The impact of Economics Freedom on Economics Growth

--- Empirical Studies Based on a Machine Learning Indicator

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Abstract

This paper empirically examines the impact of economic freedom level on economic growth by using a machine-learning constructed economic freedom index that measure four basic areas - government influence, legal structure and property rights, open markets, and access to sound money. This paper selects SVR model with linear kernel to construct the new economic freedom index, after comparing 6 different machine learning models - Support Vector Regression (SVR) model with three different kernels, Random Forest, Decision Tree, and Neural Network. The empirical results show that economic freedom is a significant determinant of economic growth, even when education, health and openness are taken into account.

keywords: economics freedom index, machine learning, Support Vector Regression, economic growth

1. Introduction

Economists has been trying to understand the cause of economics growth, since Adam Smith inquired the nature of the nations' wealth. Solow (1956) addressed the role of labor, capital, technology in promoting the economic growth. More recent growth theory emphasizes the impact of human capital as well. (Lucas (1988), Romer (1990)) Since the new century, cultural norms and institutions are often believed to explain the economic growth. (Jakob de Haan, Jan-Egbert Sturm, 2002) One of the important questions in this area is the role of economic freedom. In fact, there are much literature indicating the relationship of economics freedom and economic growth. For example, Leblang (1996), and Nelson and Singh (1998) found that there exists a positive correlation between economic freedom and economic growth. Goldsmith (1995) also pointed out that both economic and political freedom are related to the economic growth. Gwartney, Lawson and Block (1999) even developed a measurement of economic freedom which extracted the political freedom effects and concluded there is positive correlation between economic freedom and growth.

Before the economists can actually analyze the relationship between economics freedom and economic growth, they need to be able to quantify the economic freedom level of a country or an area. However, there is not a unified approach to measure economics freedom, for instance, Heckelman (2000) use Heritage economics freedom index[1]; Shi (2008) use EFW Index compiled by Fraser institute[2]; Gwartney, Lawson and Block (1999) have developed a measure of economic freedom independent of political freedom for their own research. In fact, the measurement of economics freedom has always been a controversial issue. Before the development of EFW Index and Heritage index, various methods are used to quantify the economics freedom degree. After the development of these two indices, the two indices have always been critically discussed. For instance, De Haan, Lundström & Sturm (2006) identified various shortcomings of empirical studies using EFW Index.

[1] The Index of Economic Freedom Composition (Heritage Foundation).
[2] Economic Freedom of the World (Fraser Institute)

Therefore, the key contribution of this paper is to use machine learning methods to construct a reliable economic freedom index, whose internal logic makes much more sense compared with traditional indices construction. In order to select a best model with the highest prediction accuracy, this paper compares several machine learning classification models, including Support Vector Machine with different kernels, Random Forest, Decision Tree, and Neural Network. According to the forecast mean squared error of the models for test sample, this paper eventually selects Support Vector Machine to construct the new economic freedom indicator. This method is able to greatly solve the weights and subjectivity problems of traditional economic freedom index construction.

The goal of this paper is to review and extend the empirical evidence on the relationship of economic freedom and economic growth based on an reliable economic freedom indicator.

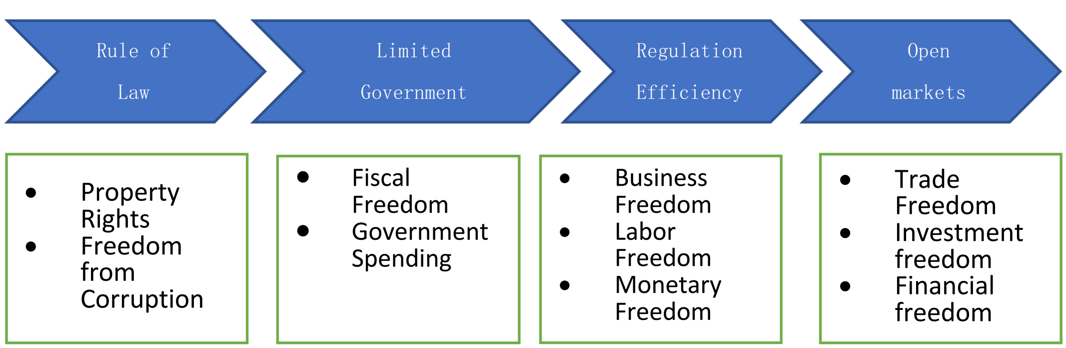
The rest of the paper is structured as follows. Section 2 discuss about constructing the new economic freedom indicator based on machine learning methods. I discuss about the limitation of traditional indices and the methods used to form sample data. In this section, I also compare several machine learning models and present the overview of new economic freedom index. Section 3 examines the impact of economic freedom level on the economic growth. This section also includes the explanation of chosen variables and data sources. Section 4 concludes.

