Linear Regression Models

GR5205/GU4205

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Outline

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 - Simple Linear Regression using OLS Method
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 - O Background, the data, and the research question
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Life Expectancy

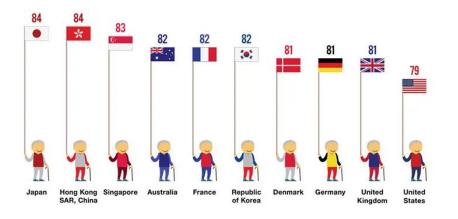
About our data:

The dataset contains life expectancy, health, immunization, economic and demographic information, a total of **21 variables**, about **179 countries** in the year of **2015**.

Data about Population, GDP, and Life Expectancy was collected from **World Bank**Data. Information about vaccinations for Measles, Hepatitis B, Polio, and Diphtheria, alcohol consumption, BMI, HIV incidents, mortality rates, and thinness was collected from **World Health Organization** public datasets. Information about schooling was collected from the **Our World in Data** which is a project of the University of Oxford.

Life Expectancy - Research Question

Among all the health, economic and demographic variables, which ones of them help predict a country's life expectancy in the year of 2015?

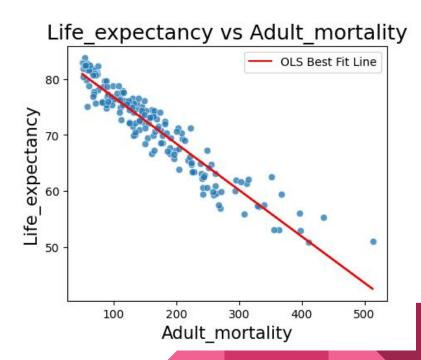


Life Expectancy - Simple Linear Regression

Ordinary Least Squares Regression:

Response: **Life_expectancy** (Average life expectancy of both genders)

Predictor: **Adult_mortality** (deaths of adults per 1000 population)



Life Expectancy - OLS Regression Results

		OLS Regres	sion Results			
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Life_expectancy OLS Least Squares Thu, 27 Apr 2023 01:05:14 179 177 1 nonrobust		Adj. R-squared: F-statistic:		0.901 0.900 1609. 8.79e-91 -415.01 834.0 840.4	
	coef	std err	t	P> t	[0.025	0.975]
const Adult_mortality	84.9897 -0.0826	0.384 0.002	221.054 -40.118	0.000 0.000	84.231 -0.087	85.748 -0.079
Omnibus: Prob(Omnibus): Skew: Kurtosis:	0.324 0.850 0.028 3.108		Durbin-Watson: Jarque-Bera (JB): Prob(JB): Cond. No.		2.218 0.110 0.947 388.	

Life Expectancy - Multiple Linear Regression

Response: Life_expectancy (Average life expectancy of both genders)

Predictors:

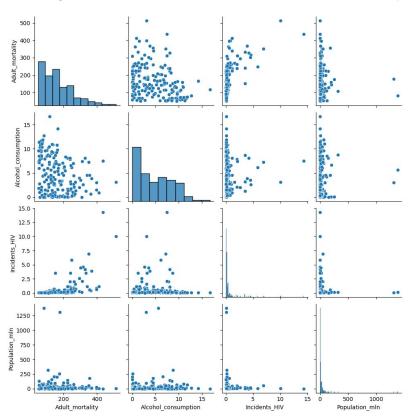
Adult_mortality (deaths of adults per 1000 population)

Alcohol_consumption (Represents alcohol consumption that is recorded in liters of pure alcohol per capita with 15+ years old)

Incidents_HIV (Incidents of HIV per 1000 population aged 15-49)

Population_mln (Total population of a country in millions)

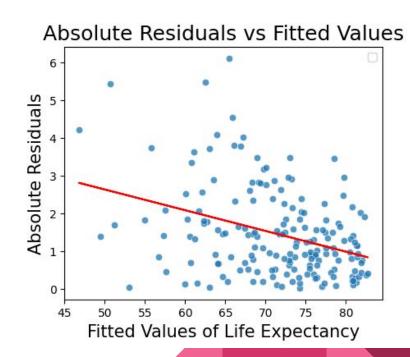
Life Expectancy - Multiple Linear Regression



Life Expectancy - WLS Multiple Linear Regression

Estimating the Weights for WLS:

