Project 5 - FYS3150 Computational Physics

Fredrik Østrem (fredost)
github.com/frxstrem/fys3150

Joseph Knutson (josephkn)
github.com/mathhat/Computational_Physics

December 7, 2016

Abstract

Abstract

Contents

1 Result

In all our simulations, we run 1000 runs with 10^7 transactions each.

a,b) We start the simulation with the simplest model: Initial amount $m_0 = 1$ with no saving ($\lambda = 0$) and no preference for transaction partners ($\alpha = 0, \gamma = 0$). In this case, we expect the Gibbs distribution

$$w_m = \beta \exp(-\beta m)$$

where $\beta = \langle m \rangle^{-1} = m_0^{-1}$.

In fact, when we run the simulations, we get the distribution shown in figure 1, we see that the distribution matches almost exactly up with the distribution be would expect, where $\beta = m_0^{-1} = 1$. This is further comfirmed by plotting the y axis logarithmically, in which case we get figure 2, which clearly shows this relation.

We know that the variance of the Gibbs distribution is $\sigma_m^2 = \beta^{-2} = m_0^2$, and we can use this to find out how many transactions we need to get equalibrium. Before any transactions, the variance is zero (as every agent has the same amount of money); after equalibrium is reached, we expect the variance to vary around the theoretical variance. In figure 3 we see the calculated variance of the simulated distribution plotted against the number of transactions, for different number of agents. We can see that it takes only about 10^2–10^3 transactions to reach equalibrium, and that this number is roughly proportional to N.

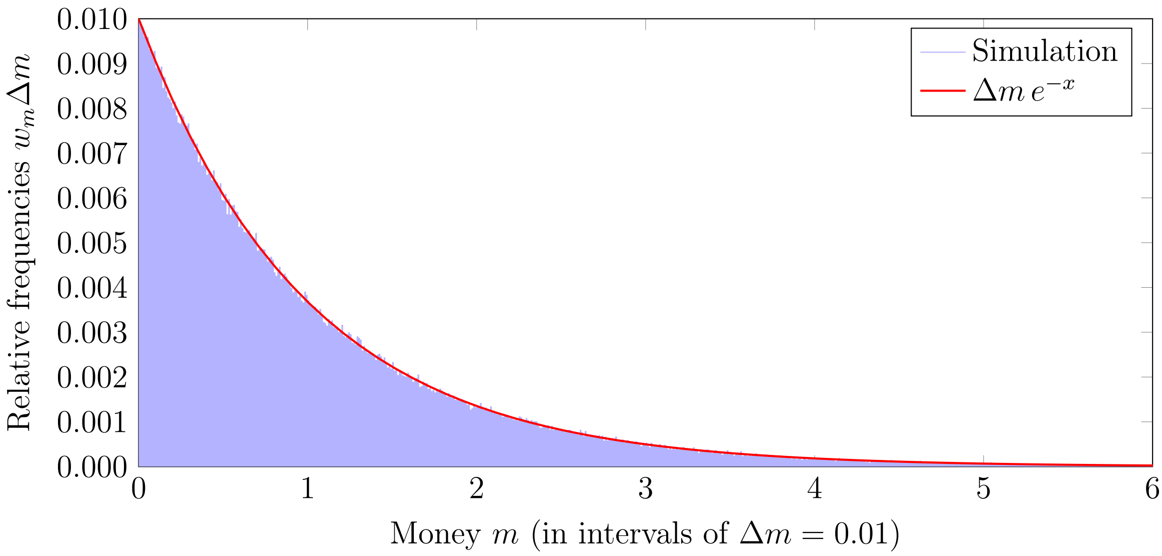

Figure 1: Histogram of the distribution of wealth after running the simple model ($\lambda = 0, \alpha = 0, \gamma = 0$) with 10^7 transactions 10^3 times, compared with the theoretical Gibbs distribution. Bin width is $\Delta m = 0.01$.

