Constraints on neutron star radii and tidal deformabilities from qLMXBs and LIGO

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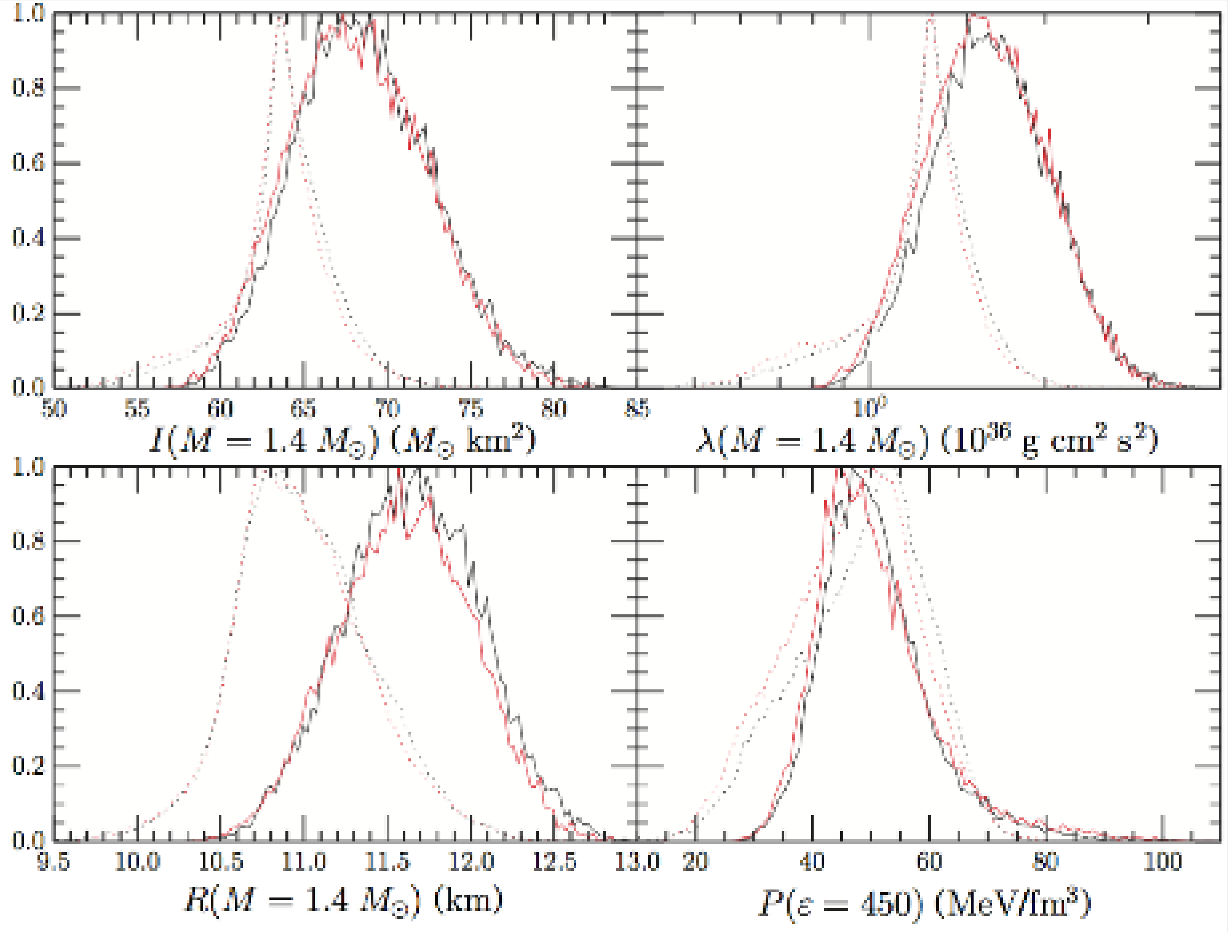
Work in this talk completed in collaboration with: Arash Bahramian, **Spencer Beloin**, Slavko Bogdanov, **Xingfu Du**, Farrukh Fattoyev, Stefano Gandolfi, **Sophia Han**, Craig Heinke, Wynn C. G. Ho, Jeremy W. Holt, Chengkui Li and Will Newton.

