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Determinants of Sovereign Defaults

An examination of fundamental factors derived from credit ratings

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Abstract

Credit rating agencies have in recent literature been found to base their sovereign ratings on the same range of macroeconomic fundamentals. The purpose of this study is to find out whether these credit rating determinants are valid predictors when explaining actual defaults and not only affect the perceived creditworthiness of sovereigns. By studying a sample of 106 sovereign issuers in a logistic panel data framework this thesis finds that GDP per capita, economic growth and external debt works as determinants for actual sovereign defaults in addition to their role in determining credit ratings. The impact of the individual variables on the risk of default is also found to be in line with what is expected from earlier research and economic intuition.

Keywords: Sovereign Defaults, Credit Ratings, Rating Determinants, Random Effects, Panel Data, Binary Choice, Logit.

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1. Introduction

A country's creditworthiness governs whether or not it has access to affordable credit through the international capital markets. The creditworthiness is determined by credit rating agencies which are assessing the country's risk of default by evaluating a broad range of elements. Credit rating agencies such as Moody's, S&P's and Fitch have an important position when issuing these ratings. Not only because they indirectly control the country's access to the international capital markets but also due to the ceiling that is set for domestic entities associated with the country as well as the effect they have on investment decisions (Jaramillo, 2010).

Recent studies on determinants of credit ratings have shown, while employing slightly different methodologies, that the four fundamental variables; per capita income, GDP growth, inflation and external debt all significantly affects the rating agencies evaluations (see for example; Cantor and Packer, 1996; Afonso, 2003; Rowland and Torres, 2005; Afonso, Gomes and Rother, 2007). The credit rating is often questioned on its accuracy, consistency and rationale. This thesis brings this issue to light with the purpose to test whether the fundamental variables that govern the ratings in a broad range of the recent literature actually can explain the probability of a sovereign default and if so, to what degree the individual variables influence the creditworthiness of the country. The rationale being that variables shown to explain creditworthiness by explaining the rating systems of different rating agencies also are likely to explain the core event of a sovereign default. If a variable affects the creditworthiness of a country in a certain direction the credit agency will adjust its rating accordingly. Following this logic the same variable is assumed to affect the actual likelihood of default for the given country, not solely the perception of the credit agency.

The hypothesis is tested in a panel data framework by using a probability model where the dependent variable is the binary choice between the country being in default and not being in default. The model is estimated with data for a sample of 106 sovereign issuers during the period between 1983 and 2010. The data material is based on 106 of the 108 sovereign issuers covered in Moody's Sovereign Default and Recovery Rates (Moody's, 2011) and is limited to the years Moody's have been issuing notch ratings.

This study builds on the existing literature on determinants of sovereign creditworthiness in several ways. A new perspective on the validity of the determinants used by the credit rating agencies is given through the comparison with actual defaults. The methodology used in this thesis is a novel feature in the universe of creditworthiness and can be used as a complement to, as well as an evaluation of existing studies on credit rating determinants. Another important factor of this study is the size of the data sample. The amount of total observations is large in comparison with the majority of recent studies on credit rating determinants (for overview see Jaramillio, 2010) and the idea is to give a perspective on creditworthiness as accurate and balanced as possible. By using odds ratios the individual impact of each of the evaluated variables is examined and compared to the in the recent literature frequently used sign studies.

My results shows that GDP per capita, GDP growth and external debt significantly explains the actual default of a country in the random effects framework. The odds ratios related with each explanatory variable in the random effects framework gives consistent and realistic values and the results obtained are in line of what is expected from earlier research. Also consistent with the literature on determinants of creditworthiness are the poor results obtained from the observation-wise mutilated fixed effects estimation, the exception being the GDP growth which is significant through all estimated models.

The rest of the thesis is organized as follows. Section 2 provides background information on credit ratings and creditworthiness as well as a look into the recent literature on the subject. Section 3 explains the methodological choices. Section 4 describes the data and presents the empirical results. Section 5 summarizes the main findings of the study.

2. Background

2.1 Historical primer

A big part of the American capital need of the nineteenth century was due to the expansion of the railroad system. Most U.S railroads were organized as private companies and raised capital as such. In the beginning when the railroad enterprises were still small they raised money by issuing equity and through bank credit but as the companies grew larger and expanded into undeveloped territories, few investors and local banks were willing or able to continue to finance them. As a solution to the financing problem a huge bond market for the railroad debt was developed. This was the birth of the corporate bond market and can be dated back as early as 1850 (Sylla, 2001).

The modern Credit Rating Agency was born in 1909 with the founding of Moody's and the publishing of "Moody's Analyses of Railroad Investments" in which railroad securities were graded with letter grades. The American corporate bond market was by this time much bigger than its counterparties in other parts of the world and that the first Credit Rating Agency was found in America was in that sense not unlikely. In 1914 the idea was expanded to include ratings for almost every bond market in the world and Moody's Investor Services was created (Sylla, 2001). As the size of the bond markets increased, the demand for credit ratings started to grow and Moody's was followed by Poor's Publishing Company in 1916, the Standard Statistics Company in 1922 and the Fitch Publishing Company in 1924 (White, 2010). In 1941 Poor's Publishing Company merged with the Standards Statistics Company creating Standard & Poor's. In 1962 Dun & Bradstreet bought Moody's and in 2000 they spun it off. Today Moody's, Standard & Poor's and Fitch are the three main issuers of Credit Ratings in the World and they control approximately 95 percent of the credit rating market.

The interrelation between the financial markets of the world and the greater availability of the international bond markets have led to an increase in demand for transparency and information about the bond markets and its products. Credit Rating Agencies handles this demand by assigning grades to issuers of certain kind of debt obligations. For the big three agencies the grades are based on a letter scale, ranging from "prime quality" to "in default" for the rated entities. An important discrepancy is also made between investment grade and non-investment grade products. More about this scale can be found in Appendix 7.1.

Today these ratings play an important role in the investment process and as a measurement of an entity's creditworthiness the credit ratings affects both companies and countries price of debt in the capital markets. On a sovereign level the recommendations from credit rating agencies can directly affect the interest rate of the loans given to the debtor country and result in whether or not the country have access to the capital markets when it needs to raise new capital or refinance existing debt. Because of the high stakes it is not unusual for a downgraded country to question the consistency and rationale of the credit rating agencies especially because the underlying criteria of the rating systems can be complex both taking politics and the fundamental macroeconomic situation of the assessed country in regard. In their statement of rating criteria, Moody's and S&P's list numerous social, political and economic factors that represent their ratings and in such influence the perceived creditworthiness of corporations and sovereigns.

Countries that default are not new phenomena. The first recorded sovereign defaults date back as early as 400 BC when ten out of thirteen Greek municipalities in the Attic Maritime Association defaulted on their obligations towards the Delos temple (Winkler, 1933). As years went by and the complexity of the global economy increased so did the number of fiscal crises and since the start of the tumultuous times of the nineteenth and twentieth century hundreds of sovereign defaults have been recorded, including both emerging markets and advanced economies (Reinhart, Rogoff and Savastano, 2003). Moody's reported that a total of 12 countries have defaulted between 1983 and 2010. Ecuador and Ukraine two times each. Even though Moody's sample begins in 1983, the first defaults during this period occurred in July 1998 when Venezuela defaulted on a domestic currency bond coupon payment.

