Penalties and Premiums in Sovereign Credit Ratings*

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Abstract

Credit rating agencies collapse high-dimensional borrower characteristics into summary statistics of creditworthiness, facilitating capital flows. But biases embedded in these rating algorithms may lead to misallocation. We test for bias in sovereign credit ratings across a wide array of borrower-country characteristics, training machine learning models to estimate ratings as a function of countries' observable economic, political, and borrower history fundamentals. Even after accounting for these fundamentals, ratings agencies tend to favor the "clubs" of the Western world, namely the members of the G7, EU, and OECD, while penalizing emerging Latin American and Asian nations. Using data on sovereign bond issues, we find that these penalties and premiums increase coupon spreads between the G7 (the most overrated) and Southeast Asia (the most underrated) by 62.7 basis points. We show that it is possible to earn risk-free excess returns by using our algorithm to construct an unbiased portfolio of investment-grade bonds, suggesting persistent mispricing.

Keywords: sovereign debt, credit ratings, algorithmic bias, international finance, machine learning

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1. Introduction

By issuing sovereign debt, the world's governments rely on international capital flows to help finance public expenditures. The global sovereign debt market is a large and liquid source of needed capital; in 2020, OECD governments borrowed some USD 18 trillion from the bond market, nearly 30 percent of their GDP, while developing countries issued over USD 1 trillion (OECD 2020). As with all credit markets, investors in international sovereign bonds face a fundamental information problem regarding the creditworthiness of borrowers, which in turn influences capital allocation decisions (Wittenberg-Moerman 2008). The specific set of commitment and monitoring problems that characterize sovereign bond markets only heightens this problem (Tomz & Wright 2007). The risk of default, asymmetric information on borrower quality, and the absence of established bankruptcy procedures, means that sovereign bonds may be particularly risky (Aguiar & Amador 2021). Indeed, with growing debt distress and rising global interest rates, the International Monetary Fund is signaling a sense of urgency in recent press releases about "financial stability risks" across the developing world.

Credit rating agencies play a key role in overcoming debt market frictions through the ratings they assign, which are meant to aggregate all available information about a borrower's credit risk (Fitch Investor Services 2020, Moody's Investor Services 2019, Standard & Poor's 2017). These ratings influence a sovereign's ability to place international bonds, the range of possible creditors, and ultimately the coupon rate paid on external debt (Canuto et al. 2012).[1]

The fairness or objectivity of the assigned ratings is thus of fundamental importance to both the issuers of and investors in sovereign bonds. But over the years, scholars and policymakers have questioned the credit ratings process. Ratings agencies have been beset by allegations of bias from policymakers and calls for reform by international institutions (United Nations 2021, Fofack 2021, Yalta & Yalta 2018, Fuchs & Gehring

[1]For example, the bonds of countries with less than "investment-grade" ratings generally will not be purchased by such institutional buyers as pension funds or insurance companies (White 2010).

2017, Ozturk 2014).[2] Following a credit downgrade in 2022, for example, the Finance Ministry of Ghana stated: "We are gravely concerned about what appears to be an institutionalized bias against African economies."(Landers & Aboneaaj 2022)

In principle, a credit rating should be formed on the basis of a standard set of criteria relevant for predicting default – macroeconomic fundamentals, borrower history, and political institutions. But a substantial literature has detected a variety of ratings penalties and premiums that do not appear to be based on these criteria, from home country preferences (Fuchs & Gehring 2017) to biases against left-wing governments (Cotoc et al. 2021, Barta & Johnston 2018), suggesting that such allegations may not be entirely unfounded. Clearly, rating agencies rely on both "hard" (e.g. data-driven fundamentals) and "soft" information, the latter capturing the qualitative impressions and, potentially, the preferences and biases of the members of the sovereign debt rating committees. Reliance on soft information may therefore lead to penalties divorced from fundamentals, burdening countries with higher interest rates and rationed credit, or premiums that subsidize credit for the favored. If these patterns correlate with existing cross-country income differences, biased ratings can exacerbate global inequality.

This study revisits the debate over penalties and premiums in sovereign credit ratings. We assemble an annual country panel to test for bias in credit ratings conditional on a comprehensive set of economic and political fundamentals, with covariates selected by machine learning. We test for biases against or in favor of numerous country characteristics, including region, colonial origin, legal system, language, and membership in international institutions. We find large ratings differentials across many of these characteristics that cannot be explained by differences in fundamentals. Using data on sovereign bond placements, we show that ratings provide substantial input to financial markets over and above fundamentals, and that investors may transmit the biases in these ratings into bond coupons. Using the penalty and premium estimates, we calculate the coupon cost (or gain) of ratings bias. Finally, as a market test of our hypothesis,

[2] Chinese officials often accuse the big three firms of biases following downgrades of China's sovereign debt rating. In response, China's Dagong rating agency began providing sovereign ratings in 2010, which systematically underrate democracies and overrate authoritarian regimes (Hillman 2020).

we show that it is possible to construct an unbiased portfolio of investment-grade bonds using our ratings algorithm that achieves excess risk-adjusted returns relative to a portfolio based on observed ratings. This suggests that ratings bias causes the market to persistently misprice sovereign bonds relative to underlying country risk.

We begin by estimating unconditional differences in credit ratings by country-level characteristics. Unsurprisingly, we find large and significant ratings differentials across a variety of country covariates. Developed industrial countries, US military allies, and OECD and EU members tend to be highly rated, while emerging nations in South Asia, Latin America, and Africa, as well as those allied with China and Russia, tend to have lower ratings. It is these unconditional differences that motivate much of the literature on ratings bias. These unconditional differences also correspond to similar spreads in initial coupon rates on sovereign bonds.

However, these unconditional differences omit the country fundamentals that determine ratings. We therefore control for a comprehensive set of payoff-relevant, time-varying economic, political, and borrower history observables. At the same time, conditional estimates of bias may be sensitive to specification choice, and ad-hoc covariate selection magnifies the problem of researcher degrees of freedom, or "forking paths" (Kasy 2021). We therefore discipline our estimation using machine learning methods that automate model selection. We begin with a rich set of country covariates, and use Random Forest (Breiman 2001) and LASSO to minimize the out-of-sample prediction error. We compare the performance of these algorithms to a "kitchen sink" approach using OLS, as well as to models that select ex-ante subsets of covariates (i.e., only economic or political) We find that LASSO both disciplines the model by dropping uncorrelated variables, and improves out of sample prediction performance relative to OLS by roughly 5% in root mean squared error. Our final post-LASSO (Belloni & Chernozhukov 2013) model achieves an out-of-sample R^2 exceeding 0.9. We therefore use the LASSO-selected covariates as our preferred specification.

With the ratings model in hand, we proceed to estimate conditional ratings penalties and premiums. We find that many of the unconditional ratings penalties and premiums disappear or change sign when we condition on the LASSO-selected fundamentals; out of 24 bias variables, 17 are unconditionally significant, while only 10 remain conditionally significant. We find that ratings agencies underrate Asian and Latin American nations relative to their fundamentals and borrower history, while overrating members of such western-country blocs as the OECD, EU, and G7. Contrary to widespread perceptions, we actually find overoptimism about the creditworthiness of African nations. These results offer an explanation for recent deterioration in the performance of African sovereign debt, most notably in Zambia and Ghana – overoptimistic initials ratings helped catalyze excessive credit flows to these sovereigns. For all of our bias estimates, we consider robustness to model specification and measurement choices, machine learning algorithms, differential estimates by rating agency, and the impact of global macroeconomic shocks. The results are broadly unchanged.

We then consider the how ratings bias shapes borrowing costs using bond-level data on sovereign placements. We find ratings to be robustly and negatively correlated with initial coupons, even conditional on the LASSO-selected covariates, consistent with results from White (2010).[3] This suggests that ratings mould investor expectations of creditworthiness, so that ratings bias may have important implications for country borrowing costs. We estimate analogous penalty/premium models using bond coupons as the outcome and conditioning on LASSO-selected covariates. We find that these broadly correspond to the results of the ratings analysis. Furthermore, when we additionally control for ratings, several coupon biases either shrink toward zero or disappear entirely. We then conduct a back-of-the-envelope calculation of the costs of ratings bias, predicting borrowing costs by multiplying ratings penalties by the elasticity of borrowing costs to ratings. We find that ratings bias increases coupon spreads between the G7 – our most overrated group - and Southeast Asia – our most underrated – by 62.7 basis points.

This evidence suggests ratings bias can cause bond yields to diverge from underlying risk, creating market inefficiencies. We use a simple market test to falsify this argument. If ratings bias induces mispricing, it should be possible to construct an investment-

[3] This relationship is nonlinear, with discontinuities at ratings thresholds such as investment-grade.

grade bond portfolio that provides excess return without additional risk. To do so, we use predicted annual ratings from our post-LASSO model to create an unbiased portfolio of bonds, which we compare to a portfolio selected on observed ratings. At the margin, our unbiased portfolio substitutes in bonds that provide speculative yields at investment-grade risk, while dropping those that provide only investment-grade yields at speculative-grade risk. Daily yield data reveal a positive spread between the de-biased and actual portfolios, which persists over the life of the average bond, suggesting that secondary markets do not correct for ratings-induced biases at issue. The unbiased portfolio provides excess returns over time without increasing risk for all maturities, yielding an additional 14 basis points annually, while reducing the portfolio variance by 2%. The Sharpe ratio of the unbiased portfolio is higher in nearly every year of our sample. This exercise validates our fundamentals-only ratings algorithm, and suggests that biased credit ratings lead to mispricing of country risk.

We make several contributions. First, we show that interpreting differences in average ratings across country groups as evidence of bias depends critically on the assumption that all payoff-relevant country characteristics have been conditioned on (selection on observables). Previous work aimed at identifying ratings biases has often relied on ad-hoc inclusion of a small set of covariates (Fofack 2021, Yalta & Yalta 2018). We consider an extensive set of possible covariates, and unlike Fuchs & Gehring (2017) our method reduces the risk of misspecification and disciplines covariate selection by using machine learning methods.[4] After imposing this more stringent model, a variety of unconditional biases identified in the literature – such as those against left-wing executives (Barta & Johnston 2018) or sub-Saharan African governments (Fofack 2021) – do not find support.

We further extend this literature by incorporating data on sovereign bond issues in order to estimate how ratings biases affect demand for sovereign debt and the cost of borrowing. We are able to quantify the direct role of ratings bias in determining borrowing costs, and provide compelling, market-driven evidence that ratings bias leads

[4]As such, our work relates to recent work on algorithms and bias in credit scoring (Fuster et al. 2021, Alaminos et al. 2021)

bond yields to diverge from underlying country risk.

Second, we add to a substantial body of work that assesses the determinants of sovereign ratings, originating with an oft-cited paper by Cantor & Packer (1996); a voluminous literature has since developed (Aguiar & Amador 2021, Tomz & Wright 2007). We add to this literature both methodologically, by using machine learning, and empirically, by examining the implications of bias for borrowing costs and misallocation. We use a more comprehensive set of fundamentals, data-driven covariate selection, and test for bias across a wide array of previously untested country characteristics. More broadly, we contribute to the literature on sovereign bonds and sovereign defaults, much of which ignores the role of credit rating agencies (Tomz & Wright 2007, Chapman & Reinhardt 2013, Aguiar & Amador 2021, Leonardo Martinez & Zettelmeyer 2022).

Lastly, there is a growing social science literature on bias, discrimination, and algorithmic decision-making in credit markets (Rambachan et al. 2020, Fuster et al. 2021, Alaminos et al. 2021). We expand the scope of this literature by considering the effects of algorithmic discrimination in sovereign bond markets. We show that portfolios constructed from machine learning predictions achieve higher risk-adjusted returns than those imbued with the biases of human decision-making.

2. Data

We consider two models of interest: *i*) a country-year specification in which ratings is the outcome variable and *ii*) a bond-level model that estimates expected initial coupon rates. We therefore assemble two datasets. The first contains ratings, country characteristics, and fundamentals at the country-year level. The second contains bond-level information on coupons, size, and other loan characteristics, merged with ratings and country-level covariates. Finally, we also assemble a bond-day panel of yields to construct investment-grade portfolios. Throughout, we consider the period 2002-2019 unless otherwise specified.

2.1. Sovereign Ratings

Our primary dependent variable is a sovereign's foreign currency debt rating provided by the three major rating agencies: Moody's, Fitch, and S&P. We retrieve ratings information via Trading Economics, which contains the rating, agency, outlook, and date of each rating announcement. In total, we obtain 3,501 unique rating announcements from 2002-2019 for 151 individual countries. For our empirical analysis, we translate the ratings of each agency into the standard 21-point scale (see Appendix Table A1). We then calculate annual average ratings for each country-agency-year, where weights are the number of months within a year that a country obtained a given rating score. We then take the simple average of these annualized ratings across the all agencies for which ratings are available for that country-year. For all years in which a country does not experience a rating change from any of the agencies, it maintains its rating from the previous period. A distribution of our weighted mean rating, and time-series plots of the number of rated countries by year can be found in Appendix Figures A1 and A2. Ratings are highly correlated across agencies (see Appendix Table A2).

2.2. Country Fundamentals

Ratings agencies use a core set of fundamental financial, economic, and political indicators to score sovereign credit risk (Fitch Investor Services 2020, Moody's Investor Services 2019, Standard & Poor's 2017). The ratings process, however, also relies on the qualitative assessment of analysts; to capture these assessments, we augment the specification with a variety of additional explanatory variables from Fuchs & Gehring (2017) and Cantor & Packer (1996) in order to control for all of the economic and political factors that should determine creditworthiness and therefore predict ratings.

To account for the sovereign's economic performance, we consider the following set of annual fundamentals: log GDP per capita, inflation, GDP growth and its square, natural resource rents as a share of GDP, current account balance as a share of GDP, trade as a share of GDP, central government debt as a share of GDP, the log of foreign assets in the sovereign's banking system, FDI net inflows as a share of GDP, and the external balance on goods and services as a share of GDP. We measure fundamentals as either *i*) the level of the variable in the current year, or *ii*) the average value of the variable over the previous three years, depending on the specification. In addition to these economic performance indicators, we also include several borrower history characteristics: an indicator for whether a country has ever defaulted, if the sovereign is newly rated, and a financial risk measure from the International Country Risk Guide (ICRG).[5]

We measure a sovereign's political and institutional performance with the following indicators: annual polity2 scores; an indicator for left wing governments; the tenure of the chief executive is in office; whether a presidential election was held that year; indices of external conflict, civil war, law and order, and terrorism from the ICRG; and the World Bank's World Governance Indicators (WGI) for regulatory quality, government effectiveness, political stability, rule of law, control of corruption, and voice and accountability. To account for incentive problems in the ratings process, we use a dummy indicator for countries that solicit ratings in the year they are issued.[6]

We draw these variables from the World Development Indicators (WDI), International Monetary Fund, World Governance Indicators (Kaufmann et al. 2010), the Polity IV project (Marshall 2020), the Database of Political Institutions (Cruz et al. 2021), the ICRG (PRS Group et al. 1991), and Gibert (2019). Our final sample is composed of all country-year observations for which ratings and country fundamentals in our most comprehensive specification are non-missing. This yields a total of 1,268 unique country-years covering 95 countries in total, from 2002-2019. Appendix Table (A3) provides summary statistics for ratings and covariates for our estimation sample.

[5]A plot of the number of defaults & restructurings over time can be found in Appendix Figure (A3)

[6]Since ratings fees are paid by the debt issuer, rating agencies may have incentives to issue a better rating to a higher risk borrower in order to retain its business. Further, a borrower may have incentives to only solicit ratings when fundamentals are temporarily high.

2.3. Country Characteristics

Economists and policymakers have alleged numerous regional biases in the rating agency process in recent years. Prior research, for example, suggests a bias against African and Middle Eastern countries in sovereign credit ratings (Yalta & Yalta 2018, Fofack 2021), though these may not be robust to the inclusion of substantial control variables. At the same time, one might expect an agency bias against Latin American countries based on historically-conditioned perceptions of riskiness driven by a few serial defaulters (Afonso et al. 2011). In contrast, we hypothesize a potential ratings premium for North American and Western European countries, driven by home bias (Fuchs & Gehring 2017), cultural similarity, or other mechanisms.

Perceptions of country risk may also be shaped by a country's membership in the leading international organizations. This could be "payoff relevant" to the extent that members-states would prefer that their colleagues not default, given potential spillover effects. Further, members might care about the internal political stability of another state, leading them to help "bailout" a country that risks a default. To test whether membership in multilateral organizations influences a sovereign rating, we generate indicators for membership in G7, G20, OECD, and the NATO military alliance based on the timing of membership. We also consider whether institutional legacies affect contemporary ratings by including dummies for French, British, and Spanish/Portuguese colonies (Acemoglu et al. 2001), and for French (civil) and British (common law) legal origins (Porta et al. 2008). Additionally, we account for Anglophone biases by including a dummy for English-speaking nations (Fuchs & Gehring 2017).

Based on the considerations discussed above, we employ 24 sovereign and regional specific variables of interest to test for the existence of penalties and premiums in sovereign ratings: G7, NATO, G20, EU, OECD, Asian Infrastructure Investment Bank (AIIB), Arab League, and ASEAN membership, Africa, South Asia, Europe and Central Asia, East Asia and Pacific, Middle East and North Africa, Latin America, French colony, British colony, Spanish/Portuguese colony, French legal system, British legal system, socialist state, English language, and Russia/China/US ally dummies.

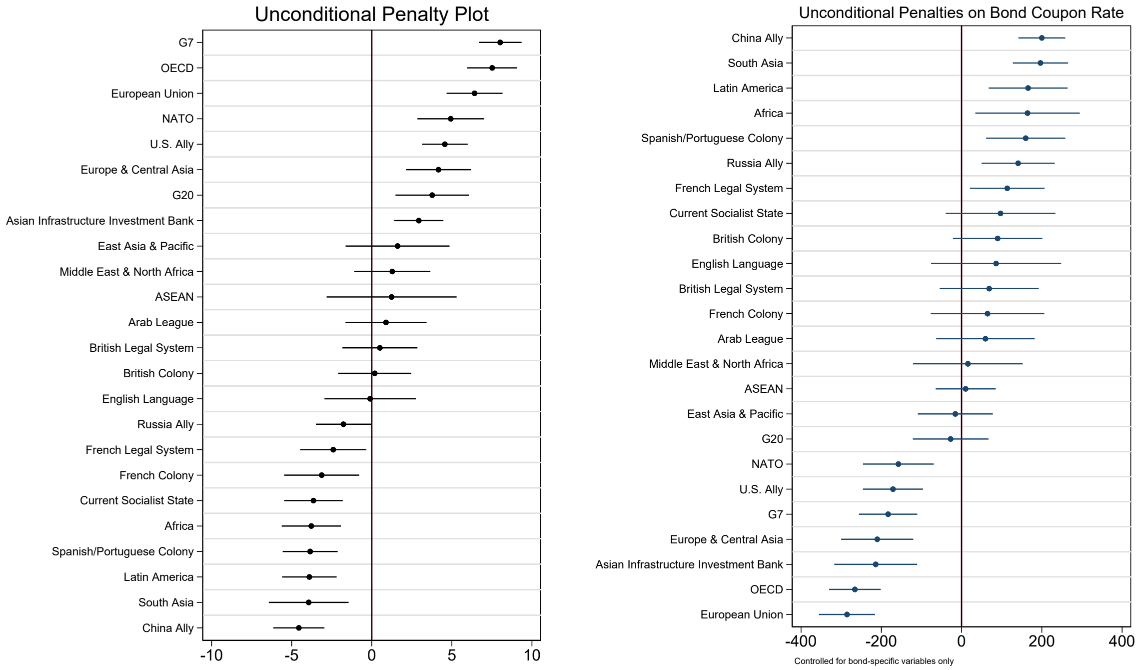
2.4. Bond-level data

The presence of ratings bias may transmit into borrowing costs if investors use them to assess a sovereign's creditworthiness. To estimate the effect of ratings bias on borrowing costs, we collect bond-level data on sovereign placements from Cbonds, a global bond-trading platform with data on over 330,000 domestic and international bond issues from 170 countries. From the Cbonds dataset we take coupon rate, nominal bond value, maturity, placement date, and currency for all international sovereign bonds. We transform fixed and variable rate coupons, as well as those of varying payment schedules, into to average annual coupons. Using monthly exchange rates, we convert all non-dollar denominated bond values into current US dollars. We then merge our bond-level dataset with the sovereign issuer's most recent credit rating at placement, as well as the country-year fundamentals described in Section 2.2. The result is 931 international bond issues from 2002-2019 for which observe coupons, ratings, and all of the country fundamentals. Summary statistics for international bond issues are in Appendix Table (A15).

2.5. Unconditional penalties and premiums

Figure (1) displays unconditional penalties and premiums derived from bivariate regressions of the outcome on each variable in our set of characteristics. Panel (a) uses the ratings outcome in the country-year sample, while panel (b) uses the bond-level data and initial coupon as the outcome.[7] Western, developed country groups such as the G7, OECD, and NATO tend to be highly rated, while socialist, African, South Asian, and Latin American countries, are poorly rated. British origins, language, and legal systems are generally uncorrelated, while French and Spanish colonies are rated lower on average. Countries allied to the United States are rated higher, while those allied to Russia and China – as measured by UN voting behavior – exhibit lower average ratings. The pattern

[7]Panel (b) further controls for basic bond-level characteristics, including maturity and an own-currency dummy.



(a) Ratings (b) Coupons

Figure 1: Unconditional penalties and premiums

Note: Figure plots estimates and confidence intervals for unconditional differences in credit scores (a) and bond coupons (b) across various country characteristics. Panel (a) sample is the country-year panel, while (b) is the sample of sovereign bond issues. Bond models control for maturity and and currency of issue.

of bond coupons in Panel (b) is very similar; perhaps unsurprisingly, country-groups that tend to be more highly rated also tend to have lower borrowing costs.

The ratings spreads in Panel (a) are unconditional, and may well be driven by country fundamentals rather than bias in the ratings algorithm. Similarly, the coupon spreads in Panel (b) may be driven by fundamentals, ratings bias, investor bias, or some other mechanism. To disentangle these forces, we turn to our econometric strategy.

3. Econometric strategy

We propose a two-part, partial equilibrium approach to estimating the economic costs of ratings bias. In the first step, we develop an econometric model to assess the extent to which countries with similar economic, political, and borrower history fundamentals are rated differently based on (conditionally) non-payoff-relevant observable characteristics. In the second step, we model bond prices as a function of ratings, and bond and country characteristics. Finally, using the estimated ratings bias coefficients and elasticities of prices to ratings, we predict the costs associated with each source of bias, all else equal.

3.1. Ratings regression

Ratings agencies assess the creditworthiness of sovereign borrowers based on observable, payoff-relevant characteristics. Consistent with the definition in Becker (1971), we consider a rating process "biased" if, conditional on observable fundamentals, the residual variation in ratings can be systematically predicted by non payoff-relevant country identity characteristics.

The problems with inferring bias in decision-making from observational regression analysis are well-known (Guryan & Charles 2013). Ideally, we might conduct a randomized experiment wherein ratings agencies were assigned to evaluate otherwise identical country cases, randomly varying country identity, following an extensive literature on audit/correspondence experiments (Bertrand & Duflo 2016). Unfortunately, this is implausible in our context; the interpretation of bias in our observational data therefore depends on an assumption of selection on observables. In order for an estimate of bias to be credible, we must ensure that we have controlled for a sufficiently rich set of fundamentals that determine ratings and may be correlated with the characteristic of interest. Our innovation – explained below – is to apply a machine learning approach to the selection of these covariates.

To test for the existence of multilateral, regional, and institutional legacy biases in sovereign ratings, we proceed as follows. First, we estimate regression models to identify the fundamental economic, political, and borrower history characteristics that predict ratings across countries and over time. Second, we estimate regressions for a wide set of penalty variables, conditional on the fundamentals.

