



The effect of correlations in models of the nuclear equation of state on neutron star inference

Isaac Legred (Caltech)

N3AS Seminar

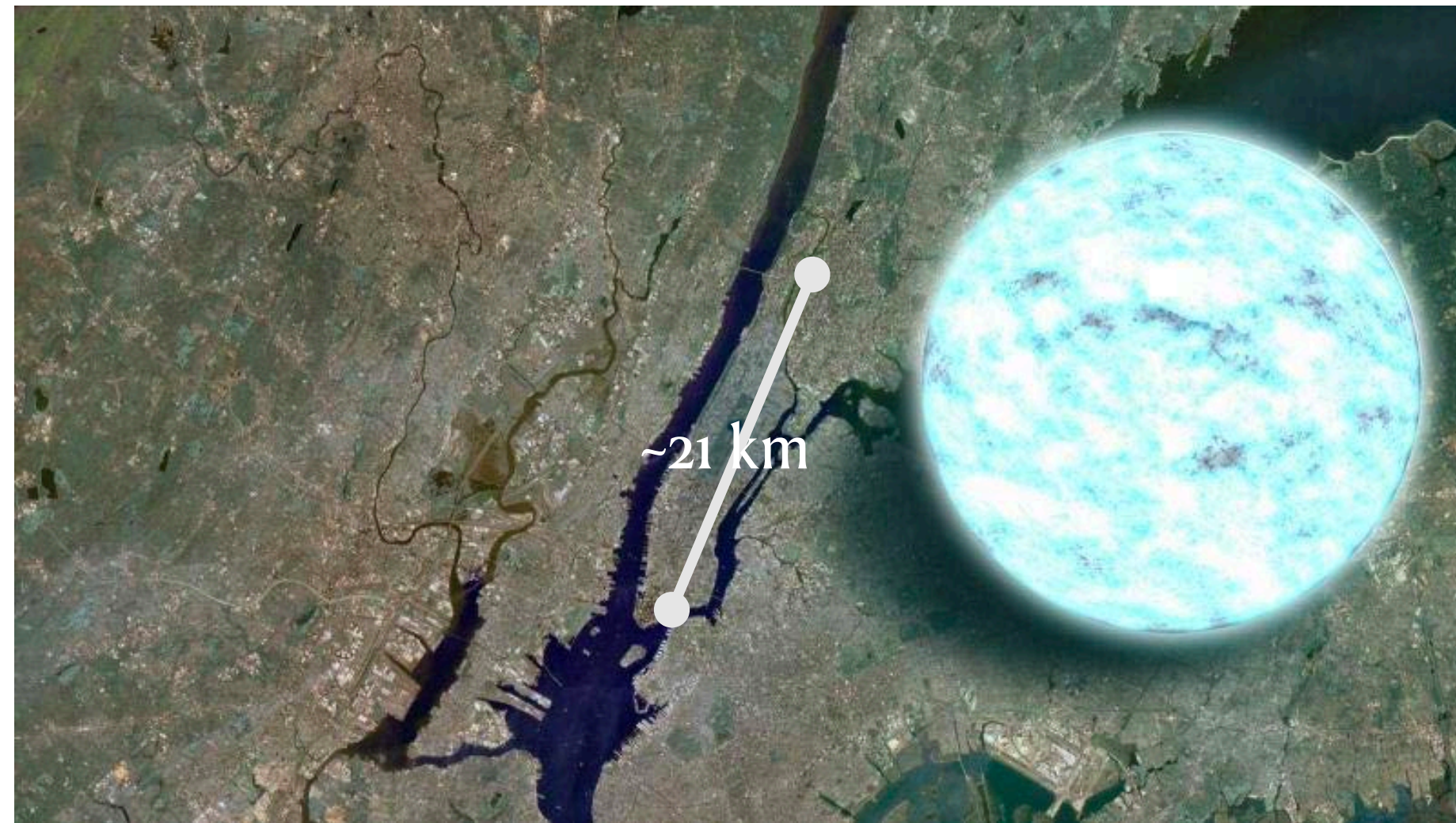
May 17, 2022

Work with: Katerina Chatziioannou,
Reed Essick, and Philippe Landry

Caltech

10.1103/PhysRevD.105.043016
<https://arxiv.org/abs/2201.06791>

Why Study Neutron Stars?



GR matters when GM/Rc^2 is not small

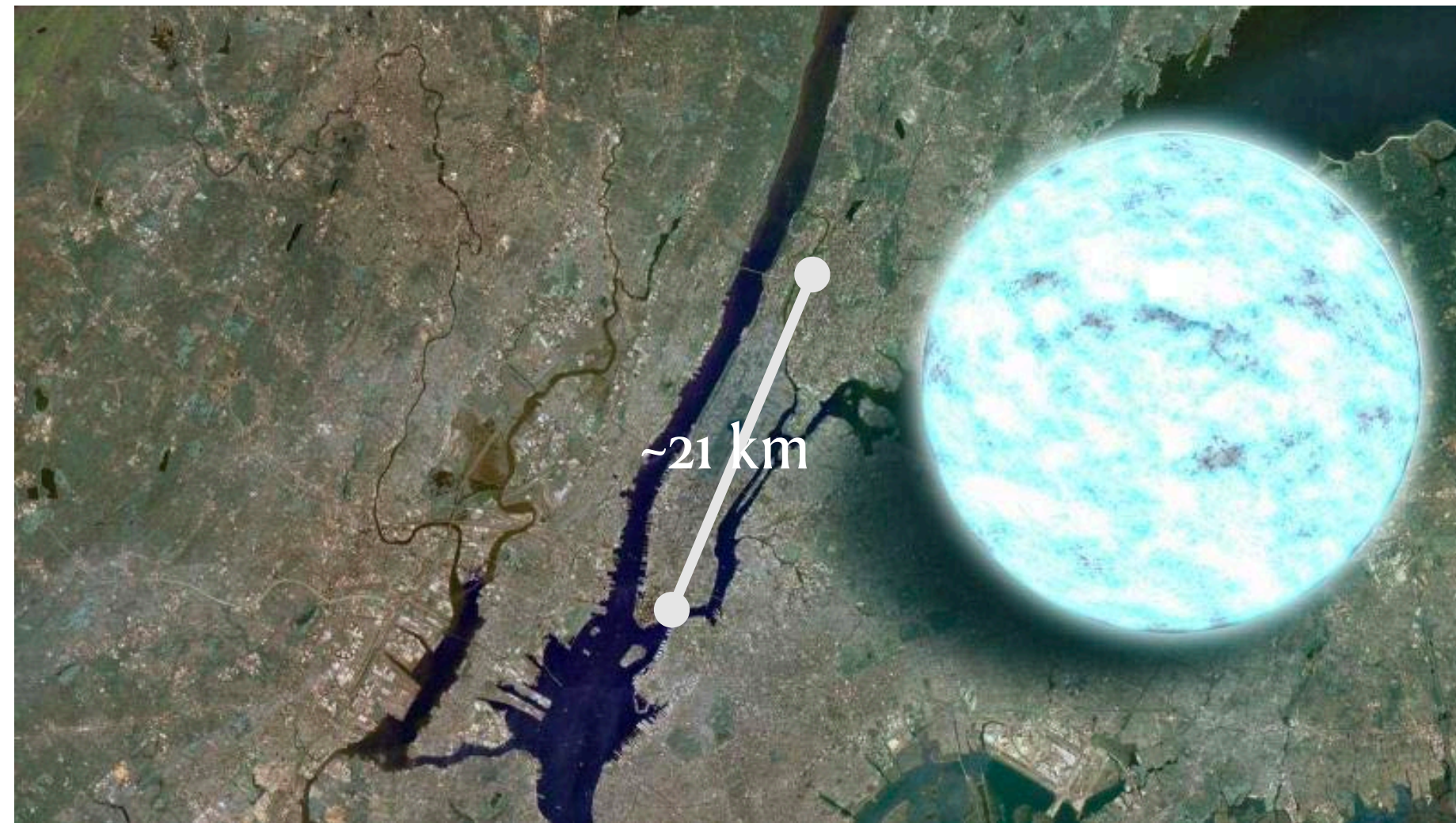
NS: $GM/Rc^2 \sim 1/3$

Behavior of nuclear matter is uncertain when n/n_{nuc} is not small*

NS: $n_{\text{max}}/n_{\text{nuc}} \sim 4 - 7?$

Neutron Stars give us laboratories to Study nuclear physics along with general relativity

Why Study Neutron Stars?



GR matters when GM/Rc^2 is not small

NS: $GM/Rc^2 \sim 1/3$

Behavior of nuclear matter is uncertain when n/n_{nuc} is not small*

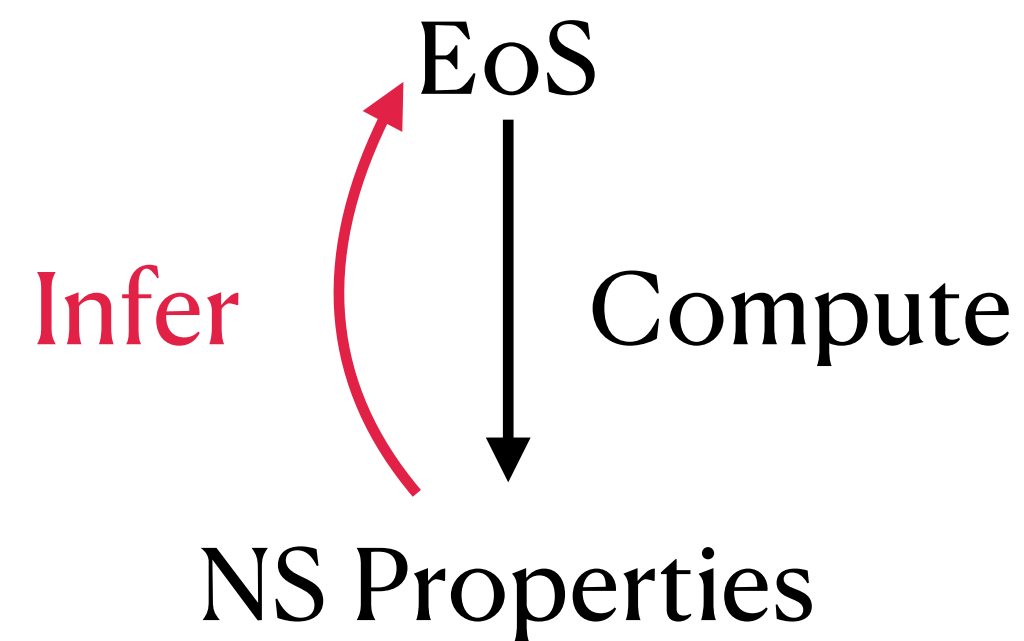
NS: $n_{\text{max}}/n_{\text{nuc}} \sim 4 - 7?$

Neutron Stars give us laboratories to Study nuclear physics along with general relativity

We Really do need Both!

Inferring the EoS — Motivation

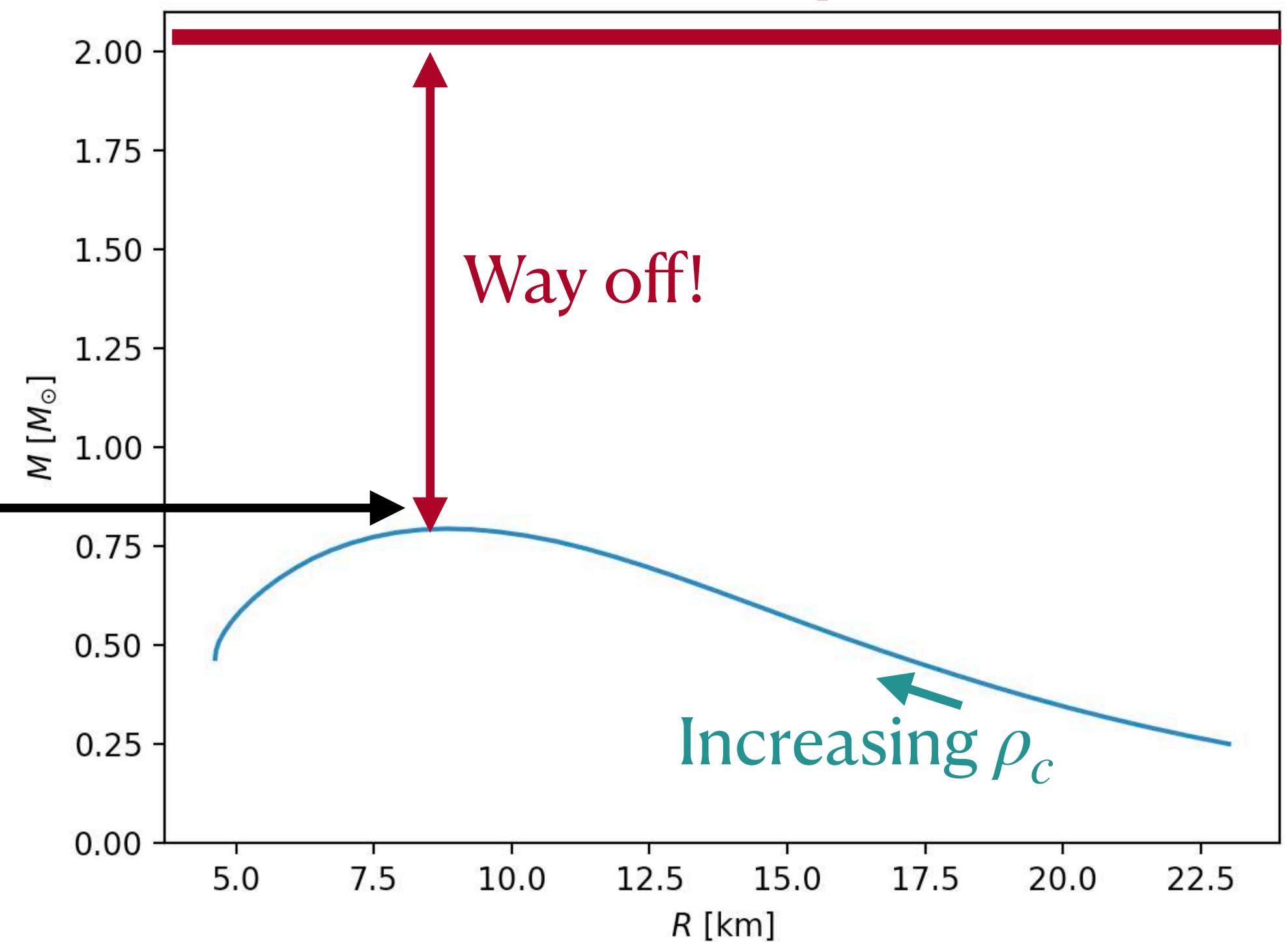
“Microphysics \Leftrightarrow Macrophysics”



5/3 Polytrope “degenerate neutrons (Non-Rel)”

Most massive observed pulsar ([Fonseca 2021](#))

Most massive
NS w/ EoS



Inferring the EoS — In practice

- Want to establish a probability distribution on candidate equations of state given observed astrophysical data

Equation of state candidate

$$P(\varepsilon_i | d) = P(\varepsilon | d_1, d_2, \dots) \propto P(d_1, d_2, \dots | \varepsilon_i) \times \boxed{P(\varepsilon_i)}$$

Prior

Astrophysical data

Inferring the EoS — In practice

- Want to establish a probability distribution on candidate equations of state given observed astrophysical data

Equation of state candidate

$$P(\varepsilon_i | d) = P(\varepsilon | d_1, d_2, \dots) \propto P(d_1, d_2, \dots | \varepsilon_i) \times P(\varepsilon_i)$$

Astrophysical data

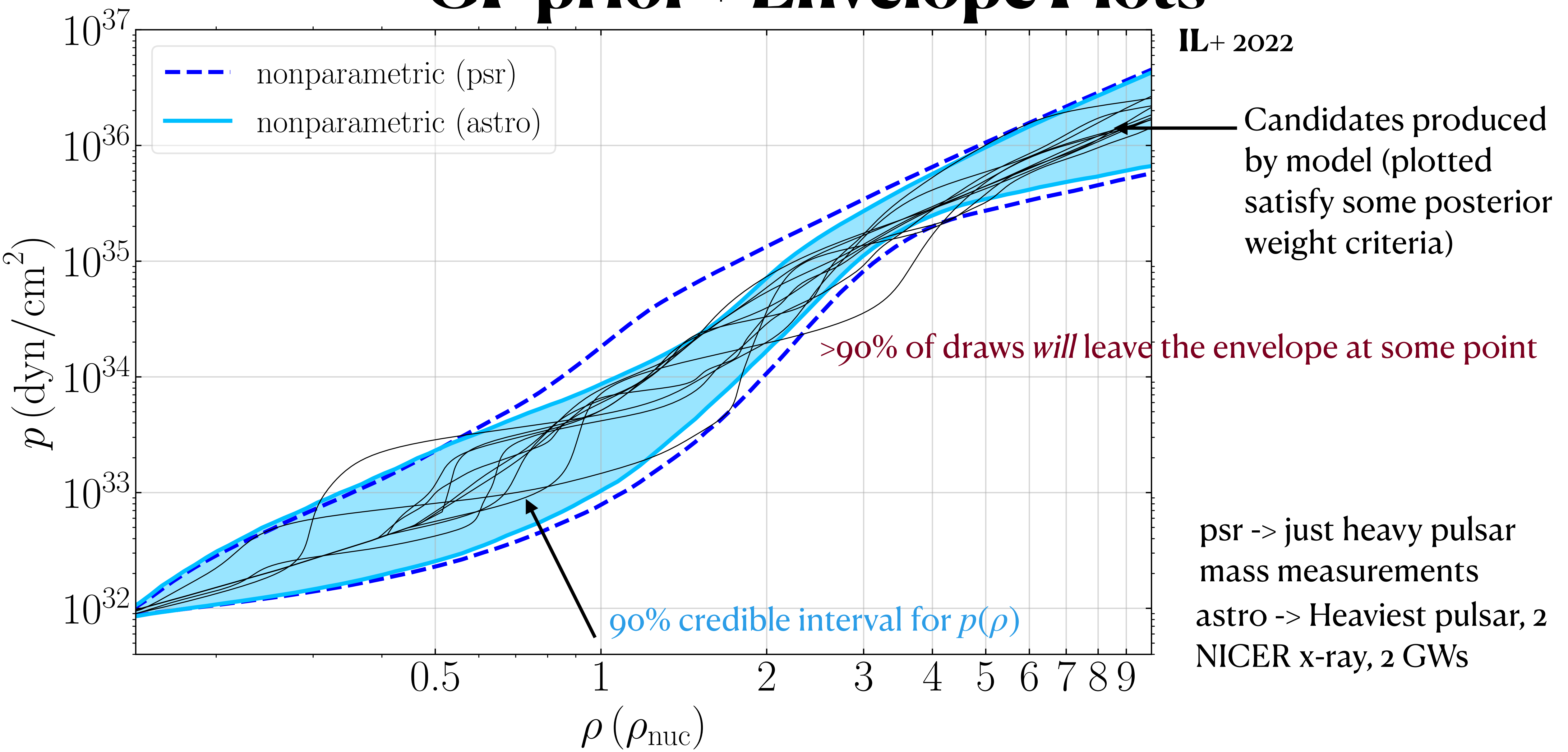
Phenomenological

Parametrize a *functional form* (i.e. Spectral, Piecewise-polytrope)

Nonparametric methods, i.e. Gaussian process (GP)

Tabulated models from nuclear theory

GP prior + Envelope Plots



Nonparametric: Gaussian Process

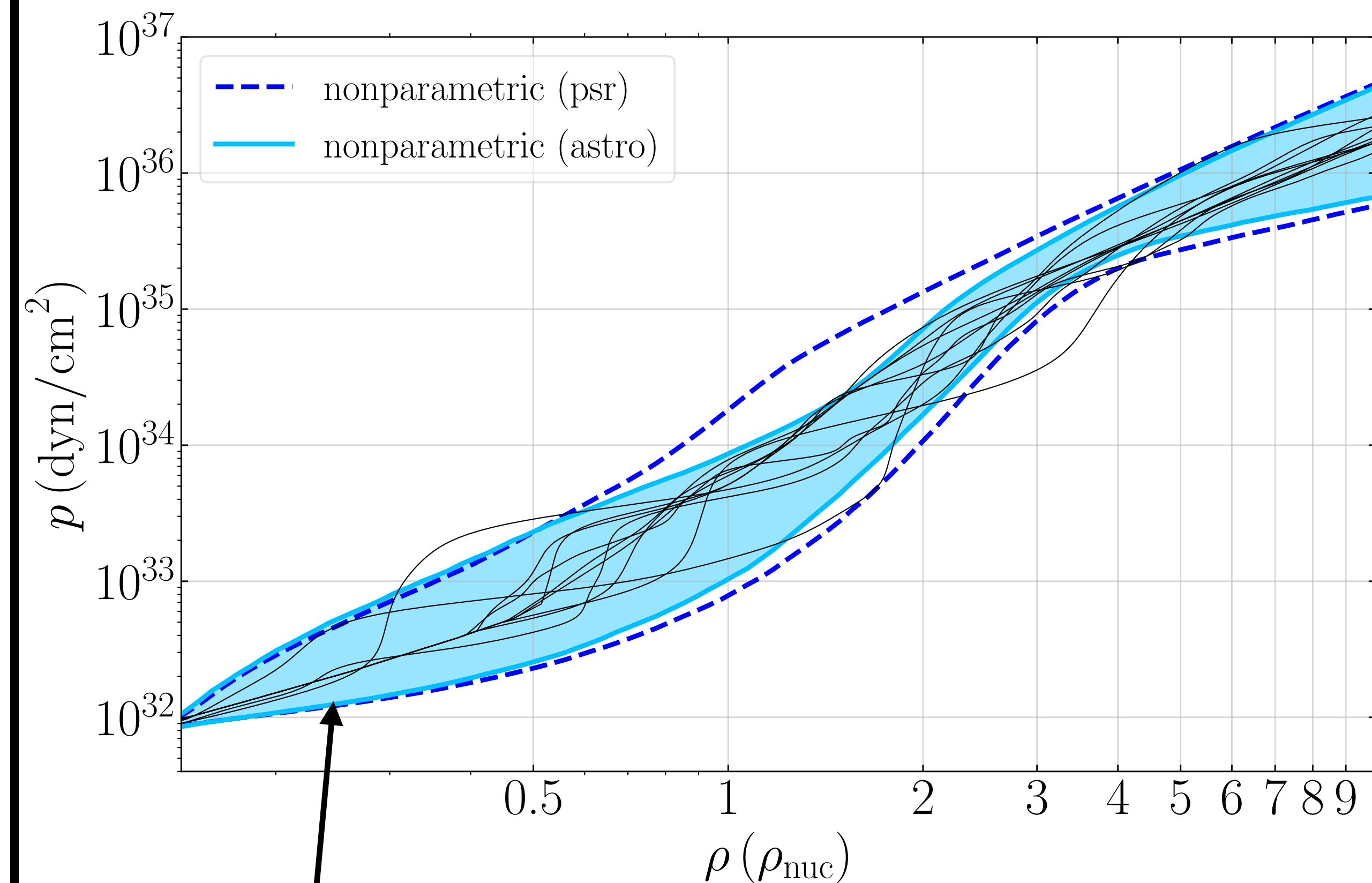
Gaussian Process Regression (Landry and Essick 2018)