2.2 Literature review

In recent time an extensive list of publications has treated the subject of credit rating determinants and creditworthiness. In an early paper Cantor and Packer (1996) tested the relative significance of eight variables which have been frequently cited by S&P's and Moody's to be used in their ratings of sovereigns. In their study they used a multiple regression OLS framework where Moody's and S&P's difference in credit ratings served as the dependent variable. The explanatory variables per capita income, GDP growth, inflation, external debt ratio, economic development and default history all rendered significant results. Although the methodology has varied, the same variables have been determining the credit

ratings in numerous recent studies (see for example; Afonso, 2003; Rowland, 2004; Rowland and Torres, 2005; Afonso, Gomes and Rother, 2007).

Two main strands of econometric approaches exist in the literature of credit ratings (Afonso, Gomes and Rother, 2007). The first one applies linear regression methods on a numerical representation of credit ratings (Cantor and Packer, 1996; Afonso, 2003; Butler and Fauver, 2007). Using OLS analysis on a numerical representation of the credit ratings also allows for a straightforward generalization to panel data by fixed or random effects estimation (Monfort and Mulder, 2000; Eliasson, 2002). The second strand uses ordered response models. Credit ratings being of qualitative ordinal nature, the established wisdom argue for the use of ordered probit/logit estimation, this methodology has been used by several studies in recent time (Hu et al, 2001; Bissoondoyal-Bheenick, 2005; Mellios and Paget-Blanc, 2006).

Afonso, Gomes and Rother (2007) included both strands in their methodology and employed panel estimation and a random effects ordered probit specification to evaluate several macroeconomic and public governance variables. Jaramillo (2010) used a random effects binomial logit model on a sample consisting solely of emerging market countries, the binary dependent variable being either investment grade status or non-investment grade status. Rowland and Torres (2004) examined emerging markets sovereign issuer spreads over US Treasuries. They also examined the creditworthiness of mentioned issuers and found that credit ratings and credit spreads in large shared the same determinants. The relationship between credit spreads and credit ratings is intuitive through the idea of creditworthiness. Cantor and Packer (1996) also prove this relationship in their earlier mentioned article. They find evidence that the rating agencies opinions independently affect credit spreads and that the evaluated macroeconomic variables are effectively engulfed by the credit ratings and therefore strongly correlated with the market determined credit spreads.

2.3 Definition of sovereign default

Debt incurred by governments is referred to as sovereign debt. Just like any private person or company a country can default on its payments if it fails to meet the conditions of the debt contract. Unlike the person or the company the country is not subject to normal bankruptcy laws and it has the potential to escape its payments during a default although not without severe implications. Disregarding political implications, a major concern for the defaulting country would be surging interest rates and the loss of access to the capital markets and cheap loans most countries need to meet financial requirements in the form of deficits and government spending in general.

The definition of a sovereign default can vary according to what source that is studied. A failure on the repayment of a country's debt often involves either a failure for the debtor country to pay the full obligated amount, a change in the terms of the repayment schedule between the debtor country and its creditor or a combination of the two scenarios. These events can include scenarios like a reduced principal amount, extended maturities, lower coupon, different currency of payment or effective subordination (Standard & Poor's, 2011). In this thesis the definition of sovereign default is delimited to Moody's definition of sovereign default as it is described in the Sovereign Default and Recovery Rates, 1983-2010. It includes the following types of default events:

1. A missed or delayed disbursement of a contractually obligated interest or principal payment (excluding missed payments cured within a contractually allowed grace period), as defined in credit agreements and indentures.

2. A distressed exchange whereby:
i) The issuer offers creditors a new or restructured debt, or a new package of securities, debt or assets, that amounts to a diminished financial obligation relative to the original obligation; and
ii) The exchange has the effect of allowing the obligor to avoid a payment default in the future.

This definition of sovereign default will be used in three different ways in the probability model. Consider chapter 3.3 for details.

3. Model specification

3.1 Econometric framework

As mentioned in the literature review an array of different methodologies have been employed when studying the creditworthiness of countries. A panel data framework is used for empirical analysis in this study. This means pooling observations on a cross-section of a country over several time periods. There are many benefits of using a panel data approach compared to using pure cross-sectional and time series models. Panel data gives more information, less collinearity among the explanatory variables, more degrees of freedom and a higher efficiency. Compared with cross-sectional models, panels also incorporate the adjustment dynamics. Panels have the attributes to relate experiences at different points in time. Effects that would have been impossible to discover by solely using a cross-section or time series methodology can appear in a panel data setting. Panel data also allows for creation of more complex models and helps alleviate aggregation bias (Rowland and Torres, 2004). The panel data framework has its shortcomings too where the most apparent being that the majority of panels suffer from a short time series dimension. An assumption for the asymptotical arguments to hold completely is that the number of countries would tend to infinity. This would be impossible as the cost of getting more of related observations would be too high. For additional problems and limitations of panel data analysis consider econometric textbooks (see for example: Baltagi, 1995; Veerbeek, 2008).

The dependent variable of the model in this study is defined in binary form. The dummy is made equal to 1 when the country at the given year is going through a default and 0 for the years when the country is not going through a default. The general idea is pictured in the following equation:

$$D^{*}{}_{it} = X^{'}{}_{it}\beta + \alpha_i + u_{it}$$

where

$$D_{it} = 1 \;\; if \; D^{*}{}_{it} > 0 \; and \; D_{it} = 0 \; otherwise$$

In the equation the index i (i=1,…,N) denotes the sovereign and the index t (t=1,…,T) represents the period which is on an annual basis. D_{it} is the binary variable, X_{it} is a vector consisting of the time varying explanatory variables, α_i represents the individual effects for

each country and u_{it} are the disturbances which are assumed independent across sovereign and time. To avoid problems relating to linear binary choice models (for examples see; Verbeek, 2008), the binary choice in this study is modeled with a standard logistic distribution function, a logit model.

Estimating the model can be done by random effects, fixed effects and pooled OLS. Under normal conditions where the regressors of the model are uncorrelated with the disturbances will these three estimation techniques all be consistent but with a clear difference in efficiency. Random effects being the most effective followed by fixed effects and pooled OLS (Brooks, 2008, p. 500). Pooled OLS does not control for unobserved country effects in addition to being the inferior choice with regards to efficiency. Therefore will it not be considered as a potential estimator and the discussion will be focused on the remaining two methods.

The choice of what estimation technique to apply is in some parts dependent on whether the normal conditions of uncorrelated disturbances and regressors are fulfilled. Correlations between disturbances affect the likelihood function of the models and complicate estimation. This control is performed with a Hausman test where the null hypothesis is no correlation between the regressors and the errors. Because we want to use the most efficient consistent model of the three, accepting the null hypothesis would mean that random effects would be preferable with regards to efficiency while rejecting the null hypothesis would mean that we would prefer fixed effects as estimator because random effects would not be consistent.

