Exploration over parameters in the ABM model (2^{nd} part)

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Executions

The ABM has been explored over two parameters (β and η), after fixing three of them to the most stable values (g, k and w): The parameters appear in the ABM as:

- k is the capital intensity, fixed to 1.0.
- w is the real wage, fixed to 0.7.
- g is the bankruptcy cost, fixed to 1.2.
- β is the skewness, varying in [0.02, 0.03, 0.04, 0.05].
- η is the inverse of the elasticity of demand ($1/\varepsilon$), varying in [0.0001, 0.1, 0.3, 0.5, 0.8].

For each combination of the varying parameters, the model has been run 10 times using a Montecarlo method. So a total of 200 executions of the model have been done (20 combinations, 10 times each).

GDP and market power

The first realization about GDP is that, greater the eta is, lower the GDP we have, and stronger the fall and variation of the output in our firms, till the paroxism of $\eta = 0.8$ (an extreme monopolistic market with a ridiculous Y), as Figure 1 shows:

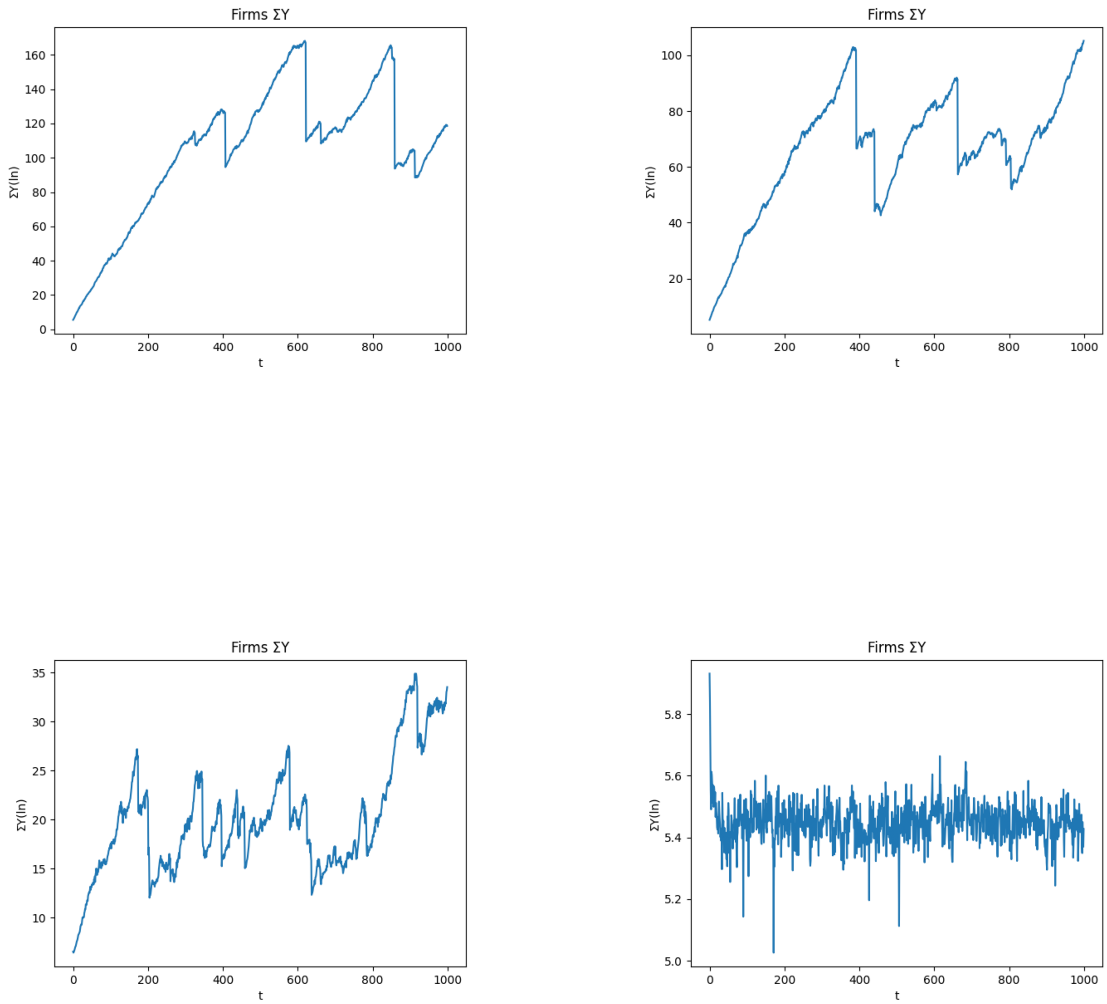

Figure 1: Fixing beta=0.02, and exploring GDP varying eta=0.0001 (top left), eta=0.1 (top right), eta=0.3 (bottom left) and eta=0.8 (bottom right)