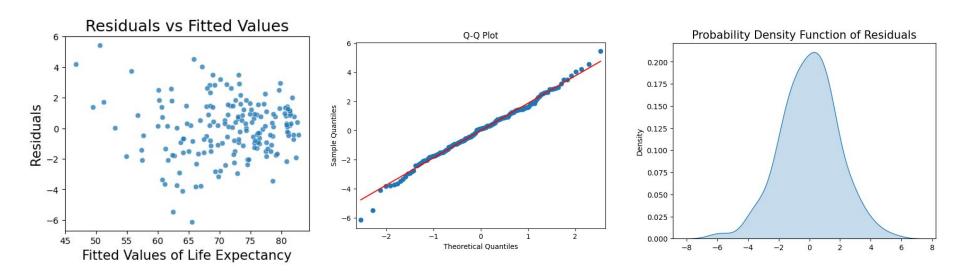
- Estimate the standard deviations (red line in the figure) by regressing the absolute residuals and the OLS fitted values of the response variable.
- 2. Estimate the variances by squaring the fitted values of the regression model
- 3. Calculate the weights by taking the reciprocal of the estimated variances



Life Expectancy - OLS vs. WLS Results

OLS Regression Results						WLS Regression Results							
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Life_expect Least Sqi Thu, 27 Apr 02::	OLS Ad uares F- 2023 Pr 17:50 Lo 179 AI 174 BI 4			0.943 0.941 715.5 7.70e-107 -366.01 742.0 758.0		Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:		WLS 2 uares 2 2023 2 28:23 2	R-squared: Adj. R-squared: F-statistic: Prob (F-statist Log-Likelihood: AIC: BIC:	ic):	0.941 0.940 693.8 9.57e-106 -350.65 711.3 727.2	
	coef	std err	t	P> t	[0.025	0.975]		coef	std er	 r t	P> t	[0.025	0.975
const Adult_mortality Alcohol_consumption Incidents_HIV Population_mln	83.4165 -0.0849 0.3395 0.5900 -0.0007	0.446 0.002 0.041 0.112 0.001	187.167 -40.167 8.286 5.259 -0.756	0.000 0.000 0.000 0.000 0.451	82.537 -0.089 0.259 0.369 -0.003	84.296 -0.081 0.420 0.811 0.001	const Adult_mortality Alcohol_consumption Incidents_HIV Population_mln	83.7669 -0.0866 0.3285 0.5622 -0.0009	0.38 0.00 0.03 0.14 0.00	2 -39.427 3 10.041 5 3.889	0.000 0.000 0.000 0.000 0.289	83.010 -0.091 0.264 0.277 -0.003	84.52 -0.08 0.39 0.84 0.00
Omnibus: Prob(Omnibus): Skew: Kurtosis:	-1	0.260 Ja 0.136 Pr	rbin-Watson: irque-Bera (JB ob(JB): ind. No.):	2.204 2.489 0.288 613.		Omnibus: Prob(Omnibus): Skew: Kurtosis:	-	0.606 0.134	Durbin-Watson: Jarque-Bera (JB Prob(JB): Cond. No.		2.128 1.107 0.575 522.	

Life Expectancy - Diagnostic Tests





Life Expectancy - Diagnostic Tests

Jarque-Bera Test Statistic: 2.49

P-value: 0.288

Null Hypothesis: The distribution of residuals is Normal.

Conclusion: Failed to reject the null hypothesis. There is no evidence to indicate the distribution is not Normal.

Skewness: -0.136

Kurtosis: 3.5

Durbin-Watson Test Statistic: 2.20

Null Hypothesis: There is no first-order autocorrelation in the residuals.

Conclusion: Failed to reject the null hypothesis. There is no evidence to indicate the presence of

autocorrelation.

Breusch-Pagan Test Statistic: 68.10

P-value: 1.088e-14

Null Hypothesis: The variance of the residuals is constant (homoscedastic).

Conclusion: Reject the null hypothesis. There is strong evidence to indicate the presence of heteroscedasticity.

Normality

No Autocorrelation

X Heteroscedasticity

Life Expectancy - Diagnostic Tests

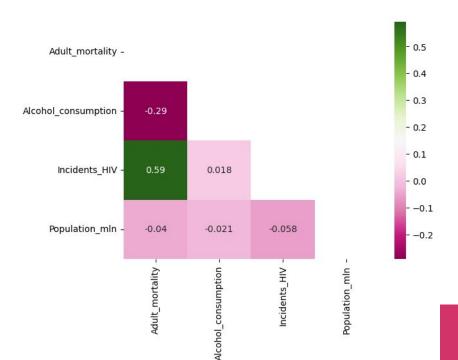
Variance Inflation Factors

Adult_mortality: 2.22

Alcohol_consumption: 1.59

Incidents_HIV: 1.52 Population_mln: 1.07

✓ No Multicollinearity



Life Expectancy - Backtesting

We back-tested both of the OLS and WLS models using 2014 life expectancy data:

OLS:

MSE: 3.58

R-squared: 0.944

WLS:

MSE: 3.57

R-squared: 0.945

The low MSE and high R-squared values indicate that both of the models fit 2014 data well.