One of the more common views when choosing between fixed effects and random effects is based on focusing on the conditionality of the individual effects (Verbeek, 2008). The fixed effects approach is conditional upon the values of the individual effects while the random effects estimator is said to “integrate them out”. The countries used in the sample of this study are chosen because they all are Moody’s rated sovereign issuers and would under this rationale not be considered as a random draw from the entire population of countries on earth. Following this logic would suggest fixed effects as the preferable choice of estimation. Unfortunately does the fixed effects estimator suffer from several drawbacks. A main drawback that is not a concern in this study but worth mentioning is that the impact of non-time varying country characteristics cannot be assessed. The dependent variable must be measured on at least two occasions for each individual and the independent variables must change across time for some substantial portion of the individuals (Allison, 2009, p. 38).The

fixed effects logit model also has the disadvantage that only countries where the dependent variable switches can be included in the estimation which would mean that a large amount of observations has to be dropped. This is a big drawback for the fixed effects estimator and a main reason to why most of the existing similar studies have chosen to focus on the random effects estimator despite the fact that the countries cannot be regarded as a random draw from the entire population(Rowland and Torres, 2004; Afonso, Gomes and Rother, 2007; Jaramillo, 2010). In this study both the fixed effects and the random effects estimators will be considered and compared but the drawbacks of each model will be accounted for.

3.2 Explanatory variables

Building on evidence from the existing literature on determinants of sovereign defaults, the explanatory variables that are being tested whether they can explain the event of default in this thesis have earlier been shown to explain the creditworthiness of countries through different studies of credit ratings. The result from this thesis is expected to be in line with the results from the existing literature and can thus be seen as a methodological complement to recent studies with similar explanatory variables.

GDP per capita has been frequently shown to be an important determinant of credit ratings in the recent literature of credit rating determinants (see for example; Cantor and Packer, 1996; Afonso, 2003; Rowland, 2004; Mellios and Paget-Blanc, 2006). This macroeconomic variable covers the output of a country's enterprises domestically in a given period of time. The greater the income of a country is, the broader the tax base and the greater ability to repay its debts. GDP per capita can also work as a proxy for a country's level of political stability as well as a proxy for economic development. It's expected from intuition and earlier research to have a positive impact on a country's creditworthiness and ability to evade a default. The rate the GDP grows for a country has also proven to be an important factor (Cantor and Packer, 1996; Afonso, 2003; Rowland, 2004; Rowland and Torres, 2004; Archer et al., 2007). Higher economic growth boosts the tax revenues for the government due to the increased income from companies and individuals of the country. The existing debt burden will be easier to service over time. GDP growth is expected to have a positive impact on a country's creditworthiness.

Another variable that has been reoccurring in the recent literature of credit rating determinants is the inflation rate (see for example; Cantor and Packer, 1996; Afonso, 2003; Rowland, 2004;

Mellios and Paget-Blanc, 2006). Since most debt is fixed in nominal value, higher inflation would erode its real value. Higher inflation would boost tax revenues but also push up spending on state benefits and public sector wages. A low inflation rate hints of a sustainable monetary and exchange rate policies. The expected net effect is debatable.

The last variable examined in this study is the external debt (Cantor and Packer, 1996; Afonso, 2003; Rowland, 2004; Rowland and Torres, 2004). A higher debt burden is expected to correspond to a higher risk of default. The weight of the burden increases as the foreign currency related debt increases relative to its foreign currency related earnings, its exports.

There are several other economic variables that have been explaining the credit ratings in recent literature although not as frequently and with the same consistent results as the ones examined in this thesis. Of the variables left out economic development is the one which rendered the best results. In this study will use the GDP per capita as a proxy for economic development instead of including it in the model as a separate variable.

3.3 Dependent variable

As a way to receive more balanced results and gain different perspectives on the results, three different methods on how to consider a sovereign default in the statistical model are used and compared. The idea of using three methods instead of one is because of the difference in characteristics of each default and the different possibilities to theoretically delimit and treat these defaults. In this study and with these methods the dependent variable in the model is either classified as being “in default (1)” or “not in default (0)”.

The first method is solely based on the actual year the country has defaulted on its payments. Properties surrounding the default, like the defaulted amount and recovery rate are not taken into consideration in this model. The dependent variable is assigned the value 1 for the year the country defaulted whereas for the remaining years the dependent variable is assigned the value 0.

The second method is taking the relative amount the country defaulted on and the severity of the situation into consideration by evaluating the recovery rate of the defaulted sovereign bonds. In 1998 Venezuela missed a coupon payment on local currency bonds held by local residents. In this case the bonds did not have a grace period and even if the payments were

made a week later the situation amounted to a default (Moody's, 2011). A small default event like Venezuela's is considerably different from big defaults like Russia's default in 1998 or Argentina's default in 2001 considering the defaulted amount, the time needed for the country to recover and the possible consequences (Moody's, 2011). I introduce the term "insignificant default" for defaults that were resolved in a quick manner. Insignificant defaults are based on Average Trading Price (% of PAR) which is a measure used by Moody's in Sovereign Default and Recovery Rates and represents the average issuer-weighted trading price on a country's defaulted bonds 30 days after the first missed payment (Moody's, 2011). In the second method insignificant defaults are cleared and treated as they never occurred. For an insignificant default the dependent variable is assigned the value 0 and the Average Trading Price limit is set at 90. This means that the defaults of the Dominican Republic, Jamaica and Venezuela are treated as insignificant with this method. The Average Trading Price limit was set to 90 based on a case to case evaluation. In the context of the 12 defaulting countries Jamaica and the Dominican Republic had ATP values of 90 respectively 95. The third largest ATP value was 76 and belonged to Belize. This selection method is based on the significant difference in ATP values between the mentioned defaults and the severity of the defaults judged on a case to case basis. Venezuela was not rated in the ATP context but due to the circumstances surrounding its default it will also be classified as insignificant (Moody's, 2011). For details on the individual defaults consider appendix 7.4.

The third method is an extension of the first method in the way that it also treats both the year before and the year after the default as years being in default. This is a way to capture the crisis surrounding a sovereign default.

4. Empirical Analysis

4.1 Data

The sample consists of 106 of the 108 sovereign issuers covered in Moody's Sovereign Default and Recovery Rates (Moody's, 2011). The 107th and 108th countries Bermuda and Macao were not included due to limited data availability. The entire list of countries included in the study can be found in the appendix, part 7.2. The variables are observed between 1983 and 2010 on an annual basis. The sample period starts in 1983 due to the fact that Moody's started issuing notch ratings in addition to letter ratings at this time. Data for the series GDP growth, GDP per capita and inflation was obtained from IMF (WEO). Data for the external debt variable was obtained from the World Bank (GDF) and was at the time only available for non-industrial countries. Thus the external debt variable was attributed value 0 for industrial countries. The regressions were run in STATA and missing observations were automatically removed by the program. GDP per capita is measured in constant prices with logarithms of thousand U.S. dollars as unit. GDP growth is measured in constant prices with percentage change as unit. Inflation is measured as the percentage change of the yearly averages of the consumer price index. External debt is measured as one hundredth of the quote between external debt and exports. Consider table 1 for an overview of the explanatory variables.

