Norwegian School of Economics
Bergen, spring semester 2020

ECN430: Assignment II

NORWEGIAN SCHOOL OF ECONOMICS

Table of Contents

Question 1: Inflation and stock returns (IV estimator)

TASK A

There are two ways to determine if an equation in a system of equations is identified: the order condition and the rank condition.

Order condition

The order condition is met, i.e. an equation is identified, if the number of instruments is equal to or greater than the number of endogenous regressors. It is also called the exclusion restriction. Compared to the rank condition, it is necessary, but not sufficient. This means that while every identified equation meets the order condition, fulfilling it does not necessarily mean that the equation of interest really is identified.

In order to evaluate the order condition, we need to find the number of instruments and the number of endogenous regressors.

In this case, it makes sense to assume inflation as an endogenous regressor in the returns equation and returns as an endogenous regressor in the inflation equation as they both influence each other. That means that in the returns equation, not only does inflation influence the returns, the returns might conceivably also influence the inflation.

Finding the number of instruments is proving more difficult. In order for an instrument to be valid, it needs to fulfill two conditions:

1) Instrument relevance: $Cov(z, x) \neq 0$
2) Instrument exogeneity: $Cov(z, u) = 0$

where z is the instrumental variable, x is the endogenous regressor and u is the error term.

An instrument is relevant if it has an effect on the endogenous regressor. In order for an instrument to be exogenous, it needs to be uncorrelated with the error term of the equation of interest and must not have a direct effect on y, the dependent variable. As the second condition cannot be tested, we will base the determination of instrument exogeneity on economic theory.

We choose the instrument relevance according to the significance for the respective endogenous variable in the correlation matrix below.

```
pwcorr inflation returns dmoney dprod rterm dcredit dspread, sig
```

	inflat~n	returns	dmoney	dprod	rterm	dcredit	dspread
inflation	1.0000						
returns	0.0050	1.0000					
	0.9289						
dmoney	-0.2674	0.0112	1.0000				
	0.0000	0.8407					
dprod	0.0202	-0.0227	-0.1304	1.0000			
	0.7166	0.6832	0.0187				
rterm	0.0412	-0.0229	-0.0871	-0.0022	1.0000		
	0.4594	0.6805	0.1170	0.9691			
dcredit	0.0441	0.0360	-0.0118	0.1411	0.0097	1.0000	
	0.4286	0.5175	0.8315	0.0109	0.8611		
dspread	-0.3493	-0.1729	0.2108	-0.0550	0.0027	0.0154	1.0000
	0.0000	0.0018	0.0001	0.3229	0.9616	0.7822	

Table 1.1: Correlation matrix

	Instrument relevance	Instrument exogeneity
dcredit	No	No
dprod	No	No
dmoney	No	No
dspread	Yes	Yes
rterm	No	Yes

Table 1.2: *Inflation Equation: instruments for the endogenous regressor (i.e. returns*

	Instrument relevance	Instrument exogeneity
dcredit	No	Yes
dprod	No	No
dmoney	Yes	Yes
dspread	Yes	No
rterm	No	No

Table 1.3: *Returns equation: instruments for the endogenous regressor (i.e. inflation)*

It is important to remember that even though a variable fulfills the criterion of instrument relevance, it might be weak. Weak instruments are instruments that explain little of the variation in the endogenous regressors. This can lead to inconsistent IV regressions or untrustworthy inference based on IV regressions. (Bjørnland und Thorsrud 2015) We can test for weak instruments using the F-statistic where a value larger than 10 indicates a relevant instrument.