Outline

- LIGO and tidal deformability
- EOS of dense matter
- From EOS to composition through NS cooling
- Bayesian Inference + Differential Geometry

2015: Predictions for LIGO

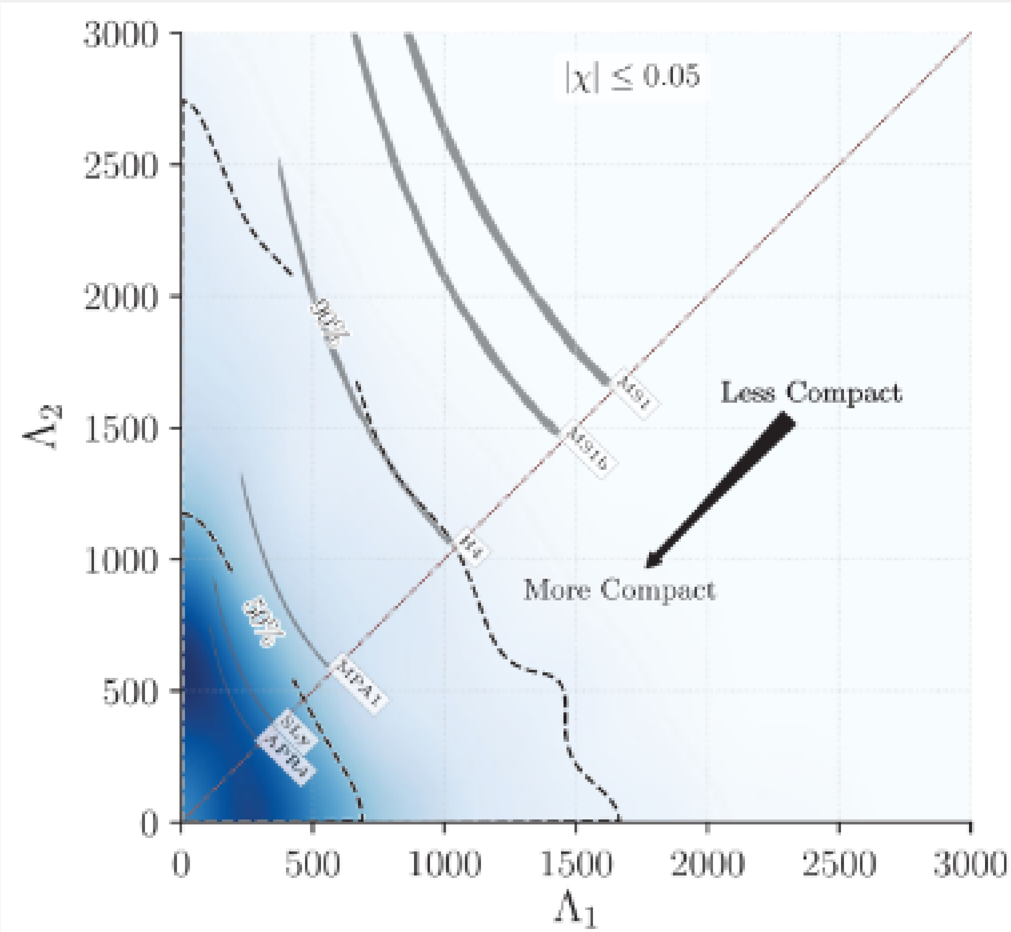
- Use X-ray data to compute I and λ



Steiner, Gandolfi, Fattoyev, Newton (2015)

- Transforming to a dimensionless version Λ, the upper limit in these predictions is about $\Lambda \sim 1000$

