



Exoplanet Occurrence Rate with Age for FGK Stars in Kepler

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Abstract

We measure the exoplanet occurrence rate as a function of isochrone and gyrochronology ages using confirmed and candidate planets identified in Q1–17 DR25 Kepler data. We employ Kepler's pipeline detection efficiency to correct for the expected number of planets in each age bin. We examine the occurrence rates for planets with radii $0.2 \leq R_p \leq 20 R_\oplus$ and orbital periods $0.2 \leq P \leq 100$ days for FGK stars with ages between 1.5 and 8 Gyr using the inverse detection-efficiency method. We find no significant trend between the occurrence rate and stellar age; a slight decreasing trend (within 1.5σ – 2.5σ) only emerges for the low-mass and metal-rich stars that dominate our sample. We isolate the effects of mass and metallicity on the occurrence rate trend with age, but find the results to be inconclusive, due to weak trends and the small sample size. Our results hint that the exoplanet occurrence rate may decrease over time due to dynamical instability from planet–planet scattering or planet ejection, but accurate ages and larger sample sizes are needed to resolve a clear relation between the occurrence rate and age.

Unified Astronomy Thesaurus concepts: [Exoplanet astronomy \(486\)](#); [Exoplanet dynamics \(490\)](#); [Exoplanet evolution \(491\)](#)

1. Introduction

NASA's Kepler mission revolutionized the field of exoplanets and motivated population studies to understand the occurrence rate and diversity of planets in the Galaxy (W. J. Borucki et al. 2010; D. G. Koch et al. 2010). The number and diversity of exoplanets have enabled studies across multiple planet parameters, such as planet size, orbital period, and mass (see G. D. Mulders et al. 2018 and W. Zhu & S. Dong 2021 and references therein for reviews). Many have also considered the effects of stellar properties—given the mutual relationship between planets and their host stars—such as metallicity (e.g., D. A. Fischer & J. Valenti 2005; E. A. Petigura et al. 2018; K. M. Boley et al. 2024), stellar mass (and effective temperature; e.g., J.-Y. Yang et al. 2020), and binaries (e.g., M. Moe & K. M. Kratter 2021). Others have focused on planet population studies for a specific spectral type of host star, such as M dwarfs (e.g., K. K. Hardegree-Ullman et al. 2019; K. Ment & D. Charbonneau 2023), or stellar populations, such as thin- and thick-disk (e.g., J. K. Zink et al. 2023) and halo stars (e.g., K. M. Boley et al. 2021). NASA's TESS mission has already found hundreds of planets in its short tenure thus far (G. R. Ricker et al. 2015), motivating recent planet occurrence rate studies with TESS data (e.g., M. Beleznyay & M. Kunimoto 2022; T. Gan et al. 2023; M. Temmink & I. A. G. Snellen 2023). However, while these studies inform us about the occurrence of diverse planet types, they provide few clues about exoplanet system evolution over time.

Investigation of planetary system evolution requires an understanding of planet demographics as a function of stellar age. Quantifying the relationship between age and the occurrence rate of planets allows us to constrain the frequency of planets lost due to dynamical instability, planet engulfment, or other processes, while also constraining the prevalence of free-floating planets. However, detailed studies of the exoplanet occurrence rate with age are rare, given the absence of accurate ages for field stars in large numbers. Theoretical models of planet formation rely on the timescales at which planets evolve, which are difficult to constrain without confidence in age. Although stellar mass and metallicity can be used as age proxies, their effects must be isolated to probe age dependence.

Two popular methods for inferring stellar ages are isochrone fitting and gyrochronology. Isochrone fitting works well for stars in clusters, as well as for older and more massive stars (e.g., D. R. Soderblom 2010). This method enables the straightforward derivation of stellar parameters with input observables, such as parallax, photometry, and stellar metallicity, combined with a vast grid of stellar models. Alternatively, gyrochronology relies on the relationship between stellar rotation and age (A. Skumanich 1972); stars lose angular momentum as they progress through their lifetime due to the interaction between magnetic fields and stellar winds (e.g., S. D. Kawaler 1988; S. A. Barnes 2003; J. L. van Saders et al. 2016; T. S. Metcalfe & R. Egeland 2019; O. J. Hall et al. 2021; N. Saunders et al. 2024), which can be leveraged to derive ages for thousands of stars. However, gyrochronology relies strongly on empirical calibration. Gyrokinematic ages (R. Angus et al. 2020; Y. L. Lu et al. 2021), which combine the vertical velocity dispersion of a star with other measurable stellar properties (such as the rotation period, effective temperature, G magnitude, and Rossby number) to derive stellar ages, have recently been used to calibrate a



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consistent gyrochronology model to infer gyrochronology ages for single field stars (Y. Lu et al. 2024).

To date, there have been a handful of studies of the exoplanet occurrence rate and stellar ages (e.g., J. H. Hamer & K. C. Schlaufman 2019; T. J. David et al. 2021; J. L. Christiansen et al. 2023; C. Swastik et al. 2023; S. Vach et al. 2024; J.-Y. Yang et al. 2023; R. Fernandes et al. 2025, in preparation). However, the majority of these studies have investigated young planets in clusters and associations; for instance, J. L. Christiansen et al. (2023) studied the occurrence rate of hot sub-Neptunes in Praesepe with an age of <800 Myr, while S. Vach et al. (2024) focused on systems with ages below 200 Myr.

Motivated by the recent breakthrough in Gaia's parallax measurements, as well as the recent availability of stellar ages for a large sample of Kepler stars, we explore the relationship between the exoplanet occurrence rate and stellar age up to 8 Gyr. Although previous studies have used a variety of methods to measure the occurrence rate, such as approximated Bayesian computation (e.g., D. Foreman-Mackey et al. 2014; S. Bryson et al. 2020; M. Kunitomo & S. Bryson 2020; M. Kunitomo & J. M. Matthews 2020; M. I. Shabram et al. 2020), we employ the inverse detection-efficiency method, which relies on the completeness of the planet-search algorithm in Kepler (C. J. Burke et al. 2015; J. L. Christiansen et al. 2020). Recent analyses with K2 and TESS have focused on short-period planets; our work extends to longer periods that may resolve the evolution of planet radius valley with time. Understanding the correlation between stellar age and the exoplanet occurrence rate can inform our target selection for future planet-search surveys as well as provide insight into planet formation.

2. Sample Selection

We construct a sample of stars with available and reliable isochrone ages from T. A. Berger et al. (2020; hereafter, B20) and gyrochronology ages from Y. Lu et al. (2024; hereafter, L24) for confirmed or candidate Kepler planets. We briefly describe the age determination method for both the isochrone and gyrochronology age samples below, and we refer the reader to B20 and L24 for more detailed overviews.

