BUSI 525 Problem Set #3

Finite Sample Bias in Predictive Regressions

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```
In [1]:
         using Plots, Random, Statistics, Bootstrap, Distributions, LinearAlgebra,StatsBase
         function Stambaugh(T,rho uv;B=250,alpha=0.0,beta=0.015,sigma u=0.053,theta=0,sigma v=0.044,rho=0.98)
             d1 = MvNormal(zeros(2),[sigma u^2. rho uv*sigma u*sigma v;rho uv*sigma u*sigma v sigma v^2])
             est beta = zeros(B)
              for b = 1:B
                 uv = rand(d1, T)
                 u = uv[1,:]
                 v = uv[2,:]
                 x = zeros(T)
                 r = zeros(T)
                  for t = 1:T
                      if t == 1
                          x[t] = theta + rho*0.0 + v[t]
                          r[t] = alpha + beta*0.0 + u[t]
                      else
                      x[t] = theta + rho*x[t-1] + v[t]
                      r[t] = alpha + beta*x[t-1] + u[t]
                      end
                 X = hcat(ones(T), x)
                 estimator = (X'X)\setminus(X'r)
                  est_beta[b] = estimator[2]
             end
             beta_percentiles = [percentile(est_beta, 5),mean(est_beta),percentile(est_beta,95)]
              return beta_percentiles
        Info: Precompiling Plots [91a5bcdd-55d7-5caf-9e0b-520d859cae80] @ Base loading.jl:1317
```

Out[1]: Stambaugh (generic function with 1 method)

Part 1: Finite Sample Bias

```
In [4]:
    Ts = 120:120:1200
    beta_plots = zeros(length(Ts),3)
    for i=1:length(Ts)
        beta_plots[i,:]=Stambaugh(Ts[i],-0.8)
    end
    plotlyjs();
    pl = plot(xlabel="T",ylabel="Est. Beta",legend=:bottomright)
    pl = plot!(Ts,beta_plots[:,1],label = "5% percentile")
    pl = plot!(Ts,beta_plots[:,2],label = "Mean")
    pl = plot!(Ts,beta_plots[:,3],label = "95% percentile")
```

Out [4]:

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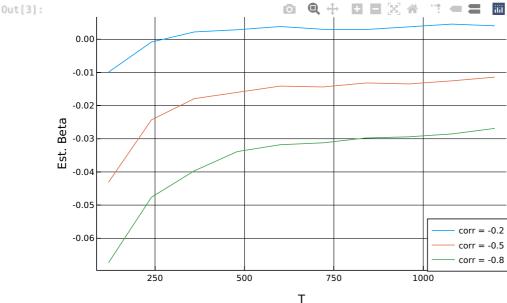
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The larger T becomes, the smaller bias is in absolute sence. The 95 percentile of the biases approaches to zero. However, the gain is not significant if we have more than 1000 observations and the estimator has negative bias.

Part 2 - Effect of residual correlation

```
rho_uvs = [-0.2,-0.5,-0.8]
beta_plots_corr = zeros(length(Ts),length(rho_uvs))
for j = 1:length(rho_uvs)
    for i=1:length(Ts)
        beta_plots_corr[i,j]=Stambaugh(Ts[i],rho_uvs[j])[2]
    end
end

p2 = plot(xlabel="T",ylabel="Est. Beta",legend=:bottomright)
p2 = plot!(Ts,beta_plots_corr[:,1],label = "corr = -0.2")
p2 = plot!(Ts,beta_plots_corr[:,2],label = "corr = -0.5")
p2 = plot!(Ts,beta_plots_corr[:,3],label = "corr = -0.8")
```



As the corrleation between the errors becomes stronger, the estimates have larger negative bias. Larger sample size mitigates the bias.

```
In []:
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