Title: Parameter estimation and model selection using spinning hybrid waveforms.

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URL: http://pirsa.org/10060076

Abstract: Most searches with ground-based detectors for gravitational-wave signals from the inspirals of stellar-mass compact binaries use template based methods. Those work well for non-spinning systems but since the dimensionality of the parameter space of spinning waveforms is large a template bank search is not feasible. We describe Bayesian and Markov-chain Monte-Carlo methods for parameter estimation of spinning waveforms using hybrid spinning waveforms matching the ringdown from Numerical Relativity results. We compare those results when using post-Newtonian only waveforms. We explore the parameter space and discuss different ways to overcome its high dimensionality and multi-modality.

PhenSpin MCMC

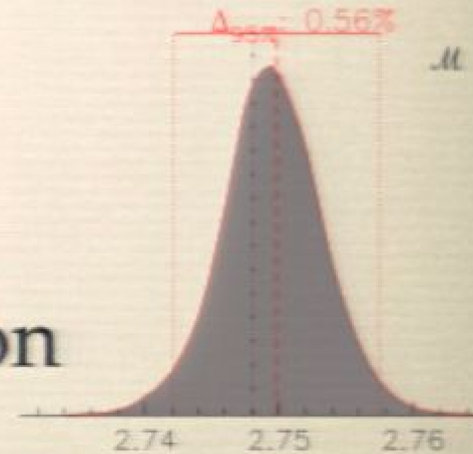
Parameter estimation and model selection using spinning phenomenological waveforms

Vivien Raymond, Marc van der Sluys, Ilya Mandel, Vicky Kalogera

CIERA
CENTER FOR INTERDISCIPLINARY EXPLORATION AND RESEARCH IN

Capra / NRDA 2010, June 25, Perimeter Institute

GOAL(S)



- parameter estimation:
    - probability density function
- assume detection ($\sim t_c$)
- full parameter space (up to 15-D)
    - fast but accurate templates

Bayesian Inference

- stochastic sampling of high likelihood points

$$p(\vec{\lambda}|\vec{x}, M) = \frac{p(\vec{\lambda}|M)\, p(\vec{x}|\vec{\lambda}, M)}{p(\vec{x}|M)}$$

$$\left(posterior = \frac{prior * likelihood}{evidence} \right)$$

- model selection

Markov-Chain Monte Carlo

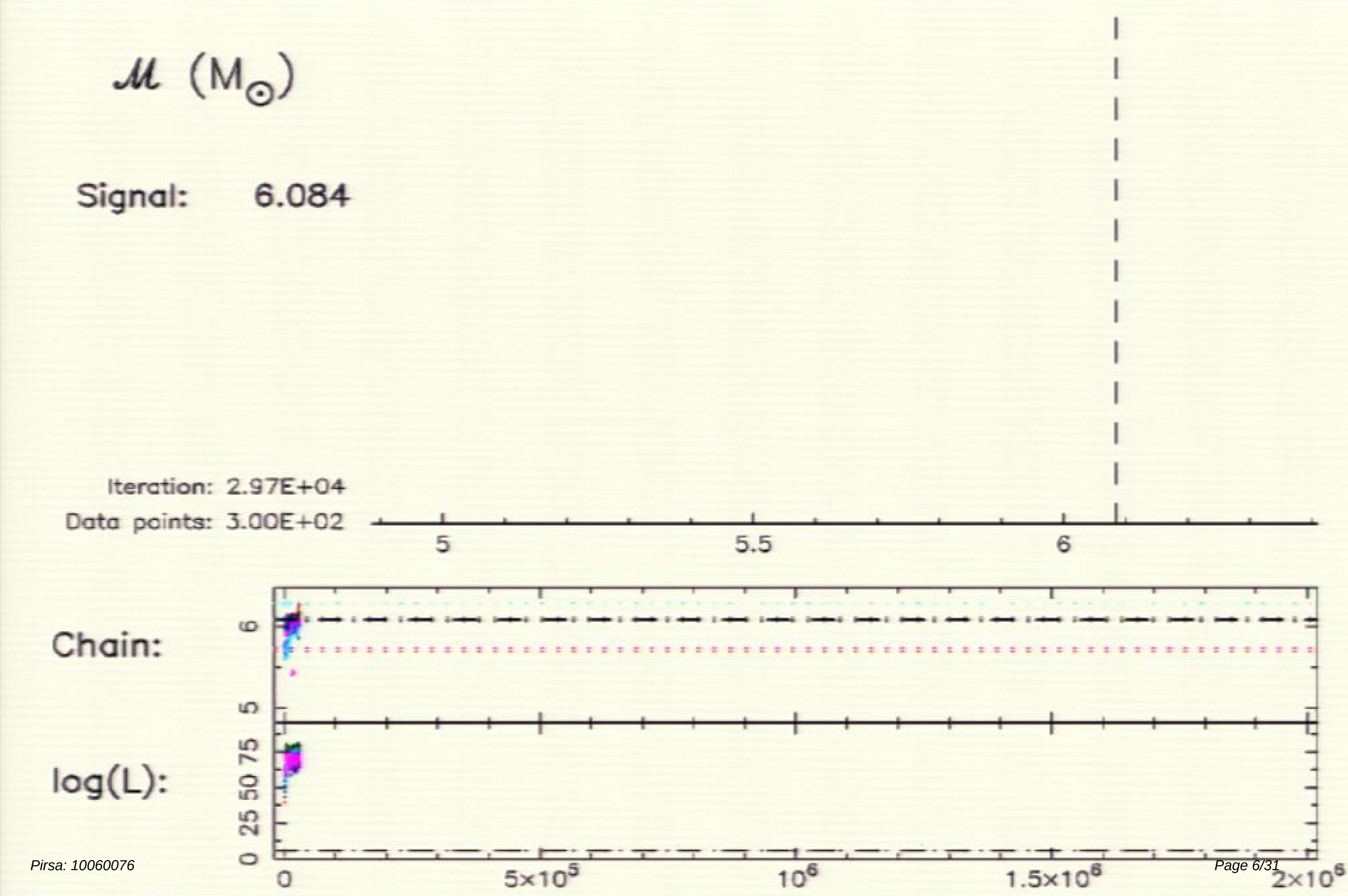
- walk through parameter space

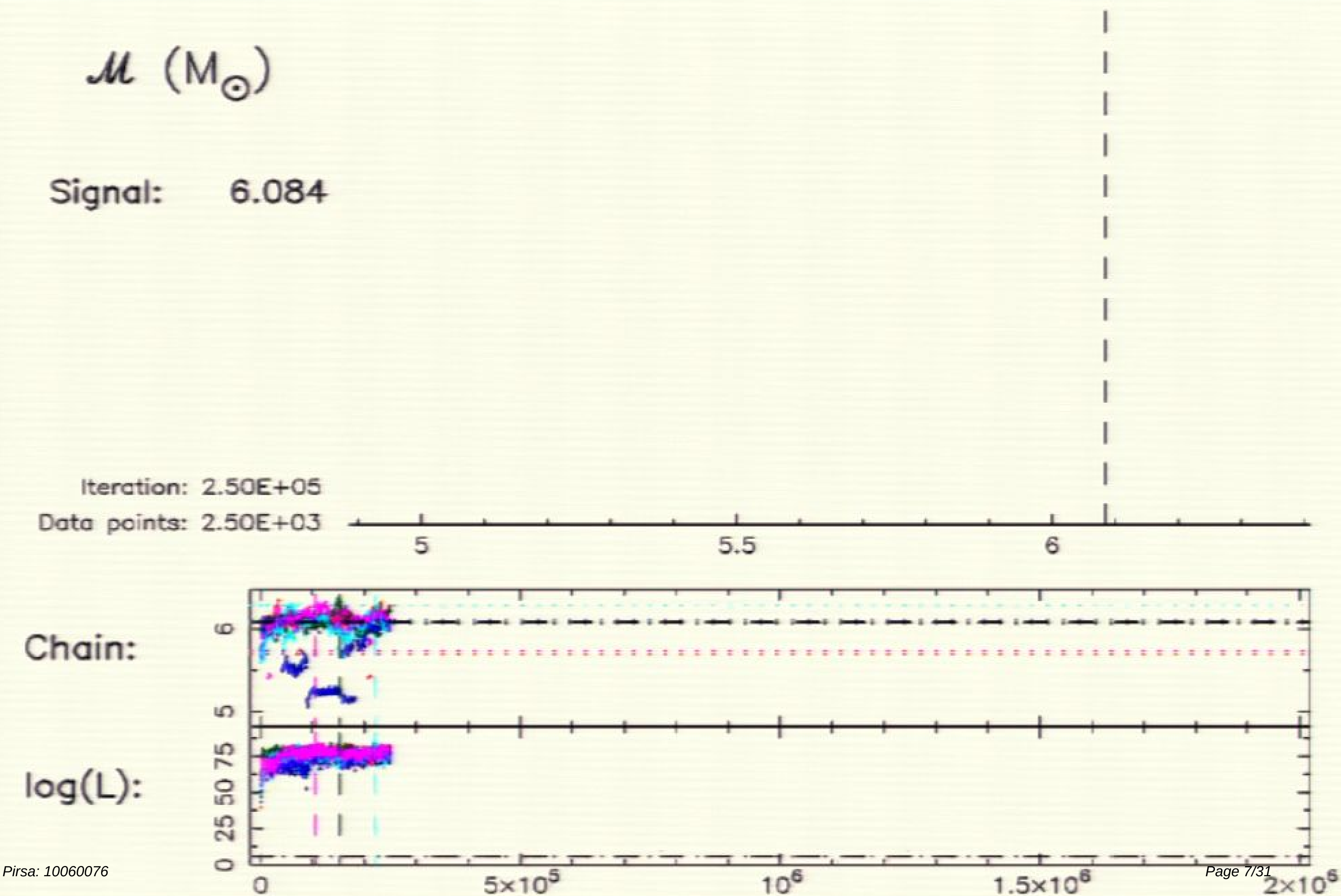
$$\frac{p(\vec{\lambda}_{i+1}|M)}{p(\vec{\lambda}_i|M)}\frac{p(\vec{x}|\vec{\lambda}_{i+1},M)}{p(\vec{x}|\vec{\lambda}_i,M)} > r$$

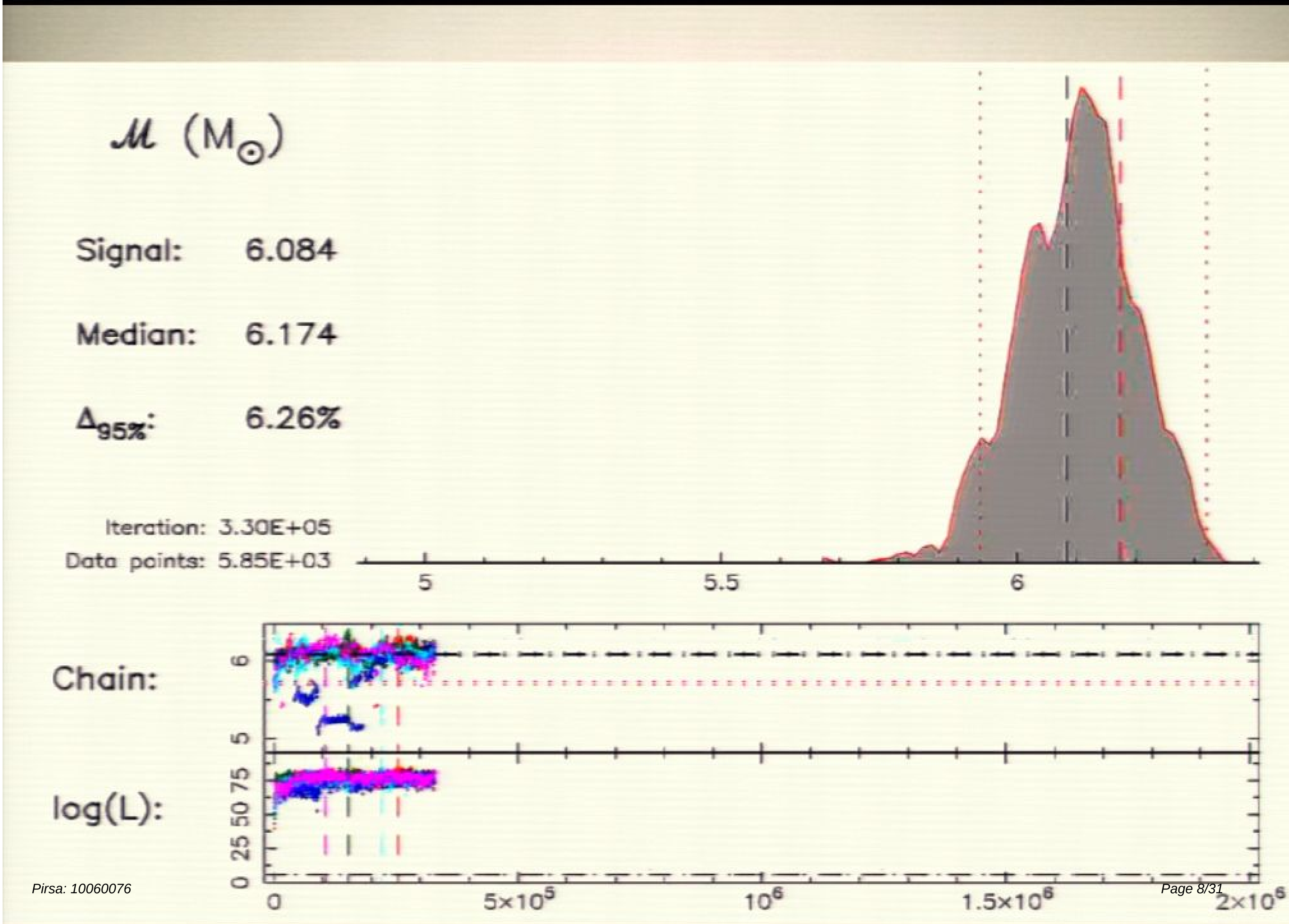
$$\frac{(prior)_{i+1}}{(prior)_i}\frac{(likelihood)_{i+1}}{(likelihood)_i} > r$$