2. Constructing the New Machine Learning Economic Freedom Indicator

i. Limitation of Traditional Indices

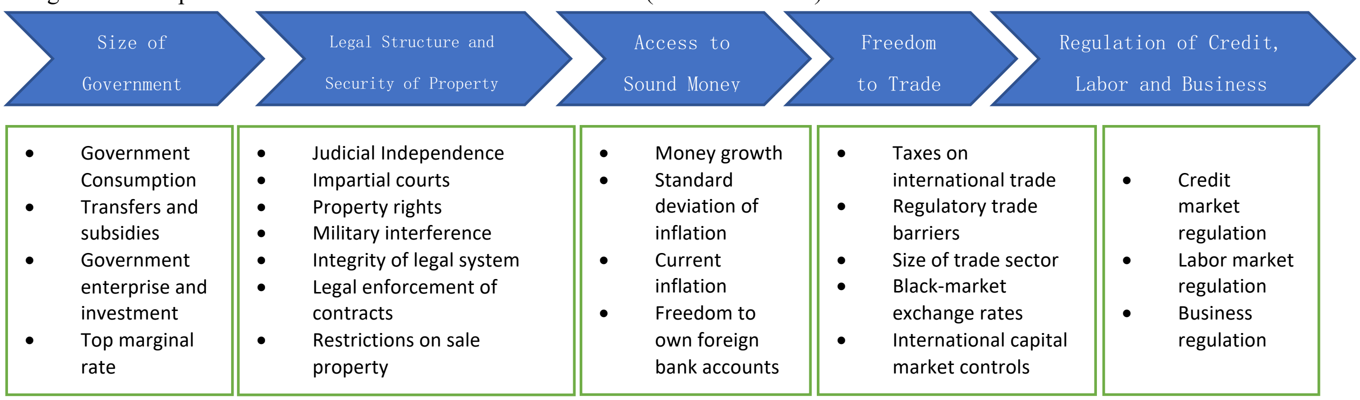
Basically, there are now two most popular indices to measure economic freedom level of countries. Related literature mainly use them, although the two indices have always been criticized. One is the Index of Economic Freedom Composition (Heritage Foundation). This index has four broad categories composed of total 10 factors.

Figure 1 – Components of Index of Economic Freedom Composition (Heritage Foundation)



The other one is Economic Freedom of the World (Fraser Institute). This index measures economics freedom through five broad areas of measurement which encompass 23 categories and include 42 variables.

Figure 2 – Components of Economic Freedom of the World (Fraser Institute)



There are two main concerns about these two indices, which are mainly about weights and subjectivity. First, the Heritage index average the factors "so that the overall score will not be biased toward any one component or policy direction" with equal weight. Also, the scores are not normalized, inherently weighting the various factors because of the large variation in means.

Second, these two indices all introduce the elements of subjectivity, particularly the factors regarding perceptions. The basic logic of these two indices is just that estimate each factor with various kinds of methods, and obtain a final number, then average the numbers of all factors with particular weights. It's no wonder that they would be criticked as subjective.

