Mapping Distances across the Perseus Molecular Cloud Using CO Observations, Stellar Photometry, and Gaia DR2 Parallax Measurements

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Received 2018 March 23; revised 2018 October 16; accepted 2018 October 16; published 2018 December 13

Abstract

We present a new technique to determine distances to major star-forming regions across the Perseus Molecular Cloud, using a combination of stellar photometry, astrometric data, and 12CO spectral-line maps. Incorporating the Gaia DR2 parallax measurements when available, we start by inferring the distance and reddening to stars from their Pan-STARRS1 and Two Micron All Sky Survey photometry, based on a technique presented by Green et al. and implemented in their 3D “Bayestar” dust map of three-quarters of the sky. We then refine their technique by using the velocity slices of a CO spectral cube as dust templates and modeling the cumulative distribution of dust along the line of sight toward these stars as a linear combination of the emission in the slices. Using a nested sampling algorithm, we fit these per-star distance–reddening measurements to find the distances to the CO velocity slices toward each star-forming region. This results in distance estimates explicitly tied to the velocity structure of the molecular gas. We determine distances to the B5, IC 348, B1, NGC 1333, L1448, and L1451 star-forming regions and find that individual clouds are located between ≈275 and 300 pc, with typical combined uncertainties of ≈5%. We find that the velocity gradient across Perseus corresponds to a distance gradient of about 25 pc, with the eastern portion of the cloud farther away than the western portion. We determine an average distance to the complex of 294 ± 17 pc, about 60 pc further than the distance derived to the western portion of the cloud using parallax measurements of water masers associated with young stellar objects. The method we present is not limited to the Perseus Complex, but may be applied anywhere on the sky with adequate CO data in the pursuit of more accurate 3D maps of molecular clouds in the solar neighborhood and beyond.

Key words: dust, extinction – ISM: clouds – methods: statistical

Supporting material: animation

1. Introduction

As the most active site of star formation within the solar neighborhood (≤300 pc, Bally et al. 2008), the Perseus Molecular Cloud complex has been the subject of a wealth of continuum and spectral-line observations in recent years. These studies have targeted both the global properties of the molecular cloud and the properties of discrete, high-density pockets of gas and dust in which small groups or clusters of stars are forming (e.g., L1451, L1448, NGC 1333, B1, IC 348, and B5; see Figure 1). Distance estimates to these well-known star-forming regions show a wide degree of dispersion—varying anywhere between 200 and 350 pc—and are based on a variety of techniques. Nevertheless, accurate distance measurements are critically important for constraining properties such as clump mass or star formation efficiency of the gas across Perseus, whose proximity to the Sun facilitates high-resolution observations of the star formation process.

Černis (1990, 1993) uses interstellar extinction to find distances to both the eastern (IC 348 at 260 pc) and western (NGC 1333 at 220 pc) portions of Perseus. Because optical light is extinguished by molecular clouds, Černis (1990, 1993) determines photometric distances to unextinguished foreground and extinguished background stars, thereby constraining the distance of the jump in extinction. More recently, Hirota et al. (2008, 2011) determine distances to the western portion of Perseus by obtaining trigonometric parallax measurements of water masers associated with young stellar objects (YSOs) embedded in the NGC 1333 and L1448 regions—finding a distance of 235 pc (Ω = 4.25 ± 0.32 mas, where Ω is hereafter parallax) for the former and 232 pc (Ω = 4.31 ± 0.33 mas) for the latter. Adopting a slightly different technique, Lombardi et al. (2010) calculate a distance to Perseus by comparing the density of low-extinction foreground stars (determined by the NICEST color excess method; Lombardi 2009) with the prediction for foreground stellar density from the Besançon Galactic model (Robin et al. 2003), finding a distance of 260 pc to B1 and B5 and 212 pc to L1448.

Schlafly et al. (2014) are the first to systematically map distances across the entire Perseus Complex. Schlafly et al. (2014) first obtain distances and reddening to batches of stars in over a dozen sightlines throughout Perseus using optical photometry (as outlined in Green et al. 2014). Then, Schlafly et al. (2014) adopt a model whereby the stellar distances and reddening are caused by a single dust screen, to which they find the distance using a Markov Chain Monte Carlo (MCMC) analysis. The results of Schlafly et al. (2014) suggest a distance gradient, but often with large uncertainties on individual lines of sight (≈10%–20%) and with greater distances, overall, than suggested in Hirota et al. (2008, 2011), typically around 260–315 pc.

One possible explanation for the distance discrepancies is that the Perseus Complex consists of clouds at several distances along the line of sight, a scenario bolstered by the large velocity gradient (≈5–10 km s⁻¹) observed across the cloud in CO
contours to this map (Pineda et al. 2008). We frame each region of interest (B5, IC 348, B1, NGC 1333, L1448, and L1451) via the green rectangles. The beam size (5′) is shown in white in the bottom left corner. (b) The Perseus Molecular Cloud, as seen in integrated 12CO emission (Ridge et al. 2006). The beam size (46′) is shown in black in the bottom left corner. To delineate boundaries around the cloud, we apply integrated intensity contours to this map (at ≤5–15 K km s−1, depending on the region) and find the intersection between these contours and the classical regions of extinction, as shown in panel (a). The final boundaries are shown via the green polygons in panel (b). (c) The positions of the stars (yellow scatter points) considered in our analysis for each region, after masking out lines of sight with high extinction (∆(V) > 4 mag). An additional cut is also made to remove stars with the worst chi-squared values.

(Ridge et al. 2006). However, unlike for clouds outside the solar neighborhood, this velocity gradient cannot be mapped to a distance gradient via a Galactic rotation curve (by the so-called “kinematic distance” method, see Roman-Duval et al. 2009) because the distance resolution of the kinematic method is coarser than the typical peculiar motions for objects so close to the Sun.

In this analysis, we build upon the work of Schlafly et al. (2014) and present a new technique to map velocities to distances across the Perseus Molecular Cloud by combining information on the spatial distribution of CO emission with distance and reddening estimates toward thousands of stars obtained from Green et al. (2018, hereafter G18). By using the velocity slices of a CO spectral cube as dust templates and modeling the cumulative distribution of dust along the line of sight as a linear combination of optical depth in CO velocity slices, we perform a Monte Carlo analysis to determine which distance configuration for the velocity slices is most consistent with the distance and reddening estimates to sets of stars in regions across Perseus.

In Section 2, we introduce the key data sets in this analysis, including the photometry used to derive the stellar distance and reddening estimates, the astrometric data used to inform the stellar distances, and the CO spectral-line data used as a dust tracer. In Section 3, we briefly explain how the stellar distance and reddening estimates are derived from the photometric catalogs discussed in Section 2. In Section 4, we discuss our target selection and the batch of stars we consider toward each region of interest. In Section 5, we present our Bayesian model for the line-of-sight distribution of dust as a function of the CO velocity slices. In Section 6, we discuss the nested sampling algorithm we use to perform the parameter estimation. In Section 7, we present our distance estimates to the CO slices for major star-forming regions across the Perseus Molecular Cloud and compare our results with distance estimates from the literature. We discuss the implications of our results in Section 8 and conclude in Section 9.

2. Data

Determining distances to molecular clouds based on the distribution of their CO emission is a two-step process. In the first step, we obtain the per-star posterior probability density function (PDF) of distance and reddening for stars toward the Perseus Molecular Cloud, based on their optical (Pan-STARRS1, hereafter PS1) and near-infrared (Two Micron All Sky Survey, hereafter 2MASS) photometry. When available, we fold in existing knowledge on the distance to each star, based on its Gaia DR2 parallax measurement. In the second step, we use the slices of a CO spectral cube as dust templates—by multiplying each slice by a gas-to-dust conversion coefficient—and sample for the probable range of distances to each velocity slice given the distance and reddening estimates to stars toward the same region.

In this section, we briefly describe the key data sets necessary for this analysis.

2.1. Pan-STARRS1 Photometry

The Pan-STARRS1 3π survey is a deep optical survey of the three-quarters of the sky north of δ = −30° (Chambers et al. 2016). The PS1 observations are obtained using a 1.8 m
telescope situated on Mount Haleakala in Hawaii, which has been equipped with a Gigapixel camera with a 3° field of view and pixel scale of 0.258″. The survey observes in five broadband filters, the grizy\(\rho_1\) bands, spanning 400–1000 nm (Chambers et al. 2016). The images are processed by the PS1 Image Processing Pipeline, which automatically performs photometric and astrometric measurements on the reduced data (Magnier et al. 2016). The stellar posteriors on distances and reddening we utilize in this work (from G18; see Section 3) are based on catalog coadds of single-epoch photometry derived from the PS1 DR1 3° steradian survey, which reaches typical single-exposure depths of 22.0, 21.8, 21.5, 20.9, and 19.7 mag (\(AB\)) in the g, r, i, z, and y\(\rho_1\) bands, respectively (Chambers et al. 2016).

### 2.2. 2MASS Photometry

The 2MASS is a near-infrared survey of the full sky targeting the J, H, and K\(_s\) bandpasses at 1–2 \(\mu\)m (Skrutskie et al. 2006). The 2MASS observations are obtained via two 1.3 m telescopes located on Mount Hopkins, Arizona and Cerro Tololo, Chile, both of which are equipped with a three-array survey camera with an 8/5 field of view and a pixel scale of 2″ (Skrutskie et al. 2006). Like PS1, the image processing pipeline automatically performs photometric and astrometric measurements on the reduced images. The resulting catalogs achieve typical 10\(\sigma\) point-source depths of 15.8, 15.1, and 14.3 magnitudes (Vega) for the J, H, and K\(_s\) bands, with bright sources possessing photometric uncertainties of the order of <0.03 mag. To derive the stellar posteriors on distance and reddening based on G18, we specifically use the 2MASS “high-reliability” catalog (see Section 3.3 in G18 for more details).

### 2.3. Gaia DR2 Astrometric Data

Gaia DR2 is an intermediate data release from the Gaia mission (Gaia Collaboration et al. 2016), and includes proper motion and parallax measurements for one billion stars, accompanied by all-sky broadband optical photometry (in the G, G\(\text{BP}\), and G\(\text{RP}\) bands) and radial velocity measurements for stars at the bright end (G < 13 mag). We only utilize the astrometric catalog (Lindegren et al. 2018) and defer potential incorporation of Gaia photometry to future work. The astrometric catalog has a limiting magnitude of G = 21 mag and a bright limit of G = 3 mag, with uncertainties at the brightest end of \(\approx\)0.04 mas and at the faintest end of 0.7 mas. For a full treatment of the astrometric processing pipeline, see Lindegren et al. (2018). We implement the same quality cuts for the Gaia data as given in Equation (11) of Lindegren et al. (2018).