- i) Isochrone ages were derived from a custom-interpolated MIST (B. Paxton et al. 2011, 2013, 2015; J. Choi et al. 2016; A. Dotter 2016) grid of ~ 7 million models with ages between 0.1–20 Gyr and -2.0 – 0.5 dex in $[\text{Fe}/\text{H}]$. The code `isoclassify` was used to derive stellar parameters—including age—using input observables: photometry (Sloan Digital Sky Survey g and Two Micron All Sky Survey K_s), Gaia DR2 parallaxes, red-giant evolutionary flags, and spectroscopic metallicities.
- ii) Gyrochronology ages were derived using a newly calibrated gyrochronology relation that is most reliable for single field dwarf stars between 1.5 and 14 Gyr of solar metallicity. Extra rotation period measurements were first obtained using the Zwicky Transient Facility (IRSA 2022a, 2022b), and the relation is then calibrated using gyrokinematic ages (R. Angus et al. 2020; Y. L. Lu et al. 2021) and known cluster members (J. L. Curtis et al. 2020; R. Dungee et al. 2022), with a 2D Gaussian process using `tinygp` (D. Foreman-Mackey et al. 2024). Testing on reproducing asteroseismic ages (V. Silva Aguirre et al. 2017) shows a median absolute deviation of

1.35 Gyr, and testing age predictions for wide binary pairs (K. El-Badry et al. 2021; D. Gruner et al. 2023) agree within 0.83 Gyr.

Quality cuts in both the B20 and L24 samples were performed to ensure a high-fidelity sample. In the B20 sample, we select stars with a Gaia renormalized unit weight error (RUWE) ≤ 1.2 (to exclude potential binaries and contaminated photometry), terminal age main sequence (TAMS) less than 20 Gyr, and model goodness of fit above 99%. This reduces the B20 sample from 186,301 to 119,518 stars. We use stars with available spectroscopic metallicity to ensure a good age constraint (as indicated in B20), reducing the sample to 40,213 stars, and require that the error on TAMS is below 50%, to reduce biases toward older stars. For the L24 sample, we select stars with RUWE ≤ 1.2 to remove potential binaries.

We further reduce both stellar samples to a specific region of the Hertzsprung–Russell (H-R) diagram, selecting stars with T_{eff} between 3900 and 7300 K as the definition of FGK stars (from M. Kunitomo & J. M. Matthews 2020) and stellar radii (fit with isochrones from B20) below $1.15 R_{\odot}$. Furthermore, to ensure high confidence in planet detection, we require a data span of at least 2 yr and duty cycle above 60%. We also limit the sample to stars found in both B20 and L24, in order to derive a relationship between the occurrence rate and age consistent with both samples. Finally, we restrict the samples to ages between 1.5 and 8 Gyr, given the inaccuracy of gyrochronology ages below 1.5 Gyr. Of the 7362 stars with isochrone ages and 17,192 stars with gyrochronology ages, 2658 stars are found in both B20 and L24.

Figure 1 shows the B20 and L24 samples on an H-R diagram before and after quality cuts (left panel), as well as the age distribution for 2658 overlapping stars (middle and right panels). While the isochrone ages span the entire age range, there are less older stars with gyrochronology ages. The right panel of Figure 1 shows a large disagreement in isochrone and gyrochronology age for the same stars, demonstrating the difficulty in age derivation for dwarf field stars. The red points show the median isochrone and gyrochronology age within five equal age bins (in log space). The error bars indicate the 16th and 84th percentiles of isochrone ages. The median absolute deviation of the residual is 1.05 Gyr. It is important to note that neither the isochrone nor the gyrochronology ages are the “ground truth” in this work. Therefore, the exaggerated level of scatter in the right panel is expected, since we are plotting an uncertain measurement against another uncertain measurement, rather than comparing an uncertain quantity to a confident measurement. Furthermore, both the isochrone and gyrochronology methodologies used to produce ages here were calibrated and compared favorably to open clusters and asteroseismic constraints (see B20 and T. A. Berger et al. 2024 for more details). As such, while the large disagreement between the isochrone and gyrochronology ages suggests randomness in the ages used in this work, they are calibrated on more confident age measurements.

To create our planet sample, we select confirmed and candidate Kepler planets in Q1–17 in DR25 on the NASA Exoplanet Archive, restricted to planets with orbital periods between 0.2 and 100 days and planet radii between 0.2 and $20 R_{\oplus}$ for our 2658 hosts; 235 planets satisfy these conditions.

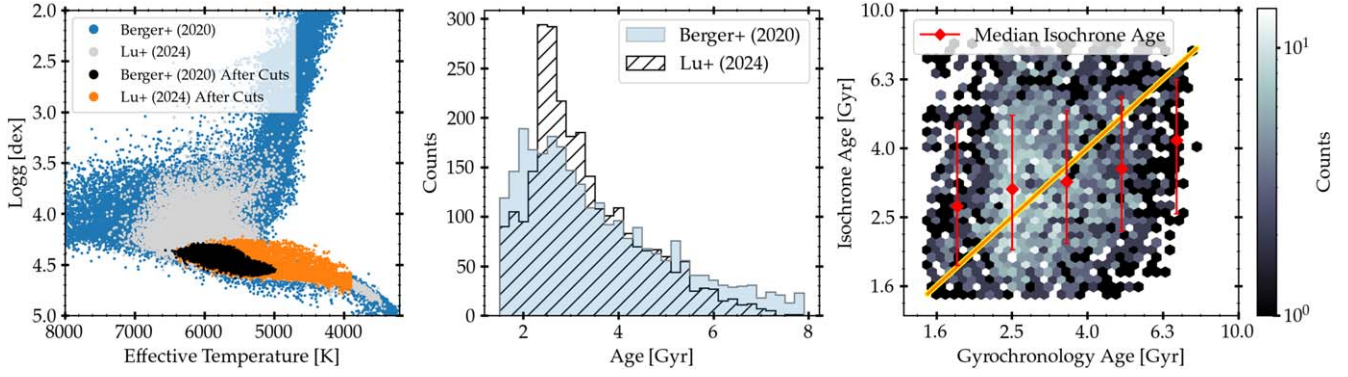


Figure 1. Left: stellar sample from B20 and L24 on an H-R diagram before and after quality cuts. Middle: age distribution of isochrone and gyrochronology ages for 2658 stars in both sets. Right: comparison of gyrochronology and isochrone ages with an rms of 1.79 Gyr. The red points show the median isochrone and gyrochronology ages within age bins, where the error bars show the 16th and 84th percentiles of the isochrone age. The yellow line indicates perfect agreement between the two age samples. There is a significant deviation between both ages for overlapping stars; stars with gyrochronology ages are preferentially younger than those with isochrone ages and cover a larger parameter space than isochrone ages.