To solve these two concerns, I am going to develop a novel approach of economics freedom measurement based on machine learning methods. The idea is inspired by Gründler and Krieger (2016), but I have made improvements on their idea and also discussed more machine learning models that may be applied to this problem.

ii. Construct Economic Freedom Index Based on Machine Learning Models

a) Basic Theoretical Framework of Machine Learning Models

The economic freedom indicator $F_{i,t}$ of country i at time t can be expressed as a function of various features,

$$F_{i,t} = F(x_{i,t}^{1}, x_{i,t}^{2}, x_{i,t}^{3}, \ldots, x_{i,t}^{n})$$

As for the features to be included in the models, I basically combine all the key component concepts of these two indices to be most comprehensive but delete some repetitive factors. The features I considered can be divided into 4 categories, which are mainly government influence, legal structure and property rights, open markets, and access to sound money. The variables consist of the index of government integrity, size of government, government spending, tax burden, legal system & property rights, business freedom, monetary freedom, trade freedom, investment freedom, financial freedom, and sound money.

We can use different machine learning models to estimate this function, and then apply it to the whole dataset to get the economic level of any country at any time. The models I consider include SVR model with radial basis function kernel/linear kernel/polynomial kernel, Random Forest model, Decision Tree model and Neural Network model. SVR model is the continuous version of SVM model, which can output the continuous index basically range from 0 to 10. The rest three model outputs the discrete index from 1 to 10 that indicates the economic freedom level of countries.

The biggest advantage of machine learning models is that we can estimate the non-linear or complex relationships between features and outputs. Although the mechanism of each machine learning model is different, they all tend to capture the complex functions, rather than linear regression. This characteristic makes our constructed index much more reliable and closer to reality than the linearly composed traditional indices.

The objective function of SVR is to minimize the *l*2-norm of the coefficient vector and SVR model tend to find an appropriate hyperplane to fit the data. The Decision Tree model predicts the output by learning simple decision rules inferred from the data features. The Random Forest model consists of many decision trees and tend to create an unrelated forest of trees to predict more accurate outputs. The Neural Network model transforms the input to the output by various activation functions which link multiple hidden layers.

b) Data

The data of features capture 100 countries from year 2000 to 2017. The data of government integrity, government spending, tax burden, business freedom, monetary freedom, trade freedom, investment freedom, and financial freedom variables from 2000 to 2017 come from Heritage Index dataset.[3] The data of sound money, size of government, and legal system & property rights variables from 2000 to 2017 come from EFW Index panel data report.[4]

c) Methods

This paper's methods refer to Gründler and Krieger (2016), but I have made improvements. Gründler and Krieger (2016) investigate the relationship of democracy degree and economic growth. They applied a report which reports the countries regarded as either "completely democratic" or "completely undemocratic". If the country is always recognized by the public as "democratic", they set its democracy index as 1, inferring it's "completely democratic", vice versa. Then they use such information to form a training dataset and perform the SVR method to construct a new democracy index, which is continuous between 0 and 1.

Instead of finding out the countries which recognized as completely economic free or unfree, I take advantage of the two existing indices. I divided the countries in each index report into 10 groups by quantiles. So, the first group refers to the countries of top 10% economic freedom degree, the second group refers to the countries of top 10%-20% economic freedom degree, and so on. Because there are 187 countries in the Heritage index report and 167 countries in the EFW index report, each group of Heritage index has 19 countries and each group of EFW index has 17 countries.[5] Then I extract the countries which are in the same rank groups of both indices, for example, the countries that are in both the top 10% group of Heritage index and the top 10% group of EFW index. In fact, among 147 countries common in both index report,

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[3] Details refer to https://www.heritage.org/index/.

[4] Details refer to https://www.fraserinstitute.org/economic-freedom/dataset?geozone=world&page=dataset&min-year=2&max-year=0&filter=0.

