
LIGO SCIENTIFIC COLLABORATION AND VIRGO COLLABORATION

(See the end matter for the full list of authors.)

Received 2016 May 27; accepted 2016 September 22; published 2016 November 30

ABSTRACT

This article provides supplemental information for a Letter reporting the rate of (BBH) coalescences inferred from 16 days of coincident Advanced LIGO observations surrounding the transient (GW) signal GW150914. In that work we reported various rate estimates whose 90% confidence intervals fell in the range 2–600 Gpc⁻³ yr⁻¹. Here we give details on our method and computations, including information about our search pipelines, a derivation of our likelihood function for the analysis, a description of the astrophysical search trigger distribution expected from merging BBHs, details on our computational methods, a description of the effects and our model for calibration uncertainty, and an analytic method for estimating our detector sensitivity, which is calibrated to our measurements.

Key words: gravitational waves – stars: black holes

Supporting material: data behind figures

The first detection of a gravitational-wave (GW) signal from a merging binary black hole (BBH) system was described in Abbott et al. (2016d). Abbott et al. (2016g) reported on inference of the local BBH merger rate from surrounding Advanced LIGO observations. This Supplement provides supporting material and methodological details for Abbott et al. (2016g, hereafter referred to as the Letter).

1. SEARCH PIPELINES

Both the pycbc and gstlal pipelines are based on matched filtering against a bank of template waveforms. See Abbott et al. (2016c) for a detailed description of the pipelines in operation around the time of GW150914; here we provide an abbreviated description.

The pycbc pipeline’s detection statistic, however, is based on a likelihood ratio (Cannon et al. 2013, 2015) constructed from the single-detector S/Ns and a signal-consistency statistic. An analytic estimate of the distribution of astrophysical signals in multiple-detector S/N and signal-consistency statistic space is compared to a measured distribution of single-detector triggers without a coincident counterpart in the other detector to form a multiple-detector likelihood ratio.

Both pipelines rely on an empirical estimate of the search background, making the assumption that triggers of terrestrial origin occur independently in the two detectors. The background estimate is built from observations of single-detector triggers over a long time (gstlal) or through searching over a data stream with one detector’s output shifted in time relative to the other’s by an interval that is longer than the light travel time between detectors, ensuring that no coincident astrophysical signals remain in the data (pycbc). For both pipelines it is not possible to produce an instantaneous background estimate at a particular time; this drives our choice of likelihood function, as described in Section 2.

The gstlal pipeline natively determines the functions \( p_0(x) \) and \( p_1(x) \), for its detection statistic \( x \), for this analysis a threshold of \( x_{\text{min}} = 5 \) was applied, which is sufficiently low that the trigger density is dominated by terrestrial triggers near a threshold. There were \( M = 15,848 \) triggers observed above this threshold in the 17 days of observation time analyzed by gstlal.

For pycbc, the quantity \( x' \) is the re-weighted S/N detection statistic.\(^{137}\) We set a threshold \( x'_{\text{min}} = 8 \), above which \( M' = 270 \) triggers remain in the search. We use a histogram of triggers collected from time-shifted data to estimate the terrestrial trigger density, \( p_0(x') \), and a histogram of the recovered triggers from the injection sets described in Section 2.2 of the Letter to estimate the astrophysical trigger density, \( p_1(x') \). These estimates are shown in Figure 1. The uncertainty in the distribution of triggers from this estimation procedure is much smaller than the uncertainty in the overall rate from the finite number statistics (see, for example, Figure 5). The empirical estimate is necessary to properly account for the interaction of the various single- and double-interferometer thresholds in the pycbc search (Abbott et al. 2016c). At high S/N, where these thresholds are irrelevant, the astrophysical triggers follow an approximately flat-space volumetric density (see Section 3) of

\[
p_1(x') \simeq \frac{3x'^3}{x'^4},
\]

but they deviate from this at smaller S/N due to threshold effects in the search.

For the pycbc pipeline, a detection statistic \( x' \gtrsim 10.1 \) corresponds to an estimated search false alarm rate (FAR) of one per century.

2. DERIVATION OF POISSON MIXTURE MODEL LIKELIHOOD

In this section we derive the likelihood function in Equation (3) of the Letter. Consider a search of the type described in

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\(^{137}\) When quoting pipeline-specific values we distinguish pycbc quantities with a prime.
The astrophysical rate can, in principle, also depend on redshift, but in this paper we assume that the BBH coalescence rate is constant in the comoving frame.