### 2.4. CO COMPLETE Data

We employ maps of the \(^{12}\)CO (1–0) transition in Perseus, taken from the COMPLETE Survey of Star-forming Regions.\(^4\) We have chosen the COMPLETE data due to their high angular resolution (half-power beamwidth \(\approx\)46″) and their relatively low noise (mean rms per channel \(\approx\)0.35 K). The spectral resolution of the data in the \(^{12}\)CO (1–0) line is 0.06 km s\(^{-1}\). The total areal coverage of the COMPLETE survey toward Perseus is 6.25 \(\times\) 3 deg\(^2\).

We have chosen the \(^{12}\)CO (1–0) line primarily because it is more abundant and has more extended emission, which allows us to target larger areas of the sky (and therefore more stars), enabling better distance estimates. In theory, we could employ maps targeting the rarer CO isotopologues (e.g., \(^{13}\)CO, \(^{18}\)CO) in lieu of or in addition to the \(^{12}\)CO data. There are several arguments to be made for using the \(^{13}\)CO (1–0) line in particular, most notably that it is optically thinner and tends to be more linear with extinction than the \(^{12}\)CO (1–0) line (Pineda et al. 2008). According to Pineda et al. (2008), the \(^{12}\)CO line typically saturates in Perseus (and is thus nonlinear with reddening) around \(A(V) \approx 4\) mag, while the \(^{13}\)CO line typically saturates around \(A(V) \approx 5\) mag. Thus, in theory, \(^{12}\)CO allows us to probe one magnitude deeper, and thereby spatially closer to the densest star-forming cores. However, gaining an extra magnitude does not translate to an appreciable increase in the number of stars available for analysis, since few stars are visible behind such a high column density of dust. Moreover, because of the higher critical density of \(^{13}\)CO (it becomes self-shielded at \(A(V) \approx 2\) mag, versus \(A(V) \approx 1\) mag for \(^{12}\)CO; see Tables 4 and 6 in Pineda et al. 2008), it is a comparatively poor dust template in the more diffuse, extended envelopes of the clouds, from which we draw the bulk of our stars.\(^5\) Thus, all the results presented in this work utilize the \(^{12}\)CO line, toward sightlines where \(^{12}\)CO does not saturate.

### 3. Obtaining Stellar Distance and Reddening Estimates

Based solely on the PS1 (Section 2.1) and 2MASS (Section 2.2) photometry, we obtain stellar distance and reddening estimates for stars across Perseus based on the work of G18. We then process the distance–reddening stellar posteriors to incorporate the Gaia DR2 parallax information. The methodology used to derive the distance and reddening posteriors is given in Green et al. (2014, 2015). In brief, G18 infers a distance modulus \(\mu\), reddening \(E\), and stellar type \(\Theta\) for a star, where \(\Theta\) is parameterized by the star’s absolute PS1 \(r\)-band magnitude, \(M_r\), and its metallicity, \([\text{Fe}/\text{H}]\). By adopting a set of stellar templates that map the star’s intrinsic stellar type to its absolute magnitude in different photometric bands, G18 obtains the following relation for the modeled apparent magnitudes for each star:

\[
m_{\text{mod}} = M(M_r, [\text{Fe}/\text{H}]) + A(E, R(V)) + \mu, \tag{1}
\]

where the vector notation indicates that \(m_{\text{mod}}, M\), and \(A\) are considered over a range of passbands (e.g., \(m_{\text{mod}} = [m_{\text{mod},g}, m_{\text{mod},r}, m_{\text{mod},i}, \ldots]\)). Then, fixing the extinction curve...\(^5\)

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\(^4\) All the COMPLETE data are publicly available and can be downloaded from the Harvard Dataverse at https://dataverse.harvard.edu/dataverse.xhtml?alias=complete. The corresponding DOI for the \(^{13}\)CO COMPLETE cube of Perseus is doi:1090410072 (Ridge et al. 2006).

\(^5\) For the clouds we target in Section 4 (see Figure 1), we find that the inclusion of regions with total line-of-sight visual extinction \(A(V) < 4\) mag typically only increases our star count by approximately a few dozen to a few hundred, enlarging our sample size by only about 5%–15%. As discussed in Section 4, we delineate cloud boundaries using \(^{12}\)CO integrated intensity contours. However, since \(^{13}\)CO is less extended (both spatially and kinematically) we would need to adopt a comparatively higher \(^{12}\)CO integrated intensity threshold to produce reliable dust templates. In cases such as L1448, the adoption of even a generous low-level \(^{13}\)CO integrated intensity contour (roughly coincident with the \(A(V) \approx 2\) mag self-shielding threshold for \(^{13}\)CO) reduces our star count by a factor of three, because we target less area toward the outer envelopes of the clouds (better traced by \(^{12}\)CO), from which most of our stars are drawn.
and assuming \( R(V) = 3.3 \) (Schlafly et al. 2016), the likelihood of observing a star with apparent PS1 and 2MASS magnitudes \( m \), assuming independent Gaussian photometric uncertainties \( \sigma \), is a multivariate normal with mean \( m_{\text{model}} \) and standard deviation \( \sigma \), evaluated at \( m \). Prior knowledge of the number density and metallicity of stars across the Galactic disk and halo (Ivezić et al. 2008; Juric et al. 2008), as well as on the stellar luminosity function (Bressan et al. 2012), is also incorporated into the model.

Combining the likelihood function and priors, G18 draws from the posterior distribution function of \( \mu \), \( E \), and \( \Theta \) for individual stars using an affine-invariant ensemble MCMC sampler (Goodman & Weare 2010). While we adopt the same likelihood function and priors as G18, we infer the stellar posteriors using brute-force grid evaluation rather than MCMC. This has the added benefit of producing the same results every time, and is free from convergence issues inherent in MCMC sampling.

After marginalizing over the \( \Theta \) parameters and taking a kernel density estimate of the samples, we produce a two-dimensional gridded stellar posterior describing the probable range of the distance and reddening to each star over the domain \( 0 < E(B-V) < 7 \) mag and \( 4 < \mu < 19 \) mag. Before running our line-of-sight fits, we post-process the gridded distance–reddening posteriors in order to fold in knowledge on the distance to each star based on its Gaia DR2 parallax measurement, when available. This term is multiplicative along the \( \mu \) axis and functionally acts as an additional Gaussian likelihood term of the following form:

\[
P(\Omega | \mu) = \frac{1}{\sigma_\Omega \sqrt{2\pi}} \exp \left[ -\frac{(\Omega - 10^{\mu/2})^2}{2\sigma_\Omega^2} \right],
\]

where \( \Omega \) is the observed Gaia parallax measurement in arcseconds, \( \sigma_\Omega \) is the uncertainty on the parallax measurement (also in arcseconds), and \( \mu \) is the distance modulus bin in the gridded distance–reddening posterior. Gaia stellar parallaxes are available for 65% of our sample, with typical fractional parallax errors of \( \approx 20\% \) for stars with \( \mu < 8 \) mag. Folding in these Gaia parallax data has two major effects on our stellar posteriors. First, for stars in the solar neighborhood, it substantially narrows the posteriors along the \( \mu \) axis when the uncertainties are low, constraining the distance to the star to a few hundredths of a magnitude in distance modulus. Second, for stars that are farther away but with posteriors that are multi-modal in distance modulus, Gaia can usually discriminate between the two modes, and it suppresses the incorrect mode significantly. These Gaia-informed posteriors are the ones we implement in our model (see Section 5).

3.1. A Note on \( R(V) \)

We adopt a fixed value of \( R(V) = 3.3 \) across the entire Perseus complex. However, there is evidence for grain growth across the Perseus Molecular Cloud (Foster et al. 2013). Foster et al. (2013) use a Hierarchical Bayesian approach to examine the extinction curve in both the eastern and western portions of Perseus, and they find a strong correlation between \( A(V) \) and \( R(V) \), which they interpret as evidence of grain growth occurring once moderate optical depths are reached. For the range of \( A(V) \) we are probing (\( A(V) \approx 2-4 \) mag), our adopted value of \( R(V) \) is generally consistent with the finding of Foster et al. (2013). They find that for \( A(V) \approx 3 \) mag, the typical \( R(V) \) is \( \approx 3.5 \). This is also consistent with initial results from the APOGEE reddening survey, which targets bright red giant stars through dense sightlines along Perseus in order to study the shape of the extinction curve in nearby molecular clouds (E. F. Schlafly et al. 2018, in preparation)—they find that for \( A(V) \approx 3 \) mag, the mean \( R(V) \) in Perseus is consistent with 3.3.

The adoption of a fixed extinction curve will lead to small systematic uncertainties in our distance determinations. In other dust clouds of similar column density and at similar distances (e.g., Hercules), changing \( R(V) \) by 1–2 changes distance modulus \( \mu \lesssim 0.1 \) mag (C. Zucker et al. 2018, in preparation). Since most of our power to constrain distance comes from the Gaia parallaxes, this effect should be small, because these measurements are insensitive to \( R(V) \). \( R(V) \) will additionally have an effect on the inferred reddening, but ultimately we only need enough accuracy to constrain the step in reddening associated with the cloud, which is quite large. That said, there will be some degeneracy between \( R(V) \) and the gas-to-dust coefficients we infer. To help accommodate small errors in the extinction curve, we have added an uncertainty of 0.05 mag in \( E(B-V) \) to our reddening estimates by smoothing our surfaces by this amount along the reddening axis. The distance axis is not smoothed.

