

# Swap Regression with US GDP and Public Debt

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## Contents

<b>1</b>	<b>Motivation</b>	<b>2</b>
<b>2</b>	<b>Theory for Data Collection</b>	<b>2</b>
<b>3</b>	<b>Data Collection</b>	<b>2</b>
<b>4</b>	<b>Analysis of Data</b>	<b>2</b>
4.1	Testing Bi Directional Causality . . . . .	2
4.2	Testing Stationarity in Residuals . . . . .	3
<b>5</b>	<b>Transforming Data</b>	<b>3</b>
<b>6</b>	<b>Modelling the Regression</b>	<b>3</b>
6.1	Setting up the Variables . . . . .	3
6.2	Relation to GMM . . . . .	3
6.3	Proposed Algorithm . . . . .	4
6.3.1	Iterations . . . . .	4
6.3.2	Stopping Criterion . . . . .	4
<b>7</b>	<b>Data Analysis</b>	<b>5</b>
7.1	Prior on US GDP . . . . .	5
7.2	Prior on Public Debt . . . . .	5
<b>8</b>	<b>Testing the Model</b>	<b>5</b>
8.1	Simple Linear Regression . . . . .	6
8.2	Simple Quadratic Regression . . . . .	6
8.3	SWAP Linear Regression . . . . .	6
8.4	SWAP Quadratic Regression . . . . .	6
<b>9</b>	<b>Testing Goodness of SWAP</b>	<b>7</b>

# 1 Motivation

The idea for SWAP Regression came from a paper published by Mosuk Chow et al, to use alternating predictors to find the relation between human tolerance to temperature and pressure.[1] In such situations, it is not possible to get certain measurements such as pressure, with a set temperature, and vice versa. In such cases, we have to remove the assumption that one variable is regressing the other, as in such cases, for some data points, the role of regressors and predictors switches.

## 2 Theory for Data Collection

Our idea is that SWAP Regression holds for any Bi Directional causal data points. In this discussion, we limit ourselves to Economic indicators. Glauco De Vita et al concluded that Public Debt and GDP Growth are Bi Directional Causal for the American market.[2] However, in our research, we took US Public Debt and Nominal GDP.

## 3 Data Collection

The data was found easily on Kaggle, US Public Debt Quarterly Data(in Billion \$) and US Nominal GDP Quarterly Data(in Million \$), in quarters. Public Debt data was available from 1966-01-01 to 2023-01-01, and Nominal GDP data from 1966-01-01 to 2023-01-01.

## 4 Analysis of Data

### 4.1 Testing Bi Directional Causality

To test Bi Directional Causality, we used the **grangertest** function from the **vars** package. Here, X represents the Nominal GDP, and Y represents Public Debt.

```
Granger causality test

Model 1: X ~ Lags(X, 1:4) + Lags(Y, 1:4)
Model 2: X ~ Lags(X, 1:4)
      Res.Df Df      F      Pr(>F)
1      216
2      220 -4 18.538 4.107e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Granger causality test

Model 1: Y ~ Lags(Y, 1:4) + Lags(X, 1:4)
Model 2: Y ~ Lags(Y, 1:4)
      Res.Df Df      F      Pr(>F)
1      216
2      220 -4 4.8931 0.0008519 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Fitting the model also showed the significance of each term in the model.

Since for the models trained on GDP, we can find a lag of Public Debt, which is significant, and vice versa, we can conclude Bi Directional Causality.

```

Estimation results for equation X:
=====
X = X.l1 + Y.l1 + X.l2 + Y.l2 + X.l3 + Y.l3 + X.l4 + Y.l4 + const

      Estimate Std. Error t value Pr(>|t|)
X.l1  1.265e+00  8.644e-02  14.629 < 2e-16 ***
Y.l1  1.235e-01  1.574e-02   7.849 1.93e-13 ***
X.l2 -1.932e-01  1.308e-01  -1.477  0.1410
Y.l2 -1.396e-01  2.613e-02  -5.341 2.34e-07 ***
X.l3  6.275e-02  1.209e-01   0.519  0.6043
Y.l3  2.903e-02  2.765e-02   1.050  0.2949
X.l4 -1.417e-01  7.596e-02  -1.866  0.0634 .
Y.l4 -1.222e-02  1.758e-02  -0.695  0.4878
const 1.031e+04  6.200e+03   1.663  0.0978 .

