

# Joint Bayesian inference of gravitational-wave & NICER data

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**UMass Dartmouth &**

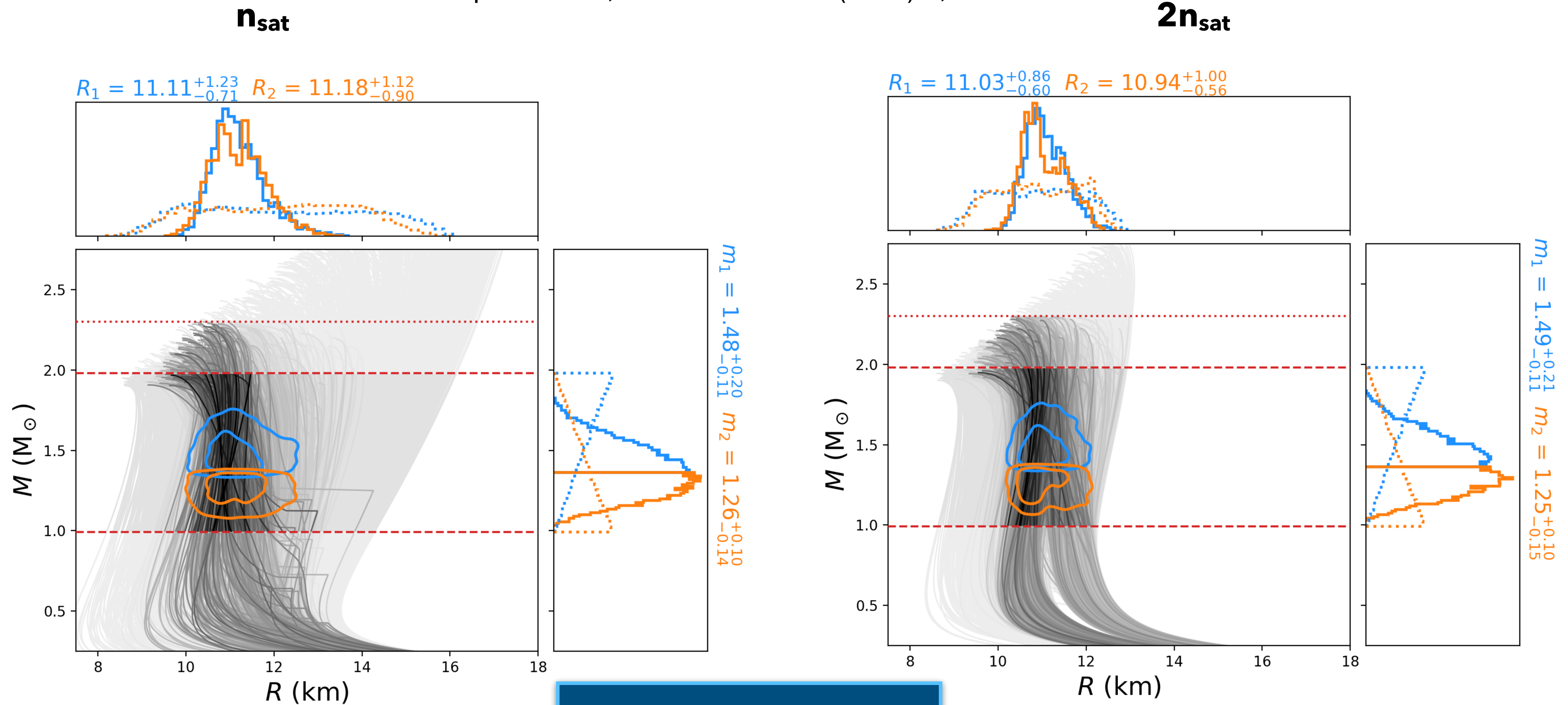
**Max Planck Institute for Gravitational Physics Hannover**

# Overview

- Combining results from NICER and GW data provides best constraints on neutron-star equation of state (EOS)
- NICER results are dependent on hotspot configuration
- Our goal: reanalyze NICER/XMM Newton data jointly with GW data to see if we get a different preferred hotspot configuration & EOS constraint
- Caution: work-in-progress! Today demonstrating proof of concept
- Collaborators: Chaitanya Afle (Syracuse University), Duncan Brown (Syracuse University), Ingo Tews (LANL), Rahul Somasundaram (IPNL)