One important realization is what generates the falls in GDP, as the one in left figure in Figure 2, where the output of firms has a strong reduction in a moment around t=750. GDP is connected in the formulation of the model with K, and K is related with A, in a manner that plotting Y and A are exactly the same. And also the huge amount of K in figure at right in Figure 2, but this is a cause and effect due to the formulas, not an explanation.

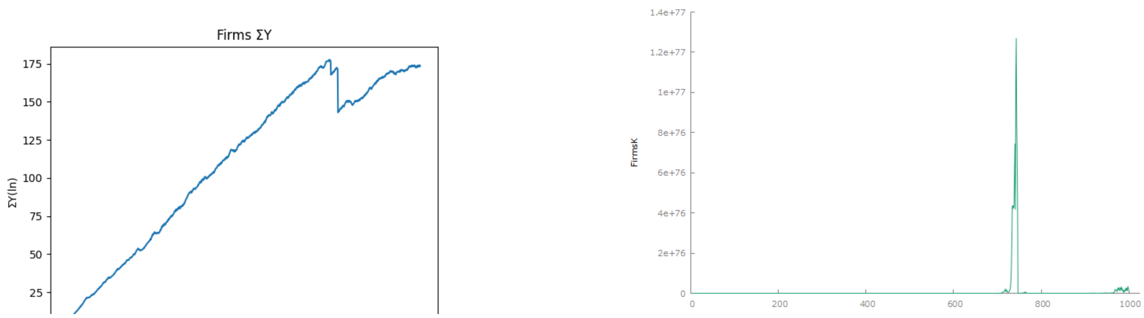

Figure 2: Execution with parameters beta=0.02, g=1.0, k=1.1, w=0.6 and eta=0.3. Left logarithm GND and right the K without logarithm.

The key is to focuse on the affection of failures around that instant t=750. If we see Figure 3, the number of failures is similar during the execution, but the bad debt of the bank due to that failures is incredible high in our critical moment around t=750. That's the problem for the companies (and the bank sector) in our model: to success to the shock with huge amounts of loans, because those fails are the ones that creates the crisis.

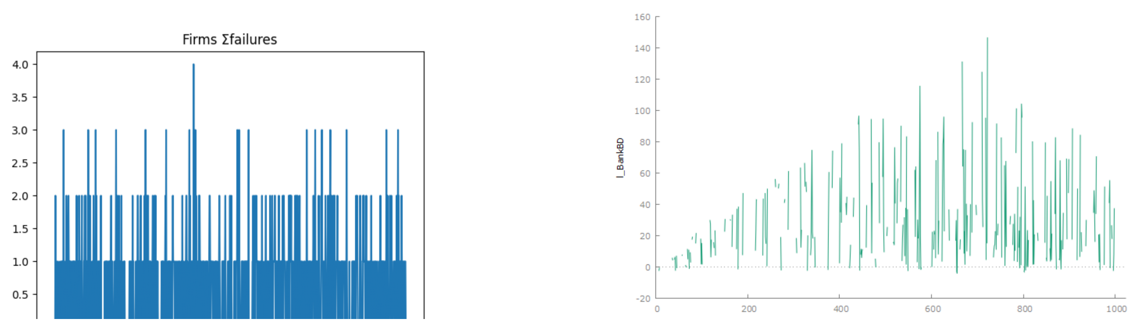

Figure 3: Execution with parameters beta=0.02, g=1.0, k=1.1, w=0.6 and eta=0.3. Left number failures right the bad debt in logarithm.