Section 1 over $N_T$ intervals of time, of width $\delta_i$, $i = 1, \ldots, N_T$. Triggers above some fixed threshold occur with an instantaneous rate in time and detection statistic $x$ given by the sum of the terrestrial and astrophysical rates:

$$\frac{dN}{dtdx}(t, x) = R_0(t)p_0(x; t) + R_1(t)V(t)p_1(x; t),$$

where $R_0(t)$ is the instantaneous rate (number per unit time) of terrestrial triggers, $R_1(t)$ is the instantaneous rate density (number per unit time per unit comoving volume) of astrophysical triggers, $p_0(x)$ is the instantaneous density in the detection statistic of terrestrial triggers, $p_1(x)$ is the instantaneous density in the detection statistic of astrophysical triggers, and $V(t)$ is the instantaneous sensitive comoving redshifted volume (Abbott et al. 2016a; see also Equation (15) of the Letter) of the detectors to the assumed source population. The astrophysical rate $R_1$ is to any reasonable approximation constant over our observation intervals so we will drop the time dependence of this term from here on.\(^{138}\) Note that $R_0$ and $R_1$ have different units in this expression; the former is a rate (per time), while the latter is a rate density (per time-volume). The density $p_1$ is independent of source parameters as described in Section 3. Let

$$\frac{dN}{dt} \equiv \int dx \frac{dN}{dtdx} = R_0(t) + R_1V(t).$$

If the search intervals $\delta_i$ are sufficiently short, they will contain at most one trigger and the time-dependent terms in Equation (2) will be approximately constant. Then the likelihood for a set of times and detection statistics of triggers, $\{(t_j, x_j)|j = 1, \ldots, M\}$, is a product over intervals containing a trigger (indexed by $j$) and intervals that do not contain a trigger (indexed by $k$) of the corresponding Poisson likelihoods

$$L = \left\{ \prod_{j=1}^M \frac{dN}{dtdx}(t_j, x_j) \exp \left[ -\delta_j \frac{dN}{dt}(t_j) \right] \right\} \times \left\{ \prod_{k=1}^{N_T-M} \exp \left[ -\delta_k \frac{dN}{dt}(t_k) \right] \right\},$$

(4)

(see Farr et al. 2015, Equation (21), or Loredo & Wasserman 1995 Equation (2.8))\(^{139}\) Now let the width of the observation intervals $\delta_i$ go to zero uniformly as the number of intervals goes to infinity. Then the products of exponentials in Equation (4) become an exponential of an integral, and we have

$$L = \prod_{j=1}^M \left[ \frac{dN}{dtdx}(t_j, x_j) \right] \exp \left[ -N \right],$$

(5)

where

$$N = \int dt \frac{dN}{dt}$$

(6)

is the expected number of triggers of both types in the total observation time $T$.

As discussed in Section 1, in our search we observe that $R_0$ remains approximately constant and that $p_0$ retains its shape over the observation time discussed here; this assumption is used in our search background estimation procedure (Abbott et al. 2016c). The astrophysical distribution of triggers is universal (Section 3) and also time-independent. Finally, the detector sensitivity is observed to be stable over our 16 days of coincident observations, so $V(t) \approx \text{const}$ (Abbott et al. 2016b). We therefore choose to simply ignore the time dimension in our trigger set. This generates an estimate of the rate that is sub-optimal (i.e., has larger uncertainty) but consistent with using the full data set to the extent that the detector sensitivity varies in time; since this variation is small, the loss of information about the rate will be correspondingly small. We do capture any variation in the sensitivity with time in our Monte Carlo procedure for estimating $\langle VT \rangle$, which is described in Section 2.2 of the Letter.

If we ignore the trigger time, then the appropriate likelihood to use is a marginalization of Equation (5) over the $t_j$. Let

$$\tilde{L} = \int \left[ \prod_j dt_j \right] L$$

(7)

$$= \prod_j \left[ \Lambda_0 p_0(x_j) + \Lambda_1 p_1(x_j) \right] \exp \left[ -\Lambda_0 - \Lambda_1 \right],$$

where

$$\Lambda_0 p_0(x) = \int dt R_0(t)p_0(x; t),$$

(8)

and

$$\Lambda_1 p_1(x) = \int dt R_1V(t)p_1(x; t),$$

(9)

with

$$\int dx p_0(x) = \int dx p_1(x) = 1.$$

\(^{138}\) The astrophysical rate can, in principle, also depend on redshift, but in this paper we assume that the BBH coalescence rate is constant in the comoving frame.

\(^{139}\) There is a typo in Equation (2.8) of Loredo & Wasserman (1995). The second term in the final bracket is missing a factor of $\delta_t$.\n
Figure 1. Inferred terrestrial ($p_0$; blue) and astrophysical ($p_1$; green) trigger densities for the pycbc pipeline as described in Section 1. (The data used to create this figure are available.)
Poisson uncertainty in the terrestrial count is
search. Contours are drawn at the 10%, 20%, ...
variables are
near the Poisson uncertainty in the total count. Because this uncertainty is much
Poisson distribution. We have chosen to leave
If we assume that
Figure 2.
The data used to create this figure are available.
If we assume that $R_1$ is constant in (comoving) time, and
measure $p_1(x)$ by accumulating recovered injections through-
out the run as we have done, then this expression reduces to the
likelihood in Equation (3) of the Letter. A similar argument
with an additional population of triggers produces Equation
(10) of the Letter.