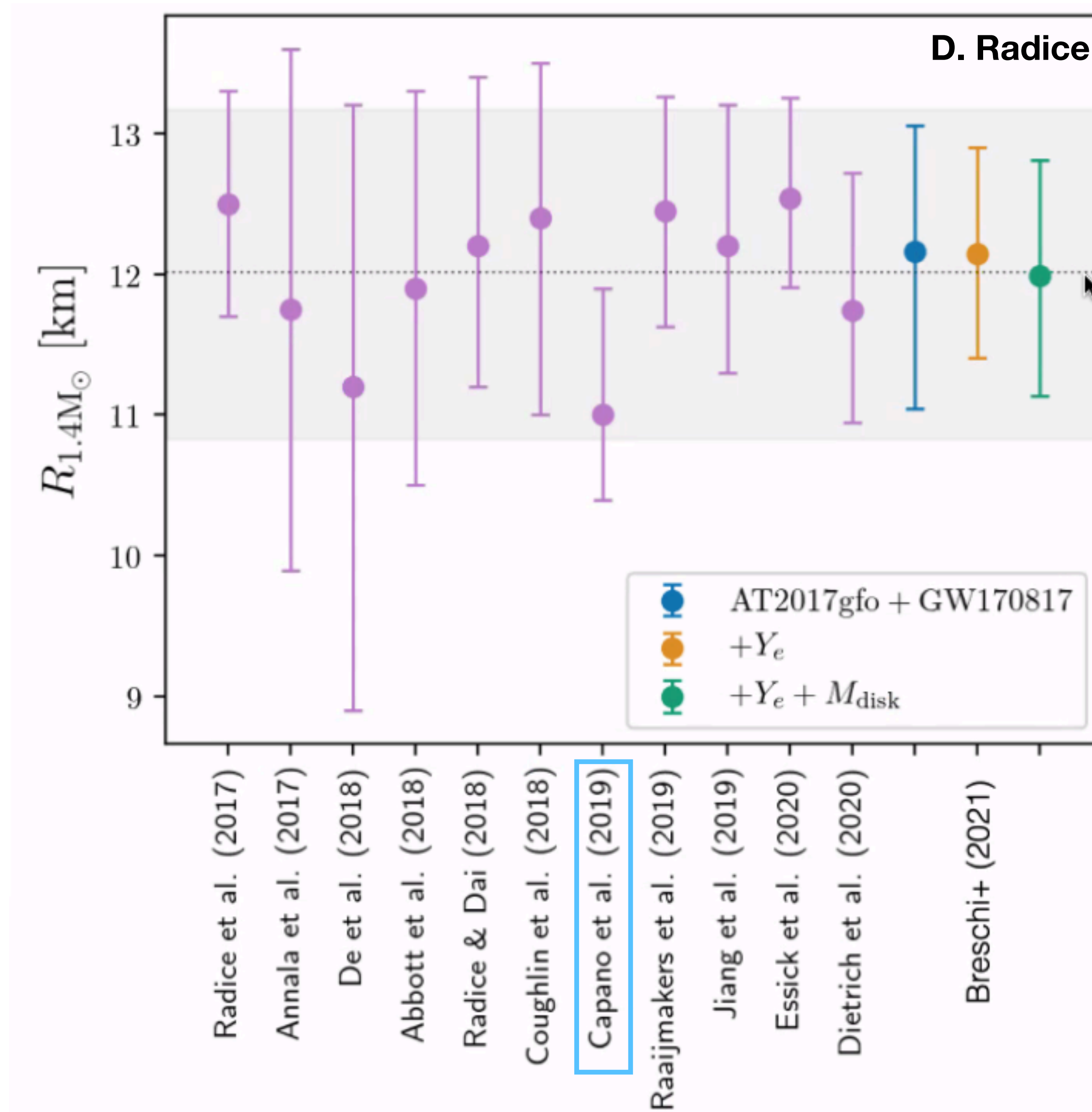
# Motivation

Capano et al., Nature Astron. 4 (2020) 6, 625-632



$$R_{1.4 M_{\odot}} = 11.0^{+0.9}_{-0.6} \text{ km}$$

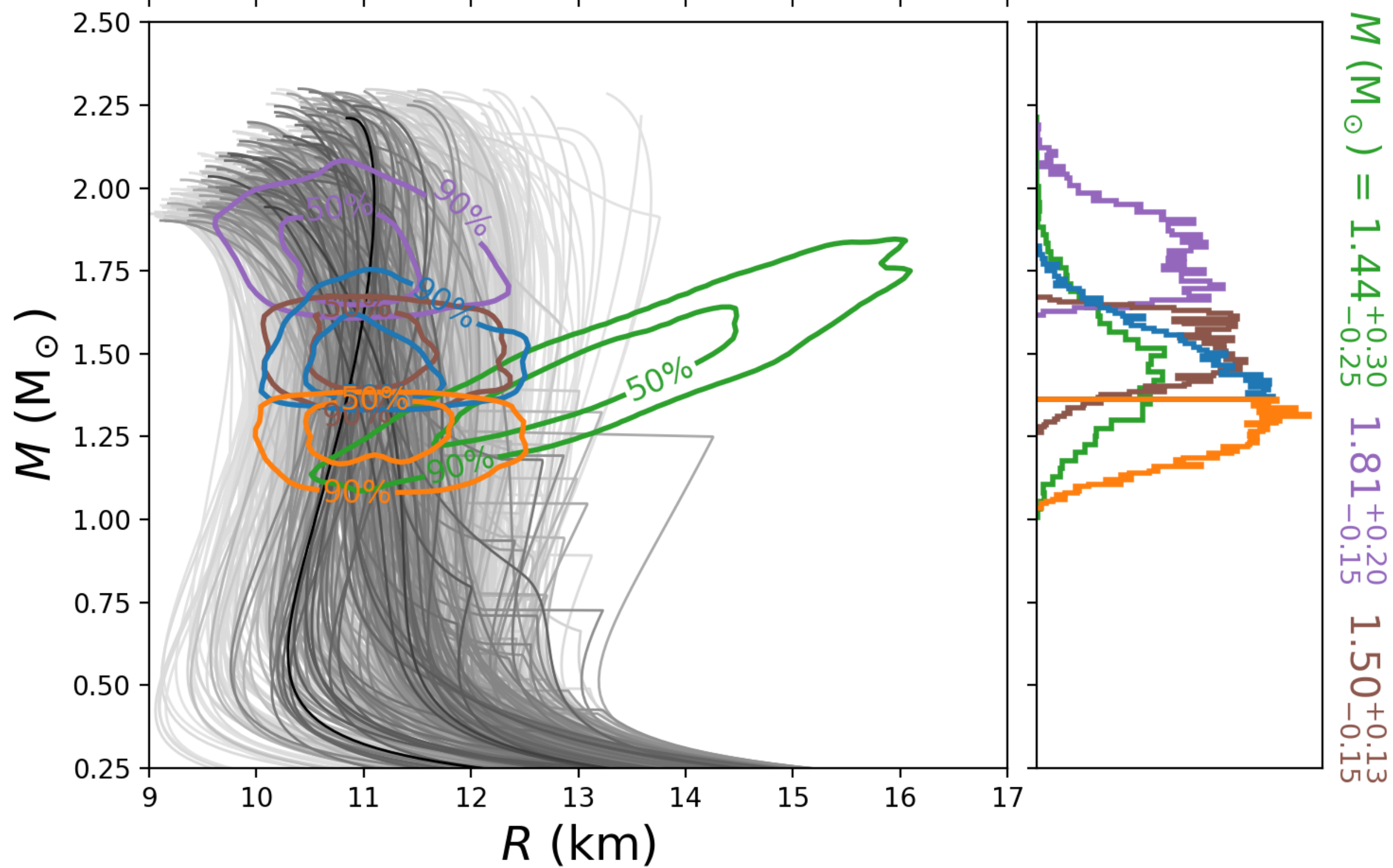
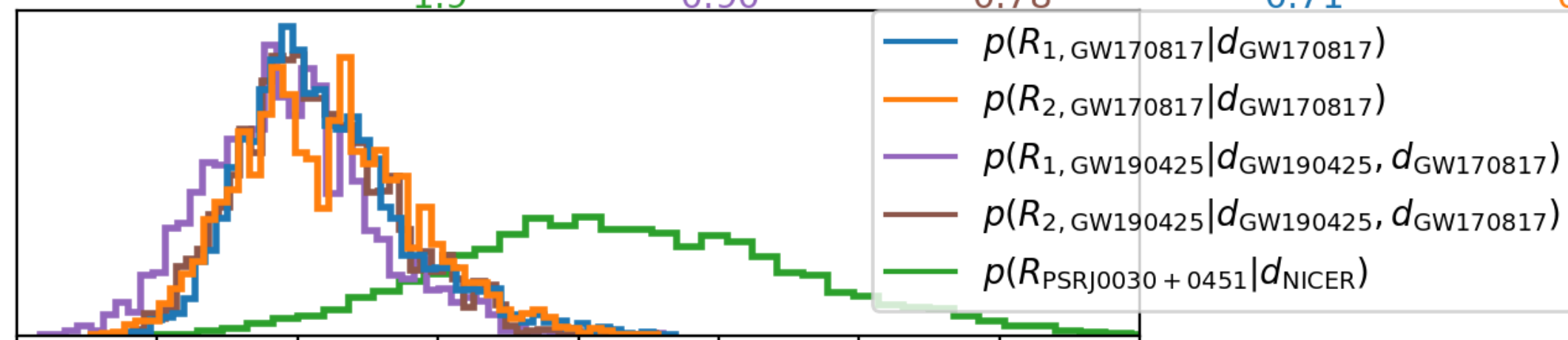
# One of these is not like the others...



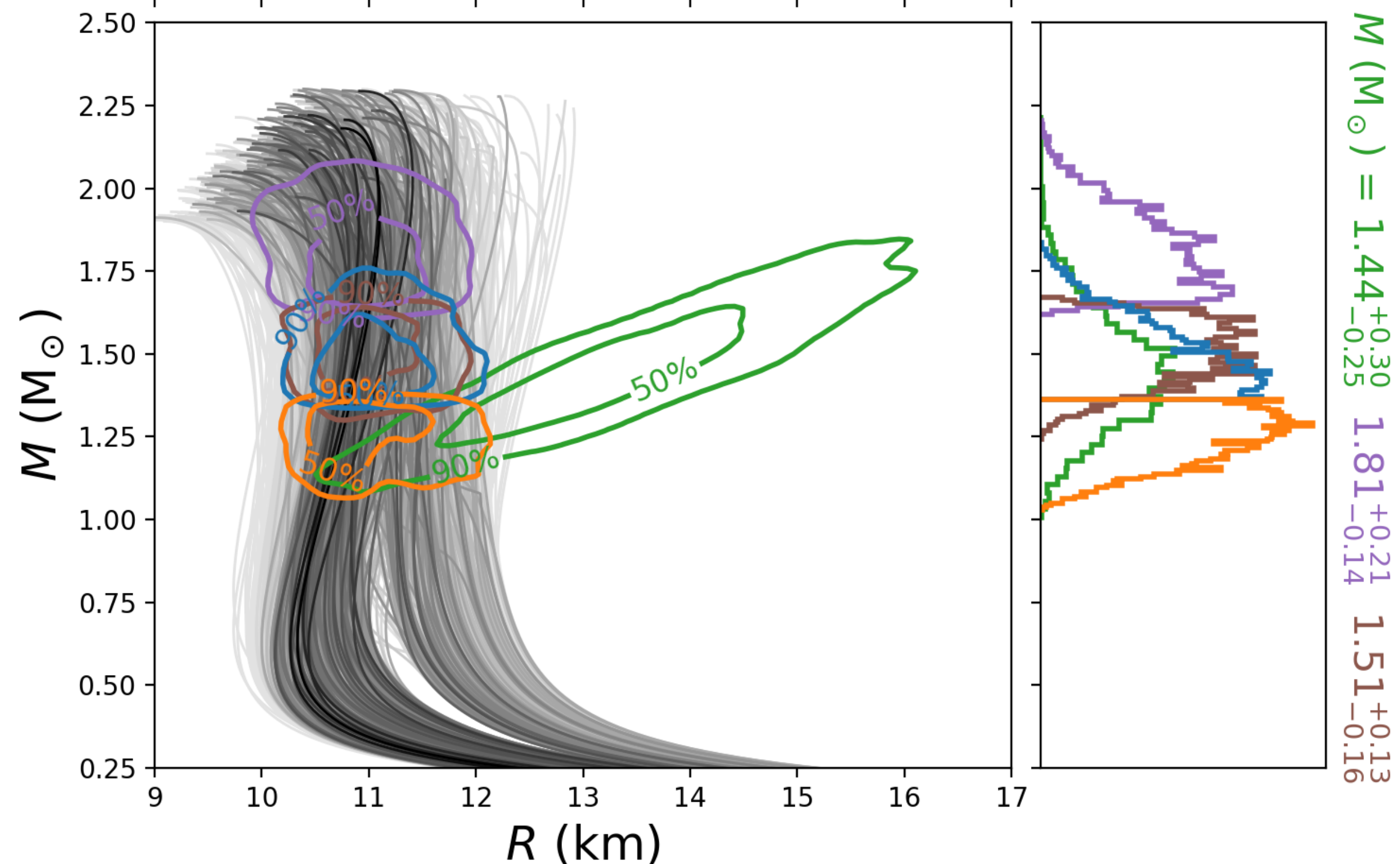
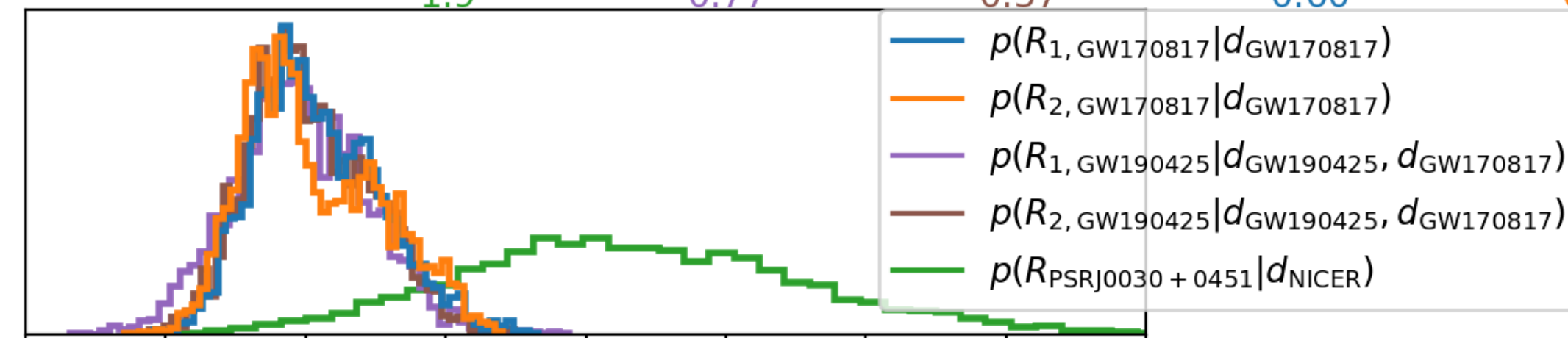


