Does a democratic government attract more foreign direct investment? Evidence from machine learning approaches

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Abstract

This paper aims to uncover the intrinsic effect of democracy on Foreign Direct Investment (FDI). Firstly, I present an approach for measuring democracy indicators based on Support Vector Machines. The output index is continuous on the [0,1] interval for 166 countries in the period between 1981 and 2011. In addition, based on the newly constructed democracy data set and "difference" GMM estimation strategy, I find a robust positive relationship between democracy and FDI. Besides, the undermining role of natural resources does not exist in my estimation. Finally, I compare six different estimation strategies for the prediction of FDI. The results show that the best one is Lasso regression combined with cross validation.

keywords: FDI, democracy, machine learning.

1 Introduction

Foreign direct investment (FDI) serves as a catalyst for employment, technological progress, productivity improvements, and finally economic growth. More importantly, FDI is a mechanism of technology transfer between countries, particularly to the less-developed nations. Because of these significant benefits, attracting FDI has become one of the integral parts of economic development strategies in many countries, especially developing countries.

The discussion among policymakers and academics, for the past two decades, has shifted from whether FDI should be encouraged to how developing countries can attract FDI. Until now, many of the countries that want to attract FDI still have weak democracies or nondemocratic governments. Therefore, understanding the effect of democratization on FDI is important. For instance, if democracy undermines FDI, then countries face a tradeoff between increased democratization and attracting more FDI (Asiedu and Lien, 2011).

There exists a large and growing literature on the relationship between political regime and FDI. However, answers to this issue could not be disclosed from theory because the theoretical impact of democracy on FDI is unclear. Li and Resnick (2003) build their theory on the logic of why firms invest abroad and derive a theory suggesting that democratic institutions affect FDI inflows both positively and negatively. The positive transmission mechanism is through property rights protection. A democratic government tend to offer more friendly policies regarding to property issue. The negative pathway considers the oligopolistic or monopolistic positions, which might be more easily obtained by Multinational Enterprises (MNEs) when operating in autocratic countries. No related literature tends to incorporate both effects in the same analysis framework and solve for the equilibrium.

Empirically, by using different estimation methodology and data sets, different scholars arrive at totally different conclusions.

Utilizing both cross-section and panel data analysis, Busse (2003) finds that democracy raises FDI inflows in emerging countries. Jensen (2003) empirically assesses the positive predictions about the political preconditions for attracting FDI using data from 114 countries. Jensen (2008) finds that democracy in emerging countries reduces expropriation risk for foreign investors. Jakobsen and De Soysa (2006) examine the same issue, and find that a negative relationship between democracy and FDI is fully dependent on sample size and estimation methodology. Their results support a strong positive relationship between democracy and FDI inflows to emerging countries. Guerin and Manzocchi (2009) test the effect on bilateral FDI flows from advanced to emerging countries between 1992 and 2004 and find that it is positive.

Nevertheless, some other scholars argue that this relationship is negative. According to Li and Resnick (2003), when the level of property right protection is controlled, democracy reduces FDI in developing countries.

Oneal (1994), Alesina and Dollar (2000), Büthe and Milner (2008) did not find a significant relationship between democracy and FDI. The most recent literature investigating on this causal effect is Kazemi and Azman-Saini (2017). This paper assesses the simultaneous role played by economic freedom and democracy in attracting FDI inflows. Employing a dataset covering 87 countries over the period of 1981-2010, Kazemi and Azman-Saini (2017) manifest that the influence of economic freedom on FDI inflows is positive and significant. On the other hand, the democracy has no significant role in attracting FDI.

Asiedu and Lien (2011) use natural resource as an interpretation of the controversy in literature and find that natural resources in host countries alter the relationship between FDI and democracy. Based on their conclusion, democracy promotes FDI if and only if the value of the share of minerals and oil in total exports is less than some critical value. Mathur and Singh (2013) put more emphasis on the importance of economic freedoms rather than political freedoms. They find that more democratic countries may receive less FDI flows if economic freedoms are not obtained.

This paper argues that the controversy in literature mainly comes from the statistical strategy with regard to the composition of existing democracy indicators. The major problem comes from the method employed to integrate the secondary data. It has been testified that the existing indicators do not fully uncover the information of political events and regime changes (Gründler and Krieger, 2016). Thus, one of the major contribution of this paper is to take advantage of machine learning approaches to recalculate the democracy index. By using the constructed new indicators, I would show the robust effect of democracy on FDI inflow.