Tabulate a draw $\phi(p_i) = \ln(1/c_s^2(p_i) - 1)$ @
Pressures p_i from a multivariate Gaussian distribution

Parameters for the covariance kernel are chosen to
Control “shape” of EoS distribution

Model-Agnostic Prior (broadest range of models)

IL+ 2022



90% credible interval for $p(\rho)$

psr -> just heavy pulsar mass measurements

astro -> Heaviest pulsar, 2 NICER x-ray, 2 GWs

Parametric

Spectral (Lindblom 2010)

Parametrize the adiabatic index

$$p(\rho) = \rho^{\Gamma(x)} \quad \Gamma(x) = \sum_{i=0}^n \gamma_i (\log(x))^i$$

Piecewise-polytrope (Read 2008)

A polytrope with multiple segments

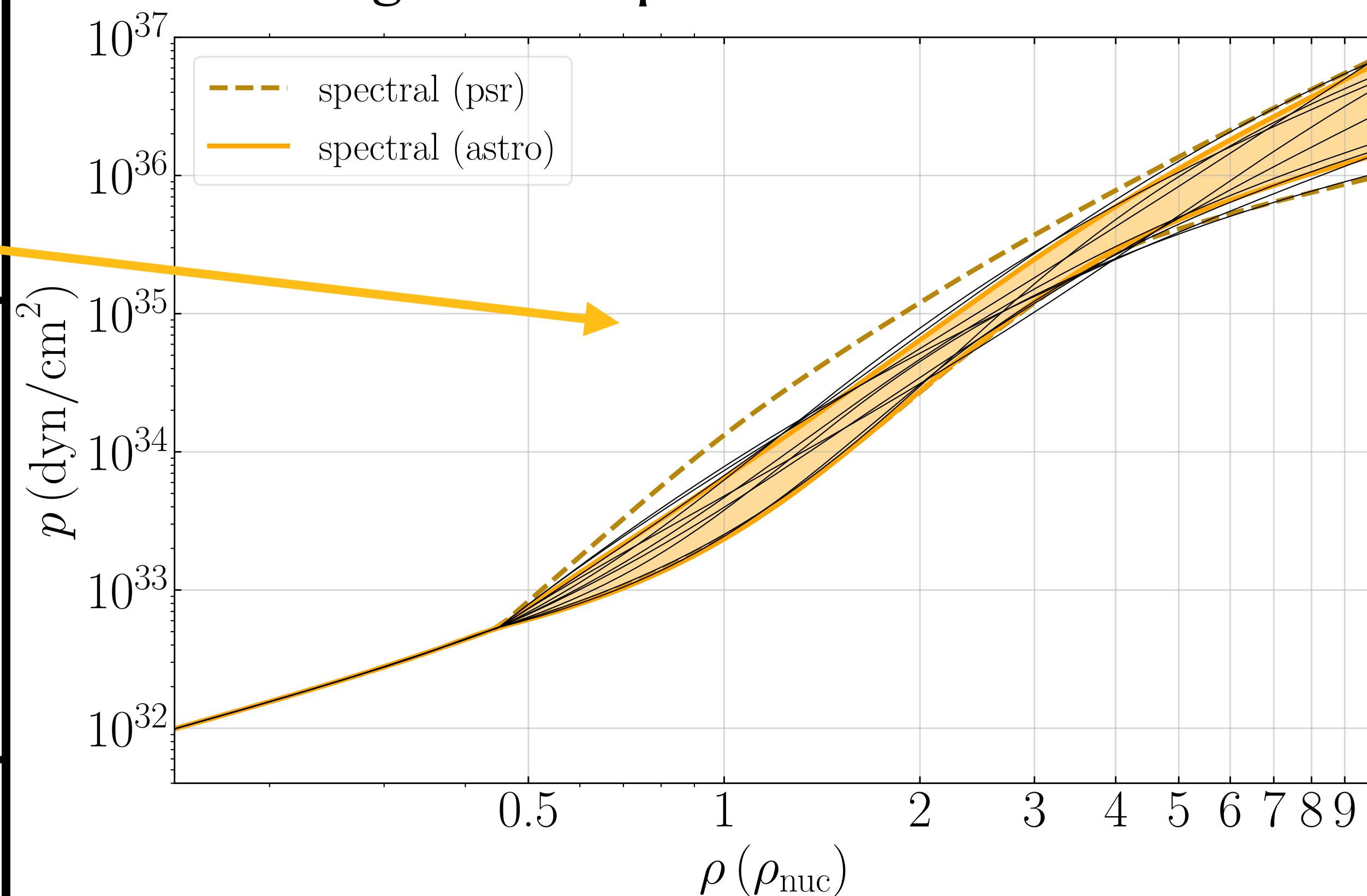
$$p(\rho) = \begin{cases} K_1 \rho^{\Gamma_1} & : \rho < \rho_1 \\ K_2 \rho^{\Gamma_2} & : \rho_1 < \rho < \rho_2 \\ K_3 \rho^{\Gamma_3} & : \rho_2 < \rho \end{cases}$$

Direct speed-of-sound (Greif 2018)

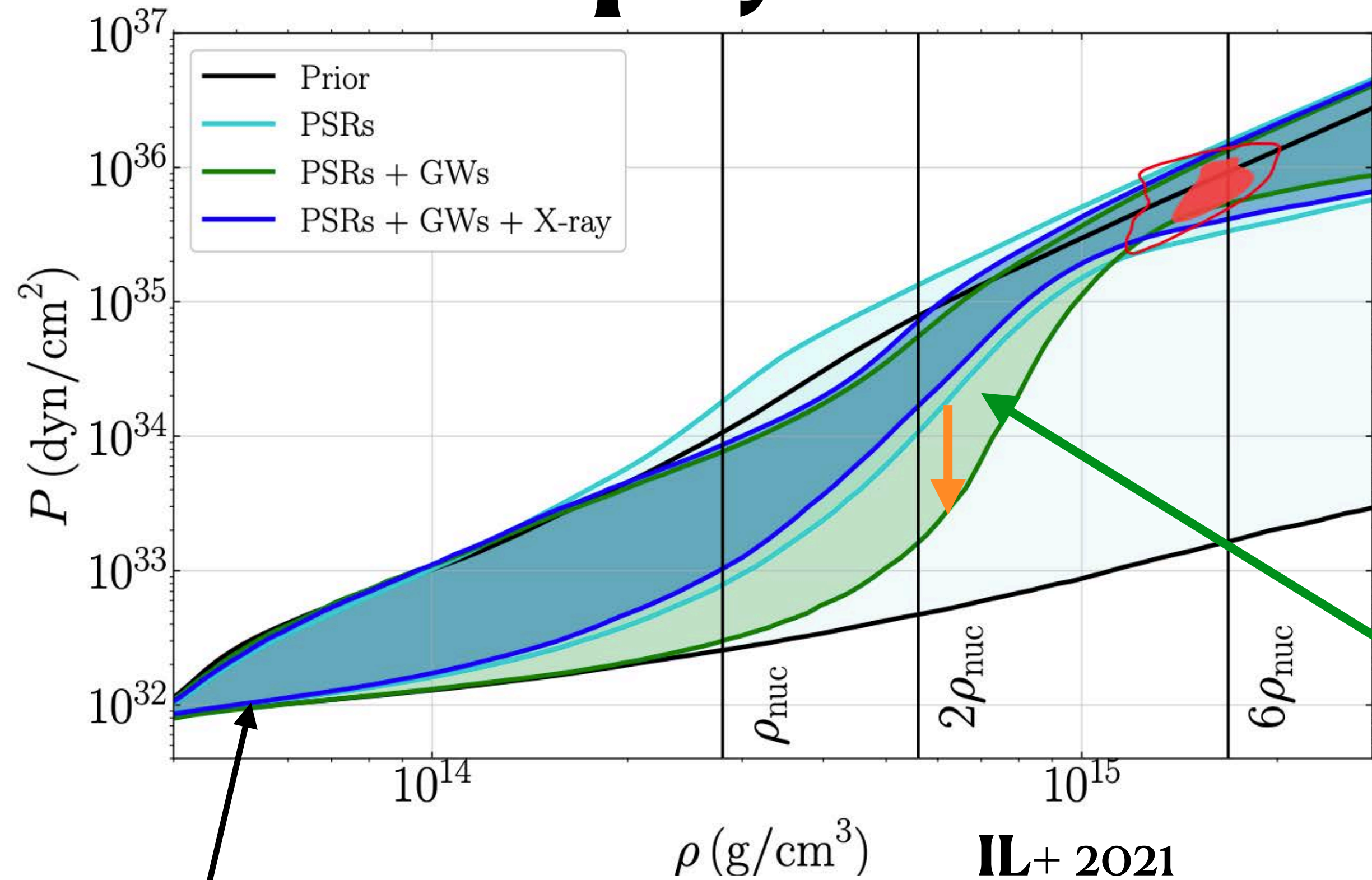
A bump in the speed of sound before asymptotic behavior

$$\frac{c_s^2(z)}{c^2} = a_1 e^{-\frac{1}{2}(z-a_2)^2/a_3^2} + a_6 + \frac{\frac{1}{3} - a_6}{1 + e^{-a_5(z-a_4)}}$$

E.g. for the Spectral Parametrization



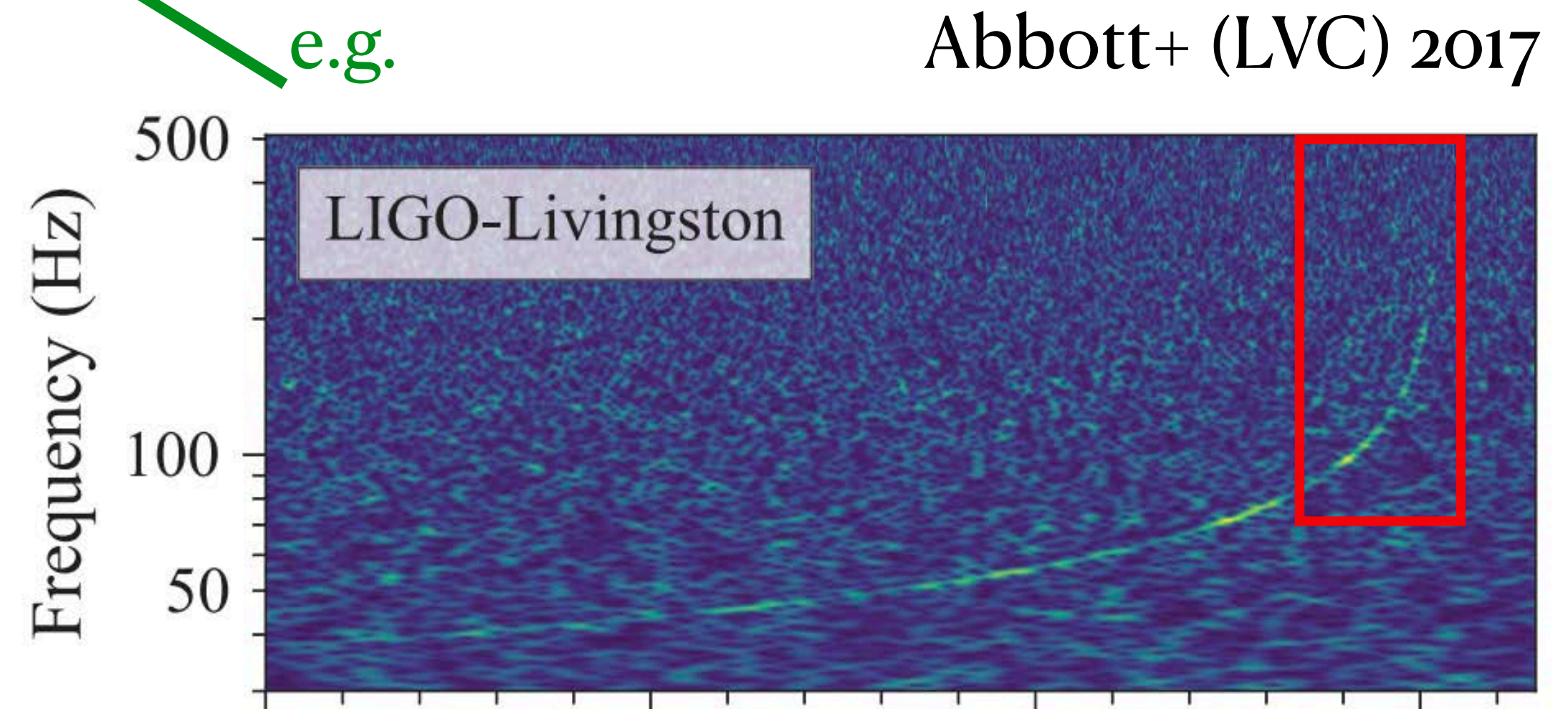
Astrophysical Data and Density Scales



We *infer* the EoS at different density scales
Using different types of astrophysical **data**

90% credible region for $p(\rho)$

$$P(\varepsilon_i | d) = P(\varepsilon | d_1, d_2, \dots) \propto P(d_1, d_2, \dots | \varepsilon_i) \times P(\varepsilon_i)$$



Astrophysical Data and Density Scales

What about measuring the NS radius?

Neutron Star Interior Composition Explorer (NICER)
(Currently operating on ISS!)

Measured Mass and radius of two pulsars

J0030 (2019)

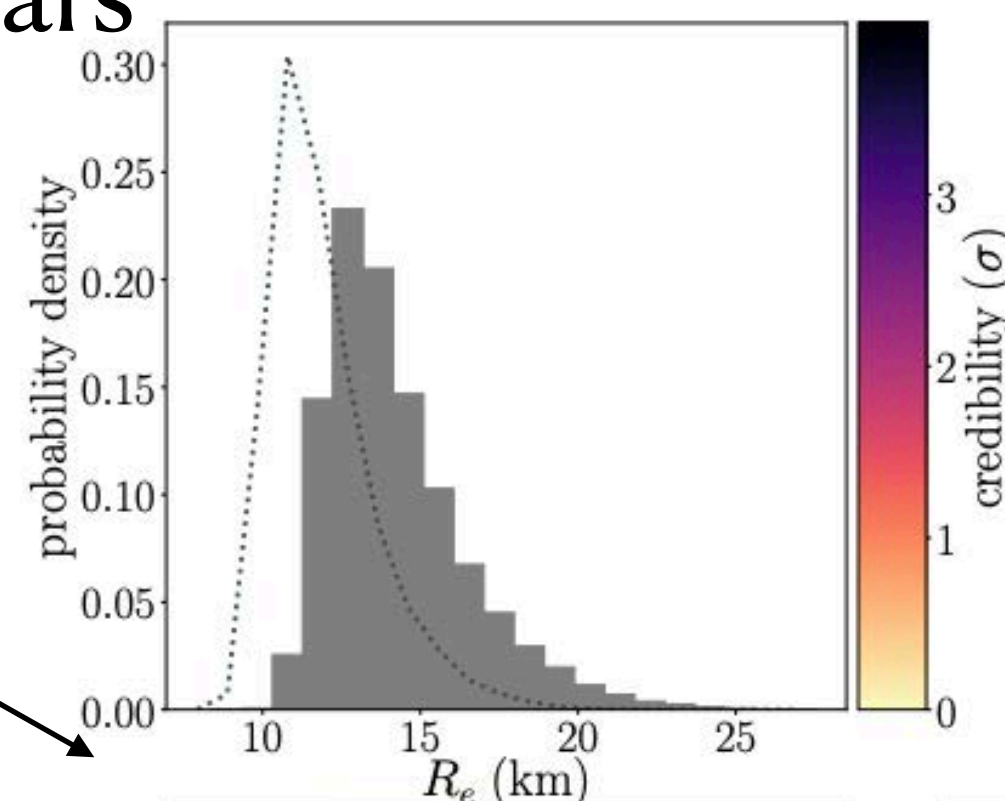
J0740 (2021)

Miller et al.

Miller et al.

Raaijmakers et al.

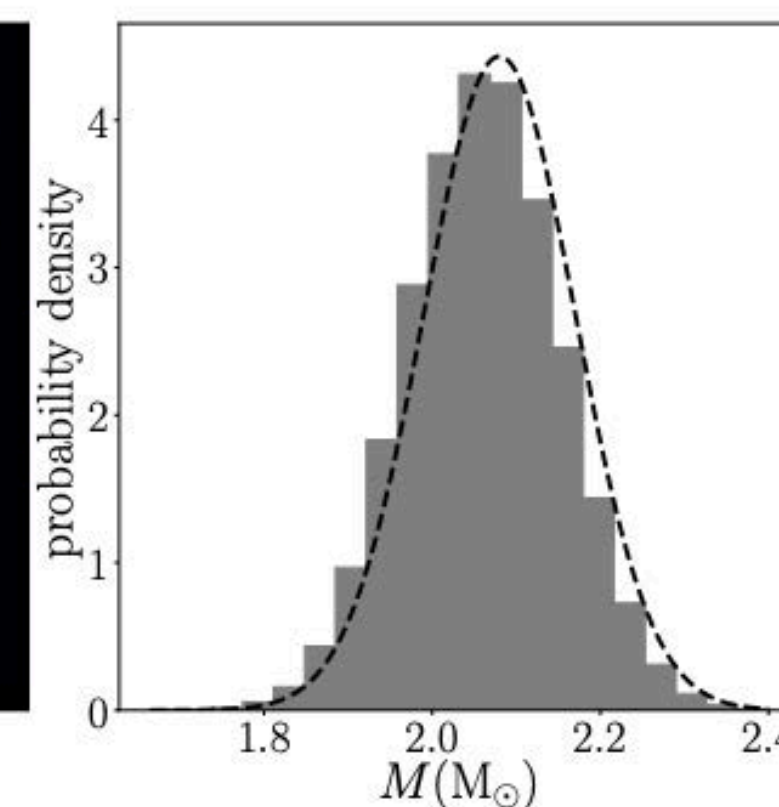
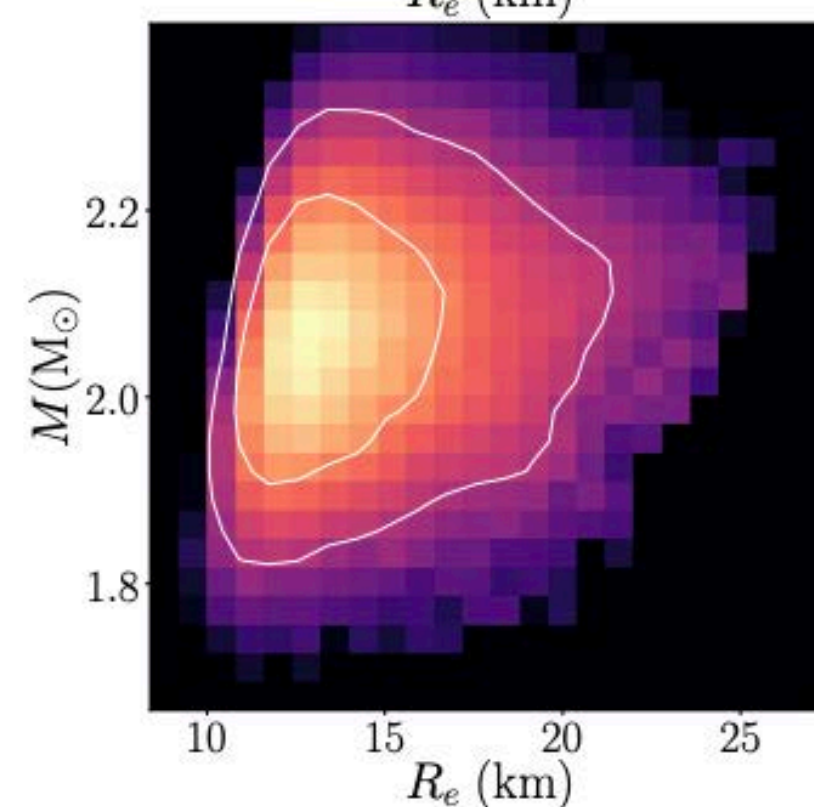
Riley et al.



NICER + XMM



Use gravitational lensing of x-rays to
infer the compactness of the star
Also used XMM-Newton to calibrate
pulse rate



Astrophysical Data and Density Scales

What about measuring the NS radius?

Neutron Star Interior Composition Explorer (NICER)
(Currently operating on ISS!)