2.1. The Expected Number of Background Triggers

The procedure for estimating $p_0(x)$ in the 	exttt{pycbc} pipeline
also provides an estimate of the mean number of background
events per experiment $\Lambda_0$ (Abbott et al. 2016c). The procedure
for estimating $p_0$ used in the 	exttt{gstlal} pipeline, however, does
not naturally provide an estimate of $\Lambda_0$; instead 	exttt{gstlal}
estimates $\Lambda_0$ by fitting the observed number of triggers to a
Poisson distribution. We have chosen to leave $\Lambda_0$ as a free
parameter in our canonical analysis with a broad prior and infer
it from the observed data, rather than using the 	exttt{pycbc}
background estimate to constrain the prior, which would result
in a much narrower posterior on $\Lambda_0$. This is equivalent to the
\texttt{gstlal} procedure for $\Lambda_0$ estimation in the absence of signals;
the presence of a small number of signals in our data here does
not substantially change the $\Lambda_0$ estimate due to the over-
whelming number of background triggers in the data set.

Using a broad prior on $\Lambda_0$ is conservative in the sense that it
will broaden the posterior on $\Lambda_1$ from which we infer rates.
However, because there are so many more triggers in searches
of terrestrial origin than there are in those of astrophysical
origin there is little correlation between $\Lambda_0$ and $\Lambda_1$, so there is
little difference between the posterior we obtain on $\Lambda_1$ and the
posterior we would have obtained had we implemented the tight prior on $\Lambda_0$. Figure 2 shows the two-dimensional posterior
we obtain from Equation (5) of the Letter on $\Lambda_0$ and $\Lambda_1$.

We have checked that using a $\delta$-function prior
\begin{equation}
 p(\Lambda_0) = \delta(\Lambda_0 - 270)
 \end{equation}
in the 	exttt{pycbc} analysis that is the result of the pipeline $\Lambda_0$
estimate from timeslides\footnote{While the statistical uncertainty on the pipeline $\Lambda_0$ estimate is not precisely zero, $\sigma_{\Lambda_0}/\Lambda_0 \lesssim 10^{-3}$, it is so small that a $\delta$-function prior is appropriate.} (Abbott et al. 2016c) and using a
looser prior that is the result of a 	exttt{gstlal} estimate on a single
set of time-slid data produce no meaningful change in our
results. Figure 3 shows our canonical rate posterior inferred
with the 	exttt{pycbc} $\Lambda_0$ prior in Equation (11) and our canonical
broad prior.

3. UNIVERSAL ASTROPHYSICAL TRIGGER DISTRIBUTION

Both the 	exttt{pycbc} and 	exttt{gstlal} pipelines rely on the $S/N$ as part of their detection statistic, $x$. The $S/N$ of an astrophysical
trigger is a function of the detector noise at the time of
detection and the parameters of the trigger. Schutz (2011) and
Chen & Holz (2014) demonstrate that the distribution of the
expected $S/N (\rho)$ in a simple model of a detection pipeline that
simply thresholds on $S/N$, with sources in the local universes is universal, that is, independent of the source
properties. It follows
\begin{equation}
 p(\rho) = \frac{3\rho_{\Lambda_0}^2}{\langle \rho \rangle^3}
 \end{equation}

This result follows from the fact that the expected value of the $S/N$ in a matched-filter search for compact binary coalescence
(CBC) signals scales inversely with transverse comoving distance (Hogg 1999):
\begin{equation}
\langle \rho \rangle = \frac{A(m_{1}, m_{2}, a_{1}, a_{2}, S(f), z)B(\text{angles})}{D_M}
\end{equation}

where $A$ is an amplitude factor that depends on the intrinsic
properties (source-frame masses and spins) of the source, the
detector sensitivity expressed as a noise power spectral density
$S(f)$ as a function of observer frequency and redshift $z$, and $B$
is an angular factor depending on the location of the source in
the sky and the relative orientations of the binary orbit and
detector. The redshift enters $A$ only through shifting the source
waveform to lower frequency at higher redshift, changing $A$
because the sensitivity varies with observer frequency $f$. For the
redshifts to which we are sensitive to BBH in this observation
period this effect on $A$ is small.

If we assume that the distribution of source parameters is constant over the range of distances to which we are sensitive, and ignore the small redshift-dependent sensitivity correction
mentioned above, then the distribution of $S/N$ will be governed
entirely by the distribution of distances of the sources, which,
in the local universe, is approximately
\begin{equation}
 p(D_M) \propto D_M^3
 \end{equation}
yielding the distribution of $S/N$ given in Equation (12).
suitable for our purposes, independent of the source parameters. Figure 4 shows the distribution of recovered detection statistics for the various injection campaigns with varying source distribution used to estimate sensitive time-volumes in the \texttt{pycbc} pipeline. In each injection campaign \( O(1000) \) signals were recovered. For loud signals, the detection statistic is proportional to \( S/N \) in this pipeline, and the distribution is not sensitive to the complicated thresholding in the pipeline, so we recover Equation (12); for quiet signals the interaction of various single-detector thresholds in the pipeline causes the distribution to deviate from this analytic approximation, but it remains independent of the distribution of sources. Note that the empirical distribution of detection statistics, not the analytic one, forms the basis for \( p_i \), the foreground distribution used in this rate estimation work.