LIGO Result and the GW 170817 Merger

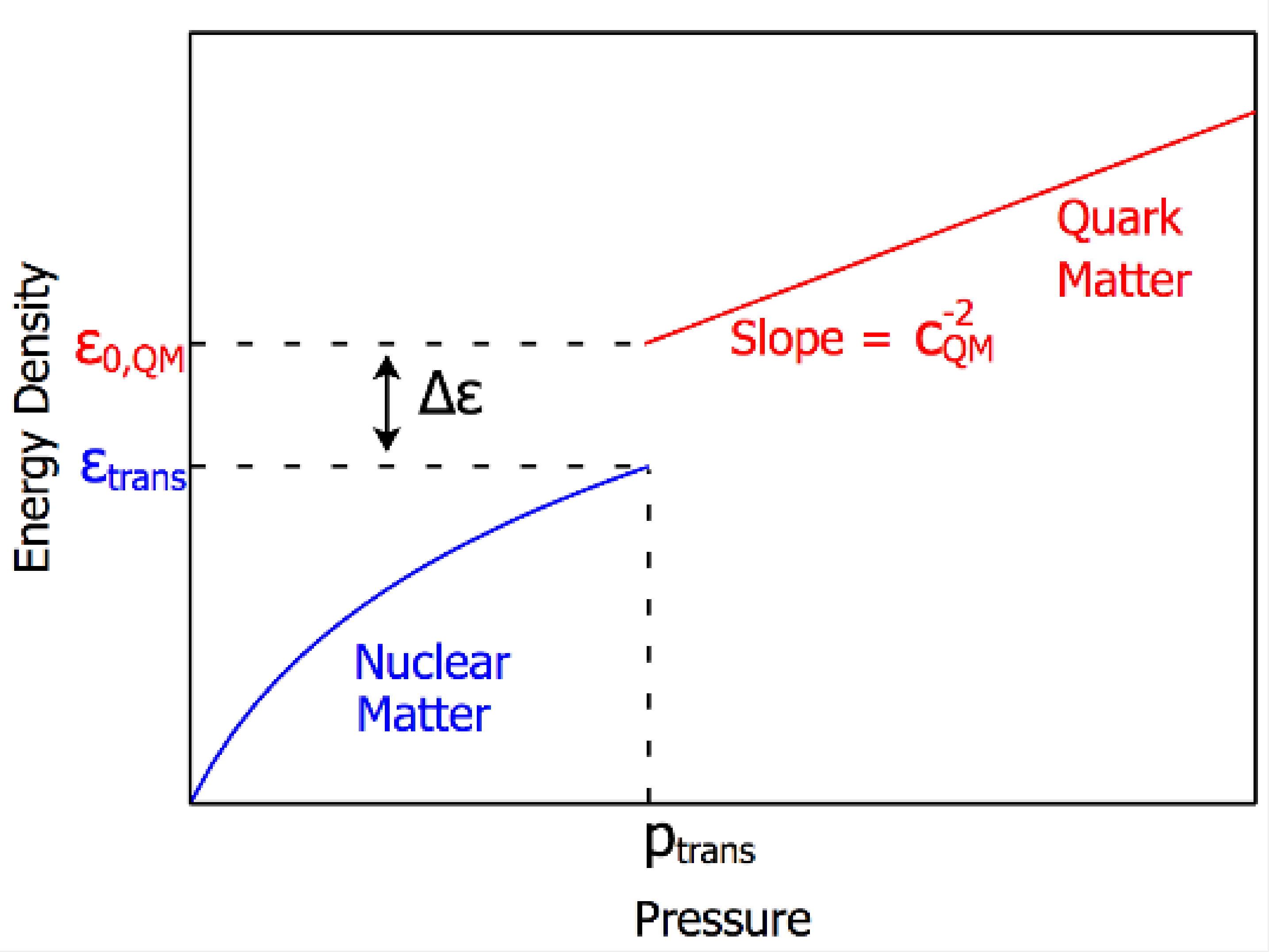


A 95% upper bound inferred with the low-spin prior, $\Lambda(1.4M_{\odot}) \leq 970$, begins to compete with the 95% upper bound of 1000 derived from x-ray observations in [168].

