Incorporating neutron star physics into gravitational wave inference with neural priors

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Motivation

- Bayesian inference depends on choice of priors:

$$\mathcal{P}(\theta_{\mathrm{GW}}|d) \propto \frac{\mathcal{L}(d|\theta_{\mathrm{GW}})\pi(\theta_{\mathrm{GW}})}{\mathcal{Z}}$$

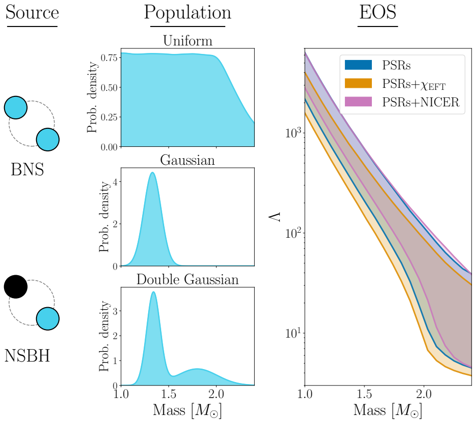
- By default, we use agnostic priors, but what if we *do* have non-trivial prior information?
- Case study: neutron stars (NSs) and information from
  - Population models
  - Equation of state (EOS) constraints

Neural priors

Flexible way to encode NS physics into GW inference

Key idea

Train normalizing flow (NF) on samples informed by populations and EOS $\rightarrow$ **neural prior**



$$p_{\mathrm{NF}}(m_1^{\mathrm{src}}, m_2^{\mathrm{src}}, \Lambda_1, \Lambda_2 | \mathcal{H})$$

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NS population models

Three fiducial population models for NS masses:

1. **Uniform** [1–3]:
   - Only use EOS constraints for maximum mass (M_{TOV})
   - NS mass $\sim U[1\,\mathrm{M}_\odot, M_{\mathrm{TOV}}]$

2. **Gaussian** [4]:
   - NS mass $\sim \mathcal{N}(1.33\,\mathrm{M}_\odot, (0.09\,\mathrm{M}_\odot)^2)$

3. **Double Gaussian** [5, 6]:
   - Weighted mixture of two Gaussians
   - $0.65 \times \mathcal{N}(1.34\,\mathrm{M}_\odot, (0.07\,\mathrm{M}_\odot)^2) + 0.35 \times \mathcal{N}(1.80\,\mathrm{M}_\odot, (0.21\,\mathrm{M}_\odot)^2)$

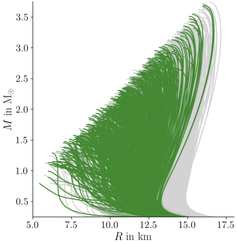
For NSBH systems:

- BH mass m_1^{src}: from $[M_{\mathrm{TOV}}, 5\,\mathrm{M}_\odot]$
- NS mass m_2^{src}: above models

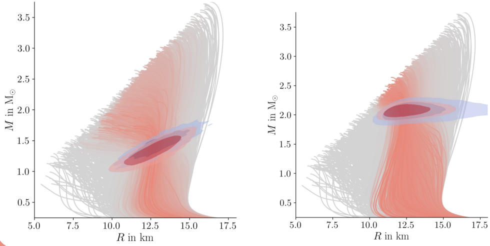
EOS constraints

- We use three EOS constraints [7]:
  1. **Heavy pulsars**: must support $2\,M_\odot$ NSs
  2. **Chiral EFT** (χ_{EFT}): nuclear theory predictions (softer EOS)
  3. **NICER**: mass-radius observations of NSs (stiffer EOS)
- Posterior samples obtained with JESTER [8]