  - memoryless

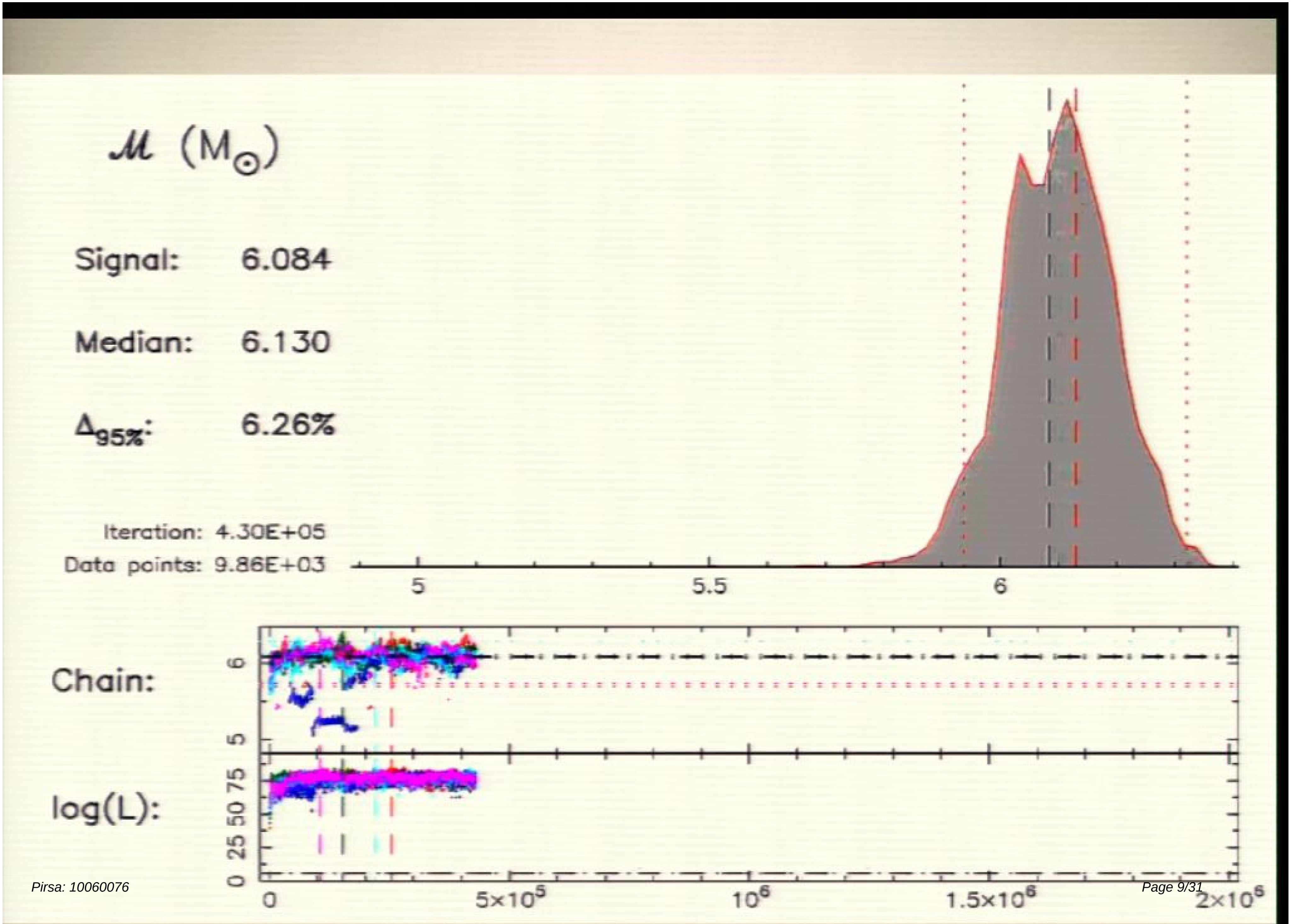
- asymptotic convergence towards the posterior PDF


$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Iteration: 2.97E+04
Data points: 3.00E+02
5
5.5
6
Chain:
6
5
log(L):
0 25 50 75
0
5×10^5
10^6
1.5×10^6
2×10^6

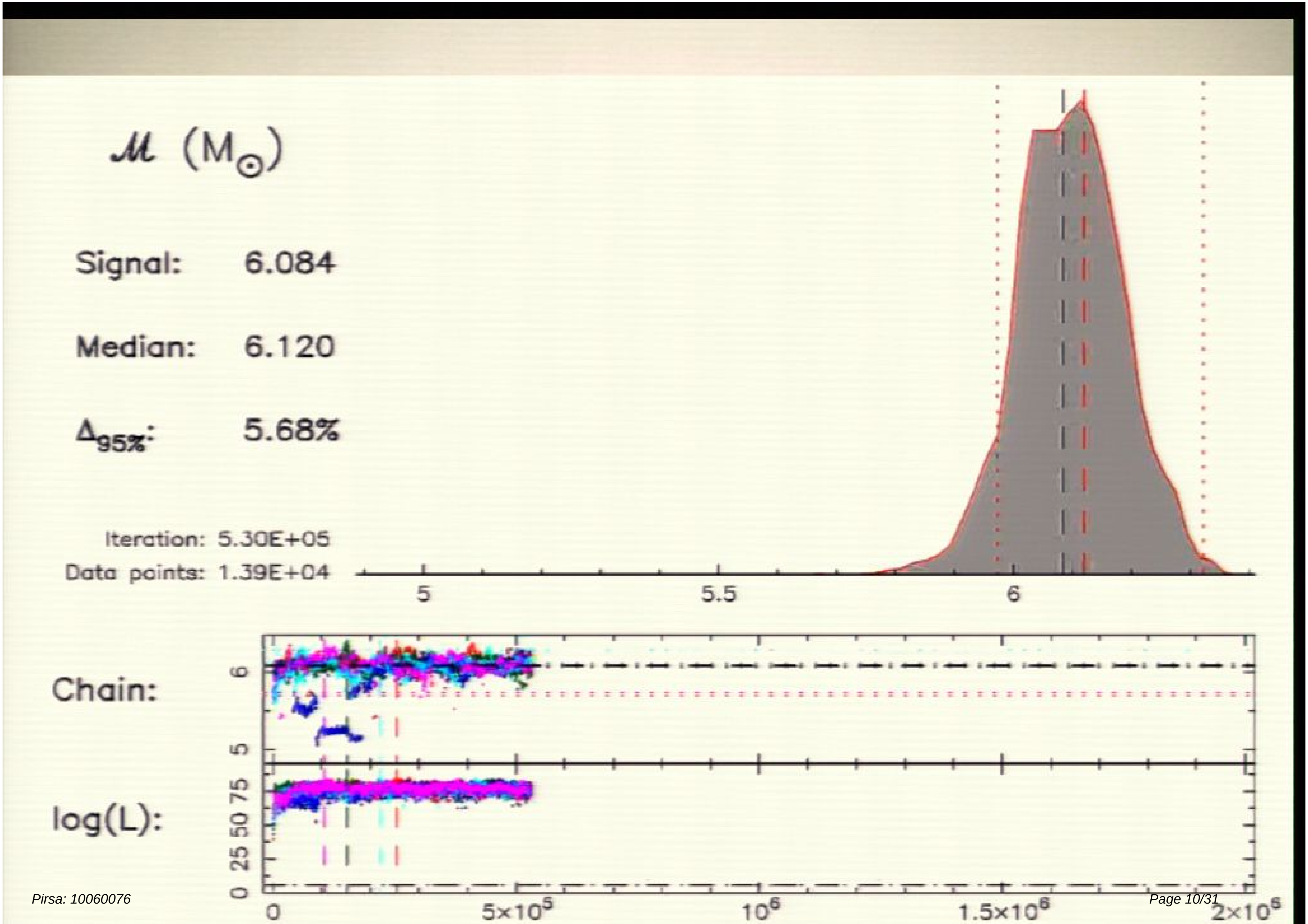

$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Iteration: 2.50E+05
Data points: 2.50E+03
5
5.5
6
Chain:
6
5
log(L):
75
50
25
0
0
5×10^5
10^6
1.5×10^6
2×10^6

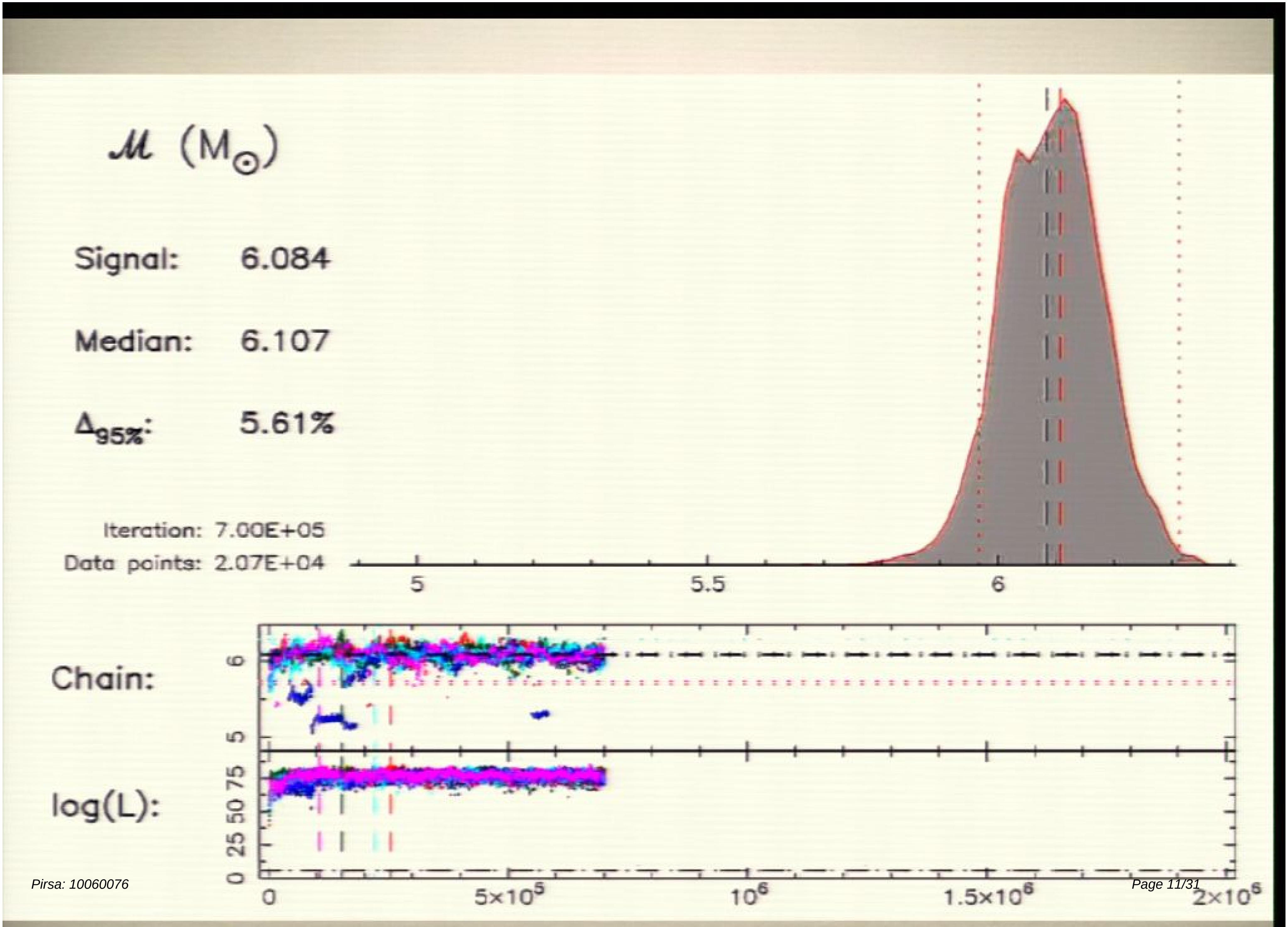


$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Median: 6.174
$\Delta_{95\%}$: 6.26%
Iteration: 3.30E+05
Data points: 5.85E+03
5
5.5
6
Chain:
6
5
log(L):
75
50
25
0
0
5×10^5
10^6
1.5×10^6
2×10^6