Another contribution of this paper is to compare different estimation strategies of the prediction of FDI. I test six different methods including OLS Regression, Cross Validation, Ridge Regression, Lasso Regression, Support Vector Machine and Random Forest. The results show that the mean squared error (MSE) of Lasso Regression combined with Cross Validation is the smallest.

The remainder of the this paper is organized as follows. Section 2 presents the algorithm I use for the calculation of democracy and the new indicators in a world map. Section 3 discusses the bench model I take advantage of for the estimation of the effect of democracy on FDI inflow. I also show the empirical results in this section. Section 4 compares different machine learning strategies, and Section 5 concludes.

2 Recalculating democracy indicators

2.1 Limitations of traditional methods

A complete algorithm to calculate democracy indicators revolves around three steps. According to Munck and Verkuilen (2002), first of all, a definition of democracy has to be settled down. Secondly, based on the definition, some instrument variables have to be selected. Thirdly, some computational method for adding these variables should be taken advantage of.

Each step of the algorithm could be problematic. For instance, the democracy indicators mentioned in Dahl (1973), Rawls (2009) and Vanhanen (2000) are three representative traditional sources. Since there was no agreement on the definition of democracy, different sources take reference of quite different instrument variables. Dahl (1973) mainly focuses on election process. Rawls (2009) adds human rights and social inequality into the variable list. Vanhanen (2000) takes competitiveness in elections and participation as the measurement. The common problem with respect to these three indicators is the limited number of variables for calculation. Although narrowing the scope of variable selection could give us more year-country data points for analysis, limitation of the variable number would definitely give rise to measurement error. Two mostly referenced sources of democracy indicator are Polity IV score brought up by Marshall et al. (2014) and House (2014). These two data sources have quite similar definition of democracy level. However, they both suffer from the problem with aggregation strategy. They simply add up the underlying secondary data to arrive at the final index which is neither dichotomous nor continuous.

Acemoglu et al. (2019) come up with an approach to obtain a dichotomous indicator. Based on this approach, a country-year pair is documented as democratic if the House (2014) classified it as free or partly free and the Polity IV indicator is larger than zero. To deal with the cases where there is confliction between Polity IV and Freedom House, Acemoglu et al. (2019) further take advantage of Boix et al. (2013) and Cheibub et al. (2010). The drawback of this approach is that dichotomous variable is not a good way to manifest nuanced difference between countries.

Overall, the two major problems of democracy indicators include the selection of the instruments and the computational algorithm of the aggregation process. To solve these two problems, inspired by Gründler and Krieger (2016), this paper would take eight instrument variables into the analysis framework and use Support Vector Machines (SVM) approach for the democracy index output. The final indicator is a continuous variable from 0 to 1.

2.2 Recalculate democracy using Support Vector Machines

2.2.1 Basic theoretical framework of SVM

The democratization indicator $D_{i,t} \in \mathcal{D} \subseteq \mathbb{R}$ of country i in period t can be expressed as a function of several conditions, i.e.

$$D_{i,t} = F\left(x_{i,t}^{1}, \ldots, x_{i,t}^{m}\right) \quad \forall (i,t)$$

However, it is infeasible to have a perfect estimate of the function due to unobserved conditions. The very aim of using support vector regression in this case is to give less penalty on the points which have been correctly categorized but far from the hyperplane.

2.2.2 Algorithm

This paper references the algorithm mentioned in Gründler and Krieger (2016).

Firstly, I need to choose the feature variables for the measurement of democracy. Traditionally, there were two sets of variables to be considered: political participation and political competition. Inspired from Gründler and Krieger (2016), I also include the civil liberty and non-government institutions independence. For political participation, I include altogether three variables: voter turnout (Vanhanen, 2000), rating of political freedom (House, 2014), political oppression and violence indicator (Gibney et al., 2016). I further take advantage of the political competition score in Vanhanen (2000). Besides, the quality of civil liberties is provided by House (2014). At last, independence of the non-government institutions could be found from the INJUD data set in Cingranelli et al. (2014). In sum, there are six different variables in my basic feature space.

Secondly, I construct a sample data set by selecting the country-year pairs which could be definitely categorized as either democracy or autocratic. If the corresponding democracy indicator in Unit (2013) is over 8.0, I would view the country-year pair as democracy. On the other hand, I classify countries as autocratic if the Economist Intelligence Unit's Democracy Index is 3.0 or below.

Thirdly, I randomly select country-year pairs in the sample data set and create training set.