4. Cloud Selection

We target every major star-forming region inside the boundaries of the CO COMPLETE survey (see Section 2.4) in this analysis. This includes B5, IC 348, B1, NGC 1333, L1448, and L1451. We show an extinction map of the Perseus complex in Figure 1(a) (Pineda et al. 2008) and box these regions with green rectangles, which are apparent as pockets of very high optical depth. We also show a \( ^{12}\text{CO} \) integrated intensity map of the Perseus complex in Figure 1(b) (Ridge et al. 2006). To define boundaries around each cloud we apply integrated intensity contours to the cloud’s corresponding \( ^{12}\text{CO} \) emission (\( W(\text{CO}) \approx 5–15 \) K km s\(^{-1} \), depending on the region). In cases where we cannot obtain a closed contour, we find the intersection between a reasonable semi-closed integrated intensity contour and the “classical” regions of extinction as established in previous studies of Perseus (green rectangles in Figure 1(a); see, for instance Kirk et al. 2007; Bally et al. 2008; Rosolowsky et al. 2008; Sadavoy et al. 2014). These boundaries are ad hoc, but they are inclusive of previous definitions of these regions, and we find that our results are

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\(^5\) The work of Schlafly et al. (2016) does not directly measure \( R(V) = A(V)/E(B-V) \) because their observations are insensitive to the gray component of the extinction vector. Rather, Schlafly et al. (2016) build a proxy for \( R(V) \) using the quantity \( (A_g - A_{rg2})/(A_r - A_g) \), where \( g \) and \( r \) are the Pan-STARRS1 \( g \)- and \( r \)-band magnitudes and \( W_2 \) is the WISE band-two magnitude. Thus, the \( R(V) = 3.3 \) value we quote is actually the proxy \( R(V) \) that Schlafly et al. (2016) calculate for their mean extinction vector. See Section 5.3 in Schlafly et al. (2016) for more details.

\(^6\) We refer readers to Green et al. (2014) for a full treatment of these priors. See their Section 4.2.1 for a description of the number density prior, Section 4.2.2 for the metallicity prior, and Section 4.2.3 for the stellar luminosity prior.

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\(^8\) The integrated intensity contours are applied to the same moment-zero map, computed by integrating over all channels in the \(^{12}\text{CO} \) cube provided by the COMPLETE survey (\texttt{doi:10994/10072}). In reality, only the velocity channels between ⋅$2$ and 12 km s\(^{-1} \) have significant emission.
robust to modest changes in boundary definition. The final boundaries we use for each region are shown as green polygons in Figure 1(b). The R.A. and decl. values corresponding to the geometric centroid of each green polygonal boundary shown in Figure 1(b). In column (4) we show the velocity range toward each region in which CO emission is not saturated and also above the noise level. Given the native spectral resolution of the CO data (≈0.06 km s$^{-1}$; Ridge et al. 2006), there are typically dozens of velocity slices in this velocity range toward each cloud. As a result, we have downsampled the cube along the spectral axis, and in column (5) we list the number of downsampled velocity slices toward each region. In column (6) we summarize the CO intensity-weighted mean velocity of each downsampled CO slice, computed using only pixels along sightlines where the CO does not saturate (see Section 4 and Section 5.1). In column (7) we indicate the spectral width of the downsampled slices toward each region; to maintain uniformity across the complex, the spectral width is chosen to be close to 2 km s$^{-1}$ while covering the desired velocity range for each cloud with an integer number of slices.

### 5. Model

Our model for the cumulative reddening in $E(B - V)$ along the line of sight out to distance modulus $\mu$—hereafter called the “reddening profile”—is denoted by

$$E_{B-V}(\mu; \alpha),$$

where $\alpha$ is some set of parameters describing the reddening profile. As in G18, the posterior probability density of our $\alpha$ parameters is determined by the product of the integral over $\mu$ through the individual stellar posterior density functions (derived from the set of PS1 and 2MASS photometry $\{m\}$) following $E_{B-V}(\mu; \alpha)$:

$$p(\alpha|\{m\}) \propto p(\alpha) \prod_{i}^{\text{stars}} \int p(\mu_i, E_{B-V}(\mu_i; \alpha)|m) \, d\mu_i,$$

where $p(\alpha)$ constitutes our priors and the product of the integral through the individual stellar posterior arrays is our likelihood function. This is simply Bayes’ rule, modulo the normalizing constant in the denominator and assuming independence among stars.

G18 parameterizes the reddening profile as a piecewise linear function in distance modulus, so $\alpha$ is given by a set of parameters denoting the increase in reddening, $\Delta E_{B-V}$, in fixed distance bins equally spaced in distance modulus between $\mu = 4$ mag (63 pc) and $\mu = 19$ mag (63 kpc). Here, however, we do not sample the increase in reddening directly or in fixed distance bins along the entire line of sight. Rather, for an individual star lying in CO pixel $j$ we parameterize Perseus’ contribution to the line-of-sight reddening profile toward this pixel as the sum of the CO emission in a set of $n$ velocity slices $\{v_1, v_2, \ldots, v_n\}$ that lie at distances $\{d_1, d_2, \ldots, d_n\}$ and whose corresponding CO emission intensities $\{I_{v_1}, I_{v_2}, \ldots, I_{v_n}\}$ can be converted to reddening by multiplying by a set of gas-to-dust coefficients $\{c_1, c_2, \ldots, c_n\}$. The distances are the primary free parameters of interest, to be constrained by the model fit. Since the CO emission along the line of sight differs for stars in different pixels, the reddening profile will vary from star to star.

We also assume that there is an angularly uniform foreground dust cloud, whose reddening is not accounted for in the total CO emission given by the velocity slices. We

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Table 1: Velocity of the Downsampled CO Slices that We Model as Dust Screens in Our Analysis

| Cloud Name | R.A. (deg) | Decl. (deg) | Velocity Range (km s$^{-1}$) | Downsampled Slice Count | Slice Velocities (km s$^{-1}$) | Slice Width (km s$^{-1}$) |
|------------|-----------|-------------|-----------------------------|--------------------------|-------------------------------|-------------------------|
| L1451      | 51.0      | 30.5        | $-1.1$ to $7.4$             | 4                        | $[0.3, 2.3, 4.2, 5.8]$       | 2.1                     |
| L1448      | 51.2      | 30.9        | $-2.2$ to $7.9$             | 5                        | $[-0.7, 0.8, 2.9, 4.8, 6.6]$ | 2.0                     |
| NGC 1333   | 52.2      | 31.2        | $-1.3$ to $10.1$            | 6                        | $[-0.1, 1.7, 3.5, 5.5, 7.3, 8.8]$ | 1.9                     |
| B1         | 53.4      | 31.1        | $-0.2$ to $9.6$             | 5                        | $[1.1, 2.8, 4.8, 6.7, 8.2]$  | 2.0                     |
| IC 348     | 55.8      | 31.8        | $4.2$ to $11.8$             | 4                        | $[5.4, 7.4, 9.0, 10.4]$      | 1.9                     |
| B5         | 56.9      | 32.9        | $6.7$ to $12.4$             | 3                        | $[8.3, 9.7, 11.0]$           | 1.9                     |

Note. In column (1) we list the name of the star-forming region. In columns (2) and (3) we list the R.A. and decl. for the cloud, computed using the geometric centroid of each green polygonal boundary shown in Figure 1(b). In column (4) we show the velocity range toward each region in which CO emission is not saturated and also above the noise level. Given the native spectral resolution of the CO data (≈0.06 km s$^{-1}$; Ridge et al. 2006), there are typically dozens of velocity slices in this velocity range toward each cloud. As a result, we have downsampled the cube along the spectral axis, and in column (5) we list the number of downsampled velocity slices toward each region. In column (6) we summarize the CO intensity-weighted mean velocity of each downsampled CO slice, computed using only pixels along sightlines where the CO does not saturate (see Section 4 and Section 5.1). In column (7) we indicate the spectral width of the downsampled slices toward each region; to maintain uniformity across the complex, the spectral width is chosen to be close to 2 km s$^{-1}$ while covering the desired velocity range for each cloud with an integer number of slices.

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The regridding is done via bilinear interpolation.
parameterize the foreground dust cloud as lying at a distance \(d_{\text{fore}}\), and with a reddening contribution in \(\Delta E_{B-V}\) given by \(E_{\text{fore}}\). For a star \(i\) in CO pixel \(j\), the reddening profile is parameterized as follows:

\[
E_{B-V}(\mu_i; \alpha) = E_{B-V}(\mu_i; d_{\text{fore}}, E_{\text{fore}}, \{d_1, d_2, ..., d_n\}, \{c_1, c_2, ..., c_n\}),
\]

where our free parameters are \(d_{\text{fore}}, E_{\text{fore}}, \{d_1, d_2, ..., d_n\}\), and \(\{c_1, c_2, ..., c_n\}\). The profile takes the form of a step function. Assuming that our velocity slices are ordered by distance \(d_1 < d_2 < ... < d_n\), the total line-of-sight reddening out to a distance \(d\) for a single star, coincident with CO pixel \(j\), would be

\[
E_{B-V} = \begin{cases} 
0 & d \leq d_{\text{fore}} \\
E_{\text{fore}} + \sum_{k=1}^{n} I_{j,k} c_k & d_{\text{fore}} \leq d \leq d_1 \\
E_{\text{fore}} + I_{j,1} c_1 & d_1 \leq d \leq d_2 \\
... & \ldots \\
E_{\text{fore}} + \sum_{k=1}^{n} I_{j,k} c_k & d > d_n.
\end{cases}
\]

The assumption of the velocity slices increasing monotonically in distance (such that \(v_1 < v_2 < ... < v_n\), so \(d_1 < d_2 < ... < d_n\)) is only for notational purposes above, and is not actually imposed when we perform our line-of-sight fits. In actuality, the velocity slices have the freedom to switch their order.

In Figure 2, we show a cartoon line-of-sight reddening profile for a very simple one-slice model (lying at velocity \(v_1\)), where the CO emission toward our region of interest is described by a single distance component \(d_1\). In such a model, we can parameterize the total line-of-sight reddening profile as having a jump in reddening \(E_{\text{fore}}\) at distance \(d_{\text{fore}}\), plus a second jump in reddening at distance \(d_1\), the magnitude of which is given by the CO emission in slice \(v_1\) coincident with the star, multiplied by some gas-to-dust coefficient \(c_1\). The free parameters defining our reddening profile are \(d_{\text{fore}}, E_{\text{fore}}, d_1\), and \(c_1\), which are fixed across all stars. The only variation in the reddening profile from star to star stems from the magnitude of the reddening jump at distance \(d_1\), which is dependent on the CO pixel \(j\) coincident with each star on the plane of the sky. This single-template model is similar to the one implemented in Schlafly et al. (2014), with the exception that they use the angular distribution of the Planck emission (Planck Collaboration et al. 2011) instead of CO velocity slices as their dust templates and fix \(d_{\text{fore}}\) to 0 pc. In comparison to Planck, our more complex multi-slice CO velocity model is better able to trace the underlying molecular H\(_2\) and probe the structure of the cloud along the line of sight.