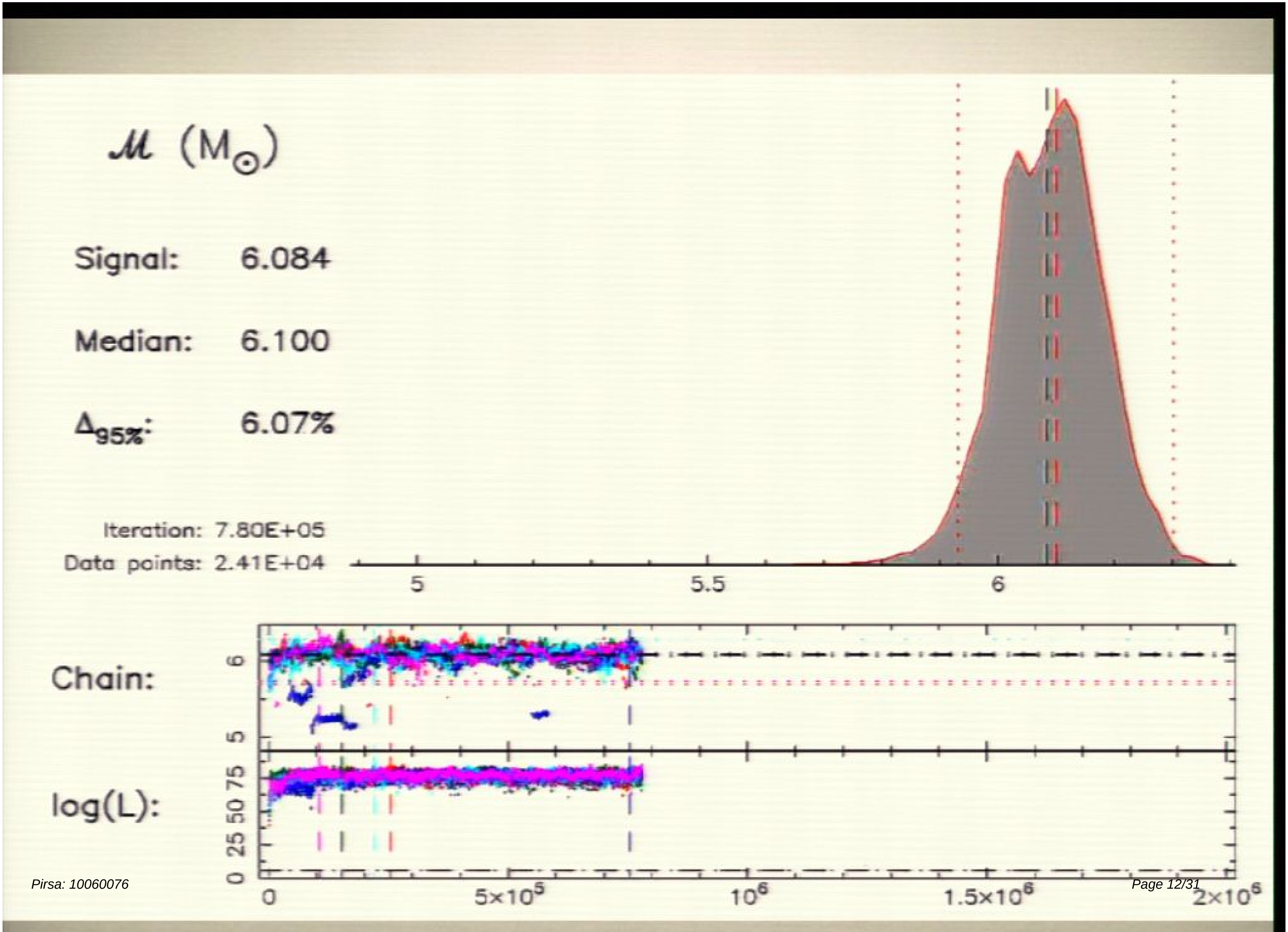


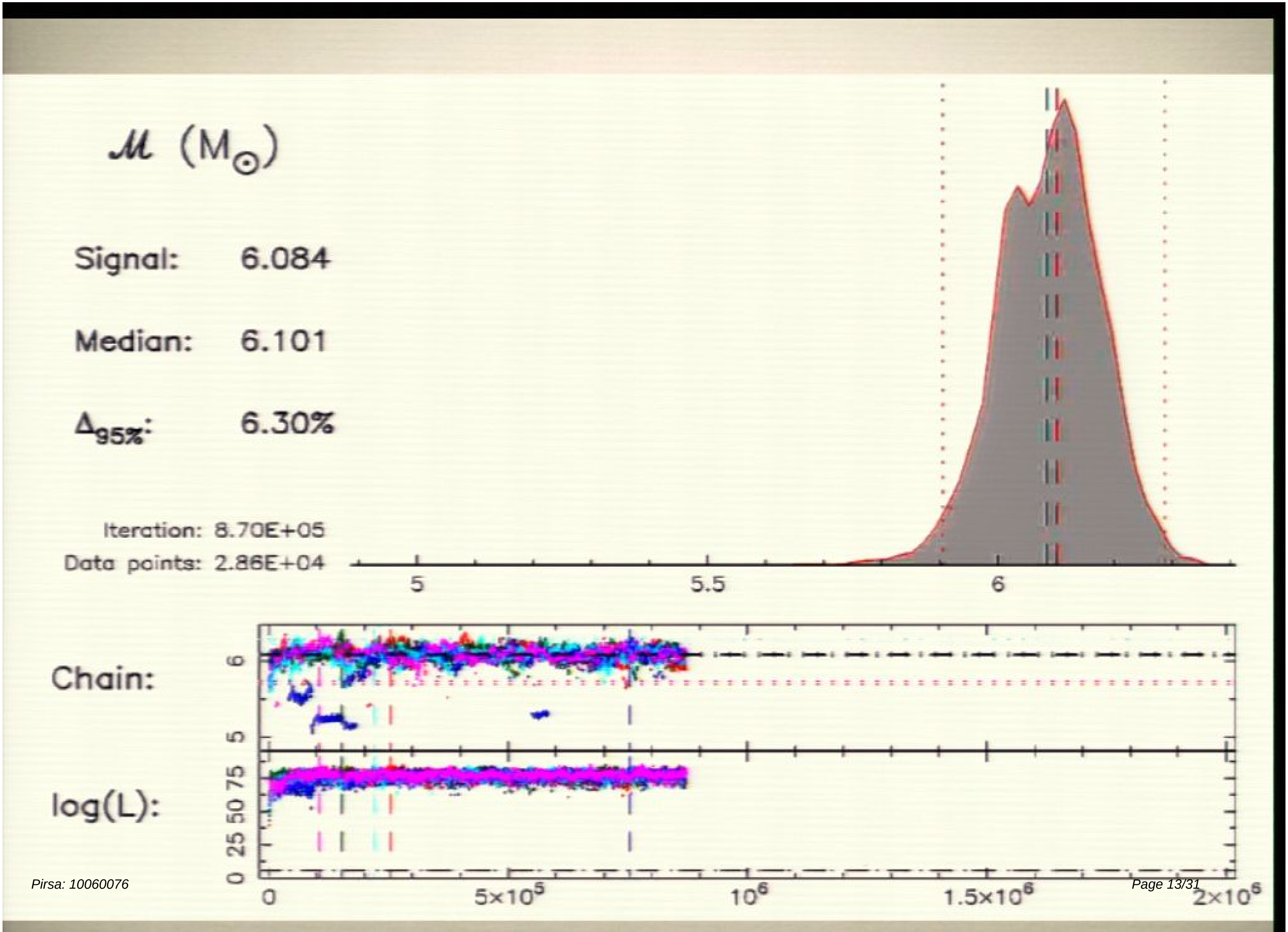
$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Median: 6.130
$\Delta_{95\%}$: 6.26%
Iteration: 4.30E+05
Data points: 9.86E+03
5
5.5
6
Chain:
log(L):
0
25
50
75
0
5×10^5
10^6
1.5×10^6
2×10^6


$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Median: 6.120
$\Delta_{95\%}$: 5.68%
Iteration: 5.30E+05
Data points: 1.39E+04
5
5.5
6
Chain:
log(L):
0
5×10^5
10^6
1.5×10^6
2×10^6



$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Median: 6.107
$\Delta_{95\%}$: 5.61%
Iteration: 7.00E+05
Data points: 2.07E+04
5
5.5
6
Chain:
log(L):
0 25 50 75
0
5×10^5
10^6
1.5×10^6
2×10^6


$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Median: 6.100
$\Delta_{95\%}$: 6.07%
Iteration: 7.80E+05
Data points: 2.41E+04
5
5.5
6
Chain:
6
5
log(L):
0 25 50 75
0
5×10^5
10^6
1.5×10^6
2×10^6


$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Median: 6.101
$\Delta_{95\%}$: 6.30%
Iteration: 8.70E+05
Data points: 2.86E+04
5
5.5
6
Chain:
6
5
log(L):
0 25 50 75
0
5×10^5
10^6
1.5×10^6
2×10^6

