Estimating the Contribution of Dynamical Ejecta in the Kilonova Associated with GW170817

LIGO Scientific Collaboration and Virgo Collaboration

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

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Abstract

The source of the gravitational-wave (GW) signal GW170817, very likely a binary neutron star merger, was also observed electromagnetically, providing the first multi-messenger observations of this type. The two-week-long electromagnetic (EM) counterpart had a signature indicative of an r-process-induced optical transient known as a kilonova. This Letter examines how the mass of the dynamical ejecta can be estimated without a direct electromagnetic observation of the kilonova, using GW measurements and a phenomenological model calibrated to numerical simulations of mergers with dynamical ejecta. Specifically, we apply the model to the binary masses inferred from the GW measurements, and use the resulting mass of the dynamical ejecta to estimate its contribution (without the effects of wind ejecta) to the corresponding kilonova light curves from various models. The distributions of dynamical ejecta mass range between $M_{ej} = 10^{-3} - 10^{-2} M_\odot$ for various equations of state, assuming that the neutron stars are rotating slowly. In addition, we use our estimates of the dynamical ejecta mass and the neutron star merger rates inferred from GW170817 to constrain the contribution of events like this to the r-process element abundance in the Galaxy when ejecta mass from post-merger winds is neglected. We find that if $\gtrsim 10\%$ of the matter dynamically ejected from binary neutron star (BNS) mergers is converted to r-process elements, GW170817-like BNS mergers could fully account for the amount of r-process material observed in the Milky Way.

Key words: gravitational waves – methods: data analysis – stars: neutron

1. Introduction

On 2017 August 17, 12:41:04 UTC, the Laser Interferometer Gravitational-wave Observatory (LIGO)/Virgo gravitational-wave (GW) observatory network, composed of LIGO Hanford Observatory, LIGO Livingston Observatory, and Virgo, recorded GWs consistent with a binary neutron star (BNS) inspiral and merger (Abbott et al. 2017c). This signal was subsequently named GW170817.

In addition to the GW signature, the merger of a BNS system is expected to have multiple electromagnetic (EM) signatures over different timescales (Nakar 2007; Metzger & Berger 2012). The LIGO/Virgo sky localization of GW170817 (Abbott et al. 2017c) spurred an intensive multi-messenger campaign covering the whole EM spectrum to search for counterparts (see Abbott et al. 2017d for an extended list). Within hours, broadband observations—backed by archival data investigation—revealed an optical transient (Arcavi et al. 2017; Coulter et al. 2017; Lipunov et al. 2017; Pian et al. 2017; Soares-Santos et al. 2017; Tanvir et al. 2017; Valenti et al. 2017), a type of transient called a kilonova (Li & Paczynski 1998; Metzger 2017) originating from neutron-rich matter unbound from the system (e.g., Evans et al. 2017; McCully et al. 2017; Smartt et al. 2017; Troja et al. 2017).

Broadly, two types of ejecta are expected to contribute to kilonovae: dynamical ejecta produced at the time of the merger (Rosswog et al. 1999; Metzger et al. 2010; Roberts et al. 2011; Barnes & Kasen 2013; Bauswein et al. 2013; Hotokezaka et al. 2013; Rosswog 2013; Tanaka & Hotokezaka 2013; Bovard et al. 2017; Dietrich & Ujevic 2017; Dietrich et al. 2017b; Radice et al. 2016; Sekiguchi et al. 2016), and post-merger winds produced by the remnant system, for example from an accretion disk around a black hole or massive neutron star (Dessart et al. 2009; Perego et al. 2014; Fernández et al. 2015; Kasen et al. 2015; Kiuchi et al. 2015; Martin et al. 2015; Foucart et al. 2016; Ciolfi et al. 2017; Fujibayashi et al. 2017; Shibata et al. 2017; Siegel & Metzger 2017).

Both EM and GW measurements rely on models to connect the underlying properties and composition of the ejecta to their respective observations. The process of interpreting ejecta based on EM observations is described in Alexander et al. (2017), Arcavi et al. (2017), Chornock et al. (2017), Covino et al. (2017), Cowperthwaite et al. (2017), Diaz et al. (2017), Drout et al. (2017), Evans et al. (2017), Kasen et al. (2017), McCully et al. (2017), Nicholl et al. (2017), Pian et al. (2017), Smartt et al. (2017), Tanaka et al. (2017), Troja et al. (2017), and Abbott et al. (2017d). We use phenomenological calculations that estimate the dynamical ejecta mass from the pre-coalescence binary properties, which GW observations can constrain. This mass is a critical ingredient needed to predict the contribution of dynamical ejecta to the EM light curve associated with this kilonova transient. Going forward, this procedure would also assist in the interpretation of future follow-up observations where a dim counterpart was detected, or none at all.