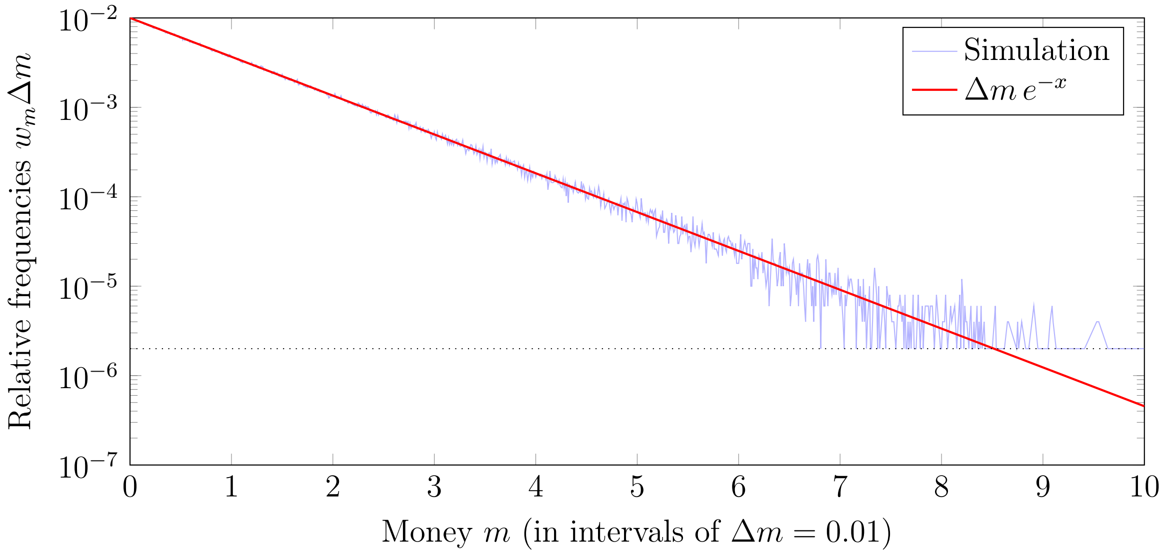

Figure 2: The distribution from figure 1, plotted on a logarithmic y axis.

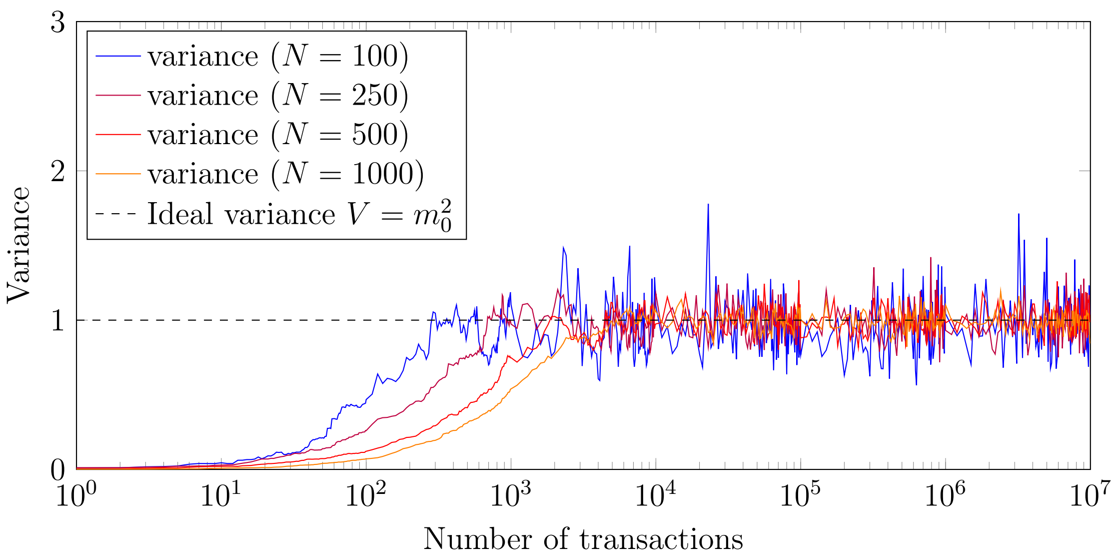

Figure 3: Simulated distribution variance as a function of number of transactions, for different numbers of agents. Dashed black line marks the “ideal” variance (theoretical variance at equalibrium).

