Per Capita Consumption Functions of Slovenia

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I. Introduction

This essay presents a consumption function for Slovenia for the period of 1990 to 2019, estimating consumption per capita against GDP per capita. How GDP per capita determines consumption per capita in countries like Slovenia is examined. Linear model and log-log model is tested by ordinary least squares. The data is obtained from the Penn World Tables.

II. Methodology

1. Brief description of the data

As can be seen in figure1, real consumption of Slovenia grew steadily from 30 billion to around 56 billion during the period of 1990 and 2019. Similarly, its real GDP followed the same trend, while the population of Slovenia increases by only less than 3% in total during the given period. Therefore, it can be expected that little effect will be imposed on the linear relationship between consumption and GDP if both variables are divided by population.

Figure 1. Real Consumption, Population, and Real GDP in Slovenia, 1990-2019

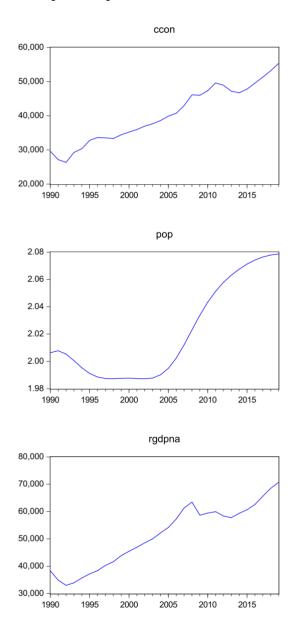


Table2 shows the average of these three data, as well as its standard deviation. As can be seen, during the period of 1990 and 2019, the average consumption was comparatively small, with a value of nearly four-fifth of and the average GDP. Moreover, the standard deviation of the consumption was around one-third less than that of GDP, representing a more stable consumption growth.

Table 2. Statistics of Real Consumption, Population, and Real GDP

	Obs.	Mean.	Std	Max.	Min.	Sum	Sum Sq. Dev.
			Dev.				_
Consumption	30	40234.1	8356.422	55288	26339	1207024	2.03E+09
Population	30	2.0209	0.0350	2.0786	1.9873	60.626	0.0354
GDP	30	51260.5	11374.62	70660	32968	1537815	3.75E+09

2. Estimation of a linear model of consumption function

Time series data on household and government consumption expenditure per capita and GDP per capita for Slovenia from 1990 to 2019 is used. In order to estimate the consumption functions, a linear model is first created. The model is presented as under:

$$con_{pci} = \alpha + \beta g dp_{pci} + \mu_i$$

Where:

 con_{pc} = real consumption per capita at current PPS (in 2017US\$)

 gdp_{pc} = gross domestic products per capita (in 2017US\$)

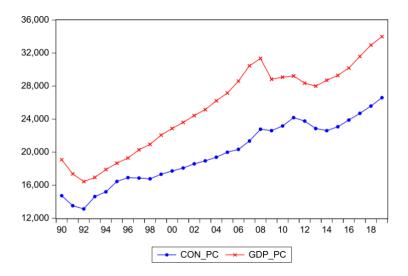
Table 2.1. Statistics of Consumption per capita and GDP per capita

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	Obs.	Mean.	Std. Dev.	Max.	Min.	Sum	Sum Sq. Dev.
con_pc	30	19857.10	3826.411	26597.98	13134.34	595712.9	4.25E+08
gdp_pc	30	25301.52	5288.718	33993.15	16439.99	759045.6	8.11E+08

Marginal propensity to consume and elasticity of consumption per capita with respect to GDP per capita are workout as follow:

$$\begin{split} \text{MPC} &= \frac{d \ con_{pci}}{d \ gdp_{pci}} = \ \beta \\ &Elasticity_{cd} = \frac{d \ con_{pci}}{d \ gdp_{pci}} * \ \frac{gdp_{pci}}{con_{pci}} \end{split}$$

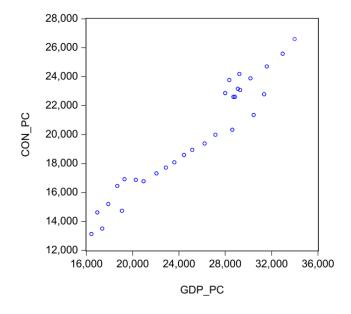
Figure 3. CON_PC and GDP_PC in Slovenia: 1990-2019



The movements in consumption per capita (CON_PC) and GDP per capita (GDP_PC) in the current year in Slovenia during the period from 1990 to 2019 can be observed in Figure 3. As shown in the graph, it is clear that the consumption per capita and the GDP per capita are moving in the same direction and the gap between two variables seems to increase after 1996.

