The Interaction of Government Systems and Wealth

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Theory

My research project seeks to answer the question: How does a country's system of government affect its wealth? I arrived at this research question due to my exploration into how democracies versus non-democracies operate in the economic sector. I found that politicians make foreign and domestic decisions regarding a country's economic policy based on whether it is a democracy (Zoellick, 2020). Thus, I wanted to understand if there were trends in economic prosperity related to a country's system of government that could lead to more informed policy decisions.

I theorize that democratic countries are likely to have larger wealth than non-democratic countries due to their investment in human capital. Thus, the expectation is democratic countries will have, on average, greater wealth than non-democratic countries. This theory claims that democracies have large GDPs because they invest in human capital which leads to a productive labor force. To explore whether this causal mechanism is credible, I will evaluate if there is reverse causality[1], covariation[2], and confounding variables. Furthermore, it relies on several assumptions about the order of the world. It assumes that democratic governments effectively invest and its citizens and that they have ample access to the global market. Additionally, it presumes that democracies prioritize education, healthcare, and infrastructure investment, which creates a productive and motivated workforce. Thus, the theory assumes non-democracies do not or rarely invest in human capital.

I hypothesize that if a country is a democracy, then it will have a greater gross domestic product (GDP) than non-democracies. While my theory aims to determine whether there is a relationship between a country's system of government and its wealth, the causal mechanism is

[1] Reverse causality: the dependent variable causes the change in the independent variable
[2] Covariation: the independent variables is associated with the dependent variable

vital to understand why exploring this question may aid policymakers and economists. I believed that democracies would have higher GDPs than non-democracies because they invest more in human capital, which is the knowledge and health of individuals. However, investment in the well-being of the population is not typically prioritized when a country desires economic growth. Economists and policymakers consider a multitude of factors when creating domestic and foreign economic policy. For instance, they evaluate the export balance, consumer spending, and business investment. However, human capital investment may lead to greater wealth and may be the key to a stable and dedicated work force. Furthermore, current human capital is a long-term investment that is likely to benefit future generations (Ehrlich & Pei, 2020). If a country is investing in the education and health of its working class, there is a higher probability of innovation than if only small pockets of the population are educated and healthy. However, simply because a country does not invest in human capital, it does not mean that it cannot experience economic growth or wealth; this theory aims to evaluate whether that is typically the case. If nation states see evidence that determines a causal relationship between the investment in human capital by democracies to a larger GDP, they may adapt their policies to benefit the majority of the population, their initiatives prioritizing the health and prosperity of their citizens. I am using a large-n, observational design[3] with an Ordinary Least Squares (OLS) regression model[4] in order to explore the relationship between a country's system of government and its wealth. Additionally, I employ cross-sectional analysis, since I am examining data from one year (2019) and across multiple countries. Because I am investigating a relationship between many cases across the globe, it would be difficult to collect the data myself. Furthermore, it would be

[3] A large-n observational design is where the researcher does not have command over the administration of the independent variable.
[4] An OLS regression model is a method to approximate the relationship between one independent variable or more and a dependent variable.

incredibly expensive to design an experiment in which I assigned countries a system of government. Thus, an observational design allows me to use a large amount of data from most countries. In an ideal world, I would design an experiment where countries were randomly selected to either be democracies or non-democracies and their wealth was evaluated over multiple years.

Data

For my research design, I used the International Political Economy Data Resource, which was formed by international affairs scholars Benjamin A. T. Graham and Jacob R. Tucker of the University of Southern California. The data set was created by combining widely used data resources (97 in total) in the sector of international political economy (IPE) (Graham & Tucker, 2016). The resources were gathered by downloading the data from the original producer. The unit of space or analysis for this dataset is country-year. All variables are from this dataset.

Variables

In order to measure a country's wealth, I used a continuous variable that measures GDP (gdp_WDI_PW) from 2019 across 200 countries; it is collected from the World Bank, which collates data from the host governments and then discards observations from regions and small states that are not included in the Gleditsch Ward system. It measures GDP using the constant 2005 $ as its unit. The variable from the IPE dataset I used to measure a country's system of government is democracy_BX, taken from Boix, Miller, and Rosato Democracy Data [BX]; it spans from 2019 and includes 209 countries. The variable is a dichotomous measure of whether countries are democratic or not based on 3 conditions: how the executive is chosen in popular elections and if she is directly responsible to her constituents or to legislature, if the legislature is

chosen in free and fair elections, and if most adult men have suffrage. Because the data uses a dichotomous measure, democracy_BX is coded as 0, non-democracy, or 1, democracy.

