

# ECON 8185 - HW 2

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The model is:

$$\max_{c_t, x_t, l_t} E \sum_{t=0}^{\infty} \beta^t \frac{(c_t l_t^\psi)^{1-\sigma}}{1-\sigma} N_t$$

S.T.

$$c_t + (1 + \tau_{xt})x_t = r_t k_t + (1 - \tau_{ht})w_t h_t + T_t$$

$$N_{t+1} k_{t+1} = [(1 - \delta)k_t + x_t] N_t$$

$$h_t + l_t = 1$$

$$S_t = PS_{t-1} + Q\epsilon_t, \quad S_t = [\ln z_t, \tau_{ht}, \tau_{xt}, \ln g_t]$$

$$c_t, x_t \geq 0$$

Where  $N_t = (1 + \gamma_n)^t$  and firm technology is  $Y_t = K_t^\theta (Z_t L_t)^{1-\theta}$ .  $\gamma_z$  is the rate of labor-augmenting technical progress. The stochastic shocks hitting this economy affect technology, tax rates, and government spending and the stochastic processes are modeled as a VAR(1) process. The resource constraint is  $Y_t = N_t(c_t + x_t + g_t)$ . We must work with detrended variables, we should use "hat" variables, but typing this is time consuming so from now on all variables should be understood as detrended unless I say something about them.

Defining some parameters:

```

In [189]: using Plots, NLSolve, ForwardDiff, DataFrames, LinearAlgebra, QuantEcon, Plots
, Optim, Statistics
#Parameters:
 $\delta$  = 0.0464 #depreciation rate
 $\theta$  = 0.35 #capital share of output
 $\beta$  = 0.9722 #Discounting
 $\sigma$  = 1 #Elasticity of Intertemporal Substitution
 $\psi$  = 3 #Labor parameter
 $\gamma_n$  = 0.015 #Population growth rate
 $\gamma_z$  = 0.016 #Productivitu growth rate
gss = 0.01 #average g
 $\tau_{xss}$  = 0.05 #average  $\tau_x$ 
 $\tau_{hss}$  = 0.05 #average  $\tau_h$ 
zss = 0.0 #average z (z is in logs)

#Parameters to be estimated in the next homework
#Autocorrelations
 $\rho_g$  = 0.9
 $\rho_x$  = 0.1
 $\rho_h$  = 0.1
 $\rho_z$  = 0.9

# Cross-correlations
 $\rho_{zg}$  = 0.0
 $\rho_{zx}$  = 0.0
 $\rho_{zh}$  = 0.0
 $\rho_{hz}$  = 0.0
 $\rho_{hx}$  = 0.0
 $\rho_{hg}$  = 0.0
 $\rho_{xz}$  = 0.0
 $\rho_{xh}$  = 0.0
 $\rho_{xg}$  = 0.0
 $\rho_{gz}$  = 0.0
 $\rho_{gx}$  = 0.0
 $\rho_{gh}$  = 0.0

#Variances
 $\sigma_g$  = 0.001
 $\sigma_x$  = 0.001
 $\sigma_z$  = 0.01
 $\sigma_h$  = 0.01
#Covariances
 $\sigma_{zg}$  = 0.0
 $\sigma_{zx}$  = 0.00
 $\sigma_{zh}$  = 0.00
 $\sigma_{hx}$  = 0.00
 $\sigma_{hg}$  = 0.00
 $\sigma_{xg}$  = 0.00

```

Out[189]: 0.0

The detrended FOC's of this model are:

$$c_t + (1 + \gamma_z)(1 + \gamma_n)k_{t+1} - (1 - \delta)k_t + g_t = y_t = k_t^\theta (z_t h_t)^{1-\theta}$$

$$\psi \frac{c_t}{1 - h_t} = (1 - \tau_{ht})(1 - \theta) \left( \frac{k_t}{h_t} \right)^\theta z_t^{1-\theta}$$

$$c_t^{-\sigma} (1 - h_t)^{\psi(1-\sigma)} (1 + \tau_{xt}) = \beta (1 + \gamma_z)^{-\sigma} E_t c_{t+1}^{-\sigma} (1 - h_{t+1})^{\psi(1-\sigma)} (\theta k_{t+1}^\theta (z_{t+1} h_{t+1})^{1-\theta} + (1 - \delta)(1 + \gamma_n)k_{t+1})$$