This Letter shows how dynamical ejecta masses obtained from GW parameter estimates of GW170817 via phenomenological fits to numerical models for the mass and velocity of dynamically ejected matter in BNS systems (Dietrich & Ujevic 2017, hereafter DU17) can predict kilonova light curves.
Similar numerical work has produced fitting formulae in the case of neutron-star black-hole (NSBH) binaries (Kawaguchi et al. 2016). While the GW detection of GW170817 cannot rule out the presence of a black-hole companion, the BNS interpretation is favored (Abbott et al. 2017c). Consequently, we do not include the NSBH scenario in this work, and only employ the fitting formulae for ejecta mass and velocity from BNS simulations (DU17). The GW170817 analysis extracted the BNS source parameters using Bayesian inference (Abbott et al. 2017c), and those results are used here to estimate the mass of the dynamical ejecta. This approach accounts for the dependence of the amount of ejected matter on the size and stiffness (Kawaguchi et al. 2016) of the components of the binary, characterized by the equation of state (EOS) and its influence on the mass–radius relationship (Lattimer & Prakash 2001; Özel & Freire 2016).

Bayesian inference with a GW signal model applied to the strain data provides a posterior distribution of component masses ($m$) and dimensionless spin ($\chi = e \theta / GM^2$, where $\theta$ is the angular momentum of the neutron star) consistent with the observations (Veitch et al. 2015). Assuming NS spins are small ($\chi \leq 0.05$, hereafter “low-spin”), we obtain distributions of ejecta between $10^{-2}$ and $10^{-1} M_\odot$. Allowing for larger NS spins ($\chi \leq 0.89$, hereafter “high-spin”) pushes some ejecta values higher, of the order of $10^{-1} M_\odot$ at its highest. In this Letter, we focus on dynamical sources, so it is important to recall that this analysis may not account for a significant fraction of the ejecta mass; winds could produce comparable or even more ejecta than from dynamical sources. Using the GW-derived dynamical ejecta estimates, the derived light curves vary significantly between the adopted models, in both color evolution and time and magnitude of peak emission; in extreme cases, they can reach beyond 15th magnitude in optical bands.

Like supernovae (Terasawa et al. 2001), neutron star mergers are believed to contribute to the abundance of heavy elements (Lattimer & Schramm 1974) through r-process nucleosynthesis (Burbridge 1954). Using our GW estimates of dynamical ejecta masses and the merger rates inferred from the BNS discovery ($1540_{-1220}^{+3200}$ Gpc$^{-3}$ yr$^{-1}$; Abbott et al. 2017c), we estimate a present-day r-process density of $10^{-2}$–$10^{-3} M_\odot$ Mpc$^{-3}$ contributed by BNS mergers. Under the assumption that all BNS mergers produce the same amount of dynamical ejecta that we infer for GW170817, this estimate is consistent with the Galactic values and suggests that the associated nucleosynthesis is one of the primary contributors to r-process abundances.

2. Predicted Dynamical Ejecta Mass

In general, the amount of ejecta from binary mergers depends on the masses and EOS of the two components, their rotation, and, most importantly for post-merger winds, the neutrino/radiation hydrodynamics and the magnetic fields, e.g., Hotokezaka et al. (2013), Martin et al. (2015), Dietrich et al. (2017b), Radice et al. (2016), Sekiguchi et al. (2016), and Siegel & Metzger (2017). Based on detailed numerical studies of merging, irrotational binaries, the phenomenological fits devised by DU17 relate the dynamical ejecta mass $M_{ej}$ to the gravitational mass of the component stars ($M_\star$), their baryonic mass ($m_b$), and their radii $R$ (or equivalently compactnesses $C = GM/Rc^2$). Contributions due to winds were not included in the simulations used by DU17, and thus are not part of the fits for $M_{ej}$, even though they may lead to comparable ejecta masses.

Because the EOS in neutron stars is poorly constrained, two approaches are taken to describe the bulk properties of the binary components. In the first approach, we assume an EOS and infer $m_b$ and $C$ from the binary’s measured gravitational masses using a zero-temperature non-rotating model (computed using the Oppenheimer–Volkoff equations, Oppenheimer & Volkoff 1939). Different EOSs will predict different radii and baryonic masses for the same gravitational masses and, as such, will affect the amount of ejecta and the predicted light curve of the kilonova. The EOS of cold, dense, degenerate matter is poorly constrained (see Oertel et al. 2017 for a recent review), so we evaluate a representative selection of the EOS considered in Özel & Freire (2016). The tidal deformabilities allowed by GW170817 (Abbott et al. 2017c) do disfavor stiffer EOSs; however, many remain compatible with our measurements. Due to observational constraints, we restrict ourselves to EOSs that have a maximum mass above 1.97 $M_\odot$ (Demorest et al. 2010; Antoniadis et al. 2013). Specifically, we consider EOS calculations from Glendenning (1985, GNH), Muther et al. (1987; MPA1), Wiringa et al. (1988; WFF1-2), Engvik et al. (1996; ENG), Müller & Serot (1996; MS1, MS1b), Akmal et al. (1998; APR3-4), Douchin & Haensel (2001; SLy), and Lackey et al. (2006; H4).