I chose 3 confounding variables that would allow me to isolate the relationship between GDP and democracy and ensure the findings were useful. I used population (pop_WDI_PW); it was created using data from the Penn World Tables (PWT) and the World Bank. It is a continuous variable that gives the number of individuals in a country which I chose because of the effect it has on a country's labor force and number of voters. Thus, I believed it would be important to account for, as it affects democracy and GDP**.** Democracies may struggle to carry out the will of its people if there are too many interests to represent, weakening the country's system of government (Bartels et al., 2023). Furthermore, a country with a greater population will in turn have a larger labor force which results in a greater GDP. Then, I employed control of corruption (cce_WGI) that was collected from the World Bank and 198 countries. The range is from approximately -2.5 to 2.5 in which the lower the number is, the more politically unstable a country is. Political stability is vital for democracies and non-democracies to function effectively and for their constituents to have trust in institutions. GDP is affected by control of corruption, as a high level of control fosters development and decreases the costs on citizens and their government (The White House, 2021). For my final confounding variable, I included labor tax and contributions (pt_lab_BZ), a continuous variable, which is from the World Bank and covers 190 countries. Labor taxes may have multiple effects on GDP and democracy. High labor taxes may cause rising discontent in voters, possibly weakening democratic institutions. Furthermore, they directly influence how much money workers take from their paycheck, affecting their consumption and, thus, the country's GDP.

Variables Statistics					
Variables	Democracy	GDP	Population	Control of Corruption	Labor Taxes
Measures of Central Tendency	Mode: 1	Mode: 1.997e13 Median: 3.898e10 Mean: 4.388e11	Mode: 1.398e9 Median: 8.676e6 Mean: 3.922e7	Mode: -0.449 Median: -0.259 Mean: -0.064	Mode: 0 Median: 13.90 Mean: 16.19
Measures of Dispersion	Variation Ratio: 0.39	Range: 1.997e13 IQR: 2.076e11 Variance: 3.422e24 Standard Deviation: 1.85e12	Range: 1.397e9 IQR: 2.667e7 Variance: 2.105e16 Standard Deviation: 1.455e8	Range: 3.94 IQR: 1.443 Variance: 0.989 Standard Deviation: 0.995	Range: 51.7 IQR: 14.65 Variance: 112.72 Standard Deviation: 10.62

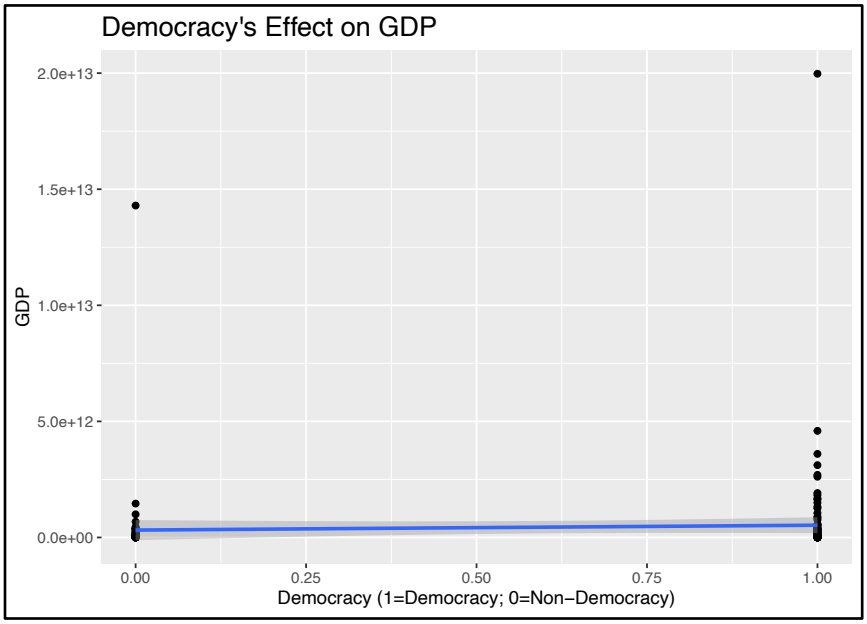
Table 1. A descriptive statistics table describing the measures of central tendency and measures of dispersion