Substituting for  $c$ , we get an equation for  $k$ , and one for  $h$ . Below, I find the Steady State values:

```
In [190]: #Function with the FOCs
zss = exp(zss)

function SS!(eq,vector::Vector)
    k,h, c= vector
    eq[1]=k/h-((1+τxss)*(1-β*(1+γz)^(-σ)*(1-δ))/(β*(1+γz)^(-σ)*θ*zss^(1-θ)))^(1/(θ-1))
    eq[2]=c-( (k/h)^(θ-1)*zss^(1-θ) -(1+γz)*(1+γn)+1-δ)*k+gss
    eq[3]=ψ*c-( (1-τhss)*(1-θ)*(k/h)^θ *zss^(1-θ))*(1-h)
end

SteadyState = nlsolve(SS!, [3,0.25,.4],ftol = :1.0e-20)
kss,hss,css = SteadyState.zero
```

```
Out[190]: 3-element Array{Float64,1}:
 1.6707265229440968
 0.22844261316599446
 0.31866093597940304
```

```
In [191]: #GDP
yss = kss^(θ)*(zss*hss)^(1-θ)
xss = (1+γz)*(1+γn)*kss-(1-δ)*kss
```

```
Out[191]: 0.12971520724137942
```

## Question 1

### a) Iterate on Bellman's equation

Due to the curse of dimensionality, I won't pursue this path.

### b) Map it to a linear quadratic problem

Recall from lecture notes, we have to map the original problem into the following LQ problem:

$$\max_{\{u_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t (X_t' Q X_t + u_t' R u_t + 2X_t' W u_t)$$

s.t.

$$X_{t+1} = A X_t + B u_t + C \epsilon_{t+1}$$

$X_0$  given.

In this case, we have:  $u_t = [k_{t+1}, h_t]'$

Note that in this problem  $X_t$  may be decomposed as:

$$X_t = \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix}_t$$

Where  $X_1$  are the individual states,  $X_2$  are the aggregate or exogenous states with known laws of motion, and  $X_3$  are the aggregate states with laws of motion that are unknown and need to be computed in equilibrium. We have that:

$$X_1 = [1, k_t]', X_2 = [\tau_{xt}, \tau_{ht}, g_t] \text{ and } X_3 = [K_t, H_t]$$

Finally, rewrite  $y_t = [\tilde{X}_1, \tilde{X}_2]'$  and the problem constraint becomes:

$$y_{t+1} = \tilde{A}_y y_t + \tilde{B}_y \tilde{u}_t + A_z \tilde{X}_{3t}$$

Where tilde variables are the undiscounted counterpart of each variable. Matrices  $\tilde{A}_y$ ,  $\tilde{B}_y$ ,  $Q$ ,  $R$  and  $W$  may be found by second and first order Taylor expansions of the utility function and constraints. Matrix  $A_z$  is for now unknown. Following the methods in the lecture notes (using Big K, little k trick) this problem may be solved. We mapped it to a LQ problem and we solve it using the modified Vaughan's method in the next section:

### c) Apply Vaughan's method.

I use the modified Vaughan method using the log linearized FOC's as in the lecture notes.

Log-linearizing the FOC equations we get the following system of equations:

$$\begin{aligned} 0 &= E_t [a_1 \tilde{k}_t + a_2 \tilde{k}_{t+1} + a_3 \tilde{h}_t + a_4 \tilde{z}_t + a_5 \tilde{\tau}_{ht} + a_6 \tilde{g}_t] \\ 0 &= E_t [b_1 \tilde{k}_t + b_2 \tilde{k}_{t+1} + b_3 \tilde{k}_{t+2} + b_4 \tilde{h}_t + b_5 \tilde{h}_{t+1} b_6 \tilde{z}_t + b_7 \tilde{\tau}_{xt} + b_8 \tilde{g}_t + b_9 \tilde{z}_{t+1} + b_{10} \tau_{xt+1} + b_{11} \tilde{g}_{t+1}] \end{aligned}$$