In addition, a relatively distinct linear relationship of GDP per capita and consumption per capita can be roughly revealed in figure 4:

Figure 4. Linear relationship of CON_PC and GDP_PC in Slovenia



To find the coefficients, consumption function is tested empirically by using the ordinary least squares:

Table5. Linear Regression Result of the Per Capita Consumption of Slovenia

Variable	Coefficient	Std. Error	t-Statistic	Prob.	R^2	Adjusted R [^] 2
С	2171.049	911.1766	2.382687	0.0242	0.933439	0.931062
GDP_PC	0.699011	0.035275	19.81578	0		

Table 5 reports that the constant term is 2171.049 and the coefficient of GDP per capita is positive as expected. The t-statistic is 19.81578, and the p-value is zero. Thus the coefficient of GDP per capita is statistically significant in the linear regression. In addition, the value of marginal propensity to consume is 0.699, evincing the fact that a 1 unit increase in GDP per capita raises the consumption per capita by approximately 0.699 units during the given period in Slovenia.

Since the variables are significant, GDP per capita is proved to be a determinant of consumption and the model is good enough to be used to fit the data in the case of Slovenia.

To verify if the accuracy of the coefficients, a rough comparation is workout between the graph of actual consumption per capita and the predicted value. A variable "pred" is generated using the coefficients calculated.

$$pred = 1935.422 + 1.513692 * gdp_{pc}$$

As can be seen in Figure 6, the prediction (red line) is close to the actual consumption per capita (blue line), which shows a relatively accurate prediction of coefficients.

28,000 26,000 24,000 22,000 18,000 16,000 12,000 90 92 94 96 98 00 02 04 06 08 10 12 14 16 18 — CON_PC — PRED

Figure 6. Comparation of actual CON_PC and the prediction

3. Testing for heteroscedasticity and autocorrelation.

Firstly, to verify if there is a heteroscedasticity problem, squared residuals (e2) is obtained from the regression. Then, the squared residuals by GDP per capita is sorted by the GDP per capita. The relationship between squared residuals and GDP per capita is shown in the Figure 7:

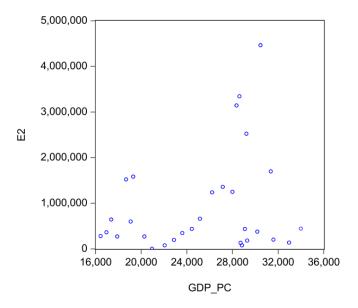


Figure 7. Relationship between squared residuals and GDP_PC

It's hard to see a strong relationship between e2 and GDP per capita. We continually use a white's test, a more general test, to figure out the heteroscedasticity of the OLS estimation. In this test, the following estimated model: $con_{pci} = \alpha + \beta * gdp_{pci} + \mu_i$ is used, running an auxiliary regression to the squared residuals. Testing the hypothesis of H_0 : $\sigma_i^2 = \sigma^2$, H_1 : $\sigma_i^2 \neq \sigma^2$, since $nR^2(2.238) < \chi^2_{2,0.995}$ (5.991), we cannot reject the null at 5% significance level, which means that the data is not heteroscedastic.

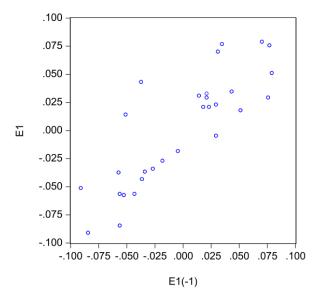
Table8. Result of White Test

Heteroskedasticity Test: White					
F-statistic	1.0884	Prob. F(2,27)	0.3511		
Obs*R-squared	2.2383	Prob. Chi-Square(2)	0.3266		
Scaled explained SS	1.3164	Prob. Chi-Square(2)	0.5178		

Variable	Coefficient	Std. Error	t-Statistic	Prob.	R^2	Adjusted R^2
C	-3452387	5321602	-0.64875	0.522	0.074609	0.006061
GDP_PC^2	-0.00526	0.008987	-0.58538	0.5632		
GDP_PC	312.4065	445.219	0.701692	0.4889		

Subsequently, the auto-correlation of the OLS is tested to figure out if the assumptions of the GM theorem are violated in the consumption function. As shown in Figure 9, there seems to be a linear relationship between the residual(E1) and the lagged residual(E1(-1)).

Figure 9. Residual and Lagged residual



Run a regression of residuals and their first lag: $\mu_t = \rho_1 \mu_{t-1} + \nu_t$, with the t-statistic value of 7.948 and p-value of zero, ρ_1 is statistically significant. The auto correlation coefficient is 0.8223 (<1), evincing the fact that there is a positive correlation in this linear regression model.

Table 10. Regression Result of Residual and Lagged Residual

Variable	Coefficient	Std. Error	t-Statistic	Prob.	Durbin-Watson
E1(-1)	0.822337	0.10347	7.947618	0	1.224929

Continuously, a correlogram is plotted to reveal autocorrelation and partial autocorrelation functions of the residuals. The number of spikes indicates that the correlation can workout the second lag.