Measured Mass and radius of two pulsars

J0030 (2019)

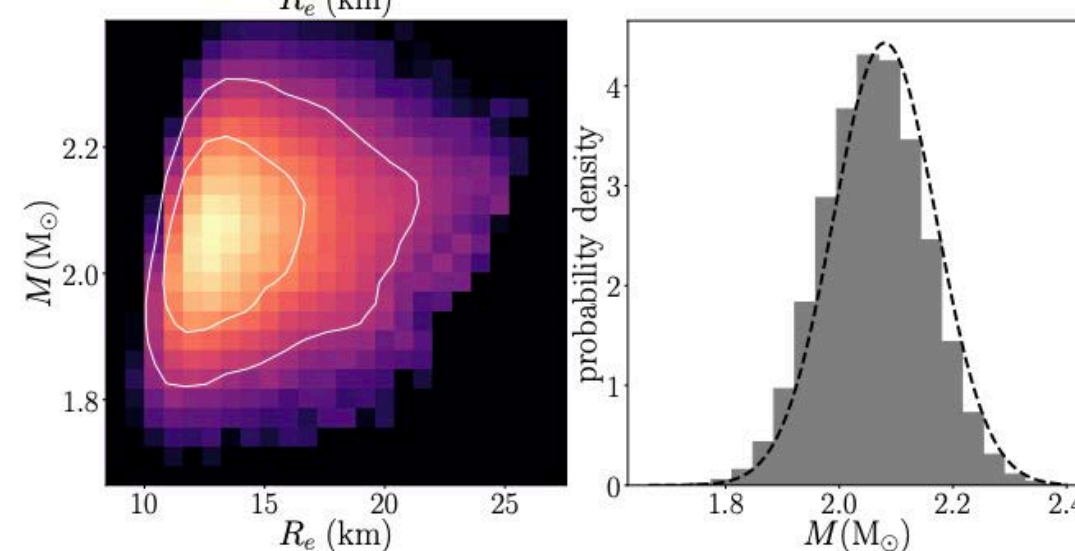
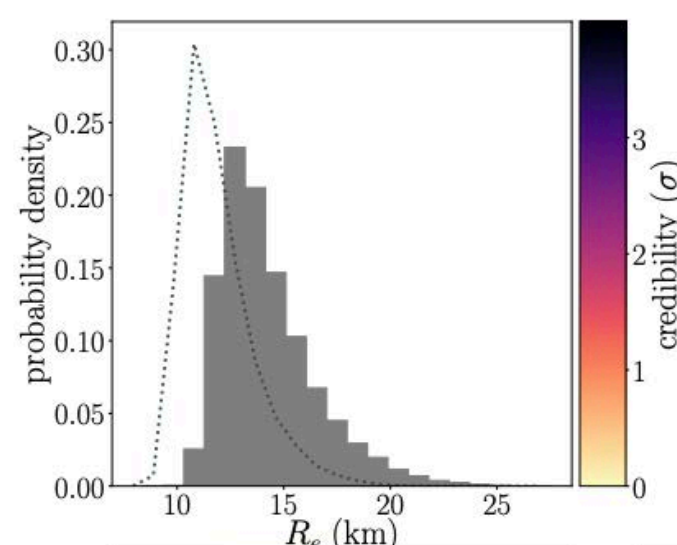
J0740 (2021)

Miller et al.

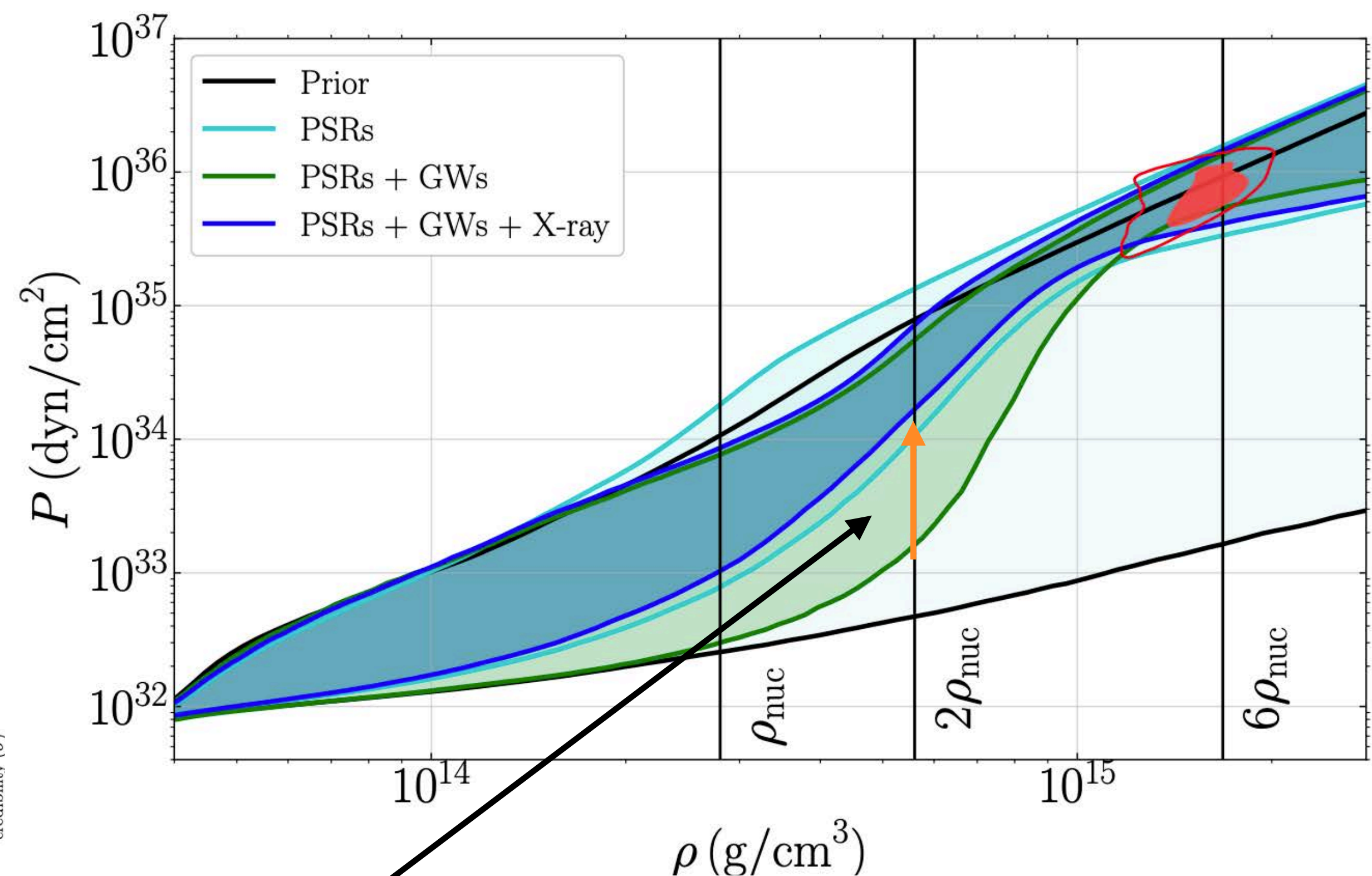
Miller et al.

Raaijmakers et al.

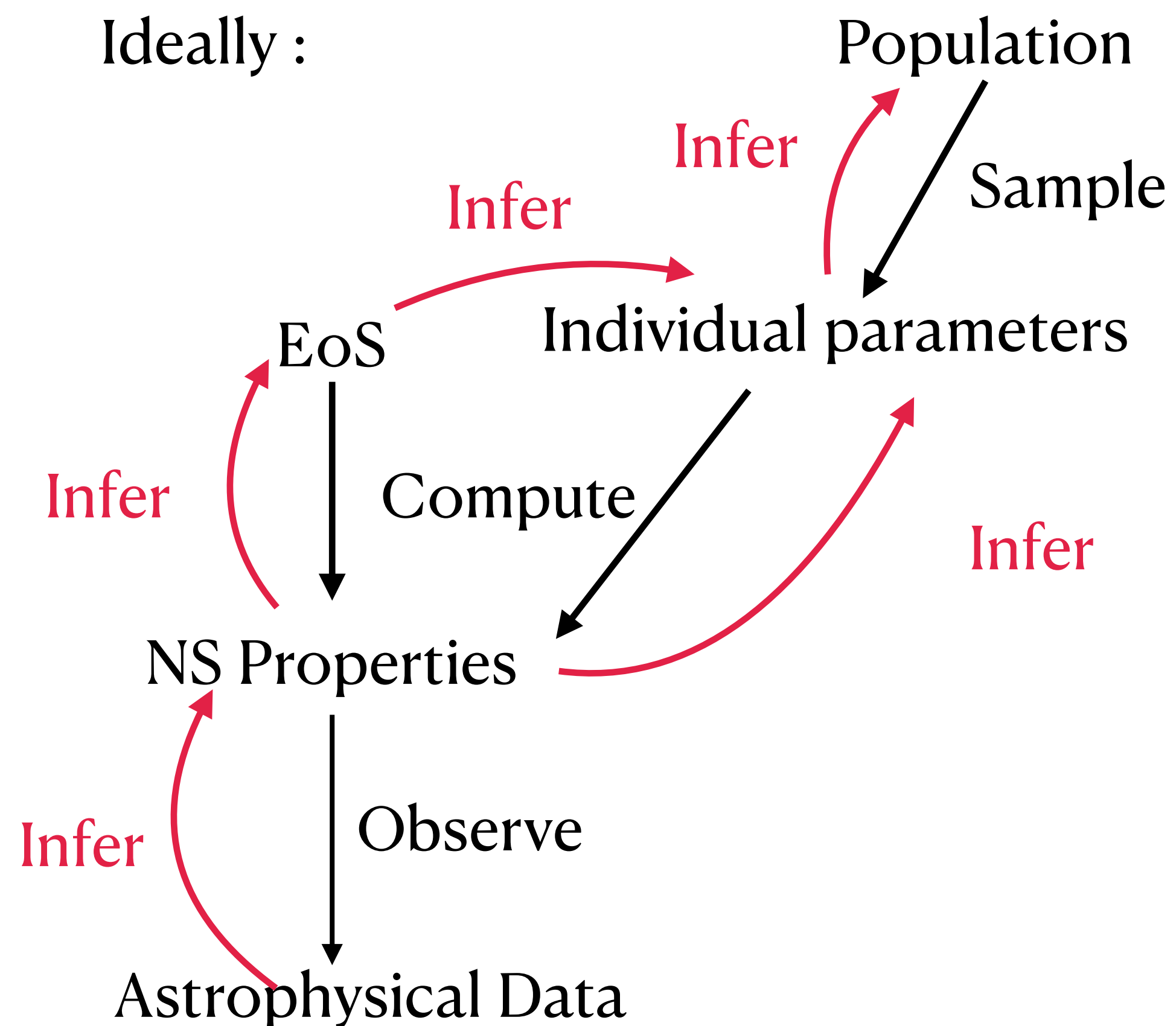
Riley et al.



Use gravitational lensing of x-rays to
infer the compactness of the star
Also used XMM-Newton to calibrate
pulse rate



Astrophysical Data (Brief Aside)



Lots of details

- (1) Selection Effects
- (2) Interpreting data (GW waveforms, x-ray pulse profiles)
- (3) Poorly characterized population of NSs

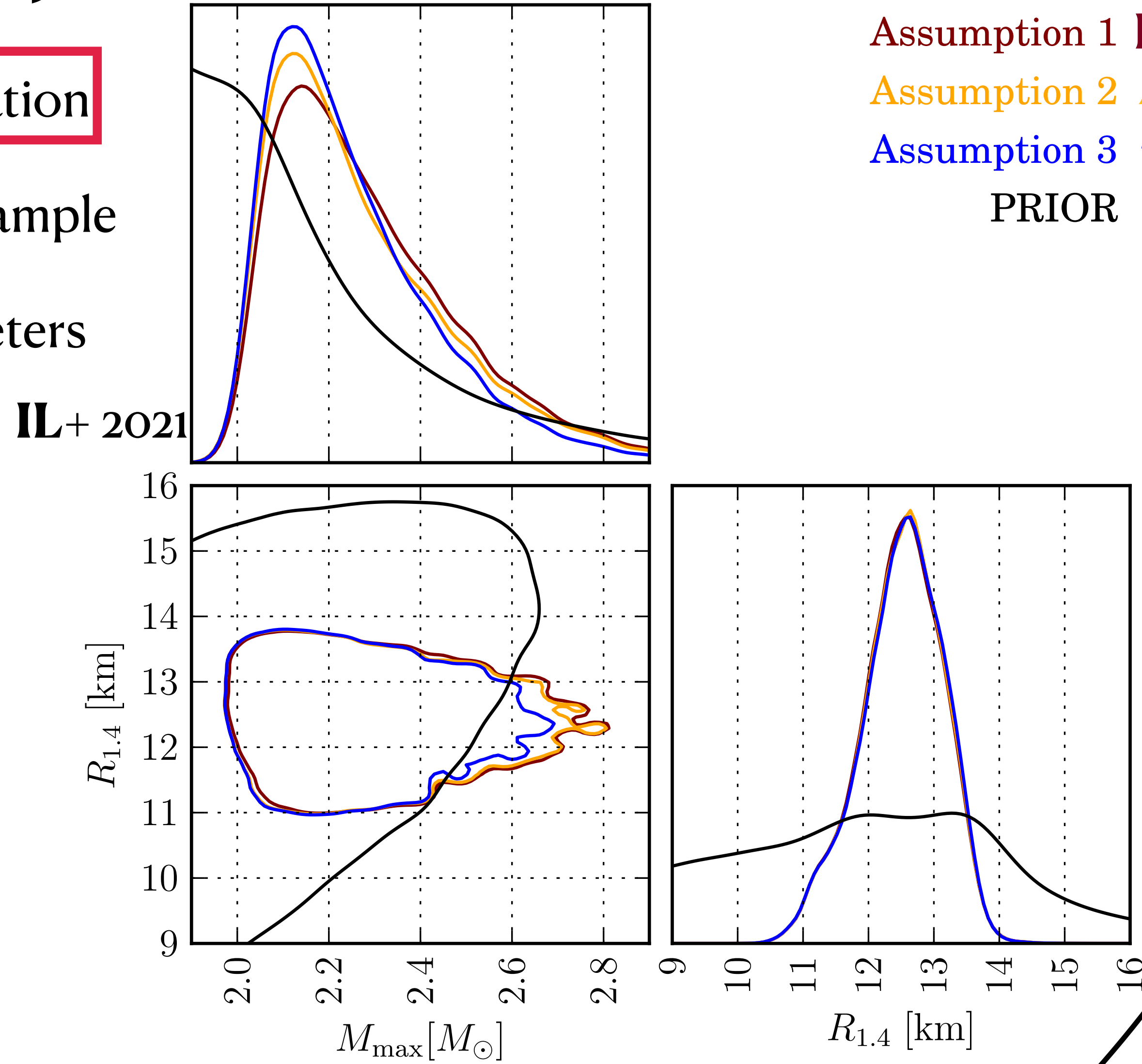
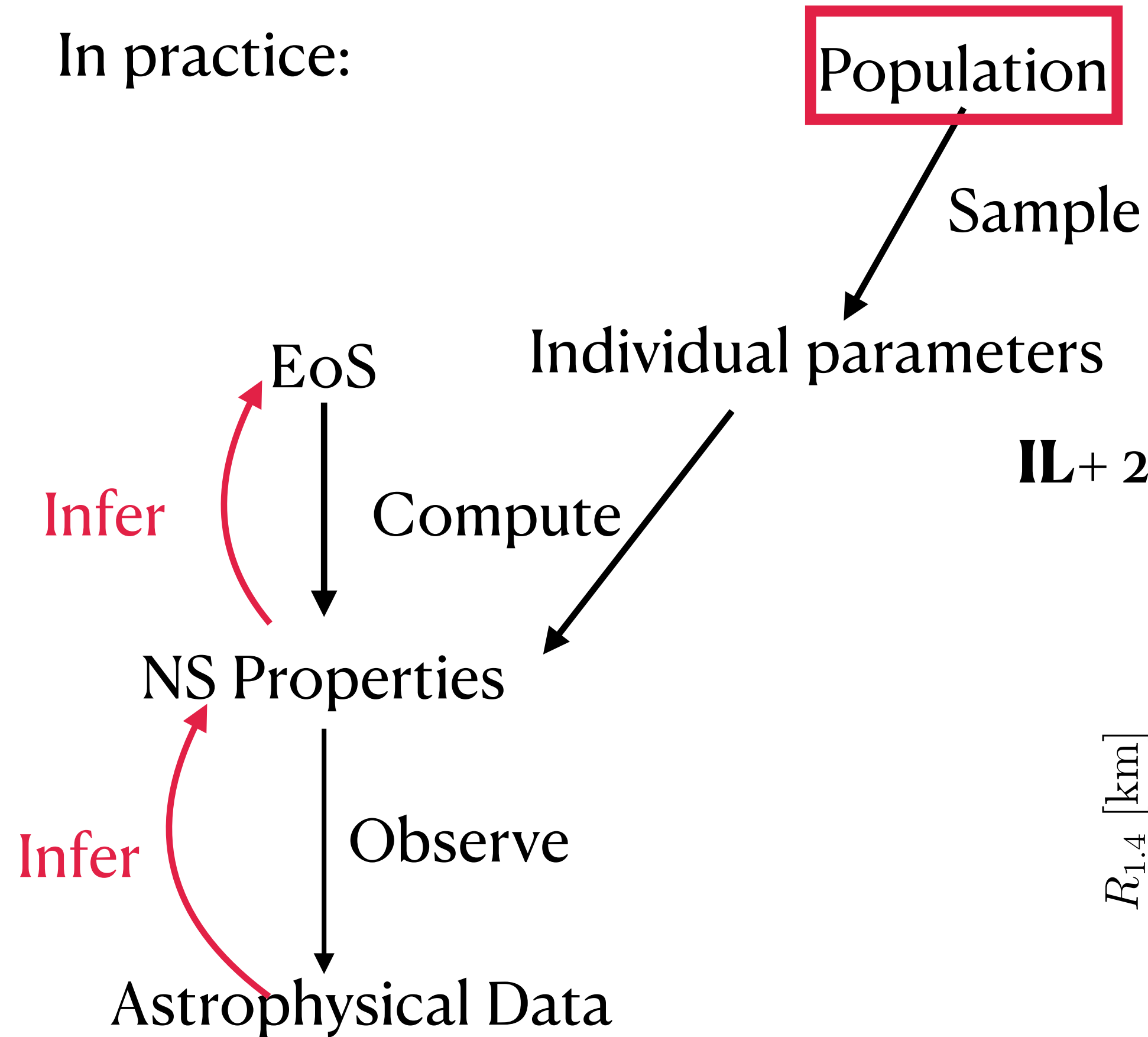
$$P(\varepsilon_i | d) = P(\varepsilon | d_1, d_2, \dots) \propto P(d_1, d_2, \dots | \varepsilon_i) \times P(\varepsilon_i)$$

$$P(d_1, d_2, \dots | \varepsilon_i) = P(d_1 | \varepsilon_i) \times P(d_2 | \varepsilon_i)) \dots$$

$$P(d_1 | \varepsilon_i) = \sum_{\text{NS sources}} P(d_1 | \text{NS source}) \times P(\text{NS Source} | \varepsilon_i, (\text{Population Model}))$$

Astrophysical Data (Brief Aside)

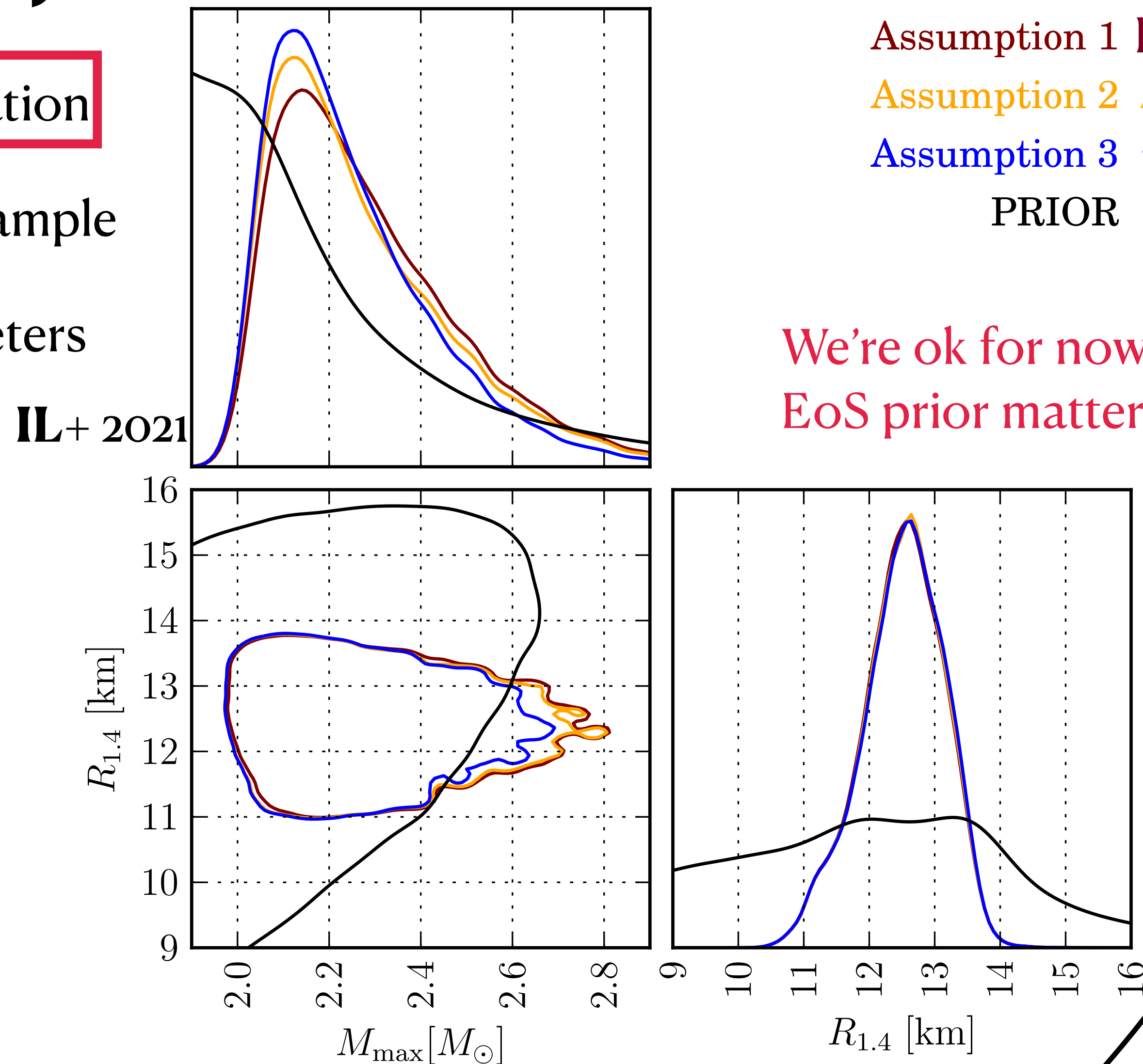
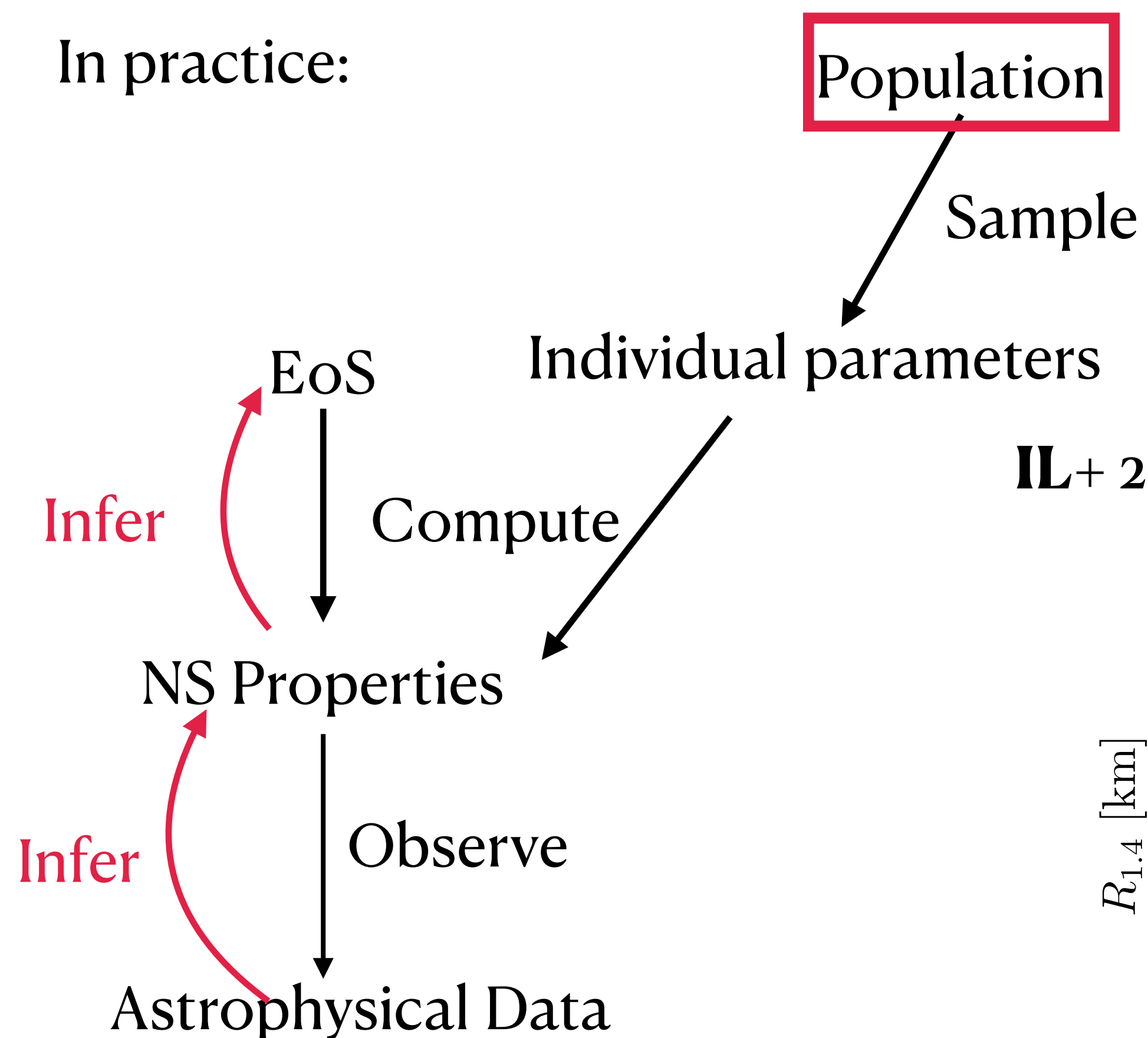
In practice:



$$P(d_1 | \varepsilon_i) = \sum_{\text{NS sources}} P(d_1 | \text{NS source}) \times P(\text{NS Source} | \varepsilon_i, (\text{Population Model}))$$

Astrophysical Data (Brief Aside)

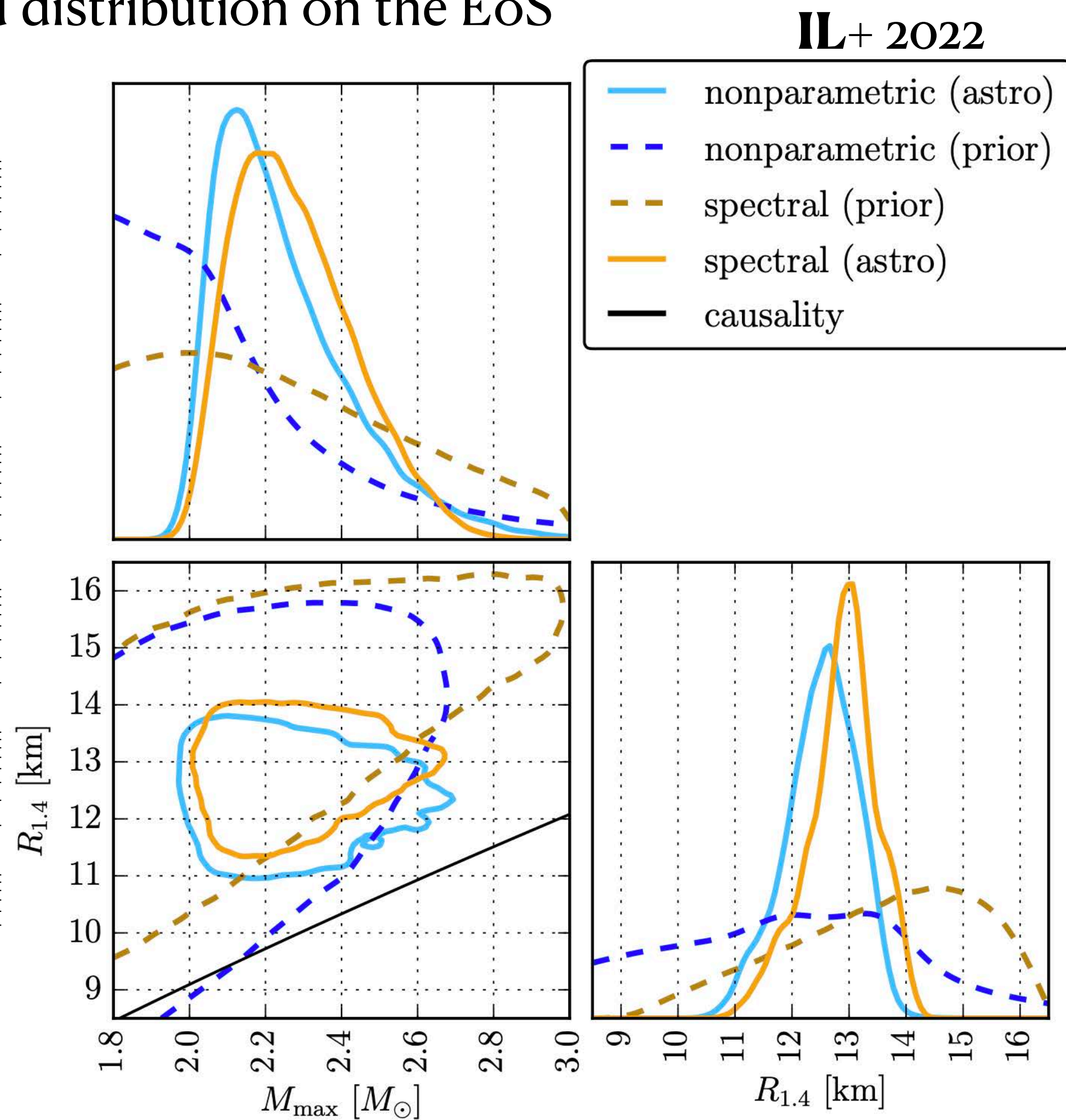
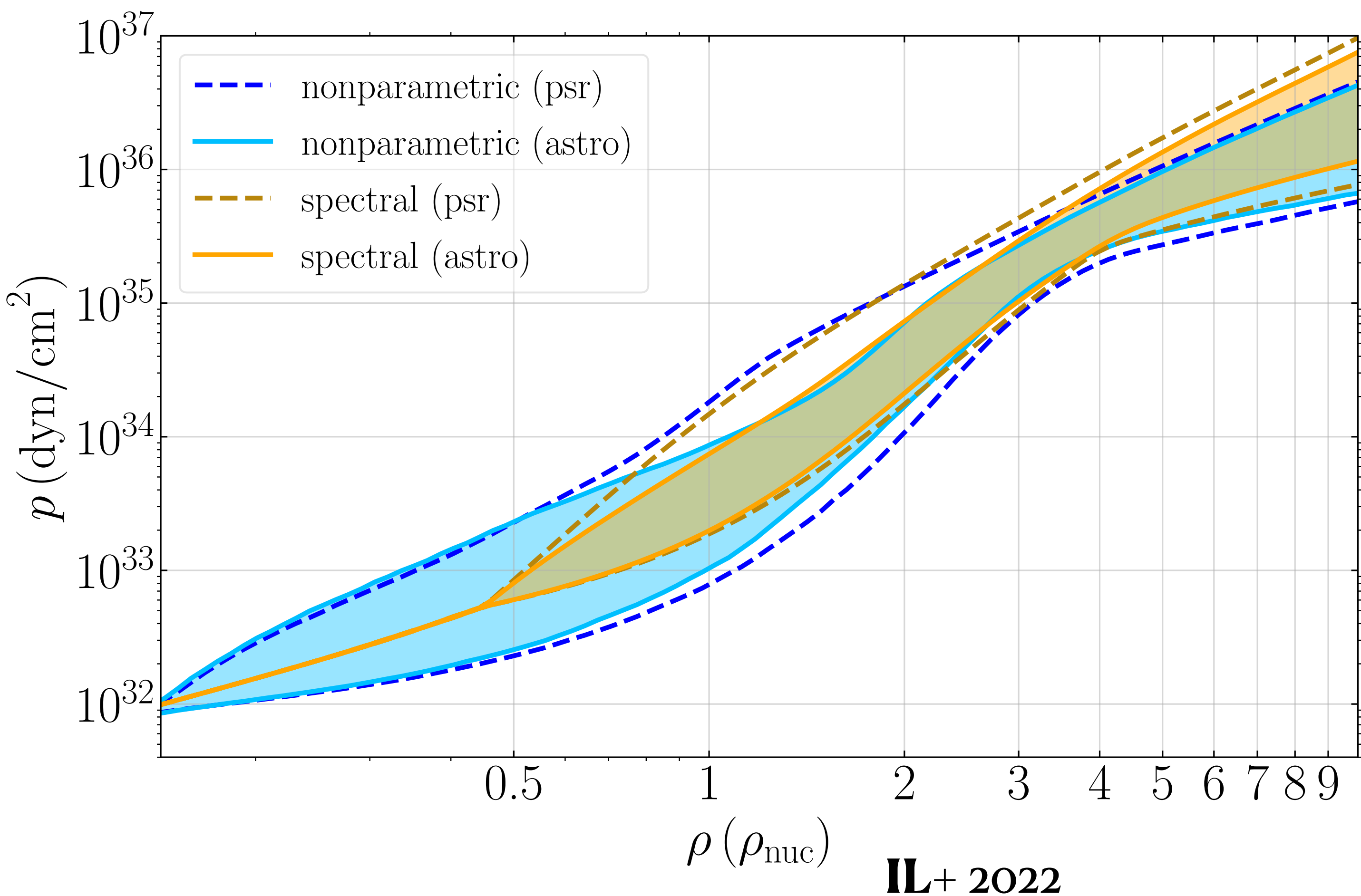
In practice:



$$P(d_1 | \varepsilon_i) = \sum_{\text{NS sources}} P(d_1 | \text{NS source}) \times P(\text{NS Source} | \varepsilon_i, (\text{Population Model}))$$

Different Priors, Different Results

We know that the choice of prior does impact our recovered distribution on the EoS
 Hold all other things constant (astrophysical data, pop.)



Different Priors, Different Results

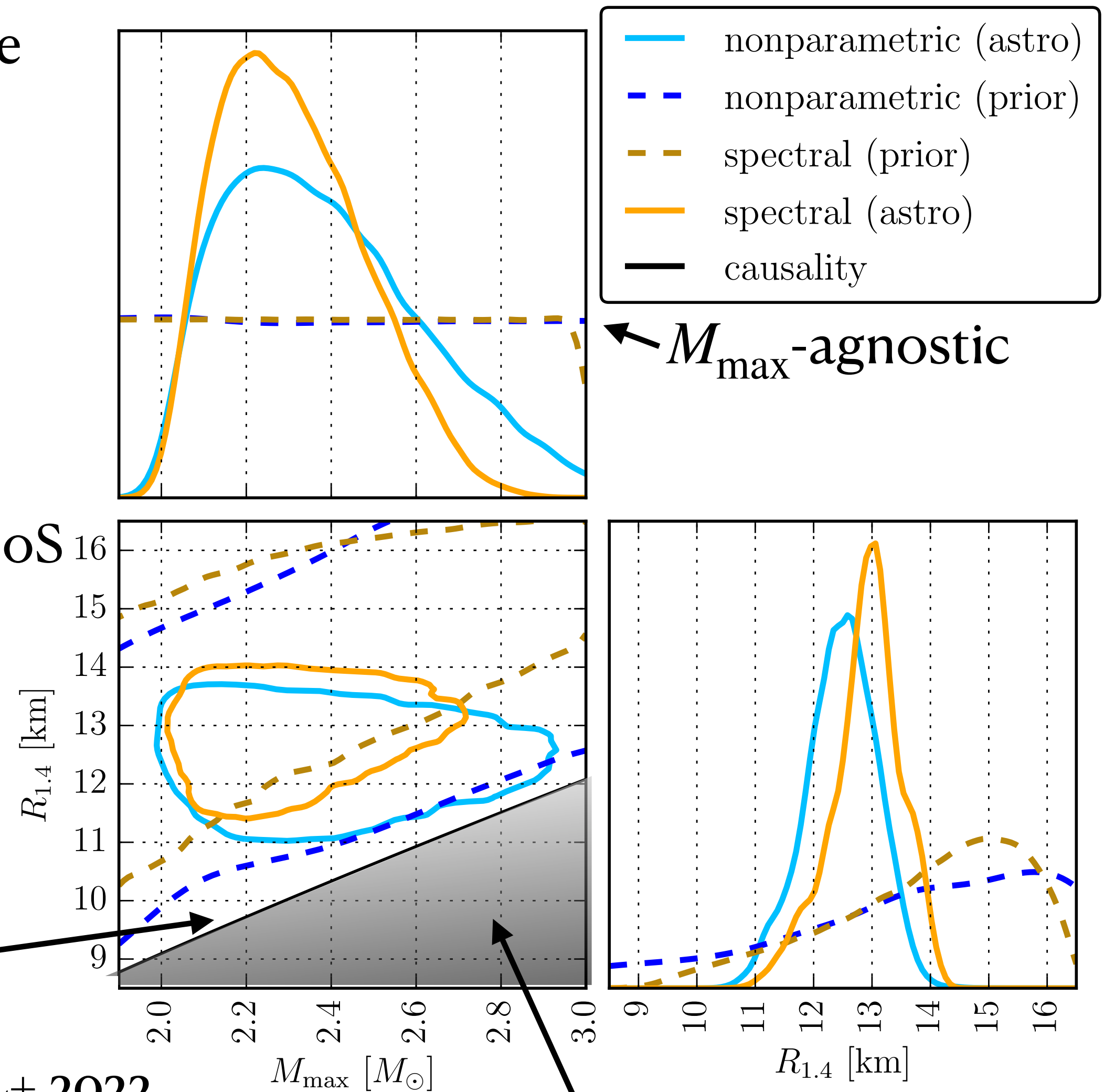
TOV maximum mass and radius of a 1.4 solar mass NS are correlated among equation of state candidates due to causality

This rules out certain configurations in “ $M_{\max} - R_{1.4}$ ” space

The boundary is “fuzzy” — depends on the low density EoS

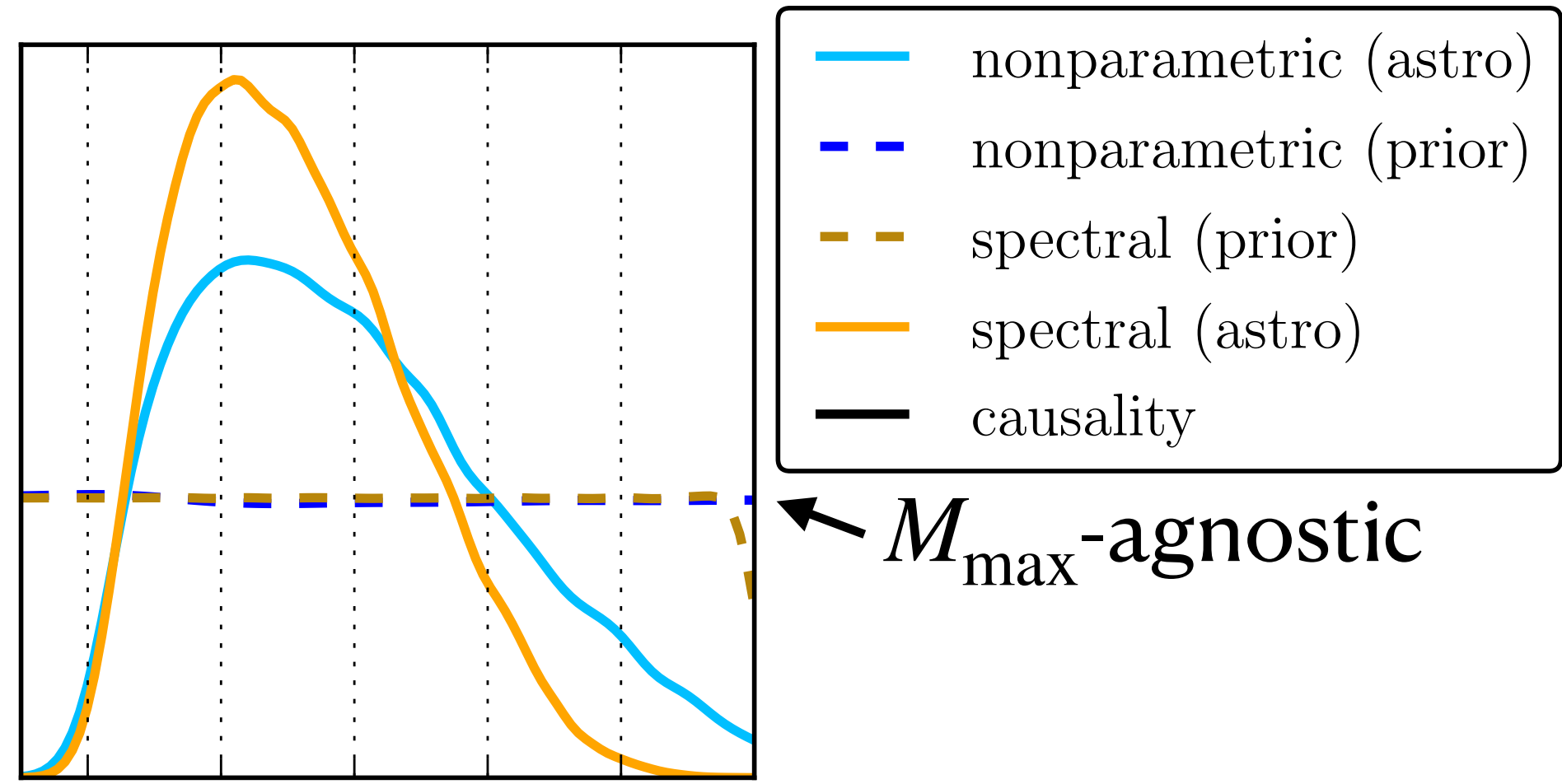
Parametrized by
Stitching density to
 $c_s^2 = c^2$ EoS

IL+ 2022



Causality (Kalogera + Baym 1996)

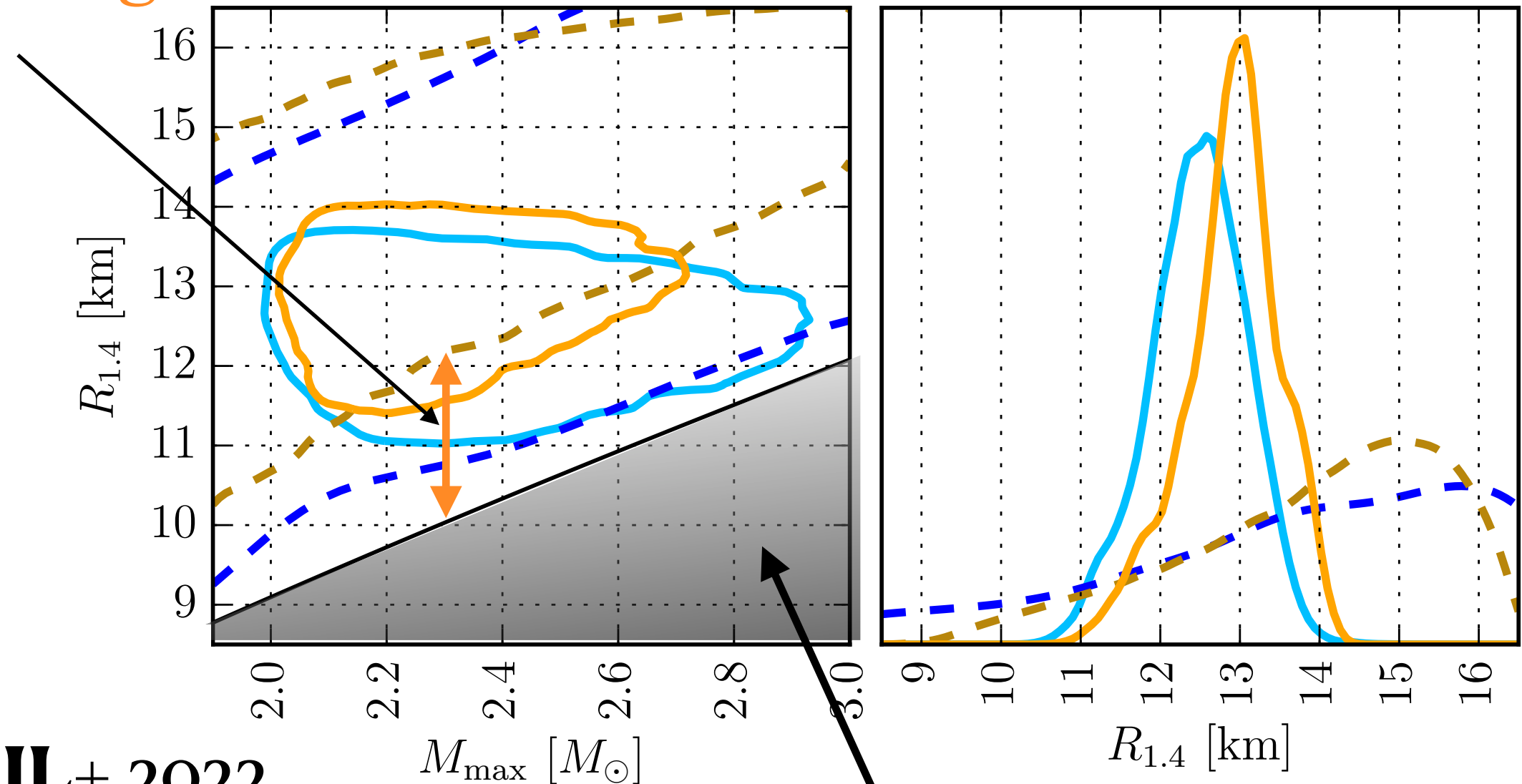
Different Priors, Different Results



TOV maximum mass and radius of a 1.4 solar mass NS are correlated among equation of state candidates due to causality

Spectral model sees a “tighter correlation” than the Nonparametric model — not likely due to causality!