c) Next, we introduce saving into the equation: every time a transaction happens, each of the agents save a fraction λ before each transaction. We run three simulations with saving fractions $\lambda = 0.25, 0.50, 0.90$, and look at how these alter the distribution of money. In figure 4 we see the distributions of these simulations. We see that having a high saving fractions lowers lowers wealth inequality, and at very high saving fractions ($\lambda = 0.90$), the money is distributed according to an approximate narrow Gaussian distribution centered at $m_0 = 1$.

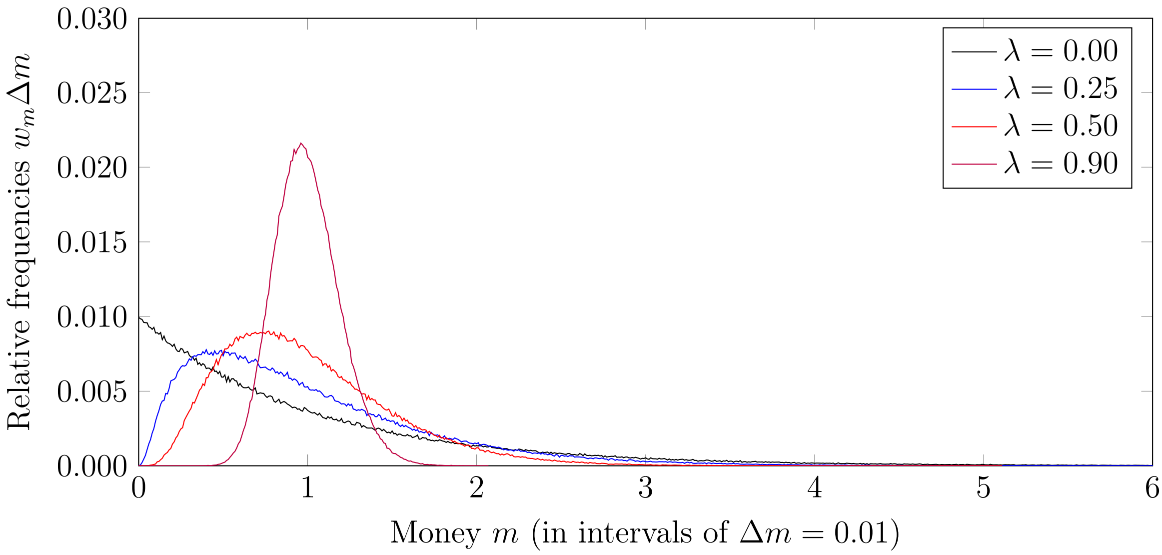

Figure 4: Simulated distributions after we introduce a saving fraction λ in the model.

d) We then introduce a new parameter α, that affects the agents preference for transaction partners with wealth close to their own (as described in section [what]). We run eight new simulations with parameters $\lambda = 0.00, 0.25$ and $\alpha = 0.5, 1.0, 1.5, 2.0$ for $N = 500$ and $N = 1000$.

In figure 5 and 6 we see the wealth distributions of these models. From these distributions we can tell that a higher value of α will cause more people to have less money, giving a more narrow distribution and less wealth inequality among agents.

In figure 7, we have plotted the same data for $N = 100$ with logarithmic axes. We expect this plot to be similar to figure 1 of Goswami and Sen (2014). Indeed, our plot is very similar, except that our plot does not reproduce the kink at $m \approx 2 \times 10^{-2}$ for the larger α values.

