

# Modeling the Mass Distribution of Binary Black Hole Mergers with GWTC-3 LIGO Surf 2022 Interim Report 1

JINGYI ZHANG,<sup>1</sup> SUPERVISED BY: ALAN J. WEINSTEIN,<sup>2</sup> AND JACOB GOLOMB<sup>2</sup>

<sup>1</sup>*Smith College*

<sup>2</sup>*LIGO Laboratory, California Institute of Technology*

## ABSTRACT

With 70 binary black hole merger (BBHs) events detected by the LIGO -Virgo Collaboration, it is possible to infer the overall character of the black hole population in the universe. Specifically, the mass distribution of BBHs provides us with valuable information on stellar evolution and binary formation channel. We here aim to test the current estimation of BBHs population mass distribution based on the third Gravitational-wave Transient Catalog (GWTC-3). The project involves: (1) Examine agreement between the observed data and the fitted mode by conducting goodness-of-fit tests; (2) identifying outliers and examining the impact of non-conventional events with leave-one tests on population parameter estimation; (3) adjusting model to better characterize astrophysical phenomena and describe observed result; (4) compare different theoretical models that may describe the BBHs distribution by fitting observed data to multiple models.

## 1. BLACK HOLE POPULATION IN THE UNIVERSE

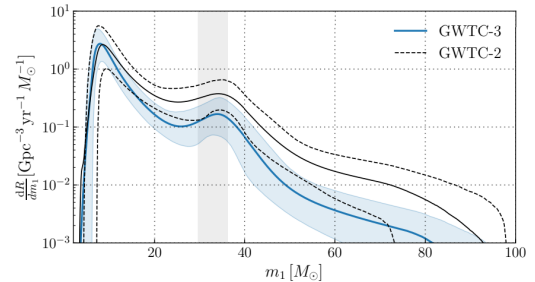
Based on the third Gravitational-wave Transient Catalog (GWTC-3), [The LIGO Scientific Collaboration et al. \(2021\)](#) looked into the mass and spin distribution, overall merger rate, as well as the cosmological evolution of the merger rate of binary black holes. These information provides valuable information on high mass star formation and history of stellar evolution, as well as how compact objects fit in the evolution of the universe.

The BBHs population has been fitted with models and described with the associated population hyper-parameters. For example, Figure 1 shows the estimated primary mass distribution of BBHs using the most popular *POWER LAW + PEAK* model (PP) model.

Aiming to evaluate the population inference’s performance, compare different black hole population models, discuss effects of outliers, and improve the general modeling process; we want to conduct goodness-of-fit tests on each step of the hyper-parameter estimation. In addition to supplement the GWTC-3 estimations, the test can also help to better understand the expected polulation from the upcoming forth observation run (O4.) For this project, I focus on the mass distribution of BBHs.

## 2. STRAIN, EVENTS, AND POPULATION

We obtained the estimation of hyper-parameters with two steps. First, the intrinsic parameters such and mass and spin and extrinsic parameters such as redshift and inclination of the individual BBHs are estimated from



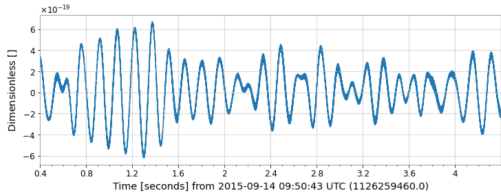
**Figure 1.** Probability density function of the primary mass distribution for the fiducial Power-Peak (PP) model. (For more on the model, please see [Talbot & Thrane \(2018\)](#)) The solid lines show the posterior population distribution (PPD) and the region shows the 90 percent credible interval of GWTC-3 (blue) and GWTC-2 (black), respectively. As shown in the figure, GWTC-3 suggests that the primary mass has more prominent peaks than we previously observed. ([The LIGO Scientific Collaboration et al. 2021](#))

the strain data from the interferometer. The individual BBHs parameters are then used to estimate the astrophysical distribution of the population. The two-step approach, also known as the hierarchical Bayesian inference ([Talbot et al. 2019](#)), is described below.