[5] Here I use the 2017 annual report for both indices.

there are only 52 countries whose ranking range are consistent, although many component concepts of the two indices are similar, which reflects the unreliability of the two indices to some degree.[6]

Because these countries' ranking range is consistent in the two popular indices, they are considered as widely recognized by the public about their economics freedom degree. In this way, we can basically consider the economic freedom degree of these countries as common sense, which decreases the influence of subjectivity a lot. Then I set the freedom degree as 10 for the countries in both top 10% groups; set the degree as 9 for the countries in both top 10%-20% groups, and so on. Finally, we form a sample dataset of 52 countries for training and testing. It tends to provide more accurate results compared to the dataset in Gründler and Krieger (2016), which has only two values, 0 and 1. By performing the machine learning models, we solve the weight problem naturally.

d) Model Comparison

I performed different classification model to the sample data, in order to select the model that provides the best prediction. Table 2 compares the forecast mean squared error associated with test data for each model.

Table 1- forecast MSE comparison

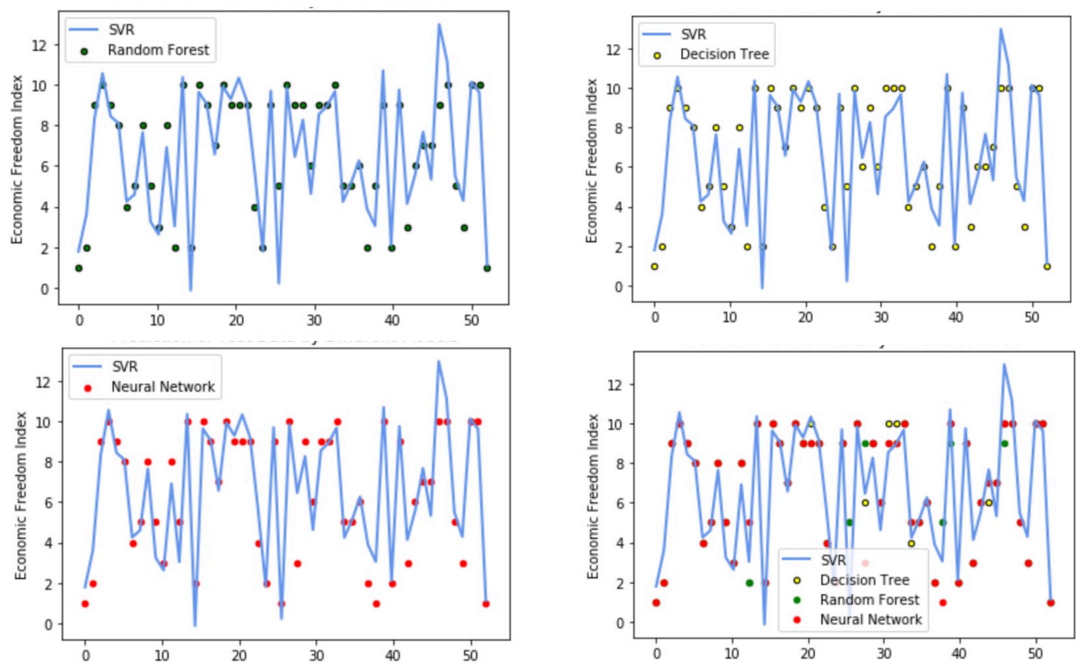
Models		Forecast MSE
SVR	RBF kernel	2.9923008
	linear kernel	0.9754689
	polynomial kernel	1.16029322
Random Forest		1.07692308
Decision Tree		1.15384615
Neural Network		1.30769231

The SVR model with linear kernel results in the least FMSE, following by Random Forest, Decision Tree, and Neural Network. This indicates SVR model provides a best prediction. It's worth mentioning that the mean squared error of in-sample comparison (associated with training data) is meaningless in this case. Because the objective function of SVR model is not

6 See Table 4 – Groups of Countries Consistent with Their Ranks in Both Indices in Appendix.

to minimize the MSE, but to minimize the coefficient. In fact, we have the flexibility to define how much error (MSE of training data) we can tolerate. But the comparison of forecast mean squared error associated with testing data is still meaningful, indicating whether it can provide an better prediction. From Figure 3, we can see the predictions of SVR model (linear) are very similar to the predictions of Random Forest, which has the second least forecast MSE.