Modeling?

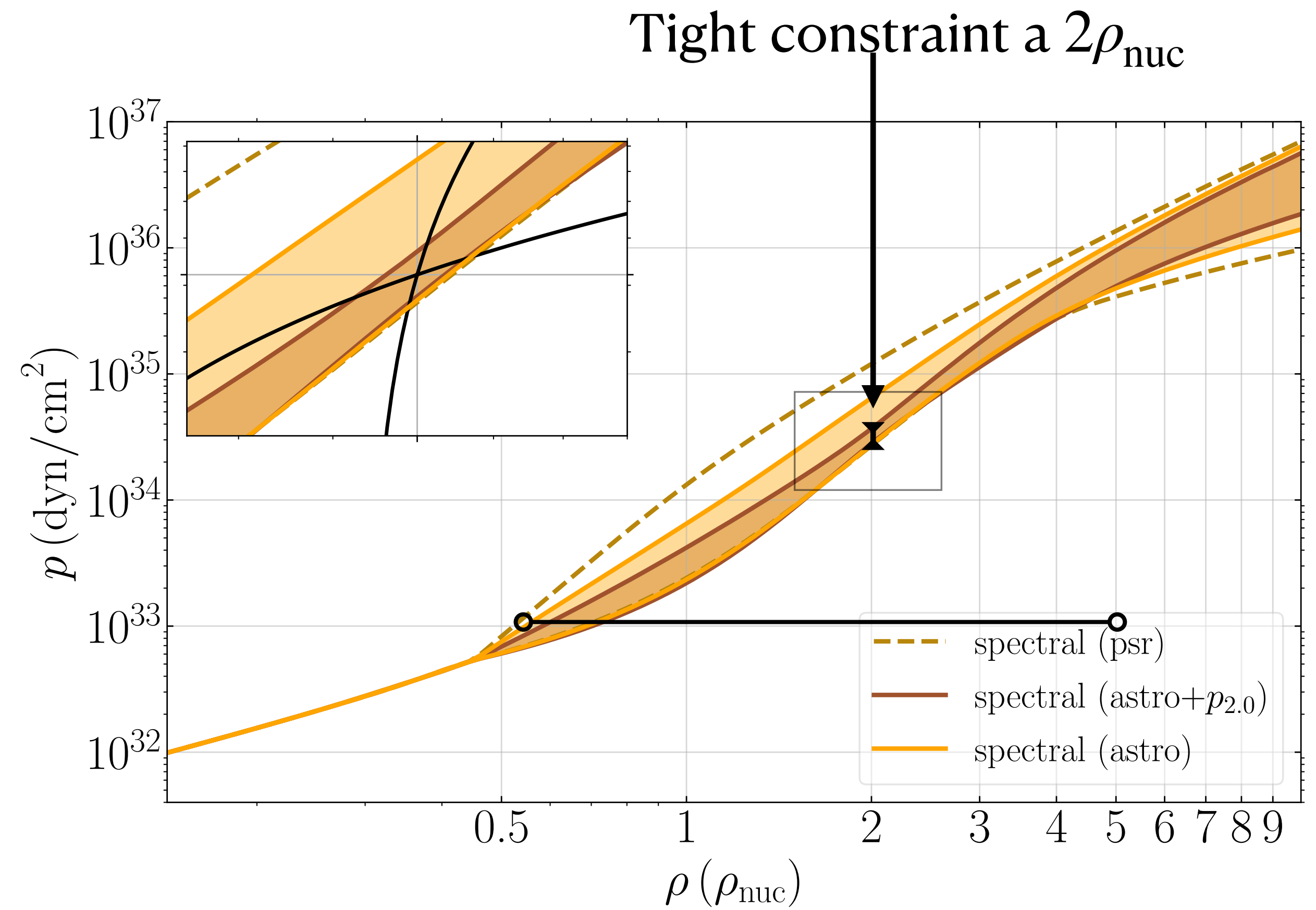
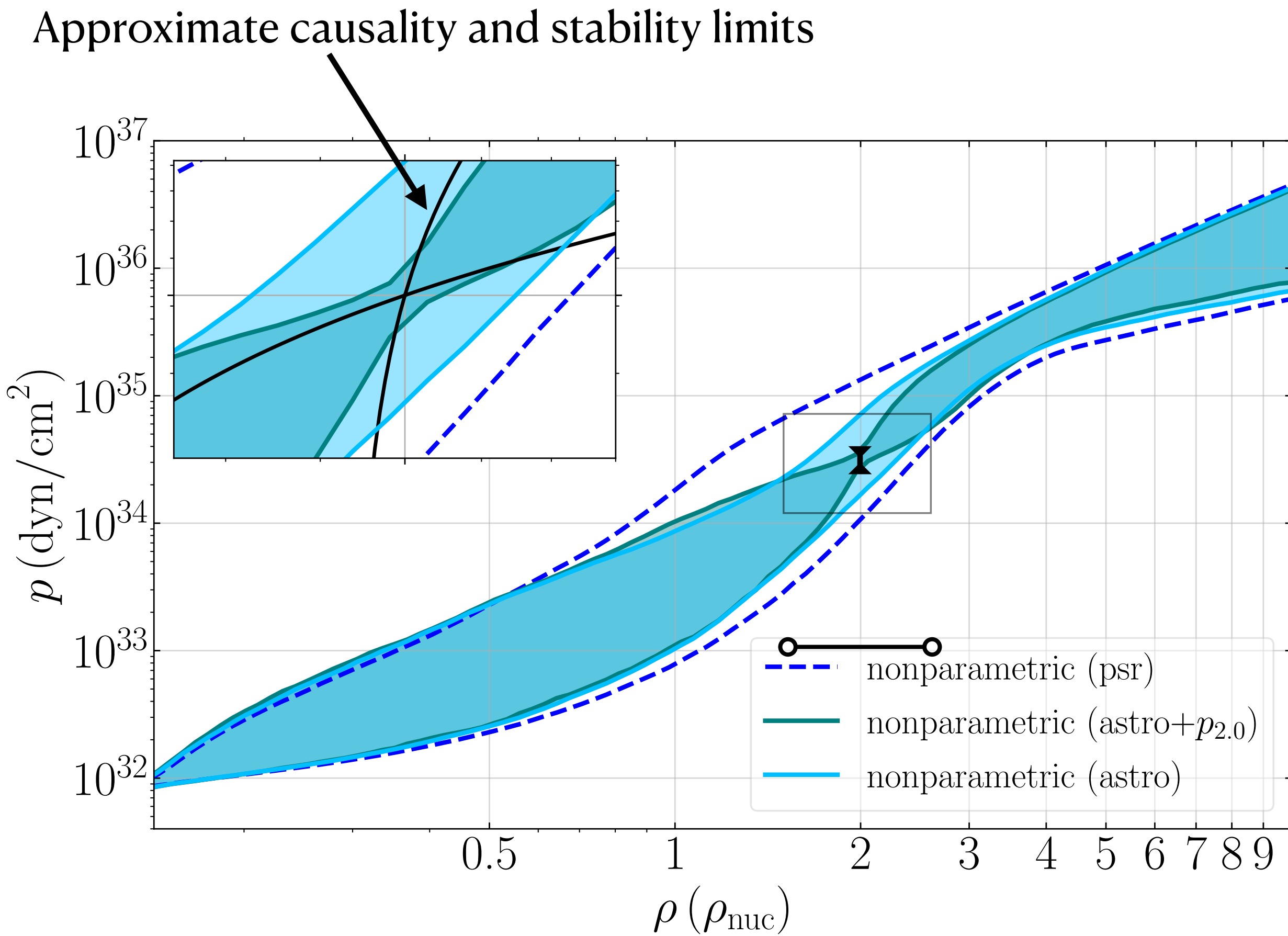


IL+ 2022

Causality (Kalogera + Baym 1996)

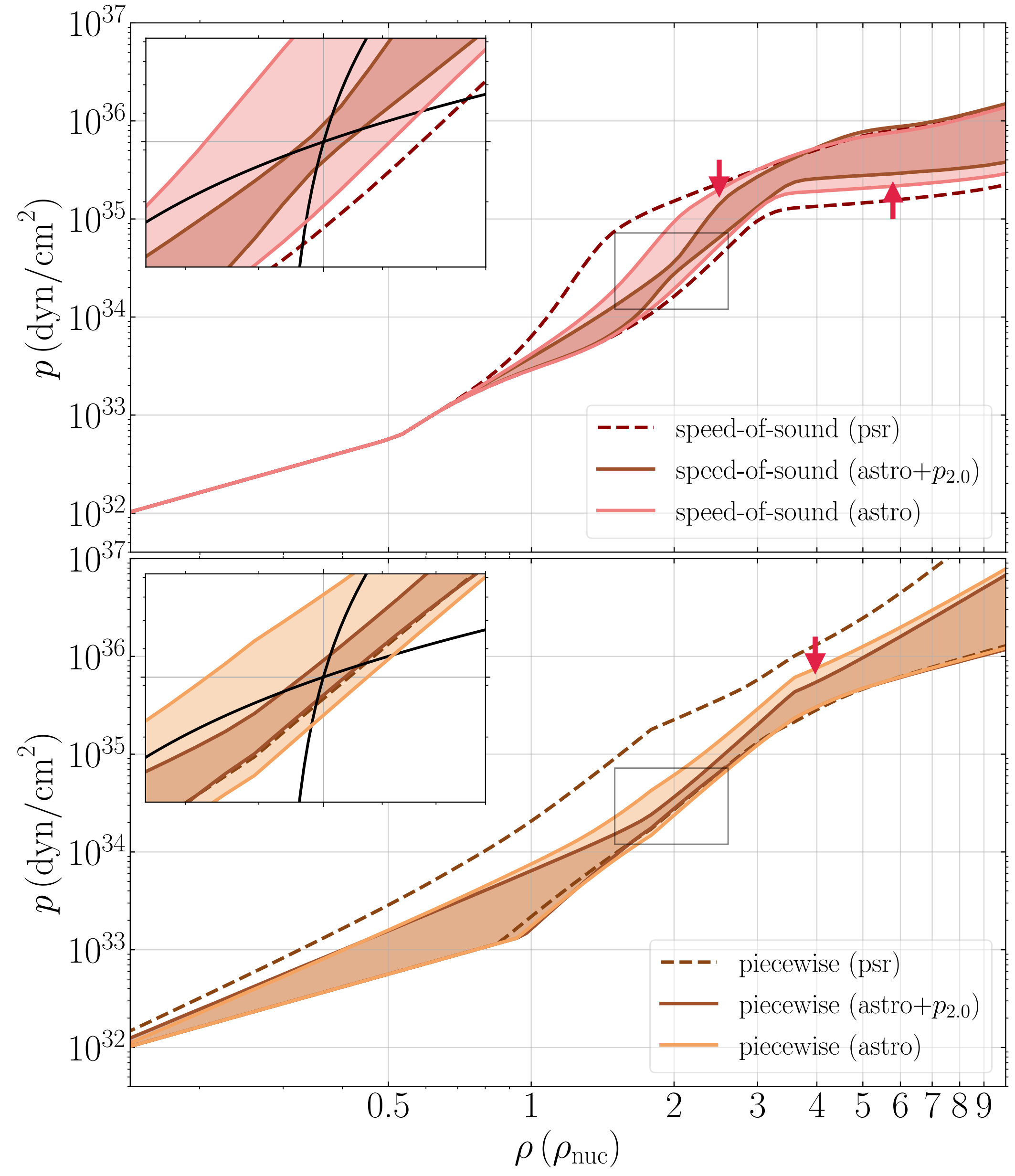
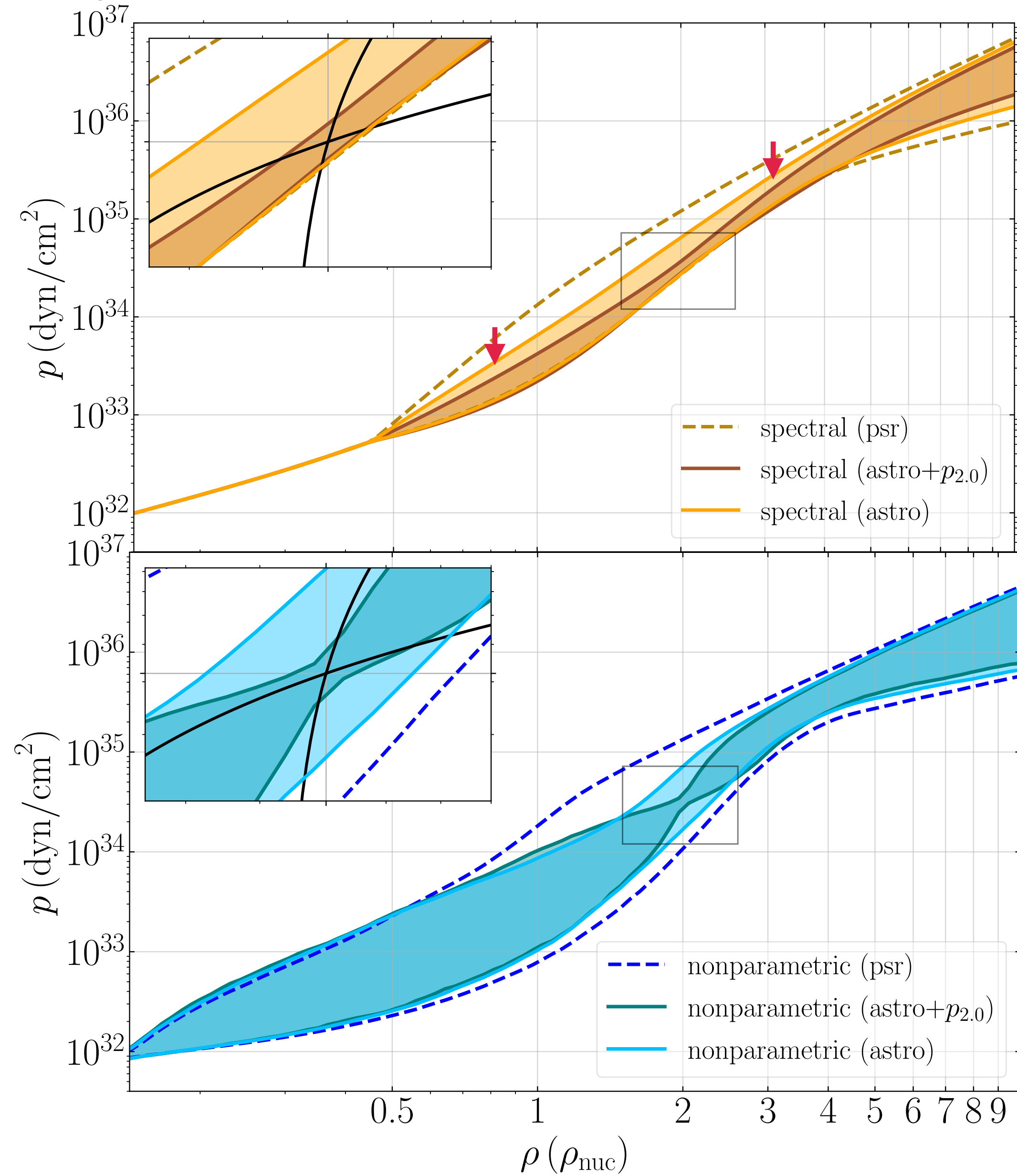
Correlations

Correlations between astro observables \Leftrightarrow Correlations between density scales



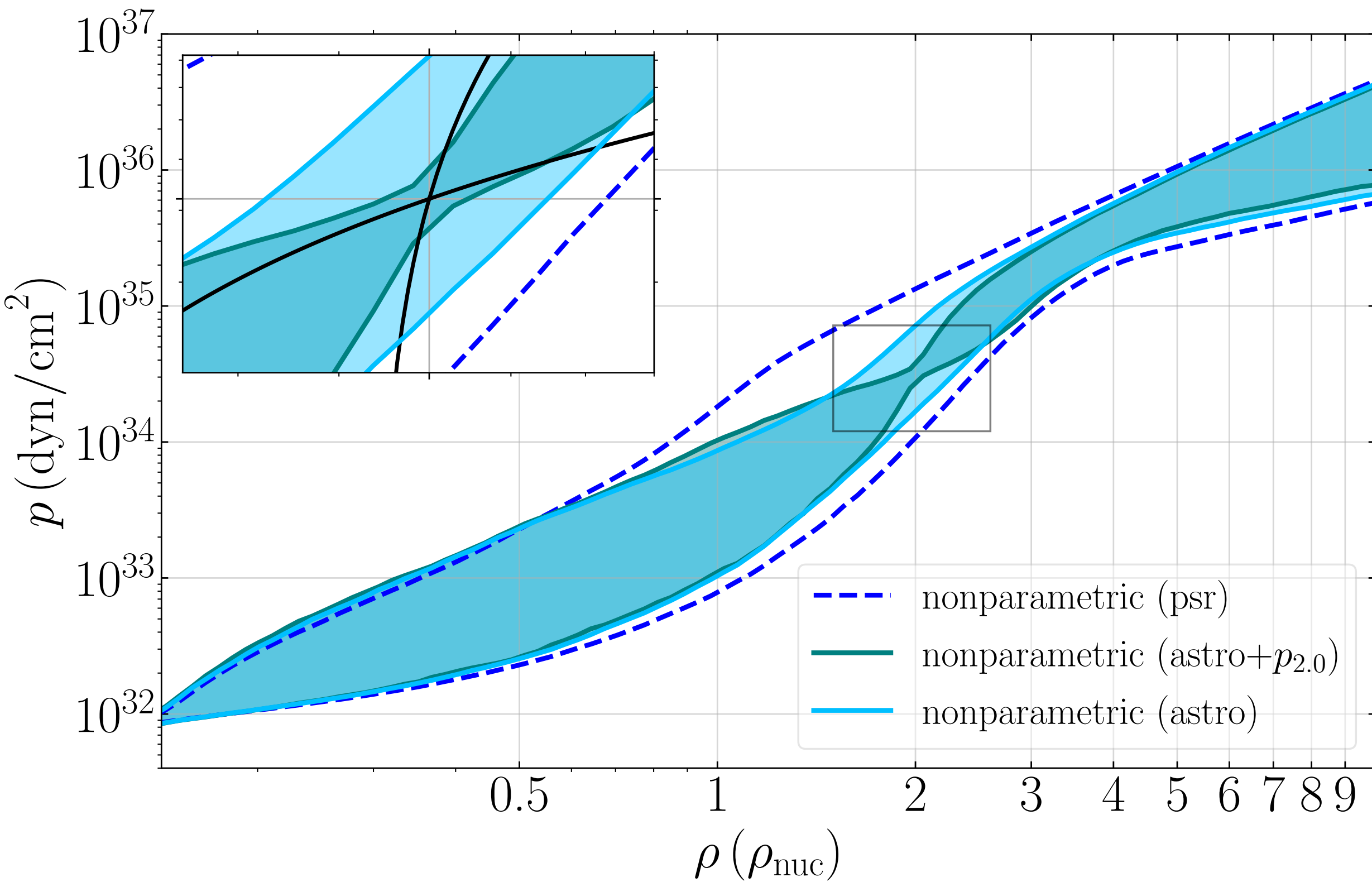
Implicit Correlations

IL+ 2022



Implicit Correlations

IL+ 2022



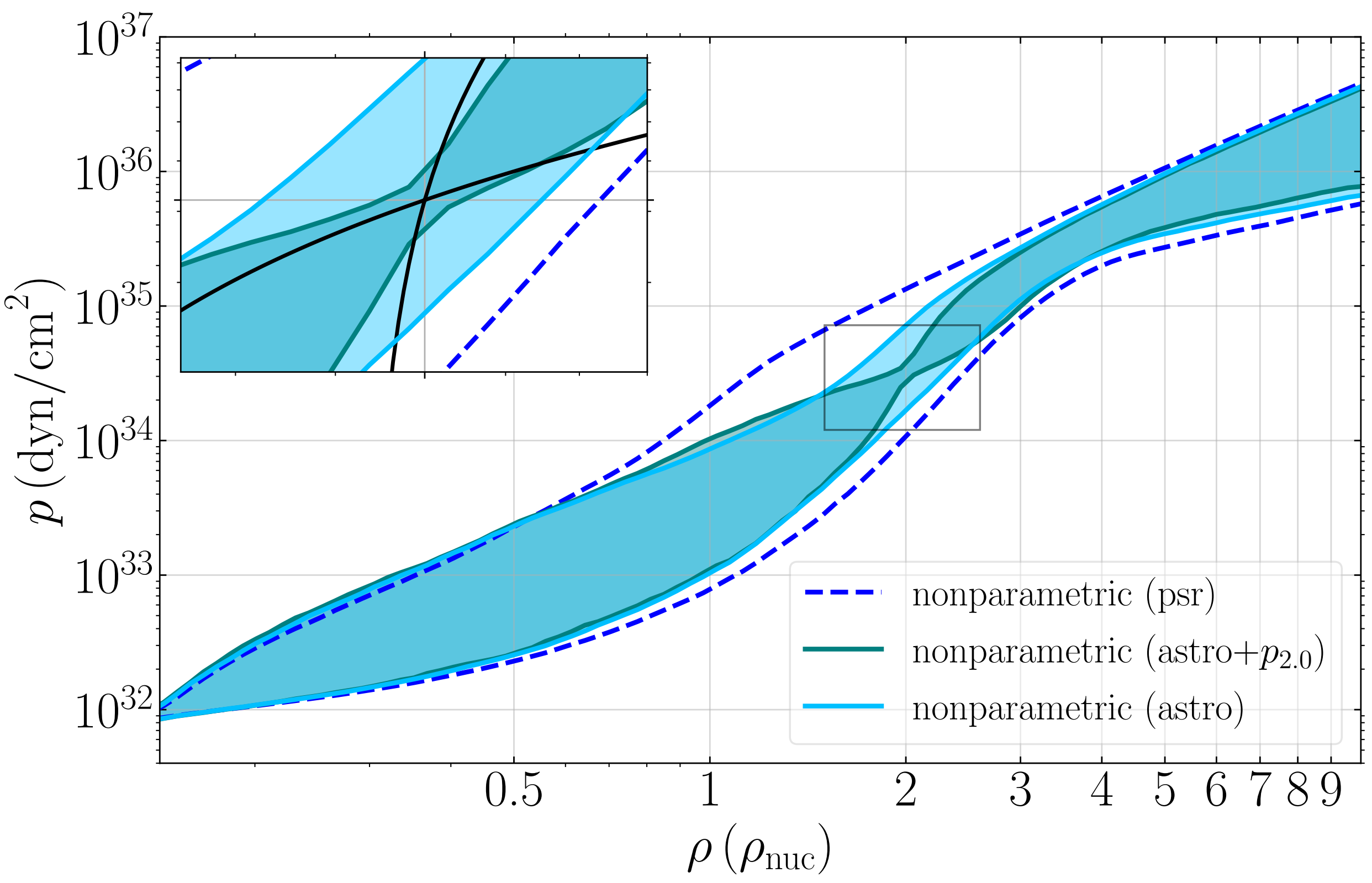
Quantifying correlations — Mutual Information