**$n_{\text{sat}}$** 

$$R \text{ (km)} = 13.3^{+2.2}_{-1.9} \quad 10.92^{+1.12}_{-0.90} \quad 11.08^{+1.06}_{-0.78} \quad 11.11^{+1.23}_{-0.71} \quad 11.18^{+1.12}_{-0.90}$$

 **$2n_{\text{sat}}$** 

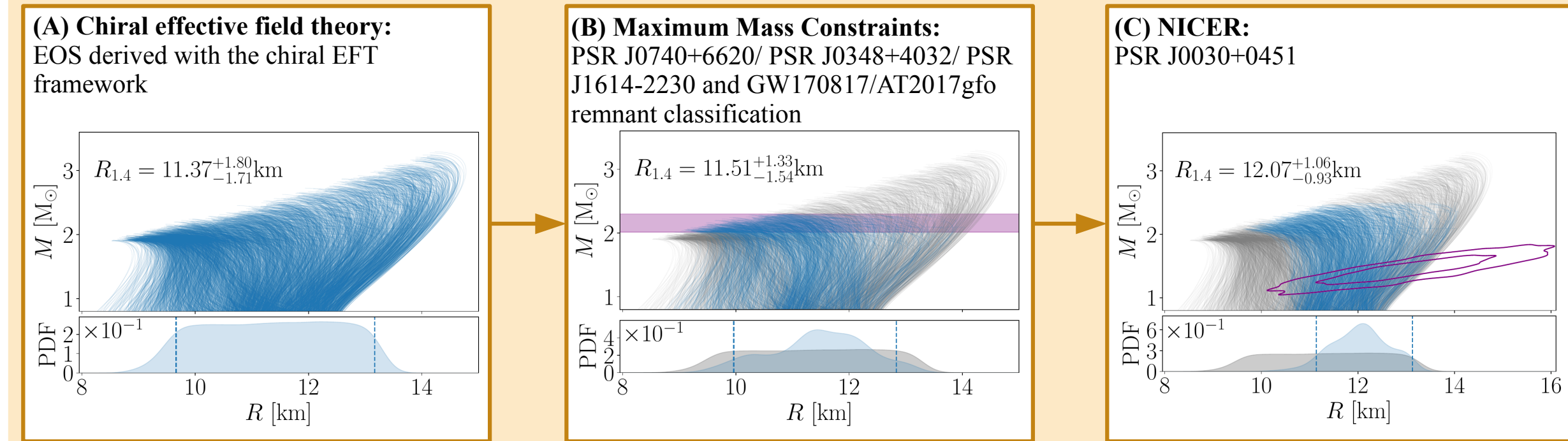
$$R \text{ (km)} = 13.3^{+2.2}_{-1.9} \quad 10.94^{+0.81}_{-0.77} \quad 10.98^{+0.79}_{-0.57} \quad 11.03^{+0.86}_{-0.60} \quad 10.94^{+1.00}_{-0.56}$$



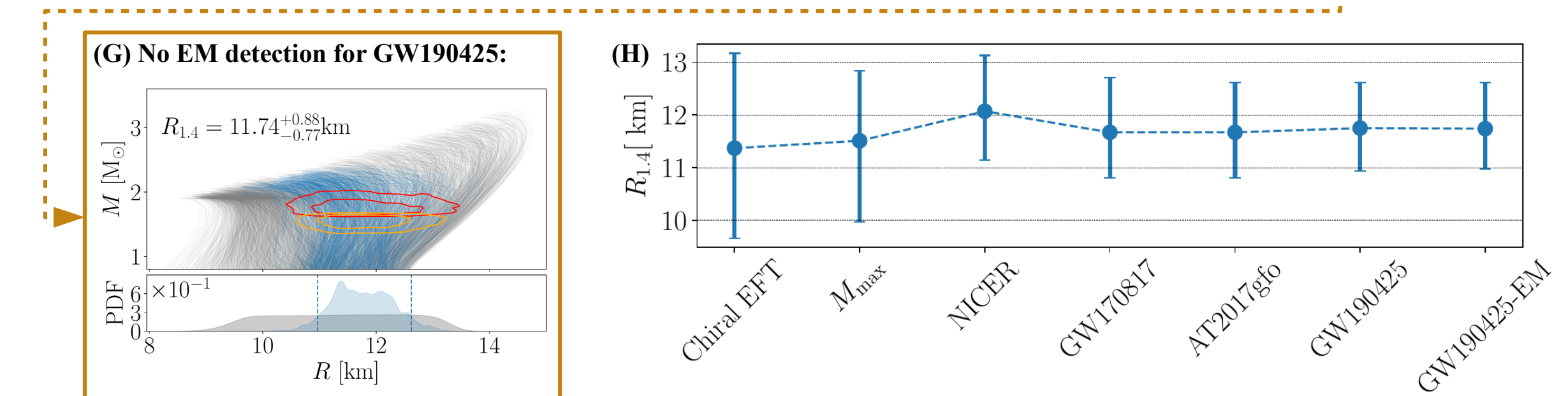
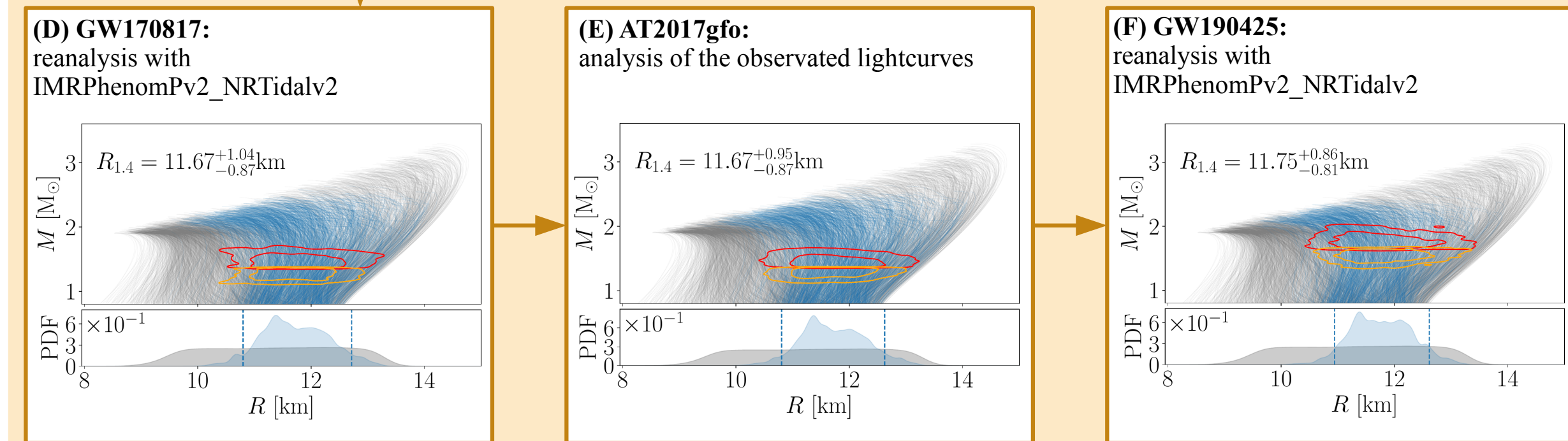
NICER J0030+0451 posterior (green) from Miller et al., ApJL 887, L24 (2019)