In the second case, we take an approach that does not assume a specific EOS to compare against our EOS-specific results. The internal structure of the NSs in a binary is encoded in the gravitational waveform through the (dimensionless) tidal deformabilities (denoted $\Lambda$) of the NSs (Flanagan & Hinderer 2008; Damour et al. 2012; Del Pozzo et al. 2013; Wade et al. 2014). One can infer $m_b$ and $C$ from the binary’s measured gravitational masses and tidal deformabilities by applying fits from Coughlin et al. (2017) and Yagi & Yunes (2017), which give $m_b(m, C)$ and $\Lambda(m, C)$, respectively. While some error is incurred using these additional fits, it is small compared to the estimated uncertainty of the fits for the dynamical ejecta properties and the intrinsic uncertainty in current numerical relativity simulations. Specifically, for the EOS considered by Yagi & Yunes (2017), the error in the tidal deformability-compactness relation is $<10\%$ for the nuclear EOS, while for the baryonic mass fit, the maximum error found by Coughlin et al. (2017) is $<3\%$. When applying these fits, we also exclude cases with component masses above 3 $M_\odot$, a standard upper bound on NS masses (Kaloger & Baym 1996), and restrict the compactness to be below the Buchdahl bound (Buchdahl 1959) of $4/9 \approx 0.44$, which similarly only affects a few cases.

2.1. Sources of Uncertainties in Ejecta Mass Estimation

Many caveats must be considered when assessing the uncertainty in estimates of $M_{ej}$. The amount of ejecta from mergers also depends on various microphysics, such as the particular treatment of thermal effects, neutrino transport, and magnetic fields (Dessart et al. 2009; Bauswein et al. 2013; Perego et al. 2014; Radice et al. 2016; Sekiguchi et al. 2016; Bovard et al. 2017; Ciolfi et al. 2017), which lead to uncertainties about the ejecta’s structure, angular distribution, and composition (Kasen et al. 2013; Tanaka & Hotokezaka 2013; Barnes et al. 2016). These parameters are not included in the $M_{ej}$ fits in DU17. Additionally, the DU17 fits ignore the effects of spin on dynamical ejecta, which can change the amount of ejecta (Kastaun & Galeazzi 2015; Dietrich et al. 2017a; Kastaun et al. 2017). In particular, aligned spin can...
increase torque in the tidal tail and lead to more ejecta, which is most notable for unequal mass configurations. To understand the effect of spin on dynamical ejecta, additional better resolved simulations are needed.

Systematic uncertainties are also of concern. The accuracy of the $M_{\text{ej}}$ fit from DU17 relies on the underlying numerical relativity simulations. Simulation choices for input physics (nuclear EOS and microphysics), inclusion of different neutrino transport models, and chosen grid resolution can all result in large systematics. For example, comparisons of numerical relativity predictions of $M_{\text{ej}}$ differ by a factor of $\sim 4$ (Lehner et al. 2016; Sekiguchi et al. 2016; Bovard et al. 2017). Further, the error on ejecta masses from numerical simulations likely has an absolute component, leading to increasing relative errors for low ejecta masses—for additional discussion see Endrizzi et al. (2016) and Ciolfi et al. (2017). An error at low masses is not symmetric as $M_{\text{ej}}$ cannot be negative, potentially biasing the phenomenological fits of DU17 to an overestimation of the ejecta mass. Additionally, there are also systematic uncertainties introduced by the specific form of the fit, where all EOS effects are contained in the values of $m_0$ and $C$ for a given $m$.

Finally, as discussed in Abbott et al. (2017c) and Section 2.2, the waveform model used to infer the masses and tidal deformabilities from the GW signal introduces its own systematic uncertainties, though these are estimated to be smaller than those of the DU17 $M_{\text{ej}}$ fit.

All of these considerations contribute to the uncertainty in the $M_{\text{ej}}$ fit from DU17; the error is a mixture of systematic errors that need investigation with dedicated future studies and numerical simulations. To model some part of this error, we will treat the average relative error of the fit quoted in DU17 (72%) as a statistical error for any results used here, and defer a more robust error analysis to future work. We include an estimate of the error of the $M_{\text{ej}}$ fit from DU17 by replacing each ejecta mass sample with a random value consistent with a Gaussian distribution in $\log_{10}M_{\text{ej}}$ centered on the value and with standard deviation of $\log_{10}1.72$, as motivated in Section 2.1. This method excludes zero ejecta masses, and errors for small ejecta masses $\lesssim 10^{-3}M_\odot$ are not well modeled. The ejecta mass fit is based on simulations with nonzero ejecta mass. The full parameter space likely also contains cases with little or no ejecta mass, for example, systems exhibiting prompt black-hole formation. Since we reported in Abbott et al. (2017b) that prompt collapse can only be excluded for extreme EOSs such as MS1, and the fit at values below $3 \times 10^{-3}M_\odot$ strongly overestimates the ejecta mass compared to the numerical relativity (NR) data points, the fit cannot reliably exclude zero ejecta mass below this value. Figure 1 shows that, in the low-spin cases, the number of samples less than $M_{\text{ej}} < 3 \times 10^{-3}M_\odot$ is typically $\sim 10\%$--15\% of the cumulative total for most. In extreme cases, this fraction is up to 50\%, but also arises from EOSs that have been disfavored in Abbott et al. (2017c). In the high-spin cases, this number is typically smaller, around 5\%--10\%, but can reach up to 25\% in the extreme cases. We also discard the few samples where the fit predicts a negative value.