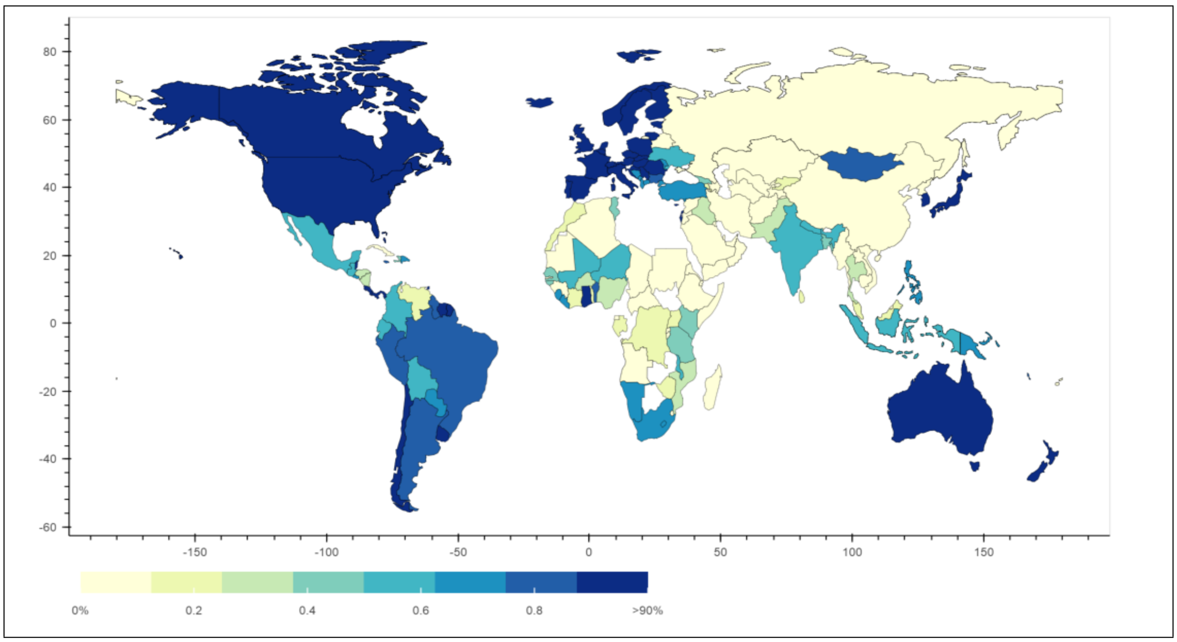
The fourth step is for the estimation of function F. To better approximate the real function, I use the kernel trick. Gaussian Kernel is taken advantage of.

In the fifth step, I utilize the estimated function F to calculate democracy indicator $D_{i,t} \in [0, 1]$ to all of the pairs. I further use bootstrapping to have a robust result.

2.2.3 Overview of democracy level in the world

The democracy output covers altogether 166 countries ranging from 1981 to 2011 due to data limitation. Figure 1 presents an overview of democracy level in the world in year 2011. Deeper color represents democracy. The picture manifests a segregation pattern of democracy. Almost all of the countries in Europe, North America and South America have democracy score over 0.8. However, a fair number of developing countries in Africa and Asia are highly autocratic. It could be inferred from the figure that a country's democracy level is positively correlated with its neighboring countries'.

Figure 1: Democracy in the world, 2011



The segregation or polarization pattern becomes apparent when I plot the kernel estimate of democracy index, shown in Figure 2. The data suggests that both in 1981 and 2010, the number of countries with high democracy level or high autocracy level largely outweighs that of the countries in the middle. In 1981, it is presented that there existed a significant number of countries with democracy index close to zero. Besides, there were also numerous countries where strong democratic institution was obtained. Figure 2 also manifests that although relative fraction of autocratic countries was extraordinarily high in 1981, in 2010, the fraction decreased. That is, we could observe a substantially higher number of democratic countries and a lower number of autocratic countries in 2010.