Importance of β

Till now, we have vary eta having fixed β to 0.02. Let's repeat the previous work, but fixing eta to 0.0001 and discover how affects β to our model. But if we look at GDP, the impact is not so clear, as Figure 4 shows:

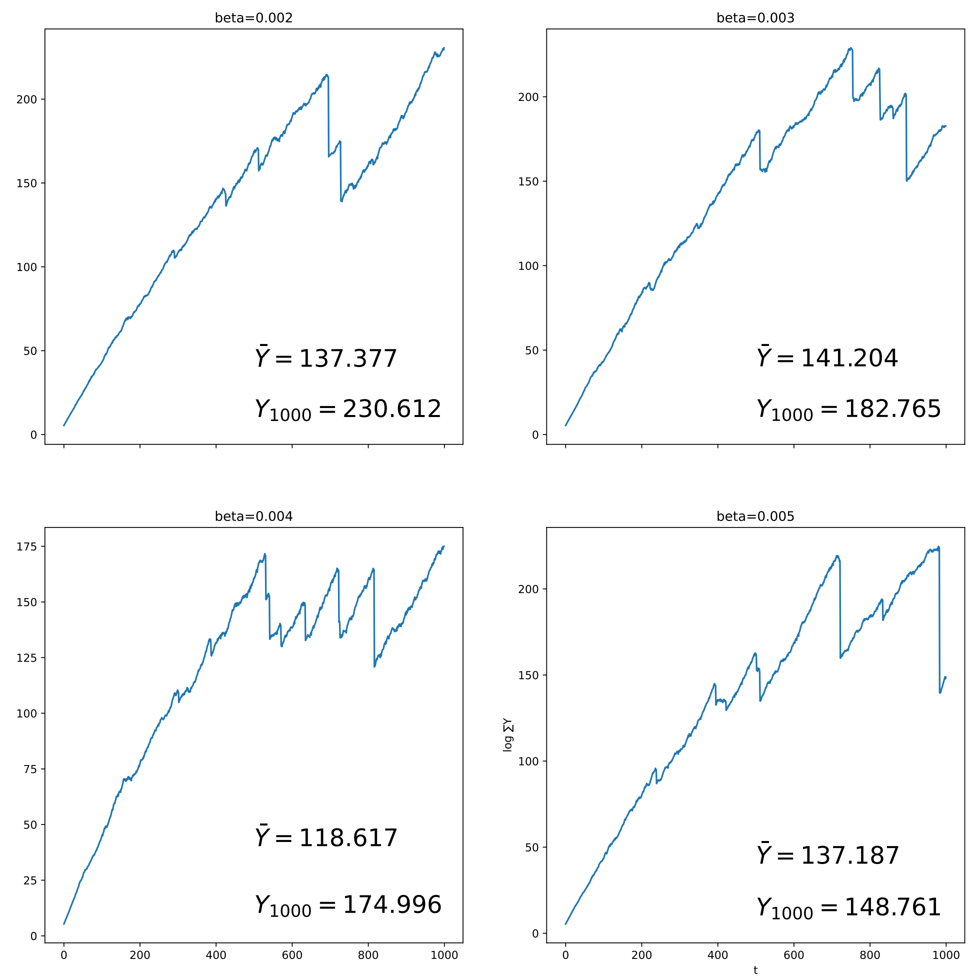

Figure 4: Fixing eta=0.0001, and exploring GDP varying beta=0.02 (top left), beta=0.03 (top right), eta=0.04 (bottom left) and eta=0.05 (bottom right)