2.2. Ejecta Mass Predictions

We evaluate the $M_{\text{ej}}$ fit using the binary parameters derived from the GW analysis (Abbott et al. 2017c). These parameters include the gravitational masses, tidal deformabilities, and spins of the component stars, though the spins are not used in evaluating the fit. Bayesian inference provides a distribution of these parameter values as a set of independent samples drawn from the posterior (Veitch et al. 2015; Abbott et al. 2016a). As a quantity that derives from these binary parameters, $M_{\text{ej}}$ then is also represented as a statistical sample.

While the estimate of $M_{\text{ej}}$ does not include the component spins as an input, they are an important degree of freedom in the waveform models used in the GW analysis. We consider two sets of GW parameter samples, defined by the choices for the prior on the spin magnitude. The two spin priors considered here are $\chi = 0.89$ (our “high-spin” case with the upper limit dictated by the waveform model used), and $\chi \leq 0.05$ (our “low-spin” case, slightly above the largest inferred spin at the merger of an NS in a BNS system that will merge within a Hubble time (Burgay et al. 2003)). While the waveform models used only include the effects of the spin components along the orbital angular momentum, the spin priors assume isotropic spin directions. The very highest spins allowed in the high-spin posterior set exceed the mass-shedding limit ($\chi \sim 0.7$ for the EOS considered in Lo & Lin 2011), but the small density of posterior samples in this region lies outside the 90\% credible intervals. More importantly, the high-spin posterior on the primary mass contains samples with masses well above the maximum mass allowed for a static NS for any of the EOSs we consider; we simply exclude from consideration any samples with such unsupported masses for each EOS.

There are also systematic errors introduced by the waveform model used. As discussed in Abbott et al. (2017c), analysis with a different waveform model changes the 90\% credible bounds on the masses by $\sim 15\%$ in the high-spin case (with no changes in the low-spin case), and the bounds on the tidal deformabilities by $\sim 20\%$--$30\%$ in both low- and high-spin cases. As these differences are below the systematic errors of the DU17 fit, we do not attempt to account for them here. The true systematic errors from waveform models may be significantly larger than those estimated in this comparison; making such assessments is the subject of future work.

Figure 1 reports cumulative probability distributions for the dynamical ejecta for a selection of the EOS tested. While all of
the cases predict ejecta concentrated between $10^{-3}$ and $10^{-2} M_\odot$, the high-spin results allow for larger median ejecta values in general—maximum values can exceed a tenth of a solar mass. Since the DU17 fits for $M_{ej}$ neglect spin, the differences in ejecta for the cases shown in Figure 1 are driven by the imprint of the spin choices inherent in the GW analysis that was input into this analysis.

Figure 2 shows the distribution of ejecta masses using the SLy EOS, illustrating how the ejecta mass tends to scale with the component mass distribution. Among the EOSs tested, SLy is closer to the lower side of ejecta distributions in both the estimated median and maximum ejecta. The fits themselves imply an ejecta distribution strongly dependent on the mass of the primary ($m_1$) and the difference between the primary and secondary masses. However, applying the fit uncertainty smears the ejecta distribution over the difference of the component masses. This effect is most evident in the marginal distributions plotted as histograms on the sides of the Figure 2 panels. Since the high-spin distribution has more posterior samples away from equal mass systems, as well as larger primary masses overall, more samples give rise to larger ejecta masses. While this only affects the high-spin case, those EOSs that allow for larger maximum masses also allow for a larger maximum ejecta values, typically $M_{ej} > 10^{-1} M_\odot$ (above the maximum ejecta mass of $6.5 \times 10^{-2} M_\odot$ in the simulations to which the $M_{ej}$ fit has been calibrated). This is a natural consequence of larger maximum masses corresponding to larger differences between $m_1$ and $m_2$, as illustrated in Figure 2.

3. Kilonova Light Curve Models

Current kilonova emission models (Li & Paczynski 1998; Barnes et al. 2016; Metzger 2017; Tanaka et al. 2017) produce spectral energy distributions between the ultraviolet (UV) and the near-infrared (NIR). Generally, there are two different physical processes that require modeling. First, the conversion of dynamical and wind ejecta material into $r$-process elements (i.e., the nucleosynthesis; Kasen et al. 2013, 2015; Barnes et al. 2016; Metzger 2017; Rosswog et al. 2017), and second, the production of an associated EM transient (Metzger et al. 2010; Kasen et al. 2013; Barnes et al. 2016; Rosswog et al. 2017). Beyond these considerations, there are still several important nuclear physics ingredients that are unknown, such as opacity and heating rate, and can lead to large uncertainties in light curve prediction (see, e.g., Rosswog et al. 2017). We do not attempt to model these uncertainties.

