

UC Merced

UC Merced Electronic Theses and Dissertations

Title

An Exploration from Small Scales to Large Scales in Galaxy Simulations: Considering Open Cluster Chemistry and Bar Resonances in Galaxy Simulations

Permalink

<https://escholarship.org/uc/item/50c5x0gg>

Author

Bhattarai, Binod

Publication Date

2025

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA, MERCED

**An Exploration from Small Scales to Large Scales in Galaxy Simulations:
Considering Open Cluster Chemistry and Bar Resonances in Galaxy Simulations**

A dissertation submitted in partial satisfaction of the
requirements for the degree
Doctor of Philosophy

in

Physics

by

Binod Bhattarai

Committee in charge:

Dr. Jay Sharping, Chair
Dr. Sarah R. Loebman
Dr. Anna Nierenberg
Dr. Melissa K. Ness

2025

Copyright
Binod Bhattarai, 2025
All rights reserved.

The dissertation of Binod Bhattarai is approved, and
it is acceptable in quality and form for publication on
microfilm and electronically:

(Dr. Sarah R. Loebman)

(Dr. Anna Nierenberg)

(Dr. Melissa K. Ness)

(Dr. Jay Sharping, Chair)

University of California, Merced

2025

DEDICATION

To the eternal curiosity that binds us to the cosmos, and to those who
taught me to look up, not with fear, but with wonder.

EPIGRAPH

”Smaller than the smallest, greater than the greatest, The Self breathes silently in the hidden heart of all things — Veiled in the starlight, it guides the rhythm of the cosmos.”

—Adapted from Śvetāśvatara Upaniṣad 3.20

TABLE OF CONTENTS

	Signature Page	iii
	Dedication	iv
	Epigraph	v
	Table of Contents	vi
	List of Figures	viii
	List of Tables	xiv
	Acknowledgements	xv
	Vita and Publications	xvii
	Abstract	xxii
Chapter 1	Introduction	1
Chapter 2	Strong Chemical Tagging in FIRE: Intra and Inter-Cluster Chemical Homogeneity in Open Clusters in Milky Way-like Galaxy Simulations	6
	2.1 Introduction	6
	2.2 Data and Methodology	12
	2.2.1 Simulations	12
	2.2.2 Star Cluster Identification	14
	2.2.3 Chemical Difference Metric	20
	2.3 Results	21
	2.3.1 The relationship between $[Fe/H]$ & birth radius for OCs	21
	2.3.2 Inter and Intra Cluster Metallicity Dispersion	26
	2.3.3 Intra and Inter-Cluster Chemical Difference Metric	28
	2.3.4 Intra and Inter-Cluster Chemical Difference Metric with APOGEE errors in simulated OCs	31
	2.4 Discussion and Conclusions	35
	Appendix A. Correlation between different elements	43
	Appendix B. Chemical Difference Metric using only 3 elements	45

Chapter 3	Tracing the Radial Metallicity Gradient and Considering Sampling Bias Using Simulated Open Clusters in FIRE Galaxies	51
3.1	Introduction	51
3.2	Data and Methodology	57
3.2.1	Simulations	57
3.2.2	Simulated Open Clusters	59
3.2.3	Two Component fit of the Metallicity Gradient	63
3.3	Results	67
3.3.1	Scatter in Mean $[\text{Fe}/\text{H}]$ vs R	67
3.3.2	Two-component fit for the radial metallicity gradient traced using MCMC for the FIRE OC dataset with a fixed average observational error in $[\text{Fe}/\text{H}]$ and realistic observational error in each cluster.	70
3.3.3	Two-component fit of the radial metallicity gradient using OCs in the region fixing the sun at 4 different azimuthal positions 8 kpc away from the center and separated by 90 degrees	70
3.3.4	Two-component fit using bootstrapped samples using full sample with replacement	75
3.3.5	Random sampling with replacement using a fixed sample size of 100, 150 and 200, 250, and 300	76
3.4	Discussion and Conclusion	79
3.5	Acknowledgments	83
	Appendix A. Corner Plots	84
Chapter 4	Resonance Sweeping in Barred Galaxy Simulations	90
4.1	Impact of Large Scale Galactic Structures like Bars on stellar dynamics	90
4.1.1	Resonance Sweeping in Barred Galaxy Simulations	91
4.1.2	Results	92
Chapter 5	Conclusion	99

LIST OF FIGURES

Figure 1.1:	Pleiades Open Cluster	3
Figure 2.1:	Number of young (<3 Myr) massive OCs identified in the last ~100 Myr of the simulations. OC selection has been run at a 3 Myr interval to avoid double-counting. m12i indicated by dashed lines colored in indigo, m12f indicated by dashed-dotted lines colored in red, and m12m indicated by solid blue lines. A varying rate of star cluster formation is observed in all three simulations, with m12m having the lowest number of clusters produced throughout the 100 Myr period. This reflects a globally suppressed star formation rate for m12m at present day. See § 2.2.2 for further discussion.	15
Figure 2.2:	Mass distribution of the OCs from all three simulations. m12i indicated by dashed lines colored in indigo, m12f indicated by dashed-dotted lines colored in red, and m12m indicated by solid blue lines. The slope of the cluster mass function is similar for all three simulations, with m12i having a shallower slope with a few high-mass outliers.	16
Figure 2.3:	Snapshots from three <i>Latte</i> simulation	17
Figure 2.4:	Distribution of mean [Fe/H] (upper panel) and dispersion of [Fe/H] in the cluster sample of all three simulations. m12i indicated by dashed lines colored in indigo, m12f indicated by dashed-dotted lines colored in red, and m12m indicated by solid blue lines. m12f has a larger range of mean and scatter in [Fe/H].	18
Figure 2.5:	Scatter plot of mean [Fe/H] vs birth radius of OCs from 3 simulations: m12i (top panel), m12f (middle panel), m12m (bottom panel). The blue dots indicate the mean [Fe/H] of each cluster, and the solid black curve represents the median trend for data in 0.5 kpc radial bins. The grey shaded area represents the $\pm 1\sigma$ range within 0.5 kpc bins. The blue horizontal line represents the average of all OCs in the sample, and the blue horizontal shaded region represents the typical $\pm 1\sigma$ scatter of [Fe/H] within any given cluster. It can be seen that the metallicity distribution varies differently in the inner disk than the outer, and many clusters have similar mean [Fe/H] despite being found at varying locations across the disk.	24

Figure 2.6:	The $[\text{Fe}/\text{H}]$ distribution for a subset of OCs from the subsample highlighted in blue from Fig. 2.5 for each simulation. Each smoothed histogram represents the metallicity distribution for a single OC and was generated using Gaussian kernel smoothing. The shaded region indicates the $\pm 1\sigma$ from the overall mean of the distribution of all clusters from that simulation. Despite their locations in the disk, it is possible to find OCs that have similar abundance distributions at different R.	25
Figure 2.7:	For each of the simulations in each panel, Blue: Intra cluster dispersion indicated as the mean dispersion per element. Indigo: the dispersion around the average dispersion. The indigo splines indicate the $\pm 1\sigma$ around it. The grey-shaded region highlights the typical measurements of such dispersion from observations, with a grey horizontal line indicating the upper limit. Dashed Red: Inter-cluster dispersion. m12f has larger dispersion in both inter and intra-cluster abundances, most probably due to an LMC-like merger resulting in a more mixed disk compared to other simulations that don't incorporate such a merger.	29
Figure 2.8:	Histograms of the chemical difference metric for pairs of stars within OCs indicated by blue histograms(intra-cluster pairs) and between OCs indicated by the dashed red histograms(inter-cluster pairs) for each simulation m12i(top), m12f(middle), and m12m(bottom) in each panel. These clusters were selected to fall within $\pm 1\sigma$ from the overall mean distribution of $[\text{Fe}/\text{H}]$ in each simulation. The bin with the smallest chemical difference metric obtained for both inter and intra-cluster pairs is abundantly populated, indicating that such difference is pretty small to uniquely identify the chemistry of individual clusters.	33
Figure 2.9:	Histograms of the chemical difference metric for pairs of stars with mock APOGEE errors in OCs (blue) and between OCs (dashed red) for each simulation. These clusters were selected to fall within the mean $\pm 1\sigma$ of the typical intra-cluster dispersion from the overall mean distribution of $[\text{Fe}/\text{H}]$ in each simulation. The bins with the most of the chemical difference metric obtained for both inter and intra-cluster pairs are abundantly populated, indicating that such difference is pretty small to uniquely identify the chemistry of individual clusters.	34

- Figure 2.10: Left to right, top to bottom: $[X/H]$ vs $[Fe/H]$ for C, N, O, Mg, Si, and Ca for stars from OCs presented in this paper in m12i. Elements are highly correlated with $[Fe/H]$ as indicated by the Pearson correlation coefficient, which is labelled on each plot (> 0.99 for all elements considered). The dotted diagonal red line is the one-to-one line. Note that the slope of the $[X/H]$ vs $[Fe/H]$ is similar to the one-to-one line, and there is limited scatter in $[X/H]$ at any value of $[Fe/H]$. This indicates that all the elements considered carry similar discriminating power as $[Fe/H]$ 44
- Figure 2.11: Left to right, top to bottom: $[X/Fe]$ vs $[Fe/H]$ for C, N, O, Mg, Si, and Ca for stars from OCs presented in this paper in m12i. Elements have a very tight scatter for a given value of $[Fe/H]$, as indicated by the small range in $[X/Fe]$ shown on the y-axis. The scatter is more substantial at lower values of $[Fe/H]$; however, the scatter decreases substantially at $[Fe/H] \geq 0.19$ dex. 45
- Figure 2.12: Correlation between $[X/H]$ vs $[Y/H]$ for C, N, O, Mg, and Ca color-coded by $[Fe/H]$ (shown in the colorbar). Elements are highly correlated with one another, as indicated by the Pearson correlation coefficient (≥ 0.989 for all elements considered). The dotted diagonal red line is the one-to-one line. Note that the slope of the $[X/H]$ vs $[Y/H]$ is similar to the one-one line, and there is limited scatter in $[X/H]$ at any value of $[Y/H]$. This indicates that all the elements considered carry similar discriminating power. 46

Figure 2.13:	Histograms of the chemical difference metric for pairs of stars within OCs indicated by blue histograms (intra-cluster pairs) and between OCs indicated by the dashed red histograms (inter-cluster pairs) for each simulation m12i (top), m12f (middle), and m12m (bottom). The chemical difference distributions shown in each column are computed as using the method presented §2.2.3, but leverage different elements to compute the chemical difference metric. The left panel is a reproduction of Fig. 2.8, which was generated using all relevant elements in our simulations (C, N, O, Mg, Si, S, Ca, Ne). The middle column shows the chemical difference distribution calculated using three elements (Mg, C, N). The right column shows the chemical difference distribution calculated using a difference subset of three elements (Mg, C, O). We note that decreasing the number of elements increases both the number of intra-cluster pairs and inter-cluster pairs that populate the smallest chemical difference metric bin. There is slightly more contamination from inter-cluster pairs when fewer elements are used to calculate the chemical difference metric. While broadly all of the distributions presented here look very similar, the maximum difference between the inter and intra-cluster global distributions is found when all elements are used to calculate the metric.	49
Figure 3.1:	Snapshots from three <i>Latte</i> simulation	52
Figure 3.2:	Scatter plot of mean [Fe/H] vs birth radius of OCs from 3 simulations: m12i (top panel), m12f (middle panel), m12m (bottom panel). Error bars represent the average observational error in mean [Fe/H] and 5% error per kpc from a fixed distance assumed to be a solar radius (8 Kpc). It can be seen that the metallicity distribution varies differently in the inner disk than the outer, and many clusters have similar mean [Fe/H] despite being found at varying locations across the disk.	55
Figure 3.3:	Scatter plot of mean [Fe/H] vs birth radius of OCs from 3 simulations: m12i (top panel), m12f (middle panel), m12m (bottom panel). Error bars represent a random simulated APOGEE error in mean [Fe/H] for each cluster and 5% error per kpc from a fixed distance assumed to be a solar radius (8 Kpc). With errors randomly assigned to each cluster, we observe larger error bars in several clusters.	56
Figure 3.4:	Scatter plot of mean [Fe/H] vs birth radius of OCs for m12i with the Sun at four azimuthal positions at $R = 8$ kpc separated by 90 degrees. Each panel shows clusters within a cylindrical radius of 8.25 Kpc from each of the assumed locations of the Sun.	60

Figure 3.5:	Scatter plot of mean $[\text{Fe}/\text{H}]$ vs birth radius of OCs for m12f with the Sun placed at four azimuthal positions with $R = 8$ kpc separated by 90 degrees. Each panel shows clusters within a cylindrical radius of 8.25 Kpc from each of the assumed locations of the Sun.	61
Figure 3.6:	Scatter plot of mean $[\text{Fe}/\text{H}]$ vs birth radius of OCs for m12m with the Sun placed at four azimuthal positions 8 kpc away from the galactic center, separated by 90 degrees. Each panel shows clusters within a cylindrical radius of 8.25 Kpc from each of the assumed locations of the Sun.	62
Figure 3.7:	MCMC two-component fit of the OC samples shown in Fig. 3.2. OCs are color-coded by the number of stars, as in previous figures. The top, middle, and bottom panels are for m12i, m12f, and m12m, respectively. Position of the knee obtained using the fit is indicated by the dotted red line. All of the fits agree on a steeper inner slope and flatter outer slope.	68
Figure 3.8:	MCMC two-component fit of the OC samples shown in Fig. 3.3. The top, middle, and bottom panels are for m12i, m12f, and m12m, respectively. Nature of the fit changes drastically in m12i compared to the other two simulations.	69
Figure 3.9:	MCMC two-component fit of the OC samples shown in Fig. 3.4. .	72
Figure 3.10:	MCMC two-component fit of the OC samples shown in Fig. 3.5. .	73
Figure 3.11:	MCMC two-component fit of the OC samples shown in Fig. 3.6. .	74
Figure 3.12:	MCMC two component fit using bootstrapping with replacement for the full sample shown in Fig. 3.3.	77
Figure 3.13:	Histograms of the fit parameters for all three simulations obtained after bootstrapping the full sample with replacement for 1000 iterations for the sample shown in Fig.3.3. m12i represented in dashed navy, m12f in dotted dashed red, and m12m in solid blue. Each panel shows the histogram for the fit parameters inner slope(m1), intercept(b), outer slope(m2), and knee(k). The corresponding standard deviation for each fit parameter from each simulation is also indicated.	78
Figure 3.14:	Histograms of the fit parameters obtained after randomly sampling at different sample sizes (100 samples represented in black, 150 in blue, 200 in green, 250 in orange and 300 in brown) with replacement for 1000 iterations for the sample shown in Fig. 3.3. m12m excluded in this analysis due to the small number of OCs.	80
Figure 3.15:	Standard deviation of the fit parameters obtained after randomly sampling at different sample sizes with replacement for 1000 iterations for the sample shown in Fig. 3.3.	81
Figure 3.16:	Corner Plot for the MCMC fit for m12i from Fig. 3.7	84
Figure 3.17:	Corner Plot for the MCMC fit for m12f from Fig. 3.7	85
Figure 3.18:	Corner Plot for the MCMC fit for m12m from Fig. 3.7	86

Figure 3.19: Corner Plot for the MCMC fit for m12i from Fig. 3.8	87
Figure 3.20: Corner Plot for the MCMC fit for m12f from Fig. 3.8	88
Figure 3.21: Corner Plot for the MCMC fit for m12m from Fig. 3.8	89
Figure 4.1: Diagonal ridges in V_ϕ/R space in Gaia DR2	92
Figure 4.2: Velocity distribution of test particle stars	93
Figure 4.3: Top-down view of the simulated galaxy. A well-evolved bar can be observed at the center. The color bar indicates the number of stars in the region.	94
Figure 4.4: Velocity distribution vs radius for test particle stars	95
Figure 4.5: Pattern speed of the bar over time in our simulation. The bar pattern speed decreases over time, thus matching the slowing bar case from Chiba et al. 2021.	95
Figure 4.6: V_ϕ vs R in N-body simulation with resonance stars	96
Figure 4.7: Resonance sweeping of stars tracked after 1.5 Gyr	97

LIST OF TABLES

Table 2.1:	Chemical difference metric analysis using all elements versus a subset of elements (Mg, C, N and Mg, C, O)	48
Table 2.2:	Purity percentage of intra-cluster pairs	50
Table 2.3:	Chemical difference metric statistics	50

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my advisor, Dr. Sarah Loebman, for her unwavering support, guidance, and patience throughout every stage of my PhD journey. Her encouragement, support, commitment to scientific rigor, and personal growth have profoundly shaped not just this thesis, but my academic journey and who I aspire to be as an educator and a researcher.

I am sincerely thankful to the members of my thesis committee — Dr. Jay Sharping, Dr. Anna Nierenberg, and Dr. Melissa Ness — for their valuable feedback, motivation, and time that have enriched the direction and depth of my research journey.

I highly appreciate Dr. Melissa Ness for her motivation and guidance that has shaped my research direction. I am also grateful to Dr. Jason Hunt with whom I worked on one of my research projects at the CCA, Flatiron Institute as a part of the galaxy dynamics summer school. I would also like to thank Dr. Andrew Wetzel from the FIRE collaboration, Dr. Peter Frinchaboy, Dr. Emily Cunningham, and Dr. Kate Daniel for their guidance throughout my research projects. I would also like to thank Dr. David Strubbe for enabling me to start my research with my advisor even before she joined UC Merced by accepting me into his group. I would also like to thank Dr. Henry Throop for always being my mentor and motivator. I am also grateful to all other mentors, collaborators, and colleagues I have had the privilege to learn from along the way — in lectures, seminars, research groups, hallway conversations, and conferences. Each interaction, no matter how brief, has left a lasting impact on my understanding of science and my place in it.

I would also like to thank and acknowledge my friends and fellow batch mates, lab mates, for all the brainstorming sessions, practice talks, shared frustrations, and shared laughter. Your support has been a source of strength and joy throughout this journey. I would like to thank my friends Subhaya, Patrick, Arabi, Adityaa, Abhinav, and all my batch mates for their support throughout the journey. I would like to thank my lab mates Micah, Dylan, Jamie, Joey, Maverick, Bornna, Maria, Emmy, and Charles, with whom I have had the opportunity to learn, laugh, and live all these years at UC Merced. I would also like to thank John, Alessa, Jonah, and Natalie from TCU, with whom I have learned a lot during our journal club meetings and interactions discussing our research projects.

I would also like to thank Dr. Karen Masters and Dr. Gail Zasowski for the insightful discussions on numerous topics during our journal club meetings.

I would also like to thank my friends from different departments and cohorts with whom I have spent my time here in Merced. I would like to thank Bishal, Samrajya, Yogesh, Sneha, Nabin, Prabin, Rijan, Srijana, Deepak Dai's Family, Ashok, Saurav, Mamata, and Sachin, who helped me feel at home while being miles away from home. I would also like to thank Bailey, Albert, De and Diego, Dishanka, Giovanni, and Belinda for being my support here at Merced. I would also like to mention my friends from Reno with whom I have spent a good amount of time during these years. I would like to thank Rabin, Anju, Manish, Kabita, Prakash, Sirisha, and Nisha, who helped to keep me sane and motivated during life's ups and downs. I would also like to thank my friends from school to batch mates from St. Xavier's College in Kathmandu who have been a constant source of motivation. I would like to thank Ankit, Mohit, Krishna, late Rabin, Keshav, Amit, Sankar, Prem, Nirajan, Birendra, Prabesh, Bishal Dumre, Biswash, and Birendra Bashyal, whose friendship and encouragement have always energized me.

Above all, I owe everything to my family for their unconditional love, quiet resilience, and unwavering belief in me, even during times when I struggled to believe in myself. I would like to dedicate this thesis to my father and mother, who have always put my education first and whose unwavering support has shaped every step of my journey. Through their lives and values, they have taught me that hard work and resilience are the keys to success, and that above all, it is most important to be a good human being — humble, kind, and grounded. Their example continues to guide me every day. To my wife Renu, for her patience, strength, and belief in me through every challenge, and to my son Atharva, whose laughter and curiosity remind me daily of why this journey matters — your love and support have been my deepest source of joy and motivation. I would also like to thank my siblings, Binaya and Bijaya, whose quiet encouragement and steady presence have always meant more than words.

My work is a result not only of my own efforts, but of the trust, generosity, and kindness of many. I feel humbled and grateful to have known and been known by everybody I crossed paths with.

BINOD BHATTARAI

4407 Pickworth Ct, Merced, CA 95438

 bbhattarai@ucmerced.edu —  +1 (209) 500-9429

Github:  binodbhtr — Webpage:  www.binodbhattarai.info.np

Education

- **Ph.D. in Physics, MS in Physics** PhD Expected May 2025, MS Conferred 2022
University of California, Merced
Advisor: Dr. Sarah Loebman
Ph.D. Research Focus: **Computational astrophysics** with an emphasis on chemodynamics of clustered star formation using high-resolution Milky Way-like galaxy simulations.
- **M.Sc. in Physics** with dissertation, Computational Physics & Astrophysics 2018
St. Xavier's College, Maitighar, Kathmandu (Tribhuvan University, Nepal)
Research: Analyzed geomagnetic disturbances due to solar storms using cross-correlation and wavelet analysis.
- **B.Sc. in Physics** with Computer Science 2014
St. Xavier's College, Maitighar, Kathmandu (Tribhuvan University, Nepal)

Skills

Programming Languages: Python (data analysis, visualization), C, C++, MATLAB, SQL

Data Science & Machine Learning: Regression, Classification, Data Clustering (FoF, DBSCAN, HDBSCAN), Time Series Analysis and Prediction, Wavelet Transform Techniques, Data Pipeline Construction

Data Visualization & Reporting: Numpy, SciPy, Scikit-learn, Pandas, Matplotlib for data analysis and visualization; Git for code and metadata management

High-Performance Computing: Experience with cloud environments and high-performance supercomputing resources like XSEDE, NOIR Data Lab. HPC Resource management and parallel computing using SLURM

Software Development: Developed, published, and maintained Python packages; MATLAB programs

Research and Communication: Research planning, execution, collaborative leadership, reporting, and technical presentation. Also adept at mentorship, training, and stakeholder engagement with several years of teaching experience from secondary school level to university level (Physics, Computer Science, and General Science).

Professional Experience

Graduate Research Assistant: Computational Astrophysics 2021 – Present
University of California, Merced

- Designed and implemented data pipelines to analyze billion-particle galaxy simulations using HPC systems.
- Led research on the chemistry and dynamics of star clusters, applying advanced statistical methods and Monte Carlo simulations to both observational and simulation

data. This work demonstrated expertise in data analysis, modeling, and the ability to handle complex datasets.

- Developed predictive models in Python to analyze chemo-dynamic trends in high-resolution galaxy simulations, applying machine learning techniques such as regression and classification to enhance understanding of clustered star formation.
- Conducted data analysis and visualization using Python to derive meaningful insights from large astrophysical datasets; results communicated through published papers, posters, and conference presentations.
- Developed a custom Python package, *mycolorpy*, being used by over 160 repositories, demonstrating expertise in software development and open-source contributions.

Mentor: Data Science Challenge

May 2021 – June 2021

Lawrence Livermore National Laboratory (LLNL)

- Mentored 3 undergraduate students to solve data science problems in a 3-week virtual event, using Python and SQL for data extraction, cleaning, and analysis of unstructured data sets.
- Developed Machine Learning algorithm to identify asteroids with $\sim 90\%$ accuracy from images

Teaching Assistant: PHYS 08/18 Lab

2019 – 2021

University of California, Merced

- Taught 4 undergrad lab and discussion sections with ~ 100 students, including grading homework, quizzes, and conducting office hours.
- Helped conduct virtual physics lab experiments using Beyond Labz during COVID pandemic.

Conferences & Presentations

- **AAS 245 Meeting** – Presented dissertation talk "Exploring the Efficacy of Strong Chemical Tagging and Tracing the Radial Metallicity Gradient in Simulated Open Clusters: Insights from FIRE-2 Galaxy Simulations" AAS 245, National Harbor, Maryland (January 12 - 16, 2025)
- **GalFRESKA 2024** – Presented a talk on chemical homogeneity in simulated open clusters, *Carnegie Science Observatories*, Pasadena, CA (Sept 19 - 20, 2024)
- **Cosmo-Gal 2024** – Presented a research talk, *UC Merced* (May 02, 2024)
- **ADONIS 2024** – Presented a talk on abundance gradients in open clusters, *MI-APbP - Munich Institute for Astro-, Particle and BioPhysics*, Garching, Germany (April 8 - 19, 2024)
- **Astronomy on Tap 2024** – Guest speaker, *UC Merced Astronomy Club* (March 06, 2024)
- **Surveying the Milky Way 2023** – Presented a poster on chemical homogeneity in FIRE open clusters, *IPAC, Caltech, CA* (Oct 23 - 27, 2023)
- **Carl-Zeiss-Stiftung Summer School 2023** – Participated in a halo finding Machine Learning related group project using TNG simulations, *Heidelberg, Germany* (Aug 14 - 18, 2023)

- **240th Meeting Of The American Astronomical Society** – Presented a poster: Bhattarai, B., Loebman, S., Ness, M., Cunningham, E., Wetzel, A., & Benincasa, S. (2022). Intra and Inter-Cluster Metallicity Dispersion in FIRE Open Clusters. *AAS Meeting*, Vol. 54, No. 6, pp. 201-07 (ADS)
- **Contributed Poster** – Wiggins, A., Bhattarai, B., Loebman, S., Myers, N., Frinchaboy, P., Otto, J., ... & Donor, J. (2024). Only the Special Survive: Star Cluster Disruption in Milky Way-like Galaxy Simulations. *AAS Meeting Abstracts*, Vol. 56, No. 2, pp. 458-20 (ADS)
- **Contributed Poster** – Otto, J., Loebman, S., Orr, M., Wetzel, A., Bhattarai, B., Oeur, M., ... & Peek, J. (2022). Star Clusters on FIRE: Classifying Star Clusters in Synthetic Galaxy Images using Machine Learning. *AAS Meeting*, Vol. 54, No. 6, pp. 201-12 (ADS)
- **CCA Predoctoral Symposium 2022** – Presented research results from my participation at the CCA Predoctoral program *Flatiron Institute, NYC* (June 24, 2022)
- **DDA 53 Annual Meeting 2022** – Presented a talk: Bhattarai, B., Hunt, J., Pearson, S., Loebman, S., Daniel, K., & McClure, R. (2022). Resonance Sweeping in Barred Galaxy Simulations. *AAS/Division of Dynamical Astronomy Meeting*, Vol. 54, No. 4, pp. 400-03 (ADS)
- **California State University, Stanislaus 2021** – Presented an invited talk on dynamics of open clusters
- **ISM 2021** – Presented a talk on star clusters in FIRE simulations, *Virtual Event* (May 11 - 14, 2021)
- **ICPS 2017** – Presented a talk at the International Conference of Physics Students, *Turin, Italy*
- **IAU Symposium 335** – Presented a poster: Effect of Geomagnetic Storms in Low Latitude Stations. *University of Exeter, Devon, United Kingdom* (July 17 - 21, 2017)

Leadership & Outreach

- **Academic Affairs Officer:** Graduate Student Association (GSA), *UC Merced* (2021 — 2022)
Advocated for academic resources and networking opportunities for graduate students.
- **Education and Outreach Officer:** International Association of Physics Students (IAPS), *Mulhouse, France* (2017 — 2018)
Led outreach initiatives of IAPS focused on increasing accessibility of science education across 41 countries.
- **Founder President:** LC-Kathmandu, International Association of Physics Students (IAPS), and **President:** St. Xavier's Physics Council (SXPC), *Nepal* (2016 — 2017)
Established global collaboration through IAPS and resource-sharing among physics students in Nepal.
- **Vice President:** St. Xavier's Physics Council, *Nepal* (2015 — 2016)
- **Member:** St. Xavier's Physics Club, *Nepal* (2014)

Awards & Grants

- **\$750**, Physics Professional Development Award, *UC Merced* (2024)
- **\$400**, Graduate Student Association Travel Award, *UC Merced* (2023)
- **\$500**, MacKenzie Scott Travel Fellowship, *UC Merced* (2023)
- **\$1000**, DDA Supplemental Travel Grant, *American Astronomical Society* (2022)
- **Physics Department Summer Fellowship**, *UC Merced* (2021)
- **\$3000**, Interdisciplinary Small Grants Program, *UC Merced* (2021 — 2022)
Co-I: Interdisciplinary Seminar Series: Big Data & Machine Learning P-I: Dr. Sarah Loebman
- **€1000**, ICPS Worldwide Grant (2017) Participation at the "International Conference of Physics Students"
- **€496**, IAU Travel Grant (2017) Participation at the "IAU Symposium 335 (IAUS-335)"

Publications

ORCID:  <https://orcid.org/0000-0002-7707-1996>

 **Google Scholar Link**

- **Bhattarai, Binod**, Sarah R. Loebman, Melissa K. Ness, Andrew Wetzel, Emily C. Cunningham, Hanna Parul, and Alessa Ibrahim Wiggins. "Strong Chemical Tagging in FIRE: Intra-and Intercluster Chemical Homogeneity in Open Clusters in Milky Way-like Galaxy Simulations." *The Astrophysical Journal* 977, no. 1 (2024): 70. (DOI:10.3847/1538-4357/ad8bac)
- Parul, Hanna, Jeremy Bailin, Sarah R. Loebman, Andrew Wetzel, Megan Barry, and **Binod Bhattarai**. "Effect of gas accretion on α -element bimodality in Milky Way-mass galaxies in the FIRE-2 simulations." *Monthly Notices of the Royal Astronomical Society* 537, no. 2 (2025): 1571-1585. (DOI:10.1093/mnras/staf137)
- Adhikari, Binod, Subodh Dahal, Nirakar Sapkota, Prashrit Baruwal, **Binod Bhattarai**, Krishna Khanal, and Narayan P. Chapagain. "Field-Aligned Current and Polar Cap Potential and Geomagnetic Disturbances: A Review of Cross-Correlation Analysis." *Earth and Space Science*, 5, no. 9 (2018): 440-455. (DOI:10.1029/2018EA000392) *My Contribution: Performing Cross-Correlation and Continuous Wavelet Analysis and writing results.*
- Khanal, Krishna, Binod Adhikari, Narayan P. Chapagain, and **Binod Bhattarai** (2019). "HILDCAA Related GIC and Possible Corrosion Hazard in Underground Pipelines: A Comparison Based on Wavelet Transform." *Space Weather*, 17 (2019). (DOI:10.1029/2018SW001879) *My Contribution: Performing and writing results from Continuous Wavelet Analysis.*
- Adhikari, Binod, Nirakar Sapkota, **Binod Bhattarai**, Roshan Kumar Mishra, S. Bohara, Narayan P. Chapagain, and B. Regmi. "Study of interplanetary parameters, polar cap potential, and polar cap index during quiet event and high intensity long duration continuous AE activities (HILDCAAs)." *Russian Journal of Earth Sciences*, 18, no. 1 (2018). (DOI:10.2205/2018es000609) *My Contribution: Performing and writing results from Continuous Wavelet Analysis.*
- Adhikari, Binod, Nirakar Sapkota, Subodh Dahal, **Binod Bhattarai**, Krishna Khanal, and Narayan P. Chapagain. "Spectral characteristic of geomagnetically induced cur-

rent during geomagnetic storms by wavelet techniques." *Journal of Atmospheric and Solar-Terrestrial Physics* (2018). (DOI:10.1016/j.jastp.2018.01.020) *My Contribution: Performing and writing results from Continuous Wavelet Analysis.*

- Adhikari, Binod, Roshan Kumar Mishra, Drabindra Pandit, **Binod Bhattarai**, and Narayan Prasad Chapagain. "Ionospheric Effect Of Non-storm Hildcaa (High Intensity Long Duration Continuous Auroral Activity)." *Journal of Institute of Science and Technology*, 22, no. 1 (2017): 34-40. (DOI:10.3126/jist.v22i1.17737) *My Contribution: Performing and writing results from Continuous Wavelet Analysis.*
- **Contributed Poster** – Wiggins, A., **Bhattarai, B.**, Loebman, S., Myers, N., Frinchaboy, P., Otto, J., ... & Donor, J. (2024). Only the Special Survive: Star Cluster Disruption in Milky Way-like Galaxy Simulations. *AAS Meeting Abstracts*, Vol. 56, No. 2, pp. 458-20 (ADS)
- **Contributed Poster** – Otto, J., Loebman, S., Orr, M., Wetzel, A., **Bhattarai, B.**, Oeur, M., ... & Peek, J. (2022). Star Clusters on FIRE: Classifying Star Clusters in Synthetic Galaxy Images using Machine Learning. *AAS Meeting*, Vol. 54, No. 6, pp. 201-12 (ADS)

ABSTRACT OF THE DISSERTATION

An Exploration from Small Scales to Large Scales in Galaxy Simulations: Considering Open Cluster Chemistry and Bar Resonances in Galaxy Simulations

by

Binod Bhattarai

Doctor of Philosophy in Physics

University of California Merced, 2025

Dr. Jay Sharping, Chair

Open star clusters are the essential building blocks of the Galactic disk; “strong chemical tagging” – the premise that all star clusters can be reconstructed given chemistry information alone – is a driving force behind many current and upcoming large Galactic spectroscopic surveys. In this work, we characterize abundance patterns for 9 elements (C, N, O, Ne, Mg, Si, S, Ca, and Fe) in open clusters (OCs) in three galaxies (m12i, m12f, and m12m) from the *Latte* suite of FIRE-2 simulations to investigate if strong chemical tagging is possible in these simulations. We select young massive ($\geq 10^{4.6} M_{\odot}$) OCs formed in the last ~ 100 Myr and calculate the intra- and inter-cluster abundance scatter for these clusters.

We compare these results with analogous calculations drawn from observations of OCs in the Milky Way and find the intra-cluster scatter of the observations and simulations to be comparable. While the abundance scatter within each cluster is minimal ($\lesssim 0.020$ dex), the mean abundance patterns of different clusters are not unique. We also calculate the chemical difference in intra- and inter-cluster star pairs and find it, in general, to be so small that it is difficult to distinguish between stars drawn from the same OC or from different OCs. Despite tracing three distinct nucleosynthetic families (core-collapse supernovae, white dwarf supernovae, and stellar winds), we conclude that these elemental abundances do not provide enough discriminating information to use strong chemical tagging for reliable OC membership.

Open clusters are relatively bright, easy to measure objects that are thought to be reliable tracers of the overall galactic radial metallicity gradient. Studies have shown that open clusters decrease in metallicity with increasing distance from the Galactic center; this distribution has often been modeled with a two-component linear fit, with a transition (knee) occurring between 10 and 16 kpc. Recent work from the APOGEE collaboration has significantly increased (> 150) the sample size of open clusters with robust measurements of chemistry across the Galactic disk.

However, the susceptibility of this fit to the effects of sampling bias has been yet to be explored and could have large implications for the inferences drawn from the radial metallicity gradient. We selected young massive clusters less than 3 Myr old in our simulations and fit the radial metallicity gradient using the MCMC technique and find that sampling of open clusters significantly alters the observed trend of the fit parameters inner slope (m_1), intercept (b), outer slope (m_2) and knee (k). We performed bootstrapping of the fit to find that sampling can have an impact on the outer slope but significantly impacts the inner slope and the location of the knee. Using both bootstrapping and fixed sized random sub-samples of open clusters, we find that for reliable recovery of the fit parameters, we require at least 200-250 clusters spread across a wide range of galactocentric radii. With smaller or spatially biased samples, the fit parameters become highly sensitive to the sampling bias.

It has been shown that more than 50% of the disk galaxies, including our Milky Way galaxy, has a central bar with billions of stars clustered together. Theory suggests that galactic bars spin down throughout their evolution due to an angular momentum exchange with the inner parts of their dark matter halos. As opposed to a bar with a fixed pattern speed, Chiba et al. (2019) proposed that ‘resonance sweeping’ due to a decelerating galactic bar can explain local kinematic substructure in the solar neighborhood, like the Hercules stream. To date, resonance sweeping - a process of trapping and dragging the orbits of stars - has been explored both analytically and with test particle simulations that lack self-gravity. Here, we take such analyses a step further and examine resonance sweeping with a high resolution ($\sim 10^9$ particles) self-consistent N-body simulation. We identify stars in Corotation Resonance and Outer Lindblad Resonance and find a significant number of stars remain in resonance later in time, suggesting resonant

sweeping of orbits due to the decelerating bar. This result in a more realistic, self-gravitating disk indicates that the method of resonance sweeping can indeed be applied to Gaia data.

Chapter 1

Introduction

We are now at an exciting time in astrophysics research – one where our understanding of the Milky Way is being reshaped and redefined. Thanks to the Gaia space telescope [62], we now have, for the first time, access to accurate positions and velocities for more than a billion stars across the Milky Way – a milestone once unimaginable. This data, combined with chemistry and age information derived from APOGEE [115], GALAH [44], LAMOST [36], Kepler [90], and TESS [152], allows us to construct the largest, most precise three-dimensional map of our Galaxy ever made. With this vast, rich dataset comes the opportunity to explore fundamental questions about the origins of our Galactic home.

While surveys have revolutionized our view of the Milky Way, they provide us with only a single snapshot in time — a frozen moment in the ongoing evolution of the Galaxy. The complex processes that shape Galactic structure, star formation, and chemical enrichment that unfold over billions of years is far beyond the reach of direct observation. To bridge this gap, we can utilize cosmological simulations, which allow us to model the dynamical and chemical evolution of galaxies in a physically grounded framework. These simulations provide a laboratory to test theories, explore scenarios that we cannot observe directly, and make predictions to guide and interpret our observations. This work is focused on characterizing the chemo-dynamic properties of star clusters and understanding their dynamic evolution in the Milky Way’s disk using galaxy simulations.

Star clusters are groups of stars that are born together and remain approximately gravitationally bound for some time. Since cluster stars are born together, they share a

common heritage that is seeded by the giant molecular gas cloud they are born in. There are three types of star clusters: globular clusters, nuclear star clusters and open clusters.

Globular clusters are some of the oldest structures seen in galaxies; they contain hundreds of thousands to millions of stars that have remained bound over the majority of the lifetime of the universe. Globular clusters mostly live far from the Galactic disk and span diameters of 20 to 100 parsecs or more (1 parsec = 3.26 light-years and 1 light year = ~ 9.46 trillion km). Globular clusters have been found to be located in the halo of most of the large galaxies that have been observed. For instance, M13 (NGC 6205) is one of the brightest globular clusters in our galaxy and is 7.6 kpc away from the Sun. It is located in the constellation Hercules, comprises of roughly a 100 thousand stars that are estimated to be 11.66 billion years old [133] and span a radius of ~ 46 parsecs.

Nuclear star cluster is a type of star cluster that has a high density of stars that are of high luminosity and are located near the center of mass of most galaxies [155, 158]. Such star clusters are also known as compact stellar nuclei or young stellar nuclei. Nuclear star clusters are the densest of all star cluster types and can be 40 times as bright as a typical globular cluster. They contain a mixture of both old and young stellar populations.

Open clusters (OCs), on the other hand, are smaller than both globular clusters and nuclear star clusters, live almost always in galactic disks, and are comprised of only relatively young stellar populations. Relative to *all* other galactic structures, they are physically the smallest objects – they typically have a radius between one to ten parsecs in size – and contain between a few dozen to tens of thousands of stars within them. In Fig. 1.1, we can see an image of a typical well studied OC: Pleiades OC. It contains ~ 1000 stars, is estimated to ~ 100 Myr old and spans a diameter of ~ 3.4 parsecs. While OCs have many fewer stars than globular clusters and are far less densely packed, they still contain many more stars than are typically found together in the general Galactic field. To get a perspective on how dense OCs are, the core radius of Pleiades is ~ 3 parsecs while the next nearest star system to the Sun is ~ 1.5 parsecs away. Now imagine putting ~ 1000 stars inside a region twice as large as the distance to our next nearest neighbor. Certainly, that would be a much brighter and more complex environment than the one we currently live in. Despite this, we do think that most disk stars, our Sun included, likely formed inside an OC. Thus, to truly understand our own origin story, we need to

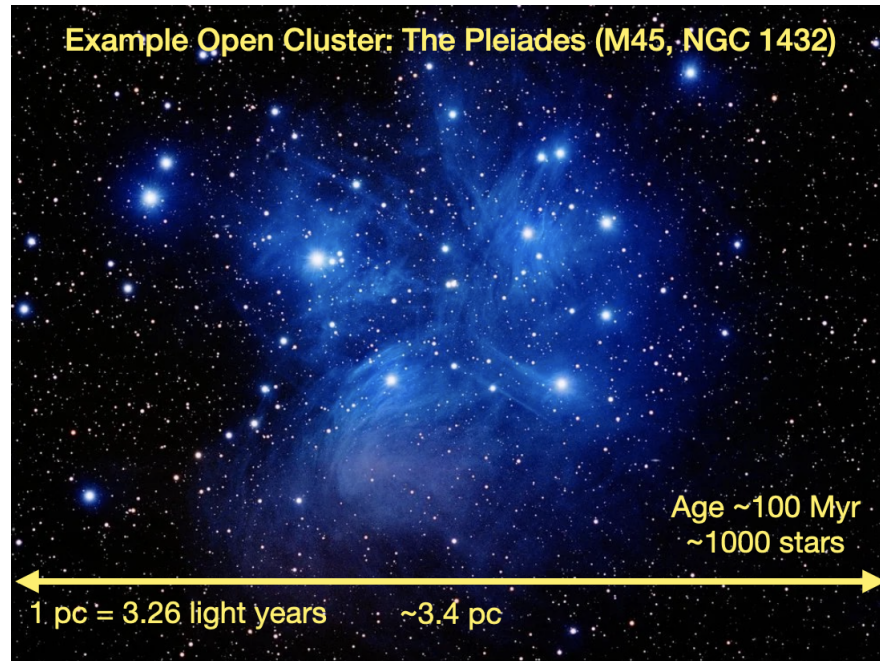


Figure 1.1: Pleiades Open Cluster
(Image Credit: Tony Hallas/Science Faction/Corbis)

consider OC formation and evolution.

An often cited definition by Lada and Lada classifies OCs as a group of 35 or more physically related stars whose stellar mass density exceeds one solar mass within a spherical volume having a radius of 1 parsec – this gives a benchmark metric for assessing if a group of stars should be labeled an OC within the Milky Way (MW). Lada and Lada also note that OCs typically consist of very young stars, and as such, they are valuable probes of the star formation process, stellar evolution, and the dynamics of many-body systems. In general, OCs are bright and abundant (with today ~3000 of them observed in the MW and will reach ~5000 in the footprint covered by SDSS-V’s Milky Way Mapper by the end of survey) and because stars within them lie at a ~common distance away from us and have ~similar motion, with precise astrometric information from Gaia, they are increasingly straightforward to identify and study.

Of the three star cluster types, the focus of this thesis is on OC, as they are thought to be the essential building blocks of galactic disks, and our understanding of them in the era of Gaia is rapidly evolving [28]. “Strong chemical tagging” – the premise that

all-star clusters can be reconstructed given age and chemistry information alone [54] – is the driving force behind many current and upcoming large Galactic spectroscopic surveys (*e.g.*, APOGEE [115], GALAH [44], Milky Way Mapper [91], and WEAVE [39]). However, despite their central nature to current and forthcoming observational studies, robust theoretical connections between OC properties and the larger Galactic environment remain substantially unexplored [96]. This work aims to understand if OC properties, specifically chemistry, age, and phase space information, uniquely map onto distinct formation sites in the Galactic disk using simulations. This work explores if this information can ultimately be leveraged to reconstruct dispersed OCs. This, in turn, will be useful to derive the initial conditions that many if not most of stars in the field the MW’s disk were born in.

In Chapter 2, I test a premise for strong chemical tagging. Stars that belong to an OC are considered to be formed from the same molecular cloud. Based on this assumption, stars within a given OC are believed to share a similar chemical signature [*e.g.*, 41, 43, 17, 20, 116]. The chemical similarity of stars has been widely used to reconstruct cluster memberships. The method known as strong chemical tagging [54] relies on the chemistry of the stars to define cluster membership [*e.g.*, 114, 120, 72]. Recently, Spina et al. [162] have shown using the Gaia data that chemical tagging can be used to recover OC membership using clustering analysis in the elemental abundance space. However, a robust comparison with the simulations does not exist and researchers aim to characterize the precision requirements for metallicity measurements to ensure star cluster reconstruction can be conducted using chemistry alone. I characterize the amplitude of OC scatter in individual abundances across all *Latte* simulations to explore the implications this result holds for all spectroscopic surveys given typical uncertainties.

In Chapter 3, I discuss the radial metallicity gradients that I measure across *Latte* disks using OCs. The term “radial metallicity gradient” refers to the relationship between average metallicity in a given radial bin as a function of Galactocentric radius. It is considered an important metric to study the processes that drive the formation of the galaxy and its evolution [34, 128, 66, 11]. The inside-out disk formation model by Larson [101] proposes that the metallicity gradient is a natural consequence of star formation that proceeds inside out across the galactic disk over time. This theory is

also supported by the theoretical work of Matteucci and Francois [124]. This has also been seen in Galactic simulations; however, the effect is mediated by radial flows and stellar migration [64]. In the Milky Way there are many probes that can be used to study the radial metallicity gradient like Cepheids [e.g. 103, 107], H II regions [e.g. 9, 6], planetary nebulae [e.g. 108, 165], low mass and massive stars [e.g. 19, 77, 3, 24]. However, OCs are considered to be the best probes as it is straightforward to measure their ages and distances. OCs have long been used as tracers of the structure and evolution of the Milky Way [e.g. 84, 55, 131, 134] and its metallicity gradient [e.g. 85, 169, 180, 109, 27, 82, 32, 47, 161]. However, it is yet to be explored how sampling bias affects the inferred radial metallicity gradient that is measured using OCs. I provide an insight into this in Chapter 3 using *Latte* OCs. As observational capabilities continue to advance and the number of known open clusters is expected to increase, this work offers valuable insight into the minimum number of open clusters required to robustly constrain the Milky Way’s radial metallicity gradient. That is, the *Latte* simulations provide a great test-bed to study the radial metallicity gradient as measured by OCs.

In Chapter 4, I explore how groups of stars in the Galactic disk are influenced by large scale dynamical structures like the bar. It has been shown that more than 50% of the disk galaxies, including the Milky Way, have a central bar made up of billions of stars that are clustered together [156, 26]. Theories suggest that the bar pattern speed slows over time and can induce resonance sweeping — a process where resonances like the co-rotation resonance (CR) and outer Lindblad resonance (OLR) move outward as the bar slows down, thus dynamically trapping and dragging stars across the disk. Using a high-resolution, billion-particle N-body simulation without gas, I explore how these resonances restructure the phase space of the disk over time. My results show that as the bar decelerates, stars at resonance locations develop coherent ridges in V_ϕ vs R space, closely resembling observed moving groups like the Hercules stream in Gaia data. I further demonstrate that stars can remain trapped in resonance for over a Gyr, migrating outward, providing evidence that resonance sweeping is a viable mechanism for the origin of some kinematic substructures in the solar neighborhood.

Chapter 2

Strong Chemical Tagging in FIRE: Intra and Inter-Cluster Chemical Homogeneity in Open Clusters in Milky Way-like Galaxy Simulations

(Published in *The Astrophysical Journal*, 977(1), 70. Bhattarai et al. [15])

2.1 Introduction

Uncovering the history of the Milky Way’s stellar disk is a fundamental goal of Galactic astronomy and is tied to the smallest-scale structures where star formation occurs, open clusters (OCs). OCs are groups of stars that are born together and remain gravitationally bound for a period of time; Lada and Lada [97] define an OC as a group of young stars that survive tidal disruption for a period as long as 100 Myr. In numerical simulations, OCs are usually defined as groups of co-forming stars that share a common origin [e.g., 46, 67].

OCs are often leveraged to study the dynamical and chemical history of the Galactic disk, as these bright structures are relatively straightforward to observe and characterize [e.g., 58, 135, and references therein]. OCs are considered the building blocks of the Galactic disk because a significant fraction of star formation occurs within them, and

the majority are thought to dissolve quickly [97, 17, 94, 96]. One of the important objectives of near-field astronomy is to reconstruct the structures that have dispersed due to dynamical processes in the disk, specifically, reassembling structures like OCs using present-day stellar observables.