We tested the instruments separately and only dmoney in the inflation equation turned out to be a non-weak instrument (Table 1.1). For the returns equation, the regression on dspread resulted in an F-statistic of 9.95 (Table 1.2). Because that is very close to 10, we also chose to consider dspread to be a non-weak instrument.

```
. regress inflation dmoney

      Source |       SS           df       MS      Number of obs   =       325
-------------+----------------------------------   F(1, 323)       =     24.88
       Model |  2.43717151         1  2.43717151   Prob > F        =    0.0000
    Residual |  31.6417901       323  .097962198   R-squared       =    0.0715
-------------+----------------------------------   Adj R-squared   =    0.0686
       Total |  34.0789616       324  .10518198    Root MSE        =    .31299

------------------------------------------------------------------------------
   inflation |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      dmoney |  -.0041671   .0008354    -4.99   0.000    -.0058106   -.0025235
       _cons |    .258215    .018044    14.31   0.000     .2227164    .2937137
------------------------------------------------------------------------------
```

Table 1.4: OLS regression (inflation on dmoney)

```
. regress returns dspread

      Source |       SS           df       MS      Number of obs   =       325
-------------+----------------------------------   F(1, 323)       =      9.95
       Model |  203.912661         1  203.912661   Prob > F        =    0.0018
    Residual |  6619.73178       323  20.4945256   R-squared       =    0.0299
-------------+----------------------------------   Adj R-squared   =    0.0269
       Total |  6823.64444       324   21.060631   Root MSE        =    4.5271

------------------------------------------------------------------------------
     returns |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     dspread |  -7.281879   2.308555    -3.15   0.002    -11.82358   -2.740176
       _cons |   .5703315   .2511588     2.27   0.024     .0762178    1.064445
------------------------------------------------------------------------------
```

Table 1.5: OLS regression (returns on dspread)

Consequently, we have only one instrument for each equation. This means that both equations are exactly identified as the number of instruments is equal to the number of endogenous repressors. Because the equations are exactly identified, there is no need to test for over identification.

Rank condition

The rank condition states that the excluded variables in the equation of interest must have non-zero coefficients in the other equation(s) in the system of equations. If the variables are zero in the equations where it is included, they are not valid instruments for IV estimation. This condition is necessary and sufficient. This means that if we can achieve identification using this condition, we can be certain that the equation of interest is identified. We therefore can use it to check the result of the order condition.

We create a matrix for determination and give a weight of 0 to the variables that are not included in the respective equation and a weight of 1 to the variables that are included.

	dprod	dspread	dmoney	dcredit	rterm
inflation	1	0	1	1	0
returns	1	1	0	0	1

Table 1.6: Matrix for rank condition

Consequently, dspread and rterm need to be non-zero in the returns equation in order for the inflation equation to be identified and dmoney and dcredit need to be non-zero in the inflation equation in order for the returns equation to be identified. According to the regressions we conduct later (see Appendix A), all four variables are estimated to be non-zero. Therefore, all excluded variables from one equation are non-zero in the other one and we therefore have two identified equations.

TASK B

According to both the order and the rank condition as discussed in task A, the instrument in the inflation equation for the endogenous regressor returns is dspread while the instrument in the returns equation for the endogenous regressor inflation is dmoney because only they are non-weak and significant.

TASK C

In the following regressions, we started out by including all independent variables in the estimation and then reestimate, only including the determined significant variables. As it turns out, the RMSE almost does not change if we exclude the insignificant variables. We therefore decided to exclude them for the regressions. We employ two-stage least squares (TSLS or 2SLS) for our IV regression and only use the valid instruments as determined in task A. There is no need to test for overidentification as we have exactly one instrument and one endogenous regressor in each equation, i.e. each equation is exactly identified. For the Stata output, see Appendix A.

Inflation equation

It is apparent that in the OLS regression, the returns are not significant. However, they are in the IV estimation where it is treated as an endogenous regressor. Using the built-in Stata command to test for endogeneity that pertains to the assumed endogenous regressor in the equation of interest, we can reject the null hypothesis of an exogenous variable and confirm our hypothesis of returns as an endogenous regressor in the inflation equation. Using the results of the IV estimation only including significant variables, our inflation equation now looks as follows:

$$inflation_t = 0.1909 + 0.1181 * returns_t - 0.0045 * dmoney_t + u_{1t}$$

When comparing the OLS to the IV results, the estimated coefficients only change slightly for the independent variables, but strongly for the returns variable. This makes sense as returns is an endogenous variable and leads to inconsistent results with an OLS regression.