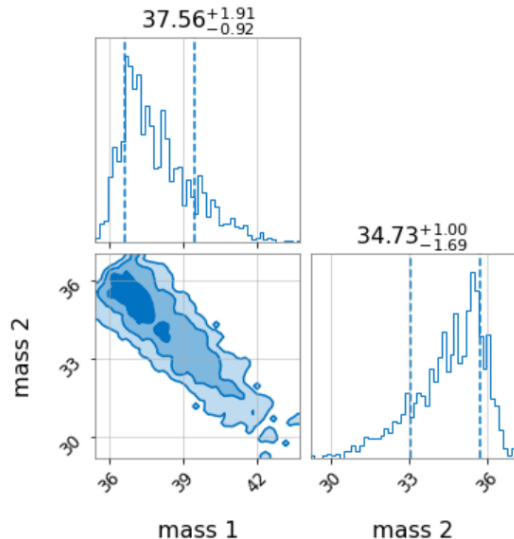
### 2.1. Single event parameters

15 parameters describes an individual BBHs events: 8 intrinsic parameters that characterized the spin and mass of the two black holes, 7 extrinsic parameters that

53 describe the binary’s position and orbit as seen by us.  
 54 Packages such as BILBY (Ashton et al. 2019) and LAL-  
 55 INFERENCE (Veitch et al. 2015) use bayesian inference to  
 56 estimate the parameters from the strain data. (Figure  
 57 2.) The result is given in the form of posterior samples.  
 58 Each sample contain a possible combination of the pa-  
 59 rameters that may create the obseved signal. The distri-  
 60 bution of parameters in the posterior sample represent  
 61 the probability distribution of each parameters includ-  
 62 ing how they may be correlated, as shown in Figure 3.



**Figure 2.** The strain data of BBHs event GW150914 at the LIGO Hanford observatory. The strain contains 4 seconds of data around the event. (Abbott et al. 2021a)



**Figure 3.** The posterior distribution of primary mass ( $m_1$ ), and secondary mass ( $m_2$ ) of GW150914 and their correlation. In this corner plot, all other parameters are marginalized. The dotted line marked the 90 percent credibility interval—90 percent of the posterior sample is in this mass range.

63 One thing to note is that the estimated parameters  
 64 are in the detector frame, the properties we see on earth.  
 65 However, many BBHs events happened far away enough  
 66 that we must take cosmology into consideration. We can  
 67 directly estimate the luminosity distance from the strain  
 68 data. With the assumption of current date cosmologi-  
 69 cal parameters from Planck 2015, we can calculate the

70 redshift of the event. (Hogg 1999) The redshift can then  
 71 be used to calculate the source frame parameters of the  
 72 events. The source frame parameter is independent of  
 73 the observer and reflect the astrophysical information  
 74 that we would like to use.

## 2.2. Population Hyper-Parameters

75  
 76 Similar to single event parameter estimation where  
 77 we take in observed strain data as the likelihood to ob-  
 78 tain the posterior distribution, (In this case, as we don’t  
 79 know much about the event, we use uninformative prior  
 80 in the bayesian inference.) we use ”data” of the in-  
 81 dividual events to obtain posterior distribution of the  
 82 population hyper-parameter. Here, the ”data” is the  
 83 parameter estimation of all events. (Talbot et al. 2019)

84 We first define the hyper-parameters we want to esti-  
 85 mate with our model. For instance, the most important  
 86 ones of the *POWER LAW + PEAK* model are the index  
 87 of the power law  $\alpha$ , the lower mass cutoff  $m_{min}$ , the  
 88 position of the peak  $\mu_m$ , the width of the peak  $\sigma_m$ , and  
 89 the contribution of the peak in the entire distribution  
 90  $\lambda_{peak}$ . Several other hyper-parameters describe the de-  
 91 tailed shape of the distribution, but they may not be as  
 92 important.

93 With the hyper-parameters defined, we can construct  
 94 the likelihood for the bayesian inference. For each  
 95 BBHs, we can calculate the probability of getting such  
 96 events under a defined population model (the model is  
 97 characterized with hyper-parameters). Given that all  
 98 events are independent, the probability of getting all the  
 99 events—the likelihood—is the product of all individual  
 100 probability.