Where tilde variables are log deviations from Steady State. Stacking up the equations we get:

$$0 = E_t \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & b_3 & b_5 \end{bmatrix} \begin{bmatrix} \tilde{k}_{t+1} \\ \tilde{k}_{t+2} \\ \tilde{h}_{t+1} \end{bmatrix} + \begin{bmatrix} 0 & -1 & 0 \\ a_1 & a_2 & a_3 \\ b_1 & b_2 & b_4 \end{bmatrix} \begin{bmatrix} \tilde{k}_t \\ \tilde{k}_{t+1} \\ \tilde{h}_t \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_4 & a_5 & 0 & a_6 & 0 & 0 & 0 & 0 \\ b_6 & 0 & b_7 & b_8 & b_9 & 0 & b_{10} & b_{11} \end{bmatrix}$$

We call the first matrix  $A_1$ , and the second  $A_2$ . The code below log-linearizes and find these matrices:



```

In [192]: function loglineq1(vector::Vector)
           k,k1,h,z,th,g= vector

           c = k * ((z *h)^(1-θ))^(1/θ) - ((1+γz)*(1+γn)*k1-(1-δ)*k+ g )^(1/θ)
           eq =(ψ *c)^(1/θ) - (k/h)*((1-h)*(1-τh)*(1-θ)*z^(1-θ))^(1/θ)

           return eq
       end
       function loglineq2(vector::Vector)
           k,k1,k2,h,h1,z,tx,g,z1,tx1,g1 = (vector)
           c = k * ((z *h)^(1-θ))^(1/θ) - ((1+γz)*(1+γn)*k1-(1-δ)*k+ g )^(1/θ)
           c1 = k * ((z1 *h1)^(1-θ))^(1/θ) - ((1+γz)*(1+γn)*k2-(1-δ)*k1+ g1 )^(1/θ)
           eq = (c^(-σ) * (1-h)^(ψ*(1-σ))*(1+τx) - (1-δ)*(1+τx1)* β*(1+γz)^(-σ) * c1
           ^(-σ) * (1-h1)^(ψ*(1-σ)))^(-1/θ) -
               (β*(1+γz)^(-σ) * c1^(-σ) * (1-h1)^(ψ*(1-σ)) * θ*(z1*h1)^(1-θ))^(-1/θ)* k1
           return eq
       end

       #Log deviations
       T=ForwardDiff.gradient(loglineq1,[kss,kss,hss,zss,thss,gss])
       a =[-kss*T[1]/(kss*T[1]),-kss*T[2]/(kss*T[1]),-hss*T[3]/(kss*T[1]),
       -zss*T[4]/(kss*T[1]),-thss*T[5]/(kss*T[1]),-gss*T[6]/(kss*T[1])]
       #if ψ==0
       #     a[1],a[2:end]=-1,zeros(5)
       #end

       T=ForwardDiff.gradient(loglineq2,[kss,kss,kss,hss,hss,zss,txss,gss,zss,txss,gs
       s])
       b = [kss*T[1]/(-kss*T[1]),kss*T[2]/(-kss*T[1]),kss*T[3]/(-kss*T[1]),hss*T[4]/(
       -kss*T[1]),
       hss*T[5]/(-kss*T[1]),zss*T[6]/(-kss*T[1]),txss*T[7]/(-kss*T[1]),gss*T[8]/(-kss
       *T[1]),
       zss*T[9]/(-kss*T[1]),txss*T[10]/(-kss*T[1]),gss*T[11]/(-kss*T[1])]

       A1 = [1 0 0; 0 0 0; 0 b[3] b[5]]
       A2 = [0 -1 0; a[1] a[2] a[3]; b[1] b[2] b[4]]
       U = [0 0 0 0 0 0 0;
       a[4] a[5] 0 a[6] 0 0 0 0;
       b[6] 0 b[7] b[8] b[9] 0 b[10] b[11]]

       A1,A2

Out[192]: ([1.0 0.0 0.0; 0.0 0.0 0.0; 0.0 -1.01871 1.56869], [0.0 -1.0 0.0; -1.0 -0.191
08 2.77059; -1.0 2.01043 -1.65162])

```

We look for a solution of the form:

$$\begin{aligned}\tilde{k}_{t+1} &= A\tilde{k}_t + BS_t \\ Z_t &= CX_t + DS_t \\ S_t &= PS_{t-1} + Q\epsilon_t\end{aligned}$$