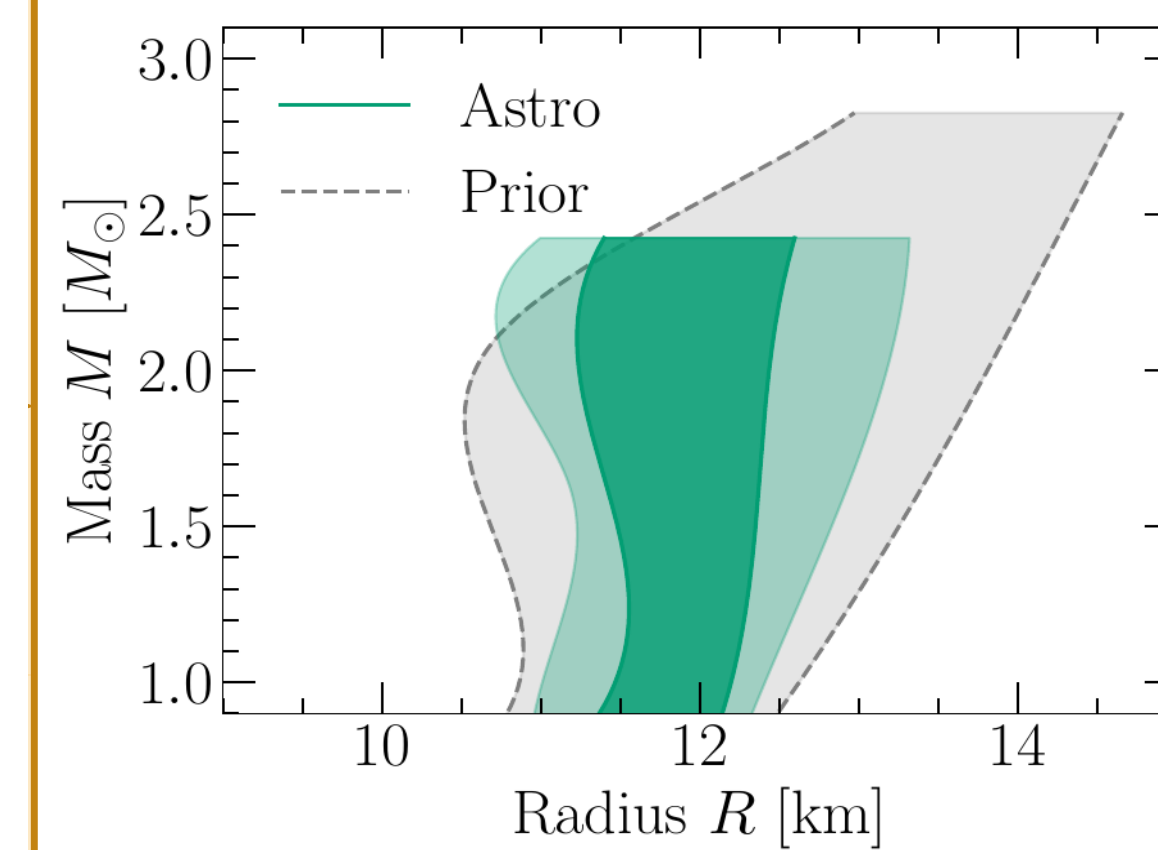
### Prior construction



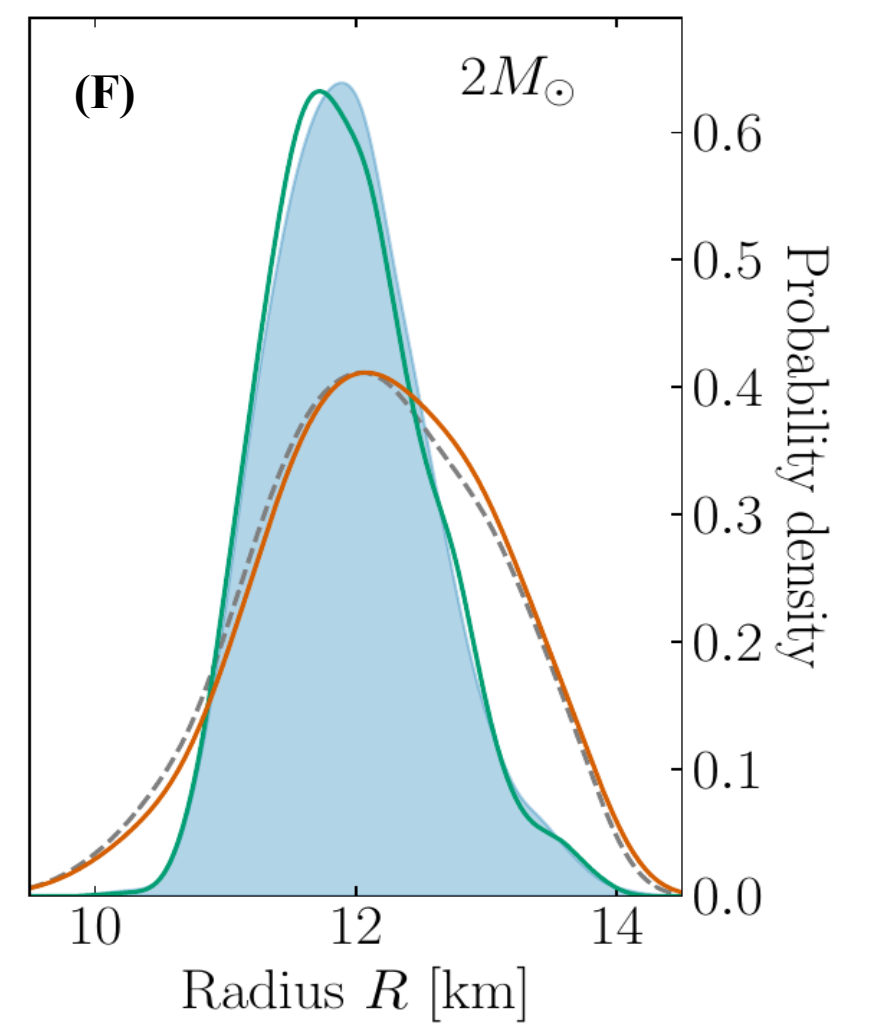
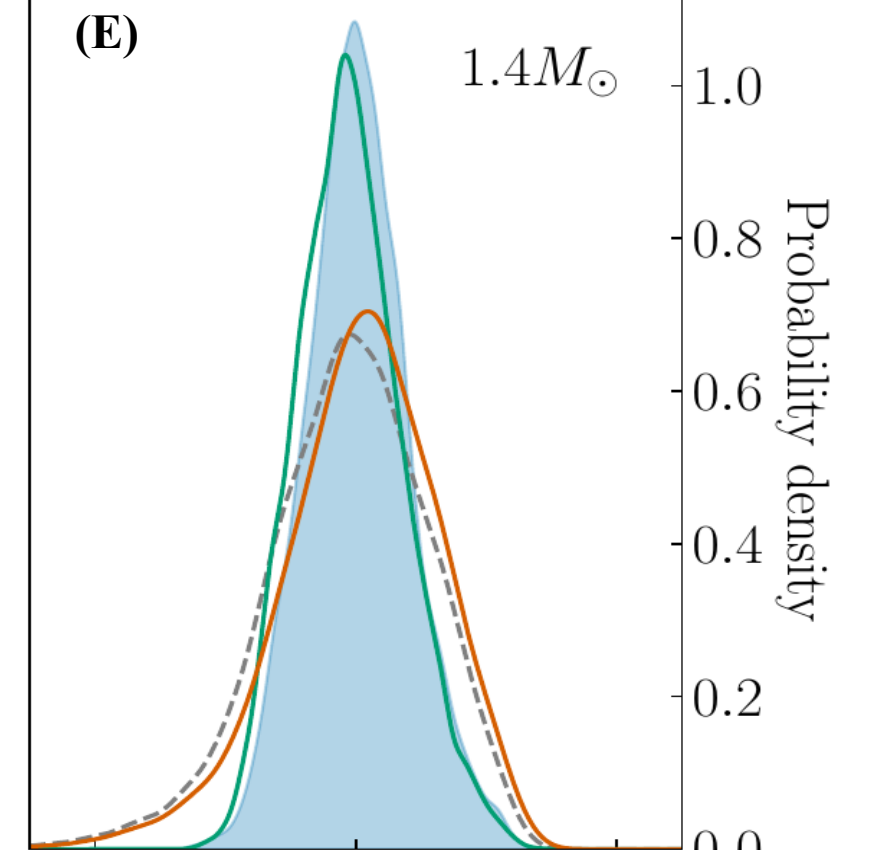
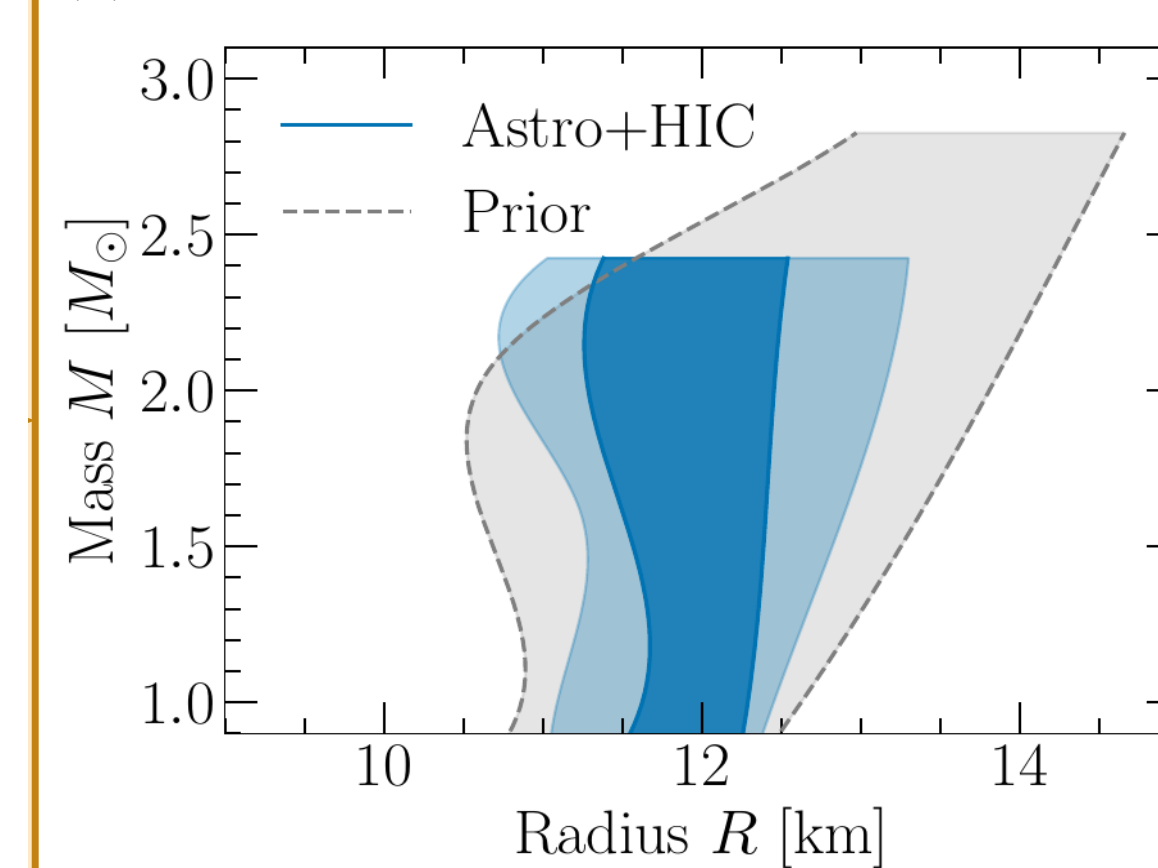
### Parameter estimation



