Are the Credit Rating Agencies Biased Against MENA Countries?

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Abstract

We investigate the claims on regional biases in the sovereign credit ratings assigned by Fitch Ratings, Moody's and Standard & Poor's credit rating agencies (CRAs) for a group of 99 countries by using a series of econometric models that consider a wide range of macroeconomic, financial, institutional, regional and geopolitical indicators. Our empirical results based on the seemingly unrelated regressions (SUR) estimates indicate a strong home country bias towards the United States while there seems to be no special biases against individual group of countries such as the Middle East and North Africa (MENA) countries. We also demonstrate how modeling errors in the form of omitted variables can easily cause misleading results portraying the CRAs as biased towards or against different country groups.

Keywords: Sovereign ratings, Credit-rating agencies, credit risk, seemingly unrelated regressions

1 Introduction

Thanks to the globalized financial markets, sovereign credit ratings have increasingly become a crucial metric for determining the terms of a country's access to international capital sources. When ratings

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provide sufficient information, they help investors in making reliable risk assessments. They also benefit governments, savers, intermediaries as well as regulatory bodies by increasing transparency and improving the efficiency of the allocation of financial resources. Credit ratings are especially important for developing countries, which usually rely on external resources to finance their investments. Because many international funds have mandates requiring an investment grade rating before permitting allocations, a favorable credit rating increases the capability of a developing country to access the foreign capital it needs. An unfavorable rating, on the other hand, can not only impede growth, but also damage economic and political stability by increasing the cost of borrowing.[1]

As is well known, currently there are three leading credit rating agencies (CRAs) that provide sovereign credit ratings. These are Fitch Ratings, Moody's, and Standard and Poor's (S&P). Due to the increased importance of credit ratings, these agencies have become a target for criticisms concerning conflicts of interest, lack of transparency, and erroneous ratings especially prior to financial crises. In fact, it has become commonplace to suggest that sovereign credit ratings do not always reflect the economic fundamentals in a realistic and sufficient manner. Accordingly, allegations of biased credit ratings towards certain countries have come to the forefront in recent discussions. Especially bureaucrats and politicians from the developing countries have been vocal about their disapproval of the rating agencies. European Commission President (Reuters, 2011), Russia Finance Minister (The Telegraph, 2015), China Finance Minister (Bloomberg, 2016), Turkish President (Reuters, 2016), India's chief economic advisor (The Times of India, 2017) have all alleged that the CRAs were biased against their home countries.

The claims on unfair decisions attract attention in the academic literature as well. However, there are currently only a few papers investigating the potential biases in sovereign credit ratings. These include Reinhart (2002), who examines data on 40 countries for the period 1979-1999 and concludes that, following a currency or banking crisis, CRAs downgrade an emerging economy with greater severity. Gultekin-Karakas et al. (2011) employ an ordered probit model and report that CRAs treat developing countries differently and give higher credit ratings to developed countries. Erdem and

[1] Brooks et al. (2004) shows that rating downgrades have a negative impact on domestic stock market, market returns, and the dollar value of the domestic currency. In a recent study, Hanusch et al. (2016) finds that a downgrade to sub-investment grade raises the treasury bill yield on a country's short-term bonds by an average of 1.38 percentage points. This presents a considerable increase in the cost of borrowing for many developing countries.

Varli (2014) analyze the determinants of the sovereign credit ratings of emerging markets and conclude that S&P's credit rating for Turkey was lower than their estimates. Ozturk (2014), on the other hand, argues that the apparently biased behavior of CRAs can be attributable to the ignorance of institutional factors in the empirical analyses, suggesting that improved quality of institutions would greatly stimulate higher credit ratings. In a recent study, using data from nine agencies, Fuchs and Gehring (2017) investigate empirically if there is systematic evidence for a home bias in sovereign credit ratings. They conclude that CRAs assign higher ratings not only to their respective home countries but also to those countries which are economically, geopolitically, and culturally aligned with them.

In this paper, we aim to contribute to the rather scarce literature on the issue of objectivity of sovereign credit ratings by examining whether the three major credit rating agencies are biased towards or against certain countries or regional groups. For this purpose, we perform a comprehensive econometric analysis of the determinants of sovereign credit ratings assigned to 99 countries by Fitch, Moody's, and S&P. Our paper differs from earlier research in the following ways. First, we evaluate the ratings for eight different country groups plus the U.S. to see if the CRAs can be considered as regionally biased. More specifically, we focus on the Middle East and North Africa (MENA) countries. A striking observation on the sovereign credit ratings is that no Muslim majority country has a triple A score despite the fact that there exists several good candidates such as Kuwait, UAE, and Qatar. We also see countries such as Turkey and Egypt, which consistently receive ratings that are substantially lower than various similar countries in other regions. Hence, we want to empirically examine whether the credit ratings given to these countries are justified solely by economic fundamentals. In addition to regional biases, we also investigate whether there is a "home bias" effect. Recently, it has been argued by Fuchs and Gehring (2017) that the CRAs give higher ratings to their home countries. We revisit this hypothesis within a more extensive empirical framework. Third, most of the aforementioned studies in the literature consider the ratings given by one CRA. Nevertheless, the analysis of credit ratings in terms of inter-institutional consistency is also important. Last but not least, unlike any earlier research, we apply the seemingly unrelated regressions (SUR) method in our study. The SUR approach is particularly useful for this kind of analysis because it takes into account cross-firm correlations in disturbances, thereby providing substantially more efficient estimates.

Our paper is related with the literature on the determinants of credit ratings as well. Over the last 20 years, the growing size and importance of global credit markets have triggered a number of studies which assess the determinants of sovereign credit ratings. These include Cantor and Packer (1996), Afonso (2003), Bissoondoyal-Bheenick (2005), Bissoondoyal-Bheenick et al. (2006), Afonso et al. (2011), and Chee et al. (2015) among others. Such studies employ both regression as well as case-based methods and provide varying results regarding the impact and significance of different macroeconomic variables on credit ratings. The current paper also builds on this literature by appraising a large variety of factors affecting sovereign credit ratings.

The paper proceeds as follows: Section 2 provides a brief review of sovereign credit rating systems. Section 3 introduces our empirical methodology and the data set. This is followed by Section 4, which presents the estimation results. The final Section 5 discusses policy implications, and concludes.

2 Sovereign Credit Rating Systems

In this study we focus on the three leading CRAs namely Fitch, Moody's, and S&P. These agencies attempt to measure the probability of a default and assign credit scores while also reporting medium term outlooks and forecasts for a large number of sovereign countries. They have a dominant status in the global market thanks to being accepted by the Securities and Exchange Commission as the three nationally recognized rating organizations in the U.S.