To quantify the deviations from universality, we have preformed two-sample Kolmogorov-Smirnov (KS) tests between all six pairings of the sets of detections statistics recovered in the injection campaigns described in Sections 2 and 3 of the Letter and featured in Figure 4. The most extreme KS \( p \)-value occurred with the comparison between the injection set with BBH masses drawn flat in \( \log m \) and the one with masses drawn from a power law (both described in Section 3 of the Letter); this test gave a \( p \)-value of 0.013. Given that we have performed six identical comparisons we cannot reject the null hypothesis that the empirical distributions used for rate estimation from the \texttt{pycbc} pipeline are identical even at the relatively weak significance \( \alpha = 0.05 \). Certainly any differences in detection statistic distribution attributable to the BBH population are far too small to matter with the few astrophysical signals in our data set (compared with \( O(1000) \) recovered injections in each campaign).

Because the distribution of detection statistics is, to a very good approximation, universal, we cannot learn anything about the source population from the detection statistic alone; we must instead resort to parameter estimation (PE) follow-up (Veitch et al. 2015; Abbott et al. 2016e) of triggers to determine their parameters. The parameters of the waveform template that produced the trigger can be used to guess the parameters of the source that generated that trigger, but the bias and uncertainty in this estimate are very large compared to the PE estimate. We therefore ignore the parameters of the waveform template that generated the trigger in the assignment of triggers to BBH classes.

4. COUNT POSTERIOR

We impose a prior on the \( \Lambda \) parameters of:

\[
p(\Lambda_1, \Lambda_0) \propto \frac{1}{\sqrt{\Lambda_1}} \frac{1}{\sqrt{\Lambda_0}}.
\]  

(15)

The posterior on expected counts is proportional to the product of the likelihood from Equation (3) of the Letter and the prior from Equation (15):

\[
p(\Lambda_1, \Lambda_0 | \{x_j\}_{j=1}^M)
\propto \prod_{j=1}^M \left[ \Lambda_1 p_1(x_j) + \Lambda_0 p_0(x_j) \right]
\propto \exp \left[ -\Lambda_1 - \Lambda_0 \right] \frac{1}{\sqrt{\Lambda_1 \Lambda_0}}.
\]  

(16)

For estimation of the Poisson rate parameter in a simple Poisson model, the Jeffreys prior is \( 1/\sqrt{\Lambda} \). With this prior, the

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**Figure 3.** Posterior on the population-based rate obtained from our canonical analysis (blue) and an analysis where the expected background count, \( \Lambda_0 \), is fixed to the value measured by the \texttt{pycbc} pipeline, \( \Lambda_0 = 270 \) (green). There is no meaningful change in the rate posterior between the two analyses.

(The data used to create this figure are available.)

**Figure 4.** Distribution of detection statistics in the \texttt{pycbc} pipeline for the signals recovered in the injection campaigns used to estimate sensitive time-volumes for various BBH population assumptions (see Sections 2 and 3 of the Letter). The solid line gives the analytic approximation to the distribution from Equation (12), which agrees well with the recovered statistics for loud signals; for quieter signals the interaction of various thresholds in the pipeline causes the distribution to deviate from the analytic approximation, but it remains independent of the source distribution.

(The data used to create this figure are available.)
posterior mean on $\Lambda$ is $N + 1/2$ for $N$ observed counts. With a prior proportional to $1/\Lambda$ the mean is $N$ for $N > 0$, but the posterior is improper when $N = 0$. For a flat prior, the mean is $N + 1$. Though the behavior of the mean is not identical with our mixture model posterior, it is similar; because we find $\langle \Lambda \rangle \gg 1/2$, the choice of prior among these three reasonable options has little influence on our results here.

For the \texttt{pycbc} data set we find the posterior median and 90% credible range $\Lambda_1 = 3.2^{+4.9}_{-2.4}$ above our threshold. For the \texttt{gstlal} set we find the posterior median and 90% credible range $\Lambda_1 = 4.8^{+7.9}_{-3.8}$. Though we have only one event (GW150914) at exceptionally high significance, and one other at marginal significance (LVT151012), the counting analysis shows these to be consistent with the possible presence of several more events of astrophysical origin at a lower detection statistic in both pipelines.

The thresholds applied to the \texttt{pycbc} and \texttt{gstlal} triggers for this analysis are not equivalent to each other in terms of either S/N or FAR; instead, both thresholds have been chosen so that the rate of triggers of terrestrial origin ($\Lambda_0 p_0$) dominates near the threshold. Since the threshold is set at different values for each pipeline, we do not expect the counts to be the same between pipelines.

The estimated astrophysical and terrestrial trigger rate densities (Equation (1) of the Letter) for \texttt{pycbc} are plotted in Figure 5. We select triggers from a subset of the search parameter space (i.e., our bank of template waveforms) that contains GW150914 as well as the mass range considered for possible alternative populations of BBH binaries in Section 3 of the Letter. There are $M' = 270$ two-detector coincident triggers in this range in the \texttt{pycbc} search (Abbott et al. 2016c). Figure 5 also shows an estimate of the density of triggers that comprise our data set, which agrees well with our inference of the trigger rate.

Based on the probability of astrophysical origin inferred for LVT151012 from the two-component mixture model in Equation (16) and shown in Figure 6, we introduce a third class of signals and use a three-component mixture model with expected counts $\Lambda_0$ (terrestrial), $\Lambda_1$ (GW150914-like), and $\Lambda_2$ (LVT151012-like) to infer rates in Sections 2.1 and 2.2 of the Letter.