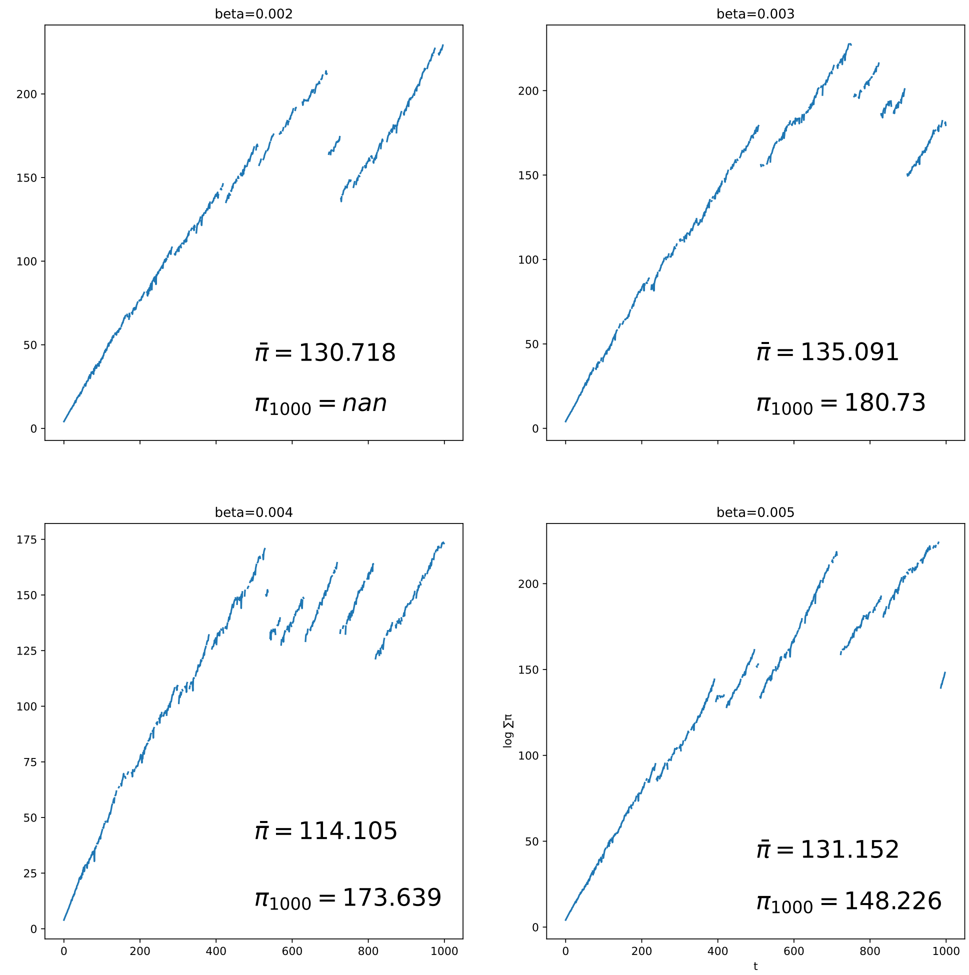

Figure 5: Same as previous figure, but with profits.

β is also relevant, because is connected with the determination of the interest rate, as Figure 6 shows: greater the β, greater the average r, and logically it should generate greater γ, which generates less K and so on.