Returns equation

Inflation is not significant in the returns equation neither using OLS nor using IV for estimation. After testing it for endogeneity as with the inflation equation, it turns out that it is not an endogenous regressor in the equation. It also is not significant as an independent variable. This means that there is no endogenous regressor and therefore no need for IV estimation. Consequently, we can simply use OLS for our regression and also receive a more efficient result. Thus, the return equation without insignificant variables according to the result in the OLS regression looks like this:

$$returns_t = 0.5703 - 7.2819 * dspread_t + u_{2t}$$

The values for the variable coefficients change more strongly from the OLS to the IV regression compared to the inflation equation, mainly for the inflation variable. This might be the case because in the IV estimation, inflation is treated as an endogenous variable even though it is not.

TASK D

We chose the three-stage least squares (3SLS) regression as our method to estimate the system of equations allowing for correlation between the error terms. It works by first applying 2SLS and then adds efficiency gains to the 2SLS regression by considering the cross-equation between the error terms. Leaving out the insignificant variables in the 3SLS regression has little to no effect on the RMSE both for the inflation and the returns equation. We therefore exclude them in our regression.

The 3SLS regression automatically considers the inflation and the returns to be endogenous because usually, the endogenous regressors are dependent variables in another equation in the system of equations. According to the Wu-Hausman test we conducted earlier, inflation is not endogenous. But because it also is not significant, we do not include it in the returns equation and therefore considering it as endogenous does not pose a problem.

Looking at the results, it is apparent that the marginal effects, i.e. the coefficients, are almost the same as in the regression equations above and thus confirm them. Therefore, we also can confirm our assumptions from the earlier regressions, namely that the returns are endogenous while the inflation is not.

Three-stage least-squares regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
inflation	**325**	**2**	**.6508367**	**-3.0396**	**15.79**	**0.0004**
returns	**325**	**1**	**4.513137**	**0.0299**	**10.01**	**0.0016**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
inflation						
returns	**.1250887**	**.0413155**	**3.03**	**0.002**	**.0441117**	**.2060657**
dmoney	**-.0032028**	**.0008889**	**-3.60**	**0.000**	**-.0049451**	**-.0014605**
_cons	**.1794055**	**.0412064**	**4.35**	**0.000**	**.0986424**	**.2601686**
returns						
dspread	**-7.281879**	**2.301441**	**-3.16**	**0.002**	**-11.79262**	**-2.771137**
_cons	**.5703315**	**.2503848**	**2.28**	**0.023**	**.0795863**	**1.061077**

Endogenous variables: inflation returns
Exogenous variables: dmoney dspread

Table 1.7: 3SLS regression for inflation and returns

Question 2: Var Model

TASK A

The data provided cover the period from the first quarter 1960 to first quarter 2008 and are collected quarterly.

Two different methods can be used to calculate the requested growth rates of the “index of industrial production” lip_t, and “unemployment rate” ur_t out of the level time series. The first lag difference calculates the growth from quarter to quarter; consequently no growth can be determined for the first quarter. In order to determine the growth between the seasonal quarters, level values of the annually consecutive quarters are differentiated. As a result, the first four quarters of the time series do not contain a growth rate. In this case, this means that no values are calculated for the four quarters of 1960.

First Log Difference of index of industrial production: $\Delta_1 lip_t = \ln(ip_t) - \ln(ip_{t-1})$

Seasonal Difference of the unemployment rate: $\Delta_4 ur_t = ur_t - ur_{t-4}$

By calculating a rate of change in a variable, via a periodic difference or via the seasonal difference, the time series become most likely stationary. (Tremayne und McCabe 1995)

We have performed a vector auto regression with $K = 3$ variables $p = 8$ lags.

$$y_t = \mu + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_8 y_{t-8} + e_t$$

The values of the previous eight quarters are used to explain the values in quarter t. Thus, at least eight previous quarters (values) are needed to estimate a fitted value. Because the time series starts with the previous loss by calculating the seasonal difference with the first quarter 1961, the first estimated value is calculated for the first quarter 1963.