Chiral EFT



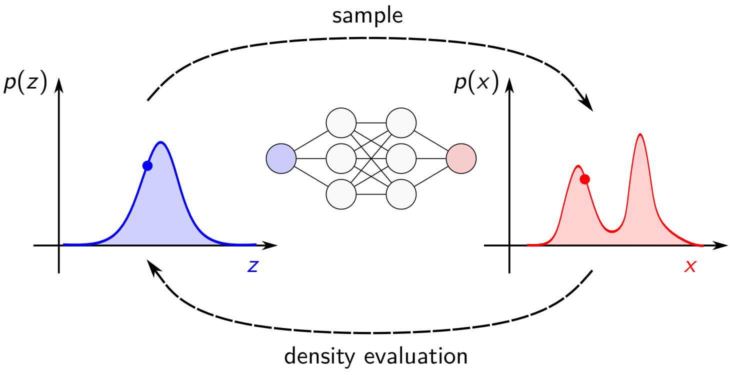
NICER



Normalizing flows

Normalizing flows [9, 10]

- Neural density estimators: trainable bijections
- Often used in PE, e.g., DINGO [11, 12], NESSAI [13, 14]
- Generate samples, evaluate density: can be used as priors [15]



Construction of neural priors

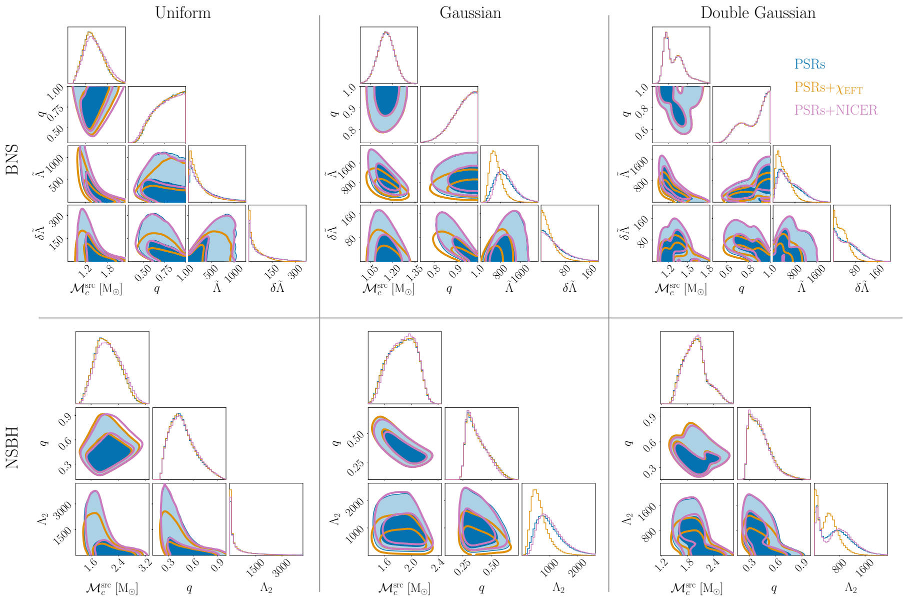
Steps to generate training data:

1. Draw EOS posterior curve: determines M_{TOV}, $\Lambda(m)$
2. Draw masses from population model
3. Compute $\Lambda_i = \Lambda(m_i)$ for NSs (NSBH: $\Lambda_1 = 0$)

Implementation:

- Created with GLASFLOW [16, 17]
- `CouplingNSF` architecture (neural spline flows [18])
- Use as a `JointPrior` in BILBY (`NFPrior`)
  - Sample & logpdf: evaluate NF
  - Rescale: unit hypercube $\rightarrow$ multivariate Gaussian $\xrightarrow{\mathrm{NF}}$ data space

All neural priors



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Setup

Analyze GW170817, GW190425, GW230529 with:

- 4096 live points, multibanding likelihood
- `IMRPhenomXP_NRTidalv3`
- Neural priors for m_i, Λ_i (standard priors for other parameters)

Two contributions:

1. Narrower constraints with neural priors
2. Model selection with Bayes factors

Jeffreys' scale for Bayes factors ($\log_{10}$ scale)

$\log_{10}(\mathcal{B}_1^2)$	Interpretation	Color
$[0, \frac{1}{2}]$	Barely worth mentioning	
$[\frac{1}{2}, 1]$	Substantial	
$[1, \frac{3}{2}]$	Strong	
$[\frac{3}{2}, 2]$	Very strong	
> 2	Decisive	