Interpretation of Table.1

The mode of democracy is 1, which represents the center for categorical variables such as this one. Thus, it indicates the most common value in the dataset is 1, meaning most countries are democracies. Its variance ratio, the percent of cases not in the modal category, is 39%, demonstrating 39% of countries are not democratic. Regarding GDP, the median is 3.898e10, the exact center of the GDP values when ranked from smallest to largest. It is smaller than the mean, so the data is skewed to the right, meaning there is a positive skew to the data. In addition, there may be possibly large outliers towards the right. The IQR of GDP is 2.667e7, representing the middle 50 percent of the dataset. Since the GDP is skewed, it is an important measure of variability, as it is less sensitive to outliers. The population median is 8.76 and is greater than its

mean, indicating the data is skewed to the left. Thus, there are more values towards the right, but there is a negative skew due to extremely small values towards the left. The standard deviation, the spread of values around the mean, is 1.455e8, demonstrating a large amount of variation and possible outliers. Control of corruption is on a smaller scale, so its descriptive statistics are far smaller but still important to understand. The negative mean shows that there is less control of corruption on average in countries, but it is only slightly negative. Therefore, I would not make concrete conclusions about the true population's control of corruption. Also, the IQR of 1.443 demonstrates a large spread around the median and a considerable amount of variability. The median of labor taxes illustrates that there may be higher labor taxes that skew to the data to the right, as the median is smaller than the mean. The range shows that there is a high amount of variability in the data and possible outliers, since the maximum value is multiple standard deviations away from the median.

Democracy and GDP



Graph #1: Scatterplot of Relationship between Democracy and GDP

The scatterplot shows that there is a slight positive correlation between democracy and GDP. I believe the models' confounders are causing the relationship to be less apparent, as I expect there to be a strong, positive relationship between the two.

Regression Models

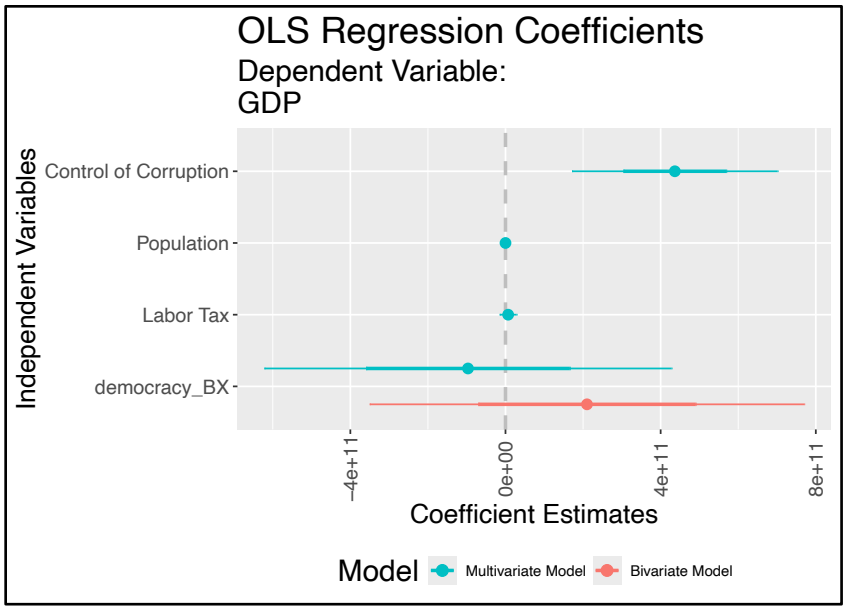
Bivariate Model:

$$gdp\_WDI\_PW = \hat{\beta} + \hat{\beta} * democracy\_BX$$

Multivariate Model:

$$gdp\_WDI\_PW = \hat{\beta} + \hat{\beta}_1 * democracy\_BX + \hat{\beta}_2 * cce\_WGI + \hat{\beta}_3 * pop\_WDI\_PW + \hat{\beta}_4 * pt\_lab\ \_BZ$$

For democracy_BX within the bivariate and multivariate model, I expect it to have a positive relationship with gdp_WDI_PW and a positive coefficient. If I am incorrect, democracy_BX will have a negative coefficient. I believe that cce_WGI and pop_WDI_PW will also have a positive relationship with gdp_WDI_PW and positive coefficients; they will have negative coefficients if I am mistaken. However, because higher labor taxes decrease the amount of consumer spending workers are capable of, I expect pt_lab_BZ and gdp_WDI_PW to have a negative relationship. If my expectation is wrong, pt_lab_BZ's coefficient will be positive.