[Power law of tail???]

e) Finally, we introduce the parameter γ that affects the agents preference for previous transaction partners (as described in section [what]). We run 20 simulations with parameters $\lambda = 0.00, 0.25$, $\alpha = 1.0, 2.0$ and $\gamma = 0.0, 1.0, 2.0, 3.0, 4.0$, with $N = 1000$ agents.

In figure 8 and 9, we have again plotted the distribution of these simulations with linear and logarithmic axes. [How does γ affect the distributions?]

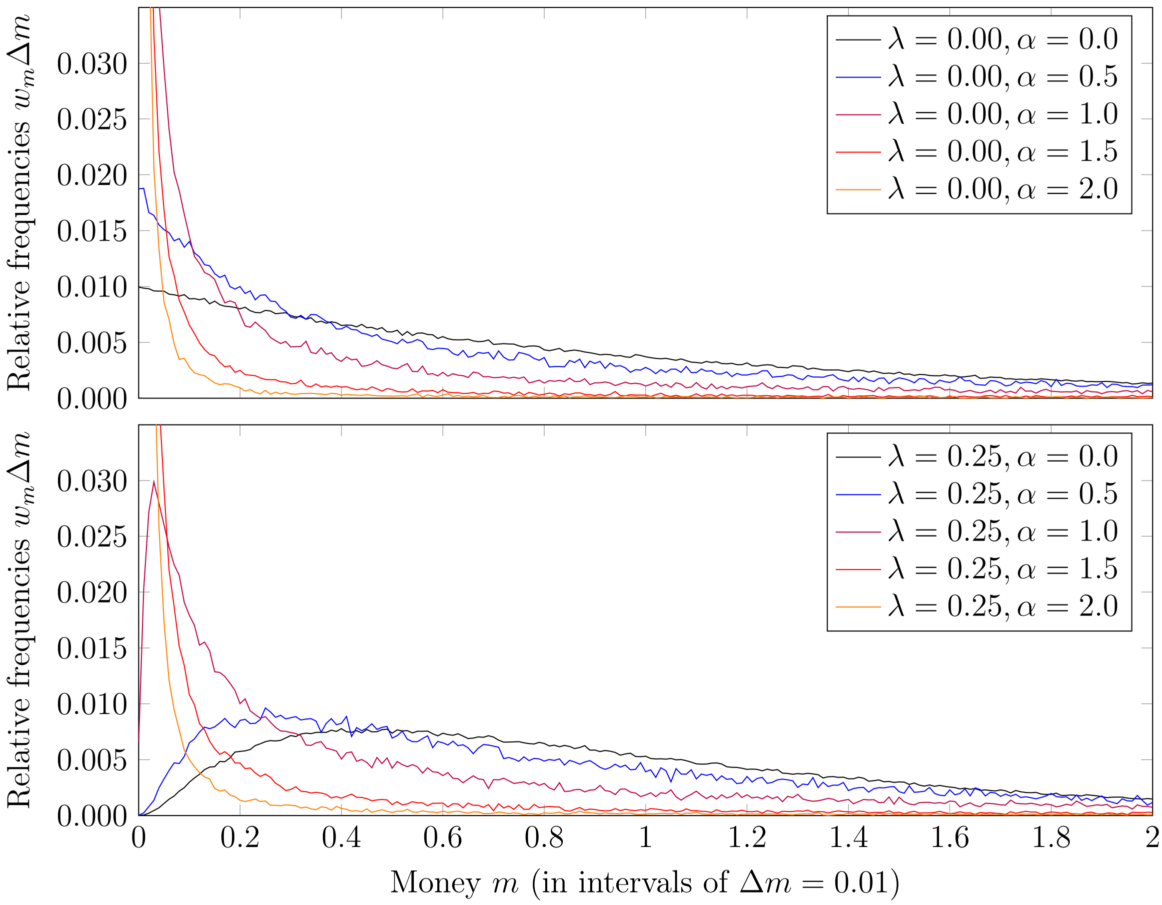

Figure 5: Simulated distributions after a "wealth preference" parameter α is introduced into the model. Number of agents is $N = 500$.