Table 1. Explanatory variables

Explanatory variable	Unit	Notes	Observations
GDP growth	Percentage change	Constant prices	Yearly, 1983-2010
GDP per capita	U.S. dollars(000s)	Constant prices	Yearly, 1983-2010
Inflation	Percentage change	Yearly averages of CPI	Yearly, 1983-2010
External debt	External debt/exports	Total debt service	Yearly, 1983-2010

Table 2 presents an overview of the descriptive statistics for the variables included in the regression. The dataset contain some extreme outliers, the majority have been identified not to be related with errors in the data collection. These extreme outliers represent extreme situations in a country's history and will not be removed due to the potential loss of information. Consider for example the maximum rate of inflation included in table 2. This is the average inflation Bolivia experienced in the year 1985. The hyperinflation of Bolivia peaked at 60,000 percent but the yearly average inflation was 11,728 percent. It is important

to keep in mind that these extreme outliers have had a big impact on the descriptive statistics in table 2.

Table 2. Descriptive statistics						
Explanatory Variable	Observations	Median	Mean	Std. Dev.	Min	Max
GDP per capita	2694	8.430	8.458	1.420	2.901	11.691
GDP growth	2752	3.866	3.665	5.212	-42.195	50.688
Inflation	2767	0.044	0.532	4.439	-1	117.279
External debt	2728	0.018	0.098	0.140	0	1.522

4.2 Regression results

Before choosing an estimation technique a test for autocorrelation will be conducted. Autocorrelation can be a problem in macro panels with long time series and can affect the efficiency of the estimators by altering their standard deviations. As a method to detect autocorrelation Wooldridge's test for autocorrelation in panel data is used. The null hypothesis being that there is no first order autocorrelation. The null hypothesis is accepted across all models. See table 3 for details.

Table 3. Wooldridge's test for autocorrelation			
	Method 1	Method 2	Method 3
p-value	0,6497	0,6630	0,6542
Autocorrelation	No	No	No

To achieve optimal results it is appropriate to use the Hausman test to control whether the random effects model is consistent as well as being the most efficient estimator. The null hypothesis that the unobserved effect is uncorrelated with the explanatory variables is accepted both for the first and the second method meaning that random effects as well as fixed effects would be a consistent estimator but that the random effects estimator would be preferable efficiency wise. The Hausman test for the third method rejected the null hypothesis. This means that the random effects estimator isn't consistent when estimating models where the dependent variable is chosen according to the third method and those results will not be considered in the following parts of the thesis. Consider table 4 for the results from the Hausman test.

Table 4. Hausman Test			
	Method 1	Method 2	Method 3
p-value	0,3074	0,2188	0,0001
H_0	Accepted	Accepted	Rejected

Studying the results from the three different methods we can see that the explanatory variables are jointly different from zero and the models are affirmed in every case except the fixed effects estimation of the first method. It is interesting to note that the random effects estimations for every model are affirmed on the one percent level.

Studying the significance of the variables on an individual basis we discover that in the random effects framework GDP per capita, GDP growth and external debt are all significant on a five percent level across all three methods with an exception of the second method's external debt that is also significant but on the ten percent level. For the random effects estimator the rate of inflation has an insignificant impact on the risk of default for both the first and the second method. The results suggest that the explanatory powers of three of the variables are good across the methods in the random effects framework. GDP per capita, GDP growth and external debt are all rendering good results in explaining the event of a sovereign default. These results confirm earlier studies results that these determinants make an impact on the credit agencies ratings, as well as they fill an explanatory function of actual sovereign defaults. Table 5 shows p-values for the joint significance as well as the individual p-values across the variables for the three methods.

Table 5. Regression Results, p-values						
	Random effects			**Fixed effects**		
	Method1	Method2	Method3	Method1	Method2	Method3
GDP per capita	0.049 **	0.028 **	0.041 /	0.456	0.124	0.389
GDP growth	0.012 **	0.032 **	0.030 /	0.045 **	0.084 *	0.035 **
Inflation	0.345	0.290	0.099 /	0.101	0.103	0.068 *
External debt	0.027 **	0.063 **	0.028 /	0.902	0.689	0.363
Prob>chi2	0.002 ***	0.009 ***	0.002 /	0.147	0.094 *	0.034 **

*Note: *** stands for statistical significance at the one percent level,** for statistical significance at the five percent level and * for statistical significance at the ten percent level. / stands for inconsistency.*

When estimating the model with fixed effects the only variable that had a significant influence on the dependent variable across the three evaluated methods was the GDP growth. Inflation was significant on the ten percent level in the third method but insignificant in the first two cases. GDP per capita and external debt both showed an insignificant influence across all three methods. These results are poor in the sense that they are not in line of what is expected from earlier studies of creditworthiness, economic intuition or the obtained results from the random effects framework in this study. The fixed effects model explores the relationship between predictor and outcome variables within an entity and looks for determinant of within-subject variability. If there doesn't exist any variability within the country, there is nothing to examine. In other words does the fixed effects estimator only consider observations from countries that have experienced defaults during the studied timeframe. The properties of the fixed effects within estimation limits the sample drastically and in that sense fails to capture the balance needed to make any form of contribution to the existing literature. The results from the fixed effects estimation will at most fill a supporting role to the random effects binomial logit model in this thesis.

A consequence of this trait of the fixed effects estimator is that instead of including all the 106 Moody's rated sovereign issuers, only the 12 country's that defaulted on their payments between 1983 and 2010 are considered. The total observations between the two different estimators are dropped from 2572 in the random effects framework to 295 in the fixed effects framework. Limiting down the study to only the 12 defaulting countries would not produce any meaningful results due to several different reasons. It is not a good representation of the population of sovereign issuers studied in this thesis. The entire 12 country sample consists solely of emerging markets with an overrepresentation of countries from South and Central America. The entire sample of countries also shares the fact that they all defaulted during the evaluated time frame. This means that they are likely to share many common characteristics and correlations and would thus lack the diversity of a more representative sample from the studied population.

In terms of interpreting the coefficients of the estimated models we will consider the odds ratios. Consider as an example the first method and the odds ratio for the GDP growth in the random effects model. This odds ratio is 0.905 and is interpreted as if the yearly GDP growth increases by one percent the odds that the country will be in default is multiplied by 0.905. As

expected will an increase in the economic growth for a country result in a decrease in the probability of that country being in default. This result is both easy to understand as well as expected on the basis of the earlier research done on creditworthiness where most studies have shown that an increase in economic growth often results in a higher credit grade or a tighter bond spread between the country and its benchmark. GDP growth was the only variable with a significant impact across all methods for both estimation techniques. The multiplier for a yearly increase in the economic growth rate of one percent varied between 0.905 for the random effects estimation of the first method to 0.930 for the fixed effects estimation of the third method. This feels intuitively as a small spread and the numbers are reliable if put into a real world context where economic growth often serves as a foundation of a country's well being and would as expected make the debt burden easier to service and reduce the risk for the country to default. Table 6 gives an overview of the odds ratios and their standard deviations across the variables for the different methods.