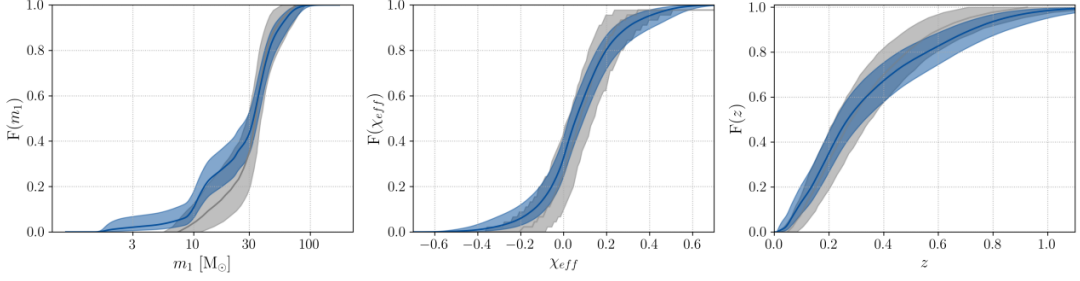
$$\mathcal{L}(d|\Lambda) = \prod_i^N P(\theta_i|\Lambda) \quad (1)$$

102 Where  $\Lambda$  is the hyperparameters and  $\theta_i$  is the parameter  
 103 of the  $i^{th}$  event.

104 However, we do not have the exact value of the pa-  
 105 rameter describing each single events. We can only infer  
 106 their probability distribution from the strain data.

$$\mathcal{L}(d|\Lambda) = \prod_i^N \int d\theta_i \mathcal{L}(d_i|\theta_i) p(\theta_i|\Lambda) \quad (2)$$

108 Here the  $\mathcal{L}(d_i|\theta_i)$  term is the probability of getting  $\theta_i$   
 109 for the  $i^{th}$  event given the strain data, also referred to  
 110 as the likelihood. We integrate over all  $\theta_i$  that we can  
 111 get from the strain data to get the total probability,  
 112 hence the  $\int d\theta_i \mathcal{L}(d_i|\theta_i)$  term. In reality, we do not have  
 113 a smooth probability distribution, but rather discrete  
 114 samples that represent the events. The relative num-  
 115 ber of samples per bin represent the probability (similar



**Figure 4.** The empirical cumulative density function of primary mass, effective inspiral spin, and redshift. The blue region represent the distribution from GWTC-3, while the grey represent the distribution from GWTC-2. The solid lines show the median while the shaded area are 90 percent credible interval. (The LIGO Scientific Collaboration et al. 2021) For this project, we hope to conduct similar comparison between the observed GWTC-3 population and the theoretical modeled population.

116 to how histogram is used to describe probability density.) Instead of reintegration, we add up the probability of each sample to construct our hyper-parameter likelihood.

$$\mathcal{L}(d|\Lambda) = \prod_i \sum_{\theta_i \sim \mathcal{L}(d_i|\theta_i)} p(\theta_i|\Lambda) \quad (3)$$

$$\mathcal{L}(d|\Lambda) \propto \frac{\prod_i \sum_{\theta_i \sim \mathcal{L}(d_i|\theta_i)} p(\theta_i|\Lambda)}{p_{\text{det}}(\Lambda)^N} \quad (4)$$

122 Finally, like all other astronomical observation, gravitational detection is subjected to selection effect: more massive black holes that create stronger signals are easier to detect. As we are interested in the astrophysical properties of black hole population, we correct this bias by including a "detection probability" term.

$$\mathcal{L}(d|\Lambda) \propto \frac{\prod_i \int d\theta_i \mathcal{L}(d_i|\theta_i) p(\theta_i|\Lambda)}{p_{\text{det}}(\Lambda)^N} \quad (5)$$

$$p_{\text{det}}(\Lambda) = \int p(\theta|\Lambda) p_{\text{det}}(\theta) d\theta \quad (6)$$

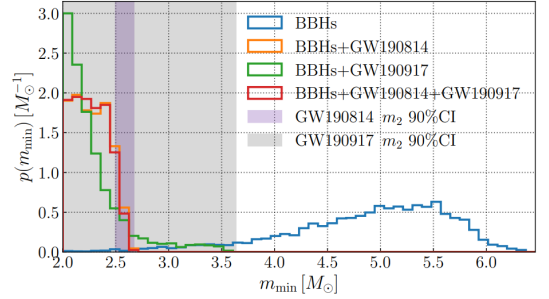
131 The "detection probability" term include the probability of detecting each parameter and the probability of detection such parameter under certain model.