$\mathcal{M}\ (M_\odot)$

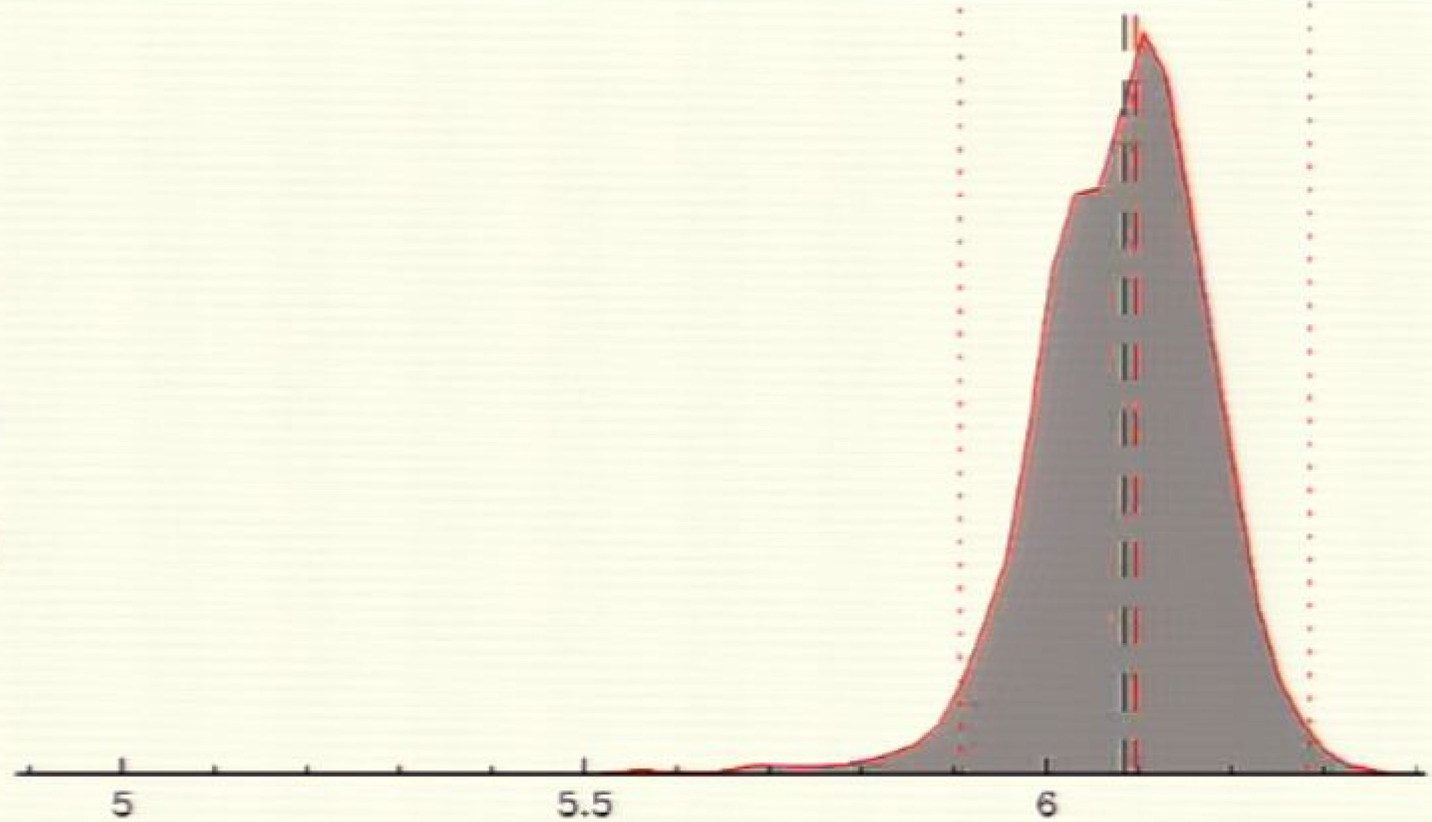
Signal: 6.084

Median: 6.096

$\Delta_{95\%}$: 6.21%

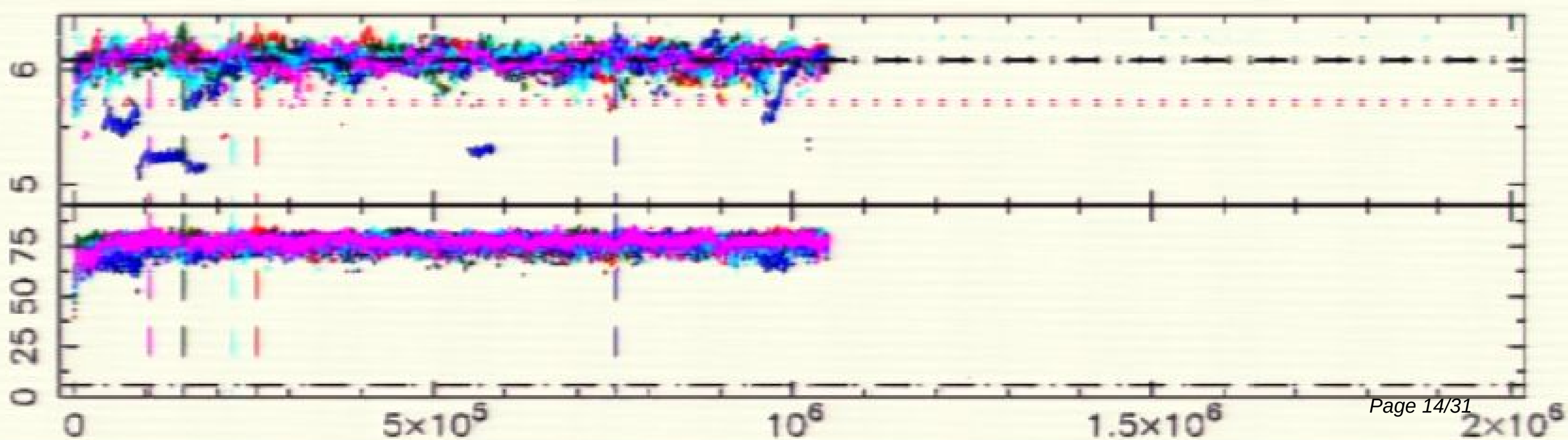
Iteration: 1.05E+06

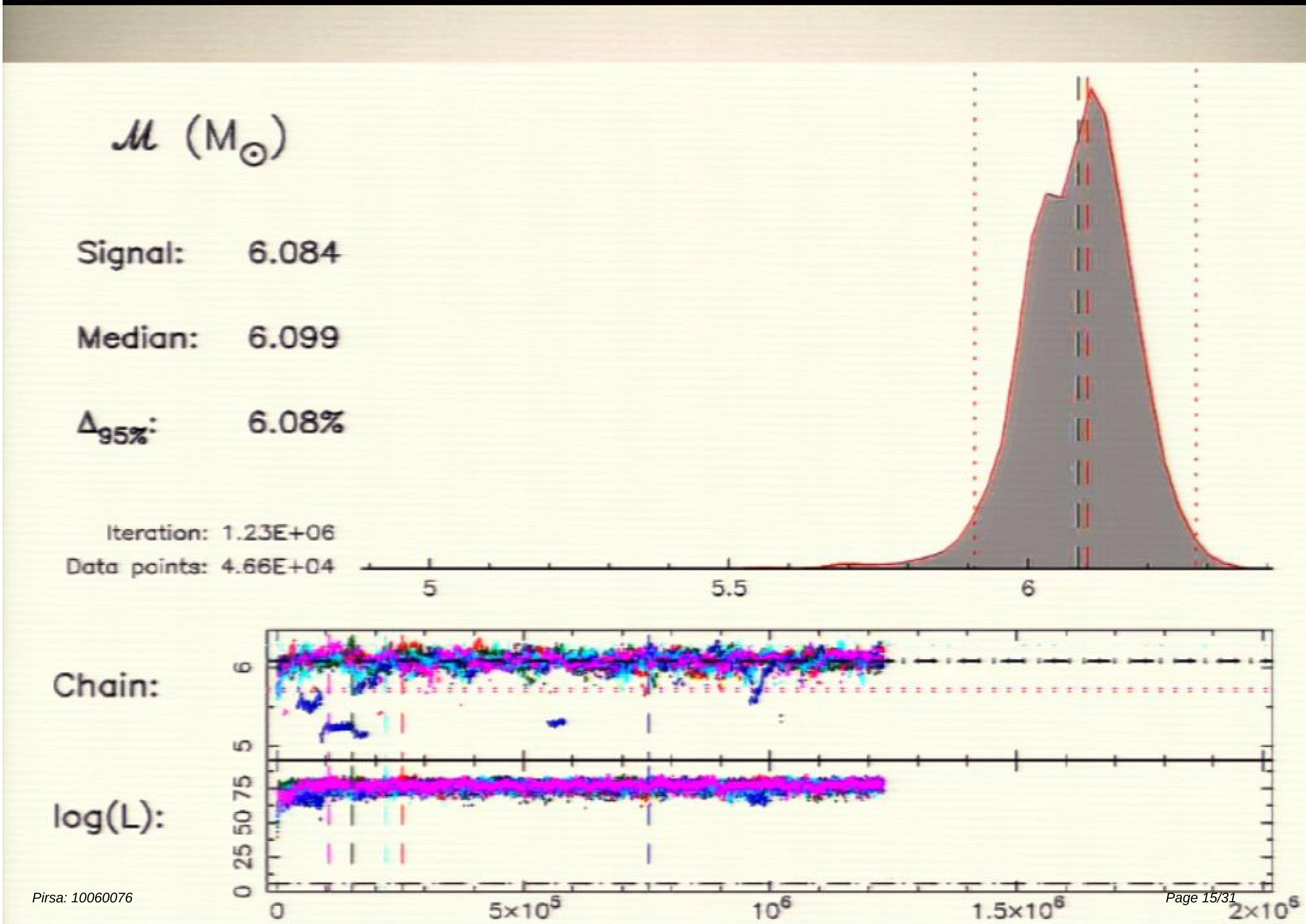
Data points: 3.76E+04



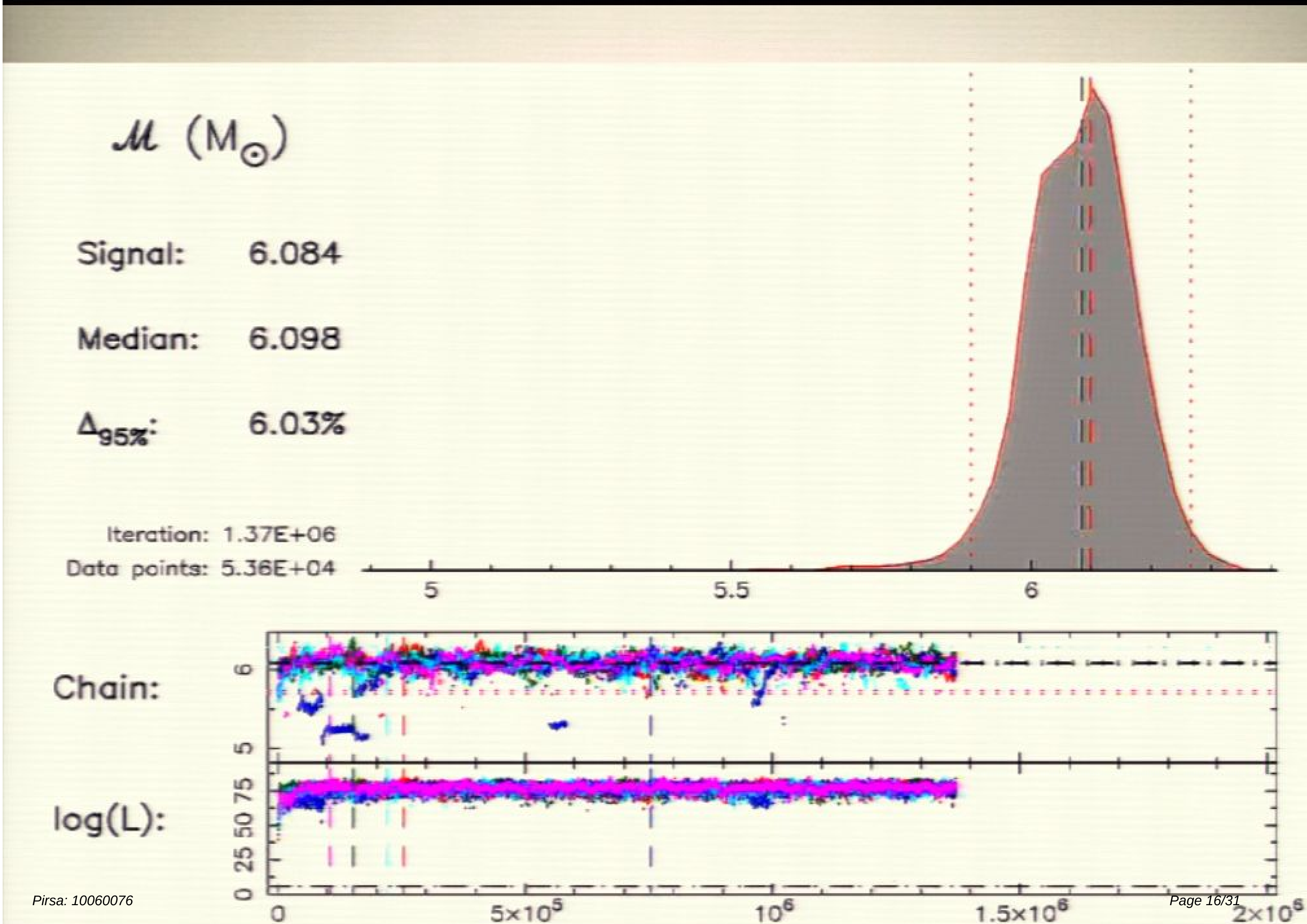
Chain:

log(L):