One stellar observable of particular interest is elemental abundance. This is because stars that belong to a particular OC are thought to form from a common well-mixed molecular cloud with a similar underlying chemistry [160, 126, 149, 52]. Based on this assumption, stars that were born within a given OC are believed to have a similar chemical “fingerprint” that would enable OC reconstruction based on chemistry alone [e.g., 54, 41, 42, 17, 20, 116]. This is the premise behind strong chemical tagging [54], which relies on accurate measurement of multiple elements in stars to reconstruct cluster membership [e.g., 114, 120, 72, 20, 162].

The feasibility of strong chemical tagging is a key motivation for several current and upcoming spectroscopic surveys [e.g., GALAH, APOGEE, WEAVE 44, 25, 115, 38, 91]. For strong chemical tagging to work, the member stars within an OC should be nearly chemically homogeneous, i.e., they should have *small intra-cluster dispersion*. In addition, each cluster should have a unique chemical signature so that it can be well distinguished from the stars that belong to other OCs, i.e., there should be *significant inter-cluster dispersion* [98].

Whether there is typically a small level of intra-cluster dispersion (i.e., the level of similarity in the element abundances of member stars) in OCs is still a matter of debate [16, 150]. However, in the limit of small samples, the chemistry of stars that belong to a particular OC has often been shown to share a similar signature when compared with the chemistry of stars that belong to different clusters [e.g., 130, 114, 120, 72, 40, 143]. This indicates that stars that belong to an OC could have a measurable signature that is distinct from other OCs, in the limit that measurement uncertainties in stellar abundances are smaller than the level of the intrinsic element abundance scatter, so that the amplitude of homogeneity in OCs can be uniquely assessed [136, 137].

Large surveys have extended studies of OCs to more substantial samples and determined the intrinsic scatter to be < 0.03 dex within clusters for up to 15 element abundances [20, 137, 14, 148]. Interestingly, Blanco-Cuaresma et al. [16] find distinct

chemical signatures for stars in different evolutionary stages that belong to the same open cluster. In fact, theoretical expectations lead to a prediction that intra-cluster scatter is non-zero when processes like non-thermal equilibrium, atomic diffusion, mixing, the influence of binarity, and planetary engulfment are included in stellar abundance calculations. These predictions have been born out both observationally and in theoretical models [106, 49].

Besides debates about intra-cluster homogeneity, there are also several discussions in the literature about the level of inter-cluster homogeneity throughout the Milky Way. For example, there is an expectation that the inter-cluster homogeneity could be a function of galactocentric radius [164]. In fact, a negative radial gradient in the Milky Way’s disk has been found in observations [e.g., 18, 2, 48, 135, 112], while radial and azimuthal variations have been detected in several nearby galaxies as well [e.g., 153, 132, 92, 104], which could be taken as an indication for the uniqueness of abundances in star clusters found at particular galactocentric location. However, Blanco-Cuaresma et al. [16] find significant overlap of multiple chemical abundances in their sample of 31 OCs within the Milky Way. Moreover, Ting et al. [168] show that overdensities in chemical space do not guarantee that such overdensities arise due to a single set of stars from a common birth cloud, thus suggesting an overlap in the inter-cluster metallicity distribution.

A differing perspective has been found by Lambert and Reddy [98], who show significant inter-cluster variation in the chemical composition of heavy elements (La, Ce, Nd, and Sm) for red giants in a sample of 28 OCs, where all the clusters had nearly solar metallicity. Moreover, Manea et al. [117] find that neutron-capture elements carry a more discerning signature than the lighter elements that have been traditionally considered in the current generation of spectroscopic surveys. However, in the limit of elemental abundances available in APOGEE [113], Ness et al. [137] find field stars have similar chemistry as the members of OCs, suggesting an overlap of birth cluster signatures with the field stars. Furthermore, in a different study, Ness et al. [138] find that, at a fixed $[\text{Fe}/\text{H}]$, chemistry is a deterministic property of age that does not necessarily change with the birth location.

The perhaps most critical consideration in assessing the viability of chemical tagging is not simply how chemically homogeneous OCs are themselves, but how homogeneous

stars within a cluster are relative to random field stars. The contamination rate using 20 abundances in Ness et al. [137] was found to be around 1 percent at $[\text{Fe}/\text{H}] = 0$. That is, while the intra-cluster dispersion is small, on the order of < 0.03 dex, around 1 percent of random field stars at solar $[\text{Fe}/\text{H}]$ are as chemically similar as stars within the same cluster. This is very prohibitive for any chemical tagging pursuit. However, what remains critically unclear is the theoretical expectation for inter and intra-cluster homogeneity from simulations. In this work, we test this expectation using galaxy simulations that resolve OCs in a cosmological context.

Previous simulation studies have shown that turbulent mixing plays an important role homogenizing molecular clouds and reducing stellar abundance scatter [125]. This can be particularly significant during cloud assembly, potentially explaining the observed chemical homogeneity of stars that originate from the same molecular cloud [52]. Extending this work, Armillotta et al. [7] zoom in on the collapse of one giant molecular cloud extracted from a galaxy simulation and study the formation of individual stars down to a spatial resolution of $\approx 10^{-3}$ pc. They find that the star formation process defines a natural size scale of ~ 1 pc for chemically homogeneous star clusters, suggesting stars within ~ 1 pc of each other share similar chemical properties. However, these simulations assume metals are well coupled with gas, overlooking potential effects of metals in the form of dust grains. Taking a different approach to identify co-natal stars, Kamdar et al. [87] evolve 4 billion stars over 5 Gyr in a realistic potential with various galactic structures. They find that combining chemical and phase space information enhances the identification of co-natal populations, suggesting co-moving pairs of stars with velocity separation < 2 km/s and metallicity separation < 0.05 dex are likely to be co-natal. Nevertheless, these simulations lack direct N-body effects on clusters and individual stars, as well as essential feedback processes.

In this paper, we examine chemical abundance trends in OCs identified in high-resolution cosmological hydrodynamic galaxy simulations generated with the FIRE-2 [Feedback in Realistic Environments, 75] model. These simulations have an adaptive spatial resolution, which enables modeling a large dynamic range (from Mpc down to pc), and include many relevant star cluster-scale feedback processes. In this work, we utilize three MW-mass galaxies from the *Latte* suite [177, 176] of FIRE-2 simula-

tions to assess the viability of strong chemical tagging via inter-cluster and intra-cluster chemical homogeneity analysis. Importantly, this study is possible now because FIRE-2 implements physically motivated processes (e.g., subgrid turbulent metal diffusion, stellar feedback, and chemical enrichment from core-collapse supernovae, white-dwarf supernovae, and stellar winds) and has high enough resolution in *Latte* (up to ~ 1 pc) to distinguish individual star-forming regions.

Previously in FIRE-2, Bellardini et al. [10] showed that their MW-mass galaxies have azimuthal scatter in gas at $z = 0$ similar to that observed in nearby galaxies of similar mass. Bellardini et al. [11] investigated abundance trends in all young stars across the *Latte* disks, considering the evolution over time. They found that azimuthal variation dominates at $z \gtrsim 0.8$, whereas radial gradients dominate at late times. Subsequently, Carrillo et al. [31] explored distributions in mono-age populations in one *Latte* disk, m12i, as a function of $[\text{Fe}/\text{H}]$, $[\text{X}/\text{Fe}]$, birth and present day locations, and found some evidence for inside-out radial growth for stars with ages < 7 Gyr. Carrillo et al. [31] also examined the age- $[\text{X}/\text{Fe}]$ relation across the disk and found that the qualitative trends agree with observations (apart from C, O, and Ca) with small intrinsic scatter ($0.01 < \sigma < 0.04$ dex). Additionally, Carrillo et al. [31] found the σ to be metallicity dependent, with $\sigma \approx 0.025$ dex at $[\text{Fe}/\text{H}] = -0.25$ dex versus $\sigma \approx 0.015$ dex $[\text{Fe}/\text{H}] = 0$ dex. A similar metallicity dependence is seen in the GALAH survey for the elements in common [159, 31]. Moreover, like Bellardini et al. [11], Carrillo et al. [31] found that σ is higher in the inner galaxy, where stars are older and formed in less chemically homogeneous environments.

Building on the work of Bellardini et al. [11], Graf et al. [63] recently showed that the radial metallicity gradient as a function of stellar age in the *Latte* disks follows similar trend as in Milky Way, albeit with shallower gradients in FIRE. Additionally, Graf et al. [63] showed that at present day the vertical metallicity gradient is steepest for the youngest stellar populations, which is again qualitatively consistent with the Milky Way, despite weaker trends in FIRE. Finally, both Bellardini et al. [11] and Graf et al. [63] considered the azimuthal scatter of $[\text{Fe}/\text{H}]$ in stars in *Latte*, and found it to be similar to the Milky Way [relative to 2].

While the FIRE studies discussed above focus on all stars in simulated galactic disks,

our focus in this study is on chemical trends in OCs specifically. Along this line, in 2023, Grudić et al. mapped giant molecular clouds formed self-consistently in a *Latte* simulation on to a cluster population according to a giant molecular cloud-scale cluster formation model calibrated to higher resolution simulations. This approach enabled them to explore the galaxy’s star clusters as a function of mass, metallicity, space, and time. Grudić et al. [67] concluded that massive clusters do not form with metallicities differing from other stars forming within the galaxy.

In this work, we take a different approach: we directly identify young massive OCs in the *Latte* simulations at present day to measure their chemical homogeneity in the full galactic context. As of yet, a robust comparison between the chemical homogeneity of observed OCs and OCs formed in cosmological Milky Way-mass galaxy simulations does not exist, and we aim to characterize the precision requirements for metallicity measurements to ensure that star cluster reconstruction could be conducted using chemistry alone. In this study, we leverage OCs identified within the last ~ 100 Myr of the simulations, and select OCs younger than 3 Myrs, which allows us to study truly co-forming populations often still embedded in their natal environment. We calculate the intra and inter-cluster metallicity dispersion for our OC population and compare it to results from spectroscopic OC observations. Finally, we calculate a chemical difference metric between intra-cluster and inter-cluster pairs of stars and discuss the viability of chemical tagging using such chemical differences.

This paper, published in *The Astrophysical Journal*, 977(1), 70 [15] is structured as follows: in §2.2, we discuss our data and methodology. Specifically, in §2.2.1 we introduce the simulations, in §2.2.2 we discuss how we identify OCs in these simulations, and in §2.2.3 we introduce the chemical difference metric we use to characterize the similarity of elemental abundances. In §2.3, we present our results, and finally, in §2.4 we present our discussion in the context of the observational literature and our conclusions.

2.2 Data and Methodology

2.2.1 Simulations

We use the *Latte* suite of FIRE-2 cosmological Milky Way-mass galaxy simulations [177, 176] to study properties of OCs. As mentioned earlier, FIRE stands for Feedback in Realistic Environments; the code is able to simulate the interplay between ISM and the stellar feedback processes in a cosmological environment [73, 75]. As detailed in Hopkins [73], these simulations use the Lagrangian Meshless Finite Mass (MFM) hydrodynamics method implemented in Gizmo. Gizmo solves the fluid equations using a moving particle distribution that is automatically adaptive to resolution.

FIRE-2 uses a physically motivated metallicity-dependent radiative transfer heating and cooling approach for gas that includes free-free, photoionization and recombination processes, Compton scattering, photoelectric heating, and collisional dust effects, as well as molecular, metal-line, and fine structure processes. The implementation of FIRE we use in this work additionally includes magnetohydrodynamics, where the equations of ideal magnetohydrodynamics are solved explicitly [76].

We use versions of these simulations that we resimulated over the final 110 Myr specifically to store finer snapshot time spacing (1 Myr) than in the original simulations (≈ 22 Myr). This enables us to track OCs in detail in phase space across time. While these resimulations are not publicly available, snapshots of the original simulations are publicly available [176].

FIRE-2 tracks 11 elements (H, He, C, N, O, Ne, Mg, Si, S, Ca, Fe) across a temperature range of 10 to 10^{10} K. These simulations incorporate a spatially uniform, redshift-dependent UV background as described by Faucher-Giguère et al. [51]. As typically done by observers, metallicity and elemental abundances are scaled to solar values; in these simulations, we use values for the Sun from Asplund et al. [8].

Star formation proceeds according to the following recipe in these simulations: each star particle is generated from a self-gravitating gas cell that is Jeans-unstable, cold ($T < 10^4$ K), dense ($n > 1000 \text{ cm}^{-3}$), and molecular [following 95]; when star formation criteria are met, there is a one-to-one conversion of a gas cell into a star particle. That is, a star particle acquires its mass and elemental makeup from the gas cell it originates from

and depicts a simple stellar population characterized by a Kroupa initial mass function [93]. Each star particle is individually evolved assuming a standard stellar population model [STARBURST99 v7.0, 102] and produces time-resolved stellar feedback from both core-collapse and white-dwarf supernovae. The rates of core-collapse supernovae are based on STARBURST99 [102], and the rates of white-dwarf supernovae are from [118]. FIRE-2 also incorporates stellar feedback due to continuous mass loss, radiation pressure, photoionization, and photoelectric heating. The nucleosynthetic yields we use are based on Iwamoto et al. [80] for white-dwarf supernovae and Nomoto et al. [140] for core-collapse supernovae. Stellar wind yields are sourced primarily from O, B, and AGB stars; we use a model for this assembled by Wiersma et al. [179] which incorporates expectations from van den Hoek and Groenewegen [170]; Marigo [119]; Izzard et al. [81]. Further details on this can be found in Appendix A from Carrillo et al. [31] and in Hopkins et al. [75].

FIRE-2 incorporates sub-grid diffusion and mixing of elemental abundances in gas, which occurs through unresolved turbulent eddies [166, 50, 75]. Our model assumes sub-grid mixing is primarily influenced by the largest unresolved eddies, which effectively smooths out abundance variations among gas elements. Escala et al. [50] demonstrated that incorporating this sub-grid model is essential for accurately replicating observed distributions of stellar metallicities in galaxies. Bellardini et al. [10] showed that while the details of this diffusion model do not significantly affect radial or vertical gradients in FIRE-2 MW-mass galaxies, they do affect the azimuthal scatter. Bellardini et al. [10] also showed that these galaxies have azimuthal scatter in gas at $z = 0$ similar to that observed in nearby galaxies of similar mass.

The *Latte* suite contains several Milky Way-like galaxies; in this work, we analyze three *Latte* simulations (m12f, m12i, and m12m). The galaxies we analyze represent some of the most massive Milky Way-like isolated disks in the *Latte* suite and span a range of assembly histories. Key differences among these simulations are that m12i has a massive disk with a late-forming Milky Way mass halo, m12f has an LMC-like satellite merger with the Milky Way-like disk 3 Gyr prior to the present day, and m12m has a strong bar at high redshift and an earlier forming halo [see 154]. A full description of the criteria used to generate these galaxies and their properties at the present day can be

found at Wetzel et al. [176] and references therein. A brief description of relevant details to this work is as follows. Each galaxy simulation assumes a flat Λ CDM cosmology with parameters consistent with the Planck Collaboration et al. [146]: $h = 0.68 - 0.71$, $\Omega_\Lambda = 0.69 - 0.734$, $\Omega_m = 0.266 - 0.31$, $\Omega_b = 0.0455 - 0.048$, $\sigma_8 = 0.801 - 0.82$ and $n_s = 0.961 - 0.97$.¹

In this work, Milky Way-like refers to the total mass of each galaxy at the present day. The *Latte* galaxies were selected to have halo masses roughly the same as the Milky Way's: $M_{200} = 1-2 \times 10^{12} M_\odot$ where M_{200} refers to the total mass within the radius containing 200 times the mean matter density of the Universe. These simulations contain three types of material: dark matter, stars, and gas. The resolution of each dark matter particle is $3.5 \times 10^4 M_\odot$, and the initial mass resolution of baryonic material is $7070 M_\odot$. As noted earlier, each star particle should be thought of as a single stellar population. Because of this, as a star particle ages, it loses a portion of its stellar mass. Thus, at $z = 0$ a typical star particle has a mass of $\sim 5000 M_\odot$. In the *Latte* galaxies, star and dark matter particles have a fixed gravitational force softening length of 4 and 40 pc (Plummer equivalent), respectively. Gas cells have adaptive gas smoothing: in regions where there is a high density of gas cells, the gravitational force softening length can resolve down to a minimum of 1 pc.

Given its spatial and mass resolution, the *Latte* simulations can resolve massive star clusters with multiple star particles that represent portions of each OC. And, as mentioned earlier, with the temporal resolution for snapshots of 1 Myr for these re-simulations, they can track in detail how star particles in OCs evolve in phase space over time. See §2.2.2 for more details on OC selection and characteristics.

2.2.2 Star Cluster Identification

We identify OCs in our simulations using the friends-of-friends (FoF) algorithm [60]. It works by identifying members within a fixed distance known as the linking length; in this work, we adopt a linking length of 4 pc, which corresponds to our softening length.

¹Where h is the dimensionless equivalent of the Hubble Parameter H_0 , Ω_Λ is the cosmological constant or vacuum density at present time, Ω_m is the total matter (dark plus baryonic) density today, Ω_b is baryonic matter density, σ_8 is the root mean squared fluctuation of density perturbations at $8 h^{-1} Mpc$ scale and n_s is the scalar spectral index.

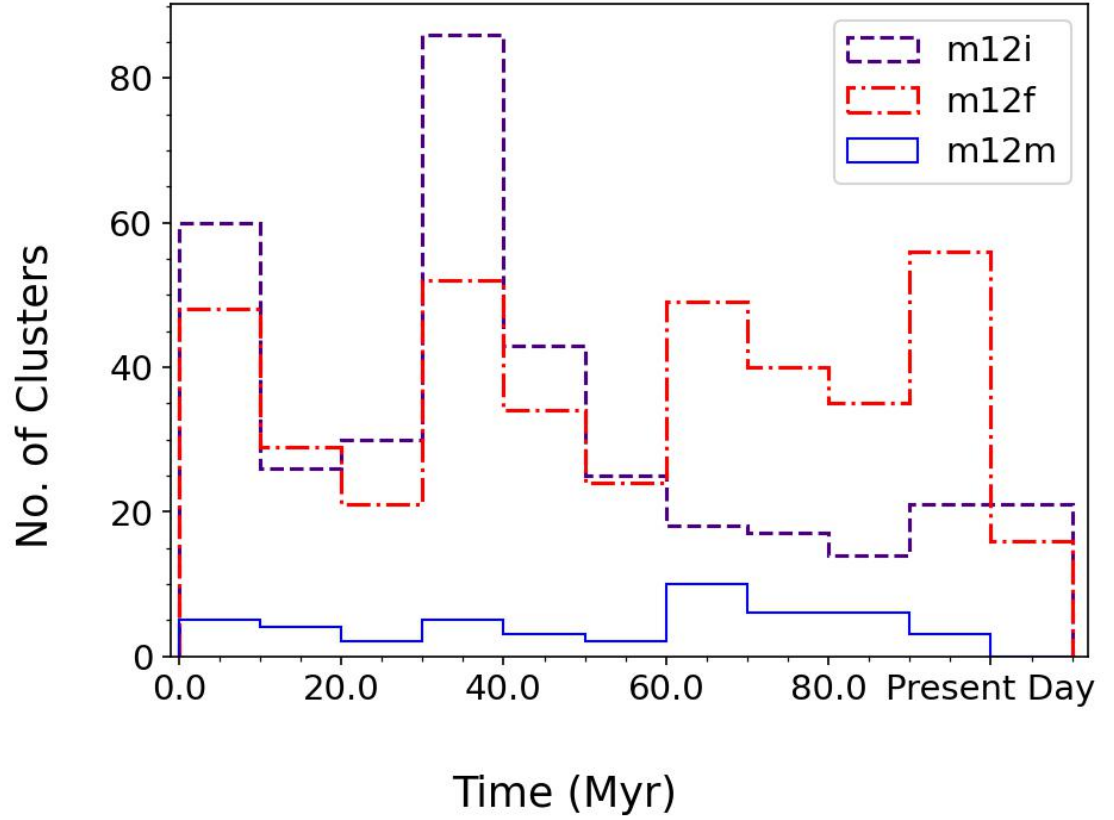


Figure 2.1: Number of young (<3 Myr) massive OCs identified in the last ~ 100 Myr of the simulations. OC selection has been run at a 3 Myr interval to avoid double-counting. m12i indicated by dashed lines colored in indigo, m12f indicated by dashed-dotted lines colored in red, and m12m indicated by solid blue lines. A varying rate of star cluster formation is observed in all three simulations, with m12m having the lowest number of clusters produced throughout the 100 Myr period. This reflects a globally suppressed star formation rate for m12m at present day. See § 2.2.2 for further discussion.

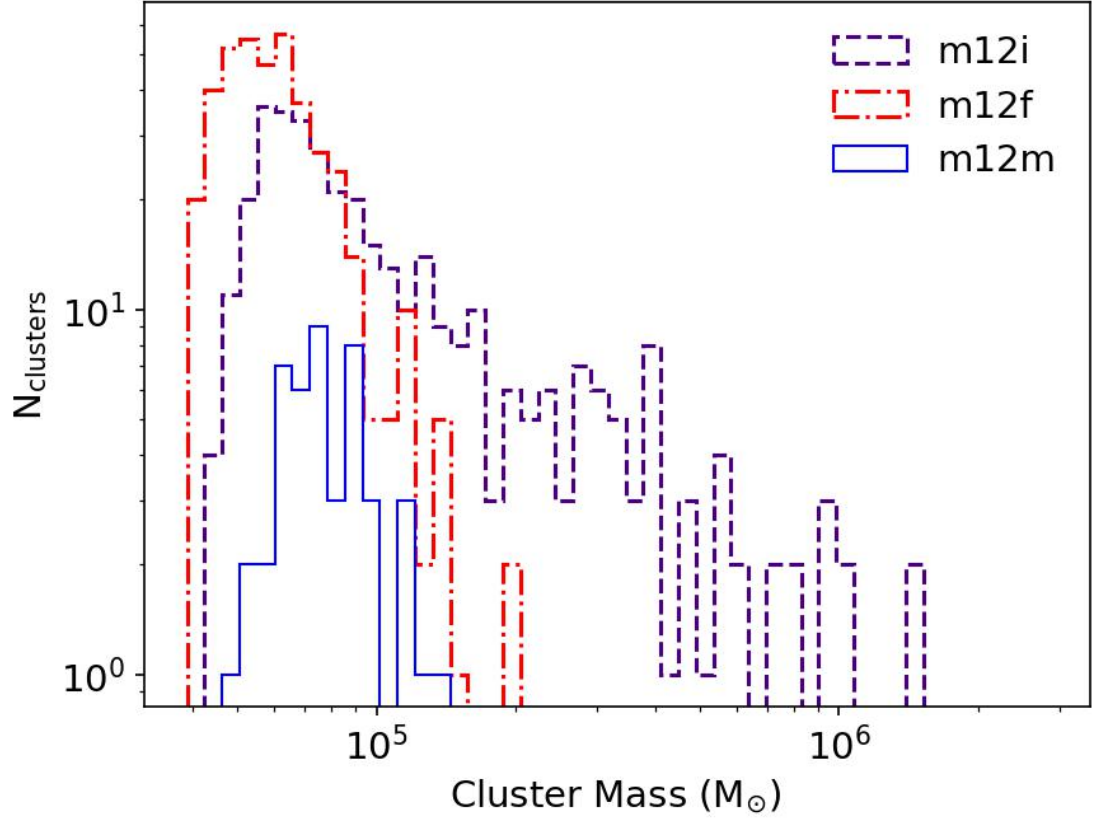


Figure 2.2: Mass distribution of the OCs from all three simulations. m12i indicated by dashed lines colored in indigo, m12f indicated by dashed-dotted lines colored in red, and m12m indicated by solid blue lines. The slope of the cluster mass function is similar for all three simulations, with m12i having a shallower slope with a few high-mass outliers.

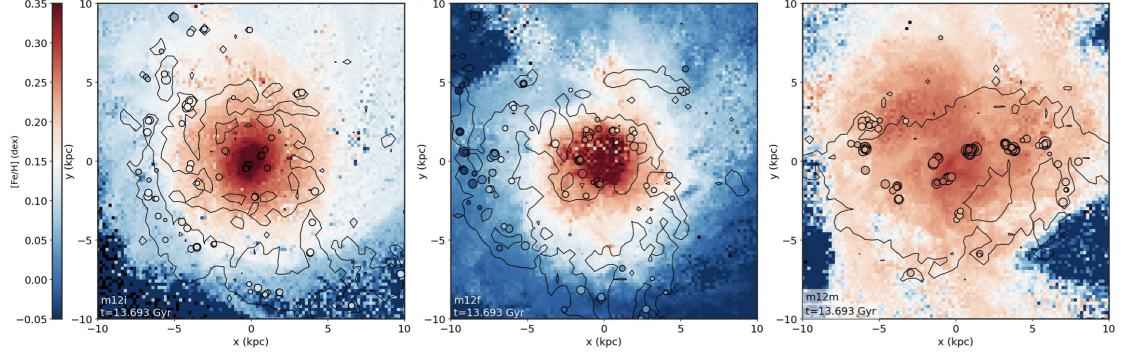


Figure 2.3: A snapshot from three *Latte* simulations m12i, m12f and m12m. Background: mean [Fe/H] for gas in the disk of each simulation. The corresponding values are shown by the color bar on the left. Contours: density of stars < 50 Myr old, which highlights the spiral arms. Circles: mean [Fe/H] of OCs and associations identified at 13.693 Gyr. Note, the mean [Fe/H] of the clustered star formation reflects the global metallicity distribution of the gas in the disk.

To ensure that the OCs are identified before the onset of core-collapse supernovae, we select OCs from star particles that are less than 3 Myr old over the last 110 Myr of these simulations. We require a minimum of 5 star particles for a cluster to be identified, and thus with our fiducial mass resolution ($7070 M_{\odot}$) we resolve cluster down to a cluster mass of $10^{4.6} M_{\odot}$.

With these selection criteria, the OCs we identify have a characteristically small velocity dispersion ($\sigma_{1D} \sim 4$ km/s), small size ($R_{\text{half}} \sim 3$ pc), and small spread in age ($\sigma_{\text{age}} \sim .25$ Myr). We do not require that the natal giant molecular cloud be bound for our OCs to form inside them; despite this, roughly half of the clusters that we identify are born bound ($\log_{10}(2KE/PE) \geq 0$) and the global population follows a Gaussian distribution of boundedness peaked at 0. While the size and boundedness of the population that we identify may be better described as OCs and associations, for the purposes of this study, which aims to characterize the spread in metallicity inside and between small clustered star forming environments across a full galactic disk, we find it sufficient not to distinguish between OCs and associations. We also note that the age selection criteria that we adopted do not significantly impact any of these properties [122]. Because of this, we feel that the OC populations that we identify sufficiently resemble OCs within a full simulated cosmological Milky Way-like galaxy environment to proceed with the

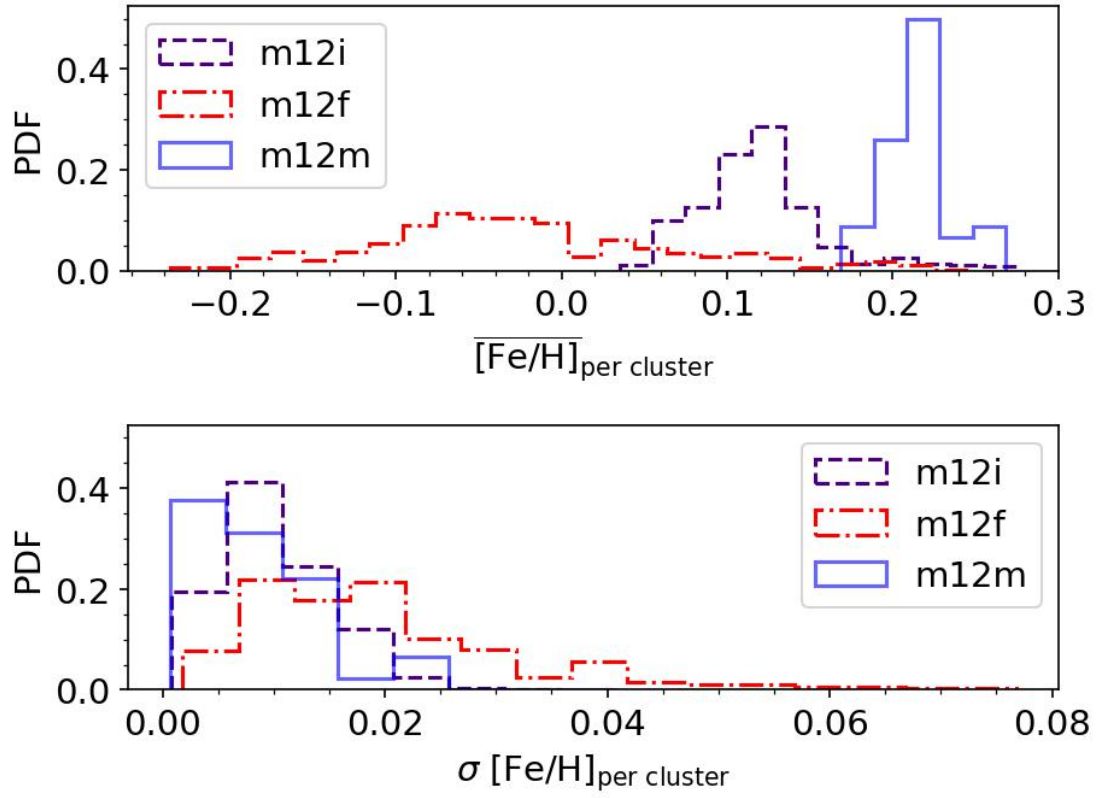


Figure 2.4: Distribution of mean $[\text{Fe}/\text{H}]$ (upper panel) and dispersion of $[\text{Fe}/\text{H}]$ in the cluster sample of all three simulations. m12i indicated by dashed lines colored in indigo, m12f indicated by dashed-dotted lines colored in red, and m12m indicated by solid blue lines. m12f has a larger range of mean and scatter in $[\text{Fe}/\text{H}]$.

elemental abundance study we present here; a more detailed study that focuses on the impact of the selection criteria we use on the resultant properties of the OCs we identify can be found in Masoumi [122]. Note that we identify star clusters similarly in all three Milky Way-like analog simulations mentioned in 2.2.1.

In this work, we identify a total of 361, 404, and 46 unique OCs in m12i, m12f, and m12m, respectively, using the criteria discussed above. We analyze the OCs from each galaxy simulation as a single dataset. In Fig. 2.1 we show a histogram of the number of clusters identified throughout the final 110 Myr of the simulations. These 3 simulations (m12i, m12f, and m12m) represent a varying rate of star cluster formation over the 110 Myr epoch; m12m has a relatively consistent albeit low number of clusters formed over this period of time, while m12i forms roughly a quarter of all the clusters over just a 3 Myr span, and finally m12f has a fluctuating rate of cluster formation that oscillates on a ~ 30 Myr timescale. We note that the low rate of m12m's cluster formation reflects the overall depressed star formation rate of the entire galaxy at the present day.

The cluster mass distribution of these simulations is shown in Fig. 2.2. We note that m12f and m12m have similar slopes for the cluster mass function. However, m12i has a shallower slope and contains a few high-mass outliers that form during a period of vigorous star formation in the plane of the disk. These OCs are best thought of as Young Massive Clusters (YMCs) and will be discussed further in Masoumi et al. (in prep).

In Fig. 2.3, we show a top-down view of m12i, m12f, and m12m near the present-day (13.693 Gyr). Here we show gas in the background, which has been binned in $200 \text{ pc} \times 200 \text{ pc}$ squares and colored by the mean value of $[\text{Fe}/\text{H}]$ in each volume. Plotted on top of the average $[\text{Fe}/\text{H}]$ distribution for gas are contours of the density distribution of stars that are less than 50 Myr old. These contours highlight where there is an active star formation corresponding to the spiral structure. The circles overlayed on top indicate the mean $[\text{Fe}/\text{H}]$ of OCs and associations (linking length $\leq 18 \text{ pc}$) that were identified at this moment in time; while we have included larger associations here for visualization purposes, in this paper, we only include OCs found using a linking length of 4 pc for analysis. We note that Fig. 2.3 shows that the average $[\text{Fe}/\text{H}]$ of OCs and associations generally reflects the gas metallicity distribution across the disk.

We note that the top-down perspective on the galactic disks shown in Fig. 2.3

highlights the overall radial metallicity gradient in all three galaxies; while each galaxy has a different normalization and slope of the radial metallicity gradient, overall it is clear that a negative radial gradient is present in the global disk for gas at present-day [see 10, for further discussion]. While here we have shown the distribution of $[\text{Fe}/\text{H}]$, we will be using a total of 9 elemental abundances (Fe, C, N, O, Mg, Si, S, Ca, Ne) throughout the remainder of this work. We note that these elements are highly correlated with each other in our simulations. We show this correlation in Appendix 2.4 in Fig. 2.10 and Fig. 2.12. Such a strong correlation is also seen in the Milky Way [65]; in fact, Ness et al. [139] show that, using a linear regression fit to Fe and Mg alone, one can predict eight supernova elements within 5% accuracy. Despite such strong correlations, we elect to use all elements at our disposal in this work.

In Fig. 2.4, we show normalized histograms of the mean $[\text{Fe}/\text{H}]$ (upper panel) and standard deviation of $[\text{Fe}/\text{H}]$ (lower panel) for OCs in all three simulations. The upper panel shows the presence of scatter in mean $[\text{Fe}/\text{H}]$. While m12f has a large range of OC mean $[\text{Fe}/\text{H}]$, m12i and m12m have a narrower range of values. Each of these populations peaks at a different value of $[\text{Fe}/\text{H}]$; however, there is some overlap between these samples. The standard deviation histogram for each galaxy shown in the bottom panel of Fig. 2.4 illustrates that there are very few OCs that have a large standard deviation of $[\text{Fe}/\text{H}]$; moreover, the peak of each distribution is at a small value. Given these essential properties – there is scatter in average $[\text{Fe}/\text{H}]$ in OCs in the simulations, and there is a small spread in $[\text{Fe}/\text{H}]$ in each OC – in this work, we are able to test the feasibility of uniquely identifying stars from the same OC using their elemental abundances alone.

2.2.3 Chemical Difference Metric

The goal of this investigation is to understand the similarity of stellar abundances for stars within a given OC; to simplify this, we define a simple chemical difference metric using a pseudo-Cartesian measurement of distance in abundance space. A similar approach is used in Ness et al. [137], which was adapted from Mitschang et al. [130]. The metric is defined as:

$$d_{nn'}^2 = \sum_{i=1}^I [x_{ni} - x_{n'i}]^2$$

Where n and n' are two stars being compared, with star n containing the abundance x_{ni} and star n' containing the abundance $x_{n'i}$ for all elements 1 to I . Simply put, this metric evaluates the squared chemical difference between any two stars, summed over all available elements, and provides a single number that assesses the chemical similarity for each pair of stars. In this work we initially evaluate the chemical difference metric summed over 8 element abundances ([Mg/Fe], [Ca/Fe], [S/Fe], [Si/Fe], [Ne/Fe], [O/Fe], [N/Fe], [C/Fe]) without any errors being considered.

After this initial assessment, we further consider the chemical difference metric with APOGEE errors added to our simulated OCs [drawn from Chemical Abundances and Mapping Survey, 135]. The difference metric with added errors is defined as:

$$d_{nn'}^2 = \sum_{i=1}^I \frac{[x_{ni} - x_{n'i}]^2}{\sigma_{ni}^2 + \sigma_{n'i}^2}$$

Where σ_{ni} refers to the error measurement for x_{ni} and $\sigma_{n'i}$ represents the error measurement for $x_{n'i}$. Note that we omit Ne (neon) from the above list of elements in this analysis, as it is a relatively rare element that isn't measured in APOGEE OCs.

2.3 Results

2.3.1 The relationship between $[Fe/H]$ & birth radius for OCs

In this section, we consider the radial metallicity gradient: the average $[Fe/H]$ as a function of galactocentric radius, which is often thought to be a unique indicator of where stars are born [e.g., 129]. Here we measure the radial metallicity gradient using OCs, as has often been done in the literature [85, 157, 164, 112]. Our goal is to assess how truly unique the mean $[Fe/H]$ is for OCs in our simulations. We note that the dispersion in each cluster does not change substantially across the disk.

In Fig. 2.5, we show the mean $[Fe/H]$ vs the birth radius (R_{birth}) for all OCs identified over the final 110 Myr in m12i (top panel), m12f (middle panel), and m12m (bottom panel). Note that the range of values indicated on the y-axis is slightly different for each galaxy, which is very important when comparing slopes between each system. Each blue dot indicates the mean $[Fe/H]$ value of an individual OC. We calculate a running median using a bin size of 0.5 kpc (shown in a black solid line) and indicate the $\pm 1\sigma$ confidence

region around the median values, shaded in grey. In addition to this, we indicate on each figure the global average $[\text{Fe}/\text{H}]$ (solid blue horizontal line) of all our OCs and also the average dispersion of $[\text{Fe}/\text{H}]$ (shaded blue region) inside a typical OC. We later subsample OCs drawn from this blue-shaded region to perform a chemical difference metric test (see § 2.3.3).

We find a very different trend in the metallicity gradient in the three galaxies we assess. For m12i (top panel), there is a steep gradient within $R_{\text{birth}} < 6$ kpc (with a slope of ~ -0.02 dex kpc^{-1}) and a small scatter about the median trend line (with scatter < 0.01 dex). This combination of steep slope and small scatter means that, within this region, $[\text{Fe}/\text{H}]$ strongly constrains birth location. However, at $R_{\text{birth}} > 6$ kpc, the slope of the radial metallicity gradient substantially flattens out and the scatter significantly increases (> 0.02 dex). Moreover, outside of 10 kpc, there is an inversion in the slope of the metallicity gradient. Taken together, there is no longer a one-to-one mapping of $[\text{Fe}/\text{H}]$ and birth radius outside 6 kpc, and $[\text{Fe}/\text{H}]$ should not be taken as a reliable indicator of the birth location.

However, when we consider m12f (middle panel), the predictive power of $[\text{Fe}/\text{H}]$ as a unique indicator of birth location extends to a significantly larger region (out to 10 kpc). Within this radial range, there is a small scatter around the median trend line (< 0.02 dex). Moreover, like m12i, within the inner region of m12f, the slope has a constant negative value of -0.04 dex kpc^{-1} . It is noteworthy that, for m12f, outside of 10 kpc, the scatter increases significantly, doubling to ~ 0.04 dex in the outer regions of the disk. And, like m12i, at the largest Galactocentric birth radii, there is a subtle upturn in the median trend line. Thus, again, at large Galactocentric radii, $[\text{Fe}/\text{H}]$ no longer has strong predictive power as an indicator of birth location.

Finally, m12m (lower panel), has a significantly smaller number of clusters than the other two systems, and these clusters are all found at Galactocentric radii < 9 kpc. While the slope of the radial metallicity gradient for m12m is negative, it is substantially shallower (< -0.008 dex kpc^{-1}) than m12i and m12f. Moreover, while the typical scatter about the median trend line is similar to the inner region of m12i (~ 0.01 dex), in combination with the relatively shallow gradient, there is limited discerning power for $[\text{Fe}/\text{H}]$ to indicate birth location in this system.

Overall all three systems appear to have a negative gradient at small radii that generally flattens at larger radii consistent with the analysis of these galaxies in Bellardini et al. [11]. Such a gradient and flattening in the average metallicity of OCs as a function of radius has often been modeled in the Milky Way using a two-component fit [e.g., 48, 164, 135]. The presence of such a transition in the gradient is an indicator that variation in abundances is different for different regions of our Galactic disk.

Note, in section 2.3.3 we will discuss the shaded blue region in Fig. 2.5 and further consider the additional power of individual abundances to draw connections to birth location. This can be done by selecting OCs that fall within $\pm 1\sigma$ of a fixed $[\text{Fe}/\text{H}]$ value. As we mentioned earlier, σ is set by the typical dispersion within an OC, while the fixed $[\text{Fe}/\text{H}]$ value is set by the average $[\text{Fe}/\text{H}]$ of all the OCs discussed here.

In Fig. 2.6, we show the metallicity distribution function for a subset of OCs found within the fixed $[\text{Fe}/\text{H}]$ range discussed above. These histograms were generated using a Gaussian kernel smoothing technique. Each curve is color-coded by where the OCs formed in the disk. The density shown on the y-axis is calculated such that the area under the curve is 1 using a bin width of 0.001. The black dashed line along the center replicates the horizontal line in Fig. 2.5, which represents the global mean $[\text{Fe}/\text{H}]$ for all clusters in a given simulation, and the grey-shaded region inside the black dotted lines indicates the 1σ dispersion from the typical standard deviation inside each OC.

The clusters shown in Fig. 2.6 represent a subset of all clusters shown in the blue shaded region of Fig. 2.5 and probe a large range of R_{birth} across the disk. The short vertical line on each curve indicates the mean value of $[\text{Fe}/\text{H}]$ for that OC. Here we can see that while these clusters have similar mean $[\text{Fe}/\text{H}]$ (all fall within the grey-shaded region), their individual metallicity distribution function can vary in shape. While these clusters form at a very large range in radii, their metallicity distribution function does not map uniquely onto their formation location. Notably, the mean $[\text{Fe}/\text{H}]$ of a young OC does not always map strictly onto the formation location, nor does the dispersion of $[\text{Fe}/\text{H}]$ inside a given OC. This reinforces the idea that the mean metallicity may not be enough to uniquely determine the formation locations of OCs.

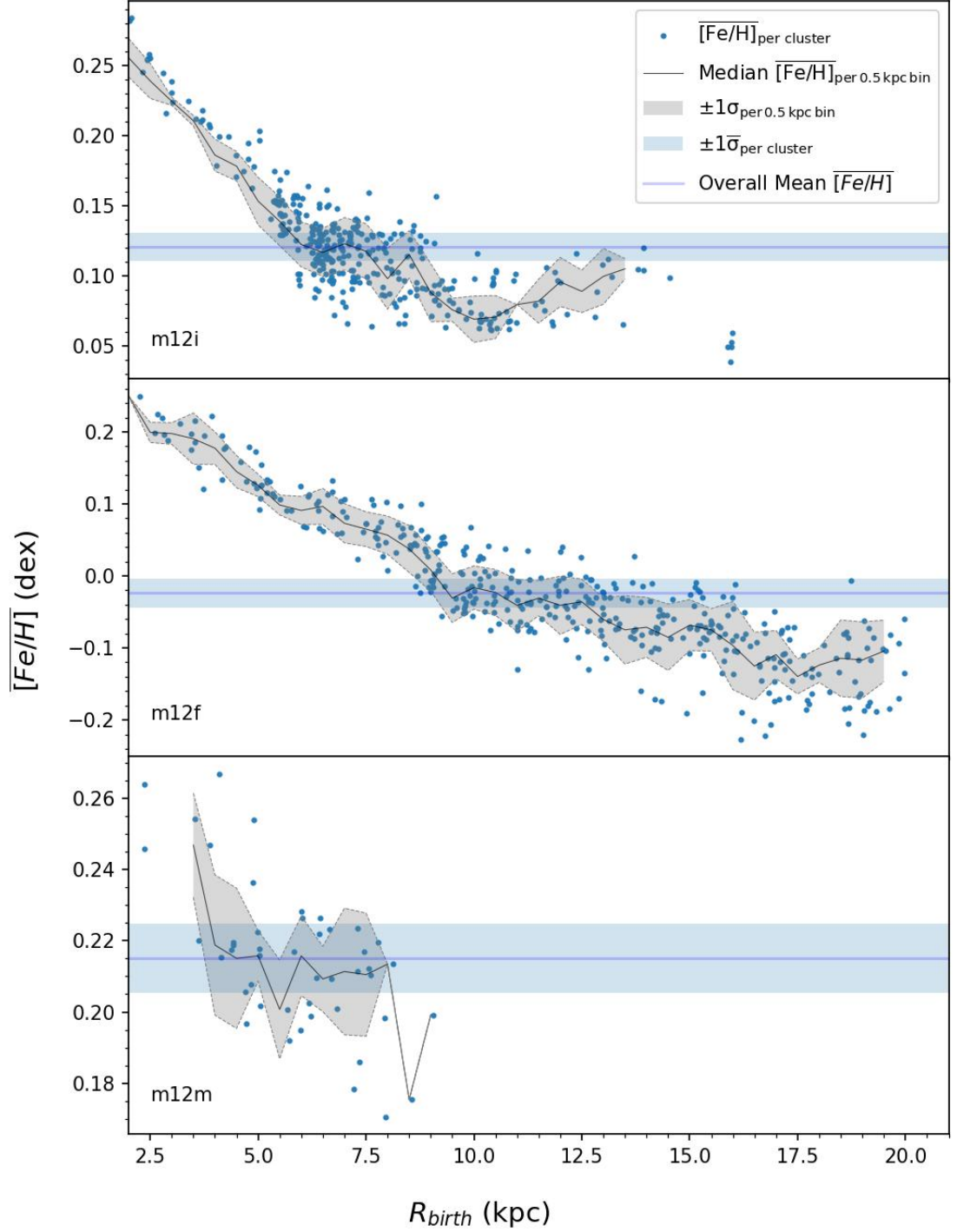


Figure 2.5: Scatter plot of mean $[\text{Fe}/\text{H}]$ vs birth radius of OCs from 3 simulations: m12i (top panel), m12f (middle panel), m12m (bottom panel). The blue dots indicate the mean $[\text{Fe}/\text{H}]$ of each cluster, and the solid black curve represents the median trend for data in 0.5 kpc radial bins. The grey shaded area represents the $\pm 1\sigma$ range within 0.5 kpc bins. The blue horizontal line represents the average of all OCs in the sample, and the blue horizontal shaded region represents the typical $\pm 1\sigma$ scatter of $[\text{Fe}/\text{H}]$ within any given cluster. It can be seen that the metallicity distribution varies differently in the inner disk than the outer, and many clusters have similar mean $[\text{Fe}/\text{H}]$ despite being found at varying locations across the disk.