Summary

When modeling the life expectancy of countries, the dataset exhibited heteroscedastic pattern in the error terms. In order to address the issue, we used the WLS method. The OLS and WLS methods turned out to generate very similar models with small MSE.

Given the fact that the OLS estimator was unbiased but inefficient, and the WLS estimator was biased but close to the OLS estimator and more efficient, we conclude that the WLS estimator was better.

In practice, when WLS is used to address heteroscedasticity, in order to obtain the best linear unbiased estimator (BLUE), it is important to use expert knowledge to decide the weights of the independent variables. If that knowledge is not available, then one can use estimated weights to obtain a robust WLS estimator. If the estimated coefficients differ substantially from the coefficients obtained by OLS, then iterate the WLS process by using residuals from the WLS fit to re-estimate the variance and then obtain revised weights. This process is called iteratively reweighted least squares.

Bitcoin

Bitcoin (BTC) is a cryptocurrency, a virtual currency designed to act as money and a form of payment outside the control of any one person, group, or entity, thus removing the need for third-party involvement in financial transactions. It is rewarded to blockchain miners for the work done to verify transactions and can be purchased on several exchanges.

Bitcoin was introduced to the public in 2009 by an anonymous developer or group of developers using the name Satoshi Nakamoto. It has since become the most well-known cryptocurrency in the world. Its popularity has inspired the development of many other cryptocurrencies. These competitors either attempt to replace it as a payment system or are used as utility or security tokens in other blockchains and emerging financial technologies.

Bitcoin

Research Question:

What time series variables can help predict the price of Bitcoin?

About our data:

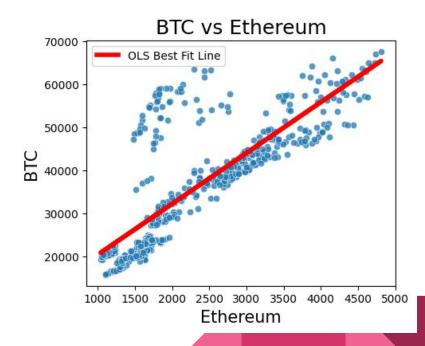
The dataset contains **549** historical data points from **2/02/2021 to 4/10/2023** that represent the daily dollar amounts in **6** variables: Bitcoin, Bitcoin Trade Volume, number of My Wallet transactions using Bitcoin per day, Nvidia Stock Price, Ethereum Stock Price, and Dow Jones Index.

Bitcoin - Simple Linear Regression

Ordinary Least Squares Regression:

Response Variable: **BTC** (Bitcoin Price)

Predictor: **Ethereum** (Ethereum Price)



Bitcoin - OLS Regression Results

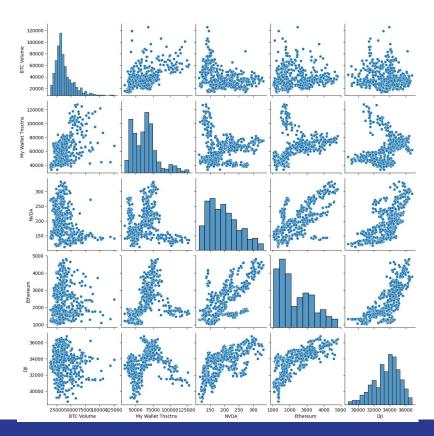
```
OLS Regression Results
                                                                       0.636
Dep. Variable:
                                 BTC
                                      R-squared:
                                 OLS Adj. R-squared:
Model:
                                                                       0.635
Method:
                       Least Squares F-statistic:
                                                                       954.4
                    Thu, 27 Apr 2023 Prob (F-statistic):
Date:
                                                                   5.03e-122
Time:
                            01:23:58 Log-Likelihood:
                                                                     -5747.8
No. Observations:
                                 549 AIC:
                                                                   1.150e+04
Df Residuals:
                                 547 BIC:
                                                                   1.151e+04
Df Model:
Covariance Type:
                           nonrobust
                coef
                        std err
                                               P>|t|
                                                          [0.025
const
           8614.1776 964.796 8.929
                                               0.000
                                                        6719.020
                                                                  1.05e+04
Ethereum
             11.7928
                          0.382
                                    30.893
                                               0.000
                                                          11.043
                                                                      12.543
Omnibus:
                             224.787 Durbin-Watson:
                                                                       0.018
Prob(Omnibus):
                               0.000 Jarque-Bera (JB):
                                                                     661.249
Skew:
                               2.061 Prob(JB):
                                                                   2.58e-144
Kurtosis:
                                      Cond. No.
                               6.451
                                                                    6.69e + 03
```