Figure 2: Kernel density estimate of democracy index

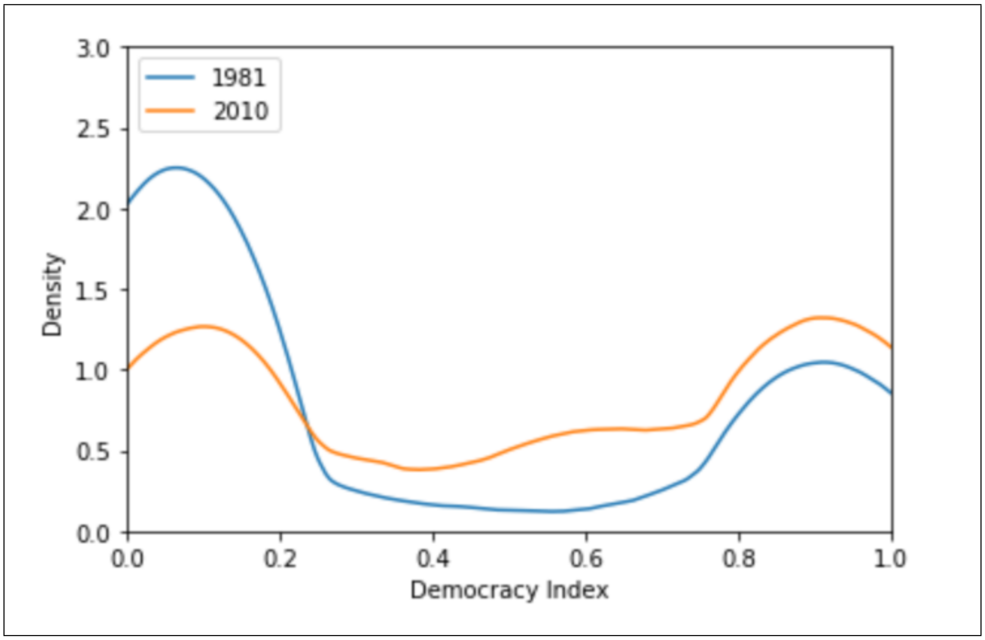
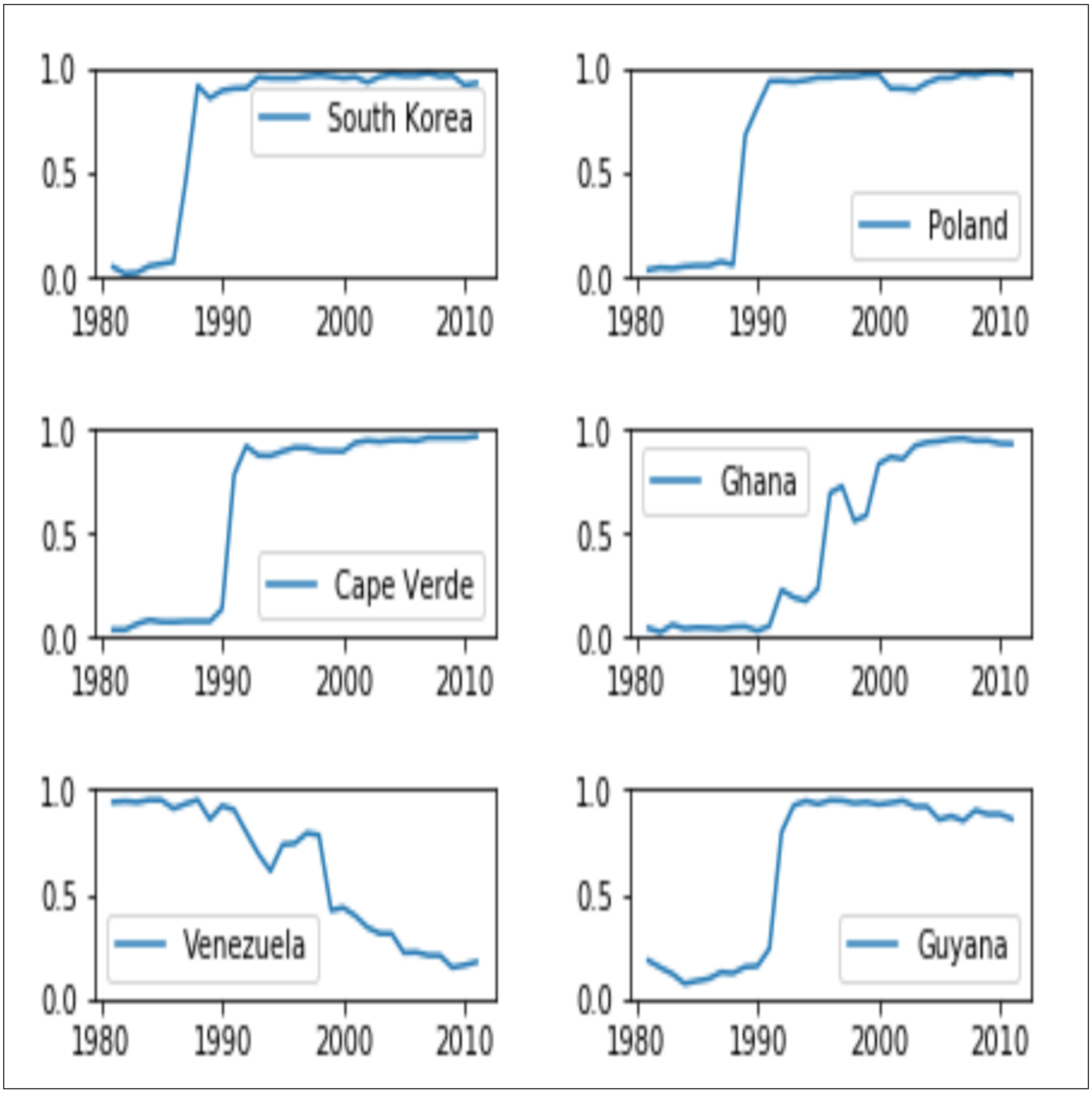