Estimation results for equation Y:
=====
Y = X.l1 + Y.l1 + X.l2 + Y.l2 + X.l3 + Y.l3 + X.l4 + Y.l4 + const

      Estimate Std. Error t value Pr(>|t|)
X.l1 -1.185e+00  4.725e-01  -2.507  0.01290 *
Y.l1  8.038e-01  8.602e-02   9.345 < 2e-16 ***
X.l2 -2.368e-01  7.147e-01  -0.331  0.74074
Y.l2  2.129e-01  1.428e-01   1.491  0.13753
X.l3  1.875e+00  6.610e-01   2.836  0.00500 **
Y.l3  2.913e-01  1.511e-01   1.928  0.05520 .
X.l4 -4.176e-01  4.152e-01  -1.006  0.31566
Y.l4 -2.941e-01  9.606e-02  -3.061  0.00248 **
const 6.922e+03  3.389e+04   0.204  0.83834

```

## 4.2 Testing Stationarity in Residuals

We got the residuals by fitting the models from the Granger Causality Test, as mentioned above. We applied Augmented Dickey Fuller Test to test stationarity of the residuals. The residuals of both the models gave ap value of less than 0.01 on Augmented Dickey Fuller test, which we applied using the `adf.test` function in R.

## 5 Transforming Data

We have scaled the gdp and public debt data by a factor of  $10^{-6}$ .

## 6 Modelling the Regression

### 6.1 Setting up the Variables

Let us denote  $X_0, Y_0$  as the points where  $Z = 0$ , and  $X_1, Y_1$  where  $Z = 1$ .

For  $Z = 1$ ,  $Y_{1i} = g(X_{1i}) + \epsilon_{1i}$ ,  $\epsilon_{1i} \sim N(0, \sigma_1^2)$

For  $Z = 0$ ,  $X_{0j} = g^{-1}(Y_{0j}) + \epsilon_{0j}$ ,  $\epsilon_{0j} \sim N(0, \sigma_0^2)$

Here, we have the latent variable  $Z$ . If we had the variable  $Z$  given to us, we could have easily gotten the Likelihood function using

$$f(x, y \mid z = 0) = \frac{1}{\sqrt{2\pi\sigma_0^2}} e^{-\frac{(x - g^{-1}(y))^2}{2\sigma_0^2}} f(y \mid z = 0)$$

$$f(x, y \mid z = 1) = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(y - g(x))^2}{2\sigma_1^2}} f(x \mid z = 1)$$