We briefly describe here three parameterized models used to generate light curves in this work. Wollaeger et al. (2017) use radiative transfer simulations and provide analytic fits for the peak time, bolometric luminosity, and color corrections as a function of ejecta parameters. The Wollaeger et al. (2017) light curves are scaled as a function of ejecta mass and velocity, which changes both the time of peak luminosity as well as peak magnitude. We obtain the velocity from additional fits in DU17, and assume an opacity of $10 \text{ cm}^2 \text{g}^{-1}$, thus modeling the presences of lanthanides. Conversely, Metzger (2017) provide a toy model for blue kilonova with opacity $0.1 \text{ cm}^2 \text{g}^{-1}$ for lanthanide-free matter. DU17 use the radiative Monte-Carlo (MC) simulations of Tanaka & Hotokezaka (2013) and derive an analytical model for kilonova emission driven by dynamical ejecta from a BNS merger. No wind contribution is included in DU17, although winds can potentially dominate (Kiuchi et al. 2015; Ciolfi et al. 2017; Siegel & Metzger 2017). The dynamical ejecta models tend to predict redder and more slowly rising NIR than wind-driven models.

Light curves from dynamical ejecta models depend significantly on the thermalization efficiency, the radiation transport simulations used, and other assumptions (Metzger & Fernandez 2014; Coughlin et al. 2017; Rosswog et al. 2017). In our analysis we do not consider observational error from
these two models, originally brighter in the blue and NIR bands—

blue, and a faster fade in the NIR. The model in Metzger

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themselves

include 1 mag errors on the intervals to account for errors in the models

extinction in the light curve prediction, as it is likely smaller than the systematic error of the models (Kawaguchi et al. 2016).

4. Predicted Kilonova Light Curves

In conjunction with the mass and tidal estimates for the low-spin case, we calculate the mass and velocity of dynamical ejecta as described in Section 2. Using the light curve models of DU17, Metzger (2017), and Wollaeger et al. (2017), we show the absolute and apparent magnitudes consistent with these estimates of dynamical ejecta in Figure 3. Here, we employ the D22 model from Wollaeger et al. (2017), and set 40 Mpc (near the median of the GW distance posterior (Abbott et al. 2017a, 2017c)) as the fiducial distance to the event for calculating the apparent magnitudes. DU17 exhibits the features of most lanthanide-rich dynamical ejecta models, with a rapid fade in the blue and a late rise in the NIR. Wollaeger et al. (2017), which also considers the contribution from the wind ejecta of 0.005 $M_\odot$, is brighter, has a slower fade in the blue, and a faster fade in the NIR. The model in Metzger (2017)—adopted here only considering dynamical ejecta—is between these two models, originally brighter in the blue and NIR bands

(g, r, i, z) than either of these models, but fades more quickly than Wollaeger et al. (2017).

Employing the lower-opacity blue-peaked model in Metzger (2017) and GW inferred distance, we can calculate the distribution of peak times and observed peak magnitudes in a given photometric band. As the source resides at a low redshift, we neglect the cosmological redshift of the source. Figure 4 shows the peak i-band magnitudes from those light curves versus the time of peak i-band magnitude when considering the low-spin distribution. The samples from the high-spin distribution produce the peaks that are brighter by one magnitude on average. This is understood from the ejecta distributions in Figure 2—the low-spin distribution tends to produce less ejecta and hence is less luminous. We note again that the light curves in Figure 3 are calculated with a distance fixed to the source, while the magnitudes in Figure 4 fold in the distance inferred from the GW data. Thus, a wider spread arises from the variance in the GW-only distance posterior distribution. Including the distance values from the GW posteriors provides a better estimation of the variation that would arise in a prediction from GW information alone, as opposed to having constraints from EM measurements.

The estimates presented here are a proof-of-principle study with which to illustrate what is presently possible with forward modeling from GW observations. In particular, if it is available before EM observations begin, or in a situation before a confident counterpart has been identified (e.g., due to poor sky localization), analysis driven by the GW data can inform EM follow-up observations and interpretation, particularly in cases where (due to geometric effects and observational delays) the effect of dynamical ejecta on the light curve is enhanced. Predictions of peak times in the emission and the color evolution are useful for comparison with early observations, and provide falsifiable predictions with which to evaluate models of the source.
5. Abundance of r-Process Material

The r-process and s-process are the two known mechanisms by which heavy elements can be synthesized (Burbridge et al. 1957). To assess the contribution of the r-process to the observed abundances of heavy elements (Arnould et al. 2007; Sneden et al. 2008), one can identify the abundances expected from the s-process alone, and hence the r-process residual. SNe II can produce r-process elements, but they may not produce the observed abundance patterns (e.g., Freiburghaus et al. 1999). BNS mergers could also account for these elements. However, quantifying the contribution of those mergers has remained elusive due to poor constraints on both the rate of mergers as well as the amount of matter ejected in each merger. With GW170817, we are able to constrain both of these quantities significantly from data.