All the eigenvalues of the estimated VAR_8 lie inside the unit circle, therefore it satisfies the stability condition. Intuitively the response to the shocks error terms in any of the equations will eventually die out. The model is therefore stable. Stability Condition:

$$det(I_{Kp} - Az) = det(I_K - A_1 z - \cdots - A_p z^p) \neq 0, for\ |z| \leq 1$$

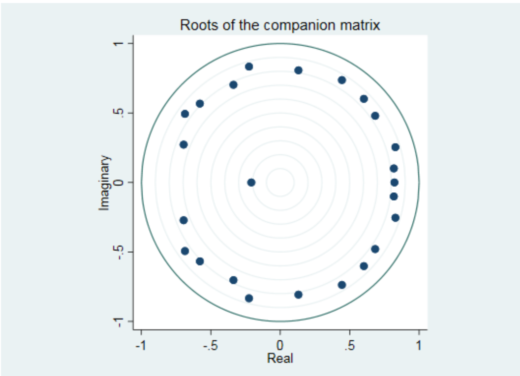

Figure 2.1: Unit Circle of estimated VAR_8

TASK B

We have performed a second vector auto regression with $K = 3$ variables $p = 3$ lags.

$$y_t = \mu + A_1 y_{t-1} + A_2 y_{t-2} + A_3 y_{t-3} + e_t$$

All the eigenvalues of the estimated VAR_3 lie inside the unit circle, therefore it satisfies the stability condition. Intuitively the response to the shocks error terms in any of the equations will eventually die out. The model is therefore stable.

Stability Condition:

$$det(I_{Kp} - Az) = det(I_K - A_1 z - \cdots - A_p z^p) \neq 0, for\ |z| \leq 1$$

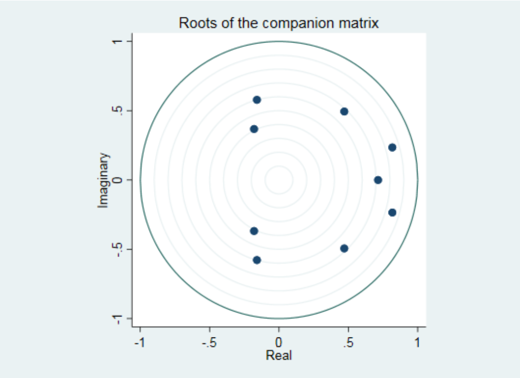

Figure 2.2: Unit Circle of estimated VAR_3

To compare this new estimated model VAR_3 with the previous one VAR_8 regarding the information criteria the values which are calculated are beginning the first quarter in 1963. (Kuha 2004)

The first component of the Akaike information criterion and the Bayesian information criterion is a function, which is the probability of obtaining the data given. To the first component of both information criteria is a second component added based on an adjustment on the number of estimated parameters. (John Wiley & Sons, Inc. 2014).

$$AIC = -2 \log L(\hat{\theta}) + 2k$$

$$BIC = -2 \log L(\hat{\theta}) + k \log n$$

In our case $n = 181$ in the BIC for both estimated model. So we are actually able to compare the values of both models.

$$AIC_8 = -869.9634 < AIC_3 = -810.5697$$

$$BIC_8 = -630.0762 > BIC_3 = -714.6148$$

Based on the calculated values it can be seen that after AIC the 8-lags model seems to be better, while the BIC prefers the 3-lags model.

TASK C

Likelihood Ratio statistic:

$$LR = (T - k)(\ln|\Sigma_3| - \ln|\Sigma_8|)$$

Assumption that VAR(3) is nested in VAR(8).

```
Likelihood-ratio test                                LR chi2(45) =    149.39
(Assumption: varB nested in varA)                    Prob > chi2 =    0.0000
```

Figure 2.3: Likelihood ratio test – STATA output

As can be seen in Figure 2.3, the p-value of the likelihood ratio test performed is zero $p = 0.00$. This results in a rejection of H_0: *VAR(3) is nested in VAR(8)*

TASK D

The applied Granger causality test calculates a p-value of $p = 0.173$ for the Granger causality between the seasonal difference of the unemployment rate and the logarithmic change in the index of industrial production. From this it can be concluded that a change in $\Delta_4 ur_t$ does not Granger cause a change in $\Delta_1 lip_t$. On the other hand, a Granger causality in the other direction can be statistically determined $p = 0.000$. The second direction of impact can be proven by a broad economic literature. (N. Gregory Mankiw 2012)