3. Methods

3.1. Detection Efficiency

For a single target, we can calculate the detection efficiency, or Kepler pipeline completeness, over a grid of planet radii and orbital periods. The completeness of the Kepler survey relies on three individual probabilities: the detection probability (P_{det}), geometric probability (P_{geom}), and window function (P_{win}). The completeness can therefore be defined as

$$P_{\text{comp}} = P_{\text{geom}} \times P_{\text{det}} \times P_{\text{win}}. \quad (1)$$

We briefly describe the analytic forms of each probability below and direct the reader to C. J. Burke et al. (2015) for a more complete discussion.

The geometric probability, P_{geom} , is given by

$$P_{\text{geom}} = \frac{1}{a/R_*} \frac{1}{1 - e^2} \quad (2)$$

and requires as input the semimajor axis of the orbit a , the stellar radius R_* , and eccentricity e (D. M. Kipping 2014). We assume a circular orbit for our analysis and discuss the shortcomings of this later.

Given broadband red noise, as is the case with Kepler light curves, the Transiting Planet Search (TPS) algorithm considers the multiple-event statistic (MES) to measure the strength of a potential transit signal. In the presence of a signal, the MES is distributed as a Gaussian with unit variance and an average proportional to the signal-to-noise ratio of the transit signal. The MES is defined as the average of the transit signal strength over multiple transit events:

$$\text{MES} = \sqrt{N_{\text{tr}}} \frac{\Delta}{\sigma_{\text{cdpp}}}, \quad N_{\text{tr}} = \frac{T_{\text{obs}}}{P_{\text{orb}}} \times f_{\text{duty}}, \quad (3)$$

where N_{tr} is the expected number of transit events, T_{obs} is the transit baseline, and f_{duty} is the observing duty cycle. The expected transit signal depth, Δ , is

$$\begin{aligned} \Delta &= 0.84 \Delta_{\text{max}}, \\ \Delta_{\text{max}} &= k^2 (c + sk), \\ k &= Rp/R_*, \end{aligned} \quad (4)$$

where c and s are fit by a linear relationship that varies with the limb-darkening profile of stellar intensity. For G dwarfs,

C. J. Burke et al. (2015) determine the best-fit values to be $c = 1.0874$ and $s = 1.0187$. In Equation (3), σ_{cdpp} refers to the combined differential photometric precision (CDPP; D. G. Koch et al. 2010; J. L. Christiansen et al. 2012), as the time-varying noise in the light curve, averaged over the relevant transit duration. For a given transit duration, τ_{dur} , we interpolate within a grid of 14^8 robCDPP values, to estimate the noise (σ_{cdpp}) for that duration, where transit duration takes as input P_{orb} , a , e , and R_* and is defined as

$$\tau_{\text{dur}} = 4 \left(\frac{P_{\text{orb}}}{1 \text{ day}} \right) \left(\frac{R_*}{a} \right) \sqrt{1 - e^2} \text{ hr}. \quad (5)$$

The P_{det} , which is only a function of MES, is defined as the fraction of transit signals present in the data that are recovered by TPS, given by

$$P_{\text{det}}(\text{MES}) = \frac{1}{2} + \frac{1}{2} \text{erf} \left[\frac{(\text{MES} - \text{MES}_{\text{thresh}})}{\sqrt{2}} \right], \quad (6)$$

where $\text{MES}_{\text{thresh}} = 7.1$ (J. M. Jenkins 2002; J. M. Jenkins et al. 2002). However, relying on only MES results in an over 50% false detection rate. The observed pipeline completeness is therefore suppressed by the theoretical expectation, which can be quantified by

$$P_{\text{gamma}}(x|a, b) = \frac{1}{b^a \Gamma(a)} \int_0^x t^{a-1} \exp^{-t/b} dt, \quad (7)$$

where $x = \text{MES} - 4.1 - (\text{MES}_{\text{thresh}} - 7.1)$, $a = 4.65$, and $b = 0.98$.

Last, the transit window function, P_{win} , accounts for the probability that the number of transits required for detection, $N_{\text{tr}} \geq 3$, occurs in the observational data. The analytic form for P_{win} can be approximated as a binomial:

$$\begin{aligned} P_{\text{win}, \geq 3} &= 1 - (1 - f_{\text{duty}})^M - M f_{\text{duty}} (1 - f_{\text{duty}})^{M-1} \\ &\quad - \frac{M(M-1)}{2} f_{\text{duty}}^2 (1 - f_{\text{duty}})^{M-2}, \end{aligned} \quad (8)$$

where $M = T_{\text{obs}}/P_{\text{orb}}$. C. J. Burke et al. (2015) found a negligible difference in the pipeline completeness for shorter periods, $P_{\text{orb}} \leq 300$ days, when using the analytic window

⁸ 1.5, 2.0, 2.5, 3.0, 3.5, 4.5, 5.0, 6.0, 7.5, 9.0, 10.5, 12.0, 12.5, and 15.0 in hr.

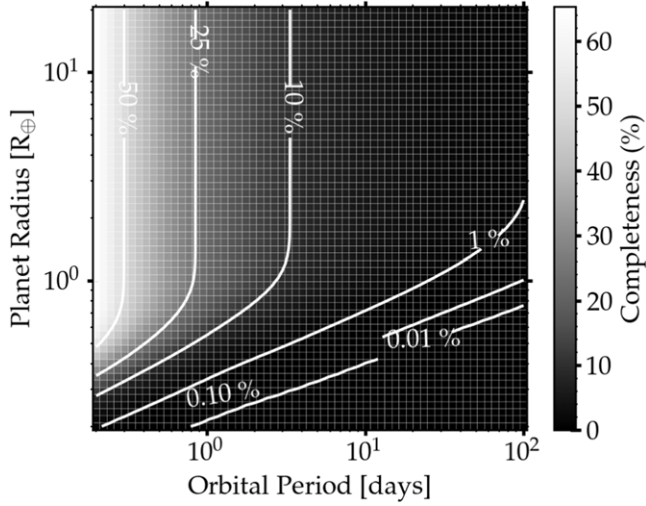


Figure 2. Integrated detection efficiency for the full sample of 2658 stars with available isochrone and gyrochronology ages over a grid of orbital period and planet radius. The contours and grid lines are shown for reference.

function (Equation (8)) and a more accurate numerical pipeline completeness model.