There are a number of limitations to our model, most notably that intensity structures in position–position–velocity \((p\textit{--}p\textit{--}v)\) space do not necessarily correspond to physical density structures in position–position–position \((p\textit{--}p\textit{--}p)\) space (see Beaumont et al. 2013). As discussed in Beaumont et al. (2013), there are two ways this lack of one-to-one correspondence
between density and intensity can manifest itself. First, if there exists an internal velocity gradient, a single density structure could split into two velocity structures. And second, two or more density structures could merge into a single velocity structure, if two structures at two different distances along the line of sight possess the same velocity. With this in mind, we have given our velocity slices the freedom to switch distance order, and we also permit placing two different velocity components at the same distance. This addresses the issue of a single density structure splitting into two velocity structures. However, our model is not flexible enough to handle the case where one velocity structure splits into two density structures, at two different distances. If this occurs, the model would be a poor description of the data. By building the “co” coefficients into our model, controlling how much reddening is assigned to each slice, we should be able to compensate for this to some degree by assigning adjacent slices more or less reddening.

We discuss the distance parameters of the CO slices \((d_1, d_2, \ldots, d_n)\) in more detail in Section 5.1, the gas-to-dust coefficients \((\{c_1, c_2, \ldots, c_n\})\) in Section 5.2, the foreground dust cloud parameters in Section 5.3 and our method for handling outliers in Section 5.4.

### 5.1. Cloud Distance Parameters

For each cloud of interest (B5, IC 348, B1, NGC 1333, L1448, and L1451), we have a set of parameters \(\{d_1, d_2, \ldots, d_n\}\) that describe the velocity moduli to velocity slices \(\{v_1, v_2, \ldots, v_n\}\) containing the CO emission for that cloud. The typical velocity range of the CO emission observed toward each cloud spans \(\approx 5–10\) km s\(^{-1}\), meaning that, in general, there are several dozen to hundreds of velocity slices along the line of sight. However, because these velocity channels are highly correlated with one another, we choose to downsample the cube along the spectral axis. Because we want to preserve the total CO emission along the line of sight, we downsample by summing to produce downsampled cubes with a channel width of \(\sim 2\) km s\(^{-1}\) for each velocity slice. Specifically, toward each region (green polygonal boundaries in Figure 1(b)), we determine the minimum and maximum velocity slice in which CO emission appears above the noise level and the \(^{12}\text{CO}\) line is not saturated.\(^{10}\) We then group the velocity slices across this velocity range into \(n\) batches (where \(n\) is chosen so that the velocity range of each batch is \(\approx 2\) km s\(^{-1}\)), sum the CO emission in each batch, and assign the downsampled slice the \textit{CO intensity-weighted} mean velocity of that batch. The CO intensity-weighted mean slice velocities are computed using only the pixels along sightlines where CO never saturates (see footnote 10). This choice of downsampled spectral resolution (\(\sim 2\) km s\(^{-1}\)) yields between three and six velocity slices toward our target regions, meaning that each cloud is composed of 3–6 distance components \((d_1, d_2, \ldots, d_n)\). This slice range allows for the freedom to place the velocity slices at multiple distances along the line of sight, while preventing our parameter space from becoming overly redundant or highly covariant. The velocity range of each cloud, along with the number of downsampled velocity slices and the CO intensity-weighted mean velocity of each slice, can be found in Table 1.

The average distances we present in Section 7 are robust to our choice of downsampled velocity slice width. We tested our method using two alternatives for the slice width. First, we tested a slice width equal to \(\approx 1\) km s\(^{-1}\). Second, we tested a slice width equal to the entire velocity range for the cloud shown in Table 1. In both cases, the average distances agree with those reported in Table 3. However, as the number of velocity slices increases, the reddening in each slice decreases, and those slices with the least amount of reddening become even less informative to the fit. We need two additional parameters for every velocity slice, and the larger parameter space means the fit takes longer to converge. Thus, while the model of a single velocity slice is unable to capture the presence of multiple distance components, the choice of a downsampled spectral width \(\leq 2\) km s\(^{-1}\) does not provide any additional information about the cloud that cannot be captured with fewer slices.

We place a uniform, flat prior on the distance moduli to the velocity slices \(\{d_1, d_2, \ldots, d_n\}\) in the range \(6.5\) mag \(< \mu < 8.5\) mag, corresponding to 200 pc \(< d < 400\) pc. This is consistent with the range of potential distances to the Perseus Molecular Cloud from the literature (see Černis 1990, 1993; de Zeeuw et al. 1999; Hirota et al. 2008, 2011; Schlafly et al. 2014). None of our distance parameters, particularly those associated with slices with higher amounts of CO emission, is strongly prior-constrained, so we anticipate our adoption of a flat prior in distance modulus (rather than distance) to have a negligible effect on our results.\(^{11}\)

### 5.2. Gas-to-dust Conversion Factor Parameters

For each of our velocity slices \(\{v_1, v_2, \ldots, v_n\}\) in each cloud, we have a set of parameters \(\{c_1, c_2, \ldots, c_n\}\) that describes how gas relates to dust at each slice distance \(\{d_1, d_2, \ldots, d_n\}\). Specifically, it converts the amount of integrated CO emission in K km s\(^{-1}\) in each downsampled velocity slice to the amount of reddening, \(E(B-V)\), in units of magnitudes. In theory, we could fix this parameter in our model. However, neither of the parameters that constitute this conversion coefficient (i.e., the \(^{12}\text{CO}\) factor and the \(^{12}\text{H}_2\)-to-reddening factor, as discussed below) is well constrained, varying in column density and likely physical density of the cloud. We estimate a central value for the prior on the CO-to-reddening coefficient and allow it to vary about this value in our fits.

To derive an average literature value for this coefficient, we adopt a \(^{12}\text{CO}\) X-factor of \(1.8 \times 10^{20}\) cm\(^{-2}\) K\(^{-1}\) km\(^{-1}\) s from Dame et al. (2001), where the X-factor converts \(^{12}\text{CO}\) integrated intensity to \(^{12}\text{H}_2\) column density. Next, assuming that all the hydrogen traced by the reddening is in molecular form—the same assumption made in Pineda et al. (2008)—we adopt an \(^{12}\text{H}_2\) column density to reddening ratio of \(2.9 \times 10^{21}\) cm\(^{-2}\) mag\(^{-1}\) from Bohlin et al. (1978), which converts \(^{12}\text{H}_2\) column density to reddening. Combining the two factors, we get an average gas-to-dust \(^{12}\text{CO}\) factor equal to 0.062 mag/(K km s\(^{-1}\)). In practice, we integrate over the \(\approx 2\) km s\(^{-1}\) velocity channels (defined in Section 5.1) by summing the CO emission in kelvin and multiplying by the

\(^{10}\) Recall that we determine where \(^{12}\text{CO}\) becomes saturated using the analysis of Pineda et al. (2008), which finds that \(^{12}\text{CO}\) becomes nonlinear with reddening around \(A(V) = 4\) mag. Thus, we only consider the CO emission over the same area as we select our stars (i.e., sightlines inside the green polygonal boundaries in Figure 1(b)) with corresponding NICER A \((V) < 4\) mag. These areas are shown overlaid with yellow points (constituting our target stars) in Figure 1(c). See discussion in Section 4 for more details.

\(^{11}\) This was determined by looking at the corner plots (see Appendix B). If our results were strongly prior-constrained, the posteriors for the distance parameters would either be flat over the range \(\mu = 0.5–8\) mag or frequently bump up against the boundaries of our flat distance prior. Our corner plots indicate that this is not the case for almost all of our distance parameters.
radiation dependent on the metallicity of the gas and the strength of the background UV field, which can cause CO molecules to dissociate (Pineda et al. 2008; Shetty et al. 2011). Pineda et al. (2008) find that the CO factors within Perseus can vary by at least a factor of two, depending on which star-forming region is used in the fit (e.g., NGC 1333 versus B5; see their Table 4) or whether it is determined in saturated or unsaturated regimes.
6. Parameter Estimation Using Nested Sampling

For each of our target regions (see Figure 1) we sample a set of \(3 + 2n\) model parameters \((d_{\text{true}}, E_{\text{true}}, P_b, (d_1, d_2, \ldots, d_n))\), where \(n\) is the number of velocity slices using the nested sampling code \textit{dynesty}\(^{14}\) (J. S. Speagle et al. 2018, in preparation). Nested sampling (Skilling 2006) is similar to traditional MCMC algorithms in that it generates samples that can be used to estimate the posterior PDF given in Equation (4). The nested sampling algorithm relies on iteratively drawing samples (or “live” points) from the constrained prior distribution, where the likelihood value of a new sample must be greater than the lowest likelihood value of existing samples. In this way, the live point with the lowest likelihood is replaced by a new live point of higher likelihood at every iteration. As this process progresses, the live points sample a smaller and smaller region of the prior “volume.” One continues sampling until some stopping criterion is reached and the remaining live points occupy the region of highest likelihood.

There are several reasons to use \textit{dynesty} over more commonly used affine-invariant ensemble MCMC samplers. Ensemble MCMC sampling codes such as \textit{emcee} (Foreman-Mackey et al. 2013) have been shown to have “undesirable properties” in higher-dimensional parameter spaces \((n_{\text{param}} \gtrsim 10–20)\). When the number of model parameters is high, ensemble samplers may not only fail to converge to the target distribution, but may also visually appear to have converged without actually having done so (Huijser et al. 2015). Nested sampling has been shown to perform well in higher-dimensional parameter spaces and is also efficient at exploring multi-modal distributions (Feroz et al. 2009; Handley et al. 2015). Additional benefits of \textit{dynesty} include a user-defined stopping criterion that can act as a convergence metric, so the number of generated samples does not have to be predefined beforehand. Finally, \textit{dynesty} can quantify the statistical uncertainties in a single run using a combined reweighting/bootstrapping procedure (Higson et al. 2017, 2018).