Abbott et al. (2017) citing Steiner, Gandolfi, Fattoyev, Newton (2015)

- Glass half full interpretation: LIGO confirmed our prediction
- Glass even more half full interpretation: **Gravitational wave detectors may eventually be better at measuring neutron star radii than X-ray satellites**

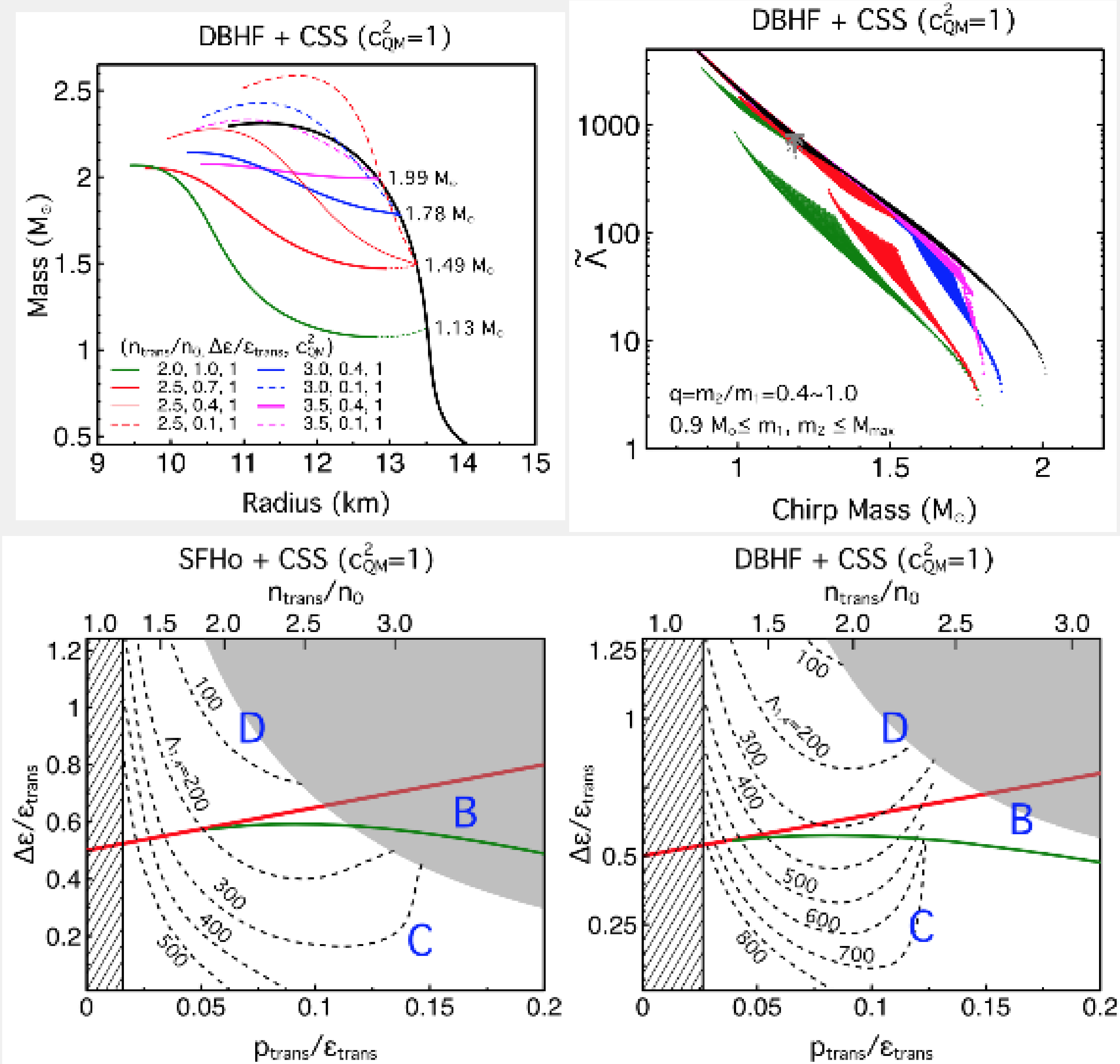
Constant Speed of Sound EOS



Alford, Han, and Prakash (2013)

- Three parameters: $\Delta\varepsilon$, $n_{\rm trans}$, $c^2_{s,\rm QM}$

Mapping out Λ space (Han et al. in prep)