We use the Stan and \texttt{emcee} Markov Chain Monte Carlo samplers (Foreman-Mackey et al. 2013; Stan Development Team 2015a, 2015b) to draw samples from the posterior in Equation (5) of the Letter for the two pipelines. We have assessed the convergence and mixing of our chains using empirical estimates of the autocorrelation length in each parameter (Sokal 1996), the Gelman-Rubin $R$ convergence statistic (Gelman & Rubin 1992), and through visual inspection of chain plots. By all measures, the chains appear to be well-converged to the posterior distribution.

Table 1 contains the full results on expected counts and associated sensitive time-volumes for both pipelines.

5. CALIBRATION UNCERTAINTY

The LIGO detectors are subject to uncertainty in their calibration, in both the measured amplitude and the phase of the GW strain. Abbott et al. (2016b) discussed the methods used to calibrate the strain output of the detector during the 16 days of coincident observations discussed here. Abbott et al. (2016b) estimated that the reported strain is accurate to within 10% in amplitude and 10 degrees in phase between 20 Hz and 1 kHz throughout the observations.

The S/Ns reported by our searches are quadratically sensitive to calibration errors because they are maximized over arrival time, waveform phase, and a template bank of waveforms (Allen 1996; Brown & LIGO Scientific Collaboration 2004). Abbott et al. (2016c) demonstrated that the other search pipeline outputs are also not affected to a significant degree by the calibration uncertainty present during our observing run. Therefore, we ignore the effects of calibration on the pipeline detection statistics $x$ and $x'$ that we use here to estimate rates from the \texttt{pycbc} and \texttt{gstlal} pipelines.

The amplitude calibration uncertainty in the detector results, at leading order, in a corresponding uncertainty between the luminosity distances of sources measured from real detector outputs (Abbott et al. 2016e) and the luminosity distances used to produce injected waveforms used to estimate sensitive time-volumes in this work. A 10% uncertainty in $d_L$ at these redshifts corresponds to an approximately 30% uncertainty in volume. We model this uncertainty by treating $\langle VT \rangle$ as a
parameter in our analysis, and imposing a log-normal prior:

$$p(\log \langle VT\rangle) \propto N\left(\log \mu, \frac{\sigma}{\mu}\right),$$

(17)

where $\mu$ is the Monte Carlo estimate of sensitive time-volume produced from the injection campaigns described in Section 2.2 of the Letter and

$$\sigma^2 = \sigma^2_{\text{cal}} + \sigma^2_{\text{stat}},$$

(18)

with $\sigma_{\text{cal}} = 0.3\mu$ and $\sigma_{\text{stat}}$ is the estimate of the Monte Carlo uncertainty from the finite number of recovered injections reported above. In all cases $\sigma_{\text{cal}} \gg \sigma_{\text{stat}}$.

Since the likelihood in Equations (3) or (10) of the Letter does not constrain $\langle VT\rangle$ independently of $R$, sampling over $\langle VT\rangle$ at the same time as $\Lambda$ and $R$ has the effect of convolving the log-normal distribution of $\langle VT\rangle$ with the posterior on $\Lambda$ in the inference of $R$. In spite of the 30% relative uncertainty in $\langle VT\rangle$ from calibration uncertainty, the counting uncertainty on $R$ from the small number of detected events dominates the width of the posterior on $R$. 

### Table 1

<table>
<thead>
<tr>
<th></th>
<th>pycbc</th>
<th>gstatl</th>
<th>$\langle VT\rangle$/Gpc$^3$yr</th>
</tr>
</thead>
<tbody>
<tr>
<td>GW150914</td>
<td>2.1^{+4.1}_{-1.1}</td>
<td>3.6^{+6.9}_{-2.9}</td>
<td>0.130^{+0.004}<em>{-0.001} $\times$ 0.21$^{+0.014}</em>{-0.008}$</td>
</tr>
<tr>
<td>LVT151012</td>
<td>2.0^{+4.0}_{-1.3}</td>
<td>3.0^{+6.8}_{-1.2}</td>
<td>0.032^{+0.002}<em>{-0.001} $\times$ 0.048$^{+0.001}</em>{-0.009}$</td>
</tr>
<tr>
<td>Both</td>
<td>4.5^{+5.5}_{-3.1}</td>
<td>7.4^{+9.2}_{-3.1}</td>
<td>... $\times$ ...</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>pycbc</th>
<th>gstatl</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flat in log mass</td>
<td>3.2^{+4.9}_{-2.4}</td>
<td>4.8^{+7.9}<em>{-3.8} $\times$ 0.050^{+0.003}</em>{-0.001} $\times$ 0.080^{+0.005}_{-0.003}</td>
</tr>
<tr>
<td>Power Law (-2.35)</td>
<td>0.0154^{+0.0006}<em>{-0.0009} $\times$ 0.024^{+0.003}</em>{-0.009}</td>
<td></td>
</tr>
</tbody>
</table>

**Note.** See Sections 2.1, 2.2, 3, and 4 of the Letter.
6. ANALYTIC SENSITIVITY ESTIMATE

As a rough check on our $\langle VT \rangle$ estimates and the integrand $d\langle VT \rangle/dz$, we find that the following approximate, analytic procedure also produces a good approximation to the Monte Carlo estimate in Table 1.

