Political Forecasts Based On Macroeconomic Phenomenon

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I. Abstract

This paper first conducts two types of panel data regressions – Fixed Effects and Random Effects, with a total of 18 regressions, on a data set comprising of the 50 States of the USA over a 15-year time frame (from 2006-2020). It uses a combination of 3 economic variables (GDP Growth Rate, Unemployment Growth Rate and Inequality Growth Rate) to understand if certain political orientations are better suited to dealing with certain economic phenomenon. It analyses the data set using the hypothesis that right-wing governments, proxied by the Republican Governor, are better suited to efficiency, while the left-wing Democrat leader is designed to create equality. Furthermore, this paper aims at creating a baseline model that can predict the party of the next governor of a state, given their economic conditions.

II. Introduction

Most governments in the world today are democratically lead. There are free and competitive elections, checks on political power, economic activities that boost citizen welfare and the continuous expansion of civil rights. However, democracy has evolved over time, to root itself into the orientation of the government that leads it, which, by definition, takes the side of either the left wing, the right wing, or a weighted amalgamation of the two, that they use to define their position on the political, social, ideological and economic spectrums.

Traditionally, the right wing has always been labelled as the 'conservative' orientation or wing, in many democracies, the key right-wing party also shares the moniker of the 'conservative party'. This is partially because of the right wing's ideas to 'keep the nation first' which implied closed economic policy, with little dependence on external outcomes, policies that favour current and most importantly free-market orientation without interference from government, with the notion that the 'the market can correct for inefficiencies by itself'. This type of government tends to focus on efficiency, and prioritizes this efficiency over equality, therefore, right-wing leaders endeavour to improve growth, reduce unemployment, and attempt to improve productivity.

On the other hand, the left-wing has almost always been considered the liberal-side of government, that focuses on reducing barriers to trade, international participation, equality in policy, in citizenship and even in economic livelihoods of the public. The left-wing, is also usually labelled as the progressive side, denoted as the 'progressive-left', their chief objective being, the reduction of disparity and inequality through government-augment redistribution efforts. The progressive-left also champions the cause of social equality, in terms of the advocation of women's empowerment, LGBTQ rights, and so on. Economically, this paper hypothesizes that the left-wing government will reduce income inequality, as is explained by Kohli (1989).

III. Literature Review

Understanding the impact of democracy on growth, has been an area of study that has warranted much attention, especially over the course of the last decade, with drastic changes in the way institutions function, and countries witnessing numerous changes in political institutions, within short spans of time. Acemoglu et al.'s (2018), seminal work on Democracy causing growth, conclusively established the long run impacts of Democracy being a 20-25% increase in real gdp per capita (Acemoglu et al. 2018). Various other authors also work in similar areas as they uncover links between inequality, growth and unemployment from a democratization context. However, a magnified look within a Democratic nation, to understand the links between political orientations and economic growth, has not seen as much comprehensive work.

Most of the economic and econometric literature in this area is region specific. For instance, Ahrend (2007)'s research on the impact of political institutions on growth, is focused on 77 Russian from 1990 -1998. Another paper by Cheliotis and Xenakis (2020), focuses on political orientations, economic conditions and incarceration in Greece. This paper explains how certain political orientations are more likely to increase forms of punishment in society, increasing fear and thus efficiency and public dissatisfaction. It attempts to provide a generally applicable juxtaposition between fear and efficiency using the political orientations of the Syrian-led government in Greece. In a series of essays edited by Kohli and Basu (1998), the authors look at regions within India that share similar cultures, and attempt to understand the links between democratic institutions, violence, and economic growth. While their main focus was to understand the impact of levels of democratic institutionalization on growth, they also found that, depending on culture and authority, nationalistic parties carry the ability to exercise power to limit violence and improve growth.

One reason for such geo-centric work, is perhaps because of the existence of region-specific effects such as culture, that affect how citizens elect leaders, and spending behaviour as well. This may lead to endogeneity, when we look at geographically-diverse data sets and perhaps even lead to misleading interpretations. Even when controlling for such individual or time-specific effects, by using perhaps a 'within' panel estimation, there could be factors such as the growth rate of population, that change over time and our specific to the country, that lead to endogeneity. The series of essays (Kohli and Basu, 1998), lends support to this claim. Alternatively, one may also prefer region-specific regressions due to the availability of data, and the orientation of the research idea. This paper utilizes a region-specific approach, precisely because the orientation of the research topic is specifically suited to the United States of America.