We first estimate the following linear regression for country i at year t:

$$y_{it} = \alpha + X_{it}'\beta + Z_{it}'\psi + D_{it}'\phi + \delta_t + \varepsilon_{i,t} \tag{1}$$

y_{it}, the outcome variable, is the weighted average rating across the three rating agencies. X_{it}, Z_{it}, and D_{it} are time-varying, country-specific economic, political, and borrower history variables, respectively. In the analysis, we consider many different combinations of variables within and between these categories. δ_t is a time fixed effect to capture global macroeconomic shocks common to all countries and $\varepsilon_{i,t}$ is the idiosyncratic error term. We cluster our standard errors at the country level to account for serial correlation in outcomes and regressors over time within countries.

We test coefficient stability and explanatory power across many combinations and subsets of X_{it}, Z_{it}, and D_{it} in the analysis. This raises the possibility of ad-hoc model selection, increasing researcher degrees of freedom (Kasy 2021). We discipline this process by automating covariate selection using a post-LASSO estimation procedure (Belloni & Chernozhukov 2013). We first estimate a LASSO regression – a linear model with an L1 penalty – of Y on the full set of possible X_{it}, Z_{it}, and D_{it} variables. We then estimate equation (1) using the subset of these variables selected by the LASSO procedure. We estimate the optimal LASSO complexity parameter using 5-fold cross validation.

Let $\tilde{X}_{it}$, $\tilde{Z}_{it}$, and $\tilde{D}_{it}$ denote the economic, political, and borrower history fundamentals selected by the LASSO procedure. To test for penalties and premiums in sovereign credit ratings, we estimate the following specification for country i at time t:

$$y_{it} = \alpha + \vartheta p_{it} + \tilde{X}_{it}'\beta + \tilde{Z}_{it}'\psi + \tilde{D}_{it}'\phi + \delta_t + \epsilon_{i,t} \tag{2}$$

p_{it} is an indicator variable for a given country characteristic. These characteristics may vary over time within countries (e.g., EU membership) or remain constant over time (e.g., regional location).[8] In our framework, $\vartheta > 0$ implies a ratings premium

[8] Because of these time-invariant country characteristics p_i, we are unable to include country fixed effects in our regression. In addition, we are interested in explaining cross-sectional variation in credit ratings,

for characteristic p, while $\vartheta < 0$ implies a ratings penalty. In order for ϑ to be interpreted as bias, we assume that all payoff-relevant characteristics are included in the model. One reasonable objection to this interpretation is that ratings analysts consider not only quantitative information about a sovereign's ability to repay, but qualitative judgements about its willingness. For this reason, we include the borrower default history characteristics D. This history may shape how analysts perceive idiosyntractic differences in a sovereign's willingness to repay its debt.

Note that our models, explained in detail in Section 4.2, estimate ratings as a function of a comprehensive set of machine-selected country fundamentals. Still, it remains possible that unobserved, payoff-relevant characteristics drive the observed country identity penalties and premiums. While it is impossible to rule this out completely, we consider unobservable "soft" information or raters' qualitative impressions not as confounders per se, but rather as mechanisms by which bias may enter the ratings process.

3.2. Bond-level Regression

For bond b from country issuer i at date d in year t, we estimate the following:

$$r_{bidt} = \alpha + g(\theta, y_{idt}) + \gamma p_{it} + B_b'\pi + \tilde{X}_{it}'\beta + \tilde{Z}_{it}'\psi + \tilde{D}_{it}'\phi + \delta_t + \epsilon_{i,t} \tag{3}$$

Where r_{bidt} is the coupon rate for bond b and B_b are controls for bond-level characteristics, including loan size, maturity, and an indicator for dollar-denomination. g is a potentially nonlinear function of the most recent rating y_{idt} for country i as of bond placement date d. In some specifications, we allow for nonlinearity in the effect of ratings on coupons in order to model discontinuities in perceived creditworthiness around major thresholds, such as investment grade ratings (White 2010).[9]

We estimate three different versions of equation (3). First, we consider whether ratings add information for investors over and above fundamentals. This consists of

rather than restricting to within-country variation.

[9]In this case, we estimate g semi-parametrically by including indicators for the following bins of the ratings variable: AAA, AA, A, BBB and BB, with B or below as the omitted group.

removing p_{it} and testing whether $\theta < 0$. Second, we test whether investors replicate the same penalties and premiums we observe in the credit ratings model in equation (2). In this model, we remove $g(\theta, y_{idt})$ and test whether $\gamma \neq 0$. However, this result may have multiple interpretations – investors may either be incorporating the biases of credit ratings into interest rates, or simply transmitting their own independent biases into prices. In order to disentangle these interpretations, we lastly test whether these penalties and premiums in sovereign bond prices are driven by ratings bias. For this specification, we include all variables in (3). If θ remains significant but $\gamma = 0$, we conclude that bias in sovereign issues is primarily driven through a ratings channel.

Our final step is to compute the average impact of a given source of ratings bias on borrowing costs. This elasticity is defined as

$$\xi^r_{it} = \frac{\partial r}{\partial p} = g'(\theta, y_{idt})\hat{\vartheta} \tag{4}$$

Note that this quantity may vary across observations if $g(.)$ is nonlinear in ratings.[10]

3.3. Identification Challenges

This strategy raises several empirical challenges. First, since the experimental approach is impossible, we must be confident in our selection on observables assumption. In order to bolster the plausibility of this assumption, we include a rich set of covariates covering country-level time-varying economic and political fundamentals. We begin with the standard set of fundamentals considered in the literature (Cantor & Packer 1996, Fuchs & Gehring 2017). To this we add additional variables that account for default history to rule out lagged effects of prior defaults that may correlate with fixed country characteristics and influence ratings perceptions. We also include rating recency, since countries may self-select into initial ratings. In order to maximize the out of sample predictive power of our ratings model, we discipline the selection of these covariates

[10] In the linear case, ξ^r reduces to the multiplication of two regression coefficients. In the nonlinear case, to calculate the mean borrowing cost effect, we would average over all i, t for which $p_{it} = 1$, weighting by total country-year borrowing.

according to a machine learning procedure detailed in Section 4.2.

The size of the control set generates the possibility of inducing selection bias by conditioning on collider variables, also known as the "bad controls" problem (Guryan & Charles 2013). For example, many of the fundamentals explicitly considered by ratings agencies are derived from summary indices that proxy for underlying characteristics, such as political stability (Fitch Investor Services 2020, Moody's Investor Services 2019, Standard & Poor's 2017). If these country indices are also systematically biased, then controlling for these introduces colliders in the ratings regression.[11] More broadly, if any other mechanisms induce causality between country fixed characteristics and the economic and political covariates that determine ratings, our penalty estimates will be biased. Model complexity (size of covariate set) therefore presents a trade-off between selection and collider bias. As a result, we compare the results of the main post-LASSO specification to numerous other several specifications varying in complexity: unconditional, X_{it} and D_{it} only, Z_{it} only, and all of X_{it}, D_{it}, and Z_{it}.

The bond-level regression also contains endogeneity when ratings enter the right-hand side. Even though we control for the determinants of ratings and bond characteristics, unobserved bond-specific shocks may correlate with ratings and coupon rates. In order to estimate the price effects of ratings bias, the elasticity of coupons to ratings must be causally identified. To validate our main OLS results, we also estimate a version of equation (3) that leverages ratings changes and secondary market trading prices in an event-study framework.

Finally, we obtain an estimate of the cost of bias, ξ^r, by simply multiplying $g'(\theta)$ from equation (3) with the ratings bias coefficient from equation (2). This is a counterfactual quantity, and therefore requires rather strong partial equilibrium assumptions in absence of a fully-specified credit market model. For example, large positive shocks to the ratings of many penalized countries simultaneously may not only affect the coupon rate of country i as estimated in equation (3), but may also cause reallocations of investor

[11] For example, consider a situation where the World Bank Governance Indicators are overly pessimistic for African countries. At a given level of the WGI, African countries will therefore be positively selected relative to others, resulting in an underestimation of their ratings penalty.

portfolios across countries, changing equilibrium asset prices. Similarly, supply-side effects may also affect the interpretation if countries respond to own and neighbors' ratings shocks by changing the quantity of debt issued. In order for ξ^r to represent the counterfactual of interest, we must assume that these general equilibrium spillovers do not occur. This is perhaps plausible for a small change in ratings in an individual country, but unlikely for large changes across entire country groups. The magnitudes should therefore be interpreted with caution.

4. Results: Ratings Regressions

4.1. Baseline Regression Results

We begin with equation (1), which estimates the determinants of sovereign ratings. We show the results of our baseline regressions in Appendix Table A4. We consider three baseline models – political variables only (column 1), economic variables only (columns 2 and 3), and economic and political variables (columns 4 and 5). Economic variables are measured either annually (columns 2 and 4) or as three-year lagged averages (columns 3 and 5). All models include borrower history indicators for ever default and solicited rating, as well as a linear term for time since last rating.

Column (1) presents the political variables only model. We find that the level of democracy (Polity2 Index), civil war & terrorism indices, the level of financial risk, government effectiveness, regulatory quality, and ever defaulting are all statistically significantly correlated with ratings. The model attains an R^2 of 0.88, meaning that political variables alone predict a large share of the variation in sovereign credit ratings.

Economic fundamentals are often considered to be the key criteria in setting sovereign ratings. In our economic variables only model (column 2), we observe that log GDP per capita, log population, inflation levels, external debt, central government debt, rating recency, and default history are significantly correlated with sovereign credit ratings. Coefficient estimates are generally in the expected direction. The results indicate that ever defaulting is associated with a 2 point ratings reduction, suggesting a long-run negative impact of default on risk perceptions. The model attains an R^2 of 0.866, interestingly slightly lower than the political-only model in (1). Using lagged three year average economic variables (column 3) generates similar point estimates, but increases R^2 to 0.878 by smoothing out noise in the covariates.

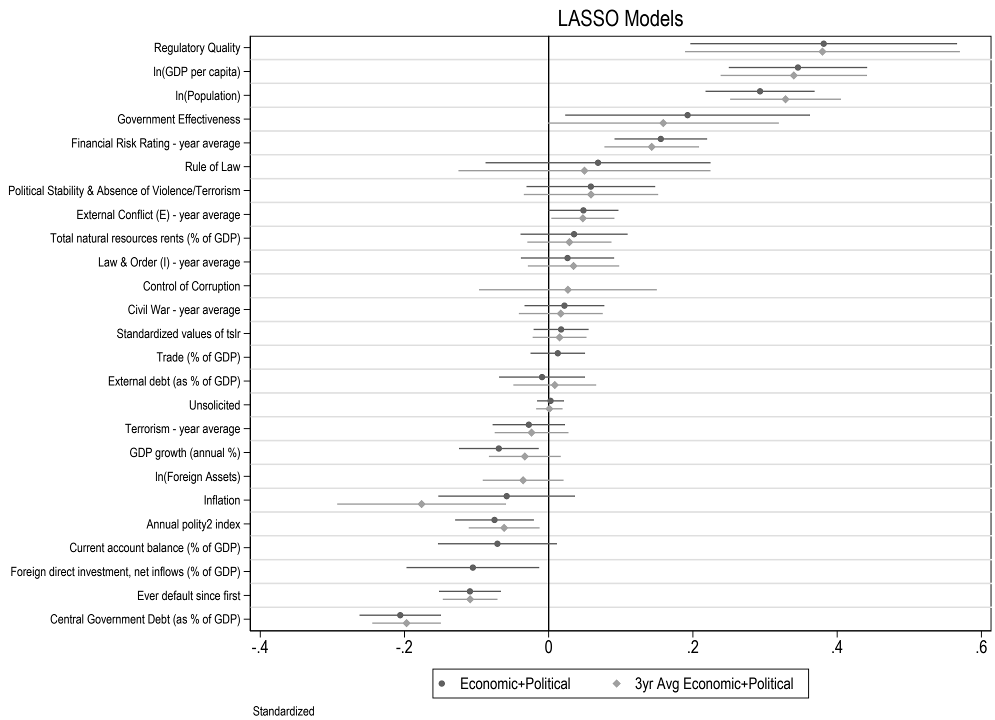


Figure 2: Post-LASSO standardized coefficient plots

Note: Figure shows coefficient estimates and 95% confidence intervals on country fundamentals from the primary post-LASSO specification, where the coefficients are standardized for comparability. We plot estimates for models using economic fundamentals measured in the current year as well as the three-year average.

Economic and political variables are likely to be highly correlated and so must be included jointly. In column (4) we model ratings as a combination of economic (and averaged economic) and political variables as in equation (1). The inclusion of economic variables does not substantially change the set of significant political variables, though several economic variables change significance after the inclusion of political factors. Similar to the political and economic variable models, we observe that default is associated with a 1.2-point ratings penalty, robust to all specifications. The joint model increases the in-sample R^2 to 0.934. Results are similar when including lagged economic averages in column (5), with an R^2 of 0.94.

Figure (2) visualizes the estimates of Appendix Table A4 columns (6) and (7), the post-LASSO models, plotting standardized coefficients from these models to compare magnitudes across variables.[12] We find that the most quantitatively important economic determinants of sovereign credit ratings are log GDP per capita, population, ever defaulting, and government debt. We also find that most influential institutional factors are regulatory quality, government effectiveness, democracy.[13]

4.2. Model selection

Modeling the determinants of ratings is primarily a prediction problem, rather than one of causal inference (Mullainathan & Spiess 2017, Athey & Imbens 2019). Unless we employ a consistent model selection criteria, we risk overfitting to our specific set of countries and time periods, and employing ad-hoc model selection procedures that magnify researcher degrees of freedom (Simmons et al. 2011, Kasy 2021). To solve these issues, we consider estimators that minimize the out of sample mean squared error, comparing the performance of two commonly-used machine-learning approaches to model selection – LASSO and Random Forest (Hastie et al. 2017) – to our baseline specifications. In Section 4.3, we test the robustness of the penalties and premiums to numerous different model specifications. Ultimately, however, we use the automated linear covariate selection of post-LASSO as our preferred penalty estimates when calculating borrowing cost effects, given the attractive properties of this estimator (Belloni & Chernozhukov 2013) and its superior out-of-sample prediction performance.

[12]Standardized coefficient plots for the political, economic, and economic 3-year average models in Appendix Figures (A4-A6)

[13]In Appendix Tables A5-A11, we consider the robustness of our results to disaggregating by rating agency. The results are unchanged. Table A12 estimates the post-LASSO models interacting the covariates with a post-2008 dummy, to account for changes in the ratings process in the aftermath of the Global Financial Crisis.

We first split our data into training and testing data at a 3:1 ratio, using clustered sampling at the country level. This procedure generates independent training and testing samples, accounting for within-country autocorrelation by sampling the full panel of a given country, rather than individual country-year observations. We then use the training data to estimate each of the following models: i) OLS-Pol, ii) OLS-Econ, iii) OLS-All, iv) LASSO, v) RF, and vi) an ensemble predictor. Models $i) - iii)$ are simply OLS regressions that include economic, political, or all fundamentals, as in Section 4.1.

Model iv) is a linear regression which minimizes the sum of squared errors subject to an L1 penalty term, which regularizes the model to avoid overfitting. As such, the LASSO estimation algorithm drops covariates discretely in order to satisfy the penalty constraint. The weight on the penalty term, λ, selects model complexity and therefore the location along the bias-variance frontier. We choose the λ that maximizes predictive power in a five-fold cross-validation procedure, employing the 1-standard error rule for complexity parameter selection (see Hastie et al. (2017)).

Model v) is a Random Forest algorithm, which aggregates predictions from many individual decision trees (we set the number of trees to 500). Random forest uses a bootstrap aggregating (bagging) procedure in which subsets of covariates and observations are resampled with replacement (Breiman 2001) to generate individual decision trees of maximal complexity. These predictions are then averaged to reduce the variance of any individual tree without increasing bias. The potential value of the random forest relative to linear models is its ability to capture potentially complex interactive effects by leveraging the nonparametric nature of the decision tree algorithm.

Finally, model vi) is a linear ensemble combination of LASSO and Random Forest, in which we regress the observed ratings in the test sample on the estimated out-of-sample predicted values for each model. We then use these regression coefficients as convex weights in a weighted average prediction. Further details of the machine learning estimation procedures are in Appendix Figures A7-A9.

For each model, we take the estimated prediction functions and calculate out of sample prediction error (R^2 and root mean-squared-error) on the testing sample, shown in Figure 3. OLS with ad-hoc model selection obtains lower R^2 than those with all covariates included. The use of three-year lagged averages for the economic variables if anything slightly reduces the R^2 of the full model.

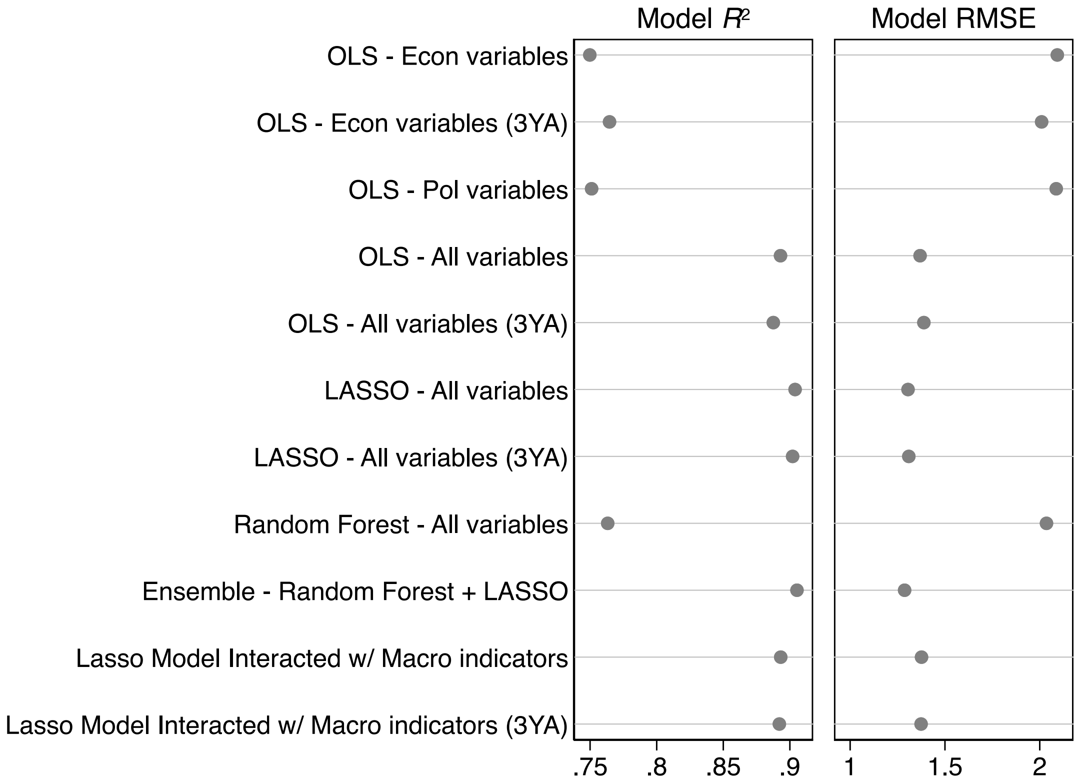


Figure 3: Out of sample forecast error

Note: This figure presents the out of sample R^2 and root mean-squared error (RMSE) of the OLS, LASSO, Random Forest, and Ensemble models used to predict credit ratings. 3YA indicates that economic variables are averaged over the past three years. The interacted macro indicators are VIX, EMBI and US T-bill rate. Training sample is 25% of the country-year panel, randomly selected with clustered sampling.

However, all of the OLS models obtain lower R^2 in the out of sample test than when estimated in-sample on the full sample. For example, the full in-sample R^2 of the OLS model with all variables is 0.934 (Table A4) but falls to 0.893 when we predict out of sample, suggesting a moderate amount of overfitting. As such, this implies that LASSO may be able to improve predictive power and discipline model selection. We find that LASSO improves R^2 from 0.893 to 0.904 in the test sample, and reduces RMSE from

1.368 to 1.305, a 4.6% improvement. In order to reduce model compelexity and mitigate overfitting, the optimal LASSO penalty leads 7 covariates to be dropped from the main model. A list of selected covariates can be found in Appendix Table A13.

Finally, the Random Forest algorithm performs rather poorly relative to either OLS or LASSO, achieving an out of sample R^2 of 0.763, similar to the OLS with only economic or political variables. This poor performance may be driven in part by the fact that the data generating process that determines ratings is approximately linear. More importantly, however, our training set contains just 940 observations. Random Forest is a data-intensive algorithm since it trains decision trees, which are fundamentally constrained in their complexity by the number of observations that can be grouped in a given split (Breiman 2001).[14] If the maximum tree complexity allowed by a given sample size is well below the optimal level of complexity for out of sample prediction, then the resulting average predictor across trees will perform relatively poorly. This appears to be the case in our context; we find an individual decision tree estimated on the whole training sample fails to attain optimal complexity in cross-validation.[15]

Despite this poor performance, the Random Forest identifies orthogonal variation in ratings that has predictive power over and above the LASSO prediction function. As such, the ensemble model assigns a small positive weight to the Random Forest prediction, leading to a very small increase in the out of sample R^2, to 0.9053. However, given the negligible improvement and the strong performance of LASSO alone, we focus on the post-LASSO model when estimating our preferred specification of equation (2).

Lastly, we also consider the possibility that accounting for the role of global macro-financial conditions may improve the predictive power of the LASSO model if creditworthiness deferentially responds to macro shocks by country characteristics. To that end, we estimate the out of sample error for LASSO models in which we interact country fundamentals with time-varying global measures of financial conditions, including the VIX, EMBI, and 10-year US T-bill rate. These models, in the bottom two rows of Figure

[14] This minimum split size is typically set to 5, and of course is bounded below at 1.

[15] The cross-validated prediction error is strictly decreasing in tree depth over the feasible range of model complexity. Results available upon request.

3, do not improve forecast error, and so we use the more parsimonious LASSO models.

4.3. Penalties and Premiums

Our main findings are in Figure 4, which plots estimates of γ in equation (2) for a wide array of characteristics p_{it}.[16] All models use post-LASSO estimation for covariate selection. Table 1 provides quantitative estimates for select country characteristics for our main models – economic and political covariates (columns 1-2), and LASSO-selected covariates (columns 3-4).[17] Column (3) shows our preferred post-LASSO specification.

Our results suggest significant biases in sovereign ratings. To test whether membership in international institutions leads to more favorable ratings, we include dummies for G7, OECD, OECD, and NATO membership. Each of these dummy variables is associated with a significant ratings premium, the largest of which accrues to the G7 countries, which are rated an average 1.2 points higher, conditional on fundamentals. We also observe a significant premium for EU member states. Importantly, since we control for economic and political fundamentals, these premiums are not driven by either the selection criteria for membership in these organizations or the economic and political benefits that they may generate. For example, G7 membership reflects economic size; EU membership likely generates large economic benefits (Campos et al. 2014); NATO membership may enhance political stability. To the extent that our selected model accounts for these factors and predicts over 90% of the variation in ratings, the estimated coefficients γ isolate the non-payoff-relevant portion of these ratings premia. The unconditional penalty and premium estimates in Figure 1 underscore this point. The G7, OECD, EU, and NATO premia are all more than twice as large in the unconditional specification, suggesting that fundamentals are able to explain a large share of the unconditional ratings gap. However, the existence of large and significant residual gaps is strongly suggestive of ratings' bias.

[16] Note that some of these characteristics are fixed, like region or colonial history, while others may vary offer time, such as multilateral group membership.

[17] Penalty estimates for all combinations of characteristics and models are in Appendix Table A14.