Figure 3- Predictions of Different Models



I also tune the parameter of Decision Tree and Neural Network model. It turns out that the parameter values have very limited influence on accuracy of these two models. As for SVR model, Gründler and Krieger (2016) advised to set c = 1 and gamma = 0.05 to make index mainly fall in the range between 0 and 1. But In fact, when I set the parameter as (1, 0.05), there is still a small proportional of points falling out of 0-10 range, and the forecast mean squared error still remains the same. So, I use the automatically setting parameter values for simplicity.

The SVR model with linear kernel has the least MSE, and the continuity of its output index allow us to estimate the impact of lag of economic freedom index more accurately, since the lag of economic freedom level has a large probability of being the same as concurrent economic freedom level in the discrete output. Therefore, I selected SVR model with linear kernel to construct the new index.

iii. Overview of Economic Freedom Level in the World

The new constructed economic freedom index covers 107 countries ranging from year 2000 to year 2017. And Figure 4 presents an overview of economic freedom level all around the world in year 2017. The index values in Figure 4 has been normalized. Most of North American area, most of North European area and Australia area are of high economic freedom level, while East Asia, most of African area and South American area are of low economic freedom level. There seems to exist the geography clustering for economic freedom level.

Figure 4 - 2017 Economic Freedom Index Map[7]

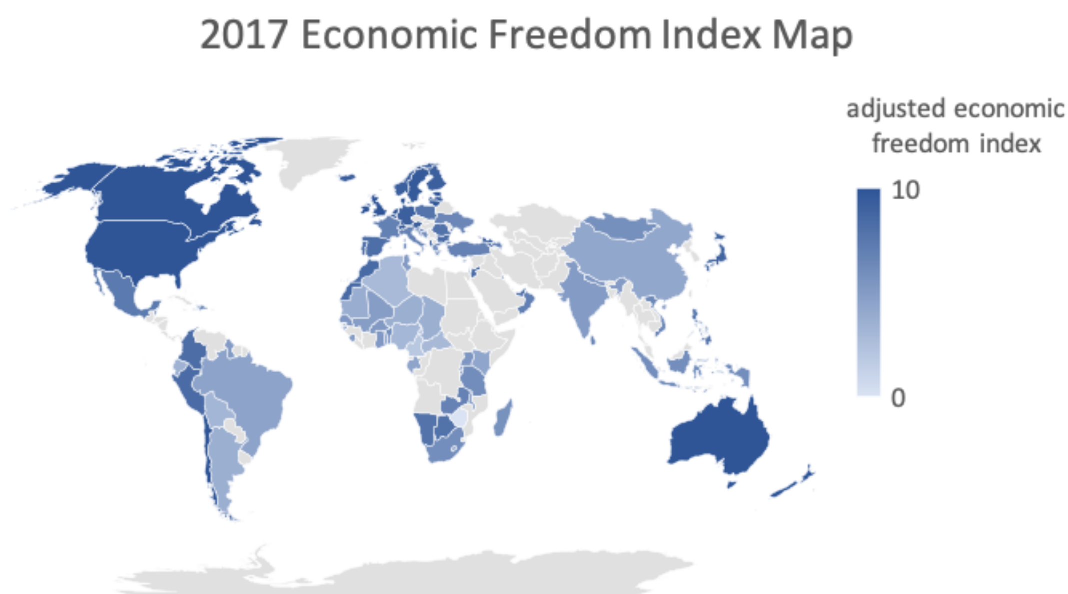
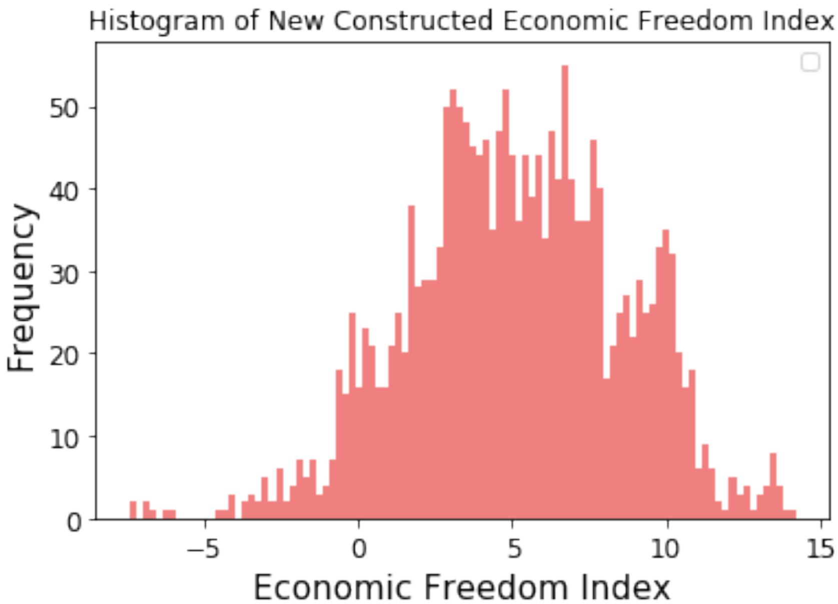