Figure 3 plots the democracy index for South Korea, Poland, Cape Verde, Ghana, Venezuela and Guyana over the period from 1981 to 2011. The figure shows the significant improvement of democracy during the late 1980s and 1990s. This trend is mentioned later in the literature as "Democracy's Third Wave" (Gründler and Krieger, 2016). A large number of countries were affected by "Democracy's Third Wave", including Asia Pacific countries, Eastern European countries and Latin American countries. South Korea, Poland and Guyana could all be classified as highly democratic countries in 2010, whereas in the early 1980s, they were all definitely autocratic countries. Similar movements towards democracy could also be observed in other Eastern European countries after the fall of the Iron Curtain in 1989. One thing about South American countries is that while "Democracy's Third Wave" covered large parts of the continent, Venezuela was not affected by this cross-national decrease of autocracy. In the early 1980s, Venezuela was a highly democratic country. However, from the late 1980s, the democracy level began decreasing in the late 1980s, which might be caused by several uprisings began in 1989. Cape Verde and Ghana, whose democracy level also increased from early 1990s, are two representative countries in Africa. Difference is that the democratization path of Ghana is more tortuous than that of Cape Verde.

Figure 3: Democratization path, 1981-2011



3 Estimating the effect of democracy on FDI

3.1 Model specification

A linear dynamic panel data (DPD) model is employed to capture the effect of lagged FDI on current FDI. DPD models contain unobserved panel-level effects that are correlated with the lagged dependent variable, which engenders inconsistent standard estimators. Arellano and Bond (1991) proposed the GMM estimator for DPD models. Referred to as the "difference" GMM estimator, this estimator usually takes the first difference of the data and then uses lagged values of the endogenous variables as instruments.

Blundell and Bond (1998) proposed a more efficient estimator, the "system" GMM estimator to mitigate the poor instruments problem by using additional moment conditions. However, the "system" estimator has a disadvantage that keeps it away from my analysis: too many instruments are used. Sargen tests of the "system" GMM failed with my data set. Thus, I only utilize "difference" GMM estimator as my estimation strategy.

The bench model is as follows:

$$y_{it} = \rho y_{it-1} + \lambda D_{it} + \beta \mathbf{X}_{it} + \theta_i + \epsilon_{it}$$

where y_{it} is the log of net FDI inflow in country i at 5-year period t, D_{it} is the democracy index, and $\mathbf{X}_{it}$ includes all the covariates of the regression.

3.2 Variables

The empirical analyses of this paper use a panel data of 166 countries over the period 1981 to 2011. Following the theoretical framework of Li and Resnick (2003), the dependent variable is net FDI as share of GDP. I further use trade/GDP as a measure of openness and the rate of inflation as a representation of macroeconomic uncertainty. Gross fixed capital formation as a share of GDP and the number of telephones per 100 population are used as the proxy variables to capture the level of infrastructure development in host countries. GDP per capita is a measure of domestic incomes. All else being equal, openness to trade, lower inflation and a better physical infrastructure should have a positive effect on FDI. Higher domestic incomes imply a greater demand for goods and services and therefore make the host country more attractive for FDI. According to Asiedu and Lien (2011), measures of natural resources are employed to capture a country's natural resource export intensity. The descriptive statistics of the variables is reported in Table 1.

