Development - Summary of the take home exam

Adam Wilczyński

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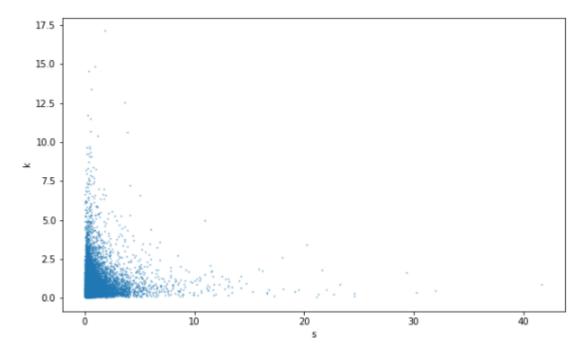


Figure 1: Q1.1. Scatter plot of s and k. Mean value of s and k is 1. Since ln(s) has higher variance, maximum value of s reaches over 40, comparing to k that reaches 17.5

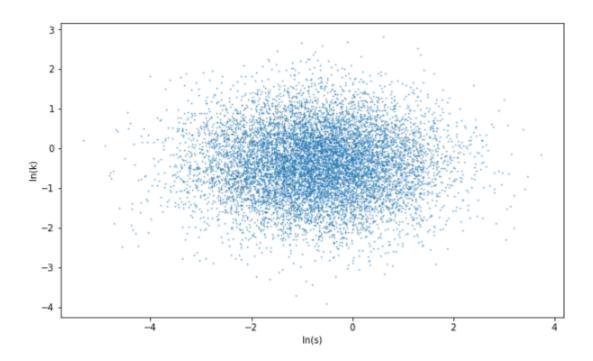


Figure 2: Q1.1. Scatter plot of $\ln(s)$ and $\ln(k)$. Correlation is zero and mean values are below zero such that mean of s and k is approximately 1.

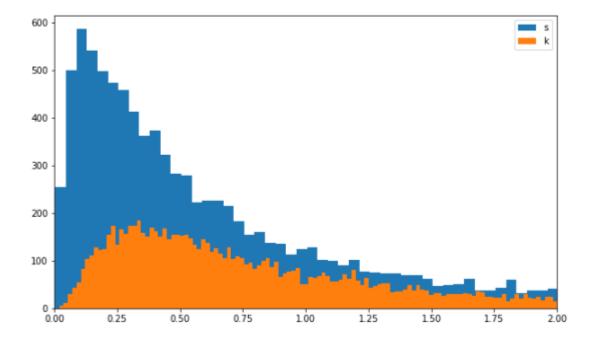


Figure 3: Q1.1. Histogram of s and k. We see that again s has higher variance, this bins and tail are wider.

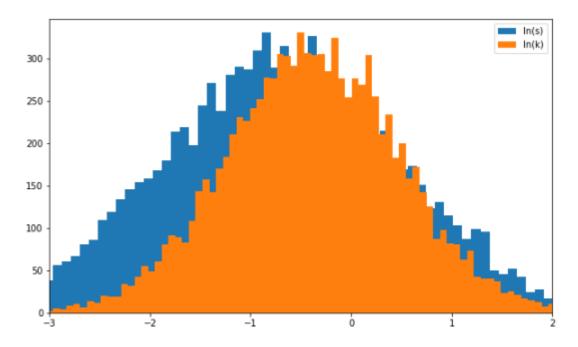


Figure 4: Q1.1. Histogram of $\ln(s)$ and $\ln(k)$.