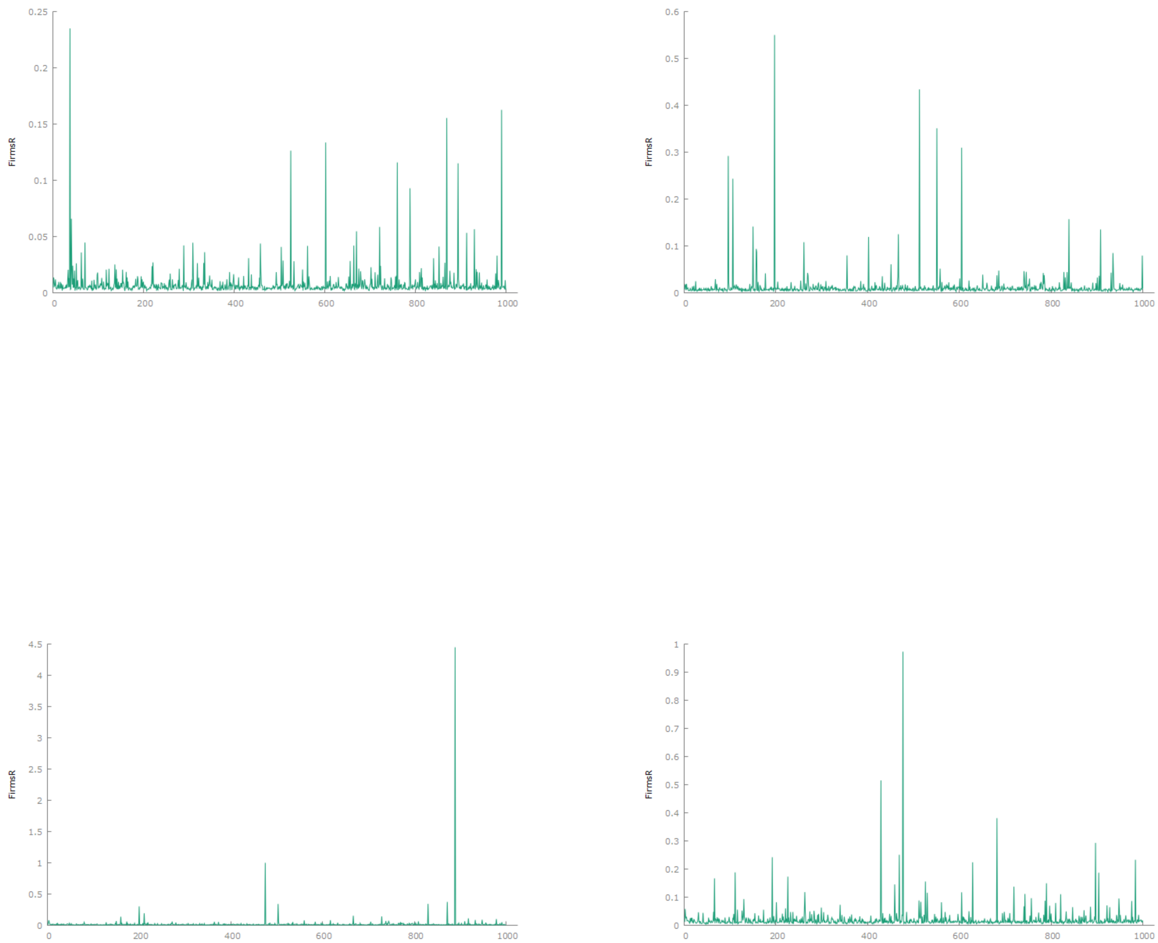

Figure 6: Fixing eta=0.0001, and exploring average interest rates varying beta=0.02 (top left), beta=0.03 (top right), eta=0.04 (bottom left) and eta=0.05 (bottom right)

From the point of view of the bank sector, the impact of   may could be present in the profits:

$$\pi_{b,t} = \sum r_{i,t} L_{i,t} - r(D_t + A_{b,t})$$

The profits for the bank sector have two different components: at the left of the addition the profits due to the interest rate charged to the loans to the companies. At the right, the payments the bank gives for deposits and net worth, using the average r in each instant of time. In Figure 7 we can realize that this two components have similar response after altering β.

At the end, from the point of view of the firms, one of the effects is the increment in bankruptcies in the firms when we increment , as Figure 8 shows:

The impact is not comparable to the number of failures varying eta (Figure 9) but needs an explanation: the increment in interest rate driven by beta provokes a reduction (not really important, but present) in the benefits of the bank sector, that drives to a reduction in net worth that generates in next iterations to minorate the loans and so, problems for the firms.

Gretl

Correlate bad debt and output (GNP) is not easy due to the presence of zeros in the bad debt series. After not finding the way to add a modified series where 0 is replaced by a value close to zero but greater than it, the solution has been to add a new calculated series $log_B D = log(BankBD + 0.0001)$, and then discover a negative correlation between BD and Y, as figure Figure 10 shows (and not Y and BD, what was my first attempt):