### (B) Multi-messenger astrophysics:



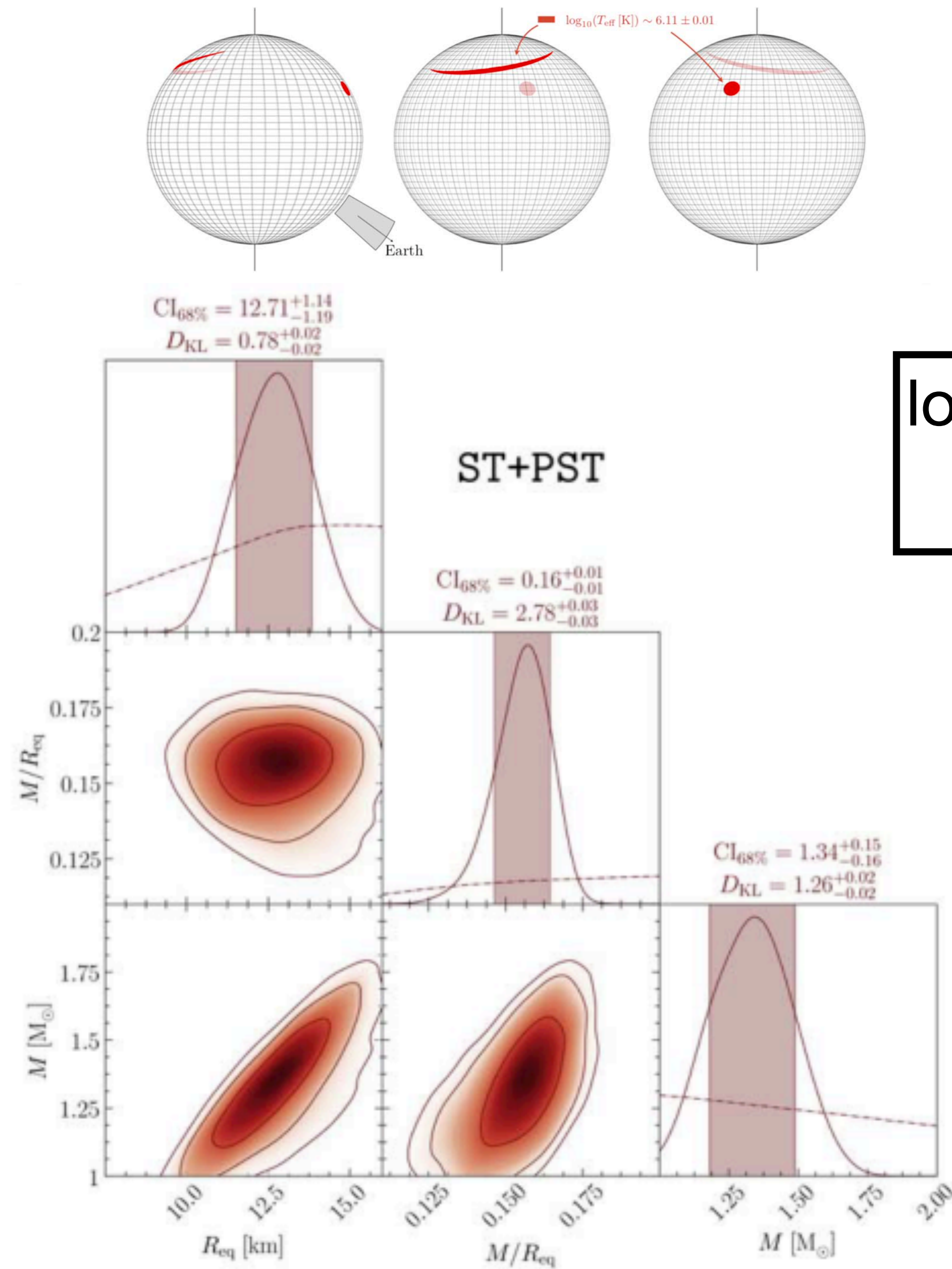
### (D) HIC and Astro combined:



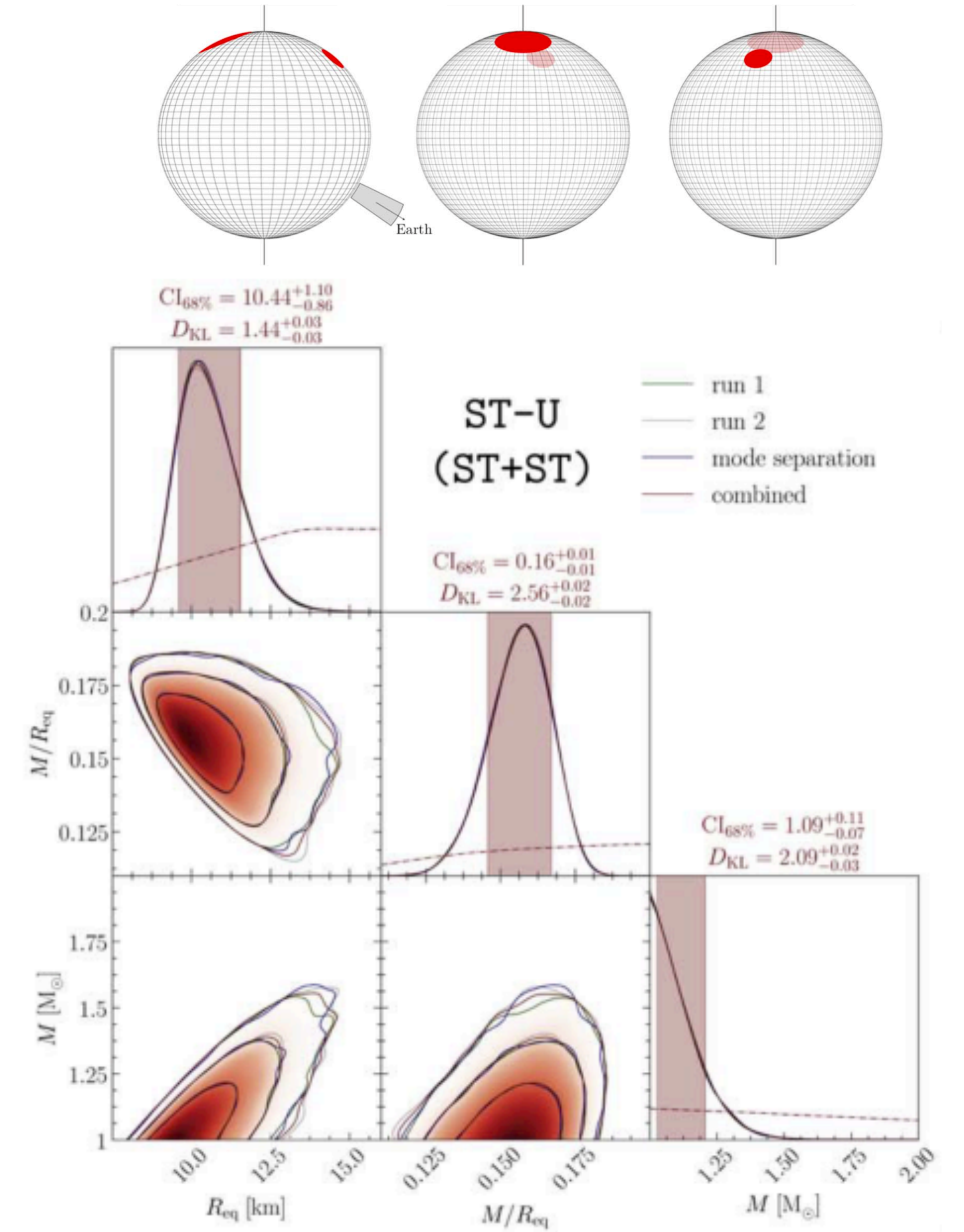
Huth et al., Nature 606, 276-280 (2022)