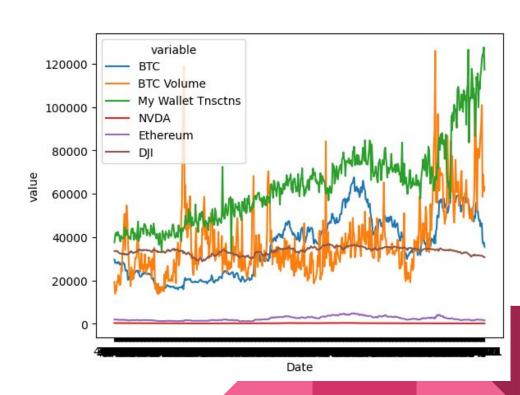
Using Generalized Least Squares Method for Multiple Linear Regression:

Response Variable: **BTC** (Bitcoin Price)

Predictors:

BTC Volume (Bitcoin Volume - mln)
Number of My Wallet transactions using Bitcoin per day
Nvidia Stock price
Ethereum Stock Price
DJI (Dow Jones Index)





Estimating the Covariance Matrix for GLS:

We assumed that the process generating the regression errors is stationary: That is, all of the errors have the same expectation (assumed to be 0) and the same variance (σ^2), and the covariance of two errors depends only upon their separation s in time:

$$C(\varepsilon_t, \varepsilon_{t+s}) = C(\varepsilon_t, \varepsilon_{t-s}) = \sigma^2 \rho_s$$

where ps is the error autocorrelation at lag s. And our error covariance matrix would have this structure:

$$\Sigma = \sigma^{2} \begin{bmatrix} 1 & \rho_{1} & \rho_{2} & \cdots & \rho_{n-1} \\ \rho_{1} & 1 & \rho_{1} & \cdots & \rho_{n-2} \\ \rho_{2} & \rho_{1} & 1 & \cdots & \rho_{n-3} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} = \sigma^{2} \mathbf{P}$$

$$\begin{bmatrix} 1 & \rho_{1} & \rho_{2} & \cdots & \rho_{n-1} \\ \rho_{2} & \rho_{1} & 1 & \cdots & \rho_{n-3} \\ \vdots & \vdots & \vdots & \vdots \\ \rho_{n-1} & \rho_{n-2} & \rho_{n-3} & \cdots & 1 \end{bmatrix}$$

Estimating the Covariance Matrix for GLS:

We chose the first-order auto-regressive process, AR(1), as our stationary time-series model:

$$\varepsilon_t = \phi \varepsilon_{t-1} + \nu_t$$

where the random shocks vt are assumed to be Gaussian white noise, NID(0, σ (v)^2). Under this model, $\rho 1 = \varphi$, $\rho s = \varphi$ ^s, and σ ^2 = σ (v)^2/(1 - φ ^2).

To estimate φ , we used OLS residuals and the AR(1) model.

Then, we estimated ρi using $\rho 1 = \phi$, $\rho s = \phi^s$.

Lastly, we estimated σ^2 by dividing the variance of the residuals of the AR(1) model by (1 – ϕ^2).

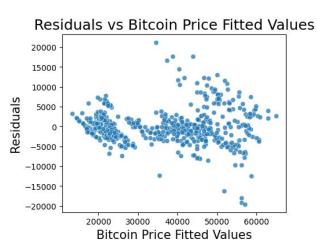
$$\Sigma = \sigma^{2} \begin{bmatrix} 1 & \rho_{1} & \rho_{2} & \cdots & \rho_{n-1} \\ \rho_{1} & 1 & \rho_{1} & \cdots & \rho_{n-2} \\ \rho_{2} & \rho_{1} & 1 & \cdots & \rho_{n-3} \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \rho_{n-1} & \rho_{n-2} & \rho_{n-3} & \cdots & 1 \end{bmatrix} = \sigma^{2} \mathbf{P}$$