In the process of assigning and monitoring sovereign creditworthiness, the CRAs perform various analyses and estimations based on data provided by various national statistical sources in the U.S. as well as international sources. A general discussion of their methodology as well as the indicators used are provided in their respective publications namely Fitch (2017); Moody's (2017a); S&P (2008). These indicators include a large number of quantitative variables such as GDP per capita, external debt, and default history as well as different qualitative variables such as government transparency or institutional quality. After determining which variables to include, the CRAs assign specific weights to each indicator and represent credit ratings on a letter scale ranging from A to D. The highest grade by Fitch, Moody's, and S&P are AAA, Aaa, and AAA in that order, which is given to countries with

the lowest credit risk. As the risk of defult increases, a country receives a lower credit rating such as B and C. Their lowest scores are D, C, and D respectively, which is assigned to countries already in default of some or all of their debt obligations. Although there are slight differences in terms of the correspondence of letters, the methodology used by the three agencies is ultimately the same.

Recently, the above methodology is often criticized on two grounds: First, it is argued that the rating process is not transparent because the CRAs do not give details regarding how they assign specific weights to different indicators (Ozturk, 2014; Bhogal, 2017). Second, some authors suggest that the ratings may be based on the judgments and perceptions of the analysts toward certain countries, which make the nature of these ratings highly subjective (Bhogal, 2017). Because there are numerous factors influencing sovereign credit ratings, it is important to examine the ones that specifically play an important role. As a result, a series of papers have emerged in the literature assessing the determinants of sovereign credit ratings.

Cantor and Packer (1996) is one of the first studies investigating the importance of determinants of sovereign credit ratings. Based on the ratings by Moody's and S&P for 49 developed and developing countries, they find that per capita income, GDP growth, inflation, external debt, level of economic development, and default history are the main variables affecting sovereign credit ratings. Using data from 81 developed and developing countries, Afonso (2003) suggests that sovereign credit ratings can be explained by GDP per capita, external debt-to-exports ratio, level of economic development, default history, real growth rate, and inflation rate. He also argues that factors affecting the credit ratings are different for developed and developing countries. For developed countries, credit ratings can be explained to a large extent by GDP per capita, while external debt is more important for developing countries. Similar to these studies, Rowland (2004) finds that GDP per capita, growth rate, inflation rate, external-debt ratios, debt-service ratios, level of international reserves, and the openness of the economy are the main factors of sovereign credit ratings. Afonso et al. (2011) distinguish between the short run and long run effects of macroeconomic variables on sovereign credit ratings. They find that GDP per capita, GDP growth, and government debt are important in the short run; while government effectiveness, external debt, foreign reserves, and default history have an impact in the long run. Bissoondoyal-Bheenick (2005) undertakes an extensive analysis considering 95 developed and developing countries using an ordered response model and concludes that the economic

variables explaining the sovereign credit ratings vary across CRAs. Later studies consider additional variables to explain the determinants of sovereign credit ratings such as technological development (Bissoondoyal-Bheenick et al., 2006), the role democratic institutions (Beaulieu et al., 2012), country's rule of law and judicial independence (Biglaiser and Staats, 2012) as well as political factors (Block and Vaaler, 2004; Archer et al., 2007; Biglaiser and Staats, 2012).

Based on this background, we turn to our analysis of the determinants as well as the question of regional biases regarding sovereign credit ratings.

3 Methodology and Data

Our empirical methodology is based on the seemingly unrelated regression (SUR) estimation developed by Zellner (1962). SUR is a panel data technique which is used to estimate a system of equations where, even though the equations seem independent, they are actually related through correlations in the errors. This contemporaneous correlation allows a joint estimation procedure which takes into account the unobserved factors linked in the systems error structure. More specifically, we employ the following system of equations:

$$\begin{aligned} R_{fi} &= \beta_{0f} + \sum_{k=1}^{K} \beta_{kf} X_{kfi} + \epsilon_{fi} \\ R_{mi} &= \beta_{0m} + \sum_{k=1}^{K} \beta_{km} X_{kmi} + \epsilon_{mi} \\ R_{si} &= \beta_{0s} + \sum_{k=1}^{K} \beta_{ks} X_{ksi} + \epsilon_{si} \end{aligned} \tag{1}$$

Here, the dependent variable R refers to the credit ratings given by the three CRAs for country i. The subscripts f, m, and s denote Fitch, Moody's, and S&P respectively. Also, X is a $K \times 1$ vector of macroeconomic, financial, institutional, regional, and geopolitical variables affecting sovereign credit ratings. Finally, β are coefficients to be estimated, and ϵ are the error terms.

In our analysis, the assumption that ϵ_{fi}, ϵ_{mi}, and ϵ_{si}, are linked can be explained with the influence of many factors that have to be omitted from the equations due to lack of data or multicollinearity concerns. Since the three CRAs employ similar rating methodologies, the effects of omitted factors

on credit ratings are also expected to be similar. In this case, the error terms capturing such factors will be correlated. Hence, the motivations for the use of the SUR method in our analysis of sovereign credit ratings are twofold: First, this approach allows estimating multiple models simultaneously while considering the unobservable country-specific or cross-country correlations in the credit ratings. Second, it provides more efficient coefficient estimates thanks to the cognizance of such correlations.

Our dataset includes the credit rating scores of 99 countries assigned by Fitch, Moody's, and S&P. The ratings data are obtained from the individual CRAs, current as of September 2017. The alphanumeric credit ratings used by the agencies are linearly transformed into numeric scores on 17 and 21 point scales following the literature (Afonso et al., 2007; Fuchs and Gehring, 2017). Table 1 presents the alphabetic ratings used by three CRAs along with their characterizations as well as the corresponding numerical transformations.

Table 1: Fitch, Moody's and S&P Ratings and Linear Transformations

Characterization	**Rating**			**Transformation**	
	Fitch	**Moody's**	**S&P**	**Linear21**	**Linear17**
Highest quality	AAA	Aaa	AAA	21	17
High quality	AA+	Aa1	AA+	20	16
	AA	Aa2	AA	19	15
	AA-	Aa3	AA-	18	14
Strong payment capacity	A+	A1	A+	17	13
	A	A2	A	16	12
	A-	A3	A-	15	11
Adequate payment capacity	BBB+	Baa1	BBB+	14	10
	BBB	Baa2	BBB	13	9
	BBB-	Baa3	BBB-	12	8
Likely to fulfil obligations with ongoing uncertainty	BB+	Ba1	BB+	11	7
	BB	Ba2	BB	10	6
	BB-	Ba3	BB-	9	5
High credit risk	B+	B1	B+	8	4
	B	B2	B	7	3
	B-	B3	B-	6	2
Very high credit risk	CCC+	Caa1	CCC+	5	
	CCC	Caa2	CCC	4	
	CCC-	Caa3	CCC-	3	
Near default with recovery possibility	CC	Ca	CC	2	1
	C				
In default	DDD	C	D		
	DD			1	
	D				