Therefore, taking each of the 2658 stars as input, we calculate the detection probability over a grid of planet properties. We construct a grid with 61 logarithmically spaced orbital period bins between 0.2 and 100 days, and 60 logarithmically spaced planet radius bins between 0.2 and $20 R_{\oplus}$, where the choice of radius bins is similar to the limits chosen by G. D. Mulders et al. (2018). Although many planet demographic studies select planets at orbital periods within 10 days, we chose 100 days as the upper limit, as 10 days was too restrictive for our sample (B. J. Fulton et al. 2017). This grid choice ensures that smaller periods are sampled more than larger periods over the wide range of periods, which accounts for the fact that close-in planets are more common in the data. Similarly, even though larger planets are more common in the data than smaller planets, the large number of bins in the narrow range of R_p ensures that the R_p parameter space is also well sampled.

Figure 2 shows the combined completeness for the sample of 2658 stars in our sample. The completeness is constant for all periods for larger planets, above $\sim 3 R_{\oplus}$. Our detection-efficiency contours are similar to those of G. D. Mulders et al. (2018) and A. Dattilo et al. (2023), where the latter found a similar result for larger planets. As expected, we find a higher efficiency for larger and closer planets, since those are easier to detect.

3.2. Inverse Detection Efficiency Method

The occurrence rate, Γ , using the inverse detection-efficiency method is described by the following equation:

$$\Gamma_i = \frac{n_{i,\text{planets}}}{N_{i,\text{stars}}} \frac{1}{\bar{Q}_i}, \quad (9)$$

where i denotes a given bin in age, Q_i is the detection efficiency, and Γ_i is the occurrence rate. For each bin, we calculate the observed rate of planets per star, $n_{\text{planets}}/N_{\text{stars}}$, and correct for this observed rate by dividing by the mean detection efficiency Q in the respective bin. In Equation (9),

n_{planets} is the uncorrected number of planets. To summarize, we calculate the occurrence rate in three steps:

- for all stars, j , in a given age bin, we find the mean Q over the grid (e.g., $Q_1, Q_2, \dots, Q_j$), then calculate the average detection efficiency of those stars, $\bar{Q}_i$, in a given bin;
- we calculate the rate of the observed number of planets and stars in each bin, $\frac{n_{i,\text{planets}}}{N_{i,\text{stars}}}$; and
- we correct for the observed rate of planets per star by the detection efficiency, $\bar{Q}_i$.

The distribution of Q values for a given star over the $R_p - P$ grid (3660 values) produced a right-skewed histogram, instead of a normal distribution. We compared the mean, median, and mode of the stars in each age bin and found that the distribution of Q values across age bins did not deviate; however, the range of each of mean, median, and mode varied significantly with ranges between 0.10–0.18, 0.04–0.08, and 0.40–0.85, respectively. We experimented with different summary statistics, but the relative shape of the final distribution of the occurrence rate did not deviate; only the absolute scale of the occurrence rate varied based on the statistic used (i.e., when using the median Q , the occurrence rate was higher than when using the mode Q). Therefore, we chose to calculate the mean Q , since the values were not on either extreme.

3.3. Uncertainties

We describe the uncertainty in the rate of observed planets per star by a binomial distribution, where, in a given bin, k is the number of successes (or planets discovered), n is the number of trials (or stars found), and p is the success rate (or rate of planets per star). The standard error in the rate of planets per star is given by the following:

$$\sigma_R = \sqrt{\frac{p(1-p)}{n}}. \quad (10)$$

The error on $\bar{Q}_i$ is the standard deviation of the $\bar{Q}_i$ distribution. As a result, the relative uncertainty on the occurrence rate Γ can be found via error propagation:

$$\sigma_{\Gamma} = \Gamma \times \sqrt{\left(\frac{\sigma_R}{R}\right)^2 + \left(\frac{\sigma_Q}{Q}\right)^2}, \quad (11)$$

where R and σ_R denote the rate of observed planets and its error, respectively.

4. Results

4.1. Trends with Age

We now apply our method to derive the planet occurrence rate as a function of age, given 235 (candidate or confirmed) Kepler planets and 2658 stars with isochrone and gyrochronology ages, binned in five bins equally spaced logarithmically. Table 1 shows the bin limits and average age error as well as the number of planets and stars in each bin for both isochrone and gyrochronology samples from B20 and L24, respectively.

Figure 3 shows the results of our analysis: from left to right, we show the detection efficiency, rate of planets per star, and occurrence rate as a function of isochrone age in blue and gyrochronology age in black. Although the detection efficiency increases as a function of isochrone age but decreases as a function of gyrochronology age (as seen in the first panel), the

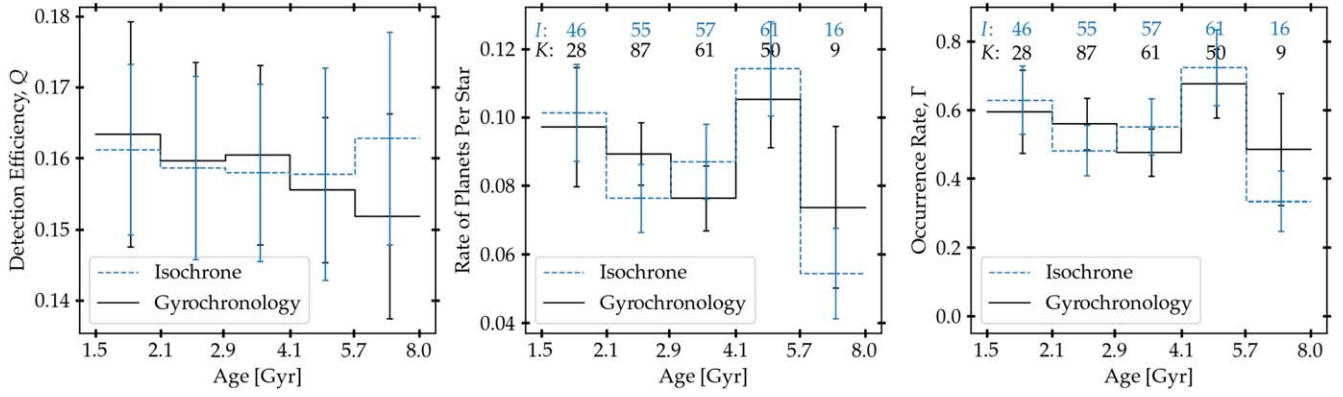


Figure 3. Planet occurrence rate as a function of isochrone age (blue, dashed line) and gyrochronology age (black, solid line). Left: detection efficiency, Q , per age bin, where the error bars are the standard deviation of Q in each bin. Middle: number of planets per star, where the error bars indicate binomial errors (Equation (10)). Right: occurrence rate of planets per age bin, where the error bars indicate the propagated error (Equation (11)) from the detection efficiency and rate of planets. The text in the middle and right panels indicates the number of observed planets in each bin for stars with isochrone ages (blue) and gyrochronology ages (black); see Table 1 for the number of stars in each bin. We find no significant trend in the exoplanet occurrence rate as a function of age for both samples.