With a p-value of $p = 0.012$, the Granger causality test indicates that a change in the interest rate s_t spread leads to a change in the logarithmic change in the index of industrial production $\Delta_1 lip_t$. These results go along with the economic theory. (Breeden 1986)

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
D_lnindpro	s_ur	4.9897	3	0.173
D_lnindpro	intspread	11.001	3	0.012
D_lnindpro	ALL	18.05	6	0.006
s_ur	D.lnindpro	36.435	3	0.000
s_ur	intspread	29.452	3	0.000
s_ur	ALL	67.227	6	0.000
intspread	D.lnindpro	5.9388	3	0.115
intspread	s_ur	13.962	3	0.003
intspread	ALL	29.474	6	0.000

Table 2.1: Results of Granger causality Wald tests

TASK E

Variance decompositions give the proportion of movements in each of the dependent variables that are due to their 'own' shocks, versus shocks to the other variables.

Variance Decomposition of s_t

	Variance Decomposition		
Forward Horizon	s_t	$\Delta_1 lip_t$	$\Delta_4 ur_t$
1	0.9390	0.0456	0.0154
4	0.7858	0.1957	0.0185
8	0.6253	0.3571	0.0176

Table 2.2: Variance Decomposition of s_t

Variance Decomposition of $\Delta_1 lip_t$

	Variance Decomposition		
Forward Horizon	s_t	$\Delta_1 lip_t$	$\Delta_4 ur_t$
1	0	1	0
4	0.0416	0.9437	0.01473
8	0.0813	0.8969	0.0218

Table 2.3: Variance Decomposition of s_t

Variance Decomposition of $\Delta_4 ur_t$

	Variance Decomposition		
Forward Horizon	s_t	$\Delta_1 lip_t$	$\Delta_4 ur_t$
1	0	0.3601	0.6399
4	0.0084	0.6926	0.2989
8	0.2066	0.5696	0.2238

Table 2.4: Variance Decomposition of $\Delta_4 ur_t$

The three previous tables show that an orthogonal shock on the three different variables is transmitted to the other variables at different velocities. A shock on $\Delta_1 lip_t$ will only affect itself in the first period. And even in the 8-step ahead forecast 89.69% of the error variance is caused by innovations of $\Delta_1 lip_t$.

The opposite is the case with an orthogonal shock to the seasonal difference in the unemployment rate. Here only 63.99% of the forecasting error variance is explained by the variable itself. Accordingly, another 36.01% of the variance in the forecasting errors are already explained by the variance in the logarithmic differentiated industrial production. It is not surprising that, in a 1-step ahead forecast, the variance in the error terms in the interest rate spread is not yet a proportion of the variance. Very interesting in the result is that in the 4-step and 8-step forecast the majority of the variance in the error terms is explained by the proportion in $\Delta_1 lip_t$. 69.26% and 56.96%.

TASK F

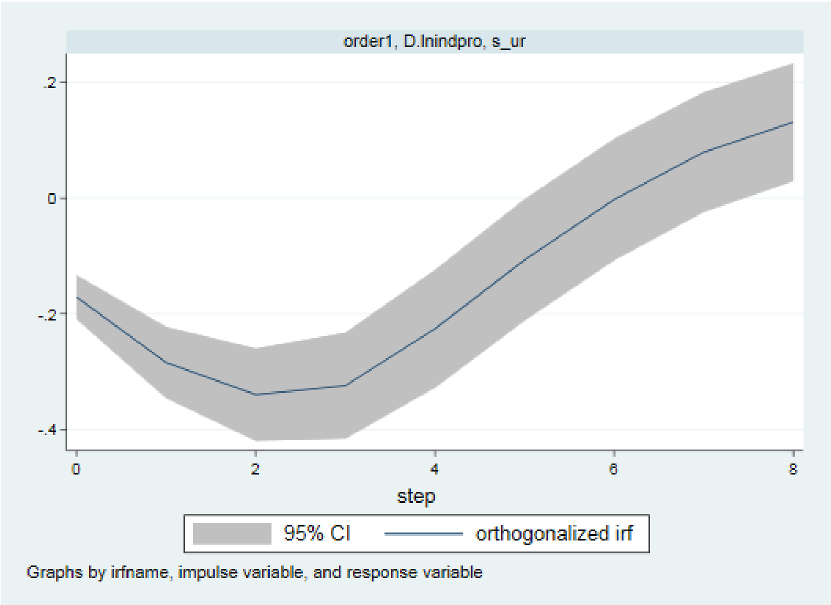

Figure 2.4: Impulse response function of change in unemployment rate on a shock in industrial production