As for the vector of dependent variables explanatory of sovereign credit ratings, we consider a wide range of macroeconomic, financial, institutional, regional and geopolitical indicators categorized into six groups of variables as follows:

The first group of variables we include in our analysis is a series of macroeconomic ratios. First, *budget balance to GDP ratio* is expected to be inversely related with the ratings because with an increasing financial deficit the government will be more susceptible to borrowing, or increase taxes. Second, *government debt to GDP ratio* is an important factor negatively affecting credit ratings because the higher the stock of outstanding government debt, the higher will be the interest burden. Third, *current account balance to GDP* ratio is usually expected to decrease the credit ratings of a country as well. As the current account deficit rises, it can become more difficult to finance, leading to questions in terms of its sustainability. However, it is also pointed out in the literature that a large current account deficit can reflect a rapid accumulation of fixed investments, leading to a higher growth rate and improved sustainability over the medium term (Afonso et al., 2007). Fourth, *GDP per capita* is expected to positively affect the credit rating of a country because as the potential tax base increases, the ability of a government to repay its debt also improves. Fifth, the rate of *unemployment* is negatively associated with credit ratings because it causes a fiscal burden on the government. Sixth, the *inflation* rate can have a positive or negative effect on credit ratings. While an increase in inflation reduces the real stock of outstanding government debt in domestic currency, it can also indicate structural problems in the economy. Furthermore, public dissatisfaction with inflation may lead to political instability (Cantor and Packer, 1996). Finally, an increase in the *exchange rate* and the *interest rate*, due to being indicators of deteriorating economic conditions, are expected to be negatively related with sovereign credit ratings as well. All of these variables are obtained from Trading Economics (2017), which provides up to date official data on a large number of relevant indicators, helping us to avoid a smaller sample constructed from varied sources. In addition to the above macroeconomic variables, we include a dummy variable for *G20 countries* to control the effect of overall economic power on credit ratings. We also use a dummy variable for *fuel exporting countries*, based on classifications by the United Nations (2017), in order to account for the improved debt payment capacity that it provides.

It is emphasized in the literature that countries with excessive debt and default history are per-

ceived as high-risk. As a result, in the second group of variables we allow for these two factors. First, in order to control for excessive debt, we employ a dummy variable for *heavily indebted countries* reported by United Nations (2017) Second, to take into account default history, we construct a dummy variable showing those countries that have *defaulted in 10 years*, based on data from Moody's (2017b).

As the third group of variables, we consider governance and institutional quality. Existing literature discussed earlier suggests that the improvements in the institutional quality of a country is associated with higher ratings. Hence, we employ the institutional development indicators based on Kaufmann et al. (1999), and are obtained from World Bank (2017). This measure includes a set of institutional quality variables in six broad groups namely accountability, political stability government effectiveness, regulatory quality, rule of law, and corruption control. We consider all of these six measures as well as their averages after normalizing them to the $[0, 10]$ range. However, due to the high degree of collinearity between these variables, we only report the results using the *government effectiveness* measure. This indicator is prefered in previous studies such as Afonso et al. (2007) and Ozturk (2014) for being more relevant to sovereign credit ratings thanks to providing a joint measure for the credibility of government's commitments to policies, the quality of bureaucracy, and the independence of civil servants from political pressures. It was found to provide a better goodness-of-fit in our models as well.

As a fourth group of variables, we take into account national conflict risk and intensity. In the recent years it has been argued that, in addition to economic conditions, the level of peace and security is also important in sovereign credit worthiness. If a country is open to the risk of humanitarian crisis or internal conflicts, it has to take measures to avoid or to cope with these problems. This in turn can lead to a deterioration of economic fundamentals, impeding growth and development efforts. The importance of civil disorders and internal conflict is pointed out in the various announcements and press releases of the CRAs as well.[2] However, this issue is usually neglected in the previous literature dealing with the determinants of sovereign credit ratings. To control for these effects, we consider the *national conflict intensity* measure provided by InfoRM (2017), which is a collaborative project of the

[2]For example, after the assassination of Benazir Butto in Pakistan, S&P announced that Pakistan's sovereign credit rating could be lowered because of political instability (Reuters, 2007).

Inter Agency Standing Committee (IASC) formed by various UN and nonUN humanitarian partners. A lower value (closer to 0) represents a lower risk and a higher value (closer to 10) represents a higher risk in this data set.

Our fifth group of variables is regarding the testing of a U.S. home bias effect. It has been documented in the literature that the CRAs depend on their home governments. One reason for this compliancy is that the European Union or the U.S. officially recognize only the ratings of certain CRAs to determine the companies' capital requirements (White, 2010). Furthermore, agency employees can also be reluctant to downgrade the home country if they believe that this decision would have a detrimental impact on their home country (Fuchs and Gehring, 2017). Therefore, to test for the home bias suggested in the literature, we consider three additional variables. First, we use a dummy variable for the *home country*. Following Fuchs and Gehring (2017), we define an agency's home country as the country in which the headquarters of the agency is physically located. Because all three CRAs in our study are located in the U.S., our dummy variable takes the value of one for the U.S., and zero for the rest of the countries. If a home bias is present, the countries which have close economic or military ties with the US can be expected to receive higher ratings as well. To identify which countries have closer economic relations with the U.S., we include *U.S. trade share*, showings the percentage of the country in the U.S. foreign trade (Census Bureau, 2017). In order to control for the military interests of the U.S., we also include the dummy variable *U.S. military presence* which indicates the countries with active U.S. military personnel deployed (Defense Manpower Data Center, 2017).

The sixth group of variables involves a series of dummy variables for our testing for the existence of regional biases in the credit ratings. Specifically, we consider eight country groups namely pre-2004 European Union countries (*EU 15*), the *rest of Europe*, *transition economies* as well as countries in the *MENA* region, *Latin America*, *sub-Sahara* in Africa, *Central and South Asia*, and the *Pacific Region*. These country groups, which are based on (United Nations, 2017), are shown in Table 2.