1. Generate inspiral–merger–ringdown waveforms in a single detector at various redshifts from the source distribution $s(\theta)$ with random orientations and sky positions.
2. Using the high-sensitivity early Advanced LIGO noise power spectral density from Abbott et al. (2016f), compute the S/N in a single detector.
3. Consider a signal found if the S/N is greater than 8.

Employed with the source distributions described above, this approximate procedure yields $\langle VT \rangle_1 \approx 0.107$ Gpc$^3$ yr and $\langle VT \rangle_2 \approx 0.0225$ Gpc$^3$ yr for the sensitivity to the two classes of merging BBH system. Figure 7 shows the sensitivity time-volume integrand,

$$d\langle VT \rangle/dz \equiv T \frac{1}{1 + z} \frac{dV_T}{dz} \int d\theta \, s(\theta) f(z, \theta),$$  \hspace{1cm} (19)

estimated from this procedure for systems with various parameters superimposed on the Monte Carlo estimates from the injection campaign described above.

The authors gratefully acknowledge the support of the United States National Science Foundation (NSF) for the construction and operation of the LIGO Laboratory and Advanced LIGO, as well as the Science and Technology Facilities Council (STFC) of the United Kingdom, the Max-Planck-Society (MPS), and the State of Niedersachsen/Germany for support of the construction of Advanced LIGO and construction and operation of the GEO600 detector. Additional support for Advanced LIGO was provided by the Australian Research Council. The authors gratefully acknowledge the support of the NSF, STFC, MPS, INFN, CNRS, and the State of Niedersachsen/Germany for the provision of computational resources. This article has been assigned the document number LIGO-P1500217.

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AUTHORS

B. P. Abbott$^1$, R. Abbott$^1$, T. D. Abbott$^2$, M. R. Abernathy$^1$, F. Acernese$^{3,4}$, K. Ackley$^5$, C. Adams$^6$, T. Adams$^7$, P. Addesso$^1$, R. X. Adhikari$^1$, V. B. Adya$^8$, C. Affeldt$^8$, M. Agathos$^9$, K. Agatsuma$^{10}$, N. Aggarwal$^{10}$, O. D. Aguiar$^{11}$, L. Aiello$^{12,13}$, A. Ain$^{14}$, P. Auth$^{15}$, B. Allen$^{8,16,17}$, A. Allocca$^{18,19}$, P. A. Altin$^{20}$, S. B. Anderson$^1$, W. G. Anderson$^{15}$, K. Arau$^{1}$, M. Araya$^{1}$, C. C. Arceneaux$^{21}$, J. S. Areeda$^{22}$, N. Arnaud$^{23}$, K. G. Arun$^{24}$, S. Ascenzi$^{13,25}$, G. Ashton$^{26}$, M. Ast$^{27}$, S. M. Aston$^{8}$, P. Astone$^{28}$, P. Aufmuth$^{8}$, C. Aulbert$^{8}$, S. Babak$^{29}$, P. Bacon$^{30}$, M. K. M. Bader$^{2}$, P. T. Baker$^{31}$, F. Baldaccini$^{32,33}$, G. Ballardin$^{34}$, S. W. Ballmer$^{35}$, J. C. Barayoga$^1$, S. E. Barclay$^{36}$, B. C. Barish$^4$, D. Barker$^{37}$, F. Baron$^{34}$, B. Barr$^{38}$, L. Barsotti$^{10}$, M. Barsuglia$^{30}$, D. Barto$^{39}$, J. Bartlett$^{2}$, I. Bartos$^{39}$, R. Bassiri$^{39}$, A. Basti$^{18,19}$, J. C. Batch$^{37}$, C. Baune$^{6}$, V. Bavigadda$^{34}$, M. Bazzan$^{41,42}$, B. Behnke$^{26}$, M. Bejger$^{39}$, A. S. Bell$^{36}$, C. J. Bell$^{36}$, B. K. Berger$^{1}$, J. Bergmann$^{37}$, G. Bergmann$^{6}$, C. P. L. Berry$^{44}$, D. Bersanetti$^{45,46}$, A. Bertolini$^{37}$, J. Betzwieser$^{6}$.