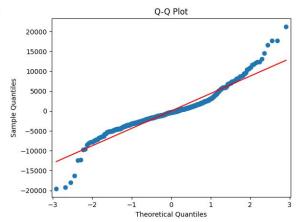
Bitcoin - OLS vs. GLS Results

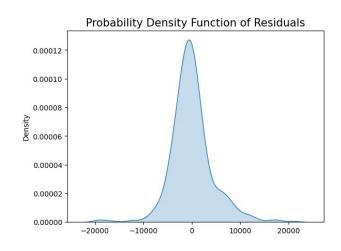
Dep. Variable:		BTC	R-squared:	0.	904			
Model:		OLS	Adj. R-square	d:	0.	903		
Method:	Least Squares		F-statistic:		1019.			
Date:			Prob (F-stati	stic):	3.35e-273			
Time:		17:55:02	Log-Likelihoo	d:	-5382.6			
No. Observations:		549	AIC:		1.078€	1.078e+04		
Df Residuals:		543	BIC:		1.080e+04			
Df Model:		5						
Covariance Type:	ne	onrobust						
	coef	std err	t	P> t	[0.025	0.975		
const	-3.104e+04	5817.850	-5.336	0.000	-4.25e+04	-1.96e+04		
BTC Volume	0.0716	0.015	4.891	0.000	0.043	0.100		
My Wallet Tnsctns	0.4106	0.014	29.504	0.000	0.383	0.438		
NVDA	9.4982	6.328	1.501	0.134	-2.932	21.928		
Ethereum	7.3551	0.400	18.408	0.000	6.570	8.140		
DJI	0.5794	0.189	3.071	0.002	0.209	0.95		
Omnibus: 75.498		Durbin-Watson:		0.274				
Prob(Omnibus):	0.000		Jarque-Bera (JB):		407.826			
Skew:		0.447	Prob(JB):		2.77e-89			
Kurtosis:		7.127	Cond. No.		2.58e+06			

Dep. Variable: Model:		BTC GLS	R-squared: Adj. R-square	d:	0.670 0.667		
Method:	Least	Squares	F-statistic:		220.2		
Date:	Sun, 30 Apr 2023		Prob (F-stati	stic):	4.34e-128 -4745.9		
Time:			Log-Likelihoo	d:			
No. Observations:	549		AIC:		9504.		
Df Residuals:		543	BIC:		9530.		
Df Model:		5					
Covariance Type:	n	onrobust					
	coef	std err	t	P> t	[0.025	0.975	
const	-3709.4961	5914.201	-0.627	0.531	-1.53e+04	7908.01	
BTC Volume	0.0301	0.006	5.034	0.000	0.018	0.042	
My Wallet Tnsctns	0.0970	0.011	8.813	0.000	0.075	0.119	
NVDA	-11.8976	8.278	-1.437	0.151	-28.158	4.363	
Ethereum	9.7779	0.415	23.552	0.000	8.962	10.593	
DJI	0.3614	0.201	1.795	0.073	-0.034	0.75	
======================================	145.932		 Durbin-Watson:		1.279		
Prob(Omnibus):		0.000	Jarque-Bera (JB):		530.	373	
Skew:		1.190	Prob(JB):		6.78e-116		
Kurtosis:		7.186	Cond. No.		1.29e	+06	

Bitcoin - Diagnostic Tests







X No Linearity

Bitcoin - Diagnostic Tests

Jarque-Bera Test Statistic: 407.83 X No Normality

P-value: 2.77e-89

Null Hypothesis: The distribution of residuals is Normal.

Conclusion: Reject the null hypothesis. There is strong evidence to indicate the distribution is not Normal.

Skewness: 0.45

Kurtosis: 7.13 (leptokurtic)

Durbin-Watson Test Statistic: 0.27

Null Hypothesis: There is no first-order autocorrelation in the residuals.

Conclusion: Reject the null hypothesis. There is strong evidence to indicate the presence of autocorrelation.

Breusch-Pagan Test Statistic: 180.39

P-value: 6.15e-38

Null Hypothesis: The variance of the residuals is constant (homoscedastic).

Conclusion: Reject the null hypothesis. There is strong evidence to indicate the presence

of heteroscedasticity.