If BNS mergers are to produce most of the observed r-process elements in the Milky Way (MW), the mergers must occur with a sufficiently high rate and eject significant amounts of r-process material. Assuming dynamical ejecta dominate over winds, the mass fraction \( X_{\text{rp}} \) of r-process nuclei in the MW should be proportional to the merger rate density \( \mathcal{R} \) and dynamical ejecta mass \( M_{\text{ej}} \), with a proportionality constant set by the local galaxy density and the MW age and mass. Following Qian (2000), we estimate that the merger rate and ejecta per event are approximately related by \( \mathcal{R} \approx 600 (f_{\text{rp}} M_{\text{ej}}/10^{-5} M_{\odot})^{-1} \) Gpc\(^{-3}\) yr\(^{-1}\). In this relationship, \( f_{\text{rp}} \equiv M_{\text{ej}}/M_{\text{ej}} \) is the fraction of matter dynamically ejected in NS mergers that is converted to heavy r-process elements rather than lighter products, e.g., \( \alpha \) particles. The value of \( f_{\text{rp}} \) depends on details of the dynamics, geometry, and neutrino illumination of the ejected matter, all of which change the electron fraction (\( Y_e \)) distribution of ejected matter (see, e.g., Goriely et al. 2015; Kasen et al. 2015). However, various studies have suggested significant r-processing of ejecta material (e.g., Goriely et al. 2011, 2015; Wanajo et al. 2014; Just et al. 2015; Radice et al. 2016). The red band in the left panel of Figure 5 shows this relationship between \( \mathcal{R} \) and \( M_{\text{ej}} \) for \( f_{\text{rp}} \in [0.5, 1] \) (e.g., Goriely et al. 2015). Also shown in the left panel are the constraints on the local rate density of BNS mergers from GW170817 (gray) and the range of ejecta masses typically considered in the literature (blue). The overlap of these constraints suggests that BNS mergers could account for all of the observed r-process abundance.

A more detailed calculation of r-process enrichment from the dynamical ejecta of BNS mergers can be done using the specific distributions of \( M_{\text{ej}} \) and \( \mathcal{R} \) inferred from GW170817. Under the assumption that all binary mergers have the same ejecta mass as that inferred from GW170817, we calculate the average dynamically ejected local r-process material density according to

\[
\rho_{\text{rp}} = f_{\text{rp}} M_{\text{ej}} \mathcal{R} \int_0^{t_{\text{delay}}} \int_0^{t} \rho_\alpha(t) P_{\text{delay}}(t - \tau) d\tau dt \int_0^{t} \rho_\alpha(t) P_{\text{delay}}(t - \tau) d\tau.
\]  

where \( t_{\text{delay}} \) is the Hubble time.\(^{164}\)

In this expression, \( \rho_\alpha \) is the cosmological star formation rate, assumed to follow Madau & Dickinson (2014); \( P_{\text{delay}} \) is the delay time distribution of NS mergers, \( \rho_{\text{delay}}(t) \propto t^{-1} \) (see, e.g., O’Shaughnessy et al. 2008; Dominik et al. 2012), with a minimum delay time of 10 Myr; and \( \mathcal{R} \) is the present-day merger rate density for NS mergers. The denominator is a normalization factor that scales the present-day merger rate density to \( \mathcal{R} \).

In the right panel of Figure 5, we plot the distribution of \( \rho_{\text{rp}}/\rho_\alpha \) for a few representative EOSs using our \( M_{\text{ej}} \) distributions and the rates inferred from GW170817. On the top axis, we also show \( X_{\text{rp}}/\rho_{\text{rp}} = (\rho_{\text{rp}}/\rho_\alpha)/\rho_\alpha \), where \( \rho_\alpha = \int_0^{t_{\text{delay}}} \rho_\alpha(t) dt \). If \( f_{\text{rp}} = 1 \), the range \( 10^{-7} M_{\odot} \text{ Mpc}^{-3} \)–\( 10^{-3} M_{\odot} \text{ Mpc}^{-3} \) brackets our 90% credible intervals on \( \rho_\alpha \) for all EOSs. Both \( \rho_\alpha \) and \( X_{\text{rp}} \) are shown normalized to \( f_{\text{rp}} \), as \( f_{\text{rp}} \) depends on unknown details of the merger. The gray band in the right panel of Figure 5 shows the MW mass abundance of r-process elements, derived from Arnould et al. (2007). As long as \( f_{\text{rp}} \gtrsim 10\% \) of the dynamically ejected mass is converted to heavy r-process elements, dynamical ejecta could account for all of the MW

\[^{164}\]We assume \( \Lambda \)CDM cosmology with TT+lowP+lensing+ext parameters from Ade et al. (2016).
r-process abundance. We have not factored in modeling details such as the relative abundance pattern of r-process elements, the value of $f_{\text{rp}}$, the relative contribution of dynamical versus wind ejecta, and uncertainties in the star formation history of the Universe.