The expanse of literature centered around understanding political orientations in the US States is surprisingly minimal, much less predicting political orientations. Given the diversity in social groups, economic policy preferences, ideologies, and even cultures, one would generally expect a myriad of resources as reference when working on such similar research. However, in actuality, this is far from the case. This paper aims to introduce work in this academic spectrum and allow for significant dialogue and economic analysis to take place accounting for Diversity. Eventually, this work can and should be extended to various other nations, as we account for individual cultures and connotations in the same manner as authors have done.

IV. Data and Descriptive Statistics

We are using a multitude of resources to gather our data points, and as we use them to understand our values, it becomes imperative to understand how these are defined to understand the impact of each variable.

1. **Real GDP Growth:**

   One of our primary areas of study is the effect of a governor on the state's real Gross Domestic Product (GDP) growth. Our hypothesis suggests that a right-wing government would result in increases in GDP Growth. This variable has been procured by data from the *Bureau of Economic Analysis* (BEA)[1]. We estimate GDP Growth Rate via two methods – GDP Growth Rate and Log Differences in GDP. (For details on how these were calculated, please see Appendix C.I)

2. **Income Inequality Growth**:

   To understand the hypothesis of the different political orientations improving different economic variables, we are also considering the impact of the left wing (Democrats) on income inequality. To calculate income inequality, we are using the Interquartile range of the income distribution, and then normalizing this by the median. This data has been gathered by using the Monthly Household Income Data from US Census archives, presented by *IPUMS USA* [2]. The formula utilized to estimate the income inequality is given below:

$$Ineq_{i,t} = \frac{Income\ at\ 75th\ percentile_{i,t}\ -\ Income\ at\ 25th\ percentile_{i,t}}{Median\ Income_{i,t}}$$

   We use two methods to estimate the Inequality Growth Rate, and get Income Inequality Growth Rate and Log Differences in Income Inequality. (Please see Appendix C.II for further details)

3. **Unemployment Growth:**

   A metric for the growth rate of unemployment has also been captured. The main idea behind utilizing this particular variable is that, it is related to both income inequality

[1] Bureau of Economic Analysis, Real GDP Data, Organised by State - https://www.bea.gov/data/gdp/gdp-state
[2] US Census Data for Social, Economic and Health Research - https://usa.ipums.org/

(*positively* - as with an increase in the unemployment rate, it is more likely that economically poorer sections of society face the most impact, and therefore see drops in their income), and real GDP Growth(*negatively* – there is no dearth of economic literature that informs us of the inverse relationship between GDP growth and unemployment growth – for instance, Okun's Law (Klenton and Scott, 2020)). This data has been gathered from the *Bureau of Labour Statistics* (BLS). Once again we estimate this growth rate using two methods, and find Unemployment Growth Rate and Log Differences in Unemployment Growth. (Please see Appendix C.III for further details)

4. **Governor of State (GOS)**:- Perhaps the most important data variable that is required for the purpose of this paper is the governor of each state at every year in our sample. This has been encoded as a dichotomous(dummy) variable which denotes if the governor of the state was a Republican by the value 0, or a Democrat by the value 1, in each state at every year. In other words Republican = 0, and Democrat = 1 per this index[3]. We consider, for all intents and purposes of this paper, that Democrats represent the left-wing, while Republicans represent the right-wing orientation.

   In our time frame, two governors, identified as members of independent parties (neither Democrat nor Republican) and a secondary analysis has been conducted to assign these candidates to one side of the spectrum (please see footnote[4] for explanation). These governors are:-

   a. Alaska (2014-2017) – Gov. Bill Walker identified as an independent candidate, and for this paper has been 'converted' to a 'Democrat' representative, and shows the value '1' for his tenure as governor. This is because his policies were relatively left-wing, and he had also formed a coalition with a Democrat member to contest elections. It is assumed that one would not work with a candidate who does not share similarities in policy or ideology or both.
   b. Rhode Island (2011-2012) – Gov. Lincoln Chaffee identified as an independent candidate, and for this paper has been 'converted' to a 'Democrat' representative, and shows the value '1' for his tenure as governor. This is because his tax-policy was to increase taxes, which identifies as a traditional left-wing policy.