How much information is gained about other density Scales by knowing the EoS at some fixed density

$$I(p_a, p_b) \equiv \int dp_a dp_b P(p_a, p_b) \ln \left(\frac{P(p_a, p_b)}{P(p_a)P(p_b)} \right)$$

Implicit Correlations

IL+ 2022



Quantifying correlations — Mutual Information

How much information is gained about other density Scales by knowing the EoS at some fixed density

$$I(p_a, p_b) \equiv \int dp_a dp_b P(p_a, p_b) \ln \left(\frac{P(p_a, p_b)}{P(p_a)P(p_b)} \right)$$

Also a K-L divergence!

$$I(p_a, p_b) = \int dp_a P(p_a) \int dp_b P(p_b | p_a) \ln \left(\frac{P(p_b | p_a)}{P(p_b)} \right)$$

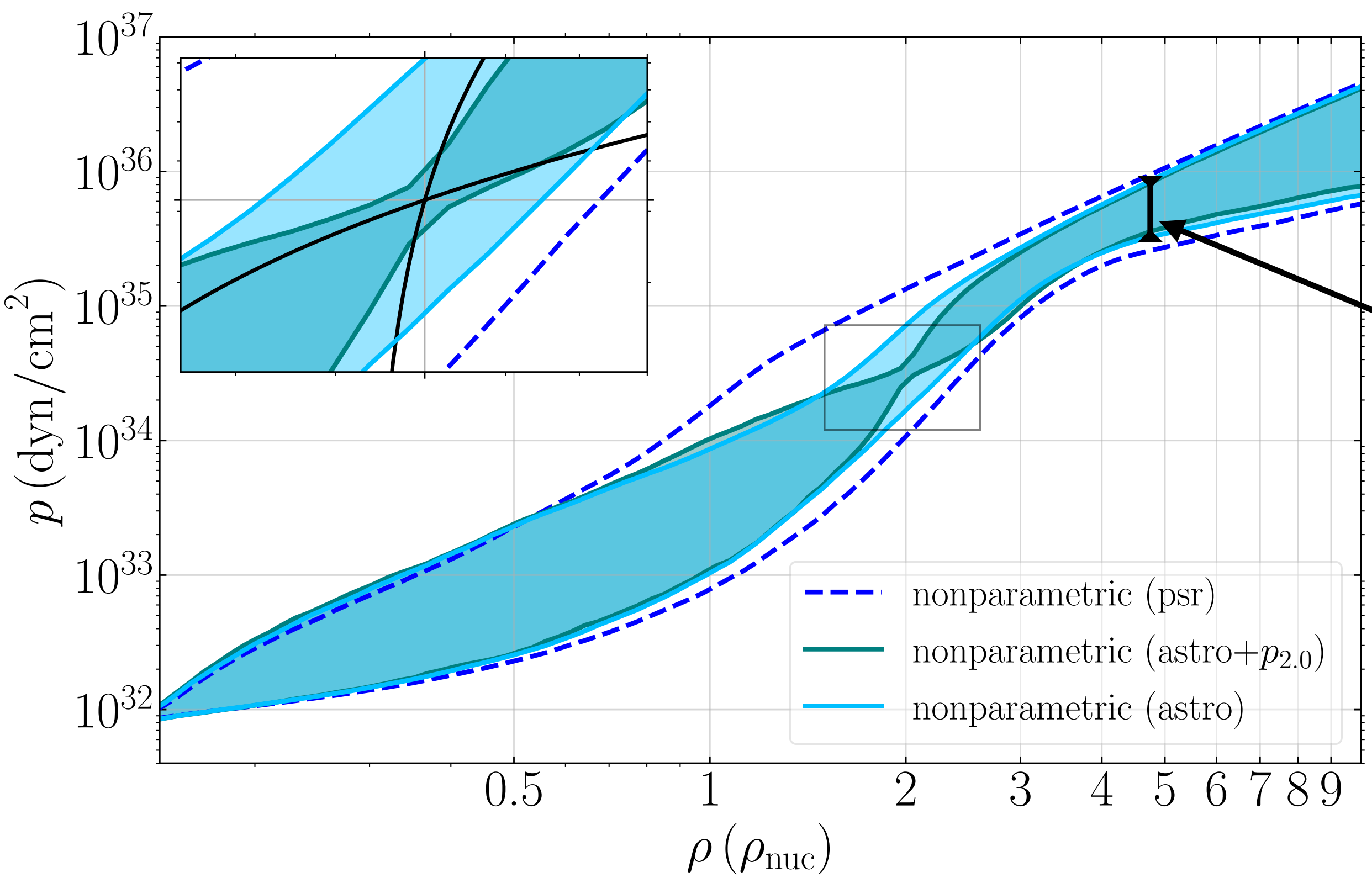
Difference in knowledge about p_b after learning p_a

Changing this analogous to adding a tight Pressure “mock-measurement”

Implicit Correlations

IL+ 2022

$$I(p_a, p_b) = \int dp_a P(p_a) \int dp_b P(p_b | p_a) \ln \left(\frac{P(p_b | p_a)}{P(p_b)} \right)$$

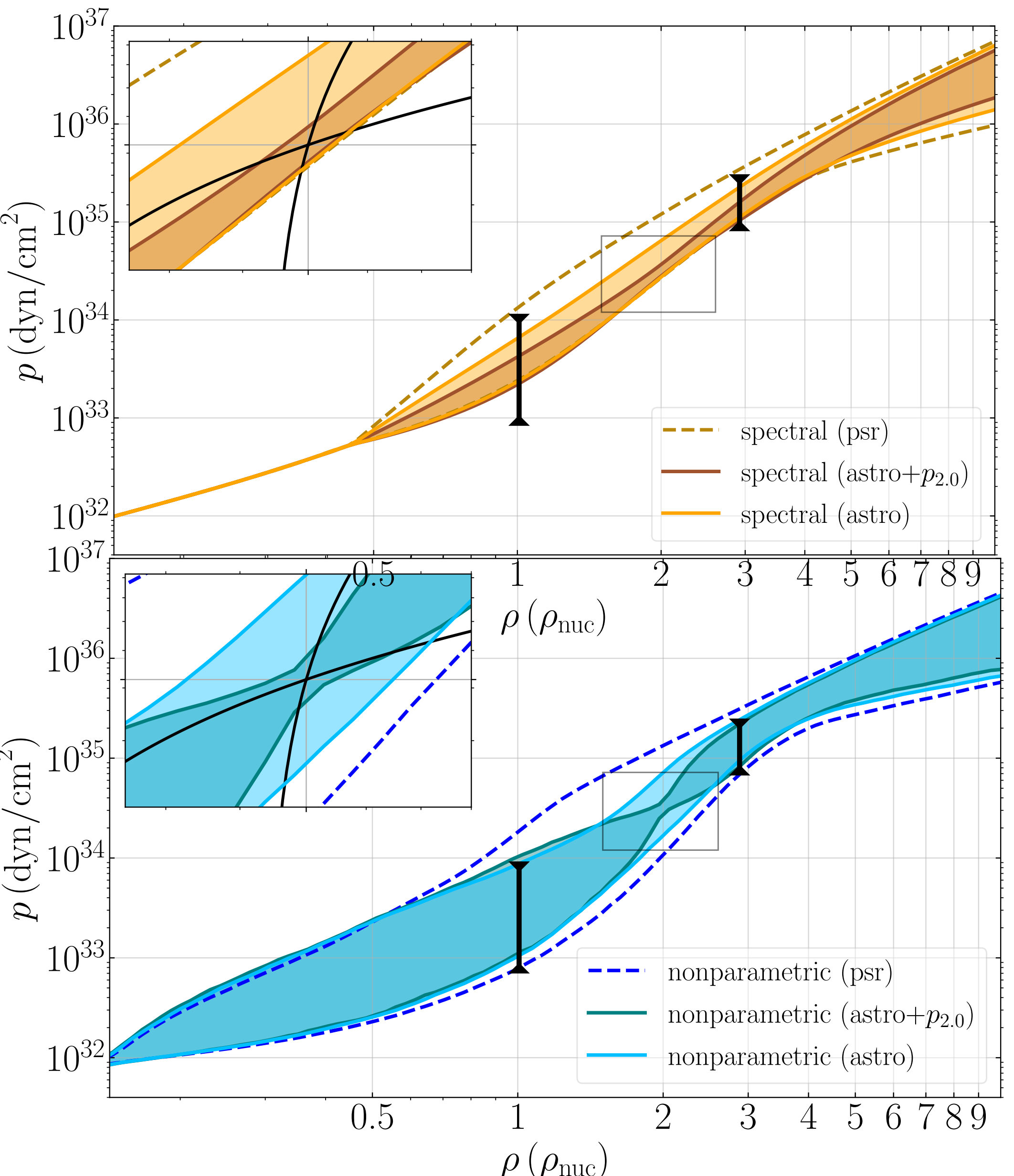


Scales with overall uncertainty of marginal distributions

Want to keep I small even with large entropy in Marginal distributions $P(p_a), \dots$

Implicit Correlations

IL+ 2022



$$I(p_a, p_b) = \int dp_a P(p_a) \int dp_b P(p_b | p_a) \ln \left(\frac{P(p_b | p_a)}{P(p_b)} \right)$$

↓ Caveats!

Scales with overall uncertainty of marginal distributions

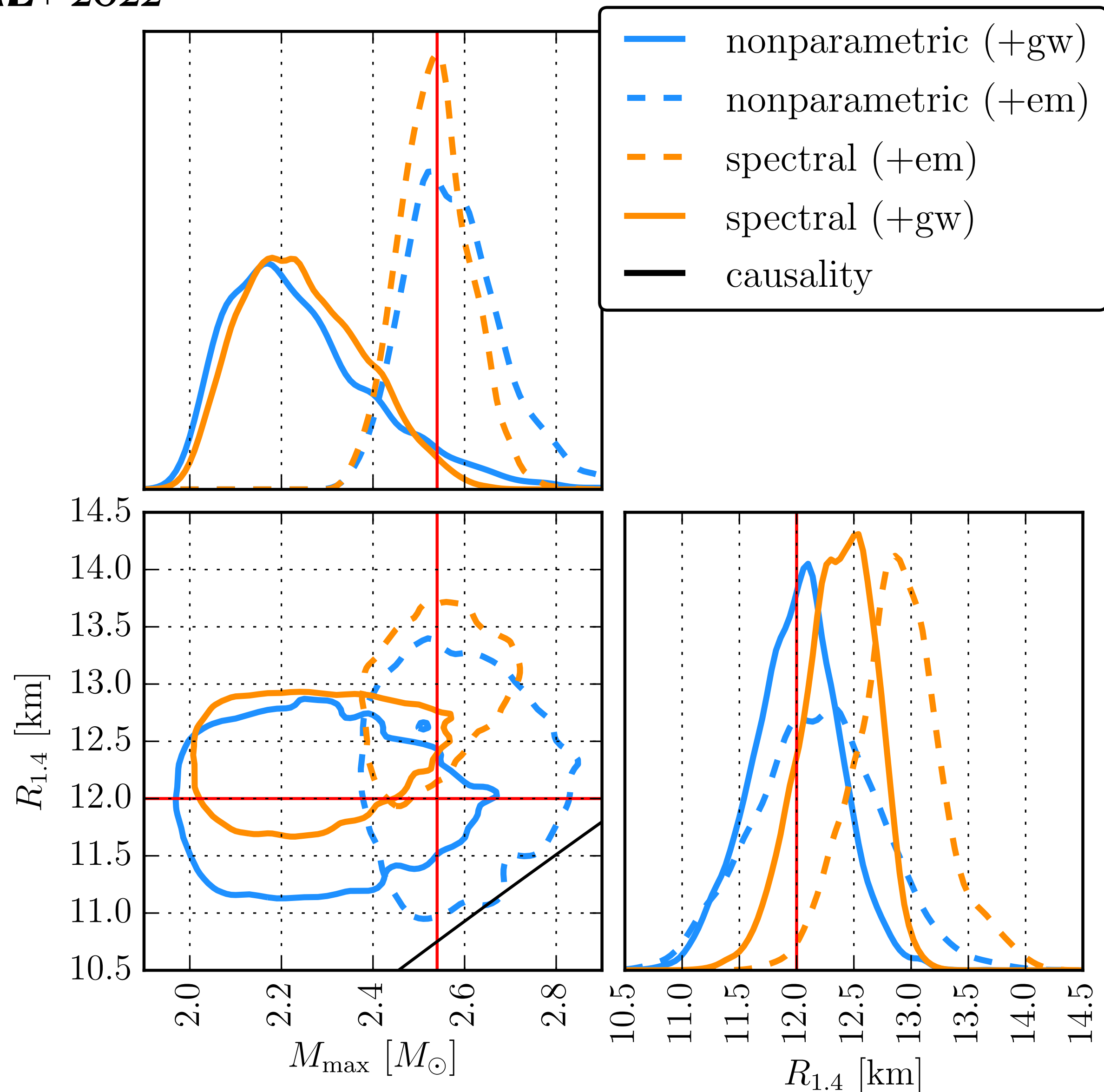
Want to keep I small even with large entropy in Marginal distributions $P(p_a), \dots$

$$I(\ln(p_{1.0}), \ln(p_{1.5}), \ln(p_{2.0}), \ln(p_{3.0}), \ln(p_{4.0}))$$

	PSR	Astro	Astro+p _{2.0}
Nonparametric	3.7	3.1	2.9
Spectral	6.6	5.5	4.7
Polytrope	5.7	4.6	3.8
Speed of sound	5.0	4.7	4.3

Simulated Astrophysical Data

IL+ 2022

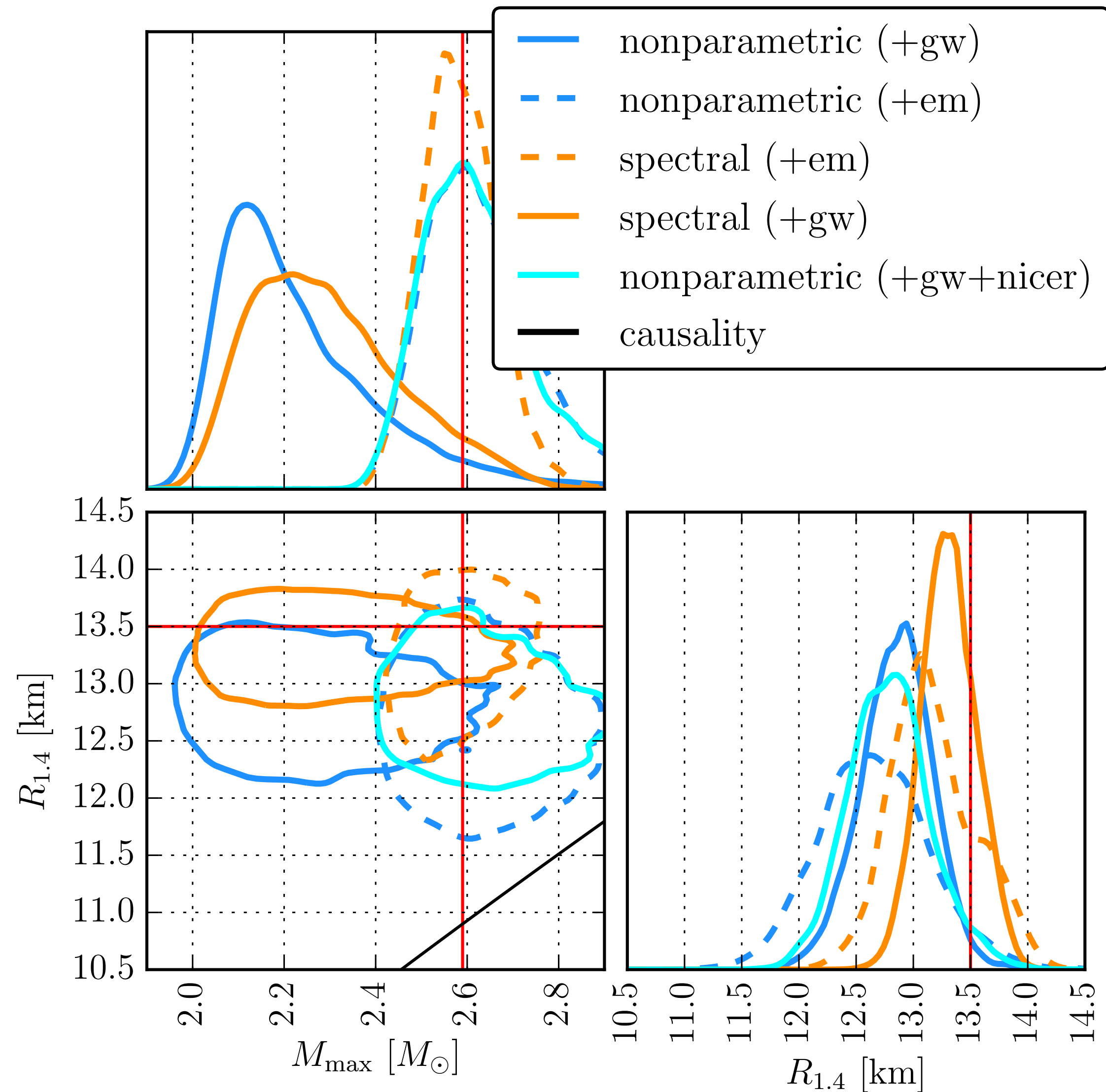


We inject gravitational-wave (gw) and x-ray-radio (em) observations on top of existing constraints

We intentionally choose an **EoS** that we expect the **Spectral** model to fail to recover

Gives a sense of tension that may arise from combining constraints using models with unphysical correlations

Simulated Astrophysical Data



We inject gravitational-wave (gw) and x-ray-radio (em) observations on top of existing constraints

Inverse Problem : Spectral Eos \rightarrow NP analysis

Slow convergence, but no bias

Modified parametric priors

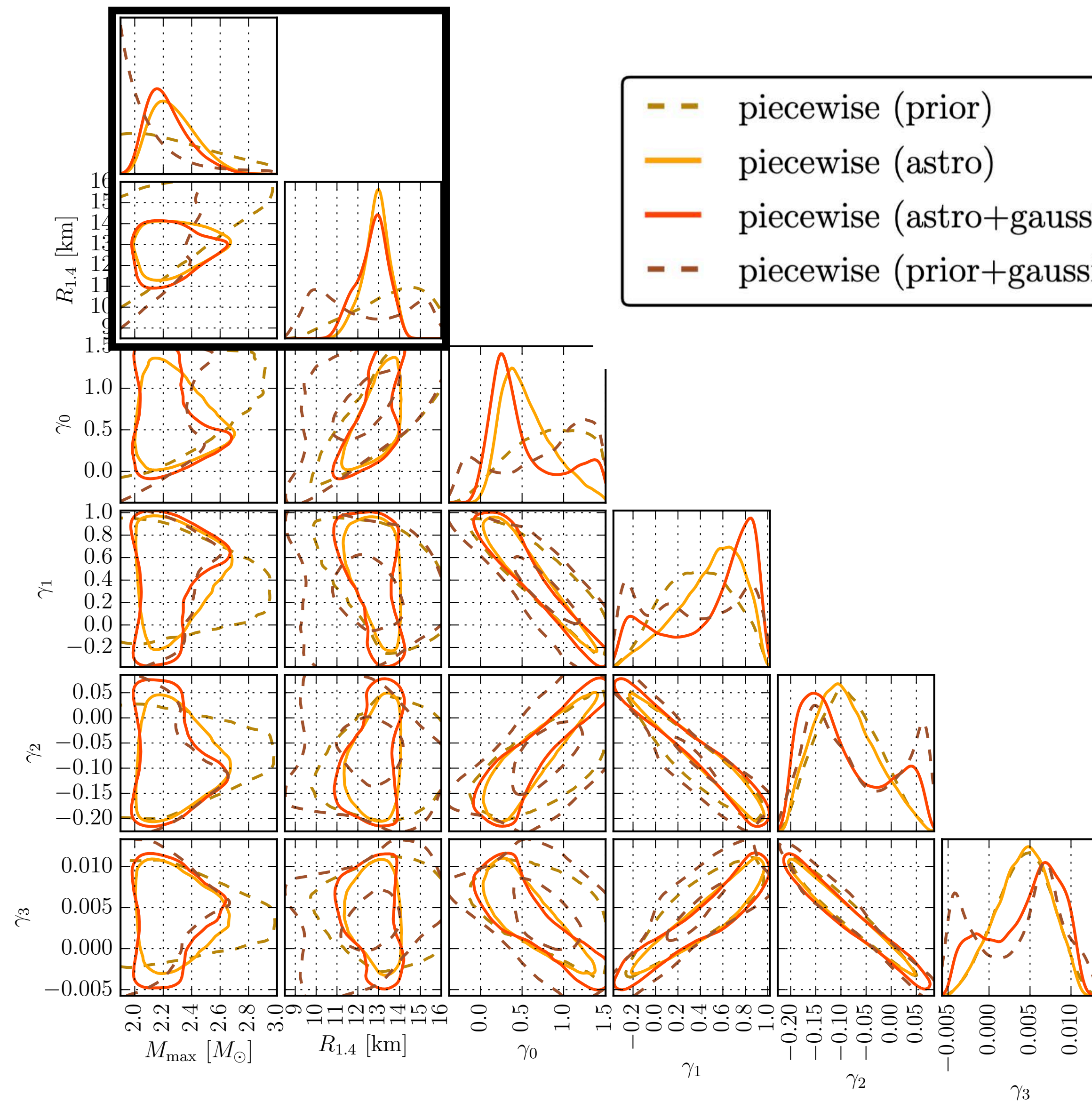
Why not just modify the parametric models to get more flexibility?