Figure 2.4 shows very clearly that a positive shock to industrial production leads to a significate decrease in unemployment. This significant decrease disappears only after the 5th or 6th period.

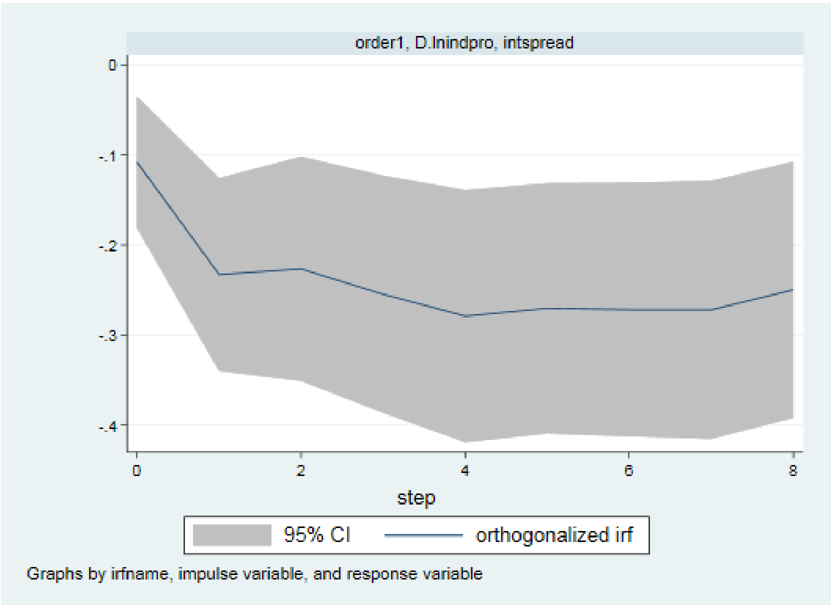

Figure 2.5: Impulse response function of interest rate spread on shock in industrial production

Figure 2.5 shows the decline in the interest rate due to a positive shock on industrial production. The decline in the first period in response to the shock is still comparatively small. However, unlike the unemployment rate, the decline remains significant in both the short and long term. Furthermore, the minimum will be reached much later.

Appendix A:

Inflation equation

Table A.1: OLS with all variables

```
. regress inflation returns dcredit dprod dmoney
```

Source	SS	df	MS
Model	2.51001401	4	.627503502
Residual	31.5689476	320	.098652961
Total	34.0789616	324	.10518198

Number of obs	=	325
F(4, 320)	=	6.36
Prob > F	=	0.0001
R-squared	=	0.0737
Adj R-squared	=	0.0621
Root MSE	=	.31409

inflation	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
returns	.0004197	.0038064	0.11	0.912	-.007069	.0079085
dcredit	1.51e-06	1.89e-06	0.80	0.423	-2.20e-06	5.23e-06
dprod	-.0123933	.032412	-0.38	0.702	-.0761609	.0513743
dmoney	-.0042026	.0008456	-4.97	0.000	-.0058664	-.0025389
_cons	.2495684	.0224498	11.12	0.000	.2054005	.2937362

Table A.2: OLS with significant variables and endogenous regressor

```
. regress inflation returns dmoney
```

Source	SS	df	MS
Model	2.43933175	2	1.21966587
Residual	31.6396298	322	.09825972
Total	34.0789616	324	.10518198