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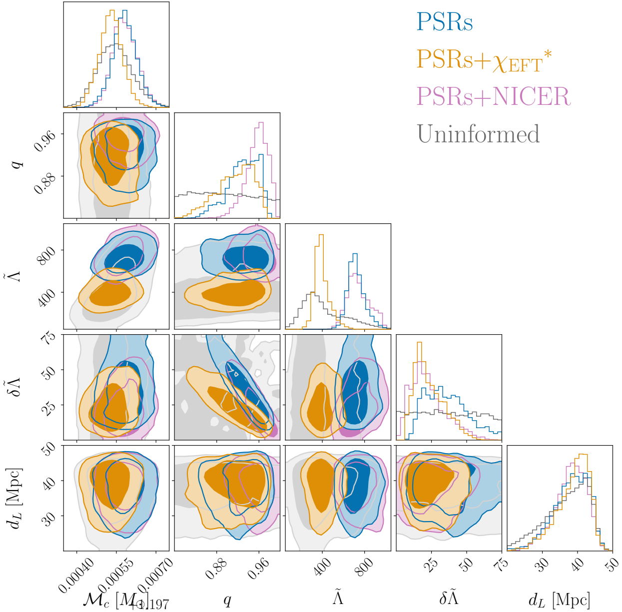
GW170817: Source classification

Showing $\log_{10}$ Bayes factors relative to model with highest evidence

Source	Population	EOS	GW170817
BNS	Uniform	PSRs	-1.83
		PSRs+χ_{EFT}	-0.80
		PSRs+NICER	-1.58
	Gaussian	PSRs	-0.68
		PSRs+χ_{EFT}	**ref.**
		PSRs+NICER	-0.76
	Double Gaussian	PSRs	-1.36
		PSRs+χ_{EFT}	-0.59
		PSRs+NICER	-0.92
NSBH	Uniform	PSRs	-224.65
		PSRs+χ_{EFT}	-224.66
		PSRs+NICER	-224.66
	Gaussian	PSRs	-224.67
		PSRs+χ_{EFT}	-224.66
		PSRs+NICER	-224.66
	Double Gaussian	PSRs	-224.67
		PSRs+χ_{EFT}	-224.68
		PSRs+NICER	-224.67


PSRs
PSRs+$\chi_{\rm EFT}$*
PSRs+NICER
Uninformed
q
0.96
0.88
$\tilde{\Lambda}$
800
400
$\delta\tilde{\Lambda}$
75
50
25
d_L [Mpc]
50
40
30
0.00040
0.00055
0.00070
+1.197
$\mathcal{M}_c$ [$M_\odot$]
0.88
0.96
q
400
800
$\tilde{\Lambda}$
25
50
75
$\delta\tilde{\Lambda}$
30
40
50
d_L [Mpc]

GW170817: Discussion

Source classification:

- Decisive evidence for BNS over NSBH
- Prefer Gaussian population model
- Slight preference for softer EOS (PSRs$+\chi_{\rm EFT}$)

Parameter constraints:

- More equal mass ratio: $q \geq 0.9$
- Constrained tidal deformability $\tilde{\Lambda}$
- Higher luminosity distance compared to agnostic prior
- Matches multimessenger analyses of GW170817 [19–23]

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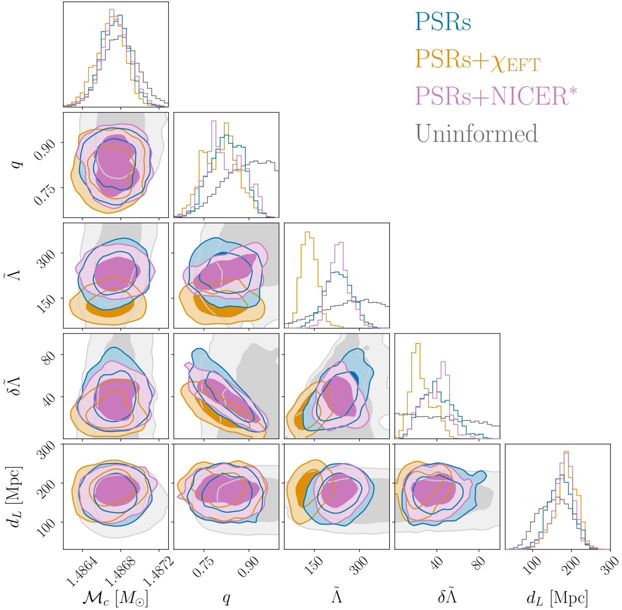
GW190425: Source classification