# NICER J0030+0451

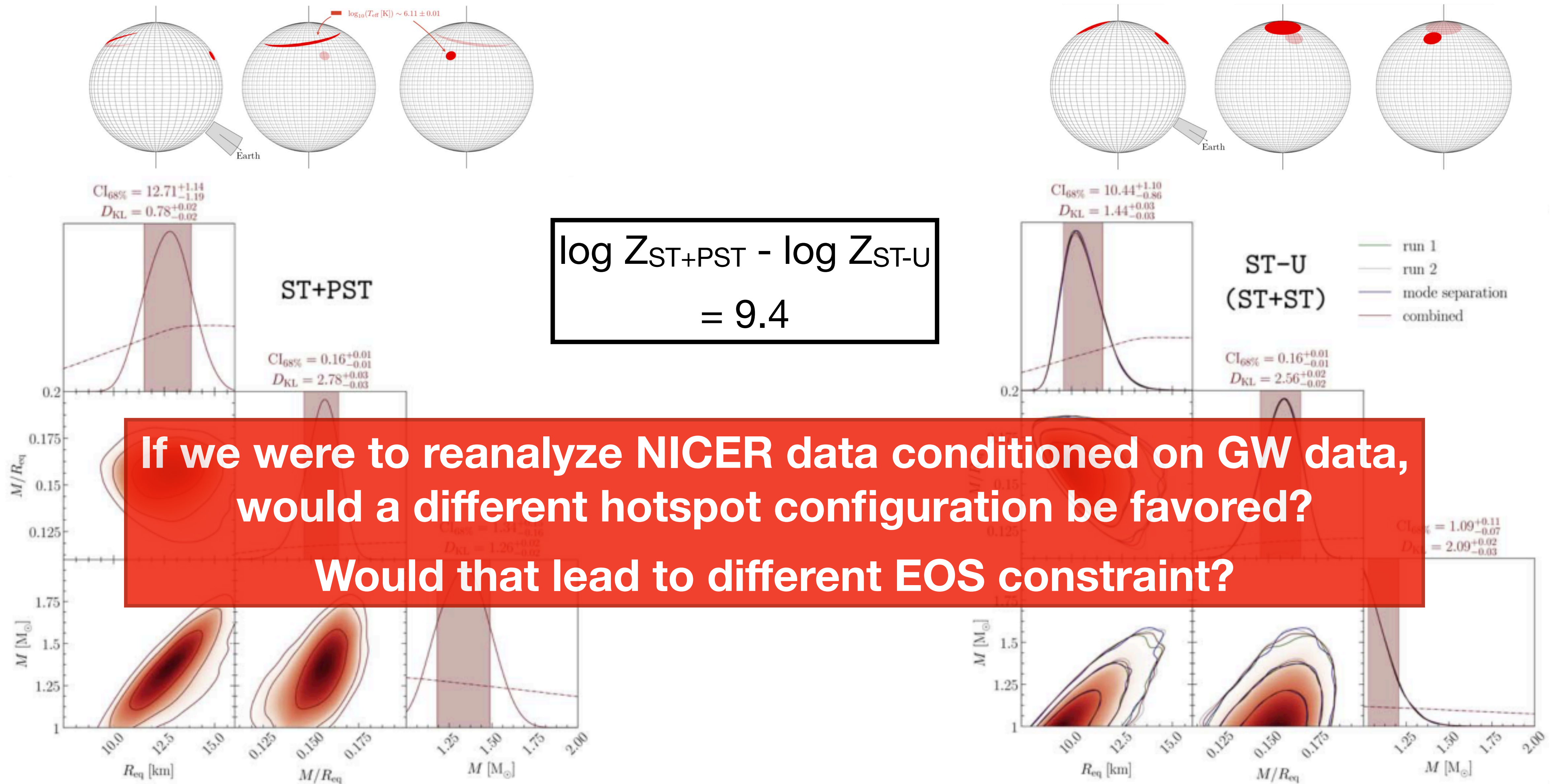


$$\log Z_{\text{ST+PST}} - \log Z_{\text{ST-U}} = 9.4$$





# NICER J0030+0451



# How to input GW results into NICER/XMM analysis

## Option 1: Use the GW170817 EOS posterior as a prior for NICER analyses

- Problem: difficult to get Bayesian evidence this way.
  - Most nested samplers (e.g., MultiNest, dynesty) cannot take arbitrary prior distributions.
  - MCMC solutions require parallel tempering: computationally expensive and hard to get reliable evidence estimate.



# How to input GW results into NICER/XMM analysis

**Option 2: Jointly analyze GW & NICER data together** (i.e., do one giant Bayesian inference analysis over GW170817, PSR J0030 and/or PSR J0740)

- Advantages: can use nested samplers; get better constraints on all parameters; potentially learn about correlations between unexpected parameters
- Challenges:
  - Not scalable — but doable for a few events at a time
  - Requires combining code & analysis methods from very different disciplines\* (here, GW and X-ray astronomy)

\*but see Pang et al., arXiv:2205.08513

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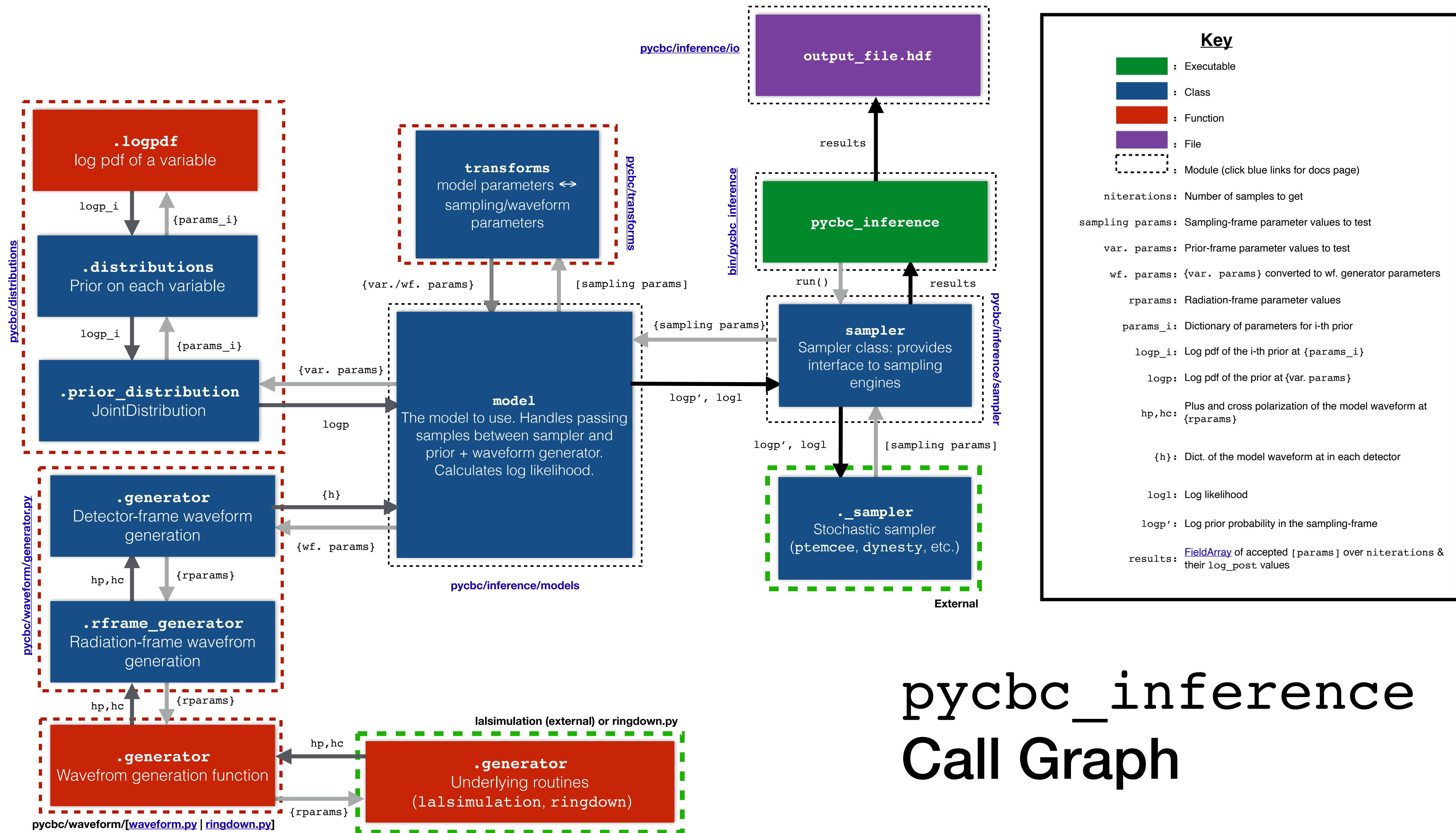
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    - ▶ **Problem: No one likes using other people's code.**