E.g.

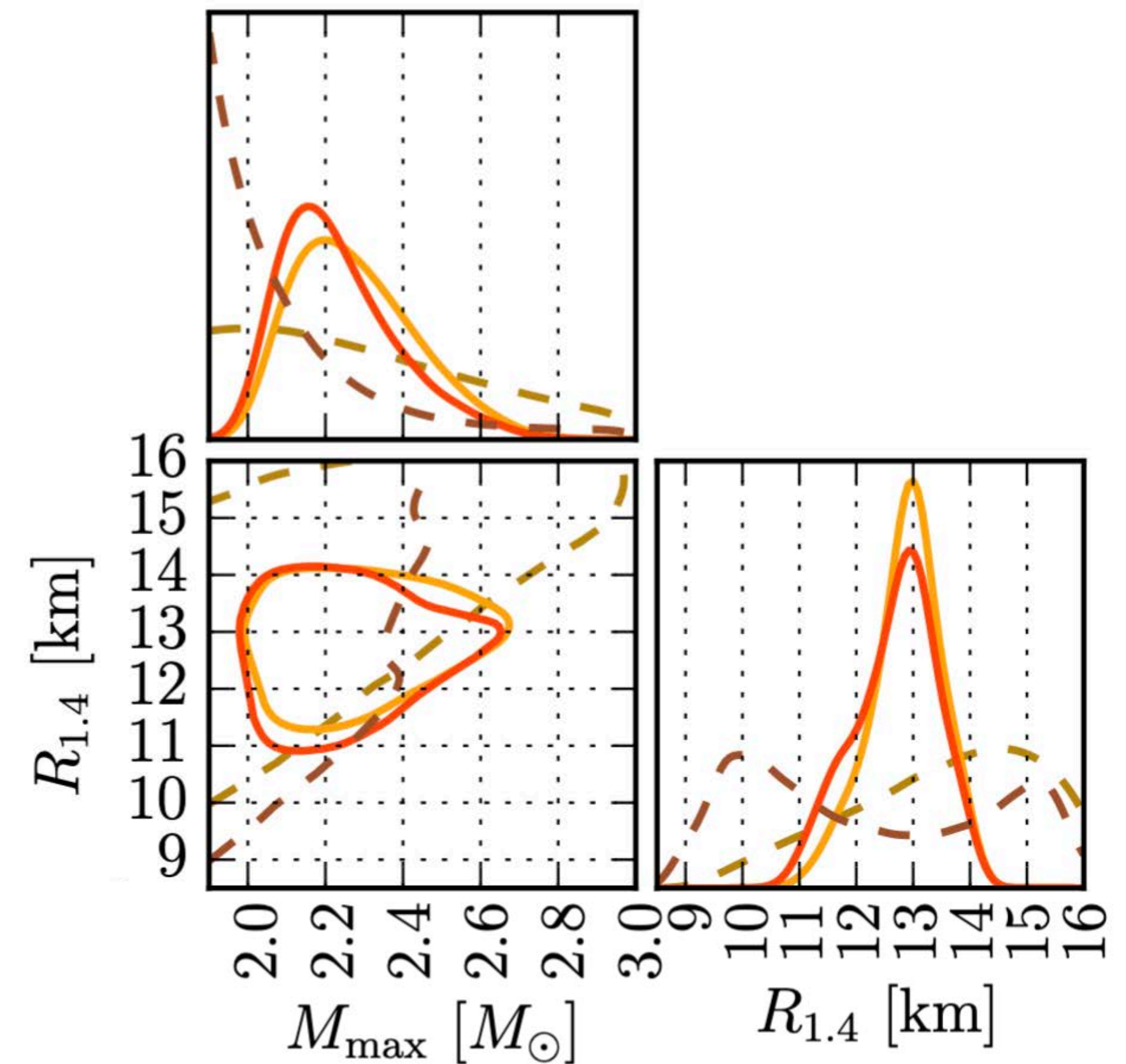
$$p(\rho) = \rho^\Gamma; \quad \Gamma(p) = \sum_{i=0}^3 \gamma_i \log(p/p_0)^i + \text{more terms}$$

Modified parametric priors

IL+ 2022

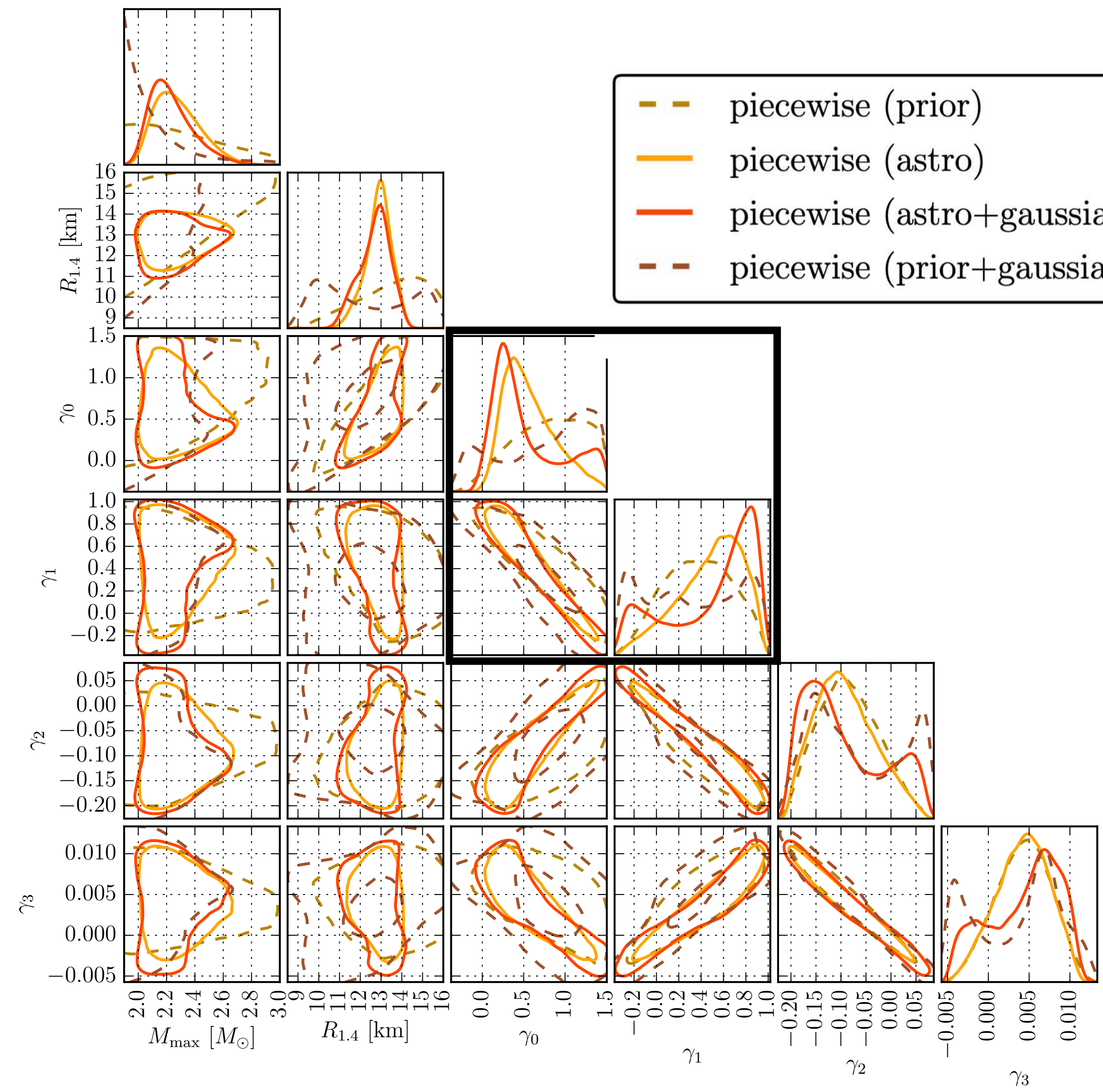


We find changing the
Prior on parameters doesn't
Remove the correlations



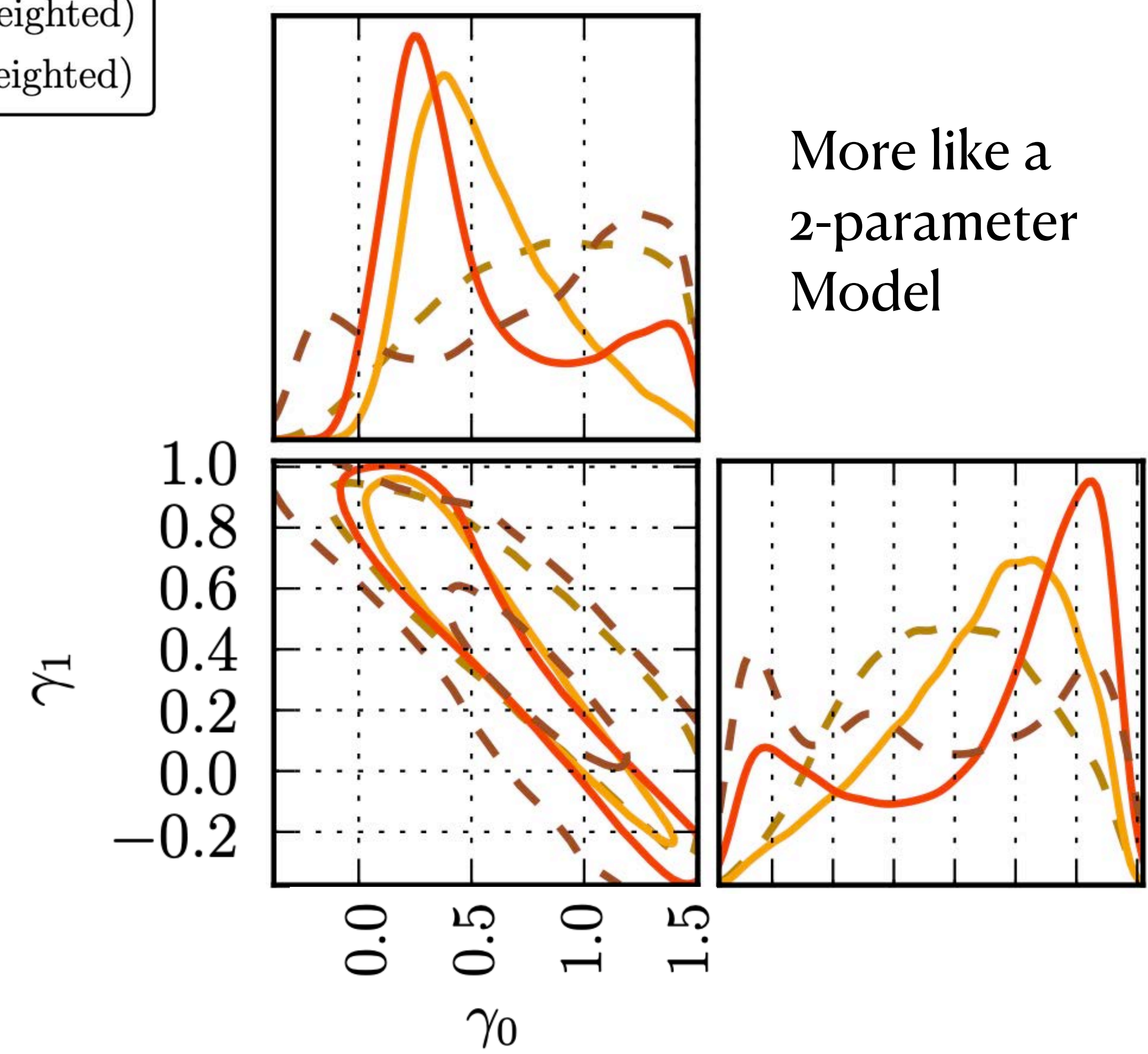
IL+ 2022

Modified parametric priors



- - - piecewise (prior)
 — piecewise (astro)
 — piecewise (astro+gaussian-reweighted)
 - - - piecewise (prior+gaussian-reweighted)

With the current data we only Really only infer γ_0 & γ_1



More like a 2-parameter Model

Modified parametric priors

Why not just modify the parametric models to get more flexibility?

Models are either

- (1) fine-tuned => extending them without breaking is difficult (spectral + speed of sound)
- (2) Need overhaul-type improvements (piecewise-polytrope + speed of sound)

This is already being done!

i.e. Steiner+ 2016 -> better piecewise-polytrope models

But... Extensions are nontrivial.

Best to understand limitations of each model while using it

Not all Correlations are Bad!

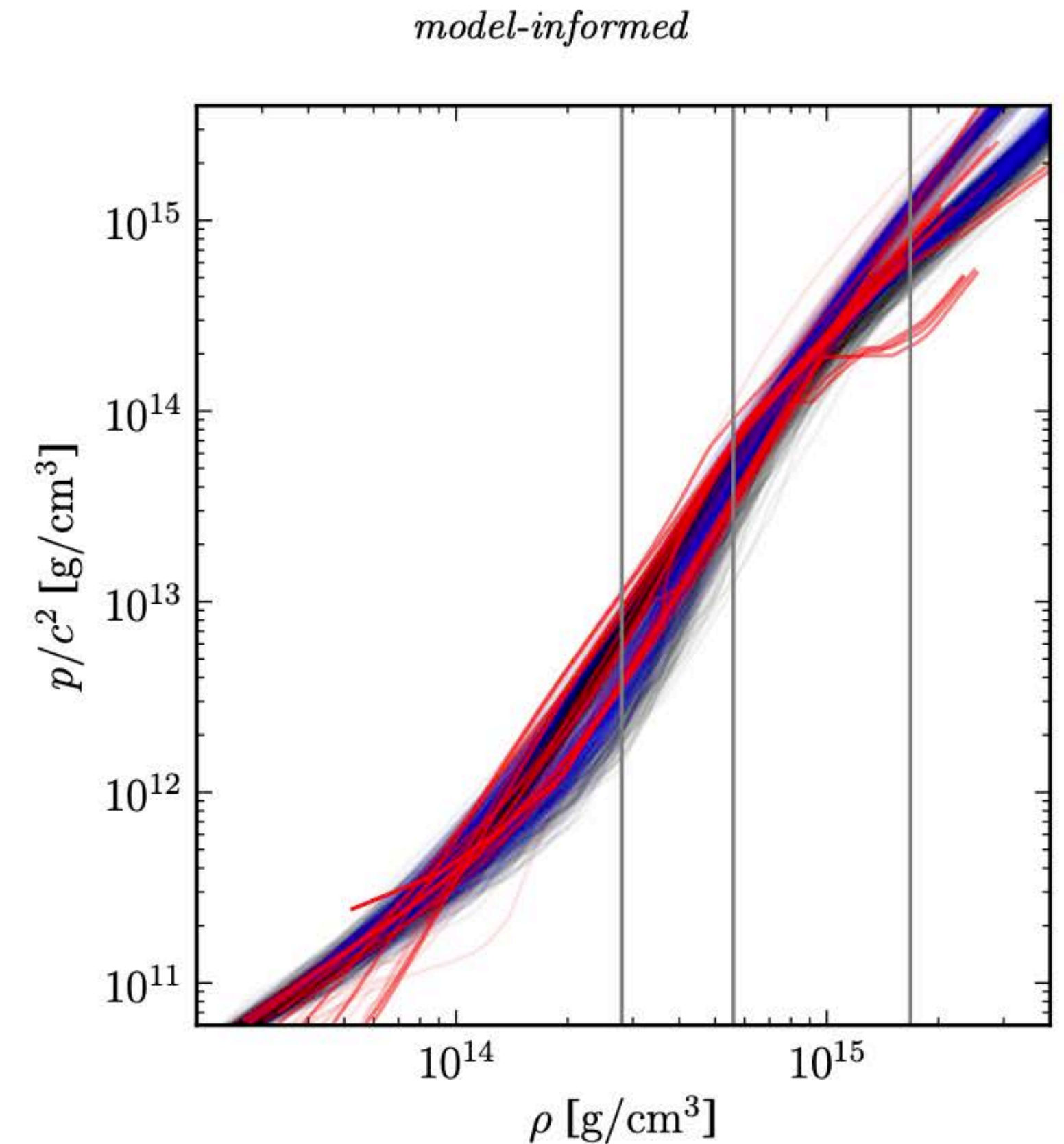
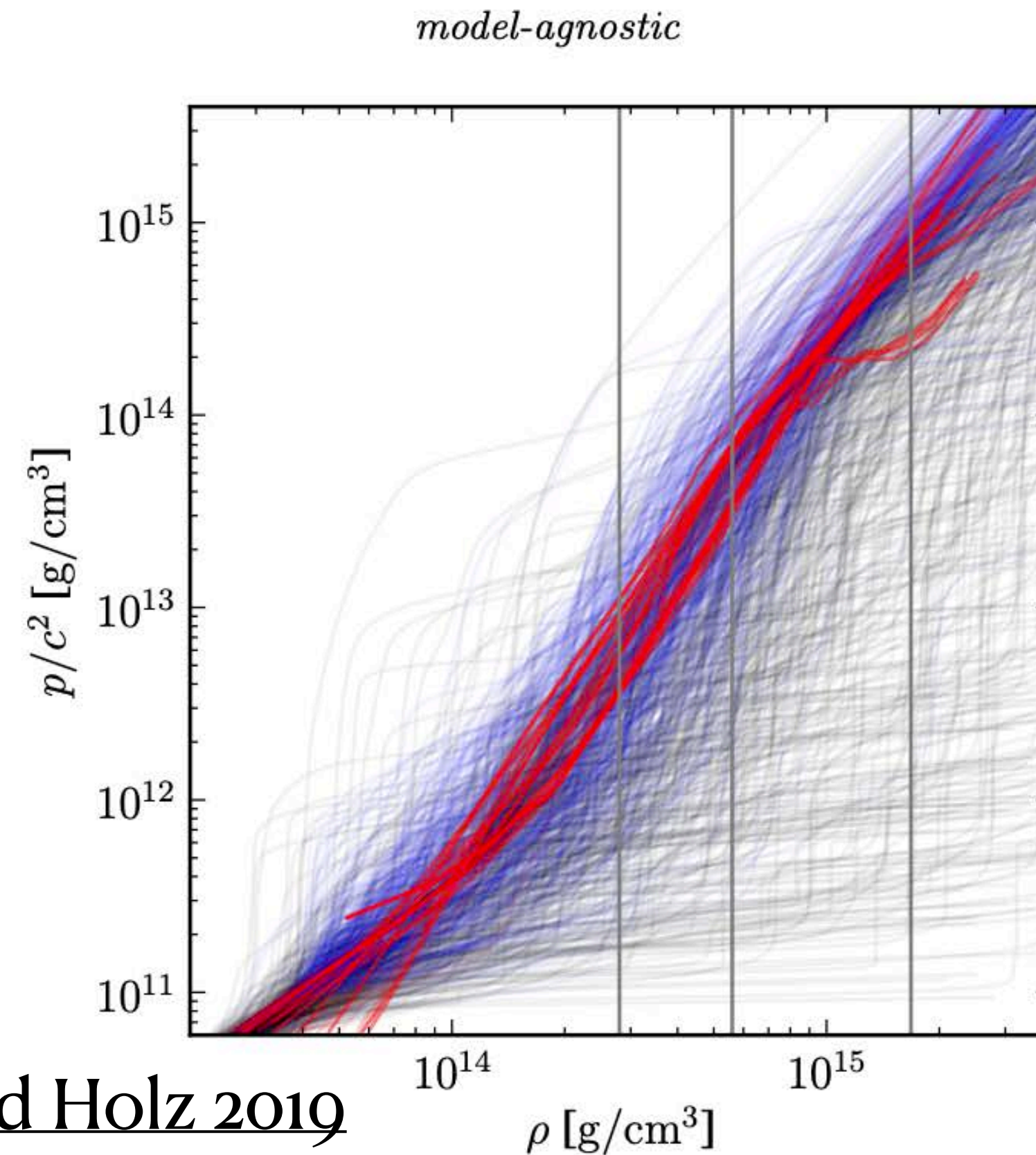
Physical theories have correlations between quantities “ $F=ma$ ”