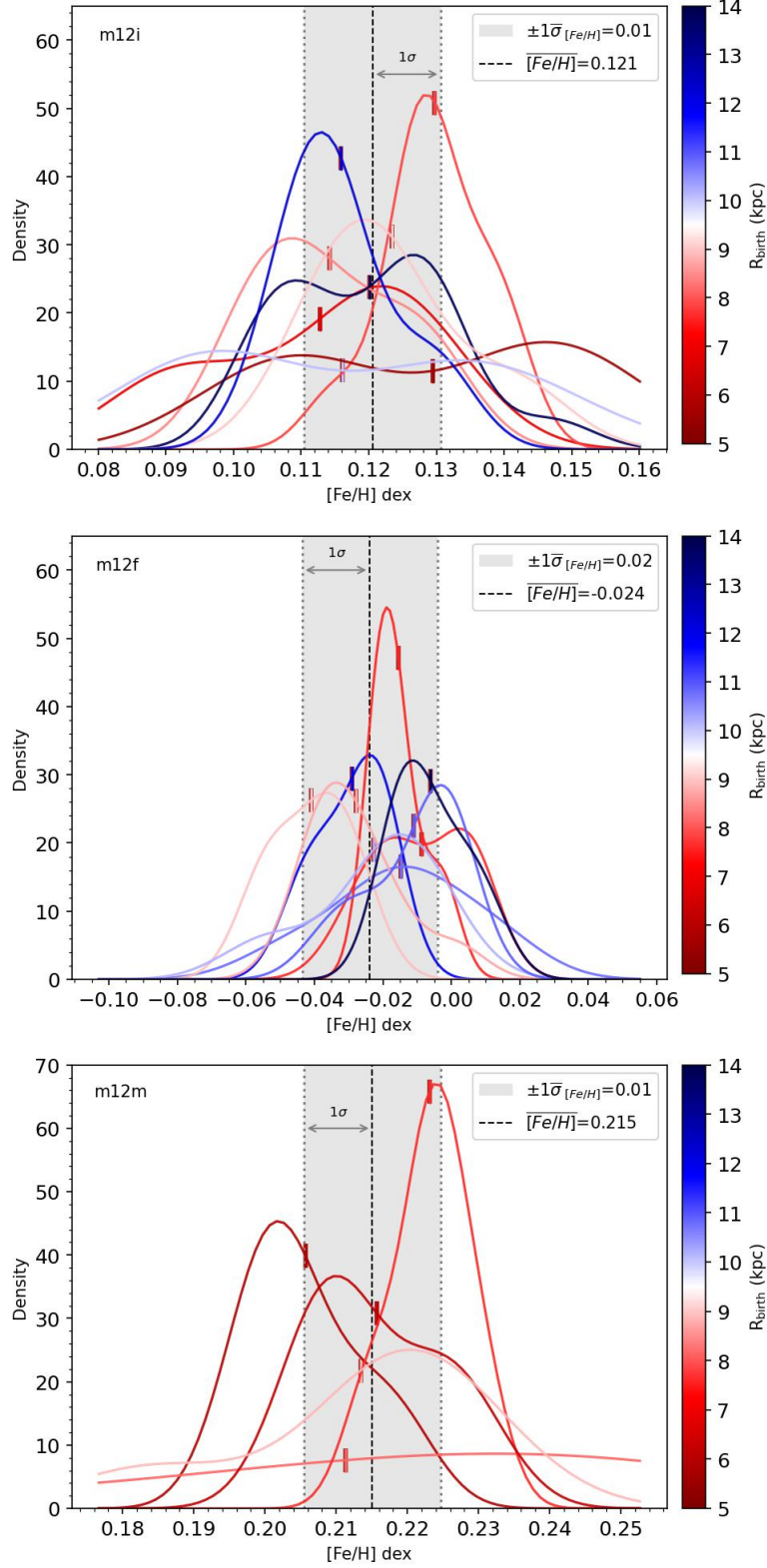


Figure 2.6: The [Fe/H] distribution for a subset of OCs from the subsample highlighted in blue from Fig. 2.5 for each simulation. Each smoothed histogram represents the metallicity distribution for a single OC and was generated using Gaussian kernel smoothing. The shaded region indicates the $\pm 1\sigma$ from the overall mean of the distribution of all clusters from that simulation. Despite their locations in the disk, it is possible to find OCs that have similar abundance distributions at different R .

2.3.2 Inter and Intra Cluster Metallicity Dispersion

The intra-cluster dispersion provides a measure of the chemical homogeneity of member stars within a given cluster for a given element. If such a measurement is small, it indicates a similarity in the elemental abundance of member stars inside a cluster. Here, we define the intra-cluster dispersion as the weighted mean of the dispersion inside each cluster across all OCs for each simulation. Here, the weight is proportional to the number of star particles in each cluster.

Similarly, inter-cluster dispersion can provide a measure of the scatter in the mean elemental abundance between different clusters. A large value of inter-cluster dispersion indicates a significant difference in the mean elemental abundance (e.g., $\overline{[\text{Fe}/\text{H}]}$) between OCs. One might expect the inter-cluster dispersion to be higher than the intra-cluster dispersion, especially when comparing clusters across a large range of radii. In this limit, one might expect strong chemical tagging to be feasible. With a larger dispersion between clusters and a smaller dispersion inside a cluster, it would be easier to identify stars that belong to the same. However, as we saw in §2.3.1, regions of the disk can have a weak radial metallicity gradient. Because of this, it is valuable to quantify the comparative significance of the intra versus inter-cluster dispersion to test the feasibility of strong chemical tagging. We will further discuss the comparative significance of these dispersions utilizing a chemical difference metric in the next section.

In Fig. 2.7, we show the intra and inter-cluster dispersion for all OCs in each simulation for each of the 9 elements that we trace (Fe, C, N, O, Mg, Si, S, Ca, and Ne). M12i, m12f, and m12m are shown in the top, middle, and bottom panels respectively; within each panel, the lower curve in blue indicates the weighted average intra-cluster dispersion per element, hereafter represented by the symbol $\overline{\sigma}_{[X/H]}$. The vertical indigo lines corresponding to each element indicate the $\pm 1\sigma$ scatter of the intra-cluster dispersion in all clusters. Since this is a dispersion of the dispersion, it was calculated by first converting these standard deviations into variances. For n standard deviations: $\sigma_1, \sigma_2, \dots, \sigma_n$, the variance of the sample standard deviations can be calculated as:

$$\text{Var}(\sigma_i) = \sigma_i^2$$

We then calculate the average of these variances as:

$$\text{Mean}(\text{Var}) = \frac{1}{n} \sum_{i=1}^n \text{Var}(\sigma_i)$$

Finally, the standard deviation of the standard deviation is:

$$\text{Standard Deviation}(\sigma_\sigma) = \sqrt{\text{Mean}(\text{Var})}$$

The typical measurements of the intrinsic dispersion from observations for these elements fall under the shaded grey region [drawn from 137]. The upper red curve indicates the measurement of inter-cluster dispersion (hereafter represented by the symbol $\sigma_{\overline{[X/H]}}$). This has been calculated as the weighted standard deviation of the mean elemental abundance, $\overline{[X/H]}$, in each cluster.

As indicated by these measurements, the average intra-cluster dispersion inside each FIRE OC is quite small and generally less than 0.020 dex; these measurements are comparable to the intrinsic dispersion calculated by several observational studies, which find OCs have intrinsic dispersion <0.03 dex [e.g., 20, 137, 14, 148]. This is also consistent with previous studies of m12i, which has considered the global dispersion for stars in the disk at present day. As mentioned in § 2.1, Carrillo et al. [31] investigated intrinsic dispersion at fixed metallicity for all disk stars in m12i, and found it to be ≈ 0.025 dex at $[\text{Fe}/\text{H}] = -0.25$ dex and ≈ 0.015 dex at $[\text{Fe}/\text{H}] = 0$ dex. The dispersion of intra-cluster dispersion shown by the vertical indigo splines spanning $\pm 1\sigma$ of the intra-cluster dispersion tells us the width of the distribution of intrinsic scatters. These measurements are also very small which is an indication that our simulated clusters have some element scatter that is non-zero which is similar for all clusters.

Similarly as indicated by the upper red curves, the inter-cluster dispersion measurements for all three simulations m12i, m12f, and m12m is larger than the intra-cluster dispersion as expected. We measure mean inter-cluster dispersion of ≈ 0.03 dex for m12i, ≈ 0.09 dex for m12f, and ≈ 0.02 dex for m12m. We further test if we can use individual element abundances to discriminate between clusters. To do this, we examine pairs of stars within and between clusters to measure their chemical similarity. A requirement of reconstructing the formation conditions of stars using only their individual abundances is that the chemical distance between stars within a cluster (intra-cluster pairs) is smaller than that of stars between clusters (inter-cluster pairs). A minimum requirement that a pair of stars is from the same cluster is that they have the same $[\text{Fe}/\text{H}]$. We therefore

now work only in a narrow $[\text{Fe}/\text{H}]$ bin near the overall mean $[\text{Fe}/\text{H}]$ of the OCs in each simulation.

2.3.3 Intra and Inter-Cluster Chemical Difference Metric

In this section, we discuss the chemical difference metric to see if we can distinguish between two stars that are formed in one OC and two stars randomly drawn from different OCs. We employ the chemical difference metric described in §2.2.3, which calculates the squared chemical difference between two stars for each element and is summed over all elemental abundances. Such a metric allows us to consider how chemically similar two stars are via one number, which is small (approaching zero) when two stars are similar.

We take the same sample of OCs highlighted in blue from Fig. 2.5 that is within $\pm 1\sigma$ of the galaxy-wide mean $[\text{Fe}/\text{H}]$. We use this sample to calculate the chemical difference between member stars to explore if we can discern the difference within and between clusters. We first draw all possible pairs of stars from within an OC and calculate the chemical difference for each pair. This procedure is iteratively repeated for each OC in our sample and the results are presented in the blue histogram in Fig. 2.8. To maintain a comparative framework, we applied the same metric for an equivalent number of random pairs but this time, each star is drawn from a different randomly selected OC. This distribution is shown in the red histogram in Fig. 2.8. We form 17,747 intra and inter-cluster pairs in m12i, 1,685 pairs in m12f, and 374 in m12m.

In Fig. 2.8, the blue histogram consists of the difference metric for the pairs of stars drawn from the same OC. The majority of the pair's chemical difference falls within the smallest bins of the histogram for all three simulations. If two stars are measured with such a small chemical difference, one would naively assume they come from the same OC. However, these smallest chemical difference metric bins are also significantly populated by stars from inter-cluster pairs, as indicated by the red histograms. In m12i, $\approx 86 / 73\%$ of the total intra / inter-cluster pairs have a difference metric of < 0.0002 . Similarly, in m12f, $\approx 66 / 43\%$ of the total intra / inter-cluster pairs have a difference metric of < 0.0002 . Finally, in m12m, $\approx 84 / 65\%$ of the total intra / inter-cluster pairs have a difference metric of < 0.0002 . Because of this, if we observe two stars with a

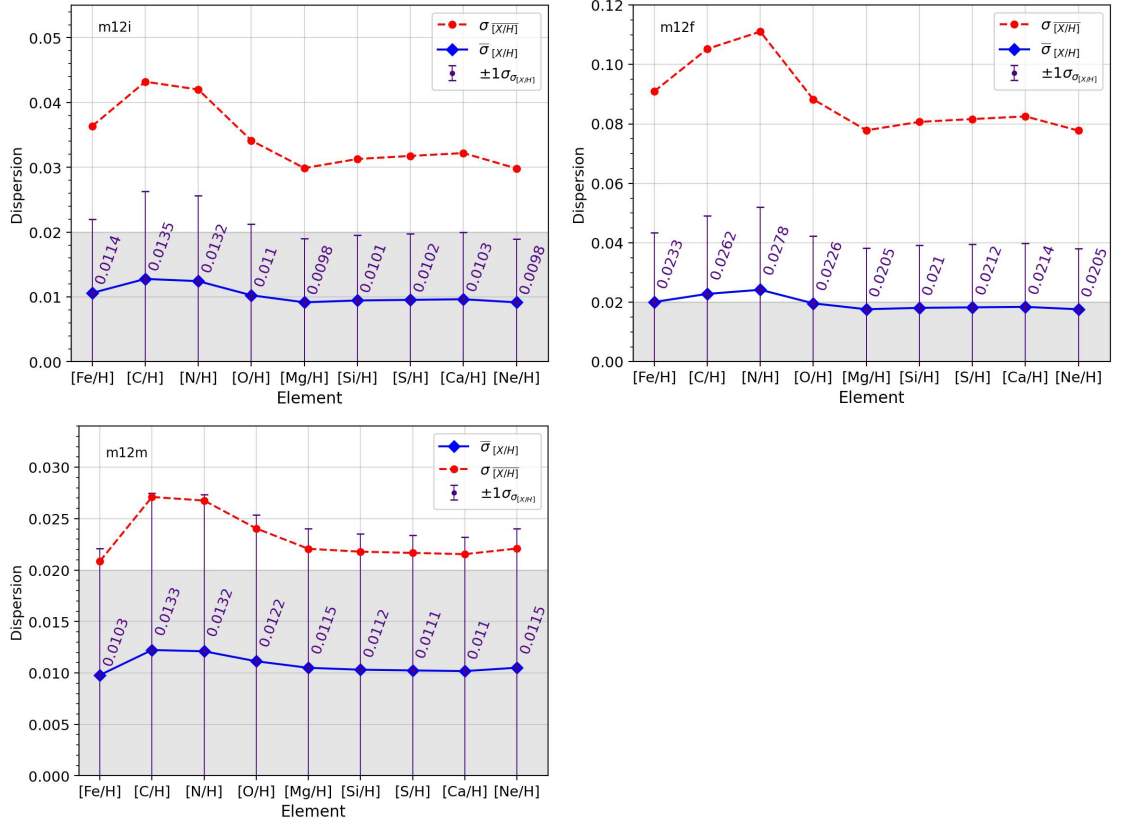


Figure 2.7: For each of the simulations in each panel, Blue: Intra cluster dispersion indicated as the mean dispersion per element. Indigo: the dispersion around the average dispersion. The indigo splines indicate the $\pm 1\sigma$ around it. The grey-shaded region highlights the typical measurements of such dispersion from observations, with a grey horizontal line indicating the upper limit. Dashed Red: Inter-cluster dispersion. m12f has larger dispersion in both inter and intra-cluster abundances, most probably due to an LMC-like merger resulting in a more mixed disk compared to other simulations that don't incorporate such a merger.

chemical difference of < 0.0002 , it would be extremely difficult to know if these two stars came from the same OC or were drawn from two different OCs.² That is, for the majority of pairs, it would be difficult to distinguish between stars that fall within the same OCs or different OCs using the vector of abundances for these elements alone. Given that typical uncertainties in the abundance measurements are ≈ 0.03 dex [137], it is unlikely that strong chemical tagging is feasible. To further illustrate the impact of uncertainties in observed chemical differences, we calculate the chemical difference metrics for intra and inter-cluster pairs after adding the APOGEE errors, which we discuss in §2.3.4.

To better quantify the degree of inherent similarity between the two distributions shown in Fig. 2.8, we perform a two-sample Kolmogorov-Smirnov (K-S) test. Essentially, such a K-S test quantifies the likelihood that the observed datasets were drawn from the same underlying distribution and generates the probability that observed differences between the two in-hand datasets are due to chance selection. There are two metrics reported from a K-S test: the K-S statistic and the p-value; both metrics need to be considered together to fully understand the significance of the differences between the observed datasets. The K-S statistic measures the maximum discrepancy between the cumulative distributions of two datasets. The p-value indicates the probability of observing such a discrepancy by random chance alone if the null hypothesis is true; in a two-sample K-S test, the null hypothesis is that the two observed datasets were drawn from the same underlying distribution. Values of the K-S statistic and the p-value range between 0 and 1. A high value of K-S statistic (> 0.6) and a small p-value (< 0.05 ³) suggests that the observed samples are very different and are very likely to be drawn from two different underlying distributions. Whereas, a low value of K-S statistic (< 0.4) and a small p-value (< 0.05) suggest that while the observed samples are similar, it is still very likely that they are drawn from two different underlying distributions.

²We choose < 0.0002 as selection criteria here, as it is close to the mean chemical difference in all three simulations (see Table:2.3 for relevant statistics for the chemical difference metric for each simulation. In Appendix 2.4 we explore the impact of changing the statistic we use and of the number of elements we leverage to discern between intra and inter-cluster pairs. Table:2.1 shows that regardless of the statistic we use for subdividing our sample for the smallest chemical difference metric values, we always see significant contamination with inter-cluster pairs. We note that using fewer elements to calculate the chemical difference metric marginally decreases the ability to discern between the intra- and inter-cluster pairs at small values of the chemical difference metric.

³What is considered a “small” p-value is based on the chosen level of significance. In this work, we choose the level of significance to be 5% thus, we can trust the K-S statistic if the p-value is < 0.05 .

We obtain a K-S statistic of 0.19 for m12i, which indicates a small maximum difference between the CDFs of the calculated chemical difference metric for the inter and intra-cluster pairs. However, the p-value is quite small (~ 0.00 for m12i), thus indicating that it is unlikely that these two samples are drawn from the same global distribution. In other words, while there are some similar aspects to both datasets (the maximum discrepancy to the global CDF is small), they are not in fact drawn from the same parent distribution. This can be seen visually by inspecting the red and blue lines in the top panel of Fig. 2.8; while both distributions are strongly peaked at the lowest values of the chemical difference metric, at larger values, the shape of the inter-cluster distribution (shown in red) is different from the shape of the intra-cluster distribution (shown in blue). The K-S statistic is 0.25 for m12f; this is slightly higher than m12i’s K-S statistic, but still a critically low value, indicating that there is similarity in the two observed m12f datasets. However, again, the p-value is very low (~ 0.00 for m12f), which indicates that it is highly unlikely that both datasets are drawn from the same underlying distribution. Finally, m12m has the largest K-S statistic (~ 0.37) of all three simulations; however, it still falls below the 0.4 threshold, thus we can say that the maximum differences in m12m’s distributions are quite slight. Despite this, yet again, the p-value is vanishingly small (~ 0.00 for m12m), indicating that it is extremely unlikely that these samples were drawn from the same parent distribution.

Overall, we conclude that while the intra and inter-cluster chemical difference metric datasets were drawn from two different global distributions, there is little power with this set of elements in using small values of the chemical difference metric to select stars that definitely came from one OC. That is, the contamination rate of inter-cluster pairs at the smallest chemical difference metric is far too significant to trust OC reconstruction.

2.3.4 Intra and Inter-Cluster Chemical Difference Metric with APOGEE errors in simulated OCs

In order to test how the incorporation of errors in abundance measurements affects our chemical difference metric calculations, in this section, we add errors drawn from an observational cluster catalog to our simulated OCs. The errors we use come from OCCAM VI [Open Cluster Chemical Abundances and Mapping Survey, 135], which

was derived from APOGEE DR17 [1]. To add errors to the simulation, we first generate a normal distribution for each element for each star; the mean of the distribution is set to the true value from the simulation. We set the standard deviation of the distribution by calculating the mean error for each element from the OCCAM cluster catalog. We then draw from this distribution a single value to represent the chemical abundance with error included that is assigned to each star. This process is repeated for all elements and all stars. In this analysis, we use the 7 elements ([C/Fe], [N/Fe], [O/Fe], [Mg/Fe], [Si/Fe], [S/Fe] and [Ca/Fe]) that are in common with the OCCAM sample. We use the same sample of clusters discussed in §2.3.3 for our analysis here.

In Fig. 2.9, each panel shows the histograms for the chemical difference metric from the intra and inter-cluster star pairs with APOGEE errors included; we show each distribution with a blue solid and red dashed line, respectively. Again, the top, middle, and bottom panels correspond to m12i, m12f, and m12m, respectively. With errors included, the shape and the extent of the distribution shown in Fig. 2.9 change substantially. The distribution now peaks closer to the degree of freedom, which is equal to the number of elements used to calculate the chemical difference metric. That is, each element contributes equally to the error-included chemical difference metric. Unlike histograms of the metrics with no error in abundance measurements that peaked at the smallest chemical difference, the histograms now peak at ≈ 7 . All three panels from different simulations show a similar trend with the addition of errors, and most of the bins until the metric value of 15 for each simulation are almost equally populated by both intra and inter-cluster pairs. Considering a limit of 7 which is closer to the mean of chemical difference metrics for both intra and inter-cluster pairs, $\approx 55 / 56\%$ of the total intra / inter-cluster pairs have the difference metric of < 7 in m12i. Similarly, for m12f, $\approx 55 / 54\%$ of the total intra / inter-cluster pairs have a difference metric of less than 7. For m12m, the percentages of pairs with the difference metric of < 7 are $\approx 52 / 56\%$ for intra / inter-cluster pairs respectively. Also, the maximum PDF obtained for either the intra and inter-cluster pairs is slightly below ≈ 0.13 at the mean difference metric, thus indicating there is no prospect of identifying if the star pairs are coming from the same cluster or different clusters. This analysis clearly shows that with errors, there is not enough chemical difference between the stars to identify them uniquely.

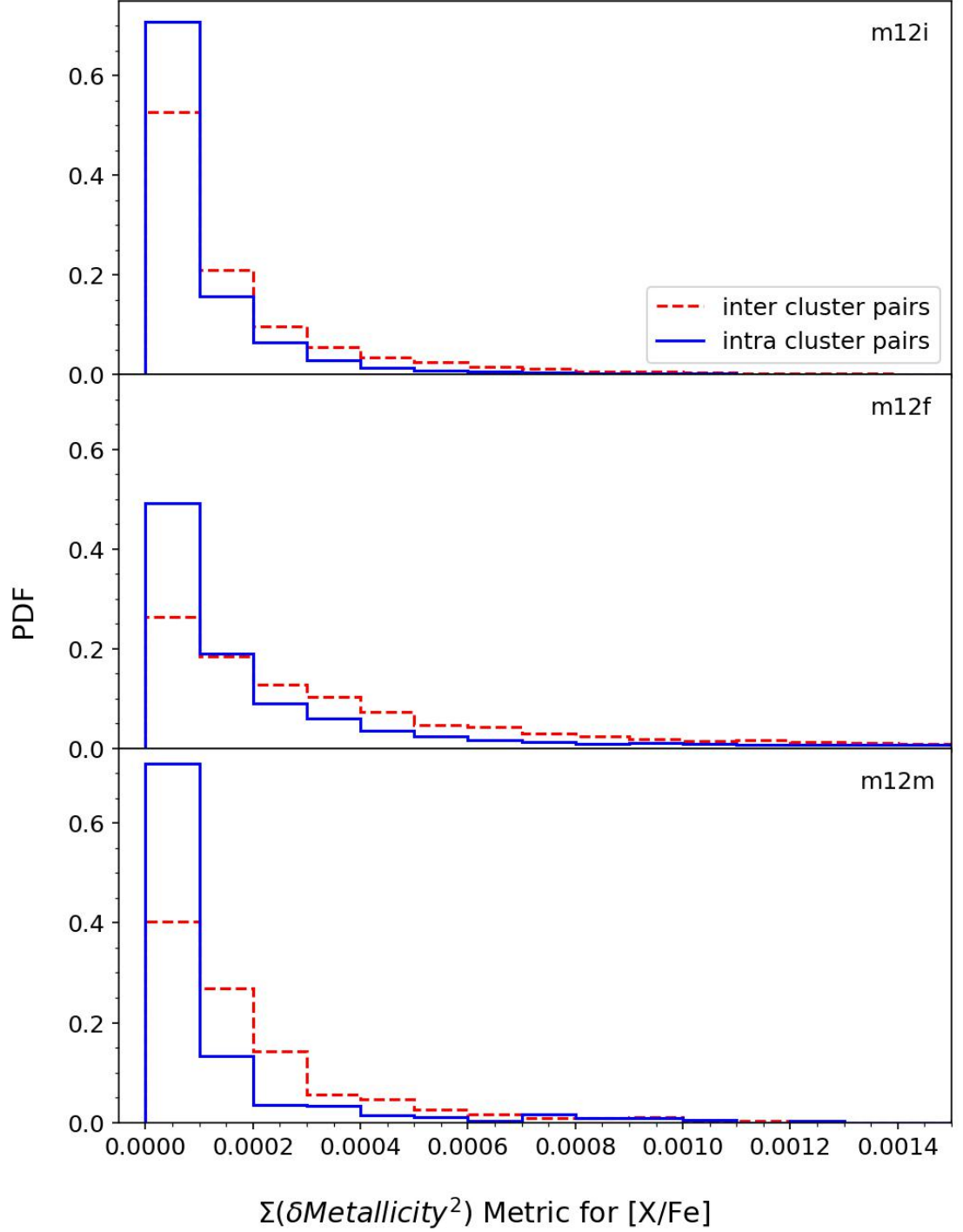


Figure 2.8: Histograms of the chemical difference metric for pairs of stars within OCs indicated by blue histograms(intra-cluster pairs) and between OCs indicated by the dashed red histograms(inter-cluster pairs) for each simulation m12i(top), m12f(middle), and m12m(bottom) in each panel. These clusters were selected to fall within $\pm 1\sigma$ from the overall mean distribution of [Fe/H] in each simulation. The bin with the smallest chemical difference metric obtained for both inter and intra-cluster pairs is abundantly populated, indicating that such difference is pretty small to uniquely identify the chemistry of individual clusters.

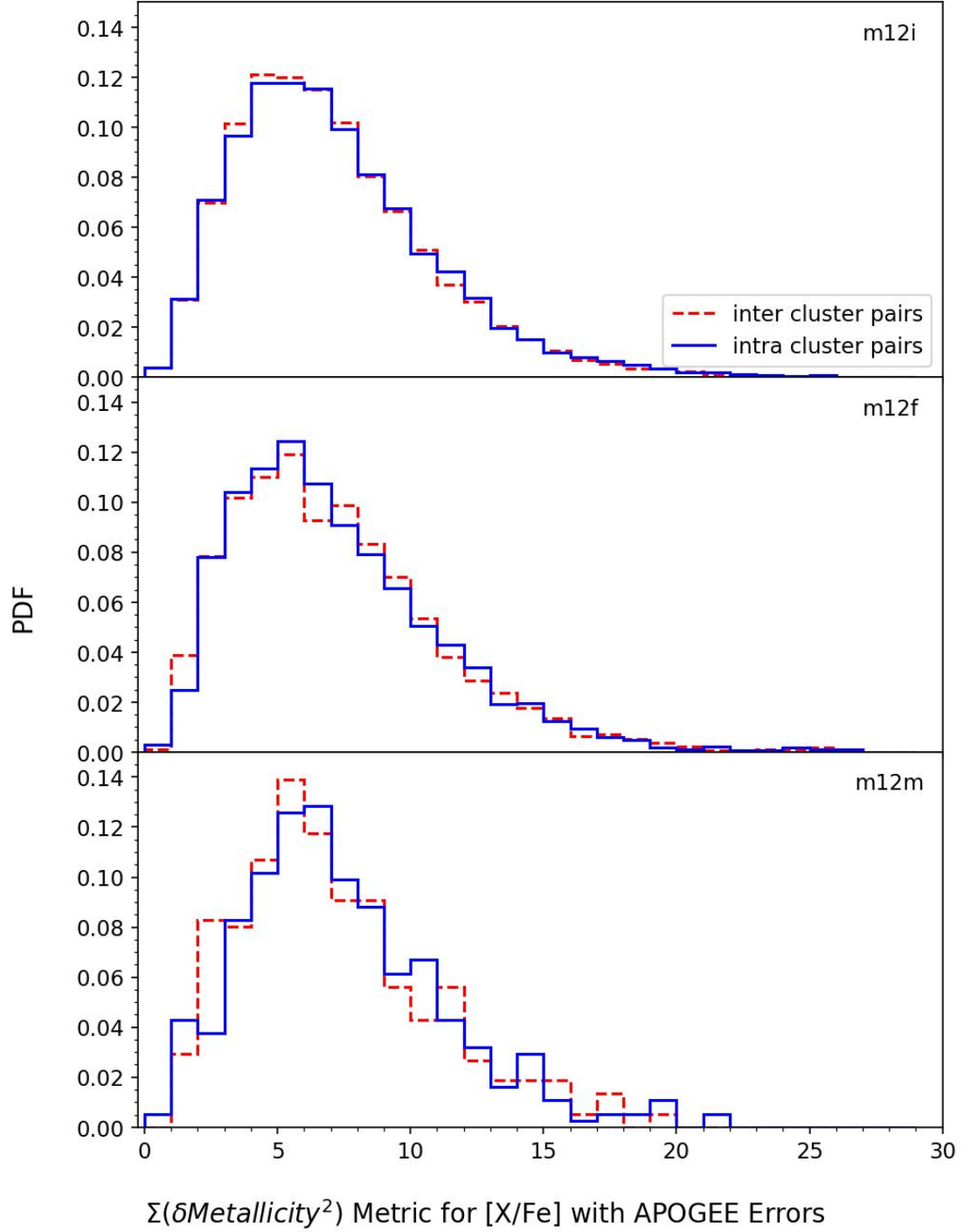


Figure 2.9: Histograms of the chemical difference metric for pairs of stars with mock APOGEE errors in OCs (blue) and between OCs (dashed red) for each simulation. These clusters were selected to fall within the mean $\pm 1\sigma$ of the typical intra-cluster dispersion from the overall mean distribution of $[\text{Fe}/\text{H}]$ in each simulation. The bins with the most of the chemical difference metric obtained for both inter and intra-cluster pairs are abundantly populated, indicating that such difference is pretty small to uniquely identify the chemistry of individual clusters.

2.4 Discussion and Conclusions

In this paper, we have characterized the degree of scatter in abundance distributions in young OCs identified in three galaxies from the *Latte* suite of FIRE-2 simulations (m12i, m12f, and m12m). Using a range of elements (C, N, O, Ne, Mg, Si, S, Ca, Fe) that are generated from three distinct nucleosynthetic families (core-collapse supernovae, white-dwarf supernovae, and stellar winds), we have shown that the abundance dispersion in FIRE OCs is comparable to observations from Ness et al. [137].

In this section, we compare our results with other observational studies that have measured the level of chemical homogeneity present in individual OCs using spectroscopic analysis. Dispersions measured from observations are influenced by two factors: intrinsic scatter – the true difference in elemental abundance between stars within an OC – and observational noise, which originates from measurement uncertainties. Most observational studies consider an OC to be chemically homogeneous if the metallicity dispersion inside a cluster is less than or equal to the typical measurement uncertainties. While measurement uncertainties vary between studies [e.g., 0.03 dex vs. 0.008–0.036 dex, from 137, 105, respectively], typically measurement uncertainty is ≤ 0.03 dex [20, 167].

Simulations do not suffer from observational uncertainties, and the typical intrinsic dispersion inside a simulated *Latte* OC is < 0.02 dex. This is broadly consistent with the intrinsic dispersion measured for these elements from observational studies. In *Latte*, such homogeneity is a consequence of two dominant factors: 1) at present day, gas within individual GMCs is very well-mixed [see Figure 7, 10], and 2) star formation within an individual OC is typically short-lived ($\sigma_{\text{age}} < 1$ Myr, Masoumi, et al. in prep), which limits internal enrichment.

Note, some level of inhomogeneity is expected in observations driven by, among other things, atomic diffusion, mixing processes, and planet engulfment [16, 13, 163]. Such processes are expected to have an impact on the metallicity of evolved populations and are not resolved in *Latte* OCs, as star particles have a fixed abundance throughout their lifetime. In observational studies, dispersion measurements that make use of both main sequence and giant stars within an OC are expected to have an increased metallicity dispersion; as a result, some studies consider dwarf and giant stars separately [16, 33].

Moreover, different types of elements (e.g., light versus heavy elements) are expected to have a different amount of scatter [42, 117]. While the current generation of *Latte* simulations do not track heavy elements, such an improvement is anticipated in upcoming generations of FIRE.

With this somewhat complicated observational context in mind, we now present results from the literature. Note, as much as possible, we try to include both the stellar populations and the elements studied in each work. In one of the earliest spectroscopic studies on intra-cluster homogeneity, De Silva et al. [40] analyzed the heavy elements Zr, Ba, La, Ce, and Nd in dwarf stars in the Hyades OC; they showed that the chemical scatter within this system is below their measurement uncertainties, which ranged from 0.047–0.048 for Zr and Ba, to 0.025–0.026 dex for La, Ce and Nd. 22 Thus, De Silva et al. [40] conclude that Hyades is chemically homogeneous. In a follow-up study, De Silva et al. [41] analyzed abundances of the light elements Na, Mg, Si, Ca, Mn, Fe, and Ni in 12 red giant stars in the OC Collinder 261, and estimated the intrinsic scatter is < 0.05 dex across these elements. Because their measurement uncertainty ranged between 0.01–0.05 dex, they concluded Collinder 261 is chemically homogeneous. They also compared Collinder 261, Hyades, and the moving group HR 1614 to each other and found all three systems have small scatter (< 0.05 dex) consistent with homogeneity [41].

In line with De Silva et al., many other groups have found that OCs are chemically homogeneous from spectroscopic analysis. For example, Pancino et al. [143] three red clump stars in each of five OCs: Cr110, M37, NGC 2420, NGC 7789, and M67, and they found the dispersion in $[\text{Fe}/\text{H}]$ indicated chemical homogeneity for all five systems. Likewise, using 12 subgiants, Ting et al. [167] showed that variation in $[\text{X}/\text{H}]$ for Na, Al, Mg, Si, Ca, Ti, Cr, Ni, Fe, Zn, and Ba is < 0.03 dex in IC 4756. Additionally, Cunha et al. [37] studied Na and O abundances for 11 APOGEE red giants in the old, super-solar OC NGC 6791, with measurement errors of ~ 0.05 dex. They concluded this system is chemically homogeneous, with an abundance dispersion of ~ 0.05 – 0.07 dex; this conclusion is consistent with results for NGC 6791 presented by Bragaglia et al. [23]. Bovy [20] also used APOGEE spectra for 49 giants in M67, NGC 6819, and NGC 2420 and showed that the scatter is < 0.03 dex for 15 elemental abundances (C, N, O, Na,

Mg, Al, Si, S, K, Ca, Ti, V, Mn, Fe, and Ni). Among these elements, C and Fe had strong limits (< 0.02 dex at 95% confidence); however, for Na, S, K, Ti, and V, the scatter was < 0.05 dex. Poovelil et al. [148] also calculated the abundance scatter in APOGEE red giants in 10 OCs for 8 elements, Mg, Al, Si, Ca, Fe, Si, Mn, and Ni, and found that the dispersion for these clusters were within the limits indicated by Bovy [20] of < 0.03 dex for most of the elements, with only Mg, Al, and Si having larger scatter, which could be consistent with dredge-up effects that preferentially impact light elements.

However, some studies have found measurable chemical inhomogeneity larger than the measurement uncertainties in OCs [e.g., 16, 105, 13, 33]. For example, Liu et al. [105] studied the abundances of 19 elements (C, O, Na, Mg, Al, Si, S, Ca, Sc, Ti, V, Cr, Mn, Fe, Co, Ni, Cu, Zn, and Ba) in 16 solar-type stars in the Hyades cluster, with abundance errors ranging from a low of 0.008 dex for Si to a high of 0.036 dex for S. For most elements, the abundance dispersion they measured was significantly larger than measurement errors, by a factor of $\approx 1.5 - 2$. They conclude that Hyades is chemically inhomogeneous at ≥ 0.02 dex level, which contrasts with the conclusions for Hyades drawn from De Silva et al. [40] and De Silva et al. [41]. Liu et al. [105] suggest pollution of metal-poor gas into portions of the proto-cluster cloud combined with supernova ejection into other regions with incomplete mixing is the root cause of such dispersion.

Overall, we find that different observational studies have differing criteria to determine if an OC is chemically homogeneous. This conclusion can be impacted by the stellar sample used (containing evolved, main sequence or a combination of the two populations), elements considered (light and/or heavy elements), and measurement errors (which is instrument resolution and line-fitting methodology dependent). Dwarf stars and heavy elements show the greatest discriminating power for the measurement of homogeneity. Most studies agree that the typical level of intra-cluster scatter inside Milky Way OCs is ≤ 0.03 dex for most elements; OCs with scatter less than this per element relative to H are considered chemically homogeneous. In our simulations, the intrinsic OC intra-cluster scatter in $[X/H]$ for C, N, O, Ne, Mg, Si, S, Ca, Fe is ≤ 0.02 dex; these *Latte* OCs would be considered chemically homogeneous by most observational studies.

While there is abundant research supporting small intra-cluster dispersion in OCs, the assumption of large inter-cluster dispersion, which is crucial for strong chemical

tagging to work, has only recently been explored [e.g., 16, 98]. The first study to systematically consider inter-cluster dispersion was De Silva et al. [42]. They aggregated abundance information from the literature for 10 elements (Na, Si, Ca, Mn, Zn, Rb, Zr, Ba, Nd, and Eu) from 24 OCs and showed that different clusters exhibit varying levels of dispersion for each element. Despite likely systematic differences in their sample due to varying methodologies and scales, as well as the inclusion of both evolved and main sequence stars, introducing additional scatter in inter-cluster dispersion (particularly in light elements like Na), they were still able to conclude that different clusters exhibit differing elemental abundance patterns. In particular, they found an inter-cluster scatter of ≥ 0.20 dex in heavy elements like Mn and Ba, which they concluded is an indication of abundance variation between clusters.

In the time since, there have been several significant studies that investigate chemical abundances in large spectroscopic samples of OCs surveyed in homogeneous manner. These include the Bologna Open Clusters Chemical Evolution project [BOCCE 22], the WIYN Open Cluster Study [123, 83], Gaia ESO OC papers such as Magrini et al. [110], and APOGEE studies such as the Open Cluster Chemical Abundance and Mapping Survey [OCCAM 135]. While these studies provide tremendous insight into radial trends in the Milky Way, unfortunately, as of yet, they do not explicitly consider inter-cluster trends.

Subsequent to De Silva et al. [42], Mitschang et al. [130] used 30 distinct OCs from the literature and measured both the inter- and intra-cluster dispersion. They found a typical inter-cluster dispersion of ~ 0.120 dex and considerably smaller intra-cluster scatter of ~ 0.045 dex (i.e., the inter-cluster dispersion is ~ 3 times greater than the intra-cluster dispersion). Thereafter, the first study (to our knowledge) that considered inter-cluster scatter is Blanco-Cuaresma et al. [16]. In this work, they compiled stellar spectra from 31 old and intermediate-age OCs to determine 17 abundance species and showed that stars at different evolutionary stages have distinct chemical patterns. Upon separating stars into dwarfs and giants, they found that only a few OCs show distinct chemical signatures, with the majority of them possessing a high degree of overlap. They also analyzed five OCs (IC4651, M67, NGC2447, NGC2632, and NGC3680) with stars in various evolutionary stages and found that differences in abundances for $[\text{Fe}/\text{H}]$ and

$[X/Fe]$ were less than 0.05 dex for almost every element considered, except for Na, which can be enhanced in giants. Such enhancement likely occurs as a result of mixing from the first dredge-up in giant stars.

On the other hand, Lambert and Reddy [98] studied inter-cluster abundance differences for 23 elements in 70 red giants from 28 OCs. Their analysis was comparable in scope and accuracy to that reported by Blanco-Cuaresma et al. [16], except that their selection included several additional heavy elements – La, Ce, Nd, Sm, and Eu – which are produced by neutron-capture processes. Using a set of 20 clusters, they calculated scatter in light elements, which was 0.16 dex for Na and Al, 0.12 dex for Mg and Si, and 0.11 dex for Ca [see Table 1 from 98]. They observed inter-cluster scatter up to 0.5 dex for heavy elements like La and Ce, with uncertainty $<0.07\text{--}0.08$ dex. Lambert and Reddy [98] point out that while the inter-cluster scatter for heavy elements is large, many clusters are individually chemically homogeneous in heavy elements with unique chemical patterns. They suggest that combining measurements of one or more light elements like Mg, Al, Si, Cu, and Zn with heavy elements like La, Ce, Nd, Sm, and Eu in future chemical tagging studies might produce insightful results [98].

Overall, at present, there is limited discussion of inter-cluster scatter in the literature, and differing perspectives are offered in the two most recent works. Blanco-Cuaresma et al. [16] have found a high degree of overlap (small inter-cluster scatter) in the chemical signatures of light elements across OCs; however, they don't directly quantify the inter-cluster scatter in their analysis. Whereas Lambert and Reddy [98] have found a significant inter-cluster scatter in heavy neutron-capture elements (up to 0.5 dex) and a smaller scatter in lighter elements (on average ≈ 0.13 dex). As previously mentioned, at this time, we only track light elements in our simulations. In this limit, the OC inter-cluster scatter we measure for $[X/H]$ for C, N, O, Ne, Mg, Si, S, Ca, & Fe is 2–5 times larger than the intra-cluster dispersion in individual OCs. Specifically, when averaged across all 9 elements, the inter vs intra-cluster dispersion is for m12i: 0.03 vs 0.01, for m12f: 0.09 vs 0.02, and for m12m: 0.02 vs 0.01. We find that when inter-cluster scatter is considered by element, only C and N have a slightly higher scatter than the average (albeit at a very small level, see Fig. 2.7). This is consistent with the result presented by Mitschang et al. [130], which showed that the inter-cluster dispersion is ~ 3 times greater than the

intra-cluster dispersion. Lambert and Reddy [98] have shown inter-cluster dispersion to be ~ 10 times larger than the intra-cluster dispersion for heavy elements like La, Ce, Nd, and Sm (e.g., 0.4 dex of intra-cluster scatter vs 0.03 dex of inter-cluster scatter for La). However, if we assume that the individual OCs from Lambert and Reddy [98] are homogeneous at ≈ 0.03 dex level, then the ratio of inter to intra-cluster scatter for light elements is ~ 4 , which is in line with our results.

As one might expect, the inter-cluster scatter that we report for OCs is less than what has been seen for *all* young stars in the *Latte* disks. For example, Bellardini et al. [11] selected young stars (< 500 Myr old) at present day from 11 of the *Latte* galaxies at a range of radii and showed that at small radii, the scatter across the entire annulus is 0.03–0.04 dex. Moreover, in the present day, the typical variation across the fiducial solar cylinder ($R = 8$ kpc) in $[\text{Fe}/\text{H}]$ is ≈ 0.05 dex [see top panel Figure 9, 11, 63]. However, at this annulus, the inter-cluster scatter for OCs in $[\text{Fe}/\text{H}]$ is only 0.02 dex.

In addition to intra- and inter-cluster scatter, we have calculated a chemical difference metric similar to the one first introduced by Mitschang et al. [130]. Such a metric helps to determine if one can distinguish pairs of stars formed in the same OC from pairs formed across different OCs. We calculated the percentage of pairs that have small chemical difference metric values ($<$ than the mean chemical difference for the entire sample) with the hope that this population would be predominantly populated by intra-cluster pairs. However, for m12f, 43% of the inter-cluster and 66% of the intra-cluster pairs had similar indistinguishably small chemical difference values. Moreover, in the other two galaxies, the rate of chemical difference overlap was even greater: 65% vs 84% for m12m and 73% vs 86% for m12i in inter vs intra-cluster pairs. We find it noteworthy that a significant fraction of the smallest chemical difference values belong to inter-cluster pairs, which one would typically assume to be populated by only intra-cluster pairs.

Mitschang et al. [130] used the chemical difference metric to compare 30 distinct OC from across the literature. Their abundance measurements ranged from 5 to 23 elements per cluster across 291 stars. They found a distinct peak in the distribution of the chemical difference metric for both the intra- and the inter-cluster distributions. In their analysis, the two distributions had a critical crossing point at a chemical metric value of ~ 0.07 — at this value, both the intra and inter-cluster star pairs showed identical

chemical differences distributions and thus the metric had no constraining power for strong chemical tagging. In our simulated OCs, such a crossing-point occurs at a very small chemical difference value (~ 0.0001); this crossing point is near the median of both skewed Gaussian distributions, and is very well sampled by both intra and inter-cluster pairs. Notably, the chemical difference metric has no constraining power to determine origin at this location. In our extended analysis of the chemical difference metric, we added APOGEE errors to the abundance measurements of our OCs. We find that the error added chemical metric distributions for intra and inter-cluster pairs overlap significantly at almost all measured values, further reinforcing that there is little prospect of discerning intra and inter-cluster pairing using the chemical difference metric from light elements alone.

In a slightly different scenario, leveraging 600 intra-cluster pairs and 1,018,581 field pairs with similar $\log(g)$ and T_{eff} values, Ness et al. [137] utilized 20 element abundances to calculate the chemical difference metric. The chemical difference distribution for intra-cluster and field star pairs was visibly distinct but not totally disjoint, with 0.3% of field stars having similar chemical differences as the median difference in intra-cluster pairs. When stars of a fixed solar metallicity ($[\text{Fe}/\text{H}] = 0 \pm 0.02$) were considered, the percentage of field star pairs with overlapping intra-cluster chemical difference values increased to $\sim 1.0\%$. Ness et al. [137] refer to these field stars as solar "doppelgangers." They conclude that such a significantly populated doppelganger population implies that strong chemical tagging in a strict sense would not work with this dataset. While we are intrigued by this result, we leave a similar calculation utilizing our OC sample and *Latte* field stars to future work.

In conclusion, OCs in FIRE show realistic intra-cluster homogeneity (typical OC elemental dispersion $\lesssim 0.02$ dex) and comparable inter-cluster dispersion to observations (2-5 times larger than intra-cluster dispersion). However, when using a chemical difference metric to distinguish between intra and inter-cluster pairs, we do not find significantly large chemical differences to distinguish OC origin for the majority of stars. This is likely due to limited and/or redundant information encoded in the light elements we track (C, N, O, Ne, Mg, Si, S, Ca, Fe); with the addition of heavy elements, the chemical difference metric may produce more reliable results for chemical tagging in

the future. However, as informed by our simulated OC sample (drawn from three realistic Milky Way-mass cosmological galaxy simulations with varied merger histories and environments), in the limits of light elements only, we are dubious that strong chemical tagging can reconstruct individual OCs reliably to a high level of confidence.

Acknowledgements

BB and SL would like to thank Peter Frinchaboy and Natalie Myers for their help with integrating APOGEE OCCAM errors into the simulation data. BB acknowledges support from the Center for Computational Astrophysics (CCA), which enabled his remote participation in the 2021 pre-doctoral program.

BB acknowledges support from NSF grant AST-2109234. SL acknowledges support from NSF grant AST-2109234 and HST grant AR-16624 from STScI. AW received support from: NSF via CAREER award AST-2045928 and grant AST-2107772; NASA ATP grant 80NSSC20K0513; HST grant GO-16273 from STScI. ECC acknowledges support for this work provided by NASA through the NASA Hubble Fellowship Program grant HST-HF2-51502 awarded by the Space Telescope Science Institute, which is operated by the Association of Universities for Research in Astronomy, Inc., for NASA, under contract NAS5-26555.

We generated simulations using: XSEDE, supported by NSF grant ACI-1548562; Blue Waters, supported by the NSF; Frontera allocations AST21010 and AST20016, supported by the NSF and TACC; Pleiades, via the NASA HEC program through the NAS Division at Ames Research Center.

FIRE-2 simulations [176] <http://flathub.flatironinstitute.org/fire> are publicly available. Additional FIRE simulation data is available at <https://fire.northwestern.edu/data>. A public version of the GIZMO code is available at <http://www.tapir.caltech.edu/~phopkins/Site/GIZMO.html>.

Software: IPython [144], Matplotlib [79], Numpy [68], Scipy [172], `halo_analysis` [175], `gizmo_analysis` [174].

Appendix A. Correlation between different elements

In this appendix, we consider the scatter and correlation between elemental abundances for all stars in all OCs found in m12i and presented in this paper. A discussion of how yields are implemented in FIRE-2 can be found in Appendix A in Carrillo et al. [31] and in Hopkins et al. [75].

In Fig. 2.10, we consider $[X/H]$ versus $[Fe/H]$ for $X=C, N, O, Mg, Si, Ca$. We find that each of these elements is highly correlated with $[Fe/H]$, as indicated by the Pearson correlation coefficient (> 0.99 in all cases). This can be seen by comparing the trend in the data in each panel to the diagonal red dotted one-to-one line. Not only is there limited scatter in elemental abundance at any value of $[Fe/H]$ (as shown in Fig. 2.11, which presents $[X/Fe]$ versus $[Fe/H]$ to highlight the limited scatter at any value of $[Fe/H]$), but also, the data in Fig. 2.10 follows a simple linearly increasing trend in all panels, with a slope that is nearly identical to the one-to-one line. While there are some slight departures from a single linear distribution (e.g., at $[Fe/H] \sim 0.15$, a transition to a shallower slope for $[Mg/H]$ and a transition to a steeper slope $[C/H]$ and $[N/H]$), to first order, all the elements we consider in this paper carry largely the same chemical signature as $[Fe/H]$. That is, modulo a normative offset, given a value of $[Fe/H]$ for any star in any of our OCs in m12i, $[X/H]$ can be predicted with high confidence for C, N, O, Mg, Si, and Ca.