Showing $\log_{10}$ Bayes factors relative to best model

Source	Population	EOS	GW190425
BNS	Uniform	PSRs	-0.07
		PSRs+χ_{EFT}	-0.11
		PSRs+NICER	**ref.**
	Gaussian	PSRs	-6.89
		PSRs+χ_{EFT}	-8.47
		PSRs+NICER	-5.45
	Double Gaussian	PSRs	-0.55
		PSRs+χ_{EFT}	-0.79
		PSRs+NICER	-0.57
NSBH	Uniform	PSRs	-1.52
		PSRs+χ_{EFT}	-1.35
		PSRs+NICER	-1.63
	Gaussian	PSRs	-0.82
		PSRs+χ_{EFT}	-1.11
		PSRs+NICER	-1.43
	Double Gaussian	PSRs	-4.11
		PSRs+χ_{EFT}	-3.83
		PSRs+NICER	-24.31

GW190425: Parameter constraints (Uniform)



GW190425: Discussion

Source classification:

- Prefer BNS over NSBH (but less conclusive than GW170817)
- Most consistent with uniform population
- Masses are outliers compared to galactic binaries

Parameter constraints:

- Less equal masses: $q \leq 0.9$
- $\tilde{\Lambda} \approx 200$ (more prior-dominated due to lower SNR)
- Higher luminosity distance: 182^{+41}_{-49} Mpc vs. 157^{+64}_{-65} Mpc (90% credibility)

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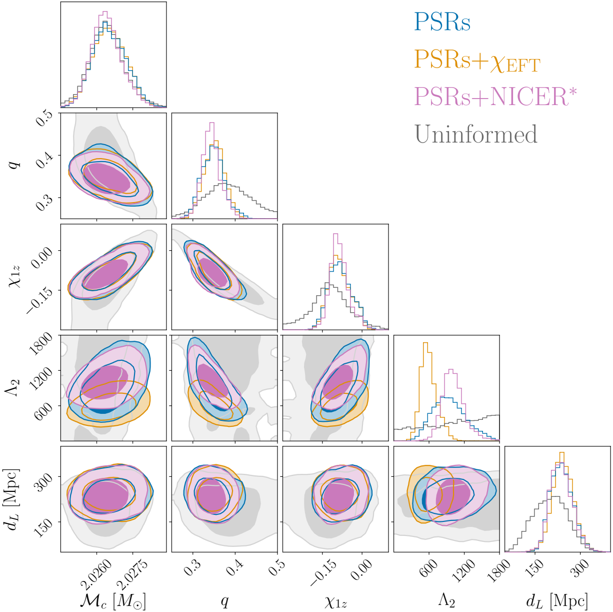
GW230529: Source classification

Showing $\log_{10}$ Bayes factors relative to best model

Source	Population	EOS	GW230529
BNS	Uniform	PSRs	-13.14
		PSRs+χ_{EFT}	-13.12
		PSRs+NICER	-12.92
	Gaussian	PSRs	-18.82
		PSRs+χ_{EFT}	-18.83
		PSRs+NICER	-18.81
	Double Gaussian	PSRs	-13.75
		PSRs+χ_{EFT}	-13.77
		PSRs+NICER	-13.71
NSBH	Uniform	PSRs	-0.08
		PSRs+χ_{EFT}	-0.02
		PSRs+NICER	-0.25
	Gaussian	PSRs	-0.05
		PSRs+χ_{EFT}	-0.20
		PSRs+NICER	**ref.**
	Double Gaussian	PSRs	-0.14
		PSRs+χ_{EFT}	-0.13
		PSRs+NICER	-0.05

GW230529: Parameter constraints (Gaussian)



GW230529: Discussion

Source classification:

- Decisive evidence for NSBH over BNS (agrees with LVK [24])
- No evidence between hypotheses (low SNR)

Parameter constraints:

- Mass ratio more constrained: $q \leq 0.4$
  - As a result, improved spin constraints (χ_{1z} closer to zero)
- Tidal deformability posteriors dominated by priors
- Luminosity distance: 235^{+59}_{-58} Mpc vs. 201^{+84}_{-97} Mpc (90% credibility)
- Less tidal information: `NRTidalv3` tapers at (90% credibility)
  - 641^{+318}_{-158} Hz (agnostic priors)
  - 858^{+113}_{-108} Hz (neural prior, reference model)

Contents

Conclusion

- PE often uses agnostic priors, missing valuable information
- **Neural priors**: flexible way to encode non-trivial prior information
- Case study: neutron star physics from
  - Population models
  - EOS constraints
- Two highlights:
  1. **Bayesian source classification** (BNS vs. NSBH)
  2. **Informed parameter constraints** (narrower posteriors)
- Implemented in BILBY
- Data-driven approach: easy to extend/generalize

Thanks for listening!

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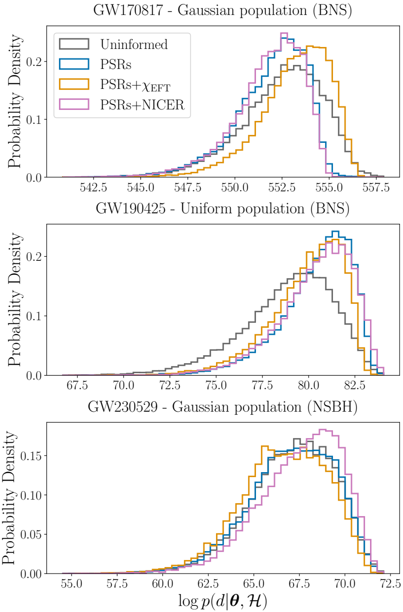
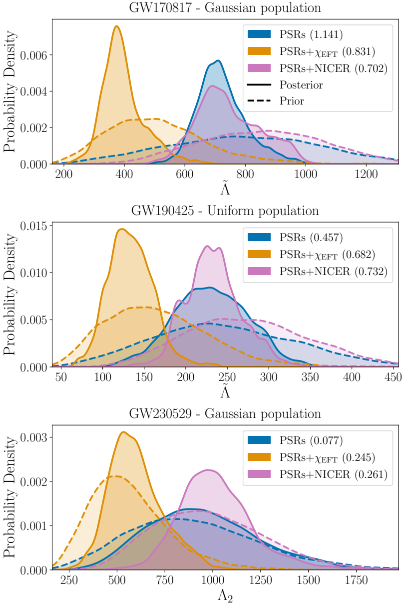
Likelihood distributions

- Likelihood distributions, obtained from final posterior samples



Information gain

- "Prior" $= \Lambda_i$ computed from EOSs conditioned on the posterior source-frame masses m_i^{src}
- "Posterior" $= \Lambda_i$ from posterior samples
- KL divergence between prior and posterior in brackets