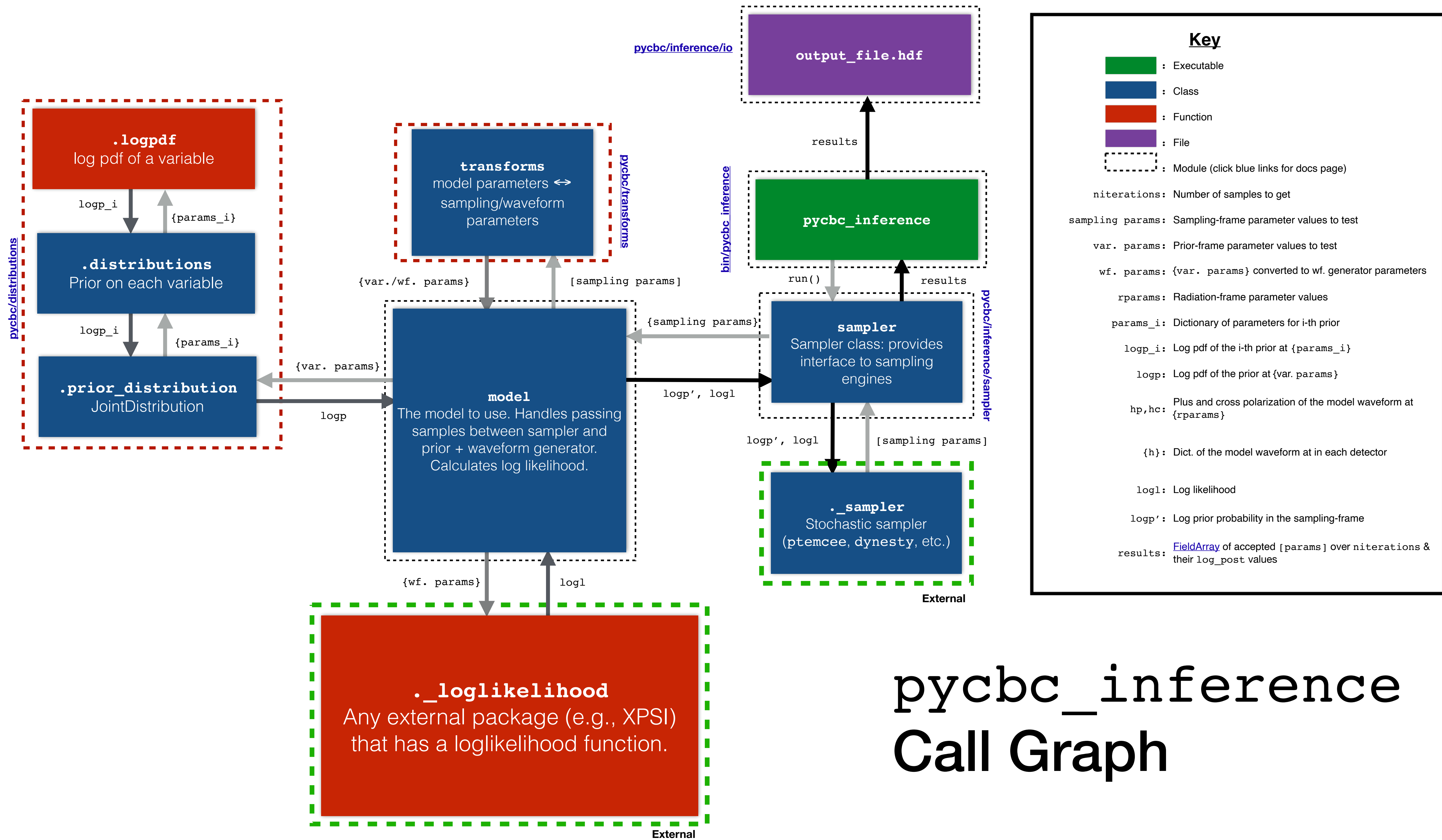
\*but see Pang et al., arXiv:2205.08513

# PyCBC Inference

- Python package for doing Bayesian inference with gravitational waves
- Part of the larger PyCBC package
- Nature of GW problems — different model waveforms, different types of analyses (regular inference, testing GR problems) — forced us to make PyCBC Inference very modular
  - i.e., various steps involved in general Bayesian inference are abstracted into smaller component modules.
- What data to analyze and signal/noise model to use set by config text files









# Plug-in models

- Python has the ability to create “plug-in” packages
  - we make use of this to support “plug-in models” in PyCBC
- Say you have your own code that analyzes some EM data (or anything else)
- You can use it with PyCBC without needing to modify/interact with/curse at the PyCBC source code.
- Wrap your likelihood function with the appropriate API and add the appropriate lines to your installation file.
- PyCBC will automatically detect it at run-time, and can use it in `pycbc_inference`

# An XPSI plug-in for PyCBC

- **XPSI<sup>1</sup>**: developed by Riley et al. to analyze NICER & XMM Newton data [see Serena Vinciguerra's talk]
- Used in analysis of PSR J0030+0451<sup>2</sup> & PSR J0740+6620<sup>3</sup>
- Here, we create a XPSI plugin for PyCBC

```

import xpsi
from pycbc.inference.models import BaseModel

class XPSIModel(BaseModel):
    """Model wrapper around XPSI likelihood function."""
    name = 'xpsi'

    # we need to alias some of the parameter names to be compliant with
    # pycbc config file sections
    _param_aliases = {
        'XTI__alpha': 'nicer_alpha',
        'PN__alpha': 'xmm_alpha'
    }

    def __init__(self, variable_params, star, signals, num_energies, **kwargs):
        super().__init__(variable_params, **kwargs)
        # set up the xpsi likelihood
        self._xpsi_likelihood = xpsi.Likelihood(star=star, signals=signals,
                                                num_energies=num_energies,
                                                externally_updated=True)

        # store a dictionary of param aliases
        self.param_aliases = {p: p for p in self._xpsi_likelihood.names}
        self.param_aliases.update(self._param_aliases)

    def _loglikelihood(self):
        # map the current parameters to the ordered list
        params = self.current_params
        # update the underlying likelihood
        for p in self._xpsi_likelihood.names:
            try:
                self._xpsi_likelihood[p] = params[self.param_aliases[p]]
            except StrictBoundsError:
                return -numpy.inf
        # check additional constraints
        if not self.apply_additional_constraints():
            return -numpy.inf
        logl = self._xpsi_likelihood()
        # FIXME: for some reason, this occasionally returns arrays of len 1
        # if so, force to float
        if isinstance(logl, numpy.ndarray):
            logl = logl.item()
        return logl

    @classmethod
    def from_config(cls, cp, **kwargs):
        args = cls.xpsi_args_from_config(cls, cp, **kwargs)
        return cls(**args)

```

59,19

2%

```

#!/usr/bin/env python
"""
Setup file for XPSI plugin model for PyCBC.
"""

from setuptools import setup, find_packages

VERSION = '0.1.dev0'
NAME = 'pycbc_xpsi'
URL = 'https://github.com/cdcapano/pycbc-xpsi-plugin'

setup(
    name=NAME,
    version=VERSION,
    description='XPSI plugin model for PyCBC',
    author='Collin Capano',
    author_email='cdcapano@gmail.com',
    url=URL,
    download_url='{}/tarball/v{}'.format(URL, VERSION),
    keywords = ['pycbc', 'xpsi', 'nicer', 'bayesian inference',
                'gravitational waves', 'x-ray astronomy',
                'multimessenger astronomy'],
    install_requires = ['pycbc', 'xpsi'],
    packages=find_packages(),
    entry_points = {
        "pycbc.inference.models": "pycbc_xpsi = pycbc_xpsi:XPSIModel",
    },
    classifiers=[
        'Programming Language :: Python',
        'Programming Language :: Python :: 3',
        'Intended Audience :: Science/Research',
        'Natural Language :: English',
        'Topic :: Scientific/Engineering',
        'Topic :: Scientific/Engineering :: Astronomy',
        'Topic :: Scientific/Engineering :: Physics',
        'License :: OSI Approved :: GNU General Public License v3 (GPLv3)',
    ],
)

```

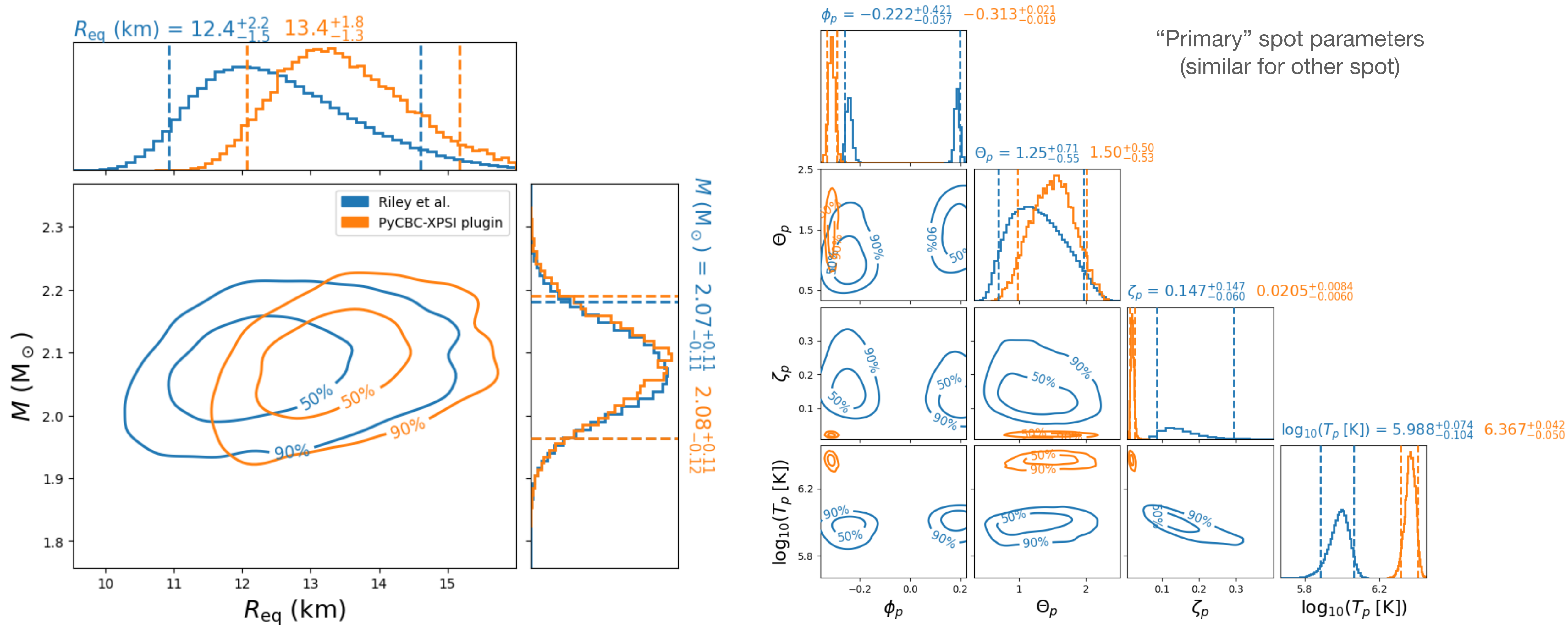
6,45

All

1. <https://github.com/xpsi-group/xpsi>
2. Riley et al., ApJL 887 L21 (2019)
3. Riley et al., ApJL 918 L27 (2021)



# Test: replicate J0740 analysis with PyCBC (NICER+XMM only)



- ▶ Close, but some bugs to work out, especially with hotspot orientation.
- ▶ Differences possibly due to mismatch between XPSI version used in publication & version used here.