Where  $Z_t = [\tilde{k}_{t+1}, \tilde{h}_t]'$  and  $S_t$  are the stochastic exogenous variables. We compute the generalized eigenvalues and eigenvectors for matrices  $A_1$  and  $-A_2$  because  $A_1$  is not invertible. Thus,  $A_2V = -A_1V\Pi$  and we can get  $A$  and  $C$  by:

$$\begin{aligned}A &= V_{11}\Pi_{1,1}V_{1,1}^{-1} \\ C &= V_{2,1}V_{1,1}^{-1}\end{aligned}$$

```
In [193]: eig = eigen(A1,-A2)
V=eig.vectors
Π = eig.values
#Sorting
for j=1:3
for i=1:2
    if eps(Float64)<abs(Π[i+1])<abs(Π[i])
        Π[i],Π[i+1] = Π[i+1],Π[i]
        V[:,i],V[:,i+1] = V[:,i+1],V[:,i]
    elseif abs(Π[i]) < eps(Float64)
        Π[i],Π[end] =Π[end],Π[i]
        V[:,i],V[:,end]=V[:,end],V[:,i]
    end
end
end
if abs(Π[1])>1
    error("All Eigen Values outside unit circle")
end
Π= Diagonal(Π)
```

```
Out[193]: 3×3 Diagonal{Float64,Array{Float64,1}}:
 0.614295  .  .
 .  0.928641  .
 .  .  1.25286e-16
```

```
In [194]: A = V[1,1]*Π[1,1]*inv(V[1,1])
C = V[2:end,1]*(V[1,1])
C = hcat(C,zeros(2,1))
```

```
Out[194]: 2×2 Array{Float64,2}:
 0.614295  0.0
 0.178568  0.0
```

```
In [195]: P = [pz pzh pzx pzg;
phz ph phx phg ;
pxz pxh px pxg ;
pgz pgh pgx pg]
Q = [sz szh szx szg;
szh sh shx shg ;
szx shx sx sxg ;
szg shg sxg sg]
```

```
Out[195]: 4x4 Array{Float64,2}:
 0.01  0.0   0.0   0.0
 0.0   0.01  0.0   0.0
 0.0   0.0   0.001  0.0
 0.0   0.0   0.0   0.001
```

Finally, to get the matrices  $B$  and  $D$ , we just need to solve a linear system of equations (see Ellen's notes):

```
In [196]: function system!(eq,vector::Vector)
    #vector = rand(8)
    #eq= rand(8)
    B=vector[1:4]'
    D2 = vector[5:8]'

    eq[1:4] = a[2].*B .+ a[3].*D2 .+ [a[4] a[5] 0 a[6]]
    eq[5:8] = b[2].*B .+ b[3].*A.*B .+ b[3].*B*P .+ b[4].*D2 .+ b[5].*C[2].*B
    .+ b[5].*B*P.+
    [b[6] 0 b[7] b[8]].+[b[9] 0 b[10] b[11] ]*P
    return eq
end

Sol = nlsolve(system!, ones(8),ftol = :1.0e-20, method = :trust_region , autos
cale = true)
D=ones(2,4)
D[1,:]= Sol.zero[1:4]
D[2,:]= Sol.zero[5:8]
```

```
Out[196]: 4-element Array{Float64,1}:
 0.8407449660264878
-0.0777902887745693
-0.001597364530493627
 0.00039623988701692134
```

## Question 2



For this question I use the solution of question 1-c).

First, I will rewrite the model in the form:

$$X_{t+1} = AX_t + B\varepsilon_{t+1}$$

$$Y_t = CX_t + \omega_t$$

Where,  $X_t = [k_t, s_t]$ ,  $s_t = [z_t, \tau_{ht}, \tau_{xt}, g_t]$ ,  $Y_t = [y_t, x_t, h_t]$  and as before:

$$s_{t+1} = Ps_t + Q\varepsilon_{t+1}$$

We need to log linearize  $y, x$  since we already done it for labor:

```
In [197]: #Rewritting
A = hcat(vcat(C[1],zeros(4,1)),vcat(D[1,:]',P))
B = hcat(zeros(5,1),vcat(zeros(1,4),Q))

#We have h as function of states. To find the Matrix B, we need to find y and
x
#as a function of states

function kt1(vector::Vector)
    k,z,th,tx,g = vector
    tilde = log.([k,z,th,tx,g]).-log.([kss,zss,thss,txss,gss])
    for i = 1:length(tilde)
        if isnan(tilde[i])
            tilde[i] = 0
        end
    end
    k1= A[1,:]' * tilde
    return k1
end

function ht(vector::Vector)
    k,z,th,tx,g = vector
    tilde = log.([k,z,th,tx,g]).-log.([kss,zss,thss,txss,gss])
    for i = 1:length(tilde)
        if isnan(tilde[i])
            tilde[i] = 0
        end
    end
    h = C[2,1]*(log(k)-log(kss)) + D[2,:]' * tilde[2:end]
    return h
end
```

```
Out[197]: ht (generic function with 1 method)
```

```

In [198]: #Log-linearizing y as a function of states
function yt(vector::Vector)
    k,z,th,tx,g = vector
    h = exp(ht(vector)+log(hss))
    y = k^θ * (z*h)^(1-θ)
    return y
end

#GDP
yss = kss^(θ)*(zss*hss)^(1-θ)

T=ForwardDiff.gradient(yt,[kss,zss,thss,txss,gss])
ycoefs = [kss*T[1]/yss,zss*T[2]/yss,thss*T[3]/yss,txss*T[4]/yss,gss*T[5]/yss]

#Log linearizing x as function of states
function xt(vector::Vector)
    k,z,th,tx,g = vector
    k1 = exp(kt1(vector)+log(kss))
    x= (1+γn)*(1+γz)k1 - (1-δ)k

    return x
end
xss = (1+γz)*(1+γn)*kss-(1-δ)*kss
T=ForwardDiff.gradient(xt,[kss,zss,thss,txss,gss])
xcoefs = [kss*T[1]/xss,zss*T[2]/xss,thss*T[3]/xss,txss*T[4]/xss,gss*T[5]/xss]

#We have the matrix C!
C = [ycoefs[1] ycoefs[2] ycoefs[3] ycoefs[4] ycoefs[5];
xcoefs[1] xcoefs[2] xcoefs[3] xcoefs[4] xcoefs[5];
C[2,1] D[2,1] D[2,2] D[2,3] D[2,4];
0 0 0 0 1]

```

```

Out[198]: 4×5 Array{Float64,2}:
 0.466069  1.19648 -0.0505637 -0.00103829  0.000257556
-4.12306  10.0146 -0.992297 -0.307635 -0.000780533
 0.178568  0.840745 -0.0777903 -0.00159736  0.00039624
 0.0       0.0       0.0       0.0       1.0