Number of obs	=	325
F(2, 322)	=	12.41
Prob > F	=	0.0000
R-squared	=	0.0716
Adj R-squared	=	0.0658
Root MSE	=	.31346

inflation	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
returns	.0005627	.003795	0.15	0.882	-.0069033	.0080287
dmoney	-.0041684	.0008368	-4.98	0.000	-.0058147	-.0025222
_cons	.2578942	.0182005	14.17	0.000	.2220874	.2937011

Table A.3: IV with all variables

```
. ivregress 2sls inflation dprod dcredit dmoney (returns = dspread)

Instrumental variables (2SLS) regression          Number of obs   =        325
                                                  Wald chi2(4)    =      14.54
                                                  Prob > chi2     =     0.0058
                                                  R-squared       =          .
                                                  Root MSE        =     .62076

------------------------------------------------------------------------------
   inflation |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     returns |   .1177072    .041546     2.83   0.005     .0362784    .1991359
       dprod |   .0143975   .0647343     0.22   0.824    -.1124794    .1412744
     dcredit |  -7.90e-07   3.82e-06    -0.21   0.836    -8.28e-06    6.70e-06
      dmoney |  -.0044123   .0016729    -2.64   0.008    -.0076911   -.0011335
       _cons |   .1942586   .0483722     4.02   0.000     .0994509    .2890663
------------------------------------------------------------------------------
Instrumented:  returns
Instruments:   dprod dcredit dmoney dspread

.
end of do-file

. estat endog

  Tests of endogeneity
  Ho: variables are exogenous

  Durbin (score) chi2(1)          =  32.688  (p = 0.0000)
  Wu-Hausman F(1,319)             = 35.6724  (p = 0.0000)
```

Table A.4: IV with significant variables

```
. ivregress 2sls inflation dmoney (returns = dspread)

Instrumental variables (2SLS) regression          Number of obs   =        325
                                                  Wald chi2(2)    =      14.18
                                                  Prob > chi2     =     0.0008
                                                  R-squared       =          .
                                                  Root MSE        =     .62256
```

inflation	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
returns	.1181417	.0420431	2.81	0.005	.0357388	.2005446
dmoney	-.0044587	.001665	-2.68	0.007	-.007722	-.0011954
_cons	.1908569	.0431596	4.42	0.000	.1062656	.2754482

```
Instrumented:  returns
Instruments:   dmoney dspread

.
end of do-file

. estat endog

  Tests of endogeneity
  Ho: variables are exogenous

  Durbin (score) chi2(1)          =  32.1714  (p = 0.0000)
  Wu-Hausman F(1,321)             =  35.2664  (p = 0.0000)
```

Returns equation

Table A.5: OLS with all variables

```
. regress returns inflation dprod dspread rterm
```

Source	SS	df	MS
Model	237.564884	4	59.3912211
Residual	6586.07956	320	20.5814986
Total	6823.64444	324	21.060631

```
Number of obs   =        325
F(4, 320)       =       2.89
Prob > F        =     0.0227
R-squared       =     0.0348
Adj R-squared   =     0.0228
Root MSE        =     4.5367
```

returns	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
inflation	-.8791445	.8302205	-1.06	0.290	-2.512524	.7542355
dprod	-.2702487	.4600713	-0.59	0.557	-1.175395	.6348978
dspread	-8.268706	2.47263	-3.34	0.001	-13.13337	-3.404041
rterm	-.3246138	.8963926	-0.36	0.717	-2.088181	1.438954
_cons	.8111171	.3226527	2.51	0.012	.1763287	1.445906

Table A.6: OLS with significant variables and the endogenous regressor

```
. regress returns inflation dspread

      Source |       SS           df       MS      Number of obs   =       325
-------------+----------------------------------   F(2, 322)       =      5.56
       Model |   227.78225         2  113.891125   Prob > F        =    0.0042
    Residual |  6595.86219       322  20.4840441   R-squared       =    0.0334
-------------+----------------------------------   Adj R-squared   =    0.0274
       Total |  6823.64444       324   21.060631   Root MSE        =    4.5259

------------------------------------------------------------------------------
     returns |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   inflation |  -.8931779   .8274149    -1.08   0.281       -2.521     .734644
     dspread |  -8.210685   2.463133    -3.33   0.001    -13.05655   -3.364819
       _cons |   .7772346   .3158886     2.46   0.014     .1557686    1.398701
------------------------------------------------------------------------------
```

