***
	(0.003)	(0.005)	(0.006)
EU	0.771***	0.976***	omitted
	(0.128)	(0.358)	
LAC	-0.77***	-1.056**	omitted
	(0.166)	(0.42)	
Default History	-3.123**	-2.462***	-2.584***
	(1.484)	(0.608)	(0.577)
R^2 (overall)	0.8746	0.8375	0.6191
RMSE	1.7367	1.3111	1.2345
Countries		59	59
Observations	1044	1044	1044
Breuch-Pagan Test: p (χ^2)		0.00 (1112.61)	
F-Test: p ($F_{p,N-p}$)			0.00 (20.67)
Hausman Test: p (χ^2)		0.00 (112.92)	

Table A.1.4: Linear Estimation Results for S&P (*basic linear model*)

	Pooled OLS (robust)	**Random Effects**	**Fixed Effects**
Constant	5.437***	7.795***	11.286***
	(0.299)	(0.501)	(0.661)
World Government Indicator	3.815***	4.096***	4.125***
	(0.098)	(0.176)	(0.314)
Real GDP per Capita	0.816***	0.536***	0.024
	(0.032)	(0.066)	(0.097)
Real GDP Growth	0.111***	0.078***	0.054***
	(0.025)	(0.017)	(0.017)
Unemployment Rate	-0.081***	-0.155***	-0.187***
	(0.01)	(0.016)	(0.018)
Inflation	-0.023*	-0.012***	-0.014***
	(0.012)	(0.003)	(0.003)
Current Account	0.089***	0.046***	0.042***
	(0.009)	(0.009)	(0.009)
Government Debt	-0.023***	-0.038***	-0.045***
	(0.002)	(0.002)	(0.003)
External Debt	0.001	0.008*	0.01*
	(0.002)	(0.004)	(0.005)
EU	1.055***	1.168***	omitted
	(0.114)	(0.347)	
LAC	-0.204	-0.679*	omitted
	(0.147)	(0.407)	
Default History	-3.393**	-3.186***	-3.28***
	(1.526)	(0.556)	(0.537)
R^2 (overall)	0.8969	0.8626	0.7357
RMSE	1.5155	1.0688	1.023
Countries		59	59
Observations	1024	1024	1024
Breuch-Pagan Test: p (χ^2)		0.00 (1448.46)	
F-Test: p ($F_{p,N-p}$)			0.00 (25.17)
Hausman Test: p (χ^2)		0.00 (56.52)	

Table A.1.5: Linear Estimation Results for Fitch (*basic linear model*)

	Pooled OLS (robust)	**Random Effects**	**Fixed Effects**
Constant	5.276***	6.829***	10.001***
	(0.333)	(0.521)	(0.727)
World Government Indicator	3.395***	3.732***	3.796***
	(0.119)	(0.187)	(0.348)
Real GDP per Capita	0.953***	0.759***	0.32***
	(0.035)	(0.068)	(0.101)
Real GDP Growth	0.109***	0.079***	0.057***
	(0.028)	(0.018)	(0.018)
Unemployment Rate	-0.101***	-0.153***	-0.176***
	(0.011)	(0.017)	(0.019)
Inflation	-0.021*	-0.01***	-0.012***
	(0.012)	(0.003)	(0.003)
Current Account	0.061***	0.036	0.037
	(0.01)	(0.01)	(0.011)
Government Debt	-0.026***	-0.04***	-0.047***
	(0.002)	(0.002)	(0.003)
External Debt	-0.004	0.007	0.015**
	(0.003)	(0.005)	(0.006)
EU	1.401***	1.601***	omitted
	(0.107)	(0.345)	
LAC	-0.77***	-1.005**	omitted
	(0.169)	(0.425)	
Default History	-3.032	-2.444***	-2.528***
	(2.128)	(0.616)	(0.595)
R^2 (overall)	0.8931	0.8631	0.7202
RMSE	1.46	1.0302	0.9926
Countries		55	55
Observations	928	928	928
Breuch-Pagan Test: p (χ^2)		0.00 (1289.93)	
F-Test: p ($F_{p,N-p}$)			0.00 (28.06)
Hausman Test p (χ^2)		0.00 (28.50)	

Table A.1.6: Linear Estimation Results for Moodys (*Mundlak model*)

	Pooled OLS (robust)	**Random Effects**	**Fixed Effects**
Constant	5.955***	5.862***	11.121***
	(0.363)	(0.733)	(0.059)
World Government Indicator (SR)	3.79***	4.127***	4.207***
	(0.493)	(0.378)	(0.379)
World Government Indicator (LR)	3.687***	3.713***	omitted
	(0.119)	(0.243)	
Real GDP per Capita (SR)	-0.208	-0.13	-0.113
	(0.151)	(0.114)	(0.114)
Real GDP per Capita (LR)	0.852***	0.85***	omitted
	(0.033)	(0.079)	
Real GDP Growth (SR)	0.092***	0.076***	0.074***
	(0.028)	(0.02)	(0.02)
Real GDP Growth (LR)	-0.02	-0.003	omitted
	(0.052)	(0.112)	
Unemployment Rate (SR)	-0.208***	-0.207***	-0.206***
	(0.026)	(0.021)	(0.021)
Unemployment Rate (LR)	-0.081***	-0.088***	omitted
	(0.012)	(0.031)	
Inflation (SR)	-0.026*	-0.015***	-0.013***
	(0.013)	(0.003)	(0.003)
Inflation (LR)	-0.022***	-0.01**	omitted
	(0.013)	(0.005)	
Current Account (SR)	0.024*	0.001	-0.002
	(0.014)	(0.011)	(0.011)
Current Account (LR)	0.055***	0.068*	omitted
	(0.014)	(0.039)	
Government Debt (SR)	-0.056***	-0.054***	-0.054***
	(0.004)	(0.003)	(0.003)
Government Debt (LR)	-0.015***	-0.014**	omitted
	(0.002)	(0.005)	
External Debt (SR)	0.015**	0.021***	0.022***
	(0.006)	(0.006)	(0.006)
External Debt (LR)	-0.002	-0.003	omitted
	(0.003)	(0.007)	
EU	0.745***	0.753**	omitted
	(0.115)	(0.315)	
LAC	-0.716***	-0.724*	omitted
	(0.166)	(0.373)	
Default	-3.275***	-2.658***	-2.584***
	(1.167)	(0.582)	(0.577)
R^2 (overall)	0.8986	0.8970	0.0361
RMSE	1.5674	1.2475	1.2345
Countries		59	59
Observations	1044	1044	1044
Breuch-Pagan Test		0.00 (1167.06)	
F-Test: p ($F_{p,N-p}$)			0.00 (225.85)
Hausman Test		0.9997 (0.86)	

Table A.1.7: Linear Estimation Results for S&P (*Mundlak model*)

	Pooled OLS (robust)	**Random Effects**	**Fixed Effects**
Constant	5.668***	5.543***	11.079***
	(0.318)	(0.732)	(0.05)
World Government Indicator (SR)	3.66***	4.063***	4.125***
	(0.399)	(0.315)	(0.314)
World Government Indicator (LR)	3.628***	3.701***	omitted
	(0.102)	(0.242)	
Real GDP per Capita (SR)	-0.081	0.009	0.024
	(0.142)	(0.097)	(0.097)
Real GDP per Capita (LR)	0.799***	0.792***	omitted
	(0.029)	(0.079)	
Real GDP Growth (SR)	0.07***	0.054***	0.054***
	(0.024)	(0.017)	(0.017)
Real GDP Growth (LR)	0.005	0.011	omitted
	(0.04)	(0.111)	
Unemployment Rate (SR)	-0.217***	-0.189***	-0.187***
	(0.023)	(0.018)	(0.018)
Unemployment Rate (LR)	-0.04***	-0.043	omitted
	(0.011)	(0.031)	
Inflation (SR)	-0.025*	-0.015***	-0.014***
	(0.015)	(0.003)	(0.003)
Inflation (LR)	-0.021	-0.01**	omitted
	(0.015)	(0.004)	
Current Account (SR)	0.075***	0.045***	0.042***
	(0.012)	(0.009)	(0.009)
Current Account (LR)	0.124***	0.135***	omitted
	(0.013)	(0.038)	
Government Debt (SR)	-0.046***	-0.045***	-0.045***
	(0.003)	(0.003)	(0.003)
Government Debt (LR)	-0.016***	-0.015***	omitted
	(0.002)	(0.005)	
External Debt (SR)	0.011**	0.011**	0.01*
	(0.005)	(0.005)	(0.005)
External Debt (LR)	-0.004**	-0.004	omitted
	(0.002)	(0.007)	
EU	1.005***	1.022***	omitted
	(0.103)	(0.314)	
LAC	-0.178	-0.248	omitted
	(0.14)	(0.373)	
Default	-3.69***	-3.317***	-3.28***
	(1.128)	(0.54)	(0.537)
R^2 (overall)	0.9164	0.9148	0.0167
RMSE	1.3702	1.0304	1.0230
Countries		59	59
Observations	1024	1024	1024
Breuch-Pagan Test		0.00 (1532.79)	
F-Test: p ($F_{p,N-p}$)			0.00 (305.74)
Hausman Test		0.5849 (7.50)	

Table A.1.8: Linear Estimation Results for Fitch (*Mundlak model*)

	Pooled OLS (robust)	**Random Effects**	**Fixed Effects**
Constant	5.599***	5.154***	11.506***
	(0.414)	(0.954)	(0.052)
World Government Indicator (SR)	3.475***	3.747***	3.796***
	(0.43)	(0.347)	(0.348)
World Government Indicator (LR)	3.272***	3.4***	omitted
	(0.127)	(0.3)	
Real GDP per Capita (SR)	0.188	0.303***	0.32***
	(0.161)	(0.102)	(0.101)
Real GDP per Capita (LR)	0.883***	0.911***	omitted
	(0.034)	(0.088)	
Real GDP Growth (SR)	0.069**	0.058***	0.057***
	(0.027)	(0.018)	(0.018)
Real GDP Growth (LR)	-0.006	0.008	omitted
	(0.056)	(0.135)	
Unemployment Rate (SR)	-0.206***	-0.177***	-0.176***
	(0.026)	(0.019)	(0.019)
Unemployment Rate (LR)	-0.053***	-0.05	omitted
	(0.012)	(0.037)	
Inflation (SR)	-0.023	-0.013***	-0.012***
	(0.014)	(0.003)	(0.003)
Inflation (LR)	-0.018	-0.008*	omitted
	(0.014)	(0.004)	
Current Account (SR)	0.068***	0.04***	0.037***
	(0.014)	(0.011)	(0.011)
Current Account (LR)	0.108***	0.117***	omitted
	(0.014)	(0.041)	
Government Debt (SR)	-0.047***	-0.047***	-0.047***
	(0.003)	(0.003)	(0.003)
Government Debt (LR)	-0.016***	-0.017***	omitted
	(0.002)	(0.006)	
External Debt (SR)	0.021***	0.017***	0.015**
	(0.005)	(0.006)	(0.006)
External Debt (LR)	-0.008**	-0.006	omitted
	(0.003)	(0.009)	
EU	1.285***	1.374***	omitted
	(0.098)	(0.318)	
LAC	-0.539***	-0.538	omitted
	(0.173)	(0.393)	
Default	-3.225**	-2.583***	-2.528***
	(1.598)	(0.599)	(0.595)
R^2 (overall)	0.9130	0.9113	0.0069
RMSE	1.3226	1.0007	0.9926
Countries		55	55
Observations	928	928	928
Breuch-Pagan Test		0.00 (1210.79)	
F-Test: p ($F_{p,N-p}$)			0.00 (256.54)
Hausman Test		(-6.93)	

Table A.1.9: Ordered Probit Estimation Results for Moody's (*Mundlak model*)

	Ordered Probit (robust)	**RE Ordered Probit**
World Government Indicator (SR)	2.513***	3.621***
	(0.359)	(0.347)
World Government Indicator (LR)	2.697***	3.537***
	(0.107)	(0.255)
Real GDP per Capita (SR)	-0.217**	-0.122
	(0.111)	(0.104)
Real GDP per Capita (LR)	0.596***	0.783***
	(0.031)	(0.081)
Real GDP Growth (SR)	0.026	0.035*
	(0.019)	(0.018)
Real GDP Growth (LR)	-0.037	-0.027
	(0.037)	(0.105)
Unemployment Rate (SR)	-0.149***	-0.173***
	(0.018)	(0.019)
Unemployment Rate (LR)	-0.046***	-0.068**
	(0.008)	(0.029)
Inflation (SR)	-0.017**	-0.01***
	(0.008)	(0.003)
Inflation (LR)	-0.015*	-0.008*
	(0.008)	(0.004)
Current Account (SR)	0.015	0.002
	(0.009)	(0.01)
Current Account (LR)	0.074***	0.117***
	(0.012)	(0.04)
Government Debt (SR)	-0.045***	-0.055***
	(0.003)	(0.003)
Government Debt (LR)	-0.014***	-0.017***
	(0.002)	(0.005)
External Debt (SR)	0.008**	0.019***
	(0.004)	(0.005)
External Debt (LR)	0.007***	0.009
	(0.002)	(0.007)
EU	0.382***	0.498
	(0.091)	(0.314)

LAC	-0.372***	-0.446
	(0.11)	(0.35)
Default	-2.413***	-2.618***
	(0.937)	(0.581)
Cut 1	-2.84	-3.462
Cut 2	-1.707	-2.116
Cut 3	-1.267	-1.517
Cut 4	-0.56	-0.543
Cut 5	-0.084	0.092
Cut 6	0.233	0.519
Cut 7	1.038	1.56
Cut 8	1.85	2.659
Cut 9	2.549	3.544
Cut 10	3.018	4.123
Cut 11	3.416	4.613
Cut 12	3.922	5.252
Cut 13	4.741	6.245
Cut 14	5.245	6.852
Cut 15	5.88	7.749
Cut 16	6.364	8.443
Countries	59	59
Observations	1044	1044
Log-Likelihood	-1505.3366	-1362.7157
AIC	3080.673	2797.431
BIC	3253.952	2975.661
McFadden R^2	0.4293	0.6994
LR Test p ($\bar{\chi}^2(1)$)		0.00 (285.24)

Table A.1.10: Ordered Probit Estimation Results for S&P (*Mundlak model*)