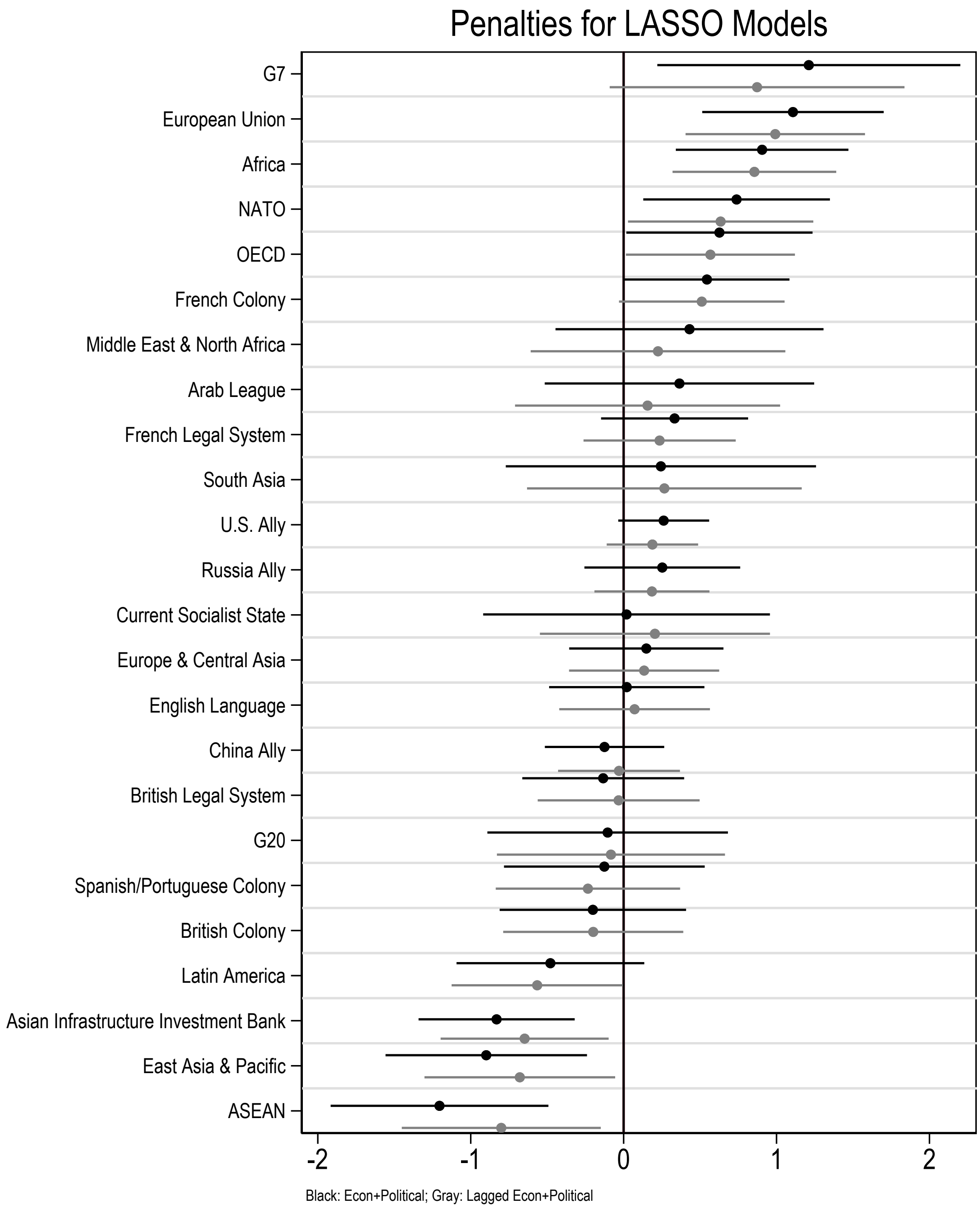


Figure 4: LASSO-selected model penalty plot

Note: Figure shows the penalty and premium estimates and 95% confidence intervals obtained from separate OLS regressions of credit rating on each variable p_{it}, as well as the LASSO-selected covariates from Appendix Table A13. Sample is the full country-year panel.

We also find evidence of substantial ratings penalties. Most notably, despite their positive unconditional ratings premia, many groups of Asian countries appear underrated in our model. Countries in the East Asia and the Pacific region are rated roughly 0.89 points lower on average, while members of the AIIB are similarly underrated. The largest gaps are for Southeast Asian (ASEAN) nations, who suffer a penalty of 1.2 rating levels on average, a result which is statistically significant across all specifications. We also observe a bias of roughly 0.48-0.66 points against Latin American states, though this relationship is not significant in all models.[18]

Contrary to existing work that suggests a ratings penalty (Fofack 2021), we find that African countries are significantly *over*-rated, nearly 1 point higher, relative to their fundamentals. This relationship holds even if we restrict to sub-Saharan countries. We attribute this discrepancy to our rich set of covariates, many of which have not be accounted for in previous studies. We find no evidence of a premium for English language,[19] British colonial history, or, significantly, common law institutions. Lastly, we note that in some cases, global economic institutions may partially explain residual ratings differences in ways not captured by fundamentals. For example, ratings analysts may believe that African sovereigns will be bailed out by international financial institutions, based on previous experiences such as the HIPC Initiative. Similarly, EU nations might be supported by internal transfers or monetary policy actions by the ECB. Analysts may therefore rationally assess these as lower credit risks, without any bias. However, this institutional mechanism does not explain the majority of our results.

As robustness tests, Appendix Figures A10-A16 show penalty estimates for the various other non-LASSO ratings models, as well as by rating agency. The results are largely unchanged. Appendix Figure A17 plots estimates from a post-LASSO model that interacts the penalties variables with a post-2008 indicator to test whether the Global Financial Crisis affected ratings bias. The penalty estimates are nearly always of the

[18]In Appendix Table A14, we show that Spanish/Portuguese colonies are also consistently under-rated, as are countries with French legal systems, though these penalties are not always significant and appear sensitive to specification.

[19]This contrasts with the findings of Fuchs & Gehring (2017), who find a role for common language in explaining home bias in ratings.

Table 1: Credit rating penalty and premium estimates

	P+E	P+EYA	L:P+E	L:P+EYA
	(1)	(2)	(3)	(4)
French Colony	0.740***	0.593**	0.545**	0.511*
	(0.284)	(0.284)	(0.272)	(0.273)
Africa	1.084***	1.053***	0.906***	0.855***
	(0.316)	(0.307)	(0.284)	(0.270)
Latin America	-0.657**	-0.654**	-0.479	-0.565**
	(0.310)	(0.307)	(0.309)	(0.282)
East Asia & Pacific	-0.868**	-0.882**	-0.898***	-0.679**
	(0.392)	(0.406)	(0.332)	(0.314)
NATO	0.719**	0.674**	0.739**	0.635**
	(0.327)	(0.336)	(0.307)	(0.305)
G7	1.182**	1.019**	1.211**	0.873*
	(0.501)	(0.487)	(0.499)	(0.486)
European Union	1.151***	1.080***	1.108***	0.992***
	(0.326)	(0.319)	(0.299)	(0.296)
ASEAN	-1.148***	-1.156***	-1.204***	-0.800**
	(0.391)	(0.391)	(0.359)	(0.328)
Asian Infrastructure Investment Bank	-0.755***	-0.606**	-0.831***	-0.647**
	(0.231)	(0.244)	(0.257)	(0.277)
OECD	0.643**	0.586**	0.627**	0.568**
	(0.301)	(0.295)	(0.307)	(0.278)

Note: * $p < 0.05$, ** $p < 0.01$,*** $p < 0.001$. Standard errors in parentheses; clustered at the country level. This table presents credit ratings penalty and premium estimates for selected country characteristics. Outcome variable is country sovereign credit rating. Covariate model is indicated in table header. P - Political variables only; E - Economic variables only; EYA - Lagged 3 year average economic variables only; L: - LASSO.

same sign before and after 2008, though in some cases there are noticeable differences in magnitudes. However, for the most pronounced biases, the estimates appear relatively stable over time. Finally, "peso problems" also complicate the interpretation of the results (Krasker 1980). It may be that country-specific penalties reflect accurate assessments of default risk over longer time horizons than our sample period, since defaults are rare events. However, as explained in Section 4, our post-LASSO models include an "ever-default" indicator, which captures pre-sample information on default history going back to 1975, using data from Asonuma & Trebesch (2016).

5. Results: Bond-level Regressions

We move to our analysis of bond-level data to answer three related questions: *i*) how much do initial coupons respond to ratings, conditional on fundamentals, *ii*) do bond prices absorb the biases of ratings agencies, and *iii*) what are the implications of ratings bias for borrowing costs.

5.1. Coupons and ratings

Table 2 estimates equation (3) on a sample of 931 international bond issues across 73 countries for which we have data, including bound and country-level fundamentals as well as a linear function of ratings. Column (1) includes only bond-level characteristics – the duration, placement size, and an indicator for whether the bond is issued in the home currency, as well as country and year fixed effects. The estimate on rating shows that a one-point increase in credit rating is associated with a reduction in the initial coupon rate of 30.4 basis points, significant at 1%.

Table 2: Bond coupons at issue and credit ratings

	B	B+E	B+P	B+(L:E+P)	B+(L:E+P)	B+E+P	B+E+P
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Weighted Mean Rating	-30.370***	-27.507***	-18.019***	-25.963***	-18.902**	-22.718***	-15.822*
	(3.342)	(5.803)	(5.035)	(3.464)	(6.161)	(3.720)	(6.657)
Bond Variables							
Duration (year)	3.108***	3.014***	3.297***	3.026***	3.178***	2.934***	3.166***
	(0.439)	(0.428)	(0.435)	(0.440)	(0.427)	(0.437)	(0.423)
Placement amount	1.627***	1.512***	1.650***	1.474***	1.689***	1.558***	1.667***
	(0.401)	(0.392)	(0.397)	(0.385)	(0.391)	(0.384)	(0.389)
Home Currency	35.067	60.611**	41.682*	9.193	52.554**	7.753	65.561***
	(18.920)	(18.729)	(18.696)	(16.672)	(18.436)	(16.659)	(18.492)
Economic Variables		Y		Y	Y	Y	Y
Political Variables			Y	Y	Y	Y	Y
Country FE	Y	Y	Y		Y		Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	931	931	931	931	931	931	931
Countries	73	73	73	73	73	73	73
Adjusted R^2	0.771	0.791	0.785	0.706	0.797	0.714	0.805
Within R^2	0.144	0.218	0.194	0.662	0.241	0.673	0.268

Note: * $p < 0.05$, ** $p < 0.01$,*** $p < 0.001$. Standard errors in parentheses; coupon rate in basis points; placement amount in billions of US dollar; home currency is a dummy variable that takes 1 if the bond is issued in a country's home currency. Outcome variable is coupon rate at issue. Covariate model is indicated in table header. B - Bond variables only; P - Political variables only; E - Economic variables only; L: - LASSO.

Columns (2)-(7) progressively add country-level fundamentals to the model, which reduce the size of the estimate on ratings. This is expected, as these fundamentals capture correlated, public information that investors use in forming expectation about country risk. When both economic and political fundamentals are accounted for in column (7), we find that a one-unit increase in ratings is associated with a reduction in coupons of 15.8 basis points, slightly less than half the estimate in column (1). In our preferred specification of column (4) – which includes only the LASSO-selected covariates and bond-level controls – the effect size is nearly 26 basis points, significant at 1%. The results suggest that even after all payoff-relevant fundamentals are accounted for, investors still rely on sovereign credit ratings to form their expectations of creditworthiness. One implication is that ratings biases may transmit to coupon rates.[20]

The relationship between coupons and credit ratings may be nonlinear if specific thresholds like investment grade and AAA might generate larger responses, despite the fact that the underlying risk is continuous. Appendix Figure A18 plots the (binned) unconditional relationship between ratings and bond-level coupon rates. The results indicate several clear thresholds, at the investment grade threshold (12), the A/B threshold (15), and at triple-A. Appendix Table A18 re-estimates column (4) of Table 2, using ratings group dummies instead of a linear term for ratings. The results confirm the nonlinear effects, which the largest coming at the A/B threshold (133 basis points).

The bond regression may be endogenous if, for example, there is information or sentiment observed by both ratings analysts and markets but not the econometrician, in which case the correlation in Table 2 would not reflect the effect of a change in ratings, holding fundamentals constant. To address this problem, we test whether credit ratings are treated as new information by financial markets using event studies around ratings changes. Appendix Figure A19 plots secondary market bond prices before and after ratings upgrades and downgrades, comparing these to prices in control countries without ratings changes. The results show that prices respond significantly in the expected

[20]Given missing issue yield data, we focus on coupons for our main results because this measure maximizes the sample size. In Appendix Table A16, however, we use the issue yield rather than the coupon rate, finding similar magnitudes.

direction, especially to credit downgrades, with broadly parallel pre-trends. The results are consistent with the simple OLS coupon regression, suggesting that market prices follow the signals of credit ratings, even after existing information has been priced in.

5.2. Penalties and Premiums

Are the biases of credit ratings reflected in borrowing costs? We begin by regressing coupon rates on our LASSO-selected fundamentals and the penalty characteristics used in Section 4.3. Assuming our fundamentals model does systematically not omit payoff-relevant public information, residual differences in borrowing costs by country characteristics may reflect either independent investor biases, or credit ratings biases transmitted into investor behavior via the relationship in Table 2. We differentiate these hypotheses by further controlling for credit ratings in the coupon penalty regressions.

The results of this analysis are in Figure 5, which plots bond-level coupon penalties and premiums for our set of characteristics, showing models with and without controlling for the credit rating. Though mixed, the results on balance suggest that ratings biases are indeed transmitted to borrowing costs.

For example, consider cases where Figure 4 shows a positive ratings premium – NATO, OECD, EU, G7, OECD, and French colony. For each of these characteristics, there is a significant conditional coupon premium. However, this premium consistently shrinks toward zero when the credit rating channel is controlled for. In the most extreme case – the G7 premium – there is no remaining coupon after controlling for both fundamentals and ratings. This suggests that the entire G7 conditional borrowing premium is driven by ratings bias. A similar pattern emerges for Latin America, a ratings penalized region, which has positive and significant coupon penalty. This penalty falls toward zero and is insignificant after controlling for ratings, suggesting, again, the transmission of agency biases to borrowing costs. Finally, the characteristics for which we do not observe any ratings bias also do not see any meaningful difference between the bond-level estimates with and without ratings. This suggests that in cases where there is no ratings bias to transmit, the residual differences in borrowing costs are explained

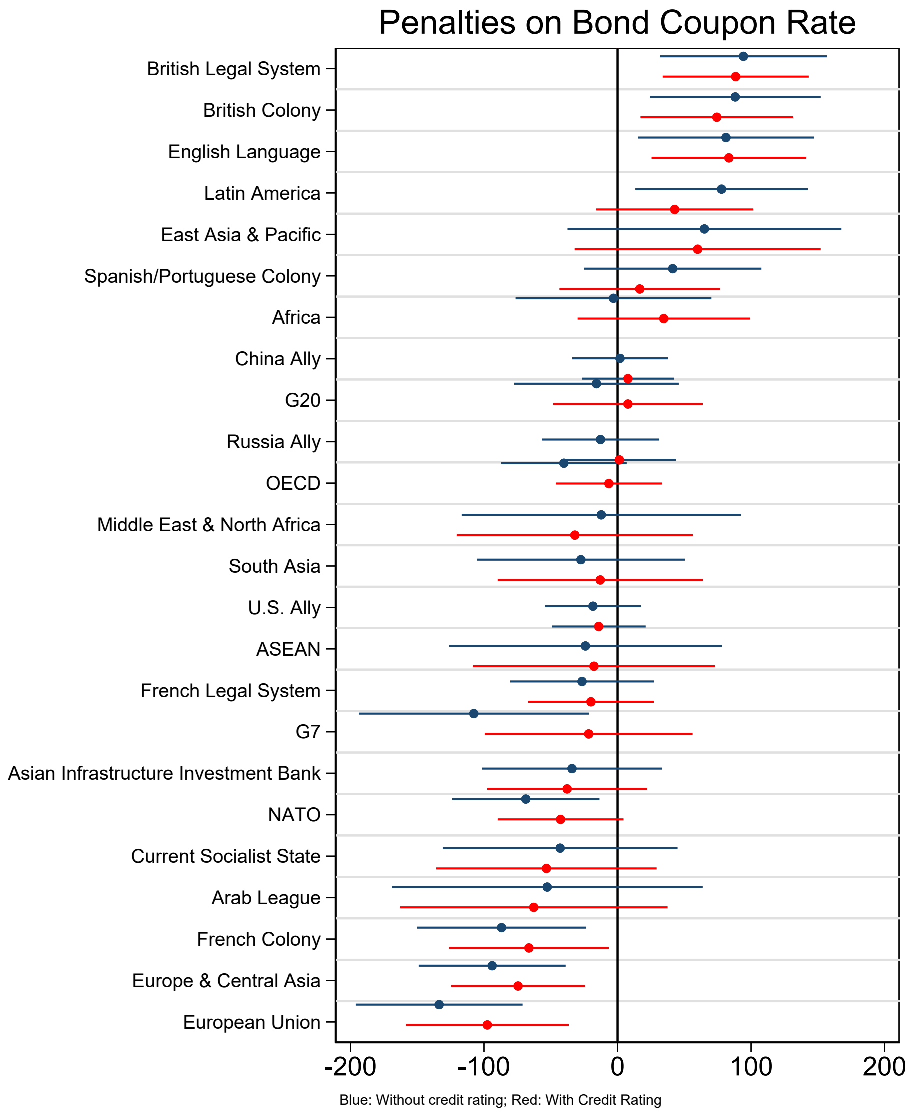


Figure 5: Penalties: Coupon Rates

Note: Figure shows the penalty and premium estimates and 95% confidence intervals obtained from separate OLS regressions of initial bond coupon on each variable p_{it}, as well as the LASSO-selected covariates from Appendix Table A13. All regressions further control for bond maturity, home currency, and placement amount. Sample is the bond issue-level cross-section. Estimates are presented with and without the inclusion of the credit rating on the right-hand side.

solely by orthogonal investor beliefs.

Finally, we conduct a back-of-the-envelope exercise to calculate the costs of ratings bias. Using the linear estimates for equations (2) and (3), the formula in equation (4) reduces to the multiplication of two coefficients – the size of the ratings penalty in Table (1), column (3), and the response of coupons to ratings from Table (2), column (4).

The results are in Table 3 for each penalty variable, with columns indicating the model chosen for penalty estimation. Using our preferred specification of LASSO-selected covariates without country FE (column 1) reveals that ratings bias increases borrowing costs for ASEAN nations, AIIB members, East Asian countries, and Latin American countries by 31.3, 21.6, 23.3, and 12.4 basis points, respectively. Conversely, ratings premiums reduce borrowing costs for African, G7, EU, NATO, and OECD nations by 23.5, 31.4, 28.8, 19.2, and 16.3 basis points, respectively. The results are broadly unchanged depending on specification, though the inclusion of country fixed effects in the second stage in columns (2) and (4) tends to increase the variance of the estimates.

6. Unbiased Portfolio

Section 4.3 demonstrates systematic biases in sovereign credit ratings unexplained by country fundamentals. Furthermore, Section 5 shows that these biases appear to transmit into coupon rates when countries place bonds on international markets. We therefore argue that biased credit ratings may induce mispricing in the bond market. In this section, we consider a simple market test to validate this argument.

In particular, it should be possible to construct an "unbiased" bond portfolio that achieves greater spread without additional risk. To demonstrate this, we consider the common strategy of investing in a portfolio of bonds rated investment-grade. These bonds are selected on the basis of biased ratings and may yield biased returns, but carry an underlying true risk based only on fundamentals. Some bonds in the portfolio will yield only investment-grade returns but carry speculative-grade risk, while some bonds not included in the portfolio will yield higher speculative-grade returns at investment-grade risk. Correcting this bias weakly increases the portfolio yield and reduces portfolio variance, improving risk-adjusted returns. However, if secondary markets correct the biases of the bond issue, this extra spread may shrink over time.

Table 3: Cost of ratings bias

Specification	LASSO		Econ. and Pol.	
	(1)	(2)	(3)	(4)
OECD	-16.27**	-11.85	-14.61**	-10.18
	(8.21)	(8.36)	(7.43)	(8.03)
Africa	-23.52***	-17.12	-24.63***	-17.15
	(8.63)	(10.81)	(8.42)	(12.79)
G7	-31.44**	-22.89	-26.86*	-18.70
	(14.87)	(16.54)	(13.75)	(15.47)
European Union	-28.75***	-20.93	-26.16**	-18.22
	(10.32)	(13.03)	(10.75)	(13.67)
NATO	-19.18**	-13.96	-16.35*	-11.38
	(8.97)	(9.44)	(8.95)	(9.08)
French Colony	-14.14*	-10.30	-16.81**	-11.71
	(8.17)	(7.85)	(7.58)	(9.29)
East Asia & Pacific	23.33**	16.98	19.72*	13.74
	(9.40)	(11.49)	(10.38)	(11.46)
Asian Infrastructure Investment Bank	21.56***	15.70*	17.14***	11.94
	(7.65)	(9.36)	(6.17)	(8.54)
Latin America	12.43	9.05	14.92*	10.39
	(8.22)	(7.39)	(7.70)	(8.25)
ASEAN	31.26***	22.76	26.08**	18.17
	(10.75)	(14.51)	(10.97)	(14.23)
Year FE (both stage)	Y	Y	Y	Y
Country FE (second stage)		Y		Y

Note: * $p < 0.05$, ** $p < 0.01$,*** $p < 0.001$. Standard errors in parentheses, clustered at the country level, obtained from combining estimators of ϑ and θ across equations (2) and (3); coupon rate is measured in basis points. Specifications of the first-stage ratings regression are either the LASSO-selected covariates, or all economic and political variables, as indicated in table header. Second-stage bond-level regression always includes placement amount in billions of US dollar, a home currency indicator variable, and bond maturity in years. Some models, indicated in table footer, additionally include country fixed effects in the second-stage bond regression.

We construct a portfolio that invests in all international sovereign bonds of investment-grade quality, rated above BB+, obtaining the prevailing market yield; we call this the "actual" portfolio. At the same time, we predict counterfactual ratings based on the post-LASSO coefficients (see Section 4.2), which are fundamentals-only and therefore purged of possible biases in the error term. We then use use these predicted ratings to construct the "unbiased" investment-grade portfolio of all bonds carrying a fundamentals-only, LASSO-predicted rating greater than BB+. Both portfolios equally weight all investment-grade bonds for which we have price data.[21] We trim outliers in the bond-day yield series at the 1st and 99th percentiles to reduce noise. The unbiased portfolio swaps out bonds at the margin of inclusion, generating moderate changes in the portfolio composition. 232 bonds are upgraded for inclusion at some point, while 99 are downgraded, 24.4% and 10.4% of the whole unbiased portfolio, respectively. The list of marginal sovereigns is included in Appendix Table A19.