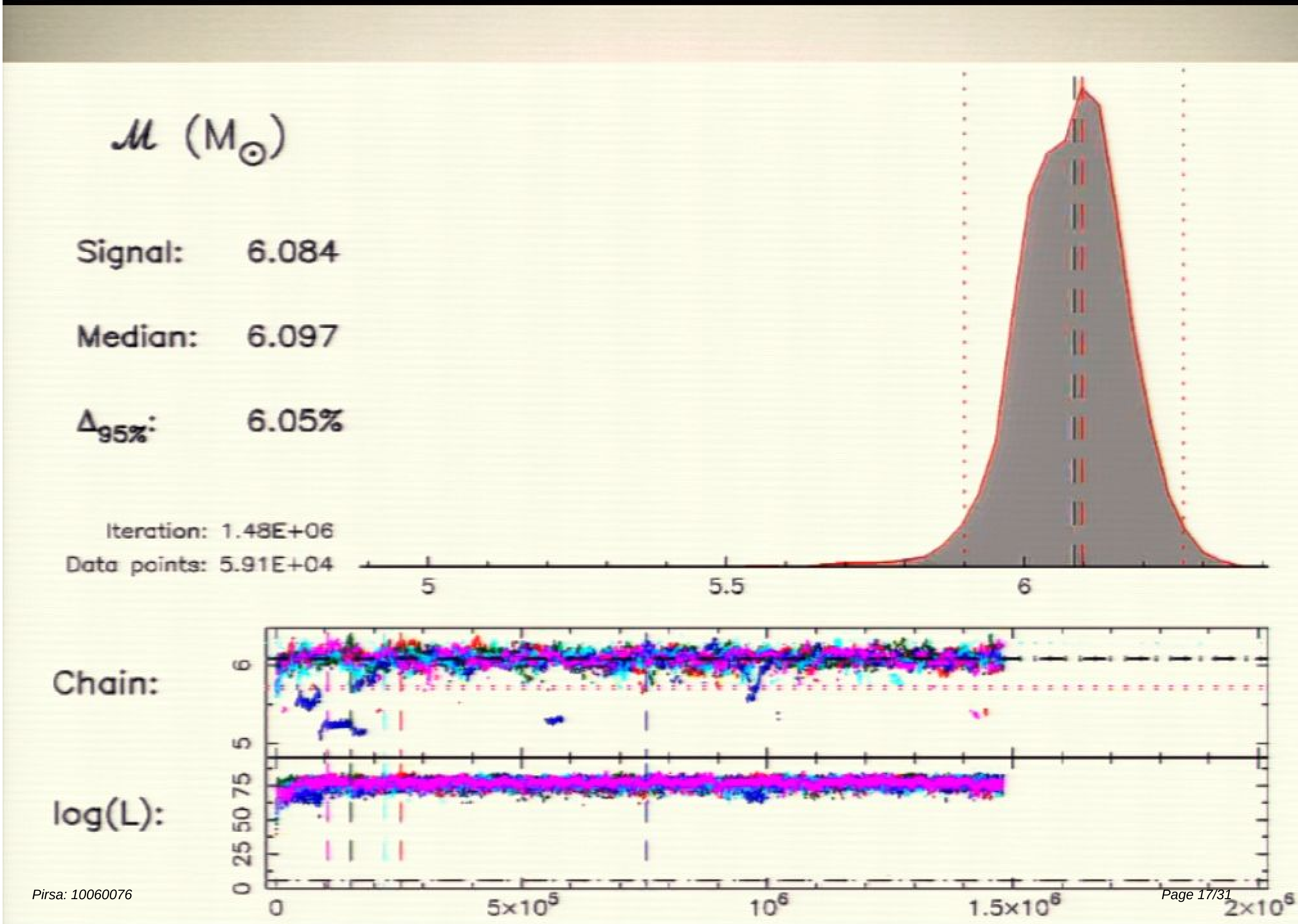


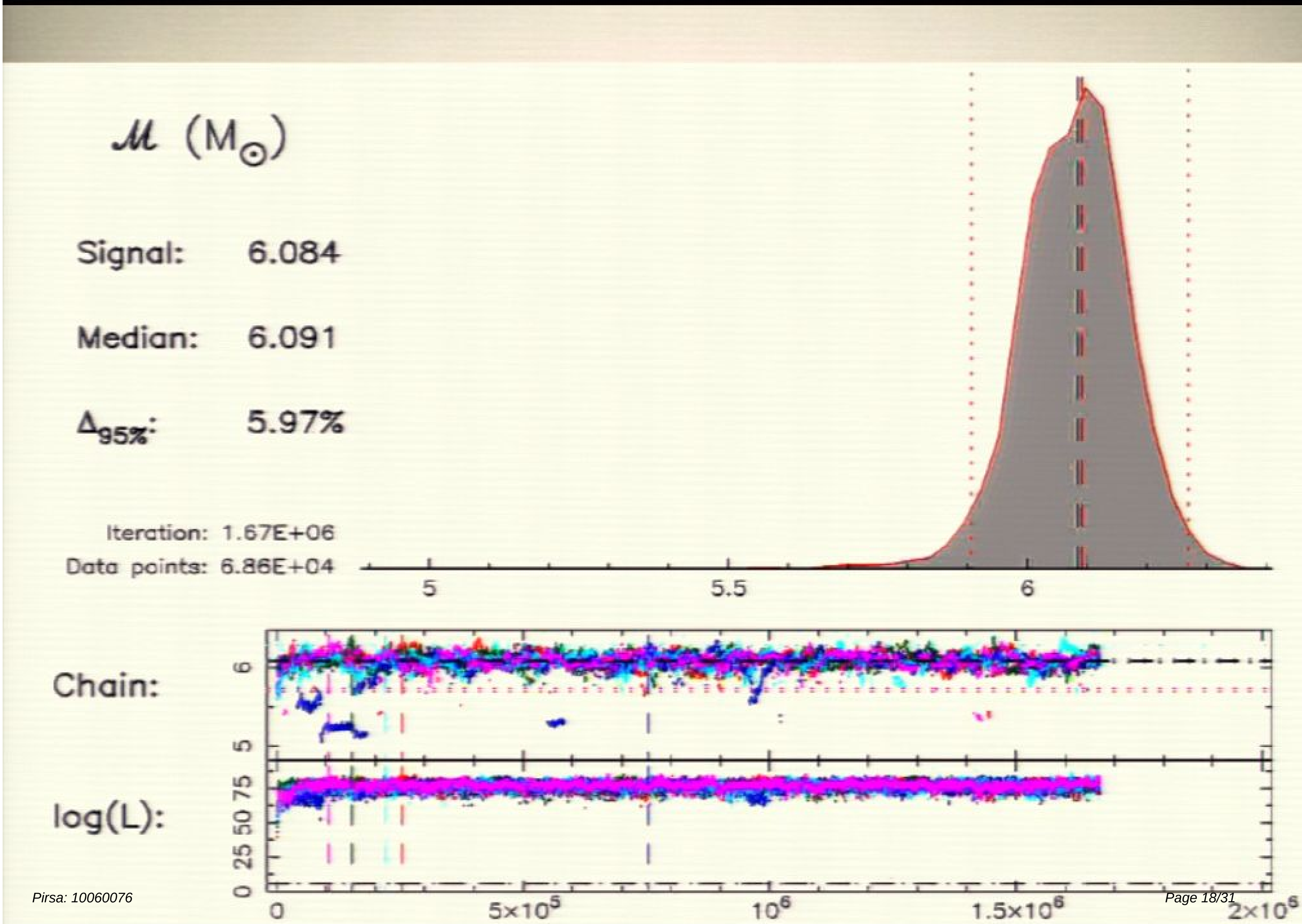


$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Median: 6.099
$\Delta_{95\%}$: 6.08%
Iteration: 1.23E+06
Data points: 4.66E+04
5
5.5
6
Chain:
6
5
log(L):
0 25 50 75
0
5×10^5
10^6
1.5×10^6
2×10^6

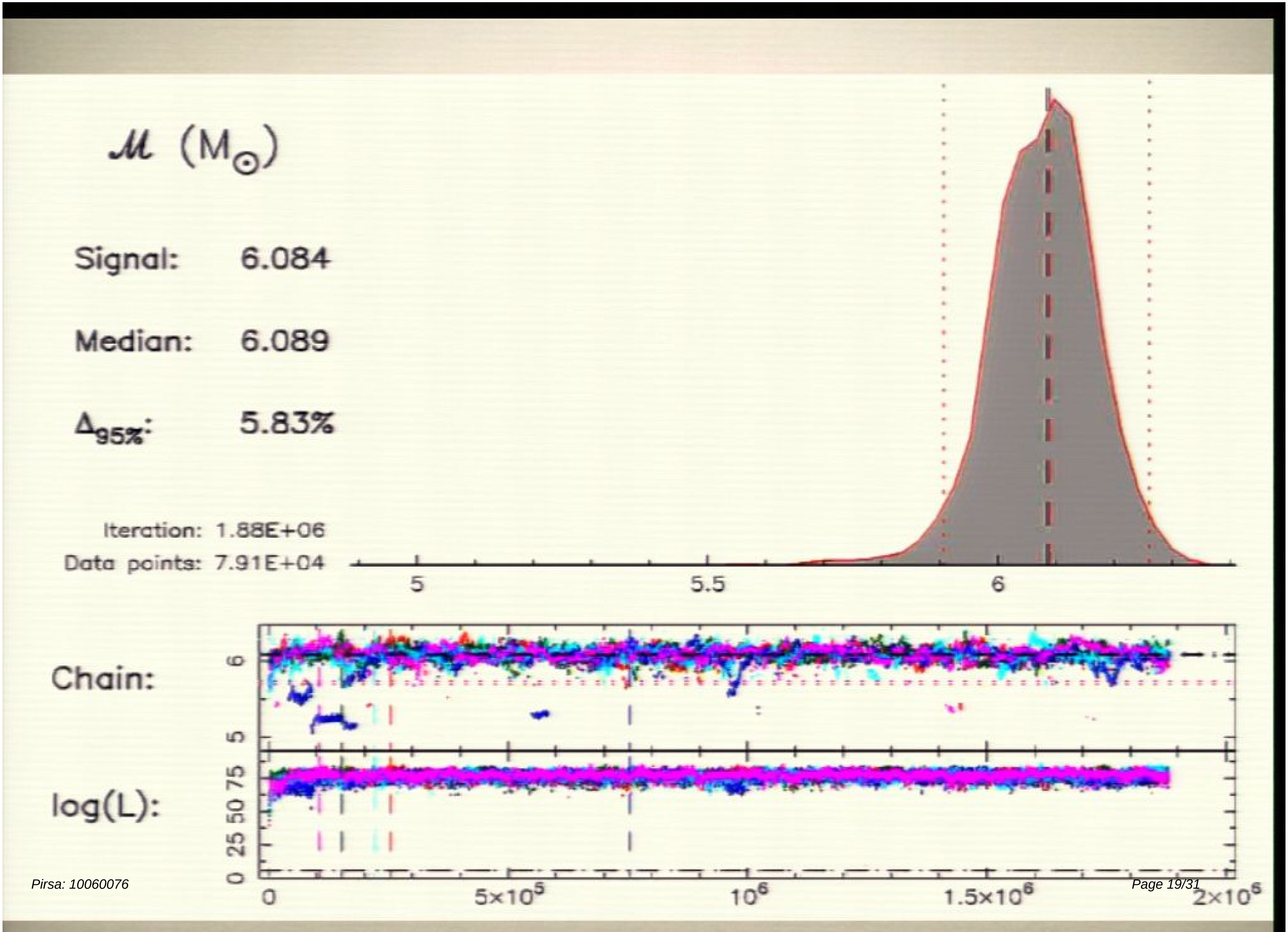


$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Median: 6.098
$\Delta_{95\%}$: 6.03%
Iteration: 1.37E+06
Data points: 5.36E+04
5
5.5
6
Chain:
6
5
log(L):
0 25 50 75
0
5×10^5
10^6
1.5×10^6
2×10^6


$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Median: 6.097
$\Delta_{95\%}$: 6.05%
Iteration: 1.48E+06
Data points: 5.91E+04
5
5.5
6
Chain:
6
5
log(L):
0 25 50 75
0
5×10^5
10^6
1.5×10^6
2×10^6

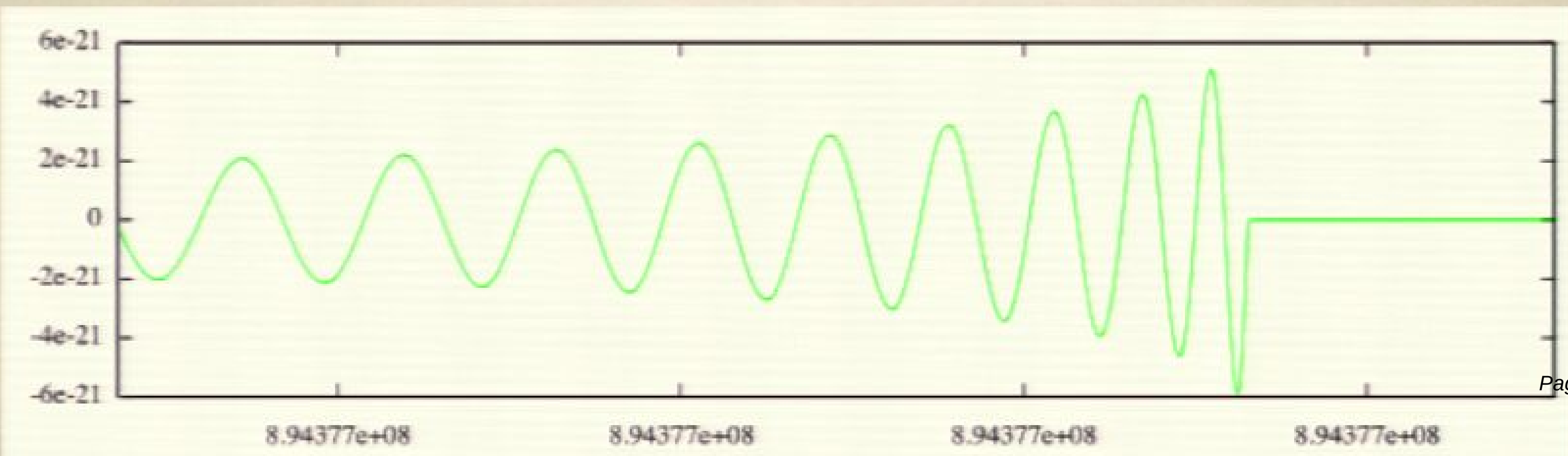


𝓜 (M⊙)
Signal: 6.084
Median: 6.091
Δ95%: 5.97%
Iteration: 1.67E+06
Data points: 6.86E+04
5
5.5
6
Chain:
log(L):
0
5×10^5
10^6
1.5×10^6
2×10^6