Finally, in addition to the above variables, we take into account a variety alternative variables in order to check for the robustness of the results. These include credit rating scores transformed into the 17 point scale instead of 21, as shown in Table 1. As for the explanatory variables, we consider dummy variables for OPEC member countries, NATO member countries, eurozone countries as well

Table 2: Country Groups

Home Country	**Pacific Region**	**EU 15**	**Rest of Europe**
United States	Australia	Austria	Bulgaria
	Canada	Belgium	Croatia
Latin America	China	Denmark	Cyprus
Argentina	Hong Kong	Finland	Czech Republic
Bolivia	Indonesia	France	Estonia
Brazil	Japan	Germany	Hungary
Chile	South Korea	Greece	Iceland
Colombia	Malaysia	Ireland	Latvia
Costa Rica	New Zealand	Italy	Lithuania
Ecuador	Philippines	Luxembourg	Malta
El Salvador	Singapore	Netherlands	Norway
Guatemala	Thailand	Portugal	Poland
Jamaica	Vietnam	Spain	Romania
Mexico		Sweden	Slovak Republic
Panama		United Kingdom	Slovenia
Paraguay	**MENA**		Switzerland
Peru	Bahrain	**Sub-Sahara**	
Suriname	Egypt	Angola	
Uruguay	Iraq	Cameroon	
Venezuela	Israel	Congo, Rep.	
	Kuwait	Ethiopia	**Transition**
	Lebanon	Ghana	**Economies**
Central and	Morocco	Kenya	Azerbaijan
South Asia	Oman	Mozambique	Belarus
Bangladesh	Qatar	Nigeria	Georgia
India	Saudi Arabia	Rwanda	Kazakhstan
Mongolia	Tunisia	South Africa	Russia
Pakistan	Turkey	Uganda	Serbia
Sri Lanka	UAE	Zambia	Ukraine

as landlocked countries and small island countries. Furthermore, for default history, we substitute dummy variables showing defaults in the past 5 years, and past 15 years. Again, for national conflict risk and intensity we also consider internal conflict score, and human hazard score by InfoRM (2017) as well as the Global Peace Index by Institute for Economics and Peace (2017). Due to multicollinearity concerns, all of these variables can only be used interchangeably with the other similar variables discussed earlier. Because they provide similar empirical findings often with a slightly lower goodness-of-fit, we choose to report the results with the former sets of variables in order to conserve space. Table 3 provides the summary statistics on the primary variables in our empirical analysis.

Table 3: Summary Statistics

Variable	Mean	Std.Dev.	Median	Minimum	Maximum
Fitch21	12.7071	5.2416	12.0000	2.0000	21.0000
Moodys21	12.6061	5.4207	12.0000	3.0000	21.0000
SP21	12.6768	5.3181	12.0000	1.0000	21.0000
Budget to GDP ratio	−3.4516	4.4692	−2.6000	−20.8000	4.8000
Debt to GDP ratio	58.2529	37.6697	47.9000	9.5000	250.4000
CA to GDP ratio	−1.4969	7.2078	−1.3000	−37.9000	19.0000
GDP per capita	20.7578	22.2232	11.0282	0.5112	111.0010
Unemployment	7.6632	5.1850	6.2000	0.1000	27.7000
Inflation	11.7403	74.2445	2.4000	−0.5000	741.0000
Exchange rate	615.1760	2730.4100	7.3400	0.3000	22717.0000
Interest rate	4.8504	6.0110	2.9500	−0.7500	27.7500
Gov. effectiveness	6.0048	2.0187	5.6662	2.1629	10.0000
National conflict	0.0909	0.6403	0.0000	0.0000	5.0000
Heavily indebted	0.0909	0.2889	0.0000	0.0000	1.0000
Defaulted in 10 years	0.0707	0.2576	0.0000	0.0000	1.0000
G20 country	0.4343	0.4982	0.0000	0.0000	1.0000
Fuel exporting country	0.2020	0.4036	0.0000	0.0000	1.0000
EU 15	0.1515	0.3604	0.0000	0.0000	1.0000
Rest of Europe	0.1616	0.3700	0.0000	0.0000	1.0000
Transition economies	0.0707	0.2576	0.0000	0.0000	1.0000
MENA	0.1313	0.3395	0.0000	0.0000	1.0000
Latin America	0.1717	0.3791	0.0000	0.0000	1.0000
Sub-Sahara	0.1212	0.3280	0.0000	0.0000	1.0000
Central and South Asia	0.0505	0.2201	0.0000	0.0000	1.0000
Pacific Region	0.1313	0.3395	0.0000	0.0000	1.0000
U.S.	0.0101	0.1005	0.0000	0.0000	1.0000
U.S. trade share	0.9896	2.7141	0.1782	0.0000	16.1879
U.S. military presence	0.9394	0.2398	1.0000	0.0000	1.0000

4 Empirical Results

4.1 Principal specification

Our first and principal model includes the standard variables generally considered in the earlier studies. These constitute our first four group of variables namely macroeconomic indicators, excessive debt and default history, governance and institutional quality, and national conflict risk and intensity.

The SUR results of the basic model is reported in the left panel of Table 5. Each column in the table presents individual regressions for Fitch, Moody's and S&P respectively. The model fullfills the standard diagnostic requirements such as residual normality or homoscedasticity. We also test for sufficient contemporaneous correlation among the three agencies using the Breusch-Pagan test for diagonal covariance matrix for residuals, where the null hypothesis of no correlation is rejected with a p-value of 0.0000. Indeed, as can be seen in the upper left part of Figure 1, the residuals from the

three equations are visibly correlated. The individual plots in the figure confirms the usefulness of the SUR analysis in all of our four models.

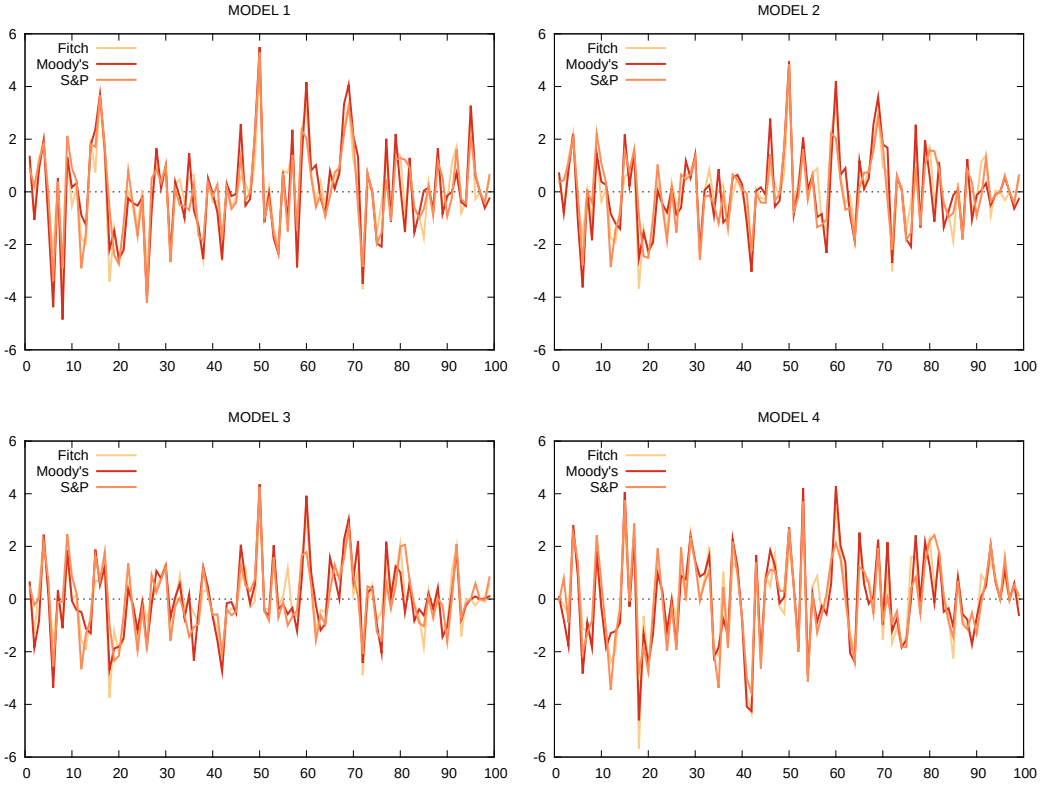

Figure 1: Combined residual plots for the system of equations from Model1 through Model4.