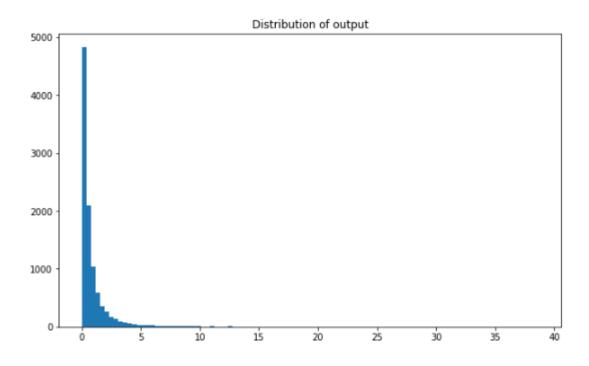


Figure 5: Q1.2. Distribution of original (true) output

Problem:
$$\max_{k_i} \sum_i s_i k_i^{\gamma}$$
 st.
$$K = \sum_i k_i$$

$$L = \sum_i s_i k_i^{\gamma} + \lambda (K - \sum_i k_i)$$
 FOC:
$$[k_i] : s_i \gamma k_i^{\gamma-1} = \lambda$$

$$[k_j] : s_j \gamma k_j^{\gamma-1} = \lambda$$
 which implies:
$$\frac{s_i}{s_j} (\frac{k_i}{k_j})^{\gamma-1} = 1$$
 so
$$k_j = (\frac{s_i}{s_j})^{\frac{1}{(y-1)}} k_i$$
 Therefore,
$$k_i = K - \sum_{j \neq i} k_j$$

$$k_i ((1 + \frac{s_i}{s_j})^{\frac{1}{(y-1)}} + (\frac{s_z}{s_z})^{\frac{1}{(y-1)}} + \dots) = K$$

$$k_i = \frac{K}{((1 + \frac{s_i}{s_j})^{\frac{1}{(y-1)}} + (\frac{s_z}{s_z})^{\frac{1}{(y-1)}} + \dots) }$$

Figure 6: Q1.3 Derivation of optimal capital

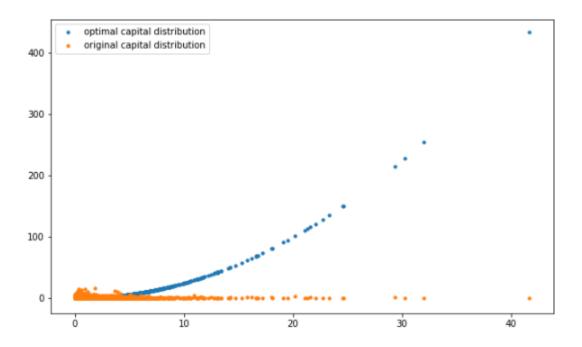


Figure 7: Q1.4 and 1.5. Comparison of optimal capital distribution and original capital distribution. Optimally, more productive agents obtained much more capital than if capital is drawn from normal distribution. Variance of random capital is 4.2 and variance of optimal output is 1248.7. This makes up Output gain equal to 2.3

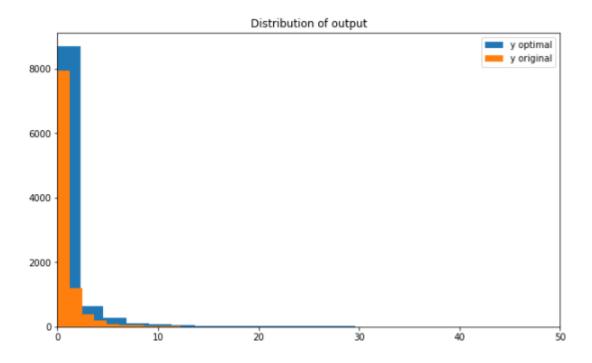


Figure 8: Q1.4 and 1.5. Distribution of output original and optimal. Optimal output is much more unequal

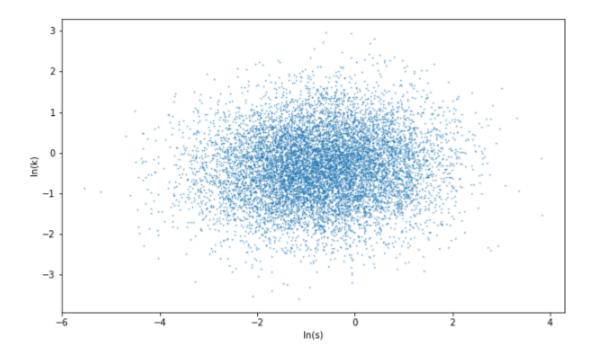


Figure 9: Q1.6. Scatter plot of ln(s) and ln(k) when correlation is 0.25. It is difficult to see the correlation on the plot, therefore I added the next plot to illustrate what kind of relation we would expect if correlation was higher