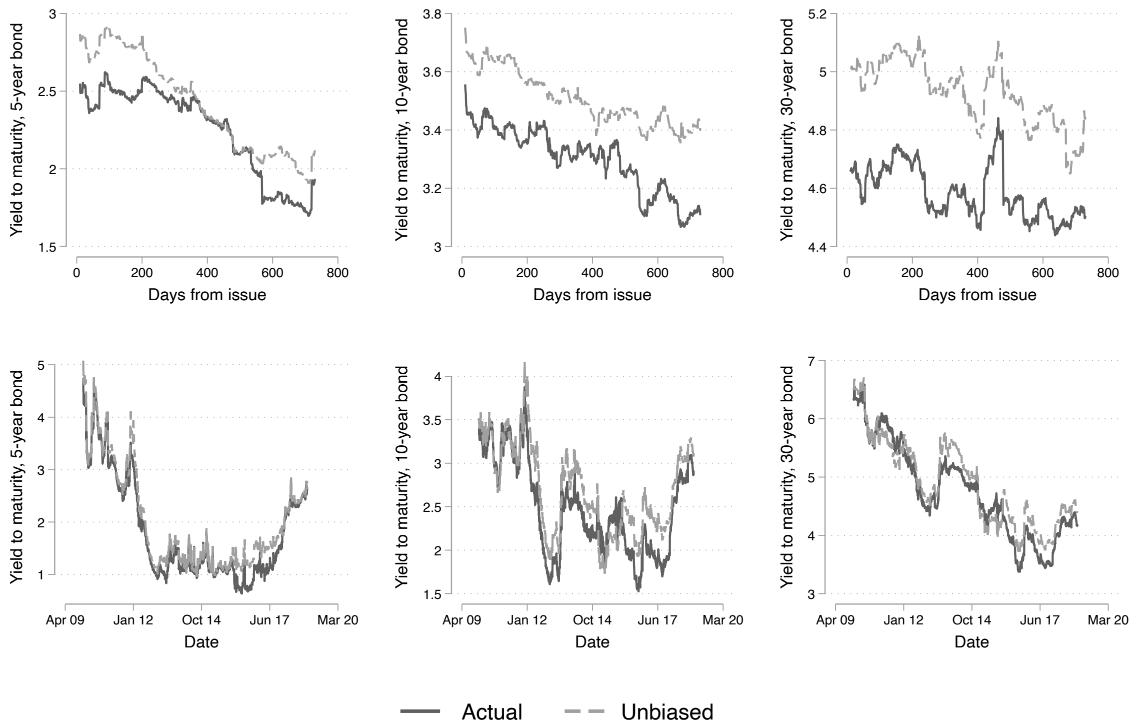


Figure 6: Portfolio yields

Note: Figure shows daily yields from portfolios constructed from all available investment-grade bonds. Actual portfolio uses the observed rating, while the unbiased portfolio uses the rating predicted from our post-LASSO model in Appendix Table A4, column (6). Portfolios weight all bonds equally. Top panel centers each bond around its issue date, while bottom panel shows yields over calendar time.

Despite the fact that de-biasing affects a relatively small fraction of the portfolio, Figure 6 demonstrates that the unbiased portfolio provides excess spread. The top row plots the average yield to maturity of bonds by days from bond issue for 5, 10, and 30-year

[21] We find that results are similar, though less precise, for a market share-weighted portfolio, available on request.

sovereign bonds. The unbiased portfolio trades at a penalty after issue and offers higher yields than the actual portfolio at all maturities. There is some evidence of convergence in the 5 year bonds roughly one year after issue, but none in the longer maturities. That these spreads generally do not converge over the life of the bond suggests that the ratings-induced biases in coupon rates persist in the secondary market.

The bottom panel of Figure 6 shows that these spreads translate into higher returns for the unbiased portfolio over time.[22] These figures plot the portfolio yield by calendar day for each maturity group. Though the two portfolios track each other relatively closely, yields are consistently higher for the unbiased portfolio. The unbiased portfolio yields 19, 22, and 20 basis points in excess spread respectively for 5, 10, and 30-year maturities. Averaging across all maturities, the excess spread of the unbiased portfolio is 14 basis points, while its standard deviation is slightly lower, at 2.03 relative to 2.07.

Of course, we should expect bonds perceived by ratings agencies (and the market) as riskier to have higher expected returns. As such, we quantify the increase in risk-adjusted returns in Appendix Figure A20, which plots the annual Sharpe ratio of each portfolio by maturity.[23] This gives us the difference in risk-adjusted excess returns relative to the corresponding risk-free bond over time. The results confirm that correcting biases in sovereign credit ratings can generate additional yield at lower risk. The results are particularly strong for 10 and 30 year bonds.[24] The results provide strong evidence of persistent bias-induced mispricing – and therefore capital misallocation – in sovereign bond markets. One concern is that changes in currency composition might affect the risk-return profile of the unbiased portfolio. Figure A21 compares Sharpe ratios, restricting the portfolios to different currency compositions. The pattern of results holds.

[22] We focus on the period 2010-2018 because it provides the best coverage for a comparable series of securities.

[23] We calculate the Sharpe ratio for a portfolio-maturity-year as the difference between the mean portfolio return over the year and the mean risk-free T-bill return of the same maturity of over the same period, divided by the standard deviation of the portfolio return.

[24] We focus primarily on within-maturity comparisons because the unbiased portfolio may differ in its maturity composition from the actual portfolio, biasing returns estimates.

7. Conclusion

Algorithmic bias is a source of growing controversy among scholars, policy-makers, and the public. This paper investigates bias among credit rating agencies with respect to their ratings of sovereign bonds. Using a comprehensive set of covariates, we find evidence of premiums and penalties in credit ratings that cannot be explained by economic and political fundamentals. We also find that these biases have real costs for those countries that are penalized, while reducing borrowing costs for some of the richest nations in the world. This implies that even as ratings facilitate credit market efficiency by summarizing information, their built-in bias may actually contribute to a non-trivial misallocation of financial capital. We confirm this intuition with a portfolio analysis exercise, which finds that ratings bias indeed causes sovereign yields to deviate from underlying country risk in a way that is not arbitraged by the market.

Our work contributes to several strands of economic literature and policy concern. First, this research advances the body of work that specifically addresses bias in sovereign credit ratings, linking it with the literature on the economics of discrimination and algorithmic bias. Second, we advance work on sovereign bond markets by providing suggestive evidence of the effect of ratings decisions on bond prices. Finally, this paper raises further concerns about the role of bias in the misallocation of global credit and the mispricing of sovereign risk. Our work suggests that increasing the transparency of the ratings assignment algorithm to eliminate the kind of qualitative judgments that may introduce bias would have important credit-market implications. Future work could provide greater precision than we have done here on the exact costs of such bias to borrower countries and aggregate credit misallocation. The institutional mechanisms that contribute to the formation of bias – such as membership in international institutions or the perception of moral hazard and bailouts – also need further exploration. We view these as productive avenues for future research.

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A. Appendix

A.1. Appendix tables

Table A1: Sovereign Ratings Linear Transformation Scale

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

Note: Table shows the linear transformation scale used for sovereign ratings in this study. Countries that receive a transformed rating of lower then 11 are considered speculative grade investments, or junk bonds.

Table A2: Rating's Correlation Matrix

	Mean Rating	Moody's Mean Rating	Fitch Mean Rating	S&P Mean Rating
Mean Rating	1			
Moody's Mean Rating	0.994***	1		
Fitch Mean Rating	0.995***	0.983***	1	
S&P Mean Rating	0.994***	0.978***	0.986***	1

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Table shows the correlation matrix of the linearly transformed ratings of the three main rating agencies country-year level.

Table A3: Summary Statistics

	Mean	SD	N
Weighted Mean Rating	12.48	4.97	1268
Moody's Weighted Mean Rating	12.89	5.08	1161
Fitch Weighted Mean Rating	13.11	4.89	1076
S&P Weighted Mean Rating	12.85	4.92	1150
ln(GDP per capita)	8.98	1.29	1268
Inflation, consumer prices (annual %)	4.73	5.53	1268
GDP growth (annual %)	3.84	3.47	1268
Growth^2	26.84	54.44	1268
Total natural resources rents (% of GDP)	6.41	10.53	1268
Current account balance (% of GDP)	-0.50	9.01	1268
External debt (as % of GDP)	25.68	31.04	1268
Trade (% of GDP)	91.75	57.47	1268
Central Government Debt (as % of GDP)	45.54	32.40	1268
ln(Foreign Assets)	26.10	3.09	1268
Foreign direct investment, net inflows (% of GDP)	5.32	13.38	1268
External balance on goods & services(% of GDP)	-0.69	13.67	1268
Ever default since first default	0.44	0.50	1268
Time since last rating	1.10	2.41	1268
ln(Population)	16.47	1.48	1268
ln(GDP per capita) (3yr Avg)	8.95	1.30	1268
GDP growth (annual %) (3yr Avg)	3.85	2.83	1268
Growth^2 (3yr Avg)	22.82	40.41	1268
Inflation(3yr Avg)	4.85	4.73	1262
Debt as % of GDP (3yr Avg)	45.28	31.86	1262
Natural Resource Rents as % of GDP(3yr Avg)	6.50	10.59	1268
Current account balance(% of GDP) (3yr Avg)	-0.36	8.36	1253
External debt (as % of GDP) (3yr Avg)	25.77	30.87	1268
Trade(% of GDP) (3yr Avg)	91.24	56.71	1264
ln(Foreign Assets) (3yr Avg)	26.09	3.06	1229
Foreign direct investment, net inflows(% of GDP) (3yr Avg)	5.37	11.39	1266
External balance on goods & services(% of GDP) (3yr Avg)	-0.61	13.35	1264
Ever default since first default	0.44	0.50	1268
Time since last rating	1.10	2.41	1268
Population, total	16.46	1.48	1268
Government Effectiveness	0.27	0.89	1268
Political Stability & Absence of Violence/Terrorism	0.01	0.87	1268
Regulatory Quality	0.33	0.81	1268
Rule of Law	0.18	0.93	1268
Control of Corruption	0.14	0.99	1268
Voice & Accountability	0.17	0.86	1268
Annual polity2 index	5.47	5.76	1268
Left Government	0.27	0.44	1268
Chief Executive Years in Office	6.42	7.53	1268
Presidential Election Held	0.12	0.32	1268
External Conflict (E) - year average	10.00	1.15	1268
Civil War - year average	3.71	0.53	1268
Law & Order (I) - year average	3.77	1.28	1268
Terrorism - year average	2.91	0.82	1268
Financial Risk Rating - year average	38.82	4.26	1268
Unsolicited	0.02	0.12	1268
Observations	1268		

Note: Table shows means, standard deviations, and sample sizes key variables from the country-year panel used in the main ratings models. Data for these summary statistics come from the World Development Indicators (WDI), International Monetary Fund, World Governance Indicators (Kaufmann et al. 2010), Polity IV project (Marshall 2020), the Database of Political Institutions (Cruz et al. 2021), the ICRG (PRS Group et al. 1991), and Gibert (2019)

Table A4: Ratings regression results

	P	E	EYA	E+P	EYA+P	L:E+P	L:EYA+P
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Annual polity2 index	-0.152*			-0.115**	-0.105*	-0.062**	-0.051*
	(0.063)			(0.041)	(0.040)	(0.023)	(0.021)
Left Government	0.150			0.039	0.053		
	(0.240)			(0.198)	(0.203)		
Chief Executive Years in Office	-0.028			-0.023	-0.023		
	(0.019)			(0.015)	(0.015)		
Presidential Election Held	0.186			-0.005	-0.004		
	(0.159)			(0.103)	(0.096)		
External Conflict (E) - year average	0.078			0.173*	0.175	0.183	0.180*
	(0.147)			(0.087)	(0.089)	(0.093)	(0.084)
Civil War - year average	0.779*			0.129	0.167	0.183	0.140
	(0.334)			(0.257)	(0.242)	(0.233)	(0.245)
Law & Order (I) - year average	0.243			0.095	0.117	0.105	0.138
	(0.189)			(0.139)	(0.130)	(0.130)	(0.127)
Terrorism - year average	-0.704**			-0.253	-0.233	-0.178	-0.153
	(0.222)			(0.159)	(0.166)	(0.163)	(0.167)
Financial Risk Rating - year average	0.266***			0.161***	0.153***	0.150***	0.138***
	(0.034)			(0.032)	(0.034)	(0.031)	(0.032)
Unsolicited	1.223			0.086	0.100	0.170	0.063
	(0.701)			(0.617)	(0.597)	(0.614)	(0.603)
Government Effectiveness	1.539*			0.977*	0.866*	1.018*	0.839
	(0.635)			(0.426)	(0.432)	(0.452)	(0.426)
Political Stability & Absence of Violence/Terrorism	0.205			0.392	0.319	0.308	0.309
	(0.344)			(0.236)	(0.230)	(0.237)	(0.247)
Regulatory Quality	2.500***			2.030***	1.946***	2.017***	2.008***
	(0.515)			(0.498)	(0.520)	(0.493)	(0.507)
Rule of Law	0.167			0.150	0.203	0.361	0.262
	(0.772)			(0.474)	(0.464)	(0.415)	(0.464)
Control of Corruption	-0.347			0.018	0.006		0.141
	(0.417)			(0.346)	(0.351)		(0.327)
Voice & Accountability	0.992			0.450	0.441		
	(0.588)			(0.378)	(0.385)		
Ever default since first default	-1.314***	-1.958***	-1.846***	-1.246***	-1.231***	-1.238***	-1.235***
	(0.358)	(0.386)	(0.375)	(0.239)	(0.227)	(0.246)	(0.217)
Time since last rating	0.029	0.188***	0.169***	0.026	0.028	0.033	0.029
	(0.051)	(0.047)	(0.045)	(0.037)	(0.036)	(0.037)	(0.036)
ln(GDP per capita)		2.749***	2.708***	1.242***	1.242***	1.209***	1.189***
		(0.190)	(0.187)	(0.190)	(0.196)	(0.169)	(0.179)
Inflation, consumer prices (annual %)		-0.107***	-0.149***	-0.021	-0.061*	-0.018	-0.061**
		(0.019)	(0.028)	(0.017)	(0.024)	(0.015)	(0.020)
GDP growth (annual %)		-0.035	0.015	-0.083**	-0.066	-0.064*	-0.047
		(0.029)	(0.051)	(0.025)	(0.047)	(0.026)	(0.035)
Growth^2		-0.000	-0.002	0.002	0.001		
		(0.001)	(0.002)	(0.001)	(0.002)		
Total natural resources rents (% of GDP)		-0.007	-0.010	0.022	0.025	0.017	0.014
		(0.018)	(0.019)	(0.016)	(0.016)	(0.018)	(0.014)
Current account balance (% of GDP)		0.005	0.028	-0.012	-0.004	-0.025	
		(0.031)	(0.033)	(0.020)	(0.024)	(0.014)	
External debt (as % of GDP)		-0.017**	-0.017**	-0.001	-0.001	-0.001	0.001
		(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
Trade (% of GDP)		0.011***	0.009**	0.003	0.002	0.001	
		(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	
Central Government Debt (as % of GDP)		-0.026***	-0.025***	-0.025***	-0.025***	-0.024***	-0.023***
		(0.007)	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)
ln(Foreign Assets)		-0.023	-0.034	-0.039	-0.045		-0.055
		(0.068)	(0.067)	(0.047)	(0.047)		(0.044)
Foreign direct investment, net inflows (% of GDP)		-0.005	0.007	-0.009**	-0.001	-0.008*	
		(0.007)	(0.014)	(0.003)	(0.006)	(0.004)	
External balance on goods & services(% of GDP)		-0.034	-0.039	-0.018	-0.018		
		(0.029)	(0.030)	(0.016)	(0.018)		
ln(Population)		0.793***	0.793***	0.707***	0.722***	0.636***	0.713***
		(0.143)	(0.146)	(0.097)	(0.093)	(0.083)	(0.084)
Observations	1268	1268	1203	1268	1203	1268	1219
Countries	95	95	95	95	95	95	95
R^2	0.881	0.866	0.878	0.934	0.940	0.932	0.939

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parenthesis, clustered at the country level. Note: P - Political variables only; E - Economic variables only; EYA - Lagged 3 year average economic variables only; L - LASSO model. This table presents the regression estimates from the OLS and post-LASSO models described in Section 4.2.

Table A5: Political Variables model by rating agency

	S&P	Moody's	Fitch
	(1)	(2)	(3)
Annual polity2 index	-0.148*	-0.152*	-0.160*
	(0.072)	(0.069)	(0.078)
Left Government	0.077	0.190	0.191
	(0.270)	(0.270)	(0.270)
Chief Executive Years in Office	-0.034	-0.016	-0.026
	(0.020)	(0.022)	(0.022)
Presidential Election Held	0.194	0.279	0.058
	(0.183)	(0.184)	(0.167)
External Conflict (E) - year average	0.103	0.022	0.195
	(0.162)	(0.163)	(0.160)
Civil War - year average	0.724*	0.663*	0.754
	(0.361)	(0.332)	(0.393)
Law & Order (I) - year average	0.321	0.118	0.296
	(0.208)	(0.198)	(0.205)
Terrorism - year average	-0.603**	-0.732**	-0.752**
	(0.225)	(0.269)	(0.245)
Financial Risk Rating - year average	0.254***	0.280***	0.257***
	(0.034)	(0.041)	(0.038)
Unsolicited	1.360*	1.074	1.344
	(0.633)	(0.762)	(0.745)
Government Effectiveness	1.496*	1.184	1.319
	(0.693)	(0.674)	(0.707)
Political Stability & Absence of Violence/Terrorism	0.213	0.391	0.011
	(0.366)	(0.372)	(0.417)
Regulatory Quality	2.322***	2.674***	2.699***
	(0.554)	(0.550)	(0.582)
Rule of Law	0.091	0.376	0.424
	(0.812)	(0.833)	(0.812)
Control of Corruption	-0.095	-0.533	-0.483
	(0.406)	(0.455)	(0.518)
Voice & Accountability	0.865	1.194	0.917
	(0.678)	(0.634)	(0.717)
Ever default since first default	-1.075**	-1.646***	-1.044**
	(0.385)	(0.392)	(0.390)
Time since last rating	0.017	0.034	0.045
	(0.052)	(0.053)	(0.056)
Observations	1150	1161	1076
Countries	91	94	87
R^2	0.878	0.862	0.869

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses; clustered at the country level. This table presents coefficients from the OLS political variables only rating model for individual rating agencies.

Table A6: Economic Variables model by rating agency

	S&P	Moody's	Fitch
	(1)	(2)	(3)
ln(GDP per capita)	2.869***	2.866***	2.944***
	(0.191)	(0.222)	(0.207)
Inflation, consumer prices (annual %)	-0.096***	-0.114***	-0.105***
	(0.021)	(0.023)	(0.023)
GDP growth (annual %)	0.012	-0.060	-0.036
	(0.038)	(0.033)	(0.031)
Growth^2	-0.002	0.001	-0.000
	(0.003)	(0.002)	(0.002)
Total natural resources rents (% of GDP)	0.000	-0.004	0.008
	(0.018)	(0.018)	(0.018)
Current account balance (% of GDP)	0.033	0.000	0.026
	(0.027)	(0.031)	(0.027)
External debt (as % of GDP)	-0.020**	-0.017**	-0.014*
	(0.007)	(0.006)	(0.006)
Trade (% of GDP)	0.013***	0.011**	0.015***
	(0.003)	(0.004)	(0.003)
Central Government Debt (as % of GDP)	-0.028***	-0.029***	-0.030***
	(0.007)	(0.008)	(0.006)
ln(Foreign Assets)	-0.036	0.012	-0.034
	(0.073)	(0.075)	(0.068)
Foreign direct investment, net inflows (% of GDP)	-0.002	-0.008	-0.004
	(0.008)	(0.007)	(0.005)
External balance on goods & services(% of GDP)	-0.073**	-0.041	-0.072**
	(0.021)	(0.031)	(0.022)
Ever default since first default	-1.588***	-2.183***	-1.765***
	(0.404)	(0.455)	(0.394)
Time since last rating	0.215***	0.173***	0.188***
	(0.056)	(0.048)	(0.052)
ln(Population)	0.725***	0.778***	0.924***
	(0.156)	(0.165)	(0.126)
Observations	1150	1161	1076
Countries	91	94	87
R^2	0.865	0.844	0.869

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses; clustered at the country level. This table presents coefficients from the OLS economic variables only rating model for individual rating agencies.

Table A7: 3yr avg. Economic Variables model by rating agency

	S&P	Moody's	Fitch
	(1)	(2)	(3)
ln(GDP per capita) (3yr Avg)	2.549***	2.429***	2.511***
	(0.207)	(0.219)	(0.245)
GDP growth (annual %) (3yr Avg)	0.044	-0.029	-0.000
	(0.047)	(0.045)	(0.042)
Inflation(3yr Avg)	-0.112***	-0.158***	-0.126***
	(0.030)	(0.031)	(0.034)
Debt as % of GDP (3yr Avg)	-0.021**	-0.022**	-0.023***
	(0.007)	(0.008)	(0.007)
Natural Resource Rents as % of GDP(3yr Avg)	-0.024	-0.019	-0.019
	(0.020)	(0.019)	(0.023)
Current account balance(% of GDP) (3yr Avg)	0.059	0.012	0.044
	(0.033)	(0.038)	(0.038)
External debt (as % of GDP) (3yr Avg)	-0.025**	-0.023**	-0.019*
	(0.008)	(0.008)	(0.008)
Trade(% of GDP) (3yr Avg)	0.003	0.001	0.004
	(0.003)	(0.004)	(0.004)
ln(Foreign Assets) (3yr Avg)	0.092	0.162*	0.149*
	(0.065)	(0.066)	(0.060)
Foreign direct investment, net inflows(% of GDP) (3yr Avg)	0.002	-0.003	-0.006
	(0.018)	(0.016)	(0.012)
External balance on goods & services(% of GDP) (3yr Avg)	-0.057	-0.019	-0.051
	(0.029)	(0.036)	(0.035)
Ever default since first default	-1.551***	-2.120***	-1.842***
	(0.426)	(0.478)	(0.466)
Time since last rating	0.198**	0.193***	0.197***
	(0.059)	(0.054)	(0.057)
Observations	1089	1102	1017
Countries	91	94	87
R^2	0.854	0.837	0.845

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses; clustered at the country level. This table presents coefficients from the OLS 3-year average economic variables only rating model for individual rating agencies.

Table A8: Economic+Political Variables model by rating agency

	S&P	Moody's	Fitch
	(1)	(2)	(3)
ln(GDP per capita)	1.315***	1.194***	1.534***
	(0.187)	(0.220)	(0.219)
Inflation, consumer prices (annual %)	-0.013	-0.009	-0.034
	(0.017)	(0.018)	(0.020)
GDP growth (annual %)	-0.048	-0.108***	-0.086**
	(0.030)	(0.030)	(0.026)
Growth^2	-0.000	0.002	0.001
	(0.002)	(0.002)	(0.002)
Total natural resources rents (% of GDP)	0.027	0.026	0.037*
	(0.015)	(0.019)	(0.016)
Current account balance (% of GDP)	0.007	-0.024	0.007
	(0.020)	(0.022)	(0.021)
External debt (as % of GDP)	-0.004	0.000	0.002
	(0.004)	(0.004)	(0.004)
Trade (% of GDP)	0.004	0.003	0.005**
	(0.002)	(0.002)	(0.002)
Central Government Debt (as % of GDP)	-0.026***	-0.026***	-0.027***
	(0.003)	(0.005)	(0.004)
ln(Foreign Assets)	-0.042	-0.045	-0.058
	(0.052)	(0.050)	(0.044)
Foreign direct investment, net inflows (% of GDP)	-0.006	-0.011**	-0.007**
	(0.004)	(0.004)	(0.003)
External balance on goods & services(% of GDP)	-0.038*	-0.022	-0.051**
	(0.017)	(0.018)	(0.017)
Ever default since first default	-0.976***	-1.574***	-1.028***
	(0.263)	(0.261)	(0.258)
Time since last rating	0.019	0.009	0.006
	(0.041)	(0.039)	(0.036)
ln(Population)	0.668***	0.759***	0.797***
	(0.103)	(0.109)	(0.102)
Annual polity2 index	-0.103*	-0.116*	-0.100*
	(0.042)	(0.046)	(0.038)
Left Government	-0.002	0.055	0.215
	(0.227)	(0.228)	(0.216)
Chief Executive Years in Office	-0.025	-0.024	-0.003
	(0.017)	(0.018)	(0.014)
Presidential Election Held	-0.057	0.087	-0.079
	(0.123)	(0.120)	(0.105)
External Conflict (E) - year average	0.204	0.134	0.238**
	(0.110)	(0.108)	(0.081)
Civil War - year average	0.085	0.031	0.001
	(0.255)	(0.285)	(0.241)
Law & Order (I) - year average	0.161	0.007	0.201
	(0.135)	(0.145)	(0.129)
Terrorism - year average	-0.216	-0.252	-0.285
	(0.153)	(0.203)	(0.157)
Financial Risk Rating - year average	0.136***	0.202***	0.156***
	(0.034)	(0.035)	(0.032)
Unsolicited	0.219	-0.179	0.093
	(0.606)	(0.647)	(0.575)
Government Effectiveness	1.079*	0.819	0.808
	(0.439)	(0.489)	(0.449)
Political Stability & Absence of Violence/Terrorism	0.348	0.583*	0.277
	(0.240)	(0.267)	(0.248)
Regulatory Quality	1.747**	2.418***	2.106***
	(0.556)	(0.568)	(0.539)
Rule of Law	0.184	0.143	0.363
	(0.567)	(0.557)	(0.530)
Control of Corruption	0.143	-0.054	-0.151
	(0.352)	(0.390)	(0.386)
Voice & Accountability	0.320	0.523	0.303
	(0.421)	(0.410)	(0.362)
Observations	1150	1161	1076
Countries	91	94	87
R^2	0.932	0.917	0.934

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses; clustered at the country level. This table presents coefficients from the OLS economic and political variables only rating model for individual rating agencies.