$\mathcal{M}$ ($M_\odot$)
Signal: 6.084
Median: 6.089
$\Delta_{95\%}$: 5.83%
Iteration: 1.88E+06
Data points: 7.91E+04
5
5.5
6
Chain:
6
5
log(L):
0 25 50 75
0
5×10^5
10^6
1.5×10^6
2×10^6

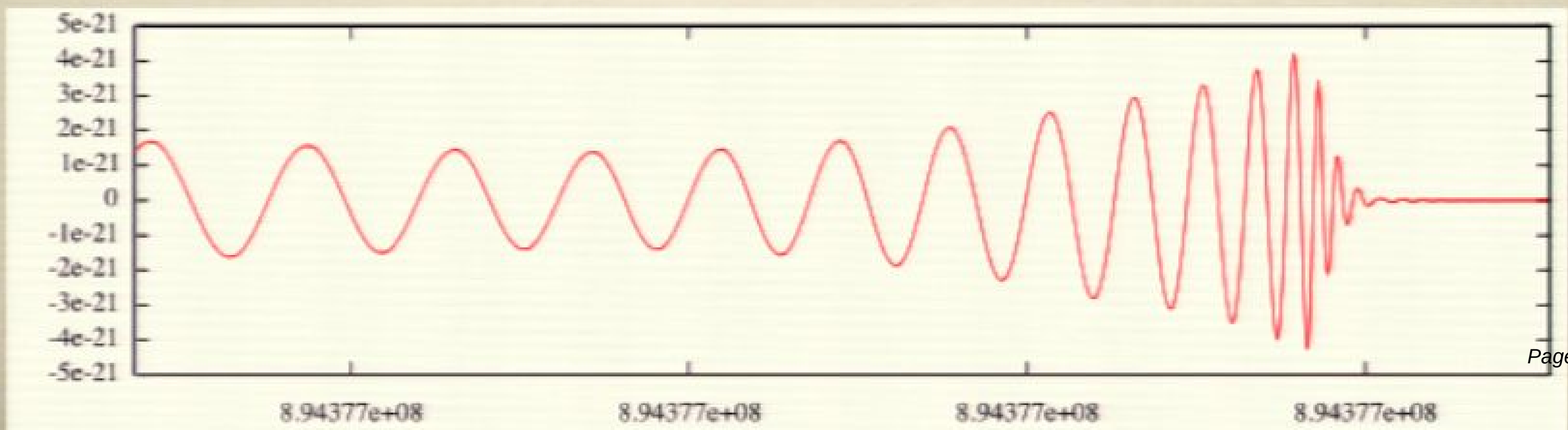
Model: SpinTaylor

- restricted post-Newtonian
  - orbital effect to 3.5 pN
  - spin effect to 2 pN
- 15 parameters



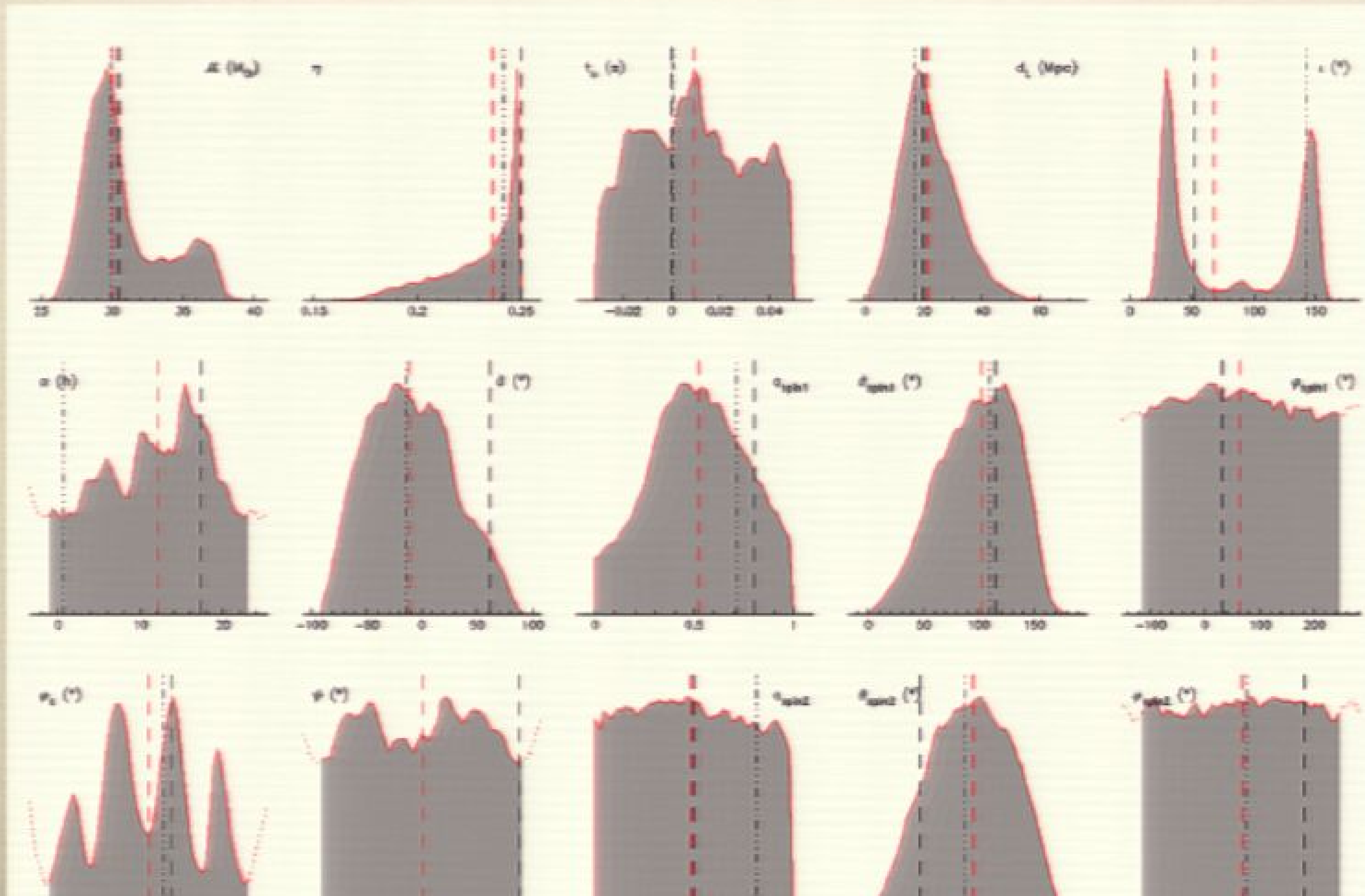
Model: PhenSpin

- SpinTaylor inspiral
- phenomenological merger+ringdown
  - calibrated with GTech NR waveforms
    $$(m_1 = m_2, a_1 = a_2 = 0.6)$$
- **see Riccardo's talk later today.**