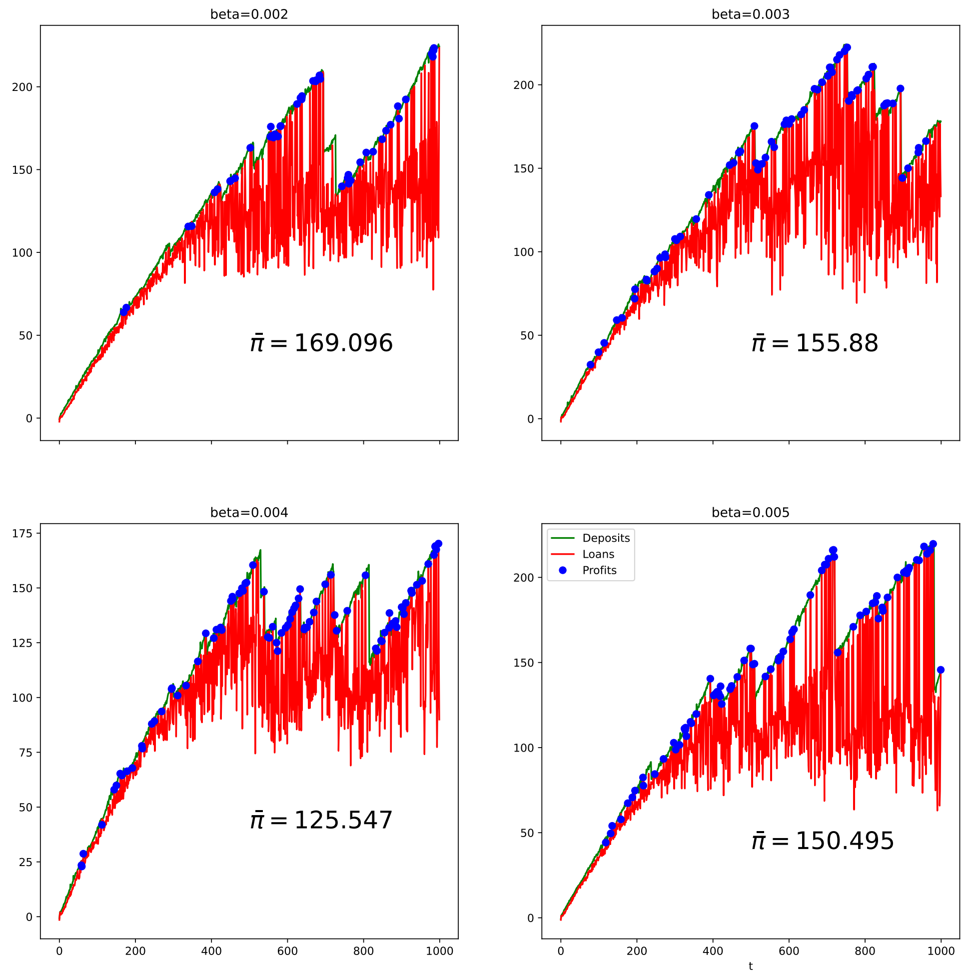

Figure 7: Fixing eta=0.0001, and exploring beta: profits of the bank sector are produced only when blue balloons, when difference between green line (revenues of loans) and red line (payments of deposits and net worth) are positive, not always possible

