QMBU 450 Final Project

Relationship Between Good Governance and Inequality

Bülent Söyler | ID: 54303

İsmail Berk Sabuncuoğlu | ID: 53623

INTRODUCTION

In this paper, the results of a data analysis are summarized, which is conducted to explore a phenomenon that is related to the field of Economic Development: The relationship between the quality of governance and inequality. The authors of the paper believe that the good governance of a country and inequality are negatively correlated. For that, the significance levels between the two is examined. Hypothesis created based on the subject is:

Hypothesis: There is a significant relationship between the good governance and inequality of a country.

In this paper, the accuracy of the hypothesis is examined.

VARIABLES

For the analysis, explanatory and dependent variables were needed. Two indicators related to good governance and inequality were chosen: World Governance Indicators (WGI) and GINI Index

World Governance Indicators (WGI): WGI is calculated by the World Bank since 1996 to measure how good the countries are governed. The calculations are based on the perceptions gathered from multiple civil rights organizations and public institutions. WGI was conducted once in two years until 2002 for over 200 countries. After 2002, it is conducted annually. According to the World Bank, WGI captures six key dimensions of governance:

- ➤ Voice and Accountability: Reflects the perceptions of the extent of participation of a country's citizens to choose their government as well as other freedoms like freedom of speech, freedom of press, and so forth.
- ➤ Political Stability and Absence of Violence/Terrorism (Political Stability No Violence): Reflects the perceptions of likelihood of political stability as well as violence that is politically motivated, including terrorism.
- ➤ **Government Effectiveness:** Reflects perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.
- ➤ **Regulatory Quality:** Reflects perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.
- ➤ Rule of Law: Reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.
- ➤ Control of Corruption: Reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests (*World Bank*, 2019).

Measurement: The values for each dimension range from -2.5 (weak governance) to 2.5 (strong governance)

GINI Index: GINI Coefficient, or GINI Index, is a statistical measurement represents the income or wealth distribution of a nation's residents. It is developed by the Italian statistician and sociologist Corrado Gini in 1912 and it is the most widely used measurement of inequality (*Chappelow*, 2020).

Measurement: The GINI coefficient for a country range from 0 (perfect equality) to 100 (perfect inequality).

DATA

For gathering the data, two Excel files were downloaded from the official website of the World Bank. One of them is the data of WGI from the year 1996 to 2018 and the other one is the data of GINI Index from the year 1960 to 2019. Both files have the data for over 200 countries. The files can be found from these websites:

For WGI: https://info.worldbank.org/governance/wgi/

For GINI Index: https://data.worldbank.org/indicator/SI.POV.GINI

MODELS AND FINDINGS

For indicating whether the hypothesis can be rejected or not, OLS Regression analysis with seven variables was conducted. The six dimensions of WGI were the explanatory variables and GINI coefficient was the dependent variable. The variables were named in the model as like this:

➤ **GINI**: GINI Index

GE: Government Effectiveness
 VA: Voice and Accountability
 CoC: Control of Corruption

> **PSNV:** Political Stability No Violence

RQ: Regulatory QualityRoL: Rule of Law

Since there is a high chance the explanatory variables are correlated, Principal Component Analysis (PCA) was also used in the analysis.

Although the WGI values for every single country were available, the GINI data did not contain the values for every single country. For that, the countries who did not contain GINI coefficient for any year were eliminated. When the elimination process was finished, 160 countries were left for observation, and the two files on Excel were merged and pulled as a one file via Python (Spyder). The first ten observations of the data are shown below:

Countries	GINI	VA	CoC	GE	PSNV	RQ	RoL
Albania	31,78571	0,100883	-0,635056948	-0,2724	-0,05382	0,061584	-0,53057
Algeria	27,6	-0,92926	-0,599621999	-0,53831	-1,20368	-0,8879	-0,75258
Angola	47	-1,15498	-1,317454506	-1,12747	-0,5664	-1,02999	-1,28438
Argentina	45,0125	0,373669	-0,390413581	-0,10186	-0,07998	-0,67456	-0,61653
Armenia	31,96471	-0,60941	-0,609088721	-0,13203	-0,12215	0,227336	-0,36942
Australia	34,22	1,414788	1,929785118	1,702943	0,956616	1,657986	1,777569
Austria	30,26667	1,386632	1,709091032	1,69054	1,161732	1,435733	1,863474
Azerbaijan	26,325	-1,31004	-1,056557613	-0,58396	-0,71158	-0,39635	-0,77972
Bangladesh	32,56667	-0,48757	-1,085489939	-0,76095	-1,35091	-0,86742	-0,82655

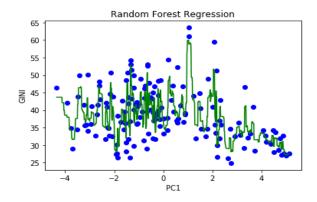
The values of the variables for each country were calculated via taking the average of the values in the 2002-2018 period for each variable. Three different models were created for the analysis.

Model 1: With 160 observations, the model was conducted via PCA and OLS Regression. For PCA, the explanatory variables were standardized, the covariance matrix was computed, and it was used to compute the Eigenvalues and Eigenvectors. With PCA, a variable named "PC1" was created with the six WGI variables.

Linear Regression was used for both PC1 and the six WGI variables for comparison. Random Forest Regression (RFR) was also used for PC1 and GINI, since RFR is not linear and can give more accurate results. First, an RFR graph was created with PC1 and GINI. After that, the data was divided into training and test data and the Mean Absolute Error (MAE) Mean Square Error (MSE), Root Mean Square Error (RMSE) and R2 values were calculated for both training and test. The training data consists of 112 observations and the test data consists of 48 observations. The results are shown below:

		0LS Reg	ression R	esults		
Dep. Variabl Model: Method: Date: Time: No. Observat Df Residuals Df Model: Covariance l	Tu tions: s:	0 Least Squar e, 19 May 20 01:48: 1	DLS Adj. res F-st D20 Prob 45 Log- L60 AIC: 158 BIC:	uared: R-squared: atistic: (F-statistic Likelihood:):	0.080 0.074 13.78 0.000284 -546.83 1098. 1104.
	coef	std err	t	P> t	[0.025	0.975]
Intercept PC1	38.8404 -0.9534	0.587 0.257	66.157 -3.713	0.000 0.000	37.681 -1.461	40.000 -0.446
Omnibus: Prob(Omnibus Skew: Kurtosis:	s):	14.9 0.6 0.6 3.7	001 Jarq 691 Prob	in-Watson: ue-Bera (JB): (JB): . No.		1.830 16.486 0.000263 2.29

		OLS Re	egress	ion Re	esults		
Dep. Variab Model: Method: Date: Time: No. Observa Df Residual Df Model: Covariance	ations: ls:	Least Squa Tue, 19 May 2 01:44 nonrol	2020 3:45 160 153 6	R-squared: Adj. R-squared: F-statistic: Prob (F-statistic): Log-Likelihood: AIC: BIC:			0.207 0.176 6.653 2.85e-06 -534.97 1084. 1105.
	coef	std err		t	P> t	[0.025	0.975]
Intercept VA CoC GE PSNV RQ RoL	38.4731 3.4027 4.9697 -2.0554 1.4162 1.3306 -10.5578	1.318 2.253 2.691 1.059 2.294	2 2 -0 1 0	.471 .582 .206 .764 .337 .580	0.000 0.011 0.029 0.446 0.183 0.563 0.000	37.347 0.799 0.519 -7.372 -0.677 -3.203 -16.304	39.600 6.006 9.421 3.261 3.509 5.863 -4.812
Omnibus: Prob(Omnibu Skew: Kurtosis:	ıs):	9 9	. 351 . 009 . 431 . 926				1.847 10.679 0.00480 13.1



With RFR:

Mean Absolute Error (MAE): 6.523316557519109

Mean Squared Error (MSE): 67.55885880128454

Root Mean Squared Error (RMSE): 8.219419614625144

R2 (Training data): 0.8581367676369575

R2 (Test data): -0.2551940732963556

Although that the probability of F-statistic is less than 5%, both SLR with PC1 and MLR with the six WGI variables cannot explain the most of variability in GINI, since their Adjusted R2 levels are very low. Also, the P-values of GE, PSNV, and RQ are higher than 5%, which shows that there is a multicollinearity between the values, and this can be shown via correlation table that shows high correlation between the values below:

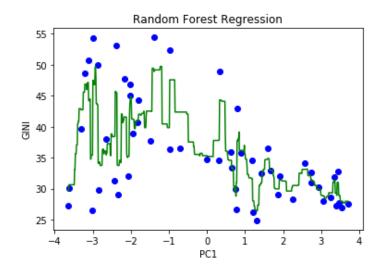
Correlation Table	VA	CoC	GE	PSNV	RQ	RoL
VA	1					
CoC	0,833207	1				
GE	0,809717	0,937356	1			
PSNV	0,752462	0,764514	0,711604	1		
RQ	0,832752	0,885494	0,949644	0,66834	1	
RoL	0,866522	0,961538	0,951996	0,791417	0,919357	1

The table shows the importance of using PCA, since it reduces these six correlated variables into one variable. When we look at the RFR, it gave high R2 value with the training data, but it gave negative R2 value with the test data, which indicates that when the model is fitted for a data, it cannot make good predictions with another data. Briefly, there is a high chance that the model is overfitting the data.

Model 2: In the Model 1, the countries that had even one GINI coefficient were included. For example, the GINI coefficient for Iraq calculated only in 2012 and in the previous data, this value for one year was considered as the average for the 2002-2018 period, which makes the estimations misleading to a certain level. For making the analysis more accurate, the countries that had more than 5 NaN GINI coefficient values for 16 years were eliminated. With the elimination process, 55 countries/territories were gathered. The same model was conducted with the new data and for the training and test split for the RFR, the training data consists of 39 observations and the test data consists of 16 observations. The results are shown below:

		OLS R	egres	sion Re	sults		
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:		Least Squ Tue, 19 May	2020 2:25 55 53 1	Adj. F-sta Prob			0.275 0.261 20.06 4.04e-05 -185.83 375.7 379.7
=======	coef	std err		t	P> t	[0.025	0.975]
Intercept PC1	35.9886 -1.8678			6.911 4.478	0.000 0.000	34.032 -2.704	37.944 -1.031
Omnibus: Prob(Omnibus Skew: Kurtosis:	s):	9 9	. 206 . 902 . 083 . 973	Jarqu			1.404 0.065 0.968 2.34

	OLS Regression Results									
Dep. Variab Model: Method: Date: Time: No. Observa Df Residual Df Model: Covariance	itions: s:	Least Squ Tue, 19 May 02:4 nonro	2020 12:25 55 48 6	Adj. F-sta Prob	uared: R-squared: atistic: (F-statistic) ikelihood:	:	0.573 0.520 10.74 1.53e-07 -171.26 356.5 370.6			
	coe	f std err		t	P> t	[0.025	0.975]			
Intercept VA CoC GE PSNV RQ ROL	35.869 11.494 6.845 -6.206 -5.550 0.994 -11.631	1 2.579 7 3.495 4 5.610 9 2.034 5 3.984	-	2.348 4.457 1.959 1.106 2.729 0.250 1.783	0.000 0.000 0.056 0.274 0.009 0.804 0.081	32.642 6.309 -0.180 -17.487 -9.641 -7.016 -24.745	39.097 16.679 13.872 5.074 -1.461 9.005 1.483			
Omnibus: Prob(Omnibu Skew: Kurtosis:	s):	- (1.463 1.107 1.398 3.992				1.956 3.706 0.157 24.5			



With RFR:

Mean Absolute Error (MAE): 7.047063053980342

Mean Squared Error (MSE): 76.09090535597694

Root Mean Squared Error (RMSE): 8.723010108671028

R2 (Training data): 0.8132761503607606

R2 (Test data): -0.3955778175131246

By eliminating the observations with high amount of NaN GINI coefficients, both SLR and MLR models were improved, since they can explain the variability in GINI more. But, when we look at the RFR results, it is visible that MAE, MSE and RMSE were increased, which means that the model makes worse predictions compared to the previous model, and the R2 value for the test data is still negative.

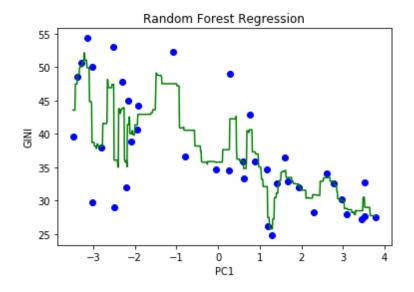
Furthermore, with this new model, the data was divided into training and test data to see whether the model's estimations changed only for the OLS Regression. Again, the data was

divided randomly: 15 observations for test and 40 observations for training. The results are shown below:

For training data:

	0LS Regre	ssion Results		
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	GINI OLS Least Squares Tue, 19 May 2020 05:28:42 40 38 1 nonrobust	Adj. R-squared: F-statistic: Prob (F-statistic): Log-Likelihood: AIC: BIC:		0.448 0.433 30.81 2.35e-06 -129.36 262.7 266.1
CO	ef std err	t P> t	[0.025	0.975]
Intercept 37.12 PC1 -2.36		37.261 0.000 -5.551 0.000	35.108 -3.232	39.142 -1.505
Omnibus: Prob(Omnibus): Skew: Kurtosis:	0.875 0.646 -0.181 3.223	Jarque-Bera (JB): Prob(JB):		1.661 0.300 0.861 2.34

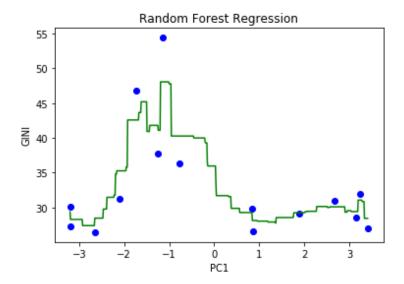
	OLS Regression Results									
Df Residuals Df Model:	el: 0LS hod: Least Squares e: Tue, 19 May 2020 e: 05:28:42 Observations: 40 Residuals: 33 Model: 6 ariance Type: nonrobust			Adj F-sta Prob	nared: R-squared: utistic: (F-statistic) ikelihood:	:	0.700 0.646 12.84 1.96e-07 -117.16 248.3 260.1			
=======	coef	std err		t	P> t	[0.025	0.975]			
Intercept VA CoC GE PSNV RQ RoL	39.0885 9.1532 7.3937 -11.6485 -5.7738 1.6403 -7.2376	2 2.889 7 3.823 6 6.376 3 2.031 3 4.173		8.600 3.168 1.934 1.827 2.843 0.393 0.938	0.000 0.003 0.062 0.077 0.008 0.697 0.355	34.813 3.275 -0.384 -24.620 -9.906 -6.849 -22.933	43.364 15.031 15.171 1.323 -1.642 10.130 8.459			
Omnibus: Prob(Omnibus Skew: Kurtosis:	5):		7.121 0.028 0.486 4.958				1.928 7.966 0.0186 29.3			



For test data:

		OLS R	egress	ion R	esults		
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:		GINI OLS Least Squares Tue, 19 May 2020 05:29:15 15 13 1 nonrobust		R-squared: Adj. R-squared: F-statistic: Prob (F-statistic): Log-Likelihood: AIC: BIC:			0.061 -0.011 0.8457 0.375 -51.500 107.0 108.4
=======	coef	std err		t	P> t	[0.025	0.975]
Intercept PC1	32.9573 -0.8146	2.079 0.886		.852 .920	0.000 0.375	28.466 -2.728	37.449 1.099
Omnibus: Prob(Omnibus Skew: Kurtosis:	5):	0 1	.314 .006 .422 .521	Jarq Prob	in-Watson: ue-Bera (JB): (JB): . No.		2.088 6.501 0.0388 2.35

	OLS Regression Results									
Dep. Variab Model: Method: Date: Time: No. Observa Df Residual Df Model: Covariance	tions: s:	Least Squa Tue, 19 May 2 05:29 nonrob	2020 9:15 15 8 6	F-sta Prob	ared: R-squared: tistic: (F-statistic) ikelihood:	:	0.703 0.480 3.155 0.0681 -42.868 99.74 104.7			
	coet	std err		t	P> t	[0.025	0.975]			
Intercept VA CoC GE PSNV RQ RoL	30.1865 20.9156 23.9303 -24.5766 1.7304 4.6095 -24.7409	7.611 8.110 6.11.440 5.120 6.10.183	- 2 - 2 (0.817 2.748 2.951 2.148 0.338 0.453 1.904	0.000 0.025 0.018 0.064 0.744 0.663 0.093	23.752 3.364 5.228 -50.957 -10.075 -18.873 -54.711	36.622 38.466 42.632 1.803 13.536 28.092 5.229			
Omnibus: Prob(Omnibu Skew: Kurtosis:	s):	0. 0.	948 623 208 172				2.072 0.127 0.939 26.5			



It is visible that although the models with the training data performed much better compared to the previous data, the SLR and MLR models with the test data came out as insignificant because the probability of F-statistic is high. When we look at the SLR with PC1, the

Adjusted R2 is negative, which means that the model cannot explain any variability in the GINI.

Model 3: The model's prediction accuracy on the countries' yearly changing GINI coefficient values was also evaluated. For this purpose, eight countries were pulled from the data, which were:

- Denmark
- Costa Rica
- Moldova
- El Salvador
- Finland
- Honduras
- Indonesia
- Belarus

These are the countries that have less than 2 NaN GINI coefficients. The data for Moldova as an example is shown below:

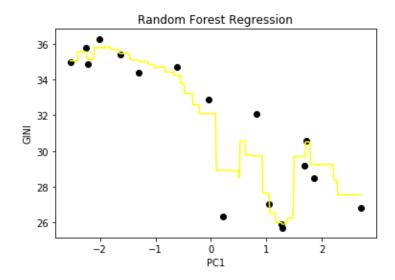
Moldova	VA	CoC	GE	PSNV	RQ	RoL	GINI
2002	-0,53	-0,95	-0,56	-0,16	-0,40	-0,60	35,8
2003	-0,49	-0,85	-0,67	-0,13	-0,45	-0,52	34,9
2004	-0,59	-0,98	-0,87	-0,22	-0,44	-0,33	35
2005	-0,55	-0,67	-0,75	-0,40	-0,46	-0,36	36,3
2006	-0,27	-0,64	-0,79	-0,37	-0,34	-0,52	35,4
2007	-0,29	-0,66	-0,82	-0,02	-0,28	-0,51	34,4
2008	-0,31	-0,63	-0,77	-0,27	-0,18	-0,43	34,7
2009	-0,30	-0,70	-0,56	-0,59	-0,13	-0,44	32,9
2010	-0,06	-0,67	-0,66	-0,38	-0,10	-0,36	32,1
2011	0,05	-0,62	-0,62	-0,05	-0,08	-0,33	30,6
2012	-0,03	-0,61	-0,57	0,05	-0,10	-0,32	29,2
2013	-0,07	-0,75	-0,41	0,00	-0,07	-0,37	28,5
2014	0,01	-0,85	-0,42	-0,16	0,02	-0,25	26,8
2015	0,03	-0,91	-0,65	-0,33	-0,07	-0,35	27
2016	-0,02	-0,95	-0,63	-0,30	-0,11	-0,49	26,3
2017	-0,03	-0,80	-0,53	-0,32	-0,04	-0,41	25,9
2018	-0,11	-0,73	-0,47	-0,35	-0,05	-0,41	25,7

The results for the countries that have too much NaN GINI coefficient values were also calculated by replacing NaN values via zero or multiple imputation. But the results came out as insignificant and that is why, they were not included in the report. The results for these 8 countries are shown below (Note: For RFR, the data was not divided into training and test data, since the number of observations for each country was not enough):

For Moldova:

, ,			0LS Re	gress	ion Re	esults		
Dep. Variabl	le:		G	INI	R-squ	ıared:		0.715
Model: OLS		0LS		R-squared:		0.696		
Method:			Least Squa			atistic:		37.68
Date:		Th	u, 21 May 2			(F-statistic):		1.90e-05
Time:			05:49	:31		_ikelihood:		-36.296
No. Observat				17	AIC:			76.59
Df Residuals	S1			15	BIC:			78.26
Df Model:				1				
Covariance 1	ype:		nonrob	ust				
	co	ef	std err		t	P> t	[0.025	0.975]
Intercept	31.26	47	0.528	59	. 169	0.000	30.138	32.391
PC1	-1.95		0.318		.139	0.000	-2.633	-1.276
Omnibus:			 2.	179	Durb	in-Watson:		0.424
Prob(Omnibus	s):		0.	336	Jarqu	ıe-Bera (JB):		1.690
Skew:			-0.	725	Prob	(JB):		0.429
Kurtosis:			2.	465	Cond	No.		1.66

	OLS Regression Results										
Dep. Variab Model: Method: Date: Time: No. Observa Df Residual Df Model: Covariance	tions: s:	Least Squ Thu, 21 May 05:4 nonro	2020 9:31 17 10 6	Adj. F-sta Prob	ared: R-squared: utistic: (F-statistic) ikelihood:	:	0.884 0.815 12.73 0.000357 -28.647 71.29 77.13				
	coef	std err		t	P> t	[0.025	0.975]				
Intercept VA CoC GE PSNV RQ RoL	31.3237 -9.4981 9.7244 -5.4338 0.8015 -6.3766 -2.1872	5.731 3.500 4.680 2.772 9.140	-	6.959 1.657 2.778 1.161 0.289 0.698 0.400	0.000 0.128 0.020 0.273 0.778 0.501 0.698	21.294 -22.267 1.925 -15.861 -5.376 -26.742 -14.377	41.353 3.271 17.523 4.993 6.979 13.990 10.003				
Omnibus: Prob(Omnibu Skew: Kurtosis:	s):	Θ - Θ	. 875 . 646 . 424 . 719				0.855 0.564 0.754 41.4				

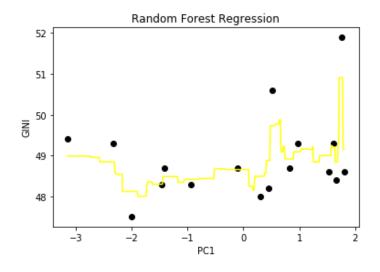


With RFR:

For Costa Rica:

	OLS Regression Results									
Dep. Variable: Model: Method: Date: Time: No. Observation Df Residuals: Df Model: Covariance Type	ns:	Least Squa Thu, 21 May 2 15:56 nonrob	2020 5:59 17 15 1	Adj. F-sta Prob	Jared: R-squared: atistic: (F-statistic): .ikelihood:		0.063 0.001 1.014 0.330 -23.633 51.27 52.93			
========	coef	std err		t	P> t	[0.025	0.975]			
	48.9294 -0.1636	0.251 0.162			0.000 0.330	48.395 -0.510	49.464 0.183			
Omnibus: Prob(Omnibus): Skew: Kurtosis:		0. 1.	113 011 331 163				1.380 5.979 0.0503 1.54			

, ,.									
	OLS Regression Results								
Dep. Variab Model: Method: Date: Time: No. Observa Df Residual Df Model: Covariance	tions: s:	Least Squ Thu, 21 May : 15:50 nonrol	2020 6:59 17 10 6	Adj. F-sta Prob	nared: R-squared: htistic: (F-statistic ikelihood:):	0.779 0.647 5.892 0.00730 -11.339 36.68 42.51		
	coef	std err		t	P> t	[0.025	0.975]		
Intercept VA CoC GE PSNV RQ ROL	54.3565 -5.1747 -0.3822 6.0015 0.7781 -13.3979 8.2278	2.851 1.848 2.739 1.462 3.161	- ((- 2	5.481 1.815 9.207 2.191 9.532 4.238 2.793	0.000 0.100 0.840 0.053 0.606 0.002 0.019	47.008 -11.527 -4.499 -0.101 -2.478 -20.442 1.664	61.705 1.178 3.735 12.104 4.035 -6.354 14.792		
Omnibus: Prob(Omnibu Skew: Kurtosis:	s):	0 -0	.610 .737 .342 .325				2.346 0.654 0.721 66.7		

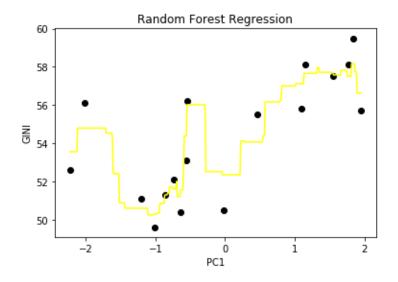


With RFR:

For Honduras:

		0LS Regr	ession	Results			
Dep. Variabl Model: Method: Date: Time: No. Observat Df Residuals Df Model: Covariance	tions:	-	S Ad s F- 0 Pr 3 Lo 7 AI 5 BI		: tistic):		0.104 0.044 1.742 0.207 -42.181 88.36 90.03
	coef	std err		t P>	t	[0.025	0.975]
Intercept PC1	54.3059 0.7099		72.70 1.32		000 207	52.714 -0.437	55.898 1.857
Omnibus: Prob(Omnibus Skew: Kurtosis:	5):	1.38 0.50 0.56 2.44	0 Ja 8 Pr	rbin-Wats orque-Bera ob(JB): ond. No.			0.643 1.128 0.569 1.39

		0LS R	egres	sion Re	sults		
Dep. Variab Model: Method: Date: Time: No. Observa Df Residual: Covariance	tions: s:	Least Squ Sun, 24 May 01:0 nonro	2020 9:03 17 10 6	Adj. F-sta Prob	ared: R-squared: utistic: (F-statistic) ikelihood:	:	0.641 0.425 2.973 0.0620 -34.413 82.83 88.66
	coef	std err		t	P> t	[0.025	0.975]
Intercept VA CoC GE PSNV RQ RoL	53.1132 7.1914 -13.1264 6.7166 -5.5954 -2.0448 6.1602	5.787 6.514 7.472 6.401 6.385		4.825 1.243 2.015 0.899 0.874 0.320 1.081	0.001 0.242 0.072 0.390 0.403 0.755 0.305	28.585 -5.702 -27.640 -9.932 -19.858 -16.272 -6.536	77.641 20.085 1.387 23.365 8.667 12.182 18.856
Omnibus: Prob(Omnibus Skew: Kurtosis:	s):	9 9	.916 .632 .021 .005				1.610 0.703 0.704 43.3

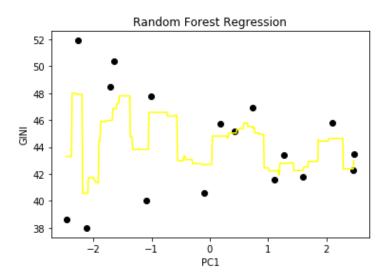


With RFR:

For El Salvador:

		(LS Regre	ssion R	esults		
Dep. Variab Model: Method: Date: Time: No. Observa Df Residual Df Model: Covariance	tions: s:	Thu, 21	GINI 0LS Squares May 2020 15:59:40 17 15 aonrobust	Adj. F-st Prob Log- AIC: BIC:):	0.019 -0.047 0.2844 0.607 -47.143 98.29
========	coe	f std	err	t	P> t	[0.025	0.975]
Intercept PC1	44.235 -0.322			44.228 -0.533			46.367 0.967
Omnibus: Prob(Omnibu Skew: Kurtosis:	s):		0.385 0.825 -0.127 2.190	Jaro Prob	in-Watson: ue-Bera (JB): (JB): . No.		0.146 0.516 0.775 1.65

	OLS Regression Results								
Dep. Variab Model: Method: Date: Time: No. Observa Df Residual Df Model: Covariance	tions: s:	Least Squa Thu, 21 May 2 15:59 nonrol	2020 9:40 17 10 6	Adj. F-sta Prob	nared: R-squared: utistic: (F-statistic) ikelihood:	:	0.766 0.626 5.456 0.00957 -34.957 83.91 89.75		
=======	coef	std err		t	P> t	[0.025	0.975]		
Intercept VA CoC GE PSNV RQ ROL	60.4126 3.2344 28.9702 -15.4652 18.4582 -11.0111 9.4747	4.068 9.208 12.067 12.899 5.777 7.619 5.136	- 1 - 1 - 1	1.851).351 2.401 1.199 3.195 1.445	0.000 0.733 0.037 0.258 0.010 0.179 0.095	51.349 -17.282 2.083 -44.206 5.585 -27.986 -1.970	69.476 23.751 55.857 13.276 31.331 5.964 20.919		
Omnibus: Prob(Omnibu Skew: Kurtosis:	s):	0. -0.	980 371 411 938				1.493 1.276 0.528 37.4		

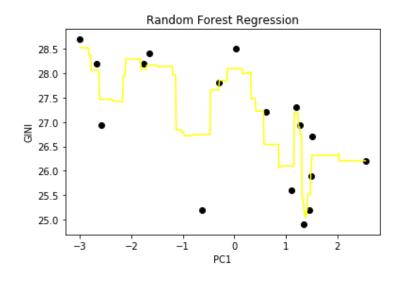


With RFR:

For Denmark:

	OLS Regression Results								
Dep. Variable Model: Method: Date: Time: No. Observat: Df Residuals Df Model: Covariance Ty	ions: :	0 Least Squar Sun, 24 May 20 01:48:	20 29 17 15 1	Adj. F-sta Prob	ared: R-squared: utistic: (F-statistic): ikelihood:		0.403 0.363 10.13 0.00617 -23.172 50.34 52.01		
	coef	std err		t	P> t	[0.025	0.975]		
Intercept PC1	26.9329 0.4589	0.244 0.144		306 183	0.000 0.006	26.413 0.152	27.453 0.766		
Omnibus: Prob(Omnibus Skew: Kurtosis:):	1.4 0.4 -0.5 2.3	74 82				0.998 1.239 0.538 1.69		

, ,.		0LS Reg	ression Res	ults		
Dep. Variable Model: Method: Date: Time: No. Observati Df Residuals: Df Model: Covariance Ty	Sui .ons:	GI 0 Least Squar 1, 24 May 20 01:48: nonrobu):	0.894 0.836 14.03 0.000235 -8.4956 30.99 36.82		
	coef	std err	t	P> t	[0.025	0.975]
Intercept VA CoC GE PSNV RQ RoL	34.7788 -3.3587 7.2231 -9.3097 -1.0846 1.9718 -1.3265	6.326 1.841 2.931 1.512 0.988 2.294 2.058	5.498 -1.824 2.464 -6.157 -1.098 0.860 -0.645	0.000 0.098 0.033 0.000 0.298 0.410 0.534	20.683 -7.461 0.692 -12.679 -3.286 -3.140 -5.912	48.874 0.744 13.755 -5.941 1.117 7.083 3.259
Omnibus: Prob(Omnibus) Skew: Kurtosis:	:	0.5 0.7 -0.3 2.5	76 Jarque			3.084 0.486 0.784 246

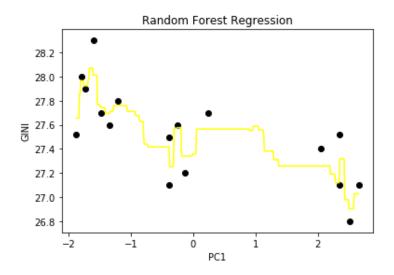


With RFR:

For Finland:

			0LS Regr	essi	on Re	sults		
Dep. Variable: Model: Method: Date: Time: No. Observatic Df Residuals: Df Model: Covariance Typ	ons:	Sun, 24	1	S 5 0 4 7 5	Adj. F-sta Prob	ared: R-squared: tistic: (F-statistic): ikelihood:		0.508 0.476 15.51 0.00132 -1.0996 6.199 7.866
	coe	f std	err		t	P> t	[0.025	0.975]
Intercept PC1	27.520 -0.158				895 938	0.000 0.001	27.378 -0.244	27.662 -0.073
Omnibus: Prob(Omnibus): Skew: Kurtosis:			0.01 0.99 0.04 2.48	4 8				1.050 0.194 0.907 1.66

	OLS Regression Results									
Dep. Variable Model: Method: Date: Time: No. Observati Df Residuals: Df Model: Covariance Ty	ions:	Least Squ Sun, 24 May 03:3 nonro	2020 5:54 17 10 6	Adj. F-sta Prob	ared: R-squared: tistic: (F-statistic) ikelihood:	:	0.730 0.568 4.502 0.0182 3.9897 6.021 11.85			
	coef	std err		t	P> t	[0.025	0.975]			
Intercept VA CoC GE PSNV RQ RoL	28.4236 -0.2976 1.7244 1.0265 -0.4747 -1.6445	0.806 1.070 0.815 0.625 0.872	- (- (- (6.277 9.368 1.612 1.260 9.759 1.886 9.783	0.000 0.720 0.138 0.236 0.465 0.089 0.452	18.333 -2.093 -0.659 -0.789 -1.868 -3.588 -5.741	38.513 1.499 4.108 2.842 0.919 0.298 2.755			
Omnibus: Prob(Omnibus) Skew: Kurtosis:):	0 0	. 272 . 873 . 198 . 726				1.845 0.164 0.921 371.			

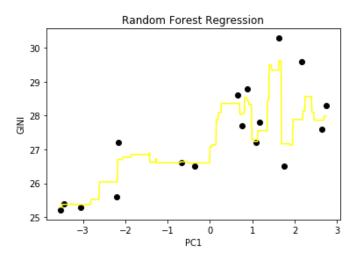


With RFR:

For Belarus:

			OLS Regr	ession F	Results		
Dep. Variat Model: Method: Date: Time: No. Observa Df Residual Df Model: Covariance	ations: ls:	Sun, 24	GIN. OL: t Square May 202 03:40:0 1	S Adj. s F-st 0 Prob 3 Log- 7 AIC: 5 BIC:			0.594 0.567 21.94 0.000294 -22.939 49.88 51.55
	coe	f std	err	t	P> t	[0.025	0.975]
Intercept PC1	27.305 -0.543		.241 .116		0.000 0.000	26.793 -0.791	
Omnibus: Prob(Omnibu Skew: Kurtosis:	ıs):		1.04 0.59 0.44 2.82	3 Jaro 4 Prob	pin-Watson: que-Bera (JB): b(JB): I. No.		1.497 0.580 0.748 2.08

OLS Regression Results								
Dep. Variable Model: Method: Date: Time: No. Observati Df Residuals: Df Model: Covariance Ty	Su ons:	0 Least Squar n, 24 May 20 03:40:	es F-stat 20 Prob 04 Log-Li 17 AIC: 10 BIC: 6	ared: A-squared: tistic: [F-statistic ikelihood:):	0.791 0.665 6.295 0.00576 -17.308 48.62 54.45		
	coef	std err	t	P> t	[0.025	0.975]		
Intercept VA CoC GE PSNV RQ RoL	28.4563 6.4485 2.9438 -3.4709 0.0239 -3.8506 -2.7999	3.928 3.239 4.724 2.621 1.128 2.123 3.513	7.244 1.991 0.623 -1.324 0.021 -1.814 -0.797	0.000 0.074 0.547 0.215 0.983 0.100 0.444	19.704 -0.768 -7.582 -9.312 -2.490 -8.580 -10.628	37.208 13.665 13.469 2.376 2.538 0.879 5.028		
Omnibus: Prob(Omnibus) Skew: Kurtosis:	:	0.2 0.8 0.1 2.7	99 Jarque 35 Prob(3			2.376 0.091 0.955 74.1		

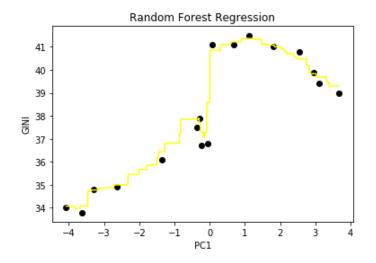


For RFR:

For Indonesia:

OLS Regression Results									
Dep. Variat Model: Method: Date: Time: No. Observa Df Residual Df Model: Covariance	ations: ls:		ast Squa 24 May 2 03:40 nonrol	2020 5:18 17 15	F-stat Prob (-squared:		0.687 0.666 32.89 3.94e-05 -30.531 65.06 66.73	
	CO	ef st	td err		t	P> t	[0.025	0.975]	
Intercept PC1	38.01 -0.92		0.376 0.161		996 735	0.000 0.000	37.215 -1.265	38.820 -0.579	
Omnibus: Prob(Omnibu Skew: Kurtosis:	ıs):		0	. 152 . 341 . 715 . 628				0.628 1.546 0.462 2.34	

OLS Regression Results								
Dep. Variab Model: Method: Date: Time: No. Observa Df Residual Df Model: Covariance	tions: s:	Least Squ Sun, 24 May	2020 6:18 17 10 6	Adj. F-sta Prob	nared: R-squared: ntistic: (F-statistic) ikelihood:	:	0.881 0.809 12.30 0.000413 -22.331 58.66 64.50	
	coet	std err		t	P> t	[0.025	0.975]	
Intercept VA CoC GE PSNV RQ RoL	52.7728 -17.8753 5.8457 -15.4243 4.8652 6.5171 12.5396	11.641 4.190 5.769 2 2.066 6.852	-	0.247 1.536 1.395 2.674 2.355 0.951 1.755	0.000 0.156 0.193 0.023 0.040 0.364 0.110	41.298 -43.812 -3.490 -28.278 0.262 -8.750 -3.381	64.247 8.061 15.181 -2.571 9.468 21.784 28.459	
Omnibus: Prob(Omnibu Skew: Kurtosis:	s):	- 0	.303 .192 .637 .615				1.515 1.418 0.492 92.3	



For RFR:

The results from each country gave mixed findings. From the regressions, it is visible that the models for Moldova, Belarus, Indonesia, Finland, and Denmark were significant, especially for the first three countries, since their Adjusted R2 values from SLR with PC1 were 50% or higher. But, when we look at their probability of F-statistic from SLR with PC1, the models for Costa Rica, El Salvador, and Honduras were insignificant, especially for El Salvador, which its probability of F-statistic was 60.2%. This issue was tried to be understood by looking at the data for El Salvador:

El Salvador	VA	CoC	GE	PSNV	RQ	RoL	GINI
2002	0,12	-0,68	-0,50	0,30	0,02	-0,51	51,9
2003	0,11	-0,37	-0,35	-0,18	-0,14	-0,46	50,4
2004	0,02	-0,42	-0,34	-0,07	0,06	-0,38	47,8
2005	-0,08	-0,45	-0,38	-0,03	-0,18	-0,45	48,5
2006	0,10	-0,30	-0,15	-0,17	0,04	-0,62	45,7
2007	0,09	-0,37	-0,20	-0,01	0,19	-0,65	45,2
2008	0,11	-0,36	-0,16	0,04	0,21	-0,67	46,9
2009	0,06	-0,25	-0,04	-0,01	0,32	-0,75	45,8
2010	0,07	-0,28	0,01	0,06	0,36	-0,81	43,5
2011	0,04	-0,26	-0,10	0,11	0,47	-0,72	42,3
2012	-0,04	-0,41	-0,13	0,23	0,33	-0,70	41,8
2013	-0,01	-0,35	-0,12	-0,03	0,31	-0,62	43,4
2014	0,15	-0,38	-0,03	-0,02	0,32	-0,48	41,6
2015	0,15	-0,42	-0,24	-0,02	0,20	-0,59	40,6
2016	0,19	-0,52	-0,29	-0,10	0,09	-0,71	40
2017	0,15	-0,51	-0,36	-0,26	-0,15	-0,86	38
2018	0,04	-0,59	-0,45	-0,33	-0,04	-0,82	38,6

When we look at the GINI coefficient for El Salvador, it is visible that it gradually decreased from 51.9 in 2002 to 38.6 in 2018, which is a positive progress in terms of reducing inequality. But when we look at the six WGI variables for El Salvador, it is also observable that the values for the current years are worse than the previous ones. This shows that the values for GINI coefficient and six WGI variables are not exactly negatively correlated, at least for El Salvador.

CONCLUSION

When the average of seven variables was taken for each country and regression models were conducted (ex. Model 1 and Model 2), the models of SLR with PC1 and MLR with the six WGI variables could not explain the majority of variability in the GINI coefficient but came out as significant. But, when the models were calculated with the test data, which was done for RFR in both Model 1 and Model 2 and for SLR and MLR in the Model 2, the models came out as insignificant with negative Adjusted R2 values. Furthermore, when the values of seven variables were taken from the year 2002 to 2018 for several countries and the models were conducted for each country individually (ex. Model 3), the models came out as significant and highly elucidator for many, but not for all the countries. For that, it can be concluded that enough evidence was not found for the assumptions and hypothesis indicated in the paper.

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