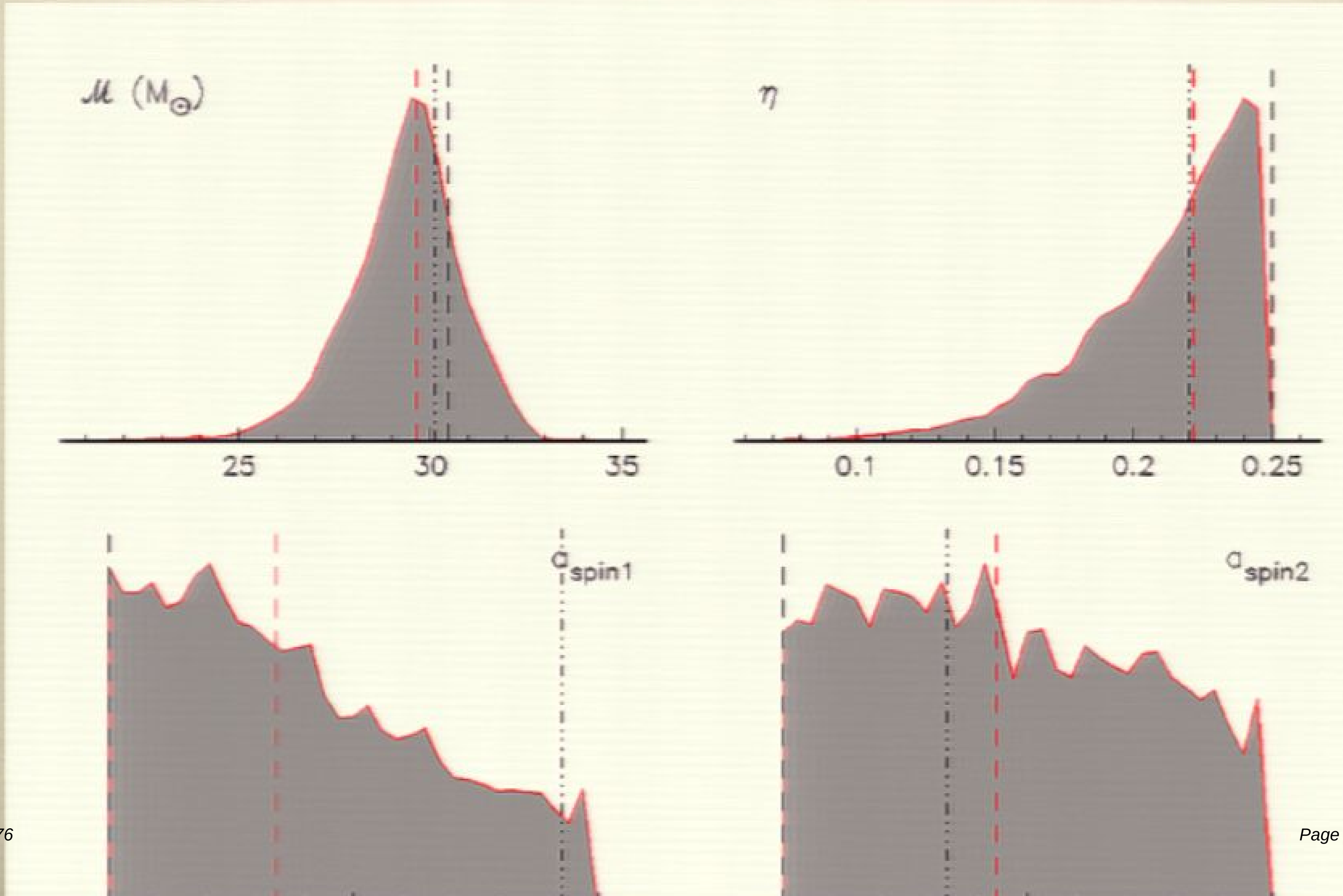


Results

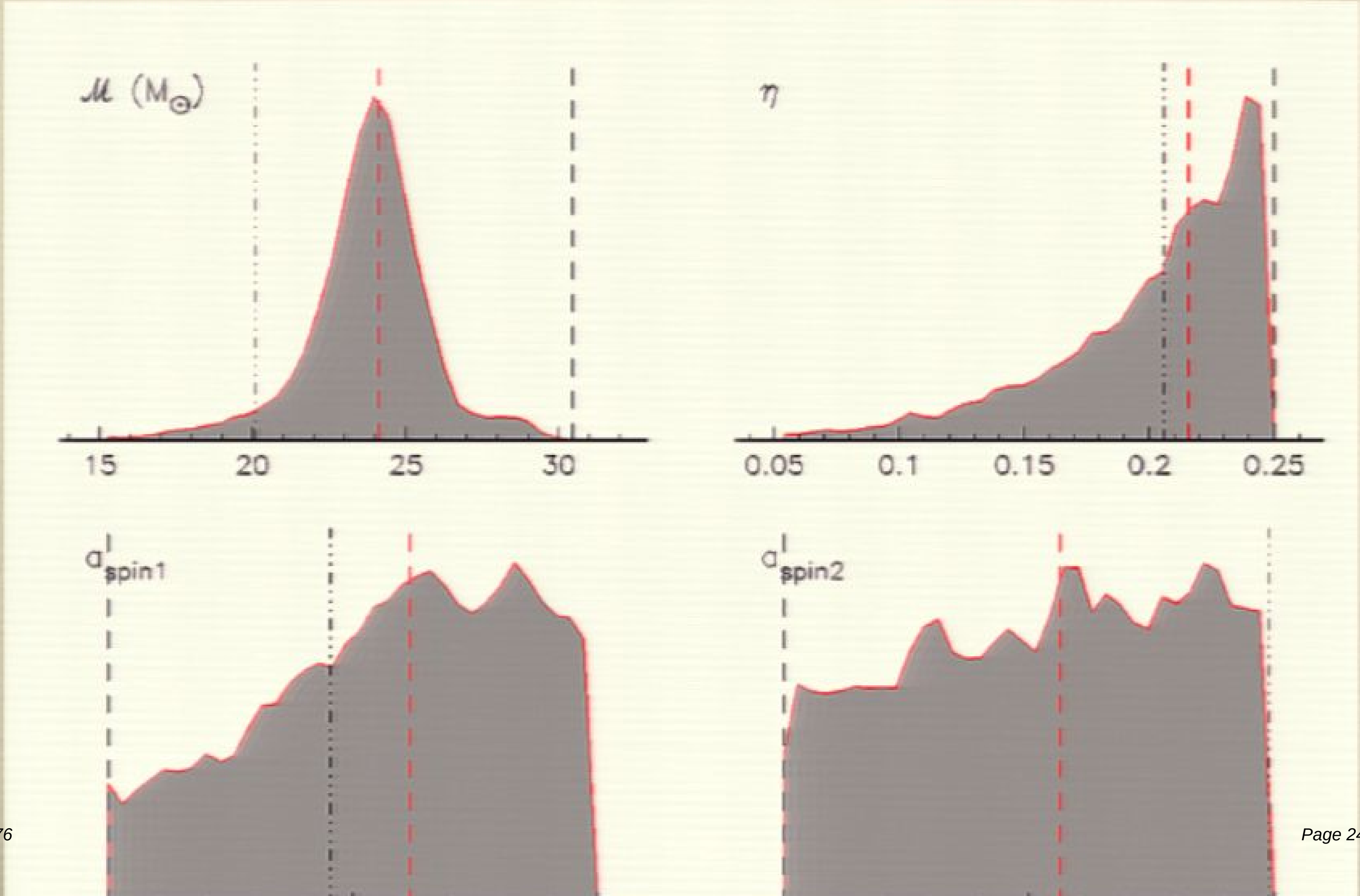
- 35 - 35 $M_\odot$, varying spins, 15-D



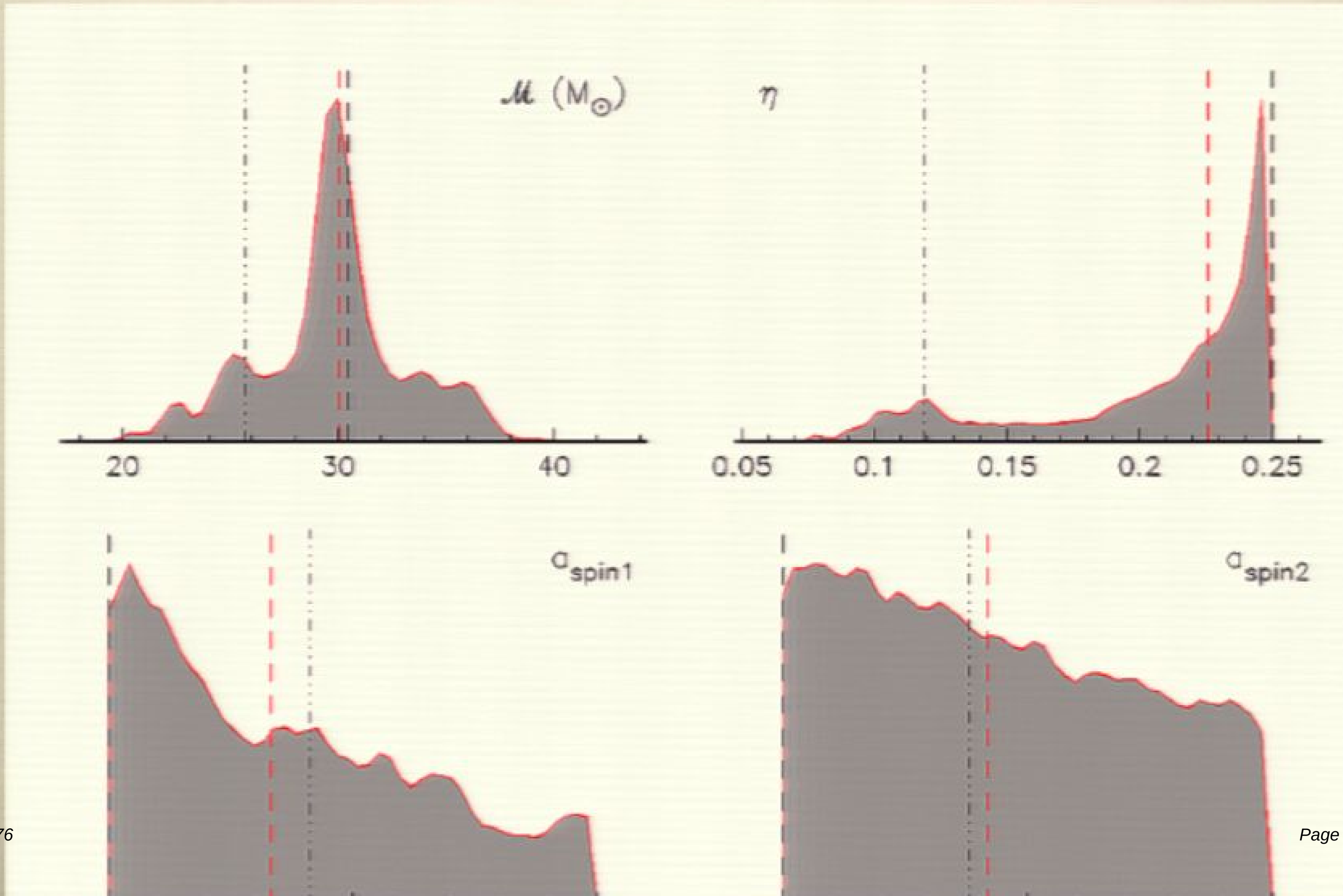
Injection: SpinTaylor
Template: SpinTaylor



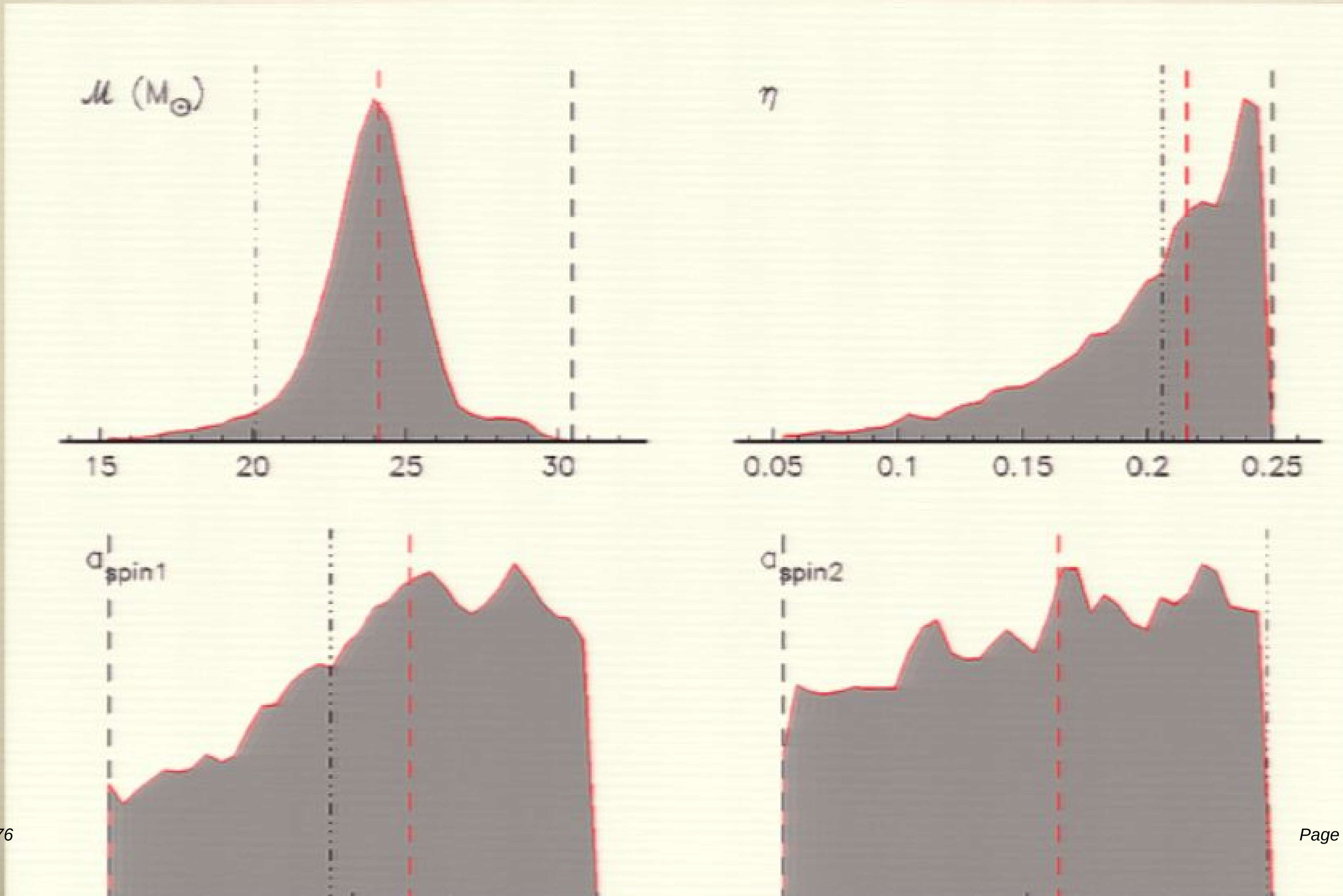
INJECTION: PHENSPIN
TEMPLATE: SPINTAYLOR