Table A9: 3yr avg. Economic+Political Variables model by rating agency

	S&P	Moody's	Fitch
	(1)	(2)	(3)
ln(GDP per capita) (3yr Avg)	1.000***	0.876***	1.180***
	(0.193)	(0.243)	(0.229)
GDP growth (annual %) (3yr Avg)	-0.046	-0.091*	-0.063
	(0.037)	(0.044)	(0.034)
Inflation(3yr Avg)	-0.019	-0.031	-0.044
	(0.023)	(0.025)	(0.024)
Debt as % of GDP (3yr Avg)	-0.022***	-0.022***	-0.023***
	(0.005)	(0.006)	(0.005)
Natural Resource Rents as % of GDP(3yr Avg)	0.017	0.022	0.030
	(0.017)	(0.023)	(0.021)
Current account balance(% of GDP) (3yr Avg)	0.012	-0.038	0.007
	(0.028)	(0.031)	(0.031)
External debt (as % of GDP) (3yr Avg)	-0.010	-0.008	-0.003
	(0.006)	(0.006)	(0.006)
Trade(% of GDP) (3yr Avg)	-0.002	-0.004	-0.002
	(0.002)	(0.003)	(0.003)
ln(Foreign Assets) (3yr Avg)	0.067	0.085	0.086*
	(0.049)	(0.051)	(0.041)
Foreign direct investment, net inflows(% of GDP) (3yr Avg)	-0.006	-0.011	-0.006
	(0.009)	(0.009)	(0.009)
External balance on goods & services(% of GDP) (3yr Avg)	-0.025	-0.004	-0.035
	(0.022)	(0.022)	(0.027)
Ever default since first default	-0.932***	-1.478***	-0.941**
	(0.273)	(0.296)	(0.301)
Time since last rating	0.034	0.053	0.041
	(0.047)	(0.047)	(0.047)
Annual polity2 index	-0.093	-0.105	-0.093
	(0.050)	(0.054)	(0.052)
Left Government	0.138	0.158	0.338
	(0.246)	(0.250)	(0.246)
Chief Executive Years in Office	-0.035*	-0.034	-0.023
	(0.016)	(0.019)	(0.015)
Presidential Election Held	-0.021	0.094	-0.027
	(0.125)	(0.126)	(0.111)
External Conflict (E) - year average	0.251	0.152	0.345**
	(0.142)	(0.137)	(0.117)
Civil War - year average	0.538*	0.593*	0.544*
	(0.239)	(0.267)	(0.260)
Law & Order (I) - year average	0.272	0.106	0.240
	(0.157)	(0.162)	(0.147)
Terrorism - year average	-0.432*	-0.539*	-0.594**
	(0.197)	(0.234)	(0.202)
Financial Risk Rating - year average	0.129***	0.189***	0.152***
	(0.034)	(0.043)	(0.038)
Unsolicited	0.992	0.654	0.955
	(0.651)	(0.708)	(0.649)
Government Effectiveness	1.589**	1.435*	1.505**
	(0.516)	(0.609)	(0.536)
Political Stability & Absence of Violence/Terrorism	-0.081	0.101	-0.245
	(0.283)	(0.312)	(0.332)
Regulatory Quality	1.618**	2.024**	1.936**
	(0.573)	(0.648)	(0.597)
Rule of Law	0.193	0.328	0.571
	(0.596)	(0.601)	(0.555)
Control of Corruption	-0.120	-0.375	-0.613
	(0.385)	(0.443)	(0.434)
Voice & Accountability	0.223	0.406	0.254
	(0.456)	(0.452)	(0.466)
Observations	1089	1102	1017
Countries	91	94	87
R^2	0.923	0.906	0.918

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses; clustered at the country level. This table presents coefficients from the OLS 3-year average economic and political variables only rating model for individual rating agencies.

Table A10: LASSO model by rating agency

	S&P	Moody's	Fitch
	(1)	(2)	(3)
ln(GDP per capita)	1.198***	1.134***	1.315***
	(0.164)	(0.194)	(0.189)
Inflation, consumer prices (annual %)	-0.014	-0.010	-0.030
	(0.016)	(0.017)	(0.018)
GDP growth (annual %)	-0.058*	-0.089**	-0.082**
	(0.024)	(0.033)	(0.025)
Total natural resources rents (% of GDP)	0.015	0.018	0.030
	(0.018)	(0.020)	(0.018)
Current account balance (% of GDP)	-0.019	-0.038*	-0.035*
	(0.017)	(0.018)	(0.014)
External debt (as % of GDP)	-0.003	-0.000	-0.000
	(0.004)	(0.005)	(0.004)
Trade (% of GDP)	0.001	0.001	0.002
	(0.002)	(0.002)	(0.002)
Central Government Debt (as % of GDP)	-0.024***	-0.024***	-0.025***
	(0.003)	(0.004)	(0.003)
Foreign direct investment, net inflows (% of GDP)	-0.007	-0.012**	-0.009**
	(0.004)	(0.004)	(0.003)
Ever default since first default	-0.932***	-1.534***	-1.149***
	(0.266)	(0.267)	(0.271)
Time since last rating	0.028	0.020	0.024
	(0.041)	(0.040)	(0.037)
ln(Population)	0.569***	0.671***	0.674***
	(0.089)	(0.097)	(0.080)
Annual polity2 index	-0.063**	-0.058*	-0.073**
	(0.023)	(0.026)	(0.027)
External Conflict (E) - year average	0.205	0.134	0.243**
	(0.117)	(0.111)	(0.089)
Civil War - year average	0.155	0.094	0.091
	(0.234)	(0.277)	(0.245)
Law & Order (I) - year average	0.132	0.009	0.212
	(0.130)	(0.139)	(0.123)
Terrorism - year average	-0.159	-0.181	-0.240
	(0.163)	(0.205)	(0.163)
Financial Risk Rating - year average	0.129***	0.187***	0.140***
	(0.034)	(0.034)	(0.032)
Unsolicited	0.343	-0.076	0.233
	(0.601)	(0.654)	(0.586)
Government Effectiveness	1.171*	0.788	0.950*
	(0.463)	(0.522)	(0.467)
Political Stability & Absence of Violence/Terrorism	0.256	0.514	0.283
	(0.246)	(0.273)	(0.263)
Regulatory Quality	1.764**	2.394***	2.156***
	(0.530)	(0.571)	(0.508)
Rule of Law	0.481	0.381	0.201
	(0.481)	(0.445)	(0.431)
Observations	1150	1161	1076
Countries	91	94	87
r2	0.928	0.914	0.930

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses; clustered at the country level. This table presents coefficients from the post-LASSO rating model for individual rating agencies.

Table A11: LASSO 3yr avg. model by rating agency

	S&P	Moody's	Fitch
	(1)	(2)	(3)
Ever default since first default	-0.947***	-1.529***	-1.139***
	(0.237)	(0.243)	(0.233)
Time since last rating	0.027	0.017	0.016
	(0.040)	(0.039)	(0.035)
ln(GDP per capita) (3yr Avg)	1.169***	1.103***	1.245***
	(0.173)	(0.216)	(0.197)
GDP growth (annual %) (3yr Avg)	-0.042	-0.083	-0.067
	(0.040)	(0.045)	(0.034)
Inflation(3yr Avg)	-0.050*	-0.059*	-0.071**
	(0.021)	(0.024)	(0.023)
Debt as % of GDP (3yr Avg)	-0.023***	-0.024***	-0.024***
	(0.003)	(0.004)	(0.003)
Natural Resource Rents as % of GDP(3yr Avg)	0.016	0.014	0.023
	(0.015)	(0.016)	(0.015)
External debt (as % of GDP) (3yr Avg)	-0.000	0.002	0.004
	(0.004)	(0.004)	(0.004)
ln(Foreign Assets) (3yr Avg)	-0.064	-0.049	-0.069
	(0.050)	(0.047)	(0.040)
Population, total	0.645***	0.749***	0.771***
	(0.089)	(0.098)	(0.085)
Annual polity2 index	-0.050*	-0.043	-0.063**
	(0.022)	(0.023)	(0.023)
External Conflict (E) - year average	0.196	0.120	0.228**
	(0.107)	(0.103)	(0.081)
Civil War - year average	0.126	0.062	-0.022
	(0.257)	(0.283)	(0.256)
Law & Order (I) - year average	0.184	0.047	0.272*
	(0.133)	(0.140)	(0.122)
Terrorism - year average	-0.141	-0.161	-0.199
	(0.166)	(0.213)	(0.169)
Financial Risk Rating - year average	0.124***	0.163***	0.126***
	(0.032)	(0.038)	(0.030)
Government Effectiveness	0.962*	0.552	0.734
	(0.420)	(0.495)	(0.446)
Political Stability & Absence of Violence/Terrorism	0.231	0.545	0.327
	(0.260)	(0.281)	(0.279)
Regulatory Quality	1.818**	2.334***	2.210***
	(0.540)	(0.602)	(0.525)
Rule of Law	0.299	0.311	0.182
	(0.523)	(0.531)	(0.500)
Control of Corruption	0.240	0.120	0.065
	(0.342)	(0.371)	(0.362)
Unsolicited	0.207	-0.176	0.098
	(0.584)	(0.642)	(0.577)
Observations	1103	1114	1029
Countries	91	94	87
r2	0.935	0.922	0.936

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses; clustered at the country level. This table presents coefficients from the post-LASSO rating model with 3-year average economic variables for individual rating agencies.

Table A12: L:E+A - Post-2008 Robustness Check

	Mean Rate	**Post-2008 Interaction**
Log GDP per Capita	0.9668***	0.2785
	(0.1779)	(0.1671)
Inflation	-0.03789**	0.02746
	(0.01844)	(0.02166)
GDP Growth	-0.003686	-0.07852**
	(0.03335)	(0.03595)
Natural Resources Rents (% of GDP)	-0.001688	0.03273
	(0.01678)	(0.01868)
Current Account (% of GDP)	-0.004898	-0.02307
	(0.01590)	(0.01939)
External debt (as % of GDP)	0.0008445	-0.002629
	(0.005129)	(0.006258)
Trade (% of GDP)	-0.002695	0.004521
	(0.002010)	(0.002588)
Debt (% of GDP)	-0.006058	-0.02467***
	(0.004196)	(0.006811)
FDI (% of GDP)	0.01449	-0.02336**
	(0.008697)	(0.009538)
Ever default since first default	-1.587***	0.5491
	(0.2733)	(0.2901)
TSLR	0.1813***	-0.1786***
	(0.04851)	(0.04966)
Polity2	-0.06401**	0.01706
	(0.02166)	(0.02415)
Mean External Conflict	0.1679	0.04045
	(0.1014)	(0.1155)
Mean Civil War	-0.0002555	0.2018
	(0.2106)	(0.2920)
Mean Law Order	0.2234	-0.1238
	(0.1379)	(0.1475)
Mean Terrorism	-0.1739	-0.05862
	(0.1455)	(0.2205)
Financial Risk Rating - year average	0.1751***	-0.04375
	(0.04255)	(0.04970)
Unsolicited	0.1183	0 (omitted)
	(0.6106)	
GEE	0.9070**	0.3321
	(0.4019)	(0.6258)
PVE	0.5233	-0.2583
	(0.2744)	(0.3654)
RQE	2.950***	-1.154**
	(0.5940)	(0.6181)
RLE	1.104	-0.4695
	(0.6605)	(0.8228)
Log Population	-0.2774	0.3519*
	(0.2029)	(0.2104)

Note: Standard errors in parentheses

This table presents the results of our robustness check w.r.t the post-2008 financial crisis, and the changes in ratings that followed. The variables used in this analysis are the LASSO selected economic and political variables from our main analysis.

*** p<0.01, ** p<0.05, * p<0.1

Table A13: Lasso covariate selection

E + P Lasso		EYA + P Lasso	
Selected	Not Selected	Selected	Not Seleted
ln(GDP per capita)	Growth^2	ln(GDP per capita) (3yr Avg)	External balance on goods & services(% of GDP) (3yr Avg)
GDP growth (annual %)	Presidential Elections Held	GDP growth (annual %) (3yr Avg)	Presidential Elections Held
Inflation	Voice & Accountability	Inflation (3yr Avg)	Voice & Accountability
Total natural resources rents (% of GDP)	Trade (% of GDP)	Debt as % of GDP (3yr Avg)	Chief Executive Years in Office
Current account balance (% of GDP)	External balance on goods & services(% of GDP)	Natural Resource Rents as % of GDP (3yr Avg)	Left Government
External debt (as % of GDP)	Left Government	External debt (as % of GDP) (3yr Avg)	Foreign direct investment, net inflows(% of GDP) (3yr Avg)
ln(Population)	Chief Executive Years in Office	ln(Foreign Assets) (3yr Avg)	Trade (% of GDP) (3yr Avg)
Central Government Debt (as % of GDP)		ln(Population) (3yr Avg)	Current account balance(% of GDP) (3yr Avg)
ln(Foreign Assets)		Ever Default Since Frist	
Foreign direct investment, net inflows (% of GDP)		Time Since Last rating	
Time Since Last Rating		Annual polity2 index	
Ever Default Since First		Left Government	
Annual polity2 index		Chief Executive Years in Office	
External Conflict (E) - year average		External Conflict (E) - year average	
Civil War - year average		Civil War - year average	
Law & Order (I) - year average		Law & Order (I) - year average	
Terrorism - year average		Terrorism - year average	
Financial Risk Rating - year average		Financial Risk Rating - year average	
Government Effectiveness		Government Effectiveness	
Regulatory Quality		Regulatory Quality	
Rule of Law		Rule of Law	
Political Stability & Absence of Violence		Control of Corruption	
Control of Corruption		Political Stability & Absence of Violence	

Note: This table presents a list of covariates selected by the LASSO algorithm described in Section 4.2, as well as those dropped by the model. Selected cvariates are presented separately for models that measure economic variables in the current year vs. those that use the three year average (deonted EYA).

Table A14: Ratings penalty and premium estimates for all models

	U	P	E	EYA	P+E	P+EYA	L:P+E	L:P+EYA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
British Colony	0.185	-1.167***	0.828**	0.825**	-0.236	-0.143	-0.201	-0.199
	(1.149)	(0.418)	(0.380)	(0.375)	(0.284)	(0.301)	(0.307)	(0.296)
French Colony	-3.125***	-0.158	0.574	0.472	0.740***	0.593**	0.545**	0.511*
	(1.180)	(0.340)	(0.394)	(0.366)	(0.284)	(0.284)	(0.272)	(0.273)
Spanish/Portuguese Colony	-3.847***	0.343	-0.735	-0.748	-0.183	-0.252	-0.126	-0.233
	(0.865)	(0.468)	(0.495)	(0.464)	(0.322)	(0.307)	(0.331)	(0.304)
English language	-0.102	-0.824**	1.122***	1.170***	0.006	0.103	0.021	0.072
	(1.437)	(0.382)	(0.394)	(0.380)	(0.274)	(0.272)	(0.256)	(0.248)
British Legal System	0.508	-1.054**	0.812**	0.865**	-0.088	0.033	-0.134	-0.032
	(1.179)	(0.421)	(0.391)	(0.383)	(0.265)	(0.284)	(0.266)	(0.266)
French Legal System	-2.405**	0.488	-0.540	-0.597*	0.381	0.253	0.333	0.235
	(1.040)	(0.368)	(0.336)	(0.318)	(0.239)	(0.240)	(0.242)	(0.251)
Africa	-3.778***	0.068	1.910***	1.813***	1.084***	1.053***	0.906***	0.855***
	(0.930)	(0.364)	(0.459)	(0.434)	(0.316)	(0.307)	(0.284)	(0.270)
Middle East & North Africa	1.282	-0.142	0.522	0.342	0.305	0.134	0.431	0.225
	(1.196)	(0.621)	(0.514)	(0.522)	(0.427)	(0.431)	(0.441)	(0.419)
South Asia	-3.939***	-0.869	0.162	0.236	0.219	0.348	0.244	0.267
	(1.255)	(0.542)	(0.562)	(0.531)	(0.499)	(0.471)	(0.511)	(0.452)
Latin America	-3.898***	-0.453	-1.042**	-0.961**	-0.657**	-0.654**	-0.479	-0.565**
	(0.858)	(0.427)	(0.482)	(0.466)	(0.310)	(0.307)	(0.309)	(0.282)
Europe & Central Asia	4.164***	1.084***	-0.361	-0.267	0.062	0.110	0.148	0.134
	(1.023)	(0.393)	(0.396)	(0.379)	(0.258)	(0.252)	(0.254)	(0.247)
East Asia & Pacific	1.612	-1.136***	-0.129	-0.305	-0.868**	-0.882**	-0.898***	-0.679**
	(1.635)	(0.377)	(0.588)	(0.555)	(0.392)	(0.406)	(0.332)	(0.314)
NATO	4.932***	1.401***	0.269	0.326	0.719**	0.674**	0.739**	0.635**
	(1.050)	(0.440)	(0.446)	(0.444)	(0.327)	(0.336)	(0.307)	(0.305)
G7	8.018***	1.809***	1.587***	1.363**	1.182**	1.019**	1.211**	0.873*
	(0.674)	(0.609)	(0.584)	(0.554)	(0.501)	(0.487)	(0.499)	(0.486)
G20	3.773***	1.634***	-0.181	-0.155	-0.097	-0.106	-0.104	-0.083
	(1.155)	(0.327)	(0.634)	(0.614)	(0.374)	(0.373)	(0.396)	(0.376)
European Union	6.418***	1.678***	0.833*	0.887**	1.151***	1.080***	1.108***	0.992***
	(0.880)	(0.484)	(0.439)	(0.417)	(0.326)	(0.319)	(0.299)	(0.296)
Arab League	0.887	0.098	0.641	0.479	0.245	0.056	0.365	0.157
	(1.276)	(0.685)	(0.576)	(0.587)	(0.437)	(0.444)	(0.444)	(0.437)
ASEAN	1.238	-1.314**	-0.519	-0.636	-1.148***	-1.156***	-1.204***	-0.800**
	(2.044)	(0.533)	(0.694)	(0.612)	(0.391)	(0.391)	(0.359)	(0.328)
Asian Infrastructure Investment Bank	2.937***	-0.326	-0.158	-0.078	-0.755***	-0.606**	-0.831***	-0.647**
	(0.773)	(0.339)	(0.323)	(0.329)	(0.231)	(0.244)	(0.257)	(0.277)
Current Socialist State	-3.641***	-0.641	0.366	0.422	0.009	0.127	0.019	0.205
	(0.920)	(0.493)	(0.468)	(0.415)	(0.467)	(0.443)	(0.472)	(0.379)
OECD	7.518***	1.971***	0.873*	0.845*	0.643**	0.586**	0.627**	0.568**
	(0.787)	(0.442)	(0.493)	(0.469)	(0.301)	(0.295)	(0.307)	(0.278)
U.S. Ally	4.562***	0.411	0.116	0.137	0.213	0.203	0.262*	0.188
	(0.718)	(0.325)	(0.281)	(0.273)	(0.157)	(0.155)	(0.150)	(0.151)
China Ally	-4.552***	-0.493	-0.062	-0.031	-0.061	-0.020	-0.125	-0.030
	(0.804)	(0.344)	(0.283)	(0.272)	(0.196)	(0.200)	(0.197)	(0.201)
Russia Ally	-1.771**	0.564	0.425	0.262	0.246	0.117	0.253	0.185
	(0.865)	(0.445)	(0.279)	(0.218)	(0.256)	(0.186)	(0.257)	(0.189)

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses; clustered at the country level. This table presents results from regressions of sovereign credit ratings on penalty variables p_{it}, with covariate model indicated in table header. U - unconditional; P - Political variables only; E - Economic variables only; EYA - Lagged 3 year average economic variables only; L - LASSO model. Sample is the full country-year sample of 1268 observations.

Table A15: Summary Statistics of Bond Variables

	Mean	SD	Min	Max	N
Duration(Years)	12.51	10.65	0.25	100.09	931
Placement Amount (USD,billions)	14.46	12.72	0.00	212.18	931
Home Currency	0.12	0.33	0.00	1.00	931
Coupon Rate (bp)	488.99	242.30	0.00	1,275.00	931

Note: Table shows summary bond characteristics statistics for sovereign bond issue-level data in our sample of international placements. Data for these summary statistics were sourced from Cbonds.com.

Table A16: Issuance yield regression results

	B	B+E	B+P	B+(L:E+P)	B+(L:E+P)	B+E+P	B+E+P
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Weighted Mean Rating	-34.210***	-31.904***	-17.940*	-24.013***	-22.164*	-20.015***	-21.194*
	(5.399)	(8.634)	(7.096)	(4.745)	(8.608)	(4.990)	(9.245)
Bond Variables							
Duration (year)	3.337***	3.397***	3.569***	3.736***	3.621***	3.627***	3.560***
	(0.549)	(0.528)	(0.538)	(0.573)	(0.526)	(0.561)	(0.515)
Placement amount	1.008*	1.057*	0.925	0.761	1.146*	0.864	1.254*
	(0.507)	(0.491)	(0.504)	(0.487)	(0.498)	(0.481)	(0.490)
Home Currency	28.974	48.831	36.084	6.993	50.389*	-3.867	51.999*
	(26.093)	(25.427)	(26.097)	(22.511)	(25.632)	(22.168)	(25.428)
Economic Variables		Y		Y	Y	Y	Y
Political Variables			Y	Y	Y	Y	Y
Country FE	Y	Y	Y		Y		Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	700	700	700	700	700	700	700
Countries	69	69	69	69	69	69	69
Adjusted R^2	0.726	0.757	0.748	0.661	0.766	0.682	0.780
Within R^2	0.113	0.214	0.185	0.617	0.242	0.640	0.287

Note: * $p < 0.05$, ** $p < 0.01$,*** $p < 0.001$. Standard errors in parentheses; yield in basis points; placement amount in billions of US dollar; home currency is a dummy variable that takes 1 if the bond is issued in a country's home currency. Table presents estimates bond-level regressions of the issuance yield on average rating at the time of issue. Covariate model indicated in table header. B - Bond variables only; P - Political variables only; E - Economic variables only; L: - LASSO.