In summary, our data set is therefore a strongly balanced, wide panel that uses data from all the 50 states, from the years 2006-2020.

[3] This data has been gathered manually by Noor Puliani who has visited various webpages and understood the orientation of the governor. It has not yet been uploaded to her website for public use.
[4] While it is commonly understood that the political spectrum, like most spectrums, is not clearly bifurcated into two parts, for the purpose of analysing and presenting the results of this paper, representing these governors as part of a dichotomous index seemed to be a relatively risk-less undertaking that allows us to make important inferences as we proceed.

V. Model and Methodology

We divide our model into 2 parts – estimation and prediction. In our first part, we endeavour to understand the relationship between the factors we have chosen and the Governor of the State. Once this relationship is defined, we can utilize the results as we focus on creating predictions for the next governor of the state.

A. *Estimation*

First, we begin by conducting a fixed and random effects model that we use to understand the data. A total of 18 regressions were run, 9 for fixed effects and 9 for random effects following the structure given in Table 1:

Table 1

S.No	Dependent Variable	Model 1	Model 2	Model 3
1	Real GDP Growth	GOS	GOS + Unemployment Growth	GOS + Unemployment Growth + Inequality Growth
2	Unemployment Growth	GOS	GOS + Inequality Growth	GOS + Inequality Growth +Real GDP Growth
3	Inequality Growth	GOS	GOS + Real GDP Growth	GOS + Real GDP Growth + Unemployment Growth

Successively, 9 Hausman Tests were run to check the viability of the Random Effects versus the Fixed Effects model. The Hausman Test, between Fixed and Random Effects, allow us to compare which model is better to be utilized in testing. The null hypothesis (H0) of the Hausman Test states that both Fixed and Random Effect models are consistent, in which case, we prefer to use the Random Effects model as it is more efficient.

We find that the Random Effects are preferred to the Fixed Effects in all 9 cases.

For ease of comprehension, 3 models (with the highest statistical significance and interpretability of the 18) have been shown below (1 from each case of Table 1):

1. **Real GDP Growth (Model 1):**

$$GDPGrowth_{i,t} = \alpha_0 + \beta GOS_{i,t} + \gamma_i + \varepsilon_{i,t}$$

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = GDP_Growth ~ GOS, data = pdf, model = "random")

Balanced Panel: n = 50, T = 15, N = 750

Effects:
                 var std.dev share
idiosyncratic 8.0753  2.8417 0.966
individual    0.2863  0.5351 0.034
theta: 0.192

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-13.5012  -1.3260   0.2229   1.4687  20.8247

Coefficients:
            Estimate Std. Error z-value Pr(>|z|)
(Intercept)  1.57627    0.16304  9.6682  < 2e-16 ***
GOS         -0.40809    0.22578 -1.8075  0.07069 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    6058.7
Residual Sum of Squares: 6032.3
R-Squared:      0.0043486
Adj. R-Squared: 0.0030175
Chisq: 3.26692 on 1 DF, p-value: 0.07069
```

In this first Random Effects model, we look at the direct impact of Governor on the GDP of the state. Since the GOS factor is a dichotomous variable (takes the value of 1 when Democrat and 0 when Republican), we can understand the above regression as the impact of the each group GDP.

The 'GOS' estimate ß(hat) explains the impact of the Democrat governor on GDP growth rate, which here is 1.16(Statistically significant at 10%). While the impact of the Republican governor [measured in the intercept, α_0(hat)] GDP is positive at 1.58 percentage points (Statistically significant at 1%).

2. **Unemployment Growth (Model 2):**

$$UGrowth_{i,t} = \alpha_0 + \beta GOS_{i,t} + \delta GDPgrowth_{i,t} + + \gamma_i + \varepsilon_{i,t}$$

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = Ugrowth ~ GOS + perchg_inc_ineq, data = pdf, model = "random")

Balanced Panel: n = 50, T = 15, N = 750

Effects:
                  var std.dev share
idiosyncratic 1460.22   38.21     1
individual       0.00    0.00     0
theta: 0

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-42.99454 -18.62910 -12.50650  -0.88046 350.63563

Coefficients:
                Estimate Std. Error z-value Pr(>|z|)
(Intercept)      4.45082    1.83722  2.4226  0.01541 *
GOS              6.30088    2.73675  2.3023  0.02132 *
perchg_inc_ineq  0.59106    0.29585  1.9978  0.04574 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1045900
Residual Sum of Squares: 1032200
R-Squared:      0.013113
Adj. R-Squared: 0.010471
Chisq: 9.92557 on 2 DF, p-value: 0.0069934
```