### 6.2 Relation to GMM

This is not exactly of the form of the GMM, where we have constant means for all the Gaussian Distributions. We also have to consider that the "mean" of the first distribution is not independent of the "mean" of the

second distribution.

Our idea is related to the ALT-OPT algorithm, where we solve the problem iteratively. We have a total of 6 parameters to predict -  $(\pi_0, \pi_1, g, Z, \sigma_0^2, \sigma_1^2)$ .

Here,  $Z_i \sim \text{Bernoulli}(\pi_1)$  and  $\pi_0 = 1 - \pi_1$ .

### 6.3 Proposed Algorithm

Let us initialize  $Z^{(0)}$  randomly. We can also initialize  $g^{(0)}$  as any suitable model for X on Y. Using that, we can get the vectors  $\epsilon_0^{(0)} = X_0^{(0)} - g^{(0)-1}(Y_0^{(0)})$  and  $\epsilon_1^{(0)} = Y_1^{(0)} - g^{(0)}(X_1^{(0)})$ . Getting the variance of those vectors, we can get  $\sigma_0^{2(0)}$  and  $\sigma_1^{2(0)}$ . We also get  $\pi_0^{(0)} = \frac{N_0^{(0)}}{N_0^{(0)} + N_1^{(0)}}$  and  $\pi_1^{(0)} = 1 - \pi_0^{(0)}$ .

#### 6.3.1 Iterations

Here, we assume that the prior distributions of X and Y are independent of Z. Let us denote them by  $h_X$  and  $h_Y$  for X and Y, respectively.

$$P(Z = 1|X, Y) \propto f(X, Y|Z = 1)P(Z = 1) \propto f(Y|X, Z = 1)P(Z = 1)P(X)$$

$$P(Z = 0|X, Y) \propto f(X, Y|Z = 0)P(Z = 0) \propto f(X|Y, Z = 0)P(Z = 0)P(Y)$$

In exact form,

$$P(z^{(t+1)} = 1|x, y) = \frac{\pi_1^{(t)} \frac{1}{\sqrt{2\pi\sigma_1^{2(t)}}} e^{-\frac{(y-g^{(t)}(x))^2}{2\sigma_1^{2(t)}}} h_X(x)}{\pi_1^{(t)} \frac{1}{\sqrt{2\pi\sigma_1^{2(t)}}} e^{-\frac{(y-g^{(t)}(x))^2}{2\sigma_1^{2(t)}}} h_X(x) + \pi_0^{(t)} \frac{1}{\sqrt{2\pi\sigma_0^{2(t)}}} e^{-\frac{(x-g^{(t)-1}(y))^2}{2\sigma_0^{2(t)}}} h_Y(y)} \quad (1)$$