Graph 2: OLS Regression Coefficients Plot

TABLE 2: COMPARING BIVARIATE AND MULTIVARIATE OLS REGRESSION MODELS

	Dependent Variable GDP	
	Bivariate Model	Multivariate Model
	(1)	(2)
DEMOCRACY	210,068,736,239.000	-96,667,644,567.000
	(279,998,819,629.000)	(262,395,885,672.000)
LABOR TAX		6,839,295,826.000
		(10,872,163,354.000)
POPULATION		7,499.667***
		(763.448)
CONTROL OF CORRUPTION		436,613,516,083.000***
		(132,459,048,693.000)
CONSTANT	317,595,251,543.000	124,146,062,329.000
	(218,990,964,356.000)	(268,806,437,932.000)
OBSERVATIONS	188	180
R^2	0.003	0.392
ADJUSTED R^2	-0.002	0.378
NOTE:	*p<0.1**p<0.05***p<0.01	
	Model (1): Bivariate OLS regression.	
	Model (2): Multivariate OLS regression.	
	Coefficients are in cells; standard errors are in parentheses.	

Analysis

The bivariate regression model has a positive coefficient for democracy, meaning my expectation for that model was correct. Despite this finding, the relationship is not statistically

significant.[5] Then, in the OLS Regression Coefficient Plot, democracy has a negative relationship with GDP, but it is still not statistically significant. Furthermore, the confidence intervals[6] of democracy in both models contain 0, suggesting there may be no relationship between democracy and GDP. In addition, the multivariate model has 180 observations compared to the 188 of the bivariate model. Thus, the multivariate model may have inaccurate or skewed results. Furthermore, in Table 2, the R^2 for the bivariate regression model indicates how much variation in the dependent variables is explained by the model. It is extremely small; the model only explains 0.3% of the variation in GDP. The adjusted R^2 describes the same concept as R^2 except it accounts for the amount of independent variables in the model. The multivariate regression model now accounts for 37.8% of the variation in GDP, a large increase from the bivariate model. However, when one is creating model to describe the world or how entire countries may operate, one hopes for above 60% of variation in the dependent variable explained. Thus, neither model is a good fit for the data, as they do not explain enough about the connection between democracy and GDP. The lack of significance suggests the model lacks a causal variable,[7] which made lead to inaccurate coefficient estimates. I cannot make conclusions about the true population's relationship regarding democracy.

Despite these issues, the three confounding variables have positive coefficients and relationships with GDP, and two had statistically significant relationships. The multivariate graph shows that population and control of corruption have a positive relationship with GDP that should be further explored, as the connections between GDP and the two are not due to chance.[8]

[5] Statistically significant: The results are not due to error or chance
[6] A confidence interval gives a range of values in which the true value of the population is likely to be.
[7] Causal variable: a variable that causes a change in another variable
[8] The asterisks indicate statistical significance.

However, I remain skeptical due to the fact only 40% of variation is explained in GDP by the model and would not draw conclusions about the true relationship of the population.

Conclusion

Despite having covariation, no reverse causality, and accounted for confounding variables, the results from the bivariate model and the multivariate model do not align with my hypothesis and do not allow to me investigate if there is a causal relationship yet. I cannot reject the possibility that there is no relationship between a country's system of government and its wealth. Although two of the variables, population and control of corruption, have a statistically significant relationship with GDP, the multivariate model does not explain enough of the variation in GDP. Thus, there is likely a causal variable missing from the model, such as inflation, that would create a better model that fits the data and result in a clear connection between democracy and GDP. Additionally, the democracy variable does not require female suffrage for a country to be considered a democracy which may cause an overestimation of the number of democratic countries. In the future, I hope to use a different democracy variable that includes female suffrage as a requirement, and future research will explore the relationship between GDP and age structure, population growth, and rule of law due to the statistical significance findings. This research is vital to comprehend what leads countries to economic prosperity and how to ensure it is sustainable.