	Ordered Probit (robust)	**RE Ordered Probit**
World Government Indicator (SR)	2.831***	4.245***
	(0.356)	(0.358)
World Government Indicator (LR)	3.038***	4.323***
	(0.123)	(0.295)
Real GDP per Capita (SR)	-0.116	-0.051
	(0.116)	(0.107)
Real GDP per Capita (LR)	0.632***	0.893***
	(0.031)	(0.091)
Real GDP Growth (SR)	0.026	0.028
	(0.017)	(0.018)
Real GDP Growth (LR)	-0.022	-0.024
	(0.032)	(0.12)
Unemployment Rate (SR)	-0.164***	-0.185***
	(0.018)	(0.02)
Unemployment Rate (LR)	-0.021***	-0.036
	(0.008)	(0.034)
Inflation (SR)	-0.019*	-0.014***
	(0.011)	(0.003)
Inflation (LR)	-0.016	-0.01**
	(0.011)	(0.005)
Current Account (SR)	0.053***	0.047***
	(0.008)	(0.01)
Current Account (LR)	0.154***	0.218***
	(0.011)	(0.045)
Government Debt (SR)	-0.042***	-0.057***
	(0.003)	(0.003)
Government Debt (LR)	-0.017***	-0.023***
	(0.002)	(0.006)
External Debt (SR)	0.008**	0.011**
	(0.004)	(0.005)
External Debt (LR)	0.005***	0.009
	(0.002)	(0.008)
EU	0.733***	0.861**
	(0.097)	(0.352)

LAC	-0.048	-0.141
	(0.111)	(0.402)
Default	-3.298***	-3.863***
	(1.021)	(0.686)
Cut 1	-3.424	-3.849
Cut 2	-2.25	-2.608
Cut 3	-1.386	-1.572
Cut 4	-0.754	-0.75
Cut 5	-0.015	0.267
Cut 6	0.817	1.446
Cut 7	1.514	2.395
Cut 8	2.317	3.439
Cut 9	2.923	4.166
Cut 10	3.618	5.038
Cut 11	4.304	5.905
Cut 12	4.998	6.768
Cut 13	5.574	7.558
Cut 14	6.302	8.761
Cut 15	7.075	10.088
Cut 16	7.978	11.506
Countries	59	59
Observations	1024	1024
Log-Likelihood	-1441.0585	-1264.6612
AIC	2952.117	2601.322
BIC	3124.718	2778.855
McFadden R^2	0.4598	0.6992
LR Test p ($\bar{\chi}^2(1)$)		0.00 (352.79)

Table A.1.11: Ordered Probit Estimation Results for Fitch (*Mundlak model*)

	Ordered Probit (robust)	**RE Ordered Probit**
World Government Indicator (SR)	2.742***	4.056***
	(0.356)	(0.407)
World Government Indicator (LR)	2.785***	3.929***
	(0.127)	(0.36)
Real GDP per Capita (SR)	0.174	0.376***
	(0.13)	(0.118)
Real GDP per Capita (LR)	0.71***	1.061***
	(0.038)	(0.108)
Real GDP Growth (SR)	0.031	0.036*
	(0.021)	(0.02)
Real GDP Growth (LR)	-0.006	0.001
	(0.048)	(0.153)
Unemployment Rate (SR)	-0.159***	-0.171***
	(0.021)	(0.022)
Unemployment Rate (LR)	-0.033***	-0.061
	(0.009)	(0.042)
Inflation (SR)	-0.015	-0.012***
	(0.01)	(0.003)
Inflation (LR)	-0.012	-0.006
	(0.01)	(0.005)
Current Account (SR)	0.05***	0.05***
	(0.011)	(0.012)
Current Account (LR)	0.145***	0.178***
	(0.015)	(0.049)
Government Debt (SR)	-0.046***	-0.065***
	(0.003)	(0.004)
Government Debt (LR)	-0.016***	-0.023***
	(0.002)	(0.007)
External Debt (SR)	0.017***	0.021***
	(0.004)	(0.007)
External Debt (LR)	0	0.003
	(0.003)	(0.011)
EU	1.098***	1.576***
	(0.099)	(0.375)

LAC	-0.324**	-0.486
	(0.137)	(0.444)
Default	-2.411**	-2.711***
	(1.222)	(0.659)
Cut 1	-3.574	-4.463
Cut 2	-2.072	-2.199
Cut 3	-1.021	-0.984
Cut 4	-0.552	-0.297
Cut 5	0.282	1.03
Cut 6	0.658	1.631
Cut 7	1.525	2.843
Cut 8	2.547	4.166
Cut 9	3.294	5.099
Cut 10	4.075	6.051
Cut 11	4.738	6.911
Cut 12	5.272	7.613
Cut 13	6.029	8.595
Cut 14	6.672	9.529
Cut 15	7.644	11.051
Cut 16	8.243	11.97
Countries	55	55
Observations	928	928
Log-Likelihood	-1248.9207	-1092.2784
AIC	2567.841	2256.557
BIC	2736.998	2430.546
McFadden R^2	0.462	0.6853
LR Test p ($\bar{\chi}^2(1)$)		0.00 (313.28)

Table A.1.12: Model-generated Cutoff-Values

Cutoff-Category	**Moody's**	**S&P**	**Fitch**
Original	-3.462	-3.849	-4.463
	-2.116	-2.608	-2.199
	-1.517	-1.572	-0.984
	-0.543	-0.75	-0.297
	0.092	0.267	1.03
	0.519	1.446	1.631
	1.56	2.395	2.843
	2.659	3.439	4.166
	3.544	4.166	5.099
	4.123	5.038	6.051
	4.613	5.905	6.911
	5.252	6.768	7.613
	6.245	7.558	8.595
	6.852	8.761	9.529
	7.749	10.088	11.051
	8.443	11.506	11.97
Shifted to Zero	0	0	0
	1.346	1.241	2.264
	1.945	2.277	3.479
	2.919	3.098	4.166
	3.554	4.116	5.493
	3.981	5.295	6.094
	5.023	6.244	7.306
	6.121	7.288	8.629
	7.006	8.015	9.562
	7.585	8.887	10.514
	8.075	9.754	11.374
	8.714	10.617	12.076
	9.707	11.407	13.058
	10.314	12.61	13.992
	11.211	13.937	15.514
	11.905	15.355	16.433
Mean-Difference Cutoffs	0.794	1.024	1.096

Table A.1.13: Monte Carlo Study with 500 Simulations, $T = 4$

N	φ	**Pooled OLS**		**Fixed Effects**		**GMM (diff.)**		**GMM (sys.)**	
		$\hat{\varphi}$-Mean	$\hat{\varphi}$-Std.	$\hat{\varphi}$-Mean	$\hat{\varphi}$-Std.	$\hat{\varphi}$-Mean	$\hat{\varphi}$-Std.	$\hat{\varphi}$-Mean	$\hat{\varphi}$-Std.
		$\hat{\beta}$-Mean	$\hat{\beta}$-Std.	$\hat{\beta}$-Mean	$\hat{\beta}$-Std.	$\hat{\beta}$-Mean	$\hat{\beta}$-Std.	$\hat{\beta}$-Mean	$\hat{\beta}$-Std.
600	0.95	0.9723	0.0029	**0.9382**	0.0045	0.9327	0.444	0.9714	0.0037
		3.0367	0.0097	**2.9824**	0.0116	2.974	0.6565	3.0336	0.0096
	0.85	0.8736	0.003	0.8389	0.0047	**0.849**	0.033	0.8713	0.0044
		3.036	0.01	2.9844	0.0117	**2.998**	0.0497	3.0329	0.0097
	0.75	0.7748	0.0033	0.7397	0.0046	**0.7513**	0.0161	0.7695	0.005
		3.0364	0.01	2.9863	0.0109	**3.0017**	0.0253	3.032	0.0095
	0.5	0.5263	0.0036	0.4919	0.004	**0.4993**	0.0077	0.5093	0.0059
		3.0372	0.0103	2.9904	0.0113	**2.9989**	0.0145	3.0238	0.01
	0.25	0.2758	0.0037	0.2442	0.0036	**0.2501**	0.0052	0.2522	0.0047
		3.0382	0.0111	2.9935	0.0102	**3.0002**	0.0122	3.0189	0.0097
	0	0.023	0.0036	-0.0044	0.0032	**-0.0003**	0.004	-0.0002	0.0041
		3.0385	0.0109	2.9962	0.0095	**3.0001**	0.011	3.0177	0.0099
300	0.95	0.9721	0.0043	**0.9387**	0.0066	0.9372	0.4813	0.9713	0.0055
		3.0362	0.014	**2.9827**	0.0161	2.9811	0.7443	3.034	0.0132
	0.85	0.8739	0.0046	0.8389	0.0064	**0.8524**	0.0561	0.8717	0.0061
		3.0376	0.0145	2.9842	0.0163	**3.003**	0.0838	3.0332	0.0137
	0.75	0.7749	0.0046	0.7393	0.0065	**0.7493**	0.0229	0.7698	0.0072
		3.0364	0.0146	2.9846	0.0161	**2.999**	0.0356	3.0318	0.0147
	0.5	0.5265	0.0049	0.4917	0.0057	**0.5002**	0.0108	0.5091	0.0083
		3.0376	0.0144	2.9893	0.0151	**2.9995**	0.0207	3.0238	0.0144
	0.25	0.2756	0.005	0.2448	0.005	**0.2494**	0.0074	0.2524	0.0068
		3.0368	0.0144	2.994	0.0146	**3.0001**	0.017	3.0178	0.014
	0	0.0232	0.0048	-0.0045	0.0047	**-0.0001**	0.0057	0.0005	0.0061
		3.038	0.015	2.9958	0.0135	**3.0005**	0.0157	3.017	0.0135
150	0.95	0.9717	0.0061	**0.9391**	0.0089	0.9122	0.598	0.971	0.0079
		3.0353	0.0207	**2.984**	0.0224	2.9448	0.9255	3.0345	0.0203
	0.85	0.8734	0.0064	0.8386	0.0089	**0.8499**	0.0959	0.8712	0.009
		3.0378	0.0201	2.9837	0.0227	**2.9999**	0.1423	3.0326	0.0193
	0.75	0.7745	0.0065	0.7388	0.0088	**0.7503**	0.0341	0.7693	0.0112
		3.0374	0.0199	2.9845	0.0225	**2.9997**	0.0529	3.0322	0.0195
	0.5	0.5264	0.0073	0.4917	0.0075	**0.4999**	0.0163	0.5089	0.0117
		3.0359	0.0209	2.9889	0.0203	**2.9971**	0.0296	3.0247	0.0205
	0.25	0.275	0.0073	0.244	0.0074	**0.2501**	0.0107	0.2522	0.0103
		3.0357	0.0206	2.9936	0.0191	**3.0001**	0.0252	3.018	0.0182
	0	0.0226	0.0066	-0.0041	0.0067	**-0.0003**	0.0077	-0.0001	0.0085
		3.0398	0.0211	2.9949	0.0201	**2.9991**	0.0214	3.0186	0.0192

Table A.1.14: Monte Carlo Study with 500 Simulations, $T = 8$

N	φ	**Pooled OLS**		**Fixed Effects**		**GMM (diff.)**		**GMM (sys.)**	
		$\hat{\varphi}$-Mean $\hat{\beta}$-Mean	$\hat{\varphi}$-Std. $\hat{\beta}$-Std.	$\hat{\varphi}$-Mean $\hat{\beta}$-Mean	$\hat{\varphi}$-Std. $\hat{\beta}$-Std.	$\hat{\varphi}$-Mean $\hat{\beta}$-Mean	$\hat{\varphi}$-Std. $\hat{\beta}$-Std.	$\hat{\varphi}$-Mean $\hat{\beta}$-Mean	$\hat{\varphi}$-Std. $\hat{\beta}$-Std.
600	0.95	0.9708	0.0018	**0.9458**	0.0015	0.937	0.0922	0.9699	0.002
		3.033	0.0066	**2.994**	0.0057	2.9803	0.1384	3.0314	0.0062
	0.85	0.8743	0.002	0.8457	0.0018	**0.8493**	0.0084	0.8691	0.0025
		3.0335	0.0064	2.9949	0.0057	**2.9994**	0.013	3.0287	0.006
	0.75	0.7771	0.0023	0.7462	0.0018	**0.7501**	0.0046	0.7641	0.003
		3.0345	0.0066	2.9962	0.0057	**3**	0.0083	3.0244	0.0061
	0.5	0.5292	0.0025	0.4971	0.0019	**0.5001**	0.003	0.5032	0.0028
		3.0365	0.0065	2.9981	0.0055	**3.0004**	0.0069	3.0167	0.0061
	0.25	0.2772	0.0026	0.2478	0.0018	**0.2499**	0.0025	0.2508	0.0025
		3.0372	0.0071	2.9992	0.0054	**2.9999**	0.0065	3.0153	0.0058
	0	0.0232	0.0023	-0.0016	0.0018	**0**	0.0024	0.0001	0.0022
		3.0387	0.0068	2.9992	0.0054	**3.0002**	0.0064	3.0149	0.0058
300	0.95	0.9708	0.0024	**0.9458**	0.0024	0.935	0.0783	0.9697	0.0027
		3.0335	0.0092	**2.9937**	0.0079	2.9773	0.1168	3.0312	0.0084
	0.85	0.8745	0.0028	0.8457	0.0023	**0.8498**	0.0119	0.8693	0.0035
		3.034	0.009	2.9947	0.0081	**2.9999**	0.0181	3.0292	0.0087
	0.75	0.777	0.0033	0.7462	0.0027	**0.7499**	0.0068	0.7643	0.0045
		3.0341	0.0092	2.9967	0.0081	**2.9997**	0.0121	3.0249	0.0086
	0.5	0.5289	0.0035	0.497	0.0026	**0.5003**	0.0044	0.5036	0.0039
		3.0361	0.0092	2.9983	0.0079	**2.9998**	0.0096	3.0169	0.0085
	0.25	0.2769	0.0035	0.2478	0.0025	**0.2502**	0.0035	0.2507	0.0032
		3.037	0.01	2.9984	0.0078	**3.0002**	0.0091	3.0156	0.0085
	0	0.0232	0.0038	-0.0016	0.0025	**-0.0001**	0.0033	0.0003	0.0029
		3.0388	0.0102	2.999	0.0074	**2.9999**	0.0092	3.0147	0.0082
150	0.95	0.9708	0.0035	**0.9457**	0.0031	0.9392	0.0987	0.9698	0.004
		3.0337	0.0128	**2.9942**	0.0112	2.9835	0.1482	3.0302	0.0127
	0.85	0.8747	0.0037	0.8457	0.0036	**0.8488**	0.0182	0.8694	0.0051
		3.0341	0.0128	2.9945	0.0106	**2.9978**	0.027	3.0297	0.0125
	0.75	0.7771	0.0044	0.7461	0.0036	**0.7502**	0.0097	0.7646	0.0064
		3.0344	0.013	2.996	0.0108	**3**	0.0167	3.0243	0.0126
	0.5	0.5288	0.0053	0.497	0.0035	**0.5002**	0.0063	0.5035	0.0058
		3.0354	0.0135	2.9975	0.0109	**2.9991**	0.014	3.0167	0.0131
	0.25	0.2769	0.0052	0.2478	0.0036	**0.2495**	0.0051	0.2505	0.005
		3.037	0.0134	**2.9999**	0.0108	2.9985	0.0132	3.0156	0.0116
	0	0.0231	0.0049	-0.0018	0.0035	**0.0001**	0.0047	-0.0001	0.0043
		3.0383	0.0138	2.9995	0.011	**3**	0.0118	3.015	0.0114

Table A.1.15: Monte Carlo Study with 500 Simulations, $T = 16$

N	φ	**Pooled OLS**		**Fixed Effects**		**GMM (diff.)**		**GMM (sys.)**	
		$\hat{\varphi}$-Mean $\hat{\beta}$-Mean	$\hat{\varphi}$-Std. $\hat{\beta}$-Std.	$\hat{\varphi}$-Mean $\hat{\beta}$-Mean	$\hat{\varphi}$-Std. $\hat{\beta}$-Std.	$\hat{\varphi}$-Mean $\hat{\beta}$-Mean	$\hat{\varphi}$-Std. $\hat{\beta}$-Std.	$\hat{\varphi}$-Mean $\hat{\beta}$-Mean	$\hat{\varphi}$-Std. $\hat{\beta}$-Std.
600	0.95	0.969	0.001	**0.9483**	0.0007	0.9454	0.0287	0.9674	0.0011
		3.0297	0.0039	**2.9979**	0.0037	2.993	0.0431	3.0273	0.004
	0.85	0.8753	0.0015	0.8483	0.0009	**0.85**	0.003	0.8639	0.0019
		3.0303	0.0042	2.9986	0.0037	**2.9996**	0.0054	3.0229	0.0042
	0.75	0.7788	0.0017	0.7483	0.001	**0.7498**	0.0021	0.757	0.0018
		3.0322	0.0047	2.9992	0.0034	**2.9998**	0.0046	3.0174	0.0043
	0.5	0.5305	0.0021	0.4988	0.0011	**0.5001**	0.0015	0.5012	0.0016
		3.0354	0.0047	2.9998	0.0033	**2.9998**	0.0039	3.0145	0.0043
	0.25	0.2774	0.0021	0.249	0.001	**0.25**	0.0014	0.2503	0.0015
		3.037	0.0048	2.9998	0.0035	**3.0001**	0.0041	3.0143	0.0039
	0	0.0231	0.0018	-0.0008	0.0012	**0.0001**	0.0013	0.0001	0.0014
		3.0382	0.0049	2.9996	0.0033	**2.9998**	0.0044	3.014	0.0039
300	0.95	0.9689	0.0015	**0.9482**	0.001	0.945	0.0325	0.9676	0.0017
		3.0297	0.0057	**2.9977**	0.0052	2.9922	0.0491	3.0269	0.0056
	0.85	0.8755	0.002	0.8483	0.0013	**0.8499**	0.0043	0.864	0.0026
		3.0303	0.006	2.9987	0.005	**2.9995**	0.0079	3.0236	0.0062
	0.75	0.7788	0.0024	0.7485	0.0013	**0.7498**	0.0031	0.7571	0.0027
		3.0317	0.0059	2.9991	0.0049	**3**	0.0066	3.0174	0.0064
	0.5	0.5306	0.0028	0.4988	0.0016	**0.5001**	0.0023	0.5012	0.0022
		3.0353	0.0062	2.9996	0.005	**3.0001**	0.0063	3.0148	0.0057
	0.25	0.2772	0.0029	0.249	0.0016	**0.25**	0.0022	0.2503	0.0021
		3.0365	0.0067	**3**	0.0048	2.9995	0.0057	3.014	0.006
	0	0.023	0.0027	-0.0007	0.0016	-0.0002	0.002	**0**	0.0018
		3.038	0.0069	2.9996	0.0049	**2.9997**	0.0061	3.0143	0.0057
150	0.95	0.9688	0.0022	**0.9483**	0.0014	0.9434	0.0372	0.9675	0.0024
		3.0291	0.0086	**2.9977**	0.007	2.9906	0.0558	3.0267	0.008
	0.85	0.8752	0.0028	0.8482	0.0018	**0.8497**	0.0061	0.8638	0.0038
		3.0303	0.0084	2.9981	0.0073	**2.9989**	0.0112	3.022	0.0087
	0.75	0.7786	0.0033	0.7485	0.0019	**0.7497**	0.0043	0.7574	0.0036
		3.0324	0.0088	2.9991	0.0069	**2.9994**	0.0093	3.0182	0.0085
	0.5	0.5302	0.0043	0.4987	0.002	**0.5003**	0.0034	0.5014	0.0033
		3.0354	0.0093	2.9998	0.007	**2.9999**	0.0086	3.0156	0.0083
	0.25	0.2772	0.0044	0.249	0.0022	**0.2499**	0.0031	0.2503	0.003
		3.0369	0.0094	**3.0001**	0.0072	2.9995	0.0082	3.0139	0.0082
	0	0.0231	0.0038	-0.0008	0.0022	0.0001	0.0027	**0**	0.0027
		3.0386	0.0106	**2.9999**	0.0073	2.9996	0.0086	3.0132	0.0086

Table A.1.16: Monte Carlo Study with 500 Simulations, $T = 32$

N	φ	**Pooled OLS**		**Fixed Effects**		**GMM (diff.)**		**GMM (sys.)**	
		$\hat{\varphi}$-Mean	$\hat{\varphi}$-Std.	$\hat{\varphi}$-Mean	$\hat{\varphi}$-Std.	$\hat{\varphi}$-Mean	$\hat{\varphi}$-Std.	$\hat{\varphi}$-Mean	$\hat{\varphi}$-Std.
		$\hat{\beta}$-Mean	$\hat{\beta}$-Std.	$\hat{\beta}$-Mean	$\hat{\beta}$-Std.	$\hat{\beta}$-Mean	$\hat{\beta}$-Std.	$\hat{\beta}$-Mean	$\hat{\beta}$-Std.
600	0.95	0.9672	0.0006	**0.9492**	0.0003	0.9491	0.0056	0.9647	0.0008
		3.0246	0.0027	**2.9992**	0.0024	2.9987	0.0085	3.0231	0.0027
	0.85	0.8761	0.0012	0.8492	0.0005	**0.8499**	0.0013	0.857	0.0011
		3.0279	0.0029	2.9995	0.0024	**2.9997**	0.0032	3.0161	0.0032
	0.75	0.7799	0.0016	0.7493	0.0006	**0.75**	0.0011	0.7529	0.001
		3.0305	0.0032	2.9997	0.0023	**2.9998**	0.0028	3.014	0.0031
	0.5	0.5308	0.0018	0.4994	0.0007	**0.4999**	0.0009	0.5006	0.0009
		3.0346	0.0036	2.9996	0.0023	**2.9999**	0.003	3.0139	0.0028
	0.25	0.2775	0.0018	0.2495	0.0007	**0.25**	0.001	0.2501	0.0009
		3.0367	0.0037	**2.9999**	0.0024	2.9998	0.0028	3.0139	0.0029
	0	0.0231	0.0017	-0.0004	0.0008	**0**	0.0009	-0.0001	0.0009
		3.0383	0.004	**3**	0.0025	**3**	0.0029	3.0136	0.0028
300	0.95	0.9671	0.0009	**0.9493**	0.0005	0.9493	0.0084	0.9646	0.0012
		3.0249	0.0038	**2.9993**	0.0032	2.999	0.0126	3.0228	0.0041
	0.85	0.8762	0.0017	0.8492	0.0007	**0.85**	0.0019	0.8571	0.0016
		3.0275	0.004	**2.9997**	0.0032	2.9996	0.0044	3.0162	0.0041
	0.75	0.7799	0.0021	0.7494	0.0008	**0.75**	0.0016	0.753	0.0014
		3.0307	0.0042	**2.9999**	0.0034	**3.0001**	0.0042	3.0142	0.0041
	0.5	0.531	0.0026	0.4995	0.001	**0.5**	0.0014	0.5005	0.0014
		3.0349	0.0048	**2.9999**	0.0034	2.9997	0.004	3.014	0.004
	0.25	0.2778	0.0025	0.2495	0.0011	**0.25**	0.0012	0.2502	0.0014
		3.0374	0.0051	**3.0001**	0.0033	2.9997	0.004	3.0138	0.004
	0	0.0229	0.0022	-0.0003	0.0011	**0**	0.0013	0.0001	0.0013
		3.0381	0.0053	**3.0001**	0.0033	2.9995	0.0039	3.0133	0.0043
150	0.95	0.9671	0.0014	**0.9492**	0.0007	0.9483	0.0116	0.9647	0.0017
		3.0249	0.0058	**2.9993**	0.0049	2.9971	0.0177	3.0232	0.0059
	0.85	0.8761	0.0023	0.8492	0.001	**0.8498**	0.0027	0.8576	0.0023
		3.0277	0.0061	2.9995	0.0048	**2.9998**	0.0064	3.0168	0.0062
	0.75	0.7797	0.0029	0.7493	0.0011	**0.75**	0.0022	0.7534	0.0021
		3.0308	0.0061	2.9997	0.0047	**2.9997**	0.006	3.0147	0.0058
	0.5	0.5306	0.0038	0.4994	0.0014	**0.5001**	0.002	0.5007	0.002
		3.0347	0.0068	**3.0001**	0.005	2.9993	0.0059	3.0135	0.006
	0.25	0.2777	0.0035	0.2495	0.0015	**0.25**	0.0019	0.2501	0.002
		3.0372	0.007	**3.0002**	0.0047	2.9996	0.0062	3.0133	0.006
	0	0.0229	0.0032	-0.0004	0.0015	**0.0001**	0.0019	**-0.0001**	0.0017
		3.0386	0.0074	**2.9997**	0.0049	2.9996	0.0062	3.0137	0.006

Table A.1.17: OLS- and FE Results for Moody's (*dynamic basic linear model*)

	OLS (robust)	**FE (robust)**
Constant	0.55***	0.192
	(0.208)	(0.853)
Moody's (lagged)	0.874***	0.789***
	(0.019)	(0.019)
World Government Indicator	0.505***	1.154***
	(0.08)	(0.243)
Real GDP per Capita	0.125***	0.36**
	(0.023)	(0.169)
Real GDP Growth	0.058***	0.057***
	(0.012)	(0.014)
Unemployment Rate	0	0.01
	(0.006)	(0.014)
Inflation	-0.004**	-0.003
	(0.002)	(0.002)
Current Account	0.021***	0.032***
	(0.005)	(0.007)
Government Debt	-0.005***	-0.012***
	(0.001)	(0.002)
External Debt	0.001	0
	(0.001)	(0.004)
EU	0.052	(omitted)
	(0.067)	()
LAC	0.015	(omitted)
	(0.065)	()
Default	-0.828***	-0.763**
	(0.309)	(0.343)
Time-Dummies		
1998	-0.062	-0.055
	(0.122)	(0.206)
2000	0.061	0.004
	(0.112)	(0.195)
2002	0.513***	0.485**
	(0.173)	(0.19)
2003	-0.037	-0.039

	(0.125)	(0.189)
2004	-0.031	-0.077
	(0.102)	(0.192)
2005	0.048	-0.025
	(0.104)	(0.195)
2006	0.014	-0.095
	(0.106)	(0.199)
2007	-0.12	-0.267
	(0.109)	(0.21)
2008	-0.25	-0.406*
	(0.161)	(0.219)
2009	-0.262**	-0.336
	(0.124)	(0.214)
2010	0.016	-0.076
	(0.145)	(0.224)
2011	-0.536**	-0.655***
	(0.217)	(0.237)
2012	-0.385**	-0.552**
	(0.195)	(0.237)
2013	-0.341**	-0.529**
	(0.14)	(0.24)
2014	-0.116	-0.337
	(0.124)	(0.242)
2015	-0.028	-0.214
	(0.107)	(0.233)
2016	-0.282**	-0.447*
	(0.11)	(0.234)
2017	-0.166	-0.346
	(0.107)	(0.242)
2018	-0.227**	-0.423*
	(0.109)	(0.249)
Observations	1042	1042
Number of Countries		59
R^2 (overall)	0.9773	0.9727

Table A.1.18: OLS- and FE Results for S&P (*dynamic basic linear model*)

	OLS (robust)	**FE (robust)**
Constant	0.728***	1.28*
	(0.228)	(0.71)
S&P (lagged)	0.87***	0.787***
	(0.016)	(0.027)
World Government Indicator	0.513***	1.183***
	(0.067)	(0.273)
Real GDP per Capita	0.105***	0.171
	(0.016)	(0.14)
Real GDP Growth	0.045***	0.038**
	(0.011)	(0.015)
Unemployment Rate	0.003	0.009
	(0.006)	(0.019)
Inflation	-0.001	-0.001
	(0.002)	(0.001)
Current Account	0.03***	0.047***
	(0.004)	(0.009)
Government Debt	-0.004***	-0.011***
	(0.001)	(0.003)
External Debt	0.001	-0.003
	(0.001)	(0.003)
EU	0.098	(omitted)
	(0.06)	
LAC	0.062	(omitted)
	(0.059)	
Default	-0.639**	-0.592***
	(0.304)	(0.219)
Time-Dummies		
1998	-0.145	-0.168
	(0.148)	(0.135)
2000	-0.111	-0.204
	(0.138)	(0.127)
2002	-0.17	-0.264*
	(0.144)	(0.132)
2003	-0.012	-0.117

	(0.14)	(0.151)
2004	0.145	0.042
	(0.153)	(0.162)
2005	-0.046	-0.128
	(0.136)	(0.138)
2006	-0.182	-0.277*
	(0.137)	(0.158)
2007	-0.137	-0.251
	(0.141)	(0.164)
2008	-0.42**	-0.519**
	(0.171)	(0.219)
2009	-0.386***	-0.421**
	(0.145)	(0.17)
2010	-0.096	-0.16
	(0.148)	(0.176)
2011	-0.239	-0.322
	(0.176)	(0.201)
2012	-0.563**	-0.662**
	(0.22)	(0.276)
2013	-0.292**	-0.4*
	(0.142)	(0.2)
2014	-0.227	-0.352*
	(0.152)	(0.204)
2015	-0.165	-0.28
	(0.138)	(0.19)
2016	-0.349**	-0.44**
	(0.145)	(0.183)
2017	-0.276*	-0.369*
	(0.146)	(0.191)
2018	-0.223	-0.327
	(0.142)	(0.21)
Observations	1018	1018
Number of Countries		59
R^2 (overall)	0.9819	0.9778

Table A.1.19: OLS- and FE Results for Fitch (*dynamic basic linear model*)

	OLS (robust)	**FE (robust)**
Constant	0.889***	1.133
	(0.23)	(1.097)
Fitch (lagged)	0.86***	0.765***
	(0.018)	(0.031)
World Government Indicator	0.496***	1.373***
	(0.07)	(0.327)
Real GDP per Capita	0.103***	0.225
	(0.022)	(0.169)
Real GDP Growth	0.037***	0.034
	(0.013)	(0.021)
Unemployment Rate	-0.002	0.002
	(0.006)	(0.021)
Inflation	-0.003**	-0.003***
	(0.001)	(0.001)
Current Account	0.027***	0.049***
	(0.005)	(0.01)
Government Debt	-0.004***	-0.013***
	(0.001)	(0.004)
External Debt	0	-0.005
	(0.001)	(0.005)
EU	0.097*	(omitted)
	(0.056)	
LAC	-0.039	(omitted)
	(0.066)	
Default	-1.088	-1.054
	(0.929)	(1.01)
Time-Dummies		
1998	-0.07	-0.084
	(0.167)	(0.132)
2000	0.072	-0.006
	(0.164)	(0.167)
2002	0.057	-0.031
	(0.149)	(0.137)
2003	0.064	-0.003

	(0.14)	(0.121)
2004	0.174	0.102
	(0.158)	(0.161)
2005	0.072	0.041
	(0.135)	(0.132)
2006	-0.024	-0.083
	(0.136)	(0.143)
2007	-0.078	-0.168
	(0.142)	(0.153)
2008	-0.376**	-0.468**
	(0.175)	(0.183)
2009	-0.137	-0.154
	(0.143)	(0.179)
2010	-0.105	-0.131
	(0.166)	(0.17)
2011	-0.146	-0.21
	(0.2)	(0.234)
2012	-0.335*	-0.411
	(0.189)	(0.247)
2013	-0.262*	-0.348*
	(0.146)	(0.203)
2014	-0.077	-0.187
	(0.136)	(0.199)
2015	-0.135	-0.218
	(0.136)	(0.173)
2016	-0.195	-0.25
	(0.136)	(0.177)
2017	-0.093	-0.149
	(0.143)	(0.201)
2018	-0.144	-0.208
	(0.135)	(0.194)
Observations	916	916
Number of Countries		55
R^2 (overall)	0.9799	0.9726

Table A.1.20: Difference-GMM Results for Moody's (*dynamic basic linear model*)

	One-step	**One-step (collapsed)**	**One-step (L1+ L2)**	**Two-step (L1+ L2)**
Moody's (lagged)	0.764***	0.939***	0.702***	0.696***
	(0.037)	(0.062)	(0.115)	(0.123)
WGI	1.238***	0.65**	1.447**	1.306**
	(0.35)	(0.304)	(0.557)	(0.542)
GDP per Capita	0.384*	0.215	0.444	0.497*
	(0.221)	(0.168)	(0.277)	(0.287)
GDP Growth	0.058**	0.053**	0.06**	0.058**
	(0.023)	(0.022)	(0.024)	(0.023)
Unem. Rate	0.004	0.049**	-0.013	-0.014
	(0.021)	(0.022)	(0.035)	(0.024)
Inflation	-0.003***	-0.001	-0.004**	-0.003**
	(0.001)	(0.001)	(0.002)	(0.002)
Current Account	0.031***	0.036***	0.029***	0.02**
	(0.01)	(0.01)	(0.01)	(0.009)
Government Debt	-0.013***	-0.005	-0.016**	-0.012*
	(0.004)	(0.004)	(0.007)	(0.007)
External Debt	0.001	-0.005	0.003	0.005
	(0.005)	(0.004)	(0.008)	(0.009)
EU	(omitted)	(omitted)	(omitted)	(omitted)
LAC	(omitted)	(omitted)	(omitted)	(omitted)
Default	-0.818**	-0.433	-0.955**	-1.145**
	(0.33)	(0.35)	(0.419)	(0.493)
Time-Dummies				
1990	(omitted)	(omitted)	(omitted)	(omitted)
1991	(omitted)	(omitted)	(omitted)	(omitted)
1992	(omitted)	(omitted)	(omitted)	(omitted)
1993	(omitted)	(omitted)	(omitted)	(omitted)
1994	(omitted)	(omitted)	(omitted)	(omitted)
1995	(omitted)	(omitted)	(omitted)	(omitted)
1996	(omitted)	0.196	(omitted)	0.056

		(0.242)		(0.164)
1997	(omitted)	(omitted)	(omitted)	(omitted)
1998	-0.057	0.153	-0.062	(omitted)
	(0.134)	(0.223)	(0.14)	
1999	(omitted)	(omitted)	(omitted)	(omitted)
2000	-0.009	0.278	-0.042	0
	(0.145)	(0.204)	(0.165)	(0.164)
2001	(omitted)	(omitted)	(omitted)	(omitted)
2002	0.471**	0.767***	0.435**	0.416
	(0.181)	(0.225)	(0.205)	(0.251)
2003	-0.039	0.157	-0.04	0.021
	(0.136)	(0.201)	(0.151)	(0.169)
2004	-0.08	0.138	-0.088	-0.051
	(0.146)	(0.174)	(0.164)	(0.183)
2005	-0.031	0.204	-0.045	0.005
	(0.149)	(0.163)	(0.167)	(0.196)
2006	-0.107	0.173	-0.136	-0.138
	(0.172)	(0.148)	(0.194)	(0.219)
2007	-0.286	0.039	-0.332	-0.285
	(0.188)	(0.131)	(0.219)	(0.261)
2008	-0.428	-0.077	-0.483	-0.378
	(0.263)	(0.136)	(0.296)	(0.295)
2009	-0.355*	-0.03	-0.4*	-0.379
	(0.2)	(0.132)	(0.234)	(0.248)
2010	-0.094	0.222	-0.136	-0.105
	(0.223)	(0.153)	(0.269)	(0.299)
2011	-0.666**	-0.389	-0.695*	-0.485
	(0.327)	(0.249)	(0.356)	(0.386)
2012	-0.572*	-0.232	-0.624*	-0.427
	(0.32)	(0.214)	(0.345)	(0.352)
2013	-0.557**	-0.163	-0.628**	-0.549*
	(0.237)	(0.131)	(0.287)	(0.314)
2014	-0.371	0.067	-0.457	-0.431
	(0.243)	(0.098)	(0.304)	(0.331)
2015	-0.245	0.167	-0.322	-0.29
	(0.23)	(0.104)	(0.283)	(0.3)
2016	-0.476**	-0.076	-0.549**	-0.501*
	(0.22)	(0.097)	(0.27)	(0.297)

2017	-0.382	0.064	-0.471	-0.433
	(0.24)	(0.084)	(0.304)	(0.321)
2018	-0.461*	(omitted)	-0.555	-0.508
	(0.269)		(0.336)	(0.347)
AB test AR(1): z	-4.05	-4.03	-3.13	-2.89
$(Pr. > z)$	(0.000)	(0.000)	(0.002)	(0.004)
AB test AR(2): z	-1.56	-1.63	-1.60	-1.50
$(Pr. > z)$	(0.118)	(0.102)	(0.109)	(0.133)
Robust Hansen: χ^2	32.97	27.20	29.40	29.40
$(Pr. > \chi^2)$	(1.000)	(0.018)	(0.247)	(0.247)
Number Instruments	364	55	66	66
Number Groups	59	59	59	59
Observations	983	983	983	983

Table A.1.21: Difference-GMM Results for S&P (*dynamic basic linear model*)

	One-step	**One-step (collapsed)**	**One-step (L1+ L2)**	**Two-step (L1+ L2)**
S&P (lagged)	0.769***	0.826***	0.608***	0.668***
	(0.042)	(0.083)	(0.1)	(0.145)
WGI	1.239***	1.056***	1.762***	1.658***
	(0.304)	(0.38)	(0.493)	(0.577)
GDP per Capita	0.19	0.13	0.362	0.282
	(0.146)	(0.164)	(0.231)	(0.278)
GDP Growth	0.038**	0.037**	0.042**	0.049***
	(0.015)	(0.014)	(0.017)	(0.018)
Unem. Rate	0.005	0.019	-0.035	-0.014
	(0.019)	(0.025)	(0.03)	(0.04)
Inflation	-0.001	0	-0.004	-0.002
	(0.001)	(0.001)	(0.003)	(0.004)
Current Account	0.047***	0.046***	0.048***	0.038***
	(0.009)	(0.009)	(0.01)	(0.011)
Government Debt	-0.012***	-0.01**	-0.018***	-0.016**
	(0.003)	(0.004)	(0.006)	(0.007)
External Debt	-0.002	-0.004	0.001	0.002
	(0.004)	(0.003)	(0.005)	(0.007)
EU	(omitted)	(omitted)	(omitted)	(omitted)
LAC	(omitted)	(omitted)	(omitted)	(omitted)
Default	-0.649***	-0.464	-1.179***	-0.546
	(0.217)	(0.345)	(0.332)	(0.78)
Time-Dummies				
1990	(omitted)	(omitted)	(omitted)	(omitted)
1991	(omitted)	(omitted)	(omitted)	(omitted)
1992	(omitted)	(omitted)	(omitted)	(omitted)
1993	(omitted)	(omitted)	(omitted)	(omitted)
1994	(omitted)	(omitted)	(omitted)	(omitted)
1995	(omitted)	(omitted)	(omitted)	(omitted)
1996	0.357*	(omitted)	(omitted)	(omitted)

	(0.212)			
1997	(omitted)	(omitted)	(omitted)	(omitted)
1998	0.189	-0.167	-0.171	-0.146
	(0.215)	(0.138)	(0.135)	(0.133)
1999	(omitted)	(omitted)	(omitted)	(omitted)
2000	0.146	-0.19	-0.269*	-0.301**
	(0.213)	(0.124)	(0.145)	(0.144)
2001	(omitted)	(omitted)	(omitted)	(omitted)
2002	0.082	-0.238*	-0.38***	-0.332*
	(0.198)	(0.127)	(0.139)	(0.169)
2003	0.227	-0.09	-0.245	-0.221
	(0.174)	(0.146)	(0.161)	(0.187)
2004	0.387**	0.069	-0.078	-0.037
	(0.176)	(0.154)	(0.188)	(0.215)
2005	0.22*	-0.108	-0.22	-0.165
	(0.129)	(0.138)	(0.173)	(0.205)
2006	0.068	-0.25	-0.402*	-0.33
	(0.128)	(0.151)	(0.201)	(0.226)
2007	0.088	-0.21	-0.437*	-0.374
	(0.117)	(0.169)	(0.235)	(0.288)
2008	-0.183	-0.474**	-0.724**	-0.611**
	(0.134)	(0.215)	(0.272)	(0.297)
2009	-0.084	-0.379**	-0.616***	-0.477*
	(0.131)	(0.166)	(0.229)	(0.271)
2010	0.177	-0.115	-0.363	-0.254
	(0.107)	(0.173)	(0.256)	(0.297)
2011	0.017	-0.284	-0.497*	-0.362
	(0.128)	(0.19)	(0.271)	(0.307)
2012	-0.322*	-0.624**	-0.836**	-0.517
	(0.184)	(0.273)	(0.337)	(0.361)
2013	-0.067	-0.348	-0.64**	-0.43
	(0.087)	(0.209)	(0.294)	(0.353)
2014	-0.022	-0.294	-0.618**	-0.431
	(0.096)	(0.214)	(0.301)	(0.358)
2015	0.053	-0.226	-0.526*	-0.327
	(0.095)	(0.199)	(0.275)	(0.334)
2016	-0.107	-0.387*	-0.683**	-0.484
	(0.098)	(0.193)	(0.268)	(0.333)

2017	-0.041	-0.307	-0.655**	-0.473
	(0.091)	(0.201)	(0.289)	(0.374)
2018	(omitted)	-0.259	-0.634*	-0.415
		(0.236)	(0.328)	(0.408)
AB test AR(1): z	-3.98	-3.78	-3.26	-3.00
$(Pr. > z)$	(0.000)	(0.000)	(0.001)	(0.003)
AB test AR(2): z	-1.56	0.00	0.09	-0.04
$(Pr. > z)$	(0.118)	(0.998)	(0.930)	(0.968)
Robust Hansen: χ^2	34.58	8.39	37.47	37.47
$(Pr. > \chi^2)$	(1.000)	(0.000)	(0.052)	(0.052)
Number Instruments	364	32	66	66
Number Groups	59	59	59	59
Observations	959	959	959	959

Table A.1.22: Difference-GMM Results for Fitch (*dynamic basic linear model*)

	One-step	**One-step (collapsed)**	**One-step (L1+ L2)**	**Two-step (L1+ L2)**
Fitch (lagged)	0.731***	0.994***	0.862***	0.98***
	(0.05)	(0.11)	(0.051)	(0.08)
WGI	1.471***	0.696	1.087***	0.83**
	(0.355)	(0.497)	(0.341)	(0.406)
GDP per Capita	0.264	-0.045	0.111	-0.118
	(0.181)	(0.187)	(0.179)	(0.193)
GDP Growth	0.035*	0.021	0.028	0.031
	(0.021)	(0.026)	(0.021)	(0.019)
Unem. Rate	-0.005	0.051	0.023	0.056**
	(0.023)	(0.037)	(0.023)	(0.026)
Inflation	-0.003***	-0.001	-0.002	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Current Account	0.049***	0.05***	0.05***	0.039***
	(0.01)	(0.009)	(0.009)	(0.012)
Government Debt	-0.014***	-0.004	-0.009**	-0.003
	(0.004)	(0.005)	(0.004)	(0.005)
External Debt	-0.004	-0.013**	-0.008*	-0.014***
	(0.006)	(0.006)	(0.005)	(0.005)
EU	(omitted)	(omitted)	(omitted)	(omitted)
LAC	(omitted)	(omitted)	(omitted)	(omitted)
Default	-1.114	-0.635	-0.877	-0.474
	(1.035)	(0.731)	(0.965)	(1.079)
Time-Dummies				
1990	(omitted)	(omitted)	(omitted)	(omitted)
1991	(omitted)	(omitted)	(omitted)	(omitted)
1992	(omitted)	(omitted)	(omitted)	(omitted)
1993	(omitted)	(omitted)	(omitted)	(omitted)
1994	(omitted)	(omitted)	(omitted)	(omitted)
1995	(omitted)	(omitted)	(omitted)	(omitted)
1996	0.239	-0.003	(omitted)	-0.15

	(0.21)	(0.186)		(0.169)
1997	(omitted)	(omitted)	(omitted)	(omitted)
1998	0.156	-0.098	-0.088	-0.32
	(0.233)	(0.214)	(0.138)	(0.247)
1999	(omitted)	(omitted)	(omitted)	(omitted)
2000	0.229	0.011	0.002	-0.195
	(0.238)	(0.225)	(0.178)	(0.239)
2001	(omitted)	(omitted)	(omitted)	(omitted)
2002	0.199	0.029	-0.004	-0.099
	(0.205)	(0.183)	(0.146)	(0.187)
2003	0.23	0.027	0.011	-0.109
	(0.194)	(0.181)	(0.131)	(0.176)
2004	0.338**	0.119	0.111	0.015
	(0.147)	(0.146)	(0.169)	(0.148)
2005	0.282*	0.022	0.034	-0.087
	(0.145)	(0.153)	(0.132)	(0.153)
2006	0.149	-0.041	-0.064	-0.152
	(0.118)	(0.109)	(0.142)	(0.137)
2007	0.052	-0.042	-0.113	-0.139
	(0.104)	(0.089)	(0.148)	(0.14)
2008	-0.254*	-0.308**	-0.399**	-0.329**
	(0.127)	(0.123)	(0.172)	(0.147)
2009	0.062	0.001	-0.087	-0.114
	(0.125)	(0.115)	(0.178)	(0.149)
2010	0.093	-0.03	-0.087	-0.015
	(0.114)	(0.108)	(0.159)	(0.103)
2011	0.017	-0.135	-0.177	(omitted)
	(0.162)	(0.235)	(0.232)	
2012	-0.182	-0.343	-0.381	-0.239*
	(0.142)	(0.211)	(0.237)	(0.123)
2013	-0.13	-0.207*	-0.287	-0.205
	(0.087)	(0.119)	(0.197)	(0.136)
2014	0.025	-0.009	-0.11	-0.054
	(0.073)	(0.079)	(0.183)	(0.132)
2015	0	-0.083	-0.16	-0.154
	(0.069)	(0.084)	(0.158)	(0.129)
2016	-0.034	-0.099	-0.185	-0.173
	(0.082)	(0.093)	(0.164)	(0.117)

2017	0.061	0.043	-0.066	-0.016
	(0.078)	(0.092)	(0.19)	(0.13)
2018	(omitted)	(omitted)	-0.119	-0.008
			(0.184)	(0.134)
AB test AR(1): z	-4.50	-3.89	-4.14	-4.25
$(Pr. > z)$	(0.000)	(0.000)	(0.000)	(0.000)
AB test AR(2): z	-1.25	-0.97	-1.12	-1.03
$(Pr. > z)$	(0.211)	(0.334)	(0.263)	(0.304)
Robust Hansen: χ^2	34.29	20.78	26.44	26.44
$(Pr. > \chi^2)$	(1.000)	(0.023)	(0.385)	(0.385)
Number Instruments	288	51	66	66
Number Groups	55	55	55	55
Observations	861	861	861	861

Table A.1.23: System-GMM Results for Moody's (*dynamic basic linear model*)

	One-step (col.)	**Two-step (col.)**	**One-step (L1+ L2)**	**Two-step (L1+ L2)**
Moody's (lagged)	1.025***	1.035***	0.913***	0.927***
	(0.038)	(0.049)	(0.019)	(0.023)
WGI	-0.065	-0.094	0.356***	0.323***
	(0.153)	(0.2)	(0.082)	(0.11)
GDP per Capita	-0.009	-0.008	0.09***	0.074***
	(0.039)	(0.047)	(0.022)	(0.026)
GDP Growth	0.052***	0.054***	0.056***	0.058***
	(0.016)	(0.015)	(0.014)	(0.017)
Unem. Rate	0.019**	0.012	0.005	0.004
	(0.01)	(0.009)	(0.006)	(0.007)
Inflation	0	0	-0.003**	-0.002
	(0.001)	(0.002)	(0.001)	(0.002)
Current Account	0.019***	0.009	0.02***	0.018***
	(0.006)	(0.007)	(0.006)	(0.006)
Government Debt	-0.001	-0.001	-0.004***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.002)
External Debt	0	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
EU	-0.074	-0.058	0.021	0.031
	(0.056)	(0.059)	(0.054)	(0.059)
LAC	0.151**	0.133**	0.049	0.045
	(0.063)	(0.058)	(0.077)	(0.09)
Default	-0.394	-0.194	-0.706**	-0.585
	(0.41)	(0.367)	(0.347)	(0.406)
Time-Dummies				
1990	(omitted)	(omitted)	(omitted)	(omitted)
1991	(omitted)	(omitted)	(omitted)	(omitted)
1992	(omitted)	(omitted)	(omitted)	(omitted)
1993	(omitted)	(omitted)	(omitted)	(omitted)
1994	(omitted)	(omitted)	(omitted)	(omitted)
1995	(omitted)	(omitted)	(omitted)	(omitted)
1996	-0.39	-0.473	0.315	0.247

	(0.292)	(0.328)	(0.257)	(0.303)
1997	(omitted)	(omitted)	(omitted)	(omitted)
1998	-0.461*	-0.521*	0.248	0.086
	(0.274)	(0.293)	(0.257)	(0.293)
1999	(omitted)	(omitted)	(omitted)	(omitted)
2000	-0.349	-0.434	0.368*	0.24
	(0.292)	(0.333)	(0.211)	(0.265)
2001	(omitted)	(omitted)	(omitted)	(omitted)
2002	0.155	-0.03	0.835***	0.683*
	(0.337)	(0.373)	(0.296)	(0.384)
2003	-0.483	-0.606*	0.262	0.204
	(0.32)	(0.328)	(0.256)	(0.295)
2004	-0.458	-0.57*	0.272	0.212
	(0.284)	(0.319)	(0.225)	(0.276)
2005	-0.367	-0.445	0.355	0.233
	(0.283)	(0.325)	(0.235)	(0.292)
2006	-0.379	-0.491	0.327	0.209
	(0.28)	(0.319)	(0.231)	(0.286)
2007	-0.494*	-0.631*	0.198	0.119
	(0.267)	(0.318)	(0.239)	(0.298)
2008	-0.602**	-0.685**	0.074	0.087
	(0.282)	(0.295)	(0.213)	(0.283)
2009	-0.648**	-0.683**	0.053	0.023
	(0.293)	(0.336)	(0.212)	(0.293)
2010	-0.363	-0.45	0.332	0.318
	(0.31)	(0.341)	(0.221)	(0.281)
2011	-0.919**	-0.737**	-0.221	-0.231
	(0.365)	(0.349)	(0.272)	(0.288)
2012	-0.69**	-0.598**	-0.05	0.057
	(0.285)	(0.272)	(0.248)	(0.245)
2013	-0.591**	-0.64**	0.009	-0.027
	(0.247)	(0.286)	(0.243)	(0.281)
2014	-0.32	-0.453	0.247	0.144
	(0.24)	(0.289)	(0.209)	(0.261)
2015	-0.256	-0.455	0.329	0.211
	(0.248)	(0.301)	(0.209)	(0.277)
2016	-0.525**	-0.656**	0.071	0.028
	(0.258)	(0.309)	(0.219)	(0.272)

2017	-0.381	-0.536**	0.194	0.096
	(0.228)	(0.267)	(0.197)	(0.256)
2018	-0.449*	-0.526*	0.13	0.079
	(0.247)	(0.27)	(0.204)	(0.248)
AB test AR(1): z	-4.10	-3.84	-4.05	-2.89
$(Pr. > z)$	(0.000)	(0.000)	(0.000)	(0.004)
AB test AR(2): z	-1.63	-1.53	-1.67	-1.50
$(Pr. > z)$	(0.118)	(0.125)	(0.109)	(0.133)
Robust Hansen: χ^2	27.88	27.88	26.69	26.69
$(Pr. > \chi^2)$	(0.046)	(0.046)	(0.993)	(0.993)
Number Instruments	59	59	89	89
Number Groups	59	59	59	59
Observations	1042	1042	1042	1042

Table A.1.24: System-GMM Results for S&P (*dynamic basic linear model*)

	One-step (col.)	**Two-step (col.)**	**One-step (L1+ L2)**	**Two-step (L1+ L2)**
S&P (lagged)	1.007***	0.964***	0.908***	0.945***
	(0.076)	(0.085)	(0.027)	(0.038)
WGI	0.009	0.141	0.369***	0.25*
	(0.277)	(0.33)	(0.118)	(0.144)
GDP per Capita	-0.011	0.025	0.071**	0.035
	(0.068)	(0.075)	(0.028)	(0.041)
GDP Growth	0.039**	0.052***	0.043***	0.053***
	(0.015)	(0.018)	(0.013)	(0.018)
Unem. Rate	0.017	0.008	0.007	0.007
	(0.012)	(0.009)	(0.006)	(0.008)
Inflation	0.003	0.002	0	0.001
	(0.003)	(0.003)	(0.001)	(0.002)
Current Account	0.02***	0.02**	0.027***	0.02***
	(0.007)	(0.009)	(0.006)	(0.006)
Government Debt	-0.001	-0.001	-0.003**	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)
External Debt	0.001	0	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
EU	-0.055	0.006	0.059	0.014
	(0.098)	(0.109)	(0.053)	(0.082)
LAC	0.094	0.06	0.07	0.113
	(0.086)	(0.097)	(0.073)	(0.094)
Default	-0.179	-0.531	-0.5	-0.708
	(0.7)	(0.752)	(0.375)	(0.454)
Time-Dummies				
1990	(omitted)	(omitted)	(omitted)	(omitted)
1991	(omitted)	(omitted)	(omitted)	(omitted)
1992	(omitted)	(omitted)	(omitted)	(omitted)
1993	(omitted)	(omitted)	(omitted)	(omitted)
1994	(omitted)	(omitted)	(omitted)	(omitted)
1995	(omitted)	(omitted)	(omitted)	(omitted)
1996	(omitted)	(omitted)	(omitted)	(omitted)

1997	(omitted)	(omitted)	(omitted)	(omitted)
1998	-0.159	-0.18	-0.153	-0.121
	(0.145)	(0.158)	(0.139)	(0.133)
1999	(omitted)	(omitted)	(omitted)	(omitted)
2000	-0.15	-0.148	-0.127	-0.14
	(0.134)	(0.118)	(0.131)	(0.1)
2001	(omitted)	(omitted)	(omitted)	(omitted)
2002	-0.144	-0.129	-0.166	-0.133
	(0.161)	(0.171)	(0.144)	(0.124)
2003	0.019	-0.006	-0.007	-0.017
	(0.173)	(0.161)	(0.154)	(0.137)
2004	0.159	0.166	0.145	0.137
	(0.181)	(0.161)	(0.167)	(0.169)
2005	-0.056	-0.008	-0.052	-0.042
	(0.135)	(0.127)	(0.126)	(0.107)
2006	-0.184	-0.157	-0.185	-0.191
	(0.149)	(0.148)	(0.139)	(0.142)
2007	-0.111	-0.137	-0.132	-0.094
	(0.149)	(0.141)	(0.133)	(0.128)
2008	-0.388*	-0.364	-0.413**	-0.393**
	(0.211)	(0.218)	(0.19)	(0.187)
2009	-0.376**	-0.3**	-0.386***	-0.325**
	(0.152)	(0.139)	(0.144)	(0.129)
2010	-0.071	0.059	-0.093	-0.054
	(0.164)	(0.136)	(0.154)	(0.133)
2011	-0.21	-0.036	-0.235	-0.14
	(0.181)	(0.179)	(0.178)	(0.191)
2012	-0.507**	-0.367*	-0.551**	-0.34
	(0.22)	(0.2)	(0.23)	(0.219)
2013	-0.176	-0.216	-0.262*	-0.171
	(0.19)	(0.159)	(0.155)	(0.144)
2014	-0.086	-0.123	-0.189	-0.102
	(0.209)	(0.169)	(0.153)	(0.143)
2015	-0.036	-0.079	-0.13	-0.045
	(0.187)	(0.167)	(0.141)	(0.134)
2016	-0.226	-0.174	-0.315**	-0.242*
	(0.183)	(0.159)	(0.142)	(0.136)

2017	-0.134	-0.214	-0.237	-0.204
	(0.198)	(0.169)	(0.145)	(0.143)
2018	-0.079	-0.079	-0.186	-0.092
	(0.186)	(0.171)	(0.137)	(0.154)
AB test AR(1): z	-3.94	-3.82	-4.14	-3.94
$(Pr. > z)$	(0.000)	(0.000)	(0.000)	(0.000)
AB test AR(2): z	-0.10	-0.10	-0.06	-0.11
$(Pr. > z)$	(0.924)	(0.920)	(0.952)	(0.912)
Robust Hansen: χ^2	29.95	29.95	34.82	34.82
$(Pr. > \chi^2)$	(0.027)	(0.027)	(0.886)	(0.886)
Number Instruments	59	59	88	88
Number Groups	59	59	59	59
Observations	1018	1018	1018	1018

Table A.1.25: System-GMM Results for Fitch (*dynamic basic linear model*)

	One-step (col.)	**Two-step (col.)**	**One-step (L1+ L2)**	**Two-step (L1+ L2)**
Fitch (lagged)	1.067***	1.016***	0.917***	0.952***
	(0.111)	(0.129)	(0.023)	(0.052)
WGI	-0.186	-0.006	0.308***	0.197
	(0.345)	(0.418)	(0.084)	(0.165)
GDP per Capita	-0.107	-0.042	0.045	0.026
	(0.115)	(0.127)	(0.033)	(0.049)
GDP Growth	0.024	0.038	0.033*	0.048**
	(0.024)	(0.024)	(0.018)	(0.022)
Unem. Rate	0.024	0.011	0.006	0.004
	(0.02)	(0.019)	(0.008)	(0.011)
Inflation	0.002	0	-0.002	-0.001
	(0.004)	(0.004)	(0.001)	(0.002)
Current Account	0.019**	0.015*	0.025***	0.019***
	(0.008)	(0.008)	(0.006)	(0.007)
Government Debt	0.001	0	-0.003*	-0.001
	(0.003)	(0.003)	(0.001)	(0.002)
External Debt	0.001	0	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.002)
EU	-0.22	-0.126	0.01	-0.004
	(0.182)	(0.183)	(0.062)	(0.078)
LAC	0.142	0.11	0.011	0.013
	(0.162)	(0.195)	(0.091)	(0.128)
Default	-0.534	0.196	-0.922	-0.102
	(0.751)	(0.469)	(0.931)	(1.084)
Time-Dummies				
1990	(omitted)	(omitted)	(omitted)	(omitted)
1991	(omitted)	(omitted)	(omitted)	(omitted)
1992	(omitted)	(omitted)	(omitted)	(omitted)
1993	(omitted)	(omitted)	(omitted)	(omitted)
1994	(omitted)	(omitted)	(omitted)	(omitted)
1995	(omitted)	(omitted)	(omitted)	(omitted)
1996	-0.234	0.065	(omitted)	0.1

	(0.741)	(0.175)		(0.17)
1997	(omitted)	(omitted)	(omitted)	(omitted)
1998	-0.316	-0.074	-0.074	-0.087
	(0.729)	(0.175)	(0.133)	(0.205)
1999	(omitted)	(omitted)	(omitted)	(omitted)
2000	-0.249	0.055	0.046	(omitted)
	(0.784)	(0.147)	(0.191)	()
2001	(omitted)	(omitted)	(omitted)	(omitted)
2002	-0.179	(omitted)	0.056	0.08
	(0.745)		(0.153)	(0.152)
2003	-0.197	0.024	0.056	0.119
	(0.721)	(0.127)	(0.138)	(0.152)
2004	-0.105	0.046	0.16	0.153
	(0.757)	(0.122)	(0.168)	(0.16)
2005	-0.247	0.014	0.048	0.074
	(0.739)	(0.117)	(0.147)	(0.138)
2006	-0.307	-0.155	-0.038	-0.012
	(0.718)	(0.109)	(0.136)	(0.154)
2007	-0.311	-0.133	-0.078	-0.022
	(0.678)	(0.141)	(0.123)	(0.15)
2008	-0.583	-0.273	-0.368**	-0.131
	(0.637)	(0.171)	(0.172)	(0.172)
2009	-0.364	-0.131	-0.136	-0.066
	(0.68)	(0.143)	(0.166)	(0.154)
2010	-0.363	-0.101	-0.113	0.077
	(0.699)	(0.186)	(0.164)	(0.172)
2011	-0.392	-0.023	-0.151	0.173
	(0.792)	(0.229)	(0.211)	(0.205)
2012	-0.565	-0.133	-0.336	-0.159
	(0.754)	(0.186)	(0.201)	(0.185)
2013	-0.415	-0.246	-0.24	-0.161
	(0.681)	(0.153)	(0.146)	(0.171)
2014	-0.189	-0.088	-0.043	0.018
	(0.61)	(0.162)	(0.143)	(0.155)
2015	-0.284	-0.134	-0.111	-0.052
	(0.62)	(0.16)	(0.141)	(0.164)
2016	-0.33	-0.193	-0.166	-0.076
	(0.625)	(0.163)	(0.149)	(0.164)

2017	-0.205	-0.12	-0.056	-0.007
	(0.615)	(0.163)	(0.137)	(0.164)
2018	-0.255	-0.1	-0.11	0.035
	(0.621)	(0.181)	(0.128)	(0.166)
AB test AR(1): z	-4.03	-3.34	–3.96	-3.96
$(Pr. > z)$	(0.000)	(0.000)	(0.000)	(0.000)
AB test AR(2): z	-0.84	-0.89	-0.95	-0.95
$(Pr. > z)$	(0.398)	(0.376)	(0.342)	(0.342)
Robust Hansen: χ^2	22.59	22.59	26.63	26.63
$(Pr. > \chi^2)$	(0.047)	(0.047)	(0.993)	(0.993)
Number Instruments	55	55	89	89
Number Groups	55	55	55	55
Observations	916	916	916	916

Table A.1.26: Moody's: Prediction Accuracy

Estimation Style	N	**Deviation:** $Y_{it} - \hat{Y}_{it}$							**Percentage Correct**		
		≤ -3	-2	-1	0	1	2	≥ 3	Correct	1 Notch	2 Notches
Random Walk	1044	15	13	45	856	91	16	8	81.99	86.3	95.02
OLS (basic)	1044	83	86	116	339	236	121	63	32.47	66.19	86.02
RE (basic)	1044	92	85	117	351	157	118	124	33.62	59.87	79.31
FE (basic)	1044	191	110	114	211	123	78	217	20.21	42.91	60.92
OLS (Mundlak)	1044	58	95	126	364	228	129	44	34.87	68.78	90.24
RE (Mundlak)	1044	60	89	122	345	255	131	42	33.05	69.17	90.24
FE (Mundlak)	1044	371	43	63	76	45	51	395	7.28	17.62	26.63
Ordered Probit	1044	67	76	152	470	144	94	41	45.02	73.37	89.65
RE Ordered Probit	1044	70	71	148	477	146	89	43	45.69	73.85	89.17
RE + ϵ_i (basic)	1044	34	76	145	442	233	93	21	42.34	78.55	94.74
RE + ϵ_i (Mundlak)	1044	26	80	127	464	258	73	16	44.44	81.31	95.96
Ordered Probit + ϵ_i	1044	37	72	158	508	188	67	14	48.66	81.8	95.12
RE Ordered Probit + ϵ_i	1044	37	72	158	508	188	67	14	48.66	81.8	95.12
OLS (dynamic)	1042	14	7	74	801	131	13	2	76.87	96.54	98.46
FE (dynamic)	1042	11	8	86	670	231	33	3	64.3	94.72	98.66
Dif.-GMM (one)	983	8	7	26	436	352	58	96	44.35	82.8	89.41
Dif.-GMM (one, col)	983	20	88	358	401	23	0	93	40.79	79.55	88.5
Dif.-GMM (one, limitted)	983	7	4	15	231	423	187	116	23.5	68.06	87.49
Dif.-GMM (two, limitted)	983	9	5	35	349	399	86	100	35.5	79.65	88.91
Sys.-GMM (one, col)	1042	13	10	64	811	124	18	2	77.83	95.87	98.56
Sys.-GMM (two, col)	1042	13	14	58	834	103	14	6	80.04	95.49	98.17
Sys.-GMM (one, limitted)	1042	13	8	65	811	130	13	2	77.83	96.55	98.57
Sys.-GMM (two, limitted)	1042	13	10	61	838	103	15	2	80.42	96.15	98.55

Table A.1.27: S&P: Prediction Accuracy

Estimation Style	N	Deviation: $Y_{it} - \hat{Y}_{it}$							Percentage Correct		
		≤ -3	-2	-1	0	1	2	≥ 3	Correct	1 Notch	2 Notches
Random Walk	1024	9	16	75	781	126	10	7	76.27	95.89	98.43
OLS (basic)	1024	55	101	126	323	264	137	18	31.54	69.62	92.86
RE (basic)	1024	56	116	125	296	219	136	76	28.91	62.51	87.12
FE (basic)	1024	129	97	162	259	106	109	162	25.29	51.46	71.57
OLS (Mundlak)	1024	39	74	157	368	284	81	21	35.94	79	94.14
RE (Mundlak)	1024	40	70	149	352	302	87	24	34.38	78.42	93.76
FE (Mundlak)	1024	356	47	69	59	64	43	386	5.76	18.75	27.54
Ordered Probit	1024	34	87	173	456	189	62	23	44.53	79.88	94.43
RE Ordered Probit	1024	41	84	169	450	190	73	17	43.95	79	94.33
RE + ϵ_i (basic)	1024	17	61	166	476	242	61	1	46.48	86.32	98.24
RE + ϵ_i (Mundlak)	1024	16	53	165	481	244	61	4	46.97	86.91	98.05
Ordered Probit + ϵ_i	1024	11	68	177	526	188	50	4	51.37	87.02	98.54
RE Ordered Probit + ϵ_i	1024	18	73	179	527	177	48	2	51.46	86.23	98.05
OLS (dynamic)	1018	8	13	84	770	137	5	1	75.64	97.35	99.12
FE (dynamic)	1018	4	11	103	652	237	10	1	64.05	97.45	99.51
Dif.-GMM (one)	959	3	0	11	149	462	236	98	15.54	64.87	89.48
Dif.-GMM (one, col)	959	10	39	242	463	104	10	91	48.28	84.35	89.46
Dif.-GMM (one, limitted)	959	1	2	0	16	60	312	568	1.67	7.93	40.67
Dif.-GMM (two, limitted)	959	2	1	1	29	171	435	320	3.02	20.95	66.41
Sys.-GMM (one, col)	1018	8	14	77	776	132	10	1	76.23	96.76	99.12
Sys.-GMM (two, col)	1018	9	13	80	782	124	9	1	76.82	96.86	99.02
Sys.-GMM (one, limitted)	1018	7	14	82	777	130	7	1	76.33	97.16	99.23
Sys.-GMM (two, limitted)	1018	9	14	77	781	127	9	1	76.72	96.76	99.02

Table A.1.28: Fitch: Prediction Accuracy

Estimation Style	N	**Deviation:** $Y_{it} - \hat{Y}_{it}$							**Percentage Correct**		
		≤ -3	-2	-1	0	1	2	≥ 3	Correct	1 Notch	2 Notches
Random Walk	928	8	13	52	718	112	12	13	77.37	95.04	97.73
OLS (basic)	928	48	80	125	316	225	118	16	34.05	71.77	93.11
RE (basic)	928	46	74	155	268	185	146	54	28.88	65.52	89.22
FE (basic)	928	123	87	120	221	134	101	142	23.81	51.18	71.44
OLS (Mundlak)	928	25	75	134	364	215	100	15	39.22	76.83	95.69
RE (Mundlak)	928	24	73	130	360	219	109	13	38.79	76.4	96.02
FE (Mundlak)	928	303	43	54	70	54	51	353	7.54	19.18	29.31
Ordered Probit	928	39	75	147	418	141	65	43	45.04	76.07	91.15
RE Ordered Probit	928	44	72	145	428	123	74	42	46.12	74.99	90.72
RE + ϵ_i (basic)	928	19	45	158	432	220	50	4	46.55	87.29	97.53
RE + ϵ_i (Mundlak)	928	18	43	144	447	222	47	7	48.17	87.61	97.3
Ordered Probit + ϵ_i	928	27	56	162	458	152	42	31	49.35	83.19	93.75
RE Ordered Probit + ϵ_i	928	34	65	170	438	152	42	27	47.2	81.9	93.43
OLS (dynamic)	916	7	10	61	701	135	2	0	76.53	97.93	99.24
FE (dynamic)	916	6	5	100	545	233	27	0	59.5	95.86	99.36
Dif.-GMM (one)	861	4	2	2	159	353	238	103	18.47	59.7	87.57
Dif.-GMM (one, col)	861	7	13	186	392	156	30	77	45.53	85.25	90.24
Dif.-GMM (one, limitted)	861	6	2	16	355	296	105	81	41.23	77.47	89.9
Dif.-GMM (two, limitted)	861	8	6	105	423	169	68	82	49.13	80.96	89.56
Sys.-GMM (one, col)	916	7	14	62	706	113	12	2	77.07	96.18	99.02
Sys.-GMM (two, col)	916	8	13	53	716	113	12	1	78.17	96.3	99.03
Sys.-GMM (one, limitted)	916	7	10	60	710	122	7	0	77.51	97.38	99.23
Sys.-GMM (two, limitted)	916	8	12	56	720	107	12	1	78.6	96.39	99.01

Table A.1.29: Moody's: Upgrades and Downgrades Predictions

Estimation Style	N	**Upgrades**			**Downgrades**		
		Sample	**Predicted**	**Correct**	**Sample**	**Predicted**	**Correct**
Random Walk	1044	87	98	15	69	67	9
OLS (basic)	1044	87	149	29	69	107	12
RE (basic)	1044	87	157	26	69	131	14
FE (basic)	1044	87	157	26	69	131	14
OLS (Mundlak)	1044	87	144	27	69	154	18
RE (Mundlak)	1044	87	140	19	69	147	19
FE (Mundlak)	1044	87	145	24	69	159	13
Ordered Probit	1044	87	139	27	69	143	21
RE Ordered Probit	1044	87	148	27	69	153	20
RE + ϵ_i (basic)	1044	87	164	29	69	140	18
RE + ϵ_i (Mundlak)	1044	87	146	28	69	151	15
Ordered Probit + ϵ_i	1044	87	126	29	69	136	19
RE Ordered Probit + ϵ_i	1044	87	126	29	69	136	19
OLS (dynamic)	1042	87	118	22	69	115	13
FE (dynamic)	1042	87	121	21	69	122	15
Dif.-GMM (one)	983	79	113	16	66	104	13
Dif.-GMM (one, col)	983	79	108	14	66	97	13
Dif.-GMM (one, limitted)	983	79	115	20	66	122	19
Dif.-GMM (two, limitted)	983	79	107	18	66	104	12
Sys.-GMM (one, col)	1042	87	126	19	69	115	13
Sys.-GMM (two, col)	1042	87	105	15	69	88	11
Sys.-GMM (one, limitted)	1042	87	119	16	69	114	11
Sys.-GMM (two, limitted)	1042	87	112	15	69	103	10

Table A.1.30: S&P: Upgrades and Downgrades Predictions

Estimation Style	N	**Upgrades**			**Downgrades**		
		Sample	**Predicted**	**Correct**	**Sample**	**Predicted**	**Correct**
Random Walk	1024	116	117	22	92	94	16
OLS (basic)	1024	116	141	31	92	108	17
RE (basic)	1024	116	148	39	92	121	19
FE (basic)	1024	116	127	35	92	133	25
OLS (Mundlak)	1024	116	130	37	92	132	24
RE (Mundlak)	1024	116	130	32	92	130	24
FE (Mundlak)	1024	116	141	36	92	147	19
Ordered Probit	1024	116	131	36	92	134	32
RE Ordered Probit	1024	116	130	36	92	126	26
RE + ϵ_i (basic)	1024	116	149	44	92	125	22
RE + ϵ_i (Mundlak)	1024	116	130	26	92	128	26
Ordered Probit + ϵ_i	1024	116	134	37	92	127	23
RE Ordered Probit + ϵ_i	1024	116	127	32	92	125	24
OLS (dynamic)	1018	114	133	22	91	114	20
FE (dynamic)	1018	114	133	29	91	122	21
Dif.-GMM (one)	959	105	116	22	89	114	17
Dif.-GMM (one, col)	959	105	125	22	89	106	17
Dif.-GMM (one, limitted)	959	105	118	27	89	117	25
Dif.-GMM (two, limitted)	959	105	111	30	89	111	25
Sys.-GMM (one, col)	1018	114	130	22	91	102	24
Sys.-GMM (two, col)	1018	114	122	20	91	100	22
Sys.-GMM (one, limitted)	1018	114	130	20	91	111	23
Sys.-GMM (two, limitted)	1018	114	120	21	91	96	18

Table A.1.31: Fitch: Upgrades and Downgrades Predictions

Estimation Style	N	Upgrades			Downgrades		
		Sample	**Predicted**	**Correct**	**Sample**	**Predicted**	**Correct**
Random Walk	928	103	107	19	66	67	6
OLS (basic)	928	103	130	34	66	90	15
RE (basic)	928	103	143	32	66	108	14
FE (basic)	928	103	126	31	66	110	14
OLS (Mundlak)	928	103	147	34	66	130	18
RE (Mundlak)	928	103	123	27	66	111	15
FE (Mundlak)	928	103	137	28	66	122	15
Ordered Probit	928	103	130	31	66	115	20
RE Ordered Probit	928	103	123	26	66	110	20
RE + ϵ_i (basic)	928	103	136	35	66	101	13
RE + ϵ_i (Mundlak)	928	103	127	27	66	108	15
Ordered Probit + ϵ_i	928	103	121	29	66	102	16
RE Ordered Probit + ϵ_i	928	103	116	26	66	99	19
OLS (dynamic)	916	101	119	21	65	81	6
FE (dynamic)	916	101	116	28	65	81	14
Dif.-GMM (one)	861	91	108	22	65	94	14
Dif.-GMM (one, col)	861	91	113	20	65	91	14
Dif.-GMM (one, limitted)	861	91	109	22	65	92	10
Dif.-GMM (two, limitted)	861	91	103	19	65	84	12
Sys.-GMM (one, col)	916	101	114	16	65	74	8
Sys.-GMM (two, col)	916	101	108	19	65	69	6
Sys.-GMM (one, limitted)	916	101	118	20	65	82	8
Sys.-GMM (two, limitted)	916	101	106	17	65	68	8

Table A.1.32: Country Analysis: Contribution of Covariates to Moody's Upgrades

	Indonesia		Romania		Slovakia	
	2000	2018	2000	2018	2000	2018
Y_{it}	B3 (2)	Baa2 (9)	B3 (2)	Baa3 (8)	Ba1 (7)	A2 (12)
RE Ordered Probit: $\hat{Y}_{it}$	NA	Baa2 (9)	Ba2 (6)	Baa2 (9)	NA	NA
Ordered Probit: $\hat{Y}_{it}$	NA	Baa2 (9)	Ba3 (5)	Baa2 (9)	NA	NA
Short-Run Expressions						
GDP per Capita	-0.707	1.033	-0.748	1.112	-0.804	0.835
GDP Growth	-7.713	-0.179	-5.899	3.368	-1.411	-0.644
Unem. Rate	-0.97	-0.737	1.225	-1.106	0.004	-3.926
Inflation	18.845	-4.91	37.905	-48.919	3.016	-4.517
Current Account	1.9	-1.72	-0.283	2.939	-3.664	1.998
Government Debt	NA	4.58	-1.738	8.864	NA	NA
External Debt	36.524	-20.345	-9.258	8.28	0	0
WGI	-0.211	0.387	-0.271	0.063	-0.168	-0.036
Level Expressions						
GDP per Capita	5.19	6.93	3.618	5.479	3.03	4.669
GDP Growth	-2.533	5	-4.033	5.233	2.733	3.5
Unem. Rate	5.53	5.763	8.211	5.88	13.7	9.769
Inflation	28.321	4.566	86.555	-0.269	7.728	0.195
Current Account	1.804	-1.816	-5.39	-2.168	-7.623	-1.961
Government Debt	NA	26.326	17.689	28.291	NA	NA
External Debt	93.491	36.623	30.437	47.975	0	0
WGI	-0.734	-0.135	-0.182	0.152	0.542	0.673
EU	0	0	0	0	0	0
LAC	0	0	0	0	0	0
Default	1	0	0	0	0	0

Table A.1.33: Country Analysis: Contribution of Covariates to Moody's Downgrades

	Portugal		Greece		Barbados	
	2000	2018	2000	2018	2000	2018
Y_{it}	Aa2 (15)	Baa3 (8)	A2 (12)	B3 (2)	Baa2 (9)	$\leq$ Caa1 (1)
RE Ordered Probit: $\hat{Y}_{it}$	Aaa (17)	Baa2 (9)	NA	NA	Baa1 (10)	$\leq$ Caa1 (1)
Ordered: $\hat{Y}_{it}$	Aaa (17)	Baa2 (9)	NA	NA	A2 (12)	$\leq$ Caa1 (1)
Short-Run Expressions						
GDP per Capita	-0.309	0.399	-0.343	0.159	-0.106	0.403
GDP Growth	2.674	0.74	2.906	-0.628	2.262	1.162
Unem. Rate	-2.529	2.911	-2.323	9.769	-0.244	-2.294
Inflation	-1.206	-2.397	-1.121	-5.135	-0.777	-1.841
Current Account	-2.533	5.353	1.827	3.057	1.031	-0.683
Government Debt	-33.251	39.396	NA	NA	-34.976	34.01
External Debt	0	0	0	0	0	0
WGI	0.098	-0.022	0.275	-0.242	0.206	-0.351
Level Expressions						
GDP per Capita	4.776	5.484	4.884	5.386	1.118	1.627
GDP Growth	4.367	2.433	3.833	0.3	2.9	1.8
Unem. Rate	5.353	10.792	11.208	23.3	12.35	10.3
Inflation	2.092	0.9	4.033	0.019	2.667	1.603
Current Account	-7.501	0.385	-3.308	-2.077	-3.009	-4.723
Government Debt	41.495	114.142	NA	NA	55.58	124.566
External Debt	0	0	0	0	0	0
WGI	1.193	1.072	0.795	0.278	1.361	0.803
EU	1	1	1	1	0	0
LAC	0	0	0	0	1	1
Default	0	0	0	0	0	1

Table A.1.34: Moodys with 4 Categories: ME of Binary Explanatory Variables

Covariates	Ordered Probit				RE Ordered Probit			
	Coef.	**MEM**	**AME**	**MER**	**Coef.**	**MEM**	**AME**	**MER**
EU	0.623***				0.761*			
Very Bad		0	-0.008***	0		0	-0.007*	0
Bad		-0.004**	-0.049***	-0.083***		-0.006	-0.043	-0.079*
Decent		-0.146***	0.008***	0.067***		-0.14	0.007	0.058
Good		0.151***	0.048***	0.016**		0.146	0.043	0.021
LAC	-0.163				-0.16			
Very Bad		0	0.003	0		0	0.002	0
Bad		0.002	0.012	0.028		0.002	0.009	0.02
Decent		0.031	-0.003	-0.025		0.025	-0.002	-0.017
Good		-0.032	-0.012	-0.003		-0.027	-0.008	-0.004
Defaulted	-3.053***				-4.163***			
Very Bad		0	0.14***	0.008		0	0.142***	0.009
Bad		0.608**	0.165***	0.843***		0.624***	0.163***	0.832***
Decent		-0.474*	-0.075***	-0.842***		-0.458*	-0.074***	-0.827***
Good		-0.134***	-0.23***	-0.008**		-0.166***	-0.232***	-0.014

Table A.1.35: Moodys with 4 Categories: ME of Significant Continuous Explanatory Variables (SR)

Covariates	Ordered Probit				RE Ordered Probit			
	Coef.	**MEM**	**AME**	**MER**	**Coef.**	**MEM**	**AME**	**MER**
GDP Growth	0.039				0.054*			
Very Bad		0	-0.0006	0		0	-0.0006	0
Bad		-0.0003	-0.0029	-0.0101		-0.0005	-0.0029*	-0.0103*
Decent		-0.0079	0.0007	0.0099		-0.0089*	0.0007	0.0099*
Good		0.0083	0.0028	0.0002		0.0094*	0.0028*	0.0004
Unem. Rate	-0.204***				-0.237***			
Very Bad		0	0.0033***	0		0	0.0028***	0
Bad		0.002***	0.014***	0.0527***		0.0024*	0.0121***	0.0452***
Decent		0.0395***	-0.0029***	-0.0516***		0.0376***	-0.0023	-0.0434***
Good		-0.0415***	-0.0144***	-0.001*		-0.04***	-0.0125***	-0.0017
Inflation	-0.014***				-0.007			
Very Bad		0	0.0003***	0		0	0.0001	0
Bad		0.0002**	0.0009***	0.0035***		0.0001	0.0004	0.0013
Decent		0.0022***	-0.0003***	-0.0034***		0.001	-0.0001	-0.0012
Good		-0.0024***	-0.0009***	-0.0001*		-0.0011	-0.0003	0
Current Account	-0.004				-0.039**			
Very Bad		0	0.0001	0		0	0*	0
Bad		0	0.0003	0.0011		0	0.002**	0.007**
Decent		0.0009	-0.0001	-0.0011		0.007**	0	-0.007**
Good		-0.0009	-0.0003	0		-0.007**	-0.002**	0
Government Debt	-0.048***				-0.059***			
Very Bad		0	0.0007***	0		0.0004	0.0007***	0
Bad		0.0005***	0.0036***	0.0125***		0.0006*	0.0032***	0.0112***
Decent		0.0094***	-0.0012***	-0.0123***		0.0093***	-0.001**	-0.0108***
Good		-0.0099***	-0.0031***	-0.0002*		-0.0099***	-0.0029***	-0.0004
External Debt	0.024***				0.033***			
Very Bad		0	-0.0003***	0		0	-0.0004***	0
Bad		-0.0002**	-0.0018***	-0.0061***		-0.0003*	-0.0019***	-0.0063***
Decent		-0.0049***	0.0005***	0.006***		-0.0056***	0.0005**	0.0061***
Good		0.0051***	0.0017***	0.0001*		0.0059***	0.0017***	0.0002
WGI	2.638***				3.588***			
Very Bad		0	-0.038***	0		0	-0.038***	0
Bad		-0.024**	-0.1921***	-0.6817***		-0.0345*	-0.1901***	-0.6849***
Decent		-0.5302***	0.042***	0.6682***		-0.5861***	0.0381	0.6588***
Good		0.5542***	0.1881***	0.0136*		0.6206***	0.19***	0.0261

A.2 Figures

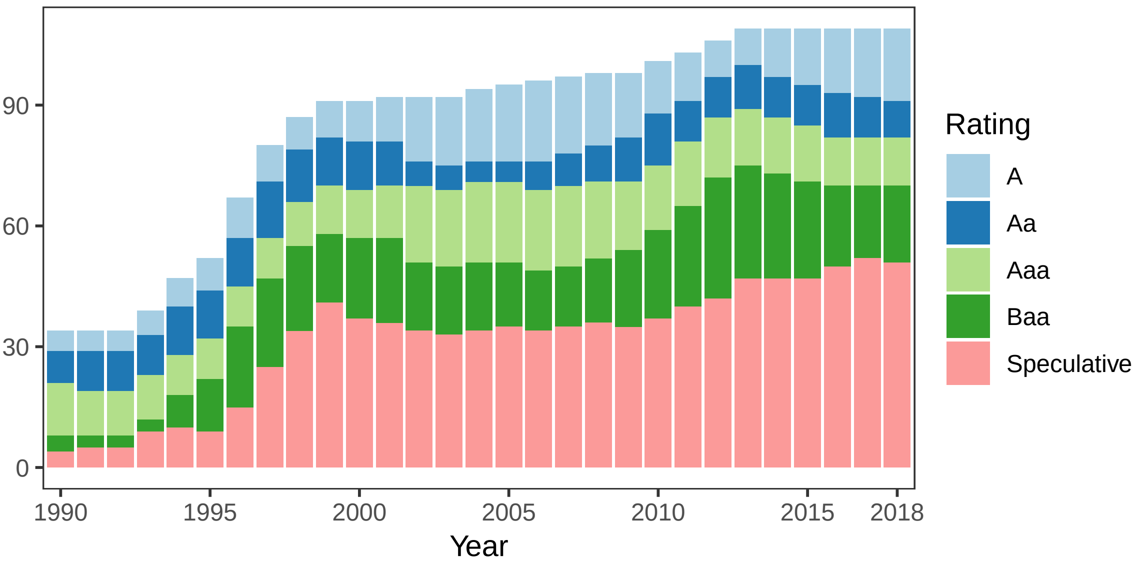

Figure A.2.1: Evolution of Ratings by Moody's

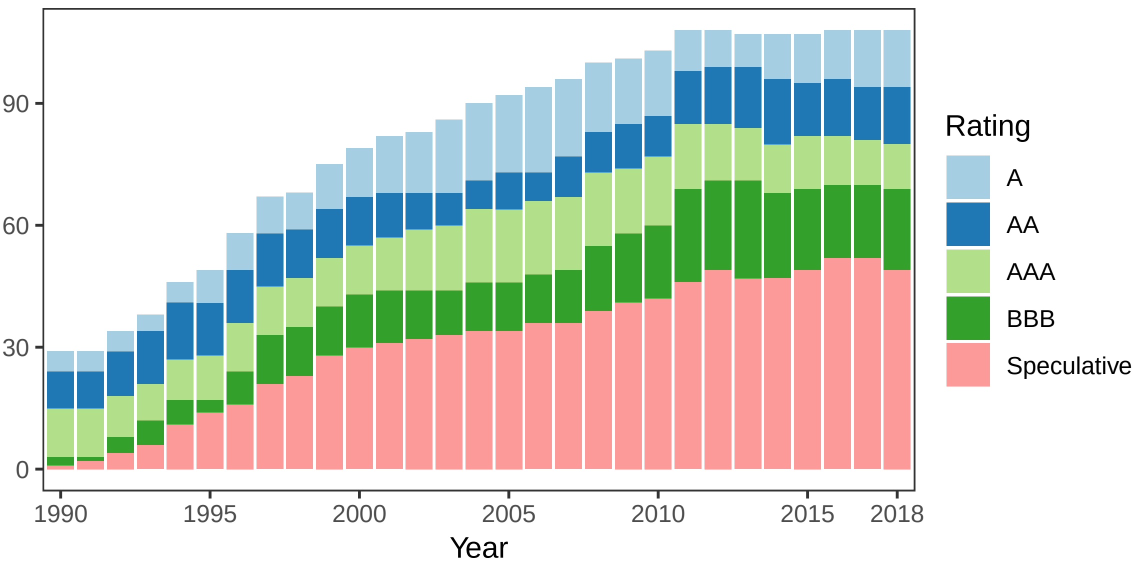

Figure A.2.2: Evolution of Ratings by S&P

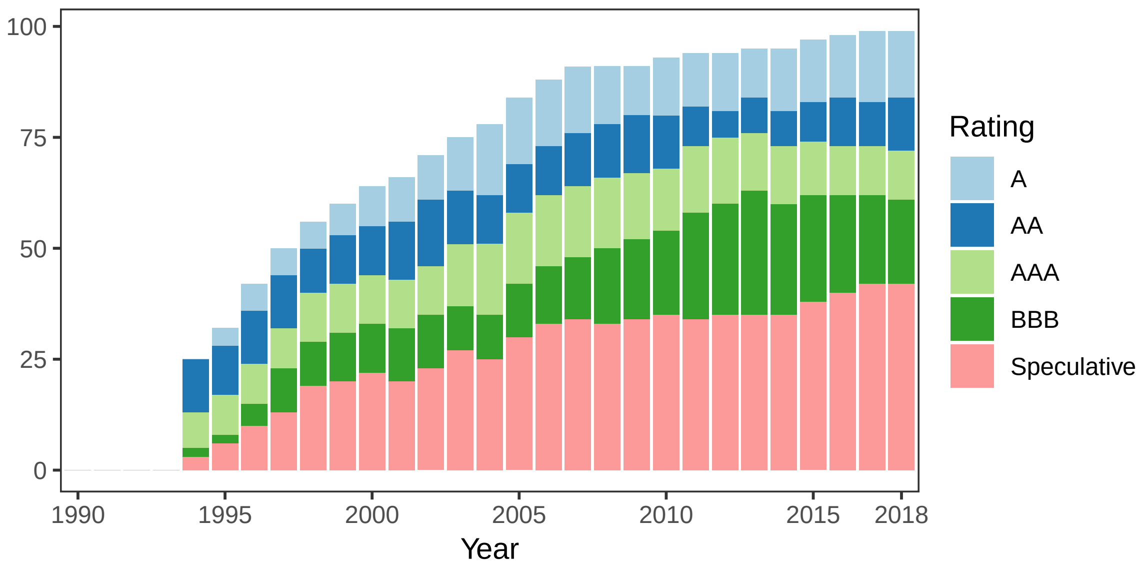

Figure A.2.3: Evolution of Ratings by Fitch

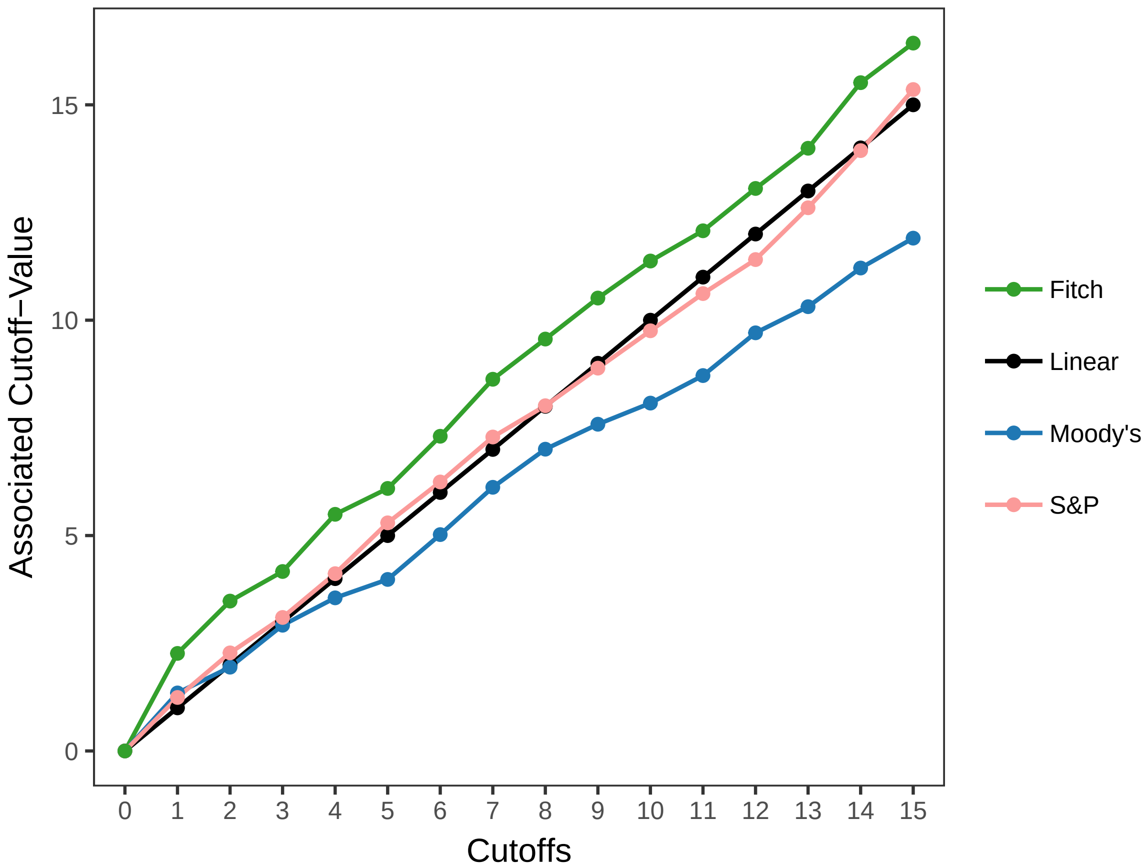

Figure A.2.4: Estimated Cutoffs

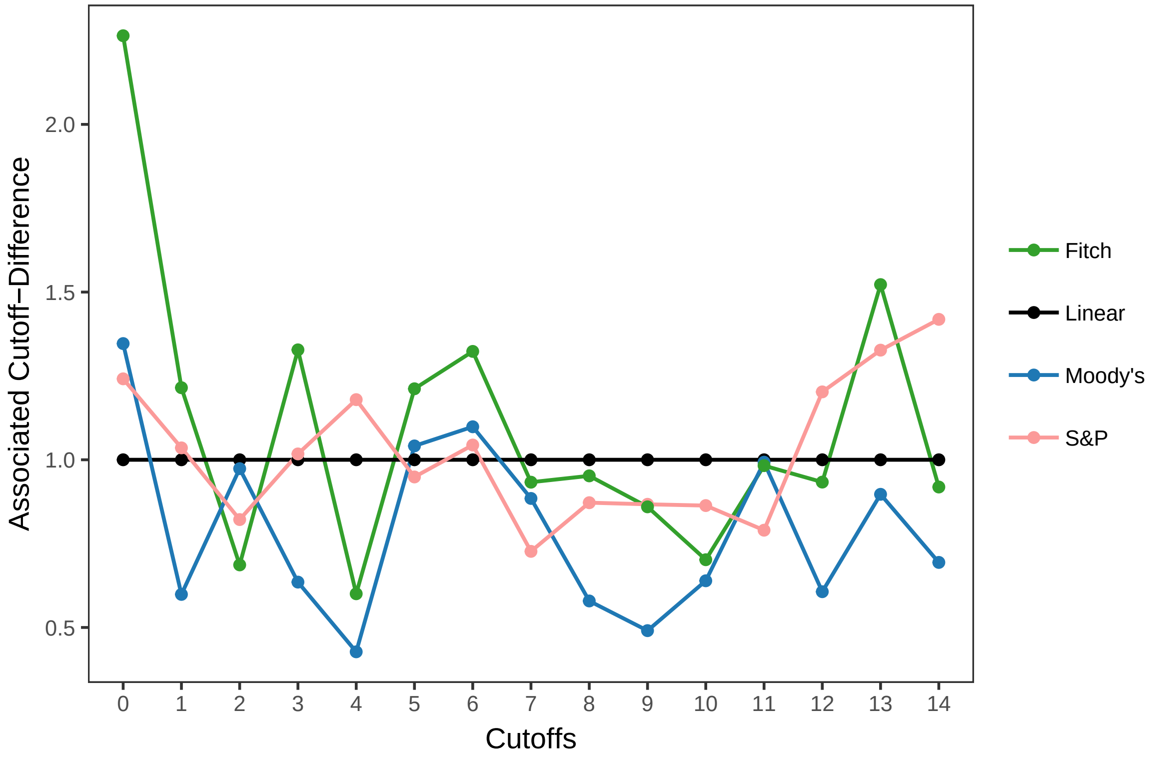

Figure A.2.5: Estimated Difference between Cutoffs

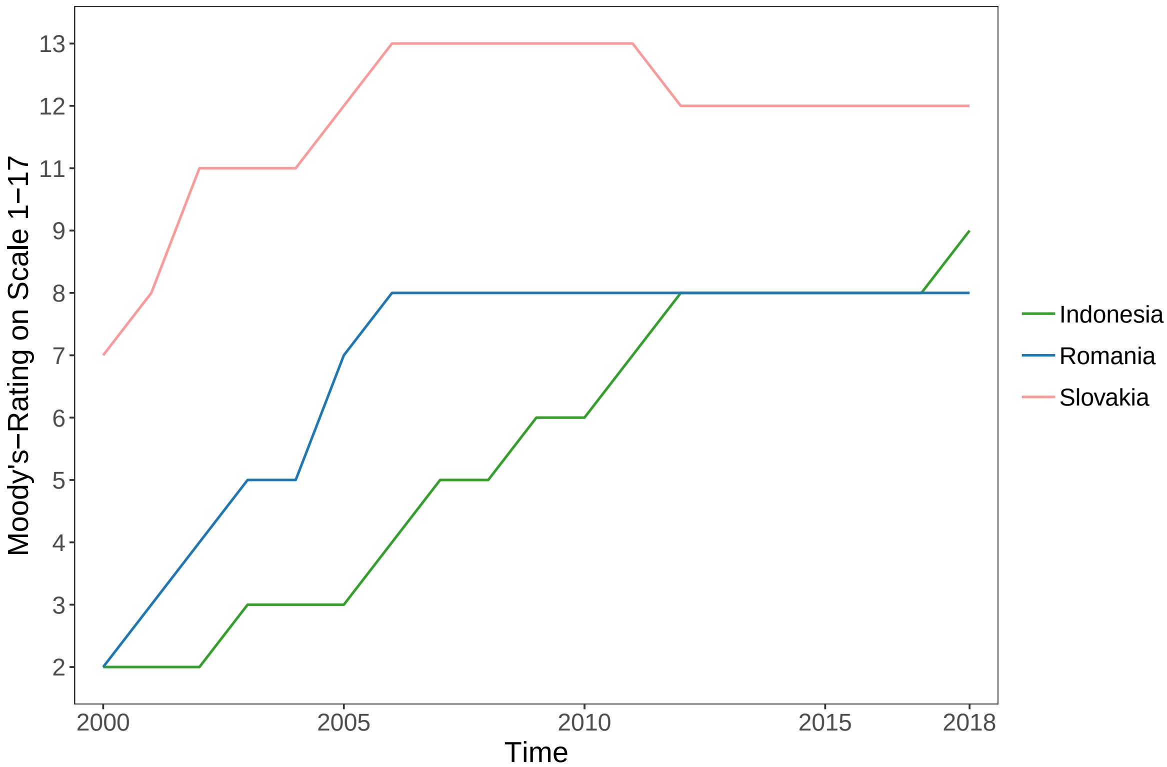

Figure A.2.6: Most Pronounced Rating Improvement by Moody's

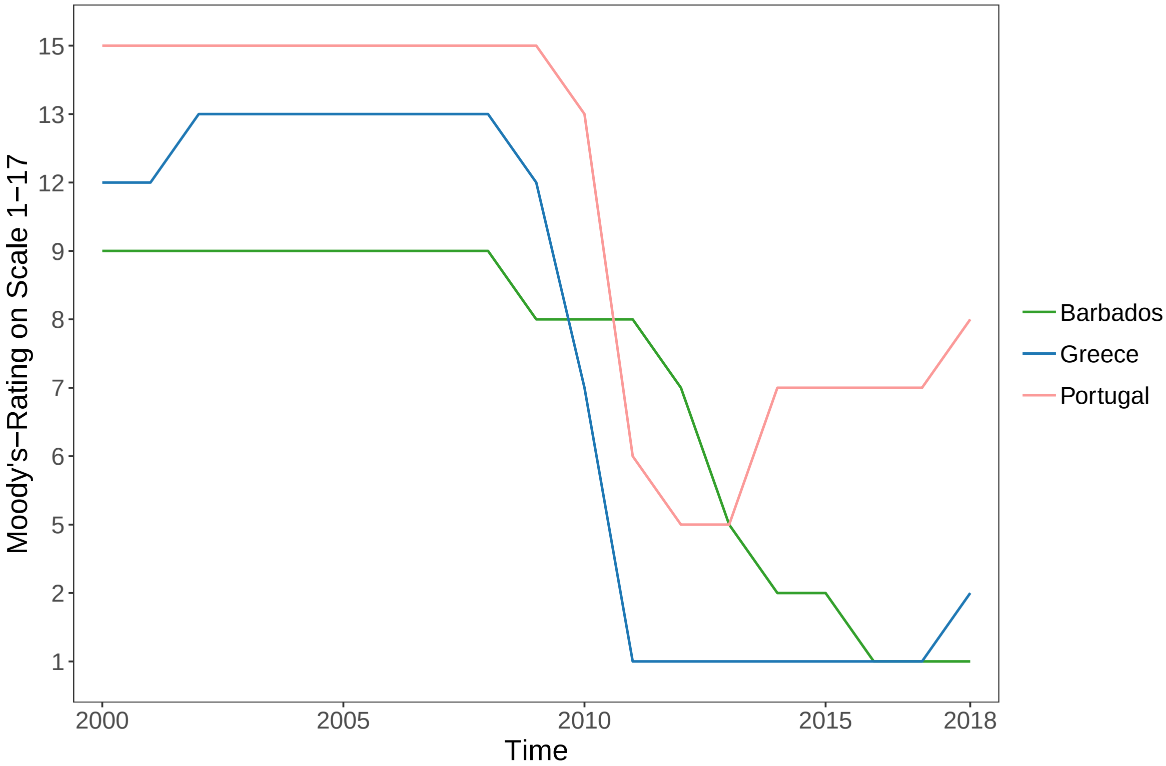

Figure A.2.7: Most Pronounced Rating Deterioration by Moody's

Statutory Declaration

I herewith declare that I have composed the present thesis myself and without use of any other than the cited sources and aids. Sentences or parts of sentences quoted literally are marked as such; other references with regard to the statement and scope are indicated by full details of the publications concerned. The thesis in the same or similar form has not been submitted to any examination body and has not been published. This thesis was not yet, even in part, used in another examination or as a course performance.

Cologne, May 12, 2020

Lennart Bolwin