$$P(z^{(t+1)} = 0|x, y) = \frac{\pi_0^{(t)} \frac{1}{\sqrt{2\pi\sigma_0^{2(t)}}} e^{-\frac{(x-g^{(t)-1}(y))^2}{2\sigma_0^{2(t)}}} h_Y(y)}{\pi_1^{(t)} \frac{1}{\sqrt{2\pi\sigma_1^{2(t)}}} e^{-\frac{(y-g^{(t)}(x))^2}{2\sigma_1^{2(t)}}} h_X(x) + \pi_0^{(t)} \frac{1}{\sqrt{2\pi\sigma_0^{2(t)}}} e^{-\frac{(x-g^{(t)-1}(y))^2}{2\sigma_0^{2(t)}}} h_Y(y)} \quad (2)$$

We have the conditional likelihood -

$$L(\theta|X, Y, Z^{(t+1)}, \theta^{(t)}) = \prod_{i=1}^{N_0^{(t)}} \frac{1}{\sqrt{2\pi\sigma_0^{2(t)}}} e^{-\frac{(X_{0i}-g^{-1}(Y_{0i}))^2}{2\sigma_0^{2(t)}}} h_Y(Y_{0i}) \prod_{i=1}^{N_1^{(t)}} \frac{1}{\sqrt{2\pi\sigma_1^{2(t)}}} e^{-\frac{(Y_{1i}-g(X_{1i}))^2}{2\sigma_1^{2(t)}}} h_X(X_{1i}) \quad (3)$$

We have  $g^{(t+1)} = \text{argmax}_g L(\theta | X, Y, Z^{(t+1)}, \theta^{(t)})$ .

#### 6.3.2 Stopping Criterion

Stop when

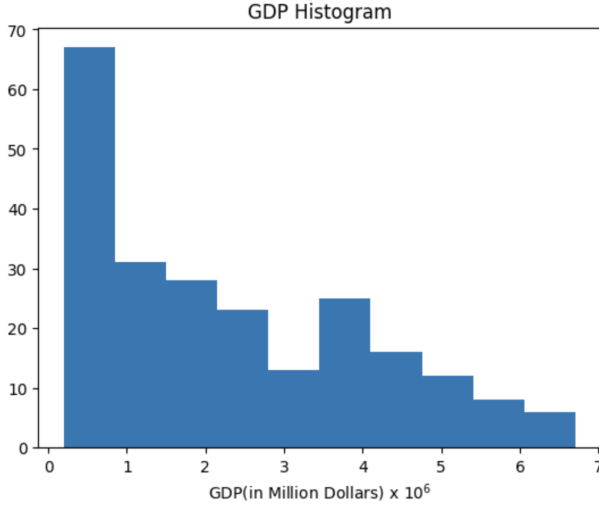
- $Z^{(t)} = Z^{(t+1)}$ .
- $\|g^{(t+1)} - g^{(t)}\| < \epsilon$
- $\text{iterations} > \text{max\_iters}$

---

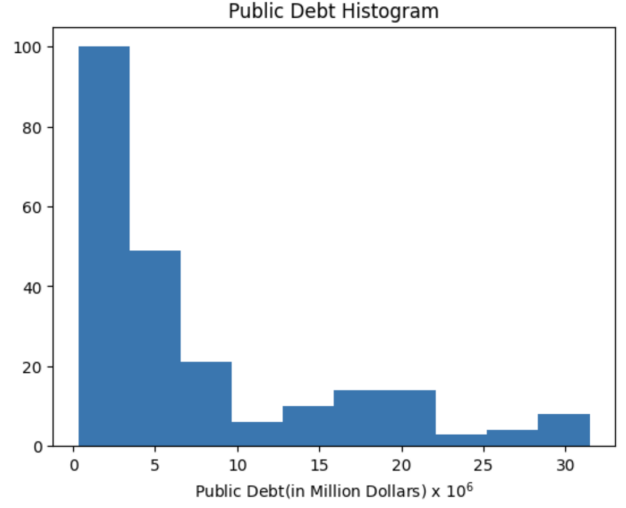
**Algorithm 1** New GMM Algorithm

---

- 1: For all  $Z_i$ , we can predict  
 $Z_i^{(t+1)} = \operatorname{argmax}(P(Z_i^{(t+1)} = 0|X_i, Y_i), P(Z_i^{(t+1)} = 1|X_i, Y_i))$ , using 1 and 2.
  - 2:  $g^{(t+1)} = \operatorname{argmin}_g \sum_i^N (\frac{(Y_i - g(X_i))^2}{\sigma_1^2(t)} I[Z_i^{(t+1)} = 1] + \frac{(X_i - g^{-1}(Y_i))^2}{\sigma_0^2(t)} I[Z_i^{(t+1)} = 0])$ , using 3.
  - 3:  $\epsilon_0^{(t+1)} = X_0^{(t+1)} - g^{(t+1)-1}(Y_0^{(t+1)})$ .
  - 4:  $\epsilon_1^{(t+1)} = Y_1^{(t+1)} - g^{(t+1)}(X_1^{(t+1)})$ .
  - 5:  $\sigma_0^{2(t+1)} = \operatorname{Var}(\epsilon_0^{(t+1)})$ .
  - 6:  $\sigma_1^{2(t+1)} = \operatorname{Var}(\epsilon_1^{(t+1)})$ .
  - 7:  $N_0^{(t+1)} = \sum_i^N I[Z_i^{(t+1)} = 0]$ .
  - 8:  $N_1^{(t+1)} = \sum_i^N I[Z_i^{(t+1)} = 1]$ .
- 



(a)



(b)