Since \textit{dynesty} can be run in multiple modes, we provide the exact setup used to derive our results in Appendix A. While it is less efficient at producing independent samples, using a more traditional sampler from \textit{emcee} produces results that are consistent with the dynamic nested sampler when comparing runs for the cloud with the largest parameter space (NGC 1333).\(^{15}\)

To get a sense of how the sampling operates, in Figure 3 we show a video that illustrates the progression of our \textit{dynesty} samples over the course of a run. We select nine stars used in our B5 fit. For each star, we use the current sample (summarized in the table at top) along with the CO emission coincident with each star to build up the star’s reddening profile (red lines), which we then overlay on its distance–reddening posterior from G18 (background grayscale in each panel). Integrating over \(\mu\) along each reddening profile, we show the individual log-likelihood for each star in the upper right corner of every panel. Adding all these individual log-likelihoods together, we get the total log-likelihood for this batch of nine stars \((\mathcal{L}_{\text{tot},9\text{stars}})\), which we list atop the panels. The samples are drawn sequentially from the \textit{dynesty} chain as we converge toward the region of highest likelihood. However, the total log-likelihood for these nine stars does not necessarily increase as the video progresses, since the samples are determined by the best fit to the full sample of stars rather than just these nine.

Finally, we note that when calculating the line-of-sight integral for the individual log-likelihoods, we interpolate between cells in the two-dimensional stellar posterior array. This mitigates the negative effects of binning on our results.

7. Results

In Table 2, we summarize the results for the six star-forming regions targeted in this study—L1451, L1448, NGC 1333, B1, IC 348, and B5. Specifically, we report the 50th percentile of the samples for each parameter: \((d_{\text{true}}, E_{\text{true}}, P_b, (d_1, d_2, \ldots, d_n))\), where \(n\) is again determined by the number of downsampled velocity slices toward each cloud (see Table 1). In order to properly estimate the posterior, we weight the samples by their posterior mass, as discussed in the \textit{dynesty} documentation.\(^{16}\) For the parameters \((c_1, c_2, \ldots, c_n)\), recall that we report the value of a multiplicative factor in front of the nominal gas-to-dust coefficient that we adopt from the literature (see Section 5.2). In addition to reporting the median value, we provide the 16th and 84th percentiles via the upper and lower bounds, equivalent to the 1\(\sigma\) range for a Gaussian distribution. We also include corner plots—showing different projections of our \textit{dynesty} samples in the \((2n + 3)\)-dimensional parameter space—in Appendix B (Figures 13–18).

We generally favor a smaller CO-to-reddening conversion factor than the nominal factor we derive from the literature (Section 5.2), suggesting a smaller \(X_{\text{CO}}\) factor than given in Dame et al. (2001) or a larger \(N_\text{H}_2\)-to-reddening factor than given in Bohlin et al. (1978). Our mean gas-to-dust coefficient across all regions is \(0.72 \times c\), where \(c\) is the nominal coefficient we adopt from the literature, equal to 0.062 mag/(K km s\(^{-1}\)). The argument for a smaller \(X_{\text{CO}}\) factor is consistent with the results of Pineda et al. (2008). After accounting for the CO self-shielding threshold, they find that the \(X_{\text{CO}}\) in unsaturated regions is \(0.72 \times 10^{20} \text{ cm}^{-2} \text{ K}^{-1} \text{ km}^{-1} \text{s}\). Assuming that our \(N_\text{H}_2\)-to-reddening factor is accurate, our typical results for the \(c\) coefficients are consistent with an \(X_{\text{CO}}\) factor of \(1.30 \times 10^{20} \text{ cm}^{-2} \text{ K}^{-1} \text{ km}^{-1} \text{s}\), which is lower than our adopted \(X_{\text{CO}}\) factor from Dame et al. (2001) \((1.8 \times 10^{20} \text{ cm}^{-2} \text{ K}^{-1} \text{ km}^{-1} \text{s})\), but not quite as low as the value of Pineda et al. (2008).

We discuss the properties of individual clouds in comparison with the literature values in more detail in the next section. We also provide an average distance and distance uncertainty to each cloud (Table 3). The average distances are computed using the distances to the set of velocity slices toward each cloud, and we weight each slice according to its total contribution to the line-of-sight reddening. Specifically, to compute the average distance to each cloud we perform a

\(^{14}\) https://dynesty.readthedocs.io

\(^{15}\) In more detail, in order to test whether our results are robust to changes in sampler, we repeat the analysis for NGC 1333 using the affine-invariant MCMC ensemble sampler from \textit{emcee} (Foreman-Mackey et al. 2013). Specifically, we run with 100 walkers, where each walker takes 20,000 steps. We set \(\text{thin} = 10\) so only every tenth sample is saved. Prior to this, we run 1000 burn-in steps. Using the stacked chain (flattened along the walker axis), we compute the median of the samples from the chain for each parameter. We find that the median of the samples agrees with our \textit{dynesty} results within the uncertainties we report in Table 2. Since we report the 16th and 84th percentiles of the \textit{dynesty} samples via the upper and lower bounds, this means that the 50th percentile of the samples derived from our \textit{emcee} run falls between the 16th and 84th percentiles of the samples from our \textit{dynesty} run.

\(^{16}\) http://dynesty.readthedocs.io/en/latest/overview.html?highlight=weight
Monte Carlo-based averaging procedure where samples are drawn at random (again, weighted by their posterior mass) from "noisy" realizations of our original dynesty chain. For each Monte Carlo draw we first construct the noisy set of samples using dynesty’s `simulate_run()` function. This process uses a combination of bootstrapping and jittering to add random noise to the original samples. This allows us to account for statistical uncertainties in the average cloud distances we report in Table 3. Then, for each realization, after drawing from our set of noisy samples, we compute a reddening-weighted average distance to the cloud using the following formula:

$$d = \frac{\sum_k n_{\text{slice}} \langle I_{\text{CO}} \rangle_k c_k d_k}{\sum_k n_{\text{slice}} \langle I_{\text{CO}} \rangle_k c_k}$$ (7)

where $\langle I_{\text{CO}} \rangle_k$ is the mean CO emission in the $k$th velocity slice, $c_k$ is the gas-to-dust coefficient in the $k$th slice for each realization, and $d_k$ is the distance to the $k$th slice for each realization. We repeat this process 500 times, producing 500 realizations of the average reddening-weighted distance to the cloud. The final average distance and uncertainty to each cloud that we report in Table 3 are the mean and standard deviation of the set of 500 average reddening-weighted distances. We show histograms of the Monte Carlo realizations of the average reddening-weighted distances toward each region in Figure 4, which are discussed further in Section 8. We compute an average distance to the entire Perseus complex of 294 pc, with a statistical uncertainty of 10 pc.

In Table 3 we also report the average reddening-weighted velocity for each cloud. Since the CO intensity-weighted mean

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**Table 3.**

| $d_{\text{fore}}$ | $E_{\text{fore}}$ | $P_d$ | $d_1$ | $d_2$ | $d_3$ | $c_1$ | $c_2$ | $c_3$ |
|-----------------|-----------------|------|-------|-------|-------|-------|-------|-------|
| 4.83 | 0.25 | 0.02 | 7.51 | 7.42 | 7.33 | 1.3 | 1.26 | 0.43 |

---

**Figure 3.** Video showing samples (summarized in the table at top) from our dynesty run toward the B5 region. The video duration is 30 s. These are not fair samples, but are intended to illustrate how variations in the reddening profile affect the log-likelihood. Nine stars (out of thousands) are selected toward the region. Each star lies in a different CO pixel, so the reddening profile varies from star to star and is dependent on the CO emission in each velocity slice corresponding to that pixel. The reddening profile is built using the sample summarized in the table at top. Individual stellar log-likelihoods (listed in the upper right corner of each panel) are calculated by integrating the reddening profile (red lines) over $\mu$ through each star’s distance–reddening posterior (background grayscale of each panel) and taking the logarithm. In each stellar posterior, the region of highest probability is marked with a lime green scatter point. The total log-likelihood for all nine stars ($L_{\text{tot,9stars}}$) is listed above the panels. The video is also available at https://youtu.be/t_iWrkB8dFQ.

(An animation of this figure is available.)

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\(^{17}\) http://dynesty.readthedocs.io/en/latest/errors.html?highlight=simulate_run#combined-uncertainties
Table 2
Results of Our Parameter Estimation for Major Star-forming Regions across the Perseus Molecular Cloud

| Cloud   | \(d_{\text{true}}\) (mag) | \(E_{\text{true}}\) (mag) | \(P_{\text{true}}\) (pc) | \(d_{1}\) (mag) | \(d_{2}\) (mag) | \(d_{3}\) (mag) | \(d_{4}\) (mag) | \(d_{5}\) (mag) | \(d_{6}\) (mag) | \(c_{1}\) | \(c_{2}\) | \(c_{3}\) | \(c_{4}\) | \(c_{5}\) | \(c_{6}\) |
|---------|----------------|----------------|----------------|---------------|---------------|---------------|---------------|---------------|---------------|--------------|--------------|--------------|--------------|--------------|--------------|
| B5      | 4.50 ± 0.32   | 0.25 ± 0.01   | 0.02 ± 0.00   | 7.56 ± 0.12  | 7.40 ± 0.05  | 7.34 ± 0.10  | 1.34 ± 0.08   | 1.24 ± 0.02   | 0.47 ± 0.03   | 0.16 ± 0.04  | 0.00 ± 0.01  | 0.05 ± 0.00  | 0.03 ± 0.03  | 0.03 ± 0.03  | 0.03 ± 0.03  |
| IC 348  | 6.14 ± 0.04   | 0.35 ± 0.00   | 0.03 ± 0.00   | 7.35 ± 0.04  | 7.34 ± 0.04  | 7.35 ± 0.05  | 1.18 ± 0.05   | 1.04 ± 0.03   | 1.08 ± 0.01   | 0.43 ± 0.03   | 0.37 ± 0.03   | 0.34 ± 0.03   | 0.34 ± 0.03   | 0.34 ± 0.03   | 0.34 ± 0.03   |
| B1      | 4.45 ± 0.07   | 0.15 ± 0.01   | 0.02 ± 0.00   | 7.13 ± 0.22  | 7.36 ± 0.16  | 7.40 ± 0.04  | 0.63 ± 0.05   | 0.38 ± 0.03   | 0.41 ± 0.02   | 0.97 ± 0.02  | 0.45 ± 0.03  | 0.38 ± 0.03   | 0.38 ± 0.03   | 0.38 ± 0.03   | 0.38 ± 0.03   |
| NGC 1333 | 5.20 ± 0.03   | 0.10 ± 0.01   | 0.02 ± 0.00   | 7.08 ± 0.70  | 7.40 ± 0.04  | 7.39 ± 0.03  | 0.33 ± 0.04  | 0.97 ± 0.03   | 0.77 ± 0.03   | 0.44 ± 0.02   | 0.83 ± 0.01   | 0.32 ± 0.02   | 0.32 ± 0.02   | 0.32 ± 0.02   | 0.32 ± 0.02   |
| L1448   | 5.64 ± 0.03   | 0.16 ± 0.01   | 0.02 ± 0.00   | 7.30 ± 0.12  | 7.30 ± 0.08  | 7.28 ± 0.07  | 0.90 ± 0.07   | 0.36 ± 0.02   | 0.37 ± 0.03   | 0.91 ± 0.02   | 1.15 ± 0.05   | 1.15 ± 0.05   | 1.15 ± 0.05   | 1.15 ± 0.05   | 1.15 ± 0.05   |
| L1451   | 4.09 ± 0.02   | 0.07 ± 0.01   | 0.02 ± 0.00   | 7.24 ± 0.15  | 6.74 ± 0.10  | 6.72 ± 0.20  | 0.53 ± 0.03   | 0.32 ± 0.02   | 1.30 ± 0.04   | 0.30 ± 0.03   | 0.30 ± 0.03   | 0.30 ± 0.03   | 0.30 ± 0.03   | 0.30 ± 0.03   | 0.30 ± 0.03   |