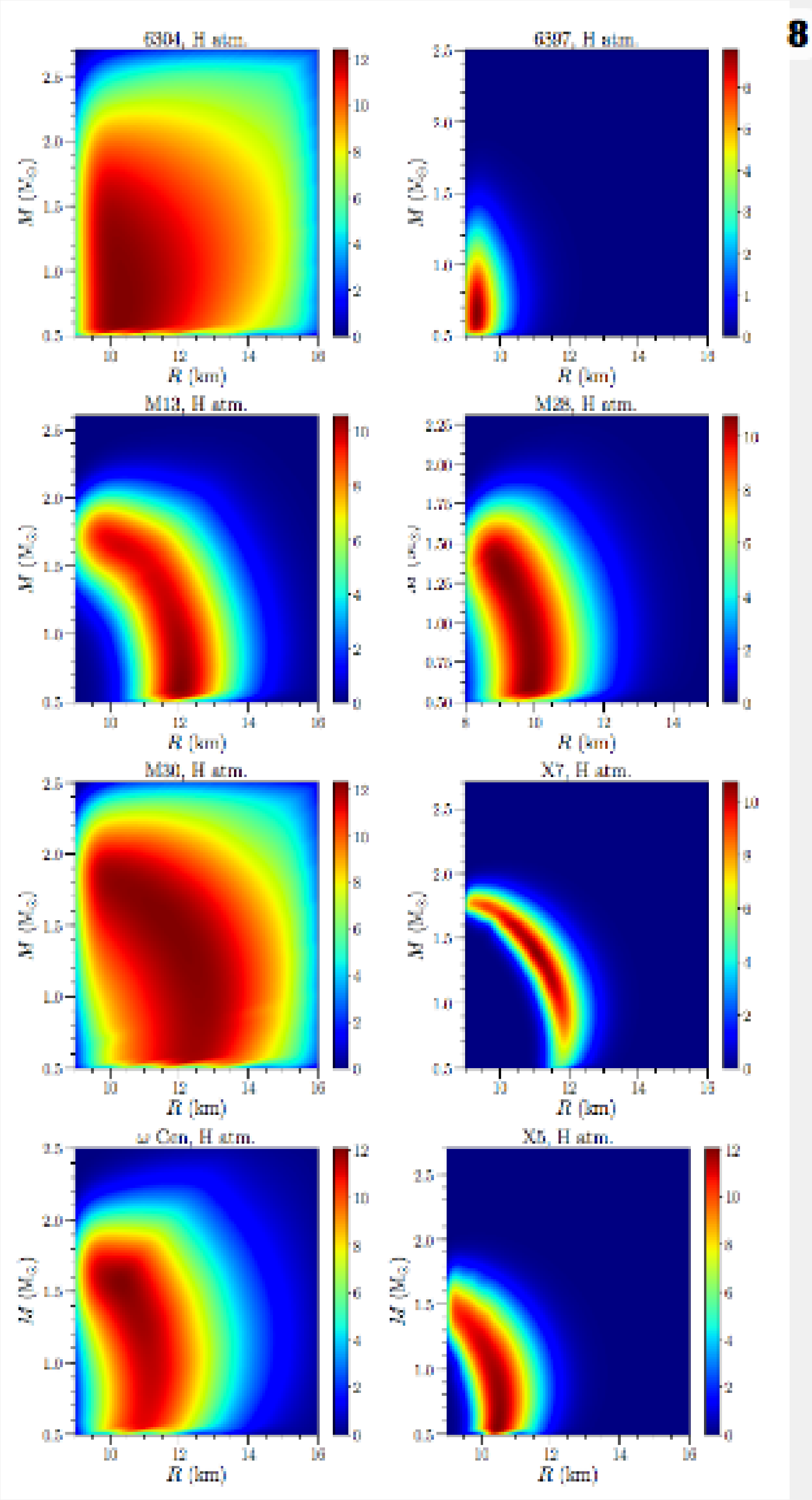
Quiescent Low-mass X-ray Binaries

- Blackbody-like spectrum of X-rays

$$F = (\sim 1) \times T_{\rm eff}^4 \left(\frac{R_\infty}{D} \right)^2$$

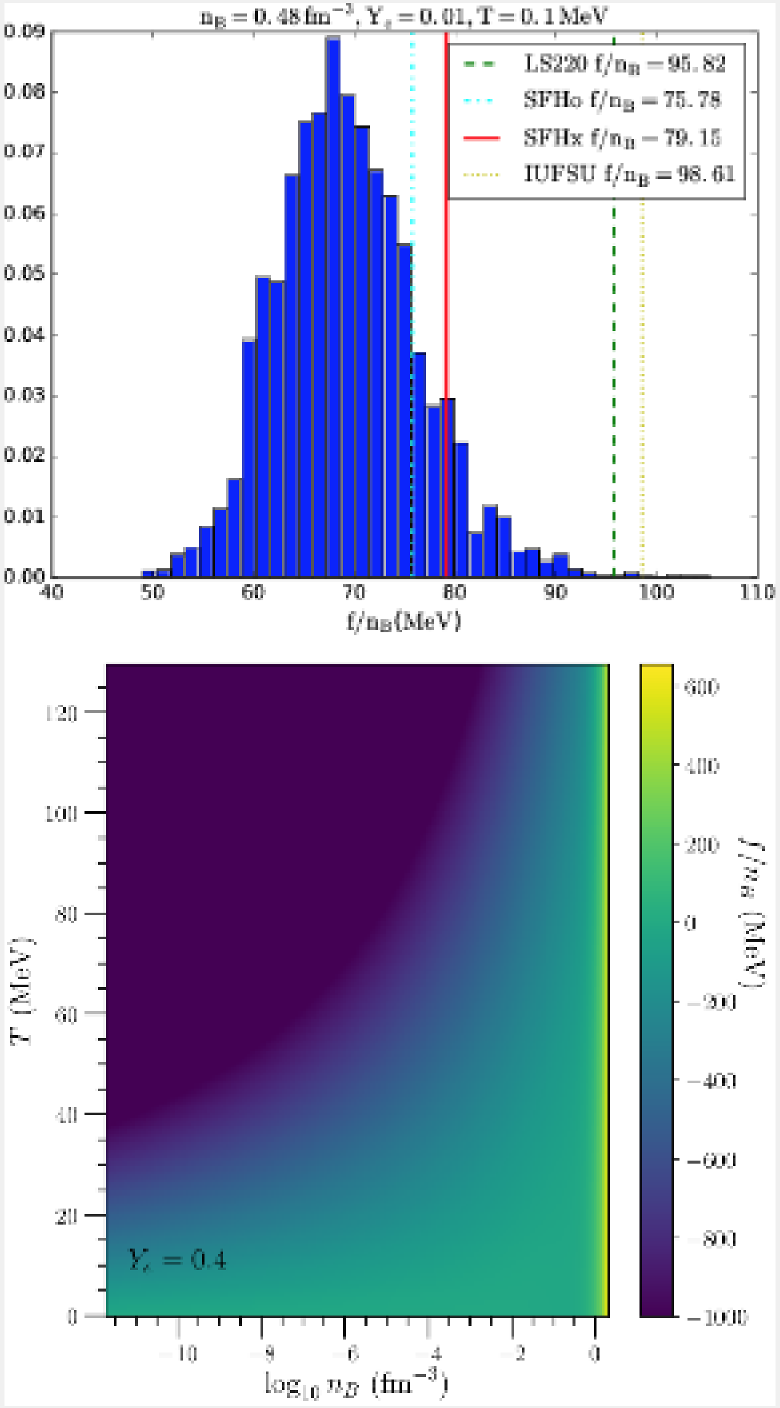
e.g. Rutledge et al. (1999)

- Tackling systematic uncertainties is an important priority for us:
  - Distance uncertainty
  - X-ray absorption
  - Atmosphere composition, H or He
  - Uneven temperature distribution
  - Phase transitions at high density
  - Neutron star maximum mass
  - X5 is an eclipsing binary
- Some evidence for $R_{1.4} < 12$ km



Steiner et al. (2018)