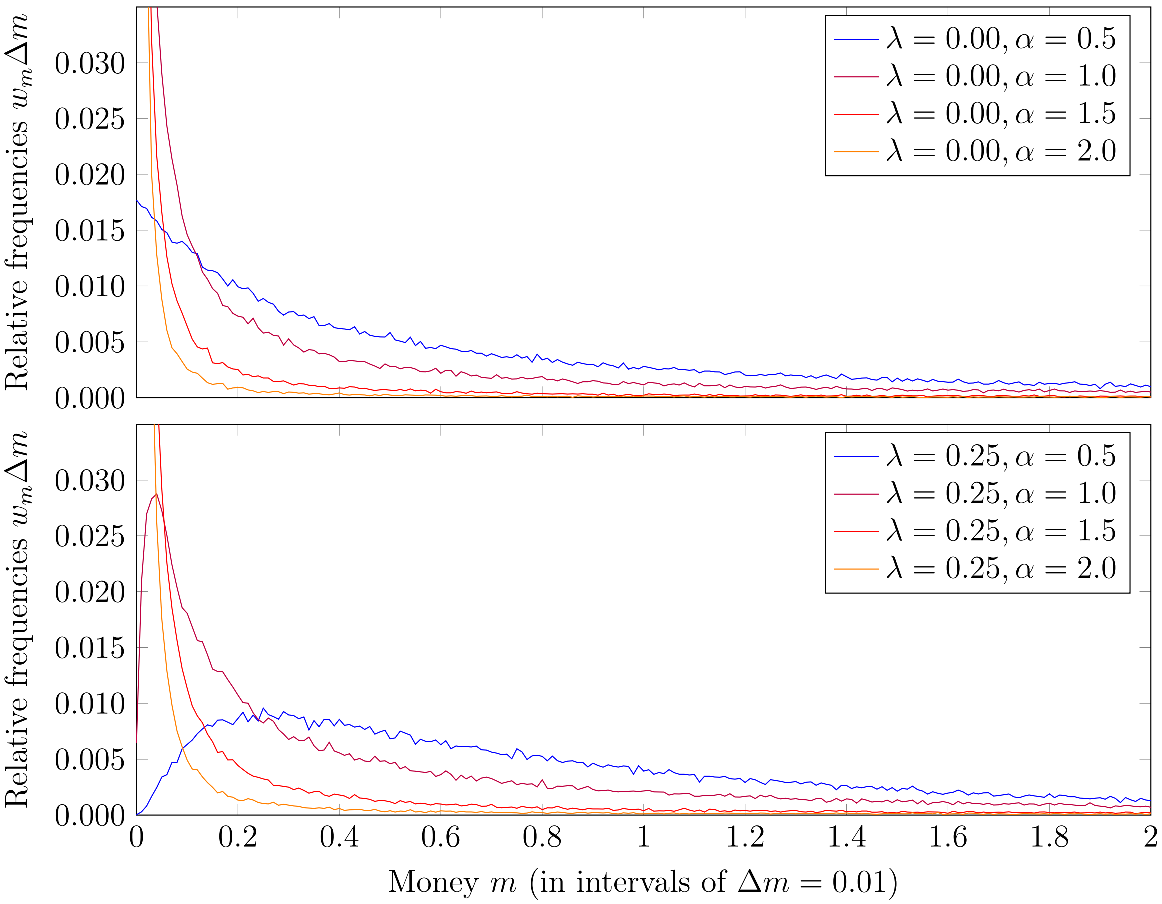

Figure 6: Same as figure 5, but with $N = 1000$ agents.