Table 1: Summary statistics

	count	mean	std	min	25%	50%	75%	max
FDI	4381	3.78	12.75	-58.32	0.46	1.69	4.30	451.72
DEMOCRACY	4850	0.48	0.39	0.01	0.06	0.47	0.92	0.98
IMPORTS	4291	41.98	24.89	0.00	25.75	36.44	53.55	236.39
EXPORTS	4291	36.26	25.25	0.01	20.19	30.72	46.64	231.19
INFLATION	4032	38.46	473.33	-17.64	2.49	5.72	11.73	23773.13
FIXED CAPITAL	3960	21.75	7.55	-2.42	17.38	21.30	25.30	89.39
FIXED TELEPHONE	4816	14.39	17.14	0.00	1.04	6.69	22.92	74.74
GDP PER CAPITA	4516	10284.54	15887.45	131.65	1030.25	3414.88	11095.57	111968.35
FUEL EXPORTS	3331	16.79	27.94	0.00	0.51	3.47	15.59	99.96
ORES AND METALS EXPORTS	3452	7.53	13.74	0.00	0.54	2.31	6.39	84.19

Note: Apart from democracy, all the other variables come from World Development Indicators. FDI is the net inflows as share of GDP. Imports and exports are imports and exports of goods and services percent of GDP respectively. Inflation is the annual inflation rate. Fixed capital is the share of gross fixed capital formation in GDP Fixed telephone is the number of telephones per 100 people. GDP per capita is in constant 2010 US dollar. Fuel exports is the share of fuel in total merchandize exports, and ores and metals exports is the share of ore and metal in total merchandize exports.

3.3 Results

I use the two-step GMM estimator, which is asymptotically efficient and robust to all kinds of heteroskedasticity. There are three main hypotheses I would like to test. (1) Does democracy have a positive effect on FDI? (2) Would natural resources undermine the effect of democracy on FDI? (3) Will different natural resources individually affect FDI? The empirical results are presented in Table 2. I use four models to test these three hypotheses respectively. The bench model, whose result is shown in column 1, is aimed to test hypothesis 1. In the second model, an interaction term between

Table 2: The effect of Democracy on FDI, difference GMM

Dependent variable: FDI/GDP	(1)	(2)	(3)	(4)
LAGGED FDI/GDP	0.544***	0.546***	0.545***	0.544***
	(0.000)	(0.000)	(0.000)	(0.000)
DEMOCRACY	0.649***	1.053**	0.567***	0.596***
	(0.004)	(0.021)	(0.003)	(0.000)
NATURAL RESOURCES	0.764	0.103***		
	(0.457)	(0.002)		
NAT×DEM		-0.071		
		(0.204)		
FUEL EXPORTS			0.029	
			(0.658)	
ORES AND METALS EXPORTS				0.146
				(0.204)
Number of Countries	131	131	133	131
Sargan test(p-value)	0.204	0.190	0.195	0.191
Serial correlation test(p-value)	0.151	0.132	0.159	0.148

Note: p-value in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

democracy index and natural resource is constructed as a way to test hypothesis 2. The third and fourth column utilize fuel exports, ore and metal exports respectively as variables to test hypothesis 3.

(1) Does democracy have a negative effect on FDI?

Firstly, I focus on the coefficient of democracy. The result is reported in the first column. Note that $\hat{\lambda}$ is positve and significant at the 1% level. It suggests that all else equal, democracy stimulates the inflow of FDI. I can use an example here to state this positive effect. Considering the two countries that have extremely different levels of democratization in my sample: Saudi Arabia and Czech Republic, the result shows that an improvement in democracy from the level of Saudi Arabia (0.184) to the level of Czech Republic (0.814) will increase FDI/GDP by about 40 percentage point, which is a huge effect. The estimated coefficient of lagged FDI, $\hat{\rho}$, is positive and significant at 1% level, suggesting that current FDI is positively correlated with future FDI. Note that the effect of one unit increase in the level of current democracy on current FDI is equal to $\hat{\lambda}$, and the long run effect on FDI is $\hat{\lambda}/(1-\hat{\rho})$. Since

$\hat{\lambda} < \hat{\lambda}/(1-\hat{\rho})$, I could find that past levels of democratization have an impact on current and future FDI flows.

(2) Would natural resources undermine the effect of democracy on FDI?
Asiedu and Lien (2011) hypothesized that natural resources have a negative effect on FDI, which is contradicted by my results. In the column 1, the sign of the coefficient is positive, although it is not significant. It could be inferred from the result that in my data sample, natural resources do not have a direct effect on FDI inflow. As for the undermining effect, Asiedu and Lien (2011) found the evidence that natural resources significantly alter the relationship between FDI and democracy. Thus, I make an interaction term in my model and test if I could get the similar result. The result shows that the interaction term is not significant even at 20% level. The joint significance test of natural resource and the interaction term also shows the jointly insignificance result. The conclusion arrived by Asiedu and Lien (2011) is highly dependent on sample size and estimation methodology. My sample ranges from 1981-2011 as compared with 1982-2007 in their paper. Financial crisis is the most significant shock in this time period, which is one of the explanations for the different results.