Correlated

Goal is to give flexibility in the choice of correlations

See e.g. Miller+2021 : GP with
“tight” correlations

Eventually one should *infer* the
correlations



Essick, Landry, and Holz 2019

Conclusions

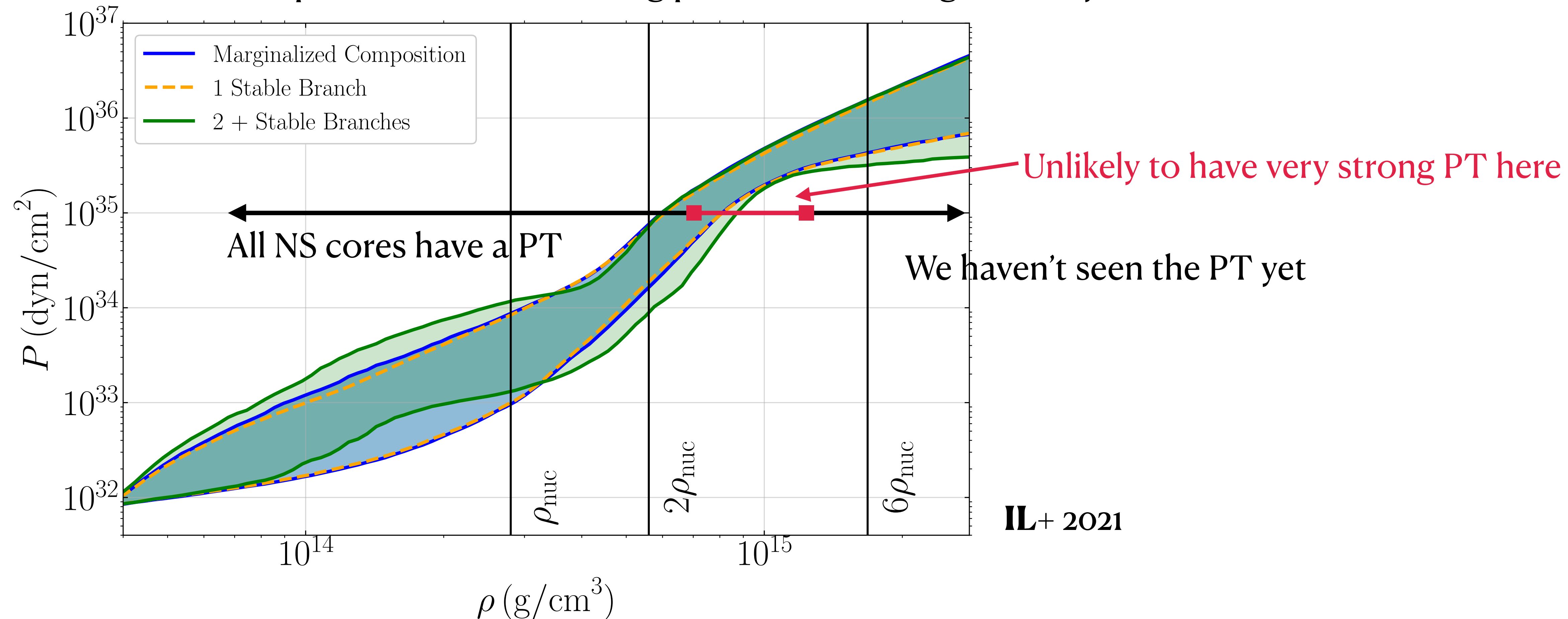
- Phenomenological models of the nuclear equation of state can build in (often hidden) correlations due to the functional form of the EoS
- Nonparametric models (such as the Gaussian Process model), can provide more flexibility in inference of the EoS (but do not guarantee it)
- These correlations affect both astrophysical inference and inference of properties of dense matter

(Backup) : Strong Phase Transitions

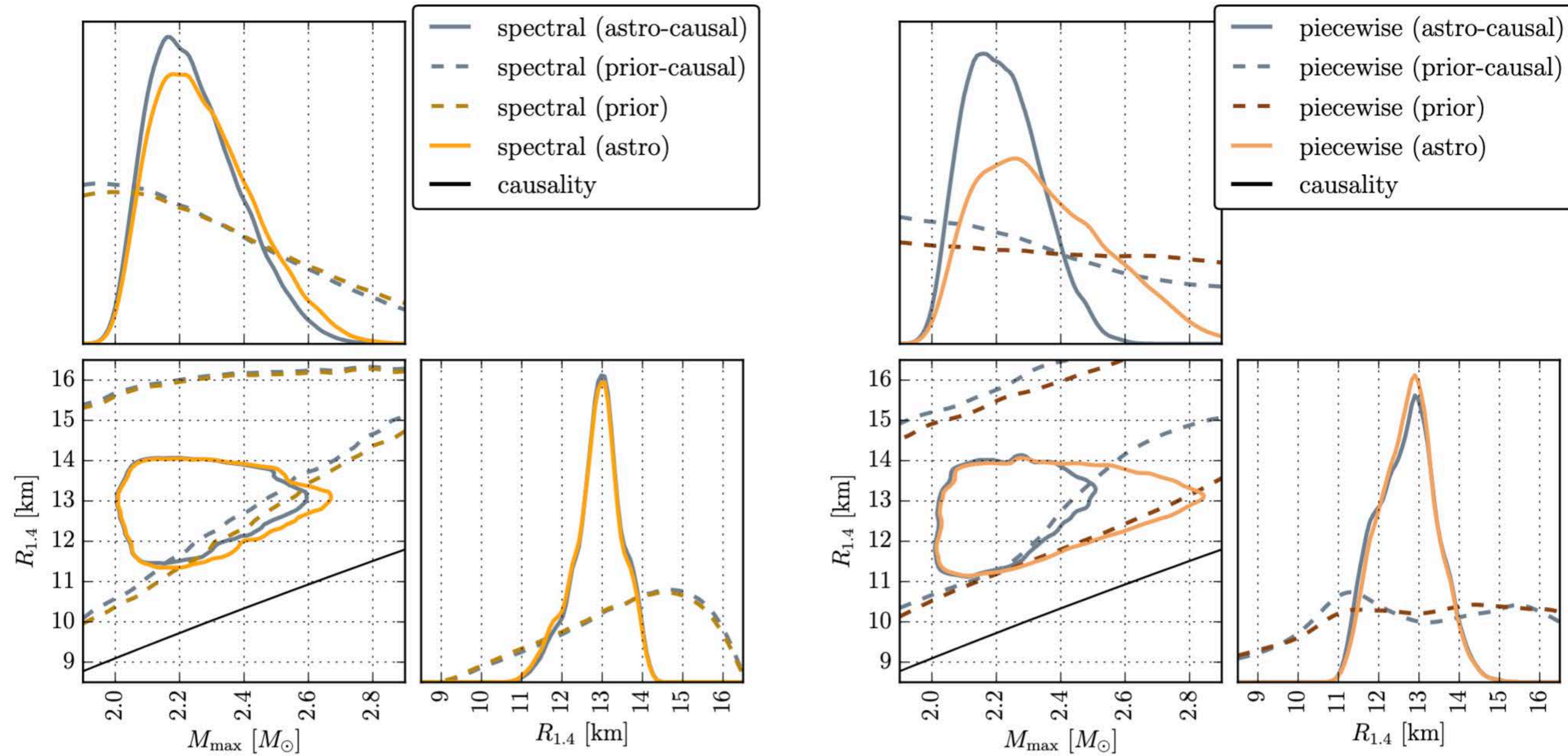
Parametric models struggle to model phase transitions

Piecewise-polytope models with variable stitching densities may be able to -> need fine tuning

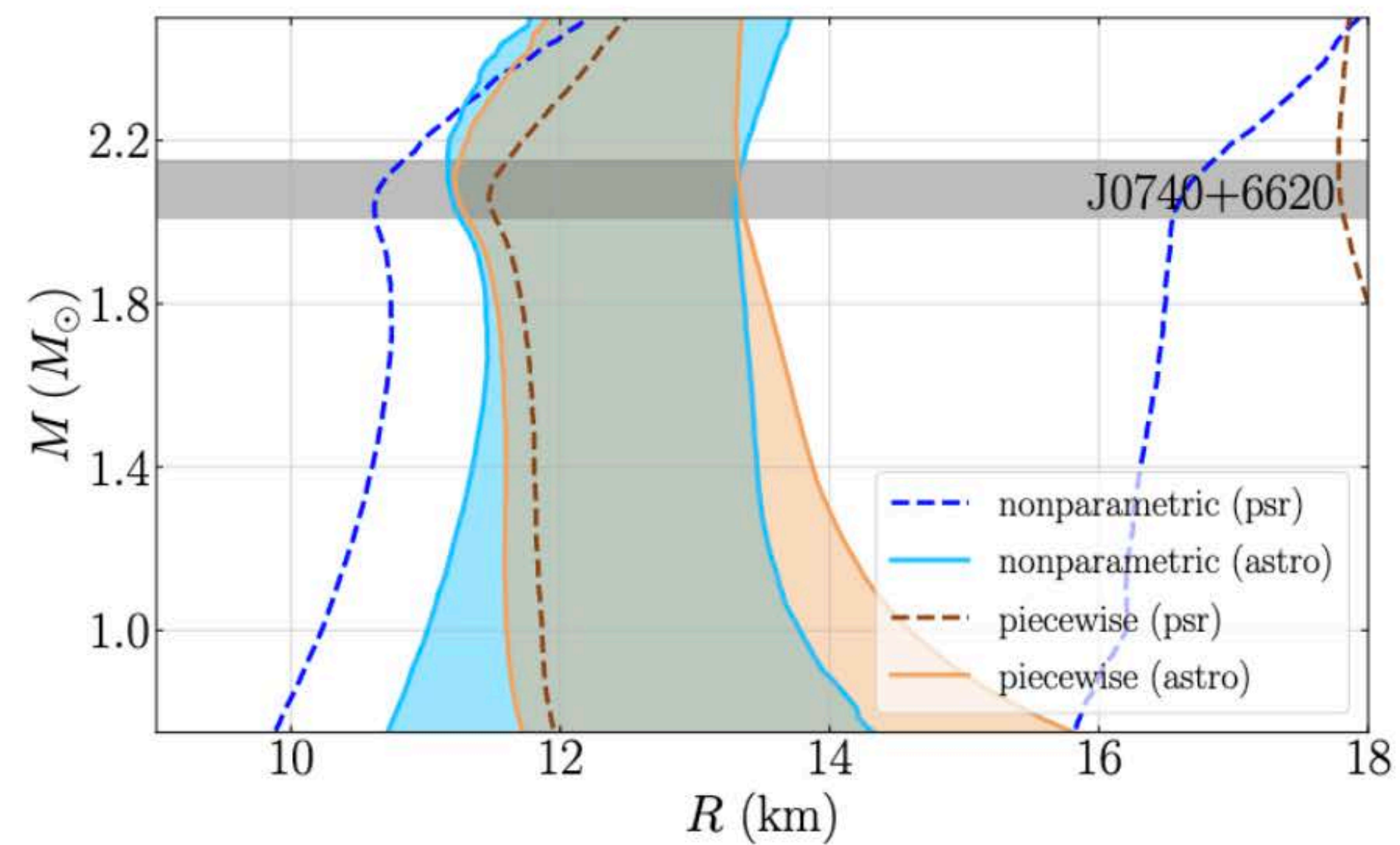
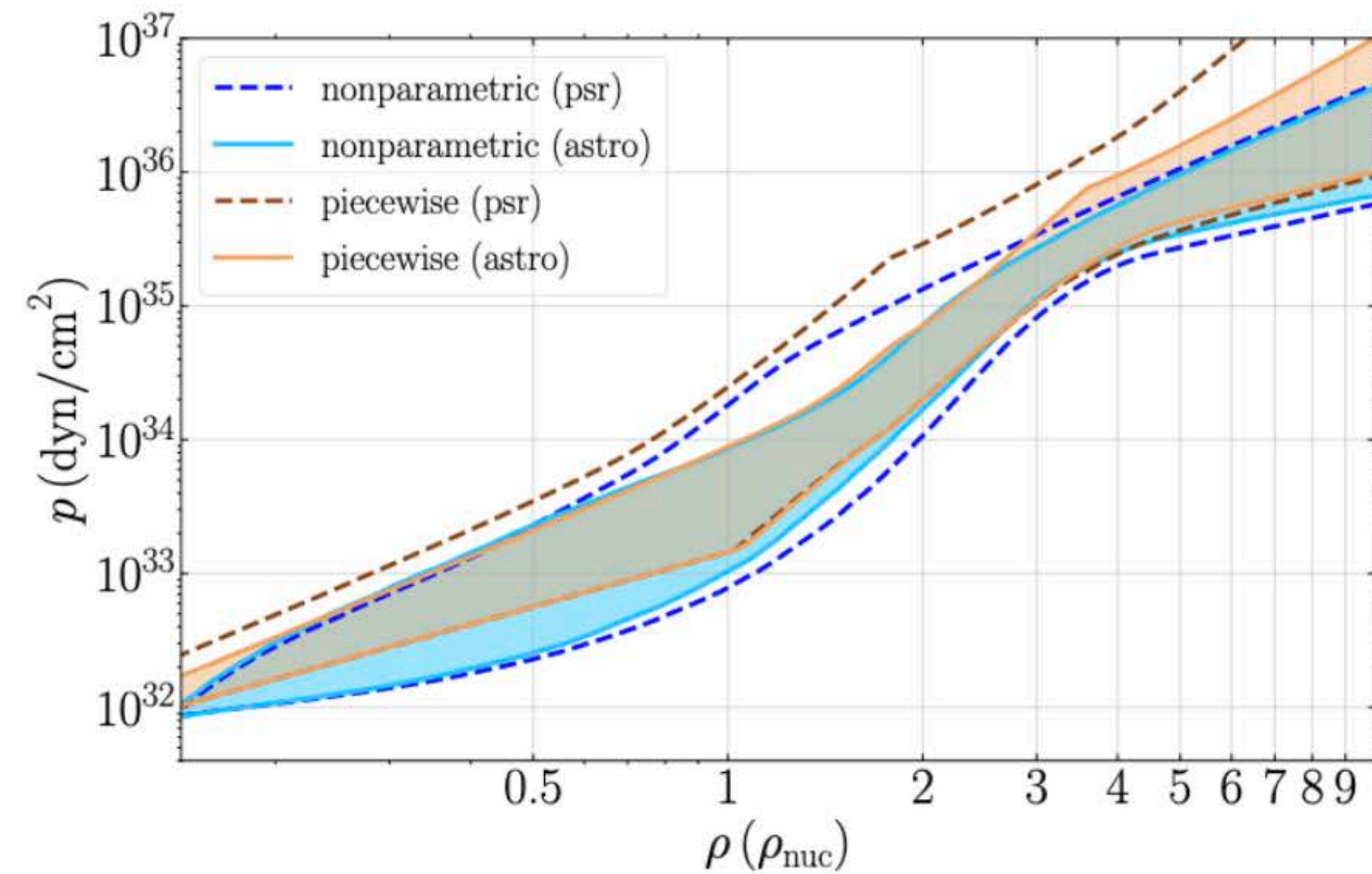
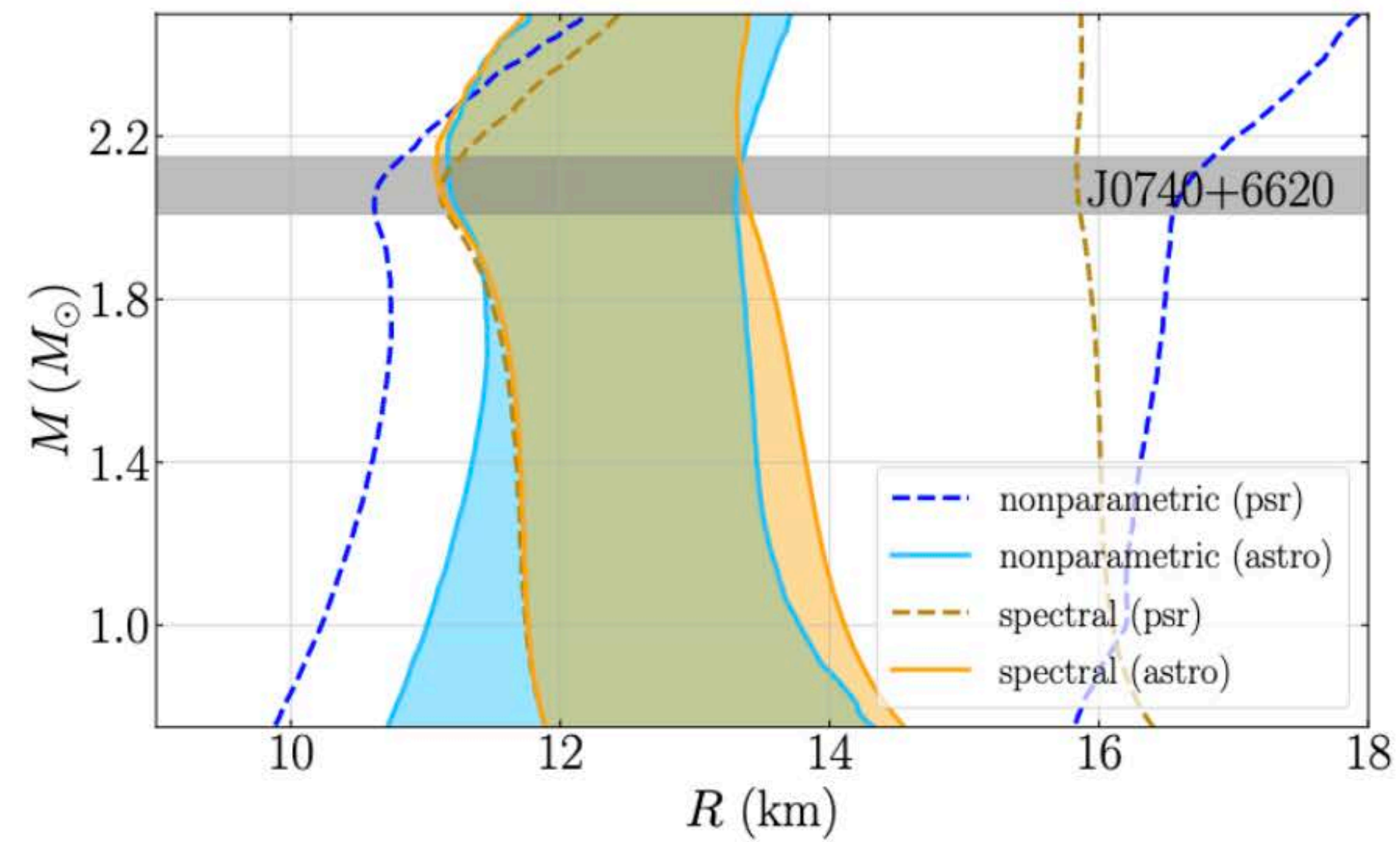
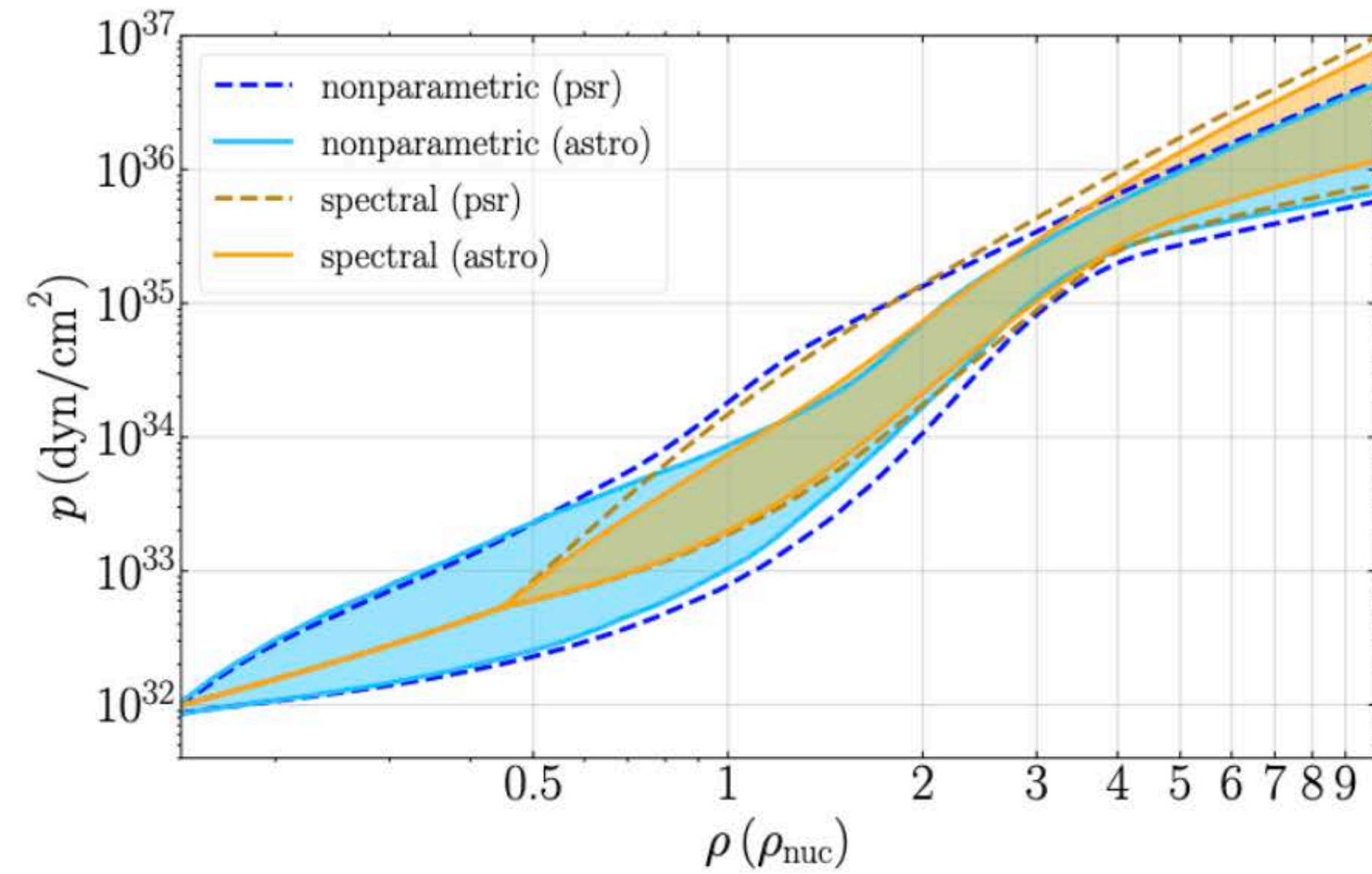
The GP model can produce EoSs mimicking phase transitions generically



(Backup): Causality in Parametric Models



(Backup): More Parametric Results



PRIOR

PSR+GW+J0030

PSR+GW+J0030+J0740

(Backup): Corner Plot