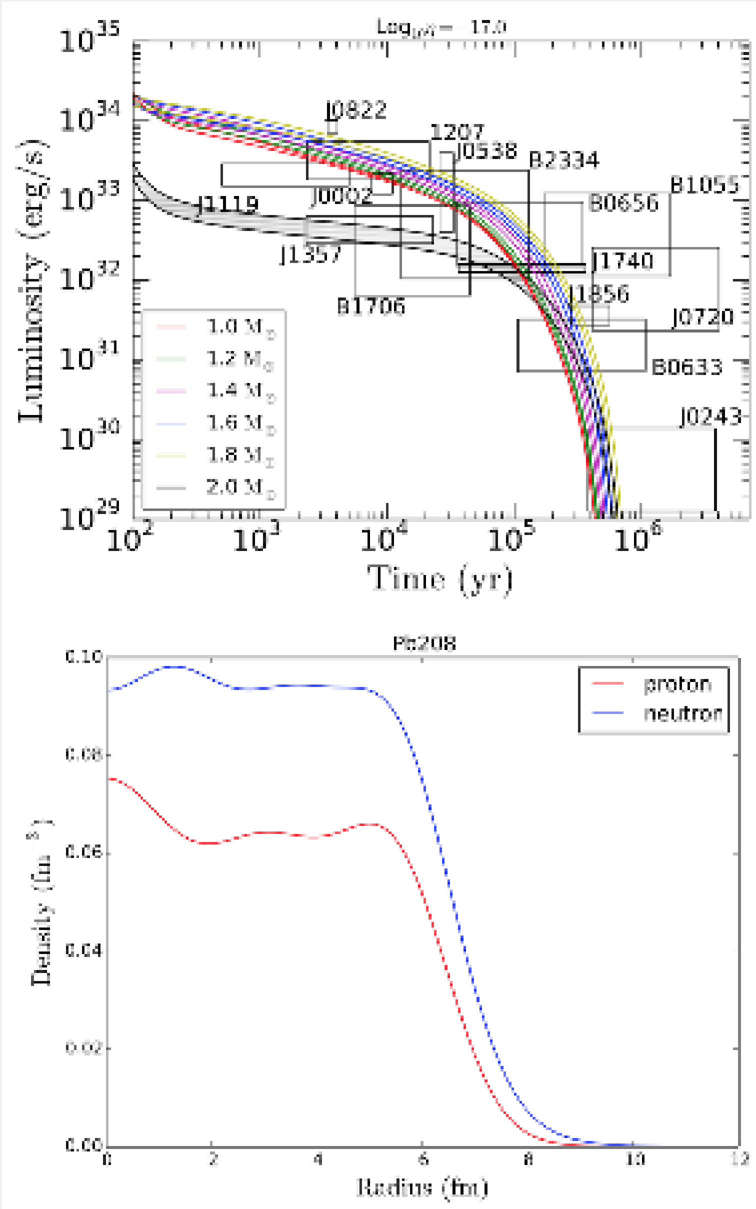
Merger simulations need good nuclear physics input