6. Conclusions

In this Letter, we derive estimates for the dynamical ejecta mass produced by the BNS merger GW170817, as well as the corresponding kilonova light curves and r-process nucleosynthesis yields, without additional photometric or EM spectral data. These estimates have the GW data as their foundation and use a fit to a wide variety of simulations to obtain dynamical ejecta masses from these data. Our predictions for light curves include a range of possible magnitudes and timescales of emission. In general, for the blue model in Metzger (2017) in the $i$-band, we predict peak magnitudes concentrated between $\sim 19$ and $\sim 17$ for a merger consistent with our low-spin results, and peak magnitude between $\sim 19$ and $\sim 16$—typically lasting twice as long—for mergers consistent with high-spin results. Such predictions can guide expectation as to whether or not future, perhaps more distant, counterparts would be observable with a given facility. The predictions from the GW inference for the dynamically unbound matter depend strongly on the allowed spin configurations in the GW model, which in turn influence the predicted light curves. The low-spin results predict smaller ejecta masses on the whole, and as such, a bright kilonova event (e.g., $>16$ magnitude) may indicate a faster spinning NS component. We stress that the phenomenological fits used to predict $M_{\text{ej}}$ themselves are not corrected for spin effects, so this increased brightness occurs because of degeneracies in the GW parameter estimates between spin and mass ratio.

We have also presented predicted light curves derived from other models in the literature. Our results show that when large amounts of ejecta mass are allowed, the light curves have brighter peaks and are longer-lived. They differ in color evolution, however (compare DU17 and Wollaeger et al. 2017, for example) and EM observations combined with these curves could hint at mixtures of different ejecta material compositions (Metzger 2017). For example, strong emission observed in both blue and red bands could imply sectors of material containing both high and low electron fractions. However, the Metzger model, as implemented here, neglects post-merger wind effects, and in general, these conclusions only hold under the assumption that dynamical ejecta dominate the mass ejection.

Our results suggest that dynamical ejecta from rare NS mergers could be an important and inhomogeneous source of r-process elements in the Galaxy (Beniamini et al. 2016; Ji et al. 2016). If more than $f_{\text{rp}} \gtrsim 10\%$ of the mass ejected from mergers is converted to r-process elements, our prediction for average r-process density in the local universe is consistent with the Galactic abundance. Our approach does not address the contribution from winds, which could eject a substantial overall mass but may (Siegel & Metzger 2017) or may not (Rosswog et al. 2017) have the wide range of $Y_e$ needed to produce all r-process abundances (i.e., the second and third r-process peak). Our approach is also not as detailed as full multi-species chemical enrichment calculations used to interpret observations of individual elements in targeted populations (see, e.g., Côté et al. 2017). As Advanced LIGO and Virgo approach design sensitivity, these observational constraints should rapidly shrink, enabling more precise tests of the BNS r-process nucleosynthesis paradigm. Additionally, present and future EM observations should provide complementary information to directly constrain those parameters that our analysis cannot.

Finally, if EM measurements are consistent with a total ejecta mass (dynamical and wind) of $\gtrsim 0.01 M_\odot$, and if we require consistency with low neutron star spins, then one possible conclusion is that winds contribute significantly to the total ejected mass. However, if winds dominate, then the dynamical ejecta mass will be an important but potentially difficult to measure component in the light curve, which our calculations can supply. Additionally, with so much material ejected per event, to be consistent with our inferred detection rate, we would predict that only a fraction of the ejecta can form r-process elements.

The coincidence of GW170817 and GRB 170817A was an exceptionally rare event, allowing for a unique set of measurements to be made about the processes driven by the BNS merger. Future observations should facilitate the refinement of these measurements. The observation of GW170817 suggests that in the upcoming year-long third observing run (Abbott et al. 2016b) with a three-instrument GW network, there will likely be more GW observations of BNSs. In the coming years, GW measurements will allow for better understanding of populations of kilonova events.

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Abbott et al.