Table 11. Correlogram

Autocorrelation	Partial Correlation
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Therefore, the Breusch-Godfrey test is used to test for the higher autocorrelation. In this process, a new regression is run: $\mu_t = \rho_1 \mu_{t-1} + \rho_2 \mu_{t-2} + \nu_t$, where μ_t are the residuals and μ_{t-1}, μ_{t-2} , are their 1st and 2nd lags. Table 12 reports the regression result, in which the 1st and 2nd lagged residual are statistically significant at 5% level.

Table 12. Regression Result of Residual and Lagged Residual

Variable	Coefficient	Std. Error	t-Statistic	Prob.	Durbin Watson
E1(-1)	1.201477	0.173429	6.927759	0	2.159958
E1(-2)	-0.46116	0.170513	-2.70451	0.0119	

4. Further verification of MPC

Wald test is used to check whether the estimation of MPC in OLS is accurate. Generating the null hypothesis H_0 : $\beta = 0.7$, and the alternative hypothesis H_1 : $\beta \neq 0.7$. As shown in the table 13, since the t-stat is-0.03 and probability is 0.98 which is obviously high, we cannot reject the null hypothesis at any significance level and the value MPC is proved to be exactly 0.7, which is close to the previous estimation of 0.699.

Table 13. Wald Test of MPC

Table 13. Wata Test of MFC							
Value	df	Probability					
-0.02803	28	0.9778					
0.000786	(1, 28)	0.9778					
0.000786	1	0.9776					
).7							
= 0)	Value	Std. Err.					
- C(2)	-0.000989	0.035275					
	-0.02803 0.000786	-0.02803 28 0.000786 (1, 28) 0.000786 1					

5. Comparations of the default standard errors with standard errors robust to heteroscedasticity.

The Huber-White standard error is used in this case. As shown in Table14, the Huber-White standard error of the MPC is 0.032, which is slightly smaller than the default error (0.035). This might because the sample size is not big enough since only 30 observations are contained in our data. However, since the gap between the OLS standard errors and the robust standard errors is too small, it should not be judged that the conclusion is absolutely unreliable.

Table 14. Huber-White Standard Error

	Tuote 14. 11 wor 17 title Statutura El 101						
Variable	Coefficient	Std. Error	t-Statistic	Prob.	R^2	Adjusted R [^] 2	
C	-3452387	5321602	-0.64875	0.522	0.074609	0.006061	
GDP_PC	312.4065	445.219	0.701692	0.4889			
GDP_PC^2	-0.00526	0.008987	-0.58538	0.5632			

6. Estimation of a log-log regression

The log linear per capita consumption function is then tested empirically by using the ordinary least squares. Time series data on per capita consumption and per capita GDP for Slovenia from 1990 to 2019 is used. The model is presented as under:

$$\log(con_{pci}) = \beta_1 + \beta_2 \log(gdp_{pci}) + \mu_i$$

Where:

 $\log(con_{pci}) = \log$ of real consumption per capita at current PPS (in mil.2017US\$) $\log(gdp_{pci}) = \log$ of gross domestic products per capita (in mil.2017US\$)

Marginal propensity to consume and elasticity of consumption per capita with respect to GDP per capita are workout as follow:

$$\begin{aligned} &\text{MPC} = \beta_2 * \frac{con_{pci}}{gdp_{pci}} = \beta_2 \\ &Elasticity_{cd} = \frac{d \log(con_{pci})}{d \log(gdp_{nci})} = \beta_2 \end{aligned}$$

Table 15. Log-log Regression Result of the Per Capita Consumption of Slovenia

Variable	Coefficient	Std. Error	t-Statistic	Prob.	R^2	Adjusted R^ 2
C	1.03024	0 429618	2.398039	0.0234	0 938092	0.935881
LNG	0.874594	01.27010	20.59822	0.0231	0.23002	0.935001

Table 15 reports that the constant term is 1.03 and the coefficient of log GDP per capita is positive. The t-statistic is 20.598 and p value is zero, thus the coefficient of GDP per capita is statistically significant at both 1% and 5% levels. In addition, the value of marginal propensity to consume is 0.875 evincing the fact that 1% growth in GDP per capita increases the consumption per capita by approximately 0.875 % during the given period in Slovenia.

Since the variables are significant, GDP per capita is proved to be a determinant of consumption and the model is good enough to be used to fit the data in the case of Slovenia.

A further verification is workout by using a rough comparation between the graph of actual consumption per capita in log terms and the predicted value, generating a variable "pred2" by using the above coefficients.

$$pred2 = 1.03024 + 0.874594 * \log(gdp_{pc})$$

In Figure 16, the prediction (red line) is close to the actual consumption per capita in log term (blue line), showing a relatively accurate prediction of coefficients.