Figure 5 presents the distribution of the new constructed index. It shows that the index values of most countries fall in the range between 0 and 10, although a small proportion are outliers. Even in the top 10% group, some countries are presenting a higher economic freedom level than others in the group. Therefore, the results are reasonable, which are able to capture the underlying difference of economic freedom level between countries.

Figure 5 - Histogram of New Constructed Economic Freedom Index

[7] Drawn by Power Map module in Excel.



3. Examining the Impact of Economic Freedom on Economic Growth

i. Model Specification

After applying these models to construct a proper economic freedom index, a fixed-effect panel model is applied to investigate the impact of economics freedom on economics growth based on the panel data of 100 countries in 2000-2017. The main model is as below:

Equation 1 - main model

$$y_{i,t} = \beta_0 + \beta_1 Index_{i,t} + \beta_2 M_{i,t} + \beta_3 Z_{i,t} + \varepsilon_{i,t}$$

where the subscript refers to country i at year t; $y_{i,t}$ is the per capita GDP of country i at year t; $Index_{i,t}$ is our new constructed economic freedom index; $M_{i,t}$ is a vector of standard economic explanatory variables, which have shown to be robustly linked with GDP by previous empirical studies; $Z_{i,t}$ is a vector of possible additional economic explanatory variables, which may be related to GDP based on previous literature; and $\varepsilon_{i,t}$ is the error term. The variables in M vector includes the investment share of GDP, the average years of schooling to proxy human capital and education, the trade share to reflect openness, the government consumption. These variables are chosen based on the findings of previous literature, such as Levine and Renelt(1992), Ferder(1982) and Romer (1989). The variables in Z vector consists of the life expectancy at birth, mortality rate of infants, population growth and inflation rate. The choice of these variables refers to the models in De Haan and Sturm (2000) and Gründler and Krieger (2016). Gründler and Krieger (2016) use life expectancy at birth and fertility rate to proxy health. Population growth is added because Baumol et al. (1989) suggested it may enhance growth. The inflation rate is added as it has been founded by Fischer (1993) and Barro (1995) that it's robustly correlated with economic growth.

In this way, most of exogenous variables linked with GDP has been included in the regression. Then I use fixed effects and MLE methods to estimate the main model, in order to eliminate the effects of countries' particular characteristics.

ii. Data

As for the data of main model, the data of GDP per capita, investment share of GDP, government expenditure, trade share of GDP, life expectancy at birth, mortality rate, inflation rate, population growth all come from the World Bank dataset.[8] De Haan and Sturm (2000) used secondary school enrollment rate as the proxy of education. But the data of secondary school enrollment rate from World Bank has a lot of missing value. So, I choose the average years of schooling as the proxy of education. This variable is also used in Gründler and Krieger (2016). The data of years of schooling is taken from the dataset of Our World in Data compiled by University of Oxford.[9]

Because there are a lot of missing value, I deleted some countries to be considered. For countries which lacked data no more than three years, I filled the null value with most recent year values. After I construct the index, there are 107 countries left in the economic free index table. During the second data cleaning process, I deleted another 7 countries due to the lack of data for exogenous variables of the main model. Finally, I collect the complete data of 100 countries in 18 years to estimate the main model.