Table 1

Number of Planets (Observed and Corrected) and Stars, as Well as the Mean Age Error, in Each Age Bin for the Sample of Isochrone and Gyrochronology Ages Used in This Work

Age (Gyr)	Isochrone Ages from B20				Gyrochronology Ages from L24			
	σ_{age} (Gyr)	Observed N_{Planets}	Corrected N_{Planets}	N_{Stars}	σ_{age} (Gyr)	Observed N_{Planets}	Corrected N_{Planets}	N_{Stars}
1.500–2.096	2.35	46	73	454	0.15	28	47	288
2.096–2.930	3.09	55	114	720	0.07	87	155	974
2.930–4.095	3.89	57	103	655	0.14	61	128	799
4.095–5.723	4.61	61	84	534	0.27	50	74	475
5.723–8.000	4.83	16	47	294	0.44	9	19	122

detection efficiencies of both samples are within 1σ of each other. The middle panel of Figure 3 shows the rate of planets per star. Table 1 lists the number of planets and stars in each age bin for both age samples.

The last panel in Figure 3 shows the occurrence rate over time when using both isochrone and gyrochronology ages. To quantify the trend shown in Figure 3, we use weighted least squares linear regression (D. Montgomery & E. Peck 1992) to calculate the slope of the distribution, using the following equation:

$$\hat{\beta} = (X^T W X)^{-1} X^T W y, \quad (12)$$

where $\hat{\beta}$ is the vector of estimated coefficients, X is the matrix of independent variables (or age in this work), W is a diagonal matrix of weights, and y is the dependent variable (or Γ in this work). We use the inverse of the σ_{Γ} to calculate weight, rather than the inverse of the variance of σ_{Γ} . We also calculate the p -value, where lower p -values correspond to more statistically significant trends, in particular if a p -value < 0.05 . In Figure 3, the slope of the occurrence rate with age is -0.03 ± 0.04 and -0.01 ± 0.02 for the isochrone and gyrochronology age samples, respectively. The p -values for both distributions are large (0.45 and 0.73, respectively), which suggests that the trends are not significant when accounting for uncertainties on the occurrence rate. Table 2 lists the slope with uncertainties and p -values in Figure 3.

However, the derived stellar ages are also dependent on mass and metallicity, which could bias the overall occurrence rate. For instance, given that older stars are rarely metal-rich, and the

exoplanet occurrence rate decreases with decreasing metallicity for giant planets (e.g., D. A. Fischer & J. Valenti 2005), an apparent decrease in the occurrence rate with age could be due to decreasing metallicity and not age. The opposite occurs for stellar mass, where the occurrence rate of exoplanets decreases with increasing stellar mass (e.g., J. A. Johnson et al. 2010; J.-Y. Yang et al. 2020). Since more massive stars tend to be younger and to have fewer planets, occurrence rate–age trends caused by mass would resemble the exoplanet occurrence rate increasing with stellar age. In order to determine the causality of the age trend, we isolate the effects of mass and metallicity by deriving the occurrence rate in bins of age, using the isochrone mass from B20 and the spectroscopic metallicity from B20.

In Figure 4, we show the distribution of stellar mass (top) and metallicity (bottom) as a function of isochrone (left) and gyrochronology (right) ages. The number density of stars in the isochrone sample peaks at around solar mass and metallicity at ~ 2 Gyr, while for the gyrochronology sample, the peak is at a range of masses and metallicity. The peak at ~ 2.5 Gyr is understood as the age for a typical star in the Kepler field, as also found by other studies (e.g., M. H. Pinsonneault et al. 2018). Furthermore, the pileup at ~ 2.5 Gyr is expected, as stars go through stalled spindown around that age (J. L. Curtis et al. 2020), which means that stars older than 2.5 Gyr appear to be younger. The number density of stars with stellar mass decreases with age for both isochrone and gyrochronology samples, as expected (Panels (A) and (B) in Figure 4). Furthermore, Figure 4(D) shows a slight trend where metallicity increases for older ages. This could be due to a

Table 2
Slope and p -value for Each Distribution Shown in Figures 3 and 5, Where the Slope Is Calculated Using Equation (12)

Age	Mass Range ($M_{\odot}$)	[Fe/H] Range (dex)	Slope (Gyr^{-1})	σ_{Slope} (Gyr^{-1})	p -value	Figure
Isochrone	...	...	-0.033	0.038	0.451	3
Gyrochronology	...	...	-0.009	0.023	0.731	3
Isochrone	Low	Poor	0.027	0.025	0.475	5(A)
Isochrone	Low	Rich	-0.044	0.036	0.433	5(B)
Isochrone	High	Poor	...	...	...	5(C)
Isochrone	High	Rich	0.003	0.029	0.932	5(D)
Gyrochronology	Low	Poor	0.077	0.041	0.313	5(A)
Gyrochronology	Low	Rich	-0.055	0.018	0.205	5(B)
Gyrochronology	High	Poor	...	...	...	5(C)
Gyrochronology	High	Rich	0.071	0.064	0.467	5(D)

Note. The “low” and “high” mass ranges refer to masses $0.8 - 1.0 M_{\odot}$ and $1.0 - 1.2 M_{\odot}$, respectively. The “poor” and “rich” metallicity ranges refer to $-0.5 - 0.0$ dex and $0.0 - 0.5$ dex, respectively. Statistically significant results usually have a p -value below 0.05.

detection bias where metal-poor stars—which have shallower convective zones and weaker dynamos—are less likely to produce the star spots that enable a rotation period measurement (e.g., V. See et al. 2021). Metal-rich stars however would have stronger dynamos and are more likely to produce star spots. Since gyrochronology ages are dependent on a rotation period measurement, the lack of metal-poor older stars in Figure 4(D) could be caused by a detection bias in Y. L. Lu et al. (2021). Figure 4 shows the existing trends with age that could bias the occurrence rate with age trends. Despite sharing the same stars, the masses and metallicities span different regimes for the two samples of isochrone and gyrochronology ages.

We incorporate more bins in mass and metallicity in Figure 5, where we derive the occurrence rate in four bins, to isolate their effects on the occurrence rate for both isochrone (blue, dashed lines) and gyrochronology (solid, black lines) ages; the stellar mass increases with rows (top to bottom), while the stellar metallicity increases with columns (left to right). The two bins in mass are $0.8 - 1.0 M_{\odot}$ and $1.0 - 1.2 M_{\odot}$, while the two bins in metallicity are $-0.5 - 0.0$ dex and $0.0 - 0.5$ dex. Therefore, we evaluate the occurrence rate as a function of age (isochrone and gyrochronology) in four bins: (i) low-mass, metal-poor (panel (A)); (ii) low-mass, metal-rich (panel (B)); (iii) high-mass, metal-poor (panel (C)); and (iv) high-mass, metal-rich (panel (D)).