J. Zweizig

(LIGO Scientific Collaboration and Virgo Collaboration)

1 LIGO, California Institute of Technology, Pasadena, CA 91125, USA
2 Louisiana State University, Baton Rouge, LA 70803, USA
3 Università di Salerno, Fisciano, I-84084 Salerno, Italy
4 INFN, Sezione di Napoli, Complesso Universitario di Monte S. Angelo, I-80126 Napoli, Italy
5 University of Florida, Gainesville, FL 32611, USA
6 LIGO Livingston Observatory, Livingston, LA 70754, USA
7 Laboratoire d’Annecy-le-Vieux de Physique des Particules (LAPP), Université Savoie Mont Blanc, CNRS/IN2P3, F-74941 Annecy-le-Vieux, France
8 Albert-Einstein-Institut, Max-Planck-Institut für Gravitationsphysik, D-30167 Hannover, Germany
9 Nikhef, Science Park, 1098 XG Amsterdam, Netherlands
10 LIGO, Massachusetts Institute of Technology, Cambridge, MA 02139, USA
11 Instituto Nacional de Pesquisas Espaciais, 12227-010 São José dos Campos, São Paulo, Brazil
12 INFN, Gran Sasso Science Institute, I-67100 L’Aquila, Italy
13 INFN, Sezione di Roma Tor Vergata, I-00133 Roma, Italy
14 Inter-University Centre for Astronomy and Astrophysics, Pune 411007, India
15 International Centre for Theoretical Sciences, Tata Institute of Fundamental Research, Bangalore 560012, India
16 University of Wisconsin-Milwaukee, Milwaukee, WI 53201, USA
17 Leibniz Universität Hannover, D-30167 Hannover, Germany
18 Università di Pisa, I-56127 Pisa, Italy
19 INFN, Sezione di Pisa, I-56127 Pisa, Italy
20 Australian National University, Canberra, ACT 0200, Australia
21 The University of Mississippi, University, MS 38677, USA
22 California State University Fullerton, Fullerton, CA 92831, USA
23 LAL, Université Paris-Sud, CNRS/IN2P3, Université Paris-Saclay, 91400 Orsay, France
24 Chennai Mathematical Institute, Chennai 600113, India
25 Università di Roma Tor Vergata, I-00133 Roma, Italy
26 University of Southampton, Southampton SO17 1BJ, UK
27 Universität Hamburg, D-22761 Hamburg, Germany
28 INFN, Sezione di Roma, I-00185 Roma, Italy
29 Albert-Einstein-Institut, Max-Planck-Institut für Gravitationsphysik, D-14476 Potsdam-Golm, Germany
30 APC, AstroParticule et Cosmologie, Université Paris Diderot, CNRS/IN2P3, CEA/Irfu, Observatoire de Paris, Sorbonne Paris Cité, F-75205 Paris Cedex 13, France
31 Montana State University, Bozeman, MT 59717, USA
32 Università di Perugia, I-06123 Perugia, Italy
33 INFN, Sezione di Perugia, I-06123 Perugia, Italy
34 European Gravitational Observatory (EGO), I-56021 Cascina, Pisa, Italy
35 Syracuse University, Syracuse, NY 13244, USA
36 SUPA, University of Glasgow, Glasgow G12 0QX, UK
37 LIGO Hanford Observatory, Richland, WA 99352, USA
38 Wigner RCP, RMKI, H-1121 Budapest, Konkoly Thege Miklós út 29-33, Hungary
39 Columbia University, New York, NY 10027, USA
40 Stanford University, Stanford, CA 94305, USA
41 Università di Padova, Dipartimento di Fisica e Astronomia, I-35131 Padova, Italy
42 INFN, Sezione di Padova, I-35131 Padova, Italy
43 CAMK-PAN, 00-716 Warsaw, Poland
44 University of Birmingham, Birmingham B15 2TT, UK
45 Università degli Studi di Genova, I-16146 Genova, Italy
46 INFN, Sezione di Genova, I-16146 Genova, Italy
47 RRCAT, Indore MP 452013, India
48 Faculty of Physics, Lomonosov Moscow State University, Moscow 119991, Russia
49 SUPA, University of the West of Scotland, Paisley PA1 2BE, UK
50 University of Western Australia, Crawley, WA 6009, Australia
51 Department of Astrophysics/IMAPP, Radboud University Nijmegen, P.O. Box 9010, 6500 GL Nijmegen, Netherlands
52 Artemis, Université Côte d’Azur, CNRS, Observatoire Côte d’Azur, CS F-06220, Nice cedex 4, France
53 MTA Eötvös University, “Lendület” Astrophysics Research Group, Budapest 1117, Hungary
54 Institut de Physique de Rennes, CNRS, Université de Rennes 1, F-35042 Rennes, France
55 Washington State University, Pullman, WA 99164, USA
56 Université degli Studi di Urbino “Carlo Bo,” I-61029 Urbino, Italy
57 INFN, Sezione di Firenze, I-50019 Sesto Fiorentino, Firenze, Italy
58 University of Oregon, Eugene, OR 97403, USA
59 Laboratoire Kastler Brossel, UPMC-Sorbonne Universités, CNRS, ENS-PSL, Research University, Collège de France, F-75005 Paris, France
60 Astronomical Observatory Wrestling Universe, 00-478 Warsaw, Poland
61 VU University Amsterdam, 1081 HV Amsterdam, Netherlands
62 University of Maryland, College Park, MD 20742, USA
63 Center for Relativistic Astrophysics and School of Physics, Georgia Institute of Technology, Atlanta, GA 30332, USA
64 Institut Lumière Matière, Université de Lyon, Université Claude Bernard Lyon 1, UMR CNRS 5306, F-69622 Villeurbanne, France
65 Laboratoire des Matériaux Avancés (LMA), IN2P3/CNRS, Université de Lyon, F-69622 Villeurbanne, Lyon, France
66 Universitat de les Illes Balears, IAC3—IEEC, E-07122 Palma de Mallorca, Spain
67 Università di Napoli “Federico II,” Complesso Universitario di Monte S. Angelo, I-80126 Napoli, Italy
68 NASA/Goddard Space Flight Center, Greenbelt, MD 20771, USA
69 Canadian Institute for Theoretical Astrophysics, University of Toronto, Toronto, ON M5S 3H8, Canada
70 Tsinghua University, Beijing 100084, China
71 Texas Tech University, Lubbock, TX 79409, USA