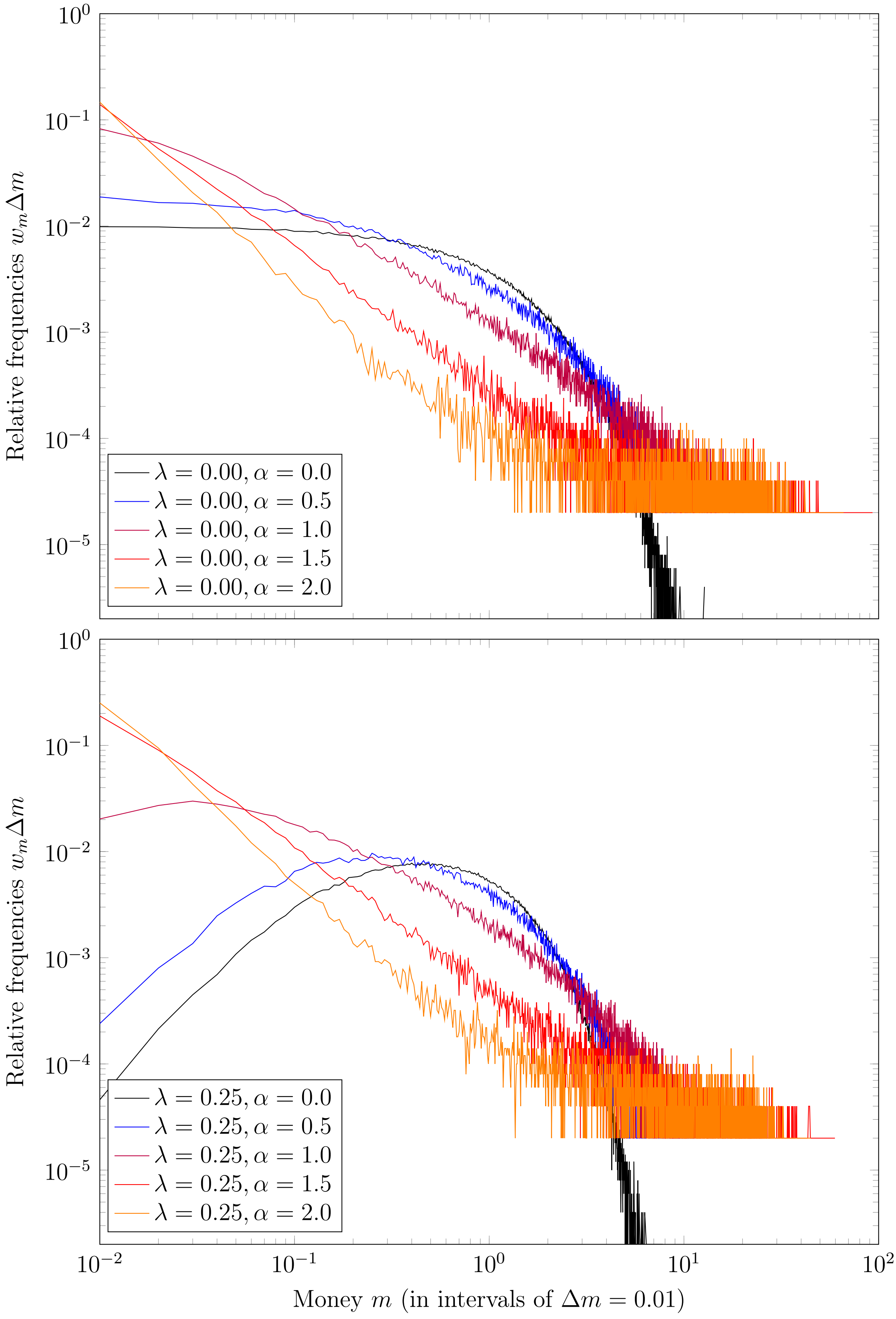

Figure 7: Same data as in figure 5, plotted with logarithmic axes.