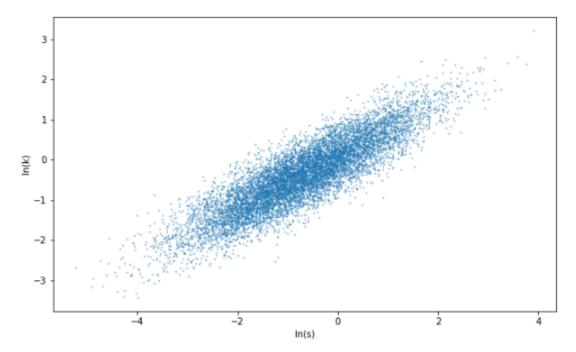


Figure 10: Q1.6. Scatter plot of $\ln(s)$ and $\ln(k)$ when correlation is 0.95. Example picture that illustrate high correlation of $\ln(s)$ and $\ln(k)$

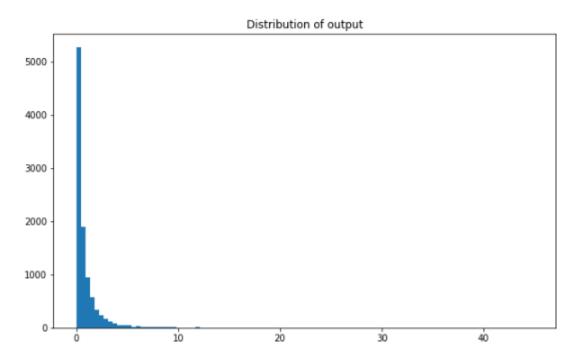


Figure 11: The variance in output is higher when gamma is 0.8 (comparing to gamma 0.5 form previous example)