Our results are inconclusive for three of the four bins in mass and metallicity: panels (A), (C), and (D). First, for the low-mass, metal-poor (panel (A)) and high-mass, metal-rich (panel (D)) samples, the uncertainties on the occurrence rate for older stars ($5.3 - 8.0$ Gyr) are significantly large enough to make the trend indistinguishable for both samples. This is consistent with their slope and p -value in Table 2; for instance, the slopes using isochrone and gyrochronology samples are 0.027 ± 0.025 (p -value = 0.48) and 0.077 ± 0.041 (p -value = 0.31) in Figure 5(A) and 0.003 ± 0.029 (p -value = 0.93) and 0.071 ± 0.064 (p -value = 0.47) in Figure 5(D). Second, for high-mass, metal-poor stars (panel (C)), the occurrence rate is zero for the last bin in isochrone age and the latter two bins in gyrochronology age, given there are no planets in this range of mass, metallicity, and age; as a consequence, no slope or p -value can be derived for the two distributions in panel (C). The remaining bin for which the trend is significant in slope is for the gyrochronology age sample in Figure 5(B), with a slope of

-0.044 ± 0.036 , where the occurrence rate with age decreases for low-mass, metal-rich stars. However, the p -value is 0.205, which suggests that the trend is not statistically significant.

Age trends are visible in samples of restricted metallicity ranges, which suggests that the apparent decrease in the planet occurrence rate as a function of age may indeed be causally driven by age and not metallicity. If metallicity alone were responsible for making older stars appear to have fewer planets, one would expect to see a difference in the occurrence rates of different-metallicity hosts, particularly in the oldest bin. The oldest bins in the top panels of Figure 5 are consistent within uncertainties, indicating that metallicity may not be a confounder. Furthermore, we also acknowledge that two broad bins in mass and metallicity may not be sufficient to reveal mass and metallicity trends. With more precise mass and metallicity measurements and a larger number of bins, future studies may be able to disentangle the effects of age, mass, and metallicity more definitively.

4.2. Assumptions and Caveats

A drawback of the inverse detection-efficiency method is that we do not incorporate errors on planet and stellar properties when calculating the detection efficiency, Q . Errors on P are negligible (average of 0.001%), but on R_p they are on average 19%, with some errors above 50%. The fractional errors on R_p are greatest between $1-5 R_{\oplus}$. The average uncertainties on stellar radius, metallicity, and mass from B20 are $\sim 2.5\%$, $\sim 3.2\%$, and $\sim 5.0\%$ for the 2658 stars in our sample, respectively, and therefore do not contribute significantly to the uncertainty on the occurrence rate.

Consequently, the quantifiable uncertainty on the occurrence rate, Γ , is driven by the relative uncertainties on the rate of planets per star and detection efficiency. The uncertainties on the former are between 5% – 12% for the majority of the bins, while the error on Q is between 5% – 10% for all bins. The error on the occurrence rate, Γ , is largely driven by the error on the rate of planets and is approximately 10% – 13% for isochrone ages and 8% – 16% for gyrochronology ages. While the error on age does not contribute to the quantifiable uncertainty on the occurrence rate, Γ , the large uncertainty impacts which age bin each star is assigned to and therefore has a major effect on the rate of planets per star.

Age uncertainties are on average 56% for the isochrone sample, which can significantly impact which bin the star is

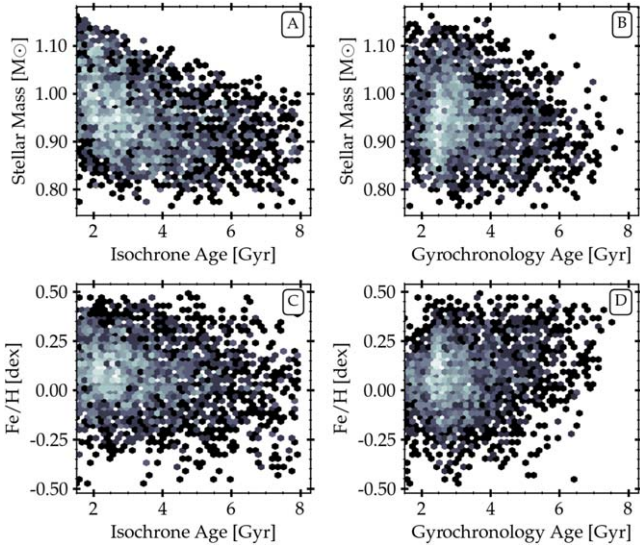


Figure 4. Distribution of stellar isochrone mass (top) and spectroscopic metallicity (bottom) with isochrone (left) and gyrochronology (right) ages, where the color indicates the number of data points in each bin, with equal numbers of bins across the four distributions. These distributions illustrate that the two samples of isochrone and gyrochronology ages span different parameter spaces in mass and metallicity, despite sharing the same stars. It also shows the relationship between mass and metallicity with age, which could bias the trend between the occurrence rate and age.

found in. While Gaia has enabled age determination for billions of stars with precise magnitudes and astrometry, these ages are not necessarily meaningful or accurate, because of the degeneracies associated with determining a stellar age from a photometric color, flux, parallax, metallicity, or set of isochrone models. See B20 for more details on age determinations and the systematics/cautions therein. As is demonstrated by J. Tayar et al. (2022), differences between the exact sets of isochrone models used can change the derived ages by $\sim 20\%$, and this is generally for main-sequence and subgiant stars. In addition, depending on where a star is located within the H-R diagram, the usefulness of isochrone ages can vary widely. For low-mass stars that do not evolve appreciably within the age of the Universe, isochrone ages are unconstrained, while for high-mass stars, the models are not as effective at reproducing observed stellar properties, in addition to the lower number of planets found around those stars.

Gyrochronology ages are calibrated via an age–velocity relation that is suitable for metal-rich stars, $[\text{Fe}/\text{H}] > -0.2$ dex (J. Yu & C. Liu 2018), which would impact older stars; however, only 11% of our sample is metal-poor (329/2658), so does not contribute significantly to our results. Moreover, the model does not take into account that metallicity can affect the rotation period of a star (L. Amard et al. 2020), which could introduce large uncertainties up to 2 Gyr in inferring gyrochronology ages in this case (e.g., Z. R. Clayton et al. 2020; L24). Binary interactions or planet engulfment could also spin up stars and introduce extra uncertainty.