To further reiterate this point, in Fig. 2.12 we explore the relationship between individual elements with one another by plotting $[X/H]$ versus $[Y/H]$ for $X, Y=C, N, O, Si, Mg, Ca$. Here, we color code each star by its $[Fe/H]$ value to reflect the trend shown in Fig. 2.10. Again, we see that these elements are highly correlated with one another when considering a Pearson correlation coefficient or inspecting the trends relative to the one-to-one line. Of all the elements, $[Mg/H]$ is the least correlated with $[C/H]$, with a Pearson correlation coefficient of 0.989. Indeed, there is a slight scatter in $[Mg/H]$ for small values of $[C/H]$ and a modest transition in slope at high values of $[C/H]$. To this end, in our subsequent chemical difference metric analysis presented in Appendix 2.4, we utilize Mg and C as maximally independent elements. However, it bears repeating that all of the elements presented here carry very similar discriminating power. Note, while this analysis indicates that chemical information is redundant in our simulations,

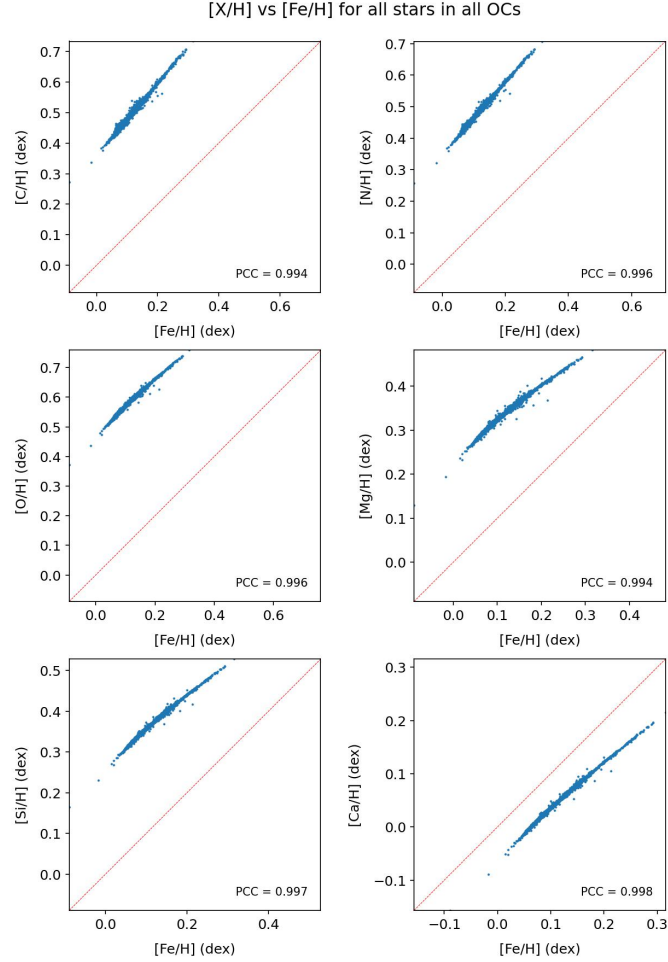


Figure 2.10: Left to right, top to bottom: [X/H] vs [Fe/H] for C, N, O, Mg, Si, and Ca for stars from OCs presented in this paper in m12i. Elements are highly correlated with [Fe/H] as indicated by the Pearson correlation coefficient, which is labelled on each plot (> 0.99 for all elements considered). The dotted diagonal red line is the one-to-one line. Note that the slope of the [X/H] vs [Fe/H] is similar to the one-to-one line, and there is limited scatter in [X/H] at any value of [Fe/H]. This indicates that all the elements considered carry similar discriminating power as [Fe/H].

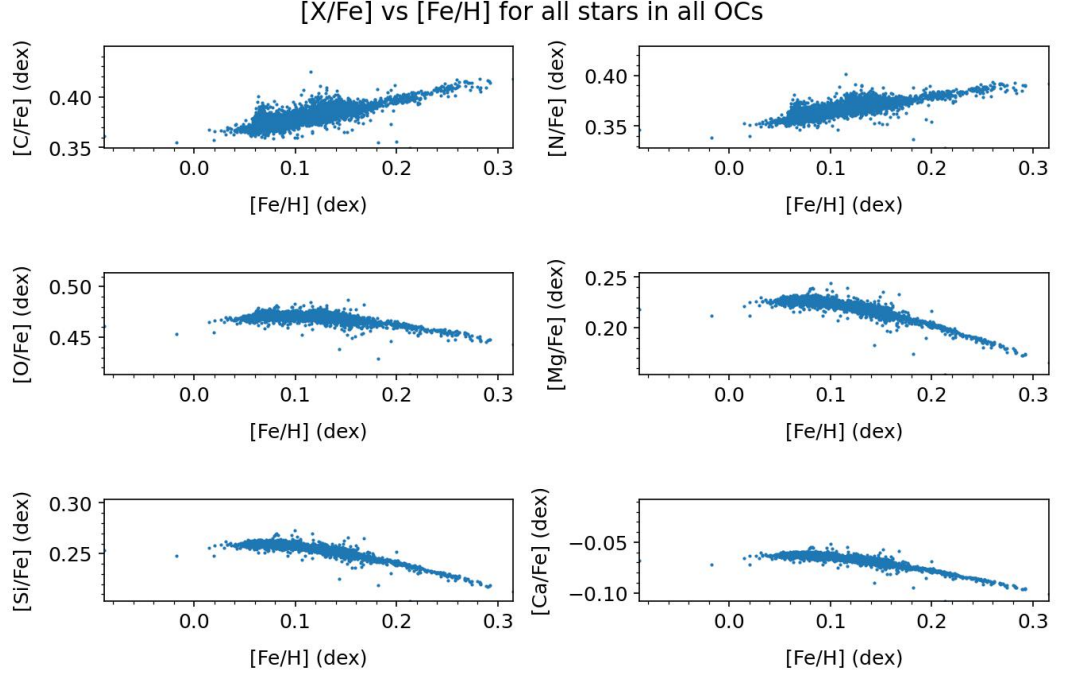


Figure 2.11: Left to right, top to bottom: $[X/Fe]$ vs $[Fe/H]$ for C, N, O, Mg, Si, and Ca for stars from OCs presented in this paper in m12i. Elements have a very tight scatter for a given value of $[Fe/H]$, as indicated by the small range in $[X/Fe]$ shown on the y-axis. The scatter is more substantial at lower values of $[Fe/H]$; however, the scatter decreases substantially at $[Fe/H] \geq 0.19$ dex.

something similar has been found in the Milky Way. For example, Griffith et al. [65] and Ness et al. [139] showed that if Fe and Mg are measured alone, then eight other supernova elements can be predicted to within 5% of their true values using a simple linear regression [see Figure 1 139, for an analogous figure to Fig. 2.12, but for the Milky Way].

Appendix B. Chemical Difference Metric using only 3 elements

Here we consider how the chemical difference metric is impacted by the number of elements used or the types of elements chosen to compute the metric. We have shown our analysis using all elements (C, N, O, Mg, Si, S, Ca, Ne) in §2.3.3. However, as

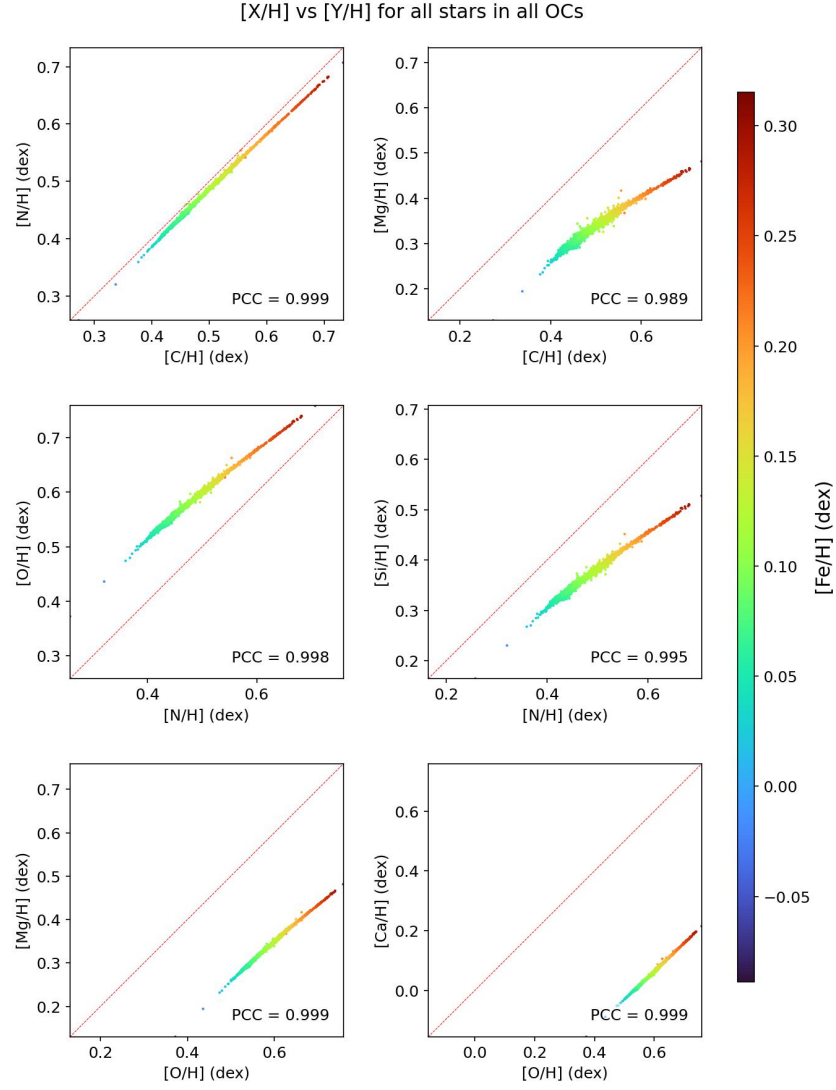


Figure 2.12: Correlation between [X/H] vs [Y/H] for C, N, O, Mg, and Ca color-coded by [Fe/H] (shown in the colorbar). Elements are highly correlated with one another, as indicated by the Pearson correlation coefficient (≥ 0.989 for all elements considered). The dotted diagonal red line is the one-to-one line. Note that the slope of the [X/H] vs [Y/H] is similar to the one-one line, and there is limited scatter in [X/H] at any value of [Y/H]. This indicates that all the elements considered carry similar discriminating power.

shown by Figs. 2.10, 2.11, and 2.12, elements are highly correlated with each other in our simulations. Thus, here we discuss the distribution of chemical differences in two other cases: calculated using only elements Mg, C and N, as well as calculated using only elements Mg, C and O. We have selected these elements as the maximally uncorrelated elements presented in Appendix 2.4. We compare these results alongside the case where we use all elements to compute the metric.

We show histograms of the chemical difference metric in Fig. 2.13 for pairs of stars within OCs indicated by blue histograms (intra-cluster pairs) and between OCs indicated by the dashed red histograms (inter-cluster pairs) for each simulation: m12i (top panel), m12f (middle panel), and m12m (bottom panel). These chemical difference distributions are computed similarly those presented in Fig. 2.8, which was generated by selecting OCs that fall within $\pm 1\sigma$ from the overall mean distribution of $[\text{Fe}/\text{H}]$ in each simulation and then applying the formula presented in §2.2.3 to relevant pairs drawn for the selected OCs. The first column on the left shows the distribution of the chemical difference metric when all elements were used. The middle column and right columns are for the cases when only 3 elements are used: Mg, C, N, and Mg, C, O. We note that decreasing the number of elements increases both the number of intra-cluster pairs and inter-cluster pairs that populate the smallest chemical difference metric bin. There is slightly more contamination from inter-cluster pairs when fewer elements are used to calculate the chemical difference metric. While broadly all of the distributions presented here look very similar, the maximum difference between the inter- and intra-cluster global distributions are found when all elements are used to calculate the metric.

In Table 2.1, we show the percentage of pairs that have a chemical difference metric smaller than the mean, median, or a fixed value when different elements are used to calculate the chemical difference metric. While there is a slight increase or decrease in the percentage of pairs falling below a chosen limit, the chemical difference overlap – that is, the relative amount of inter-cluster contamination – does not change significantly; there is always significant contamination at small values of the chemical difference metric. In Table 2.2, we present the purity (the percentage of intra-cluster pairs relative to the total pairs) of each sample for each metric. Each population is significantly impure – the contamination rate is typically 40%-50%. We conclude that no matter what metric

we use or subset of elements we consider, we always have significant contamination of inter-cluster pairs.

We note that the mean and median of the chemical difference distribution decreases very slightly when few elements are considered, and it decreases significantly when mean and median of the metrics are computed when combining the intra and inter-clusters distributions into one global distribution; we present this for completeness in Table 2.3.

Table 2.1: Chemical difference metric analysis using all elements versus a subset of elements (Mg, C, N and Mg, C, O)

Simulation	Selection of Chemical Difference Metric	Intra Cluster All Elements (%)	Intra Cluster Mg, C, N (%)	Intra Cluster Mg, C, O (%)	Inter Cluster All Elements (%)	Inter Cluster Mg, C, N (%)	Inter Cluster Mg, C, O (%)
m12i	< Intra Mean	76.23	74.94	75.94	59.61	58.82	59.07
	< Intra Median	50.00	50.00	50.00	31.60	33.23	32.16
	< Intra+Inter Mean	81.68	81.64	82.21	66.63	66.39	66.85
	< Intra+Inter Median	59.54	58.55	59.24	40.46	41.45	40.76
	< 0.00010 (Fixed)	70.47	81.66	86.79	52.36	66.41	72.92
	< 0.00020 (Fixed)	86.18	92.95	95.57	73.20	82.13	87.21
m12f	< Intra Mean	83.20	79.47	84.33	70.39	65.76	71.57
	< Intra Median	49.97	49.97	49.97	27.77	28.66	28.25
	< Intra+Inter Mean	86.94	83.98	88.07	79.11	74.24	80.71
	< Intra+Inter Median	62.08	60.42	61.36	37.92	39.58	38.64
	< 0.00010 (Fixed)	47.54	61.66	72.28	25.34	40.77	50.92
	< 0.00020 (Fixed)	65.93	76.74	85.40	43.03	61.01	73.47
m12m	< Intra Mean	83.16	81.55	82.62	62.03	67.65	66.04
	< Intra Median	50.00	50.00	50.00	17.65	19.79	16.58
	< Intra+Inter Mean	85.83	83.16	84.76	72.19	72.19	72.46
	< Intra+Inter Median	67.11	63.64	65.24	32.89	36.36	34.76
	< 0.00010 (Fixed)	70.59	79.14	82.62	38.77	61.50	67.11
	< 0.00020 (Fixed)	83.69	86.63	89.04	64.71	79.68	83.16

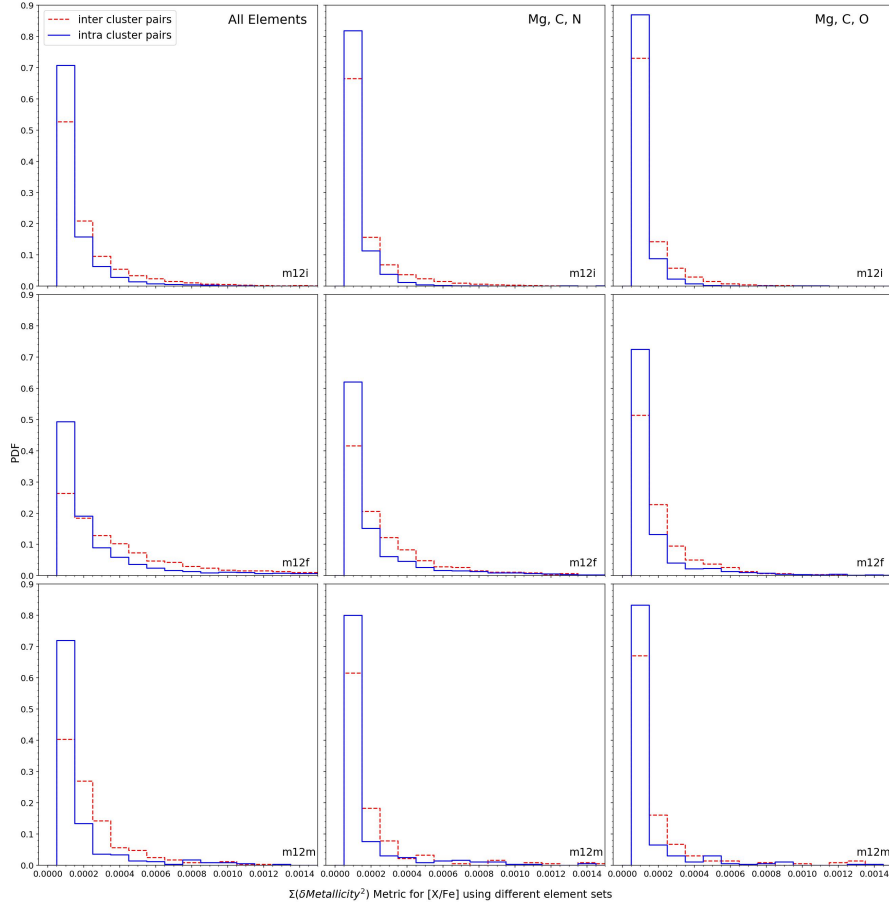


Figure 2.13: Histograms of the chemical difference metric for pairs of stars within OCs indicated by blue histograms (intra-cluster pairs) and between OCs indicated by the dashed red histograms (inter-cluster pairs) for each simulation m12i (top), m12f (middle), and m12m (bottom). The chemical difference distributions shown in each column are computed as using the method presented §2.2.3, but leverage different elements to compute the chemical difference metric. The left panel is a reproduction of Fig. 2.8, which was generated using all relevant elements in our simulations (C, N, O, Mg, Si, S, Ca, Ne). The middle column shows the chemical difference distribution calculated using three elements (Mg, C, N). The right column shows the chemical difference distribution calculated using a difference subset of three elements (Mg, C, O). We note that decreasing the number of elements increases both the number of intra-cluster pairs and inter-cluster pairs that populate the smallest chemical difference metric bin. There is slightly more contamination from inter-cluster pairs when fewer elements are used to calculate the chemical difference metric. While broadly all of the distributions presented here look very similar, the maximum difference between the inter and intra-cluster global distributions is found when all elements are used to calculate the metric.

Table 2.2: Purity percentage of intra-cluster pairs

Simulation	Statistic	All Elements Purity (%)	Mg, C, N Purity (%)	Mg, C, O Purity (%)
m12i	< Intra Mean	56.13	56.05	56.23
	< Intra Median	61.29	60.09	60.91
	< Intra+Inter Mean	55.09	55.12	55.16
	< Intra+Inter Median	59.54	58.55	59.24
	< 0.00010 (Fixed)	57.36	55.14	54.36
	< 0.00020 (Fixed)	54.08	53.12	53.21
m12f	< Intra Mean	54.14	54.56	54.94
	< Intra Median	64.69	64.52	64.15
	< Intra+Inter Mean	54.13	53.34	53.57
	< Intra+Inter Median	62.08	60.42	61.36
	< 0.00010 (Fixed)	47.54	61.66	72.28
	< 0.00020 (Fixed)	65.93	76.74	85.40
m12m	< Intra Mean	59.64	60.04	60.31
	< Intra Median	55.23	54.91	54.84
	< Intra+Inter Mean	56.03	55.47	55.23
	< Intra+Inter Median	67.11	63.64	65.24
	< 0.00010 (Fixed)	57.34	55.65	55.12
	< 0.00020 (Fixed)	54.39	53.76	53.92

Table 2.3: Chemical difference metric statistics

Simulation	Statistic	All Elements	Mg, C, N	Mg, C, O
m12i	Intra Mean	0.00007	0.00007	0.00006
	Intra Median	0.00003	0.00003	0.00002
	Intra+Inter Mean	0.00016	0.00010	0.00008
	Intra+Inter Median	0.00007	0.00004	0.00003
m12f	Intra Mean	0.00024	0.00024	0.00019
	Intra Median	0.00006	0.00006	0.00004
	Intra+Inter Mean	0.00065	0.00032	0.00026
	Intra+Inter Median	0.00017	0.00009	0.00006
m12m	Intra Mean	0.00012	0.00012	0.00010
	Intra Median	0.00002	0.00002	0.00002
	Intra+Inter Mean	0.00024	0.00014	0.00012
	Intra+Inter Median	0.00009	0.00005	0.00004

Chapter 3

Tracing the Radial Metallicity Gradient and Considering Sampling Bias Using Simulated Open Clusters in FIRE Galaxies

3.1 Introduction

Radial metallicity gradient refers to the relationship between metallicity and the galactic radius of the disk. It is considered an important metric to study the processes that drive the formation of the galaxy and its evolution [34, 128, 66, 11]. Based on the inside out disk formation model proposed by Larson [101] and later confirmed by Matteucci and Francois [124], Grand et al. [64], metallicity gradient can arise due to radial flows and stellar migration. Out of many probes that can be used to study the radial metallicity gradient like Cepheids [e.g. 103, 107], H II regions [e.g. 9, 6], planetary nebulae [e.g. 108, 165], low mass and massive stars [e.g. 19, 77, 3, 24]; open clusters(OCs) are considered as one of the best probes as it is easy estimating the age, distance and chemistry of OCs than for individual field stars. OCs are a group of stars that are born together and remain gravitationally bound for a long period, and are believed to share similar chemistry. Lada and Lada [97] define star clusters as a group of young stars

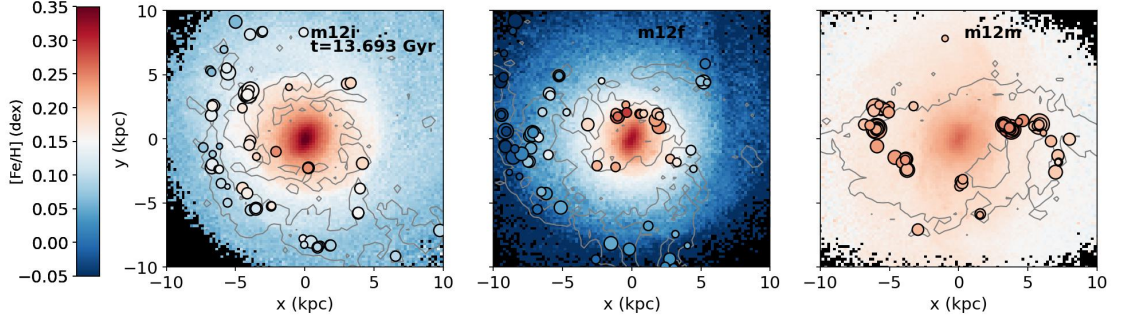


Figure 3.1: A snapshot from three *Latte* simulations m12i, m12f and m12m. Background: mean $[\text{Fe}/\text{H}]$ for stars in the disk < 1 Gyr old from each simulation. The corresponding values are shown by the color bar on the left. Contours: density of stars < 50 Myr old, which highlights the spiral arms. Circles: mean $[\text{Fe}/\text{H}]$ of OCs and associations identified at 13.693 Gyr. Note, the mean $[\text{Fe}/\text{H}]$ of the clustered star formation reflects the global metallicity distribution of the gas in the disk.

that survive tidal disruption for a period as long as 100Myr. For numerical simulations, however, star clusters are usually a bound group of stars that share a common birth origin. OCs are also considered the building blocks of the disk and are reliable tracers of age, distance, and chemistry around the galactic disk. They have been studied as far back as 1979 to show that they are reliable tracers of Galactic radial metallicity gradient Janes [85]. OCs are also considered among the best tracers of the overall Galactic metallicity distribution and of the thin disc abundance patterns [55, 141].

There are numerous studies from the past and recent years that use OCs as tracers of the structure and evolution of the Milky Way [e.g. 84, 55, 131, 134] and also the tracer of the metallicity gradient of the disk [e.g. 85, 169, 180, 109, 27, 82, 32, 47, 161]. Since the early studies by [85, 142, 86, 56, 145] it has been found that the OC population shows a significant decrease in metallicity with increasing distance from the galactic center [e.g. 142, 86, 56, 145]. Recent studies have shown that this trend can be fit into a two-function gradient with R_{GC} falling between 10kpc to 16 kpc [e.g. 157, 21, 57, 30, 180, 59, 151, 111, 47, 48].

All of these studies that have used OCs to trace the radial metallicity gradient of the disk have different sample sizes and different measured gradients. Janes [85] used 41 Ocs spanning 8 to 14 kpc from the galactic center and measured

$$\Delta[\text{Fe}/\text{H}]/\Delta R = -0.05 \pm 0.001 \text{ dex kpc}^{-1}.$$

Panagia and Tosi [142] used 17 OCs within 2 kpc from the sun (8.29 to 12.07 kpc) and calculated a slope of $-0.098 \pm 0.015 \text{ dex kpc}^{-1}$. Sestito et al. [157] used 4 OCs: Berkeley 20, Berkeley 29, Collinder 261, and Melotte 66 that span the radius of 7 to 22 kpc and supported a presence of a steep negative slope of the radial metallicity gradient up to 10-11 kpc from the galactic center. With the advent of high-quality datasets from APOGEE and SDSS, Frinchaboy et al. [59] used 22 OCs spanning from 7.9 to 14.5 kpc and calculated the radial metallicity gradient using $[\alpha/M]$ and also for $[M/H]$. Where α refers to alpha elements and M refers to metals other than hydrogen. They found no gradient in $[\alpha/M]$ and showed that $[M/H]$ indicates a gradient for $R_{GC} < 10$ kpc and flattens beyond 10 kpc. Their single fit gradient was $-0.09 \pm 0.03 \text{ dex kpc}^{-1}$ with the fitting inside 10 kpc being steeper at $-0.20 \pm 0.08 \text{ dex kpc}^{-1}$. They observed almost a flat gradient beyond 10 kpc, which was $-0.02 \pm 0.09 \text{ dex kpc}^{-1}$. Reddy et al. [151] used 28 OCs spanning a wider range of radius compared to earlier studies (5 to 24 kpc) with ages ranging from a few Myr to 9 Gyr. Their calculated gradient was of $-0.052 \pm 0.011 \text{ dex kpc}^{-1}$ for $R < 12$ kpc and it was $-0.015 \pm 0.007 \text{ dex kpc}^{-1}$ for $R \geq 12$ kpc.

A recent work and perhaps a motivation for this paper by Donor et al. [48] used a larger sample of 128 OCs, with 71 of them being deemed a high-quality sample, and performed an MCMC fit of the radial metallicity gradient. They calculated a gradient of $-0.068 \pm 0.001 \text{ dex kpc}^{-1}$ over the range of 6 to 13.9 kpc. In more recent work from the same collaboration, Myers et al. [135] used 150 OCs with 94 of them being high-quality OCs to calculate the gradient to be $-0.073 \pm 0.002 \text{ dex kpc}^{-1}$ over the range of 6 to 11.5 kpc. A very comprehensive analysis using a homogenized sample of OCs has been performed by Spina et al. [164]. The resulting homogenized sample contained $[\text{Fe}/\text{H}]$ and orbital parameters for 251 OCs, with 180 high-quality OCs. They obtained a slope of $-0.064 \pm 0.007 \text{ dex kpc}^{-1}$ with their gradient flattening beyond 12.1 ± 1.1 kpc. However, they have outlined some present and future challenges pertaining to the proper measurement of the radial metallicity gradient of the disk. Selection bias of OCs in the observations, cluster dissipation bias, role of resonances as a barrier to prevent the matter from freely flowing across the disk, and measurement errors leading to wrong calculations of the abundances are some of the challenges that are highlighted in Spina

et al. [164].

In this work, we aim to explore how the metallicity gradient traced using OCs from cosmological simulations compares to that of observations. Using a sample of OCs from three different Milky Way-like simulations that have different dynamic histories, we investigate if the way we sample our cluster data would have any impact on the measurements. *Latte* suite of FIRE-2 simulations Hopkins et al. [74, 75] provide a great test bed to study the radial metallicity gradient of the simulated Milky Way-like disk using our samples of open clusters with their well-resolved stellar populations in a cosmological context. Earlier work from the collaboration Bellardini et al. [10, 11] have used gas and stellar population from several FIRE galaxies to trace the radial and azimuthal metallicity gradients. Their comparison with the surveys in Bellardini et al. [11] using a similar number of stellar populations from FIRE galaxies at the same radial range has shown that there is an offset in the measurement of gradients. Recently, Graf et al. [63] have shown using FIRE galaxies that the radial gradient at the present time follows a similar trend as in the MW. However, the radial gradients using all stellar populations are shallower in FIRE-2 compared to those of surveys, which is in agreement with Bellardini et al. [11]. They have also shown that at present day, the gradient for younger stars is the steepest, which qualitatively agrees with the MW.

We perform a 2-component fit for the metallicity gradient of the disk using OCs that were identified using the friend-of-friends algorithm in these simulations. We use a similar technique as outlined in Donor et al. [48] that uses MCMC fit to perform the two-component fit of the radial metallicity gradient. We further compare the fit using subsamples of OCs selected randomly using different selection criteria, such as the age of the simulation at their time of birth. With simulated young OCs that are all less than 3 Myr old, identified during the last 100 Myr of the simulation, free from selection bias and measurement errors, this work provides the nature of such a fit in an ideal case.

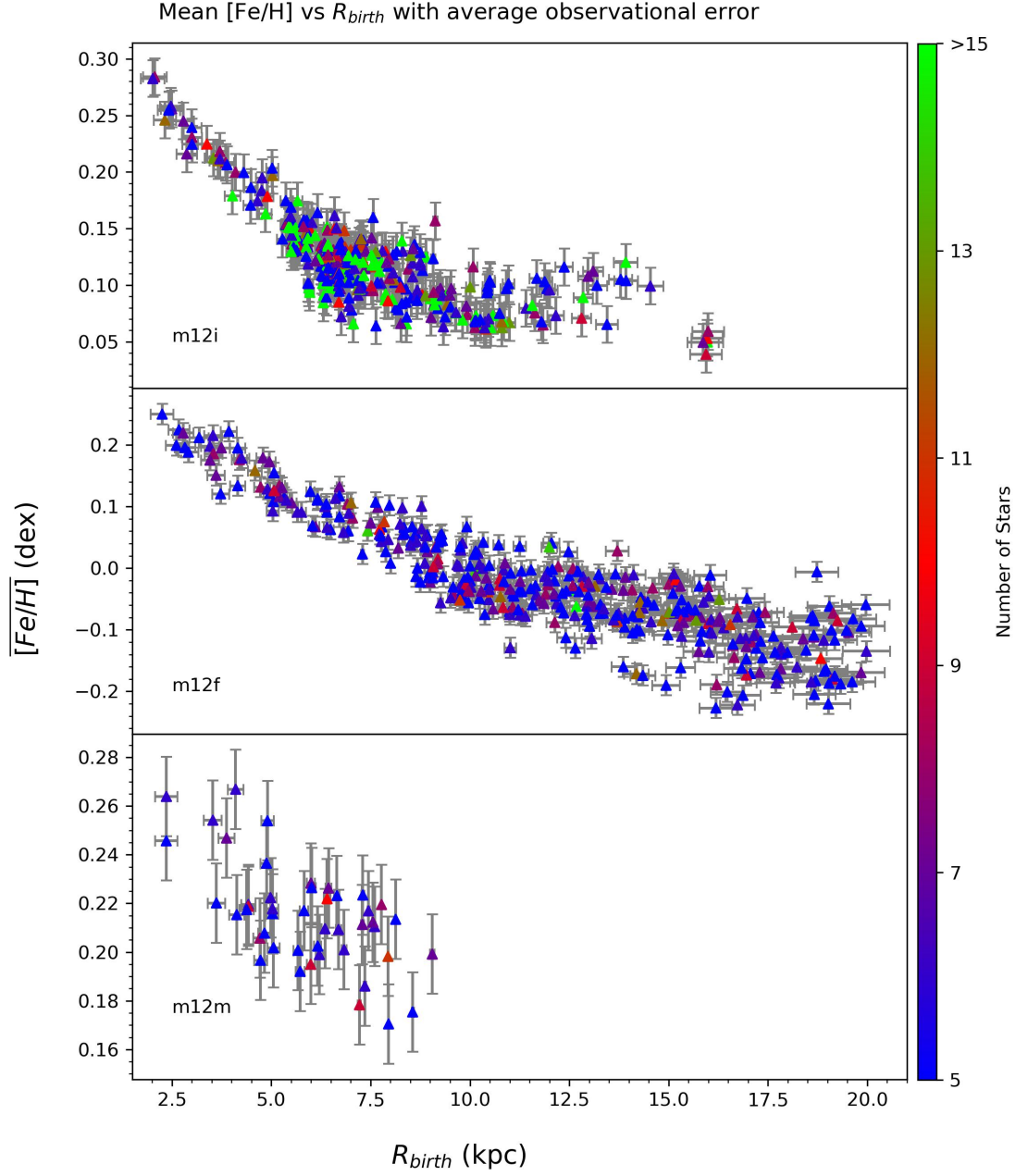


Figure 3.2: Scatter plot of mean $[\text{Fe}/\text{H}]$ vs birth radius of OCs from 3 simulations: m12i (top panel), m12f (middle panel), m12m (bottom panel). Error bars represent the average observational error in mean $[\text{Fe}/\text{H}]$ and 5% error per kpc from a fixed distance assumed to be a solar radius (8 Kpc). It can be seen that the metallicity distribution varies differently in the inner disk than the outer, and many clusters have similar mean $[\text{Fe}/\text{H}]$ despite being found at varying locations across the disk.

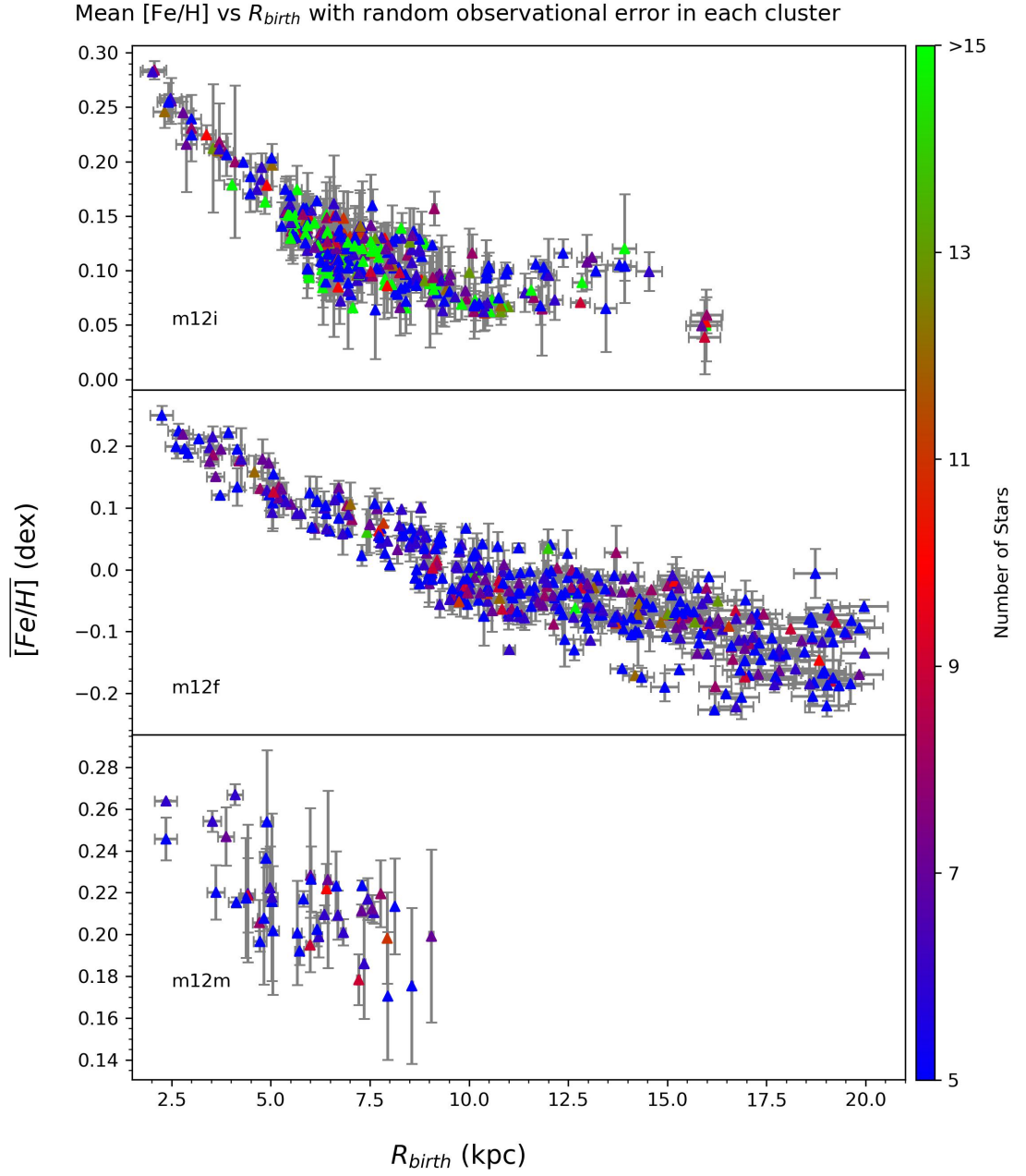


Figure 3.3: Scatter plot of mean $[\text{Fe}/\text{H}]$ vs birth radius of OCs from 3 simulations: m12i (top panel), m12f (middle panel), m12m (bottom panel). Error bars represent a random simulated APOGEE error in mean $[\text{Fe}/\text{H}]$ for each cluster and 5% error per kpc from a fixed distance assumed to be a solar radius (8 Kpc). With errors randomly assigned to each cluster, we observe larger error bars in several clusters.

3.2 Data and Methodology

3.2.1 Simulations

This work uses the *Latte* suite of FIRE-2 cosmological Milky Way-mass galaxy simulations [177, 176] to study properties of OCs. FIRE stands for Feedback in Realistic Environments; the code is able to simulate the interplay between ISM and the stellar feedback processes in a cosmological environment [74, 75]. These simulations use the Lagrangian Meshless Finite Mass (MFM) hydrodynamics method implemented in Gizmo, which is detailed in Hopkins [73]. Gizmo is used to solve the fluid equations utilizing a moving particle distribution that is automatically adaptive to resolution.

FIRE-2 uses a physically motivated metallicity-dependent radiative transfer heating and cooling approach for gas that includes free-free, photoionization and recombination processes, Compton scattering, photoelectric heating, and collisional dust effects, as well as molecular, metal-line, and fine structure processes. The implementation of FIRE we use in this work additionally includes magnetohydrodynamics, where the equations of ideal magnetohydrodynamics are solved explicitly [76]. Note, we use runs of these simulations with finer time-stepping than the fiducial outputs (1 Myr cadence) over the final 100 Myrs of the simulations, which enables us to track OCs in detail in phase space across time. While the runs analyzed in this study are not publicly available, snapshots of the FIRE-2 simulations with the fiducial treatment of feedback physics are publicly available [176]. FIRE-2 tracks 11 elements (H, He, C, N, O, Ne, Mg, Si, S, Ca, Fe) across a temperature range of 10 to 10^{10} K. These simulations incorporate a spatially uniform, redshift-dependent UV background as described by Faucher-Giguère et al. [51]. As typically done by observers, metallicity and elemental abundances are scaled to solar values; in these simulations, we use values for the Sun that can be found in Asplund et al. [8].

Star formation proceeds according to the following recipe in these simulations. Each star particle is generated from a self-gravitating gas cell that is Jeans-unstable, cold ($T < 10^4$ K), dense ($n > 1000 \text{ cm}^{-3}$), and molecular [following 95]. When star formation criteria are met, there is a one-to-one conversion of a gas cell into a star particle. That is, a star particle acquires its mass and elemental makeup from the gas

cell it originates from and depicts a simple stellar population characterized by a Kroupa initial mass function [93]. Each star particle is individually evolved assuming a standard stellar population model [STARBURST99 v7.0, 102] and produces time-resolved stellar feedback from both core-collapse supernova and supernovae Ia. The rates of core-collapse and Ia supernovae are based on STARBURST99 [102, 118, respectively]. FIRE-2 also incorporates stellar feedback due to continuous mass loss, radiation pressure, photoionization, and photoelectric heating. The nucleosynthetic yields we use are based on the work of Iwamoto et al. [80] for Type Ia supernovae and Nomoto et al. [140] for core-collapse supernovae. Stellar wind yields are sourced primarily from O, B, and AGB stars; we use a model for this assembled by Wiersma et al. [179] which incorporates expectations from van den Hoek and Groenewegen [170]; Marigo [119]; Izzard et al. [81].

FIRE-2 incorporates sub-grid diffusion and mixing of elemental abundances in gas, which occurs through unresolved turbulent eddies [166, 50, 75]. Our model assumes sub-grid mixing is primarily influenced by the largest unresolved eddies, which effectively smooths out abundance variations among gas elements. Escala et al. [50] demonstrated that incorporating this sub-grid model is essential for accurately replicating observed distributions of stellar metallicities in galaxies.

The *Latte* suite contains 14 Milky Way-like galaxies; in this work, we analyze three *Latte* simulations (m12f, m12i, and m12m) that are generated with initial conditions originating from the AGORA project [89]. The galaxies we analyze represent some of the most massive Milky Way-like isolated disks in the *Latte* suite and span a range of assembly histories. Key differences among these simulations are that m12i has a massive disk with a late forming Milky Way mass halo, m12f has an LMC-like satellite merger with the Milky Way-like disk 3 Gyr before present day, and m12m has a strong bar at high redshift and an earlier forming halo [see Table 1, 147]. A full description of the criteria used to generate these galaxies and their properties at the present day can be found at Wetzel et al. [176].

Each galaxy simulation assumes a flat Λ CDM cosmology with parameters consistent with the Planck Collaboration et al. [146]: $h = 0.68 - 0.71$, $\Omega_\Lambda = 0.69 - 0.734$,

$\Omega_m = 0.266 - 0.31$, $\Omega_b = 0.0455 - 0.048$, $\sigma_8 = 0.801 - 0.82$ and $n_s = 0.961 - 0.97$.¹

In this work, Milky Way-like refers to the total mass of each galaxy at the present day. The *Latte* galaxies were selected to have halo masses roughly the same as the Milky Way's: $M_{200} = 1-2 \times 10^{12} M_\odot$ where M_{200} refers to the total mass within the radius containing 200 times the mean matter density of the Universe. These simulations contain three types of material: dark matter, stars, and gas. The resolution of each dark matter particle is $3.5 \times 10^4 M_\odot$, and the initial mass resolution of baryonic material is $7070 M_\odot$. As noted earlier, each star particle should be thought of as a single stellar population. Because of this, as a star particle ages, it loses a portion of its stellar mass. Thus, at $z = 0$ a typical star particle has a mass of $\sim 5000 M_\odot$. In the *Latte* galaxies, star and dark matter particles have a fixed gravitational force softening length of 4 and 40 pc (Plummer equivalent), respectively. Gas cells have adaptive gas smoothing: in regions where there is a high density of gas cells, the gravitational force softening length can resolve down to a minimum of 1 pc.

Given its spatial and mass resolution, the *Latte* simulations can resolve massive star clusters with multiple star particles that represent portions of each OC.

And, as mentioned earlier, with *Latte*'s temporal resolution, these simulations are able to track in detail how star particles in OCs evolve in phase space over time.

3.2.2 Simulated Open Clusters

We use the same set of OCs used in Bhattarai et al. [15]. We have a total number of 361, 404, and 46 unique OCs in the simulations m12i, m12f, and m12m, respectively. These clusters were identified using fof algorithm [60]. This algorithm works by identifying members within a fixed distance known as the linking length. In this work, we adopt a linking length of 4 pc, which corresponds to our softening length. To ensure that the OCs are identified before the onset of core-collapse supernovae, we select OCs from stars that are less than 3 Myr old over the last 110 Myr of these simulations. We require a minimum of 5 star particles for a cluster to be identified, and thus with our fiducial

¹Where h is the dimensionless equivalent of the Hubble Parameter H_0 , Ω_Λ is the cosmological constant or vacuum density at present time, Ω_m is the total matter (dark plus baryonic) density today, Ω_b is baryonic matter density, σ_8 is the root mean squared fluctuation of density perturbations at $8 h^{-1} Mpc$ scale and n_s is the scalar spectral index.

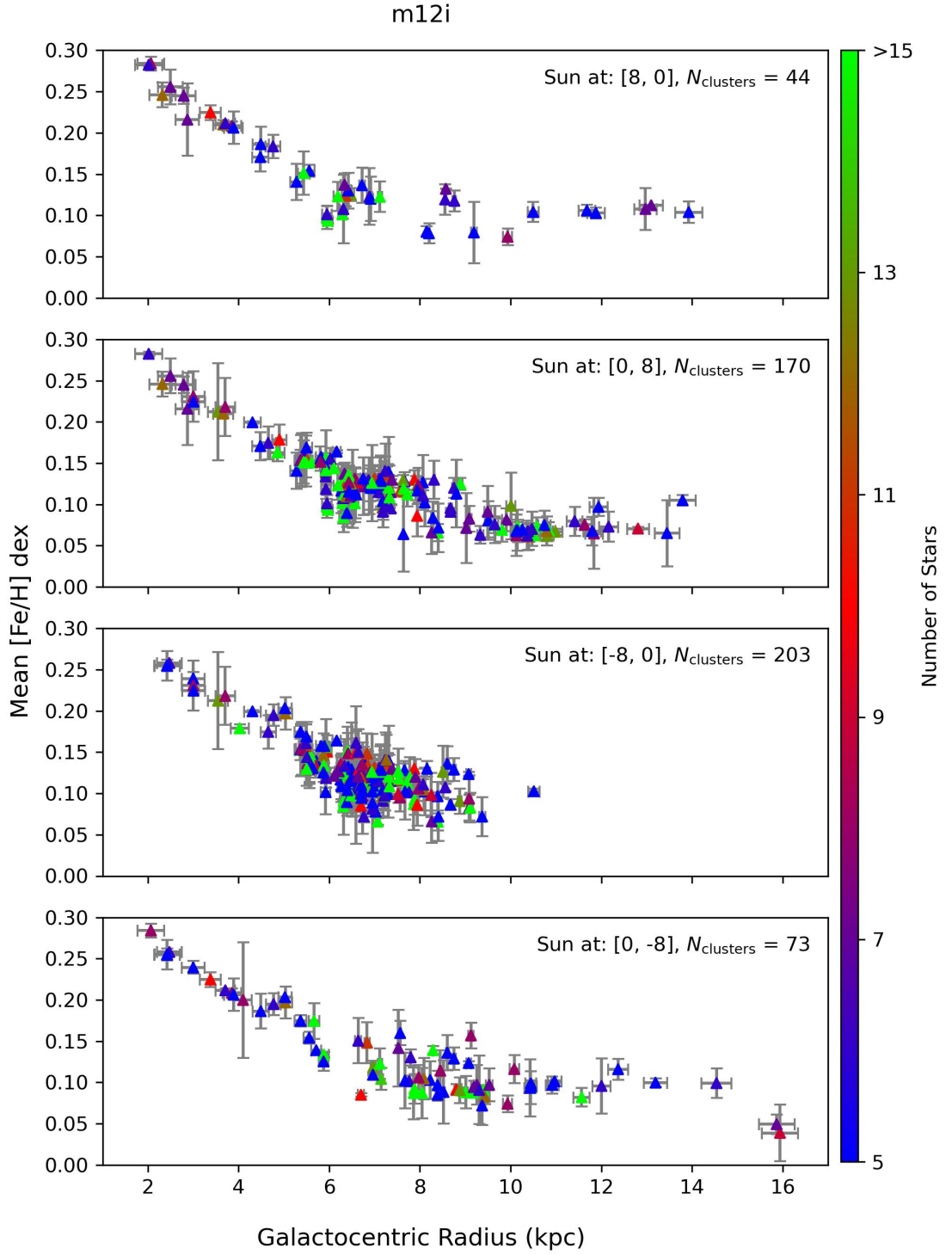


Figure 3.4: Scatter plot of mean $[\text{Fe}/\text{H}]$ vs birth radius of OCs for m12i with the Sun at four azimuthal positions at $R = 8$ kpc separated by 90 degrees. Each panel shows clusters within a cylindrical radius of 8.25 Kpc from each of the assumed locations of the Sun.