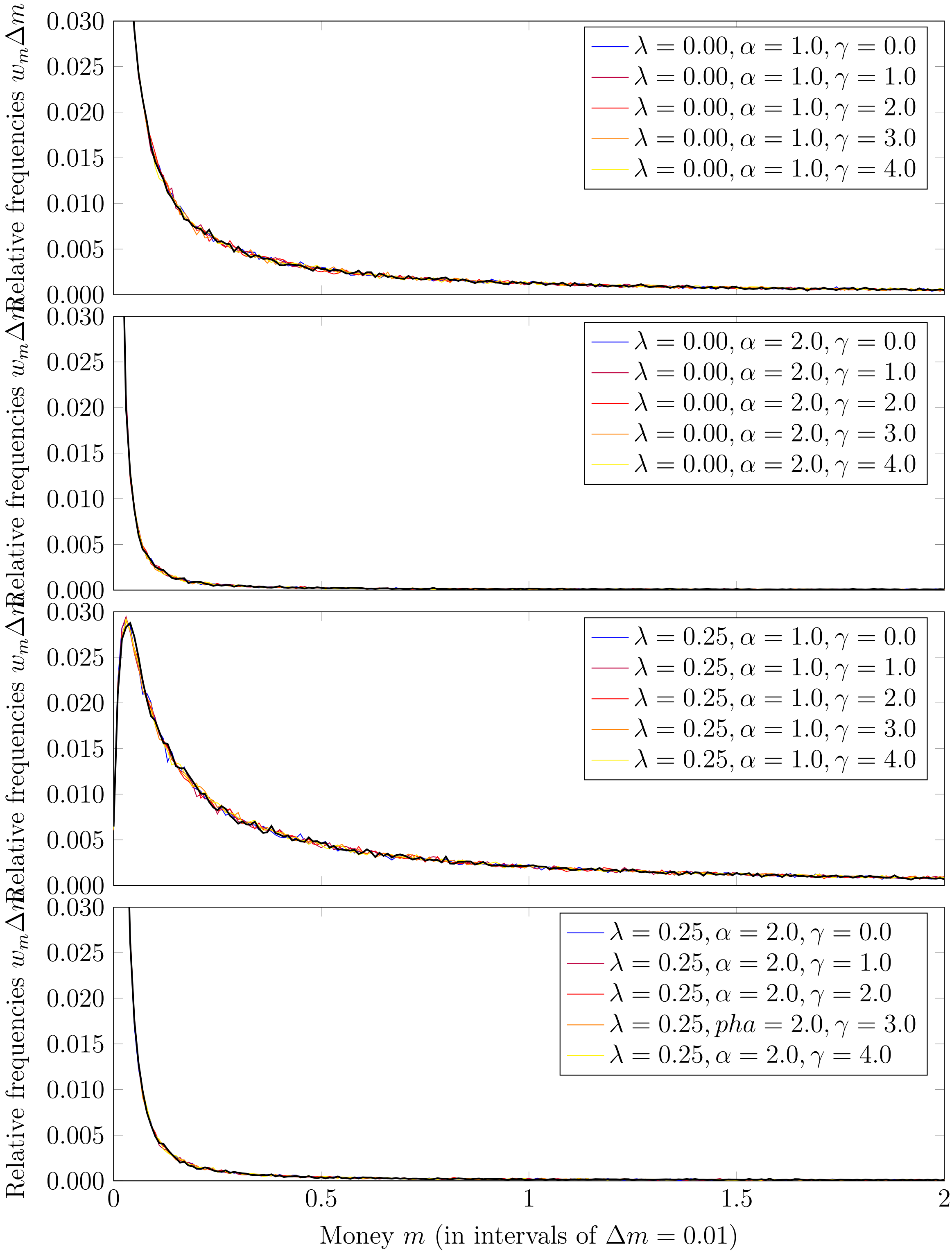

Figure 8: Simulated distributions after a "agent preference" parameter γ is introduced into the model. Number of agents is $N = 1000$.