Table A. 7: IV with all variables

```
. ivregress 2sls returns dprod dspread rterm (inflation = dmoney)

Instrumental variables (2SLS) regression          Number of obs   =        325
                                                  Wald chi2(4)    =      10.97
                                                  Prob > chi2     =     0.0269
                                                  R-squared       =     0.0129
                                                  Root MSE        =     4.5524

------------------------------------------------------------------------------
     returns |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   inflation |  -3.115532   3.966909    -0.79   0.432    -10.89053    4.659466
       dprod |  -.2688139   .4616721    -0.58   0.560    -1.173675    .6360469
     dspread |  -10.59466    4.73578    -2.24   0.025    -19.87661   -1.312699
       rterm |  -.2160723   .9189838    -0.24   0.814    -2.017247    1.585103
       _cons |   1.328718   .9542509     1.39   0.164    -.5415799    3.199015
------------------------------------------------------------------------------
Instrumented:  inflation
Instruments:   dprod dspread rterm dmoney

.
end of do-file

. estat endog

  Tests of endogeneity
  Ho: variables are exogenous

  Durbin (score) chi2(1)          =   .34003  (p = 0.5598)
  Wu-Hausman F(1,319)             =  .334102  (p = 0.5637)
```

Table A.8: IV with significant variables and the (assumed) endogenous regressor

```
. ivregress 2sls returns dspread (inflation = dmoney)

Instrumental variables (2SLS) regression          Number of obs   =        325
                                                  Wald chi2(2)    =      10.53
                                                  Prob > chi2     =     0.0052
                                                  R-squared       =     0.0041
                                                  Root MSE        =     4.5728
```

returns	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
inflation	-3.47911	3.951601	-0.88	0.379	-11.22411	4.265885
dspread	-10.89977	4.724762	-2.31	0.021	-20.16013	-1.639405
_cons	1.376261	.9498867	1.45	0.147	-.4854823	3.238005

```
Instrumented:  inflation
Instruments:   dspread dmoney

.
end of do-file

. estat endog

  Tests of endogeneity
  Ho: variables are exogenous

  Durbin (score) chi2(1)          =  .461904  (p = 0.4967)
  Wu-Hausman F(1,321)             =  .456869  (p = 0.4996)
```

OLS with significant variables

```
. regress returns dspread
```

Source	SS	df	MS
Model	203.912661	1	203.912661
Residual	6619.73178	323	20.4945256
Total	6823.64444	324	21.060631

```
Number of obs   =        325
F(1, 323)       =       9.95
Prob > F        =     0.0018
R-squared       =     0.0299
Adj R-squared   =     0.0269
Root MSE        =     4.5271
```

returns	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
dspread	-7.281879	2.308555	-3.15	0.002	-11.82358	-2.740176
_cons	.5703315	.2511588	2.27	0.024	.0762178	1.064445

References:

Bjørnland, Hilde C.; Thorsrud, Leif Anders (2015): Applied Time Series For Macroeconomics. 2. Aufl. Oslo: Gyldendal Norsk Forlag.

Breeden, Douglas T. (1986): Consumption, Production, Inflation and Interest Rates. A Synthesis. In: *Journal of Financial Economics* (16), S. 3–39.

John Wiley & Sons, Inc. (Hg.) (2014): The Basics of Financial Econometrics: Tools, Concepts, and Asset Management Applications. Unter Mitarbeit von Frank J. Fabozzi, Sergio M. Focardi, Svetlozar T. Rachev und Bala G. Arshanapalli: John Wiley & Sons.

Kuha, Jouni (2004): AIC and BIC. Comparisons of Assumptions and Performance. In: *Sociological Methods & Research* 33 (2), S. 188–229. DOI: 10.1177/0049124103262065.

N. Gregory Mankiw (2012): Macroeconomics. 8. Aufl. New York, NY 10010: Worth Publishers.

Tremayne, Andrew R.; McCabe, Brendan P.M. (1995): Testing a Time Series for Difference Stationarity. In: *The Annals of Statistics* (23), S. 1015–1028.