Furthermore, in our analysis, we assume an eccentricity of zero, which has a direct impact on the geometric probability, P_{geom} , in Equation (2). However, D. M. Kipping (2014) showed that when a non-negligible eccentricity is included, P_{geom} is enhanced by $\sim 10\%$. While this would scale our final occurrence rate, it does not affect the overall trend with stellar age. Furthermore, D. M. Kipping (2013) found that shorter-period planets are often on circular orbits. Therefore, while the

zero-eccentricity assumption has a negligible effect on short-period planets, it is possible that incorporating nonzero eccentricity for long-period planets could increase the final detection probability, to be larger than a few percent. Again, this would scale our final results but have negligible effects on the overall trend.

4.3. Comparison with Literature

Not many studies have considered the effects of age on the occurrence rate across a wide range of ages, given the difficulty in measuring stellar ages. Recently, J. K. Zink et al. (2023) and D. Bashi & S. Zucker (2022) compared planet hosts in the young thin disk and old thick disk; they found that the occurrence rate of close-in super-Earths ($R_p = 1 - 2 R_{\oplus}$ and $P = 1 - 100$ days) are higher in the thin disk. M. Haywood (2008, 2009) find that larger planets ($R \gtrsim 2 R_{\oplus}$) are more common around older stars than smaller planets. Similarly, D.-C. Chen et al. (2022) find that sub-Neptunes and giant planets are more common around thick-disk stars, which host older stellar populations. J. H. Hamer & K. C. Schlaefman (2019) found that hot-Jupiter host stars are preferentially younger as compared to a sample of field stars without hot Jupiters in Gaia DR2.

Using MIST–MESA models to estimate the ages for a sample of 2611 exoplanet-hosting stars in Gaia DR3, C. Swastik et al. (2023) find that stars hosting giant planets are younger than those hosting smaller planets. More recently, J.-Y. Yang et al. (2023) found a decreasing trend between the occurrence rate and gyrochronology ages for their sample of Kepler planets ($R_p = 0.5 - 6 R_{\oplus}$, $P = 1 - 100$ days). Similar to us, they also re-evaluated the trend after removing the effects of other stellar parameters, such as mass and metallicity, and found that while the trend does not disappear, the difference in the apparent occurrence rate between younger and older planets becomes smaller.

While others have also looked at the occurrence rate of planets with age, the sample selections differ greatly from ours. For instance, A. Sandoval et al. (2021) found that stars older than 3 Gyr are more likely to host super-Earths ($\sim 1.5 R_{\oplus}$), while younger stars (below 3 Gyr) are more likely to host sub-Neptunes ($\sim 2.5 R_{\oplus}$). Similarly, B20 also looked at the ratio of super-Earths to sub-Neptunes as a function of isochrone age and found that the ratio of super-Earths to sub-Neptunes is higher among older stars than for younger stars. However, although we both use isochrone ages, their conclusion was based on comparing stars in two age bins: younger and older than 1 Gyr. While our sample also consists of ages above 1 Gyr, we do not have any hosts below this age threshold.

5. Planetary System Evolution

Based on the results in Figure 5, we find tentative evidence for a decreasing trend between the occurrence rate of planets with age driven by low-mass, metal-rich stars. Our results suggest that either planetary systems form similarly and then evolve over time or that planetary systems that formed 8 Gyr ago are different from planetary systems that formed 1.5 Gyr ago. Although planets can be lost through varying mechanisms after the initial phase of planet formation, there is a low probability of planet addition (through formation or stellar flybys) after the circumstellar disk has cleared, which occurs in the first few million years (e.g., A. J. W. Richert et al. 2018).