X Autocorrelation

X Heteroscedasticity

Bitcoin - Diagnostic Tests

Variance Inflation Factors

BTC Volume: 10

My Wallet Bitcoin Transaction: 23.47

NVDA: 46.645 Ethereum: 19.30

DJI: 53.6

X Multicollinearity



Bitcoin - Backtesting

We back-tested both of the OLS and GLS models using daily data from 1/31/2020 to 2/01/2021:

OLS:

MSE: 534,946,834.87 R-squared: -8.35

GLS:

MSE: 64,468,795.13 R-squared: -0.127

The large MSE and negative R-squared values indicate that both of the OLS and the GLS models are predicting worse than the mean of the bitcoin price.

Summary

As you saw earlier, the Bitcoin dataset failed all of the diagnostic tests. We used GLS to model the Bitcoin price, hoping at least the issue of autocorrelation would be addressed. By comparing the results of OLS and GLS, the two methods indeed generated drastically different models.

So, which model was better? The OLS model was not appropriate as the data failed all of the assumptions required. As for the GLS model, the assumptions for linearity, normality, homoscedasticity, and multicollinearity were still not met. And the assumption of stationary regression errors might not be true in our data. Our covariance matrix might be erroneous. That means, the GLS estimator was not the BLUE, either. Furthermore, the backtest results confirmed that neither one was a good model for our time-series dataset.

In conclusion, neither OLS or GLS is suitable for time-series data. We should follow a procedure of tests, such as the Augmented Dickey-Fuller Test and the Johansen Test, to check stationarity and cointegration. If both of these tests fail, then we should consider Vector Autoregression and Vector Error Correction Model for time-series data.

Data Sources

Kaggle: https://www.kaggle.com/datasets/lashagoch/life-expectancy-who-updated

Average life expectancy of both genders in different years from 2010 to 2015: https://www.who.int/data/gho/data/indicators/indicator-details/GHO/life-expectancy-at-birth-(years)

Mortality-related attributes (infant deaths, under-five-deaths, adult mortality): https://www.who.int/data/gho/data/themes/mortality-and-global-health-estimates

Alcohol consumption that is recorded in liters of pure alcohol per capita with 15+ years old: https://www.who.int/data/gho/data/indicators/indicator-details/GHO/alcohol-recorded-per-capita-(15-)-consumption-(in-litres-of-pure-alcohol)

% of coverage of Hepatitis B (HepB3) immunization among 1-year-olds: https://www.who.int/data/gho/data/indicators/indicator-details/GHO/hepatitis-b-(hepb3)-immunization-coverage-among-1-year-olds-(-)

% of coverage of Measles containing vaccine first dose (MCV1) immunization among 1-year-olds: https://www.who.int/data/gho/data/indicators/indicator-details/GHO/measles-containing-vaccine-first-dose-(mcv1)-immunization-coverage-among-1-year-olds-(-)

% of coverage of Polio (Pol3) immunization among 1-year-olds: https://www.who.int/data/gho/data/indicators/indicator-details/GHO/polio-(pol3)-immunization-coverage-among-1-year-olds-(-)

Data Sources

% of coverage of Diphtheria tetanus toxoid and pertussis (DTP3) immunization among 1-year-olds: https://www.who.int/data/gho/data/indicators/indicator-details/GHO/diphtheria-tetanus-toxoid-and-pertussis-(dtp3)-immunization-coverage-among-1-year-olds-(-)

BMI: https://www.who.int/europe/news-room/fact-sheets/item/a-healthy-lifestyle---who-recommendations

Incidents of HIV per 1000 population aged 15-49: https://data.worldbank.org/indicator/SH.HIV.INCD.ZS

Prevalence of thinness among adolescents aged 10-19 years. BMI < -2 standard deviations below the median: https://www.who.int/data/gho/indicator-metadata-registry/imr-details/4805

GDP per capita in current USD: https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?most_recent_year_desc=true

Total population in millions: https://data.worldbank.org/indicator/SP.POP.TOTL?most recent year desc=true

Average years that people aged 25+ spent in formal education: https://ourworldindata.org/grapher/mean-years-of-schooling-long-run

Yahoo Finance:

https://finance.yahoo.com/quote/GOOG/history?period1=1644278400&period2=1675814400&interval=1d&filter=history&frequency=1d&includeAdjustedClose=true

Bitcoin My Wallet Number of Transaction Per Day: https://data.nasdaq.com/data/BCHAIN/MWNTD-bitcoin-my-wallet-number-of-transaction-per-day

Time-Series Regression and Generalized Least Squares in R*: https://socialsciences.mcmaster.ca/jfox/Books/Companion/appendices/Appendix-Timeseries-Regression.pdf

Questions?