In this case, we notice that all variables are statistically significant at the 5% level. Once again, we see the Democrat governor increases unemployment growth by more than what the Republican governor(intercept) increases it by.

Here controlling for percentage changes in income inequality lead to increases in the estimate of the impact of the Republican governor to 4.45, while there is a slight increase in the impact of the Democrat governor to 10.75. These results are only efficient if the percentage change in income inequality does not impact the governor of the state. To put it in simply, if a Texan’s tax bracket were to change, they would not change the party they vote for.

3. **Inequality Growth (Model 1):**

$$perchginc_{i,t} = \alpha_0 + \beta GOS_{i,t} + \gamma_i + \varepsilon_{i,t}$$

```
Oneway (individual) effect Random Effect Model
   (Swamy-Arora's transformation)

Call:
plm(formula = perchg_inc_ineq ~ GOS, data = pdf, model = "random")

Balanced Panel: n = 50, T = 15, N = 750

Effects:
                 var std.dev share
idiosyncratic 21.912   4.681     1
individual     0.000   0.000     0
theta: 0

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-50.155825  -2.399279   0.048291   2.550145  29.800878

Coefficients:
            Estimate Std. Error z-value  Pr(>|z|)
(Intercept) -0.78375    0.22524 -3.4796 0.0005021 ***
GOS          0.59575    0.33752  1.7651 0.0775543 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    15852
Residual Sum of Squares: 15787
R-Squared:      0.0041477
Adj. R-Squared: 0.0028164
Chisq: 3.11542 on 1 DF, p-value: 0.077554
```

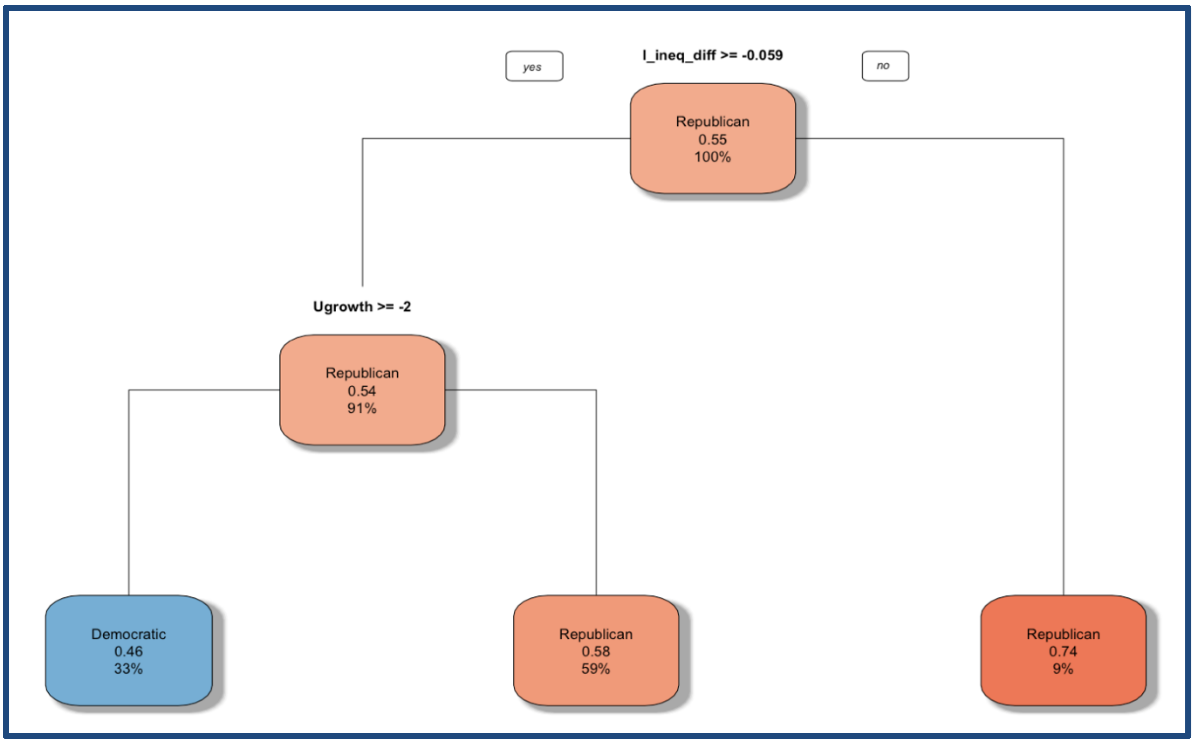
When we run this regression with a random effects model, we observe that in this case, a left-wing (Democrat) governor now only decreases the income inequality at a lower rate of .19 points, this is much lower than what the fixed effects model predicted. It is also important to note that while the fixed effects model estimated the governor's impact to be statistically significant at a 5% rate, the Random Effects model estimates the governor's impact to be significant only at the 10% rate and the standard errors are lower in the Random Effects case, as expected. Additionally, we notice that intercept is highly significant at 1%; if we consider the case of a Republican governor (where GOS = 0), then the intercept tells us the impact of the Republican governor. This would tell us that the right-wing governor reduces income inequality by .78.

