Verifying Okun's law in Sweden

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1 Research Question

Okun's law is a famous macroeconomical law that states there is an inverse relationship between GDP and Unemployment. It does come in several forms, some where its Growth of GDP, GDP gap, Unemployment in nominal terms etc. This paper will focus on verifying Okun's law and analysing the relationship between the GDP gap and Unemployment rate. Arshad verified this for a different time window using Swedish data in 2010 and using GDP gap and unemployment gap instead of rate[1]. Another very recent paper by Faramarzi and Maraui from 2022 also verified this relationship, though not using VAR models, making it an interesting comparison[2].

2 Data

The dataset used in this paper consists of 2 variables that are quarterly between 1981 Quarter 1 to 2020 Quarter 4:
BNP_gap = The gap between potential and actualized GDP according to the NIER(National institute of economic research) in Sweden.
Unemploy_perc = Unemployment rate(percentage of labor force unemployed) according to Statistics Sweden's Labor force survey.

3 Estimation Strategy

A great tool for analysing relationships between multiple time series that interact is a VAR model which will be used for this paper. As VAR models are so useful for this purpose but hard to interpret coefficient-wise directly, we will use two techniques known as impulse response analysis and forecast error variance decomposition.

4 Results

First we plot our data in figure 1 and there is a clear negative correlation. We also plot the time series in levels and differenced once, by visual inspection we suspect they might be I(1). Now we try to find out which order of integration each series has by doing an ADF/KPSS test on each. As both don't reject the null of unit root for any reasonable significance level for both test we difference them and do another ADF/KPSS test. This time the test results align and we can confidently state that we have significant evidence of these being I(1). Now as they are of the same order of integration we will have to check for cointegration using an Engle-granger test, which is just fitting one variable on the other and testing if the residuals are stationary, meaning we have cointegration. We conclude that for a 5% significance level we have evidence of cointegration. This result is not surprising as these variables often are cointegrated due to their long run relationship which other papers such as Arshad's have proposed their solutions to[1]. Usually one might use a VECM model now to solve this, but here we will just use them in levels in our VAR as them being cointegrated allows us to do this. To fit our VAR model we choose lag order 9 using AIC. Now to proceed we have to make sure some assumptions are fulfilled, which is no autocorrelation in our residuals and gaussian error terms. To verify these assumptions we use the Ljung-box and Jarques-bera tests. Violating the autocorrelation assumption can not be done reliably here, while the normality assumption is less key. Our Ljung box tests for the null of no autocorrelation up to 2,3 and 4 times P(lag order = 9) we can only reject the null of no autocorrelation at 5% for 2p while the rest can not reject. Our Jarques-bera test shows a highly significant rejection of the null of gaussian residuals, which still lets us proceed as it is not a key assumption. Next we test for granger causality between our time series. We can reject the null of GDP gap not granger-causing unemployment rate, while we can not reject the null of unemployment rate not granger causing GDP gap. This tells us there is evidence of GDP gap being useful for forecasting unemployment rate but not the other way around for our data. This can be seen in appendix too where the models coefficients are significant for the GDP gap being independent while unemployment rate is dependent but not the other way around. Now to interpret our VAR model we will estimate impulse response functions between these variables which will tell us how each variable reacts to a shock in the other for up to 10 time periods after the shock occurs in our case. We can see a positive shock in GDP gap in figure 2 leads to a decrease in unemployment rate and accelerates downward until 5 periods in the future, where the shock weakens as time passes with a small spike down again between 7 through 9 time periods in the future. For a shock in unemployment rate in figure 3 we can see no effect on GDP gap for 1 time period, then it acceleratingly decreases, until time period 4 where the shock weakens, just very slowly with some spikes up and down. Now we also do a forecast error variance decomposition in figure 4 which tells us how proportionally influenced by a shock in itself and the other variable is for 10 time periods in our case. We can see GDP gap mostly being influenced by itself for all 10 time periods, while unemployment rate is majorly influenced by itself for 1 time period then it is almost equally influenced by shocks in both variables from that point on. For this data unemployment seems to be a bad predictor for GDP gap, while GDP gap is a great predictor for unemployment. This means we can only conclude that this law stating this relationship only holds one way in our data. Conclusively one can state there is evidence in Swedish quarterly data for Okun's law between 1981 and 2020 that GDP gap and unemployment are inversely related, though only GDP gap granger causes unemployment and not the other way around. This could be due to unemployment being driven by the GDP gap and other features highly correlated with the GDP gap, while GDP gap maybe is driven only partly by unemployment and other features not correlated with unemployment. These results are partly in line with Arshads previous paper[1], where he states in his conclusion that if there is a change in GDP gap there will be a change in the reverse direction for the unemployment gap. More recently in 2014 Lang wrote a paper on this subject, that focused on if Okun's law holds up in Sweden and if it differs based on gender. This could be an interesting topic for future research[3].