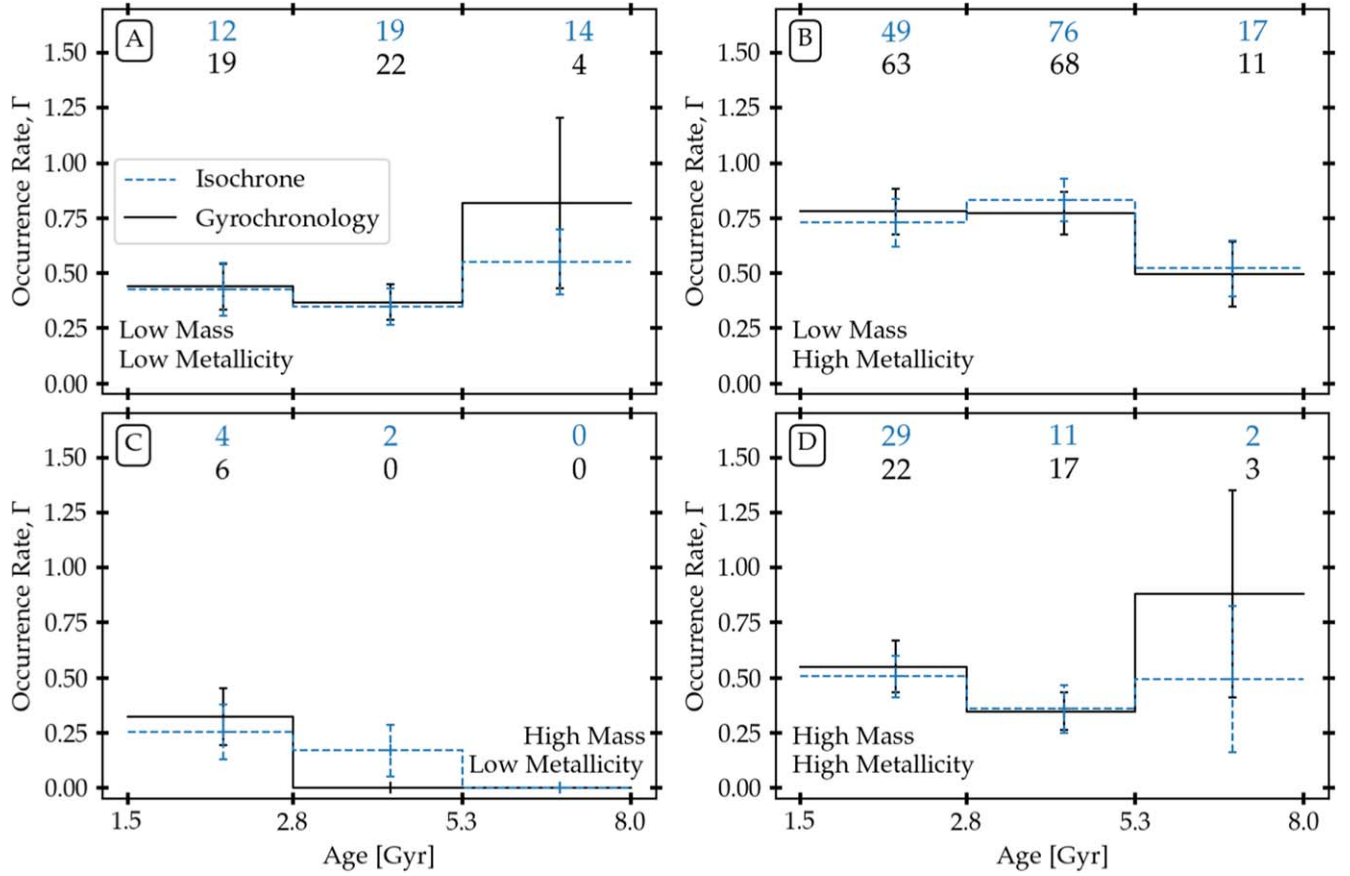


Figure 5. Planet occurrence rate as a function of isochrone age (blue, dashed line) and gyrochronology age (black, solid line), in groups of stellar mass and metallicity. The text indicates the number of observed planets in each bin. The mass increases from top to bottom, and the metallicity increases from left to right, where the low- and high-mass samples refer to mass ranges of $0.8 - 1.0 M_{\odot}$ and $1.0 - 1.2 M_{\odot}$, respectively, and low to high metallicity refers to metallicity ranges of $-0.5 - 0.0$ dex and $0.0 - 0.5$ dex, respectively. Based on the slope and p -value (see Table 2), there are no significant trends in bins of mass, metallicity, and age.

However, planets can be lost via planet engulfment, planet–planet scattering, or planet ejection throughout the system’s lifetime. We briefly describe each mechanism below and its expected impact on the occurrence rate of exoplanets.

1. *Planet engulfment.* F. Liu et al. (2024) suggest that planet engulfment occurs for 8% of late-F to G dwarfs, while L. Spina et al. (2021) suggest that this probability is closer to 20% – 35%. However, planet engulfment is more likely during the giant phase, when the star expands and engulfs close-in planets, which is less probable for our sample of FGK stars. A. Oetjens et al. (2020) showed that more massive, metal-poor stars with smaller convective envelopes evolve faster on the main sequence, which in turn favors a faster planet engulfment. Furthermore, planet engulfment timescales are shorter for more massive host stars.
2. *Planet–planet scattering.* Planet–planet scattering is more likely but would occur during the early stages of planet formation, in the presence of a protoplanetary disk, planetesimals, gas, dust, and other planet-forming materials; in fact, N-body simulations show that scattering events occur within the first 100 Myr of system formation (A. Izidoro et al. 2021; B. Bitsch & A. Izidoro 2023). B. Pu & Y. Wu (2018) show that Kepler systems with one or two planets are descendants of closely packed multiplanet systems (3 – 5 planets) that have undergone

dynamical instability. Furthermore, J.-Y. Yang et al. (2023) found a decreasing trend between planet multiplicity and gyrochronology age, which suggests that the probability of planet–planet scattering also decreases with age.

3. *Planet ejection.* Planet ejection can occur through stellar flybys or dynamical instability. It differs from planet–planet scattering, in that this mechanism removes a planet from the system, whereas planet–planet scattering changes the inclination and order of the planets in a system. Stellar flybys are fairly likely, given that most stars are born in clusters (Y. Wang et al. 2024); the multiplicity fraction is initially very high and decreases over time, and for FGK stars remains $\gtrsim 50\%$ (N. Cuello et al. 2023). In fact, K. M. Boley et al. (2021) find that 20%–40% of field stars should have experienced at least one encounter (within 300 au), while D. Malmberg et al. (2011) find that 78% of stars with masses $0.8 - 1.2 M_{\odot}$ experience at least one flyby. Simulations show that for solar-type stars ($0.8 - 1.2 M_{\odot}$), the probability of encounter decreases with the age of the cluster, from 50% at 1.5 Myr to less than 5% at 5 Myr (S. Pfalzner 2013).

6. Conclusion

We have derived the occurrence rate of Kepler exoplanets with available isochrone and gyrochronology ages from B20

and L24 between 1.5 – 8 Gyr. Using only stars with both isochrone and gyrochronology ages (2658 stars), we find no significant trend with the occurrence rate and stellar age. We tested the effect of mass and metallicity on age trends and found a slight decreasing trend ($<2\sigma$) for low-mass, metal-rich stars. We urge caution in overinterpreting our results, given the large uncertainties in both isochrone and gyrochronology ages, as well as our small sample size (235 planets and 2658 stars). We attempted to disentangle the effects of mass and metallicity (see Figure 5), but evaluating the occurrence rate along three axes—mass, metallicity, and age—significantly reduced our sample size, especially for older stars (5.3 – 8 Gyr).

Accurate ages for planet hosts are needed to effectively derive the relationship between the planet occurrence rate and age. Although asteroseismology is the only technique that can determine a star's age with uncertainty as low as $\sim 10\%$ (e.g., E. P. Bellinger et al. 2019), these data are not available for a large sample of Kepler stars. Age proxies such as lithium abundance can also be used to study the occurrence rate, given the anticorrelation between lithium and age (e.g., A. Skumanich 1972), but that is out of the scope of this paper. Our sample is restricted to FGK stars with both isochrone and gyrochronology age indicators, where the performance of our chosen age methodologies is not as accurate as in other regions of the H-R diagram.

Fortunately, the primary science goal of upcoming surveys is to detect exoplanets and oscillations in solar-like stars, which will significantly increase our confidence in planet occurrence rate studies with age. The primary goal of the upcoming PLANetary Transits and Oscillations of stars (PLATO) mission is the search for terrestrial planets around solar-like stars (H. Rauer et al. 2014, 2016). In fact, C. Boettner et al. (2024) predict that PLATO will detect 13,000 planets across the three major Galactic environments—young thin disks, older thick disks, and halos—with the majority found in the young thin disks. Furthermore, asteroseismology is a core science component of PLATO, which is expected to measure oscillation frequencies for 15,000 dwarf and subgiant stars with $V < 11$. With precise ages provided by asteroseismology, PLATO will prove instrumental in planet demographic studies as a function of stellar age. Similarly, the Nancy Grace Roman Space Telescope (Roman; D. Spergel et al. 2015; R. Akeson et al. 2019) has a dedicated Galactic Time-domain Bulge Survey that is expected to yield $\sim 60,000 - 200,000$ transiting planets toward the galactic bulge (R. F. Wilson et al. 2023). Given that Roman is expected to yield $\sim 10^6$ asteroseismic detections in the center of the galaxy (D. Huber et al. 2023), we can expect thousands of exoplanets with precise ages that will enable further occurrence rate studies. Accurate stellar ages are crucial in understanding the evolution of planetary systems over time. Upcoming missions dedicated to the discovery and characterization of exoplanets and their host stars will reveal valuable insights into planet formation and planetary system evolution with help from planet population studies.

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