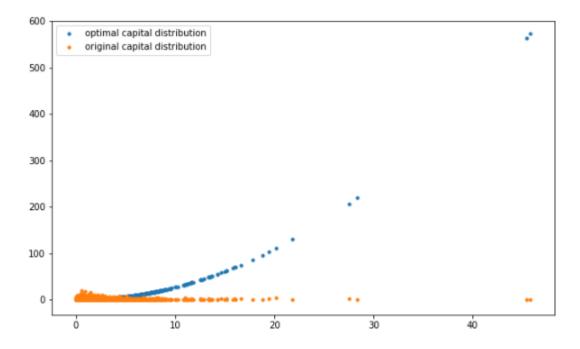


Figure 12: Q1.6 Output gain is equal to 2.2

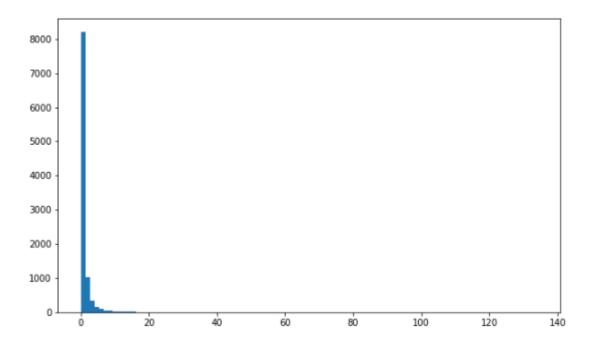


Figure 13: Q2 When gamma is 0.8 the ouptut per agent has higer variance

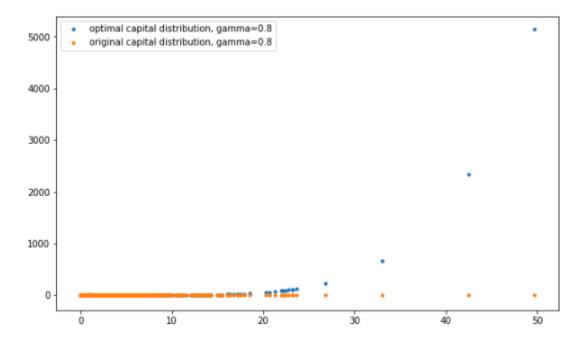


Figure 14: Q2 When gamma is 0.8 the ouptut per agent has higer variance

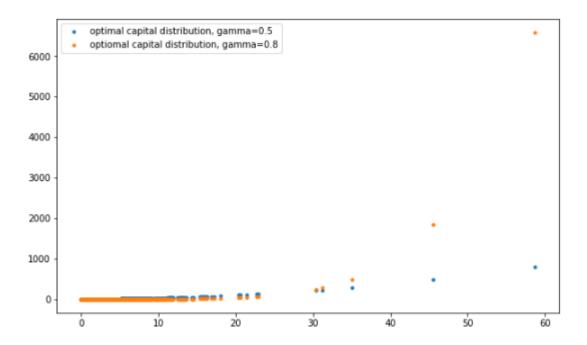


Figure 15: Q2 Comparison of optimal capital when gamma=0.5 and gamma=0.8. Weh gamma increases the more productive agents obtain optimally even more capital, so inequality increases. **However, ouptut gain is still 2.3**

Figure 16: QUESTION 3. When we optimize the output on the village level, output gain equals 1.6 which is less than under optimization on the aggregate level.

Problem:

st.

$$max_{k_i} \sum_{i} s_i(a_i, k_i) k_i^{\gamma}$$

$$K = \sum_{i} k_i$$

if $\sigma = 1$ then CES becomes Cobb-Douglas, so problem can be reformulated as:

$$max_{k_i} \sum_i a_i^{\alpha} k_i^{1-\alpha+\gamma}$$

FOC:

$$\begin{aligned} [k_i] : & (1-\alpha+\gamma)k_i^{\gamma-\alpha}a_i^\alpha = \lambda \\ [k_j] : & (1-\alpha+\gamma)k_j^{\gamma-\alpha}a_j^\alpha = \lambda \end{aligned}$$

which implies:

$$(\frac{a_i}{a_j})^{-\alpha}(\frac{k_i}{k_j})^{\gamma-\alpha}=1$$

S0

$$k_j = (\frac{a_j}{a_i})^{\frac{-a}{(p-a)}} k_j$$

Therefore,

$$k_i = K - \sum_{j \to i} k_j$$

$$k_i \left(\left(1 + \frac{a_i}{a_j} \right)^{\frac{-a}{(y - a)}} + \left(\frac{a_z}{a_z} \right)^{\frac{-a}{(y - a)}} + \dots \right) = K$$

$$k_i = \frac{K}{\left(1 + \left(\frac{a_i}{a_j} \right)^{\frac{-a}{(y - a)}} + \left(\frac{a_z}{a_z} \right)^{\frac{-a}{(y - a)}} + \dots \right)}$$

Figure 17: Q4.

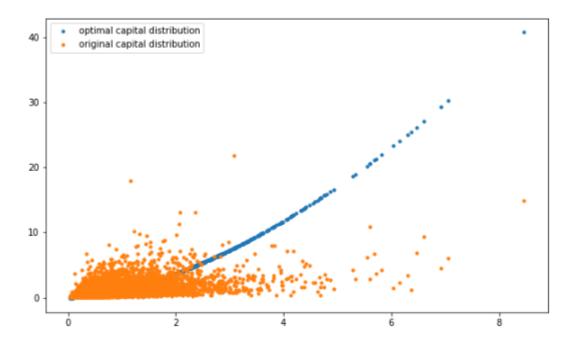


Figure 18: Q4. Optimal vs original capital distribution when sigma=1. Output gain accounts for 1.54