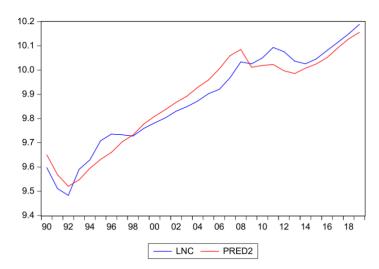


Figure 16. Comparation of actual log(con_pc) and the prediction

7. Hypothesis test of the elasticity of consumption per capita with respect to GDP per capita is 1

In the log-log model of $\log(con_{pci}) = \beta_1 + \beta_2 \log(gdp_{pci}) + \mu_i$, the elasticity of consumption per capita with respect to GDP per capita can be represented as follow: $Elasticity_{cd} = \frac{d \log(con_{pci})}{d \log(gdp_{pci})} = \beta_2$. To test the elasticity of consumption with respect to GDP is 1, the null hypothesis $H_0: \beta_2 = 1$, and the alternative hypothesis $H_1: \beta_2 \neq 1$ are generated.

Wald test is used in this case, since the p-value is 0.0063, we reject the null hypothesis. Therefore, the elasticity of consumption to GDP is not 1, evincing the fact that household and government consumption is affected by GDP. Once again, it is verified that the GDP per capita is an important determinant of consumption per capita.

Table 17. F-test of the elasticity of consumption with respect to GDP

Test Statistic	Value	df	Probability
t-statistic	-2.95353	28	0.0063
F-statistic	8.72333	(1, 28)	0.0063
Chi-square	8.72333	1	0.0031
Null Hypothesis: C(2)=1	[
Normalized Restriction (=	= 0)	Value	Std. Err.
-1 + C(2)		-0.125406	0.04246

III. Conclusion

The primary purpose of the research is to estimate the per capita consumption function for Slovenia, and the linear function and log-log function is tested. Obviously, both the linear model and log-log model fit well the case of Slovenia, and GDP per capita is an essential determinant of consumption per capita. The F-test tells that there is no structural break of the time series data; thus, the per capita consumption function is relatively stable. Based on the above analysis, the government needs to implement policies to improve the per capita GDP to increase the consumption expenditure of households and governments.

Appendix I. Data

Table 1. (1990-2019)

Years	Annual Per Capita Consumption Expenditure of Households and Government (in 2017US\$)	Annual Per Capita Gross Domestic Products of Slovenia (in 2017US\$)
1990	14733.81	19078.9
1991	13509.02	17369.02
1992	13134.34	16439.99
1993	14619.44	16947.79
1994	15203.46	17897.25
1995	16456.98	18671.8
1996	16916.72	19294.82
1997	16868.81	20280.21
1998	16774.3	20946.12
1999	17313.06	22060.42
2000	17715.3	22869.45
2001	18084.38	23608.01
2002	18592.37	24438.09
2003	18941.96	25154.16
2004	19385.78	26219.69
2005	19984.7	27150.7
2006	20336.79	28603.75
2007	21345.17	30452.99
2008	22782.9	31351.64
2009	22602.96	28831.69
2010	23160.15	29082.82
2011	24184.33	29219.7
2012	23766.86	28358.12
2013	22856.76	27994.14
2014	22603.76	28708.27
2015	23072.14	29290.28
2016	23882.83	30181.13
2017	24705.33	31594.68
2018	25580.45	32956.87
2019	26597.98	33993.15

Appendix II. Eviews Code

```
wfsave assignment.wf1
1.
ccon.stats
pop.stats
rgpdna.stats
ccon.statby pop
ccon.statby rgdpna
group data ccon pop rgdpna
data.line(m)
2.
genr gdp_pc=rgdpna/pop
genr con_pc=ccon/pop
graph conpcgdppc.scat gdp_pc con_pc
equation congdppc.ls con_pc c gdp_pc
congdppc.fit pred
graph model.line con_pc pred
3.
congdppc.makeresid e
genr e2=e^2
scat gdp_pc e2
equation white.ls e2 c gdp_pc gdp_pc^2
scalar test=white.@r2*white.@regobs
scalar critical95=@qchisq(0.95, 2)
scalar p=@chisq(test,2)
ccongdp.white(c)
genr e1=resid
scat e1(-1) e1
equation ar1.ls e1 e1(-1)
dot e1
e1.correl
equation ar2.ls e1 e1(-1) e1(-2) e1(-3)
4.
congdppc.wald c(2)=0.7
equation robust.ls(cov=huber) con_pc c gdp_pc
6.
genr lnc=log(con_pc)
```

genr lng=log(gdp_pc)
equation lncongdp.ls lnc c lng
lncongdp.fit pred2
graph model2.line lnc pred2
7.
lncongdp.wald c(2)=1