It is important to note that all of the estimated coefficients in the basic model have the a-priori expected signs in each equation. We see that the coefficients on debt to GDP ratio, GDP per capita, unemployment rate, government effectiveness, being heavily indebted, and having defaulted in the last 10 years are statistically significant for all three agencies. These variables are generally identified in the literature as the core factors affecting sovereign credit ratings. It is interesting that being a G20 country increases the ratings, indicating that countries with more economic power receive higher grades than the others. Also, the results show that the CRAs assign higher grades to fuel exporting countries.

4.2 Are the CRAs biased towards the U.S.?

In our second model, we examine the existance of a home bias effect. This involves the inclusion of the three according variables namely the U.S. dummy variable, the U.S. trade share, and the U.S. military presence.

The regression results are presented in the right panel of Table 5. It is important to note that including the home bias variables substantially improves the regression results. We see many parameters which are not statistically significant in the initial model become now significant thanks to the improved goodness-of-fit. In particular; the coefficients on inflation, exchange rate, and interest rate are now significant in all of the three equations. Moreover, the home bias variables are also uniformly significant with the expected signs.

The results show that the U.S. dummy variable has a large value with a positive sign, indicating that the U.S. receives a large boost in its credit rating with respect to the rest of the world. This can be explained in several ways. First and foremost, the U.S. is the biggest economy in the world, surpassing its closest rivals with a large margin. Second, it has the sole authority on the supply of the U.S. dollar, which is the default global currency. These two factors alone can account for the large boost the U.S. enjoys in its credit rating. On the other hand, we also see that the U.S. trade share, and the U.S. military presence variables are also positive and statistically significant. This means that the CRAs give higher grades to the countries which the U.S. has military and trade interests. Clearly, this sort of home bias is more difficult to justify on objective grounds.

4.3 Are CRAs biased against MENA countries?

The third model is our baseline model, which considers the possible regional biases on top of the U.S. home bias effect. Here, we replace the U.S. dummy variable in favor of the eight regional dummies.

The results for Model 3 are presented on the left panel of Table 6. We see that the coefficient estimates remain mostly similar to the earlier models, while the goodness-of-fit improves even further. In fact, now all of the variables except current account to GDP ratio are statistically significant with the expected signs in at least two out of the three equations. Then again, the current account to GDP ratio being insignificant is perhaps not surprising given that the relation of this variable with

sovereign credit ratings is also not clear in the literature. Although a large current account deficit can cause problems in terms of the sustainability of the debt, it can also be a result of rapid economic growth.

In the third model, we again strongly observe the U.S. home bias in the form of receiving a higher rating for being a U.S. trade partner or a military ally. Furthermore, all of the eight regional dummies are statistically significant as well. The negative coefficients show that countries from all regions receive a lower rating in comparison to the U.S., which is the reference region in this model. In other words, the negative coefficients on the region dummies are the mirror images of the positive coefficient on the U.S. dummy from the second model. Hence, they can also be explained with the economic power and the exorbitant privilege of the U.S.

Looking at the coefficients of the regional dummies, the CRAs appear to be the least biased against the MENA and the Pacific Region countries. They also seem to be the most biased against the transition economies and the rest of Europe country groups. However, such conclusions are not supported with statistical evidence. Running a series of F-tests with a null hypothesis that the coefficients are equal for all of the eight regional dummies, we obtain the p-values 0.0968, 0.003 and 0.0712 for Fitch, Moody and S&P respectively. This means we do not reject the proposition that two out of the three CRAs have the same attitude towards the eight country groups, at the 5 per cent level of significance.

The empirical results show that Fitch and S&P do not have a special bias against the MENA countries, or any country group for that matter. However, does this mean that Moody's is regionally biased? It is our understanding that one must avoid quickly reaching such conlusions. No matter how inclusive, any econometric model is an approximation of the detailed analyses which the CRAs perform routinely on a country by country basis. Therefore, modelling errors such as omitted variables can easily result in biased coefficients that portray a CRA as biased towards or against a country group.

In order to illustrate the effects of an omitted variable bias on the regression analysis of credit ratings, we estimate a fourth model where the government effectiveness variable is removed from the specification.

The results for Model 4 are shown in the second panel of Table 6. It is seen that omitting only one variable causes the model goodness-of-fit to decrease substantially. Moreover, we now see that the CRAs are increasingly biased especially against the transition economies as well as the Sub-

Saharan Africa, and the Central and South Asia country groups. This is perhaps not surprising since these countries are generally associated with a lower ranking in terms of governance and institutional quality. What is more, running the same F-tests, we now uniformly reject the null hypothesis of equal coefficients for the eight regional dummies with the p-values of 0.0002, 0.0000, and 0.0003 respectively.

Omitting the government effectiveness variable is just one form of many possible modelling errors. It is in fact a special case investigated by Ozturk (2014), who argues that the apparently biased behavior of CRAs can be due to the ignorance of institutional factors.

In order to further demonstrate the misleding results due to omitted variables, we sequentially eliminate from Model 3 all variables except the regional dummies based on the highest p-value. Figure 2 presents the relationship between the goodness-of-fit and the dispersion of the estimated regional dummy coefficients for Model 3. The plots clearly show that the standard deviation of the coefficients of the eight regional dummies increases as the adjusted R^2 falls due to more and more omitted variables. Please note that the equations of the fitted lines in the plots roughly imply a zero standard deviation if there was a perfect goodness of fit.

4.4 What causes the rating differences across the CRAs?

Figure 1 discussed above provides visual evidence of strong correlation within the errors of the three equations. This indicates that the CRAs show similar responses to the unobservable country-specific factors when determining the credit ratings. Moreover, by looking at the regression results, one can also conclude that the coefficient estimates are rather similar for most of the variables. As mentioned earlier, the methodology used by the three agencies is ultimately the same. However, the fact that there exists minor differences in the real-life ratings means that the CRAs must assign different weights to at least some of the variables. As a result, it is of interest to determine the main factors that cause the differences in rating behavior between the agencies.

An important advantage of the SUR methodology employed in our study is that it facilitates cross-equation hypothesis testing. Consequently, in Table 4 we present the average coefficients along with the *p*-values of cross-equation equality tests for the coefficients ($H_0 : \beta_{kf}$=β_{km}=β_{ks}) for Model 3.