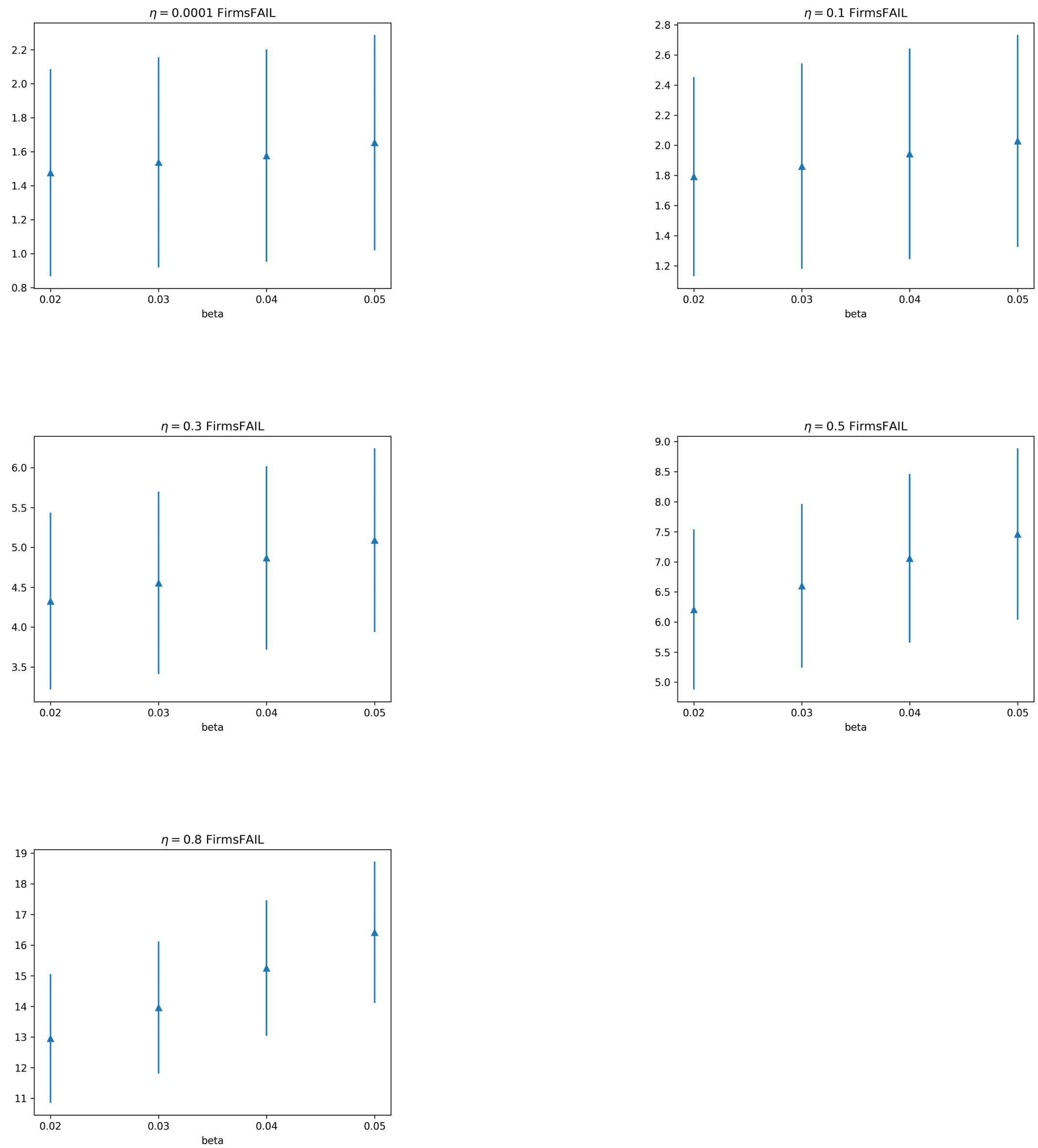

Figure 8: Average number of failures varying beta, for eta=0.0001 (top left), eta=0.1 (top right), eta=0.3 (middle left), eta=0.5 (middle right) and eta=.08 (bottom left)

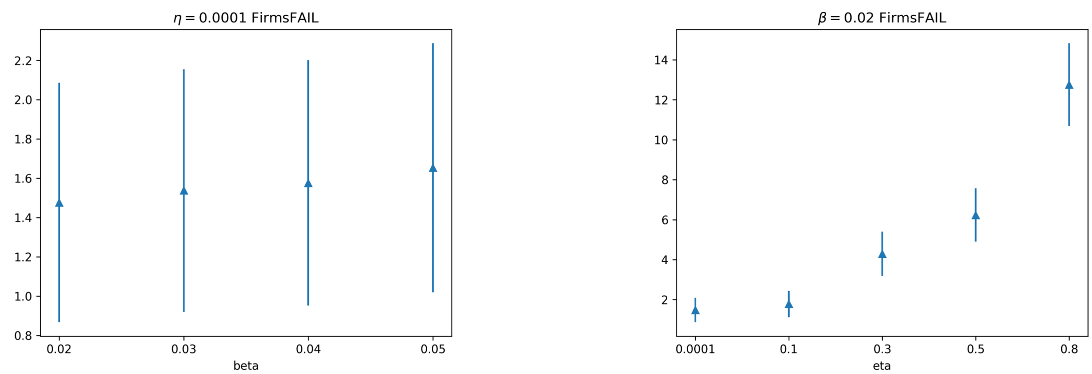

Figure 9: Average number of failures varying beta for eta=0.0001 (left) and varying eta for beta=0.02 (right)