Notes. For each parameter, we report the 50th percentile of the samples. The 16th and 84th percentiles are given via the upper and lower bounds. The columns are summarized as follows. (1) Name of the star-forming region. (2) The distance modulus of the foreground reddening cloud. Directly below it we list the corresponding distance in parsecs. (3) The reddening in \(E(B-V)\) of the foreground cloud. (4) The fraction of “bad” stars, implemented as part of a Gaussian mixture model in an attempt to mitigate outliers. (5)–(10) The distance moduli of the CO velocity slices corresponding to each region (see Table 1). Directly below them we list the corresponding distances in parsecs. (11)–(16) Multiplicative factors in front of the nominal gas-to-dust coefficient adopted in this work (\(\tau = 0.062\) mag/(K km s\(^{-1}\))), which are built into the model to account for the uncertainty in how we translate CO emission to reddening.

\(^a\) The upper and lower bounds on these parameters are uncertain to <0.005 and have been rounded off to two significant figures.
velocity of each slice is fixed (see Table 1 and Section 5.1 for details on how this is calculated) and our $c$ coefficients are well constrained, we do not perform a Monte Carlo averaging procedure, but simply weight each velocity slice by the mean CO in each slice times the median $c$ coefficient for that slice (summarized in Table 2). We also report the peak-reddening velocity for each cloud; this corresponds to the velocity of the slice with the highest reddening, and this slice dominates the total dust column density along the line of sight (see Table 1 for the velocities of the slices we consider toward each region).

Finally, we emphasize that in addition to the statistical uncertainty reported in Table 3, there is also systematic uncertainty that needs to be taken into account. Schlafly et al. (2014) quantified the systematic uncertainty to be at the $\approx 10\%$ level due to the reliability of our stellar models and the adoption of a fixed extinction curve, both of which should affect the shape of our distance–reddening posteriors. However, with the inclusion of the Gaia DR2 data, these effects should be significantly reduced, particularly because stars foreground to the cloud ($\mu \leq 8$ mag) have very well constrained distances, with $\text{parallax\_over\_error}$ values of 5:1 on average; these stars carry significant weight when fitting the distances to the velocity slices. Nevertheless, there are ancillary choices we have made, independent from our stellar models and fixed extinction curve, that will also have some small effect on our results. These include our choice of grid (e.g., bin size) for our distance–reddening posteriors, how much we smooth along the reddening axis (see Section 3.1), our choice of outlier model (see Section 5.4), and how we filter stars based on their best-fit chi-squared values (see Section 4). We have rerun our line-of-sight fits for various combinations of these choices and found that the results reported in Table 3 are robust to 0.1 mag in distance modulus, or $\approx 5\%$ in distance. As a result, we conservatively recommend that a systematic uncertainty of 0.1 mag in distance modulus ($\approx 5\%$ in distance) be adopted in quadrature with our statistical uncertainties. In Table 3, the first uncertainty term reported is the statistical uncertainty, while the second is the systematic uncertainty.

### 7.1. B5

We consider three velocity slices toward B5 (with CO intensity-weighted velocities of 8.3, 9.7, and 11.0 km s$^{-1}$) and determine $\mu$ of 7.56$^{+0.12}_{-0.11}$, 7.40$^{+0.05}_{-0.06}$, and 7.34$^{+0.10}_{-0.08}$ mag, respectively. This corresponds to distances of 325$^{+18}_{-17}$, 302$^{+8}_{-9}$, and 294$^{+13}_{-11}$ pc. All slices are consistent with being at the same distance. We find an average distance to B5 of $\mu = 7.40 \pm 0.05$ mag (302 $\pm$ 7 pc). The difference in distance between L1451 and B5 is roughly 25 pc.

The line-of-sight reddening profile for B5 determined using the median of the samples from our \\textit{dynesty} run is shown in red in Figure 5. The line-of-sight reddening profiles determined by drawing random weighted samples from the same run are shown in blue, which gives a sense of the underlying uncertainty in the parameters. While the CO intensity (and thus the magnitude of the reddening jump corresponding to each slice) changes from pixel to pixel, for illustrative purposes we take the average CO value of each velocity slice to draw the profiles. In the background grayscale, we show the stacked stellar posteriors of distance and reddening for all the stars used in the analysis. Finally, we overlay the most probable distance and reddening for each star in lime green, obtained by extracting the cell in each gridded stellar posterior array with the maximum probability.

We place B5 about 50 pc further away than Černis (1993). That study performs optical photometry on dozens of stars in the vicinity of IC 348 (including B5). From this multi-band optical photometry Černis (1993) infers a spectral type and intrinsic color for each star by assuming some extinction curve and determining where the star’s unreddened colors intersect the stellar locus of main-sequence stars in various color–color projections. The reddening then follows from the difference between the star’s observed and intrinsic colors, which can subsequently be used to determine the distance to the star through the adoption of a fixed $R(V)$ value. Černis (1993) is able to roughly bracket B5 between foreground stars with lower extinction and background stars with higher extinction, constraining the distance to B5 to $\approx 250$–270 pc, which is significantly lower than our distances of $d \approx 300$ pc. However,
considering that Černis (1993) states that their uncertainties can be as high as 25%, our two distances can still be reconciled.

Our distances to B5 agree well with the distances to the same region from Schlafly et al. (2014), which are derived using a technique similar to the one presented in this work. Recall that Schlafly et al. (2014) find distances to $0^\circ 2$ sightlines distributed systematically across the Perseus Molecular Cloud by modeling the line-of-sight reddening distribution as caused by a single dust cloud at some distance $d$, with an angular distribution given by Planck (Planck Collaboration et al. 2011). Schlafly et al. (2014) then sample the most probable distance to the cloud by determining which reddening profile is most consistent with distance and reddening posteriors (Green et al. 2014, 2015) for stars along the same line of sight. Considering sightlines in the immediate vicinity of B5 ($<0^\circ 1$ from our region of interest shown in Figure 1), with uncertainties $<20\%$, Schlafly et al. (2014) determine distances of $278^{+34}_{-25}$ pc, $321^{+24}_{-24}$ pc, and $352^{+53}_{-50}$ pc, so they also favor greater distances on average than Černis (1993).

7.2. IC 348

We consider four velocity slices toward IC 348 (with CO intensity-weighted velocities of 5.4, 7.4, 9.0, and 10.4 km s$^{-1}$) and determine $\mu$ of $7.35^{+0.05}_{-0.04}$, $7.35^{+0.04}_{-0.03}$, $7.34^{+0.04}_{-0.03}$, and $7.35^{+0.05}_{-0.05}$ mag, respectively. This corresponds to distances of $295^{+7}_{-4}$, $295^{+5}_{-4}$, $294^{+5}_{-4}$, and $295^{+7}_{-4}$ pc. The different velocity components of IC 348 correspond to nearly identical distances, and all the slices are consistent with being at the same distance given the uncertainty on each slice. We find an average distance to IC 348 of $\mu = 7.35 \pm 0.03$ mag ($295 \pm 4$ pc). The line-of-sight reddening profile for IC 348 determined using the median of the samples from our dynesty run is shown in red in Figure 6.

The distance to IC 348 has been much debated in the literature since the 1950s. Almost all distances are photometric and rely on directly or indirectly determining the color excess in $B - V$, which can then be used to calculate the distance similarly to the method of Černis (1990, 1993). Like B5, Černis (1990) places IC 348 at a distance of $\approx 250 - 270$ pc. However, similar photometric-based studies by Trullols & Jordi (1997) and Harris et al. (1954) determine distances to IC 348 of $240$ pc and $316$ pc, respectively, so there is little agreement in the literature. Our distances to IC 348 are in agreement with the distance of $297^{+43}_{-28}$ pc that Schlafly et al. (2014) calculate for a sightline intersecting IC 348 (again, derived using a very similar technique to that presented in this work). The most recent constraint comes from Ortiz-León et al. (2018), who determine a distance to the cloud using both Gaia DR2 parallax measurements and Very Long Baseline Array (VLBA) astrometric observations of young stars associated with the IC 348 cluster. Ortiz-León et al. (2018) find a distance of $320 \pm 26$ pc using the Gaia DR2 data and $321 \pm 10$ pc using the VLBA observations. While Ortiz-León et al. (2018) place the cloud at a slightly farther distance than this work, our results are consistent given the quoted uncertainties.

7.3. B1

We consider five velocity slices toward B1 (with CO intensity-weighted velocities of 1.1, 2.8, 4.8, 6.7, and 8.2 km s$^{-1}$) and determine $\mu$ of $7.13^{+0.22}_{-0.25}$, $7.36^{+0.16}_{-0.23}$, $7.48^{+0.04}_{-0.03}$, $7.53^{+0.05}_{-0.04}$, and $7.60^{+0.04}_{-0.04}$ mag.
integrates through the full posterior for each star. Of distances of $\mu$, we have taken the average of the CO emission in each slice to obtain an estimate of the reddening to B5. The blue lines are random samples with the maximum probability in each of the gridded stellar posteriors. These lime green points are shown only for reference and are not used in the fit, which always integrates through the full posterior for each star.

