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Abstract*

This paper investigates how a country's economic complexity influences its sovereign yield spread with respect to the United States. Notably, a one-unit increase in the Economic Complexity Index is associated with a reduction of about 87 basis points in the 10-year yield spread. However, this effect is largely non-significant for maturities under three years. This suggests that economic complexity affects not only the level of the sovereign yield spreads but also the curve slope. The first set of models utilizes advanced causal machine learning tools, while the second focuses on economic complexity's predictive power. Economic complexity ranks among the top three predictors, alongside inflation and institutional factors like the rule of law. The paper also discusses the potential mechanisms through which economic complexity reduces sovereign risk and emphasizes its role as a long-run determinant of productivity, output, and income stability, and the likelihood of fiscal crises.

JEL Codes: F34, G12, G15, H63, O40

Keywords: convenience yields, double-machine-learning, government debt, sovereign credit risk, XGBoost, yield curve

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1. Introduction

In the current landscape of globalization shaped by limited fiscal space, rising interest rates, and a pressing need for financing, both from developed and non-developed nations, particularly in response to the urgent need for an ecological transition to address climate change, fiscal considerations have regained paramount importance. In particular, the exploration of factors influencing a government's capacity to secure funds in international debt markets on favorable terms has garnered significant attention in academic and policy circles. This study makes a significant contribution in this respect, as it investigates the role of a country's degree of economic complexity as a determinant of sovereign credit risk or, in the case of developed countries, their convenience yield.

Economic complexity has recently gained prominence as a new paradigm for economic development. According to Balland et al. (2022), various institutions, including the European Commission, the Organisation for Economic Co-operation and Development, the World Bank, the World Economic Forum, and numerous national and regional organizations, are increasingly adopting the principles of economic complexity and incorporating its analytical framework. This concept revolves around a nation's ability to produce complex products that are not easily substitutable in global markets and are highly valued by trade partners, such as specialized machinery as opposed to basic commodities.

By leveraging recent advancements in causal machine learning, known as double machine learning (DML) (Chernozhukov et al., 2018), this paper assesses the impact of economic complexity on the sovereign credit spreads (with respect to the United States) of a diverse panel of 28 countries, encompassing both emerging and developed economies. The analysis incorporates an extensive array of control variables, including relevant factors previously identified in the literature, comprising macroeconomic, market, debt-related, and institutional variables (see Section 2 for the rationale for our control variables).

This paper is the first to comprehensively consider this range of control variables while examining the direct impact of economic complexity across various maturities on the yield spread curve, spanning from 3 months to 10 years. This approach makes it possible to effectively isolate the influence of multiple confounding factors when estimating the effects of interest across countries and maturities. This sort of analysis would be impossible using conventional panel econometrics and factor models as employed in the extant literature. This is primarily because of the substantial number of confounding variables—around 30—that must be considered when estimating the direct causal effects of complexity on spreads, given the relatively limited dataset available for both countries and over the time, and especially the low frequency of the variables (annual).

Crucially, our approach openly acknowledges the potential for researcher-induced bias when employing machine learning or related techniques to reduce the dimensionality of variables that could impact sovereign debt. This awareness is crucial for accurately estimating both direct and indirect causal effects. In contrast, prior studies that have relied on a wide array of variables to investigate the determinants of sovereign debt, contributing significantly to our understanding in this field, have overlooked this vital aspect essential for extracting causal insights from machine learning and large-dimensional factor analysis. This is exemplified by Maltritz and Molchanov (2013) who employed Bayesian Moving Averaging.

Our findings clearly highlight the influence of economic complexity on sovereign credit risk, particularly in the longer maturities. According to our baseline calculations, an increase of one standard deviation in the Economic Complexity Index (ECI) of Hidalgo and Hausmann (2009) leads to an approximate reduction of 87 basis points (bp) in the 10-year spread ($p<0.01$) and 54 bp in the 3-month spread ($p<0.10$). This highlights how economic complexity not only impacts the level of the spread, thereby affecting a country's ability to secure international funding at a lower cost, but also shapes the slope of the yield spread curve, a critical factor in a country's capacity to mitigate rollover risks without incurring the typically greater expenses of funding with longer maturity debt.

The second part of our results show the relative importance of economic complexity as a predictor of sovereign risk spreads. This analysis, employing a different machine-learning algorithm known as Extreme Gradient Boosting (XGBoost), complements our initial findings. We demonstrate that economic complexity, aside from its statistical and economic significance in determining sovereign risk, exhibits considerable predictive power. It ranks second or fourth among more than 30 variables in explaining sovereign spreads across both short and long maturities (i.e., 5 years and 10 years, respectively). Our assessment of relative performance is achieved by constructing SHAP values for the XGBoost model. Interestingly, only inflation, and occasionally institutional variables, appear to exert a stronger influence than economic complexity, which is more relevant than traditional determinants in the literature, such as real growth or the debt-to-GDP ratio.

Our contribution extends to two distinct branches of the existing literature. First, we align with a body of research that scrutinizes the long-run factors influencing sovereign yields and spreads (e.g., Bellas, Papaioannou, and Petrova, 2010; Poghosyan, 2014; Wang, Xue, and Zheng, 2021), by introducing economic complexity as a key determinant. Second, we contribute to a strand of studies that delve into the varied dynamics across different maturities of yield and spread curves (Eichler and Maltritz, 2013). These studies emphasize the significance of shifts in curve slope dynamics and changes in debt maturity in the face of different economic and political shocks (e.g., Afonso and Martins, 2012; Augustin, 2018; Sánchez, Sapriza, and Yurdagul, 2018; Wellmann and Trück, 2018).

The remainder of this document is structured as follows: Section 2 positions our study in the literature. Section 3 revisits the expected theoretical relationship between economic complexity and sovereign credit risk, with a particular focus on recent literature that stresses economic complexity as a significant determinant of economic development and fiscal performance. Section 4 provides an overview of our methodology with an emphasis on the description of our credit risk spread measure taken from Du and Schreger (2016) and the causal and non-causal machine learning tools that we use to answer our research questions. Section 5 describes our data and sources. Section 6 presents our main findings, and Section 7 concludes.

2. Related Literature

We contribute to two distinct areas of international finance. First, our study adds to the body of research that examines the factors influencing sovereign risk as measured by sovereign yields. This body of literature has emphasized the importance of fiscal discipline and potential output growth in reducing risk spreads, particularly in longer terms. For example, when distinguishing between long-term and short-term determinants, Poghosyan (2014) found that in the long run, a 1-percentage point (pp) increase in the government debt-to-GDP ratio corresponds to an approximate 2 bp increase in government bond yields.[1] Additionally, a 1-pp increase in the potential growth rate is associated with an approximate 45 bp increase in yields. In the short term, sovereign bond yields may deviate temporarily from their long-term fundamental levels, but approximately half of these deviations correct themselves within a year. Similarly, following the same distinction, Bellas, Papaioannou, and Petrova (2010) proposed that fundamental factors have a substantial influence on shaping emerging market sovereign bond spreads in the long term, while, conversely, in the short term, financial volatility emerges as a more dominant determinant. We add economic complexity to a set of long-run factors previously investigated in the field.

Other authors have explored a different set of factors influencing sovereign yields, such as the local and foreign monetary policy conditions (Arora and Cerisola, 2001; Dailami, Masson, and Padou, 2008), unconventional monetary policy interventions (De Santis, 2020; Krishnamurthy, Nagel, and Vissing-Jorgensen, 2018) and the zero lower bound of interest rates (Coroneo and Pastorello, 2020). Local inflation rates and deficit-to-GDP ratios (Liu and Spencer, 2013; Gill, 2018) have also been studied, as well as terms of trade and their volatility (Hilscher and Nosbusch, 2010; Maltritz, 2012) and market uncertainty indicators, in particular the VIX (Afonso and Jalles, 2019; Matsumura and Machado, 2010). Since numerous studies have pinpointed external factors as the main influencers of sovereign risk, a subset of research has delved into the impact of financial and trade openness on sovereign spreads (e.g., Maltritz, 2012; Maltritz and Molchanov, 2014).

[1] See also Wang, Xue, and Zheng (2021) for a recent assessment of the relationship between debt and growth.

Some studies highlight the convergence of fiscal and/or political factors in determining sovereign yields in emerging and advanced economies (Afonso and Jalles, 2019; Beqiraj, Patella, and Tancioni, 2021; Caggiano and Greco, 2012; Sanjeev, Mati, and Baldacci, 2008), including the impact of political factors (Brooks, Cunha, and Mosley, 2022; Chatterjee and Eyigungor, 2019; Eichler, 2014). Additionally, there is extensive research demonstrating the global factors that influence sovereign credit risk commonality worldwide, particularly involving the U.S. stock and bond market dynamics (Liu and Spencer, 2013; Longstaff et al., 2011), and global financial risk (Gilchrist et al., 2022). These prior studies provide the rationale for our comprehensive set of control variables and the use of DML to conduct our main analyses.

Our study also aligns with a set of research efforts that investigate how different maturities of sovereign yields and spreads respond to economic shocks. Theoretically, long-term interest rates are closely intertwined with market expectations concerning a government's future solvency and financing requirements, whereas short-term interest rates reflect concerns related to liquidity and short-term performance outlooks (Eichler and Maltritz, 2013; Freixas and Rochet, 2008). Consequently, it is reasonable to anticipate that the determinants of short- and long-term yield spreads may be different. The composition of long-term and short-term debt plays a fundamental role in emerging market economies, as highlighted by Arellano and Ramanarayanan (2012). Long-term debt serves as a safeguard against fluctuations in interest-rate spreads, whereas short-term debt effectively incentivizes prompt repayment. In a related study, Sánchez, Sapriza, and Yurdagul (2018) introduce a framework for an endogenous determination of sovereign debt maturity, which highlights that sovereign debt tends to have durations and maturities that commonly exceed one year and tend to move in harmony with the economic cycle. Secondly, it observes that sovereign yield spread curves often exhibit non-linear, upward-sloping patterns. Finally, factors like output volatility, individual impatience, risk aversion, and particularly abrupt cessation of capital inflows are identified as fundamental determinants of debt maturity.

Remarkably, Eichler and Maltritz (2013) investigate the factors influencing government bond yield spreads in Economic and Monetary Union (EMU) countries. These authors emphasize the evaluation of default risk across varying timeframes as indicated by spreads of different maturities. Their findings indicate that low economic growth and greater economic openness amplify default risk across all maturity levels. However, heightened indebtedness exclusively heightens short-term risk, while factors like net lending, trade balance, and interest rate costs predominantly impact long-term default risk.

Most prior research in this second branch has focused on extracting common factors through principal component analysis of yields (or spreads) across a broad set of countries, aiming to uncover the global factors that shape the yield (spread) curves. These studies typically identify three latent factors known as the level, slope, and curvature, which suffice to describe the time series variations in interest rates across countries (examples of this literature can be found in recent works such as Afonso and Martins 2012; Augustin 2018; Wellmann and Trück 2018; and references therein). Our approach is different. Given that economic complexity is a relatively slow-moving variable primarily associated with long-term investments in productivity and knowledge diffusion (Hidalgo, 2021), our primary focus is on understanding cross-sectional variations among countries in economic complexity that contribute to explaining sovereign risk. We do not emphasize the high-frequency time series movements, which are often the focus of more financially oriented research in this area. Nonetheless, as we examine different maturities ranging from 3 months to 10 years, our results also provide insights into this line of research by highlighting the anticipated relationship between the slope of the yield spread curve and the novel long-term determinant that we explore.

3. Complexity and Sovereign Yields, Preliminary Facts, and Theory

The level of economic complexity of a country can be assessed using the Economic Complexity Index constructed by—and publicly available from—the Harvard Growth Lab (Hausmann et al., 2014), which assigns a numerical value within -3 to 3, allowing for a quantitative assessment of the matter. In short, the ECI presents a comprehensive approach for simultaneously measuring economic development and resilience to shocks. It surpasses other broad indicators such as the Human Development Index or even the GDP, which tend to focus on specific aspects of the economy and overlook the relative position of a country in the global trade network.

A country is more complex if it produces goods that are relatively rare and combine a highly diversified set of knowledge and capabilities (Hidalgo 2021, 2023). Previous research has established significant relationships between a country's ECI and various economic and social outcomes. Countries with a high ECI have demonstrated an ability to effectively optimize their production inputs for enhanced output value (Hidalgo, 2021), exhibit resilience in the face of macroeconomic shocks (Hausmann et al., 2014), tend to experience reduced income inequality (Hartmann et al., 2017), and show a positive association with gender equality (Nguyen, 2021). Additionally, societies characterized by high economic complexity are more inclined toward technological innovation (Gala et al., 2018), enjoy greater macroeconomic stability, particularly in fiscal matters (Gomez, Uribe, and Valencia, 2023), and tend to adopt more environmentally sustainable production practices (Romero and Gramkow, 2021).

Given these established relationships, it is reasonable to expect a negative association between economic complexity and sovereign risk. At the national level, high economic complexity consistently correlates with long-term economic growth, as evidenced by numerous studies (e.g., Haussmann et al., 2014; Hidalgo and Haussmann, 2009; Ferrarini and Scaramozzino, 2016; Nepelski and De Prato, 2020; Tacchella, Mazzilli, and Pietronero, 2018;). In economic literature, it is well established that more sophisticated exports are linked to higher future economic growth (Hallak 2006; Hausmann, Hwang, and Rodrik, 2007). Furthermore, countries boasting greater economic complexity tend to exhibit more stable growth patterns due to reduced output volatility (Gu̎neri and Yalta, 2021) and enhanced total factor productivity (Sweet and Eterovic, 2019). Economic complexity plays a pivotal role in achieving export stabilization, as evidenced by the findings of Zou et al. (2023). Their research underscores the significance of product sophistication as a key factor in both initiating and maintaining stable export partnerships. These factors are crucial drivers of sustained economic expansion and contribute to fiscal budget stability, enabling nations to navigate turbulent economic periods without succumbing to fiscal crises, as demonstrated by Gomez, Uribe, and Valencia (2023). At the microeconomic level, there is compelling evidence suggesting that companies with a more complex product portfolio experience reduced fluctuations in their output (Maggioni, Turco, and Gallegati, 2016).

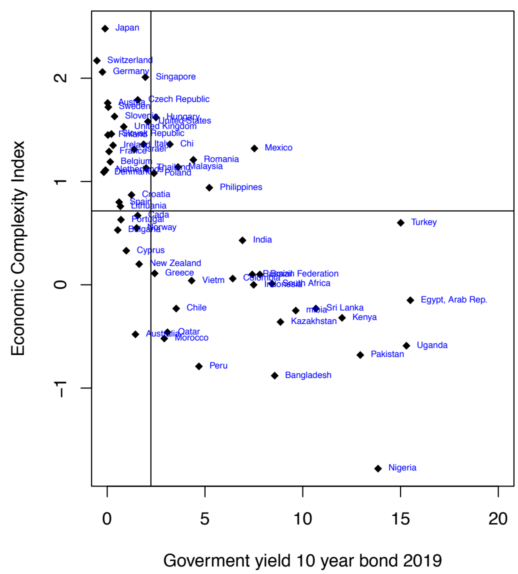
Achieving productive diversification and sophistication is critical for maintaining macroeconomic and fiscal stability. Countries heavily reliant on the production of basic and ubiquitous goods are vulnerable to fluctuations in international market prices, which can adversely impact their overall income (Deaton, 1999). Similarly, nations heavily dependent on tourism are susceptible to global economic cycles, resulting in a sharp reduction in tourism demand during periods of low global economic activity (Aronica, Pizzuto, and Sciortino, 2022). In contrast, economies equipped with the capability to produce complex goods through complex networks involving various forms of expertise and capabilities tend to exhibit greater resilience to external shocks. Consequently, they can be expected to face a lower risk of experiencing fiscal crises and enjoy a lower credit risk prospect, which is priced by the market.

Drawing a parallel to financial asset investments, a diversified portfolio, especially consisting of low-risk assets, helps mitigate risk and generate more stable income for investors over time. Similarly, countries with more complex production structures benefit from more stable income streams, leading to less fluctuation in tax revenues for governments. As a result, it can be expected that complexity is associated with lower costs of sovereign debt and reduced risk premiums.

Figure 1 shows the ECI of 60 countries for the year 2019 plotted against the sovereign yields for 10-year bonds in the same year. Our analysis excludes the years 2020 and 2021, for which ECI data is readily available, due to the extraordinary disruptions caused by the COVID-19 pandemic, which significantly influenced international debt market dynamics in a way orthogonal to our interests (see, for instance, Candelon and Moura, 2023).

As is evident from the figure, there is a distinct negative correlation (i.e. -0.65, p< 0.001) between the ECI and the yields paid. Furthermore, the stability of this relationship is evident in Figure 2, which presents the same variables as the previous figure but focuses on 27 countries with available data for the year 2000. Once again, a significant correlation (p<0.001) of -0.65 is observed between the two variables.

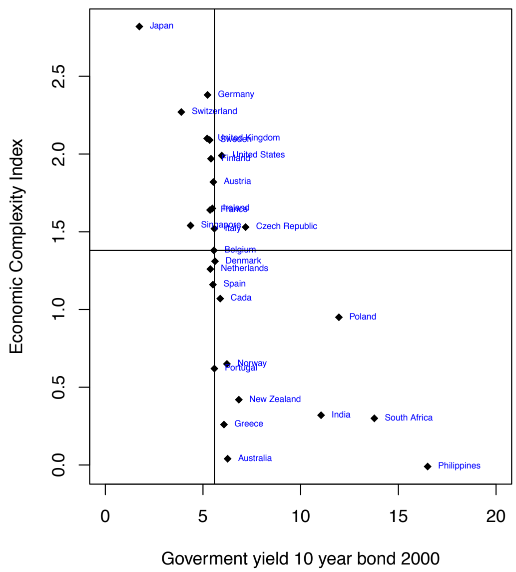
Figure 1. Plot of ECI against Sovereign Yield 10 years, 2019



Note: The figure shows the relationship between a country's economic complexity level and the yields of 10-year maturity sovereign bonds in the year 2019 for a sample of 60 countries. Correlation -0.65.

While the simple correlation between the ECI and yields serves as a useful starting point, it falls short of fully quantifying the direct causal impact of economic complexity on sovereign credit risk. To address this issue, two additional key steps are required: an adequate measure of risk and novel methodological tools from the recent causal machine learning literature. Both are explained in the next section.

Figure 2. Plot of ECI against Sovereign Yield 10 years, 2000



Note: The figure shows the relationship between a country's economic complexity level and the yields of 10-year maturity sovereign bonds in the year 2000 for a sample of 27 countries. Correlation -0.65.

4. Methodology

4.1. Sovereign Credit Risk

Since our primary concern is a country's sovereign credit risk, we employ the spread with respect to the United States for a given maturity at each year, rather than the raw yields in Figures 1 and 2. Specifically, we utilize the local currency sovereign risk indicators developed by Du and Schreger (2016) and Du, Im, and Schreger (2018).

These indicators are constructed as deviations from covered interest rate parity (CIP) between government bond yields in the United States and other countries, denoted as $\Phi_{i,n,t}$:

$$\Phi_{i,n,t} = y_{i,n,t}^{Govt} - \rho_{i,n,t} - y_{USD,n,t}^{Govt} , \tag{1}$$

here, $y_{i,n,t}^{Govt}$ represents the n-year local currency government bond yield in country i, $\rho_{i,n,t}$ represents the n-year market-implied forward premium for hedging currency i against the U.S. dollar, and $y_{USD,n,t}^{Govt}$ is the n-year U.S. Treasury bond yield.

The Treasury CIP deviation measures the distinction between the synthetic dollar borrowing cost of country i and the direct dollar borrowing cost of the United States. This makes it possible to compare sovereign borrowing costs after converting the promised cash flows of local currency sovereign bonds into U.S. dollars. The primary factors influencing CIP deviations for government bond yields include differences in default risk between U.S. and foreign government bonds, variations in convenience yields between U.S. and foreign government bonds, and financial frictions. The relative significance of these factors depends on the specific country and maturity being studied (Du and Schreger 2016; Du, Im, and Schreger 2018).

Du and Schreger (2016) attribute most of the spread variation to credit risk, particularly in the case of emerging markets. In contrast, for developed markets with negligible sovereign default risk and open capital accounts, Du, Im, and Schreger (2018) attribute the spread to convenience yields stemming from factors such as liquidity and other potential non-pecuniary benefits of U.S. bonds compared to others. This approach to constructing spreads effectively mitigates currency risk factors reflected on traditional spreads, enabling us to concentrate on the analysis of sovereign credit risk.

The second step we undertake pertains to the challenge of identifying direct causal effects amid the presence of numerous potential confounding factors within a dataset that typically contains relatively few data points (compared to typical machine learning tasks). Building on prior research, we are aware that various macroeconomic factors, spanning both the supply and demand sides of the economy, play significant roles. These factors include real growth, investment and consumption growth, institutional variables such as the rule of law and regulatory quality, global uncertainty, levels of capital account openness, terms of trade, export commodity rents, population size, and debt-related metrics like the debt-to-GDP ratio, fiscal balances, primary balances, and government revenue. All these factors are expected to exert an influence on the spread of sovereign bonds.

However, the data on spreads available from the original authors' website typically commences in the mid-2000s for emerging market countries. This is primarily due to limitations in the original data sources, such as Bloomberg. In certain cases, like

Chile, there are only three years with enough observations (2005, 2011, 2017) between 1995 and 2019 when information for the economic complexity index is available (excluding the period of the COVID-19 pandemic). Given the combination of relatively limited data points, the low frequency of economic complexity measurements (annual), and the substantial number of potential confounding variables, it becomes essential to employ non-traditional machine learning models that have been recently developed in the econometrics literature to specifically address causal inquiries in the presence of numerous confounding variables.

4.2. Double Machine Learning

We adopt the methodology developed by Chernozhukov et al. (2018),[2] closely following the presentation by Bach et al. (2023) for our exposition of the methods, adapting the notation to our case. In general, when investigating causal relationships, it is often necessary to control for other variables, which we refer to as confounders. This becomes particularly crucial in observational studies, like the one at hand, where randomization is impossible to perform, making the consideration of confounders essential to estimating both direct and indirect causal effects (Pearl, 2009).

This study has a multitude of potential control variables, encompassing macroeconomic, institutional, and fiscal factors. Therefore, it is imperative to carefully select the most pertinent variables before proceeding with the analysis, particularly when the primary focus is on examining the impact of economic complexity on sovereign credit risk. Furthermore, the interplay between these variables and their relationship with both spreads and economic complexity can be intricate, potentially involving nonlinearities and interactions.

In such scenarios, machine-learning algorithms, such as tree-based methods, and regularization and shrinkage techniques, are well suited for the task of variable selection. However, it is important to acknowledge that utilizing these methods to choose from our initially extensive set of control variables introduces a form of bias known as regularization bias or pre-selection bias, which can affect subsequent estimations of causal effects. Double debiased machine learning or, simply, double

[2] The methodology has been implemented by Bach et al. (2023) in the R package DML.

machine learning, is a method designed to estimate causal effects in the presence of a high number of confounders. In our case, we can represent our problem as a partially linear regression model-PLR (Robinson, 1988) through the following equations:

$$\Phi_{i,n,t} = \alpha ECI_{i,t} + g_0\left(X_{i,t}\right) + u_{i,n,t}, \tag{2}$$

$$ECI_{i,t} = m_0\left(X_{i,t}\right) + \nu_{i,n,t}, \tag{3}$$

with $E(u|ECI, X) = 0$, $E(v|X) = 0$ and where, $\Phi_{i,n,t}$ is defined as before, $ECI_{i,t}$ is the economic complexity index for country i at year t, and $X_{i,t}$ is a high dimensional vector of confounding variables that influence both $\Phi_{i,n,t}$ and $ECI_{i,t}$, including country and time fixed effects. DML developed by Chernozhukov et al. (2018) allows us to estimate accurately the functions $g_0(\cdot)$ and $m_0(\cdot)$, which can be linear or not. In addition, it allows us to correct for pre-selection bias by a procedure that is called post-double-selection (Belloni, Chernozhukov, and Hansen, 2014).

In essence, DML considers both spreads, $\Phi_{i,n,t}$, and complexity, $ECI_{i,t}$, as dependent on a vast array of variables encapsulated in $X_{i,t}$. It exhibits great flexibility by accommodating both linear and nonlinear relationships, which are defined by the functions $g_0(\cdot)$ and $m_0(\cdot)$ Machine learning techniques are employed twice to approximate each of these functions. Chernozhukov et al. (2018), along with other researchers in the field, have made a significant contribution to the literature, referenced therein and in what follows. In short, they have developed valid inference within this context and proposed the use of cross fitting as a strategy to alleviate overfitting, a common challenge in machine learning tasks when not adequately addressed.

The model above can be rewritten in residual form as follows, omitting year, maturity, and country indexes to ease notation. Thus, it becomes transparent that we run a single regression that uses DML for each maturity, separately, including time and country fixed effects in the set of controls X:

$$v = ECI - m_0(X), \tag{4}$$

$$w = \left(\Phi - l_o(X)\right), \tag{5}$$

$$w = v\alpha + u, \tag{6}$$

with $l_o(X) = E(\Phi|X) = \alpha m_0(X) + g_0(X)$, $E(u|ECI, X) = 0$, $E(v|X) = 0$, $m_0(X) = E(ECI|X)$. The variables w and v are just the original variables after factoring out the effect of X. This is called partialling out the effect of X. In this equation, α is identified as long as $var(v) \neq 0$.

Estimation algorithm of the PLR model reads as follows:

i. Estimate l_o and m_0 by $\hat{l}_o$ and $\hat{m}_0$, which can be done by solving the two problems of predicting Φ and ECI using a generic ML method. In our case, we use random forest[3]. In this case, the estimated residuals are given by:

$$\hat{v} = ECI - \hat{m}_0(X), \tag{7}$$

$$\hat{w} = \left(\Phi - \hat{l}_o(X)\right), \tag{8}$$

Notice that these residuals should be obtained by cross-validation, to avoid biases and over-fitting (Belloni, Chernozhukov, and Hansen, 2014).

ii. Estimate α by regressing the residual $\hat{w}$ on $\hat{v}$. This can be done using conventional inference tools as shown by Chernozhukov et al. (2018).

In terms of inference, to construct point and interval estimator with ML we use the method-of-moment estimator for α based on the empirical moment condition given by:

$$E[\psi(w; \alpha, \eta_0)] = 0, \tag{9}$$

where ψ is known as the score function, $w = (\Phi, \alpha, X)$, α is our parameter of interest which corresponds to the effect of economic complexity on the yields spread at a given maturity. η denotes nuisance functions equal to η_0 in population (i.e. functions g_0 and m_0 in equations 2 and 3). Inference relies on choosing a score function that satisfies the so-called Neyman orthogonality condition (Neyman 1979) given by:

$$\partial_\eta E[\psi(w; \alpha, \eta_0)]|_{\eta=\eta_0} = 0. \tag{10}$$

[3] See Giraldo et al. (2023) and Gu, Kelly, and Xiu (2020), which describe the advantages of tree-based models in the case of relatively small and tabular datasets like ours.

Employing a Neyman-orthogonal score makes estimation of the parameter α robust against first-order bias that arises from regularization. In the PLR model two alternatives for the score function are available following Chernozhukov et al. (2018), from which we select the partialling-out score given by:

$$\psi(w;\alpha,\eta_0) \coloneqq \Big(\Phi - l(X) - \alpha\big(ECI - m(X)\big)\Big)\big(ECI - m(X)\big), \quad (11)$$

where $\eta = (l,m), \eta_o = (l_0, m_0)$, $w = (\Phi, \mathrm{ECI}, \mathrm{X})$ and l, m are P-square-integrable functions mapping X on $\mathbb{R}$ (see Bach et al [2023] and Chernozhukov et al. [2018] for additional details).

Two methods exist to carry out the estimation with DML that consider the cross-fitting nature of the problem, and that employ a form of sample splitting to eliminate the over-fitting. For this, let us assume that we have a sample $(w_i)_{i_1}^N$, which is independent and identically distributed. To simplify notation, we also assume that N is divisible by K. Then,

$$E_N[g(w)] \coloneqq \frac{1}{N}\sum_{i=1}^{N} g(w_i). \quad (12)$$

Method 1: The sample $(w_i)_{I=1}^N$ is split into K fragments and indexed with $(I_k)_{k=1}^K$, for $[N] = \{1, \dots, N\}$, such that the size of each fragment, I_k, is $n = N/K$. For each part, $k \in [K] = \{1, \dots, K\}$, we construct a random forest estimator $\hat{\eta}_{0,k} = \eta_{0,k}\big((w_i)_{i \notin I_k}\big)$ of $\eta_{0,k}$. Notice that $x \to \hat{\eta}_{0,k}(x)$ depends only on the subset of data$(w_i)_{i \notin I_k}$. Then, for each $k \in [K]$, we construct the estimator $\hat{\alpha}_k$ as to solve the following equation:

$$\frac{1}{n}\sum_{i \in I_k} \psi\left(w_i; \hat{\alpha}_k, \hat{\eta}_{0,k}(x)\right) = 0 . \quad (13)$$

And the causal effect is obtained via aggregation as follows:

$$\tilde{\alpha}_k = \frac{1}{K}\sum_{k=1}^{K} \hat{\alpha}_k. \quad (14)$$

Method 2: The sample is split into K fragments and indexed with $(I_k)_{k=1}^K$, in the sample $[N] = \{1, \dots, N\}$ such that the size of each fragment is $n = N/K$. A random forest is constructed for each part, $k \in [K] = \{1, \dots, K\}$, $\hat{\eta}_{0,k}$. This time the estimator of the causal parameter $\tilde{\alpha}_k$ is constructed by solving the following equation:

$$\frac{1}{n}\sum_{k=1}^{K}\sum_{i \in I_k} \psi\big(w_i; \hat{\alpha}, \hat{\eta}_{0,k}\big) = 0. \quad (15)$$

We present our main estimations in the results section using both methods.

Regarding the learners used to approximate the functions $g_0(\cdot)$ and $m_0(\cdot)$, as stated before we opt for Random Forest (RF) as introduced by Breiman in 2001. RF is a versatile ensemble learning technique widely used in artificial intelligence, suitable for both classification and regression tasks. During its training phase, RF creates multiple decision trees, and the ensemble's output represents the average prediction from these individual trees. Notably, each tree is trained on a random selection of features and a distinct random subset of the training data. This built-in randomness diminishes inter-tree correlations, fostering the creation of a more resilient and precise ensemble model.

RF has notably exhibited reliable performance when compared with more advanced methods, such as Deep Learning, especially within economic-financial datasets, as highlighted by Gu, Kelly, and Xiu (2020). This effectiveness can be partly ascribed to the predominance of tabular data economics and finance, and crucially, to the observation that datasets typical to our domain are often smaller than those prevalent in fields like computer vision and natural language processing, where Deep Learning shines.

4.3. Extreme Gradient Boosting for Assessing the Relative Role of Economic Complexity as a Predictor

Finally, in the third part of our results section, we use non-causal machine learning algorithms to assess the relative importance of economic complexity as a predictor of sovereign risk. In this case, the focus is not on the estimation of a causal effect, but rather on comparing the prediction power of economic complexity in relation to a large set of macroeconomic, institutional, and debt-related variables.

Specifically, we use XGBoost, developed by Chen and Guestrin (2016), as an efficient implementation of Gradient Tree Boosting (GTB). Our model can be broadly described in the following way:

$$\Phi_{i,n,t} = \sum_{k=1}^{K} f_k(X_{it}), \quad f_k \in \mathcal{F} \quad . \tag{16}$$

In Equation 16, $\mathcal{F}$ represents the space of regression trees, $\Phi_{i,n,t}$ is the spread for country i at year t and maturity n, and X_{it} contains institutional, macroeconomic, fiscal, and financial indicators in country i, year t (see Table 1).

The model employs a regularized learning objective to understand the functions $f_k(\cdot)$, discouraging overly complex models and preventing overfitting. Additionally, it utilizes Gradient Tree Boosting (GTB) as introduced by Friedman in 2001. GTB employs decision trees as base learners. The key idea behind GTB is the iterative fitting of regression trees to the residuals of the preceding trees, aiming to minimize the loss function of the model.

In a similar vein, XGBoost operates iteratively, creating an ensemble of decision trees. Each new tree is trained to correct the prediction errors of the previous models. Notably, XGBoost is well suited for handling datasets with numerous features in relation to the number of observations. Models are fitted using any differentiable loss function, and in our case, we employ a standard square loss, optimized through gradient descent.

To interpret our model, which is a challenging task for tree-based architectures, we employ SHAP (Shapley Additive Explanations) values, a methodology introduced by Lundberg and Lee (2017). SHAP values are designed to quantify the contribution of each feature to the final prediction, considering the interactions between features (such as covariates) and the value ranges of each feature. This approach yields an accurate and intuitive explanation of how the model arrives at its predictions.

The use of SHAP values in conjunction with XGBoost is particularly valuable when it is crucial to comprehend the factors influencing the model's predictions. This is especially relevant in scenarios where we seek to understand the determinants of sovereign risk. By examining the SHAP values associated with each feature, we gain insights into which features exert the most significant influence on the spreads over time and how they relate to one another in our longitudinal data comprising a variety of countries over the years. This facilitates a more in-depth understanding of the dynamics underlying our model's predictions and complements the results on the effects obtained via DML.

5. Data

We rely on a comprehensive dataset comprising fiscal variables and associated macroeconomic, financial, and institutional factors, encompassing both emerging and advanced economies. The dataset covers 28 countries, consisting of 16 emerging markets and 12 advanced economies. The advanced economies are Australia (AUD), Canada (CAD), Switzerland (CHF), Denmark (DKK), Germany (EUR), United Kingdom (GBP), Japan (JPY), Norway (NOK), New Zealand (NZD), Sweden (SEK), Israel (ILS) and South Korea (KRW), and the emerging markets are Brazil (BRL), Chile (CLP), China (CNY), Colombia (COP), Hungary (HUF), Indonesia (IDR), India (INR), Mexico (MXN), Malaysia (MYR), Peru (PEN), Philippines (PHP), Poland (PLN), Russia (RUB), Thailand (THB), Turkey (TRY) and South Africa (ZAR). Most of the dataset features annual data points spanning from 1995 to 2019, ensuring comprehensive coverage of fiscal distress and related macroeconomic and financial upheavals in the global economy. Our dataset also includes various maturities of sovereign yield spreads relative to U.S. government yields of the same maturity. Specifically, it encompasses spreads for 3 months, 1 year, 2 years, 3 years, 5 years, 7 years, and 10 years. These spreads are computed as either an average of monthly data within a year or as observations taken on the last day of the calendar year. Spreads are only available for the 28 countries listed above.

It is important to note that we have excluded the years 2020 and 2021, for which ECI indicators are already available, from our calculations. This decision is based on our primary focus on the long-term determinants of sovereign risk, such as economic complexity. 2020 and 2021 were marked by the onset of the COVID-19 pandemic, experienced abrupt changes in spreads that may not reflect the structural transformations that are the primary interest of this study.

Table 1 presents the summary statistics of the dataset including the spreads, macroeconomic and institutional factors. We gathered an extensive array of variables that vary over time, drawing inspiration from existing literature on fiscal crises and determinants of sovereign debt. The first three columns of Table 1 provide the complete list of variables and their definitions, while the last four columns display their means, medians, standard deviations, maximum, and minimum values. Our model's baseline specification includes indicators like real growth, the debt-to-GDP ratio, interest payments, revenue from fuels, real exchange rates, and institutional quality, among others.

Our selection of variables considers well-known sources of sovereign risk identified in existing literature, and each variable is theoretically justified. To maintain theoretical coherence, we refrain from including any transformations of the original variables, such as differences, squares, or interactions, in our dataset. As for proxy of economic diversification, we have included the Economic Complexity Index from Harvard's Growth Lab, regularly updated on their Atlas of Economic Complexity webpage (Hidalgo and Haussmann, 2009). It is worth noting that the ECI data are available for the subset of 28 countries, as indicated before, which also have good information regarding both the sovereign yields and macroeconomic and institutional variables, alongside fiscal information.

Table 1. Summary Statistics of the Dataset and Source

Indicator	Abreviation	Source	Mean	Median	Std.Dev	Max.	Min.
3 month yield spread	diff_3m_end	Du's CIP web page	2.12	1.65	3.42	19.72	-5.64
1 year yield spread	diff_1y_end	Du's CIP web page	2.09	1.56	3.41	18.43	-6.02
2-year yield spread	diff_2y_end	Du's CIP web page	2.07	1.43	3.39	16.7	-5.98
3-year yield spread	diff_3y_end	Du's CIP web page	2.03	1.36	3.35	15.77	-5.89
5-year yield spread	diff_5y_end	Du's CIP web page	1.88	1.13	3.22	15.69	-5.29
7-year yield spread	diff_7y_end	Du's CIP web page	1.77	1	3.15	15.3	-5.15
10-year yield spread	diff_10y_end	Du's CIP web page	1.69	0.88	3.06	15	-4.6
Population in millions	pop	WEO	155.62	38.47	342.3	1433.78	3.72
Inflation rate, average of the year	inf_avg	WEO	3	2.34	2.67	16.33	-1.33
Real GDP growth	growth	WEO	3.21	2.97	2.71	14.25	-7.82
Log of per capita real consumption	ccon	Penn World Tables	13.49	13.47	1.18	16.19	11.21
Log of per capita domestic absorption	cda	Penn World Tables	13.8	13.78	1.2	16.8	11.48
Log of expenditure-side real GDP at current PPPs in mil. 2017US$	cgdpe	WEO	13.82	13.78	1.18	16.81	11.49

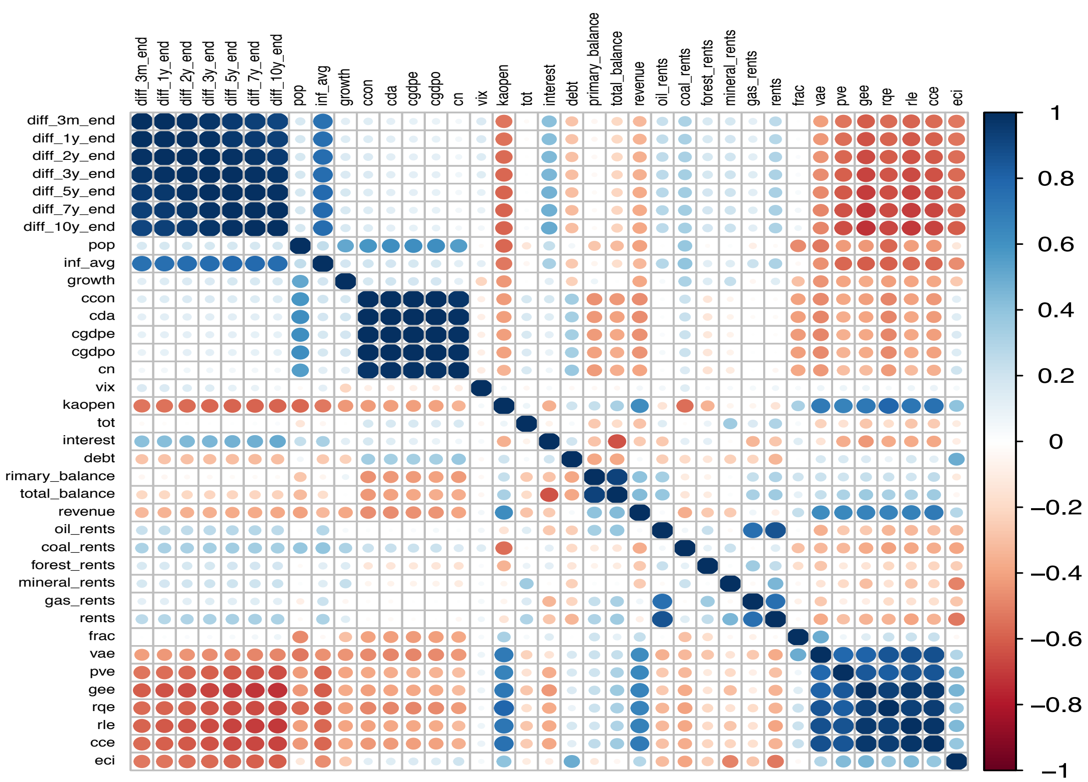
Log of output-side real GDP at current PPPs in mil. 2017US$	cgdpo	WEO	13.83	13.76	1.19	16.82	11.48
Log of capital stock at current PPPs in mil. 2017US$	cn	Penn World Tables	15.2	15.05	1.26	18.44	12.71
Chicago Board Options Exchange Volatility Index	vix	Bloomberg	19.39	16.67	6.15	32.7	11.09
Financial openness, Chinn-Ito index	kaopen	Ito's web	1.19	2.32	1.37	2.32	-1.23
Terms of trade change in %	tot	WEO	102.67	100	15.9	159.88	49.3
Interest expenses as % GDP	interest	WEO (estimate)	1.6	1.36	1.62	8.37	-3.09
Gross debt as % of GDP, general government	debt	WEO	53.37	43.67	36.78	236.14	6.86
Primary balance as % GDP	primary_balance	WEO	0.16	0.07	3.24	15.83	-8.73
Fiscal balance as % GDP	total_balance	WEO	-1.44	-1.53	4.02	18.64	-11.23
Fiscal revenue as % GDP	revenue	WEO	34.08	33.65	11.22	58.63	14.05
Oil rents as % of GDP	oil_rents	World Bank	1.36	0.39	2.25	11.6	0
Coal rents as % of GDP	coal_rents	World Bank	0.39	0.03	0.79	7.25	0
Forest rents as % of GDP	forest_rents	World Bank	0.27	0.13	0.5	4.5	0
Mineral rents as % of GDP	mineral_rents	World Bank	0.7	0.15	1.57	12.63	0
Gas rents as percent of GDP (gas_rents)	gas_rents	World Bank	0.4	0.11	0.78	4.83	0
Natural resources rents as percent of GDP	rents	World Bank	2.46	1.12	3.25	17.1	0
Historical ethnic fractionalization	frac	HIEF-Harvard	0.66	0.67	0.18	0.95	0
Voice and accountability	vae	World Bank	0.76	0.99	0.84	1.8	-1.75
Political stability and absence of violence	pve	World Bank	0.31	0.62	0.95	1.61	-2.06
Government effectiveness	gee	World Bank	1.03	1.21	0.82	2.35	-0.52

Regulatory quality	rqe	World Bank	0.96	1.11	0.76	2.09	-0.63
Rule of law	rle	World Bank	0.89	1.06	0.96	2.11	-0.97
Control of corruption	cce	World Bank	0.92	0.84	1.11	2.47	-1.13
Economic Complexity Index	eci	Harvard's Growth Lab	0.99	1	0.86	2.86	-0.84

Note: The table shows summary statistics of the variables in our sample along with their respective data sources.

Figure 3 presents the Pearson's correlation among the variables described in Table 2. Notably, the proxy variables for institutional quality in each country exhibit strong correlations with each other, including government effectiveness, regulatory quality, rule of law, and control of corruption. Likewise, there are nearly perfect correlations between the aggregate demand proxies, such as domestic absorption and real consumption. Finally, there are notably high correlations between all spreads in our dataset.

Figure 3. Plot of the Correlation among Variables in Table 1



Note: the figure shows the correlation among the continuous variables in the study sample.

Notably, sovereign yield spreads show a significant negative correlation with institutional variables and with the economic complexity index. This finding is particularly noteworthy as it sheds light on the importance of properly considering a large set of institutional quality proxies if one wants to assess the true impact of complexity on sovereign risk.

6. Results

Our results are divided into three sections: The first section provides our baseline estimates, examining the impact of economic complexity on sovereign risk spreads at various maturities, ranging from 3 months to 10 years. The second section explores alternative model specifications to assess the robustness of our main claims. We consistently find statistically significant effects for maturities exceeding three years, even when they are reduced by up to 33 percent in the most extreme cases. This reaffirms the documented economic significance of these effects. Shorter maturities, in certain specifications, may exhibit statistical non-significance, reinforcing our argument about the distinct impact of economic complexity along the yield-spread curve, particularly its slope. In the third section, we present the outcomes of a purely statistical exercise using extreme gradient boosting. Here, our focus shifts from estimating the effect of complexity to evaluating its predictive power compared to a broad set of traditional determinants of yield spreads. This new set of results emphasizes the high predictive capability of economic complexity, emphasizing its significance as a long-term determinant of sovereign risk alongside factors such as inflation and institutional quality.

6.1. Baseline Results: Effect of Economic Complexity on Sovereign Risk

Table 2 contains our primary findings, which include point and interval estimates of the impact of economic complexity on sovereign spreads of various maturities. The intervals were calculated at a 99 percent confidence level. Additionally, columns 3 to 5 present the standard errors, p-values, and t-statistics associated with these estimates.

In Panel A, we implement Method 1 as described in the methodology, while Panel B corresponds to Method 2. The table reveals that, in Panel A, the effects are statistically significant at a 90 percent confidence level for all maturities. At a 95 percent confidence level, significance holds for maturities longer than one year, and at a 99 percent confidence level, significance is observed for maturities equal to or exceeding two years. Regarding the magnitude of the effects, they exhibit a positive correlation with maturity. The smallest effects are observed for three-month maturities, where an increase of one point (equivalent to one standard deviation) in the Economic Complexity Index leads to a reduction of 54 basis points in the spread. Conversely, the most substantial effect is observed in the 10-year spread, corresponding to an 87 basis point reduction. Remarkably, the effect shows a steady increase in between.

In Panel B, the disparity between the 3-month and 10-year maturities becomes even more pronounced, ranging from 39 bps in the former case to 83 bps in the latter. Notably, for maturities less than two years, this effect does not attain statistical significance at a 95 percent confidence level. Furthermore, it remains statistically insignificant for the three-month maturity at any traditional level of confidence.

Table 2. Baseline Results: with Both Year and Country Fixed Effects
Panel A. Method 1

	Effect	S.E.	P.Value	t.Statistic	Lower.CI	Upper.CI
3-month yield spread	-0.54	0.29	0.06	-1.87	-1.28	0.20
1-year yield spread	-0.67	0.29	0.02	-2.34	-1.41	0.07
2-year yield spread	-0.73	0.26	0.01	-2.77	-1.41	-0.05
3-year yield spread	-0.72	0.25	0.00	-2.85	-1.37	-0.07
5-year yield spread	-0.84	0.23	0.00	-3.69	-1.42	-0.25
7-year yield spread	-0.84	0.21	0.00	-4.02	-1.38	-0.30
10-year yield spread	-0.87	0.20	0.00	-4.42	-1.37	-0.36

Panel B. Method 2

	Effect	S.E.	P.Value	t.Statistic	Lower.CI	Upper.CI
3-month yield spread	-0.39	0.28	0.17	-1.38	-1.13	0.34
1-year yield spread	-0.54	0.28	0.06	-1.89	-1.27	0.19
2-year yield spread	-0.62	0.26	0.02	-2.36	-1.29	0.06
3-year yield spread	-0.61	0.25	0.01	-2.46	-1.26	0.03
5-year yield spread	-0.76	0.22	0.00	-3.40	-1.34	-0.19
7-year yield spread	-0.80	0.21	0.00	-3.81	-1.33	-0.26
10-year yield spread	-0.83	0.20	0.00	-4.23	-1.33	-0.32

Note: The table shows the impact of a unitary variation in the economic complexity index on various sovereign spread maturities, ranging from 3 months to 10 years. We utilized a random forest approach with 15 trees, a minimum node size of 2, and a maximum depth limit of 5 to estimate the nuisance functions. All variables outlined in Table 1 were included as control variables, along with dummy variables for each country and year. In Panel A, cross-fitting was conducted using Method 1. In Panel B, we show the results using Method 2 as explained in the methodology. In both cases we applied a Neyman-orthogonality condition of partialling out, as detailed in Section 3.

Our findings in this respect introduce a novel perspective to the field, as prior literature has not explored the influence of economic complexity on sovereign risk and convenience yields. However, they align with certain aspects of earlier research, such as Sánchez, Sapriza, and Yurdagul (2018), who present a model for endogenously determining sovereign debt maturity and emphasize the pro-cyclical nature of sovereign debt maturity. Likewise, Eichler and Maltritz (2013) investigate the determinants of government bond yield spreads at varying maturities. Their conclusions highlight that increased indebtedness primarily affects short-term maturities, while factors like net lending, trade balance, and interest rate costs predominantly impact long-term default risk. Our results complement these prior studies and others by demonstrating the notable influence of economic complexity on longer maturities which, indeed, is associated with different effects along the spread curve, supporting previous arguments advanced by this literature.

6.2. Alternative Specifications

Tables 3 and 4 present models identical to those in Table 1, with the exception that Table 3 excludes dummy variables for countries and years in the pool of controls, and Table 4 exclusively incorporates country dummy variables. These variations aim to assess the sensitivity of the results to different model specifications. Broadly speaking, the primary findings remain consistent. Economic complexity exhibits statistical and economic significance in impacting sovereign spreads across all specifications for maturities exceeding three years. However, in most instances, the magnitude of the effects is diminished by approximately 30 percent.

We favor the results presented in our baseline specification in Table 2, as the inclusion of country and year dummy variables serves to account for potential confounding factors. The exclusion of these variables, as seen in traditional panel data specifications, could introduce biases, particularly in the context of an unbalanced panel as we have in this study. In this case, these biases appear to mitigate the impact of economic complexity on sovereign risk at all maturities.

Table 3. Effects without Year and Country Fixed Effects

Panel A. Method 1

	Effect	S.E.	P.Value	t.Statistic	Lower.CI	Upper.CI
3-month yield spread	-0.58	0.31	0.06	-1.90	-1.38	0.21
1-year yield spread	-0.64	0.29	0.03	-2.19	-1.38	0.11
2-year yield spread	-0.59	0.27	0.03	-2.21	-1.28	0.10
3-year yield spread	-0.66	0.25	0.01	-2.60	-1.30	-0.01
5-year yield spread	-0.73	0.24	0.00	-2.98	-1.36	-0.10
7-year yield spread	-0.69	0.23	0.00	-2.98	-1.29	-0.09
10-year yield spread	-0.73	0.22	0.00	-3.29	-1.30	-0.16

Panel B. Method 2

	Effect	S.E.	P.Value	t.Statistic	Lower.CI	Upper.CI
3-month yield spread	-0.40	0.30	0.19	-1.30	-1.18	0.39
1-year yield spread	-0.45	0.29	0.11	-1.58	-1.19	0.29
2-year yield spread	-0.43	0.27	0.11	-1.60	-1.11	0.26
3-year yield spread	-0.50	0.25	0.04	-2.01	-1.14	0.14
5-year yield spread	-0.59	0.24	0.01	-2.43	-1.21	0.03
7-year yield spread	-0.60	0.23	0.01	-2.59	-1.19	-0.00
10-year yield spread	-0.64	0.22	0.00	-2.91	-1.20	-0.07

Note: The table shows the impact of a unitary variation in the economic complexity index on various sovereign spread maturities, ranging from 3 months to 10 years. We utilized a RF approach with 15 trees, a minimum node size of 2, and a maximum depth limit of 5 to estimate the nuisance functions. All variables outlined in Table 1 were included as control variables. In Panel A, cross-fitting was conducted using Method 1. In Panel B, we show the results using Method 2 as explained in the methodology. In both cases we applied a Neyman-orthogonality condition of partialling out, as detailed in Section 3.

Table 4. Results with Only Country Effects

Panel A. Method 1

	Effect	S.E.	P.Value	t.Statistic	Lower.CI	Upper.CI
3-month yield spread	-0.63	0.29	0.03	-2.14	-1.38	0.13
1-year yield spread	-0.59	0.29	0.04	-2.02	-1.33	0.16
2-year yield spread	-0.64	0.28	0.02	-2.27	-1.36	0.08
3-year yield spread	-0.57	0.27	0.03	-2.13	-1.25	0.12
5-year yield spread	-0.55	0.23	0.02	-2.39	-1.13	0.04
7-year yield spread	-0.67	0.22	0.00	-3.06	-1.23	-0.11
10-year yield spread	-0.62	0.20	0.00	-3.10	-1.13	-0.11

Panel B. Method 2

	Effect	S.E.	P.Value	t.Statistic	Lower.CI	Upper.CI
3-month yield spread	-0.51	0.29	0.08	-1.76	-1.26	0.24
1-year yield spread	-0.44	0.29	0.12	-1.55	-1.18	0.30
2-year yield spread	-0.49	0.28	0.08	-1.76	-1.20	0.23
3-year yield spread	-0.44	0.26	0.10	-1.67	-1.12	0.24
5-year yield spread	-0.46	0.23	0.04	-2.05	-1.05	0.12
7-year yield spread	-0.59	0.22	0.01	-2.70	-1.15	-0.03
10-year yield spread	-0.57	0.20	0.00	-2.86	-1.08	-0.06

Note: The table shows the impact of a unitary variation in the economic complexity index on various sovereign spread maturities, ranging from 3 months to 10 years. We utilized a random forest approach with 15 trees, a minimum node size of 2, and a maximum depth limit of 5 to estimate the nuisance functions. All variables outlined in Table 1 were included as control variables, along with dummy variables for each country in the sample. In Panel A, cross-fitting was conducted using Method 1. In Panel B, we show the results using Method 2, as explained in the methodology. In both cases we applied a Neyman-orthogonality condition of partialling out, as detailed in Section 3.

The influence of economic complexity becomes particularly prominent in the case of longer debt maturities. This aspect holds significant importance, especially concerning debt restructuring during distress episodes in emerging market economies. Such episodes are often linked to increased borrowing costs, as countries are compelled to secure financing through longer-term contracts. This situation arises due to the generally positive slope of the yield curve during the debt restructuring process, which naturally results in higher borrowing costs for these countries. However, our findings indicate that this mechanism does not apply uniformly to countries with higher levels of economic complexity. All other factors being equal, these countries experience lower yields for longer maturities compared to other nations. Consequently, during times of crisis, debt restructuring for more economically complex economies is a more cost-effective option, thus alleviating pressure on these countries' government budget. In essence, economic complexity emerges as an attractive feature for risk mitigation within sovereign debt markets.

In essence, greater economic complexity enables countries to achieve a dual objective. It allows them to reduce roll-over risk during crisis episodes by issuing long-term debt instruments to replace short-term maturities, all while avoiding a substantial increase in their borrowing costs associated with this strategic shift from short to long debt. For a comprehensive exploration of the underlying mechanisms governing the choice of maturity in sovereign debt issuance, refer to Beetsma et al. (2021).

6.3. Relative Importance of Economic Complexity When Explaining Sovereign Credit Risk

Figures 4 and 5 show the SHAP values for all the predictors in our dataset, including the Economic Complexity Index, when making predictions for sovereign spreads with 5- and 10-year maturities. The abbreviations used in these figures are defined in Table 1.

The numbers next to each variable in both figures represent the SHAP values, which quantify the average impact of each predictor variable on the predictions. The colored points within the figures represent the individualized predictive influence of each variable on sovereign spreads at 5 and 10 years. Darker violet points correspond to larger values of the predictor variable, while lighter yellow points correspond to smaller values. It is important to note that the order of the variables is the focus here, as SHAP values are normalized.

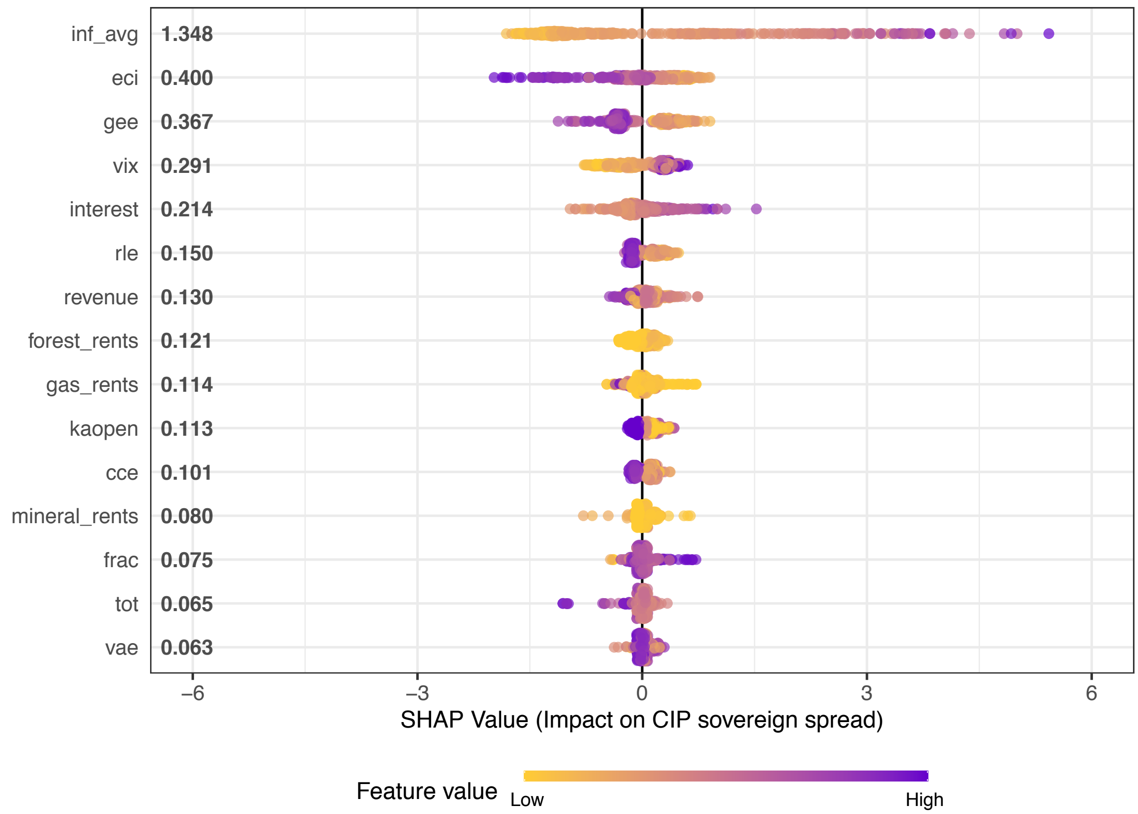
For both maturities, inflation emerges as the most influential predictor of yield spreads. Looking at Figure 4, it is evident that countries with low inflation (depicted in yellow) typically experience lower spreads. In other words, lower inflation has a negative impact on spreads, reducing the sovereign risk. Conversely, countries with high inflation (represented by darker yellow and violet shades) tend to face higher risk, as indicated by wider spreads. Remarkably, exceptionally high inflation substantially amplifies the spread, and this effect is asymmetrical, as demonstrated by the pronounced dark point on the far-right side of the figure.

The significant role of inflation as a key predictor of sovereign spreads is expected and well documented. Inflation is known to exert a substantial impact on a country's sovereign bond yields. Notably, inflation erodes the real value of bonds, particularly affecting longer-term debt instruments. As a result, it is anticipated that nations with higher inflation rates would be forced to offer greater risk compensation to investors holding their government bonds. High inflation tends to drive up a nation's nominal GDP, leading to immediate improvements in debt-to-GDP ratios—a phenomenon often referred to as "inflating debt away." This process introduces additional sources of risk. Notable studies in this field include the works of Buraschi and Jiltsov (2005), Camba-Méndez (2020), Camba-Méndez and Werner (2017), D'Amico, Kim, and Wei (2018), Gürkaynak, Sack, and Wright (2010), and Hördahl and Tristani (2012). Our findings underscore the paramount role of inflation in international debt markets from a novel methodological perspective.

Institutional quality, which is closely associated with a country's level of development, ranks as the third most relevant indicator for the 5-years spread, and second and third for the 10-years spread. In Figure 4, this third predictor is denoted as "gee," corresponding to the Government Effectiveness indicator as defined in Table 1. In Figure 5, the second most influential predictor is "rle," representing the Rule of Law indicator. Both of these are World Bank estimates.

Political institutions and the quality of governance are natural determinants of sovereign credit risk. Nations with fragile institutions and governance structures often face higher sovereign yields, reflecting the perceived greater risk of default, as noted by Eichler (2014). In broad terms, institutional risk encompasses the overall quality of a country's institutions, including its legal and political framework. Increased institutional risk typically translates into higher sovereign yields. Moreover, in line with the insights presented by Butler and Fauver (2006), the institutional environment can significantly influence sovereign credit ratings, thereby impacting a country's sovereign spreads. Our findings underline the crucial role of institutions in shaping sovereign yield spreads.

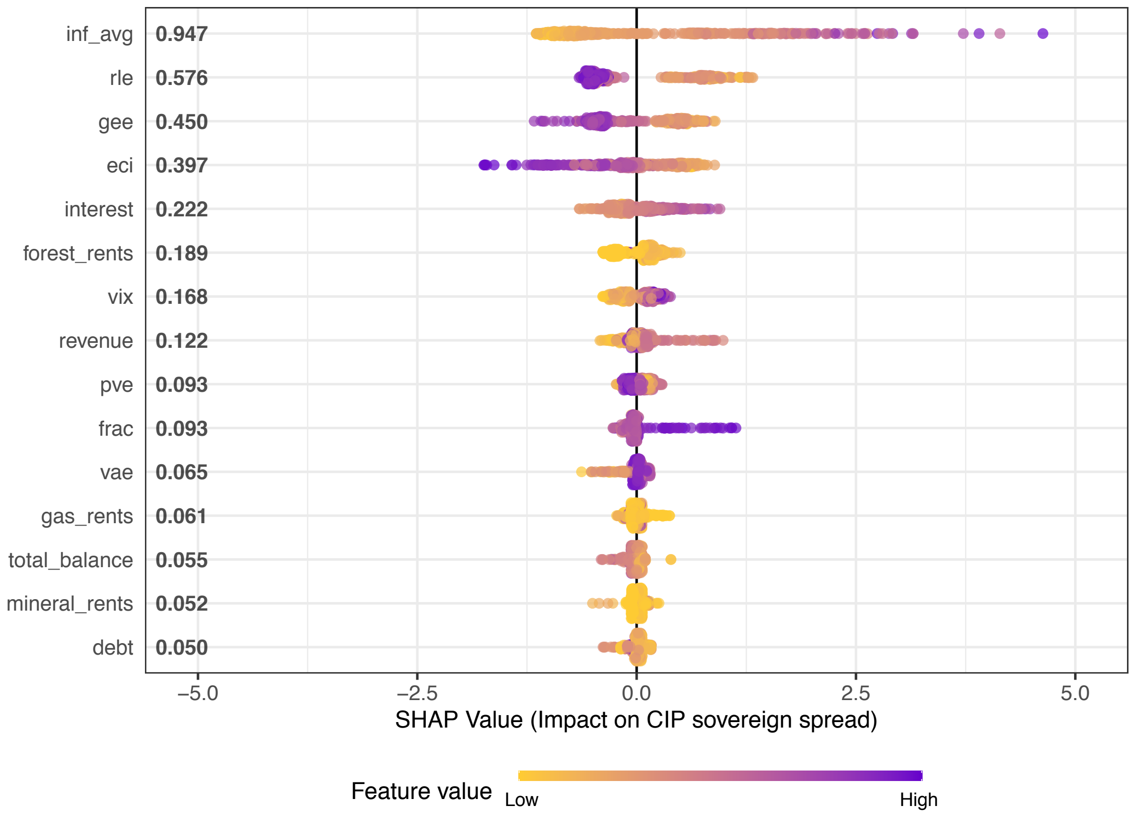
Figure 4. SHAP Value of the Top 15 Variables in Table 1 when Predicting Sovereign Spreads at 5 Years



Note: The figure shows the SHAP values of the top 15 predictor variables of sovereign spreads at five years.

Taking the second and fourth positions among the 30 variables is the economic complexity indicator in Figures 3 and 4, respectively. The magnitude of the SHAP value linked to the ECI is strikingly comparable to that of Government Effectiveness in Figure 4 for the five-year maturity. In Figure 5, the ECI's effect is approximately two-thirds of the impact of the Rule of Law indicator. This highlights the substantial relative influence of economic complexity in shaping sovereign spreads. These results align with findings in Gomez, Uribe, and Valencia (2023), which identify economic complexity as a pivotal factor in determining the likelihood of fiscal crises. In this context, complexity risk becomes relevant for nations characterized by limited productive diversification and lower resilience to economic shocks. Our study demonstrates that this type of risk is indeed factored into international debt markets, thus establishing economic complexity as a significant predictor of sovereign yield spreads.

Figure 5. SHAP Value of the Top 15 Variables in Table 1 when Predicting Sovereign Spreads at 10 Years



Note: The figure shows the SHAP values of the top 15 predictor variables of sovereign spreads at 10 years.

6.4. Hyper-parameter Tuning and Robustness of the Predictive Results

Unlike the random forest, which serves as the base model in our DML exercises, XGBoost can be sensitive to the initial hyper-parameter settings, such as the learning rate and the subsample size, aimed at mitigating overfitting. Our primary models, outlined in Figures 3 and 4, are based on an XGBoost specification with standard hyper-parameter configurations. These parameters are detailed in Table A1 in the Appendix. To assess the robustness of our findings, we conducted simulations using 100 distinct sets of randomly selected hyper-parameters and recalibrated the XGBoost model for each set (refer to Table A1 for the simulation ranges). Notably, our key results consistently exhibited resilience and stability.

Specifically, across the 100 specifications for the 5-year maturity spread, inflation consistently ranked within the top five variables and always emerged as the primary predictor, regardless of hyper-parameter values. Similarly, the ECI appeared in the top five in 98 out of 100 cases, often in the second position, but occasionally in the third or fourth spot following the institutional variables, Government Effectiveness (gee) and Rule of Law (rle). Interestingly, the VIX emerged as the third most frequently occurring variable in the top five, topping the list in 91 instances. The 'gee' variable featured in the top five in 72 percent of cases, while the Rule of Law appeared in 42 percent of cases.

For the 10-year spread, the pattern remained consistent. Both inflation and economic complexity consistently ranked within the top five across all specifications. The institutional variables 'gee' and 'rle' appeared in the top five in 95 and 93 instances, respectively, while the implicit interest rate of debt, which initially ranked fifth in our baseline specification, featured in the top five in 89 percent of cases.

In summary, our simulation results, which involve randomly configuring sensitive values for the primary hyper-parameters in our predictive XGBoost model, underscore the robustness of our reported findings. If anything, economic complexity emerges as the second most stable indicator, following inflation, which remains the most significant and pervasive predictor of sovereign spreads in terms of both magnitude and frequency.

7. Conclusions and Policy Implications

In the current global context, fiscal considerations carry first-order importance due to limited fiscal resources, rising interest rates, and the urgency of financing for various needs, including the ecological transition. We contribute by postulating economic complexity as one of the main factors influencing a country's ability to secure favorable international debt financing, especially at maturities between 5 and 10 years.

Particularly, this study investigates the role of a country's economic complexity in determining sovereign credit risk, employing DML for causal inference. The analysis covers a diverse panel of 28 countries, including both emerging and developed economies, considering a large array of control variables. Unique to the study is the simultaneous examination of the direct impact of economic complexity on yield spreads at various maturities, from 3 months to 10 years while considering a large set of controls.

In our baseline specifications the effect of economic complexity is shown to be significant for all maturities at 10 percent significance, and only for maturities greater than three years at 99 percent. Our robustness checks include constructing two different DML estimators and including only country fixed effects and non-effects in the pool of controls. In all cases the results hold. Nonetheless, in some cases they are attenuated. For instance, the effect of complexity on sovereign spreads at 10 years range between -57 bps in a model that only includes country fixed effects and uses the second method for cross fitting, and -0.87 bps in our baseline results. In all cases this effect is significant. All in all, our findings reveal that economic complexity significantly influences sovereign credit risk, particularly in longer maturities, impacting both spread level and slope.

In the second part of the study, XGBoost machine learning shows economic complexity's substantial predictive power, ranking third among over 30 variables, with only inflation and institutional variables exerting a stronger influence.

This study contributes to international finance by highlighting the importance of economic complexity as a determinant of sovereign risk and exploring how different maturities of sovereign yields respond to economic shocks. Our research topic becomes particularly pertinent amidst recent global crises, encompassing financial crises, pandemics, and war, along with disruptions in value chains and political fragmentation.

By highlighting the importance of economic complexity in securing more favorable financing terms in international debt markets for countries, we indirectly emphasize the need for diversifying their range of export products, especially for economies at low and intermediate levels of development. The effectiveness of diversification and industrial policies, whether currently in place or in the process of implementation, can be evaluated by consistently tracking a country's complexity metrics over time.

This topic has taken center stage in both academic and economic policy discussions, fueled by the pressing need for economies to enhance their resilience and adaptability. In fiscal matters, the urgency is even more pronounced, given the increasing levels of public and private debt that render economies more vulnerable to external shocks, resulting in prolonged financial pressures.

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Appendix

Table A1: Hyper-parameters of Main Specifications and Range Allowed for Simulations

Name in R:: xgboost	Description	Baseline specification	Range allowed for simulations
eta	Learning rate	0.2	0.1-0.5
gamma	Minimum split loss	2	0-10
max_depth	Maximum depth of a tree	7	5-10
min_child_weight	Minimum size of a node	2	1-2
max_delta_step	Updating rate of the model	2	1-3
subsample	Sub-sampling to prevent overfitting	0.9	0.8-1.0
lambda	Increase for more conservative models	1	0-2
alpha	Increase for more conservative models	0.5	0-2

Note: The first column corresponds to the name as designated in the 'xgboost' package for the R statistical software. The second column offers a concise description of the function associated with each hyper-parameter, whereas the third column displays the specific value assigned to that hyper-parameter in the primary specifications utilized to generate Figures 3 and 4 in the main text. The last column indicates the permissible values employed in the simulation exercise designed to assess robustness, as detailed in the main text. For parameters within the realm of real numbers, a uniform distribution was used, while resampling with replacement was applied in other instances. Hyper-parameters not deemed as critical as those listed in the table were set at their default settings.