References

[1] Z. Arshad, "The Validity of Okun's Law in the Swedish Economy," *Stockholm: Department of Economics Stockholm University*, 2010. [Online]. Available: https://www.ne.su.se/polopoly_fs/1.25832.1318427751!/menu/standard/file/Zeeshan_Arshad.pdf

[2] A. Faramarzi and F. Maraui, "Okun's law in the nordics: A time series analysis based on okun's law," 2022.

[3] P. Lang, "Okun's Law and Gender in Sweden," 2014. [Online]. Available: https://www.diva-portal.org/smash/get/diva2:790879/FULLTEXT01.pdf

5 Appendix

5.1 ADF & KPSS Tests

Table 1: ADF Tests

	statistic	parameter	alternative	p.value	data.name
Dickey-Fuller	-2.71	5.00	stationary	0.28	BNP_gap
Dickey-Fuller	-2.87	5.00	stationary	0.21	unemploy_perc
Dickey-Fuller	-5.70	5.00	stationary	< 0.01	diff(BNP_gap)
Dickey-Fuller	-4.33	5.00	stationary	< 0.01	diff(unemploy_perc)

Table 2: KPSS Tests

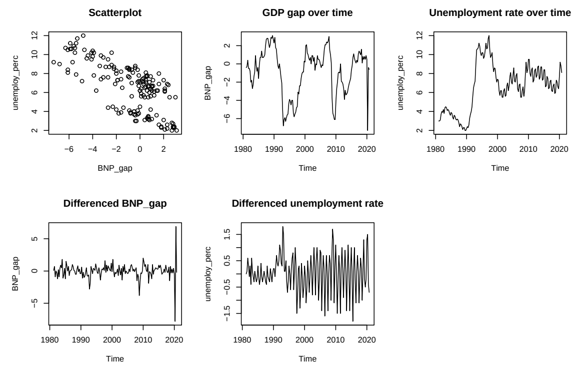
	statistic	parameter	p.value	data.name
KPSS Level	0.14	4.00	> 0.10	BNP_gap
KPSS Level	0.03	4.00	> 0.10	diff(BNP_gap)
KPSS Level	1.05	4.00	< 0.01	unemploy_perc
KPSS Level	0.09	4.00	> 0.10	diff(unemploy_perc)

5.2 Engle-Granger Test

Table 3: Cointegration test, null is no cointegration

	statistic	parameter	alternative	p.value	data.name
Dickey-Fuller	-3.71	5.00	stationary	0.03	coint$residuals

Figure 1: Scatterplot of data



5.3 Ljung-box and Jarques Bera tests & Lag selection

Table 4: Ljung box tests

	statistic	df	p.value	lags.pt
Chi-squared	52.7	36	0.035	18
Chi-squared	78.1	72	0.29	27
Chi-squared	108.2	108	0.48	36

Table 5: Jarques-bera test

statistic	parameter	p.value	data.name
994.22	4.00	$< 2.2e - 16$	Residuals of VAR object okun_var

Table 6: Lag selection using information criteria

	selection
AIC(n)	9
HQ(n)	5
SC(n)	5
FPE(n)	9

5.4 Granger causality tests

Table 7: Granger causality H0: BNP_gap do not Granger-cause unemploy_perc

Null hypothesis	statistic	df1	df2	p.value
BNP_gap do not Granger-cause unemploy_perc	3.17	9	264	0.00119
unemploy_perc do not Granger-cause BNP_gap	0.92	9	264	0.51

5.5 Impulse response functions & plots

Figure 2: Unemployment rate shock on GDP

Figure 3: GDP gap shock on unemployment rate

5.6 Forecast error variance decomposition & plots

Figure 4: Forecast error variance decomposition