We continue with studying the odds ratio for the GDP per capita. Since the GDP per capita is measured in natural logarithms and the scale in that sense being altered is this variable expected to have a significant impact on the probability of being in default. The odds ratios for the two consistent methods estimated with random effects are 0.596 and 0.468. Increasing the GDP per capita with approximately 2720 dollar would lead to a decline in the risk of the country being in default with the above mentioned multipliers. This result is also expected. A country with a higher GDP per capita and economic development hints about a more healthy and sustainable environment in that country, both in terms of economics and politics.

The odds ratios for the external debt for the three methods in the random effects framework are 26.939 and 27.970. Increasing the country's debt to exports ratio by one hundred percent would result in an increase of the risk of the country being in default with 26.939 and 27.970 times for the two methods. Unfortunately are the standard errors for the external debt odds ratios across the models very big and the 95 percent confidence interval covers decreases as well as increases in the default probability. This makes the external debt a less certain case than the two other significant explanatory variables when interpreting the impact effect. Having this in mind, an increasing external debt leads to a higher propensity for the country to default. A higher debt burden can be hard for the country to maintain with increased proportional costs as well as increased costs as a risk premium through higher rates towards

investors. The proportional lower income through exports makes the debt even harder to service and amplifies the effect of the variable.

Table 6. Odds ratio and individual significance for the three methods

	Method 1		**Method 2**	
	Random effects	Fixed effects	Random effects	Fixed effects
GDP per capita	0.596** (0.157)	0.659 (0.368)	0.468** (0.162)	0.349 (0.239)
GDP growth	0.905** (0.036)	0.907** (0.044)	0.906** (0.042)	0.914* (0.048)
Inflation	0.612 (0.318)	0.351 (0.224)	0.532 (0.317)	0.336 (0.225)
External debt	26.939** (40.221)	1.336 (3.158)	27.970* (50.197)	2.737 (6.874)

	Method 3	
	Random effects	Fixed effects
GDP per capita	0.550/ (0.161)	0.719 (0.274)
GDP growth	0.929/ (0.031)	0.930** (0.032)
Inflation	0.512/ (0.208)	0.459* (0.196)
External debt	21.550/ (30.034)	3.789 (5.549)

*Note: *** stands for statistical significance at the one percent level,** for statistical significance at the five percent level and * for statistical significance at the ten percent level. / stands for inconsistency.*

The rate of inflation was insignificant in all four estimated models estimated with method 1 and 2. Viewing the significance of the inflation rate across all the estimated models the joint results are too poor for the variable to be considered to have an impact on the default of a country and will thus be deemed as insignificant in this study. This result differs from the results obtained by research on the rate of inflations impact on credit ratings in the recent literature where it has consistently been proven to have a negative impact on the credit ratings. When considering the difference in results we have to keep in mind that the models in this study test whether inflation has an impact on actual defaults whereas the mentioned earlier research tests for impact on the perceived creditworthiness through a country's credit

ratings. The results in this study can be explained by the properties of the inflation rate and how it pulls in both directions in the context of creditworthiness. Putting a sign on the impact of inflation might be hard because of its nature. More likely to make an impact would be an extreme variation in the rate of inflation and the uncertainty that follows in its wake. The positive impact that a lower inflation has on credit ratings might not be able to transfer to actual defaults, especially when considering a potential damaging situation like deflation.

Table 7. Study Comparison-Effect on creditworthiness of the country

	Kalliomäki (2011)	**Afonso (2003)**	**Afonso,Gomes and Rother (2007)**	**Cantor and Packer (1996)**
Per capita income	+	+	+	+
GDP growth	+	+	+	+
Inflation	Insignificant	-	-	-
External debt	-	-	-	-
	Jaramillo (2010)	**Mellios and Paget-Blanc (2006)**	**Rowland (2004)**	**Rowland and Torres (2004)**
Per capita income	+	+	+	Not included
GDP growth	Not included	+	+	+
Inflation	-	-	-	-
External debt	Not included	Not included	-	-

When comparing our findings on the three significant explanatory variables with recent studies on creditworthiness we can conclude that the results from the random effects binomial logit model used in this study are very much in line with the results from similar studies on credit ratings. Table 7 presents a comparison of some of the more significant examples of these recent studies and how these four explanatory variables affect the creditworthiness of the country. All the presented variables in the table were found to be significant in its associated study. Although different methodologies were used all of the evaluated studies are consistent with the findings in this thesis with the exception for the inflation rate.

5. Conclusions

Findings in this study suggest that three out of four macroeconomic variables that determine the perceived creditworthiness though credit ratings also have an impact on actual defaults. GDP per capita, economic growth, inflation and external debt have in numerous earlier studies played an important role in determining these ratings. This thesis finds that GDP per capita, economic growth and external debt systematically explain the sovereign default over the studied models estimated with random effects and thus validates earlier similar studies in the field of rating determinants and credit spreads. Unlike a big part of the literature on creditworthiness the rate of inflation failed to make an impact in this study. Even though the rate of inflation has a negative impact on the creditworthiness in these studies its real impact on a country's creditworthiness is a debatable issue. The credit rating agencies are relating a low rate of inflation with sustainable monetary and exchange rate policies as well as politically and economically stable countries. In this thesis the inflation rate rendered insignificant results across the majority of estimated models. This can either be a sign that the models in this thesis failed to capture the nature of inflation as well as a hint of an existing difference between the perceptions of what influences a country's creditworthiness and what actually causes the same country to default.

GDP per capita and economic growth have both earlier been shown to influence an increase in the credit ratings and external debt has accounted for a decrease. Findings in this study suggest that the probability of a country being in default is lowered by the first two fundamentals and increased by the third and are thus in line with what can be expected from economic theory and earlier research. This result validates the credit agencies use of these three variables when determining a country's credit rating as well as the results obtained in recent literature on the determinants of credit ratings.

Random effects has been the estimator of choice in recent panel data studies (Rowland and Torres, 2004; Afonso, Gomes and Rother, 2007, Jaramillo 2010) and this is also the case in this thesis. Even though the sample of 106 Moody's rated countries hardly can be considered as a random draw from the entire population of countries, the random effects has proven to be the most effective type of estimator in the context of this essay. This is mainly because the fixed effects estimator and its within property limits the sample from 106 to 12 countries and thus makes the entire study biased. This rationale has been proved by earlier studies as well but plays an even more important role in this essay due to the fact that the study only includes 12 shifting variables and in that sense strips the entire contribution of its meaning. A possible

extension of this study and as a way to mend the fixed effects estimator in this context would be to consider countries that received a certain amount of bailouts, or bailouts from a certain source as defaulted. This would increase the amount of defaulting countries and thus the amount of shifting variables in the fixed effects framework.