10
72 The Pennsylvania State University, University Park, PA 16802, USA
74 National Tsing Hua University, Hsinchu City, 30013 Taiwan
75 Charles Sturt University, Wagga Wagga, NSW 2678, Australia
76 University of Chicago, Chicago, IL 60637, USA
77 Korea Institute of Science and Technology Information, Daejeon 305-806, Korea
78 Carleton College, Northfield, MN 55057, USA
79 Università di Roma “La Sapienza,” I-00185 Roma, Italy
80 University of Brussels, Brussels B-1050, Belgium
81 Sonoma State University, Rohnert Park, CA 94928, USA
82 Northwestern University, Evanston, IL 60208, USA
83 University of Minnesota, Minneapolis, MN 55455, USA
84 The University of Melbourne, Parkville, VIC 3010, Australia
85 The University of Texas Rio Grande Valley, Brownsville, TX 78520, USA
86 The University of Sheffield, Sheffield S10 2TN, UK
87 University of Sannio at Benevento, I-82100 Benevento, Italy
88 INFN, Sezione di Napoli, I-80100 Napoli, Italy
89 Montclair State University, Montclair, NJ 07043, USA
90 Università di Trento, Dipartimento di Fisica, I-38123 Povo, Trento, Italy
91 INFN, Trento Institute for Fundamental Physics and Applications, I-38123 Povo, Trento, Italy
92 Cardiff University, Cardiff CF24 3AA, UK
93 National Astronomical Observatory of Japan, 2-21-1 Osawa, Mitaka, Tokyo 181-8588, Japan
94 Indian Institute of Technology, Gandhinagar Ahmedabad Gujarat 382424, India
95 Institute for Plasma Research, Bhat, Gandhinagar 382428, India
96 University of Szeged, Dóm tér 9, Szeged 6720, Hungary
97 Embry-Riddle Aeronautical University, Prescott, AZ 86301, USA
98 University of Michigan, Ann Arbor, MI 48109, USA
99 Tata Institute of Fundamental Research, Mumbai 400005, India
100 American University, Washington, DC 20016, USA
101 University of Massachusetts-Amherst, Amherst, MA 01003, USA
102 University of Adelaide, Adelaide, SA 5005, Australia
103 West Virginia University, Morgantown, WV 26506, USA
104 University of Białystok, 15-424 Białystok, Poland
105 SUPA, University of Strathclyde, Glasgow G1 1XQ, UK
106 IISER-TVM, CET Campus, Trivandum Kerala 695016, India
107 Institute of Applied Physics, Nizhny Novgorod, 603950, Russia
108 Pusan National University, Busan 609-735, Korea
109 Hanyang University, Seoul 133-791, Korea
110 NCBJ, 00-956 Warsaw, Poland
111 IM-PAN, 00-956 Warsaw, Poland
112 Rochester Institute of Technology, Rochester, NY 14623, USA
113 Monash University, VIC 3800, Australia
114 Seoul National University, Seoul 151-742, Korea
115 University of Alabama in Huntsville, Huntsville, AL 35899, USA
116 ESPCI CNRS, F-75005 Paris, France
117 Universität di Camerino, Dipartimento di Fisica, I-62032 Camerino, Italy
118 Southern University and A&M College, Baton Rouge, LA 70813, USA
119 College of William and Mary, Williamsburg, VA 23187, USA
120 Instituto de Física Teórica, University Estadual Paulista/ICTP South American Institute for Fundamental Research, São Paulo SP 01140-070, Brazil
121 University of Cambridge, Cambridge CB2 1TN, UK
122 IISER-Kolkata, Mohanpur, West Bengal 741252, India
123 Rutherford Appleton Laboratory, HSIC, Chilton, Didcot, Oxon OX11 OQX, UK
124 Whitman College, 345 Boyer Avenue, Walla Walla, WA 99362 USA
125 National Institute for Mathematical Sciences, Daejeon 305-390, Korea
126 Hobart and William Smith Colleges, Geneva, NY 14456, USA
127 Andrews University, Berrien Springs, MI 49104, USA
128 Janusz Gil Institute of Astronomy, University of Zielona Góra, 65-265 Zielona Góra, Poland
129 University of Zielona Góra, I-54300 Siena, Italy
130 Trinity University, San Antonio, TX 78212, USA
131 University of Washington, Seattle, WA 98195, USA
132 Kenyon College, Gambier, OH 43022, USA
133 Abilene Christian University, Abilene, TX 79699, USA
134 College of William and Mary, Williamsburg, VA 23187, USA
135 Deceased, 2015 May.
136 Deceased, 2015 March.