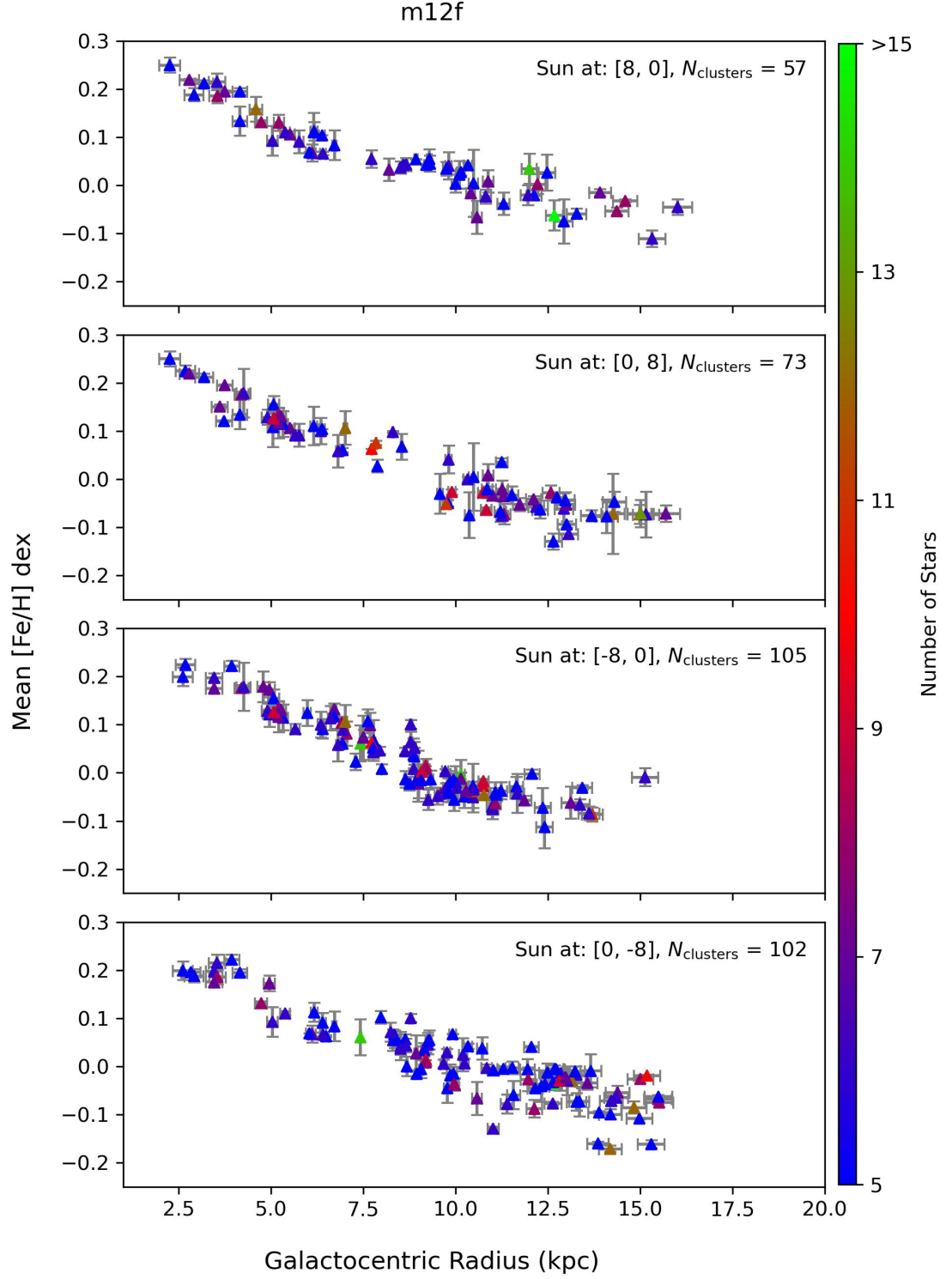


Figure 3.5: Scatter plot of mean [Fe/H] vs birth radius of OCs for m12f with the Sun placed at four azimuthal positions with $R = 8$ kpc separated by 90 degrees. Each panel shows clusters within a cylindrical radius of 8.25 Kpc from each of the assumed locations of the Sun.

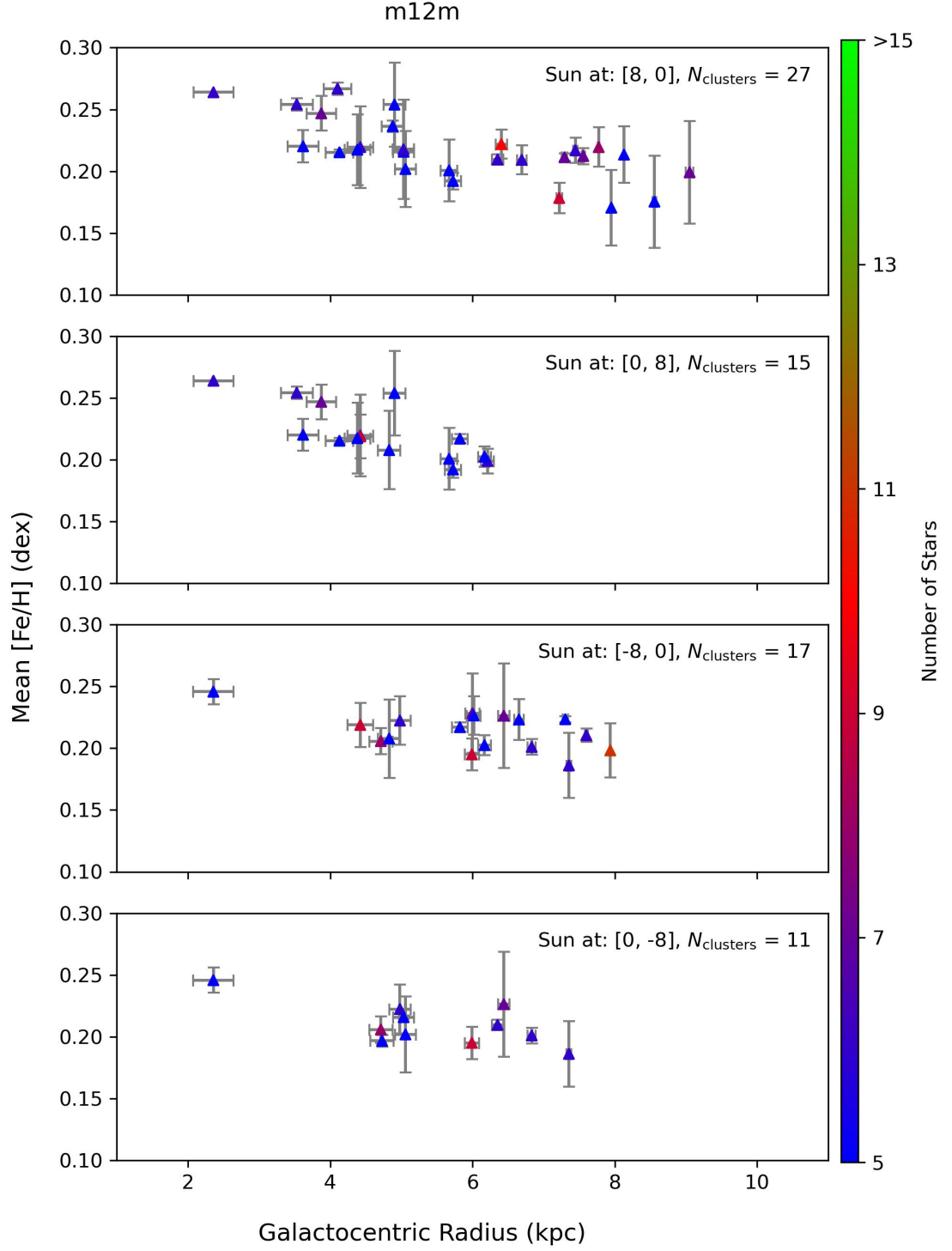


Figure 3.6: Scatter plot of mean $[Fe/H]$ vs birth radius of OCs for m12m with the Sun placed at four azimuthal positions 8 kpc away from the galactic center, separated by 90 degrees. Each panel shows clusters within a cylindrical radius of 8.25 Kpc from each of the assumed locations of the Sun.

mass resolution ($7070 M_{\odot}$) we resolve cluster down to a cluster mass of $10^{4.6} M_{\odot}$. We analyze the OCs from each galaxy simulation as a single dataset.

In Fig. 3.1, we show a top-down view of m12i, m12f, and m12m near the present-day (13.693 Gyr). The data have been binned in 200 pc x 200 pc squares and colored by the mean value of $[Fe/H]$ for stars younger than 1 Gyr old in each bin. This perspective shows the overall radial metallicity gradient in all three galaxies; while each galaxy has a different normalization and slope of the radial metallicity gradient, overall, it is clear that a negative radial gradient is present in the global disk for young stars at the present day. Plotted on top of the global average young star $[Fe/H]$ distribution are the contours of the density distribution of stars that are less than 50 Myr old. These contours highlight where there is an abundance of cold, dense gas and active star formation corresponding to spiral structure. The circles overlayed on top indicate the mean $[Fe/H]$ of OCs that were identified at this moment in time. As we see in Fig. 3.1, OCs generally reflect the global metallicity distribution of the overall disk. We note that the top-down perspective on the galactic disks shown in Fig. 3.1 highlights the overall radial metallicity gradient in all three galaxies; while each galaxy has a different normalization and slope of the radial metallicity gradient, overall it is clear that a negative radial gradient is present in the global disk for young stars at present-day [see 11, for further discussion].

3.2.3 Two Component fit of the Metallicity Gradient

We perform a two-component fit for the metallicity gradient using similar methods as in Donor et al. [48], Spina et al. [164].

We fit a piecewise linear function to the data such that the model gives us two lines that meet at a transition point called the "knee." The slopes and intercepts of these lines, as well as the position of the knee, are determined using the Markov Chain Monte Carlo (MCMC) method. Consider that the first line can be expressed by the linear equation,

$$y = m_1 \cdot x + b_1 \quad \text{for } x \leq k \quad (3.1)$$

Here, m_1 is the slope of the line and b_1 is the y-intercept.

Then the second line can be defined by another linear equation,

$$y = m_2 \cdot (x - k) + (m_1 \cdot k + b_1) \quad \text{for } x > k \quad (3.2)$$

In this case, m_2 is the slope of the second line. Then the combined equation for the two-component fit can be expressed as,

$$y = \begin{cases} m_1 \cdot x + b_1 & x \leq k \\ m_2 \cdot (x - k) + (m_1 \cdot k + b_1) & x > k \end{cases} \quad (3.3)$$

Using emcee to find the best fit parameters, we start with an initial guess of m_1 , b_1 , m_2 , k , and we perform repeated iterations until emcee finds the most likelihood estimation of these parameters. The dataset comprises measurements of the independent variable x , which is R_{birth} in our case, and the dependent variable y , which is the mean $[\text{Fe}/\text{H}]$ in each cluster.

Initial Parameter Estimation

We start the MCMC procedure with an initial guess for the parameters:

$$\theta_0 = [k_0, m_1^0, b_1^0, m_2^0] \quad (3.4)$$

where $k_0 = 10$, $m_1^0 = -0.05$, $b_1^0 = 0.1$, and $m_2^0 = -0.001$. These initial values are chosen based on prior knowledge and expectations. The knee has been known to fall within 8 to 16 kpc.

Log Prior

The log prior function incorporates prior knowledge about the parameters and ensures they remain within reasonable bounds:

$$\log P(\theta) = \begin{cases} 0 & \text{if } \begin{aligned} &k_{low} < k < k_{high}, \\ &m_{1\ low} < m_1 < m_{1\ high}, \\ &m_{2\ low} < m_2 < m_{2\ high} \\ &\text{and } b_{low} < b_1 < b_{high} \end{aligned} \\ -\infty & \text{otherwise} \end{cases} \quad (3.5)$$

Where k_{low} , k_{high} are the expected limits in k , which is decided based on the nature of the data. And similarly $m_{1\ low}$, $m_{1\ high}$ are the limits expected in m_1 , $m_{2\ low}$, $m_{2\ high}$ are the limits expected in m_2 and b_{low} , b_{high} are the limits expected in b . This function discards parameter sets that fall outside these predefined ranges to make sure that the MCMC explores only viable parameter values. All these limits are adjusted based on the nature of the dataset.

Log Likelihood Function

To evaluate how well the given set of model parameters fits the data, we define a log-likelihood function based on the assumption that the residuals between the observed and model values are normally distributed. We also assume that the measurement uncertainties are independent and Gaussian. Since we have adopted a piecewise linear fit model where the data is split at a transition point (knee), each segment is fit with its own slope.

For a given set of parameters $\theta = [m_1, b_1, m_2, k]$, we compute the model prediction for each cluster and compare it with the observed metallicity weighted by the total uncertainty at each point. We approximate the combined variance from errors in both mean $[\text{Fe}/\text{H}]$ and R_{birth} as:

$$\sigma_i^2 = \sigma_{y_i}^2 + \sigma_{x_i}^2$$

Then the log likelihood function is defined as:

$$\log L(\theta) = -0.5 \sum_{i=1}^N \left[\frac{(y_i - y(x_i|\theta))^2}{\sigma_i^2} + \log(2\pi\sigma_i^2) \right] \quad (3.6)$$

where y_i are the observed data points, $y(x_i|\theta)$ are the model predictions. This function measures the agreement between the observed data and the model predictions, taking into account the measurement errors, with a higher value indicating a better fit.

Log Probability

Log probability function is the sum of the log prior and the log likelihood:

$$\log P(\theta|\text{data}) = \log P(\theta) + \log L(\theta) \quad (3.7)$$

The value from the log probability function is used by the MCMC algorithm to evaluate the viability of the parameter sets.

MCMC Sampling

We employed the `emcee` package Foreman-Mackey et al. [53] to perform MCMC sampling. The number of walkers was set to 100, and the initial positions of the walkers were generated by perturbing the initial guess slightly:

$$\theta_i = \theta_0 + 10^{-3} \cdot \mathcal{N}(0, 1) \quad (3.8)$$

where $\mathcal{N}(0, 1)$ represents a normal distribution with mean 0 and standard deviation 1.

The MCMC sampler was run for 800 steps after resetting the sampler, with the first 500 iterations discarded as burn-in to allow the walkers to converge to the target distribution. The remaining samples were thinned and flattened to obtain the final parameter estimates. Each walker independently explored the parameter space, resulting in a posterior sample of size 100 (no. of walkers) * 800 (no. of samples) = 80,000 after flattening the chains.

The method used for the MCMC fit can be broken down into the following steps:

1. First, initialize 100 walkers around the initial guess for the four parameters (m_1, b, m_2, k) .
2. For each walker, generate a new guessed value for the parameters by taking a small random step.
3. Calculate the log prior and log likelihood for the guessed value.
4. Calculate the log probability and decide whether to accept or reject the new proposal based on the Metropolis-Hastings criterion Hastings [69].
5. Repeat the process for a specified number of iterations. In this work, we set the number of samples to be 800.

The MCMC sampling provides a distribution of parameter sets. The best-fit parameters were obtained by taking the median of the posterior distributions:

$$[k, m_1, b_1, m_2] = \text{median}(\theta) \quad (3.9)$$

Uncertainties in the parameter estimates were derived from the standard deviations of the posterior distributions.

3.3 Results

3.3.1 Scatter in Mean [Fe/H] vs R

In Fig. 3.2 we show the scatter plot for the mean [Fe/H] in each cluster vs the R_{birth} . The top, middle, and bottom panels are for m12i, m12f, and m12m, respectively. These plots set our expectations for the radial metallicity gradient. The error bars indicate a fixed mean uncertainty of 0.016 dex in mean [Fe/H] for each cluster, as derived from APOGEE data in our full OC samples using the OCCAM VI catalog from Myers et al. [135]. Similarly, to better incorporate errors into the mean [Fe/H] in each open cluster, an error in the mean [Fe/H] has been added randomly to individual clusters using the OCCAM VI catalog. As outlined in Bhattarai et al. [15], to add errors to the simulation, we first generate a normal distribution for the mean [Fe/H] of each cluster; the mean of the distribution is set to the true value from the simulation. We then set the standard deviation of the distribution by calculating the mean error for [Fe/H] from the high-quality clusters from the OCCAM cluster catalog, which is 0.022 dex. We then draw from this distribution a single value to represent the error in the mean [Fe/H] of each cluster. This process is repeated for the mean [Fe/H] value of all OCs. The distribution of this dataset with realistic APOGEE errors in each cluster is shown in Fig.3.3. The error in R_{birth} in both of these datasets has been assumed to be 5% per kpc for the distance of the cluster from a point that is 8 Kpc away from the center of the galaxy. We also further resample this dataset based on their location in the galaxy under four different assumed locations of the sun. This assumption helps to incorporate more realistic errors in R_{birth} as it helps to eliminate clusters that happen to be on the other side of the galaxy. Thus, we resample these clusters by strictly placing the sun at different quadrants. In Fig.3.4, 3.5, 3.6, we show such resampled sets of clusters that are selected based on different locations of the Sun in the galaxy. Only the clusters that are < 8.25 kpc from the assumed coordinate of the Sun are selected in each sample. We perform the two-component fit for all these sub-samples of clusters from these simulations separately in the latter sections.

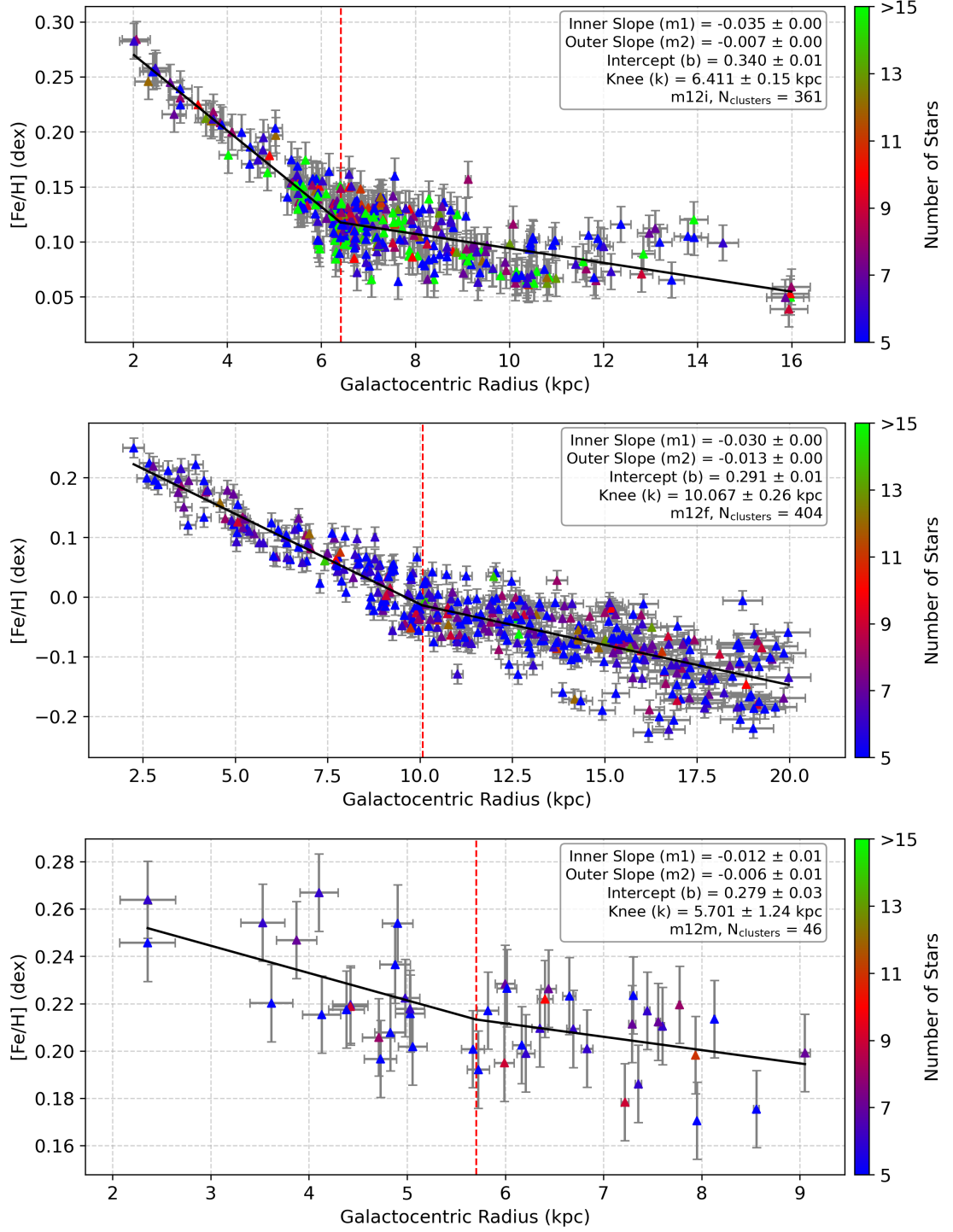


Figure 3.7: MCMC two-component fit of the OC samples shown in Fig. 3.2. OCs are color-coded by the number of stars, as in previous figures. The top, middle, and bottom panels are for m12i, m12f, and m12m, respectively. Position of the knee obtained using the fit is indicated by the dotted red line. All of the fits agree on a steeper inner slope and flatter outer slope.

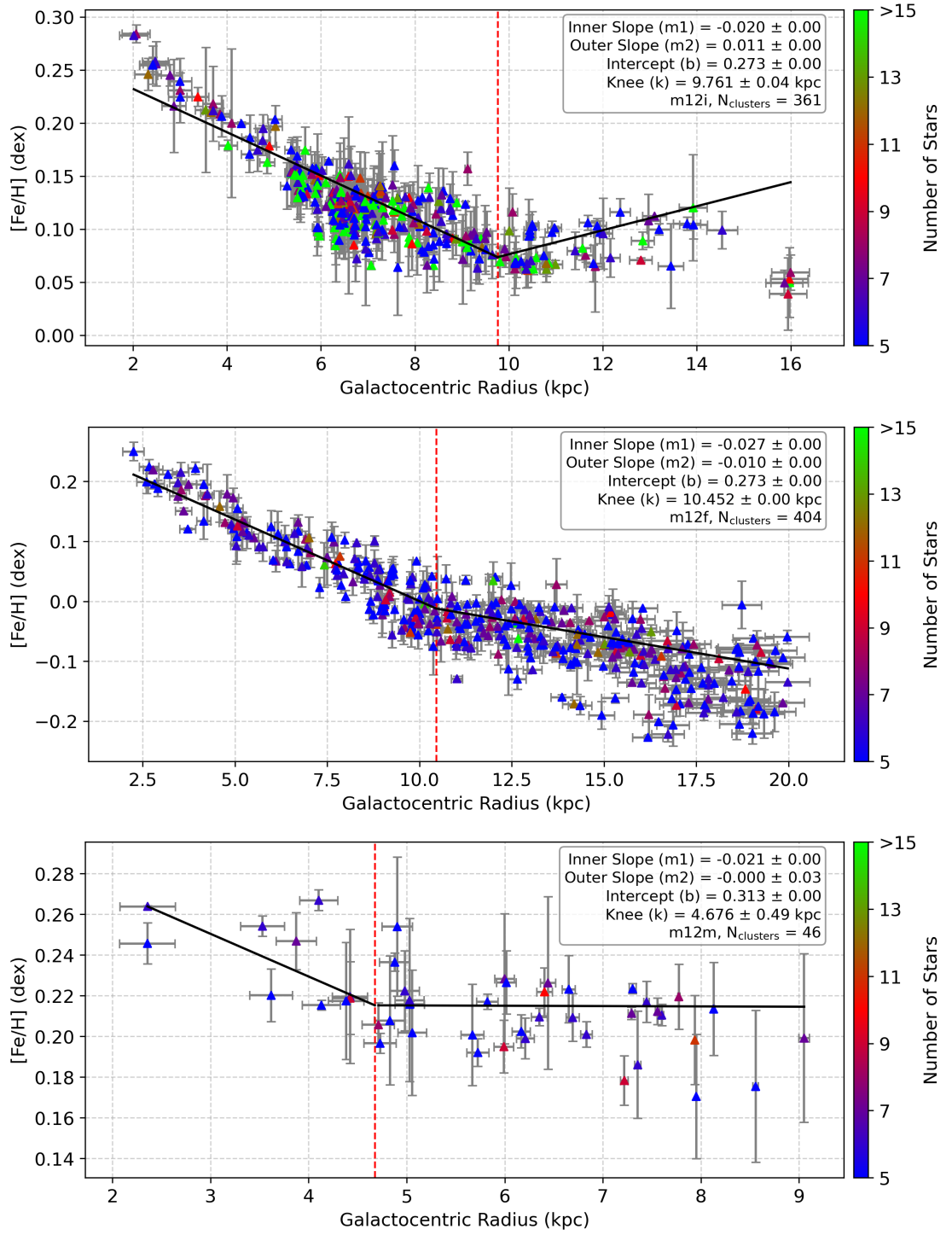


Figure 3.8: MCMC two-component fit of the OC samples shown in Fig. 3.3. The top, middle, and bottom panels are for m12i, m12f, and m12m, respectively. Nature of the fit changes drastically in m12i compared to the other two simulations.

3.3.2 Two-component fit for the radial metallicity gradient traced using MCMC for the FIRE OC dataset with a fixed average observational error in $[\text{Fe}/\text{H}]$ and realistic observational error in each cluster.

We first perform a two-component fit for the radial metallicity gradient for each simulation using the dataset shown in Fig.3.2. This is a simple case where a fixed mean error has been assumed for the mean $[\text{Fe}/\text{H}]$ of individual clusters. The resulting two-component fit for all three simulations from this dataset is shown in Fig. 3.7. We find a clear steeper inner slope and slightly flatter outer slope with a transition radius (knee) located at 6.41 kpc for m12i, 10.07 kpc for m12f and 5.70 kpc for m12m. This is in agreement with the steeper slope shown by Magrini et al. [112], Spina et al. [164], Carbajo-Hijarrubia et al. [29] in the Milky Way. We have shown the fits using more realistic errors in the next section.

We also performed the MCMC fit in the more realistic dataset with random APOGEE errors added to individual OCs. Using the dataset shown in Fig. 3.3, we now see that the nature of the fit changes. The change in the nature of fit is large for m12i compared to the other two simulations. Instead of having a flatter negative slope, we now see a positive outer slope in m12i. However, notably for m12f, the nature of the fit does not change much. This can be attributed to this simulation having the largest number of OC samples compared to the other two. The bottom panel showing the fit for m12m is poorly constrained due to a sample size of just 46.

3.3.3 Two-component fit of the radial metallicity gradient using OCs in the region fixing the sun at 4 different azimuthal positions 8 kpc away from the center and separated by 90 degrees

To mimic a more realistic case like that for observational data, we placed the sun at four different quadrants around the disk, each 8 kpc away from the galactic center. The coordinates we choose are (8,0), (0,8), (-8,0), and (0,-8). We then selected clusters that fall within the 8.25 kpc radius from the assumed location of the sun, which is realistically

closer to the extent to which surveys like APOGEE have observed OCs in the MW. This setup helps to explore how the inferred radial metallicity gradient changes when the observer's location is fixed at different azimuthal positions around the simulated galactic center. We have showcased these sub-samples for all three simulations in Fig.3.4, 3.5, and 3.6.

We then performed the two-component MCMC fit for each of these quadrant-based samples, and the results obtained from these fits for the sub-samples in m12i, m12f, and m12m are shown in Figs.3.9, 3.10 and 3.11 respectively. The corresponding fit parameters are also shown in each panel. We find that the nature of the fit changes noticeably depending on where the sun is placed, specifically for m12i and m12f. For m12i, the outer slope changes drastically in all three cases because of the way the distribution of the OCs changes in the outer regions of the disk upon making this special selection based on quadrants. Similarly, in the case of m12f, the distribution of the OCs changes drastically compared to the original distribution, thus shifting the position of the knee. In two of the cases, when the sun is placed at (0,8) and (-8,0), we find a steeper outer slope than the inner. This can be considered as an effect of under-sampled clusters in the outer region than the original dataset, and also due to large error bars in some clusters, which seem to dominate the fit. m12m, with only 46 clusters to begin with, shows the fits that are mostly unchanged when compared with the original dataset. However, due to this small sample size and even smaller sample sizes in these sub-selections based on the location of the sun, it is difficult to reliably trace the nature of the radial metallicity gradient using OCs from m12m.

These results highlight how the inferred radial metallicity gradient depends heavily on where the clusters are sampled. By changing the observer's location without changing the underlying physics of the galaxy in a relatively quiet period of the disk can produce different shapes of the gradient and the location of the knee. It further reinforces the need for azimuthally complete and unbiased cluster samples in order to accurately measure the radial metallicity gradients in the Milky Way and other disk galaxies.

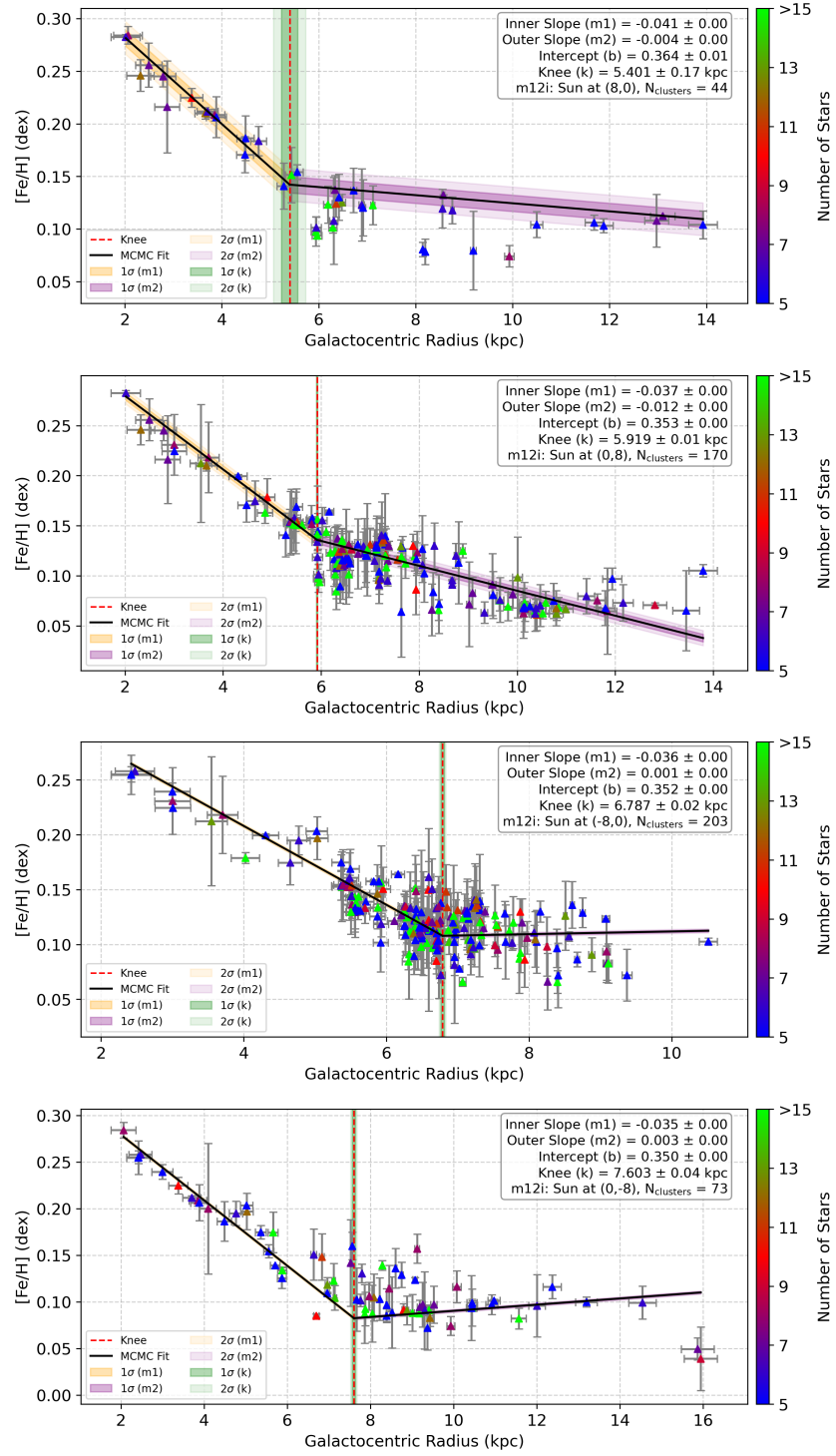


Figure 3.9: MCMC two-component fit of the OC samples shown in Fig. 3.4.

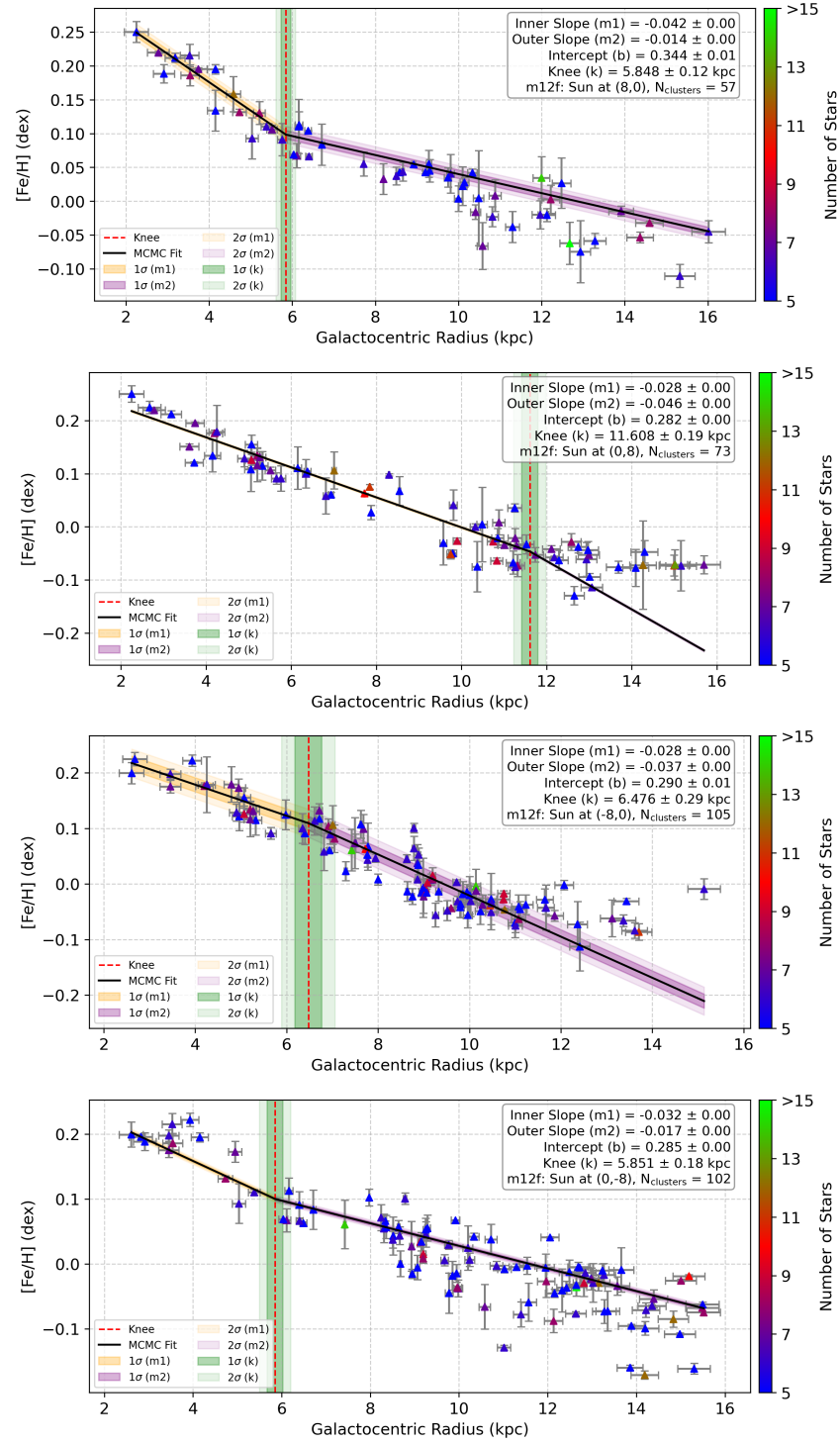


Figure 3.10: MCMC two-component fit of the OC samples shown in Fig. 3.5.

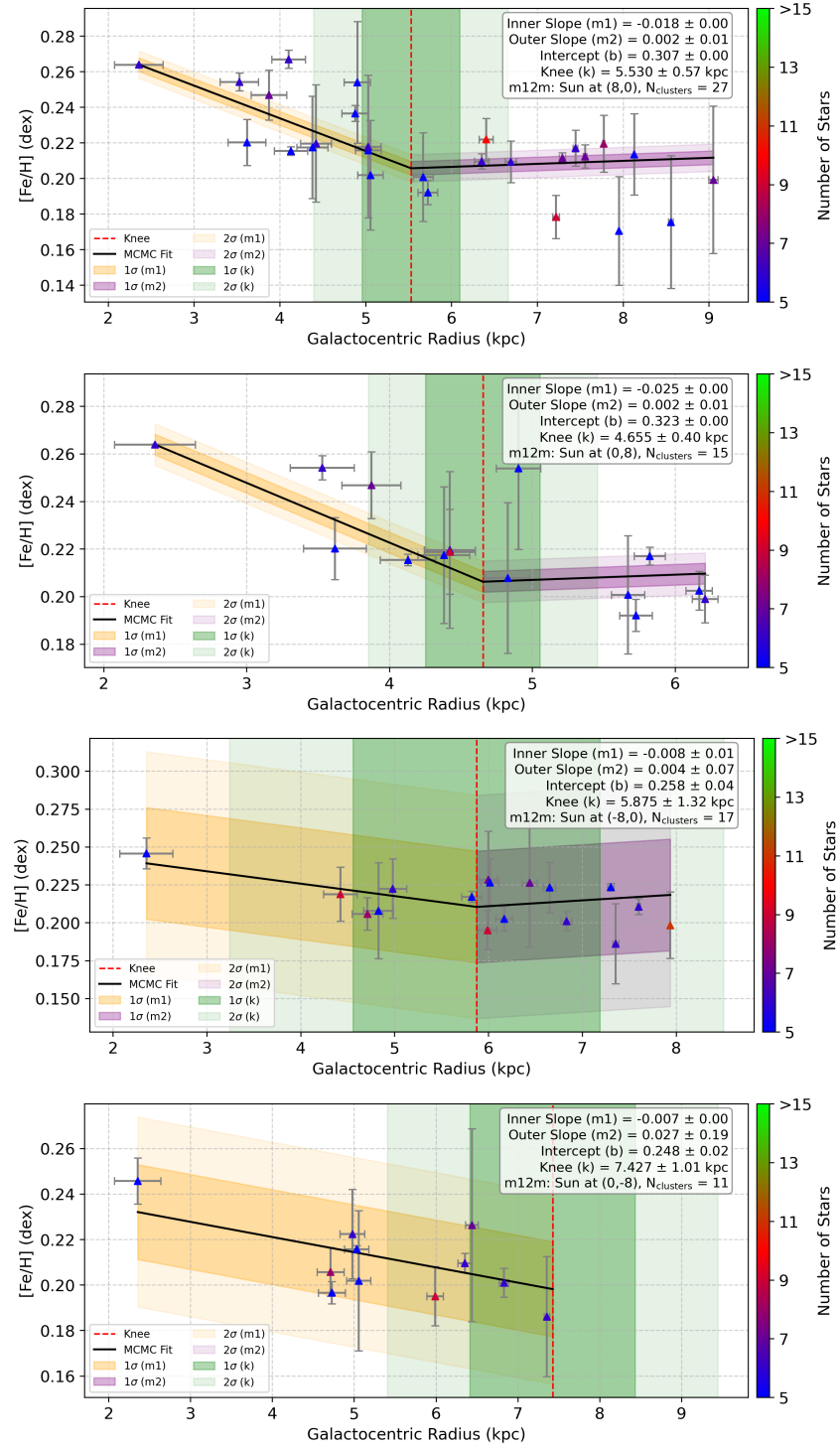


Figure 3.11: MCMC two-component fit of the OC samples shown in Fig. 3.6.

3.3.4 Two-component fit using bootstrapped samples using full sample with replacement

To better understand the impact of sampling on the radial metallicity gradient, we performed a bootstrapping analysis using the full OC samples from each simulation. We randomly selected clusters from the original dataset with replacement and repeated the two-component MCMC 1000 times for each of the simulations. A total number of bootstrapped samples was set to be equal to the total number of original samples in each case. Using this technique, we examined how much the fitted parameters inner slope(m_1), intercept(b), outer slope(m_2), and the transition radius (k) can vary as a result of drawing different realizations of the same underlying data.

In Fig.3.12 we show the best fit using bootstrapping with replacement for the entire OC sample shown in Fig. 3.3(which includes the simulated APOGEE errors for each cluster). For each simulation shown in each panel, we show the best fit line indicated by the solid black line and the 1σ and 2σ errors of these best fit parameters using bootstrapping. While the overall shape of the fit looks roughly similar to the case shown in Fig.3.8, the 1σ and 2σ ranges are larger with this overall bootstrapped result. This is an indication that different realizations of the same underlying data do impact the nature of the two-component fit.

Furthermore, to visualize how much the variability exists across these 1000 iterations, we show the distributions of these fit parameters in Fig.3.13. Each panel corresponds to the histograms for each parameter from inner slope(m_1), intercept(b), outer slope(m_2), and the transition radius (k). Similar bin-widths were used for all three simulations, and the corresponding standard deviation is labeled in each panel. The histograms for m12i, m12f, and m12m are shown in navy(dashed), red(dot-dashed), and blue(solid), respectively. These distributions provide a picture of how sensitive each simulation is to sampling. Among all the fit parameters, the position of the knee(k) is most affected by bootstrapping. There are multiple peaks in all three simulations for k , but it is interesting to note that the peaks for both m12i and m12f, however, fall between 9.5 to 10.5 kpc. Similarly, the peaks for m12i and m12f fall along a similar range for the inner slope, intercept, and the outer slope as well. The outer slope is very well constrained for all three simulations compared to all other parameters. With all three simulations showing

a peak near 0 for the outer slope, a flatter metallicity gradient after a transition point knee cannot be denied for OCs in the Milky Way.

3.3.5 Random sampling with replacement using a fixed sample size of 100, 150 and 200, 250, and 300

In §3.3.4 we demonstrated how bootstrapping the full sample of OCs from each simulation could result in a fit with a wider range of distribution. While bootstrapping helps us to understand how different realizations of the same full dataset can produce a broad range of fit parameters, to better understand how the number of OCs alone influences the reliability of the fit, we conducted an additional test where we drew sub-samples of OCs with replacement at fixed sizes. We used fixed sample sizes of 100, 150, 200, 250, and 300, and each sample size was drawn repeatedly 1000 times, and the parameters of those 1000 MCMC fits were analyzed for each sample size. This helps us understand the optimal number of OCs required to reliably trace the radial metallicity gradient using OCs. This is important from the observational perspective as the number of OCs available is limited by survey coverage, extinction, or selection criteria. By simulating this process in the simulated dataset, we get a picture of how sampling size alone can drive the uncertainty of the fit.

The resulting histograms for different sample sizes are shown in 3.14. The upper 4 panels are the resulting distributions of fit parameters from m12i, and the lower 4 panels are the resulting distributions from m12f. We didn't include m12m in this analysis as m12m has < 100 OCs. The smallest sample size (100 OCs) is shown in dot-dashed black, with increasing sample sizes plotted in dashed blue, solid green, solid orange, and dot dashed brown. As we increase our sample size from 100 to 300, the standard deviation of the fit parameters gradually decreases. This is an indication of the sampling bias in inferring the nature of the radial metallicity gradient fit using OCs. Aside from the outer slope m_2 , all other parameters are largely affected by the sampling bias in both simulations.

To better visualize this decrease in standard deviation of the fit parameters with increasing sample size, we have shown the changes in the standard deviation of these fit parameters in Fig. 3.15. The improvement in stability of the fit parameters is the

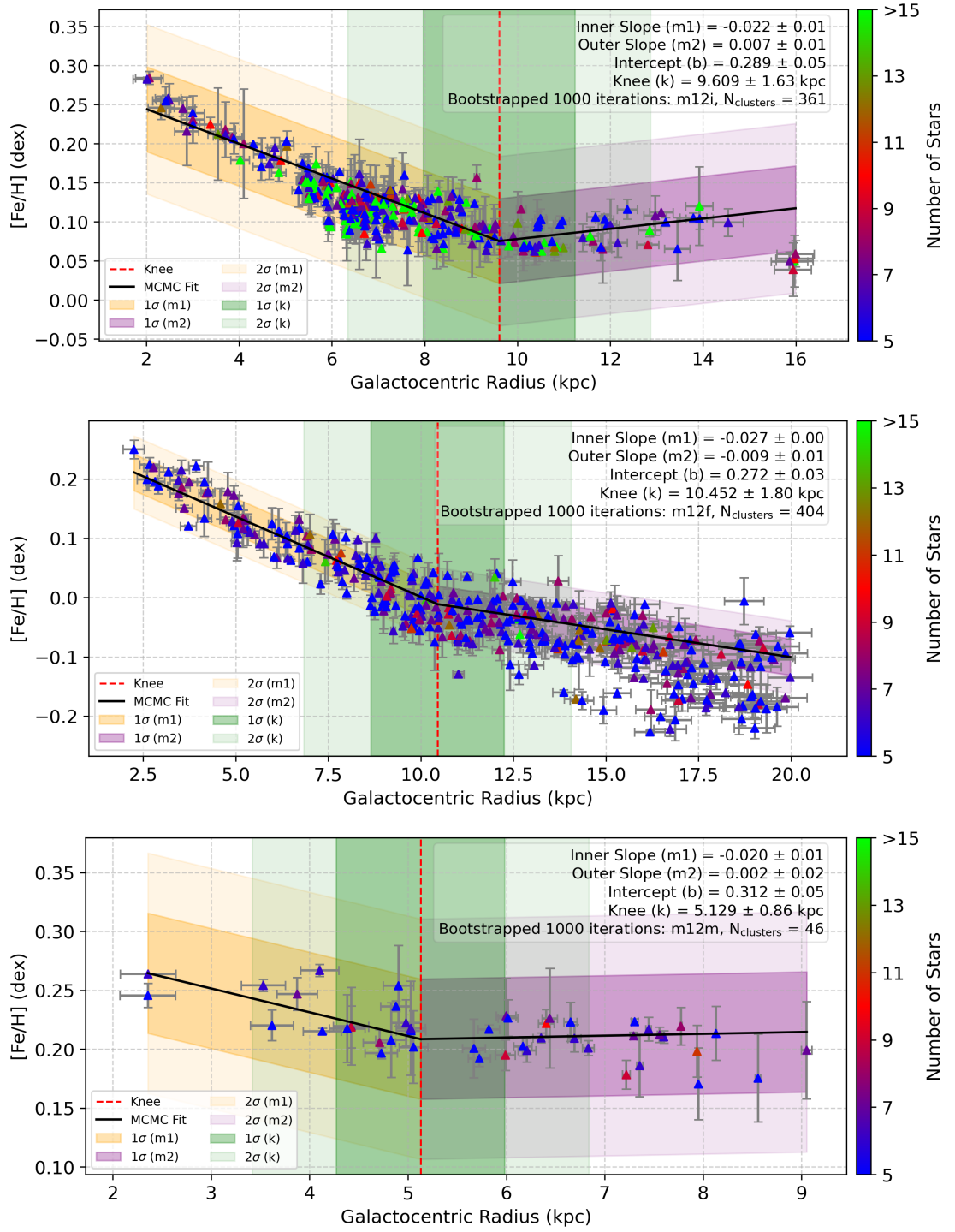


Figure 3.12: MCMC two component fit using bootstrapping with replacement for the full sample shown in Fig. 3.3.