## 7 Data Analysis

We run the model with the US GDP vs Public Debt data.

To implement the SWAP Regression model, we would have to assume a prior on X and Y.

### 7.1 Prior on US GDP

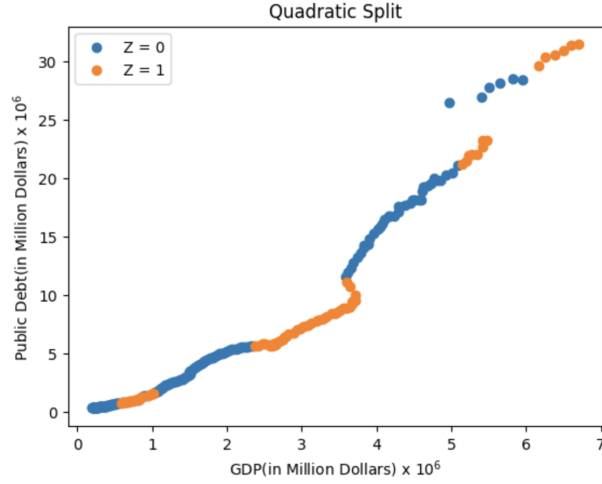
To assume a prior on US GDP, we look at the histogram of US GDP, as shown in 1a. We can see that it resembles an Exponential Distribution, and since US GDP is always Positive, that seems like a fair assumption. We can get the rate parameter  $\hat{\lambda}_{MLE} = \frac{1}{\bar{X}} = 0.438780921481478$ .

### 7.2 Prior on Public Debt

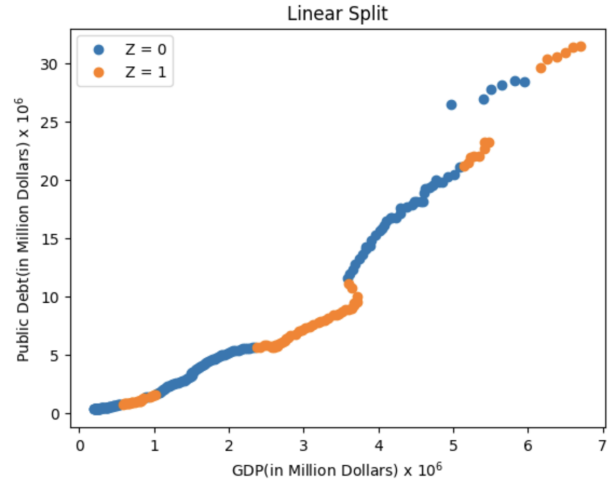
To assume a prior on Public Debt, we look at the histogram of Public Debt, as shown in 1b. We can see that it resembles an Exponential Distribution, and since Public Debt is always Positive, that seems like a fair assumption. We can get the rate parameter  $\hat{\lambda}_{MLE} = \frac{1}{\bar{Y}} = 0.13497222534768713$ .

## 8 Testing the Model

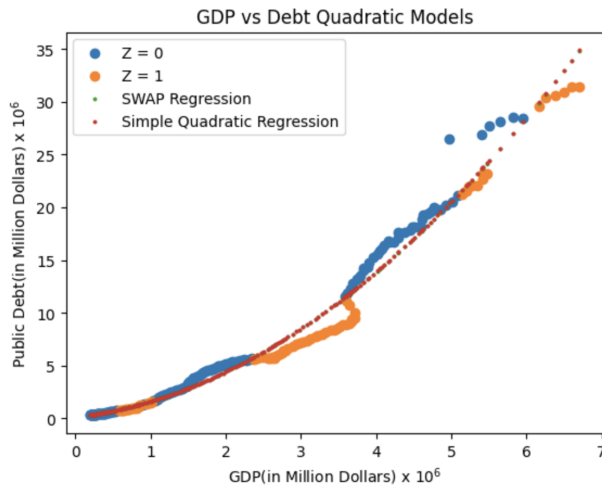
Now, since we have the prior distribution, we can implement all the models.



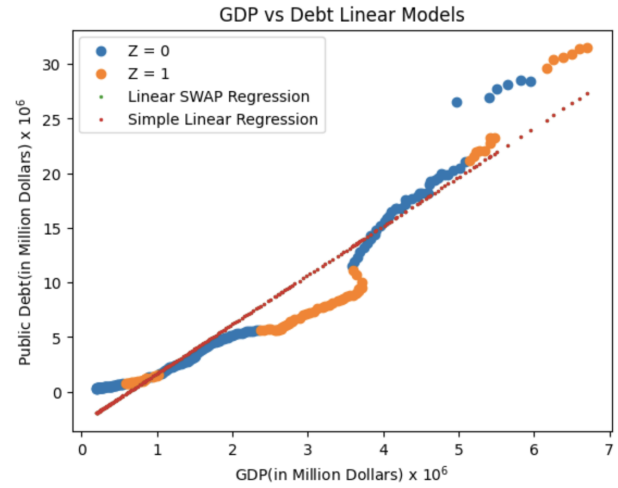
(a)



(b)



(c)



(d)

## 8.1 Simple Linear Regression

With Simple Linear Regression, we get the line,  
 $y = 4.49724771804972 x - 2.840483200739337$

## 8.2 Simple Quadratic Regression

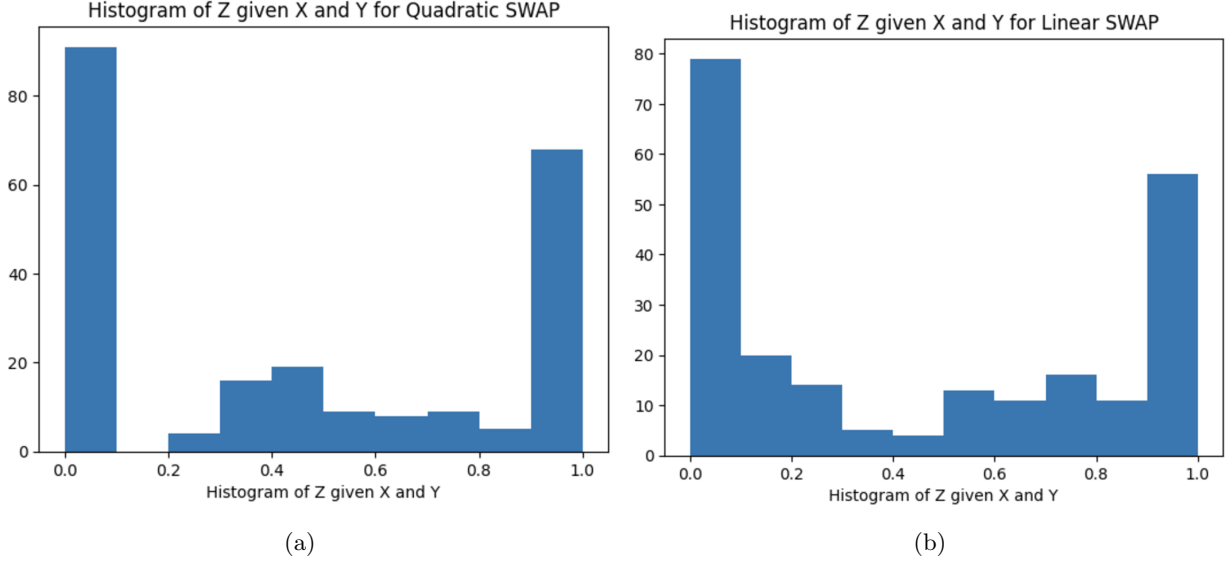
With Simple Quadratic Regression, we get the line,  
 $y = 0.6460656714354706 x^2 + 0.8578272692490471 x + 0.11587014579886798$

## 8.3 SWAP Linear Regression

With SWAP Linear Regression, we get the line,  
 $y = 4.49728064380432 x - 2.8404993840819652$

## 8.4 SWAP Quadratic Regression

With SWAP Quadratic Regression, we get the line,  
 $y = 0.6453359354453013 x^2 + 0.8581953283583627 x + 0.11630141009211563$