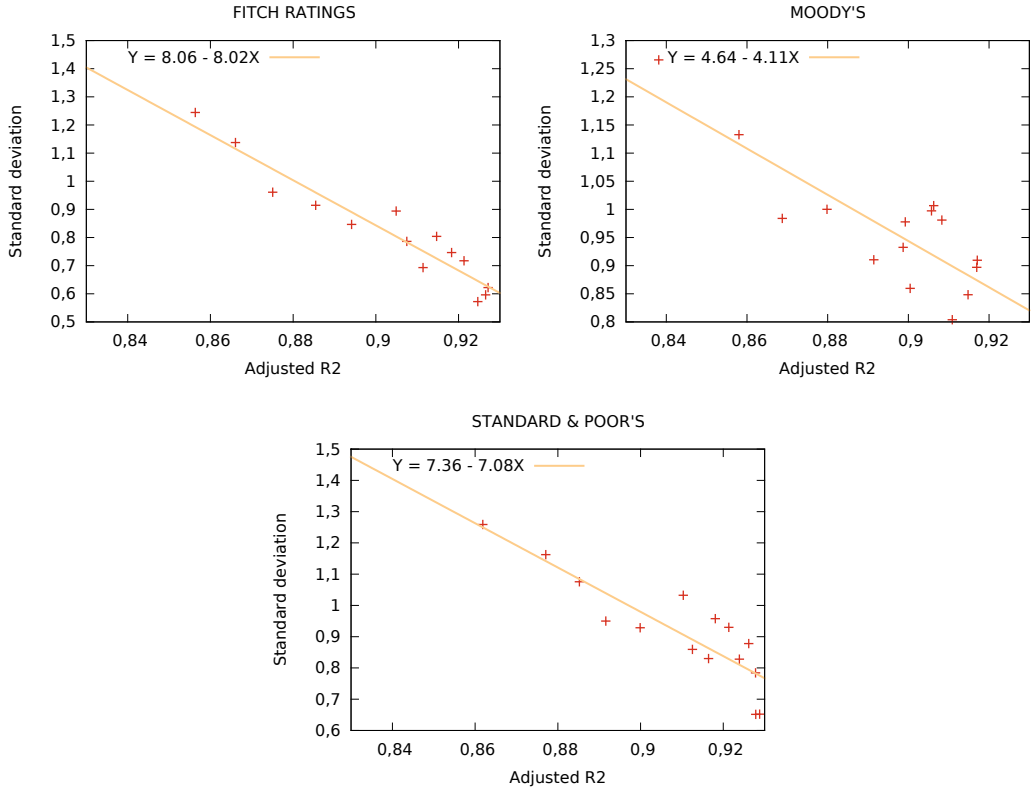

Figure 2: The relationship between the goodness-of-fit and the dispersion of the regional dummy coefficients for Model 3

It is striking that the null-hypothesis of coefficient equality cannot be rejected for 19 out of the 24 variables. Furthermore, we see that the main differences are due to the macroeconomic ratios namely budget to GDP ratio, debt to GDP ratio, and current account to GDP ratio. The results indicate that the CRAs also disagree on the relative importance of having defaulted in the last 10 years as well as being a fuel exporting country. The rest of the variables, including those regarding the U.S. home bias effect, seem to have the same weight in the rating methodologies of the three CRAs.

5 Conclusion and Policy Implications

In this paper, we performed a seemingly unrelated regressions analysis in order to examine the objectivity of sovereign credit ratings decided by the three leading CRAs namely Fitch, Moody's, and S&P. Using data for 99 countries categorized into eight regions plus the U.S., we proposed a series of econometric models for studying the determinants of sovereign credit ratings, the existence of a U.S.

Table 4: Average Coefficients and the Testing of Coefficient Equality for Model 3

Variable	**Average coeff.**	***P*-value**	**Variable**	**Average coeff.**	***P*-value**
Budget to GDP ratio	0,1265	0,0431**	G20 country	1,1901	0,4798
Debt to GDP ratio	-0,0323	0,0542*	Fuel exporting country	1,0200	0,0793*
CA to GDP ratio	-0,0060	0,0015***	EU 15	-6,3121	0,1257
GDP per capita	0,0527	0,3165	Rest of Europe	-6,7429	0,1878
Unemployment	-0,0830	0,7341	Transition economies	-7,0264	0,1966
Inflation	-0,0047	0,2006	MENA	-5,2371	0,3382
Exchange rate	-0,0002	0,5413	Latin America	-5,6851	0,3948
Interest rate	-0,0697	0,9800	Sub-Sahara	-5,8729	0,7156
Gov. effectiveness	1,3601	0,8021	Central and South Asia	-5,9533	0,2871
National conflict	-0,4136	0,4034	Pacific Region	-4,9565	0,2897
Heavily indebted	-1,5317	0,3496	U.S. trade share	0,1288	0,7847
Defaulted in 10 years	-2,6259	0,0001***	U.S. military presence	2,6755	0,1398

Note: The p-values represent the F test results for cross-equation equality of the model coefficients ($H_0 : \beta_{kf}$=β_{km}=β_{ks}).

home bias effect as well as potential regional biases.

Our study yields important insights regarding the nature of sovereign credit ratings. First, we observe a strong, robust, and statistically significant home bias in favor of the U.S. The results indicate that the U.S. as well as those countries which have closer economic and military relations with the U.S. receive substantially higher credit ratings. Second, we show that there are no special biases against individual group of countries. Third, we also demonstrate that the reason for finding biases in the previous literature can be due to modeling errors. Specifically, we show that omitted variables cause increased dispersion in the regional effects, which in turn give misleading results potentially portraying a rating agency as biased towards or against different country groups. Last but not least, we find that the three CRAs seem to consider roughly the same variables with surprisingly similar weights when assigning their ratings. The main macroeconomic factors responsible for the differences in the rating behavior are found as the budget to GDP ratio, the debt to GDP ratio, and the current account to GDP ratio.

Our findings have important policy implications. First of all, the strong evidence for home bias points out the need to establish more CRAs in different regions of the world in order to increase competition and transparency. For example, a new credit agency whose main partners consist of MENA countries can provide various crucial benefits to the region such as (1) providing guidance for the Sovereign Wealth Funds of the Gulf states with more reliable credit ratings, (2) helping the development of Islamic finance tools and instutions, (3) promoting growth and investment in the

MENA region, (4) filling the credibility gap that Fitch, Moody's, and S&P have created especially after the Global Financial Crisis. It is true that setting up such new CRAs can be difficult since the existing agencies are able to take advantage of a large economies of scale as well as the reputation that have built over time, which together put new entrants at a disadvantage. However, in the final analysis, the aim of sovereign credit ratings is to provide sound advice for investment decisions. As is the nature of any advice, such ratings are bound to be biased and changing depending on who is providing the rating. Ultimately, it is our understanding that the increase in the number of CRAs will be beneficial to provide more perspective and increase competition, which can promote transparency and reliability in the long run.