Appendix

R Code

```
#Clear the environment
rm(list=ls(all=TRUE))

#Set working directory
setwd("/Users/irisallgrove/Library/Mobile
Documents/com~apple~CloudDocs/Desktop/polr labs")

#Load pacman
library(pacman)

#Install packages
pacman::p_load(foreign, sandwich, stargazer, coefplot, car,
lmtest, ggplot2, tidyverse)

#Read in my data
ipev<-read.csv("gt_ipev5_2019na.csv")

#Look at my data
View(ipev)

#mode of VarRatio
rev(sort(table(ipev$democracy_BX)))

#Variation ratio; tells you how many countries are not
democracies
tot<-sum(table(ipev$democracy_BX))
nmod<-rev(sort(table(ipev$democracy_BX)))[1]
(tot-nmod)/tot

#Find mode, median, mean of gdp_WDI_PW
rev(sort(table(ipev$gdp_WDI_PW)))[1]
summary(ipev$gdp_WDI_PW)
#variance
var(ipev$gdp_WDI_PW, na.rm=T)
#standard deviation
sd(ipev$gdp_WDI_PW, na.rm=T)

#Mode of Population
rev(sort(table(ipev$pop_WDI_PW)))
summary(ipev$pop_WDI_PW)
#variance
var(ipev$pop_WDI_PW, na.rm=T)
#standard deviation
```

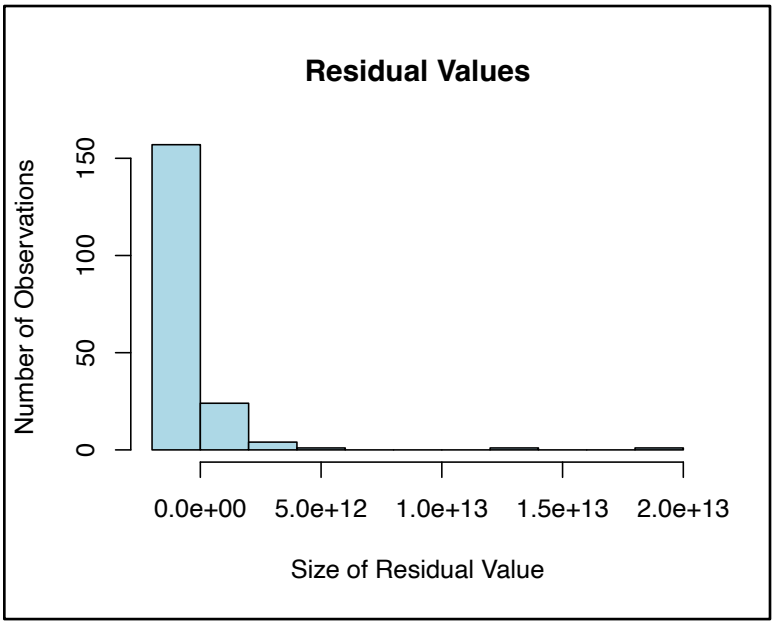
```
sd(ipev$pop_WDI_PW, na.rm=T)

#Control of Corruption
rev(sort(table(ipev$cce_WGI)))
summary(ipev$cce_WGI)
#variance
var(ipev$cce_WGI, na.rm=T)
#standard deviation
sd(ipev$cce_WGI, na.rm=T)

#Labor Taxes
rev(sort(table(ipev$pt_lab_BZ)))
summary(ipev$pt_lab_BZ)
#variance
var(ipev$pt_lab_BZ, na.rm=T)
#standard deviation
sd(ipev$pt_lab_BZ, na.rm=T)

#Create a bivariate regression model
model.1<-lm(gdp_WDI_PW ~ democracy_BX, data=ipev)
summary(model.1)

#Create a scatterplot for the bivariate model
scatplot <- ipev %>% drop_na(democracy_BX, gdp_WDI_PW) %>%
  ggplot( aes(x=democracy_BX, y = gdp_WDI_PW)) +
  geom_point() +
  theme_grey() +
  theme(axis.text.x = element_text(size = 9),
        axis.text.y = element_text(size = 9),
        axis.title.x = element_text(size = 11), axis.title.y =
element_text(size = 11),
        title = element_text(size = 13)) +
  labs(x = "Democracy (1=Democracy; 0=Non-Democracy)", y =
"GDP" ) +
  ggtitle("Democracy's Effect on GDP")
scatplot

#Line for indicating our bivariate regression model
scatplot.l <- scatplot + geom_smooth(method='lm', formula= y~x)
scatplot.l

#Create a residual plot
hist(resid(model.1), main = "Residual Values", xlab = "Size of
Residual Value", ylab = "Number of Observations", col =
"lightblue")
```

```
hist(resid(model.2), main = "Residual Values", xlab = "Size of
Residual Value", ylab = "Number of Observations", col =
"lightblue")

#Create a multivariate regression model
model.2 <- lm(gdp_WDI_PW ~ democracy_BX + pt_lab_BZ + pop_WDI_PW
+ cce_WGI, data=ipev)
model.2

#Create a stargazer model
stargazer(model.1, model.2,
          type = "html",
          title = "Table 1: Comparing Bivariate and Multivariate
OLS Regression Models",
          covariate.labels = c("Democracy", "Labor Tax",
"Population", "Control of Corruption", "Constant"),
          dep.var.caption = "Dependent Variable",
          dep.var.labels = c("GDP"),
          column.labels = c("Bivariate Model", "Multivariate
Model"),
          notes = c("Model (1): Bivariate OLS regression.",
                    "Model (2): Multivariate OLS regression.",
                    "Coefficients are in cells; standard errors
are in parentheses."),
          notes.align = "l",
          no.space = TRUE,
          omit.stat = c("f", "ser"),
          out = "CoefTable10.html")

#Create a coefficient plot
cplot <- coefplot::multiplot(model.2, model.1,
                             newNames = c(cce_WGI = "Control of
Corruption", pt_lab_BZ = "Labor Tax", pop_WDI_PW =
"Population"),
                             intercept = F,
                             names = c("Multivariate Model",
"Bivariate Model")) +
  labs(x = "Coefficient Estimates", y = "Independent Variables",
subtitle = "Dependent Variable:
GDP") +
  ggtitle("OLS Regression Coefficients") +
  theme(axis.text.x = element_text(size = 12),
        axis.text.y = element_text(size = 12),
        axis.title.x = element_text(size = 16),
        axis.title.y = element_text(size = 16),
        title = element_text(size = 18),
        strip.text = element_text(size = 16))
```