## 9 Testing Goodness of SWAP

The test of goodness of the fit can be determined by how well our method can cluster the data into  $Z = 0$  and  $Z = 1$ . We can define a good fit as one with more "surety" of  $Z$  to be 0 or 1. For the model used, we can look at the probabilities of  $Z = 1$ , as done in 1. We can get a Histogram of the probabilities to visualize it. However, since  $P_{Z|X,Y}$  is a probability, it is between 0 and 1, so we can assume it to be a Beta Distribution. Since, we want that value to be close to 0 or 1, for more "surety" of whether  $Z$  is 0 or 1, we would want  $\alpha$  and  $\beta$  to be as less than 1 as possible.

The plots 3a and 3b show that the values of  $Z$  we got are generally closer to 0 and 1 than to 0.5. To test it mathematically, we can get the Maximum Likelihood Estimates of  $\alpha$  and  $\beta$  for both distributions.

For the Quadratic Case, we get  $\hat{\alpha}_{MLE} = 0.09456035265627243$ ,  $\hat{\beta}_{MLE} = 0.1314989721991328$

For the Linear Case, we get  $\hat{\alpha}_{MLE} = 0.25023439277569504$ ,  $\hat{\beta}_{MLE} = 0.26475833796821263$

Here, we can see that the estimates for the Quadratic SWAP are smaller than the estimates for the Linear SWAP Model, and are less than 1, so we can say that the Quadratic SWAP Model is a good fit, and is better than the Linear SWAP Model.

## References

- [1] M. Chow, B. Li, and J. Q. Xue, "On regression for samples with alternating predictors and its application to psychometric charts," *Statistica Sinica*, vol. 25, no. 3, pp. 1045–1064, 2015.
- [2] G. De Vita, E. Trachanas, and Y. Luo, "Revisiting the bi-directional causality between debt and growth: Evidence from linear and nonlinear tests," *Journal of International Money and Finance*, vol. 83, pp. 55–74, 2018.