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7. Appendix

7.1 Credit Rating Scale

Moodys	S&P	Fitch	
Long-term	Long-term	Long-term	Quality
Aaa	AAA	AAA	Prime
Aa1	AA+	AA+	High grade
Aa2	AA	AA	
Aa3	AA-	AA-	
A1	A+	A+	Upper medium grade
A2	A	A	
A3	A-	A-	
Baa1	BBB+	BBB+	Lower medium grade
Baa2	BBB	BBB	
Baa3	BBB-	BBB-	
Ba1	BB+	BB+	Non investment grade
Ba2	BB	BB	
Ba3	BB-	BB-	
B1	B+	B+	Highly speculative
B2	B	B	
B3	B-	B-	
Caa1	CCC+	CCC	Substantial risks
Caa2	CCC	CCC	Extremely speculative
Caa3	CCC-	CCC	In default with little prospect for recovery
Ca	CC	CCC	
Ca	C	CCC	
C	D	DDD	In Default
/	D	DD	
/	D	D	

7.2 Sovereigns included in the study

Country	Country	Country
Albania	France	Oman
Angola	Georgia	Pakistan
Argentina	Germany	Panama
Armenia	Greece	Papua New Guinea
Australia	Guatemala	Paraguay
Austria	Honduras	Peru
Azerbaijan	Hong Kong SAR	Philippines
The Bahamas	Hungary	Poland
Bahrain	Iceland	Portugal
Bangladesh	India	Qatar
Barbados	Indonesia	Romania
Belarus	Ireland	Russia
Belgium	Israel	Saudi Arabia
Belize	Italy	Singapore
Bolivia	Jamaica	Slovak Republic
Bosnia and Herzegovina	Japan	Slovenia
Botswana	Jordan	South Africa
Brazil	Kazakhstan	Spain
Bulgaria	Korea	Sri Lanka
Cambodia	Kuwait	St. Vincent and the Grenadines
Canada	Latvia	Suriname
Chile	Lebanon	Sweden
China	Lithuania	Switzerland
Colombia	Luxembourg	Taiwan Province of China
Costa Rica	Malaysia	Thailand
Croatia	Malta	Trinidad and Tobago
Cyprus	Mauritius	Tunisia
Czech Republic	Mexico	Ukraine
Denmark	Moldova	United Arab Emirates
Dominican Republic	Mongolia	United Kingdom
Ecuador	Montenegro	United States
Egypt	Morocco	Uruguay
El Salvador	Netherlands	Venezuela
Estonia	New Zealand	Vietnam
Fiji	Nicaragua	
Finland	Norway	

7.3 Defaulted sovereigns 1

Default Date	Country	Total Defaulted Debt ($ millions)	Moody's Rating at Default	Average Trading Price (% of PAR)
Jul 98	Venezuela	270	**Ba2**	*
Aug 98	Russia	72,709	**Caa1**	**18**
Sep 98	Ukraine	1,271	**B3**	**
Jul 99	Pakistan	1,627	**Caa1**	**52**
Aug 99	Ecuador	6,604	**B1**	**44**
Jan 00	Ukraine	1,064	**Caa1**	**69**
Sep 00	Peru	4,870	**Ba3**	**NA**
Nov 01	Argentina	82,268	**Caa3**	**27**
Jun 02	Moldova	145	**Caa1**	**60**
May 03	Uruguay	5,744	**B3**	**66**
Jul 03	Nicaragua	320	**Caa1**	**NA**
Apr 05	Dom. Rep.	1,622	**B3**	**95**
Dec 06	Belize	242	**Caa3**	**76**
Dec 08	Ecuador	3,210	**Caa1**	**28**
Feb 10	Jamaica	7,900	**Caa1**	**90**

7.4 Defaulted sovereigns 2

Default Date	Country	Notes
Jul 98	Venezuela	Missed coupon payment on domestic currency bonds, very small default, cured within a short period of time
Aug 98	Russia	Defaulted on local currency treasury obligations, locally issued foreign currency obligations and principal on foreign currency bonds.
Sep 98	Ukraine	Debt restructuring took place in four stages between in 1998, 1999 and 2000. The main part of the failed bonds were external.
Jul 99	Pakistan	Defaulted on an interest payment in later 1998. Defaulted again in 1999. Resolved through a distressed exchange in 1999.
Aug 99	Ecuador	Missed payment was followed by a distressed exchange. The core of the defaulted debt was in the form of Brady Bonds.
Jan 00	Ukraine	See: Sep. 98
Sep 00	Peru	Missed payment on its Brady Bonds.
Nov 01	Argentina	A very big default. First payment missed in January 2002. Resolved through a distressed exchange with haircuts of approximately 70%.

Jun 02	Moldova	Missed payment in June 2001 and June 2002. The second default occurred despite that Moldova had bought back over 50% of its bonds.
May 03	Uruguay	Contagion from the Argentina crisis led to a currency crisis in Uruguay. Extended maturity on bonds due to restore debt sustainability in the wake of the crisis.
Jul 03	Nicaragua	In July 2003, Nicaragua completed a distressed exchange of CENI bonds (which were initially issued as Central Bank recapitalization bonds in the 2000 banking crisis and which were denominated in US dollars and payable in local currency) held by a few domestic banks.
Apr 05	Dom. Rep.	Missed payment in 2004 but cured it within 30 days. A number of missed payments in 2005 led to a debt exchange resulting in extended maturities on two outstanding foreign currency bonds.
Dec 06	Belize	Distressed exchange of external bonds as a part of a program to set Belize on a more healthy fiscal course.
Dec 08	Ecuador	Ecuador announced on ideological and political

		grounds that they would not honor their payments on 2012 and 2030 global bond because they found these to be "illegal". The default occurred in a period of relative macroeconomic strength.
Feb 10	Jamaica	Debt exchange for Jamaica's entire stock marketable domestic debt resulting in a NPV loss of approximately 20%.

7.5 Descriptive statistics

GDPpercapita

	Percentiles	Smallest		
1%	5.484091	2.901092		
5%	6.098086	3.309155		
10%	6.584497	3.429914	Obs	2694
25%	7.389889	3.543565	Sum of Wgt.	2694
50%	8.430259		Mean	8.458126
		Largest	Std. Dev.	1.420383
75%	9.660848	11.57713		
90%	10.28412	11.5815	Variance	2.017487
95%	10.56198	11.59866	Skewness	-.193928
99%	10.97478	11.69136	Kurtosis	2.323778

GDPgrowth

	Percentiles	Smallest		
1%	-12.58	-42.195		
5%	-4.1	-41.008		
10%	-1.314	-30.9	Obs	2752
25%	1.6345	-28.209	Sum of Wgt.	2752
50%	3.866		Mean	3.664766
		Largest	Std. Dev.	5.211783
75%	6.01	34.5		
90%	8.645	38.2	Variance	27.16268
95%	10.415	44.479	Skewness	-.393829
99%	16.729	50.688	Kurtosis	16.41372