Table A17: Coupon Rate Regression, by Rating Agency

	(1) SP17	(2) SP21	(3) Moody17	(4) Moody21	(5) Fitch17	(6) Fitch21
Credit Rating	-15.254*	-11.833	-15.327**	-13.280**	-18.908**	-13.498*
	(6.770)	(6.630)	(5.228)	(5.077)	(6.721)	(6.058)
Bond Vars						
Duration	3.240***	3.237***	3.168***	3.175***	3.015***	3.033***
	(0.421)	(0.421)	(0.424)	(0.424)	(0.436)	(0.437)
Placement Amount	1.513***	1.491***	1.673***	1.668***	1.778***	1.739***
	(0.387)	(0.388)	(0.387)	(0.387)	(0.397)	(0.398)
Home Currency	79.303***	79.698***	60.529**	60.424**	58.621**	60.129**
	(18.934)	(18.955)	(18.541)	(0.002)	(18.677)	(18.710)
Country FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Econ & Political Vars	Y	Y	Y	Y	Y	Y
Observations	892	892	914	914	874	874
R^2	0.808	0.808	0.804	0.804	0.797	0.796
Within R^2	0.281	0.279	0.262	0.260	0.256	0.253

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses; clustered at the country level. This table presents the results of our bond-level analysis in Table 2, disaggregated by rating agency. All columns use the model including the full set of economic and political variables.

Table A18: Coupon Rate Regression

	(1)
Bond Variables	
Duration (year)	3.213***
	(0.425)
Placement Amount	1.656***
	(0.388)
Home Currency (Dummy)	55.928***
	(18.562)
New Rate	-35.222
	(87.256)
Credit Rating	
BB	5.070
	(24.713)
BBB	-35.090
	(33.332)
A	-133.596***
	(41.999)
AA	-93.808
	(57.449)
AAA	-42.440
	(75.855)
Economic Variables	Y
Political Variables	Y
Country FE	Y
Year FE	Y
Observations	931
Countries	73
Adjusted R^2	0.806
Within R^2	0.273

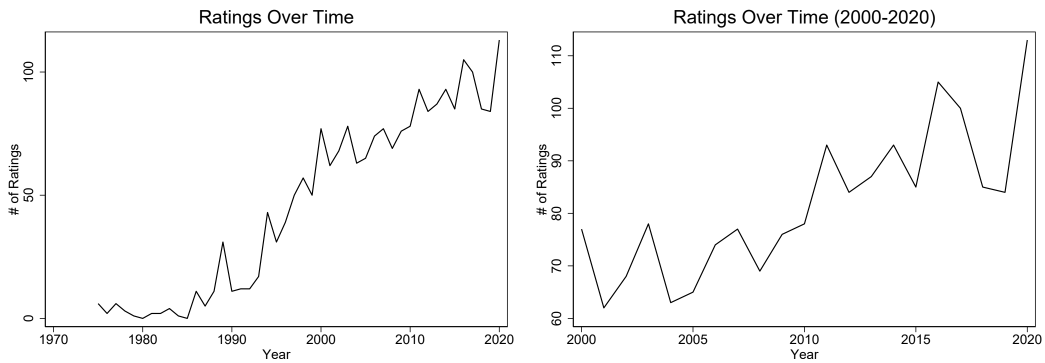
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses; clustered at the country level. This table presents the results from our coupon rate regression with non-linear credit ratings.

Table A19: Marginal Countries

Overrated			Underrated		
Country	Year	Bonds	Country	Year	Bonds
Azerbaijan	1	1	Azerbaijan	1	7
Brazil	1	26	Bahrain	3	13
Bulgaria	8	9	Colombia	2	19
Croatia	2	9	Costa Rica	2	7
Namibia	5	2	Cyprus	3	9
Slovenia	2	8	Hungary	6	26
South Africa	2	16	Indonesia	5	46
Tunisia	1	5	Latvia	2	3
Uruguay	4	23	Oman	2	11
			Portugal	5	4
			Romania	3	13
			Russia	2	17
			Turkey	4	39
			Uruguay	1	18

Note: Overrated means a country is actually rated as investment-grade, while the unbiased rating suggests that this country should be rated speculative-grade. Underrated means a country is actually rated as speculative-grade, while the unbiased rating suggests that this country should be rated as investment-grade. Year gives the number of years that a country gets overrated or underrated from 2012 to 2018. Bonds is the number of unique bonds of a given country that is traded and included in our portfolio in years when the country's rating is biased.

A.2. Appendix figures



(a) 1975-2020

(b) 2000-2020

Figure A1: Number of Rated Countries Over Time

Note: Figure shows the number of rated countries over time in from 1975-2020 (a) and 2000-2020 (b) in our country-year panel. Data on ratings events is sourced from Trading Economics.

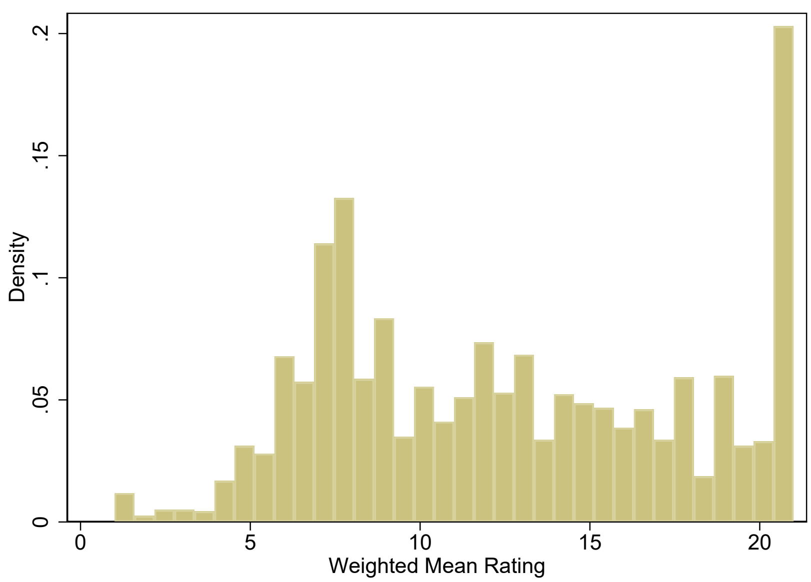
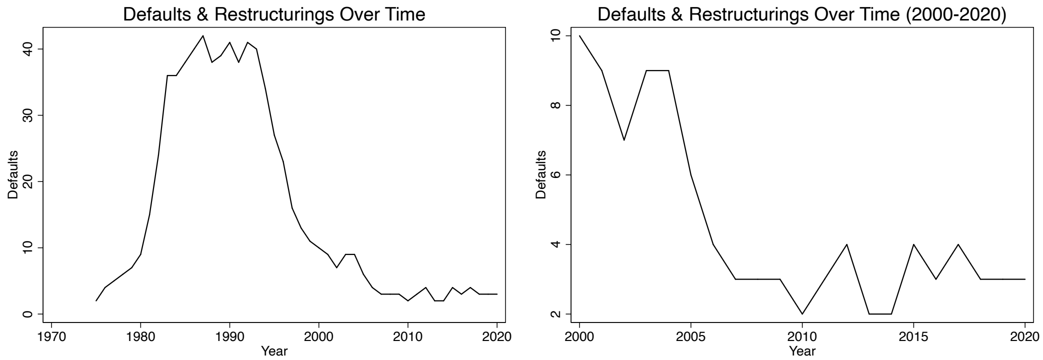


Figure A2: Ratings Distribution

Note: Figure shows the histogram of the distribution of the weighted mean rating across country-years in our sample. Data on country credit ratings is from Trading Economics.



(a) 1975-2020

(b) 2000-2020

Figure A3: Defaults & Restructurings Over Time

Note: Figure shows the number of country-level sovereign defaults & restructurings over time in two panels from 1975-2020 and 2000-2020. Data is from Asonuma & Trebesch (2016).

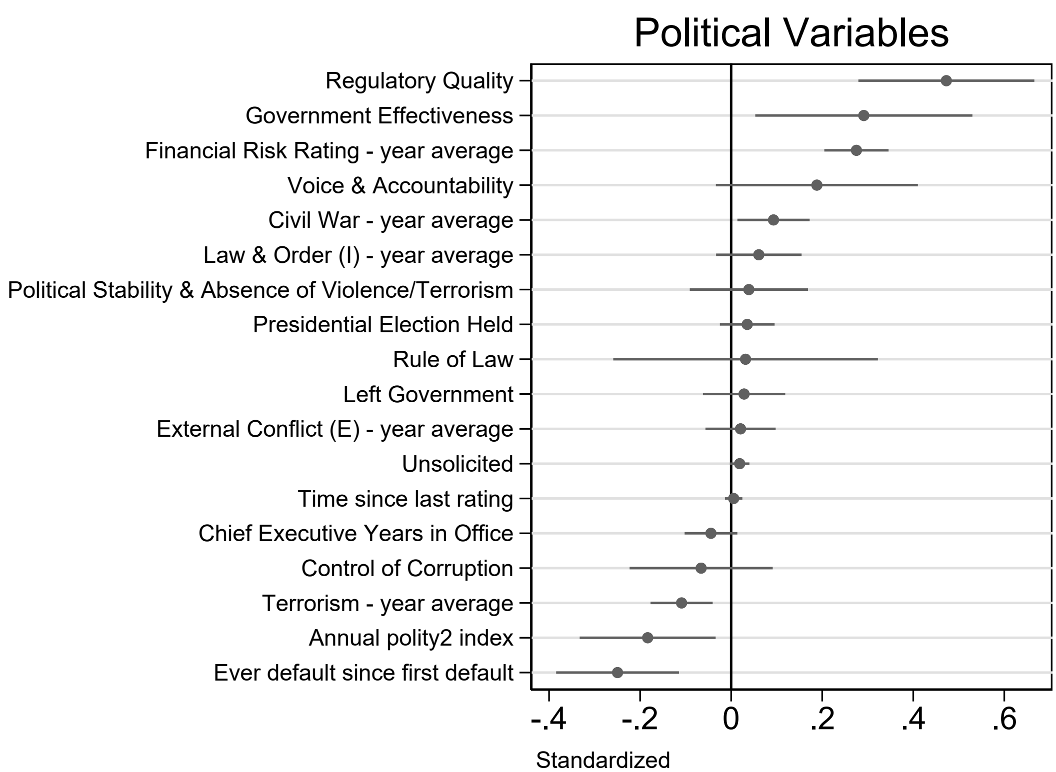


Figure A4: Political Variables Coefficient Plot

Note: Figure shows coefficient estimates and 95% confidence intervals on country fundamentals from the political variables only ratings regression model, where the coefficients are standardized for comparability.

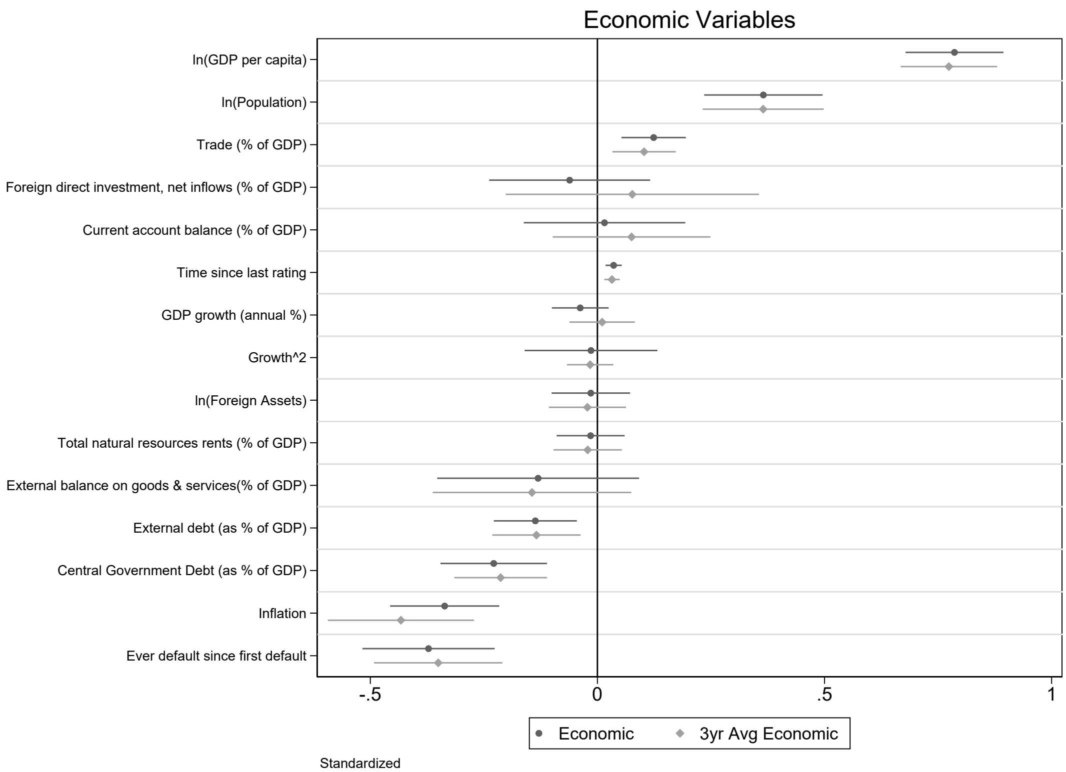


Figure A5: Economic Variables Coefficient Plot

Note: Figure shows coefficient estimates and 95% confidence intervals on country fundamentals from the economic variables only ratings regression model, where the coefficients are standardized for comparability. We plot estimates for models using economic fundamentals measured in the current year as well as the three-year average.

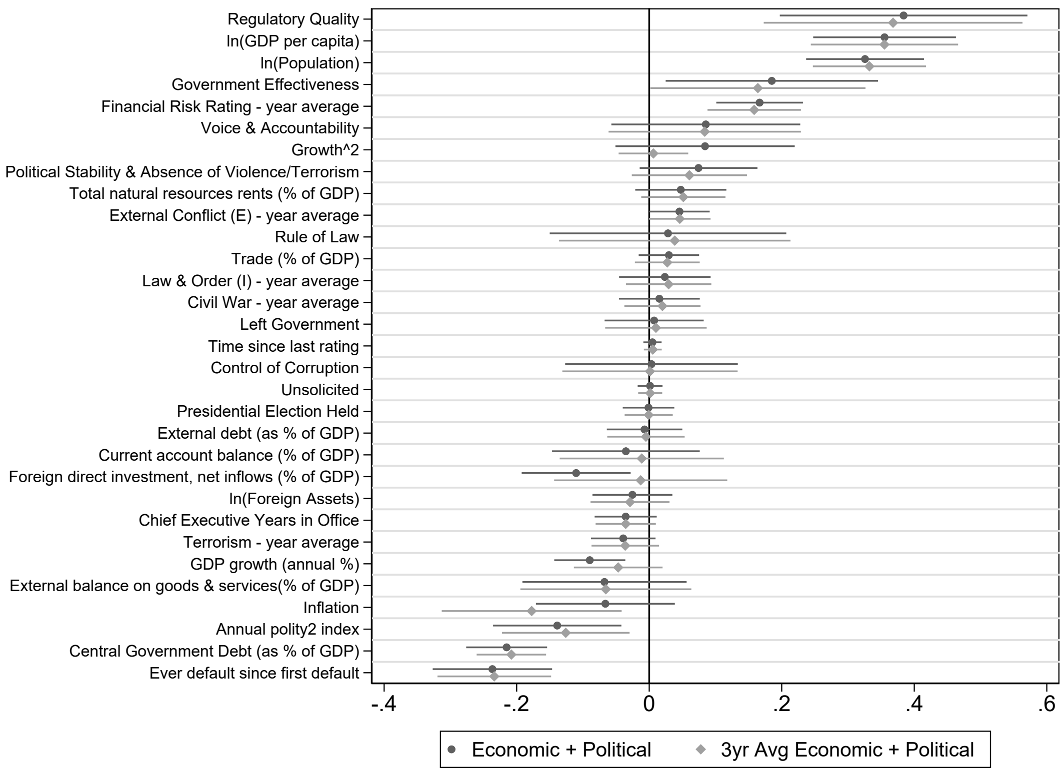


Figure A6: Economic+Political Variables Coefficient Plot

Note: Figure shows coefficient estimates and 95% confidence intervals on country fundamentals from the economic and political variables only ratings regression model, where the coefficients are standardized for comparability. We plot estimates for models using economic fundamentals measured in the current year as well as the three-year average.

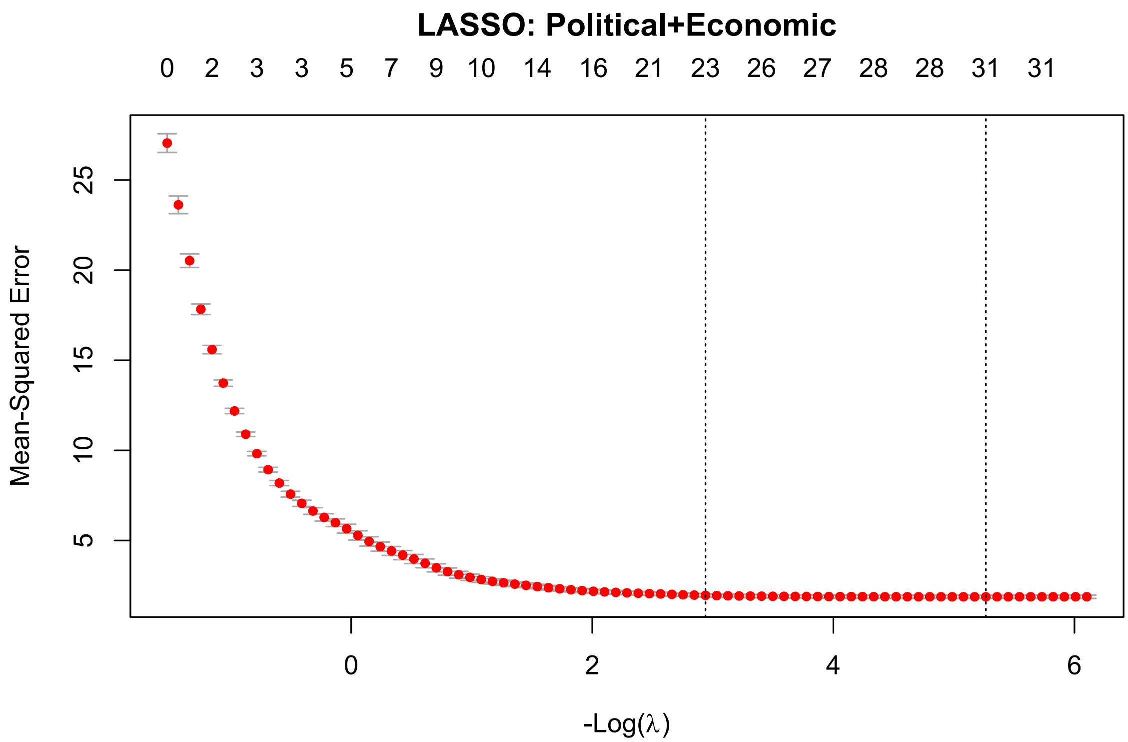


Figure A7: Cross Validation Plot for P+E Model

Note: Figure shows a cross validation plot for the LASSO model with political and economic variables. The x-axis is the negative log of λ, the tuning parameter in a LASSO regression, capturing model complexity. A higher λ is a larger L1 penalty and so less complexity. $-log(\lambda)$ therefore increases with complexity. The y-axis indicates the cross-validated MSE at each λ. The dashed lines indicate the λ that minimizes the CV MSE (right dashed line) and the 1-standard error rule (left dashed line). λ_{1se} is a specified parameter set to prevent overfitting in the model. The numbers at the top of the plot are the number of non-zero beta coefficients in the model, i.e., the number of included covariates.

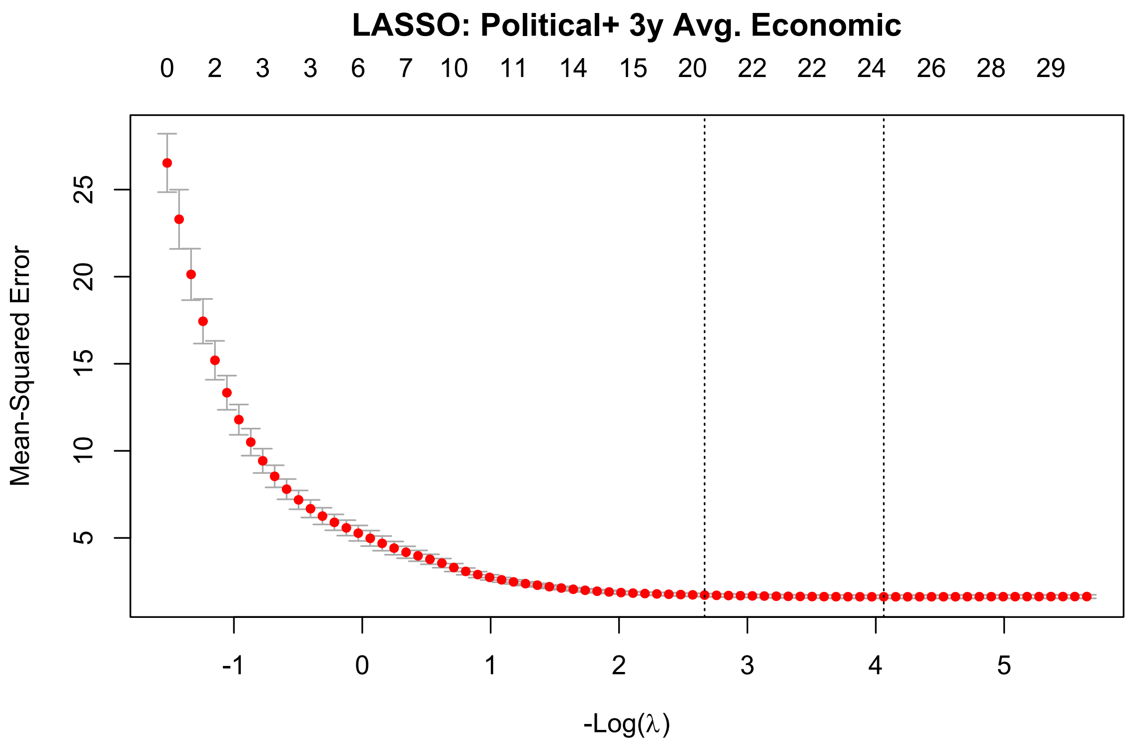


Figure A8: Cross Validation Plot for P+EYA Model

Note: Figure shows a cross validation plot for the LASSO model with political and 3-year average economic variables. The x-axis is the negative log of λ, the tuning parameter in a LASSO regression, capturing model complexity. A higher λ is a larger L1 penalty and so less complexity. $-log(\lambda)$ therefore increases with complexity. The y-axis indicates the cross-validated MSE at each λ. The dashed lines indicate the λ that minimizes the CV MSE (right dashed line) and the 1-standard error rule (left dashed line). λ_{1se} is a specified parameter set to prevent overfitting in the model. The numbers at the top of the plot are the number of non-zero beta coefficients in the model, i.e., the number of included covariates.