We consider six velocity slices toward NGC 1333 (with CO intensity-weighted velocities of $-0.1, 1.7, 3.5, 5.5, 7.3,$ and $8.8 \text{ km s}^{-1}$) and determine $\mu$ of $7.08^{+0.34}_{-0.34}, 7.40^{+0.04}_{-0.04}, 7.29^{+0.15}_{-0.10}, 7.37^{+0.08}_{-0.08}, 7.39^{+0.02}_{-0.03},$ and $7.42^{+0.05}_{-0.05}$ mag, respectively. This corresponds to distances of $260^{+29}_{-24}, 302^{+5}_{-5}, 287^{+70}_{-73}, 298^{+34}_{-34}, 301^{+3}_{-3},$ and $305^{+3}_{-3}$ pc. We find an average distance to NGC 1333 of $\mu = 7.38 \pm 0.02$ mag (299 $\pm$ 3 pc). While most of the slices are well constrained and at a similar distance ($\approx$280–300 pc), we find that the first slice, at the lowest velocity, lies at a distance of around 260 pc. Looking at a 3D volume rendering of the CO emission in NGC 1333 (from, e.g., the CO COMPLETE survey page\footnote{https://www.cfa.harvard.edu/COMPLETE/movies.html}), we see that there is actually a lower-velocity wispy-like structure in front of the bulk of the higher-velocity CO emission constituting this cloud. We find that the velocity of our first slice, $v_1$, is spatially and kinematically coincident with this wispy structure in front of NGC 1333, suggesting that our algorithm is able to place weaker dust templates, leading to more poorly constrained distances. Nevertheless, it is promising that our method is able to separate this wispy structure from the rest of the cloud. The line-of-sight reddening profile for NGC 1333 determined using the median of the samples from our $\text{dynesty}$ run is shown in red in Figure 8.

In comparison to the literature, we place NGC 1333 on average 60 pc further away than Hirota et al. (2008), who determine a distance of $235 \pm 18$ pc to NGC 1333 using astrometry of H$_2$O masers associated with a YSO embedded

| Parameter | Value |
|-----------|-------|
| $d_{\text{low}}$ | $4.50^{+0.39}_{-0.32}$ |
| $E_{\text{low}}$ | $0.25^{+0.00}_{-0.01}$ |
| $\rho_{\mu}$ | $0.02^{+0.00}_{-0.00}$ |
| $d_1$ | $7.56^{+0.17}_{-0.17}$ |
| $d_2$ | $7.40^{+0.08}_{-0.08}$ |
| $d_3$ | $7.34^{+0.10}_{-0.10}$ |
| $c_1$ | $1.34^{+0.08}_{-0.08}$ |
| $c_2$ | $1.24^{+0.03}_{-0.03}$ |
| $c_3$ | $0.47^{+0.02}_{-0.02}$ |

Figure 5. Line-of-sight reddening profile for the B5 star-forming region. The full profile is integrated out to $\mu = 19$ mag (see Figures 2 and 3), but for illustrative purposes we only show the reddening profile in the range $4 \text{ mag} < \mu < 10 \text{ mag}$. The red line indicates the reddening profile parameterized by the median of the samples for each parameter (summarized in the table above the figure), derived from our $\text{dynesty}$ run. Since the magnitude of the reddening jump depends on the amount of CO emission, we show distance–reddening stellar posteriors used in the parameter estimation (see G18), stacked on top of one another. We plot the most probable distance–reddening position for each star as a lime green scatter point, obtained by extracting the cell with the maximum probability in each of the gridded stellar posteriors. These lime green points are shown only for reference and are not used in the fit, which always integrates through the full posterior for each star.
inside the cloud. We note that the result of Hirota et al. (2008) is in agreement with the photometric distance to NGC 1333 from Černis (1990) (220 pc), which uses the same technique as implemented in Černis (1993) for B5. Hirota et al. (2008) estimate their uncertainties to be of the order of 8%, in comparison to the 25% uncertainty quoted by Černis (1990). We find the typical uncertainty on our average distance to be about 1%–2%. However, we reiterate that this only accounts for statistical uncertainty and neglects any systematic uncertainty, which we estimate to be μ = 0.1 mag or 5% in distance (see Section 7). When added in quadrature, this produces total combined uncertainties of the order of ≈5%–6%. The Gaia DR2 astrometric data release (Lindegren et al. 2018) supports a farther distance to the Perseus complex as a whole, which we discuss further in Section 8. As in the case of B5 and IC 348, the distance of Schlafly et al. (2014) to a sightline near NGC 1333 (d = 288.39 pc) is in agreement with our CO-based distances. Finally, more recently, Ortiz-León et al. (2018) find a distance to the cloud using Gaia DR2 parallax measurements of young stars associated with the NGC 1333 cluster, obtaining a value of 293 ± 22 pc. This is in strong agreement with the average distance to NGC 1333 that we present in this work.

### 7.5. L1448

We consider five velocity slices toward L1448 (with CO intensity-weighted velocities of -0.7, 0.8, 2.9, 4.8, and 6.6 km s⁻¹) and determine μ of 7.30±0.11, 7.30±0.08, 7.34±0.08, 7.28±0.07, and 7.34±0.07 mag, respectively. This corresponds to distances of 288±15, 289±10, 294±11, 286±8, and 293±10 pc. All of the velocity slices are consistent with being at the average distance to the cloud, which we find to be μ = 7.30 ± 0.04 mag (288 ± 6 pc). The line-of-sight reddening profile for L1448 determined using the median of the samples from our dynesty run is shown in red in Figure 9.

As is also the case with NGC 1333, we place L1448 approximately 50 pc further away than the parallax distance derived from maser parallax measurements. Using a similar technique to Hirota et al. (2008), Hirota et al. (2011) monitor maser activity associated with a YSO embedded in the L1448 star-forming region, and determine a parallax distance of 232 ± 18 pc. Finally, we note that Schlafly et al. (2014) also prefer a farther distance to L1448, placing the cloud at a distance of 261±36 pc, which is consistent with the average distance we find for the cloud.

### 7.6. L1451

We consider four velocity slices toward L1451 (with CO intensity-weighted velocities of 0.3, 2.3, 4.2, and 5.8 km s⁻¹) and determine μ of 7.24±0.15, 6.74±0.11, 7.33±0.04, and 6.72±0.05 mag, respectively. This corresponds to distances of 280±20, 223±11, 292±5, and 220±36 pc, respectively. The velocity slice corresponding to the highest amount of reddening lies at 292 pc, but a non-negligible amount of its dust also lies at a closer distance—between about 220 and 280 pc. We find an average distance to L1451 of μ = 7.23 ± 0.03 mag (279 ± 4 pc). The average distance to L1451 agrees well with the average distance to L1448 (288 ± 6 pc), which lies in close proximity spatially on the plane of the sky. The line-of-sight
Figure 7. Line-of-sight reddening profile for the B1 star-forming region in the range 4 mag $< \mu < 10$ mag. The meaning of points, lines, and the background grayscale is the same as in Figure 5.

Figure 8. Line-of-sight reddening profile for the NGC 1333 star-forming region in the range 4 mag $< \mu < 10$ mag. The meaning of points, lines, and the background grayscale is the same as in Figure 5.
Figure 9. Line-of-sight reddening profile for the L1448 star-forming region in the range $4 \, \mu < 10 \, \mu$. The meaning of points, lines, and the background grayscale is the same as in Figure 5.

Figure 10. Line-of-sight reddening profile for the L1451 star-forming region in the range $4 \, \mu < 10 \, \mu$. The meaning of points, lines, and the background grayscale is the same as in Figure 5.
reddening profile for L1451 determined using the median of the samples from our dynesty run is shown in red in Figure 10.

In comparison to the other regions discussed, there have been fewer attempts to determine a distance to L1451. Most studies that target L1451 either assume an average distance to the cloud based on a compilation of previous distance estimates for the entire Perseus complex ($\approx$250 pc, Pineda et al. 2011) or else assign the same distance determined via trigonometric parallax measurements for the neighboring L1448 and NGC 1333 regions ($\approx$230 pc, Storm et al. 2016; Maureira et al. 2017). The most targeted distance estimate to the cloud comes from Schlafly et al. (2014), which considers a sightline about half a degree away from the L1451-mm dense core (see Pineda et al. 2008). For that sightline, Schlafly et al. (2014) determine a distance of $266^{+27}_{-31}$ pc, which is in good agreement with our average distance.

8. Discussion

Across the entire Perseus Complex, the distances to our velocity slices typically vary in the range $d \approx 260$–310 pc. The slices constituting the bulk of the reddening for each cloud typically lie within $\mu \lesssim 0.1$ mag of each other, while the overall dispersion across the entire cloud is of the order of $\mu \approx 0.2$ mag. From east to west we find the average distances to B5, IC 348, B1, NGC 1333, L1448, and L1451 to be 302 pc, 295 pc, 301 pc, 299 pc, 288 pc, and 279 pc, respectively. We summarize our results in Figure 11, which includes plots

Figure 11. (a) Combined $^{12}$CO (red) and $^{13}$CO (blue) integrated intensity map of Perseus (Ridge et al. 2006). The boundaries we define for each region (same as in Figure 1(b)) are shown in black. The centroid of each polygon is marked with a different colored point. (b) An R.A.–velocity diagram of Perseus, with the same color scale as panel (a). The colored points show the peak-reddening velocity (dark points) and average-reddening weighted velocity (light points) as a function of R.A. for each cloud. The error bars in R.A. show the horizontal extents of the polygons overlaid in panel (a). (c) Average reddening-weighted distance to each region as a function of R.A. (d) A velocity–decl. diagram of Perseus, with the same color scale as panel (a). The colored points show the decl. as a function of peak-reddening velocity (dark points) and average-reddening weighted velocity (light points). The error bars in decl. show the vertical extents of the polygons overlaid in panel (a). (e) The average reddening-weighted distance to each region as a function of its peak-reddening velocity (dark points) and average reddening-weighted velocity (light points). We find that the cloud distances tend to increase with both average reddening-weighted velocity and R.A. In total, the velocity gradient of $\approx$5 km $s^{-1}$ maps to a distance gradient of about 25 pc. The uncertainty provided on distance accounts only for the statistical uncertainty and does not include any systematic uncertainty, which we estimate to be 0.1 mag in distance modulus or 5% in distance (see Section 7).
showing how the decl. (a), velocity (b), and average reddening-weighted distance (c) for each region vary as a function of R.A., as well as how the cloud decl. (d) and average reddening-weighted distance (e) vary as a function of cloud velocity. The background color scales in panels (a), (c), and (d) are different projections of a combined volume rendering of the $^{12}$CO (red) and $^{13}$CO (blue) Perseus COMPLETE cubes. A movie showing the full 3D volume rendering of this cube can be found on the Dataverse.19,20

In more detail, we discuss how velocity correlates with distance in Perseus in Section 8.1 and how our CO-reddening-based distance estimates compare to those derived from maser parallax observations in Section 8.2.