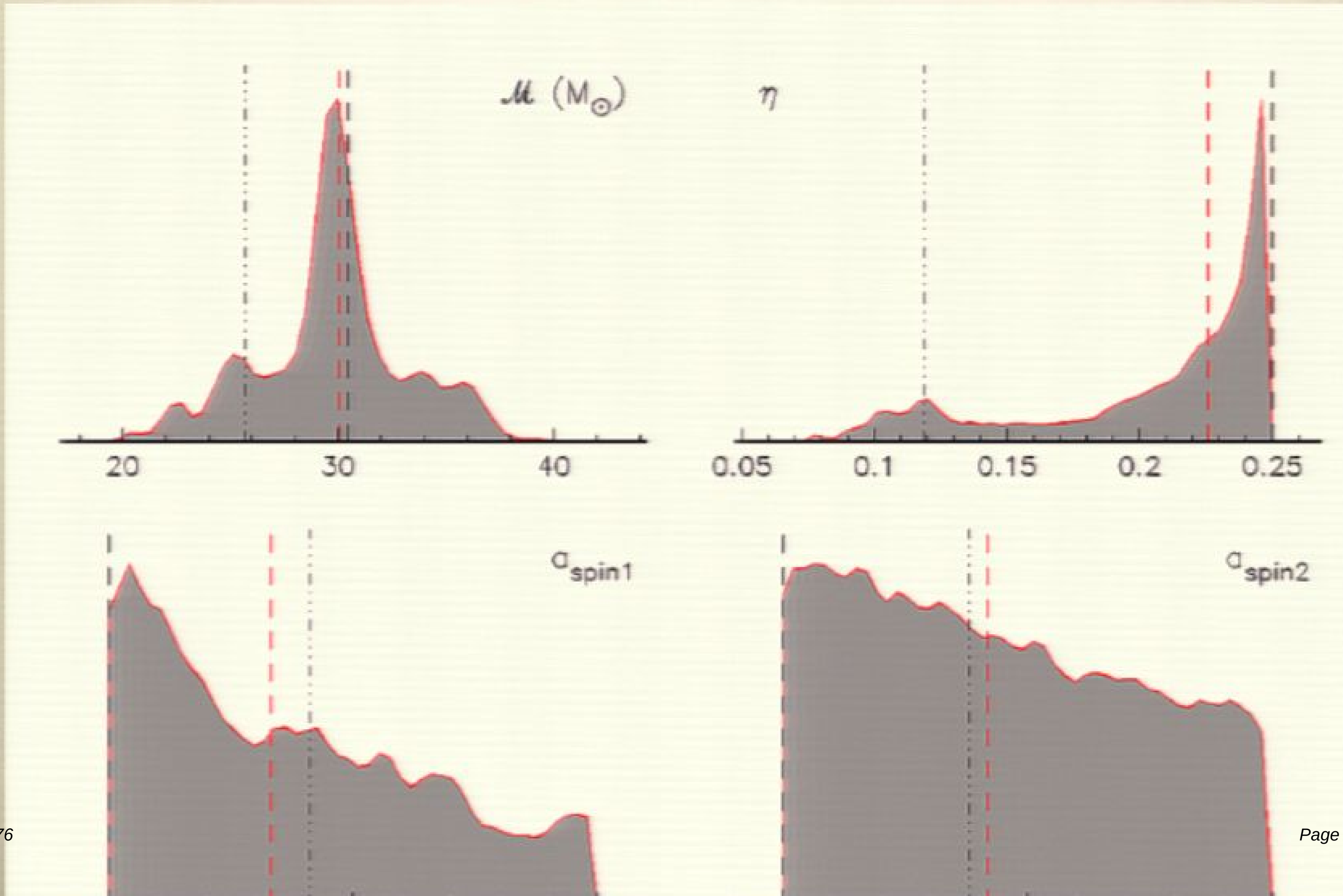
Injection: PhenSpin
Template: PhenSpin



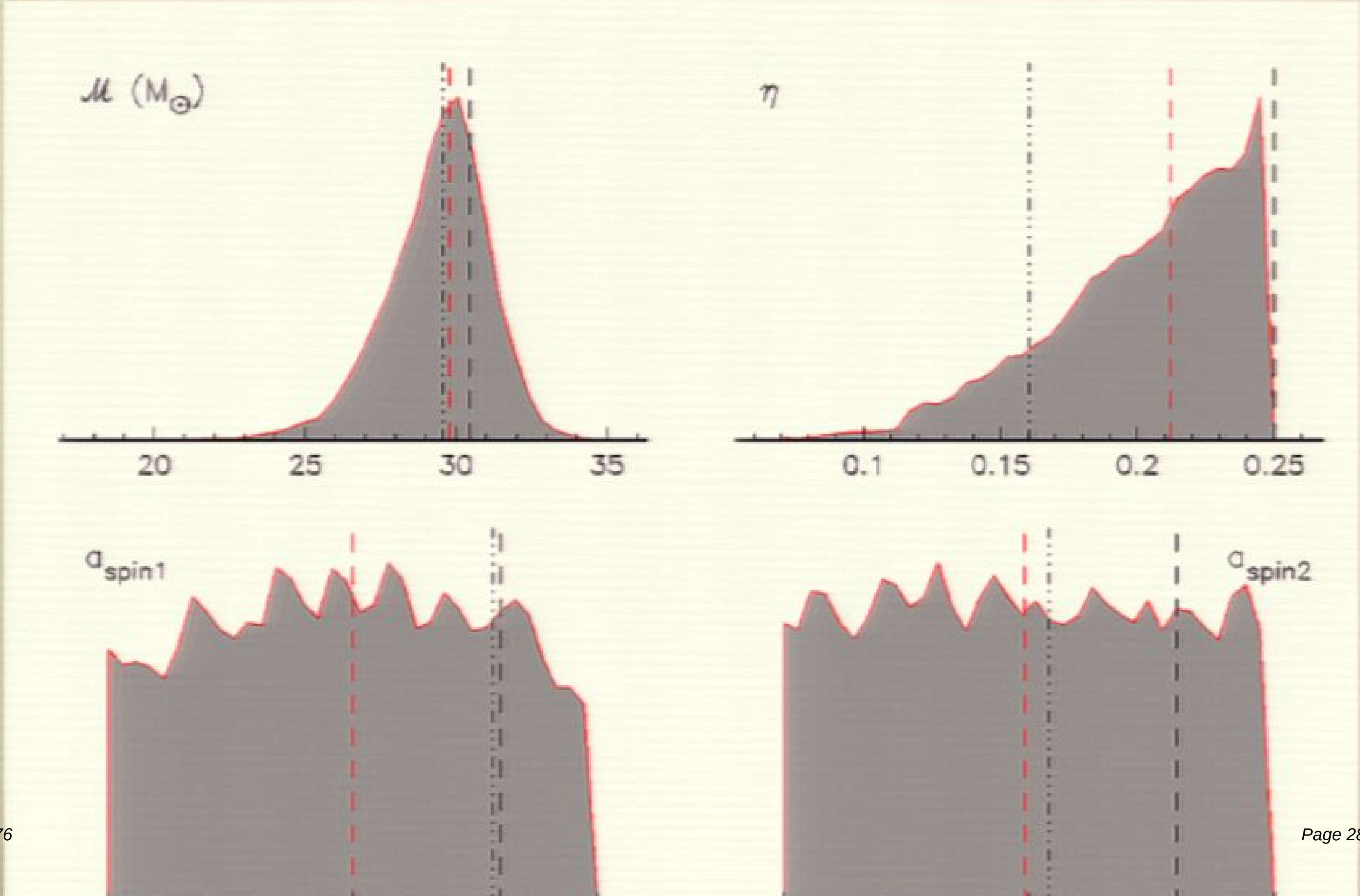
Injection: PhenSpin
Template: SpinTaylor



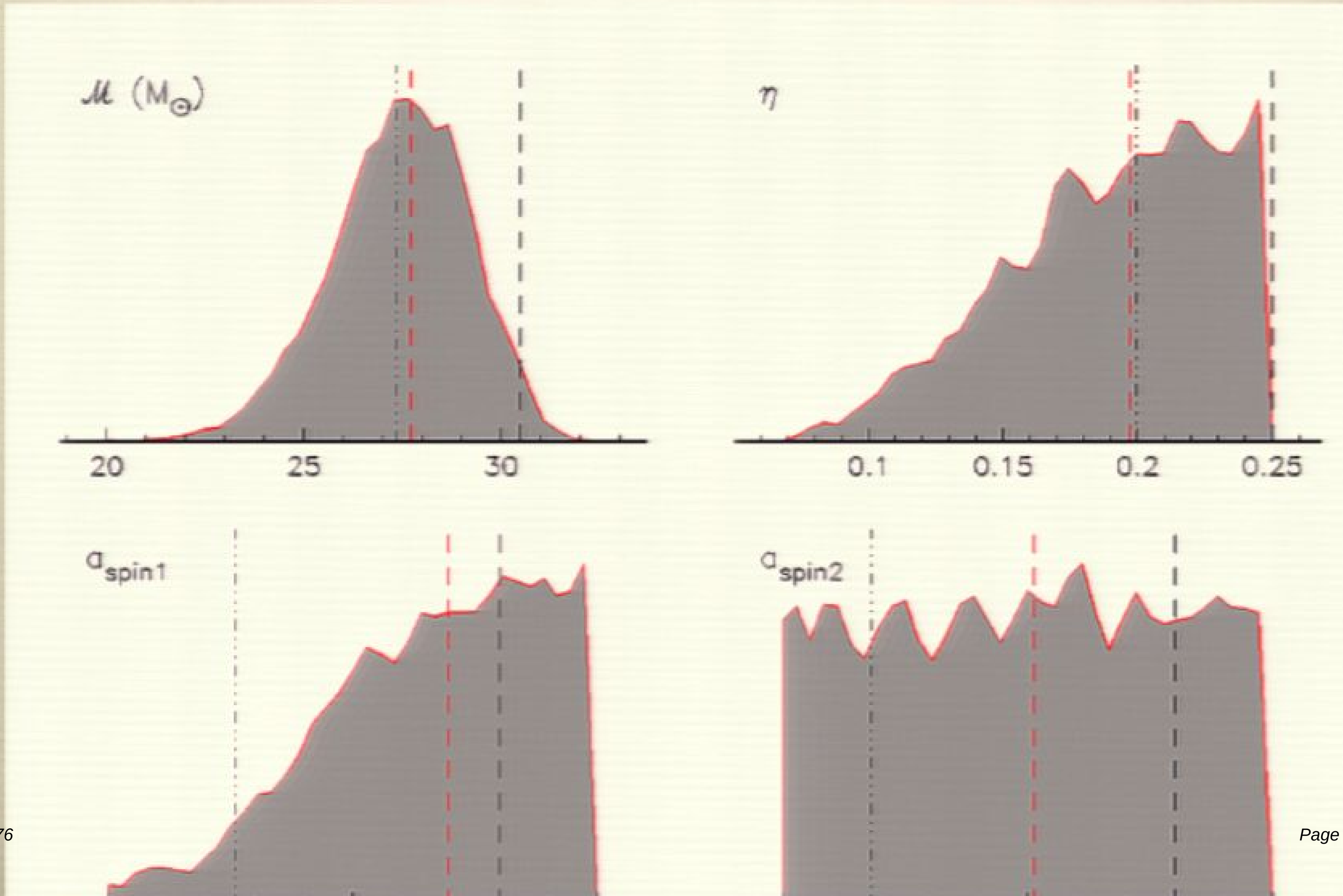
INJECTION: PHENSPIN
TEMPLATE: PHENSPIN



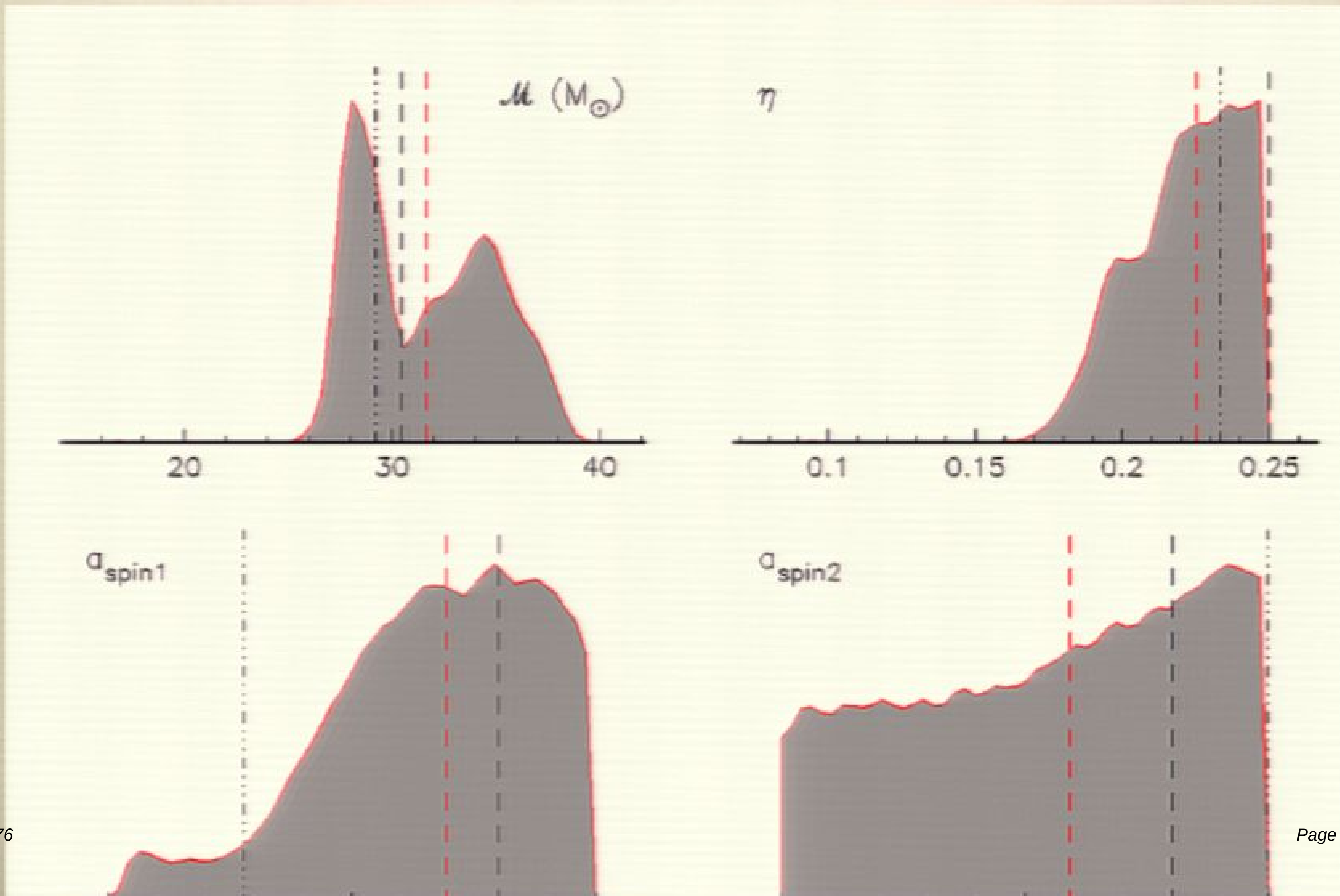
INJECTION: SPINTAYLOR
TEMPLATE: SPINTAYLOR



Injection: PhenSpin
Template: SpinTaylor



Injection: PhenSpin
Template: PhenSpin



Conclusion

- parameter estimation is improved. But:
  - additional degeneracies
  - work in progress
- NINJA2 data set !!!