(3) Will different natural resources individually affect FDI?
In this paper, the share of fuel in total merchandise exports and the share of ores and metals in total merchandise exports are two individual measurements of natural resources. According to Boschini et al. (2007), different types of natural resources have different effects on the economic growth. The question here revolves around the separate channel of different resources' influence on FDI. Based on the results in the third and fourth column, the estimation coefficients of both variables are not significant. Thus, I cannot find the evidence of separate influence.

4 Comparison of different FDI prediction models

4.1 Methods

4.1.1 Cross Validation

In this paper, I simply make use of the k-fold cross-validation. Based on the algorithm of k-fold cross-validation, the whole data set D is firstly split into k mutually exclusive folds $D_1, D_2, D_3, ..., D_k$ of almost equal size. And each time for $t \in \{1, 2, \ldots, k\}$, the data set is trained on $D \backslash D_t$ and tested on D_t. The measurement of cross-validation estimate of accuracy is the overall number of correct classifications, divided by the number of instances in the data set. Let D_i be the test set that includes instance $x_i = \langle v_i, y_i \rangle$, then the cross-validation estimate of accuracy could be expressed as:

$$\text{accuracy}_{\text{cv}} = \frac{1}{N} \sum_{\langle v_1, y_i \rangle \in D} \delta \left(\mathcal{I} \left(D \backslash D_{(i)}, v_i \right), y_i \right)$$

The algorithm further repeats cross-validation multiple times using different splits into folds. This procedure helps to provide a better Monte-Carlo estimate to the complete cross-validation (Kohavi et al., 1995).

4.1.2 Ridge Regression

In ridge regression, the cost function is altered by adding a penalty equivalent to square of the magnitude of the coefficients. Assume that the data set has N instances and p features. The new cost function could be written as the following expression:

$$Ridge\ Cost\ Function = \sum_{i=1}^{N} \left(y_i - \sum_{j=0}^{p} w_j \times x_{ij} \right)^2 + \lambda \sum_{j=0}^{p} w_j^2$$

Thus, ridge regression puts constraint on the coefficients, w. The penalty term λ regularizes the coefficients such that if the coefficients take large values, the optimization function is penalized. Based on that, ridge regression shrinks the coefficients and helps to decrease the model complexity and multi-collinearity.

4.1.3 Lasso Regression

The cost function for Lasso (least absolute shrinkage and selection operator) regression can be written as:

$$Lasso\ Cost\ Function = \sum_{i=1}^{N} \left(y_i - \sum_{j=0}^{p} w_j \times x_{ij} \right)^2 + \lambda \sum_{j=0}^{p} |w_j|$$

Similar to Ridge regression cost function, for $\lambda = 0$, the equation above reduces to the same cost function as regular regression. The only difference is that instead of taking the squared sum of the coefficients, Lasso makes use of magnitudes. This kind of regularization could cause zero coefficients, i.e. some of the features are completely neglected for the evaluation of output. So Lasso regression not only helps in reducing over-fitting but also serves as a way of feature selection. If the coefficient of democracy is close to zero in my Lasso regression, then there is possibility that the relationship between democracy level and FDI is unclear.

4.1.4 Random Forest Regression

A Random Forest is an ensemble technique capable of performing both regression and classification tasks. It takes advantage of multiple decision trees and a technique called Bootstrap Aggregation. The basic idea behind Random Forest is to combine multiple decision trees in determining the final output instead of depending on individual decision trees. The algorithm of the python module I use in this study is as follows. Firstly, the features space and the dependent variable of the data set is passed to the method built for the random forest regression model. Secondly, grid search cross validation method is utilized from the sklearn library to determine the optimal values to be used for the hyperparameters of the model. The chosen two hyperparameters, max_depth and n_estimators, are both optimized. According to sklearn documentation, max_depth refers to the maximum depth of the tree and n_estimators represents the number of trees in the forest. Finally, a random forest regressor object is created and passed to the cross_val_score function which performs

K-Fold cross validation. The output is chosen to be MSE, which can be used to determine the model performance.