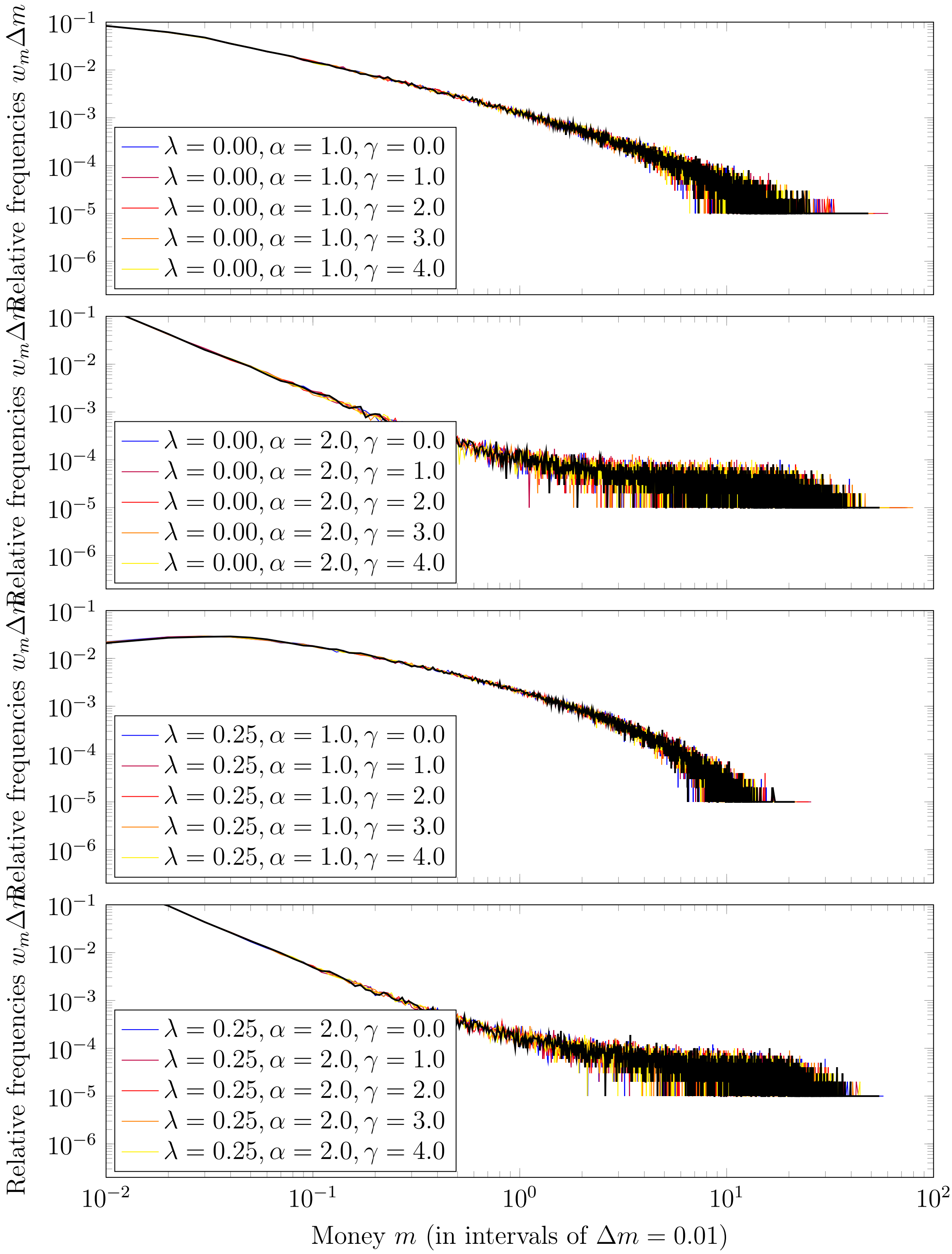

Figure 9: Same data as in figure 8, plotted with logarithmic axes.

A Appendix

[where can code etc. be found?]

B Bibliography

Goswami, Sanchari and Parongama Sen (2014). “Agent based models for wealth distirbution with preference in interaction”. In: *Psyica A: Statistical Mechanics and its Applications* 415, pp. 514–524. URL: http://www.sciencedirect.com/science/article/pii/S0378437114006967.