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[8] Details refer to https://data.worldbank.org.

[9] Details refer to https://ourworldindata.org/grapher/mean-years-of-schooling-1.

Table 2 - Summary Statistics

	GDP per capita	economic freedom index	Investment share	trade share	government consumption	life expectancy at birth	mortality rate	years of schooling	population growth	inflation rate
count	1800	1800	1800	1800	1800	1800	1800	1800	1800	1800
mean	15141.99	5.250382	23.73837	84.76955	8.89E+10	70.03874	27.4285	8.3149	1.413715	5.584358
std	20162.23	3.330837	7.360406	54.70444	2.77E+11	10.4703	28.1028	3.264539	1.559699	8.393967
min	113.5674	−6.35971	1.09681	19.79813	57387668	39.441	1.5	1.1	−9.08064	−25.9584
25%	1123.138	2.976958	19.58674	53.16341	1.46E+09	62.443	4.9	6.1	0.455856	1.482216
50%	4792.078	5.231427	22.77783	71.33072	6.39E+09	73.6285	15	8.7	1.23281	3.503722
75%	23640.54	7.665727	27.02375	100.3164	4.7E+10	78.44634	43.75	11.1	2.424802	7.50453
max	118823.6	13.34248	61.46902	437.3267	2.76E+12	84.09976	142.4	14.1	15.17708	112.6936

iii. Results

Table 1 - Estimation Results

Dependent Variable: GDP per capita							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
economic freedom	658.47*** (4.17)	648.24*** (4.10)	597.55*** (3.90)	528.29*** (3.48)	276.27* (1.89)	453.86*** (3.23)	469.17*** (3.38)
L.economic freedom	730.22*** (4.80)	730.04*** (4.81)	608.07*** (4.14)	524.69*** (3.60)	141.32 (1.00)	265.78* (1.95)	256.23* (1.90)
investment share		57.24** (1.96)	47.05* (1.67)	24.95 (0.89)	0.031 (0.00)	68.78** (2.63)	54.59** (2.11)
government consumption			1.98e-09*** (11.06)	2.02e-08*** (11.42)	1.54e-08*** (9.07)	1.50e-08*** (9.24)	1.52e-08*** (9.49)
trade share				68.56*** (7.15)	42.29*** (4.59)	33.12*** (3.73)	35.22*** (4.02)
years of schooling					3771.35*** (14.48)	3843.55*** (12.77)	3902.01*** (13.08)
life expectancy at birth						768.122*** (7.16)	739.77*** (6.98)
mortality rate						401.69*** (11.45)	390.19*** (11.25)
inflation rate							922.83*** (6.28)
population growth							30.20* (1.72)

* significant at 90% level.
** significant at 95% level.
*** significant at 99% level.

The empirical result shows that economic freedom is related to GDP with a significant positive coefficient in every model. This indicates economic freedom level exerts a strong and robust influence on economic growth. Before adding years of schooling into the regression, the lag of economic freedom has almost the same large impact on GDP with the concurrent economic freedom and also robust. The education indicator, years of schooling, increases the explanatory power of the model and generally reduce the significance of other variables. Both the impact level and the significance of the lag of economic freedom decrease after years of schooling has been taken into account. But in equation (6) and (7), it still exerts a significant and strong impact on GDP, although the impact is less than concurrent economic freedom level.

After the impact of years of schooling, life expectancy at birth and mortality rate has been taken into account, the investment share has been proved to be robustly positive related to economic growth. The government consumption exerted a significant but relatively small impact on GDP per capita in every model. The proxy of openness, education and health - trade share, years of schooling and life expectancy at birth all exert a robust and strong impact on economic growth, which is consistent with findings of previous literature. A negative sign for mortality rate is expected, however, the actual result indicates the mortality rate of infants is positively linked with GDP. Furthermore, the inflation rate and population growth has always been positively related to GDP.