```

Now, I simulate the variables with known law of motion:

```

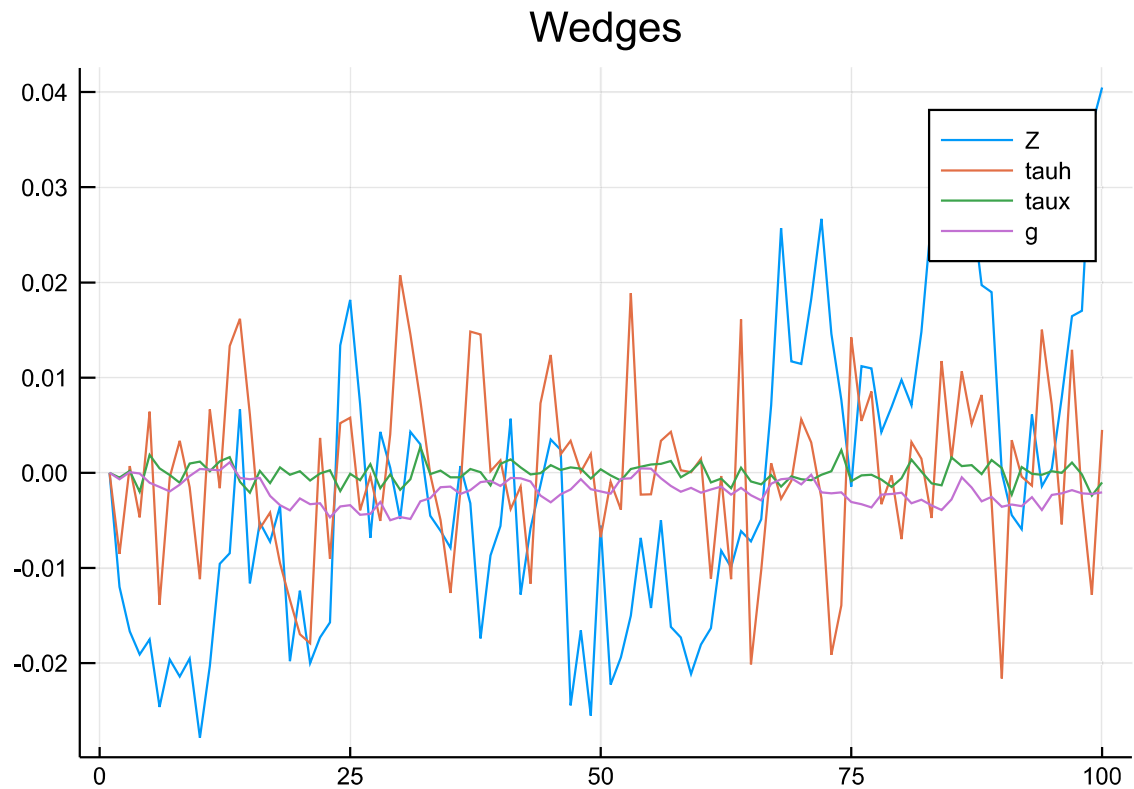
In [199]: #defining the vectors
T=100
X= ones(5,T).* [0,0,0,0,0]
Y = ones(4,T).*[0,0,0,0]
S = randn(5,T)
for t=1:T

    if t>1
        X[:,t] = A*X[:,t-1]+ B*S[:,t]
    end
    Y[:,t] = C*X[:,t]
end

plot([X[2,:],X[3,:],X[4,:],X[5,:]],title ="Wedges", labels = ["Z","tauh","taux",
x","g"])

```

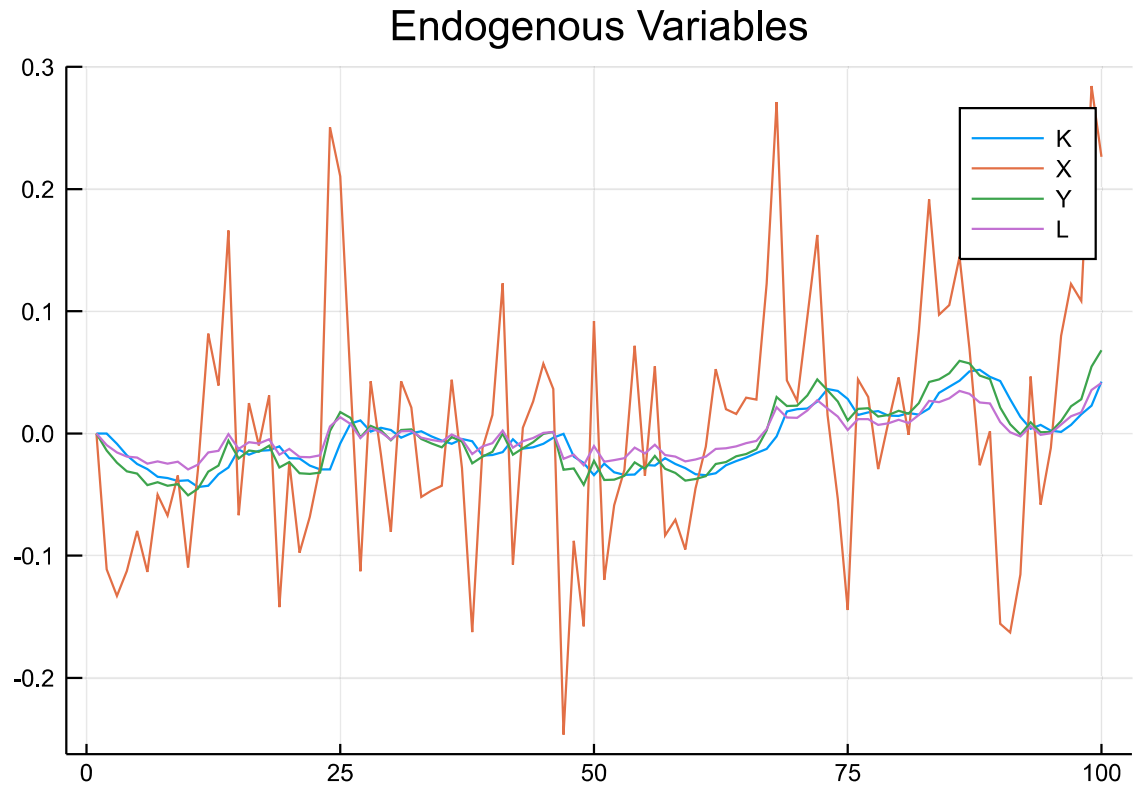
Out[199]:



Below are the endogenous variables:

```
In [200]: plot([X[1,:],Y[2,:],Y[1,:],Y[3,:]],title = "Endogenous Variables",labels = [
            "K","X","Y","L"])
```

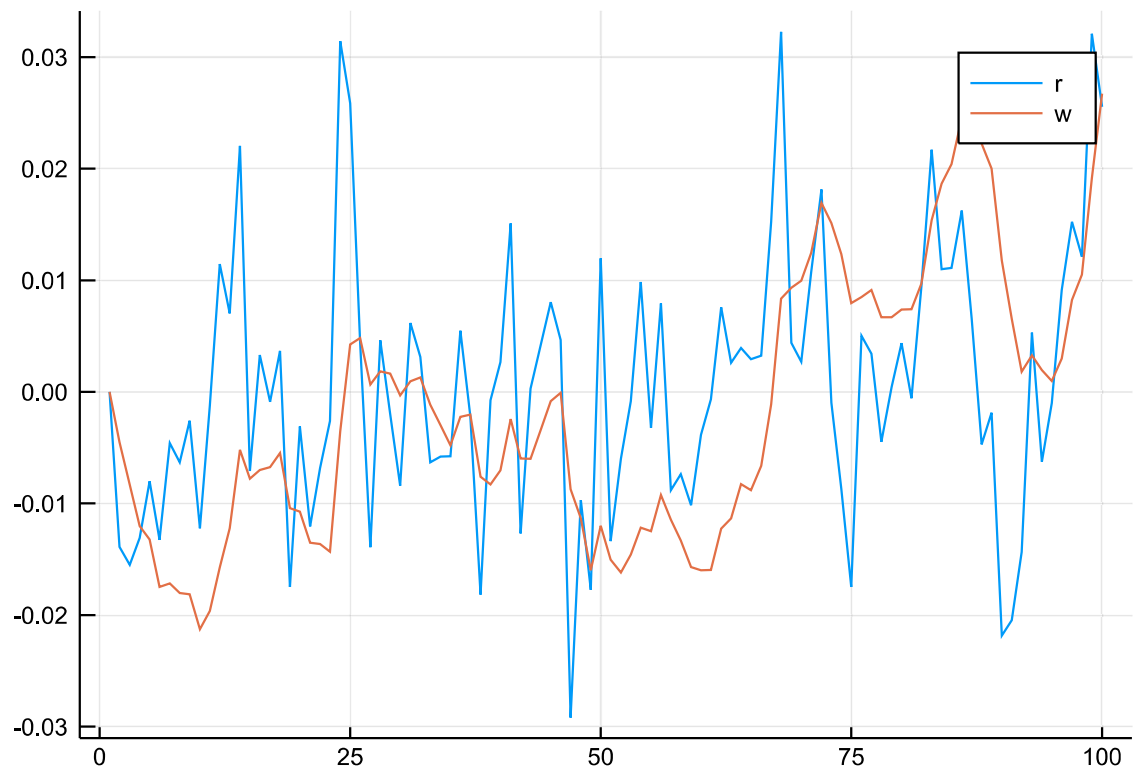
Out[200]:



In the code below, we calculate the factor prices (in log deviations):

```
In [201]: r = (θ-1) .* X[1,:] .+ (1-θ) .* (X[2,:] .+ Y[3,:])  
w = θ .* X[1,:] .+ (1-θ) .* X[2,:] .- θ .* Y[3,:]  
plot([r,w], labels = ["r","w"])
```

Out[201]:



The code above is summarized in a function `State_Space` which returns the matrices A,B,C

```
In [202]: include("State_Space.jl")
```

Out[202]: `State_Space` (generic function with 1 method)