B. Prediction

In this section of the paper, we work with the random forests to create predictions for the average US State, using our variables of interest (Real GDP, Unemployment and Inflation). First, we grow a tree using all our data. This part makes significant use of the *RPART* and *Caret* libraries on R Studio. This tree is shown below:

I. The Tree

Figure 1 – Complete Tree



Looking at the above tree, we note that, if the starting point is a Republican, then given that percentage change in income inequality is greater than or equal -0.059 percentage points, then there is a 0.74 chance that the next governor will be elected as a Republican, and a 0.54 probability that we will now consider the unemployment growth rate (Ugrowth). If Ugrowth is greater than or equal to - 2 percentage points, then there is a 0.58 probability that the incumbent Republican will remain or be reelected, otherwise, there is a 0.46 chance that Democrat governor will come into power.

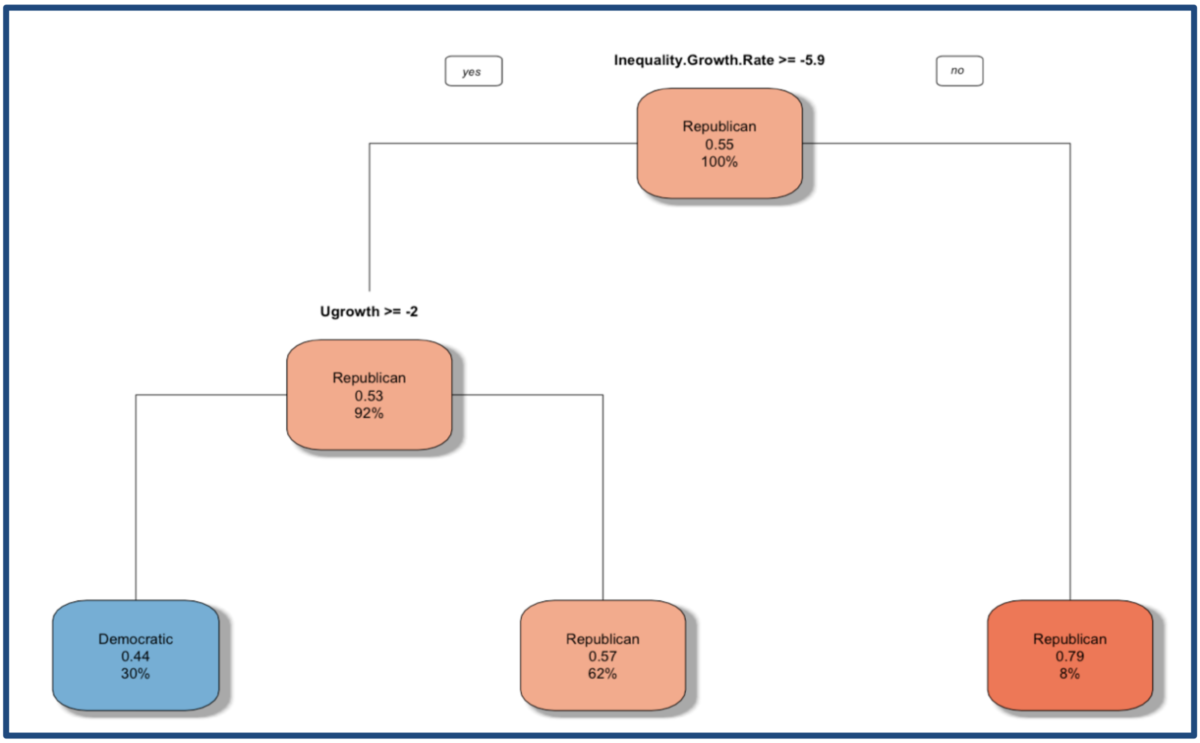
It is important to note here that the probabilities are not mutually exclusive, and hence they do not add up to 1, rather the part where a branch is created, shows the expected value of the branches. Additionally, the percentages within the boxes, represent the percentage of the data that has been used to result in that conclusion. For instance, the last 'Republican box' suggests that there is a 0.82 likelihood that a Republican will be elected, but it only uses 1% of the data to arrive at this conclusion. Perhaps the most significant data point that we have garnered from this tree is that the most significant factor is the *l_ineq_diff* or the percent changes in income inequality.

II. The test Error Rate

For this second part of the exercise, we first split the sample into training and testing sets. The training data set comprises of all the data from the years – 2006 to 2017 (80%) of our sample, whilst the test data set consists of the remainder of the year – 2018-2020 (20%) of our sample for all 50 states.

We then create a tree on the training data, a pictorial representation is given below:

FIGURE 2 – TRAINING TREE



Note: The complexity parameter has been kept constant (0.02) across both trees for consistency.