Aside from establishing new CRAs, it is possible to propose various solutions to make the existing ones more efficient and reliable as well. Some authors argue that increased disclosure can facilitate scrutiny by investors, providing a scope for outsiders to better evaluate risks (Baghai and Becker, 2016). Also, CRAs could be legally held accountable for their practices. A modern regulatory environment is a key to more fair practices.

Last but not least, our study also points out the importance of the design and use of better empirical approaches for the analysis of sovereign credit ratings. The results clearly show that omitted variables can easily cause misleading results, portraying a given CRA as biased towards or against different country groups. For example, it is seen that variables for governance and institutional quality play an important role especially for the transition economies as well as the Sub-Saharan Africa, and the Central and South Asia country groups. Similarly, the exclusion of debt related variables can give results implying biases against the European Union countries. As a result, it is important that more comprehensive modeling approaches are employed in the future studies on this subject.

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Table 5: Estimation Results for Model 1 and Model 2

	Model 1			**Model 2**		
	Fitch	**Moody's**	**S&P**	**Fitch**	**Moody's**	**S&P**
Constant	$4,7085^{***}$	$4,7296^{***}$	$5,1134^{***}$	$2,9871^{***}$	$2,5722^{**}$	$3,3269^{***}$
	(1.0915)	(1.2647)	(1.0852)	(1.0003)	(1.1457)	(1.0089)
Budget to GDP ratio	$0,0231$	$0,0533$	$0,0665$	$0,0508$	$0,0872^{*}$	$0,0940^{**}$
	(0.0483)	(0.0559)	(0.0480)	(0.0407)	(0.0466)	(0.0410)
Debt to GDP ratio	$-0,0250^{***}$	$-0,0299^{***}$	$-0,0235^{***}$	$-0,0295^{***}$	$-0,0352^{***}$	$-0,0277^{***}$
	(0.0049)	(0.0057)	(0.0049)	(0.0042)	(0.0048)	(0.0042)
CA to GDP ratio	$0,0028$	$-0,0381$	$-0,0017$	$0,0152$	$-0,0254$	$0,0073$
	(0.0334)	(0.0387)	(0.0332)	(0.0282)	(0.0323)	(0.0284)
GDP per capita	$0,0398^{***}$	$0,0400^{***}$	$0,0417^{***}$	$0,0514^{***}$	$0,0549^{***}$	$0,0545^{***}$
	(0.0129)	(0.0150)	(0.0128)	(0.0111)	(0.0128)	(0.0112)
Unemployment	$-0,0992^{**}$	$-0,0901^{**}$	$-0,1128^{***}$	$-0,0757^{**}$	$-0,0645^{*}$	$-0,0932^{***}$
	(0.0382)	(0.0443)	(0.0380)	(0.0330)	(0.0378)	(0.0333)
Inflation	$-0,0067^{***}$	$-0,0039$	$-0,0050^{**}$	$-0,0067^{***}$	$-0,0040^{*}$	$-0,0051^{**}$
	(0.0025)	(0.0029)	(0.0025)	(0.0021)	(0.0024)	(0.0021)
Exchange rate	$-0,0001^{*}$	$-0,0001$	$-0,0001$	$-0,0001^{**}$	$-0,0001^{*}$	$-0,0001^{*}$
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Interest rate	$-0,0660^{*}$	$-0,0662$	$-0,0708^{*}$	$-0,0730^{**}$	$-0,0741^{**}$	$-0,0771^{**}$
	(0.0368)	(0.0426)	(0.0366)	(0.0308)	(0.0353)	(0.0310)
Gov. effectiveness	$1,5637^{***}$	$1,6209^{***}$	$1,5340^{***}$	$1,4106^{***}$	$1,4312^{***}$	$1,3768^{***}$
	(0.1774)	(0.2055)	(0.1764)	(0.1508)	(0.1727)	(0.1521)
National conflict	$-0,1818$	$-0,3271$	$-0,2971$	$-0,2146$	$-0,3708$	$-0,3336$
	(0.2538)	(0.2940)	(0.2523)	(0.2125)	(0.2433)	(0.2143)
Heavily indebted	$-1,3508^{**}$	$-1,5756^{**}$	$-1,2303^{*}$	$-1,4631^{***}$	$-1,7331^{***}$	$-1,3684^{**}$
	(0.6576)	(0.7619)	(0.6538)	(0.5527)	(0.6331)	(0.5575)
Defaulted in 10 years	$-2,4618^{***}$	$-3,5124^{***}$	$-2,5256^{***}$	$-2,3027^{***}$	$-3,3437^{***}$	$-2,3977^{***}$
	(0.7147)	(0.8280)	(0.7105)	(0.6002)	(0.6875)	(0.6054)
G20 country	$1,1078^{***}$	$1,0909^{***}$	$1,0567^{***}$	$0,7165^{**}$	$0,6287^{*}$	$0,6804^{**}$
	(0.3329)	(0.3857)	(0.3309)	(0.2885)	(0.3304)	(0.2910)
Fuel exporting country	$1,6877^{***}$	$1,0679^{*}$	$1,1263^{**}$	$1,4601^{***}$	$0,7772$	$0,8823^{*}$
	(0.5233)	(0.6063)	(0.5203)	(0.4410)	(0.5051)	(0.4448)
U.S.				$6,5906^{***}$	$7,3108^{***}$	$5,4170^{***}$
				(1.4733)	(1.6875)	(1.4860)
U.S. trade share				$0,2058^{***}$	$0,2441^{***}$	$0,2017^{***}$
				(0.0534)	(0.0611)	(0.0538)
U.S. military presence				$2,7639^{***}$	$3,4501^{***}$	$2,8488^{***}$
				(0.6459)	(0.7398)	(0.6515)
n	99	99	99	99	99	99
$\bar{R}^2$	0.895	0.868	0.899	0.924	0.907	0.925

Note: Standard errors in parentheses. *** indicates significance at the 1% level. ** and * idem, 5% and 10%.