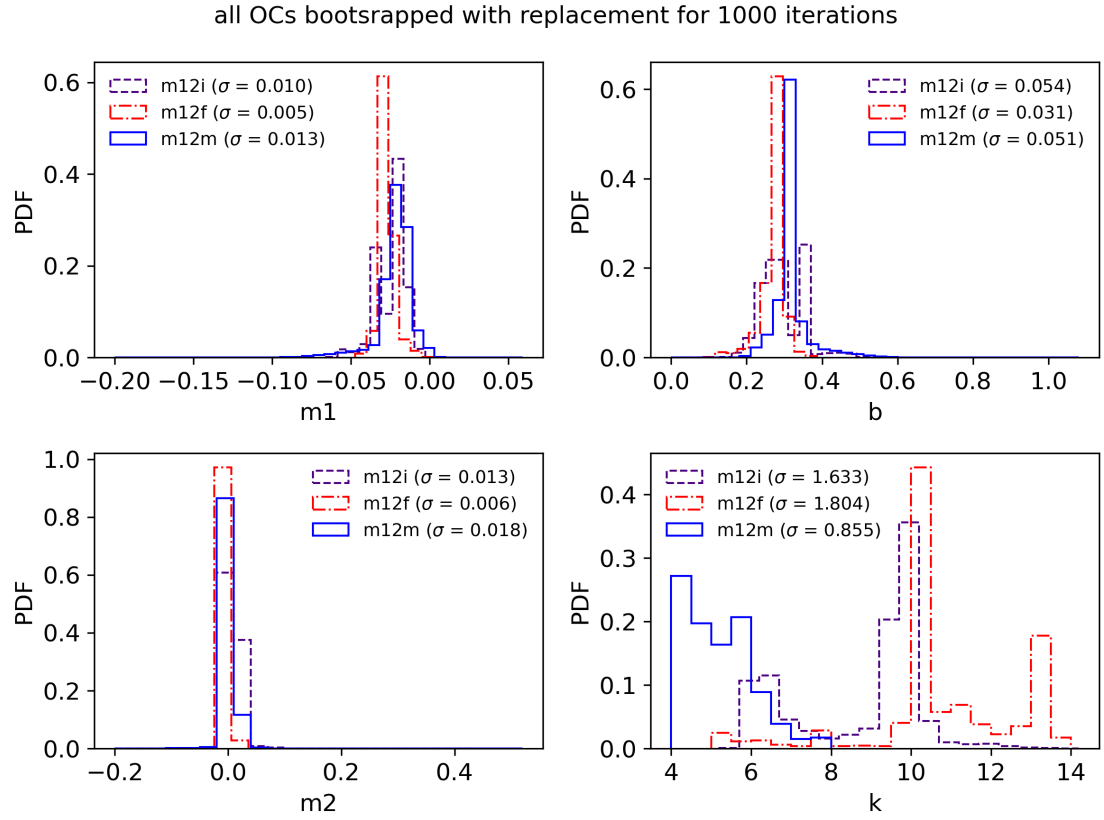


Figure 3.13: Histograms of the fit parameters for all three simulations obtained after bootstrapping the full sample with replacement for 1000 iterations for the sample shown in Fig.3.3. m12i represented in dashed navy, m12f in dotted dashed red, and m12m in solid blue. Each panel shows the histogram for the fit parameters inner slope(m1), intercept(b), outer slope(m2), and knee(k). The corresponding standard deviation for each fit parameter from each simulation is also indicated.

sharpest from 100 to 250 samples. This indicates that 250-300 well-distributed OCs can be used to reliably trace the radial metallicity gradient. These results tie directly back to the key motivation behind this work. Many past studies that used OCs to trace the radial metallicity gradient have used fewer than 100 OCs [e.g. 48, 135, 164]. Overall, this analysis reinforces the key theme of this work: sampling of OCs matters and not just how many clusters are used but also how they are distributed across the disk and the measurement uncertainties in $[\text{Fe}/\text{H}]$ and R_{birth} . While Bayesian techniques like MCMC are powerful, they are only as reliable as the data fed into them. This could be a motivation for upcoming surveys to look for OCs spanning a wide range of galactocentric radii with wide spatial coverage.

3.4 Discussion and Conclusion

In this work, we analyzed the radial metallicity gradient traced by young massive OCs formed in three cosmological simulations of the MW-mass galaxies from the *Latte* suite of FIRE-2 simulations [74, 176]. Using a two-component linear fit via the MCMC technique, we quantified the slope of the metallicity gradient and the position of the transition radius (knee) across multiple samples in all three simulations. We used an ideal full sample size with fixed and realistic error in R_{birth} and mean $[\text{Fe}/\text{H}]$ of OCs in §3.3.2, azimuthally separated datasets in §3.3.3, bootstrapped full sample in §3.3.4, and random sub-samples of fixed size in §3.3.5. Our analysis aimed not just to characterize the best fit parameters but also to understand how observational constraints – particularly sample size, measurement errors, and spatial completeness can influence the inferred nature of the radial metallicity gradient fit.

Across all three simulations, m12i, m12f, and m12m, we find strong evidence for a negative metallicity gradient with a steeper inner slope and a flatter outer slope after a transition radius. In all three simulations, the gradient is better fit by a piecewise two-component model with a transition radius located between 6 to 10 kpc. This two-component nature of the fit broadly agrees with what has been reported for the Milky Way based on recent APOGEE and Gaia OC samples, see Table 4 [29].

We also explored how the nature of the gradient is affected by observational factors.

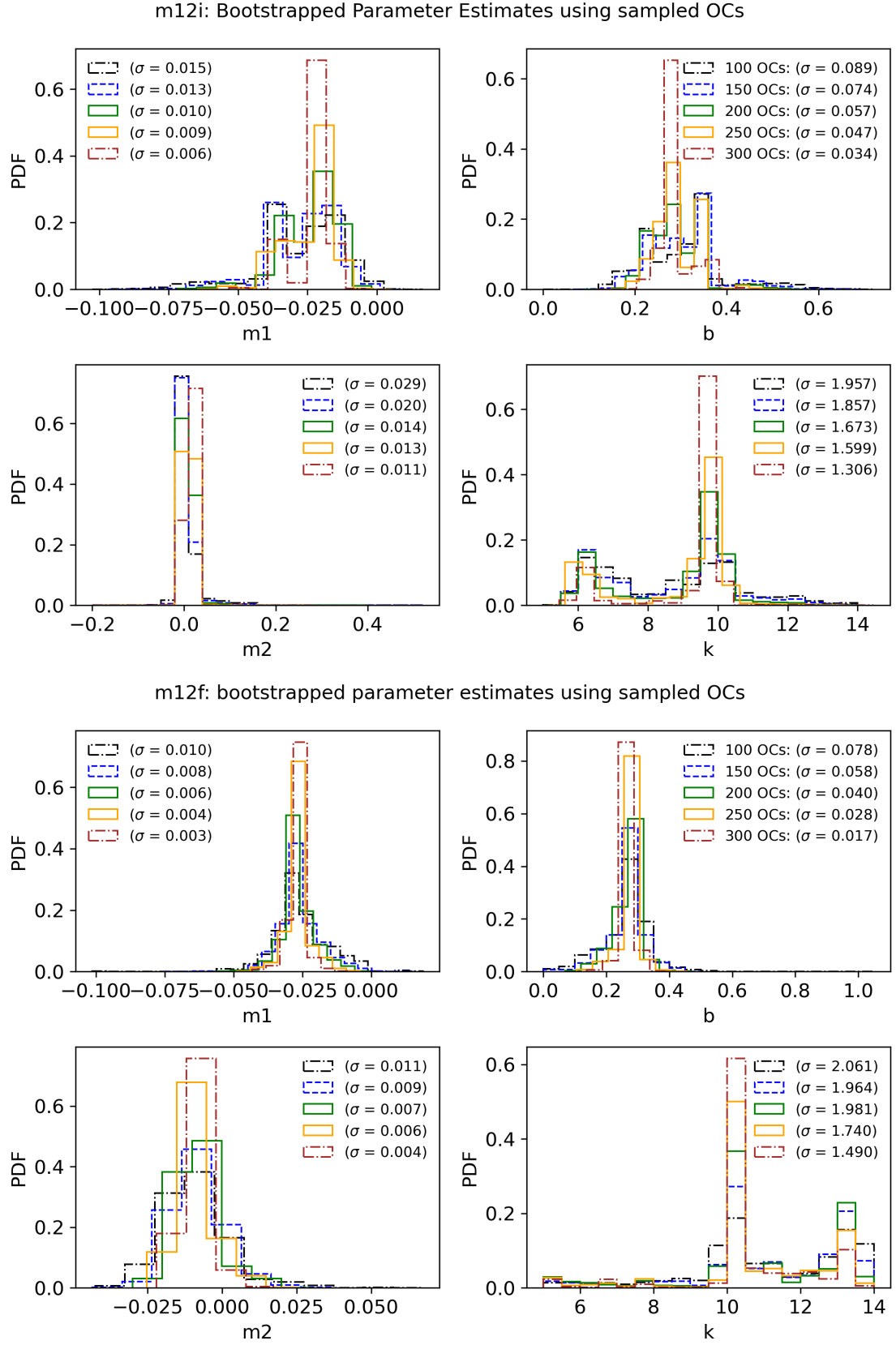


Figure 3.14: Histograms of the fit parameters obtained after randomly sampling at different sample sizes (100 samples represented in black, 150 in blue, 200 in green, 250 in orange and 300 in brown) with replacement for 1000 iterations for the sample shown in Fig. 3.3. m12m excluded in this analysis due to the small number of OCs.

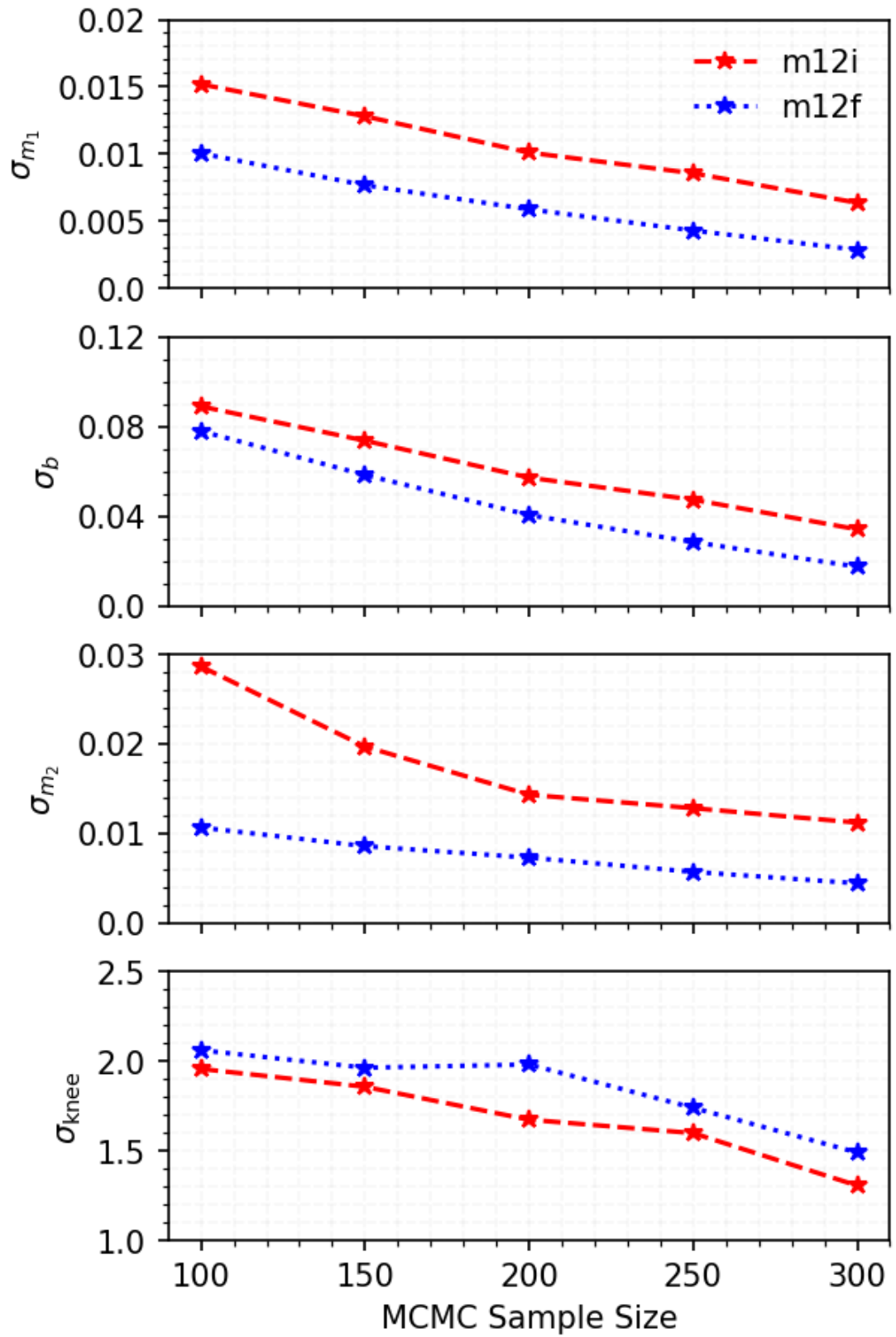


Figure 3.15: Standard deviation of the fit parameters obtained after randomly sampling at different sample sizes with replacement for 1000 iterations for the sample shown in Fig. 3.3.

When realistic $[\text{Fe}/\text{H}]$ uncertainties were added to each OCs, we find that the slope of the fit and the knee is less stable – particularly for simulations with a smaller number of clusters (e.g. m12i and m12m). Nature of the fit for m12f with a larger number of clusters (404 OCs) remained stable with very minor changes in the best fit parameters.

Our quadrant-based sampling of OCs where we positioned the observer “sun” at four different azimuthal positions separated by 90 degrees, each 8 Kpc away from the center, and only selected clusters within the 8.25 kpc circle showed that the nature of the inferred gradient could change significantly based on where the sun is located. The quadrant where we ended up with a smaller sample size was more affected. E.g., for m12f, which had a more stable fit even with fixed and realistic errors, now has fits that are not clearly constrained in all quadrants. The position of the knee is shifted way inward for ~ 10 kpc to 6 kpc. We also obtain more negative outer slopes when the sun is placed at (0,8) and (-8,0), which is mostly due to a few clusters that have dominant errors. However, azimuthal bias is clearly highlighted by all of the sub-samples as we see the diverse nature of fit parameters in the sub-samples from all four quadrants of all three simulations.

We analyzed the role of sampling bias in the nature of the radial metallicity gradient fits using OCs by conducting a bootstrapping analysis, generating MCMC fits for 1000 realizations of the full dataset from each simulation. We calculated the scatter in fit parameters and found that both the inner and outer slope has a typical scatter of 0.01, and the scatter in knee is 0.86 kpc to 1.63 kpc. The location of the knee obtained in two of the simulations with a good sample size is, for m12i with 361 OCs, the location of the knee is at 9.61 ± 1.63 kpc, and for m12f with 404 OC samples, the location of the knee is at 10.45 ± 1.80 kpc. m12m with just 46 OC samples has its knee located at 5.13 ± 0.86 kpc. The location of the knee broadly agrees with that has been shown in the MW OCs [112, 29, 164, 135, 48]. Spina et al. [164] have shown that the knee is located at 12.1 ± 1.1 kpc using a homogenized sample of 251 OCs, Magrini et al. [112] have shown that the transition point knee can be approximated at 11.2 kpc with their sample of 62 OCs.

The results of the fit parameters using sub-sampled OCs from m12i and m12f with different fixed sample sizes further reinforce the effect of sampling bias. Using sub-samples of size 100, 150, 200, 250, and 300 from the full cluster population with

replacement, we found that the fit parameters are unstable for smaller sample sizes and begin to converge around 250-300 sample sizes. These results suggest that conclusions for the nature of the metallicity gradient fit drawn from smaller datasets may be biased.

In conclusion, our results highlight sampling and observational bias while using OCs to trace the radial metallicity gradient of the disk galaxies. This emphasizes the importance of sample size, completeness, and smaller measurement uncertainties for offering a better outlook for measuring the radial metallicity gradient in the MW and beyond. As large-scale surveys like SDSS-VI, WEAVE, and LAMOST expand their coverage, improving the sample size, we would have a better understanding of our galactic home with a more accurate measure of the radial metallicity gradient.

3.5 Acknowledgments

BB acknowledges his participation in the ADONIS Symposium, which has helped to shape the motivation for this paper. ADONIS Symposium was supported by the Munich Institute for Astro-, Particle and BioPhysics (MIAPbP), which is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy EXC-2094 – 390783311. BB also acknowledges support from NSF grant AST-2109234. SL acknowledges support from NSF grant AST-2109234 and HST grant AR-16624 from STScI. AW received support from: NSF via CAREER award AST-2045928 and grant AST-2107772; NASA ATP grant 80NSSC20K0513; HST grant GO-16273 from STScI. We generated simulations using: XSEDE, supported by NSF grant ACI-1548562; Blue Waters, supported by the NSF; Frontera allocations AST21010 and AST20016, supported by the NSF and TACC; Pleiades, via the NASA HEC program through the NAS Division at Ames Research Center.

FIRE-2 simulations [176] <http://flathub.flatironinstitute.org/fire> are publicly available. Additional FIRE simulation data is available at <https://fire.northwestern.edu/data>. A public version of the GIZMO code is available at <http://www.tapir.caltech.edu/~phopkins/Site/GIZMO.html>.

Software: IPython [144], Matplotlib [79], Numpy [68], Scipy [172], emcee [53], halo_analysis [175], gizmo_analysis [174].

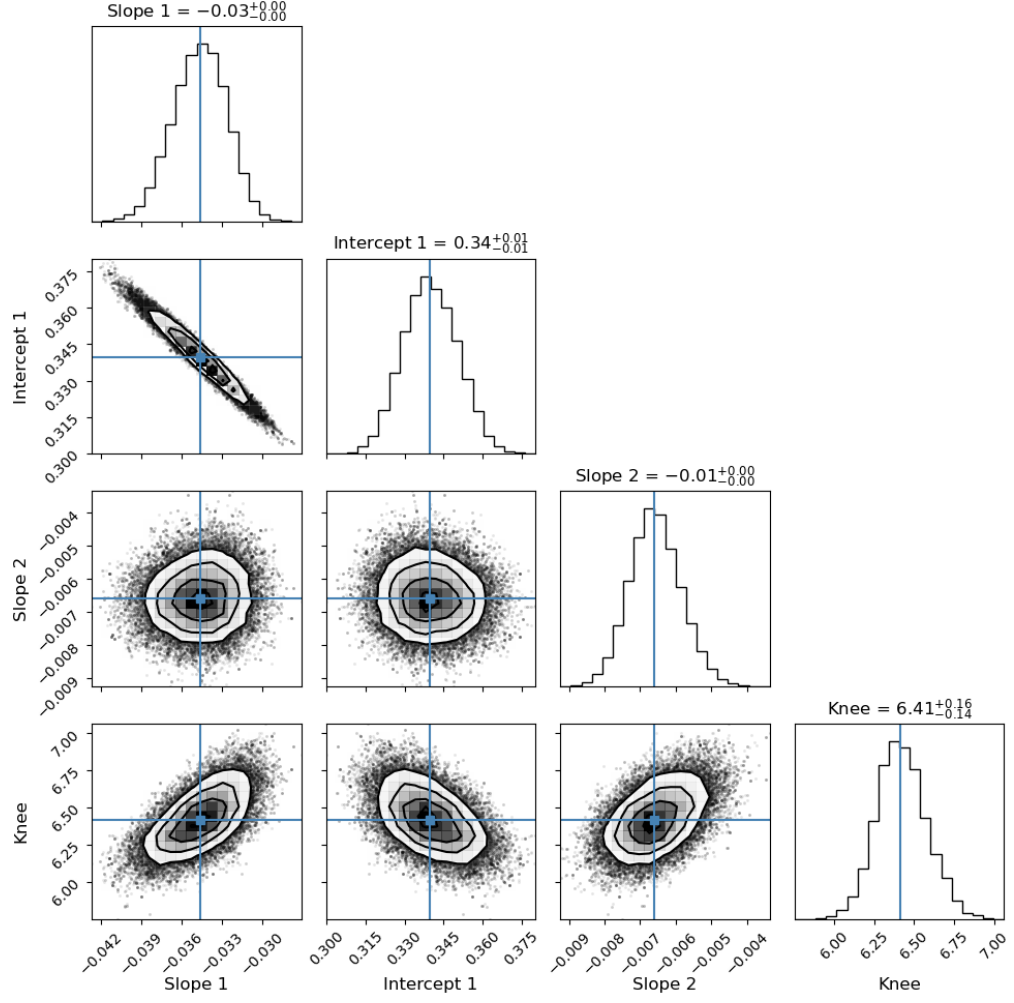


Figure 3.16: Corner Plot for the MCMC fit for m12i from Fig. 3.7

Appendix A. Corner Plots

The resulting corner plots from the fits are shown in Figs. 3.7 and 3.8 for m12i, m12f and m12m are shown here. The corner plots are well constrained for m12i and m12f, while for m12m, the contours are not very uniform. This is mostly due to a very small sample size of OCs present in m12m when compared with m12i and m12f.

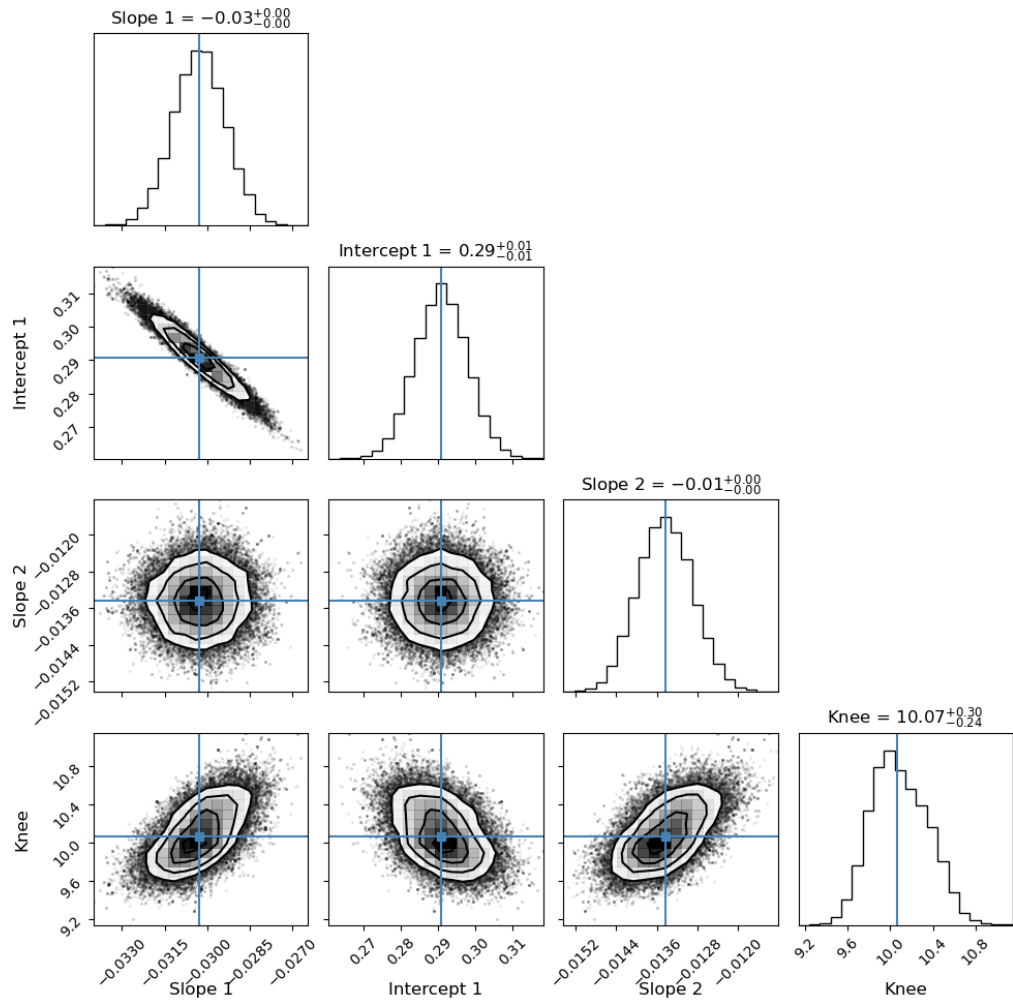


Figure 3.17: Corner Plot for the MCMC fit for m12f from Fig. 3.7

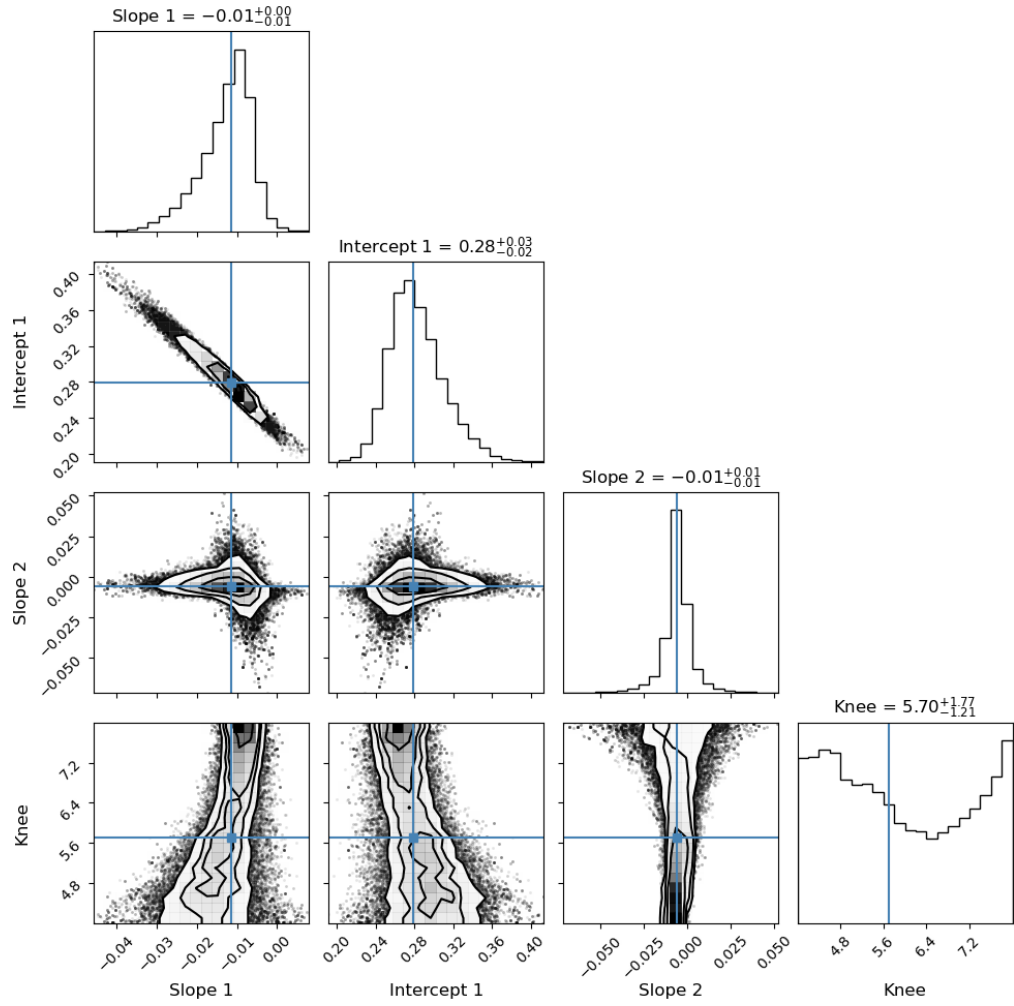


Figure 3.18: Corner Plot for the MCMC fit for m12m from Fig. 3.7

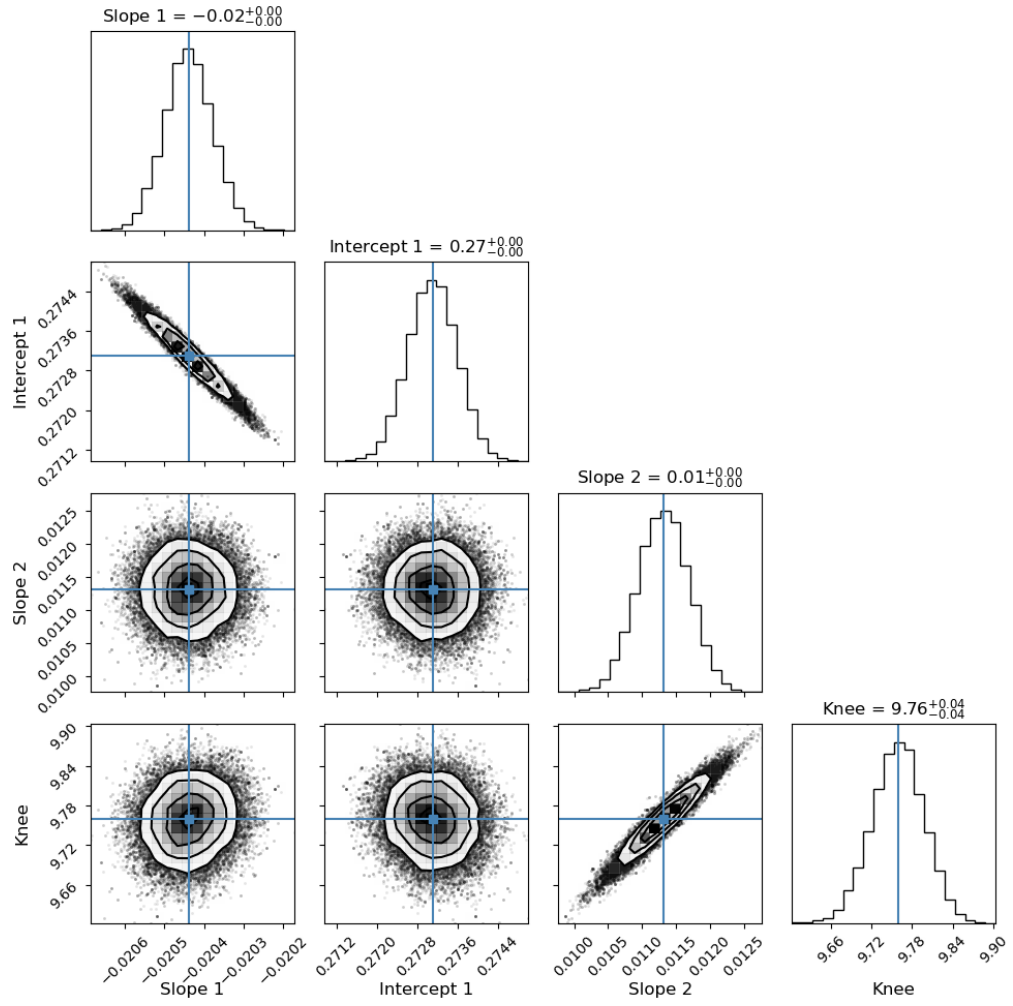


Figure 3.19: Corner Plot for the MCMC fit for m12i from Fig. 3.8

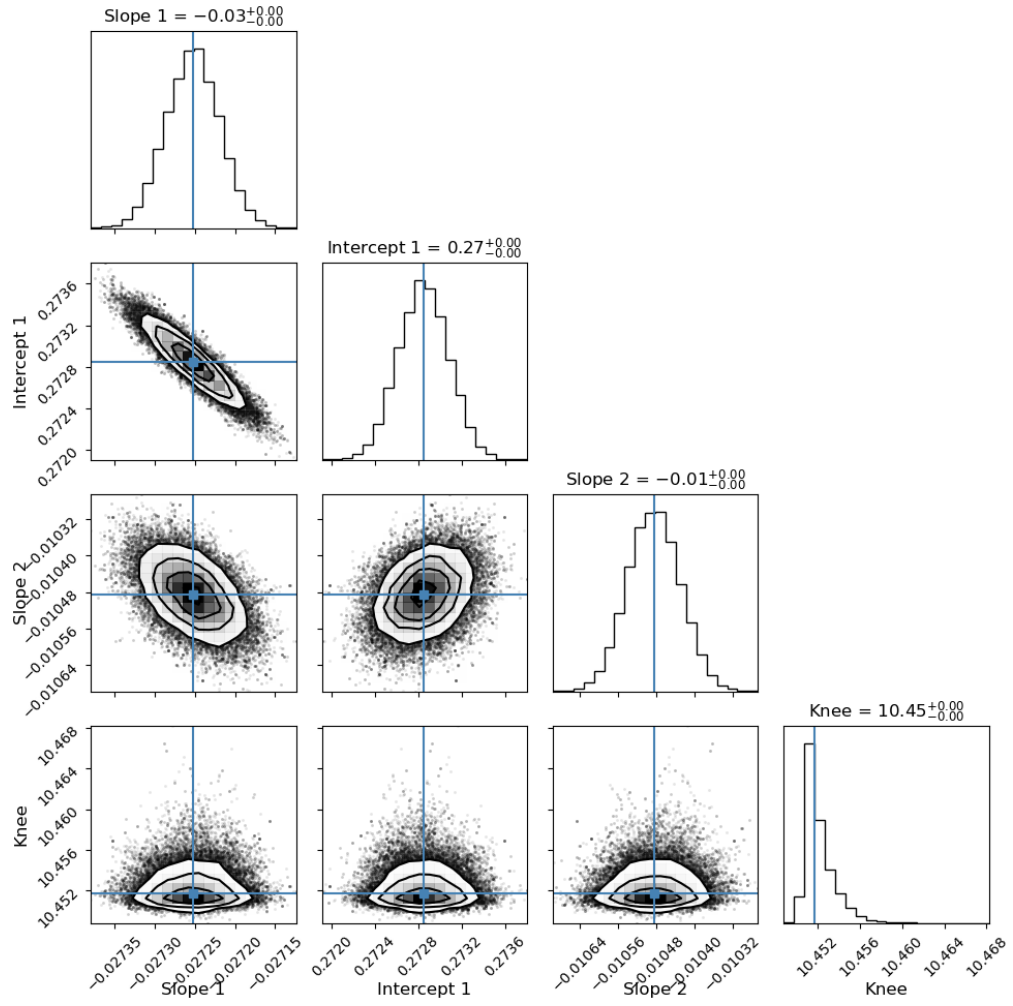


Figure 3.20: Corner Plot for the MCMC fit for m12f from Fig. 3.8

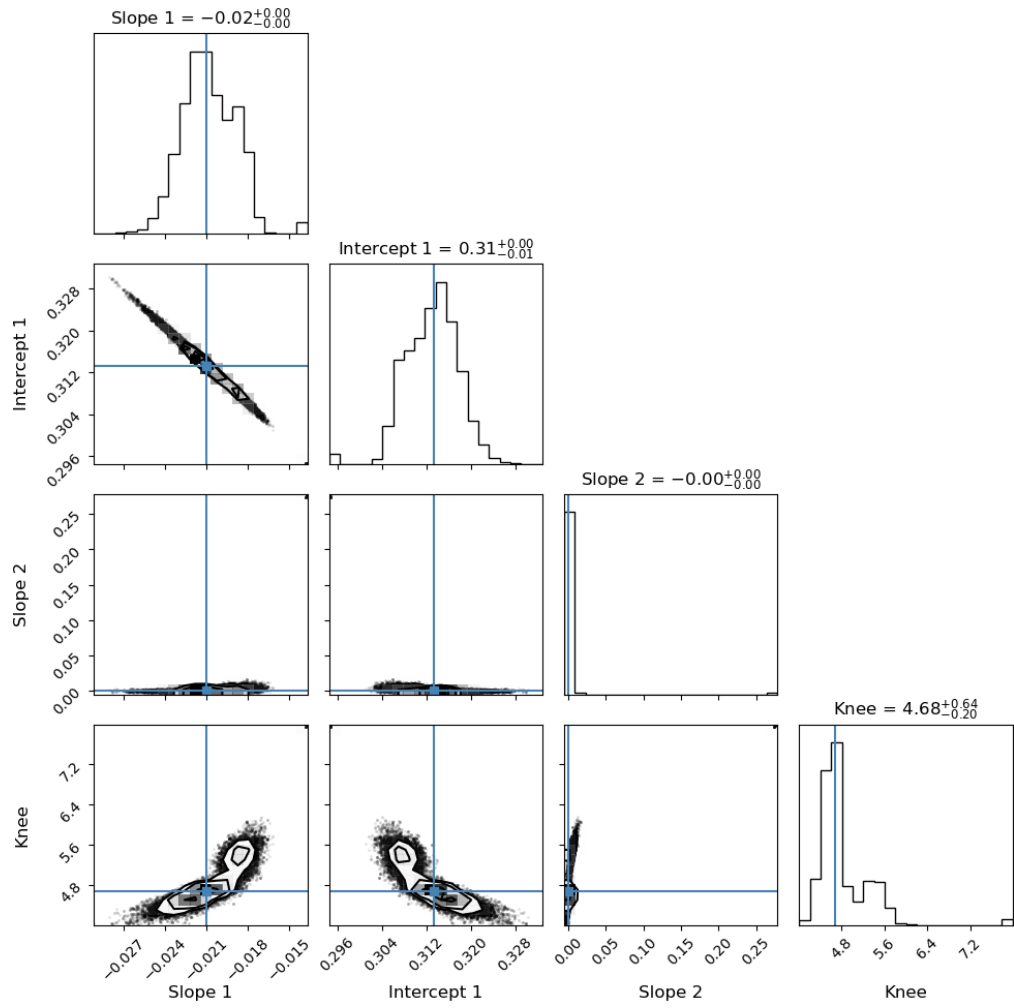


Figure 3.21: Corner Plot for the MCMC fit for m12m from Fig. 3.8

Chapter 4

Resonance Sweeping in Barred Galaxy Simulations

4.1 Impact of Large Scale Galactic Structures like Bars on stellar dynamics

OCs that are gravitationally bound dissolve in timescales of a few hundred million years as member stars get accelerated eventually due to two or more than two body interactions [61]. Once the member stars are accelerated such that their velocities are larger than their escape velocity, OCs dissolve and get mixed in the disk. The mechanism of such escape has been theoretically studied [e.g. 100, 99, 61] but has not been studied in simulations that incorporate stellar feedback processes in a cosmological context. Once the stars from the OCs escape, various dynamics in the disk can disperse them around. Large-scale structures like the galactic bar, material arms, and gas bubbles that are present in the galaxy can impact such dispersal and play a role in where such stars end up later in time. In this chapter, we study the impact of large-scale structures in stellar substructures like OCs, stellar associations, and moving groups.

Stellar associations are a group of stars that are loosely bound, unlike star clusters and moving groups are streams of stars that move together and may share common origins [96]. Such moving groups can be seen in the solar neighborhood as overdensities of stars in velocity space [4]. It is important to study how such stellar substructures form

in simulations to gain insights into the observations of the Milky Way.

4.1.1 Resonance Sweeping in Barred Galaxy Simulations

To study the impact of large-scale structures like bars, I used a different type of N-body simulation without gas from Hunt et al. [78] for this work, as it allows for controlled analysis. Without the dynamical impact of gas, it is easier to quantify the impact on stellar substructures due to a galactic bar. One of the ways a galactic bar can impact stellar dynamics is through a process called resonance. Resonance occurs when stars move at the same rate as the large-scale structures and have their orbits modified by them. Roughly half of known disk galaxies have a prominent, rotating stellar bar at its center which is an over-density of stars [e.g. 156, 26]. Galactic bars have their own rate of spin and several analytic simulations and theories have suggested that the rate of spin slows down over time due to dynamical friction. The spin rate of the bar is known as the pattern speed (Ω_p) [e.g. 173, 71, 45, 121]. In a bar that is slowing down (pattern speed decreasing), some stars that are in resonance can slow down concurrently with this deceleration. Such a process of trapping and dragging of stars across the disk is known as resonance sweeping. Orbits of stars can get trapped in resonance with the bar if the pattern speed of the bar (Ω_p) gets equal to certain combinations of the radial frequency (Ω_r) and the azimuthal frequency (Ω_ϕ) of the orbit traced by the star. The popular types of resonances that we study in this work are:

- **Corotation Resonance**

In this type of resonance, the spin rate of the bar, also known as pattern speed (Ω_p) matches the azimuthal frequency of the star (Ω_ϕ) i.e. $\Omega_p = \Omega_\phi$.

- **Outer Lindblad Resonance**

In this type of resonance, the pattern speed of the bar (Ω_p) satisfies the following condition. $\Omega_p = \Omega_\phi + \Omega_r/2$. Where Ω_r is the radial frequency of the star.

Assuming the bar slows down with time, it is important to understand how this deceleration impacts the kinematics in the solar neighborhood. Hercules stream is a moving group that can be seen in Gaia DR2 data. Resonance sweeping can be one way

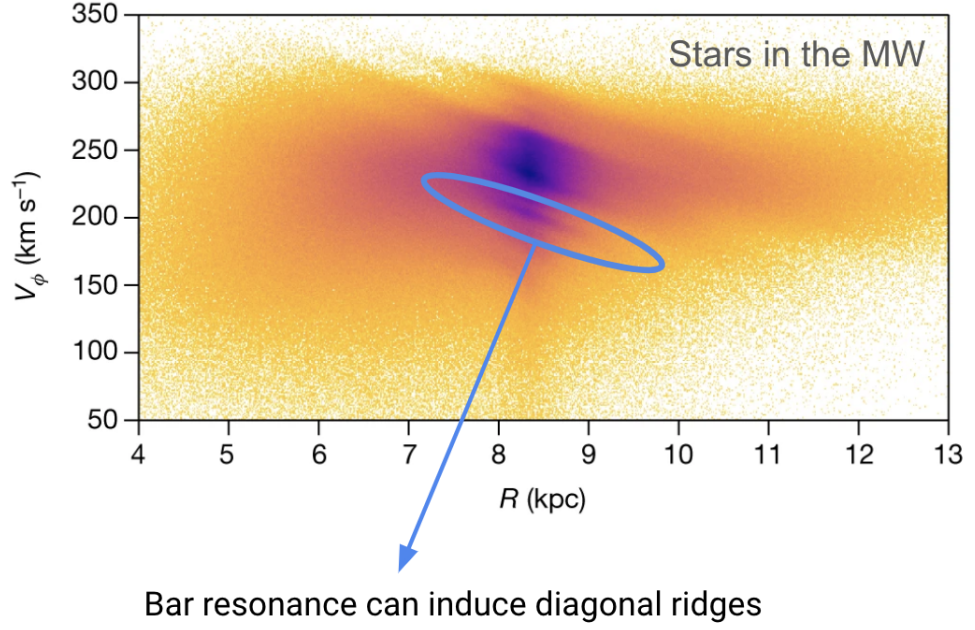


Figure 4.1: Diagonal ridges in Gaia DR2

[extracted from Antoja et al. 2018 5]

to explain this moving group (other examples include non-sweeping resonances, spiral arms, satellite perturbation of the disc, or phase mixing). Fig. 4.1 from Antoja et al. [5] shows the position and velocity distribution of stars in the Milky Way. We can see diagonal ridges with over-densities and gaps in the position velocity space, indicating a kinematic substructure which is potentially due to resonance [e.g. 127]. If it is actually due to resonance, then these stars were gravitationally captured by the rotating bar in the past. As the bar slowed down, these stars travelled further out in the galaxy, keeping their orbital period in sync with the bar's spin. We can investigate such a process of resonance sweeping in a realistic N-body simulation where the ground truth is known.

4.1.2 Results

Chiba et al. [35] in their analysis using a test particle simulation showed that different spin-down rate of bar captures different amounts of stars in corotation. In Fig. 4.2, I have a plot from Chiba et al. [35] where we can see the distribution of azimuthal velocity (V_ϕ) vs radial velocity (V_r) in the solar neighborhood for two different models. On the

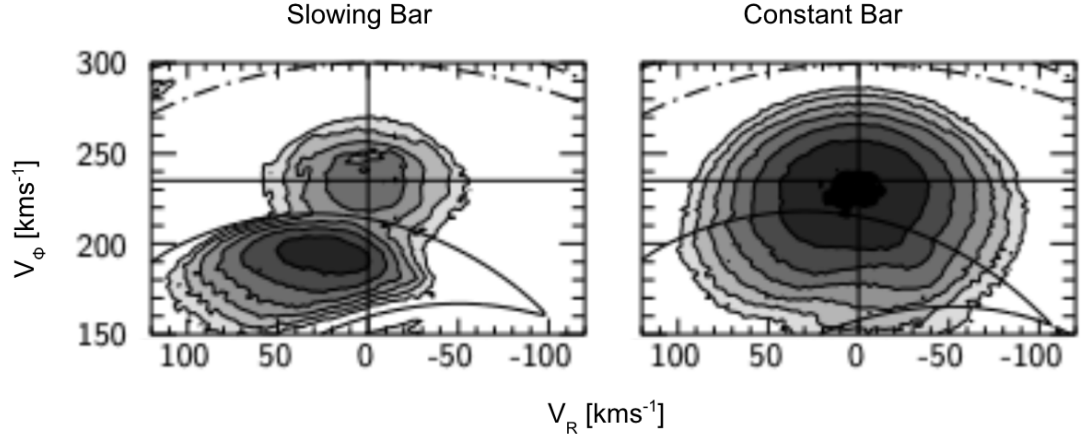


Figure 4.2: Velocity distribution of test particle stars in solar circle from Chiba et al. 2021. Using a test particle simulation they observed over-densities in V_ϕ/R space in the case of a slowing bar.

[extracted from Chiba et al. 2021 35]

right, we have a case where the bar has a constant spin rate, and on the left, we have a case where the bar has a spin rate that is slowing down. Notably, the velocity distribution is uniform in the case of a constant bar, but in the case of a bar that is slowing down, we can see a portion of the velocity distribution is captured inside the resonant separatrix (diagonal contour in left-hand panel of Fig. 4.2). In this test particle simulation, Chiba et al. [35] showed that resonance sweeping occurs when we have a bar that is slowing down. However, it remains to be seen if such an effect is noted in a more realistic simulation that contains self-gravity between particles.

This analysis using a billion particle N-body simulation represents a significant step forward, as this simulation is more realistic than the model considered by Chiba et al. [35] as it has self-gravity between particles and is evolved for a significant period of time. This simulation is based on Widrow and Dubinski [178] and Hunt et al. [78]. We can see in the top-down view of the galaxy shown in Fig. 4.3 that there is a prominent bar at the center and there are pronounced spiral arms. The gif [here](#) shows the galaxy from the bar stationary frame evolving over time.

In Fig. 4.4, we can see strong diagonal features that have evolved with time at the position where we have placed the Sun. A gif using different moments from the simulation that shows the evolution of such ridges can be accessed from this [link](#). Such

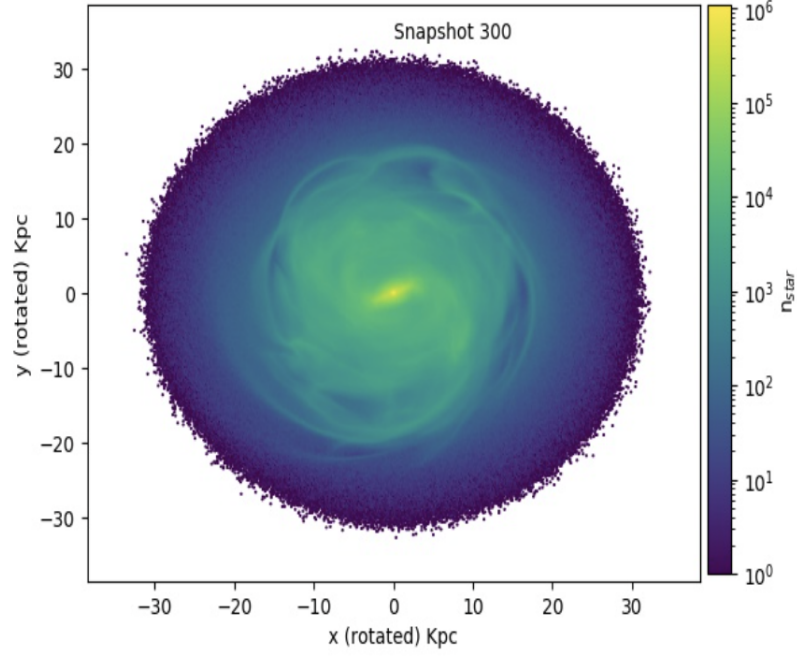


Figure 4.3: Top-down view of the simulated galaxy. A well-evolved bar can be observed at the center. The color bar indicates the number of stars in the region.

diagonal features could be due to resonances which I show in Fig. 4.4.

To check for resonance conditions mentioned in section 4.1.1, we need to calculate the frequencies of stars. One of the ways this can be done is using the Galactic dynamics Python package AGAMA [171]. To select stars that are in resonance, I have selected the stars that fall within $\pm 0.1 \text{ km s}^{-1} \text{ kpc}^{-1}$. To calculate the spin rate of the bar, I calculated the rate of change in bar angle over time. Fig. 4.5 shows the measured pattern speed of the bar in our simulation. In the first 1 Gyr of the simulation, the bar is still in a burn-in period (not in dynamic equilibrium due to the setup of the simulation) and is ignored in my analysis. After burn-in, in the earliest 2 Gyr period I consider, the bar slows down at the rate of $7.37 \text{ km s}^{-1} \text{ kpc}^{-1} \text{ Gyr}^{-1}$. These results are also comparable to the slowing rate of bar shown in Chiba et al. [35].