In this tree, we note certain similarities with our previous tree, such as the focus on features Unemployment and Income Inequality. Contrarily, one key difference is the primary parameter of interest being the Inequality Growth Rate and not the log differences in income inequality.

After growing the tree on the training data set, we use the parameters to cast predictions on the test data set, and use these predictions to estimate the accuracy and the test error rate.

The Confusion Matrix, which shows us how the predictions are mapped to true values, is shown below:

TABLE 2 – CONFUSION MATRIX

Confusion Matrix	Reference	
Prediction	Republican	Democrat
Republican	53	32
Democrat	33	32

Accuracy is calculated as the number of correctly predicted as a fraction of all outcomes. The accuracy rate of our model is 56.67% and conversely, the test error rate is 43.33%. These results also show that our data does not provide predictions that are very different from random predictions. Future areas of work would perhaps look at increasing or even replacing irrelevant features in the model, to increase the explanatory power of the model, and perhaps reduce the test error rate.

One interesting insight that was observed while growing the trees was the focus on the complexity-accuracy tradeoff. As we increase or decrease the complexity of the model to 0.025 (adjusted by the complexity parameter *cp*), we note that there is a sharp decrease in the accuracy of the model, which has changed to 44%.

It would also be prudent to analyse the model with models such as Panel VAR (See Appendix A), or Dynamic Linear Panel Models, to create statistically significant predictions.

VI. Conclusion

In this paper, we have conducted various types of regressions and analysis, and we find that our conclusions, in many areas are aligned with our hypothesis, while our predictions show room for improvement, there is a marginal improvement from a random prediction.

Our analysis shows that Republicans not only improve Real GDP Growth, they also reduce Inequality and Unemployment Growth. In one of our 18 models (See Appendix B), we find that Democrats are capable of reducing income inequality in certain cases, but this analysis generally favours the average Right-Wing Republican leader.