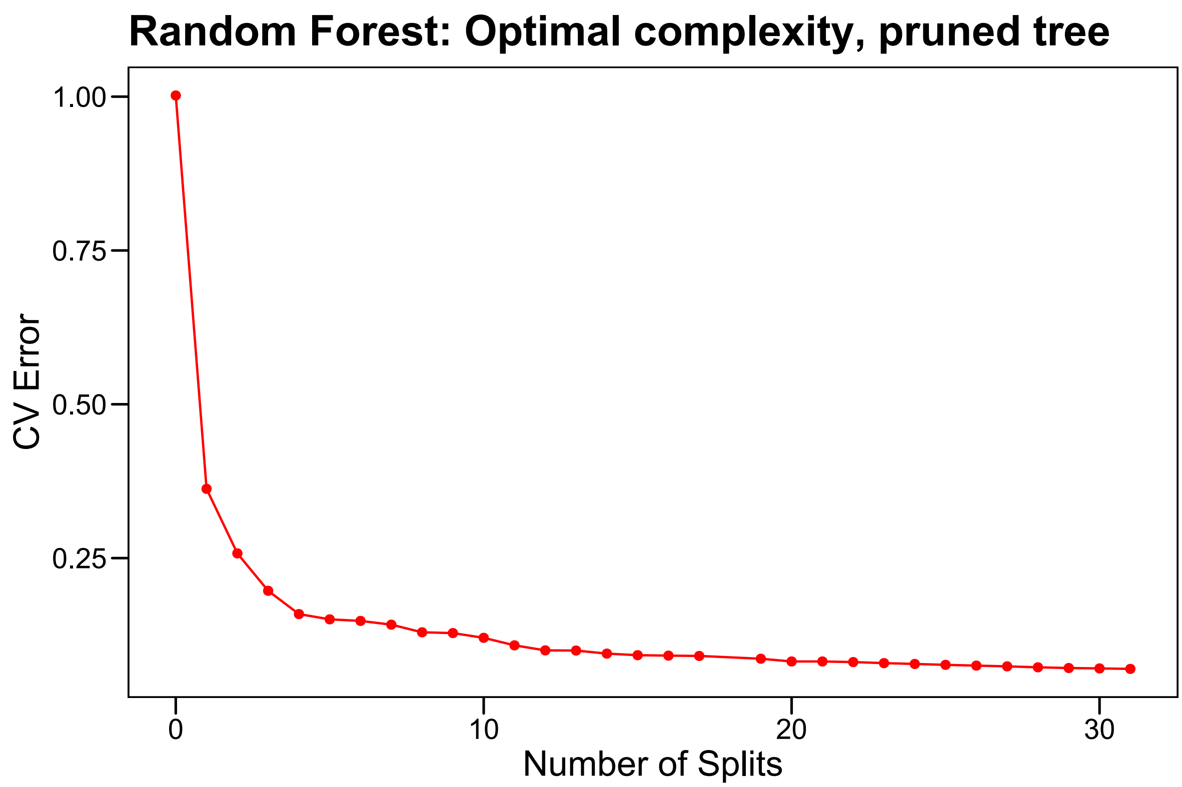


Figure A9: Complexity Plot for Random Forest Model

Note: Figure shows a complexity plot for the Random Forest model with Political+Economic variables. The x-axis represents the number of splits in the Random Forest trees computed by the model, and the y-axis represents the cross validation mean-squared error, which decreases as the number of splits increases.

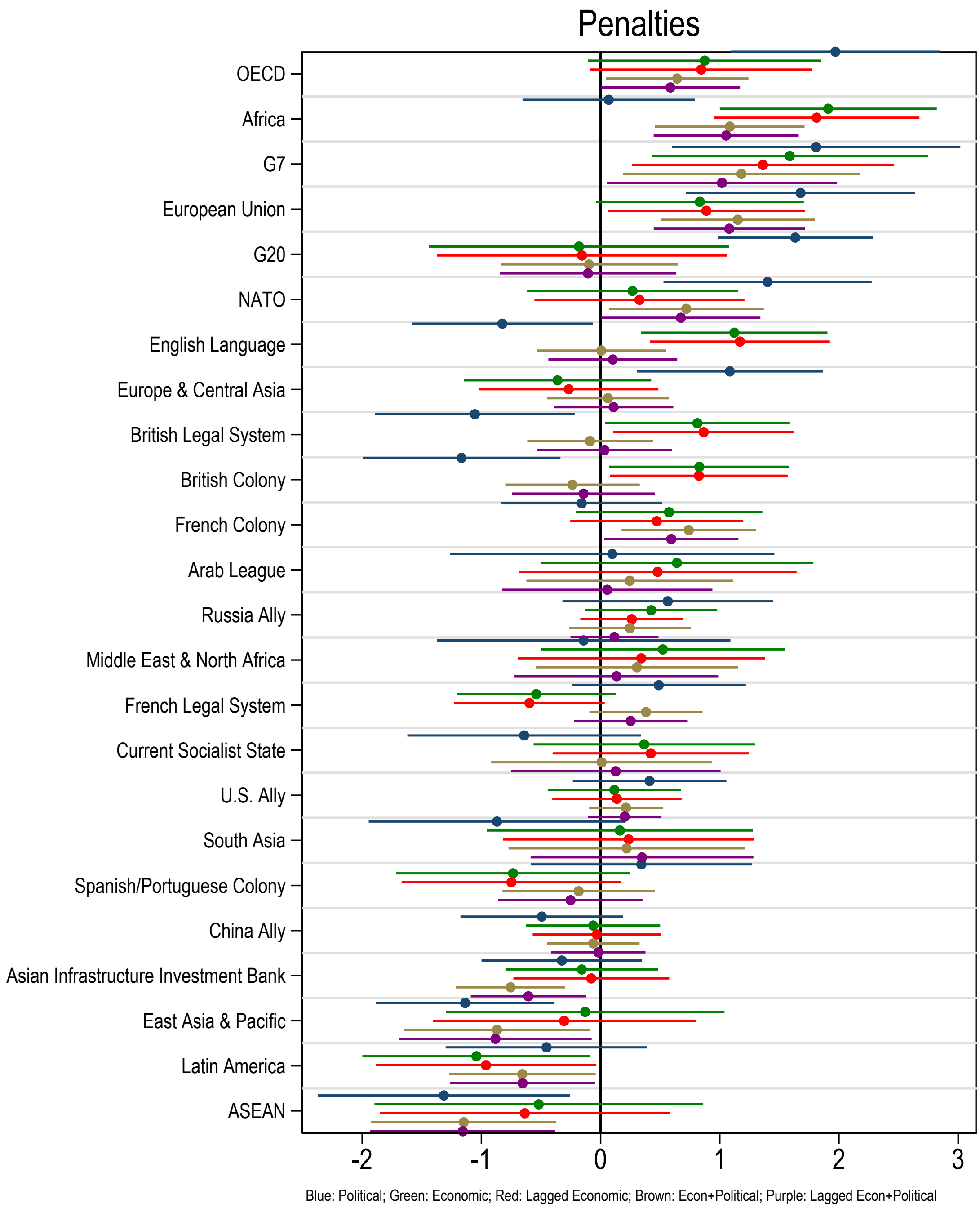


Figure A10: Penalty Plot for non-LASSO ratings models

Note: Figure shows the penalty and premium estimates and 95% confidence intervals obtained from separate OLS regressions of credit rating on each variable p_{it}, as well as the covariate model indicated in the figure notes. Sample is the full country-year panel.

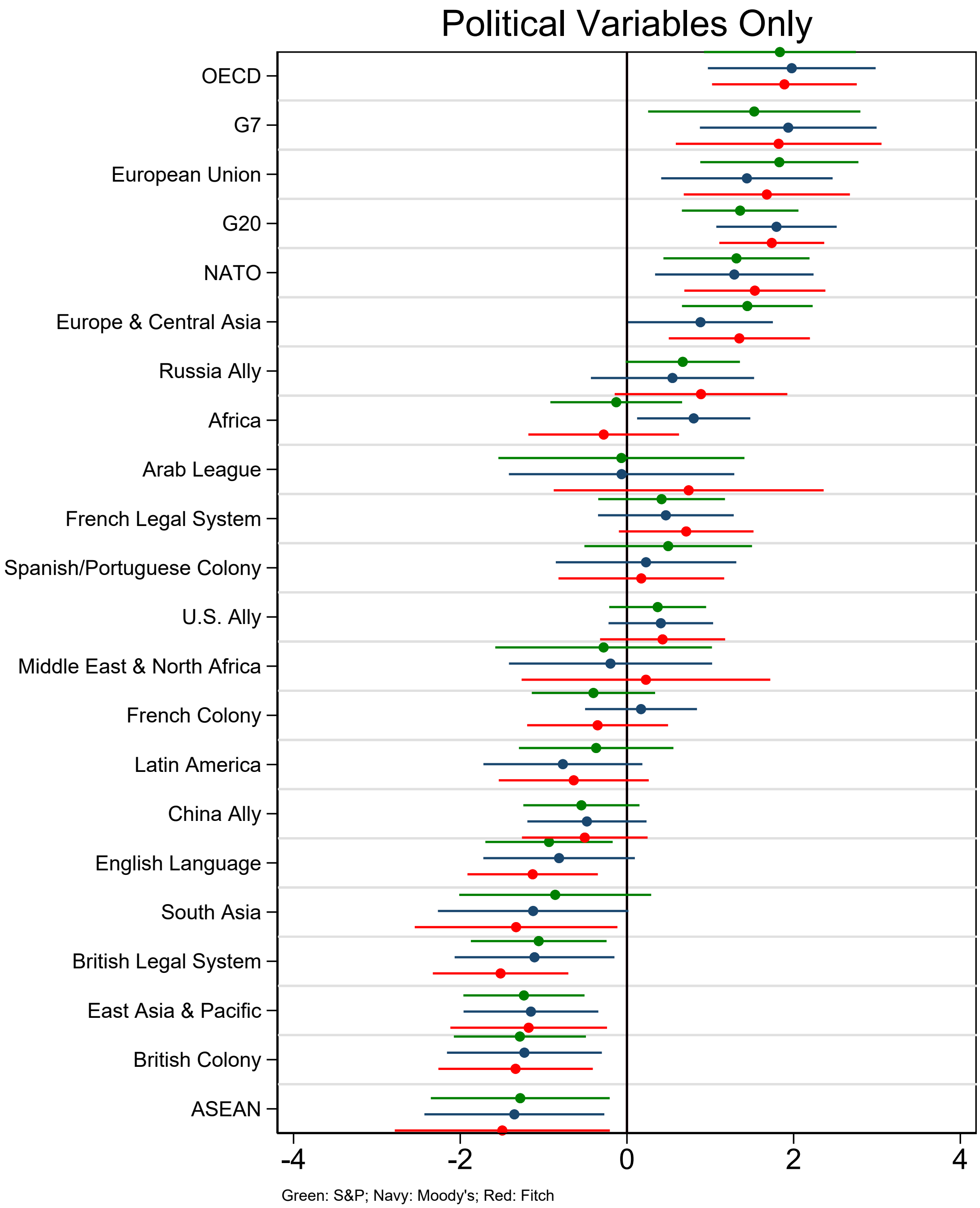


Figure A11: Rating Agency's Political Penalty Plot

Note: Figure shows the penalty and premium estimates and 95% confidence intervals obtained from separate OLS regressions of credit rating on each variable p_{it}, as well as the political variables only model, by rating agency, indicated in the figure notes. Sample is the full country-year panel.

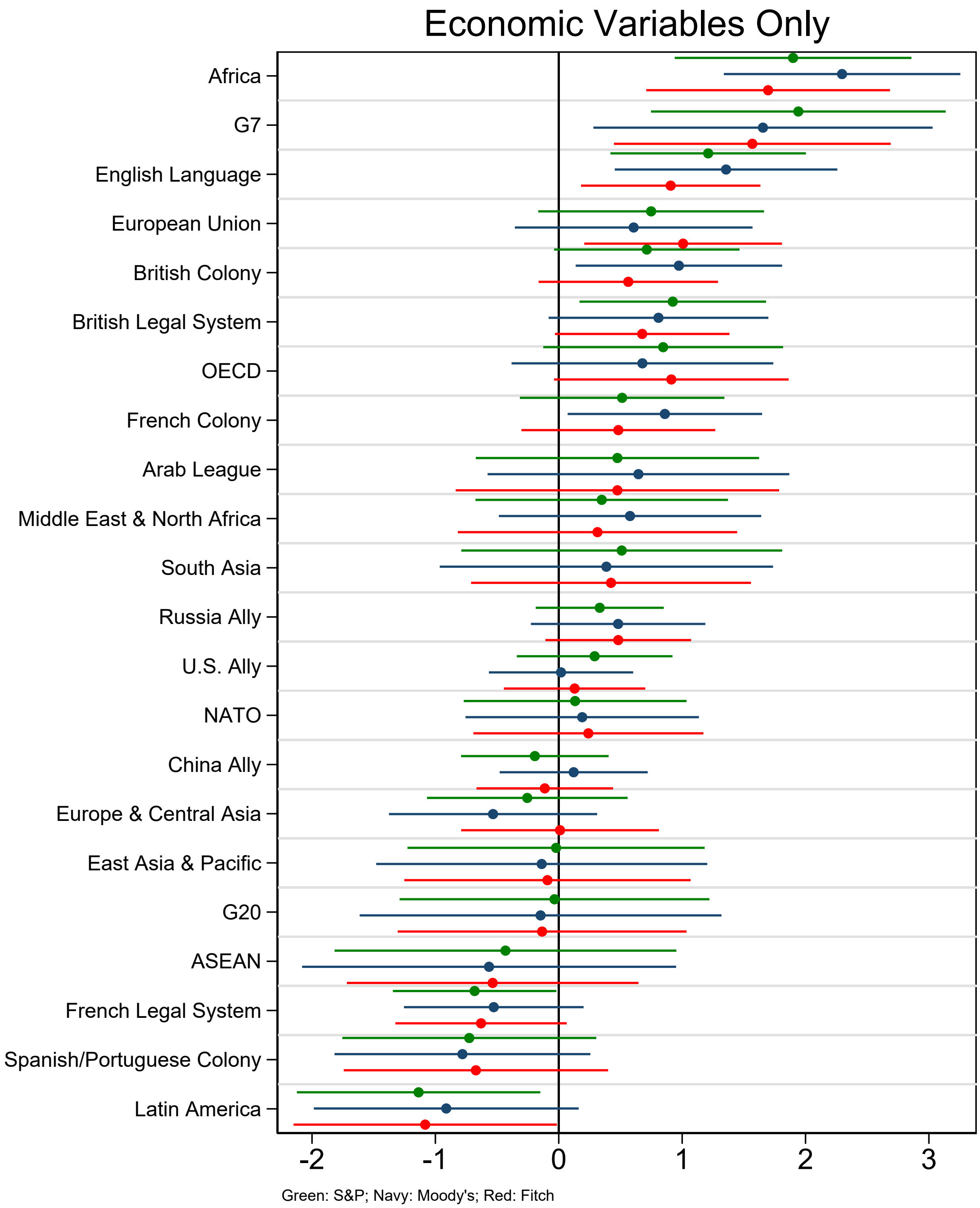


Figure A12: Rating Agency's Economic Penalty Plot

Note: Figure shows the penalty and premium estimates and 95% confidence intervals obtained from separate OLS regressions of credit rating on each variable p_{it}, as well as the economic variables only model, by rating agency, indicated in the figure notes. Sample is the full country-year panel.

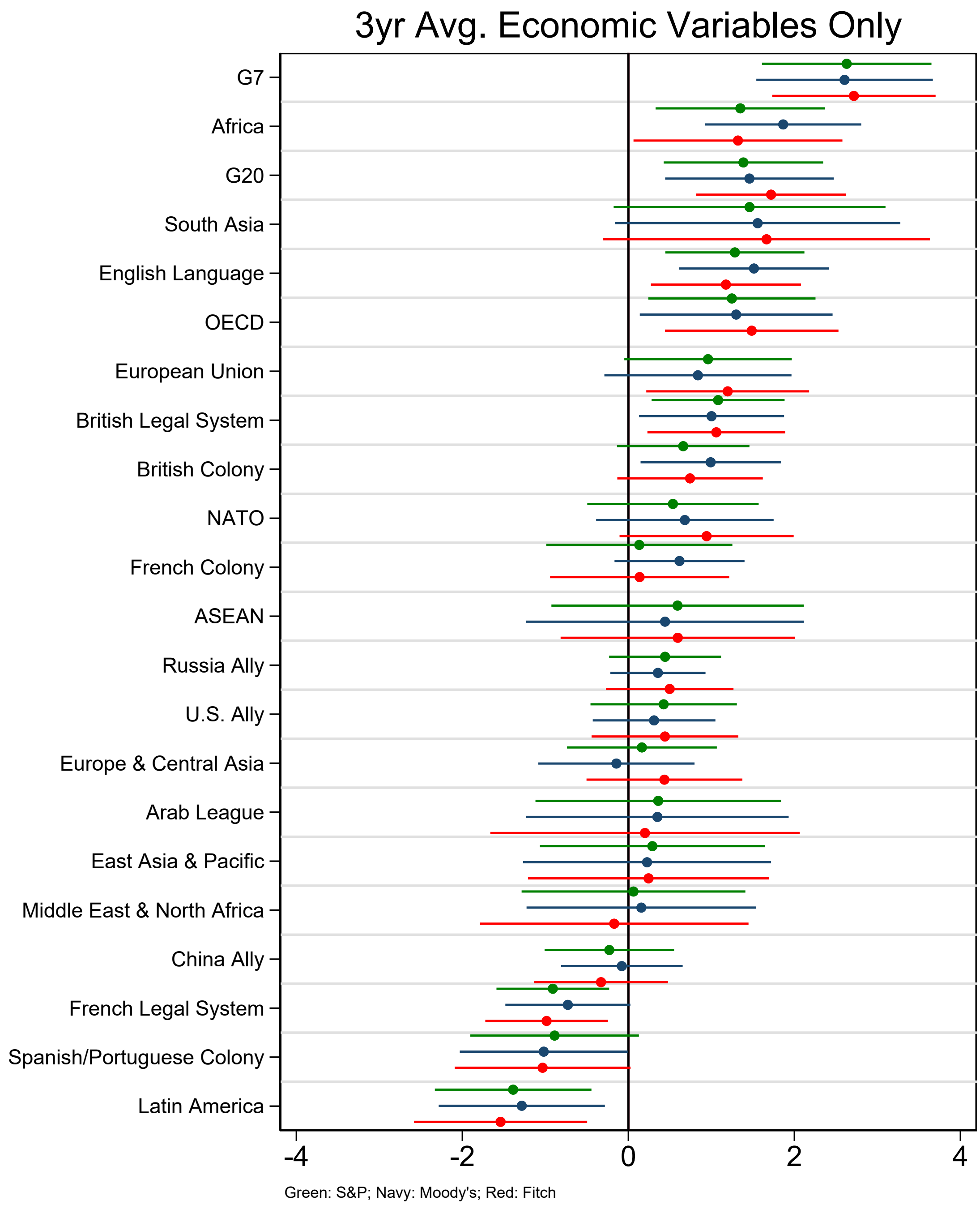


Figure A13: Rating Agency's Lagged Economic Penalty Plot

Note: Figure shows the penalty and premium estimates and 95% confidence intervals obtained from separate OLS regressions of credit rating on each variable p_{it}, as well as the 3-year average economic variables only model, by rating agency, indicated in the figure notes. Sample is the full country-year panel.

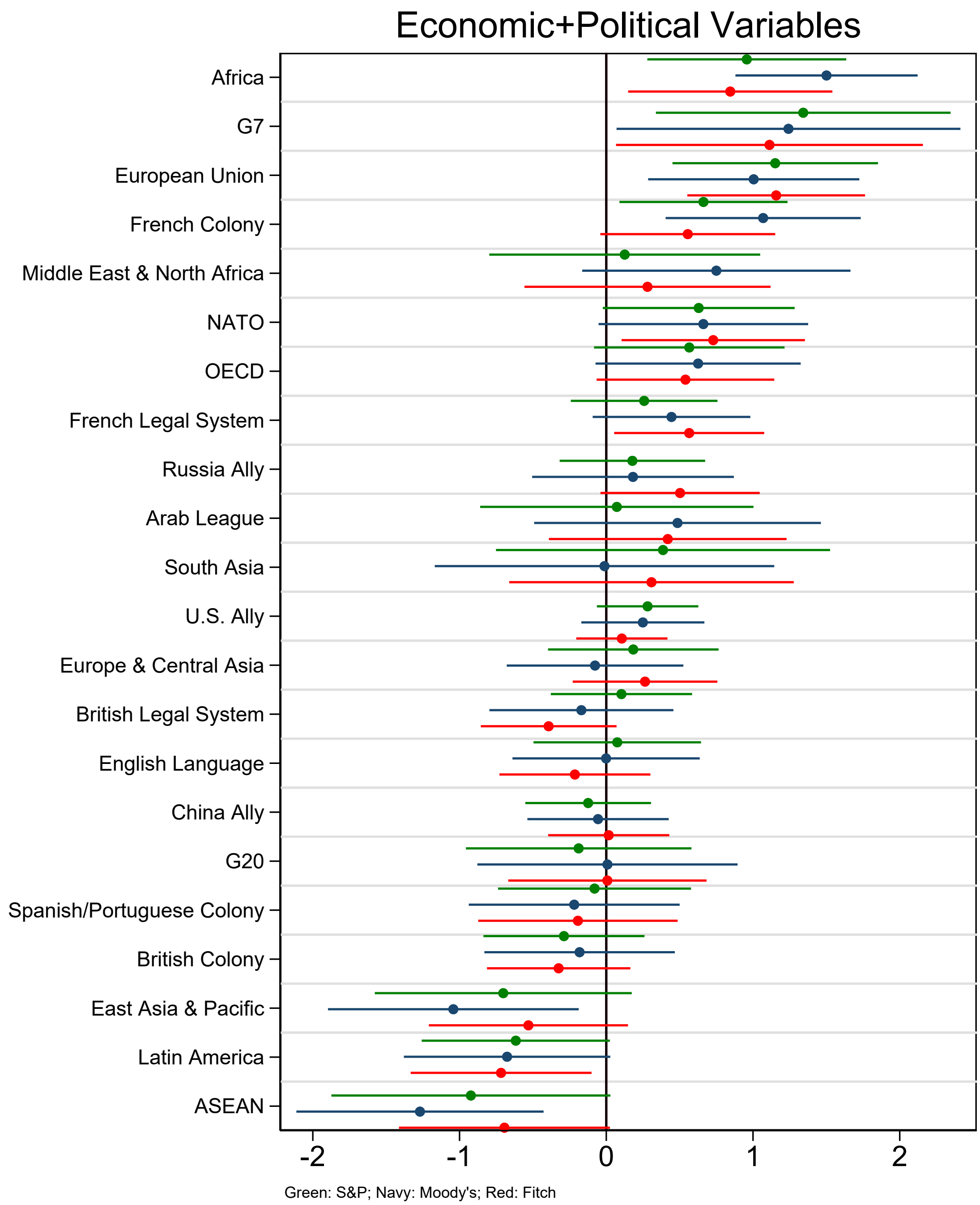


Figure A14: Rating Agency's Economic+Political Penalty Plot

Note: Figure shows the penalty and premium estimates and 95% confidence intervals obtained from separate OLS regressions of credit rating on each variable p_{it}, as well as the economic and political variables only model, by rating agency, indicated in the figure notes. Sample is the full country-year panel.