134 With the likelihood defined, we pass it to python package GWPOPULATION do the bayesian inference.

### 136 3. TESTING THE MASS DISTRIBUTION 137 ESTIMATION OF BBHS WITH GWTC-3 DATA

#### 138 3.1. Outliers and Leave-one-out Tests

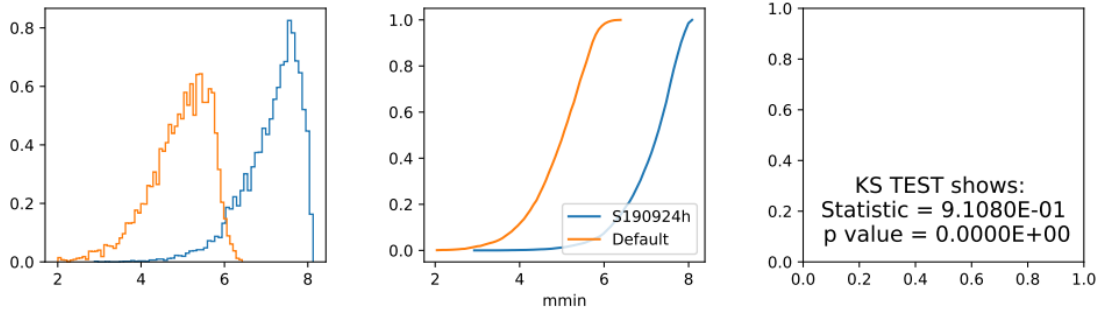
139 In previous studies, two BBHs events (GW190814 and 140 GW190917) are identified as outliers as they have very 141 low secondary mass. The rest of the population can 142 not predict the existence of these two black holes, as



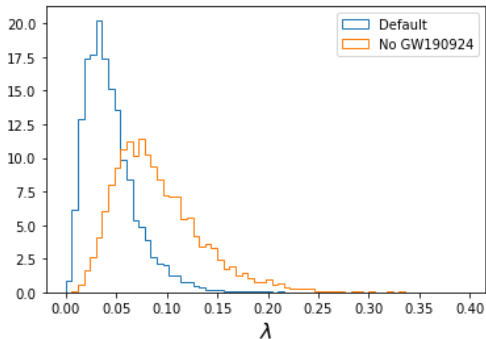
**Figure 5.** The posterior distribution of the minimum black hole mass inferred with the PP model. Posterior including and excluding GW190817 and GW190917 are shown. Inclusion of either event significantly impacted the distribution. Thus, we conclude that these two events may belong to a separate population that cannot be predicted by the rest of the events. (The LIGO Scientific Collaboration et al. 2021)

143 shown in Fig 5. The probability with and without these 144 two events have almost no overlaps, and it is very unlikely 145 that there is a value that can predict both scenario. 146 We wonder if any other events have similar constraining 147 power that with or without them in the population inference, 148 the hyper-parameters estimated would not agree.

149 Here, we conducted leave-one-out test for all 69 events 150 (excluding the previously identified outliers.) By not including 151 one event in each trial and comparing the result with the 152 result obtained from original dataset, we are able to study 153 the impact of each event. Two sample Kolmogorov–Smirnov 154 tests (KS tests) were used to compare the probability distribution 155 and quantify the differences. The two sample KS test 156 measure the difference between two population's cumulative 157 distribution function; higher KS test statistic implies that the 158 two sample are more distinct. For all hyper-parameters in 159 the PP model, the events yields the highest statistic value in 160 KS tests are picked out for closer analysis. 162



**Figure 6.** The plot on the left showed the posterior probability distribution of the minimum mass of black holes inferred from the default 69 events population and the population excluding GW190924, respectively. The middle plot shows the cumulative distribution that is used to conduct the KS test, and the KS test result is shown at the right.



**Figure 7.** The figure shows posterior probability distribution of  $\lambda$  inferred by the default population and the leave-one-out test without GW190924. The default population predicts a much lower  $\lambda$  where smaller ratio of the total population are predicted to belong to the Gaussian peak.

163 No new outliers were found as none of the events entirely disagree with the rest of the population. However, several events have strong constraining power on certain hyper-parameters and may be potential source of interests. Future observations may help clarify whether other distinct sub-populations exist. We will discuss these events of interest in the following subsections.

### 170 3.1.1. *GW190924: Low Mass*

171 The secondary black hole of GW190924 has a mass of roughly  $5 M_{\odot}$ , the lowest among all 69 events. Other lowest masses are around  $7 M_{\odot}$  (including uncertainties.) The posterior probability distribution of the leave-one out test in Figure 6 also shows this potential gap in the minimum mass. The KS test statistic value on minimum mass is over 0.9, much higher than the second highest statistic value of just over 0.1. It is possible that this black hole belongs to a separate population, or be more aligned with the two previously identified outliers. However, though the distributions are quite different, they still have significant overlap and may agree with each other. Thus, we cannot conclude GW190924 as an outlier.

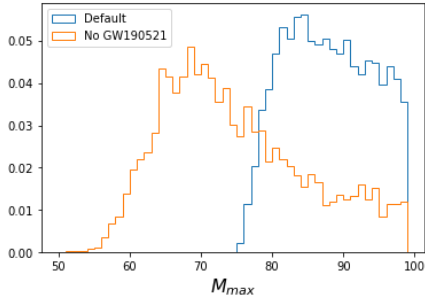
185 GW190924 also has the highest KS test statistic value on  $\lambda$ , a hyper-parameter in the PP model that characterize the normalized ratio between the black hole population falls into the Gaussian peak and the power law. Without GW190924, the inferred  $\lambda$  centered at around 0.07; with it, the he inferred  $\lambda$  centered at around 0.3. Excluding GW190924, less back holes are following the power law and more black holes are in the Gaussian peak. (Figure 7) This is highly correlated with the minimum mass: As the Gaussian peak is centered around  $35 M_{\odot}$ , the lowest mass population is dominated by the power law. The power law also predicts low mass black holes are much more common than the high mass ones. Together, small decrease on the minimum mass would significantly impact  $\lambda$  as the it allows large portion of the events to be presented at the power law dominated, lowest mass range. Similar to minimum mass, we cannot conclude GW190924 to be an outlier based on  $\lambda$  as the two result overlap significantly.

### 204 3.1.2. *GW190521: High Mass*

205 The primary mass of GW190521 is roughly  $85 M_{\odot}$ , and has been flagged as a possible high-mass outlier in GWTC-2. As shown in Figure 8, the maximum mass predicted with or without GW190521 is centered around  $85 M_{\odot}$  and  $70 M_{\odot}$ , respectively. The uncertainty of black hole mass on high mass events are often large, as the gravitational wave signal we detected are shorter and have lower frequencies. This is then reflected on the large spread on the probability distribution of maximum mass. The two distribution have significant overlap and we cannot conclude that GW190521 is an outlier. GW190521 also do not have significant impact on other hyper-parameters that defines the population as high mass events are, by nature, very rare in the total population.

220 It is worth noting that though we do not see GW190521 as an outlier, high mass events still lack an astrophysical explanation. GW190521, along

223 with GW190602.175927 and GW190519.153544 (Ab-  
 224 bott et al. 2021b), have primary mass above  $45 M_{\odot}$  at  
 225 a  $> 99\%$  confidence interval, above the mass range pre-  
 226 dicted by the PPSN model. They may involve with hi-  
 227 erarchical mergers or other unknown astrophysical pro-  
 228 cess.



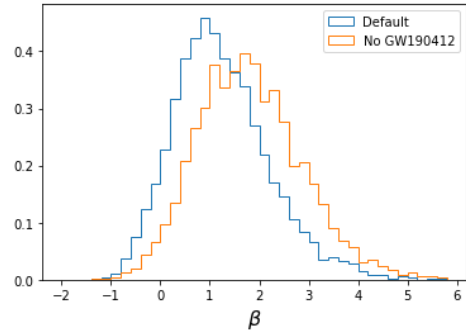
**Figure 8.** The figure shows posterior probability distribution of maximum mass inferred by the default population and the leave-one-out test without GW190521. The distribution stopped at  $100 M_{\odot}$  as the it is the highest allowed range of the prior.

229 3.1.3. *GW190412: Low mass ratio and well-measured tilt*  
 230 *angle*

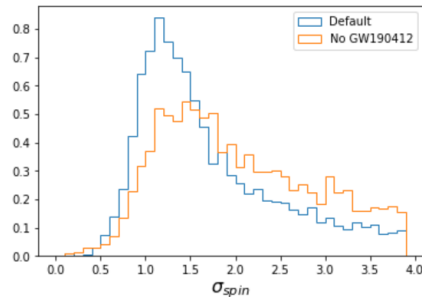
231 GW190412 is an outstanding events for both its un-  
 232 usually low mass ratio and its well-measured, positive  
 233 aligned spin.

234 The two black holes of GW190412 have masses of  
 235 around  $30 M_{\odot}$  and  $8 M_{\odot}$ , making the mass ratio be-  
 236 low 0.3, the lowest among all events. However, due to  
 237 the high uncertainty on mass ratio and the scarcity of  
 238 such unbalanced binaries, GW190412 does not signifi-  
 239 cantly change the estimation of population mass ratio  
 240 distribution, as shown in Fig 9.

241 GW190412 also has a relatively high constraining  
 242 power on the component spin tilts ( $\cos\theta$ ) and effective  
 243 inspiral spin distribution, mostly because its uncertainty  
 244 is low compare to other events. Here, we used *DE-*  
 245 *FAULT* model to describe  $\cos\theta_t$ . The model contains  
 246 two sub-population: One normal distribution centered  
 247 at  $\theta = 0$  (the spin of individual black hole is in the same  
 248 direction of the binary’s angular momentum), which is  
 249 motivated by black hole binaries that are formed to-  
 250 gether; the other one with isotropically oriented tilts  
 251 that captures the binaries that are formed separately  
 252 and with no preferred orientation.  $\sigma_{spin}$  is the width of  
 253 the aligned distribution; a lower  $\sigma_{spin}$  indicate that the  
 254 population is more concentrated and more binaries are  
 255 formed together. As shown in Figure 10, the inclusion  
 256 of GW190412 shift the peak of  $\sigma_{spin}$  distribution to an  
 257 lower value, and the uncertainty also dropped signifi-



**Figure 9.** The mass ratio of BBHs primary and secondary mass is modeled with a power law where equal mass binaries are more common. The figure shows posterior probability distribution of mass ratio power law index inferred by the default population and the leave-one-out test without GW190412. The power law index is slightly higher when excluding the unbalanced binary GW190412, but the difference is small.



**Figure 10.** The figure shows posterior probability distribution of  $\sigma_{spin}$  inferred by the default population and the leave-one-out test without GW190412. Without GW190412, the estimation is more widespread and have higher uncertainties.

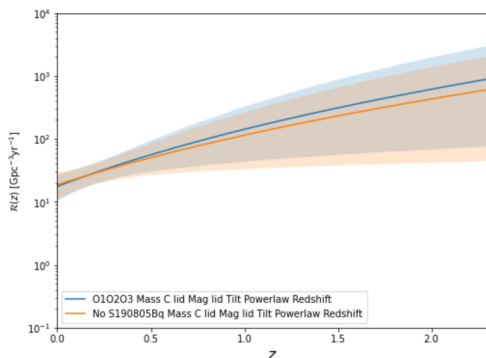
258 cantly. With future observation with lower uncertainty,  
 259 we expect to have better estimation of hyper-parameters  
 260 related with black hole spin and tilt.

261 3.2. *Redshift Evolution of BBHs Merger Rate*

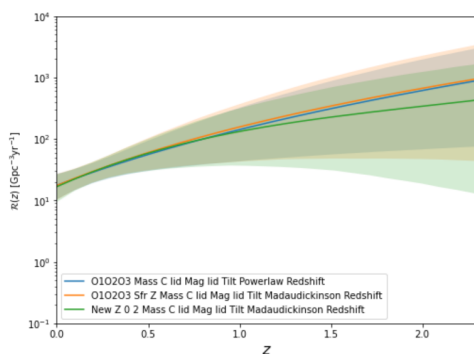
262 In previous study of BBHs population, a simple power  
 263 law is used to describe the redshift evolution of BBHs  
 264 event rate, with more events at higher redshift. With  
 265 more observation being made and the possibility of fu-  
 266 ture high redshift events, we may be able to incorporate  
 267 the theory of cosmic star formation rate evolution into  
 268 our estimation of BBHs event rate.

269 Madau & Dickinson (2014) suggests that star forma-  
 270 tion rate does not grows indefinitely with redshift, but  
 271 rather peaked at  $z = 2-3$ . The formation of stellar black  
 272 holes should obey a similar trends. Fishbach & Kalogera  
 273 (2021) suggests that for stellar black hole mergers, which  
 274 LIGO observes, the peak should be at lower redshift as





**Figure 11.** The plot shows how the BBHs event rate change with the redshift. The shaded region marks the 90% confidence interval. The blue region shows the estimation including GW190805, and the orange region shows the estimation with it. The estimation has the lowest uncertainty at  $z \approx 0.2$  where most events happened.



**Figure 12.** The plot shows BBHs rate evolution with redshift estimated with both simple power law and a broken power law motivated by cosmic stellar formation rate. The shaded area marks the 90% confidence interval. The blue region is predicted with a simple power law. The orange region is predicted by a broken power law with almost no constrain on peak position (at  $z$  between 0 to 10.) The uncertainty is slightly higher compare to the blue one due to more parameters presents in the broken power law model. The green region is also predicted by a broken power law, but with a more informative peak position (at  $z$  between 0 and 2.) We can see under this scenario, the rate may began to fall at higher redshift where observation is still technically possible.

275 the delay time between stellar black hole formation and  
276 merger is very long.

277 We cannot estimate the time delay between the stel-  
278 lar formation peak and BBHs event peak with current  
279 data, but might be able to better understand the power  
280 law index and peak position with future high redshift  
281 event. In particular, GW190805 showed us how a single  
282 high redshift event may help shape the entire distribu-  
283 tion. The events is estimated to be happened at  $z > 1$ ,  
284 much further away than most other events. As shown  
285 in Figure 11, GW190805 lift up the merger rate at high  
286 redshift.

287 More detailed model and prior selection may also  
288 yields better estimation. The current analysis use un-  
289 informative prior with large range on the inference of  
290 merger rate. In Figure 12, we show that even when  
291 keeping a uniform prior, a more informative range can  
292 change the merger rate - redshift relation. By only al-  
293 lowing the merger rate peak to happen after the cosmic  
294 noon (stellar formation peak,) we can see the slope of  
295 rate-redshift relationship become flatter.

## REFERENCES

- 296 Abbott, R., Abbott, T. D., Abraham, S., et al. 2021a,  
297 SoftwareX, 13, 100658, doi: [10.1016/j.softx.2021.100658](https://doi.org/10.1016/j.softx.2021.100658)  
298 —. 2021b, ApJL, 913, L7, doi: [10.3847/2041-8213/abe949](https://doi.org/10.3847/2041-8213/abe949)  
299 Ashton, G., Hübner, M., Lasky, P. D., et al. 2019, ApJS,  
300 241, 27, doi: [10.3847/1538-4365/ab06fc](https://doi.org/10.3847/1538-4365/ab06fc)
- 301 Fishbach, M., & Kalogera, V. 2021, ApJL, 914, L30,  
302 doi: [10.3847/2041-8213/ac05c4](https://doi.org/10.3847/2041-8213/ac05c4)  
303 Hogg, D. W. 1999, arXiv e-prints, astro.  
304 <https://arxiv.org/abs/astro-ph/9905116>  
305 Madau, P., & Dickinson, M. 2014, ARA&A, 52, 415,  
306 doi: [10.1146/annurev-astro-081811-125615](https://doi.org/10.1146/annurev-astro-081811-125615)

- 307 Talbot, C., Smith, R., Thrane, E., & Poole, G. B. 2019,  
308 PhRvD, 100, 043030, doi: [10.1103/PhysRevD.100.043030](https://doi.org/10.1103/PhysRevD.100.043030)
- 309 Talbot, C., & Thrane, E. 2018, ApJ, 856, 173,  
310 doi: [10.3847/1538-4357/aab34c](https://doi.org/10.3847/1538-4357/aab34c)
- 311 The LIGO Scientific Collaboration, the Virgo  
312 Collaboration, the KAGRA Collaboration, et al. 2021,  
313 arXiv e-prints, arXiv:2111.03634.  
314 <https://arxiv.org/abs/2111.03634>
- 315 Veitch, J., Raymond, V., Farr, B., et al. 2015, PhRvD, 91,  
316 042003, doi: [10.1103/PhysRevD.91.042003](https://doi.org/10.1103/PhysRevD.91.042003)