Therefore, we can conclude economic freedom is a significant determinant of economic growth, even when education, health and openness are taken into account.

4. Conclusion

A reliable indicator for economic freedom level is vital for investigating and understanding the significance and effects of economic freedom. The machine learning methods to construct the index can solve the limitation of traditional indices. Specifically, this paper use Support Vector Regression model with linear kernel to develop a new reliable economic freedom index.

The relationship between growth and economic freedom are analyzed for a panel of about 100 countries from 2000 to 2017 based on the new indicator. The favorable effects on growth include high investment share, high government consumption, high openness, high human capital and high health condition. After these kinds of variables are held constant, the overall effect of recent economic freedom levels on growth are still pretty strong. Besides all the economic input variables, such as human capital, investment, labor and so on, the free economic environment also functions extremely important role in economic growth.

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6. Appendix

Table 2 – Groups of Countries Consistent with Their Ranks in Both Indices

CountryID	**Country Name**	**Heritage Rank**	**Heritage Index**	**Fraser rank**	**Fraser Index**
Top 10%					
7	Australia	5	81.0	9.0	8.1
29	Canada	7	78.5	8.0	8.1
33	Chile	10	76.5	13.0	7.9
45	Denmark	18	75.1	13.0	7.9
54	Estonia	6	79.1	13.0	7.9
61	Georgia	13	76.0	12.0	7.9
78	Ireland	9	76.7	6.0	8.1
98	Lithuania	16	75.8	16.0	7.9
99	Luxembourg	14	75.9	17.0	7.9
120	New Zealand	3	83.7	3.0	8.5
147	Singapore	2	88.6	2.0	8.7
158	Switzerland	4	81.5	4.0	8.4
174	United Kingdom	12	76.4	7.0	8.1
175	United States	17	75.1	5.0	8.2
Top 10% - 20%					
6	Armenia	33	70.3	27.0	7.7
8	Austria	30	72.3	26.0	7.7
57	Finland	24	74.0	21.0	7.8
62	Germany	26	73.8	20.0	7.8
73	Iceland	22	74.4	23.0	7.7
88	Korea, South	23	74.3	33.0	7.6
92	Latvia	20	74.8	24.0	7.7
124	Norway	25	74.0	32.0	7.6
Top 20% - 30%					
11	Bahrain	44	68.5	50.0	7.4
15	Belgium	49	67.8	40.0	7.5
23	Bulgaria	47	67.9	37.0	7.5
83	Jordan	53	66.7	43.0	7.4
130	Peru	43	68.9	42.0	7.5
Top 30% - 40%					
51	El Salvador	66	64.1	63.0	7.2
131	Philippines	58	65.6	53.0	7.3
Top 40% - 50%					
90	Kyrgyz Republic	89	61.1	77.0	6.9

114	Montenegro	83	62.0	83.0	6.8
129	Paraguay	80	62.4	72.0	7.0
Top 50%-60%					
14	Belarus	104	58.6	99.0	6.6
18	Bhutan	107	58.4	87.0	6.8
112	Moldova	110	58.0	97.0	6.7
162	Tanzania	105	58.6	87.0	6.8
Top 60% - 70%					
13	Barbados	130	54.5	112.0	6.5
63	Ghana	118	56.2	103.0	6.6
118	Nepal	125	55.1	110.0	6.5
Top 70% - 80%					
22	Brazil	140	52.9	120.0	6.2
26	Burundi	139	53.2	124.0	6.2
103	Malawi	149	52.2	131.0	6.1
126	Pakistan	141	52.8	136.0	5.9
165	Togo	138	53.2	121.0	6.2
Top 80% - 90%					
5	Argentina	156	50.4	146.0	5.7
32	Chad	162	49.0	150.0	5.4
66	Guinea	169	47.6	139.0	5.9
76	Iran	155	50.5	143.0	5.7
116	Mozambique	158	49.9	149.0	5.6
122	Niger	154	50.8	142.0	5.8
Top 90% - 100%					
3	Algeria	172	46.5	159.0	4.8
179	Venezuela	179	27.0	162.0	2.6