In the upper panel in Fig. 4.6, I show the velocity and space distribution for the entire population of stars in a region of ± 5 degree slice in the disk (in an analogous volume to the Sun). In the lower panel, I have overplotted the velocity and space distribution of the stars that are in Corotation Resonance (CR), represented in black, and the stars that are

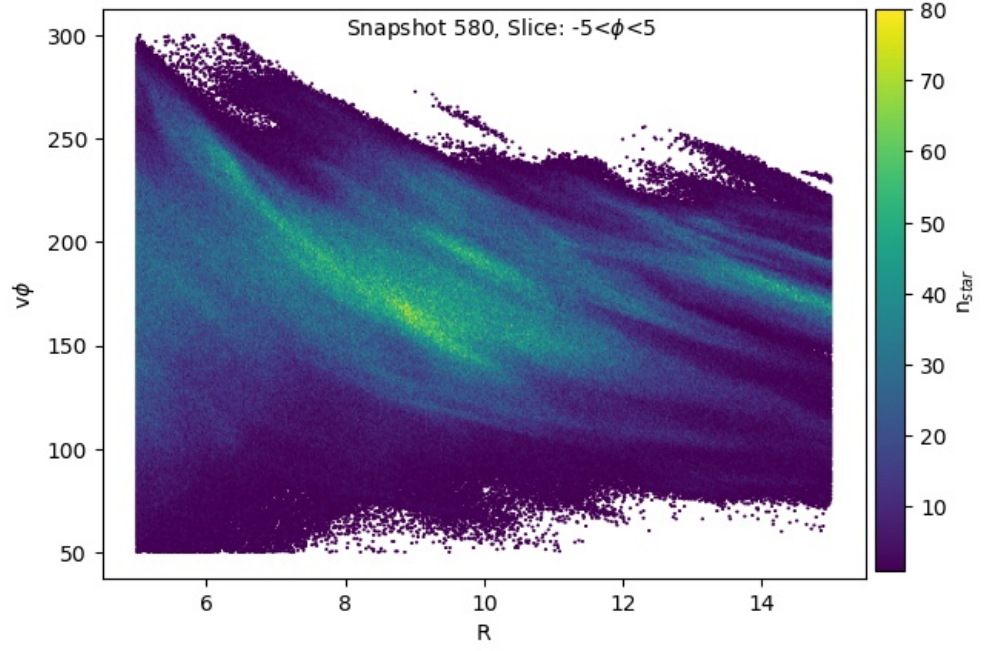


Figure 4.4: Ridge structures seen in V_ϕ/R for test particle stars from a -5 to 5 degree region in the disk.

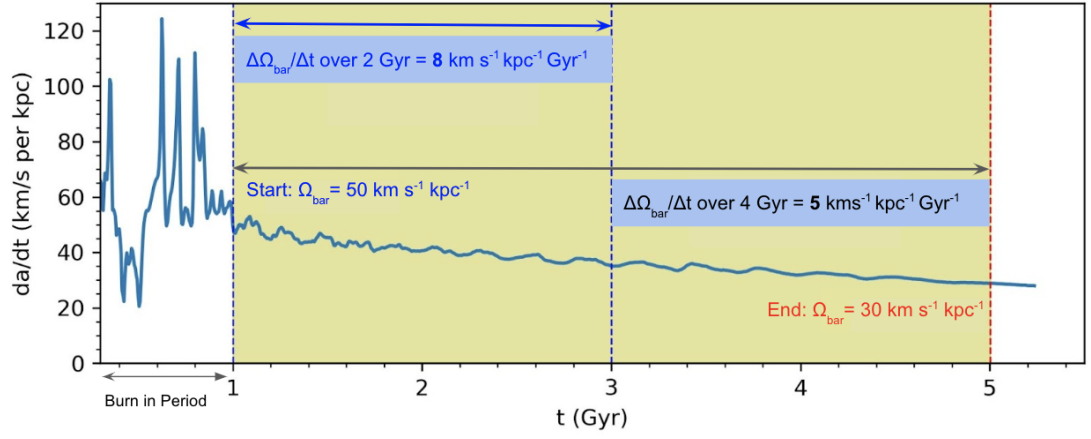


Figure 4.5: Pattern speed of the bar over time in our simulation. The bar pattern speed decreases over time, thus matching the slowing bar case from Chiba et al. 2021.

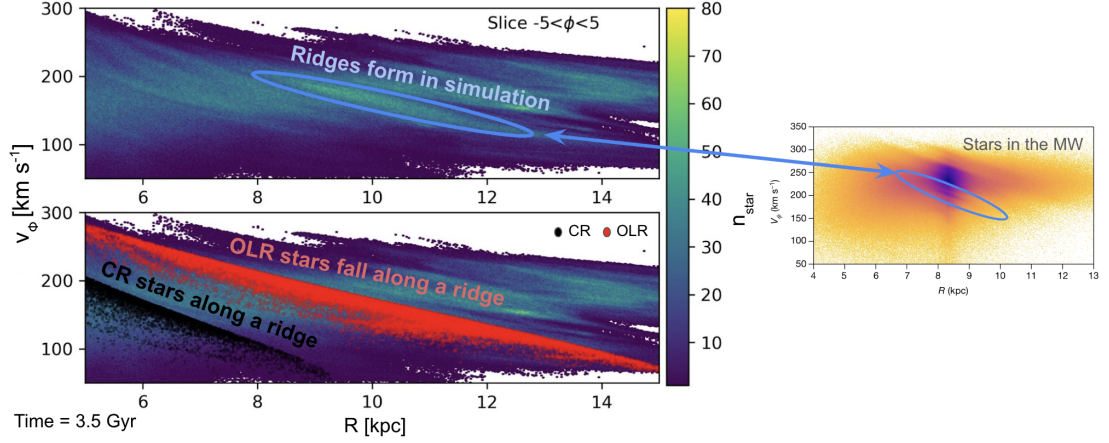


Figure 4.6: V_ϕ vs R in N-body simulation with resonance stars over-plotted in red and black. The right panel shows Fig. 4.1 with diagonal ridges seen in the Milky Way for comparison.

in Outer Lindblad Resonance (OLR), represented by red. Notably, the stars that are in resonance fall along the pronounced ridges just like ridges seen in Antoja et al. [5]. This indicates that the ridges we see in the observation data shown on the right could indeed be due to a population of stars that are in resonance.

I also tracked resonant populations forward over a long period of time as shown in Fig. 4.7. Here on the left, I show the position of stars in CR as two different moments in time separated by 1.5 Gyr. At an earlier time, stars initially in CR with the bar are shown in orange. After the bar has begun to decelerate, the stars have been swept out, which I have shown in black. A similar sort of phenomenon can be seen on the right for the stars in OLR. At an earlier time, stars initially in OLR are represented in red, and the same stars still in OLR after 1.5 Gyr are represented in yellow. These are only the population that were still in OLR and CR at these two moments in time.

These results support the phenomenon of resonance sweeping, and we can identify orbits that are being trapped and dragged due to this dynamical process from the bar. These results agree with the recent work shown by Zhang et al. [181]. Similar to Chiba, they also used a test particle simulation and found that resonant dragging by a decelerating bar could be a main driver of radial migration in the Milky Way's disc. Another work by Khoperskov et al. [88] used an N-body simulation that was previously used by them for bulge studies and phase-space comparison to the Milky Way. They

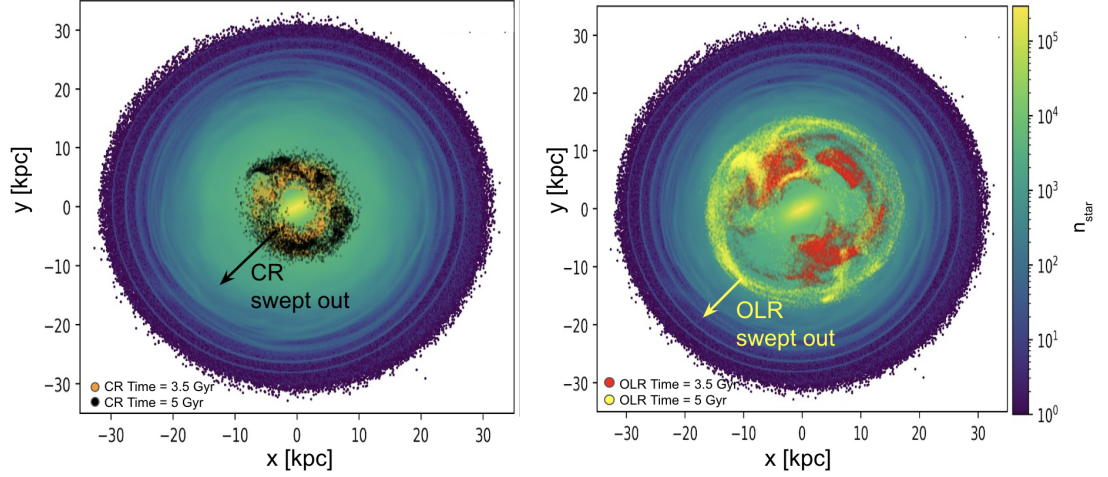


Figure 4.7: Resonance sweeping of stars tracked after 1.5 Gyr. Yellow points in the left panel show the star particles in Co-Rotation Resonance at 3.5 Gyr time in the simulation, and black points indicate the star particles in Co-Rotation Resonance at 5 Gyr time in the simulation. Red and yellow points in the right panel show star particles in Outer Lindblad Resonance at 3.5 Gyr and 5 Gyr, respectively. Star particles get swept out in both cases as the new region of the disk enters resonance.

showed that propagation of the bar resonances outward can induce the circularization of orbits of some migrating stars. They conclude that the presence of metal-rich stars in the solar vicinity & outer Galactic disc could be significantly influenced by resonant dragging by the decelerating bar. Overall, they conclude that up to 3% of stars between CR and OLR formed in the innermost region of the Milky Way. In another recent work, Haywood et al. [70] focuses on interpreting Milky Way data and looks at the low- α disc population from APOGEE across the disk. They use ages from the astroNN catalog and subdivide the populations into 1 Gyr age bins. They found that data in this space is highly structured, with a plateau between 4 and 7 kpc and a break at 10–12 kpc. They conclude that these features in the Milky Way are due to Corotation and Lindblad resonances and connect back their results to the works by Khoperskov et al. [88].

A more robust analysis of this process would need an accurate measurement of the frequencies of the stellar objects. The method we used to calculate the frequency using AGAMA assumes an axisymmetric potential. In a dynamical and rapidly evolving disk, such an assumption of the potential may not be realistic. Thus, a future and natural expansion of this work would be to explore novel techniques like NAIF by Beraldo e

Silva et al. [12] that can estimate frequencies under a more realistic non-axisymmetric potential.

Chapter 5

Conclusion

In this work, I used three galaxies from the *Latte* suite of FIRE-2 simulations (m12i, m12f, and m12m) to study the chemical homogeneity of the open clusters and measured the radial metallicity gradient using the same samples of clusters. I also studied how large-scale structures like the galactic bar impact the dynamics of the stellar groups through processes like resonances in billion-particle N-body simulations.

Specifically, in Chapter 2, I tested a premise for strong chemical tagging. The OCs from the FIRE simulations showed realistic intra-cluster homogeneity (typical OC elemental dispersion $\lesssim 0.02$ dex) and comparable inter-cluster dispersion to observations, which was 2-5 times larger than intra-cluster dispersion. When using a chemical difference metric to distinguish between intra- and inter-cluster pairs, we did not find significantly large chemical differences to distinguish OC origin for the majority of stars. This is likely due to limited and/or redundant information encoded in the light elements we track (C, N, O, Ne, Mg, Si, S, Ca, Fe); with the addition of heavy elements, the chemical difference metric may produce more reliable results for chemical tagging in the future. However, as informed by our simulated OC sample (drawn from three realistic Milky Way-mass cosmological galaxy simulations with varied merger histories and environments), in the limits of light elements only, it is impossible for strong chemical tagging to be able to reconstruct individual OCs reliably to a high level of confidence. This is a motivation for upcoming surveys to aim for measuring the chemistry of OCs at a higher precision at a wide range of elements, and also for theory and simulations to aim for simulating a wide range of elements at a higher resolution.

Building on these results, future work should focus on expanding the range of elements we trace in the simulations. Implementing r-process, s-process, and iron-peak elements beyond the current nine elements we traced would allow us to understand if elements from different nucleosynthetic channels carry more discriminating power for identifying distinct chemical signatures in open clusters. Observationally, upcoming large-scale spectroscopic surveys (e.g., SDSS-VI [91], WEAVE [38], LAMOST [36]) offer the opportunity to measure abundances for dozens of elements at higher precision across more open clusters. Combining this expanded chemical space with dynamical and spatial space from Gaia will allow for more powerful multi-dimensional analysis that could better inform us if chemical tagging works with combined chemical and orbital properties. Also, future simulations should aim to improve the mass and spatial resolution, which would enable us to capture the dynamical properties of the OCs more clearly.

In Chapter 3, I discussed the radial metallicity gradients that I measure across *Latte* disks using OCs. Our results highlight sampling and observational bias while using OCs to trace the radial metallicity gradient of the disk galaxies. Using both bootstrapping and fixed-sized random sub-samples of open clusters, we find that for reliable recovery of the fit parameters, we require at least 200-250 clusters spread across a wide range of galactocentric radii. With smaller or spatially biased samples, the fit parameters become highly sensitive to the sampling bias. This emphasizes the importance of sample size, completeness, and smaller measurement uncertainties for offering a better outlook for measuring the radial metallicity gradient in the MW and beyond. As large-scale surveys like SDSS-VI, WEAVE, and LAMOST expand their coverage, improving the sample size, we would have a better understanding of our galactic home with a more accurate measure of the radial metallicity gradient.

In Chapter 4, I explored how groups of stars are affected by large-scale dynamics in the disk, like resonances. Using a billion-particle N-body simulation without gas, I explored how moving groups like the Hercules stream can be explained through processes like bar resonances. We identified stars in Corotation Resonance and Outer Lindblad Resonance and found that a significant number of stars remain in resonance later in time, suggesting resonant sweeping of orbits due to the decelerating bar. A future

expansion of this work would be exploring the resonant populations without assuming an axisymmetric potential. AGAMA assumes an axisymmetric potential, which may not accurately reflect the interactions of a non-axisymmetric system like a Galactic bar.

All of these results share a common attribute: that is, leveraging simulations (theory) to understand what we see in observations. This highlights how we are utilizing simulations as an MW in our backyard to answer questions about our galactic home. With ever-improving computational capacity, this thesis provides a foundation and offers a road map for future work aiming to unravel the full chemo-dynamical fingerprint of our Galaxy, thus leading to answering open questions about our galactic home and beyond.

Bibliography

- [1] Abdurro'uf, Katherine Accetta, Conny Aerts, Víctor Silva Aguirre, Romina Ahumada, Nikhil Ajgaonkar, N. Filiz Ak, Shadab Alam, Carlos Allende Prieto, Andrés Almeida, Friedrich Anders, Scott F. Anderson, Brett H. Andrews, Borja Anguiano, Erik Aquino-Ortíz, Alfonso Aragón-Salamanca, Maria Argudo-Fernández, Metin Ata, Marie Aubert, Vladimir Avila-Reese, Carles Badenes, Rodolfo H. Barbá, Kat Barger, Jorge K. Barrera-Ballesteros, Rachael L. Beaton, Timothy C. Beers, Francesco Belfiore, Chad F. Bender, Mariangela Bernardi, Matthew A. Bershad, Florian Beutler, Christian Moni Bidin, Jonathan C. Bird, Dmitry Bizyaev, Guillermo A. Blanc, Michael R. Blanton, Nicholas Fraser Boardman, Adam S. Bolton, Médéric Boquien, Jura Borissova, Jo Bovy, W. N. Brandt, Jordan Brown, Joel R. Brownstein, Marcella Brusa, Johannes Buchner, Kevin Bundy, Joseph N. Burchett, Martin Bureau, Adam Burgasser, Tuesday K. Cabang, Stephanie Campbell, Michele Cappellari, Joleen K. Carlberg, Fábio Carneiro Wanderley, Ricardo Carrera, Jennifer Cash, Yan-Ping Chen, Wei-Huai Chen, Brian Cherinka, Cristina Chiappini, Peter Doohyun Choi, S. Drew Chojnowski, Haeun Chung, Nicolas Clerc, Roger E. Cohen, Julia M. Comerford, Johan Comparat, Luiz da Costa, Kevin Covey, Jeffrey D. Crane, Irene Cruz-Gonzalez, Connor Culhane, Katia Cunha, Y. Sophia Dai, Guillermo Damke, Jeremy Darling, Jr. Davidson, James W., Roger Davies, Kyle Dawson, Nathan De Lee, Aleksandar M. Diamond-Stanic, Mariana Cano-Díaz, Helena Domínguez Sánchez, John Donor, Chris Duckworth, Tom Dwelly, Daniel J. Eisenstein, Yvonne P. Elsworth, Eric Em-sellem, Mike Eracleous, Stephanie Escoffier, Xiaohui Fan, Emily Farr, Shuai Feng, José G. Fernández-Trincado, Diane Feuillet, Andreas Filipp, Sean P. Fillingham, Peter M. Frinchaboy, Sebastien Fromenteau, Lluís Galbany, Rafael A.

García, D. A. García-Hernández, Junqiang Ge, Doug Geisler, Joseph Gelfand, Tobias Géron, Benjamin J. Gibson, Julian Goddy, Diego Godoy-Rivera, Kathleen Grabowski, Paul J. Green, Michael Greener, Catherine J. Grier, Emily Griffith, Hong Guo, Julien Guy, Massinissa Hadjara, Paul Harding, Sten Hasselquist, Christian R. Hayes, Fred Hearty, Jesús Hernández, Lewis Hill, David W. Hogg, Jon A. Holtzman, Danny Horta, Bau-Ching Hsieh, Chin-Hao Hsu, Yun-Hsin Hsu, Daniel Huber, Marc Huertas-Company, Brian Hutchinson, Ho Seong Hwang, Héctor J. Ibarra-Medel, Jacob Ider Chitham, Gabriele S. Ilha, Julie Imig, Will Jaekle, Tharindu Jayasinghe, Xihan Ji, Jennifer A. Johnson, Amy Jones, Henrik Jönsson, Ivan Katkov, Dr. Khalatyan, Arman, Karen Kinemuchi, Shobhit Kisku, Johan H. Knapen, Jean-Paul Kneib, Juna A. Kollmeier, Miranda Kong, Marina Kounkel, Kathryn Kreckel, Dhanesh Krishnarao, Ivan Lacerna, Richard R. Lane, Rachel Langgin, Ramon Lavender, David R. Law, Daniel Lazarz, Henry W. Leung, Ho-Hin Leung, Hannah M. Lewis, Cheng Li, Ran Li, Jianhui Lian, Fu-Heng Liang, Lihwai Lin, Yen-Ting Lin, Sicheng Lin, Chris Lintott, Dan Long, Penélope Longa-Peña, Carlos López-Cobá, Shengdong Lu, Britt F. Lundgren, Yuanze Luo, J. Ted Mackereth, Axel de la Macorra, Suvrath Mahadevan, Steven R. Majewski, Arturo Manchado, Travis Mandeville, Claudia Maraston, Berta Margalef-Bentabol, Thomas Masseron, Karen L. Masters, Savita Mathur, Richard M. McDermid, Myles McKay, Andrea Merloni, Michael Merrifield, Szabolcs Meszaros, Andrea Miglio, Francesco Di Mille, Dante Minniti, Rebecca Minsley, Antonela Monachesi, Jeongin Moon, Benoit Mosser, John Mulchaey, Demitri Muna, Riccardo R. Muñoz, Adam D. Myers, Natalie Myers, Seshadri Nadathur, Preethi Nair, Kirpal Nandra, Justus Neumann, Jeffrey A. Newman, David L. Nidever, Farnik Nikakhtar, Christian Nitschelm, Julia E. O'Connell, Luis Garma-Oehmichen, Gabriel Luan Souza de Oliveira, Richard Olney, Daniel Oravetz, Mario Ortigoza-Urdaneta, Yeisson Osorio, Justin Otter, Zachary J. Pace, Nelson Padilla, Kaike Pan, Hsi-An Pan, Taniya Parikh, James Parker, Sebastien Peirani, Karla Peña Ramírez, Samantha Penny, Will J. Percival, Ismael Perez-Fournon, Marc Pinsonneault, Frédérick Poidevin, Vijith Jacob Poovelil, Adrian M. Price-Whelan, Anna Bárbara de Andrade Queiroz, M. Jordan Raddick, Amy Ray, Sandro Bar-

boza Rembold, Nicole Riddle, Rogemar A. Riffel, Rogério Riffel, Hans-Walter Rix, Annie C. Robin, Aldo Rodríguez-Puebla, Alexandre Roman-Lopes, Carlos Román-Zúñiga, Benjamin Rose, Ashley J. Ross, Graziano Rossi, Kate H. R. Rubin, Mara Salvato, Sebastián F. Sánchez, José R. Sánchez-Gallego, Robyn Sanderson, Felipe Antonio Santana Rojas, Edgar Sarceno, Regina Sarmiento, Conor Sayres, Elizaveta Sazonova, Adam L. Schaefer, Ricardo Schiavon, David J. Schlegel, Donald P. Schneider, Mathias Schultheis, Axel Schwope, Aldo Serenelli, Javier Serna, Zhengyi Shao, Griffin Shapiro, Anubhav Sharma, Yue Shen, Matthew Shetrone, Yiping Shu, Joshua D. Simon, M. F. Skrutskie, Rebecca Smethurst, Verne Smith, Jennifer Sobeck, Taylor Spoo, Dani Sprague, David V. Stark, Keivan G. Stassun, Matthias Steinmetz, Dennis Stello, Alexander Stone-Martinez, Thaisa Storchi-Bergmann, Guy S. Stringfellow, Amelia Stutz, Yung-Chau Su, Manuchehr Taghizadeh-Popp, Michael S. Talbot, Jamie Tayar, Eduardo Telles, Johanna Teske, Ani Thakar, Christopher Theissen, Andrew Tkachenko, Daniel Thomas, Rita Tojeiro, Hector Hernandez Toledo, Nicholas W. Troup, Jonathan R. Trump, James Trussler, Jacqueline Turner, Sarah Tuttle, Eduardo Unda-Sanzana, José Antonio Vázquez-Mata, Marica Valentini, Octavio Valenzuela, Jaime Vargas-González, Mariana Vargas-Magaña, Pablo Vera Alfaro, Sandro Villanova, Fiorenzo Vincenzo, David Wake, Jack T. Warfield, Jessica Diane Washington, Benjamin Alan Weaver, Anne-Marie Weijmans, David H. Weinberg, Achim Weiss, Kyle B. Westfall, Vivienne Wild, Matthew C. Wilde, John C. Wilson, Robert F. Wilson, Mikayla Wilson, Julien Wolf, W. M. Wood-Vasey, Renbin Yan, Olga Zamora, Gail Zasowski, Kai Zhang, Cheng Zhao, Zheng Zheng, Zheng Zheng, and Kai Zhu. The Seventeenth Data Release of the Sloan Digital Sky Surveys: Complete Release of MaNGA, MaStar, and APOGEE-2 Data. *ApJS*, 259(2):35, April 2022. doi: 10.3847/1538-4365/ac4414.

- [2] F. Anders, C. Chiappini, B. X. Santiago, H. J. Rocha-Pinto, L. Girardi, L. N. da Costa, M. A. G. Maia, M. Steinmetz, I. Minchev, M. Schultheis, C. Boeche, A. Miglio, J. Montalbán, D. P. Schneider, T. C. Beers, K. Cunha, C. Allende Prieto, E. Balbinot, D. Bizyaev, D. E. Brauer, J. Brinkmann, P. M. Frinchaboy, A. E. García Pérez, M. R. Hayden, F. R. Hearty, J. Holtzman, J. A. Johnson,

- K. Kinemuchi, S. R. Majewski, E. Malanushenko, V. Malanushenko, D. L. Nidever, R. W. O’Connell, K. Pan, A. C. Robin, R. P. Schiavon, M. Shetrone, M. F. Skrutskie, V. V. Smith, K. Stassun, and G. Zasowski. Chemodynamics of the Milky Way. I. The first year of APOGEE data. *A&A*, 564:A115, April 2014. doi: 10.1051/0004-6361/201323038.
- [3] Friedrich Anders, C Chiappini, I Minchev, A Miglio, J Montalbán, B Mosser, TS Rodrigues, BX Santiago, F Baudin, TC Beers, et al. Red giants observed by corot and apogee: The evolution of the milky way’s radial metallicity gradient. *Astronomy & Astrophysics*, 600:A70, 2017.
- [4] T. Antoja, F. Figueras, J. Torra, O. Valenzuela, and B. Pichardo. The Origin of Stellar Moving Groups. In *Lecture Notes and Essays in Astrophysics*, volume 4, pages 13–31. 2010.
- [5] T. Antoja, A. Helmi, M. Romero-Gómez, D. Katz, C. Babusiaux, R. Drimmel, D. W. Evans, F. Figueras, E. Poggio, C. Reylé, A. C. Robin, G. Seabroke, and C. Soubiran. A dynamically young and perturbed Milky Way disk. *Nature*, 561 (7723):360–362, September 2018. doi: 10.1038/s41586-018-0510-7.
- [6] K. Z. Arellano-Córdova, C. Esteban, J. García-Rojas, and J. E. Méndez-Delgado. The Galactic radial abundance gradients of C, N, O, Ne, S, Cl, and Ar from deep spectra of H II regions. *MNRAS*, 496(2):1051–1076, August 2020. doi: 10.1093/mnras/staa1523.
- [7] Lucia Armillotta, Mark R. Krumholz, and Yusuke Fujimoto. Mixing of metals during star cluster formation: statistics and implications for chemical tagging. *MNRAS*, 481(4):5000–5013, December 2018. doi: 10.1093/mnras/sty2625.
- [8] Martin Asplund, Nicolas Grevesse, A. Jacques Sauval, and Pat Scott. The Chemical Composition of the Sun. *ARA&A*, 47(1):481–522, September 2009. doi: 10.1146/annurev.astro.46.060407.145222.
- [9] Dana S. Balser, Robert T. Rood, T. M. Bania, and L. D. Anderson. H II Region

- Metallicity Distribution in the Milky Way Disk. *ApJ*, 738(1):27, September 2011. doi: 10.1088/0004-637X/738/1/27.
- [10] Matthew A. Bellardini, Andrew Wetzel, Sarah R. Loebman, Claude-André Faucher-Giguère, Xiangcheng Ma, and Robert Feldmann. 3D gas-phase elemental abundances across the formation histories of Milky Way-mass galaxies in the FIRE simulations: initial conditions for chemical tagging. *MNRAS*, 505(3): 4586–4607, August 2021. doi: 10.1093/mnras/stab1606.
- [11] Matthew A. Bellardini, Andrew Wetzel, Sarah R. Loebman, and Jeremy Bailin. 3D elemental abundances of stars at formation across the histories of Milky Way-mass galaxies in the FIRE simulations. *MNRAS*, 514(3):4270–4289, August 2022. doi: 10.1093/mnras/stac1637.
- [12] Leandro Beraldo e Silva, Victor P. Debattista, Stuart Robert Anderson, Monica Valluri, Peter Erwin, Kathryne J. Daniel, and Nathan Deg. Orbital Support and Evolution of Flat Profiles of Bars (Shoulders). *ApJ*, 955(1):38, September 2023. doi: 10.3847/1538-4357/ace976.
- [13] C. Bertelli Motta, A. Pasquali, J. Richer, G. Michaud, M. Salaris, A. Bragaglia, L. Magrini, S. Randich, E. K. Grebel, V. Adibekyan, S. Blanco-Cuaresma, A. Drazdauskas, X. Fu, S. Martell, G. Tautvaišienė, G. Gilmore, E. J. Alfaro, T. Bensby, E. Flaccomio, S. E. Koposov, A. J. Korn, A. C. Lanzafame, R. Smiljanic, A. Bayo, G. Carraro, A. R. Casey, M. T. Costado, F. Damiani, E. Franciosini, U. Heiter, A. Hourihane, P. Jofré, C. Lardo, J. Lewis, L. Monaco, L. Morbidelli, G. G. Sacco, S. G. Sousa, C. C. Worley, and S. Zaggia. The Gaia-ESO Survey: evidence of atomic diffusion in M67? *MNRAS*, 478(1):425–438, July 2018. doi: 10.1093/mnras/sty1011.
- [14] S. Bertran de Lis, C. Allende Prieto, S. R. Majewski, R. P. Schiavon, J. A. Holtzman, M. Shetrone, R. Carrera, A. E. García Pérez, Sz. Mészáros, P. M. Frinchaboy, F. R. Hearty, D. L. Nidever, G. Zasowski, and J. Ge. Cosmic variance in [O/Fe] in the Galactic disk. *A&A*, 590:A74, May 2016. doi: 10.1051/0004-6361/201527827.

- [15] Binod Bhattarai, Sarah R. Loebman, Melissa K. Ness, Andrew Wetzel, Emily C. Cunningham, Hanna Parul, and Alessa Ibrahim Wiggins. Strong Chemical Tagging in FIRE: Intra- and Intercluster Chemical Homogeneity in Open Clusters in Milky Way-like Galaxy Simulations. *ApJ*, 977(1):70, December 2024. doi: 10.3847/1538-4357/ad8bac.
- [16] S. Blanco-Cuaresma, C. Soubiran, U. Heiter, M. Asplund, G. Carraro, M. T. Costado, S. Feltzing, J. I. González-Hernández, F. Jiménez-Esteban, A. J. Korn, A. F. Marino, D. Montes, I. San Roman, H. M. Tabernero, and G. Tautvaišienė. Testing the chemical tagging technique with open clusters. *A&A*, 577:A47, May 2015. doi: 10.1051/0004-6361/201425232.
- [17] Joss Bland-Hawthorn, Mark R. Krumholz, and Ken Freeman. The Long-term Evolution of the Galactic Disk Traced by Dissolving Star Clusters. *ApJ*, 713(1): 166–179, April 2010. doi: 10.1088/0004-637X/713/1/166.
- [18] C. Boeche, A. Siebert, T. Piffl, A. Just, M. Steinmetz, S. Sharma, G. Kordopatis, G. Gilmore, C. Chiappini, M. Williams, E. K. Grebel, J. Bland-Hawthorn, B. K. Gibson, U. Munari, A. Siviero, O. Bienaymé, J. F. Navarro, Q. A. Parker, W. Reid, G. M. Seabroke, F. G. Watson, R. F. G. Wyse, and T. Zwitter. Chemical gradients in the Milky Way from the RAVE data. I. Dwarf stars. *A&A*, 559:A59, November 2013. doi: 10.1051/0004-6361/201322085.
- [19] C. Boeche, A. Siebert, T. Piffl, A. Just, M. Steinmetz, E. K. Grebel, S. Sharma, G. Kordopatis, G. Gilmore, C. Chiappini, K. Freeman, B. K. Gibson, U. Munari, A. Siviero, O. Bienaymé, J. F. Navarro, Q. A. Parker, W. Reid, G. M. Seabroke, F. G. Watson, R. F. G. Wyse, and T. Zwitter. Chemical gradients in the Milky Way from the RAVE data. II. Giant stars. *A&A*, 568:A71, August 2014. doi: 10.1051/0004-6361/201423974.
- [20] Jo Bovy. The Chemical Homogeneity of Open Clusters. *ApJ*, 817(1):49, January 2016. doi: 10.3847/0004-637X/817/1/49.
- [21] A. Bragaglia, P. Sestito, S. Villanova, E. Carretta, S. Randich, and M. Tosi. Old open clusters as key tracers of Galactic chemical evolution. II. Iron and elemental

abundances in NGC 2324, NGC 2477 NGC 2660, NGC 3960, and Berkeley 32. *A&A*, 480(1):79–90, March 2008. doi: 10.1051/0004-6361:20077904.

- [22] Angela Bragaglia and Monica Tosi. The Bologna Open Cluster Chemical Evolution Project: Midterm Results from the Photometric Sample. *AJ*, 131(3): 1544–1558, March 2006. doi: 10.1086/499537.
- [23] Angela Bragaglia, Christopher Sneden, Eugenio Carretta, Raffaele G. Gratton, Sara Lucatello, Peter F. Bernath, James S. A. Brooke, and Ram S. Ram. Searching for Chemical Signatures of Multiple Stellar Populations in the Old, Massive Open Cluster NGC 6791. *ApJ*, 796(1):68, November 2014. doi: 10.1088/0004-637X/796/1/68.
- [24] G. A. Bragança, S. Daflon, T. Lanz, K. Cunha, T. Bensby, P. J. McMillan, C. D. Garmany, J. W. Glaspey, M. Borges Fernandes, M. S. Oey, and I. Hubeny. Radial abundance gradients in the outer Galactic disk as traced by main-sequence OB stars. *A&A*, 625:A120, May 2019. doi: 10.1051/0004-6361/201834554.
- [25] S. Buder, K. Lind, M. K. Ness, M. Asplund, L. Duong, J. Lin, J. Kos, L. Casagrande, A. R. Casey, J. Bland-Hawthorn, G. M. de Silva, V. D’Orazi, K. C. Freeman, S. L. Martell, K. J. Schlesinger, S. Sharma, J. D. Simpson, D. B. Zucker, T. Zwitter, K. Čotar, A. Dotter, M. R. Hayden, E. A. Hyde, P. R. Kafle, G. F. Lewis, D. M. Nataf, T. Nordlander, W. Reid, H. W. Rix, Á. Skúladóttir, D. Stello, Y. S. Ting, G. Traven, R. F. G. Wyse, and GALAH Collaboration. The GALAH survey: An abundance, age, and kinematic inventory of the solar neighbourhood made with TGAS. *A&A*, 624:A19, April 2019. doi: 10.1051/0004-6361/201833218.
- [26] Ronald J. Buta, Kartik Sheth, E. Athanassoula, A. Bosma, Johan H. Knapen, Eija Laurikainen, Heikki Salo, Debra Elmegreen, Luis C. Ho, Dennis Zaritsky, Helene Courtois, Joannah L. Hinz, Juan-Carlos Muñoz-Mateos, Taehyun Kim, Michael W. Regan, Dimitri A. Gadotti, Armando Gil de Paz, Jarkko Laine, Karín Menéndez-Delmestre, Sébastien Comerón, Santiago Erroz Ferrer, Mark Seibert, Trisha Mizusawa, Benne Holwerda, and Barry F. Madore. A Classical Morpho-

- logical Analysis of Galaxies in the Spitzer Survey of Stellar Structure in Galaxies (S4G). *ApJS*, 217(2):32, April 2015. doi: 10.1088/0067-0049/217/2/32.
- [27] T. Cantat-Gaudin, P. Donati, A. Vallenari, R. Sordo, A. Bragaglia, and L. Magrini. Abundances and kinematics for ten anticentre open clusters. *A&A*, 588:A120, April 2016. doi: 10.1051/0004-6361/201628115.
- [28] Tristan Cantat-Gaudin. Milky Way Star Clusters and Gaia: A Review of the Ongoing Revolution. *Universe*, 8(2):111, February 2022. doi: 10.3390/universe8020111.
- [29] J. Carbajo-Hijarrubia, L. Casamiquela, R. Carrera, L. Balaguer-Núñez, C. Jordi, F. Anders, C. Gallart, E. Pancino, A. Drazdauskas, E. Stonkutė, G. Tautvaišienė, J. M. Carrasco, E. Masana, T. Cantat-Gaudin, and S. Blanco-Cuaresma. OC-CASO. V. Chemical-abundance trends with Galactocentric distance and age. *A&A*, 687:A239, July 2024. doi: 10.1051/0004-6361/202347648.
- [30] R. Carrera and E. Pancino. Chemical abundance analysis of the open clusters Berkeley 32, NGC 752, Hyades, and Praesepe. *A&A*, 535:A30, November 2011. doi: 10.1051/0004-6361/201117473.
- [31] Andreia Carrillo, Melissa K. Ness, Keith Hawkins, Robyn E. Sanderson, Kaile Wang, Andrew Wetzel, and Matthew A. Bellardini. The Relationship between Age, Metallicity, and Abundances for Disk Stars in a Simulated Milky Way. *ApJ*, 942(1):35, January 2023. doi: 10.3847/1538-4357/aca1c7.
- [32] L. Casamiquela, R. Carrera, S. Blanco-Cuaresma, C. Jordi, L. Balaguer-Núñez, E. Pancino, F. Anders, C. Chiappini, L. Díaz-Pérez, D. S. Aguado, A. Aparicio, R. Garcia-Dias, U. Heiter, C. E. Martínez-Vázquez, S. Murabito, and A. del Pino. OCCASO - II. Physical parameters and Fe abundances of red clump stars in 18 open clusters. *MNRAS*, 470(4):4363–4381, October 2017. doi: 10.1093/mnras/stx1481.
- [33] L. Casamiquela, Y. Tarricq, C. Soubiran, S. Blanco-Cuaresma, P. Jofré, U. Heiter, and M. Tucci Maia. Differential abundances of open clusters and their tidal tails:

- Chemical tagging and chemical homogeneity. *A&A*, 635:A8, March 2020. doi: 10.1051/0004-6361/201936978.
- [34] C. Chiappini, F. Matteucci, and R. Gratton. The Chemical Evolution of the Galaxy: The Two-Infall Model. *ApJ*, 477(2):765–780, March 1997. doi: 10.1086/303726.
- [35] Rimpei Chiba, Jennifer K. S. Friske, and Ralph Schönrich. Resonance sweeping by a decelerating Galactic bar. *MNRAS*, 500(4):4710–4729, January 2021. doi: 10.1093/mnras/staa3585.
- [36] Xiang-Qun Cui, Yong-Heng Zhao, Yao-Quan Chu, Guo-Ping Li, Qi Li, Li-Ping Zhang, Hong-Jun Su, Zheng-Qiu Yao, Ya-Nan Wang, Xiao-Zheng Xing, Xin-Nan Li, Yong-Tian Zhu, Gang Wang, Bo-Zhong Gu, A. Li Luo, Xin-Qi Xu, Zhen-Chao Zhang, Gen-Rong Liu, Hao-Tong Zhang, De-Hua Yang, Shu-Yun Cao, Hai-Yuan Chen, Jian-Jun Chen, Kun-Xin Chen, Ying Chen, Jia-Ru Chu, Lei Feng, Xue-Fei Gong, Yong-Hui Hou, Hong-Zhuan Hu, Ning-Sheng Hu, Zhong-Wen Hu, Lei Jia, Fang-Hua Jiang, Xiang Jiang, Zi-Bo Jiang, Ge Jin, Ai-Hua Li, Yan Li, Ye-Ping Li, Guan-Qun Liu, Zhi-Gang Liu, Wen-Zhi Lu, Yin-Dun Mao, Li Men, Yong-Jun Qi, Zhao-Xiang Qi, Huo-Ming Shi, Zheng-Hong Tang, Qing-Sheng Tao, Da-Qi Wang, Dan Wang, Guo-Min Wang, Hai Wang, Jia-Ning Wang, Jian Wang, Jian-Ling Wang, Jian-Ping Wang, Lei Wang, Shu-Qing Wang, You Wang, Yue-Fei Wang, Ling-Zhe Xu, Yan Xu, Shi-Hai Yang, Yong Yu, Hui Yuan, Xiang-Yan Yuan, Chao Zhai, Jing Zhang, Yan-Xia Zhang, Yong Zhang, Ming Zhao, Fang Zhou, Guo-Hua Zhou, Jie Zhu, and Si-Cheng Zou. The Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST). *Research in Astronomy and Astrophysics*, 12(9):1197–1242, September 2012. doi: 10.1088/1674-4527/12/9/003.
- [37] Katia Cunha, Verne V. Smith, Jennifer A. Johnson, Maria Bergemann, Szabolcs Mészáros, Matthew D. Shetrone, Diogo Souto, Carlos Allende Prieto, Ricardo P. Schiavon, Peter Frinchaboy, Gail Zasowski, Dmitry Bizyaev, Jon Holtzman, Ana E. García Pérez, Steven R. Majewski, David Nidever, Timothy Beers, Ricardo Carrera, Doug Geisler, James Gunn, Fred Hearty, Inese Ivans, Sarah Martell, Marc Pinsonneault, Donald P. Schneider, Jennifer Sobeck, Dennis Stello, Keivan G.

- Stassun, Michael Skrutskie, and John C. Wilson. Sodium and Oxygen Abundances in the Open Cluster NGC 6791 from APOGEE H-band Spectroscopy. *ApJ*, 798(2):L41, January 2015. doi: 10.1088/2041-8205/798/2/L41.
- [38] Gavin Dalton, Scott C. Trager, Don Carlos Abrams, David Carter, Piercarlo Bonifacio, J. Alfonso L. Aguerri, Mike MacIntosh, Chris Evans, Ian Lewis, Ramon Navarro, Tibor Agocs, Kevin Dee, Sophie Rousset, Ian Tosh, Kevin Middleton, Johannes Pragt, David Terrett, Matthew Brock, Chris Benn, Marc Verheijen, Diego Cano Infantes, Craige Bevil, Iain Steele, Chris Mottram, Stuart Bates, Francis J. Gribbin, Jürg Rey, Luis Fernando Rodriguez, Jose Miguel Delgado, Isabelle Guinouard, Nic Walton, Michael J. Irwin, Pascal Jagourel, Remko Stuik, Gerrit Gerlofsma, Ronald Roelfsma, Ian Skillen, Andy Ridings, Marc Balcels, Jean-Baptiste Daban, Carole Gouvret, Lars Venema, and Paul Girard. WEAVE: the next generation wide-field spectroscopy facility for the William Herschel Telescope. In Ian S. McLean, Suzanne K. Ramsay, and Hideki Takami, editors, *Ground-based and Airborne Instrumentation for Astronomy IV*, volume 8446 of *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*, page 84460P, September 2012. doi: 10.1117/12.925950.
- [39] Gavin Dalton, Scott Trager, Don Carlos Abrams, Piercarlo Bonifacio, J. Alfonso López Aguerri, Kevin Middleton, Chris Benn, Kevin Dee, Frédéric Sayède, Ian Lewis, Johan Pragt, Sergio Pico, Nic Walton, Juerg Rey, Carlos Allende Prieto, José Peñate, Emilie Lhome, Tibor Agócs, José Alonso, David Terrett, Matthew Brock, James Gilbert, Andy Ridings, Isabelle Guinouard, Marc Verheijen, Ian Tosh, Kevin Rogers, Iain Steele, Remko Stuik, Neils Tromp, Attila Jasko, Jan Kragt, Dirk Lesman, Chris Mottram, Stuart Bates, Frank Gribbin, Luis Fernando Rodriguez, José M. Delgado, Carlos Martin, Diego Cano, Ramón Navarro, Mike Irwin, Jim Lewis, Eduardo Gonzalez Solares, Neil O’Mahony, Andrea Bianco, Christina Zurita, Rik ter Horst, Emilio Molinari, Marcello Lodi, José Guerra, Antonella Vallenari, and Andrea Baruffolo. Project overview and update on WEAVE: the next generation wide-field spectroscopy facility for the William Herschel Telescope. In Suzanne K. Ramsay, Ian S. McLean, and Hideki Takami, editors, *Ground-based and Airborne Instrumentation for Astronomy V*, volume

9147 of *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*, page 91470L, July 2014. doi: 10.1117/12.2055132.

- [40] G. M. De Silva, C. Sneden, D. B. Paulson, M. Asplund, J. Bland-Hawthorn, M. S. Bessell, and K. C. Freeman. Chemical Homogeneity in the Hyades. *AJ*, 131(1): 455–460, January 2006. doi: 10.1086/497968.
- [41] G. M. De Silva, K. C. Freeman, M. Asplund, J. Bland-Hawthorn, M. S. Bessell, and R. Collet. Chemical Homogeneity in Collinder 261 and Implications for Chemical Tagging. *AJ*, 133(3):1161–1175, March 2007. doi: 10.1086/511182.
- [42] G. M. De Silva, K. C. Freeman, and J. Bland-Hawthorn. Chemically tagging the Galactic disk: abundance patterns of old open clusters. In Johannes Andersen, Nordströara, Birgitta m, and Joss Bland-Hawthorn, editors, *The Galaxy Disk in Cosmological Context*, volume 254, pages 133–138, March 2009. doi: 10.1017/S1743921308027506.
- [43] G. M. de Silva, B. K. Gibson, J. Lattanzio, and M. Asplund. On and Na abundance patterns in open clusters of the Galactic disk. *A&A*, 500(2):L25–L28, June 2009. doi: 10.1051/0004-6361/200912279.
- [44] G. M. De Silva, K. C. Freeman, J. Bland-Hawthorn, S. Martell, E. Wylie de Boer, M. Asplund, S. Keller, S. Sharma, D. B. Zucker, T. Zwitter, B. Anguiano, C. Bacigalupo, D. Bayliss, M. A. Beavis, M. Bergemann, S. Campbell, R. Cannon, D. Carollo, L. Casagrande, A. R. Casey, G. Da Costa, V. D’Orazi, A. Dotter, L. Duong, A. Heger, M. J. Ireland, P. R. Kafle, J. Kos, J. Lattanzio, G. F. Lewis, J. Lin, K. Lind, U. Munari, D. M. Nataf, S. O’Toole, Q. Parker, W. Reid, K. J. Schlesinger, A. Sheinis, J. D. Simpson, D. Stello, Y. S. Ting, G. Traven, F. Watson, R. Wittenmyer, D. Yong, and M. Žerjal. The GALAH survey: scientific motivation. *MNRAS*, 449(3):2604–2617, May 2015. doi: 10.1093/mnras/stv327.
- [45] Victor P. Debattista and J. A. Sellwood. Constraints from Dynamical Friction on the Dark Matter Content of Barred Galaxies. *ApJ*, 543(2):704–721, November 2000. doi: 10.1086/317148.

- [46] C. L. Dobbs, A. Adamo, C. G. Few, D. Calzetti, D. A. Dale, B. G. Elmegreen, A. S. Evans, D. A. Gouliermis, K. Grasha, E. K. Grebel, K. E. Johnson, H. Kim, J. C. Lee, M. Messa, J. E. Ryon, L. J. Smith, D. Thilker, L. Ubeda, and B. Whitmore. The properties, origin and evolution of stellar clusters in galaxy simulations and observations. *MNRAS*, 464(3):3580–3596, January 2017. doi: 10.1093/mnras/stw2200.
- [47] John Donor, Peter M. Frinchaboy, Katia Cunha, Benjamin Thompson, Julia O’Connell, Gail Zasowski, Kelly M. Jackson, Brianne Meyer McGrath, Andrés Almeida, Dmitry Bizyaev, Ricardo Carrera, D. A. García-Hernández, Christian Nitschelm, Kaike Pan, and Olga Zamora. The Open Cluster Chemical Abundances and Mapping Survey. II. Precision Cluster Abundances for APOGEE Using SDSS DR14. *AJ*, 156(4):142, October 2018. doi: 10.3847/1538-3881/aad635.
- [48] John Donor, Peter M. Frinchaboy, Katia Cunha, Julia E. O’Connell, Carlos Allende Prieto, Andrés Almeida, Friedrich Anders, Rachael Beaton, Dmitry Bizyaev, Joel R. Brownstein, Ricardo Carrera, Cristina Chiappini, Roger Cohen, D. A. García-Hernández, Doug Geisler, Sten Hasselquist, Henrik Jönsson, Richard R. Lane, Steven R. Majewski, Dante Minniti, Christian Moni Bidin, Kaike Pan, Alexandre Roman-Lopes, Jennifer S. Sobeck, and Gail Zasowski. The Open Cluster Chemical Abundances and Mapping Survey. IV. Abundances for 128 Open Clusters Using SDSS/APOGEE DR16. *AJ*, 159(5):199, May 2020. doi: 10.3847/1538-3881/ab77bc.
- [49] Aaron Dotter, Charlie Conroy, Phillip Cargile, and Martin Asplund. The Influence of Atomic Diffusion on Stellar Ages and Chemical Tagging. *ApJ*, 840(2):99, May 2017. doi: 10.3847/1538-4357/aa6d10.
- [50] Ivanna Escala, Andrew Wetzel, Evan N. Kirby, Philip F. Hopkins, Xiangcheng Ma, Coral Wheeler, Dušan Kereš, Claude-André Faucher-Giguère, and Eliot Quataert. Modelling chemical abundance distributions for dwarf galaxies in the Local Group: the impact of turbulent metal diffusion. *MNRAS*, 474(2):2194–2211, February 2018. doi: 10.1093/mnras/stx2858.