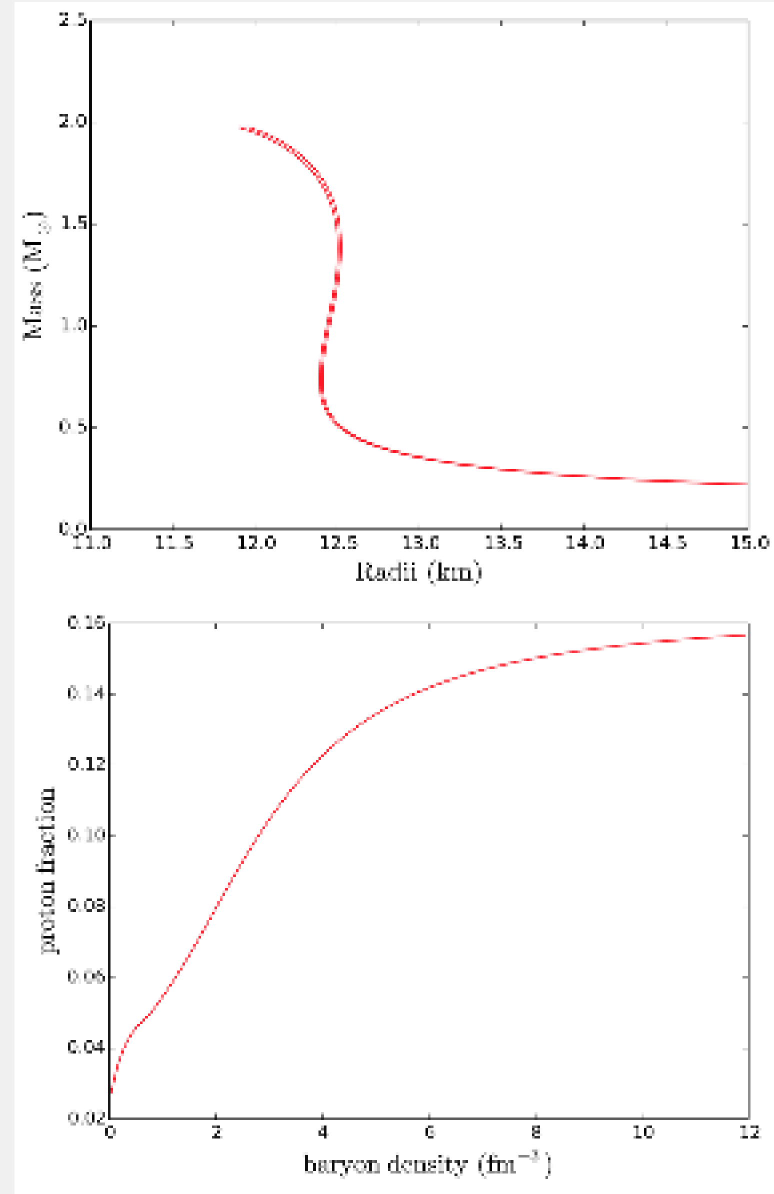


Du, Steiner, and Holt (2018)

- New phenomenological EOS for homogeneous nucleonic matter (no nuclei) for simulations [full (n_B, Y_e, T) space] with uncertainty quantification
- Match:
  - Virial expansion in low-density limit
  - Nuclear masses and charge radii near saturation
  - QMC results on neutron matter
  - Chiral interaction + Kohn-Luttinger-Ward series for finite-temperature corrections
  - Neutron star observations for high densities
- Causality correction from Constantinos and Prakash
- Thousands of new EOSs

Large Scale Inference for Composition





Beloin, Han, and Steiner (in prep.)

- Use one model to describe $R(m)$, $T(t)$, and nuclei - 60 parameters
- Completing inference results in in **composition information** in addition to EOS constraints

When Bayesian Inference Needs Differential Geometry

- The analysis of neutron star (M, R) or (T, t) data is a specific case
- Model exists in a lower-dimensional space where the data is in higher-dimensional space
- Requires embedding, e.g. one-dimensional model in two-dimensional data space

$$P(D|M) \propto \int_{c_i(\{p\})} \left\{ \prod_{i=1}^{N} \left[d\lambda_i \left| g_{jk\,i} \frac{dx_i^j}{d\lambda_i} \frac{dx_i^k}{d\lambda_i} \right|^{1/2} \right] \times M_i(\lambda_i) \mathcal{D}[x_i^1(\lambda_i), x_i^2(\lambda_i)] \right\}$$

  where c_i are curves determined by parameters p, λ_i parameterizes the curve, g_{jk} specifies the metric on the 2D space, $M_i(\lambda_i)$ allows the model to depend on the parameterization of the curve and $\mathcal{D}$ is the data or the result of a previous inference

- Easily generalizable to higher dimension embeddings (requires determinant of the metric)

Summary

- Our predictions of neutron star tidal deformabilities are, so far, spot on.
- Mapping out the tidal deformability model space
- Complete as possible with X-ray systematics
- Feeding EOS constraints back into merger simulations
- Going beyond the EOS to determine composition
- Advancing data analysis methods

Outlook

- In the context of Bayesian inference, and aside from our methodological debates (we don't always agree on the right "likelihood")
- It is obvious that we all prefer different prior probabilities
- It is difficult to use posteriors alone, because they already presume all of the prior information
- This difficulty can sometimes be addressed by releasing data and open-source code