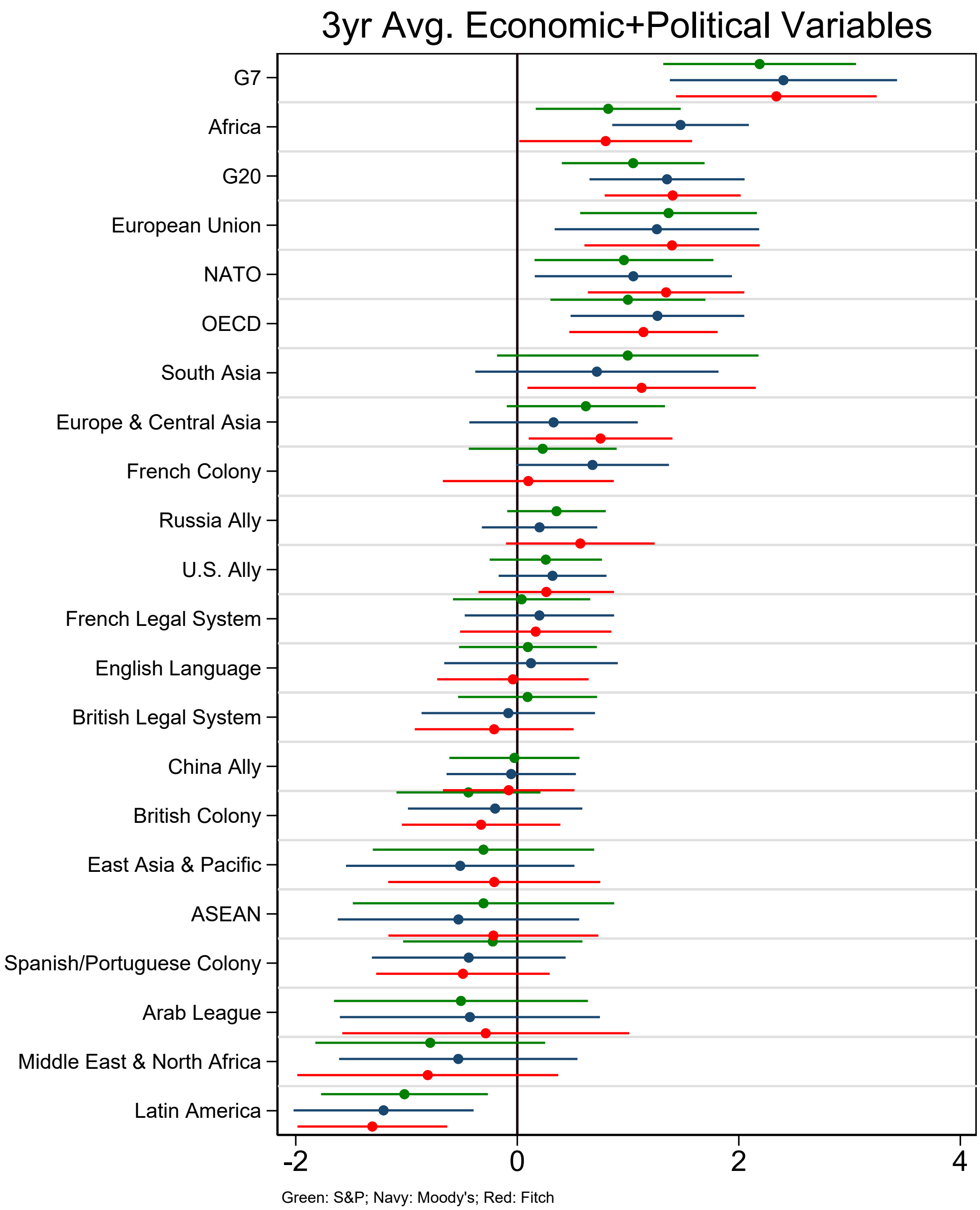


Figure A15: Rating Agency's Lagged Economic+Political Penalty Plot

Note: Figure shows the penalty and premium estimates and 95% confidence intervals obtained from separate OLS regressions of credit rating on each variable p_{it}, as well as the 3-year average economic and political variables only model, by rating agency, indicated in the figure notes. Sample is the full country-year panel.

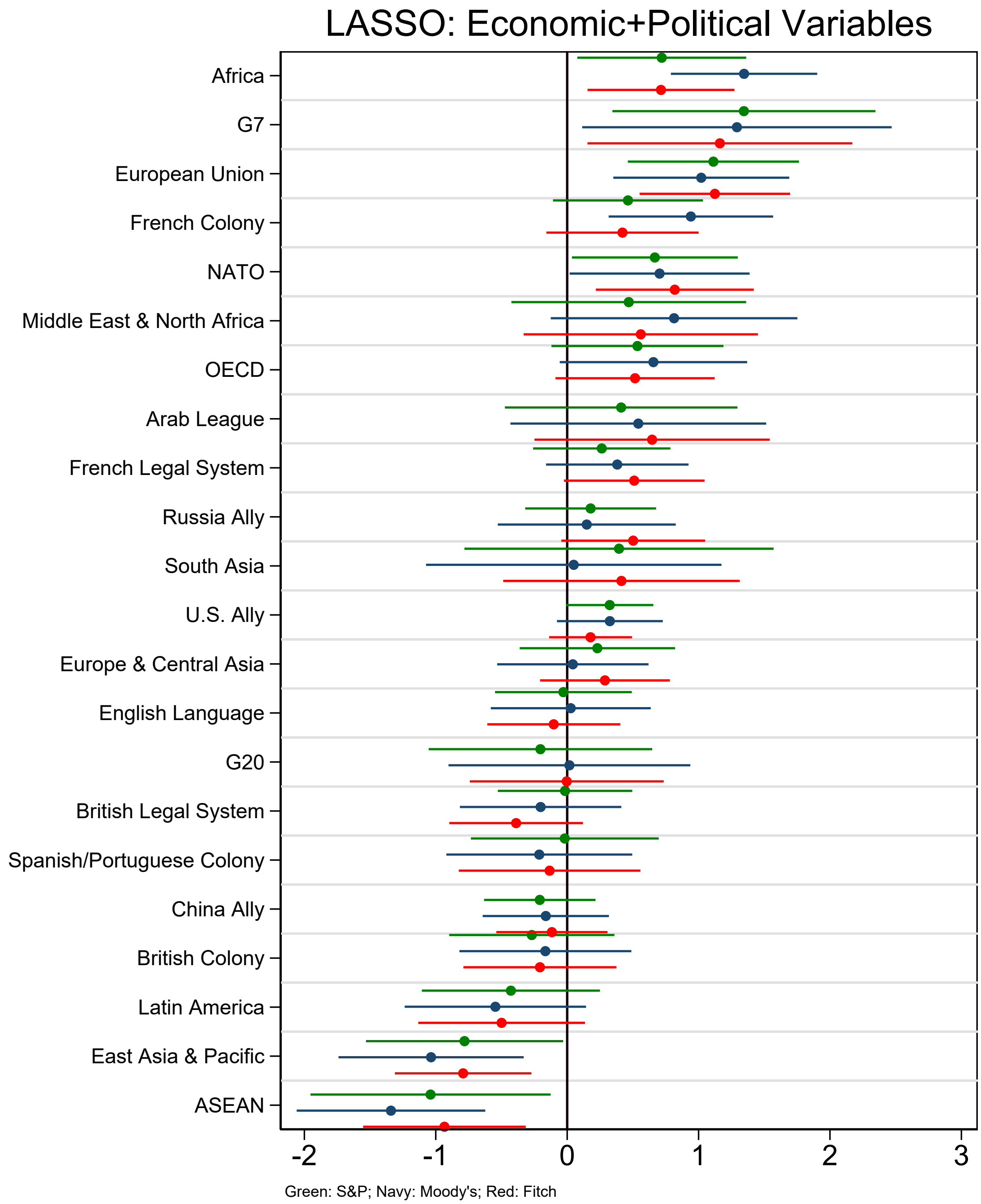


Figure A16: Rating Agency's LASSO Selected Economic+Political Penalty Plot

Note: Figure shows the penalty and premium estimates and 95% confidence intervals obtained from separate OLS regressions of credit rating on each variable p_{it}, as well as the LASSO-selected variables, by rating agency, indicated in the figure notes. Sample is the full country-year panel.

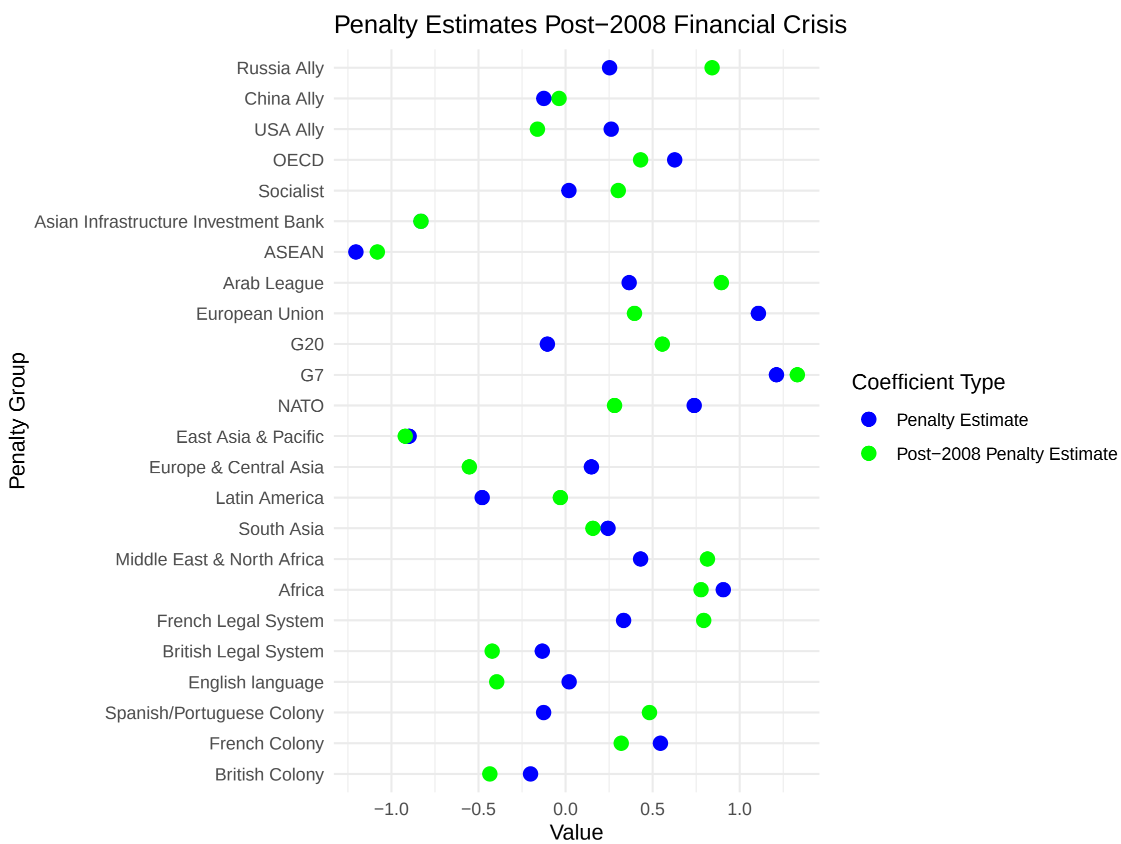


Figure A17: Post-2008 Penalty Differentials

Note: Figure shows penalty differentials after the 2008 Global Financial Crisis. The blue points show penalty estimates for the pre-2008 period, while the green points show penalties in the post-2008 period. All estimates are derived from the LASSO-selected covariates model, where penalty variables are interacted with a post-2008 dummy.

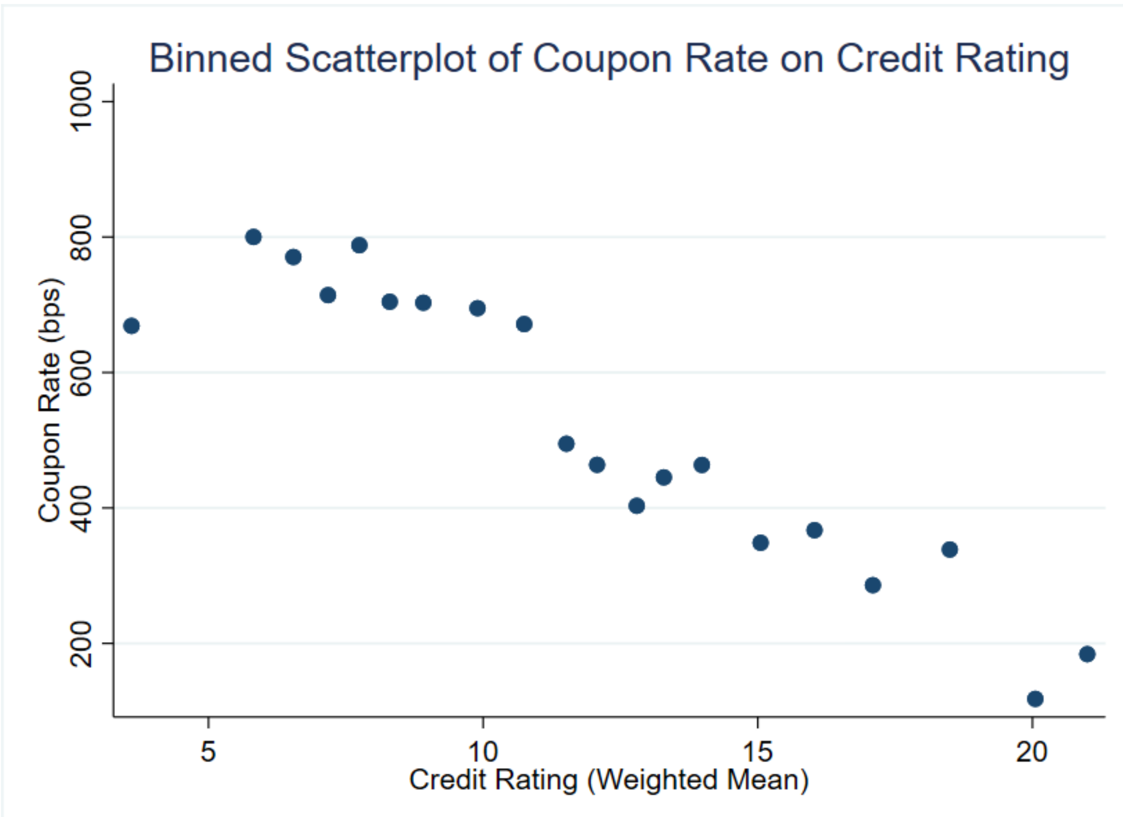


Figure A18: Nonlinear returns to ratings

Note: Figure shows a binned scatterplot of initial bond coupon rates and country-level credit ratings in our sample of sovereign bond issues. Each point represents the average coupon rates across all bonds in a given rating-level bin.

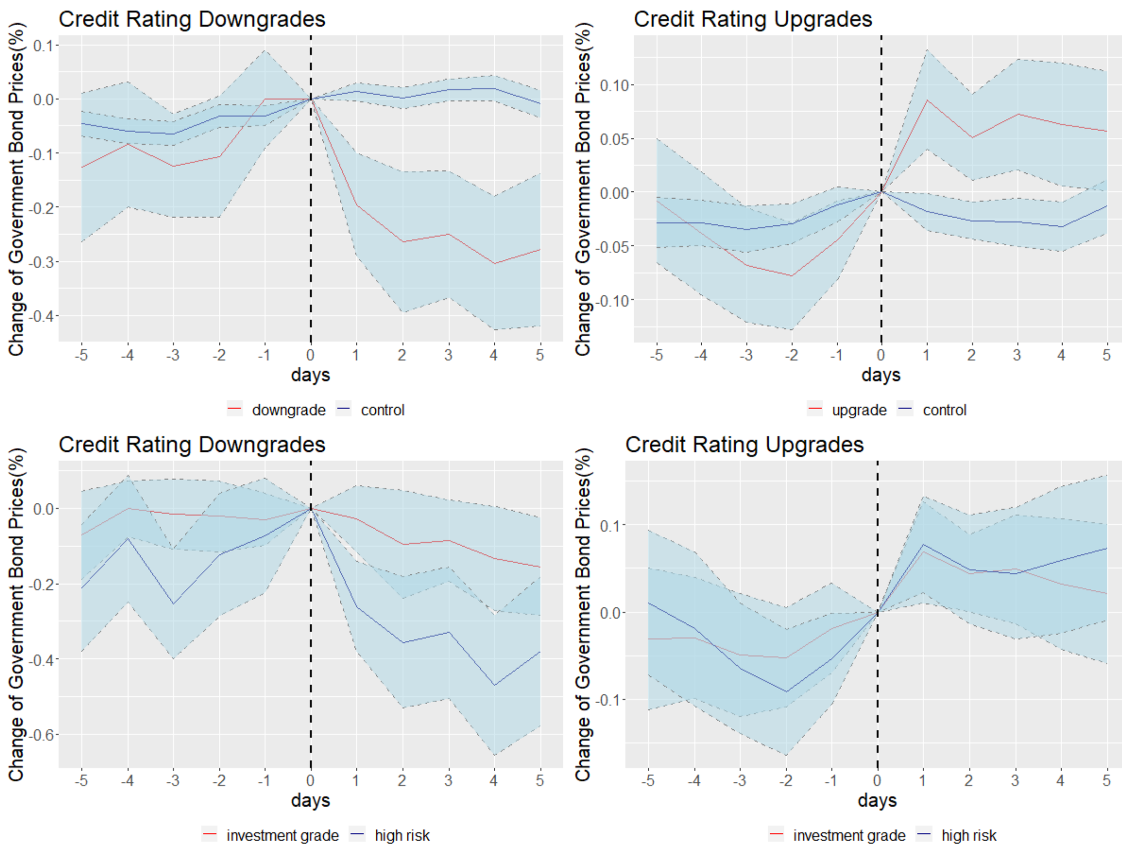


Figure A19: Government Bond Price Changes around Credit Rating Changes

Note: Figure shows average international sovereign bond price changes around credit rating change events, with a 5-day event window, collapsed at country level. Change of government bond price is measured as percentage deviation from the downgrading(upgrading) day. Downgrade - countries that are downgraded; upgrade - countries that are upgraded; control - countries that are in the same credit rating group but did not experience credit rating change. Investment grade - government bonds for countries that had above BBB (or equal) rating before rating change; high risk - government bonds for countries that had below BBB rating before rating change.

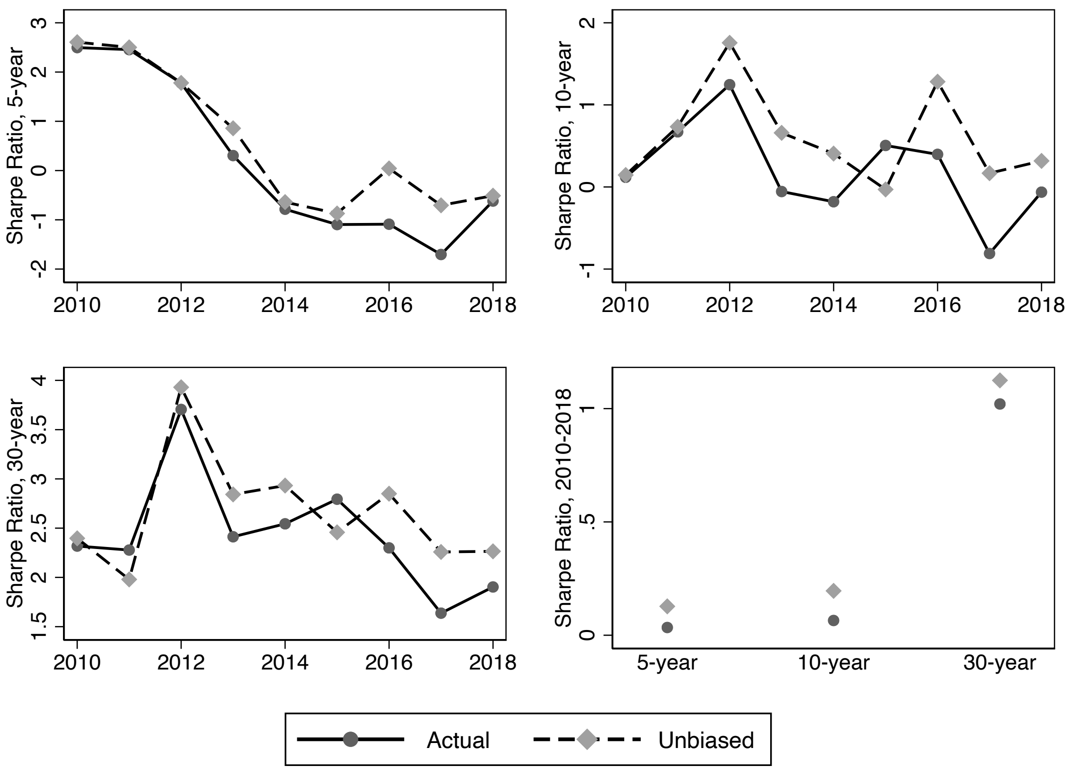


Figure A20: Sharpe Ratio for investment grade portfolios

Note: Figure shows Sharpe ratios for actual and unbiased portfolios by maturity and year from 2010-2018. Each subfigure restricts sample to bonds of different maturity by year, while bottom-right shows Sharpe ratios across the full sample period. Sharpe ratio is calculated as the average portfolio yield minus the average yield on US T-bills of the same maturity over the same period, divided by the standard deviation of yields over time. "Actual" portfolio contains all bonds rated investment grade (above BB+) in the observed data. Unbiased portfolio contains all bonds with predicted investment-grade ratings from the LASSO-selected fundamentals-only model. All portfolios are equal-weighted across all constituent bonds.

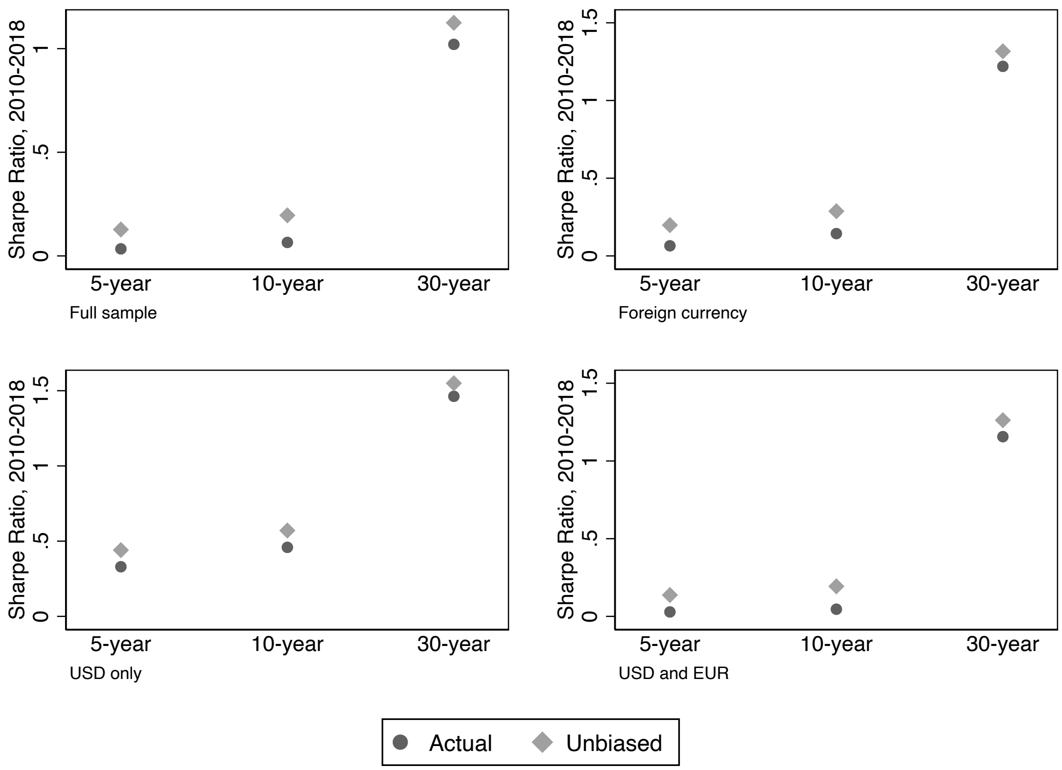


Figure A21: Sharpe Ratio for investment grade portfolios

Note: Figure shows Sharpe ratios for actual and unbiased portfolios by maturity and year from 2010-2018. Each subfigure restricts sample to bonds of different maturity and currency, across the sample period. Sharpe ratio is calculated as the average portfolio yield minus the average yield on US T-bills of the same maturity over the same period, divided by the standard deviation of yields over time. "Actual" portfolio contains all bonds rated investment grade (above BB+) in the observed data. Unbiased portfolio contains all bonds with predicted investment-grade ratings from the LASSO-selected fundamentals-only model. All portfolios are equal-weighted across all constituent bonds.