More posteriors

Event	**Pop**	**EOS**	$m_1^{\rm src}$ $[M_\odot]$	$m_2^{\rm src}$ $[M_\odot]$	q	Λ_1	Λ_2	$\tilde\Lambda$	$\delta\tilde\Lambda$	d_L [Mpc]
GW170817 (BNS)		Uninformed	$1.47^{+0.12}_{-0.11}$	$1.26^{+0.10}_{-0.10}$	$0.86^{+0.14}_{-0.12}$	286^{+473}_{-286}	448^{+603}_{-448}	364^{+403}_{-234}	0^{+158}_{-170}	38^{+8}_{-11}
	U	PSRs	$1.51^{+0.09}_{-0.06}$	$1.23^{+0.05}_{-0.07}$	$0.81^{+0.06}_{-0.09}$	413^{+110}_{-133}	1477^{+636}_{-334}	795^{+108}_{-71}	119^{+68}_{-43}	41^{+6}_{-8}
		PSRs+$\chi_{\rm EFT}$	$1.52^{+0.08}_{-0.07}$	$1.23^{+0.06}_{-0.06}$	$0.81^{+0.08}_{-0.07}$	215^{+87}_{-111}	712^{+219}_{-175}	390^{+98}_{-93}	58^{+19}_{-25}	40^{+6}_{-8}
		PSRs+NICER	$1.57^{+0.05}_{-0.07}$	$1.19^{+0.05}_{-0.03}$	$0.75^{+0.06}_{-0.05}$	264^{+86}_{-52}	1399^{+367}_{-342}	620^{+99}_{-82}	116^{+37}_{-38}	40^{+6}_{-8}
	G	PSRs	$1.41^{+0.04}_{-0.03}$	$1.32^{+0.03}_{-0.03}$	$0.93^{+0.04}_{-0.05}$	578^{+131}_{-150}	874^{+229}_{-174}	713^{+143}_{-122}	35^{+28}_{-23}	39^{+7}_{-9}
		PSRs+$\chi_{\rm EFT}$	$1.42^{+0.05}_{-0.04}$	$1.31^{+0.03}_{-0.04}$	$0.92^{+0.05}_{-0.06}$	298^{+130}_{-99}	495^{+173}_{-118}	385^{+141}_{-85}	21^{+19}_{-13}	40^{+6}_{-9}
		PSRs+NICER	$1.39^{+0.02}_{-0.02}$	$1.34^{+0.02}_{-0.02}$	$0.96^{+0.03}_{-0.03}$	641^{+186}_{-128}	826^{+277}_{-178}	729^{+219}_{-133}	21^{+22}_{-17}	38^{+7}_{-8}
	DG	PSRs	$1.40^{+0.03}_{-0.02}$	$1.33^{+0.02}_{-0.02}$	$0.95^{+0.02}_{-0.03}$	687^{+140}_{-156}	960^{+183}_{-231}	814^{+143}_{-185}	29^{+21}_{-13}	40^{+6}_{-7}
		PSRs+$\chi_{\rm EFT}$	$1.39^{+0.02}_{-0.02}$	$1.34^{+0.02}_{-0.02}$	$0.96^{+0.03}_{-0.03}$	382^{+148}_{-111}	507^{+153}_{-152}	444^{+136}_{-131}	11^{+12}_{-9}	39^{+7}_{-7}
		PSRs+NICER	$1.39^{+0.02}_{-0.02}$	$1.33^{+0.02}_{-0.02}$	$0.96^{+0.02}_{-0.03}$	703^{+184}_{-153}	934^{+200}_{-200}	806^{+157}_{-184}	26^{+14}_{-17}	38^{+7}_{-8}
GW190425 (BNS)		Uninformed	$1.75^{+0.13}_{-0.10}$	$1.56^{+0.10}_{-0.10}$	$0.89^{+0.11}_{-0.11}$	292^{+541}_{-292}	415^{+694}_{-415}	374^{+436}_{-333}	0^{+187}_{-173}	157^{+64}_{-65}
	U	PSRs	$1.81^{+0.10}_{-0.09}$	$1.50^{+0.07}_{-0.08}$	$0.83^{+0.08}_{-0.09}$	109^{+56}_{-57}	428^{+209}_{-200}	230^{+73}_{-71}	39^{+24}_{-23}	173^{+54}_{-47}
		PSRs+$\chi_{\rm EFT}$	$1.83^{+0.12}_{-0.10}$	$1.48^{+0.07}_{-0.10}$	$0.81^{+0.09}_{-0.09}$	58^{+40}_{-28}	259^{+174}_{-107}	132^{+44}_{-40}	23^{+21}_{-12}	187^{+48}_{-49}
		PSRs+NICER	$1.82^{+0.10}_{-0.12}$	$1.48^{+0.10}_{-0.07}$	$0.81^{+0.11}_{-0.09}$	108^{+81}_{-56}	449^{+132}_{-150}	232^{+57}_{-51}	40^{+15}_{-23}	182^{+41}_{-49}
	DG	PSRs	$1.93^{+0.08}_{-0.08}$	$1.41^{+0.05}_{-0.05}$	$0.73^{+0.06}_{-0.05}$	67^{+37}_{-38}	636^{+217}_{-206}	238^{+65}_{-61}	63^{+21}_{-21}	186^{+44}_{-44}
		PSRs+$\chi_{\rm EFT}$	$1.94^{+0.07}_{-0.06}$	$1.40^{+0.04}_{-0.05}$	$0.72^{+0.04}_{-0.05}$	51^{+23}_{-24}	408^{+125}_{-100}	156^{+37}_{-45}	37^{+10}_{-9}	190^{+41}_{-47}
		PSRs+NICER	$1.90^{+0.08}_{-0.07}$	$1.42^{+0.06}_{-0.05}$	$0.75^{+0.06}_{-0.06}$	96^{+41}_{-36}	690^{+188}_{-164}	283^{+45}_{-51}	66^{+18}_{-17}	186^{+41}_{-48}
GW230529 (NSBH)		Uninformed	$3.65^{+0.62}_{-0.85}$	$1.43^{+0.26}_{-0.24}$	$0.39^{+0.17}_{-0.13}$	–	2791^{+2113}_{-1950}	182^{+243}_{-182}	91^{+115}_{-91}	201^{+84}_{-97}
	U	PSRs	$3.73^{+0.28}_{-0.32}$	$1.38^{+0.10}_{-0.09}$	$0.37^{+0.06}_{-0.05}$	–	698^{+344}_{-303}	41^{+8}_{-8}	21^{+4}_{-4}	238^{+61}_{-63}
		PSRs+$\chi_{\rm EFT}$	$3.52^{+0.46}_{-0.45}$	$1.46^{+0.18}_{-0.14}$	$0.41^{+0.12}_{-0.08}$	–	322^{+206}_{-202}	26^{+8}_{-7}	13^{+4}_{-4}	220^{+70}_{-64}
		PSRs+NICER	$3.27^{+0.27}_{-0.57}$	$1.54^{+0.25}_{-0.12}$	$0.47^{+0.17}_{-0.08}$	–	368^{+213}_{-291}	40^{+13}_{-14}	19^{+6}_{-7}	237^{+65}_{-67}
	G	PSRs	$3.86^{+0.28}_{-0.26}$	$1.34^{+0.08}_{-0.08}$	$0.35^{+0.04}_{-0.05}$	–	933^{+497}_{-451}	46^{+14}_{-16}	23^{+7}_{-8}	236^{+59}_{-58}
		PSRs+$\chi_{\rm EFT}$	$3.83^{+0.25}_{-0.25}$	$1.35^{+0.07}_{-0.07}$	$0.35^{+0.04}_{-0.04}$	–	582^{+261}_{-198}	30^{+7}_{-8}	15^{+3}_{-4}	242^{+59}_{-57}
		PSRs+NICER	$3.89^{+0.22}_{-0.24}$	$1.33^{+0.07}_{-0.06}$	$0.34^{+0.04}_{-0.03}$	–	1000^{+321}_{-311}	49^{+9}_{-9}	25^{+4}_{-5}	235^{+59}_{-58}
	DG	PSRs	$3.78^{+0.23}_{-0.24}$	$1.36^{+0.07}_{-0.06}$	$0.36^{+0.04}_{-0.04}$	–	890^{+341}_{-333}	49^{+12}_{-13}	25^{+6}_{-7}	237^{+63}_{-64}
		PSRs+$\chi_{\rm EFT}$	$3.85^{+0.18}_{-0.21}$	$1.34^{+0.05}_{-0.06}$	$0.35^{+0.03}_{-0.03}$	–	516^{+194}_{-205}	26^{+8}_{-8}	13^{+4}_{-4}	237^{+66}_{-71}
		PSRs+NICER	$3.86^{+0.15}_{-0.16}$	$1.34^{+0.04}_{-0.04}$	$0.35^{+0.02}_{-0.02}$	–	1026^{+254}_{-306}	52^{+11}_{-13}	26^{+6}_{-6}	229^{+65}_{-68}