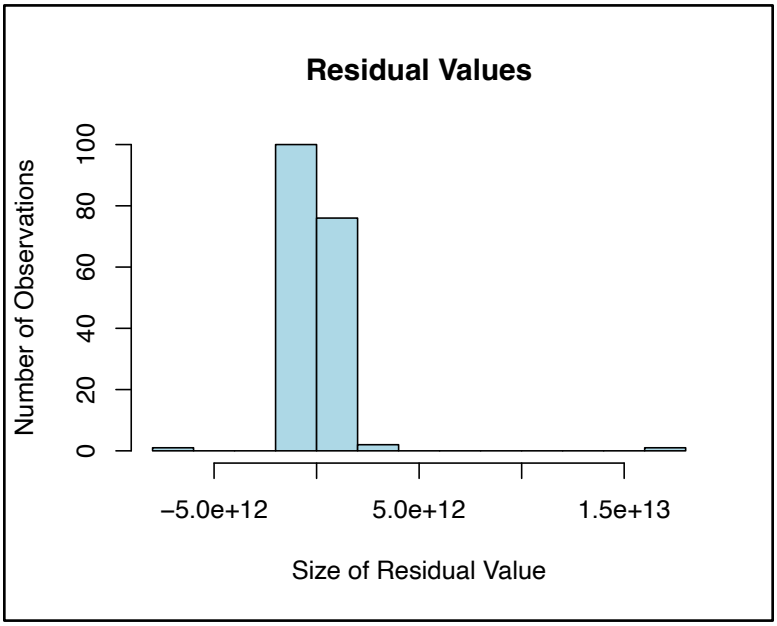
```
cplot

pdf("OLSRCoeff.pdf")
cplot
dev.off()
```

Residual Plots

Bivariate Model



Multivariate Model



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