Table 6: Estimation Results for Model 3 and Model 4

	Model 3			Model 4		
	Fitch	**Moody's**	**S&P**	**Fitch**	**Moody's**	**S&P**
Constant	$9,9564^{***}$	$9,8441^{***}$	$9,1907^{***}$	$17,3086^{***}$	$17,1132^{***}$	$16,2345^{***}$
	(1.6890)	(1.8534)	(1.6962)	(1.9963)	(2.095)	(1.9638)
Budget to GDP ratio	$0,0943^{**}$	$0,1455^{***}$	$0,1397^{***}$	$0,0741$	$0,1256^{**}$	$0,1204^{**}$
	(0.0442)	(0.0485)	(0.0444)	(0.0596)	(0.0626)	(0.0586)
Debt to GDP ratio	$-0,0313^{***}$	$-0,0358^{***}$	$-0,0299^{***}$	$-0,0292^{***}$	$-0,0336^{***}$	$-0,0278^{***}$
	(0.0042)	(0.0046)	(0.0042)	(0.0057)	(0.0060)	(0.0056)
CA to GDP ratio	$0,0151$	$-0,0386$	$0,0056$	$0,0346$	$-0,0193$	$0,0244$
	(0.0289)	(0.0317)	(0.0290)	(0.0389)	(0.0408)	(0.0382)
GDP per capita	$0,0479^{***}$	$0,0572^{***}$	$0,0529^{***}$	$0,1205^{***}$	$0,1290^{***}$	$0,1225^{***}$
	(0.0120)	(0.0132)	(0.0121)	(0.0121)	(0.0127)	(0.0119)
Unemployment	$-0,0876^{**}$	$-0,0730^{*}$	$-0,0885^{**}$	$-0,1008^{*}$	$-0,0860$	$-0,1011^{*}$
	(0.0389)	(0.0427)	(0.0390)	(0.0524)	(0.0550)	(0.0516)
Inflation	$-0,0057^{***}$	$-0,0038$	$-0,0046^{**}$	$-0,0099^{***}$	$-0,0079^{***}$	$-0,0086^{***}$
	(0.0021)	(0.0023)	(0.0021)	(0.0028)	(0.0029)	(0.0028)
Exchange rate	$-0,0002^{***}$	$-0,0002^{***}$	$-0,0001^{***}$	$-0,0002^{***}$	$-0,0002^{***}$	$-0,0002^{**}$
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Interest rate	$-0,0694^{**}$	$-0,0718^{**}$	$-0,0679^{**}$	$-0,1143^{***}$	$-0,1162^{**}$	$-0,1109^{**}$
	(0.0321)	(0.0352)	(0.0322)	(0.0428)	(0.0449)	(0.0421)
Gov. effectiveness	$1,3847^{***}$	$1,3690^{***}$	$1,3266^{***}$			
	(0.1536)	(0.1685)	(0.1542)			
National conflict	$-0,3275$	$-0,4572^{*}$	$-0,4562^{**}$	$-0,5029^{*}$	$-0,6306^{**}$	$-0,6242^{**}$
	(0.2187)	(0.2399)	(0.2196)	(0.2939)	(0.3086)	(0.2892)
Heavily indebted	$-1,6120^{**}$	$-1,8586^{**}$	$-1,1244$	$-2,0193^{*}$	$-2,2614^{*}$	$-1,5148$
	(0.8030)	(0.8812)	(0.8065)	(1.0820)	(1.1358)	(1.0644)
Defaulted in 10 years	$-2,0909^{***}$	$-3,4436^{***}$	$-2,3431^{***}$	$-2,3830^{***}$	$-3,7325^{***}$	$-2,6230^{***}$
	(0.5986)	(0.6569)	(0.6012)	(0.8067)	(0.8468)	(0.7936)
G20 country	$1,1299^{***}$	$1,3404^{***}$	$1,1001^{***}$	$1,4565^{***}$	$1,6633^{***}$	$1,4130^{***}$
	(0.3722)	(0.4085)	(0.3738)	(0.5000)	(0.5249)	(0.4918)
Fuel exporting country	$1,3277^{***}$	$0,8779^{*}$	$0,8545^{*}$	$0,1287$	$-0,3075$	$-0,2941$
	(0.4640)	(0.5091)	(0.4659)	(0.5999)	(0.6297)	(0.5901)
EU 15	$-6,4697^{***}$	$-7,1522^{***}$	$-5,3144^{***}$	$-7,4426^{***}$	$-8,1142^{***}$	$-6,2466^{***}$
	(1.4199)	(1.5581)	(1.4260)	(1.9108)	(2.0058)	(1.8796)
Rest of Europe	$-6,9293^{***}$	$-7,4749^{***}$	$-5,8245^{***}$	$-7,5340^{***}$	$-8,0727^{***}$	$-6,4039^{***}$
	(1.4305)	(1.5697)	(1.4366)	(1.9284)	(2.0243)	(1.8970)
Transition economies	$-7,0769^{***}$	$-7,9090^{***}$	$-6,0932^{***}$	$-8,1560^{***}$	$-8,9758^{***}$	$-7,1271^{***}$
	(1.5822)	(1.7361)	(1.5889)	(2.1291)	(2.2350)	(2.0944)
MENA	$-5,3618^{***}$	$-5,8916^{***}$	$-4,4580^{***}$	$-7,0174^{***}$	$-7,5285^{***}$	$-6,0442^{***}$
	(1.5357)	(1.6851)	(1.5422)	(2.0576)	(2.1599)	(2.0241)
Latin America	$-6,2176^{***}$	$-5,8172^{***}$	$-5,0205^{***}$	$-7,5676^{***}$	$-7,1519^{***}$	$-6,3139^{***}$
	(1.5417)	(1.6917)	(1.5483)	(2.0708)	(2.1738)	(2.0371)
Sub-Sahara	$-5,9200^{***}$	$-6,2948^{***}$	$-5,4037^{***}$	$-7,9149^{***}$	$-8,2671^{***}$	$-7,3149^{***}$
	(1.7152)	(1.8820)	(1.7225)	(2.2954)	(2.4095)	(2.2580)
Central and South Asia	$-6,2626^{***}$	$-6,5851^{***}$	$-5,0123^{***}$	$-8,4157^{***}$	$-8,7139^{***}$	$-7,0751^{***}$
	(1.6434)	(1.8033)	(1.6504)	(2.1943)	(2.3034)	(2.1585)
Pacific Region	$-5,4803^{***}$	$-5,2502^{***}$	$-4,1391^{***}$	$-5,2693^{**}$	$-5,0416^{**}$	$-3,9370^{*}$
	(1.5063)	(1.6528)	(1.5127)	(2.0326)	(2.1336)	(1.9995)
U.S. trade share	$0,1402^{**}$	$0,1202^{*}$	$0,1260^{**}$	$0,1130$	$0,0933$	$0,0999$
	(0.0588)	(0.0646)	(0.0591)	(0.0793)	(0.0832)	(0.0780)
U.S. military presence	$2,4398^{***}$	$3,0620^{***}$	$2,5247^{***}$	$3,4670^{***}$	$4,0777^{***}$	$3,5088^{***}$
	(0.6192)	(0.6795)	(0.6219)	(0.8214)	(0.8623)	(0.8080)
n	99	99	99	99	99	99
$\bar{R}^2$	0.926	0.917	0.928	0.868	0.864	0.876

Note: Standard errors in parentheses. *** indicates significance at the 1% level. ** and * idem, 5% and 10%.