The tree suggests that our primary parameter of interest should be income inequality, and secondly we must focus on the unemployment growth rate. It (the pruned tree) shows no indication of importance towards real GDP growth rate. The accuracy rate of the model is 56.67%, and this can be improved in future studies by modifying the features of the model.

Therefore, it would perhaps be justified to say that this paper provides some interesting results, and is instrumental in carving a space in the academic nexus of machine learning, economics and political science. We can consider presidential elections or other countries, looking at a global sample in the future. However, much more analysis using more sophisticated techniques in both estimation and prediction, would be required to impart conclusive judgments.

VII. References

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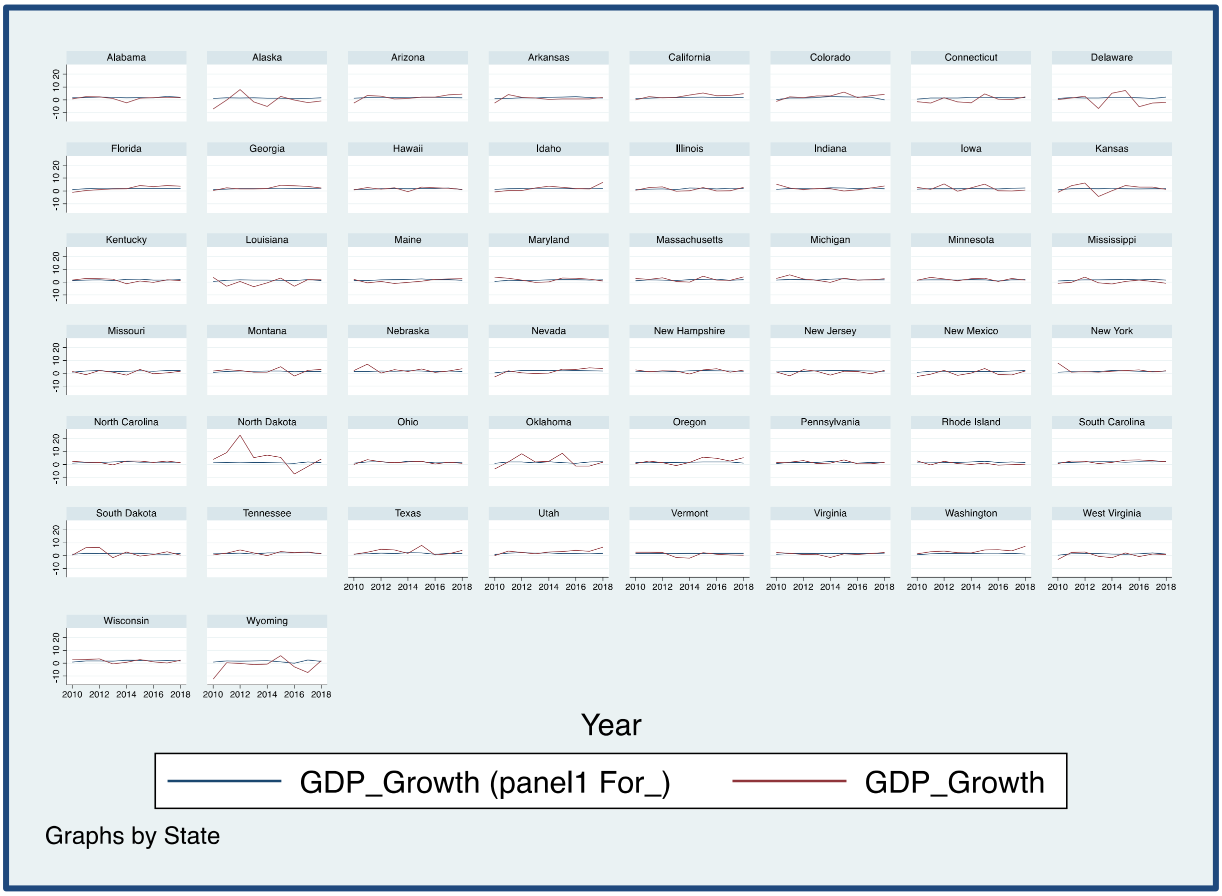
VIII. Appendix

A. Forecast Analysis For 50 States Using Stata



Note: This model has to be finetuned.