4.1.5 Mean Squared Error

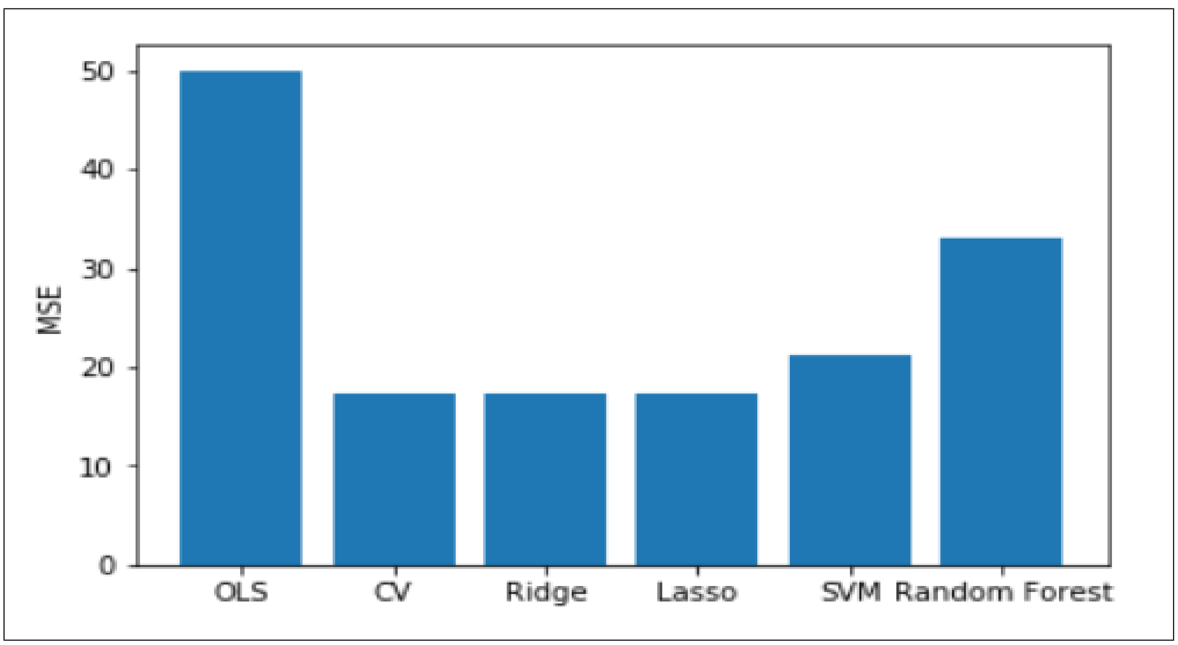
The MSE could be expressed as:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

4.2 Results

Figure 4 presents the comparison of the MSE of different estimation strategies. All of the machine learning approaches in the figure are combined with Cross-Validation. I rescale the MSE to make it lie between 0 and 50. The results show that the best three models are Cross-Validation, Ridge Regression and Lasso Regression. Besides, all of the machine learning methods have better performance than the baseline regression.

Figure 4: Comparison of MSE



Besides, Table 3 compares different coefficients of the democracy index and natural resources. The results manifest that all of the coefficients are positive with respect to the democracy, which further proves the positive correlation between democracy level and FDI inflow. In addition, the coefficient in the Lasso column sheds light on the significance of the effect of democracy on FDI. Considering the same two countries, Saudi Arabia and Czech Republic, the coefficient shows that an improvement in democracy from the level of Saudi Arabia (0.184) to the level of Czech Republic (0.814) will increase FDI/GDP by about 60 percentage point. Finally, natural resources do not have a significant effect on FDI based on the Lasso Regression, which is similar to the results in Table 2.

Table 3: Comparison of the coefficients

Dependent variable: FDI/GDP	OLS	CV	Ridge	Lasso	SVM	Random Forest
LAGGED FDI/GDP	0.544	0.323	0.698	0.985	0.562	0.433
DEMOCRACY	0.649	0.239	0.849	0.762	0.354	0.983
NATURAL RESOURCES	0.764	1.256	-0.125	0.002	-0.153	0.192

5 Conclusion

Having reliable measurements of democracy is significant for understanding of democratization and its effects on political and economic outcomes. Existing indicators have some technical deficiency, which makes scholars arrive at controversial conclusions. In this paper, I take advantage of Support Vector Machine approach and create a continuous democracy indicators database ranging from 1981 to 2011.

By using this newly constructed variable, I further estimate the effect of democracy on FDI. The results show that there is a robustly positive relationship between net inflows of FDI and the democracy level. Secondly, natural resources do not have a direct effect on FDI inflow and cannot significantly undermine the relationship between FDI and democracy as indicated by Asiedu and Lien (2011). As a matter of fact, by using the GMM models, I find that the effect natural resources place on FDI could be explained by other variables, especially the lagged FDI.

I further make use of different machine learning approaches to build FDI prediction models and test the positive effect. Lasso Regression combined with Cross-Validation model has the best performance. Comparison of the coefficients prove that democracy plays a significant role of determining FDI.

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