- [51] Claude-André Faucher-Giguère, Adam Lidz, Matias Zaldarriaga, and Lars Hernquist. A New Calculation of the Ionizing Background Spectrum and the Effects of He II Reionization. *ApJ*, 703(2):1416–1443, October 2009. doi: 10.1088/0004-637X/703/2/1416.
- [52] Yi Feng and Mark R. Krumholz. Early turbulent mixing as the origin of chemical homogeneity in open star clusters. *Nature*, 513(7519):523–525, September 2014. doi: 10.1038/nature13662.
- [53] Daniel Foreman-Mackey, David W. Hogg, Dustin Lang, and Jonathan Goodman. emcee: The MCMC Hammer. *PASP*, 125(925):306, March 2013. doi: 10.1086/670067.
- [54] Ken Freeman and Joss Bland-Hawthorn. The New Galaxy: Signatures of Its Formation. *ARA&A*, 40:487–537, January 2002. doi: 10.1146/annurev.astro.40.060401.093840.
- [55] E. D. Friel. The Old Open Clusters Of The Milky Way. *ARA&A*, 33:381–414, January 1995. doi: 10.1146/annurev.aa.33.090195.002121.
- [56] E. D. Friel and K. A. Janes. Metallicities and radial velocities of old open clusters. *A&A*, 267:75–91, January 1993.
- [57] Eileen D. Friel, Heather R. Jacobson, and Catherine A. Pilachowski. Abundances of Red Giants in Old Open Clusters. V. Be 31, Be 32, Be 39, M 67, NGC 188, and NGC 1193. *AJ*, 139(5):1942–1967, May 2010. doi: 10.1088/0004-6256/139/5/1942.
- [58] Peter M. Frinchaboy and Steven R. Majewski. Open Clusters as Galactic Disk Tracers. I. Project Motivation, Cluster Membership, and Bulk Three-Dimensional Kinematics. *AJ*, 136(1):118–145, July 2008. doi: 10.1088/0004-6256/136/1/118.
- [59] Peter M Frinchaboy, Benjamin Thompson, Kelly M Jackson, Julia O’Connell, Brianne Meyer, Gail Zasowski, Steven R Majewski, S Drew Chojnowski, Jennifer A Johnson, Carlos Allende Prieto, et al. The open cluster chemical analysis

and mapping survey: local galactic metallicity gradient with apogee using sdss dr10. *The Astrophysical Journal Letters*, 777(1):L1, 2013.

- [60] M. J. Geller and J. P. Huchra. Groups of galaxies. III. THE CfA survey. *ApJS*, 52: 61–87, June 1983. doi: 10.1086/190859.
- [61] M. Gieles. The Role of Tidal Forces in Star Cluster Disruption. In A. de Koter, L. J. Smith, and Laurens B. F. M. Waters, editors, *Mass Loss from Stars and the Evolution of Stellar Clusters*, volume 388 of *Astronomical Society of the Pacific Conference Series*, page 403, June 2008.
- [62] G. Gilmore, S. Randich, M. Asplund, J. Binney, P. Bonifacio, J. Drew, S. Feltzing, A. Ferguson, R. Jeffries, G. Micela, I. Negueruela, T. Prusti, H. W. Rix, A. Vallenari, E. Alfaro, C. Allende-Prieto, C. Babusiaux, T. Bensby, R. Blomme, A. Bragaglia, E. Flaccomio, P. François, M. Irwin, S. Koposov, A. Korn, A. Lanzafame, E. Pancino, E. Paunzen, A. Recio-Blanco, G. Sacco, R. Smiljanic, S. Van Eck, N. Walton, D. Aden, C. Aerts, L. Affer, J. M. Alcalá, G. Altavilla, J. Alves, T. Antoja, F. Arenou, C. Argiroffi, A. Asensio Ramos, C. Bailer-Jones, L. Balaguer-Nunez, A. Bayo, B. Barbuy, G. Barisevicius, D. Barrado y Navascues, C. Battistini, I. Bellas Velidis, M. Bellazzini, V. Belokurov, M. Bergemann, G. Bertelli, K. Biazzo, O. Bienayme, J. Bland-Hawthorn, C. Boeche, S. Bonito, S. Boudreault, J. Bouvier, I. Brandao, A. Brown, J. de Bruijne, M. Burleigh, J. Caballero, E. Caffau, F. Calura, R. Capuzzo-Dolcetta, M. Caramazza, G. Carraro, L. Casagrande, S. Casewell, S. Chapman, C. Chiappini, Y. Chorniy, N. Christlieb, M. Cignoni, G. Coccozza, M. Colless, R. Collet, M. Collins, M. Correnti, E. Covino, D. Crnojevic, M. Cropper, M. Cunha, F. Damiani, M. David, A. Delgado, S. Duffau, B. Edvardsson, J. Eldridge, H. Enke, K. Eriksson, N. W. Evans, L. Eyer, B. Famaey, M. Fellhauer, I. Ferreras, F. Figueras, G. Fiorentino, C. Flynn, D. Folha, E. Franciosini, A. Frasca, K. Freeman, Y. Fremat, E. Friel, B. Gaensicke, J. Gameiro, F. Garzon, S. Geier, D. Geisler, O. Gerhard, B. Gibson, A. Gomboc, A. Gomez, C. Gonzalez-Fernandez, J. Gonzalez Hernandez, E. Gosset, E. Grebel, R. Greimel, M. Groenewegen, F. Grundahl, M. Guarcello, B. Gustafsson, P. Hadrava, D. Hatzidimitriou, N. Ham-

bly, P. Hammersley, C. Hansen, M. Haywood, U. Heber, U. Heiter, E. Held, A. Helmi, G. Hensler, A. Herrero, V. Hill, S. Hodgkin, N. Huelamo, A. Huxor, R. Ibata, R. Jackson, R. de Jong, P. Jonker, S. Jordan, C. Jordi, A. Jorissen, D. Katz, D. Kawata, S. Keller, N. Kharchenko, R. Klement, A. Klutsch, J. Knude, A. Koch, O. Kochukhov, M. Kontizas, P. Koubsky, R. Lallement, P. de Laverny, F. van Leeuwen, B. Lemasle, G. Lewis, K. Lind, H. P. E. Lindstrom, A. Lobel, J. Lopez Santiago, P. Lucas, H. Ludwig, T. Lueftinger, L. Magrini, J. Maiz Apellaniz, J. Maldonado, G. Marconi, A. Marino, C. Martayan, I. Martinez-Valpuesta, G. Matijevic, R. McMahon, S. Messina, M. Meyer, A. Miglio, S. Mikolaitis, I. Minchev, D. Minniti, A. Moitinho, Y. Momany, L. Monaco, M. Montalto, M. J. Monteiro, R. Monier, D. Montes, A. Mora, E. Moraux, T. Morel, N. Mowlavi, A. Mucciarelli, U. Munari, R. Napiwotzki, N. Nardetto, T. Naylor, Y. Naze, G. Nelemans, S. Okamoto, S. Ortolani, G. Pace, F. Palla, J. Palous, R. Parker, J. Penarrubia, I. Pillitteri, G. Piotto, H. Posbic, L. Prisinzano, E. Puzeras, A. Quirrenbach, S. Ragaini, J. Read, M. Read, C. Reyle, J. De Ridder, N. Robichon, A. Robin, S. Roeser, D. Romano, F. Royer, G. Ruchti, A. Ruzicka, S. Ryan, N. Ryde, N. Santos, J. Sanz Forcada, L. M. Sarro Baro, L. Sbordone, E. Schilbach, S. Schmeja, O. Schnurr, R. Schoenrich, R. D. Scholz, G. Seabroke, S. Sharma, G. De Silva, M. Smith, E. Solano, R. Sordo, C. Soubiran, S. Sousa, A. Spagna, M. Steffen, M. Steinmetz, B. Stelzer, E. Stempels, H. Tabernero, G. Tautvaisiene, F. Thevenin, J. Torra, M. Tosi, E. Tolstoy, C. Turon, M. Walker, J. Wambsganss, C. Worley, K. Venn, J. Vink, R. Wyse, S. Zaggia, W. Zeilinger, M. Zoccali, J. Zorec, D. Zucker, T. Zwitter, and Gaia-ESO Survey Team. The Gaia-ESO Public Spectroscopic Survey. *The Messenger*, 147:25–31, March 2012.

- [63] Russell L. Graf, Andrew Wetzel, Matthew A. Bellardini, and Jeremy Bailin. Spatial Variations of Stellar Elemental Abundances in FIRE Simulations of Milky Way-Mass Galaxies: Patterns Today Mostly Reflect Those at Formation. *arXiv e-prints*, art. arXiv:2402.15614, February 2024. doi: 10.48550/arXiv.2402.15614.
- [64] Robert J. J. Grand, Facundo A. Gómez, Federico Marinacci, Rüdiger Pakmor, Volker Springel, David J. R. Campbell, Carlos S. Frenk, Adrian Jenkins, and Simon D. M. White. The Auriga Project: the properties and formation mechanisms

- of disc galaxies across cosmic time. *MNRAS*, 467(1):179–207, May 2017. doi: 10.1093/mnras/stx071.
- [65] Emily J. Griffith, David W. Hogg, Julianne J. Dalcanton, Sten Hasselquist, Bridget Ratcliffe, Melissa Ness, and David H. Weinberg. KPM: A Flexible and Data-driven K-process Model for Nucleosynthesis. *AJ*, 167(3):98, March 2024. doi: 10.3847/1538-3881/ad19c7.
- [66] V. Grisoni, E. Spitoni, and F. Matteucci. Abundance gradients along the Galactic disc from chemical evolution models. *MNRAS*, 481(2):2570–2580, December 2018. doi: 10.1093/mnras/sty2444.
- [67] Michael Y. Grudić, Zachary Hafen, Carl L. Rodriguez, Dávid Guszejnov, Astrid Lamberts, Andrew Wetzel, Michael Boylan-Kolchin, and Claude-André Faucher-Giguère. Great balls of FIRE - I. The formation of star clusters across cosmic time in a Milky Way-mass galaxy. *MNRAS*, 519(1):1366–1380, February 2023. doi: 10.1093/mnras/stac3573.
- [68] Charles R. Harris, K. Jarrod Millman, Stéfan J. van der Walt, Ralf Gommers, Pauli Virtanen, David Cournapeau, Eric Wieser, Julian Taylor, Sebastian Berg, Nathaniel J. Smith, Robert Kern, Matti Picus, Stephan Hoyer, Marten H. van Kerkwijk, Matthew Brett, Allan Haldane, Jaime Fernández del Río, Mark Wiebe, Pearu Peterson, Pierre Gérard-Marchant, Kevin Sheppard, Tyler Reddy, Warren Weckesser, Hameer Abbasi, Christoph Gohlke, and Travis E. Oliphant. Array programming with NumPy. *Nature*, 585(7825):357–362, September 2020. doi: 10.1038/s41586-020-2649-2.
- [69] W. K. Hastings. Monte Carlo Sampling Methods using Markov Chains and their Applications. *Biometrika*, 57(1):97–109, April 1970. doi: 10.1093/biomet/57.1.97.
- [70] Misha Haywood, Sergey Khoperskov, Valeria Cerqui, Paola Di Matteo, David Katz, and Owain Snaith. Timing the Milky Way bar formation and the accompanying radial migration episode. *A&A*, 690:A147, October 2024. doi: 10.1051/0004-6361/202348767.

- [71] Lars Hernquist and Martin D. Weinberg. Bar-Spheroid Interaction in Galaxies. *ApJ*, 400:80, November 1992. doi: 10.1086/171975.
- [72] David W. Hogg, Andrew R. Casey, Melissa Ness, Hans-Walter Rix, Daniel Foreman-Mackey, Sten Hasselquist, Anna Y. Q. Ho, Jon A. Holtzman, Steven R. Majewski, Sarah L. Martell, Szabolcs Mészáros, David L. Nidever, and Matthew Shetrone. Chemical Tagging Can Work: Identification of Stellar Phase-space Structures Purely by Chemical-abundance Similarity. *ApJ*, 833(2):262, December 2016. doi: 10.3847/1538-4357/833/2/262.
- [73] Philip F. Hopkins. A new class of accurate, mesh-free hydrodynamic simulation methods. *MNRAS*, 450(1):53–110, June 2015. doi: 10.1093/mnras/stv195.
- [74] Philip F. Hopkins, Andrew Wetzel, Dušan Kereš, Claude-André Faucher-Giguère, Eliot Quataert, Michael Boylan-Kolchin, Norman Murray, Christopher C. Hayward, and Kareem El-Badry. How to model supernovae in simulations of star and galaxy formation. *MNRAS*, 477(2):1578–1603, June 2018. doi: 10.1093/mnras/sty674.
- [75] Philip F. Hopkins, Andrew Wetzel, Dušan Kereš, Claude-André Faucher-Giguère, Eliot Quataert, Michael Boylan-Kolchin, Norman Murray, Christopher C. Hayward, Shea Garrison-Kimmel, Cameron Hummels, Robert Feldmann, Paul Torrey, Xiangcheng Ma, Daniel Anglés-Alcázar, Kung-Yi Su, Matthew Orr, Denise Schmitz, Ivanna Escala, Robyn Sanderson, Michael Y. Grudić, Zachary Hafen, Ji-Hoon Kim, Alex Fitts, James S. Bullock, Coral Wheeler, T. K. Chan, Oliver D. Elbert, and Desika Narayanan. FIRE-2 simulations: physics versus numerics in galaxy formation. *MNRAS*, 480(1):800–863, October 2018. doi: 10.1093/mnras/sty1690.
- [76] Philip F. Hopkins, T. K. Chan, Shea Garrison-Kimmel, Suoqing Ji, Kung-Yi Su, Cameron B. Hummels, Dušan Kereš, Eliot Quataert, and Claude-André Faucher-Giguère. But what about...: cosmic rays, magnetic fields, conduction, and viscosity in galaxy formation. *MNRAS*, 492(3):3465–3498, March 2020. doi: 10.1093/mnras/stz3321.

- [77] Yang Huang, Xiao-Wei Liu, Hua-Wei Zhang, Hai-Bo Yuan, Mao-Sheng Xiang, Bing-Qiu Chen, Juan-Juan Ren, Ning-Chen Sun, Chun Wang, Yong Zhang, Yong-Hui Hou, Yue-Fei Wang, and Ming Yang. On the metallicity gradients of the Galactic disk as revealed by LSS-GAC red clump stars. *Research in Astronomy and Astrophysics*, 15(8):1240, August 2015. doi: 10.1088/1674-4527/15/8/010.
- [78] Jason A. S. Hunt, Ioana A. Stelea, Kathryn V. Johnston, Suroor S. Gandhi, Chervin F. P. Laporte, and Jeroen Bédorf. Resolving local and global kinematic signatures of satellite mergers with billion particle simulations. *MNRAS*, 508(1):1459–1472, November 2021. doi: 10.1093/mnras/stab2580.
- [79] John D. Hunter. Matplotlib: A 2d graphics environment. *Computing in Science & Engineering*, 9(3):90–95, 2007. doi: 10.1109/MCSE.2007.55.
- [80] Koichi Iwamoto, Franziska Brachwitz, Ken’ICHI Nomoto, Nobuhiro Kishimoto, Hideyuki Umeda, W. Raphael Hix, and Friedrich-Karl Thielemann. Nucleosynthesis in Chandrasekhar Mass Models for Type IA Supernovae and Constraints on Progenitor Systems and Burning-Front Propagation. *ApJS*, 125(2):439–462, December 1999. doi: 10.1086/313278.
- [81] Robert G. Izzard, Christopher A. Tout, Amanda I. Karakas, and Onno R. Pols. A new synthetic model for asymptotic giant branch stars. *MNRAS*, 350(2):407–426, May 2004. doi: 10.1111/j.1365-2966.2004.07446.x.
- [82] H. R. Jacobson, E. D. Friel, L. Jílková, L. Magrini, A. Bragaglia, A. Vallenari, M. Tosi, S. Randich, P. Donati, T. Cantat-Gaudin, R. Sordo, R. Smiljanic, J. C. Overbeek, G. Carraro, G. Tautvaišienė, I. San Roman, S. Villanova, D. Geisler, C. Muñoz, F. Jiménez-Esteban, B. Tang, G. Gilmore, E. J. Alfaro, T. Bensby, E. Flaccomio, S. E. Koposov, A. J. Korn, E. Pancino, A. Recio-Blanco, A. R. Casey, M. T. Costado, E. Franciosini, U. Heiter, V. Hill, A. Hourihane, C. Lardo, P. de Laverny, J. Lewis, L. Monaco, L. Morbidelli, G. G. Sacco, S. G. Sousa, C. C. Worley, and S. Zaggia. The Gaia-ESO Survey: Probes of the inner disk abundance gradient. *A&A*, 591:A37, June 2016. doi: 10.1051/0004-6361/201527654.

- [83] Heather R. Jacobson, Catherine A. Pilachowski, and Eileen D. Friel. A Chemical Abundance Study of 10 Open Clusters Based on WIYN-Hydra Spectroscopy. *AJ*, 142(2):59, August 2011. doi: 10.1088/0004-6256/142/2/59.
- [84] K. Janes and D. Adler. Open clusters and galactic structure. *ApJS*, 49:425–446, July 1982. doi: 10.1086/190805.
- [85] K. A. Janes. Evidence for an abundance gradient in the galactic disk. *ApJS*, 39: 135–156, February 1979. doi: 10.1086/190568.
- [86] K. A. Janes, C. Tilley, and G. Lynga. Properties of the Open Cluster System. *AJ*, 95:771, March 1988. doi: 10.1086/114676.
- [87] Harshil Kamdar, Charlie Conroy, Yuan-Sen Ting, Ana Bonaca, Benjamin Johnson, and Phillip Cargile. A Dynamical Model for Clustered Star Formation in the Galactic Disk. *ApJ*, 884(2):173, October 2019. doi: 10.3847/1538-4357/ab44be.
- [88] S. Khoperskov, P. Di Matteo, M. Haywood, A. Gómez, and O. N. Snaith. Escapees from the bar resonances. Presence of low-eccentricity metal-rich stars at the solar vicinity. *A&A*, 638:A144, June 2020. doi: 10.1051/0004-6361/201937188.
- [89] Ji-hoon Kim, Tom Abel, Oscar Agertz, Greg L. Bryan, Daniel Ceverino, Charlotte Christensen, Charlie Conroy, Avishai Dekel, Nickolay Y. Gnedin, Nathan J. Goldbaum, Javiera Guedes, Oliver Hahn, Alexander Hobbs, Philip F. Hopkins, Cameron B. Hummels, Francesca Iannuzzi, Dusan Keres, Anatoly Klypin, Andrey V. Kravtsov, Mark R. Krumholz, Michael Kuhlen, Samuel N. Leitner, Piero Madau, Lucio Mayer, Christopher E. Moody, Kentaro Nagamine, Michael L. Norman, Jose Onorbe, Brian W. O’Shea, Annalisa Pillepich, Joel R. Primack, Thomas Quinn, Justin I. Read, Brant E. Robertson, Miguel Rocha, Douglas H. Rudd, Sijing Shen, Britton D. Smith, Alexander S. Szalay, Romain Teyssier, Robert Thompson, Keita Todoroki, Matthew J. Turk, James W. Wadsley, John H. Wise, Adi Zolotov, and the AGORA Collaboration²⁹. The AGORA High-resolution Galaxy Simulations Comparison Project. *ApJS*, 210(1):14, January 2014. doi: 10.1088/0067-0049/210/1/14.

- [90] David G. Koch, William J. Borucki, Gibor Basri, Natalie M. Batalha, Timothy M. Brown, Douglas Caldwell, Jørgen Christensen-Dalsgaard, William D. Cochran, Edna DeVore, Edward W. Dunham, III Gautier, Thomas N., John C. Geary, Ronald L. Gilliland, Alan Gould, Jon Jenkins, Yoji Kondo, David W. Latham, Jack J. Lissauer, Geoffrey Marcy, David Monet, Dimitar Sasselov, Alan Boss, Donald Brownlee, John Caldwell, Andrea K. Dupree, Steve B. Howell, Hans Kjeldsen, Søren Meibom, David Morrison, Tobias Owen, Harold Reitsema, Jill Tarter, Stephen T. Bryson, Jessie L. Dotson, Paul Gazis, Michael R. Haas, Jeffrey Kolodziejczak, Jason F. Rowe, Jeffrey E. Van Cleve, Christopher Allen, Hema Chandrasekaran, Bruce D. Clarke, Jie Li, Elisa V. Quintana, Peter Tenenbaum, Joseph D. Twicken, and Hayley Wu. Kepler Mission Design, Realized Photometric Performance, and Early Science. *ApJ*, 713(2):L79–L86, April 2010. doi: 10.1088/2041-8205/713/2/L79.
- [91] Juna A. Kollmeier, Gail Zasowski, Hans-Walter Rix, Matt Johns, Scott F. Anderson, Niv Drory, Jennifer A. Johnson, Richard W. Pogge, Jonathan C. Bird, Guillermo A. Blanc, Joel R. Brownstein, Jeffrey D. Crane, Nathan M. De Lee, Mark A. Klaene, Kathryn Kreckel, Nick MacDonald, Andrea Merloni, Melissa K. Ness, Thomas O’Brien, Jose R. Sanchez-Gallego, Conor C. Sayres, Yue Shen, Ani R. Thakar, Andrew Tkachenko, Conny Aerts, Michael R. Blanton, Daniel J. Eisenstein, Jon A. Holtzman, Dan Maoz, Kirpal Nandra, Constance Rockosi, David H. Weinberg, Jo Bovy, Andrew R. Casey, Julio Chaname, Nicolas Clerc, Charlie Conroy, Michael Eracleous, Boris T. Gänsicke, Saskia Hekker, Keith Horne, Jens Kauffmann, Kristen B. W. McQuinn, Eric W. Pellegrini, Eva Schinnerer, Edward F. Schlafly, Axel D. Schwobe, Mark Seibert, Johanna K. Teske, and Jennifer L. van Saders. SDSS-V: Pioneering Panoptic Spectroscopy. *arXiv e-prints*, art. arXiv:1711.03234, November 2017.
- [92] Kathryn Kreckel, I. Ting Ho, Guillermo A. Blanc, Simon C. O. Glover, Brent Groves, Erik Rosolowsky, Frank Bigiel, Médéric Boquéin, Mélanie Chevance, Daniel A. Dale, Sinan Deger, Eric Emsellem, Kathryn Grasha, Jenny J. Kim, Ralf S. Klessen, J. M. Diederik Kruijssen, Janice C. Lee, Adam K. Leroy, Daizhong Liu, Rebecca McElroy, Sharon E. Meidt, Ismael Pessa, Pa-

- tricia Sanchez-Blazquez, Karin Sandstrom, Francesco Santoro, Fabian Scheuermann, Eva Schinnerer, Andreas Schrubba, Dyas Utomo, Elizabeth J. Watkins, and Thomas G. Williams. Measuring the mixing scale of the ISM within nearby spiral galaxies. *MNRAS*, 499(1):193–209, November 2020. doi: 10.1093/mnras/staa2743.
- [93] Pavel Kroupa. On the variation of the initial mass function. *MNRAS*, 322(2): 231–246, April 2001. doi: 10.1046/j.1365-8711.2001.04022.x.
- [94] J. M. Diederik Kruijssen, F. Inti Pelupessy, Henny J. G. L. M. Lamers, Simon F. Portegies Zwart, and Vincent Icke. Modelling the formation and evolution of star cluster populations in galaxy simulations. *MNRAS*, 414(2):1339–1364, June 2011. doi: 10.1111/j.1365-2966.2011.18467.x.
- [95] Mark R. Krumholz and Nickolay Y. Gnedin. A Comparison of Methods for Determining the Molecular Content of Model Galaxies. *ApJ*, 729(1):36, March 2011. doi: 10.1088/0004-637X/729/1/36.
- [96] Mark R. Krumholz, Christopher F. McKee, and Joss Bland-Hawthorn. Star Clusters Across Cosmic Time. *ARA&A*, 57:227–303, August 2019. doi: 10.1146/annurev-astro-091918-104430.
- [97] Charles J. Lada and Elizabeth A. Lada. Embedded Clusters in Molecular Clouds. *ARA&A*, 41:57–115, January 2003. doi: 10.1146/annurev.astro.41.011802.094844.
- [98] David L. Lambert and Arumalla B. S. Reddy. Prospecting for Chemical Tags among Open Clusters. *ApJ*, 831(2):202, November 2016. doi: 10.3847/0004-637X/831/2/202.
- [99] H. J. G. L. M. Lamers and M. Gieles. Clusters in the solar neighbourhood: how are they destroyed? *A&A*, 455(2):L17–L20, August 2006. doi: 10.1051/0004-6361:20065567.
- [100] H. J. G. L. M. Lamers, M. Gieles, and S. F. Portegies Zwart. Disruption time

- scales of star clusters in different galaxies. *A&A*, 429:173–179, January 2005. doi: 10.1051/0004-6361:20041476.
- [101] R. B. Larson. Models for the formation of disc galaxies. *MNRAS*, 176:31–52, July 1976. doi: 10.1093/mnras/176.1.31.
- [102] Claus Leitherer, Daniel Schaerer, Jeffrey D. Goldader, Rosa M. González Delgado, Carmelle Robert, Denis Foo Kune, Duília F. de Mello, Daniel Devost, and Timothy M. Heckman. Starburst99: Synthesis Models for Galaxies with Active Star Formation. *ApJS*, 123(1):3–40, July 1999. doi: 10.1086/313233.
- [103] B. Lemasle, P. François, K. Genovali, V. V. Kovtyukh, G. Bono, L. Inno, C. D. Laney, L. Kaper, M. Bergemann, M. Fabrizio, N. Matsunaga, S. Pedicelli, F. Primas, and M. Romaniello. Galactic abundance gradients from Cepheids. α and heavy elements in the outer disk. *A&A*, 558:A31, October 2013. doi: 10.1051/0004-6361/201322115.
- [104] Zefeng Li, Emily Wisnioski, J. Trevor Mendel, Mark R. Krumholz, Lisa J. Kewley, Carlos López-Cobá, Sebastián F. Sánchez, Joseph P. Anderson, and Lluís Galbany. Spatial metallicity distribution statistics at $\lesssim 100$ pc scales in the AMUSING++ nearby galaxy sample. *MNRAS*, 518(1):286–304, January 2023. doi: 10.1093/mnras/stac3028.
- [105] F. Liu, D. Yong, M. Asplund, I. Ramírez, and J. Meléndez. The Hyades open cluster is chemically inhomogeneous. *MNRAS*, 457(4):3934–3948, April 2016. doi: 10.1093/mnras/stw247.
- [106] F. Liu, M. Asplund, D. Yong, S. Feltzing, A. Dotter, J. Meléndez, and I. Ramírez. Chemical (in)homogeneity and atomic diffusion in the open cluster M 67. *A&A*, 627:A117, July 2019. doi: 10.1051/0004-6361/201935306.
- [107] R. Earle Luck. Cepheid Abundances: Multiphase Results and Spatial Gradients. *AJ*, 156(4):171, October 2018. doi: 10.3847/1538-3881/aadcac.
- [108] W. J. Maciel, R. D. D. Costa, and O. Cavichia. Radial abundance gradients from

planetary nebulae at different distances from the galactic plane. *Rev. Mexicana Astron. Astrofis.*, 51:165, October 2015.

- [109] L. Magrini, P. Sestito, S. Randich, and D. Galli. The evolution of the Galactic metallicity gradient from high-resolution spectroscopy of open clusters. *A&A*, 494(1):95–108, January 2009. doi: 10.1051/0004-6361:200810634.
- [110] L. Magrini, S. Randich, D. Romano, E. Friel, A. Bragaglia, R. Smiljanic, H. Jacobson, A. Vallenari, M. Tosi, L. Spina, P. Donati, E. Maiorca, T. Cantat-Gaudin, R. Sordo, M. Bergemann, F. Damiani, G. Tautvaišienė, S. Blanco-Cuaresma, F. Jiménez-Esteban, D. Geisler, N. Mowlavi, C. Munoz, I. San Roman, C. Soubiran, S. Villanova, S. Zaggia, G. Gilmore, M. Asplund, S. Feltzing, R. Jeffries, T. Bensby, S. Koposov, A. J. Korn, E. Flaccomio, E. Pancino, A. Recio-Blanco, G. Sacco, M. T. Costado, E. Franciosini, P. Jofre, P. de Laverny, V. Hill, U. Heiter, A. Hourihane, R. Jackson, C. Lardo, L. Morbidelli, J. Lewis, K. Lind, T. Masseron, L. Prisinzano, and C. Worley. The Gaia-ESO Survey: Abundance ratios in the inner-disk open clusters Trumpler 20, NGC 4815, NGC 6705. *A&A*, 563:A44, March 2014. doi: 10.1051/0004-6361/201322977.
- [111] L. Magrini, S. Randich, G. Kordopatis, N. Prantzos, D. Romano, A. Chieffi, M. Limongi, P. François, E. Pancino, E. Friel, A. Bragaglia, G. Tautvaišienė, L. Spina, J. Overbeek, T. Cantat-Gaudin, P. Donati, A. Vallenari, R. Sordo, F. M. Jiménez-Esteban, B. Tang, A. Drazdauskas, S. Sousa, S. Duffau, P. Jofré, G. Gilmore, S. Feltzing, E. Alfaro, T. Bensby, E. Flaccomio, S. Koposov, A. Lanzafame, R. Smiljanic, A. Bayo, G. Carraro, A. R. Casey, M. T. Costado, F. Damiani, E. Franciosini, A. Hourihane, C. Lardo, J. Lewis, L. Monaco, L. Morbidelli, G. Sacco, L. Sbordone, C. C. Worley, and S. Zaggia. The Gaia-ESO Survey: radial distribution of abundances in the Galactic disc from open clusters and young-field stars. *A&A*, 603:A2, June 2017. doi: 10.1051/0004-6361/201630294.
- [112] L. Magrini, C. Viscasillas Vázquez, L. Spina, S. Randich, D. Romano, E. Franciosini, A. Recio-Blanco, T. Nordlander, V. D’Orazi, M. Baratella, R. Smiljanic, M. L. L. Dantas, L. Pasquini, E. Spitoni, G. Casali, M. Van der Swaelmen, T. Bensby, E. Stonkute, S. Feltzing, G. G. Sacco, A. Bragaglia, E. Pancino,

- U. Heiter, K. Biazzo, G. Gilmore, M. Bergemann, G. Tautvaišienė, C. Worley, A. Hourihane, A. Gonneau, and L. Morbidelli. The Gaia-ESO survey: Mapping the shape and evolution of the radial abundance gradients with open clusters. *A&A*, 669:A119, January 2023. doi: 10.1051/0004-6361/202244957.
- [113] S. R. Majewski, APOGEE Team, and APOGEE-2 Team. The Apache Point Observatory Galactic Evolution Experiment (APOGEE) and its successor, APOGEE-2. *Astronomische Nachrichten*, 337(8-9):863, September 2016. doi: 10.1002/asna.201612387.
- [114] Steven R. Majewski, David L. Nidever, Verne V. Smith, Guillermo J. Damke, William E. Kunkel, Richard J. Patterson, Dmitry Bizyaev, and Ana E. García Pérez. Exploring Halo Substructure with Giant Stars: Substructure in the Local Halo as Seen in the Grid Giant Star Survey Including Extended Tidal Debris from ω Centauri. *ApJ*, 747(2):L37, March 2012. doi: 10.1088/2041-8205/747/2/L37.
- [115] Steven R. Majewski, Ricardo P. Schiavon, Peter M. Frinchaboy, Carlos Allende Prieto, Robert Barkhouser, Dmitry Bizyaev, Basil Blank, Sophia Brunner, Adam Burton, Ricardo Carrera, S. Drew Chojnowski, Kátia Cunha, Courtney Epstein, Greg Fitzgerald, Ana E. García Pérez, Fred R. Hearty, Chuck Henderson, Jon A. Holtzman, Jennifer A. Johnson, Charles R. Lam, James E. Lawler, Paul Mase-man, Szabolcs Mészáros, Matthew Nelson, Duy Coung Nguyen, David L. Nidever, Marc Pinsonneault, Matthew Shetrone, Stephen Smee, Verne V. Smith, Todd Stolberg, Michael F. Skrutskie, Eric Walker, John C. Wilson, Gail Zasowski, Friedrich Anders, Sarbani Basu, Stephane Beland, Michael R. Blanton, Jo Bovy, Joel R. Brownstein, Joleen Carlberg, William Chaplin, Cristina Chiappini, Daniel J. Eisenstein, Yvonne Elsworth, Diane Feuillet, Scott W. Fleming, Jessica Galbraith-Frew, Rafael A. García, D. Aníbal García-Hernández, Bruce A. Gillespie, Léo Girardi, James E. Gunn, Sten Hasselquist, Michael R. Hayden, Saskia Hekker, Inese Ivans, Karen Kinemuchi, Mark Klaene, Suvrath Mahadevan, Savita Mathur, Benoît Mosser, Demitri Muna, Jeffrey A. Munn, Robert C. Nichol, Robert W. O’Connell, John K. Parejko, A. C. Robin, Helio Rocha-Pinto, Matthias Schultheis, Aldo M. Serenelli, Neville Shane, Victor Silva Aguirre, Jen-

- nifer S. Sobeck, Benjamin Thompson, Nicholas W. Troup, David H. Weinberg, and Olga Zamora. The Apache Point Observatory Galactic Evolution Experiment (APOGEE). *AJ*, 154(3):94, September 2017. doi: 10.3847/1538-3881/aa784d.
- [116] Catherine Manea, Keith Hawkins, and Zachary G. Maas. A GALAH view of the chemical homogeneity and ages of stellar strings identified in Gaia. *MNRAS*, 511(2):2829–2847, April 2022. doi: 10.1093/mnras/stac236.
- [117] Catherine Manea, Keith Hawkins, Melissa K. Ness, Sven Buder, Sarah L. Martell, and Daniel B. Zucker. Chemical Doppelgangers in GALAH DR3: the Distinguishing Power of Neutron-Capture Elements Among Milky Way Disk Stars. *arXiv e-prints*, art. arXiv:2310.15257, October 2023. doi: 10.48550/arXiv.2310.15257.
- [118] F. Mannucci, M. Della Valle, and N. Panagia. Two populations of progenitors for Type Ia supernovae? *MNRAS*, 370(2):773–783, August 2006. doi: 10.1111/j.1365-2966.2006.10501.x.
- [119] P. Marigo. Chemical yields from low- and intermediate-mass stars: Model predictions and basic observational constraints. *A&A*, 370:194–217, April 2001. doi: 10.1051/0004-6361:20000247.
- [120] Sarah L. Martell, Matthew D. Shetrone, Sara Lucatello, Ricardo P. Schiavon, Szabolcs Mészáros, Carlos Allende Prieto, D. A. García-Hernández, Timothy C. Beers, and David L. Nidever. Chemical Tagging in the SDSS-III/APOGEE Survey: New Identifications of Halo Stars with Globular Cluster Origins. *ApJ*, 825(2):146, July 2016. doi: 10.3847/0004-637X/825/2/146.
- [121] Inma Martinez-Valpuesta, Isaac Shlosman, and Clayton Heller. Evolution of Stellar Bars in Live Axisymmetric Halos: Recurrent Buckling and Secular Growth. *ApJ*, 637(1):214–226, January 2006. doi: 10.1086/498338.
- [122] Davoud Masoumi. *From Quark Confinement to Dynamical History of Stars*. Dissertation/thesis, University of California, Merced, United States – California, January 2024. URL <https://www.proquest.com/dissertations-theses/quark-confinement-dynamical-history-stars/docview/3084318188/>

se-2?accountid=14515. ProQuest Dissertations & Theses A&I. (ProQuest document ID: 3084318188).

- [123] R. D. Mathieu. The WIYN Open Cluster Study. In R. Pallavicini, G. Micela, and S. Sciortino, editors, *Stellar Clusters and Associations: Convection, Rotation, and Dynamos*, volume 198 of *Astronomical Society of the Pacific Conference Series*, page 517, January 2000.
- [124] F. Matteucci and P. Francois. Galactic chemical evolution : abundance gradients of individual elements. *MNRAS*, 239:885–904, August 1989. doi: 10.1093/mnras/239.3.885.
- [125] Christopher F. McKee and Jonathan C. Tan. Massive star formation in 100,000 years from turbulent and pressurized molecular clouds. *Nature*, 416(6876):59–61, March 2002. doi: 10.1038/416059a.
- [126] M. R. Meyer, F. C. Adams, L. A. Hillenbrand, J. M. Carpenter, and R. B. Larson. The Stellar Initial Mass Function: Constraints from Young Clusters, and Theoretical Perspectives. In V. Mannings, A. P. Boss, and S. S. Russell, editors, *Protostars and Planets IV*, page 121, May 2000. doi: 10.48550/arXiv.astro-ph/9902198.
- [127] Tatiana A. Michtchenko, Jacques R. D. Lépine, Angeles Pérez-Villegas, Ronaldo S. S. Vieira, and Douglas A. Barros. On the Stellar Velocity Distribution in the Solar Neighborhood in Light of Gaia DR2. *ApJ*, 863(2):L37, August 2018. doi: 10.3847/2041-8213/aad804.
- [128] I. Minchev, C. Chiappini, and M. Martig. Chemodynamical evolution of the Milky Way disk. II. Variations with Galactic radius and height above the disk plane. *A&A*, 572:A92, December 2014. doi: 10.1051/0004-6361/201423487.
- [129] I. Minchev, F. Anders, A. Recio-Blanco, C. Chiappini, P. de Laverny, A. Queiroz, M. Steinmetz, V. Adibekyan, I. Carrillo, G. Cescutti, G. Guiglion, M. Hayden, R. S. de Jong, G. Kordopatis, S. R. Majewski, M. Martig, and B. X. Santiago. Estimating stellar birth radii and the time evolution of Milky Way’s ISM metallicity

- gradient. *MNRAS*, 481(2):1645–1657, December 2018. doi: 10.1093/mnras/sty2033.
- [130] A. W. Mitschang, G. De Silva, S. Sharma, and D. B. Zucker. Quantifying chemical tagging: towards robust group finding in the Galaxy. *MNRAS*, 428(3):2321–2332, January 2013. doi: 10.1093/mnras/sts194.
- [131] André Moitinho. Observational properties of the open cluster system of the Milky Way and what they tell us about our Galaxy. In Richard de Grijs and Jacques R. D. Lépine, editors, *Star Clusters: Basic Galactic Building Blocks Throughout Time and Space*, volume 266, pages 106–116, January 2010. doi: 10.1017/S1743921309990949.
- [132] M. Mollá, S. Wekesa, O. Cavichia, Á. I. Díaz, B. K. Gibson, F. F. Rosales-Ortega, Y. Ascasibar, D. S. Wamalwa, and S. F. Sánchez. 2D-Galactic chemical evolution: the role of the spiral density wave. *MNRAS*, 490(1):665–682, November 2019. doi: 10.1093/mnras/stz2537.
- [133] L. Monaco, E. Pancino, F. R. Ferraro, and M. Bellazzini. Wide-field photometry of the Galactic globular cluster M22. *MNRAS*, 349(4):1278–1290, April 2004. doi: 10.1111/j.1365-2966.2004.07599.x.
- [134] E. Moraux. Open clusters and associations in the Gaia era. In *EAS Publications Series*, volume 80-81 of *EAS Publications Series*, pages 73–114, November 2016. doi: 10.1051/eas/1680004.
- [135] Natalie Myers, John Donor, Taylor Spoo, Peter M. Frinchaboy, Katia Cunha, Adrian M. Price-Whelan, Steven R. Majewski, Rachael L. Beaton, Gail Zasowski, Julia O’Connell, Amy E. Ray, Dmitry Bizyaev, Cristina Chiappini, D. A. García-Hernández, Doug Geisler, Henrik Jönsson, Richard R. Lane, Penélope Longa-Peña, Ivan Minchev, Dante Minniti, Christian Nitschelm, and A. Roman-Lopes. The Open Cluster Chemical Abundances and Mapping Survey. VI. Galactic Chemical Gradient Analysis from APOGEE DR17. *AJ*, 164(3):85, September 2022. doi: 10.3847/1538-3881/ac7ce5.

- [136] M. Ness, David W. Hogg, H. W. Rix, Anna. Y. Q. Ho, and G. Zasowski. The Cannon: A data-driven approach to Stellar Label Determination. *ApJ*, 808(1):16, July 2015. doi: 10.1088/0004-637X/808/1/16.
- [137] M. Ness, H. W. Rix, David W. Hogg, A. R. Casey, J. Holtzman, M. Fouesneau, G. Zasowski, D. Geisler, M. Shetrone, D. Minniti, Peter M. Frinchaboy, and Alexandre Roman-Lopes. Galactic Doppelgänger: The Chemical Similarity Among Field Stars and Among Stars with a Common Birth Origin. *ApJ*, 853(2): 198, February 2018. doi: 10.3847/1538-4357/aa9d8e.
- [138] M. K. Ness, K. V. Johnston, K. Blancato, H. W. Rix, A. Beane, J. C. Bird, and K. Hawkins. In the Galactic Disk, Stellar [Fe/H] and Age Predict Orbits and Precise [X/Fe]. *ApJ*, 883(2):177, October 2019. doi: 10.3847/1538-4357/ab3e3c.
- [139] Melissa K. Ness, Adam J. Wheeler, Kevin McKinnon, Danny Horta, Andrew R. Casey, Emily C. Cunningham, and Adrian M. Price-Whelan. The Homogeneity of the Star-forming Environment of the Milky Way Disk over Time. *ApJ*, 926(2): 144, February 2022. doi: 10.3847/1538-4357/ac4754.
- [140] Ken’ichi Nomoto, Nozomu Tominaga, Hideyuki Umeda, Chiaki Kobayashi, and Keiichi Maeda. Nucleosynthesis yields of core-collapse supernovae and hyper-novae, and galactic chemical evolution. *Nucl. Phys. A*, 777:424–458, October 2006. doi: 10.1016/j.nuclphysa.2006.05.008.
- [141] Terry D. Oswalt and Gerard Gilmore. *Planets, Stars and Stellar Systems Vol. 5*. Springer, 2013. doi: 10.1007/978-94-007-5612-0.
- [142] N. Panagia and M. Tosi. The chemical abundance gradient in the galaxy derived from an analysis of the H-R diagrams of open clusters. *A&A*, 81(3):375–378, January 1980.
- [143] E. Pancino, R. Carrera, E. Rossetti, and C. Gallart. Chemical abundance analysis of the open clusters Cr 110, NGC 2099 (M 37), NGC 2420, NGC 7789, and M 67 (NGC 2682). *A&A*, 511:A56, February 2010. doi: 10.1051/0004-6361/200912965.

- [144] Fernando Perez and Brian E. Granger. Ipython: A system for interactive scientific computing. *Computing in Science & Engineering*, 9(3):21–29, 2007. doi: 10.1109/MCSE.2007.53.
- [145] Andres E. Piatti, Juan J. Claria, and Mario G. Abadi. Chemical Evolution of the Galactic Disk: Evidence for a Gradient Perpendicular to the Galactic Plane. *AJ*, 110:2813, December 1995. doi: 10.1086/117731.
- [146] Planck Collaboration, N. Aghanim, Y. Akrami, M. Ashdown, J. Aumont, C. Bacigalupi, M. Ballardini, A. J. Banday, R. B. Barreiro, N. Bartolo, S. Basak, R. Battye, K. Benabed, J. P. Bernard, M. Bersanelli, P. Bielewicz, J. J. Bock, J. R. Bond, J. Borrill, F. R. Bouchet, F. Boulanger, M. Bucher, C. Burigana, R. C. Butler, E. Calabrese, J. F. Cardoso, J. Carron, A. Challinor, H. C. Chiang, J. Chluba, L. P. L. Colombo, C. Combet, D. Contreras, B. P. Crill, F. Cuttaia, P. de Bernardis, G. de Zotti, J. Delabrouille, J. M. Delouis, E. Di Valentino, J. M. Diego, O. Doré, M. Douspis, A. Ducout, X. Dupac, S. Dusini, G. Efstathiou, F. Elsner, T. A. Enßlin, H. K. Eriksen, Y. Fantaye, M. Farhang, J. Fergusson, R. Fernandez-Cobos, F. Finelli, F. Forastieri, M. Frailis, A. A. Fraisse, E. Franceschi, A. Frolov, S. Galeotta, S. Galli, K. Ganga, R. T. Génova-Santos, M. Gerbino, T. Ghosh, J. González-Nuevo, K. M. Górski, S. Gratton, A. Gruppuso, J. E. Gudmundsson, J. Hamann, W. Handley, F. K. Hansen, D. Herranz, S. R. Hildebrandt, E. Hivon, Z. Huang, A. H. Jaffe, W. C. Jones, A. Karakci, E. Keihänen, R. Keskitalo, K. Kiiveri, J. Kim, T. S. Kisner, L. Knox, N. Krachmalnicoff, M. Kunz, H. Kurki-Suonio, G. Lagache, J. M. Lamarre, A. Lasenby, M. Lattanzi, C. R. Lawrence, M. Le Jeune, P. Lemos, J. Lesgourgues, F. Levrier, A. Lewis, M. Liguori, P. B. Lilje, M. Lilley, V. Lindholm, M. López-Caniego, P. M. Lubin, Y. Z. Ma, J. F. Macías-Pérez, G. Maggio, D. Maino, N. Mandolesi, A. Mangilli, A. Marcos-Caballero, M. Maris, P. G. Martin, M. Martinelli, E. Martínez-González, S. Matarrese, N. Mauri, J. D. McEwen, P. R. Meinhold, A. Melchiorri, A. Mennella, M. Migliaccio, M. Millea, S. Mitra, M. A. Miville-Deschênes, D. Molinari, L. Montier, G. Morgante, A. Moss, P. Natoli, H. U. Nørgaard-Nielsen, L. Pagano, D. Paoletti, B. Partridge, G. Patanchon, H. V. Peiris, F. Perrotta, V. Pettorino, F. Piacentini, L. Polastri, G. Polenta, J. L. Puget, J. P. Rachen, M. Reinecke, M. Remazeilles, A. Renzi, G. Rocha, C. Ros-

- set, G. Roudier, J. A. Rubiño-Martín, B. Ruiz-Granados, L. Salvati, M. Sandri, M. Savelainen, D. Scott, E. P. S. Shellard, C. Sirignano, G. Sirri, L. D. Spencer, R. Sunyaev, A. S. Suur-Uski, J. A. Tauber, D. Tavagnacco, M. Tenti, L. Toffolatti, M. Tomasi, T. Trombetti, L. Valenziano, J. Valiviita, B. Van Tent, L. Vibert, P. Vielva, F. Villa, N. Vittorio, B. D. Wandelt, I. K. Wehus, M. White, S. D. M. White, A. Zacchei, and A. Zonca. Planck 2018 results. VI. Cosmological parameters. *A&A*, 641:A6, September 2020. doi: 10.1051/0004-6361/201833910.
- [147] Sam B. Ponnada, Georgia V. Panopoulou, Iryna S. Butsky, Philip F. Hopkins, Sarah R. Loebman, Cameron Hummels, Suoqing Ji, Andrew Wetzel, Claude-André Faucher-Giguère, and Christopher C. Hayward. Magnetic fields on FIRE: Comparing B-fields in the multiphase ISM and CGM of simulated L_* galaxies to observations. *MNRAS*, 516(3):4417–4431, November 2022. doi: 10.1093/mnras/stac2448.
- [148] Vijith Jacob Poovelil, G. Zasowski, S. Hasselquist, A. Seth, John Donor, Rachael L. Beaton, K. Cunha, Peter M. Frinchaboy, D. A. García-Hernández, K. Hawkins, K. M. Kratter, Richard R. Lane, and C. Nitschelm. Open Cluster Chemical Homogeneity throughout the Milky Way. *ApJ*, 903(1):55, November 2020. doi: 10.3847/1538-4357/abb93e.
- [149] Simon F. Portegies Zwart, Stephen L. W. McMillan, and Mark Gieles. