

Can corruption be held responsible for deforestation?

Aayushi Gupta, Department of Economics, University of Maryland

Abstract

Long gone are those days when the concern of forest resource was limited to a region or a nation – it is global now. This study aims to reflect this concern by revolving around the topic of the causes of deforestation. To some extent, deforestation might be necessary for the growth of an economy. But not all deforestation is good. This paper focuses on the bad reasons of deforestation. The research question of the study is to find out the impact of corruption on deforestation. Since, deforestation is a global problem, this study targets all the countries around the world. To conduct this study, I have taken data for 22 years, which is a significant time to observe change in deforestation patterns. Using this panel data, I will be performing regression analysis. The models used in this study are entity fixed effects and time fixed effects to remove unobserved omitted variable biasedness. To define corruption, the study uses two corruption datasets, namely Corruption Perception Index (CPI), and Control of Corruption. The importance of this study is to provide a quantitative basis for strategy builders and policy makers who come across the question of corruption being another cause for deforestation. The results found in the study show highly statistically significant decrease in deforestation activities with 1 unit decrease in corrupt practices in a country.

Keywords: Deforestation, Corruption, Fixed Effects

JEL Code: C330, Q560

1. Background and Literature Review

Deforestation refers to the conversion of forests and grassland to lands suitable for non-forest use like agriculture, urban development, economic growth, and much more. Loss of forests has resulted in climate change, which is known to be one of the biggest global concerns of today.

It is vital to understand that agriculture cannot substitute forests to fight climate change. Forests store large amounts of carbon in them. This carbon is prone to be released in the atmosphere, in the form of CO₂ – one of the most harmful gases if forests are cleared away. Forests are home to millions of distinct species that can only survive in specific habitats. Clearly, removing forests would not just lead to climate change, but in the long run it will also destroy the global economy of this planet. Therefore, it is crucial to do deforestation in a sustainable manner.

To some extent, one might agree that agriculture is necessary for current survival and cannot be put to hold. However, corruption is something which is necessary to be suspended indefinitely to continue living. The report by [Harwel. 2009.](#) Human Rights Watch, "Wild Money": *The Human Rights Consequences of Illegal Logging and Corruption in Indonesia's Forestry Sector.*) summarizes the loss of around \$2 billion by Indonesia, country with world's highest deforestation rates, in 2006 was due to illegal logging, corruption, and mismanagement. Exports from its flourishing timber sector were worth \$US6.6 billion in 2007, second only to Brazil. [Koyuncu. 2009.](#) *The Impact of Corruption on Deforestation: A Cross-Country Evidence.* The Journal of Developing Areas , Vol. 42, pp. 213-222. find a positive correlation between corruption and deforestation which is statistically significant. According to [Scarrow, R. 2017.](#) *Corruption drives deforestation.* Nature Plants 3, 910., corruption might not have a large impact on deforestation, but it is certainly more significant than when taking a debt from IMF to engage in heavy logging activities.

There is further evidence of involvement of government ineffectiveness and political instability that ignites corrupt practices in forests leading to deforestation. [Cassandro Mendes & Sabino Junior & Fabricio Tourruc?o. 2016.](#) *Corruption and Deforestation: A Differential Game Model.* Business and Economic Research, Macrothink Institute, vol. 6(1), pages 481-491.) uses Stackelberg differential game to depict the correlation between corruption and deforestation. The results show that better government strategies in terms of salary paid to the workers need to be implemented to avoid going on the trail of corruption. [Wilson, John K. & Damania, Richard, 2005.](#) *Corruption, political competition and environmental policy.* Journal of Environmental Economics and Management, Elsevier, vol. 49(3), pages 516-535.) indicates higher political competition would have stringent policies reducing the level of corruption, needed to achieve reduction in environmental damage. [Milledge, S.A.H., Gelvas, I. K. and Ahrends, A. 2007.](#) *Forestry, Governance and National Development: Lessons Learned from a Logging Boom in Southern Tanzania. An Overview.* TRAFFIC East/Southern Africa / Tanzania Development Partners Group / Ministry of Natural Resources of Tourism, Dar es Salaam, Tanzania. 16pp.) describes in a report how policies related to management of resources were manipulated for private gains that led to depletion of many forests in Tanzania.

With all this in mind, this research deals with the impact of corruption on deforestation in countries with different government policies and political stability.

2. Data

This study uses a rich panel dataset with 216 countries over a span of 22 years starting from 2000 to 2021. Table 2 below lists down all variables used in the study along with their definition and unit of measurement.

I have introduced two corruption datasets for reasons: 1. to get better understanding of the correlation between deforestation and corruption, and 2. to compare both corruption variables from the results obtained and use the best obtained results in this study. Therefore, this study addresses two research questions:

Hypothesis 1: Increase in Corruption Perception Index decreases deforestation

Hypothesis 2: Increase in control of corruption decreases deforestation

Table 2 Types of variables and data used

Datasets	Variable	Definition	Measurement Unit	Source
Corruption Perception Index	CPIscore	Corruption Perceptions Index (CPI) is an index which ranks countries by their perceived levels of public sector corruption	100 (very clean) - 0 (highly corrupt)	Transparency International, 2021. Corruption Perception Index. Available online: https://www.transparency.org/en/cpi/2021
Control of Corruption	CorrControl	Control of Corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption.	0 (highly corrupt) - 100 (very clean)	World Bank (2021A). Worldwide Governance Indicators. Available online: https://databank.worldbank.org/source/worldwide-governance-indicators /Type/TABLE/preview/on
Deforestation	Deforestation	Deforestation is the conversion of forest to other land use independently whether human-induced or not. It includes permanent reduction of the tree	1000ha/year	FAO (2020). Global Forest Resources Assessment.

		canopy cover below the minimum 10 percent threshold.		Available online: https://fra-data.fao.org/ITTO/fra2020/forestAreaChange/
Gross Domestic Product (constant \$2015)	GDP_2015	GDP per capita; GDP represents the sum of value added by all its producers.	Constant 2015 prices, in US dollar (\$)	World Bank (2021B) . World Development Indicators. Available Online: https://databank.worldbank.org/source/world-development-indicators/Type/TABLE/preview/on
Rural Population	RuralPop	Rural population refers to people living in rural areas as defined by national statistical offices. Difference between total population and urban population.	In percentage (%)	World Bank (2021B) . World Development Indicators. Available Online: https://databank.worldbank.org/source/world-development-indicators/Type/TABLE/preview/on
Urban Population	UrbanPop	Urban population refers to people living in urban areas as defined by national statistical offices. Difference between total population and urban population	In percentage (%)	World Bank (2021B) . World Development Indicators. Available Online: https://databank.worldbank.org/source/world-development-indicators/Type/TABLE/preview/on

				TABLE/previe w/on
Political Stability and Absence of Violence/Terrorism: Percentile Rank	PoliticStable	Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism.	0 (highly violent) - 100 (very clean)	World Bank (2021A) . Worldwide Governance Indicators. Available online: https://databank.worldbank.org/source/worldwide-governance-indicators/Type/TABLE/previe w/on
Government Effectiveness: Percentile Rank	GovtEffect	Government Effectiveness captures 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.	0 (autocratic) - 100 (democratic)	World Bank (2021A) . Worldwide Governance Indicators. Available online: https://databank.worldbank.org/source/worldwide-governance-indicators/Type/TABLE/previe w/on

The two main explanatory variables are Corruption Perception Index (CPI) and control of corruption. The data for CPI score before 2012 ranges between 0 to 10. But after 2012, it ranges between 0 to 100. To conduct regression analysis, we need to make the data compatible throughout all 22 years. Due to non-availability of calculation details, I calculated CPI score before 2012 in the following way:

$$\frac{CPI\ score\ before\ 2012}{Max\ score\ before\ 2012 - Min\ score\ before\ 2012} \times \frac{Max\ score\ after\ 2012 - Min\ score\ after\ 2012}{100 - 0}$$

The main dependent variable is deforestation. The data for deforestation is obtained from the Global Forest Resources Assessment (FRA) led by Food and Agriculture Organization (FAO). The available data has only four data points, for 1990-2000, 2000-2010, 2010-2015, and 2015-2020 for every country.

Since, the data is for 10 and 5 year long periods, I have used same value of deforestation between all years from 2000 to 2010, 2011 to 2015, and 2016 to 2020. It includes regions of forest converted to agriculture, pasture, water reservoirs, mining and urban areas, but excludes the regions where the trees have been cut off for harvesting or logging purposes, and where the forest is expected to revive inherently or with the assistance of silvicultural methods.

The covariates included are GDP, rural population, urban population, political stability (absence of violence/terrorism), and government effectiveness. To control for the factor of wealth of the country, GDP is considered in the model. The dollar figures for GDP are converted from domestic currencies of every country using 2015 official exchange rates. For the countries, the exchange rate was not available, an alternative conversion factor was used. According to various studies [Bilsborrow, R.E. 1992. *Population growth, internal migration, and environmental degradation in rural areas of developing countries*. Eur J Population 8, 125–148.](#) and [Julia C. Allen & Douglas F. Barnes. 1985. *The Causes of Deforestation in Developing Countries*. Annals of the Association of American Geographers, 75:2, 163-184.](#)) indicate a positive correlation between population growth and deforestation. Rural population expands by clearing out forests in villages and rural areas. Growing urban population would lead to escalation in production of goods made from wood and other forest products. Hence, these two are important to be included in the model to avoid any possible omitted variable biasedness. To account for the government effectiveness and political stability of different countries, we consider two variables PoliticStable and GovtEffect. PoliticStable indicates a low rank for countries with high likelihood of political instability and presence of political violence and vice versa. GovtEffect indicates a low rank for countries with less degree of independence from political pressures (definition explained in Table 2).

2.1 Summary Statistics

To investigate the data further, I conducted summary statistics represented in Table 2.1.1 below and used data visualization to easily identify correlations and patterns before moving on to conducting regression analysis.

Table 2.1.1 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
CPIscore	3368	42.423	20.84	4	100
CorrControl	4069	48.867	29.091	0	100
Deforestation	2446	89.648	380.314	0	5129.3
GDP 2015	770	12432.538	15258.128	334.016	101489.38
RuralPop	866	44.082	25.083	0	87.022
UrbanPop	866	55.918	25.083	12.978	100
GovtEffect	4057	49.102	29	0	100
PoliticStable	4125	49.263	28.834	0	100

Table 2.1.1 shows the mean value of CPI score to be 42.4 which is much closer to 0 than 100. This implies that, on an average, a country is more corrupt than being non-corrupt. The mean value of CorrControl, 48.8, indicates a parallel sense. The mean value of deforestation, 89.6, is extremely low as compared to the maximum value of 5129.3. According to my assumption, mean deforestation should have been closer to its maximum value looking at the low mean CPI score and CorrControl. However, the standard deviation, 380.3, indicates largely dispersed data, enough to be skeptical about my assumption. It would be interesting to know the regression results.

The mean and std. dev. values of CPI score and CorrControl are similar which is a good indication to treat them as two separate main explanatory variables for the two similar hypotheses of this study. The standard deviation of most variables is at most half their respective mean values or in some cases even larger than that showing a wide dispersion of data or maybe large outliers.

Further, graphs are created for all the main variables (dependent and independent) for both the hypothesis studies. The histograms had been created for all the covariates as well. However, there are not displayed in this paper. They are available in the do file for the viewer's reference. Note: The variables measured in ranks had a uniform distribution. I took natural log of all those variables as well as for the deforestation and population variables to bring their distribution closer to normal distribution and minimize their skewness.

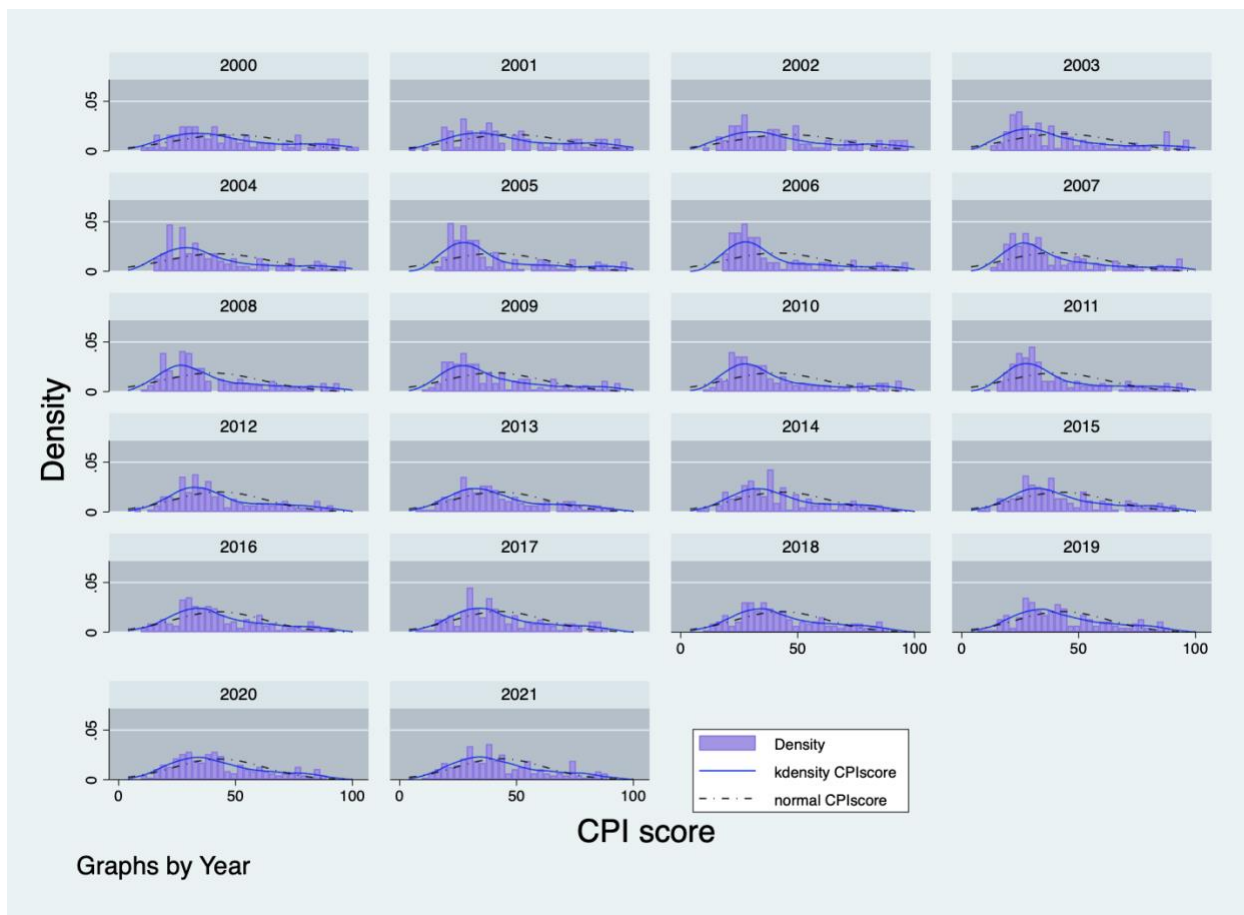


Fig. 2.1.1 CPI score distribution

Figure 2.1.1 displays histograms of CPI scores year-wise for all countries over a span of more than two decades. The data is highly dispersed as these are scores ranging from 0 to 100 indicating possibility of outliers in data. Starting from 2000, the bump (or the peak in that graph), observed from the blue line, starts rising slowly over time as we move towards 2021. Around 2005, it reaches the apex point in those 22 years. It remains relatively stable for the next couple of years experiencing slight rise and fall over the years. After 2011, it starts to dissolve again. Throughout this time, the bump stays towards the left of the center and the data is slightly skewed towards the right suggesting the median to be smaller than the mean. This also suggests that large number of countries are corrupt as compared to being clean.

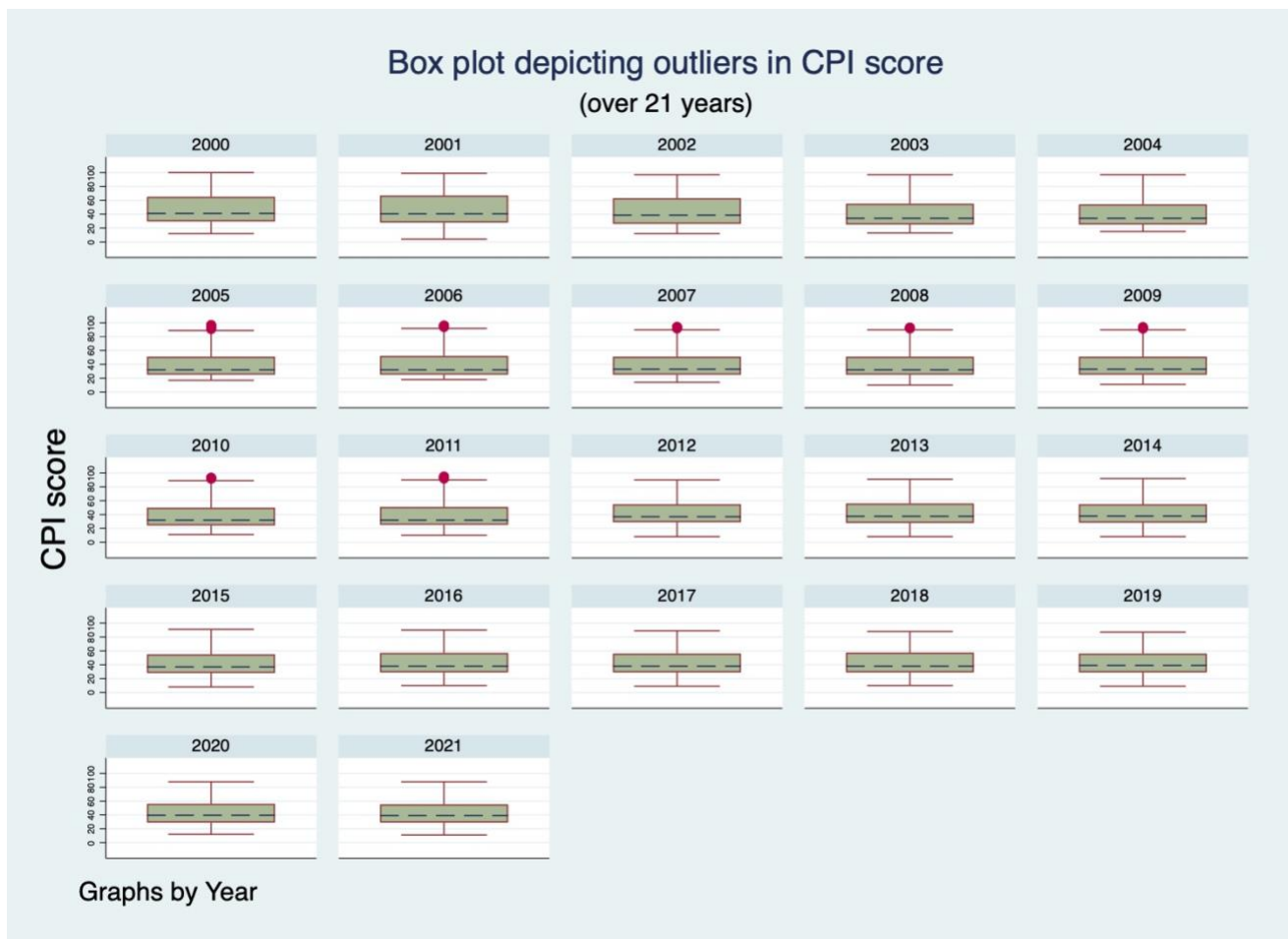


Fig. 2.1.2 Outliers in CPI score

With the help of boxplot, fig. 2.1.2 showcases the number of outliers in the form of red markers (dots) located at the top of boxplot. In alignment with afore-mentioned paragraph, the outliers appear in 2005 and last till 2011. 2005 experiences the maximum outliers pushing the peak upwards in fig 2.1.1. However, these outliers are minuscule and nothing to be concerned about.

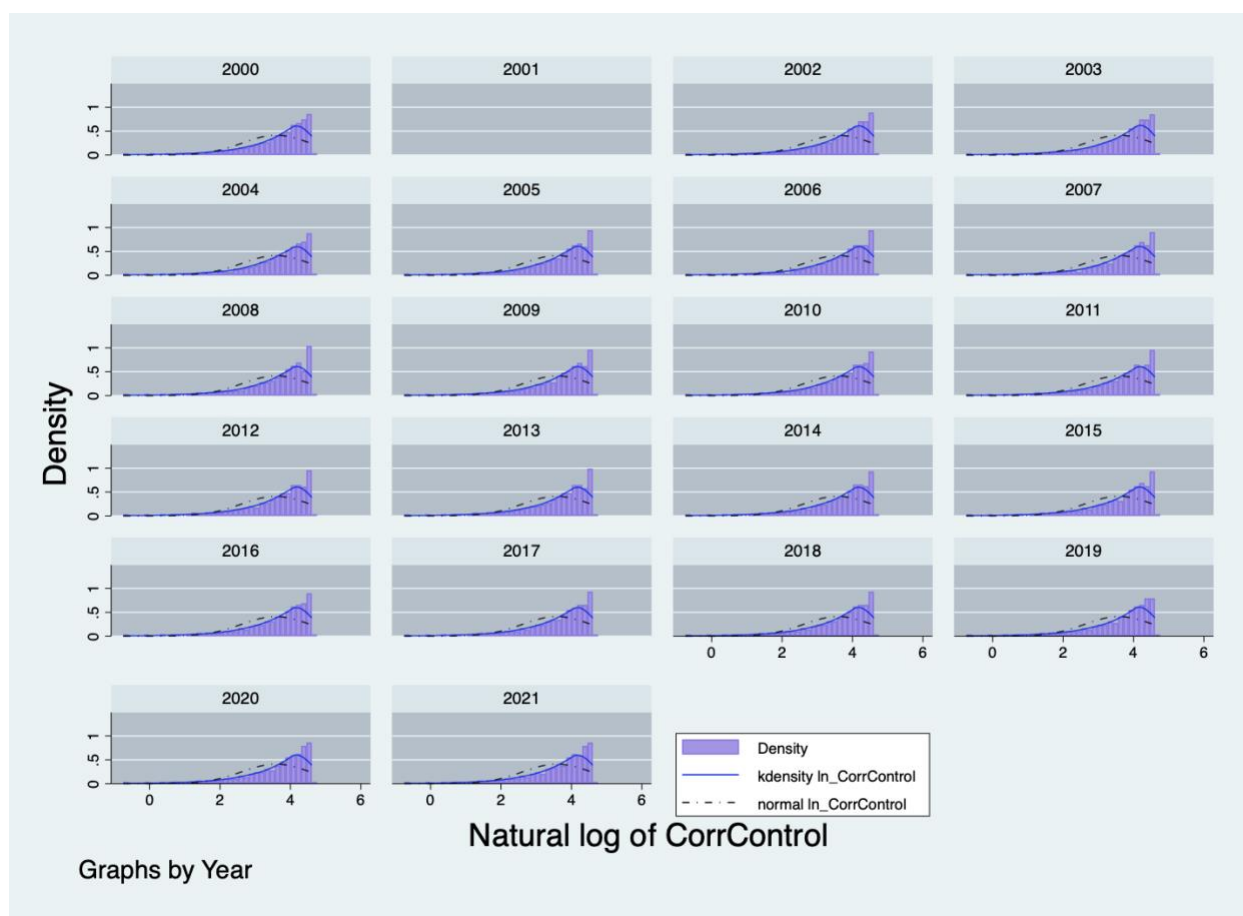


Fig 2.1.3 Natural log of control of corruption

Figure 2.1.3 displays histograms of natural log of control of corruption year-wise for all countries over the span of almost two decades. The data is skewed towards the left. The data does not reveal much change in the peak over the years. The data is not available for 2001.

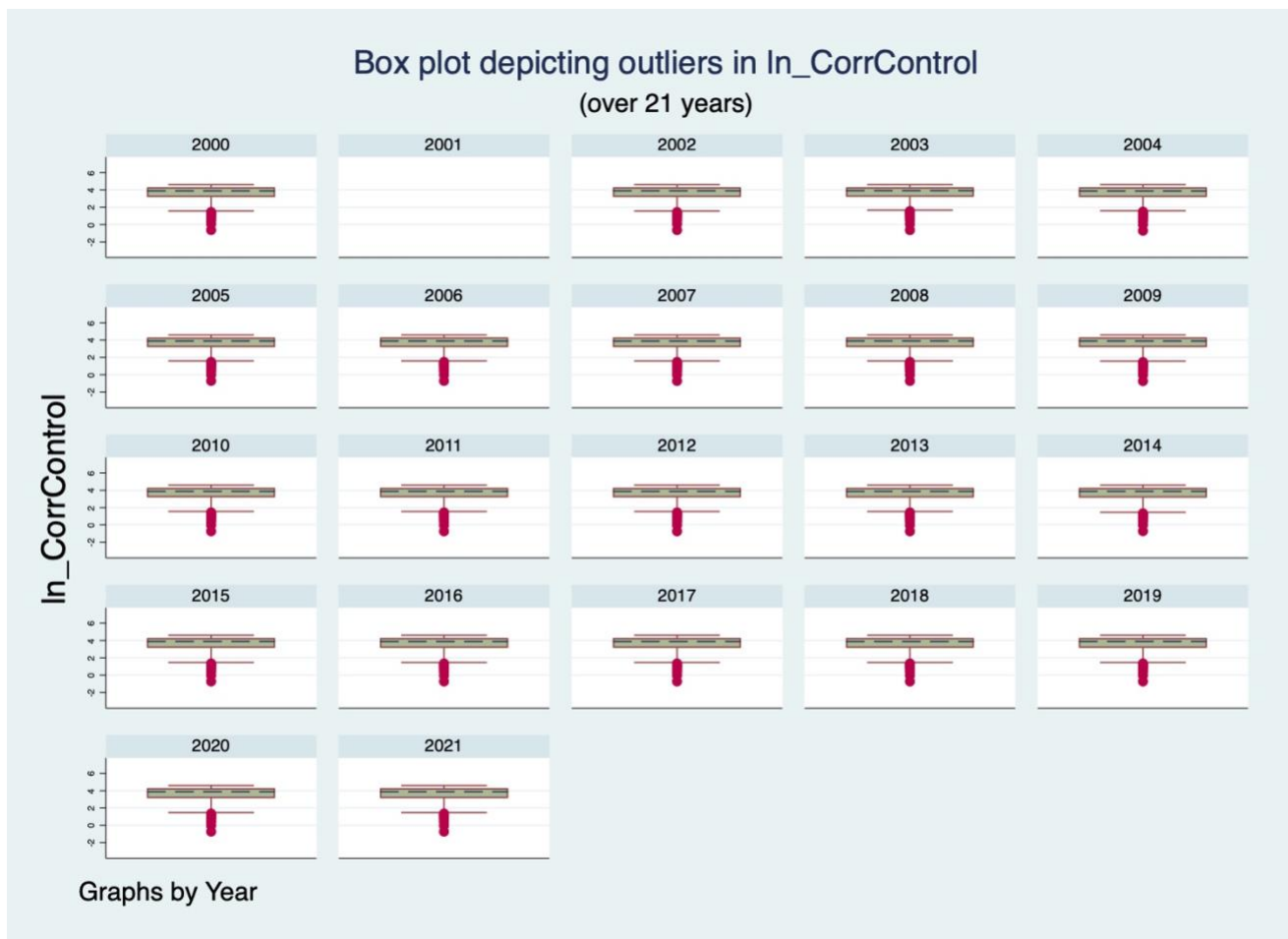


Fig 2.1.4 Outliers in natural log of control of corruption

Fig 2.1.4 displays outliers throughout the period of 2 decades. The outliers skew the distribution of this variable towards the left as seen in the fig 2.1.4. However, since the variable has an independent and identical distribution (explanation for i.i.d is given in fig 2.1.5), the outliers are ignored and the skewed distribution is accepted for the regression analysis.

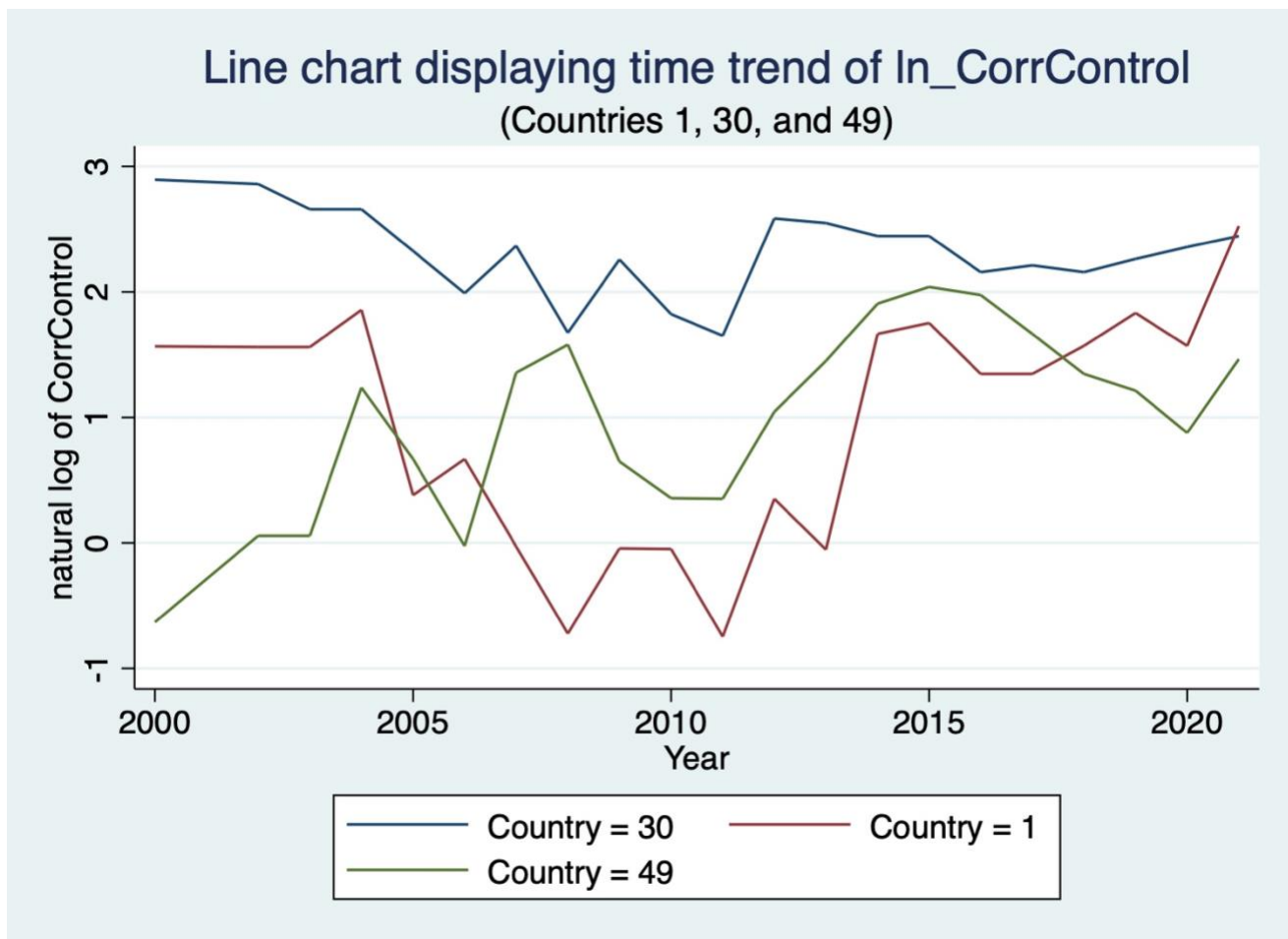


Fig 2.1.5 Time trend of natural log of deforestation

Fig 2.1.5 displays the time trend of natural log of control of corruption for 3 countries randomly selected through their id (Country) over a period of 21 years. From the trend, the variable displays a random walk suggesting no correlation between past and future behavior which indicates independent distribution. Since, the distribution is same in fig 2.1.4, the variable represents identical distribution. This implies that the variable is i.i.d.

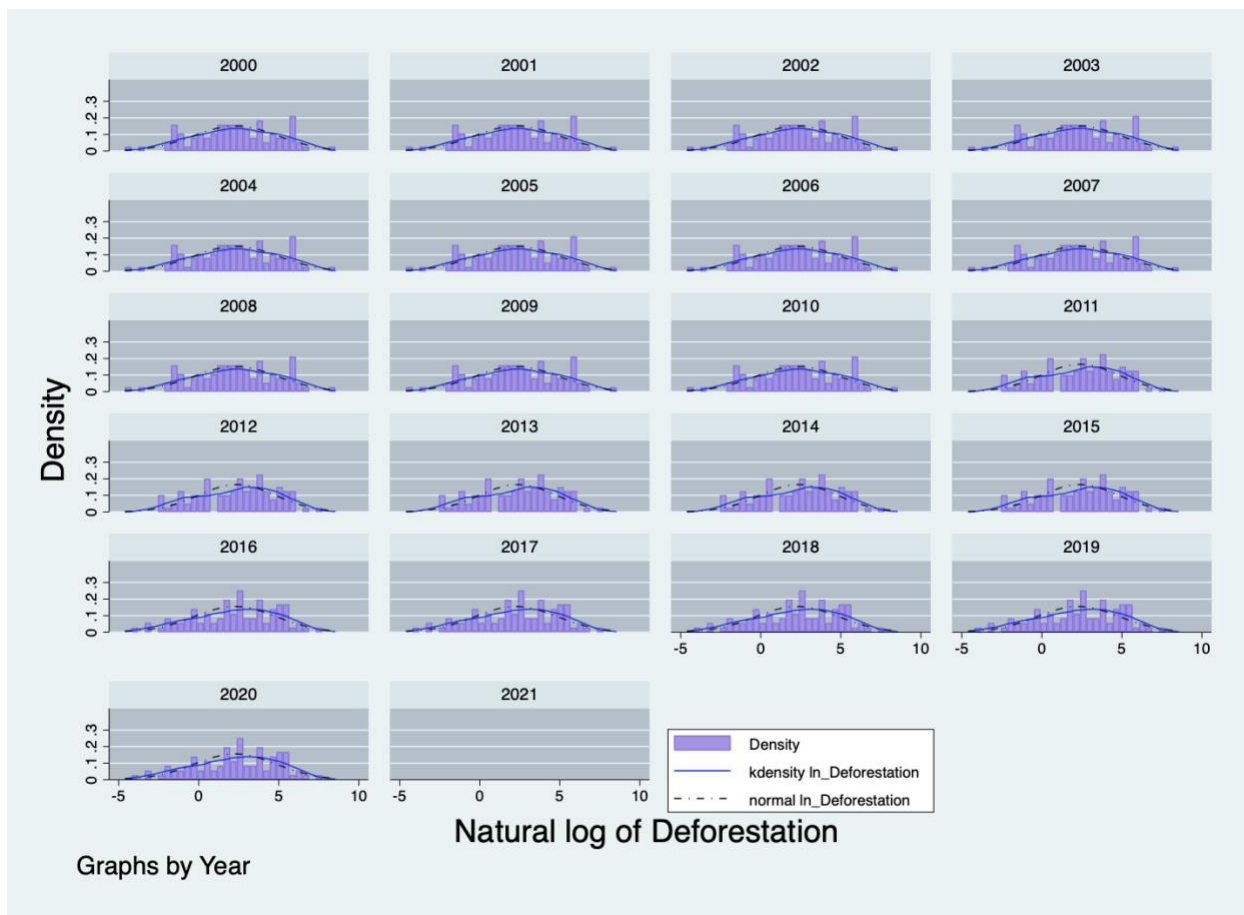


Fig 2.1.6 Natural log of deforestation

Figure 2.1.6 displays histograms of natural log of deforestation year-wise for all countries over the span of almost two decades. The kdensity curve almost overlaps the normal distribution curve completely before 2011. There appear to be two peaks from 2011 to 2015. The data is separated into two parts by a missing rectangle. After 2015, the small peak on the left disappears to again form a bell curve. However, the data does not reveal much change in the peak over the years. The data is not available for 2021.

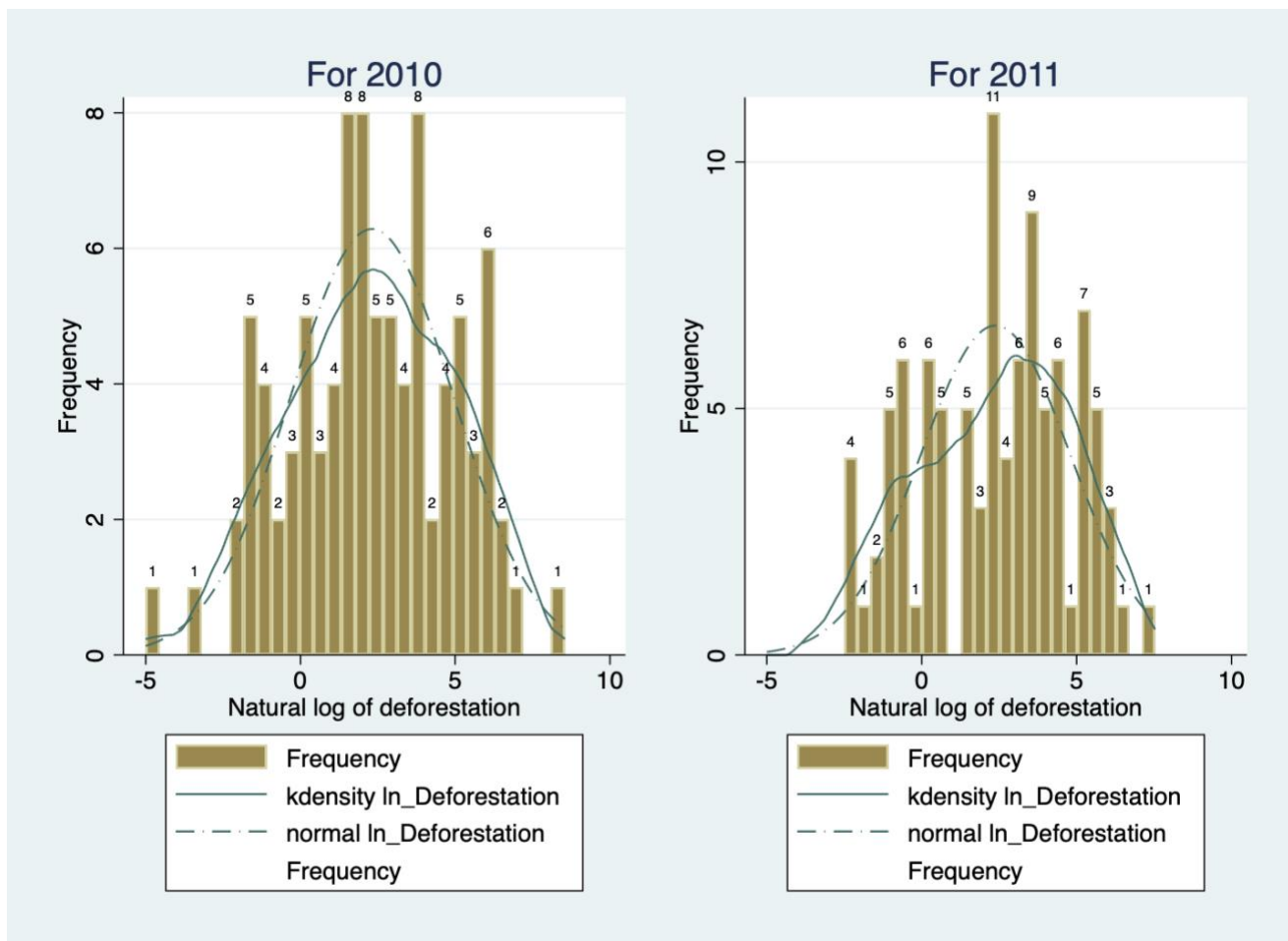


Fig 2.1.7 Natural log of deforestation

Figure 2.1.7 displays a closer look at the distribution of natural log of deforestation for the years 2010 and 2011. I tried to replicate the number of bins, and the upper and lower limit of x-axis as in the previous graph to better understand the missing rectangle from 2011 to 2015. Apart from 5 missing observations, it appears that the highest peaks in 2010 have shrunk down in 2011 resulting in a missing rectangle.

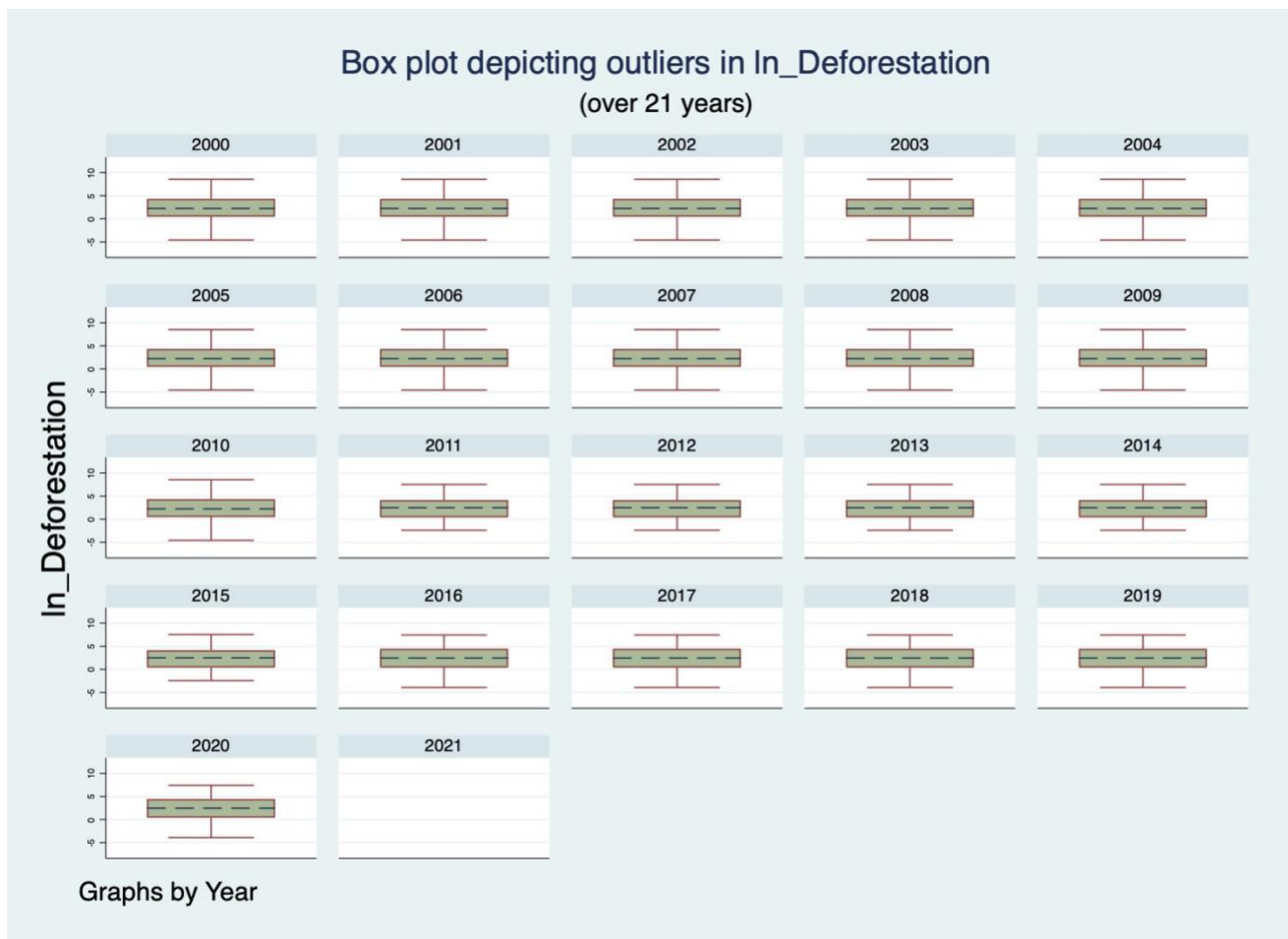


Fig 2.1.7 Outliers in natural log of deforestation

Fig 2.1.7 does not showcase any outliers. Similar to the explanation of fig 2.1.6, the variable does not display much skewness. Moreover, its distribution overlaps the line for normal distribution. Therefore, having no outliers in the boxplot is coherent.

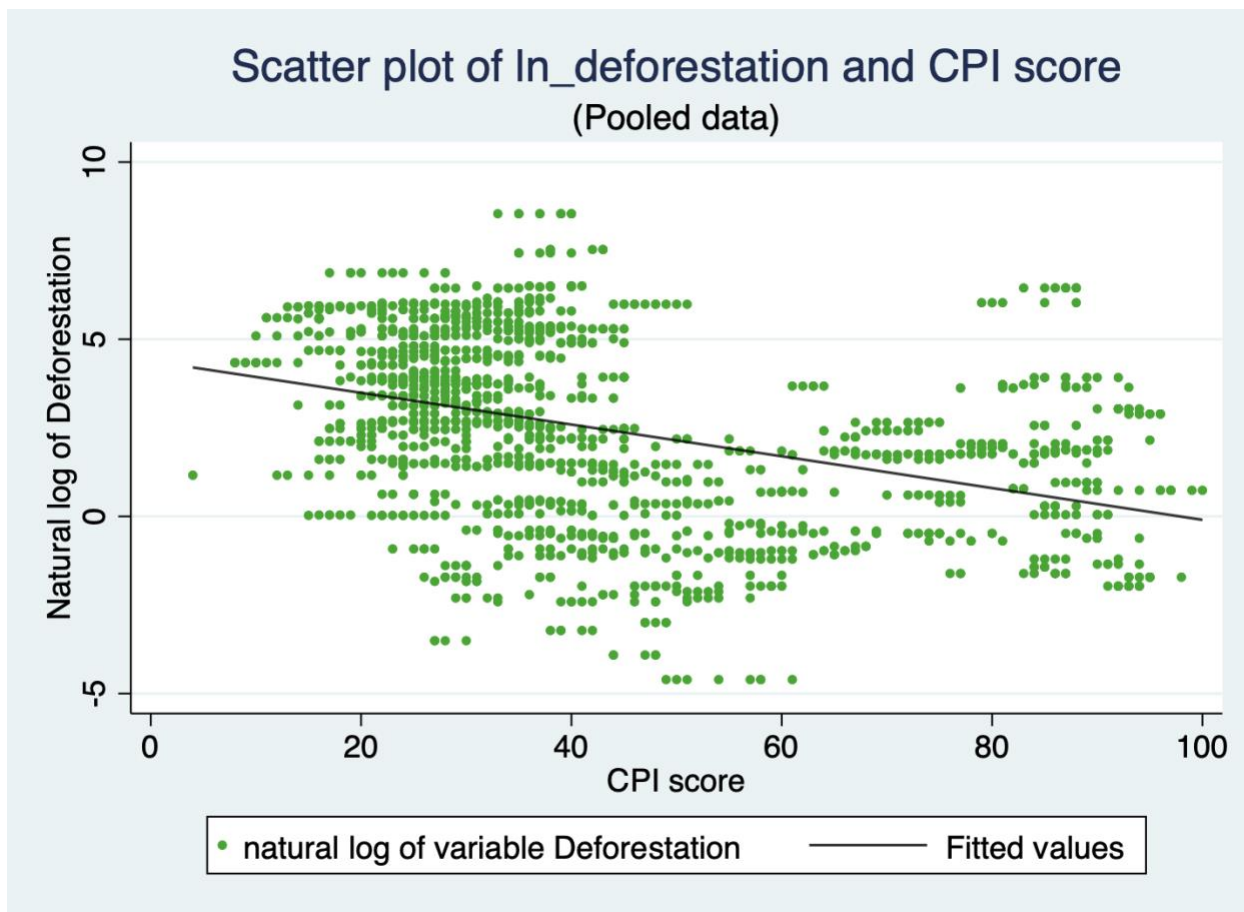


Fig 2.1.4 Scatter plot of hypothesis 1

The first hypothesis of this study is showcased by Figure 2.1.4 in the form of a scatter plot of natural log of deforestation and CPI score along with the black fitted linear trend line. The unit of observation is country represented by the green dot. The downward sloping trend line shows the negative correlation between deforestation and CPI score. However, this does not imply that the falling corruption causes decrease in deforestation. To find that out, empirical analysis would need to be conducted.

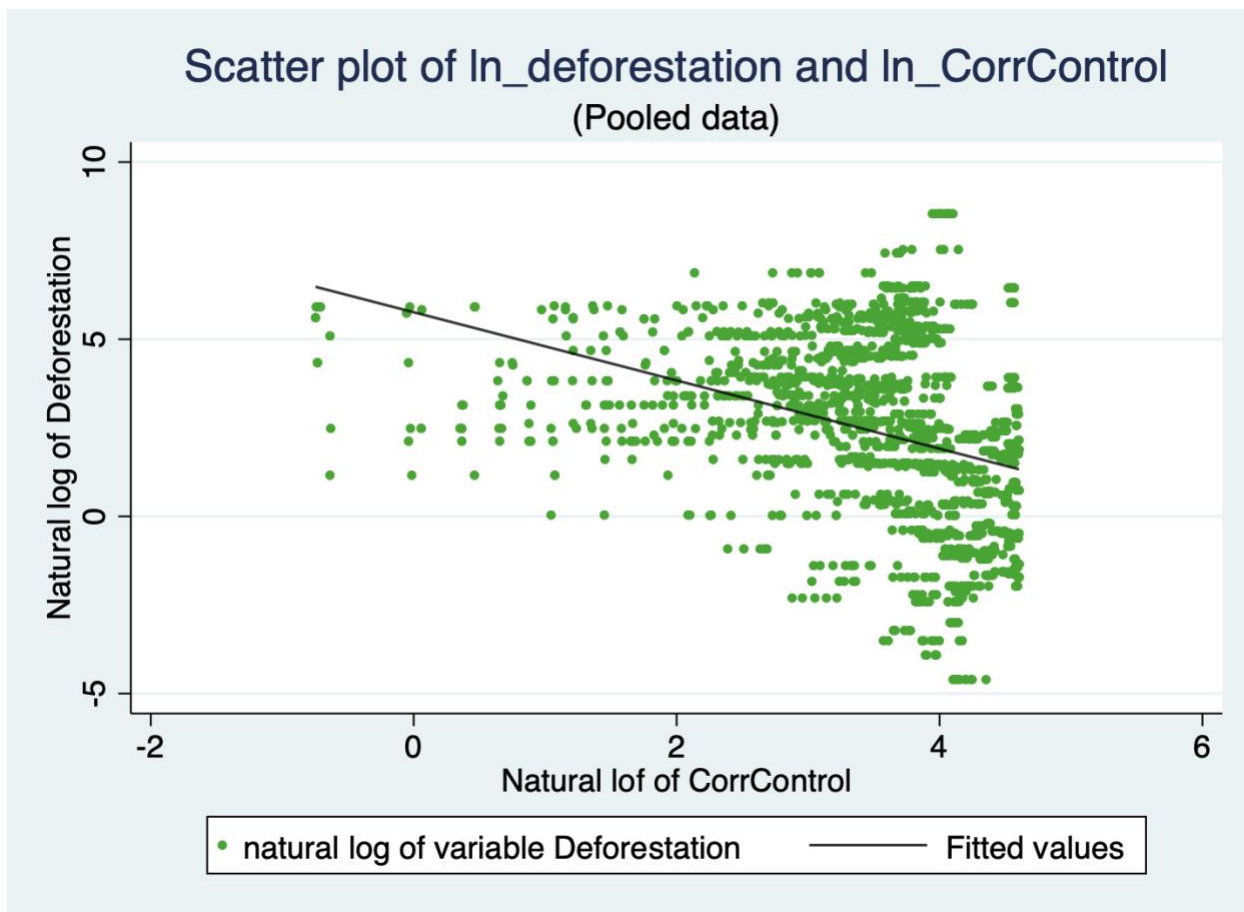


Fig 2.1.5 Scatter plot of hypothesis 2

The second hypothesis of this study is showcased by Figure 2.1.5 in the form of a scatter plot of natural log of deforestation and natural log of control of corruption along with the black fitted linear trend line. The unit of observation is country represented by the green dot. The downward sloping trend line shows the negative correlation between natural log of deforestation and natural log of control of corruption. This is in alignment with the above hypothesis.

Table 2.1.2 Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) CPIscore	1.000							
(2) ln_CorrControl	0.796	1.000						
(3) ln_Deforestation	0.353	-0.011	1.000					
(4) ln_GDP_2015	0.861	0.825	0.379	1.000				
(5) ln_RuralPop	-0.873	-0.812	-0.161	-0.848	1.000			
(6) ln_UrbanPop	0.599	0.614	-0.051	0.560	-0.884	1.000		
(7) ln_GovtEffect	0.714	0.868	0.168	0.899	-0.712	0.449	1.000	
(8) ln_PoliticStable	0.704	0.768	0.179	0.647	-0.595	0.318	0.701	1.000

The two conditions of omitted variable bias are:

1. Correlation of omitted variable with X (main explanatory variable)
2. Determinant of Y (main dependent variable)

The first condition has been fulfilled, as observed in column (1) for hypothesis 1, and column (2) for hypothesis 2, of table 2.1.2. In both columns, all variables are highly correlated with their respective main explanatory variables. To observe if these variables also fulfil condition 2, regression analysis have been conducted including and excluding each variable.

3. Methodology

Before starting with regression analysis, I would like to discuss the assumptions of OLS.

Assumption 1: The conditional mean is zero

Assumption 2: X_i and Y_i are independently and identically distributed (i.i.d)

Assumption 3: Large outliers are unlikely

Assumption 4: There is no multicollinearity (or perfect collinearity)

Assumption 5: There is homoskedasticity and no autocorrelation

Assumption 6: The linear model is linear in parameters

Assumption 7: Each observation of the error term is independent of others

The initial methodologies used are linear and multiple regression models using OLS estimator in the form of pooled data. Further, entity fixed effects and time fixed effects methods are used separately and combined.

All results are obtained using the robust command taking into consideration any possibility of heterogeneity.

The general form of regression model is,

$$\ln_deforestation_{it} = \beta_0 + \beta_1 CPIscore_{it}^1 + \beta_2 COND_{it} + u_{it}$$

; COND is all covariates

u is the error term

i are the entity fixed effects

t are the time fixed effects

3.1 Hypothesis 1: Increase in Corruption Perception Index decreases deforestation

Table 3.1.1 shows the pooled data using OLS estimation. Model 1 displays linear regression model of CPI score as the main independent variable and Deforestation as the main dependent variable. As we proceed towards Model 6, covariates are added gradually to the previous models to account for omitted variable bias by observing the change in $\widehat{\beta}_1$. All multiple linear regression models, except for Model 2, have a statistically significant $\widehat{\beta}_1$ at 95% and 99% (not Model 3) confidence interval. However, only Model 1 displays the negative effect of CPI on deforestation that was expected according to the found literature review.

¹ This is for the first hypothesis. For the second hypothesis, CPIscore would be substituted with $\ln_CorrControl$ in the suffix of β_1 .

Declining observation lower down the precision of a model. According to me, the two best models in table 3.1.1 are Model 1 and Model 6. Comparing Model 1 with Model 6, we observe the declining number of observations but the improving R-squared values. However, R-squared does not penalize for an insignificant variable or reward for a significant variable, which adjusted R-squared does. Furthermore, the positive value of $\widehat{\beta}_1$ in Model 6 is unexpected. Possibly even after controlling for endogenous variables correlated with the error term, there could remain some unobserved omitted variables which can be accounted for by using fixed effects method.

Table 3.1.1 Pooled data

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
CPIscore	-0.0448*** (0.00229)	0.0100 (0.0103)	0.0246** (0.0105)	0.0666*** (0.0196)	0.0543*** (0.0169)	0.0493*** (0.0163)
ln_GDP_2015		0.393* (0.212)	0.506** (0.209)	1.205*** (0.359)	2.966*** (0.383)	3.435*** (0.435)
ln_UrbanPop			-1.480*** (0.231)	1.767 (1.253)	2.019* (1.134)	3.030** (1.167)
ln_RuralPop				5.960*** (2.265)	6.758*** (1.945)	8.399*** (1.969)
ln_GovtEffect					-2.346*** (0.448)	-2.836*** (0.539)
ln_PoliticStable						0.487* (0.276)
Constant	4.387*** (0.112)	-1.579 (1.511)	2.651* (1.368)	-38.83** (16.00)	-48.90*** (13.37)	-62.27*** (13.90)
Observations	1,700	126	126	126	122	120
R-squared	0.154	0.151	0.264	0.307	0.502	0.520

Robust standard errors in parentheses

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

Interpretation of Model 1 (Table 3.1.1): On an average, increase in the CPI score of a country by 1 score, i.e, moving towards a corrupt free environment, would lead to a decrease in deforestation by 4.381%.²

Interpretation of Model 6 (Table 3.1.1): On an average, increase in the CPI score of a country by 1 score, i.e, moving towards a corrupt free environment, would lead to an increase in deforestation by 5.05%.

² Computation of (β_1) value for all models of type $\ln(Y)=B_0 + B_1*X + u \sim$ A change in X by one unit ($\Delta X=1$) is associated with a $(\exp(B_1) - 1)*100$ % change in Y

Table 3.1.2 shows the pooled data using OLS estimation adjusted for time fixed effects only. Just like in the previous table, Model 1 displays linear regression model and as we proceed towards Model 6, covariates are added gradually to the previous models. These models fix for any change over years, in the effect common to all countries. Therefore, they adjust for any unobserved omitted variables that are country invariant but changing over time.

On comparing the results of table 3.1.2 with the results of table 3.1.1, we observe the sign of $\widehat{\beta}_1$ to be the same for all models. However, the values of $\widehat{\beta}_1$ in table 3.1.2, all models except Model 2 and Model 3, appear to be slightly smaller than the values of $\widehat{\beta}_1$ in table 3.1.1. Furthermore, the R-squared value is greater in table 3.1.2. Although only Model 1 gives us the believed correlation direction, after taking in time fixed effects, the $\widehat{\beta}_1$ values have reduced from before which is what I hope for.

Table 3.1.2 Time fixed effects

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
CPIscore	-0.0452*** (0.00257)	0.0126 (0.0141)	0.0280** (0.0136)	0.0658*** (0.0215)	0.0492** (0.0191)	0.0462** (0.0192)
ln_GDP_2015		0.329 (0.259)	0.436* (0.242)	1.103*** (0.380)	2.809*** (0.424)	3.271*** (0.508)
ln_UrbanPop			-1.530*** (0.364)	1.436 (1.369)	1.397 (1.197)	2.482* (1.367)
ln_RuralPop				5.445** (2.425)	5.671*** (2.126)	7.458*** (2.389)
ln_GovtEffect					-2.418*** (0.387)	-2.839*** (0.465)
ln_PoliticStabl e						0.452 (0.276)
Constant	4.759*** (0.343)	-1.100 (2.145)	3.532 (2.276)	-34.70** (17.17)	-40.60*** (15.04)	-55.07*** (17.43)
Observations	1,700	126	126	126	122	120
R-squared	0.156	0.191	0.310	0.343	0.529	0.542
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Interpretation of Model 1 (Table 3.1.2): On an average, increase in the CPI score of a country by 1 score, i.e., moving towards a corrupt free environment, would lead to a decrease in deforestation by 4.419%.

Interpretation of Model 6 (Table 3.1.2): On an average, increase in the CPI score of a country by 1 score, i.e., moving towards a corrupt free environment, would lead to an increase in deforestation by 4.728%.

3.2 Hypothesis 2: Increase in control of corruption decreases deforestation

Table 3.2.1 shows the pooled data using OLS estimation. Just like in the previous tables, Model 1 displays linear regression model and as we proceed towards Model 6, covariates are added gradually to the previous models. Unlike the hypothesis 1, the $\widehat{\beta}_1$ values, for all models, are negative as well as highly statistically significant at 99% confidence interval, which makes $\ln_CorrControl$, a better variable for my study as compared to the CPI score.

Declining observation lower down the precision of a model. Comparing Model 1 with Model 6 (after adding all covariates), we observe the declining number of observations but the improving R-squared values. However, R-squared does not penalize for an insignificant variable or reward for a significant variable, which adjusted R-squared does. Model 6 gives a value of $\widehat{\beta}_1$ closer to the true value of β_1 ; the value of $\widehat{\beta}_1$ in Model 1 is underestimated, i.e., Model 6 shows higher % of deforestation decrease ($1.586 > .963$) with every 1% increase in $\ln_CorrControl$. Possibly even after controlling for endogenous variables correlated with the error term, there could remain some unobserved omitted variables which can be accounted for by using fixed effects method.

Table 3.2.1 Pooled data

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
$\ln_CorrControl$	-0.963*** (0.0572)	-1.733*** (0.185)	-1.620*** (0.181)	-1.628*** (0.182)	-0.890*** (0.286)	-1.586*** (0.347)
\ln_GDP_2015		1.542*** (0.142)	1.663*** (0.141)	1.464*** (0.273)	2.301*** (0.368)	2.727*** (0.393)
$\ln_UrbanPop$			-0.923*** (0.267)	-1.513** (0.744)	-0.890 (0.745)	0.489 (0.842)
$\ln_RuralPop$				-0.994 (1.169)	0.797 (1.258)	2.637* (1.396)
$\ln_GovtEffect$					-1.314*** (0.401)	-1.439*** (0.421)
$\ln_PoliticStable$						0.728*** (0.216)
Constant	5.764*** (0.211)	-5.188*** (0.806)	-2.920*** (1.017)	4.599 (8.898)	-9.199 (9.596)	-24.26** (10.76)
Observations	1,808	154	154	154	154	151
R-squared	0.136	0.442	0.483	0.486	0.520	0.562

Interpretation of Model 1 (Table 3.2.1): On an average, increase in the $\ln_CorrControl$ of a country by 1%, i.e., moving towards a corrupt free environment, would lead to a decrease in deforestation by 0.963%.

Interpretation of Model 6 (Table 3.2.1): On an average, increase in the $\ln_CorrControl$ of a country by 1%, i.e., moving towards a corrupt free environment, would lead to a decrease in deforestation by 1.586%.

Table 3.2.2 (on the next page) shows the pooled data using OLS estimation adjusted for time fixed effects only. Just like in the previous table, Model 1 displays linear regression model and as we proceed towards Model 6, covariates are added gradually to the previous models. These models fix for any change over years, in the effect common to all countries. Therefore, they adjust for any unobserved omitted variables that are country invariant but changing over time. Unlike the hypothesis 1, the $\widehat{\beta}_1$ values, for all models, are negative as well as highly statistically significant at 99% confidence interval, which makes $\ln_CorrControl$, a better variable for my study as compared to the CPI score; similar to the finding in previous table 3.2.1

On comparing the results of table 3.2.2 with the results of table 3.2.1, we observe the sign of $\widehat{\beta}_1$ to be the same for all models. However, the values of $\widehat{\beta}_1$ in table 3.2.2, all models except Model 5 and Model 6, appear to be slightly smaller than the values of $\widehat{\beta}_1$ in table 3.2.1. Furthermore, the R-squared value is greater in table 3.2.2. Unlike table 3.2.1, one of the covariates, $\ln_RuralPop$, lose their statistical significance in Model 6.

Table 3.2.2 Time fixed effects

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
ln_CorrControl	-0.964*** (0.0575)	-1.743*** (0.199)	-1.624*** (0.195)	-1.634*** (0.195)	-0.833*** (0.310)	-1.574*** (0.377)
ln_GDP_2015		1.554*** (0.152)	1.670*** (0.151)	1.413*** (0.291)	2.289*** (0.389)	2.676*** (0.420)
ln_UrbanPop			-0.927*** (0.282)	-1.692** (0.793)	-1.055 (0.789)	0.311 (0.913)
ln_RuralPop				-1.287 (1.245)	0.583 (1.332)	2.357 (1.509)
ln_GovtEffect					-1.403*** (0.431)	-1.465*** (0.450)
ln_PoliticStable						0.726*** (0.243)
Constant	5.730*** (0.322)	-4.821*** (1.093)	-2.560** (1.260)	7.196 (9.519)	-6.954 (10.16)	-21.36* (11.71)
Observations	1,808	154	154	154	154	151
R-squared	0.136	0.455	0.496	0.500	0.538	0.578
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Interpretation of Model 1 (Table 3.2.2): On an average, increase in the ln_CorrControl of a country by 1%, i.e., moving towards a corrupt free environment, would lead to a decrease in deforestation by 0.964%.

Interpretation of Model 6 (Table 3.2.2): On an average, increase in the ln_CorrControl of a country by 1%, i.e., moving towards a corrupt free environment, would lead to a decrease in deforestation by 1.574%.

After doing the regression analysis, it was observed that for both the hypothesis, the entity fixed effects, and the entity and time fixed effects combined did not give results that were highly statistically significant. However, the time fixed effects had good statistically significant results. Therefore, this study only compares the hypothesis 1 and 2 based on regression models with no fixed effects, and only time fixed effects. However, the results using other methodologies are displayed in the do file for the viewer's reference.

4. Conclusion and Discussion

The methods used in this study were linear regression and multiple regression, with and without time fixed effects. Although, the research was conducted using entity fixed effects only, and time and entity fixed effects together, the results obtained from these models were not statistically significant enough to be considered in the study. The results obtained from using time fixed effects only in hypothesis 2 (displayed in table 3.2.2) are the ones that are closest to the true value of β_1 , according to me. It showed that with 1% decrease in the corruption factor of a country, deforestation activities declined statistically significantly at 99% confidence interval. They are in alignment with the literature review found, and coincide with my economic intuition, i.e., declining corruption activities tend to decline deforestation in a country.

After performing regression analysis using CPI score and `ln_CorrControl` as two separate corruption variables to observe their impact on deforestation, it was found that `ln_CorrControl` gave more expected results, as compared to CPI score, as they conform with my literature review found. CPI score is one of most profoundly used corruption indices. Therefore, it is possible that the results obtained from CPI score were not as expected due to some other problem which could not be accounted for in this study. It is possible that my CPI score calculation before 2012 might not be accurate as I used simple conversion formula to convert scores ranging from 1-10 to 1-100. Furthermore, there could exist a problem of large outliers that was observed in the graphs above. The corruption factor does not limit to corrupt practices being practiced in the forest. I believe, had I considered corruption variable that only relates to things like illegal logging, or bribery offered to forest officers, I might have got larger corruption coefficient values, signifying higher decline in deforestation. This is something that I would like to explore further in my future work.

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Technical Appendix

```
.
.
. *****Summary & Graphs*****
.
. *summary statistics
. ssc install asdoc
checking asdoc consistency and verifying not already installed...
all files already exist and are up to date.

. asdoc summarize CPIscore CorrControl Deforestation GDP_2015 RuralPop UrbanPop GovtEffect
    PoliticStab
> le, separator(10)

Variable |      Obs   Mean   Std. dev.     Min       Max
-----|-----
CPIscore |    3,365  42.41783  20.82815         4        100
CorrControl |    4,069  48.86651  29.09121         0        100
Deforestation |    2,446  89.64793  380.3136         0    5129.3
GDP_2015 |      755  12045.5   15190  334.0157  101489.4
RuralPop |      851  44.53006   24.9668         0     87.022
UrbanPop |      851  55.46994   24.9668    12.978         100
GovtEffect |    4,057  49.10154  28.99973         0        100
PoliticStab |    4,125  49.26337  28.83449         0        100
Click to open File: Myfile.doc

.
. *new log variables generated
. gen ln_CorrControl = ln(CorrControl)
(693 missing values generated)

. label var ln_CorrControl "natural log of CorrControl"

.
. gen ln_Deforestation = ln(Deforestation)
(2,809 missing values generated)

. label var ln_Deforestation "natural log of variable Deforestation"

.
. gen ln_GDP_2015 = ln(GDP_2015)
(3,986 missing values generated)

. label var ln_GDP_2015 "natural log of variable GDP_2015"

.
. gen ln_RuralPop = ln(RuralPop)
(3,942 missing values generated)

. label var ln_RuralPop "natural log of RuralPop"

.
. gen ln_UrbanPop = ln(UrbanPop)
(3,890 missing values generated)

. label var ln_UrbanPop "natural log of UrbanPop"

.
. gen ln_GovtEffect = ln(GovtEffect)
(705 missing values generated)

. label var ln_UrbanPop "natural log of ln_GovtEffect"

.
. gen ln_PoliticStable = ln(PoliticStable)
(637 missing values generated)

. label var ln_UrbanPop "natural log of PoliticStable"
```

```

.
. *forming histograms
. // histogram CPIscore, fcolor("169 145 234") lcolor("136 114 228") normal
. normopts(lcolor(black%100))
> lpattern(shortdash_dot)) kdensity kdenopts(lcolor("17 0 240")) xtitle(CPI score) by(,
. legend(on at(
> 23))) name(G1, replace) by(Year, style(econ) imargin(small) cols(4))
. //
. // histogram ln_CorrControl, fcolor("169 145 234") lcolor("136 114 228") normal
. normopts(lcolor(black%100))
> kdensity kdenopts(lcolor("17 0 240")) xtitle(Natural log of ln_CorrControl) by(,
. legend(on at(23))) name(G2, replace) by(Year, style(econ) imargin(small) cols(4))
. //
. // histogram ln_Deforestation, fcolor("169 145 234") lcolor("136 114 228") normal
. normopts(lcolor(black%100))
> lpattern(shortdash_dot)) kdensity kdenopts(lcolor("17 0 240")) xtitle(Natural log of ln_Deforestation) by(,
. legend(on at(23))) name(G3, replace) by(Year, style(econ) imargin(small) cols(4))
. //
. // histogram ln_GDP_2015, fcolor("169 145 234") lcolor("136 114 228") normal
. normopts(lcolor(black%100))
> lpattern(shortdash_dot)) kdensity kdenopts(lcolor("17 0 240")) xtitle(Natural log of ln_GDP_2015) by(,
. legend(on at(23))) name(G4, replace) by(Year, style(econ) imargin(small) cols(4))
. //
. // histogram ln_RuralPop, fcolor("169 145 234") lcolor("136 114 228") normal
. normopts(lcolor(black%100))
> lpattern(shortdash_dot)) kdensity kdenopts(lcolor("17 0 240")) xtitle(Natural log of ln_RuralPop) by(,
. legend(on at(23))) name(G5, replace) by(Year, style(econ) imargin(small) cols(4))
. //
. // histogram ln_UrbanPop, fcolor("169 145 234") lcolor("136 114 228") normal
. normopts(lcolor(black%100))
> lpattern(shortdash_dot)) kdensity kdenopts(lcolor("17 0 240")) xtitle(Natural log of ln_UrbanPop) by(,
. legend(on at(23))) name(G6, replace) by(Year, style(econ) imargin(small) cols(4))
. //
. // histogram ln_GovtEffect, fcolor("169 145 234") lcolor("136 114 228") normal
. normopts(lcolor(black%100))
> lpattern(shortdash_dot)) kdensity kdenopts(lcolor("17 0 240")) xtitle(Natural log of ln_GovtEffect) by(,
. legend(on at(23))) name(G7, replace) by(Year, style(econ) imargin(small) cols(4))
. //
. // histogram ln_PoliticStable, fcolor("169 145 234") lcolor("136 114 228") normal
. normopts(lcolor(black%100))
> lpattern(shortdash_dot)) kdensity kdenopts(lcolor("17 0 240")) xtitle(Natural log of ln_PoliticStable) by(,
. legend(on at(23))) name(G8, replace) by(Year, style(econ) imargin(small) cols(4))
. //
. // twoway (scatter ln_Deforestation CPIscore, sort mcolor("0 169 24") msize(vsmall)
. msymbol(circle))
> (lfit ln_Deforestation CPIscore, lcolor("0 0 0 %80")), ytitle(Natural log of Deforestation)
> xtitle(CPI score) title(Scatter plot of ln_deforestation and CPI score) subtitle((Pooled data))
> name(S1, replace)
. //
. // twoway (scatter ln_Deforestation ln_CorrControl, sort mcolor("0 169 24") msize(vsmall)
. msymbol(circle))
> (lfit ln_Deforestation ln_CorrControl, lcolor("0 0 0 %80")), ytitle(Natural log of Deforestation)
> xtitle(Natural log of ln_CorrControl) title(Scatter plot of ln_deforestation and ln_CorrControl)
> subtitle((Pooled data)) name(S2, replace)
.
.
. *****
. *****Regression Analysis*****
. *****
.
. *correlation matrix
. asdoc corr CPIscore ln_CorrControl ln_Deforestation ln_GDP_2015 ln_RuralPop ln_UrbanPop
. ln_GovtEffect ln_PoliticStable
> t ln_PoliticStable

```

(File Myfile.doc already exists, option append was assumed)
(obs=120)

	CPIscore	ln_Corr~l	ln_Def~n	ln_~2015	ln_Rur~p	ln_Urb~p	ln_Gov~t	ln_Pol~e
CPIscore	1.0000							
ln_CorrCon~l	0.7962	1.0000						
ln_Defores~n	0.3534	-0.0107	1.0000					
ln_GDP_2015	0.8612	0.8246	0.3793	1.0000				
ln_RuralPop	-0.8727	-0.8121	-0.1610	-0.8482	1.0000			
ln_UrbanPop	0.5987	0.6144	-0.0507	0.5601	-0.8843	1.0000		
ln_GovtEff~t	0.7140	0.8677	0.1677	0.8992	-0.7125	0.4491	1.0000	
ln_Politic~e	0.7038	0.7684	0.1787	0.6469	-0.5951	0.3184	0.7007	1.0000

Click to Open File: Myfile.doc

```
.
. *****CPI score
. *pooled method using OLS
. reg ln_Deforestation CPIscore, r
```

Linear regression	Number of obs	=	1,700
	F(1, 1698)	=	383.39
	Prob > F	=	0.0000
	R-squared	=	0.1537
	Root MSE	=	2.3694

ln_Defores~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	-.0448301	.0022896	-19.58	0.000	-.0493207	-.0403394
_cons	4.387195	.1122196	39.09	0.000	4.167092	4.607298

```
. outreg2 using Myreg.doc, replace ctitle(Model 1)
Myreg.doc
dir : seeout
```

```
. reg ln_Deforestation CPIscore ln_GDP_2015, r
```

Linear regression	Number of obs	=	126
	F(2, 123)	=	11.23
	Prob > F	=	0.0000
	R-squared	=	0.1506
	Root MSE	=	2.0401

ln_Defores~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0100387	.0102766	0.98	0.331	-.0103033	.0303807
ln_GDP_2015	.3925295	.2117983	1.85	0.066	-.0267122	.8117712
_cons	-1.578604	1.510669	-1.04	0.298	-4.56888	1.411672

```
. outreg2 using Myreg.doc, append ctitle(Model 2)
Myreg.doc
dir : seeout
```

```
. reg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop, r
```

Linear regression	Number of obs	=	126
	F(3, 122)	=	14.43
	Prob > F	=	0.0000
	R-squared	=	0.2640
	Root MSE	=	1.9068

ln_Defores~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
--------------	-------------	---------------------	---	------	----------------------	--

CPIscore	.0245856	.0104837	2.35	0.021	.003832	.0453392
ln_GDP_2015	.5055253	.2089829	2.42	0.017	.0918228	.9192278
ln_UrbanPop	-1.480165	.2305171	-6.42	0.000	-1.936497	-1.023834
_cons	2.651002	1.367716	1.94	0.055	-.0565283	5.358533

. outreg2 using Myreg.doc, append ctitle(Model 3)

Myreg.doc

dir : seeout

. reg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop, r

Linear regression	Number of obs	=	126
	F(4, 121)	=	13.71
	Prob > F	=	0.0000
	R-squared	=	0.3071
	Root MSE	=	1.8578

ln_Defores~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0666268	.0195692	3.40	0.001	.0278843	.1053693
ln_GDP_2015	1.205066	.3594347	3.35	0.001	.4934703	1.916662
ln_UrbanPop	1.76655	1.252606	1.41	0.161	-.7133142	4.246413
ln_RuralPop	5.959755	2.264977	2.63	0.010	1.475635	10.44387
_cons	-38.82714	16.00265	-2.43	0.017	-70.50861	-7.145678

. outreg2 using Myreg.doc, append ctitle(Model 4)

Myreg.doc

dir : seeout

. reg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect, r

Linear regression	Number of obs	=	122
	F(5, 116)	=	19.99
	Prob > F	=	0.0000
	R-squared	=	0.5015
	Root MSE	=	1.5809

ln_Deforest~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0543042	.0169228	3.21	0.002	.0207865	.0878219
ln_GDP_2015	2.965905	.3831555	7.74	0.000	2.207017	3.724793
ln_UrbanPop	2.019093	1.133867	1.78	0.078	-.2266728	4.26486
ln_RuralPop	6.757723	1.94469	3.47	0.001	2.90602	10.60943
ln_GovtEffect	-2.34634	.4477751	-5.24	0.000	-3.233215	-1.459465
_cons	-48.89705	13.37498	-3.66	0.000	-75.38788	-22.40623

. outreg2 using Myreg.doc, append ctitle(Model 5)

Myreg.doc

dir : seeout

. reg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect
ln_PoliticStable, r

Linear regression	Number of obs	=	120
	F(6, 113)	=	16.68
	Prob > F	=	0.0000
	R-squared	=	0.5200
	Root MSE	=	1.5717

ln_Deforestation	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
------------------	-------------	---------------------	---	------	----------------------	--

CPIscore	.0493187	.0163448	3.02	0.003	.0169366	.0817007
ln_GDP_2015	3.434834	.4351805	7.89	0.000	2.572663	4.297005
ln_UrbanPop	3.030359	1.166548	2.60	0.011	.7192176	5.341501
ln_RuralPop	8.39861	1.969302	4.26	0.000	4.497066	12.30015
ln_GovtEffect	-2.835938	.5385964	-5.27	0.000	-3.902994	-1.768881
ln_PoliticStable	.4870606	.2756304	1.77	0.080	-.059013	1.033134
_cons	-62.27051	13.89544	-4.48	0.000	-89.79989	-34.74113

```
. outreg2 using Myreg.doc, append ctitle(Model 6)
Myreg.doc
dir : seeout
```

```
.
. *entity fixed effects
. encode country, gen(Country)
```

```
. xtset Country Year
```

```
Panel variable: Country (unbalanced)
Time variable: Year, 2000 to 2021, but with gaps
Delta: 1 unit
```

```
. xtreg ln_Deforestation CPIscore, fe vce(cluster country)
```

```
Fixed-effects (within) regression              Number of obs   =       1700
Group variable: Country                      Number of groups =        100

R-sq:  Within = 0.0003                      Obs per group:  min =         4
        Between = 0.1432                      avg =       17.0
        Overall = 0.1537                      max =        21

corr(u_i, Xb) = -0.4132                      F(1,99)         =        0.05
                                                Prob > F         =       0.8164
```

(Std. err. adjusted for 100 clusters in country)

ln_Defores~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.001941	.0083375	0.23	0.816	-.0146024	.0184843
_cons	2.340248	.3648926	6.41	0.000	1.616222	3.064274
sigma_u	2.5427888					
sigma_e	.48637325					
rho	.96470499	(fraction of variance due to u_i)				

```
. outreg2 using StateOnly.doc, replace ctitle(Model 1) addtext(Country Fixed Effects, Yes)
StateOnly.doc
dir : seeout
```

```
. xtreg ln_Deforestation CPIscore ln_GDP_2015, fe vce(cluster country)
```

```
Fixed-effects (within) regression              Number of obs   =        126
Group variable: Country                      Number of groups =         9

R-sq:  Within = 0.4248                      Obs per group:  min =         5
        Between = 0.0822                      avg =       14.0
        Overall = 0.1277                      max =        21

corr(u_i, Xb) = -0.5934                      F(2,8)         =        2.42
                                                Prob > F         =       0.1505
```

(Std. err. adjusted for 9 clusters in country)

ln_Defores~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0871928	.0396925	2.20	0.059	-.0043382	.1787239
ln_GDP_2015	-.1046906	.6916319	-0.15	0.883	-1.699597	1.490215


```

      _cons | -.9892446   6.150677   -0.16   0.876   -15.17273   13.19424
-----+-----
      sigma_u | 2.5965971
      sigma_e | .46024507
      rho | .96953966   (fraction of variance due to u_i)
-----

```

```

. outreg2 using StateOnly.doc, append ctitle(Model 2) addtext(Country Fixed Effects, Yes)
StateOnly.doc
dir : seeout

```

```

. xtreg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop, fe vce(cluster country)

```

```

Fixed-effects (within) regression               Number of obs   =       126
Group variable: country                       Number of groups =        9

R-sq:  Within = 0.4450                        Obs per group:  min =        5
        Between = 0.0030                      avg           =       14.0
        Overall = 0.0087                      max           =        21

corr(u_i, Xb) = -0.8320                      F(3,8)          =        3.11
                                                Prob > F         =       0.0883

```

(Std. err. adjusted for 9 clusters in country)

```

-----+-----
ln_Defores~n | Coefficient   Robust      t    P>|t|    [95% conf. interval]
              |               std. err.
-----+-----
      CPIscore | .0802412     .0287682     2.79  0.024     .0139015     .1465809
      ln_GDP_2015 | -.6500812    1.385361    -0.47  0.651    -3.844729    2.544567
      ln_UrbanPop | 3.900921     5.346       0.73  0.486    -8.426977    16.22882
      _cons     | -11.4971     13.46887    -0.85  0.418    -42.55637    19.56217
-----+-----
      sigma_u | 3.7441999
      sigma_e | .45407443
      rho | .98550577   (fraction of variance due to u_i)
-----

```

```

. outreg2 using StateOnly.doc, append ctitle(Model 3) addtext(Country Fixed Effects, Yes)
StateOnly.doc
dir : seeout

```

```

. xtreg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop, fe vce(cluster country)

```

```

Fixed-effects (within) regression               Number of obs   =       126
Group variable: country                       Number of groups =        9

R-sq:  Within = 0.4602                        Obs per group:  min =        5
        Between = 0.0005                      avg           =       14.0
        Overall = 0.0001                      max           =        21

corr(u_i, Xb) = -0.9229                      F(4,8)          =        6.20
                                                Prob > F         =       0.0142

```

(Std. err. adjusted for 9 clusters in country)

```

-----+-----
ln_Defores~n | Coefficient   Robust      t    P>|t|    [95% conf. interval]
              |               std. err.
-----+-----
      CPIscore | .0814015     .0301407     2.70  0.027     .0118969     .150906
      ln_GDP_2015 | -.4745187    1.375466    -0.34  0.739    -3.646348    2.69731
      ln_UrbanPop | 9.443437     6.95447     1.36  0.212    -6.593599    25.48047
      ln_RuralPop | 3.147619     2.919373     1.08  0.312    -3.584467    9.879704
      _cons     | -46.02238    33.53225    -1.37  0.207    -123.3479    31.30312
-----+-----
      sigma_u | 5.305052
      sigma_e | .44980537
      rho | .99286229   (fraction of variance due to u_i)
-----

```

```

. outreg2 using StateOnly.doc, append ctitle(Model 4) addtext(Country Fixed Effects, Yes)

```

StateOnly.doc
dir : seeout

```
. xtreg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect, fe
    vce(cluster co
> untry)
```

Fixed-effects (within) regression
Group variable: Country

Number of obs	=	122
Number of groups	=	9
Obs per group: min	=	5
avg	=	13.6
max	=	20

R-sq: Within = 0.4674
 Between = 0.0001
 Overall = 0.0001

corr(u_i, Xb) = -0.9311

F(5,8) = 5.97
Prob > F = 0.0136

(Std. err. adjusted for 9 clusters in country)

ln_Deforest~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0805791	.0294422	2.74	0.026	.0126853	.148473
ln_GDP_2015	-.2900379	1.448472	-0.20	0.846	-3.630221	3.050145
ln_UrbanPop	9.885823	6.742006	1.47	0.181	-5.66127	25.43292
ln_RuralPop	3.358563	3.294022	1.02	0.338	-4.237465	10.95459
ln_GovtEffect	-.0720056	.3163285	-0.23	0.826	-.8014604	.6574493
_cons	-49.75857	35.84311	-1.39	0.202	-132.4129	32.89578
sigma_u	5.514593					
sigma_e	.45584384					
rho	.99321347	(fraction of variance due to u_i)				

```
. outreg2 using StateOnly.doc, append ctitle(Model 5) addtext(Country Fixed Effects, Yes)
StateOnly.doc
dir : seeout
```

```
. xtreg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect
    ln_PoliticStable,
> fe vce(cluster country)
```

Fixed-effects (within) regression
Group variable: Country

Number of obs	=	120
Number of groups	=	9
Obs per group: min	=	5
avg	=	13.3
max	=	20

R-sq: Within = 0.5261
 Between = 0.0018
 Overall = 0.0012

corr(u_i, Xb) = -0.9334

F(6,8) = 44.95
Prob > F = 0.0000

(Std. err. adjusted for 9 clusters in country)

ln_Deforestation	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0682732	.0314823	2.17	0.062	-.004325	.1408715
ln_GDP_2015	-.5958014	1.718405	-0.35	0.738	-4.558451	3.366849
ln_UrbanPop	9.483213	6.707517	1.41	0.195	-5.98435	24.95078
ln_RuralPop	1.962457	3.527832	0.56	0.593	-6.172739	10.09765
ln_GovtEffect	-.3617024	.3216744	-1.12	0.293	-1.103485	.38008
ln_PoliticStable	.3181478	.0889637	3.58	0.007	.1129972	.5232984
_cons	-40.14101	39.16271	-1.02	0.335	-130.4504	50.16836
sigma_u	5.6432319					
sigma_e	.42752505					
rho	.99429334	(fraction of variance due to u_i)				

```
. outreg2 using StateOnly.doc, append ctitle(Model 6) addtext(Country Fixed Effects, Yes)
```

StateOnly.doc
dir : seeout

```
. *time fixed effects
. reg ln_Deforestation CPIscore i.Year
```

Source	SS	df	MS	Number of obs	=	1,700
Model	1753.77727	21	83.5132031	F(21, 1678)	=	14.74
Residual	9510.10404	1,678	5.66752326	Prob > F	=	0.0000
				R-squared	=	0.1557
				Adj R-squared	=	0.1451
Total	11263.8813	1,699	6.62971236	Root MSE	=	2.3807

ln_Defores~n	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
CPIscore	-.0451939	.0025726	-17.57	0.000	-.0502397	-.040148
Year						
2001	-.1220372	.4460342	-0.27	0.784	-.9968791	.7528047
2002	-.1722354	.43729	-0.39	0.694	-1.029927	.6854559
2003	-.2617068	.4231376	-0.62	0.536	-1.09164	.5682262
2004	-.3175551	.4172508	-0.76	0.447	-1.135942	.5008318
2005	-.4198419	.4151576	-1.01	0.312	-1.234123	.3944394
2006	-.3978318	.4110506	-0.97	0.333	-1.204058	.4083941
2007	-.4776153	.4083257	-1.17	0.242	-1.278497	.323266
2008	-.4920065	.4074253	-1.21	0.227	-1.291122	.3071088
2009	-.4611416	.4092227	-1.13	0.260	-1.263782	.3414991
2010	-.4479354	.4111374	-1.09	0.276	-1.254332	.3584607
2011	-.3766645	.4057003	-0.93	0.353	-1.172397	.4190675
2012	-.2949889	.4045714	-0.73	0.466	-1.088507	.4985289
2013	-.3098879	.4046013	-0.77	0.444	-1.103464	.4836885
2014	-.2709927	.4053881	-0.67	0.504	-1.066112	.5241269
2015	-.265469	.4053784	-0.65	0.513	-1.06057	.5296315
2016	-.3764521	.4160969	-0.90	0.366	-1.192576	.4396715
2017	-.4388778	.4120047	-1.07	0.287	-1.246975	.3692194
2018	-.4481343	.4120256	-1.09	0.277	-1.256273	.3600038
2019	-.4421448	.412012	-1.07	0.283	-1.250256	.3659667
2020	-.4405113	.4120083	-1.07	0.285	-1.248616	.367593
_cons	4.758875	.3427889	13.88	0.000	4.086536	5.431214

```
. outreg2 using TimeOnly.doc, replace ctitle(Model 1) addtext(Time Fixed Effects, Yes)
keep(ln_Defores
> tation CPIscore)
TimeOnly.doc
dir : seeout
```

```
. reg ln_Deforestation CPIscore ln_GDP_2015 i.Year
```

Source	SS	df	MS	Number of obs	=	126
Model	115.316657	22	5.24166625	F(22, 103)	=	1.11
Residual	487.422918	103	4.73226134	Prob > F	=	0.3514
				R-squared	=	0.1913
				Adj R-squared	=	0.0186
Total	602.739575	125	4.8219166	Root MSE	=	2.1754

ln_Defores~n	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0126422	.0141233	0.90	0.373	-.015368	.0406524
ln_GDP_2015	.3290219	.2589122	1.27	0.207	-.1844695	.8425132
Year						
2001	-.0063546	1.538239	-0.00	0.997	-3.05709	3.04438
2002	-.0236506	1.538234	-0.02	0.988	-3.074375	3.027074
2003	.4428511	1.408187	0.31	0.754	-2.349956	3.235658
2004	.41128	1.407963	0.29	0.771	-2.381082	3.203642
2005	.388534	1.407681	0.28	0.783	-2.403269	3.180337
2006	.3812874	1.407294	0.27	0.787	-2.409749	3.172324

2007	-.3956017	1.369364	-0.29	0.773	-3.111412	2.320209
2008	-.1039085	1.380324	-0.08	0.940	-2.841455	2.633638
2009	-.4190907	1.369543	-0.31	0.760	-3.135256	2.297074
2010	-.3805675	1.41262	-0.27	0.788	-3.182167	2.421032
2011	.5705455	1.372869	0.42	0.679	-2.152216	3.293307
2012	.2047874	1.346133	0.15	0.879	-2.46495	2.874525
2013	.2231443	1.345713	0.17	0.869	-2.445761	2.892049
2014	.2213543	1.344953	0.16	0.870	-2.446042	2.888751
2015	.2216157	1.344443	0.16	0.869	-2.44477	2.888002
2016	-1.175622	1.546516	-0.76	0.449	-4.242771	1.891528
2017	-.6612332	1.477273	-0.45	0.655	-3.591057	2.26859
2018	-.6563748	1.47653	-0.44	0.658	-3.584724	2.271974
2019	-.6488825	1.47574	-0.44	0.661	-3.575665	2.2779
2020	-.6483217	1.476515	-0.44	0.662	-3.57664	2.279997
_cons	-1.100122	2.145198	-0.51	0.609	-5.354617	3.154373

```

. outreg2 using TimeOnly.doc, append ctitle(Model 2) addtext(Time Fixed Effects, Yes)
  keep(ln_Deforest
> ation CPIscore ln_GDP_2015)
TimeOnly.doc
dir : seeout

```

```

. reg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop i.Year

```

Source	SS	df	MS	Number of obs	=	126
				F(23, 102)	=	2.00
Model	187.140872	23	8.13655964	Prob > F	=	0.0100
Residual	415.598703	102	4.07449709	R-squared	=	0.3105
				Adj R-squared	=	0.1550
Total	602.739575	125	4.8219166	Root MSE	=	2.0185

ln_Deforest~n	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0280337	.0136081	2.06	0.042	.001042	.0550253
ln_GDP_2015	.4355665	.241582	1.80	0.074	-.0436102	.9147433
ln_UrbanPop	-1.529759	.364355	-4.20	0.000	-2.252456	-.807063
Year						
2001	-.0092722	1.427337	-0.01	0.995	-2.840389	2.821844
2002	-.0287616	1.427333	-0.02	0.984	-2.85987	2.802346
2003	.1661457	1.308322	0.13	0.899	-2.428905	2.761197
2004	.1128162	1.308386	0.09	0.931	-2.48236	2.707993
2005	.0786116	1.308276	0.06	0.952	-2.516347	2.67357
2006	.0756556	1.30786	0.06	0.954	-2.518479	2.66979
2007	-.5672537	1.271295	-0.45	0.656	-3.088861	1.954353
2008	-.2975592	1.281637	-0.23	0.817	-2.83968	2.244561
2009	-.6028068	1.271556	-0.47	0.636	-3.124932	1.919319
2010	-.621767	1.312033	-0.47	0.637	-3.224179	1.980644
2011	.3764343	1.274728	0.30	0.768	-2.151982	2.904851
2012	.0713131	1.249486	0.06	0.955	-2.407036	2.549662
2013	.1134771	1.248965	0.09	0.928	-2.363839	2.590793
2014	.1204567	1.248217	0.10	0.923	-2.355376	2.596289
2015	.1364324	1.247678	0.11	0.913	-2.338331	2.611196
2016	-1.569713	1.438083	-1.09	0.278	-4.422145	1.282718
2017	-.9347434	1.372314	-0.68	0.497	-3.656721	1.787234
2018	-.9101326	1.371409	-0.66	0.508	-3.630316	1.810051
2019	-.8797222	1.370447	-0.64	0.522	-3.597998	1.838554
2020	-.8719795	1.371098	-0.64	0.526	-3.591546	1.847586
_cons	3.532296	2.275872	1.55	0.124	-.9818855	8.046478

```

. outreg2 using TimeOnly.doc, append ctitle(Model 3) addtext(Time Fixed Effects, Yes)
  keep(ln_Deforest
> ation CPIscore ln_GDP_2015 ln_UrbanPop)
TimeOnly.doc
dir : seeout

```

```
. reg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop i.Year
```

Source	SS	df	MS	Number of obs	=	126
Model	206.896279	24	8.62067828	F(24, 101)	=	2.20
Residual	395.843296	101	3.91924056	Prob > F	=	0.0035
				R-squared	=	0.3433
				Adj R-squared	=	0.1872
Total	602.739575	125	4.8219166	Root MSE	=	1.9797

ln_Deforest~n	Coefficient	std. err.	t	P> t	[95% conf. interval]
CPIscore	.0657544	.021457	3.06	0.003	.0231895 .1083193
ln_GDP_2015	1.102531	.3799861	2.90	0.005	.348741 1.856321
ln_UrbanPop	1.436138	1.368513	1.05	0.296	-1.278623 4.1509
ln_RuralPop	5.444561	2.425051	2.25	0.027	.6339126 10.25521
Year					
2001	.0034199	1.399891	0.00	0.998	-2.773587 2.780426
2002	-.0000569	1.399933	-0.00	1.000	-2.777148 2.777034
2003	.1927572	1.283209	0.15	0.881	-2.352783 2.738298
2004	.098333	1.283232	0.08	0.939	-2.447254 2.64392
2005	.0492499	1.283175	0.04	0.969	-2.496223 2.594723
2006	.0686116	1.282705	0.05	0.957	-2.475929 2.613152
2007	-.4734515	1.247538	-0.38	0.705	-2.948232 2.001329
2008	-.2305433	1.257336	-0.18	0.855	-2.72476 2.263673
2009	-.5012859	1.247914	-0.40	0.689	-2.976812 1.97424
2010	-.5843274	1.286901	-0.45	0.651	-3.137193 1.968538
2011	.4407261	1.250533	0.35	0.725	-2.039996 2.921448
2012	.1543781	1.226007	0.13	0.900	-2.27769 2.586447
2013	.2782833	1.227136	0.23	0.821	-2.156024 2.71259
2014	.3179433	1.227361	0.26	0.796	-2.116811 2.752697
2015	.3829081	1.228591	0.31	0.756	-2.054286 2.820102
2016	-1.346677	1.413913	-0.95	0.343	-4.151499 1.458146
2017	-.684228	1.350531	-0.51	0.614	-3.363319 1.994863
2018	-.5920833	1.352467	-0.44	0.662	-3.275013 2.090847
2019	-.4863537	1.355455	-0.36	0.720	-3.175213 2.202505
2020	-.4317337	1.358943	-0.32	0.751	-3.127512 2.264044
_cons	-34.69844	17.17394	-2.02	0.046	-68.76692 -.6299553

```
. outreg2 using TimeOnly.doc, append ctitle(Model 4) addtext(Time Fixed Effects, Yes)
      keep(ln_Deforest
> ation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop)
TimeOnly.doc
dir : seeout
```

```
. reg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect i.Year
```

Source	SS	df	MS	Number of obs	=	122
Model	307.576205	24	12.8156752	F(24, 97)	=	4.54
Residual	273.991666	97	2.82465635	Prob > F	=	0.0000
				R-squared	=	0.5289
				Adj R-squared	=	0.4123
Total	581.567871	121	4.80634604	Root MSE	=	1.6807

ln_Deforest~n	Coefficient	std. err.	t	P> t	[95% conf. interval]
CPIscore	.0492213	.0191021	2.58	0.011	.0113088 .0871337
ln_GDP_2015	2.809387	.4243851	6.62	0.000	1.9671 3.651674
ln_UrbanPop	1.396628	1.196522	1.17	0.246	-.978136 3.771392
ln_RuralPop	5.671222	2.125578	2.67	0.009	1.452537 9.889907
ln_GovtEffect	-2.417921	.3870202	-6.25	0.000	-3.186049 -1.649793
Year					
2002	.0268323	1.188483	0.02	0.982	-2.331977 2.385641
2003	.2634571	1.089459	0.24	0.809	-1.898817 2.425731
2004	.1046348	1.089425	0.10	0.924	-2.057572 2.266842
2005	-.1414874	1.089773	-0.13	0.897	-2.304385 2.02141
2006	.2291447	1.0893	0.21	0.834	-1.932814 2.391103

2007	-.1020025	1.060869	-0.10	0.924	-2.207533	2.003528
2008	-.2780628	1.06747	-0.26	0.795	-2.396695	1.840569
2009	-.0314232	1.062184	-0.03	0.976	-2.139565	2.076718
2010	-.070161	1.095774	-0.06	0.949	-2.244969	2.104647
2011	.032201	1.063557	0.03	0.976	-2.078665	2.143067
2012	-.4019058	1.04446	-0.38	0.701	-2.47487	1.671059
2013	-.0676043	1.043243	-0.06	0.948	-2.138153	2.002945
2014	-.142427	1.044605	-0.14	0.892	-2.215679	1.930825
2015	-.1000267	1.046025	-0.10	0.924	-2.176097	1.976044
2016	-1.264072	1.200549	-1.05	0.295	-3.64683	1.118686
2017	-.8639591	1.147039	-0.75	0.453	-3.140515	1.412596
2018	-.7509797	1.148723	-0.65	0.515	-3.030877	1.528918
2019	-.7597619	1.152001	-0.66	0.511	-3.046166	1.526642
2020	-.9822351	1.157655	-0.85	0.398	-3.27986	1.31539
_cons	-40.59747	15.03605	-2.70	0.008	-70.43986	-10.75508

```

. outreg2 using TimeOnly.doc, append ctitle(Model 5) addtext(Time Fixed Effects, Yes)
  keep(ln_Deforest
> ation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect)
TimeOnly.doc
dir : seeout

```

```

. reg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect
  ln_PoliticStable i.Y
> ear

```

Source	SS	df	MS	Number of obs	=	120
Model	315.43433	25	12.6173732	F(25, 94)	=	4.46
Residual	266.101279	94	2.83086467	Prob > F	=	0.0000
				R-squared	=	0.5424
				Adj R-squared	=	0.4207
Total	581.535609	119	4.88685386	Root MSE	=	1.6825

ln_Deforestation	Coefficient	Std. err.	t	P> t	[95% conf. interval]
CPIscore	.0462179	.019208	2.41	0.018	.00808 .0843559
ln_GDP_2015	3.271314	.5077738	6.44	0.000	2.263117 4.279511
ln_UrbanPop	2.481574	1.366594	1.82	0.073	-.2318302 5.194978
ln_RuralPop	7.45826	2.388692	3.12	0.002	2.715456 12.20106
ln_GovtEffect	-2.839384	.4652561	-6.10	0.000	-3.76316 -1.915607
ln_PoliticStable	.4522626	.2759085	1.64	0.105	-.0955602 1.000085
Year					
2002	.0720455	1.190103	0.06	0.952	-2.290931 2.435022
2003	.2383123	1.090767	0.22	0.828	-1.92743 2.404055
2004	.0910475	1.090669	0.08	0.934	-2.074502 2.256597
2005	-.1652219	1.091122	-0.15	0.880	-2.33167 2.001227
2006	.2653666	1.090718	0.24	0.808	-1.90028 2.431014
2007	-.0816708	1.062104	-0.08	0.939	-2.190503 2.027162
2008	-.20748	1.069875	-0.19	0.847	-2.331742 1.916782
2009	.0864268	1.065719	0.08	0.936	-2.029582 2.202436
2010	.0464494	1.099224	0.04	0.966	-2.136086 2.228985
2011	.3196163	1.080197	0.30	0.768	-1.82514 2.464372
2012	-.1127498	1.06208	-0.11	0.916	-2.221536 1.996036
2013	.2619387	1.064893	0.25	0.806	-1.85243 2.376308
2014	.0070785	1.070539	0.01	0.995	-2.118502 2.132658
2015	.1725773	1.074432	0.16	0.873	-1.960732 2.305887
2016	-.9999699	1.212728	-0.82	0.412	-3.40787 1.40793
2017	-.5596127	1.164051	-0.48	0.632	-2.870863 1.751638
2018	-.5023858	1.160623	-0.43	0.666	-2.80683 1.802058
2019	-.5596552	1.160436	-0.48	0.631	-2.863728 1.744417
2020	-.8172204	1.164338	-0.70	0.484	-3.129042 1.494601
_cons	-55.07355	17.42781	-3.16	0.002	-89.67688 -20.47023

```

. outreg2 using TimeOnly.doc, append ctitle(Model 6) addtext(Time Fixed Effects, Yes)
  keep(ln_Deforest
> ation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect ln_PoliticStable)

```

(Std. err. adjusted for 9 clusters in country)

ln_Defores~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0857224	.0422147	2.03	0.077	-.0116248	.1830697
ln_GDP_2015	.3418586	.9644754	0.35	0.732	-1.882226	2.565943
Year						
2001	-.0428961	.0982013	-0.44	0.674	-.2693486	.1835565
2002	-.0790136	.2411548	-0.33	0.752	-.6351175	.4770903
2003	-.3091018	.3023986	-1.02	0.337	-1.006434	.3882306
2004	-.4507852	.3713081	-1.21	0.259	-1.307023	.4054528
2005	-.5349078	.3550116	-1.51	0.170	-1.353566	.2837504
2006	-.5303393	.3276503	-1.62	0.144	-1.285902	.2252237
2007	-.5738073	.2462055	-2.33	0.048	-1.141558	-.0060564
2008	-.5288472	.1962893	-2.69	0.027	-.9814911	-.0762033
2009	-.7226476	.2921313	-2.47	0.038	-1.396304	-.0489916
2010	-.6710726	.2723625	-2.46	0.039	-1.299141	-.0430036
2011	-.7194718	.3267231	-2.20	0.059	-1.472897	.033953
2012	-.6790576	.2852704	-2.38	0.045	-1.336892	-.0212229
2013	-.5692507	.2454153	-2.32	0.049	-1.135179	-.0033221
2014	-.5348171	.2913892	-1.84	0.104	-1.206762	.1371276
2015	-.4982519	.3124689	-1.59	0.149	-1.218807	.2223028
2016	-.5298523	.3308687	-1.60	0.148	-1.292837	.2331323
2017	-.5239194	.3496746	-1.50	0.172	-1.33027	.2824317
2018	-.4753192	.3418936	-1.39	0.202	-1.263727	.3130889
2019	-.409465	.3748626	-1.09	0.306	-1.2739	.4549697
2020	-.4379171	.3327132	-1.32	0.225	-1.205155	.329321
_cons	-4.352402	7.482272	-0.58	0.577	-21.60655	12.90175
sigma_u	2.9325647					
sigma_e	.47195332					
rho	.9747537	(fraction of variance due to u_i)				

```
. outreg2 using StateTime.doc, append ctitle(Model 2) addtext(Country Fixed Effects, Yes, Time
Fixed E
> ffacts, Yes) keep(ln_Deforestation CPIscore ln_GDP_2015)
StateTime.doc
dir : seeout
```

```
. xtreg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop i.Year, fe vce(cluster country)
```

```
Fixed-effects (within) regression
Group variable: Country

Number of obs      =      126
Number of groups   =         9

R-sq:  Within = 0.5097
        Between = 0.0331
        Overall = 0.0421

Obs per group: min =         5
                avg  =      14.0
                max  =        21
```

```
corr(u_i, Xb) = -0.8459
F(8,8) = .
Prob > F = .
```

(Std. err. adjusted for 9 clusters in country)

ln_Defores~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0786059	.0327513	2.40	0.043	.0030813	.1541306
ln_GDP_2015	.0913003	1.275313	0.07	0.945	-2.849578	3.032178
ln_UrbanPop	3.069454	6.581423	0.47	0.653	-12.10733	18.24624
Year						
2001	-.0489213	.0855709	-0.57	0.583	-.2462481	.1484054
2002	-.0849994	.2151799	-0.40	0.703	-.5812053	.4112064
2003	-.325473	.2895297	-1.12	0.294	-.9931296	.3421836
2004	-.4577386	.3641516	-1.26	0.244	-1.297474	.3819965
2005	-.53731	.3507923	-1.53	0.164	-1.346239	.2716185
2006	-.536344	.3309361	-1.62	0.144	-1.299484	.226796
2007	-.5665005	.2562466	-2.21	0.058	-1.157406	.0244051
2008	-.5168159	.2333356	-2.21	0.058	-1.054889	.0212569

2009	-.7316736	.2920117	-2.51	0.037	-1.405054	-.0582935
2010	-.6976347	.2929007	-2.38	0.044	-1.373065	-.0222045
2011	-.7307061	.3221645	-2.27	0.053	-1.473619	.0122065
2012	-.6854032	.2922106	-2.35	0.047	-1.359242	-.0115643
2013	-.5939425	.24331	-2.44	0.040	-1.155016	-.0328686
2014	-.5643153	.2758182	-2.05	0.075	-1.200353	.0717226
2015	-.5467201	.2914963	-1.88	0.098	-1.218912	.1254716
2016	-.5830817	.3065996	-1.90	0.094	-1.290102	.1239383
2017	-.6034337	.3380175	-1.79	0.112	-1.382903	.1760361
2018	-.5799021	.351136	-1.65	0.137	-1.389623	.2298189
2019	-.5407266	.3946885	-1.37	0.208	-1.45088	.3694268
2020	-.5937235	.4257224	-1.39	0.201	-1.575441	.3879942
_cons	-14.0826	20.55734	-0.69	0.513	-61.4879	33.3227
sigma_u	3.8547017					
sigma_e	.46999719					
rho	.98535127	(fraction of variance due to u_i)				

```
. outreg2 using StateTime.doc, append ctitle(Model 3) addtext(Country Fixed Effects, Yes, Time
Fixed E
> ffcts, Yes) keep(ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop)
StateTime.doc
dir : seeout
```

```
. xtreg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop i.Year, fe vce(cluster
country)
```

Fixed-effects (within) regression

Group variable: Country

Number of obs = 126

Number of groups = 9

R-sq: Within = 0.5132

Between = 0.0111

Overall = 0.0138

Obs per group: min = 5

avg = 14.0

max = 21

corr(u_i, Xb) = -0.8913

F(8,8) = .

Prob > F = .

(Std. err. adjusted for 9 clusters in country)

ln_Defores~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0802953	.0336025	2.39	0.044	.0028079	.1577827
ln_GDP_2015	.0794494	1.255461	0.06	0.951	-2.81565	2.974549
ln_UrbanPop	6.038211	7.427112	0.81	0.440	-11.08874	23.16516
ln_RuralPop	1.696915	2.708423	0.63	0.548	-4.548721	7.94255
Year						
2001	-.0463096	.0887794	-0.52	0.616	-.2510352	.1584159
2002	-.0737687	.2181107	-0.34	0.744	-.5767329	.4291955
2003	-.2920736	.2794775	-1.05	0.327	-.9365498	.3524025
2004	-.4208589	.350572	-1.20	0.264	-1.229279	.3875615
2005	-.4956358	.3338211	-1.48	0.176	-1.265429	.274157
2006	-.489499	.3066066	-1.60	0.149	-1.196535	.217537
2007	-.5144436	.2215749	-2.32	0.049	-1.025396	-.0034909
2008	-.4394573	.162198	-2.71	0.027	-.8134864	-.0654281
2009	-.6786651	.26347	-2.58	0.033	-1.286228	-.0711022
2010	-.6448559	.2606123	-2.47	0.038	-1.245829	-.043883
2011	-.6524575	.3243113	-2.01	0.079	-1.400321	.0954058
2012	-.6109865	.2833508	-2.16	0.063	-1.264395	.0424216
2013	-.5133379	.2485694	-2.07	0.073	-1.08654	.0598642
2014	-.4780874	.283062	-1.69	0.130	-1.13083	.1746548
2015	-.4595488	.3046005	-1.51	0.170	-1.161959	.2428614
2016	-.4992287	.3096747	-1.61	0.146	-1.21334	.2148825
2017	-.5256468	.3391911	-1.55	0.160	-1.307823	.2565293
2018	-.5005217	.3465138	-1.44	0.187	-1.299584	.2985406
2019	-.4594812	.3829493	-1.20	0.265	-1.342564	.4236014
2020	-.5129869	.4138216	-1.24	0.250	-1.467261	.4412874
_cons	-31.79331	33.25075	-0.96	0.367	-108.4697	44.88305

sigma_u	4.5211484	
sigma_e	.47080476	
rho	.98927246	(fraction of variance due to u_i)

```
. outreg2 using StateTime.doc, append ctitle(Model 4) addtext(Country Fixed Effects, Yes, Time
Fixed E
> ffacts, Yes) keep(ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop)
StateTime.doc
dir : seeout
```

```
. xtreg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect i.Year, fe
vce(c1
> uster country)
```

```
Fixed-effects (within) regression              Number of obs   =       122
Group variable: Country                      Number of groups =        9

R-sq:  Within = 0.5152                      Obs per group:  min =        5
        Between = 0.0095                      avg   =       13.6
        Overall = 0.0084                      max   =       20

                                F(8,8)        =        .
corr(u_i, Xb) = -0.9139                    Prob > F        =        .
```

(Std. err. adjusted for 9 clusters in country)

ln_Deforest~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.0784738	.0313266	2.51	0.037	.0062345	.1507131
ln_GDP_2015	.2343443	1.399769	0.17	0.871	-2.993529	3.462218
ln_UrbanPop	7.087077	6.111025	1.16	0.280	-7.004972	21.17913
ln_RuralPop	2.005593	2.750171	0.73	0.487	-4.336312	8.347497
ln_GovtEffect	-.0656981	.2690718	-0.24	0.813	-.6861788	.5547827
Year						
2002	-.0782961	.2200416	-0.36	0.731	-.585713	.4291207
2003	-.3026574	.282249	-1.07	0.315	-.9535247	.3482099
2004	-.436143	.356008	-1.23	0.255	-1.257099	.3848129
2005	-.5199415	.3514834	-1.48	0.177	-1.330464	.2905807
2006	-.5083805	.3123984	-1.63	0.142	-1.228773	.2120114
2007	-.5344593	.2270309	-2.35	0.046	-1.057993	-.0109252
2008	-.4601906	.1623307	-2.83	0.022	-.8345257	-.0858554
2009	-.6986539	.2710722	-2.58	0.033	-1.323747	-.0735603
2010	-.6759939	.27122	-2.49	0.037	-1.301428	-.0505595
2011	-.6877432	.302704	-2.27	0.053	-1.38578	.0102935
2012	-.652653	.2566489	-2.54	0.035	-1.244487	-.0608195
2013	-.5506907	.2344161	-2.35	0.047	-1.091255	-.0101262
2014	-.5223719	.2664624	-1.96	0.086	-1.136835	.0920917
2015	-.5105495	.2957843	-1.73	0.123	-1.192629	.1715303
2016	-.5668701	.3405245	-1.66	0.135	-1.352121	.2183808
2017	-.596612	.3573236	-1.67	0.134	-1.420602	.2273777
2018	-.5764382	.3471938	-1.66	0.135	-1.377068	.2241921
2019	-.5442953	.3863685	-1.41	0.197	-1.435263	.3466722
2020	-.6067832	.4130563	-1.47	0.180	-1.559293	.3457265
_cons	-37.95297	29.34224	-1.29	0.232	-105.6163	29.71035
sigma_u	4.9884956					
sigma_e	.47910727					
rho	.99086016					(fraction of variance due to u_i)

```
. outreg2 using StateTime.doc, append ctitle(Model 5) addtext(Country Fixed Effects, Yes, Time
Fixed E
> ffacts, Yes) keep(ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect)
StateTime.doc
dir : seeout
```

```
. xtreg ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect
ln_PoliticStable
> i.Year, fe vce(cluster country)
```

```
Fixed-effects (within) regression      Number of obs   =      120
Group variable: Country               Number of groups  =       9

R-sq:  Within = 0.5724                Obs per group: min =       5
      Between = 0.0065                  avg   =      13.3
      Overall = 0.0030                  max   =      20

                                F(8,8)      =      .
corr(u_i, Xb) = -0.9158              Prob > F      =      .
```

(Std. err. adjusted for 9 clusters in country)

ln_Deforestation	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
CPIscore	.072404	.0310436	2.33	0.048	.0008174	.1439907
ln_GDP_2015	-.9870212	1.810525	-0.55	0.601	-5.162099	3.188057
ln_UrbanPop	8.094193	6.709692	1.21	0.262	-7.378386	23.56677
ln_RuralPop	1.393108	3.207153	0.43	0.675	-6.0026	8.788816
ln_GovtEffect	-.3123482	.3093322	-1.01	0.342	-1.025669	.4009731
ln_PoliticStable	.3709231	.1468897	2.53	0.036	.0321948	.7096514
Year						
2002	-.0147252	.1604245	-0.09	0.929	-.3846647	.3552143
2003	-.30007	.2495279	-1.20	0.264	-.8754825	.2753425
2004	-.3763656	.3309712	-1.14	0.288	-1.139587	.3868554
2005	-.4200734	.2990953	-1.40	0.198	-1.109788	.2696416
2006	-.3480908	.2749159	-1.27	0.241	-.982048	.2858663
2007	-.3002358	.2091062	-1.44	0.189	-.7824356	.181964
2008	-.2166293	.1881354	-1.15	0.283	-.6504703	.2172118
2009	-.4137031	.2052331	-2.02	0.079	-.8869714	.0595652
2010	-.3680295	.1914737	-1.92	0.091	-.8095688	.0735097
2011	-.2287179	.4304527	-0.53	0.610	-1.221344	.7639077
2012	-.1702125	.4552297	-0.37	0.718	-1.219974	.8795491
2013	-.0751916	.4439497	-0.17	0.870	-1.098942	.9485583
2014	-.0577401	.4947478	-0.12	0.910	-1.198631	1.08315
2015	-.0073084	.5371415	-0.01	0.989	-1.245959	1.231342
2016	-.0048343	.7036735	-0.01	0.995	-1.627508	1.61784
2017	-.0175034	.6621989	-0.03	0.980	-1.544537	1.50953
2018	-.0622183	.5870771	-0.11	0.918	-1.416021	1.291584
2019	-.0848642	.5994883	-0.14	0.891	-1.467287	1.297558
2020	-.2177774	.5866586	-0.37	0.720	-1.570615	1.13506
_cons	-29.56941	38.06178	-0.78	0.460	-117.34	58.20122
sigma_u	5.081342					
sigma_e	.44875726					
rho	.99226087	(fraction of variance due to u_i)				

```
. outreg2 using StateTime.doc, append ctitle(Model 6) addtext(Country Fixed Effects, Yes, Time
Fixed E
> ffects, Yes) keep(ln_Deforestation CPIscore ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect
ln_Pol
> iticStable)
StateTime.doc
dir : seeout
```

```
. *****ln_CorrControl
. *pooled method using OLS
. reg ln_Deforestation ln_CorrControl, r
```

```
Linear regression      Number of obs   =      1,808
                        F(1, 1806)      =      357.26
                        Prob > F          =      0.0000
                        R-squared         =      0.1357
                        Root MSE       =      2.3765
```

ln_Deforestation	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-.9627333	.0509348	-18.90	0.000	-1.062631	-.8628359
_cons	5.763946	.181322	31.79	0.000	5.408323	6.119569

```
. outreg2 using Myreg1.doc, replace ctitle(Model 1)
Myreg1.doc
dir : seeout
```

```
. reg ln_Deforestation ln_CorrControl ln_GDP_2015, r
```

```
Linear regression              Number of obs   =      154
                               F(2, 151)        =      43.75
                               Prob > F          =      0.0000
                               R-squared          =      0.4419
                               Root MSE       =      1.6767
```

ln_Deforestation	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-1.732572	.1998062	-8.67	0.000	-2.127349	-1.337795
ln_GDP_2015	1.542406	.1660927	9.29	0.000	1.21424	1.870571
_cons	-5.188016	.9148325	-5.67	0.000	-6.995541	-3.380491

```
. outreg2 using Myreg1.doc, append ctitle(Model 2)
Myreg1.doc
dir : seeout
```

```
. reg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop, r
```

```
Linear regression              Number of obs   =      154
                               F(3, 150)        =      36.17
                               Prob > F          =      0.0000
                               R-squared          =      0.4832
                               Root MSE       =      1.6189
```

ln_Deforestation	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-1.620013	.1800735	-9.00	0.000	-1.975821	-1.264205
ln_GDP_2015	1.662502	.1674927	9.93	0.000	1.331552	1.993452
ln_UrbanPop	-.9228031	.1575633	-5.86	0.000	-1.234133	-.611473
_cons	-2.920286	.8607212	-3.39	0.001	-4.62099	-1.219583

```
. outreg2 using Myreg1.doc, append ctitle(Model 3)
Myreg1.doc
dir : seeout
```

```
. reg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop, r
```

```
Linear regression              Number of obs   =      154
                               F(4, 149)        =      29.71
                               Prob > F          =      0.0000
                               R-squared          =      0.4857
                               Root MSE       =      1.6204
```

ln_Deforestation	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-1.628136	.1839638	-8.85	0.000	-1.991651	-1.264621
ln_GDP_2015	1.463886	.2117458	6.91	0.000	1.045474	1.882298
ln_UrbanPop	-1.513373	.6620969	-2.29	0.024	-2.821685	-.2050605

ln_RuralPop	-.9941259	1.004104	-0.99	0.324	-2.978249	.9899971
_cons	4.599465	7.450214	0.62	0.538	-10.12226	19.32119

```
. outreg2 using Myreg1.doc, append ctitle(Model 4)
Myreg1.doc
dir : seeout
```

```
. reg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect, r
```

Linear regression	Number of obs	=	154
	F(5, 148)	=	30.66
	Prob > F	=	0.0000
	R-squared	=	0.5204
	Root MSE	=	1.57

ln_Deforesta~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-.8903459	.3418898	-2.60	0.010	-1.565962	-.2147298
ln_GDP_2015	2.300752	.380177	6.05	0.000	1.549475	3.052028
ln_UrbanPop	-.8904644	.670366	-1.33	0.186	-2.21519	.4342609
ln_RuralPop	.7972436	1.12513	0.71	0.480	-1.426151	3.020638
ln_GovtEffect	-1.314276	.5249271	-2.50	0.013	-2.351596	-.2769557
_cons	-9.198593	8.554243	-1.08	0.284	-26.10282	7.705639

```
. outreg2 using Myreg1.doc, append ctitle(Model 5)
Myreg1.doc
dir : seeout
```

```
. reg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect
ln_PoliticStab
> le, r
```

Linear regression	Number of obs	=	151
	F(6, 144)	=	25.32
	Prob > F	=	0.0000
	R-squared	=	0.5617
	Root MSE	=	1.5212

ln_Deforestation	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-1.586084	.4157683	-3.81	0.000	-2.407881	-.7642868
ln_GDP_2015	2.727293	.4218979	6.46	0.000	1.89338	3.561206
ln_UrbanPop	.4887982	.8697131	0.56	0.575	-1.230255	2.207851
ln_RuralPop	2.637463	1.400465	1.88	0.062	-.1306621	5.405587
ln_GovtEffect	-1.439234	.5467845	-2.63	0.009	-2.519995	-.3584738
ln_PoliticStable	.7277233	.3076147	2.37	0.019	.1196997	1.335747
_cons	-24.26331	10.89345	-2.23	0.027	-45.79503	-2.731576

```
. outreg2 using Myreg1.doc, append ctitle(Model 6)
Myreg1.doc
dir : seeout
```

```
. *entity fixed effects
. xtset Country Year
```

```
Panel variable: Country (unbalanced)
Time variable: Year, 2000 to 2021, but with gaps
Delta: 1 unit
```

```
. xtreg ln_Deforestation ln_CorrControl, fe vce(cluster country)
```

Fixed-effects (within) regression	Number of obs	=	1808
Group variable: Country	Number of groups	=	101

R-sq: Within = 0.0038
 Between = 0.1577
 Overall = 0.1357

Obs per group: min = 5
 avg = 17.9
 max = 20

corr(u_i, Xb) = -0.4009 F(1,100) = 1.75
 Prob > F = 0.1893

(Std. err. adjusted for 101 clusters in country)

ln_Deforesta~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	.0791877	.05991	1.32	0.189	-.039672	.1980475
_cons	2.053074	.2133735	9.62	0.000	1.629747	2.476401
sigma_u	2.5815772					
sigma_e	.49074276					
rho	.96512446	(fraction of variance due to u_i)				

. outreg2 using StateOnly1.doc, replace ctitle(Model 1) addtext(Country Fixed Effects, Yes)
 StateOnly1.doc
 dir : seeout

. xtreg ln_Deforestation ln_CorrControl ln_GDP_2015, fe vce(cluster country)

Fixed-effects (within) regression Number of obs = 154
 Group variable: Country Number of groups = 9

R-sq: Within = 0.1512 Obs per group: min = 5
 Between = 0.1227 avg = 17.1
 Overall = 0.0928 max = 20

corr(u_i, Xb) = -0.6386 F(2,8) = 2.25
 Prob > F = 0.1673

(Std. err. adjusted for 9 clusters in country)

ln_Deforesta~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	.2085508	.1861406	1.12	0.295	-.2206902	.6377918
ln_GDP_2015	1.308562	1.165993	1.12	0.294	-1.380224	3.997347
_cons	-9.802209	9.767023	-1.00	0.345	-32.32501	12.72059
sigma_u	2.6768382					
sigma_e	.60428261					
rho	.95151031	(fraction of variance due to u_i)				

. outreg2 using StateOnly1.doc, append ctitle(Model 2) addtext(Country Fixed Effects, Yes)
 StateOnly1.doc
 dir : seeout

. xtreg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop, fe vce(cluster country)

Fixed-effects (within) regression Number of obs = 154
 Group variable: Country Number of groups = 9

R-sq: Within = 0.2697 Obs per group: min = 5
 Between = 0.0000 avg = 17.1
 Overall = 0.0026 max = 20

corr(u_i, Xb) = -0.8885 F(3,8) = 0.86
 Prob > F = 0.5009

(Std. err. adjusted for 9 clusters in country)

ln_Deforesta~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
----------------	-------------	---------------------	---	------	----------------------	--

ln_CorrControl	.1331161	.2670027	0.50	0.632	-.4825932	.7488255
ln_GDP_2015	.043588	1.267021	0.03	0.973	-2.878169	2.965345
ln_UrbanPop	6.515204	6.397458	1.02	0.338	-8.237361	21.26777
_cons	-24.67997	20.03494	-1.23	0.253	-70.88063	21.5207
sigma_u	4.6339102					
sigma_e	.56250146					
rho	.9854789	(fraction of variance due to u_i)				

. outreg2 using StateOnly1.doc, append ctitle(Model 3) addtext(Country Fixed Effects, Yes)
StateOnly1.doc
dir : seeout

. xtreg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop, fe vce(cluster country)

Fixed-effects (within) regression	Number of obs	=	154
Group variable: Country	Number of groups	=	9
R-sq: Within = 0.3295	Obs per group: min =		5
Between = 0.0153	avg =		17.1
Overall = 0.0097	max =		20
corr(u_i, Xb) = -0.7199	F(4,8)	=	1.64
	Prob > F	=	0.2557

(Std. err. adjusted for 9 clusters in country)

ln_Deforesta~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	.3199468	.1764131	1.81	0.107	-.0868625	.7267561
ln_GDP_2015	-.4964465	1.503899	-0.33	0.750	-3.964444	2.971551
ln_UrbanPop	-.8830979	4.860641	-0.18	0.860	-12.09176	10.32556
ln_RuralPop	-5.285386	4.282854	-1.23	0.252	-15.16166	4.590892
_cons	27.08182	32.27658	0.84	0.426	-47.34812	101.5118
sigma_u	3.1305245					
sigma_e	.54089141					
rho	.9710125	(fraction of variance due to u_i)				

. outreg2 using StateOnly1.doc, append ctitle(Model 4) addtext(Country Fixed Effects, Yes)
StateOnly1.doc
dir : seeout

. xtreg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect, fe
vce(cclus
> ter country)

Fixed-effects (within) regression	Number of obs	=	154
Group variable: Country	Number of groups	=	9
R-sq: Within = 0.3431	Obs per group: min =		5
Between = 0.0092	avg =		17.1
Overall = 0.0043	max =		20
corr(u_i, Xb) = -0.7560	F(5,8)	=	7.93
	Prob > F	=	0.0058

(Std. err. adjusted for 9 clusters in country)

ln_Deforesta~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	.3910983	.1630226	2.40	0.043	.0151675	.7670292
ln_GDP_2015	-.3138476	1.499891	-0.21	0.839	-3.772603	3.144908
ln_UrbanPop	.3830955	5.406794	0.07	0.945	-12.08499	12.85118
ln_RuralPop	-4.357071	4.626577	-0.94	0.374	-15.02598	6.311834

ln_GovtEffect	-.2933524	.35047	-0.84	0.427	-1.101538	.514833
_cons	18.03546	37.25589	0.48	0.641	-67.87678	103.9477

sigma_u	3.3086774					
sigma_e	.53725791					
rho	.97431059	(fraction of variance due to u_i)				

```
. outreg2 using StateOnly1.doc, append ctitle(Model 5) addtext(Country Fixed Effects, Yes)
StateOnly1.doc
dir : seeout
```

```
. xtreg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect
ln_PoliticSt
> able, fe vce(cluster country)
```

Fixed-effects (within) regression	Number of obs	=	151
Group variable: Country	Number of groups	=	9
R-sq: Within = 0.4252	Obs per group: min	=	5
Between = 0.0009	avg	=	16.8
Overall = 0.0000	max	=	20
	F(6,8)	=	28.55
corr(u_i, Xb) = -0.8379	Prob > F	=	0.0001

(Std. err. adjusted for 9 clusters in country)

ln_Deforestation	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	.1636526	.1666748	0.98	0.355	-.2207001	.5480053
ln_GDP_2015	-.405812	1.491769	-0.27	0.792	-3.845838	3.034214
ln_UrbanPop	2.656527	6.022848	0.44	0.671	-11.23219	16.54524
ln_RuralPop	-3.739221	4.462416	-0.84	0.426	-14.02957	6.551127
ln_GovtEffect	-.5432901	.3712767	-1.46	0.182	-1.399456	.3128754
ln_PoliticStable	.3615128	.0762038	4.74	0.001	.1857864	.5372392
_cons	8.032215	40.15508	0.20	0.846	-84.56556	100.63
sigma_u	3.9668428					
sigma_e	.50207596					
rho	.98423308	(fraction of variance due to u_i)				

```
. outreg2 using StateOnly1.doc, append ctitle(Model 6) addtext(Country Fixed Effects, Yes)
StateOnly1.doc
dir : seeout
```

```
. *time fixed effects
. reg ln_Deforestation ln_CorrControl i.Year
```

Source	SS	df	MS	Number of obs	=	1,808
				F(20, 1787)	=	14.07
Model	1605.06722	20	80.2533609	Prob > F	=	0.0000
Residual	10195.5015	1,787	5.70537297	R-squared	=	0.1360
				Adj R-squared	=	0.1263
Total	11800.5687	1,807	6.53047521	Root MSE	=	2.3886

ln_Deforesta~n	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-.9636749	.0574963	-16.76	0.000	-1.076442	-.8509078
Year						
2002	.0038804	.3541086	0.01	0.991	-.69063	.6983908
2003	-.0053796	.3541086	-0.02	0.988	-.6998901	.689131
2004	-.036976	.3550918	-0.10	0.917	-.7334149	.6594629
2005	-.0006857	.3550931	-0.00	0.998	-.697127	.6957557
2006	.009521	.3550958	0.03	0.979	-.6869257	.7059678
2007	.0307173	.3551048	0.09	0.931	-.6657471	.7271818
2008	.0471219	.3551149	0.13	0.894	-.6493623	.743606

2009	.0420814	.3551115	0.12	0.906	-.6543962	.7385589
2010	.0400214	.3551102	0.11	0.910	-.6564536	.7364964
2011	.1160591	.3503795	0.33	0.741	-.5711376	.8032558
2012	.113903	.3503782	0.33	0.745	-.5732912	.8010972
2013	.119501	.3503817	0.34	0.733	-.5676999	.8067019
2014	.1045974	.3503732	0.30	0.765	-.5825869	.7917817
2015	.0994521	.34947	0.28	0.776	-.5859607	.784865
2016	.0241369	.3592275	0.07	0.946	-.6804132	.7286871
2017	-.0047511	.3592195	-0.01	0.989	-.7092855	.6997832
2018	.0221055	.3603237	0.06	0.951	-.6845947	.7288056
2019	-.0121933	.3592187	-0.03	0.973	-.7167263	.6923396
2020	.0068078	.3592217	0.02	0.985	-.6977309	.7113466
_cons	5.72997	.3221562	17.79	0.000	5.098128	6.361813

```

. outreg2 using TimeOnly1.doc, replace ctitle(Model 1) addtext(Time Fixed Effects, Yes)
  keep(ln_Defore
> station ln_CorrControl)
TimeOnly1.doc
dir : seeout

```

```

. reg ln_Deforestation ln_CorrControl ln_GDP_2015 i.Year

```

Source	SS	df	MS	Number of obs	=	154
Model	345.977597	21	16.4751237	F(21, 132)	=	5.24
Residual	414.679544	132	3.1415117	Prob > F	=	0.0000
				R-squared	=	0.4548
				Adj R-squared	=	0.3681
Total	760.657141	153	4.9716153	Root MSE	=	1.7724

ln_Deforesta~n	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-1.743444	.1986338	-8.78	0.000	-2.136361	-1.350527
ln_GDP_2015	1.553983	.1518692	10.23	0.000	1.253571	1.854396
Year						
2002	-.0358954	.9207341	-0.04	0.969	-1.857199	1.785408
2003	-.1199614	.9200489	-0.13	0.896	-1.939909	1.699986
2004	-.1181647	.9201639	-0.13	0.898	-1.93834	1.70201
2005	-.3311196	.9186676	-0.36	0.719	-2.148335	1.486096
2006	-.5630877	.9176572	-0.61	0.541	-2.378304	1.252129
2007	-.2646023	.9192776	-0.29	0.774	-2.083024	1.55382
2008	-.3248026	.9188807	-0.35	0.724	-2.142439	1.492834
2009	-.556251	.9177217	-0.61	0.545	-2.371595	1.259093
2010	-.5503691	.9178096	-0.60	0.550	-2.365887	1.265149
2011	-.4338472	.8933051	-0.49	0.628	-2.200893	1.333199
2012	-.3061649	.8935427	-0.34	0.732	-2.073681	1.461351
2013	-.268878	.893651	-0.30	0.764	-2.036608	1.498852
2014	-.5552166	.8932877	-0.62	0.535	-2.322228	1.211795
2015	-.5945744	.8933324	-0.67	0.507	-2.361674	1.172525
2016	-.6520009	.988557	-0.66	0.511	-2.607464	1.303462
2017	-.7449712	.9879436	-0.75	0.452	-2.699221	1.209279
2018	-.8385324	.9873826	-0.85	0.397	-2.791673	1.114608
2019	-.9077135	.9870389	-0.92	0.359	-2.860174	1.044747
2020	-.8286439	.9874216	-0.84	0.403	-2.781861	1.124574
_cons	-4.820812	1.093018	-4.41	0.000	-6.982911	-2.658714

```

. outreg2 using TimeOnly1.doc, append ctitle(Model 2) addtext(Time Fixed Effects, Yes)
  keep(ln_Defores
> tation ln_CorrControl ln_GDP_2015)
TimeOnly1.doc
dir : seeout

```

```

. reg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop i.Year

```

Source	SS	df	MS	Number of obs	=	154
				F(22, 131)	=	5.87

Model	377.466089	22	17.1575495	Prob > F	=	0.0000
Residual	383.191052	131	2.92512254	R-squared	=	0.4962
				Adj R-squared	=	0.4116
Total	760.657141	153	4.9716153	Root MSE	=	1.7103

ln_Deforestation	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-1.624338	.1950782	-8.33	0.000	-2.010249	-1.238427
ln_GDP_2015	1.670178	.150764	11.08	0.000	1.371931	1.968425
ln_UrbanPop	-.9266889	.2824425	-3.28	0.001	-1.485428	-.3679502
Year						
2002	-.028562	.8884609	-0.03	0.974	-1.78615	1.729026
2003	-.1067638	.887806	-0.12	0.904	-1.863056	1.649528
2004	-.1064675	.887915	-0.12	0.905	-1.862975	1.650004
2005	-.3067972	.8864949	-0.35	0.730	-2.060496	1.446901
2006	-.5239399	.8855694	-0.59	0.555	-2.275807	1.227928
2007	-.2468016	.8870692	-0.28	0.781	-2.001636	1.508033
2008	-.299289	.8867037	-0.34	0.736	-2.0534	1.454823
2009	-.5092867	.8856669	-0.58	0.566	-2.261347	1.242774
2010	-.5076227	.8857319	-0.57	0.568	-2.259812	1.244566
2011	-.3610099	.8622764	-0.42	0.676	-2.066798	1.344778
2012	-.2380937	.8624694	-0.28	0.783	-1.944264	1.468077
2013	-.2005535	.8625757	-0.23	0.817	-1.906934	1.505827
2014	-.4709247	.8623565	-0.55	0.586	-2.176872	1.235022
2015	-.5065059	.8624347	-0.59	0.558	-2.212608	1.199596
2016	-.6705384	.9539201	-0.70	0.483	-2.55762	1.216543
2017	-.7566211	.9533182	-0.79	0.429	-2.642512	1.12927
2018	-.8405559	.9527704	-0.88	0.379	-2.725363	1.044251
2019	-.9014537	.9524405	-0.95	0.346	-2.785608	.9827007
2020	-.8184692	.9528128	-0.86	0.392	-2.70336	1.066422
_cons	-2.559912	1.25986	-2.03	0.044	-5.052216	-.0676092

```
. outreg2 using TimeOnly1.doc, append ctitle(Model 3) addtext(Time Fixed Effects, Yes)
    keep(ln_Defores
> tation ln_CorrControl ln_GDP_2015 ln_UrbanPop)
TimeOnly1.doc
dir : seout
```

```
. reg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop i.Year
```

Source	SS	df	MS	Number of obs	=	154
				F(23, 130)	=	5.66
Model	380.59156	23	16.5474591	Prob > F	=	0.0000
Residual	380.065581	130	2.92358139	R-squared	=	0.5003
				Adj R-squared	=	0.4119
Total	760.657141	153	4.9716153	Root MSE	=	1.7098

ln_Deforestation	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-1.633861	.1952442	-8.37	0.000	-2.020128	-1.247594
ln_GDP_2015	1.412839	.2909692	4.86	0.000	.8371916	1.988487
ln_UrbanPop	-1.692342	.7925206	-2.14	0.035	-3.260249	-.1244345
ln_RuralPop	-1.287121	1.244856	-1.03	0.303	-3.749921	1.175678
Year						
2002	-.0300425	.888228	-0.03	0.973	-1.787295	1.72721
2003	-.1104056	.8875791	-0.12	0.901	-1.866375	1.645564
2004	-.1104343	.8876893	-0.12	0.901	-1.866621	1.645753
2005	-.3119644	.8862755	-0.35	0.725	-2.065354	1.441426
2006	-.5309418	.885362	-0.60	0.550	-2.282525	1.220641
2007	-.2516568	.8868479	-0.28	0.777	-2.006179	1.502866
2008	-.3097539	.8865279	-0.35	0.727	-2.063643	1.444136
2009	-.5290746	.8856403	-0.60	0.551	-2.281208	1.223059
2010	-.5244776	.8856486	-0.59	0.555	-2.276627	1.227672
2011	-.3606678	.8620493	-0.42	0.676	-2.066129	1.344794
2012	-.2448507	.862267	-0.28	0.777	-1.950743	1.461041
2013	-.2137045	.8624422	-0.25	0.805	-1.919943	1.492534

2014	-.4848006	.8622338	-0.56	0.575	-2.190627	1.221026
2015	-.5236272	.8623665	-0.61	0.545	-2.229716	1.182462
2016	-.7127977	.9545442	-0.75	0.457	-2.601249	1.175654
2017	-.8022447	.9540879	-0.84	0.402	-2.689794	1.085304
2018	-.8928704	.9538622	-0.94	0.351	-2.779973	.9942319
2019	-.9608	.9539179	-1.01	0.316	-2.848012	.9264126
2020	-.8910056	.9551417	-0.93	0.353	-2.780639	.998628
_cons	7.195768	9.519032	0.76	0.451	-11.6365	26.02803

```
. outreg2 using TimeOnly1.doc, append ctitle(Model 4) addtext(Time Fixed Effects, Yes)
      keep(ln_Deforest
> tation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop)
TimeOnly1.doc
dir : seeout
```

```
. reg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect i.Year
```

Source	SS	df	MS	Number of obs	=	154
Model	409.422773	24	17.0592822	F(24, 129)	=	6.27
Residual	351.234368	129	2.72274704	Prob > F	=	0.0000
				R-squared	=	0.5382
				Adj R-squared	=	0.4523
Total	760.657141	153	4.9716153	Root MSE	=	1.6501

ln_Deforesta~n	Coefficient	Std. err.	t	P> t	[95% conf. interval]
ln_CorrControl	-.8327806	.3100081	-2.69	0.008	-1.446139 - .219422
ln_GDP_2015	2.289328	.3890978	5.88	0.000	1.519488 3.059167
ln_UrbanPop	-1.055352	.789469	-1.34	0.184	-2.617335 .506632
ln_RuralPop	.5834735	1.331789	0.44	0.662	-2.051504 3.218451
ln_GovtEffect	-1.402665	.4310486	-3.25	0.001	-2.255505 -.549825
Year					
2002	-.2820769	.860669	-0.33	0.744	-1.984932 1.420778
2003	-.3742261	.8603791	-0.43	0.664	-2.076507 1.328055
2004	-.3866487	.8608522	-0.45	0.654	-2.089866 1.316568
2005	-.6244518	.8606668	-0.73	0.469	-2.327302 1.078399
2006	-.6779525	.8556047	-0.79	0.430	-2.370787 1.014882
2007	-.5375851	.8603439	-0.62	0.533	-2.239797 1.164626
2008	-.5233962	.8580518	-0.61	0.543	-2.221073 1.17428
2009	-.6297864	.85524	-0.74	0.463	-2.3219 1.062327
2010	-.6811141	.8560421	-0.80	0.428	-2.374814 1.012586
2011	-.4695345	.8325859	-0.56	0.574	-2.116826 1.177757
2012	-.6037298	.8394001	-0.72	0.473	-2.264503 1.057044
2013	-.467482	.8359385	-0.56	0.577	-2.121407 1.186443
2014	-.6659544	.8339517	-0.80	0.426	-2.315948 .9840394
2015	-.6986062	.833955	-0.84	0.404	-2.348607 .9513942
2016	-1.018181	.925943	-1.10	0.274	-2.850182 .8138196
2017	-1.117174	.925807	-1.21	0.230	-2.948906 .7145573
2018	-1.141946	.9236936	-1.24	0.219	-2.969497 .6856042
2019	-1.206893	.9236717	-1.31	0.194	-3.0344 .6206138
2020	-1.281873	.9295449	-1.38	0.170	-3.121 .5572547
_cons	-6.954423	10.16349	-0.68	0.495	-27.06313 13.15428

```
. outreg2 using TimeOnly1.doc, append ctitle(Model 5) addtext(Time Fixed Effects, Yes)
      keep(ln_Deforest
> tation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect)
TimeOnly1.doc
dir : seeout
```

```
. reg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect
      ln_PoliticStab
> le i.Year
```

Source	SS	df	MS	Number of obs	=	151
				F(25, 125)	=	6.86

Model		439.781939	25	17.5912776	Prob > F	=	0.0000
Residual		320.573555	125	2.56458844	R-squared	=	0.5784
					Adj R-squared	=	0.4941
Total		760.355494	150	5.06903663	Root MSE	=	1.6014

ln_Deforestation	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-1.574421	.3769043	-4.18	0.000	-2.320361	-.8284806
ln_GDP_2015	2.675694	.4195874	6.38	0.000	1.845278	3.506109
ln_UrbanPop	.3110153	.9134234	0.34	0.734	-1.496763	2.118794
ln_RuralPop	2.356556	1.508651	1.56	0.121	-.6292512	5.342364
ln_GovtEffect	-1.464864	.4502198	-3.25	0.001	-2.355905	-.5738233
ln_PoliticStable	.7264278	.2432923	2.99	0.003	.2449222	1.207933
Year						
2002	-.5351892	.8678404	-0.62	0.539	-2.252753	1.182375
2003	-.655731	.8678271	-0.76	0.451	-2.373269	1.061806
2004	-.5618204	.8688196	-0.65	0.519	-2.281322	1.157681
2005	-.8531428	.8690505	-0.98	0.328	-2.573102	.866816
2006	-.9380193	.8692831	-1.08	0.283	-2.658439	.7823999
2007	-.7447001	.8683228	-0.86	0.393	-2.463219	.9738185
2008	-.7308905	.8681886	-0.84	0.401	-2.449144	.9873624
2009	-.8826558	.8700209	-1.01	0.312	-2.604535	.8392236
2010	-.9026393	.8694968	-1.04	0.301	-2.623481	.8182028
2011	-.5357882	.8550531	-0.63	0.532	-2.228044	1.156468
2012	-.4857839	.8623654	-0.56	0.574	-2.192512	1.220944
2013	-.3350275	.8625684	-0.39	0.698	-2.042157	1.372102
2014	-.6200977	.8724045	-0.71	0.479	-2.346695	1.106499
2015	-.5757072	.8739356	-0.66	0.511	-2.305334	1.15392
2016	-.8579443	.9411646	-0.91	0.364	-2.720626	1.004737
2017	-.9924898	.9399561	-1.06	0.293	-2.85278	.8678
2018	-1.150935	.9347223	-1.23	0.221	-3.000866	.6989966
2019	-1.286172	.9333254	-1.38	0.171	-3.133339	.5609945
2020	-1.335787	.9365409	-1.43	0.156	-3.189317	.5177441
_cons	-21.35969	11.70646	-1.82	0.070	-44.52822	1.808847

```
. outreg2 using TimeOnly1.doc, append ctitle(Model 6) addtext(Time Fixed Effects, Yes)
    keep(ln_Defores
> tation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect ln_PoliticStable)
TimeOnly1.doc
dir : seeout
```

```
. *Entity & time fixed effects
. xtreg ln_Deforestation ln_CorrControl i.Year, fe vce(cluster country)
```

```
Fixed-effects (within) regression      Number of obs      =      1808
Group variable: Country                Number of groups    =      101
```

```
R-sq:  Within = 0.0174                  obs per group: min =      5
      Between = 0.1402                  avg      =     17.9
      Overall = 0.0884                  max      =     20
```

```
corr(u_i, Xb) = -0.3381                F(20,100)          =      0.66
                                          Prob > F            =     0.8591
```

(Std. err. adjusted for 101 clusters in country)

ln_Deforestation	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	.0839617	.0578623	1.45	0.150	-.0308355	.1987589
Year						
2002	-.0003381	.0039994	-0.08	0.933	-.0082728	.0075966
2003	.0004687	.0041377	0.11	0.910	-.0077404	.0086778
2004	.0047739	.0055937	0.85	0.395	-.006324	.0158717
2005	.001612	.0046063	0.35	0.727	-.0075267	.0107507
2006	.0007227	.0046556	0.16	0.877	-.0085138	.0099592
2007	-.001124	.0056203	-0.20	0.842	-.0122746	.0100265

2008	-.0025533	.0061423	-0.42	0.679	-.0147395	.0096329
2009	-.0021141	.0060117	-0.35	0.726	-.0140412	.0098129
2010	-.0019347	.0058402	-0.33	0.741	-.0135215	.0096522
2011	.0317039	.1009849	0.31	0.754	-.1686473	.2320552
2012	.0318918	.1009489	0.32	0.753	-.1683879	.2321715
2013	.0314041	.1010513	0.31	0.757	-.1690788	.231887
2014	.0327026	.1006574	0.32	0.746	-.1669988	.2324039
2015	.03126	.1000894	0.31	0.755	-.1673144	.2298345
2016	-.1207505	.0970455	-1.24	0.216	-.3132859	.0717849
2017	-.1182336	.0970942	-1.22	0.226	-.3108656	.0743984
2018	-.1203258	.0974177	-1.24	0.220	-.3135997	.0729481
2019	-.1175852	.0971302	-1.21	0.229	-.3102886	.0751183
2020	-.1192407	.0969486	-1.23	0.222	-.3115839	.0731026
_cons	2.056015	.2083831	9.87	0.000	1.642589	2.469441
sigma_u	2.5833655					
sigma_e	.49013825					
rho	.96525383	(fraction of variance due to u_i)				

```
. outreg2 using StateTime1.doc, replace ctitle(Model 1) addtext(Country Fixed Effects, Yes, Time
Fixed
> Effects, Yes) keep(ln_Deforestation ln_CorrControl)
StateTime1.doc
dir : seeout
```

```
. xtreg ln_Deforestation ln_CorrControl ln_GDP_2015 i.Year, fe vce(cluster country)
```

```
Fixed-effects (within) regression      Number of obs   =      154
Group variable: Country                Number of groups =        9
```

```
R-sq:  Within = 0.1852      obs per group: min =      5
      Between = 0.1466      avg =      17.1
      Overall = 0.1113      max =      20
```

```
corr(u_i, Xb) = -0.8244      F(8,8) = .
      Prob > F = .
```

(Std. err. adjusted for 9 clusters in country)

ln_Deforesta~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	.1063108	.2099166	0.51	0.626	-.3777578	.5903794
ln_GDP_2015	2.174778	1.322544	1.64	0.139	-.8750127	5.224569
Year						
2002	-.240728	.2267454	-1.06	0.319	-.7636037	.2821478
2003	-.3007031	.2362086	-1.27	0.239	-.845401	.2439949
2004	-.3800681	.2390072	-1.59	0.150	-.9312197	.1710834
2005	-.4507435	.2599661	-1.73	0.121	-1.050226	.1487395
2006	-.5078387	.2971995	-1.71	0.126	-1.193182	.1775045
2007	-.5930296	.3018453	-1.96	0.085	-1.289086	.103027
2008	-.6089222	.3226863	-1.89	0.096	-1.353038	.1351938
2009	-.5925762	.336567	-1.76	0.116	-1.368701	.1835486
2010	-.6863287	.3629734	-1.89	0.095	-1.523347	.1506895
2011	-.5574707	.3987364	-1.40	0.200	-1.476958	.362017
2012	-.5449388	.3544359	-1.54	0.163	-1.362269	.2723917
2013	-.5382606	.3330722	-1.62	0.145	-1.306326	.2298053
2014	-.5768979	.3589786	-1.61	0.147	-1.404704	.2509083
2015	-.6173086	.3717203	-1.66	0.135	-1.474497	.23988
2016	-.6341599	.4998425	-1.27	0.240	-1.786799	.518479
2017	-.6801841	.5150017	-1.32	0.223	-1.86778	.5074119
2018	-.6993546	.5357131	-1.31	0.228	-1.934711	.536002
2019	-.717283	.5505746	-1.30	0.229	-1.98691	.5523443
2020	-.6860545	.5179646	-1.32	0.222	-1.880483	.5083741
_cons	-16.38016	10.61625	-1.54	0.161	-40.86127	8.100955
sigma_u	3.5788884					
sigma_e	.63580693					

rho | .96940439 (fraction of variance due to u_i)

```
. outreg2 using StateTime1.doc, append ctitle(Model 2) addtext(Country Fixed Effects, Yes, Time
Fixed
> Effects, Yes) keep(ln_Deforestation ln_CorrControl ln_GDP_2015)
StateTime1.doc
dir : seeout
```

```
. xtreg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop i.Year, fe vce(cluster country)
```

Fixed-effects (within) regression	Number of obs	=	154
Group variable: Country	Number of groups	=	9

R-sq: Within	=	0.3454	Obs per group: min	=	5
Between	=	0.0282	avg	=	17.1
Overall	=	0.0104	max	=	20

corr(u_i, Xb)	=	-0.9485	F(8,8)	=	.
			Prob > F	=	.

(Std. err. adjusted for 9 clusters in country)

ln_Deforesta~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	-.1170418	.29106	-0.40	0.698	-.7882272	.5541437
ln_GDP_2015	1.649394	1.461195	1.13	0.292	-1.720127	5.018915
ln_UrbanPop	8.099315	6.826484	1.19	0.269	-7.642586	23.84121
Year						
2002	-.1423267	.0640865	-2.22	0.057	-.2901104	.0054571
2003	-.2490957	.0830639	-3.00	0.017	-.4406414	-.0575499
2004	-.3587568	.1309851	-2.74	0.025	-.6608091	-.0567045
2005	-.4848398	.2036489	-2.38	0.044	-.954455	-.0152246
2006	-.6009836	.2872318	-2.09	0.070	-1.263341	.0613741
2007	-.6755635	.2926225	-2.31	0.050	-1.350352	-.0007749
2008	-.7411414	.3604972	-2.06	0.074	-1.572449	.0901666
2009	-.8025317	.4376211	-1.83	0.104	-1.811688	.2066244
2010	-.91234	.4880623	-1.87	0.099	-2.037814	.2131338
2011	-.7891931	.4199951	-1.88	0.097	-1.757704	.1793173
2012	-.7839737	.3773518	-2.08	0.071	-1.654149	.086201
2013	-.7921884	.3575211	-2.22	0.058	-1.616634	.0322568
2014	-.8662241	.3883404	-2.23	0.056	-1.761739	.0292905
2015	-.9441784	.4181925	-2.26	0.054	-1.908532	.0201753
2016	-.9993171	.5056132	-1.98	0.084	-2.165263	.166629
2017	-1.089702	.5465402	-1.99	0.081	-2.350026	.1706216
2018	-1.16249	.6008386	-1.93	0.089	-2.548026	.2230465
2019	-1.232266	.6408039	-1.92	0.091	-2.709962	.2454308
2020	-1.252974	.6744481	-1.86	0.100	-2.808254	.3023062
_cons	-43.2417	25.82592	-1.67	0.133	-102.7964	16.31299
sigma_u	6.7368744					
sigma_e	.57218855					
rho	.99283791	(fraction of variance due to u_i)				

```
. outreg2 using StateTime1.doc, append ctitle(Model 3) addtext(Country Fixed Effects, Yes, Time
Fixed
> Effects, Yes) keep(ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop)
StateTime1.doc
dir : seeout
```

```
. xtreg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop i.Year, fe
vce(cluster co
> untry)
```

Fixed-effects (within) regression	Number of obs	=	154
Group variable: Country	Number of groups	=	9

```
obs per group: min =      5
               avg =    17.1
               max =     20
```

$$\begin{aligned} F(8,8) &= . \\ \text{Prob } > F &= . \end{aligned}$$

In_Deforestati	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
In_CorrControl	.0814644	.1542733	0.53	0.612	-.2742904	.4372192
In_GDP_2015	.9471536	1.496642	0.63	0.544	-2.504109	4.398416
In_UrbanPop	1.627507	4.810439	0.34	0.744	-9.465386	12.7204
In_RuralPop	-4.459406	4.317141	-1.03	0.332	-14.41475	5.495937
Year						
2002	-.1700747	.0743588	-2.29	0.051	-.3415463	.001397
2003	-.2577339	.0863116	-2.99	0.017	-.4567687	-.0586991
2004	-.3562538	.1123906	-3.17	0.013	-.6154269	-.0970807
2005	-.4469502	.1548182	-2.89	0.020	-.8039615	-.0899388
2006	-.5265157	.2106191	-2.50	0.037	-1.012204	-.0408273
2007	-.6218608	.2333998	-2.66	0.029	-1.160082	-.0836398
2008	-.679555	.2851452	-2.38	0.044	-1.337101	-.0220089
2009	-.7197867	.3440381	-2.09	0.070	-1.51314	.0735665
2010	-.8145134	.3753197	-2.17	0.062	-1.680002	.0509754
2011	-.6852473	.3958647	-1.73	0.122	-1.598113	.2276183
2012	-.7099324	.3644037	-1.95	0.087	-1.550249	.130384
2013	-.7357629	.3515937	-2.09	0.070	-1.546539	.0750136
2014	-.7762314	.3548705	-2.19	0.060	-1.594564	.0421014
2015	-.8458986	.3776006	-2.24	0.055	-1.716647	.0248499
2016	-.8740827	.4702768	-1.86	0.100	-1.958543	.2103776
2017	-.9497096	.5017992	-1.89	0.095	-2.106861	.2074414
2018	-1.014217	.543996	-1.86	0.099	-2.268674	.2402397
2019	-1.079428	.5844818	-1.85	0.102	-2.427246	.268389
2020	-1.12621	.623423	-1.81	0.108	-2.563826	.3114064
_cons	3.259083	27.73801	0.12	0.909	-60.70488	67.22305
sigma_u	5.1157355					
sigma_e	.55634317					
rho	.98831138	(fraction of variance due to u_i)				

```
. outreg2 using StateTime1.doc, append ctitle(Model 4) addtext(Country Fixed Effects, Yes, Time
Fixed
> Effects, Yes) keep(ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop)
StateTime1.doc
dir : seeout
```

```
. xtreg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect
      i.Year, fe
> vce(cluster country)
```

```
Number of obs      =      154
Number of groups   =         9
```

```
Obs per group: min =      5
               avg =    17.1
               max =     20
```

$$\begin{aligned} F(8,8) &= \\ \text{Prob } > F &= \end{aligned}$$

ln_De foresta~n	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	.1443979	.1714446	0.84	0.424	-.250954	.5397498
ln_GDP_2015	1.701084	1.698086	1.00	0.346	-2.21471	5.616877

ln_UrbanPop	4.572146	4.68082	0.98	0.357	-6.221845	15.36614
ln_RuralPop	-2.60336	4.633993	-0.56	0.590	-13.28937	8.082647
ln_GovtEffect	-.5262407	.3299497	-1.59	0.149	-1.287106	.2346248
Year						
2002	-.2241694	.077375	-2.90	0.020	-.4025966	-.0457423
2003	-.3396226	.0604766	-5.62	0.001	-.4790818	-.2001634
2004	-.4552881	.0966292	-4.71	0.002	-.6781153	-.2324608
2005	-.601327	.1449584	-4.15	0.003	-.9356016	-.2670524
2006	-.6621093	.2077562	-3.19	0.013	-1.141196	-.1830225
2007	-.7808333	.2357178	-3.31	0.011	-1.3244	-.237267
2008	-.8266806	.2830353	-2.92	0.019	-1.479361	-.174
2009	-.8606945	.3352117	-2.57	0.033	-1.633694	-.087695
2010	-.9887925	.3785044	-2.61	0.031	-1.861625	-.1159598
2011	-.8695373	.3249421	-2.68	0.028	-1.618855	-.1202194
2012	-.9681352	.2805896	-3.45	0.009	-1.615176	-.3210944
2013	-.9478261	.2629788	-3.60	0.007	-1.554256	-.3413958
2014	-1.004349	.2628805	-3.82	0.005	-1.610553	-.3981457
2015	-1.085382	.2884863	-3.76	0.006	-1.750632	-.4201311
2016	-1.145946	.3555684	-3.22	0.012	-1.965889	-.3260043
2017	-1.246896	.3885514	-3.21	0.012	-2.142897	-.3508944
2018	-1.305989	.4197261	-3.11	0.014	-2.273879	-.3380986
2019	-1.385776	.4454209	-3.11	0.014	-2.412918	-.3586332
2020	-1.476882	.4419948	-3.34	0.010	-2.496124	-.4576399
_cons	-19.57777	33.37579	-0.59	0.574	-96.54248	57.38695
sigma_u	6.1716307					
sigma_e	.54080515					
rho	.99237992	(fraction of variance due to u_i)				

```
. outreg2 using StateTime1.doc, append ctitle(Model 5) addtext(Country Fixed Effects, Yes, Time
Fixed
> Effects, Yes) keep(ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop
ln_GovtEffect
> )
StateTime1.doc
dir : seeout
```

```
. xtreg ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop ln_GovtEffect
ln_PoliticSt
> able i.Year, fe vce(cluster country)
```

```
Fixed-effects (within) regression
Group variable: Country
Number of obs      =      151
Number of groups   =         9

R-sq:  Within = 0.4640
        Between = 0.0240
        Overall = 0.0118

Obs per group: min =         5
                avg  =        16.8
                max  =         20
```

```
corr(u_i, Xb) = -0.9112
F(8,8) = .
Prob > F = .
```

(Std. err. adjusted for 9 clusters in country)

ln_Deforestation	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
ln_CorrControl	.0674001	.1725783	0.39	0.706	-.3305663	.4653664
ln_GDP_2015	.7232143	2.378113	0.30	0.769	-4.760724	6.207153
ln_UrbanPop	4.149609	6.153133	0.67	0.519	-10.03954	18.33876
ln_RuralPop	-3.139391	4.835284	-0.65	0.534	-14.28958	8.010793
ln_GovtEffect	-.6132381	.415609	-1.48	0.178	-1.571634	.345158
ln_PoliticStable	.3409333	.2178729	1.56	0.156	-.1614825	.843349
Year						
2002	-.0833611	.0866725	-0.96	0.364	-.2832283	.1165061
2003	-.1818036	.0990748	-1.84	0.104	-.4102704	.0466632
2004	-.2231996	.1570493	-1.42	0.193	-.5853559	.1389567
2005	-.3400182	.2163925	-1.57	0.155	-.8390203	.1589839
2006	-.3546979	.2807917	-1.26	0.242	-1.002205	.2928089

2007		-.4728701	.3342308	-1.41	0.195	-1.243608	.2978674
2008		-.5063532	.3598597	-1.41	0.197	-1.336191	.3234848
2009		-.5337809	.3846304	-1.39	0.203	-1.42074	.3531785
2010		-.6175192	.4504266	-1.37	0.208	-1.656205	.4211665
2011		-.36902	.6380445	-0.58	0.579	-1.840353	1.102313
2012		-.4233007	.6661907	-0.64	0.543	-1.959539	1.112938
2013		-.406573	.6358715	-0.64	0.540	-1.872895	1.059749
2014		-.5148583	.7114589	-0.72	0.490	-2.155485	1.125769
2015		-.5382968	.756499	-0.71	0.497	-2.282787	1.206193
2016		-.528292	.8985647	-0.59	0.573	-2.600386	1.543802
2017		-.6198469	.9121642	-0.68	0.516	-2.723301	1.483608
2018		-.7242127	.8806065	-0.82	0.435	-2.754895	1.306469
2019		-.8267865	.8860503	-0.93	0.378	-2.870022	1.216449
2020		-.9474842	.8414799	-1.13	0.293	-2.88794	.9929718
_cons		-8.657422	45.17428	-0.19	0.853	-112.8295	95.51466

sigma_u		5.2287637					
sigma_e		.52269552					
rho		.99010579	(fraction of variance due to u_i)				

```
. outreg2 using StateTime1.doc, append ctitle(Model 6) addtext(Country Fixed Effects, Yes, Time
Fixed
> Effects, Yes) keep(ln_Deforestation ln_CorrControl ln_GDP_2015 ln_UrbanPop ln_RuralPop
ln_GovtEffect
> ln_PoliticStable)
StateTime1.doc
dir : seeout
```