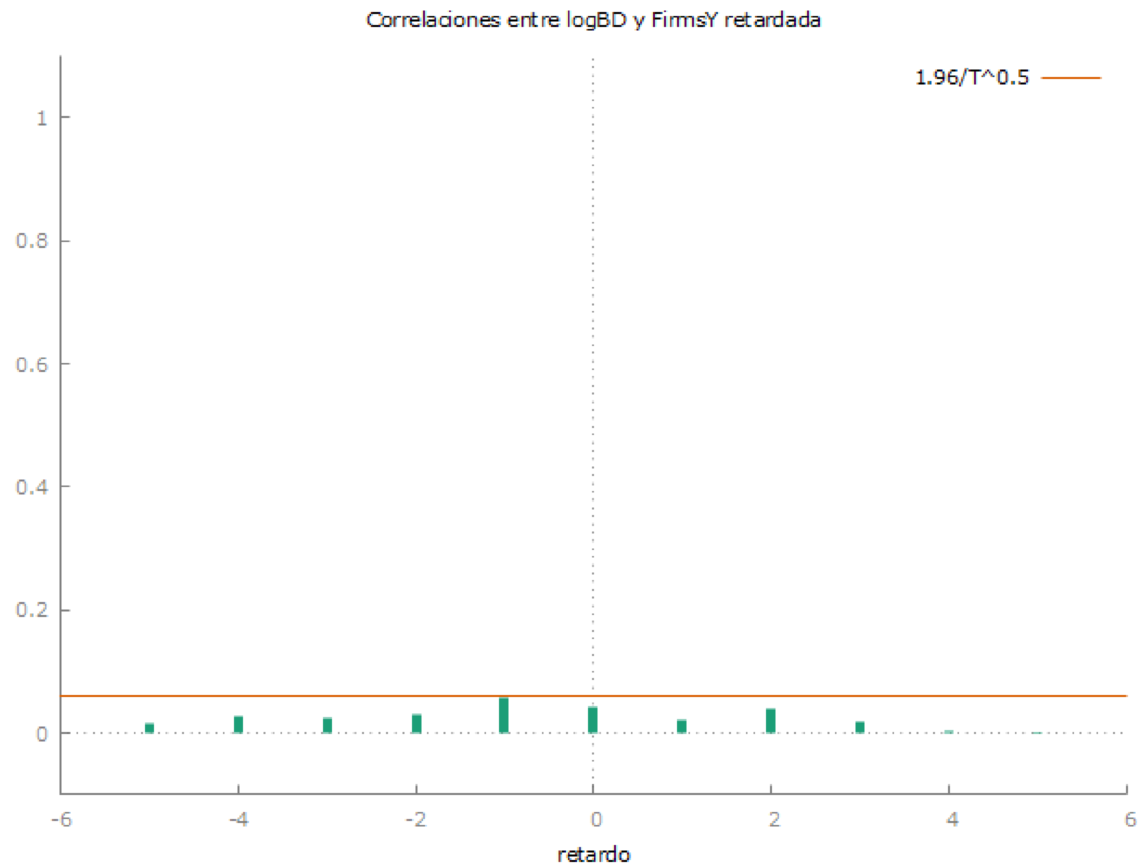

Figure 10: Cross correlogram of average #10 models with parameters beta=0.002 g=1.0 w=0.06 eta=0.3

Table with results

Table 1: Demonstration of pipe table syntax

η/β	Left	Right	Center
12	12	12	12
123	123	123	123
1	1	1	1

```
import pandas as pd
from IPython.display import Markdown
penguins = pd.read_pickle("tables\\FirmsY.pickle")
Markdown(penguins.to_markdown())

penguins = pd.read_pickle("tables\\FirmsY_std.pickle")
Markdown(penguins.to_markdown())
```

	0.0001	0.1	0.3	0.5	0.8
0.02	40.9544	23.869	5.19864	95.3069	14.3508
0.03	46.0757	21.5909	4.64703	96.0532	14.7748
0.04	40.3434	21.0393	4.3657	88.0504	15.2557
0.05	38.7117	23.2697	4.29983	84.5184	15.5253