8.1. Mapping Velocities to Distances

Because we sample for the distances to the velocity slices of CO spectral cubes, we can explicitly tie our distance measurements to the velocity structure of the molecular gas. Thus, for the first time, we can show that the velocity gradient from east to west roughly maps to a corresponding distance gradient. This distance gradient is apparent in Figure 11(e), which shows average distance as a function of both peak-reddening velocity (dark colored points) and average reddening-weighted velocity (light colored points). We note that a potential distance gradient has been proposed before (for instance, in Ridge et al. 2006) but could not be confirmed with any confidence due to the fact that our traditional method of translating the line-of-sight velocities of molecular clouds to distances (via a Galactic rotation curve, e.g., Roman-Duval et al. 2009) cannot be applied locally because peculiar motions dominate over the motions due to Galactic rotation at such close separation.

In more detail, Figure 11(e) shows that the average velocity of the slices toward B5 clouds lies at 10 km s$^{-1}$, while the slices toward L1451 lie at 4 km s$^{-1}$. As a result, the typical velocity gradient of $\approx$5 km s$^{-1}$ across the cloud translates to a distance gradient of 25 pc. There is a clear trend—clouds with higher average velocities tend to have greater average distances.

To put this distance gradient in context, the angular length of Perseus spans $\approx$5° on the plane of the sky, which corresponds to a projected length of $\approx$25 pc assuming our average distance to the complex (294 pc). This means that the line-of-sight extent of Perseus is likely equal to its projected length, giving it an aspect ratio between 1:1 and 2:1. This also suggests that Perseus is inclined to our line of sight by $\approx$45°. Given that most profiles do not show a large dispersion in distance along the line of sight (particularly for those slices that contain large amounts of reddening), it can reasonably be assumed that the cloud is relatively compact in depth, and that it does not have a “sheet”-like morphology, as has been proposed for clouds such as Musca (Tritsis & Tassis 2018).

While a single cloud distance for all of Perseus—usually around 250 pc—is often adopted (e.g., Enoch et al. 2006; Rebull et al. 2007; Arce et al. 2010; Curtis & Richer 2010; Campbell et al. 2016), our results suggest that this may be inappropriate. Again, this potential distance gradient has been discussed extensively in the literature (including in many of the cloud-wide studies that adopt a single cloud distance); however, the distance gradient has been difficult to implement due to the diversity of distance mapping techniques and the high uncertainties associated with certain methods (e.g., the photometric distance method from Černis 1990, 1993; Černis and Stražys 2003). Nevertheless, since properties such as clump mass are dependent on the distance squared, distance discrepancies of just a few tens of parsecs could produce variations in these properties as high as 50%. Our distances based on CO and stellar reddening are systematically calculated across the cloud and have typical combined statistical,
sampling, and systematic uncertainties $\approx 5\%$, so they can be used in lieu of traditional photometric methods to constrain the distances to star-forming regions in the Perseus Molecular Cloud that lie at different velocities.

8.2. Perseus Is Farther Than We Thought

Our distances to the NGC 1333 and L1448 star-forming regions are about 60 pc farther away than those derived via trigonometric parallax measurements of water masers from Hirota et al. (2008, 2011). Hirota et al. (2008, 2011) determine a maser-based distance of $d \approx 230$ pc to the NGC 1333 and L1448 star-forming regions, and they estimate their uncertainties to be $\approx 8\%$. This is the typical distance for Perseus adopted in the literature (see, e.g., Lee et al. 2015). The distances we determine for L1448 and NGC 1333 (288 and 299 pc, respectively) are consistent with the higher overall average distance we compute for the cloud as a whole (294 pc, see Table 3). Gaia DR2 parallax and $G$-band extinction ($A_G$) measurements toward stars throughout Perseus strongly favor the greater distances to the complex that we present in this work, and act as further validation for this method. This is illustrated in Figure 12. For this comparison, we select a subsample of Gaia DR2 stars along reddened sightlines throughout Perseus and we require that they have reliable measurements for both parallax and $A_G$. Specifically, we impose the criteria that the stars must lie in pixels with total line-of-sight visual extinction $A(V) > 2$ mag (from the NICER map, see also the left panel of Figure 1). Of these stars, we require their parallax error to be greater than five, and that their $\pm 1\sigma$ uncertainties on $A_G$ (a_g_percentile_lower and a_g_percentile_upper) be within 0.25 mag of the median $A_G$ value (a_g_med) reported. These stars are shown overlaid in blue on the NICER extinction map of Perseus in the left panel of Figure 12; a plot of $A_G$ versus parallax-based distance for the same stars is shown in the right panel of Figure 12. Also in the right panel, we overlay the average distance we compute for Perseus (294 pc, see Table 3), along with the $\approx 230$ pc distance often adopted to the cloud based on the results from Hirota et al. (2008, 2011). The farther distance is clearly favored by the sample of Gaia stars most likely to accurately trace the jump in reddening attributable to the Perseus complex. If anything, we could be slightly underestimating the average distance to the Complex, because the Gaia data indicate that the average jump in reddening could lie anywhere from our reported average distance up to $\approx 1$–2 standard deviations beyond it.

9. Conclusion

We present a catalog of distances to major star-forming regions in the Perseus Molecular Cloud in the velocity range $\approx -1$ to $12\, \text{km}\,\text{s}^{-1}$. We produce the catalog using a two-step process. First, we infer the distance–reddening posteriors for batches of stars across Perseus based on the technique presented in G18, and we apply a Gaia parallax-based Gaussian likelihood term as an additional distance constraint. Then, we model the reddening along the line of sight toward these stars as a linear combination of the optical depth of CO velocity slices. The result is a set of distances tied to the velocity slices defining the structure of the molecular gas toward these clouds, which we then sample using a Monte Carlo method. We target the B5, IC 348, B1, NGC 1333, L1448, and L1451 star-forming regions, and find typical cloud distances of 302 pc, 295 pc, 301 pc, 299 pc, 288 pc, and 279 pc, respectively. On average, the velocity gradient of $5\, \text{km}\,\text{s}^{-1}$ maps to a corresponding distance gradient of $\approx 25$ pc, with the eastern half of Perseus systematically farther away than the western half. We find an average distance to the Perseus Complex as a whole of 294 $\pm 17$ pc.

Typical uncertainties on our distances are of the order of 5%, with 1%–2% of that due to statistical uncertainties, and 5% due to systematics.21 We place the western portion of the Perseus Molecular Cloud (NGC 1333 and L1448) approximately 60 pc ($\approx 1\sigma$) further away than the distances derived from maser parallax measurements toward the same regions (Hirota et al. 2008, 2011). When comparing to Gaia-based parallax and G-band extinction measurements toward highly reddened lines of sight throughout Perseus, we find strong support for our greater distance.

We have only scratched the surface of what is possible through the combination of stellar photometry, CO observations, and Bayesian statistics. The accuracy of our cloud distances is directly linked to the reliability of our per-star distance and reddening posteriors, which are derived from near-infrared and optical photometry (see G18). The addition of deeper near-infrared surveys (e.g., UKIDSS; Warren et al. 2007), the incorporation of more accurate stellar parallax measurements (from Gaia DR3 and beyond), and the advent of all-sky optical surveys such as LSST will only better constrain stellar distances and reddenings, enabling us to probe deeper into dust-enshrouded regions such as Perseus. Moreover, our technique is flexible enough to incorporate models with multiple clouds along the line of sight, which would prove useful toward the inner galaxy. A similar technique (known as “kinetic tomography”; Tchernyshyov & Peek 2017; Tchernyshyov et al. 2018) has already been applied across much of the sky, resulting in a four-dimensional (position–position–distance–velocity) reconstruction of the interstellar medium, albeit at lower distance resolution. Thus, the methodology presented here for the Perseus Molecular Cloud could be applied to local molecular clouds across the full sky, paving the way for accurate cloud distances (tied to the distribution of CO molecular gas) in the solar neighborhood and beyond.

We would like to thank Mark Reid for his expertise regarding the uncertainty surrounding distance measurements derived from maser parallax observations, Thomas Dame for his expertise on the structure and properties of CO molecular gas in the Galaxy, and Charlie Conroy for insight regarding the stellar models we implemented to derive the per-star distance and reddening posteriors. All three also provided valuable comments on an early draft of this work.

Appendix A

Dynesty Setup

We use the following dynesty code to produce the chains used for parameter estimation in Section 7.

where “log-likelihood” is our log-likelihood function (described in Section 5) and “prior-transform” is a function that transforms our priors (described in Section 5) from an “ndim”-dimensional unit cube to the parameter space of interest. We set our convergence threshold, “dlogz,” equal to 0.1.

21We add the statistical and systematic uncertainties in quadrature to estimate the combined $\approx 5\%$ uncertainty on our distances.
Appendix B
Cornerplots of Dynasty Results

In Figures 13–18, we show the cornerplots of our Dynasty results for the B5, IC 348, B1, NGC 1333, L1448, and L1451 regions. The histograms of the samples for each parameter are shown along the diagonal, with the 16th, 50th, and 84th percentiles of the samples marked with the black dashed vertical lines. Different two-dimensional projections of the samples in the high-dimensional parameter spaces are shown in the rest of the panels.

Figure 13. Corner plot derived from our dynasty run toward the B5 region.
Figure 14. Corner plot derived from our *dynesty* run toward the IC 348 region.
Figure 15. Corner plot derived from our `dynesty` run toward the B1 region.
Figure 16. Corner plot derived from our dynesty run toward the NGC 1333 region.
Figure 17. Corner plot derived from our *dynesty* run toward the L1448 region.
Figure 18. Corner plot derived from our dynesty run toward the L1451 region.
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