B. Summary of Estimates

No. of independent variables	Dependent Variable - Governor Of State								
	GDP Growth Rate			Unemployment Growth Rate			Inequality Growth		
	FE	RE (Democrat)	RE(Republican)	FE	RE (Democrat)	RE(Republican)	FE	RE (Democrat)	RE(Republican)
1	-0.39174 ()	1.16818 (.)	1.57627 (***)	9.4195 (*)	10.6406 (*)	3.9876 (*)	1.04941 (*)	-0.188(.)	-0.78375(***)
	GOS			GOS			GOS		
2	-0.1969053 ()	1.3958499()	1.6502641(***)	8.78356 (*)	10.7517(*)	4.45082(*)	0.973532 (*)	0.0042 ()	0.523334 (*)
	GOS + UGrowth			GOS + Income Change			GOS + GDP Growth		
3	-0.1398498 ()	1.3842299 ()	1.6012374 (***)	7.61475 (*)	14.58813 (.)	9.53248 (***)	0.9300185 (*)	-0.0839836 ()	0.4958220 ()
	GOS + UGrowth + Inequality Growth			GOS + Inequality Growth + GDP Growth			GOS + GDP Growth + UGrowth		

C. Data and Descriptive Statistics

I. Real GDP Growth:

The two methods of Real GDP Growth:

1. **GDP Growth Rate (*GDP_Growth_Rate*)**:- Since this data was gathered in quarterly intervals, the *GDP_Growth* has been calculated using the first quarter findings. GDP Growth is measured by:

$$GDP\_Growth_{i,t+1} = \frac{GDP_{\mathrm{i,t+1}} - GDP_{\mathrm{i,t}}}{GDP_{\mathrm{i,t}}} * 100$$

Where *i* is the respective US State, and *t* is year value that varies from 2006 to 2020.

2. **Log Differences in GDP (*l_rgdp_diff*):-** We use the same data to create a second GDP growth measure, utilizing the *ln* function. This is given by:

$$l\_rgdp\_diff_{i,t+1} = l\_rgdp_{i,t+1} - l\_rgdp_{i,t}$$

Where,

$$l\_rgdp_{i,t} = ln(rgdp_{i,t})$$

And *i* is the respective US State, and *t* is year value that varies from 2006 to 2020.

II. Income Inequality Growth:

The two methods of Income Inequality Growth:

1. **Inequality Growth Rate (*Inequality_Growth*)**: The first method utilizes the percentage change in our measure of income inequality, and use it in our analysis. This is a standard percentage change formula that is given by:

$$Inequality\_Growth_{i,t+1} = \frac{Ineq_{\mathrm{i,t+1}} - Ineq_{\mathrm{i,t}}}{Ineq_{\mathrm{i,t}}} * 100$$

Where *i* is the respective US State, and *t* is year value that varies from 2006 to 2020.

2. **Log Differences in Inequality (*l_ineq_diff*):** We use the same data to create a second Inequality growth measure, utilizing the *ln* function. This is given by:

$$l\_ineq\_diff_{i,t+1} = l\_ineq_{i,t+1} - l\_ineq_{i,t}$$

Where,

$$l\_ineq_{i,t} = ln(ineq_{i,t})$$

And *i* is the respective US State, and *t* is year value that varies from 2006 to 2020.

III. UNEMPLOYMENT GROWTH:

The two methods of Unemployment Growth:

1. **Unemployment Growth Rate (*Ugrowth*)**: We estimate unemployment growth with the following formula:

$$Ugrowth_{i,t+1} = \frac{Unem\ Rate_{i,t+1} - Unem\ Rate_{i,t}}{Unem\ Rate_{i,t}} * 100$$

Where *i* is the respective US State, and *t* is year value that varies from 2006 to 2020.

2. **Log Differences in Unemployment Rates (*l_ur_diff*):** We use the same data to create a second Unemployment growth measure, utilizing the *ln* function. This is given by:

$$l\_ur\_diff_{i,t+1} = l\_ur_{i,t+1} - l\_ur_{i,t}$$

Where,

$$l\_ur_{i,t} = ln(ur_{i,t})$$

And *i* is the respective US State, and *t* is year value that varies from 2006 to 2020.