41 West Virginia University, Morgantown, WV 26506, USA
42 Università di Perugia, I-06123 Perugia, Italy
43 INFN, Sezione di Perugia, I-06123 Perugia, Italy
44 University of Minnesota, Minneapolis, MN 55455, USA
45 SUPA, University of Glasgow, Glasgow G12 8QQ, UK
46 LIGO Hanford Observatory, Richland, WA 99352, USA
47 Caltech CaRT, Pasadena, CA 91125, USA
48 Wigner RCP, RMKI, H-1121 Budapest, Konkoly Thege Miklós út 29-33, Hungary
49 Columbia University, New York, NY 10027, USA
50 Stanford University, Stanford, CA 94305, USA
51 Università di Camerino, Dipartimento di Fisica, I-62032 Camerino, Italy
52 Università di Padova, Dipartimento di Fisica e Astronomia, I-35131 Padova, Italy
53 INFN, Sezione di Padova, I-35131 Padova, Italy
54 Institute of Physics, Eötvös University, Pázmány P. s. 1/A, Budapest 1117, Hungary
55 Nicolaus Copernicus Astronomical Center, Polish Academy of Sciences, 00-716, Warsaw, Poland
56 Dipartimento di Scienze Matematiche, Fisiche e Informatiche, Università di Parma, I-43124 Parma, Italy
57 INFN, Sezione di Milano Bicocca, Gruppo Collegato di Parma, I-43124 Parma, Italy
58 Rochester Institute of Technology, Rochester, NY 14623, USA
59 University of Birmingham, Birmingham B15 2TT, UK
60 INFN, Sezione di Genova, I-16146 Genova, Italy
61 Syraçuse University, Syracuse, NY 13244, USA
62 RRCAT, Indore MP 452013, India
63 Faculty of Physics, Lomonosov Moscow State University, Moscow 119991, Russia
64 SUPA, University of Strathclyde, Glasgow G1 1XQ, UK
65 The Pennsylvania State University, University Park, PA 16802, USA
66 OzGrav, University of Western Australia, Crawley, Western Australia 6009, Australia
67 Department of Astrophysics/IMAPP, Radboud University Nijmegen, P.O. Box 9010, 6500 GL Nijmegen, The Netherlands
68 Artemis, Université Côte d’Azur, Observatoire Côte d’Azur, CNRS, CS 43229, F-06304 Nice Cedex 4, France
69 Institut FOTON, CNRS, Université de Rennes 1, F-35042 Rennes, France
70 Washington State University, Pullman, WA 99164, USA
71 University of Oregon, Eugene, OR 97403, USA
72 Laboratoire Kastler Brossel, UPMC-Sorbonne Universités, CNRS, ENS-PSL, Research University, Collège de France, F-75005 Paris, France
73 Carleton University, Northfield, MN 55057, USA
74 OzGrav, University of Adelaide, Adelaide, South Australia 5005, Australia
75 Astronomical Observatory Warsaw University, 00-478 Warsaw, Poland
76 VU University Amsterdam, 1081 HV Amsterdam, The Netherlands
77 University of Maryland, College Park, MD 20742, USA
78 Center for Relativistic Astrophysics, Georgia Institute of Technology, Atlanta, GA 30332, USA
79 Université Claude Bernard Lyon 1, F-69622 Villeurbanne, France
80 Università di Napoli “Federico II,” Complesso Universitario di Monte S. Angelo, I-80126 Napoli, Italy
81 NASA Goddard Space Flight Center, Greenbelt, MD 20771, USA
82 Dipartimento di Fisica, Università degli Studi di Genova, I-16146 Genova, Italy
83 RESCEU, University of Tokyo, Tokyo, 113-0033, Japan
84 Tsinghua University, Beijing 100084, China
85 Texas Tech University, Lubbock, TX 79409, USA
86 Kenyon College, Gambier, OH 43022, USA
87 Departamento de Astronomía y Astrofísica, Universitat de València, E-46100 Burjassot, València, Spain
88 Museo Storico della Fisica e Centro Studi e Ricerche Enrico Fermi, I-00184 Roma, Italy
89 National Tsing Hua University, Hsinchu City, 30013, Taiwan, Republic of China
90 Charles Sturt University, Wagga Wagga, New South Wales 2678, Australia
91 Center for Interdisciplinary Exploration & Research in Astrophysics (CIERA), Northwestern University, Evanston, IL 60208, USA
92 Canadian Institute for Theoretical Astrophysics, University of Toronto, Toronto, Ontario M5S 3H8, Canada
93 University of Chicago, Chicago, IL 60637, USA
94 Pusan National University, Busan 46241, Korea
95 The Chinese University of Hong Kong, Shatin, NT, Hong Kong
96 INAF, Osservatorio Astronomico di Padova, I-35122 Padova, Italy
97 INFN, Trento Institute for Fundamental Physics and Applications, I-38123 Povo, Trento, Italy
98 OzGrav, University of Melbourne, Parkville, Victoria 3010, Australia
99 Università di Roma “La Sapienza,” I-00185 Roma, Italy
100 Université Libre de Bruxelles, Brussels B-1050, Belgium
101 Sonoma State University, Rohnert Park, CA 94928, USA
102 Departamento de Matemáticas, Universitat de València, E-46100 Burjassot, València, Spain
103 Montana State University, Bozeman, MT 59717, USA
104 Universitat de les Illes Balears, IAC3, E-07122 Palma de Mallorca, Spain
105 The University of Texas Rio Grande Valley, Brownsville, TX 78520, USA
106 Bellevue College, Bellevue, WA 98007, USA
107 Institute for Plasma Research, Bhat, Gandhinagar 382428, India
108 The University of Sheffield, Sheffield S10 2TN, UK
109 California State University, Los Angeles, 5151 State University Dr, Los Angeles, CA 90032, USA
110 Università di Trento, Dipartimento di Fisica, I-38123 Povo, Trento, Italy
111 Montclair State University, Montclair, NJ 07043, USA
112 National Astronomical Observatory of Japan, 2-21-1 Osawa, Mitaka, Tokyo 181-8588, Japan
113 Observatori Astronomic, Universitat de València, E-46980 Paterna, València, Spain
114 School of Mathematics, University of Edinburgh, Edinburgh EH9 3FD, UK
115 University and Institute of Advanced Research, Koba Institutional Area, Gandhinagar Gujarat 382007, India