# Hierarchical model

- The hierarchical model in PyCBC is a model of models
  - Takes product of likelihoods from constituent models
- Use hierarchical model to combine standard GW models in PyCBC with plugin models
  - ➡ can perform joint GW + anything-else Bayesian inference
- We use the hierarchical model with our XPSI plugin to jointly analyze GW170817 with PSR J0740 (and eventually PSR J0030)



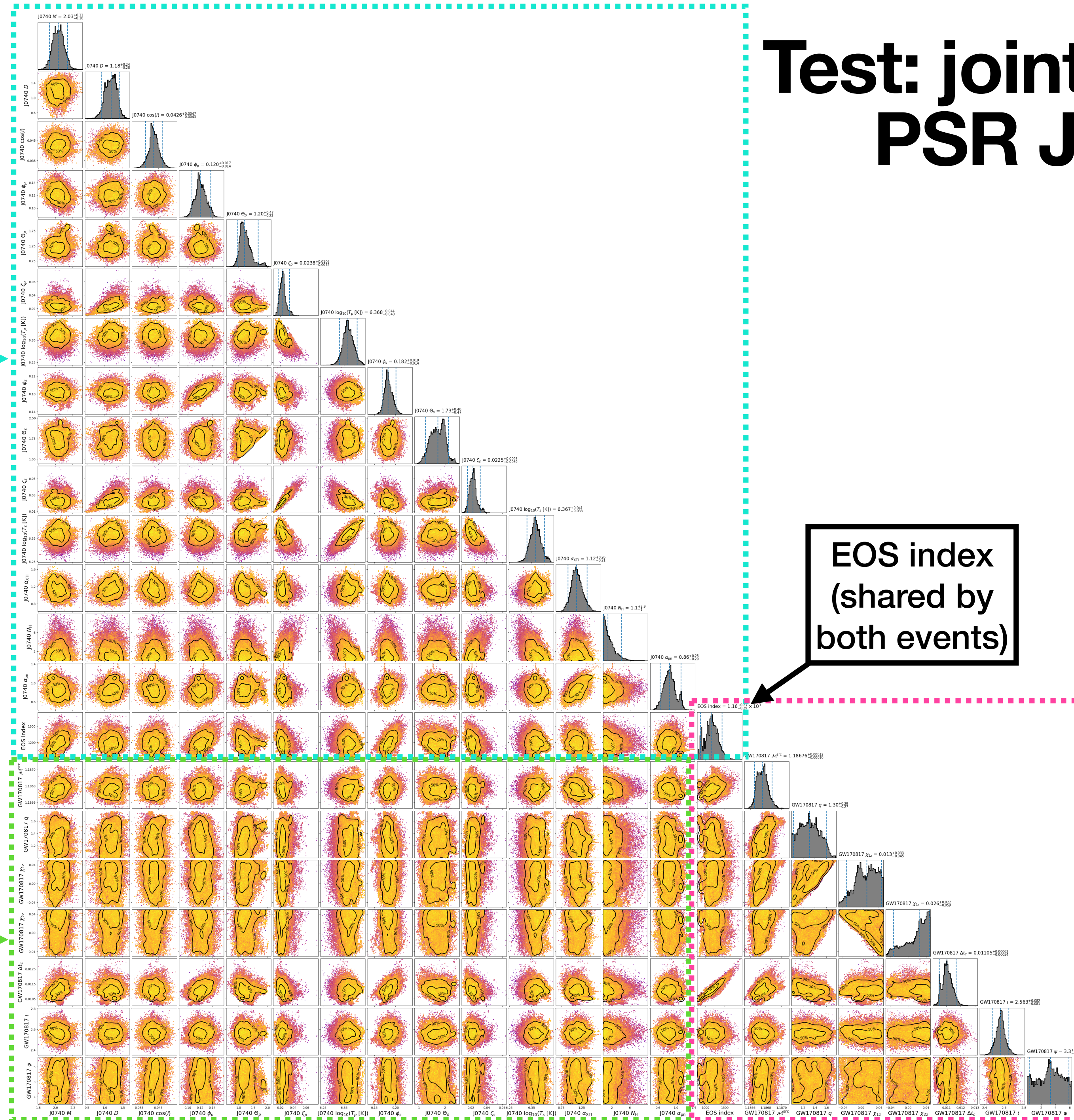
# Test: joint GW170817 + PSR J0740 analysis

PSR J0740+6620  
parameters

EOS index  
(shared by  
both events)

Correlations

GW170817  
parameters

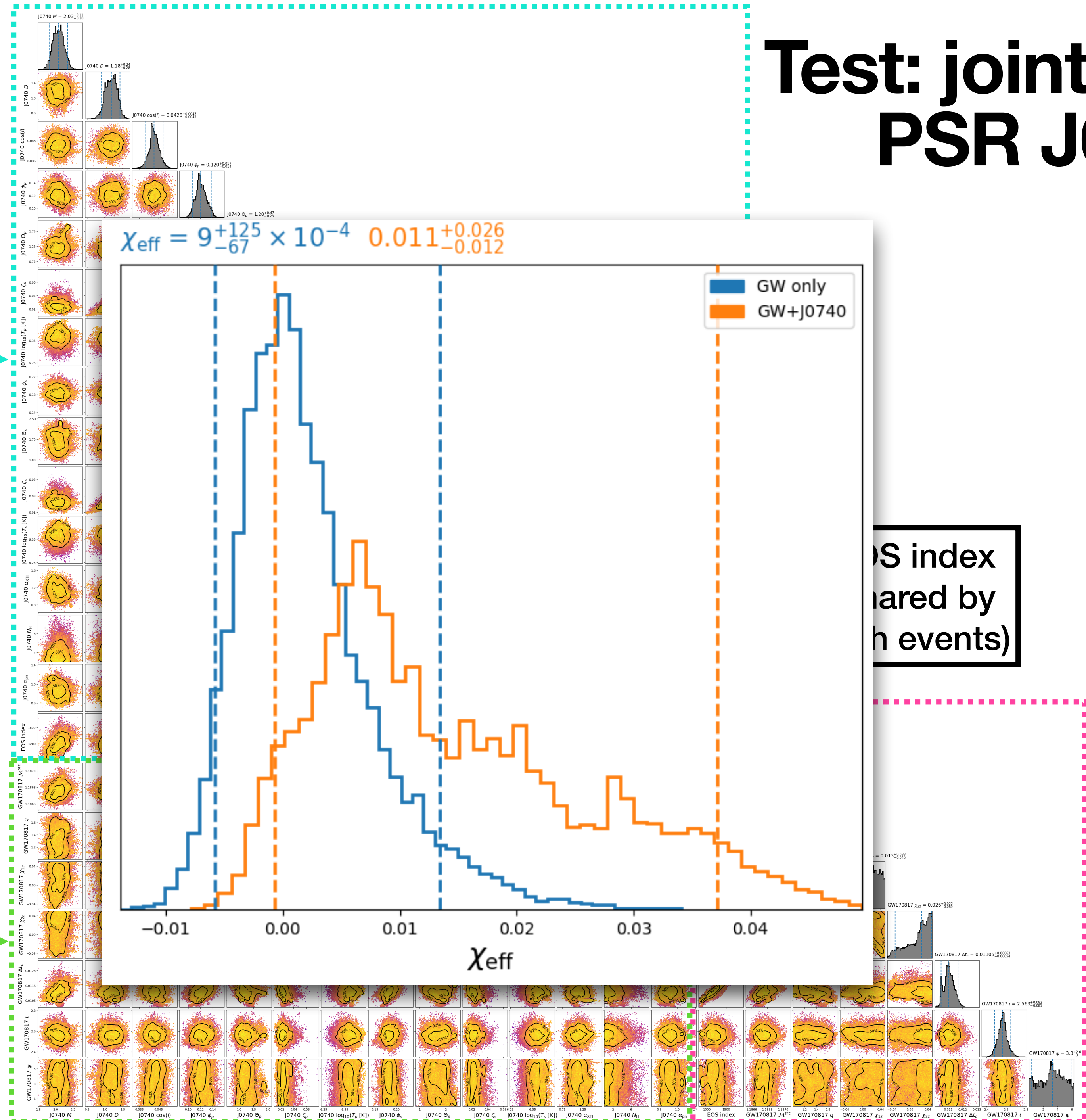




# Test: joint GW170817 + PSR J0740 analysis

PSR J0740+6620 parameters

Correlations



EOS index  
compared by  
two events)

GW170817 parameters

# Summary

- We are able to jointly analyze NICER/XMM and GW data using XPSI plugin model for PyCBC.
- Work in progress!
- Plan: test different hotspot configurations; analyze PSR J0030; sample over EOS parameters directly.
- More generally, using Python plugin modules (whether with PyCBC or something else) to do Bayesian inference over multi-messenger data very promising.
- For more on PyCBC — including documentation, tutorials, and help on building your own plugins — go to: <https://pycbc.org>

**Thank you!**

**Extras**



# Test: replicate J0740 analysis (NICER+XMM only) Full corner plot