Inflation

	Percentiles	Smallest		
1%	-.9100581	-1		
5%	-.0077897	-.9999999		
10%	.0058196	-.9999998	Obs	2767
25%	.0204082	-.9999975	Sum of Wgt.	2767
50%	.0444496		Mean	.5326856
		Largest	Std. Dev.	4.439119
75%	.1004366	70.83334		
90%	.2660654	70.83334	Variance	19.70577
95%	.6890122	74.26923	Skewness	14.98409
99%	13.79476	117.2788	Kurtosis	283.5186

Externaldebt

	Percentiles	Smallest		
1%	0	0		
5%	0	0		
10%	0	0	Obs	2728
25%	0	0	Sum of Wgt.	2728
50%	.0175256		Mean	.0976452
		Largest	Std. Dev.	.1400862
75%	.1635269	.8669469		
90%	.302962	.9507142	Variance	.0196241
95%	.3686348	1.201855	Skewness	2.105132
99%	.5446612	1.52267	Kurtosis	10.99188

7.6 Wooldridge test for autocorrelation in panel data

Method 1

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,     105) =      0.207
           Prob > F =      0.6497
```

Method 2

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,     105) =      0.191
           Prob > F =      0.6630
```

Method 3

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,     105) =      0.202
           Prob > F =      0.6542
```

7.7 Hausman-test

Method 1

	Coefficients (b) FE1	(B) RE1	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
GDPpercapita	-.4155409	-.5171896	.1016487	.4918962
GDPgrowth	-.0978061	-.099686	.0018799	.0285987
Inflation	-1.048085	-.4904052	-.5576802	.3738719
Externaldebt	.2897944	3.293609	-3.003815	1.831925

b = consistent under Ho and Ha; obtained from xtlogit
B = inconsistent under Ha, efficient under Ho; obtained from xtlogit

Test: Ho: difference in coefficients not systematic

chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 5.02
Prob>chi2 = 0.2848

Method 2

	Coefficients (b) FE2	(B) RE2	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
GDPpercapita	-1.050532	-.7583295	-.2922029	.5896254
GDPgrowth	-.090197	-.0992513	.0090542	.024115
Inflation	-1.091909	-.6311056	-.460803	.3027238
Externaldebt	1.006772	3.331139	-2.324367	1.757735

b = consistent under Ho and Ha; obtained from xtlogit
B = inconsistent under Ha, efficient under Ho; obtained from xtlogit

Test: Ho: difference in coefficients not systematic

chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 6.63
Prob>chi2 = 0.1568

Method 3

	Coefficients (b) Fixed_Effe~s	(B) Random_Eff~s	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
GDPpercapita	-.3251128	-.6495073	.3243944	.2496027
GDPgrowth	-.0750333	-.0735378	-.0014955	.0072462
Inflation	-.7798192	-.673675	-.1061442	.1418904
Externaldebt	1.670192	3.190527	-1.520335	.4181177

b = consistent under Ho and Ha; obtained from xtlogit
B = inconsistent under Ha, efficient under Ho; obtained from xtlogit

Test: Ho: difference in coefficients not systematic

chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 24.73
Prob>chi2 = 0.0001

7.8 Fixed effects regression

Method 1, coefficients

```
Conditional fixed-effects logistic regression   Number of obs      =       295
Group variable: iid                             Number of groups   =        12

                                                Obs per group: min =        17
                                                               avg =      24.6
                                                               max =        28

                                                LR chi2(4)         =      6.89
Log likelihood  = -41.028026                    Prob > chi2        =    0.1417
```

Indefault	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	-.4155409	.5578475	-0.74	0.456	-1.508902	.6778202
GDPgrowth	-.0978061	.0487984	-2.00	0.045	-.1934491	-.0021631
Inflation	-1.048085	.6397768	-1.64	0.101	-2.302025	.205854
Externaldebt	.2897944	2.363251	0.12	0.902	-4.342093	4.921682

Method 1, odds ratios

```
Conditional fixed-effects logistic regression   Number of obs      =       295
Group variable: iid                             Number of groups   =        12

                                                Obs per group: min =        17
                                                               avg =      24.6
                                                               max =        28

                                                LR chi2(4)         =      6.89
Log likelihood  = -41.028026                    Prob > chi2        =    0.1417
```

Indefault	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	.6599832	.36817	-0.74	0.456	.2211527	1.96958
GDPgrowth	.9068247	.0442516	-2.00	0.045	.8241118	.9978392
Inflation	.3506084	.2243111	-1.64	0.101	.100056	1.228574
Externaldebt	1.336153	3.157665	0.12	0.902	.0130093	137.2332

Method 2, coefficients

```
Conditional fixed-effects logistic regression   Number of obs      =       211
Group variable: iid                             Number of groups   =         9

                                                Obs per group: min =        17
                                                               avg =      23.4
                                                               max =        28

                                                LR chi2(4)         =      7.94
Log likelihood  = -30.505608                    Prob > chi2        =    0.0937
```

Indefault	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	-1.050532	.6833893	-1.54	0.124	-2.389951	.2888859
GDPgrowth	-.090197	.0521483	-1.73	0.084	-.1924059	.0120118
Inflation	-1.091909	.6691801	-1.63	0.103	-2.403477	.2196601
Externaldebt	1.006772	2.512037	0.40	0.689	-3.916731	5.930275

Method 2, odds ratios

```
Conditional fixed-effects logistic regression   Number of obs      =        211
Group variable: iid                             Number of groups   =          9

                                                Obs per group: min =         17
                                                               avg =       23.4
                                                               max =         28

                                                LR chi2(4)         =       7.94
Log likelihood  = -30.505608                    Prob > chi2        =     0.0937
```

Indefault	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	.3497515	.2390164	-1.54	0.124	.0916342	1.334939
GDPgrowth	.9137511	.0476506	-1.73	0.084	.824972	1.012084
Inflation	.3355754	.2245604	-1.63	0.103	.090403	1.245653
Externaldebt	2.736752	6.874823	0.40	0.689	.0199061	376.2578

Method 3, coefficients

```
Conditional fixed-effects logistic regression   Number of obs      =        295
Group variable: iid                             Number of groups   =         12

                                                Obs per group: min =         17
                                                               avg =       24.6
                                                               max =         28

                                                LR chi2(4)         =      10.44
Log likelihood  = -88.910829                    Prob > chi2        =     0.0337
```

Indefault	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	-.3285099	.3813884	-0.86	0.389	-1.076017	.4189976
GDPgrowth	-.0721263	.0341186	-2.11	0.035	-.1389977	-.005255
Inflation	-.7786165	.4269349	-1.82	0.068	-1.615394	.0581605
Externaldebt	1.332361	1.464207	0.91	0.363	-1.537433	4.202154

Method 3, odds ratios

```
Conditional fixed-effects logistic regression   Number of obs      =        295
Group variable: iid                             Number of groups   =         12

                                                Obs per group: min =         17
                                                               avg =       24.6
                                                               max =         28

                                                LR chi2(4)         =      10.44
Log likelihood  = -88.910829                    Prob > chi2        =     0.0337
```

Indefault	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	.7199958	.274598	-0.86	0.389	.3409507	1.520437
GDPgrowth	.9304133	.0317444	-2.11	0.035	.8702301	.9947588
Inflation	.4590406	.1959805	-1.82	0.068	.1988124	1.059885
Externaldebt	3.789981	5.549318	0.91	0.363	.2149322	66.83016

7.9 Random effects regression

Method 1, coefficients

```
Random-effects logistic regression              Number of obs      =      2572
Group variable: iid                             Number of groups   =       106

Random effects u_i ~ Gaussian                   Obs per group: min =         4
                                                               avg =      24.3
                                                               max =        28

                                                Wald chi2(4)       =     16.65
Log likelihood  =  -81.40608                    Prob > chi2        =    0.0023
```

Indefault	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	-.5171896	.2631198	-1.97	0.049	-1.032895	-.0014842
GDPgrowth	-.099686	.0395398	-2.52	0.012	-.1771826	-.0221894
Inflation	-.4904052	.5191668	-0.94	0.345	-1.507953	.527143
Externaldebt	3.293609	1.492986	2.21	0.027	.3674114	6.219808
_cons	-1.734635	2.104909	-0.82	0.410	-5.860181	2.390912
/lnsig2u	.0706223	.8871034			-1.668068	1.809313
sigma_u	1.035942	.4594939			.4342937	2.471083
rho	.2459695	.1645298			.0542223	.6498695

Likelihood-ratio test of rho=0: chibar2(01) = 2.11 Prob >= chibar2 = 0.073

Method 1, odds ratios

```
Random-effects logistic regression              Number of obs      =      2572
Group variable: iid                             Number of groups   =       106

Random effects u_i ~ Gaussian                   Obs per group: min =         4
                                                               avg =      24.3
                                                               max =        28

                                                LR chi2(4)         =     16.55
Log likelihood  =  -81.40608                    Prob > chi2        =    0.0024
```

Indefault	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	.5961937	.1568704	-1.97	0.049	.3559749	.9985169
GDPgrowth	.9051216	.0357883	-2.52	0.012	.8376268	.978055
Inflation	.6123782	.3179264	-0.94	0.345	.2213626	1.694085
Externaldebt	26.93993	40.22092	2.21	0.027	1.443992	502.6065
/lnsig2u	.0706223	.8871034			-1.668068	1.809313
sigma_u	1.035942	.4594939			.4342937	2.471083
rho	.2459695	.1645298			.0542223	.6498695

Likelihood-ratio test of rho=0: chibar2(01) = 2.11 Prob >= chibar2 = 0.073

Method 2, coefficients

```
Random-effects logistic regression              Number of obs      =      2572
Group variable: iid                             Number of groups   =       106

Random effects u_i ~ Gaussian                   Obs per group: min =         4
                                                               avg =      24.3
                                                               max =        28

                                                Wald chi2(4)       =     13.51
Log likelihood  = -64.828973                    Prob > chi2        =    0.0090
```

Indefault	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	-.7583295	.3454891	-2.19	0.028	-1.435476	-.0811833
GDPgrowth	-.0992513	.0462376	-2.15	0.032	-.1898752	-.0086273
Inflation	-.6311056	.5967916	-1.06	0.290	-1.800796	.5385844
Externaldebt	3.331139	1.79463	1.86	0.063	-.1862715	6.84855
_cons	-.5934795	2.585699	-0.23	0.818	-5.661356	4.474397
/lnsig2u	.7394883	.7765187			-.7824603	2.261437
sigma_u	1.447364	.5619527			.6762245	3.097882
rho	.3890377	.1845687			.122034	.744709

Likelihood-ratio test of rho=0: chibar2(01) = 4.42 Prob >= chibar2 = 0.018

Method 2, odds ratios

```
Random-effects logistic regression              Number of obs      =      2572
Group variable: iid                             Number of groups   =       106

Random effects u_i ~ Gaussian                   Obs per group: min =         4
                                                               avg =      24.3
                                                               max =        28

                                                LR chi2(4)         =     15.64
Log likelihood  = -64.828973                    Prob > chi2        =    0.0035
```

Indefault	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	.4684483	.1618438	-2.19	0.028	.2380021	.9220246
GDPgrowth	.9055152	.0418688	-2.15	0.032	.8270623	.9914098
Inflation	.5320033	.3174951	-1.06	0.290	.1651674	1.713579
Externaldebt	27.97019	50.19615	1.86	0.063	.8300482	942.5133
/lnsig2u	.7394883	.7765187			-.7824603	2.261437
sigma_u	1.447364	.5619527			.6762245	3.097882
rho	.3890377	.1845687			.122034	.744709

Likelihood-ratio test of rho=0: chibar2(01) = 4.42 Prob >= chibar2 = 0.018

Method 3, coefficients

```
Random-effects logistic regression              Number of obs      =      2572
Group variable: iid                             Number of groups   =       106

Random effects u_i ~ Gaussian                   Obs per group: min =         4
                                                               avg =      24.3
                                                               max =        28

                                                Wald chi2(4)       =     16.92
Log likelihood  = -152.62746                    Prob > chi2        =    0.0020
```

Indefault	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	-.5970185	.2924553	-2.04	0.041	-1.17022	-.0238166
GDPgrowth	-.073228	.0336856	-2.17	0.030	-.1392506	-.0072054
Inflation	-.669079	.4056331	-1.65	0.099	-1.464105	.1259473
Externaldebt	3.070402	1.393647	2.20	0.028	.3389036	5.801901
_cons	-2.209323	2.411085	-0.92	0.359	-6.934963	2.516318
/lnsig2u	1.944322	.5979263			.7724078	3.116236
sigma_u	2.643651	.7903543			1.471385	4.749873
rho	.6799353	.1301227			.3968902	.8727381

Likelihood-ratio test of rho=0: chibar2(01) = 53.03 Prob >= chibar2 = 0.000

Method 3, odds ratios

```
Random-effects logistic regression              Number of obs      =      2572
Group variable: iid                             Number of groups   =       106

Random effects u_i ~ Gaussian                   Obs per group: min =         4
                                                               avg =      24.3
                                                               max =        28

                                                LR chi2(4)         =     17.29
Log likelihood  = -152.62746                    Prob > chi2        =    0.0017
```

Indefault	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GDPpercapita	.5504503	.1609821	-2.04	0.041	.3102985	.9764647
GDPgrowth	.9293889	.031307	-2.17	0.030	.87001	.9928205
Inflation	.5121801	.2077572	-1.65	0.099	.2312848	1.134222
Externaldebt	21.55057	30.0339	2.20	0.028	1.403408	330.9282
/lnsig2u	1.944322	.5979263			.7724078	3.116236
sigma_u	2.643651	.7903543			1.471385	4.749873
rho	.6799353	.1301227			.3968902	.8727381

Likelihood-ratio test of rho=0: chibar2(01) = 53.03 Prob >= chibar2 = 0.000

7.10 Encountered problems

I did not find a suitable test for heteroscedasticity. The usual STATA tests for models estimated with fixed and random effects works when estimated with the command xtreg but not when the dependent variable is binary.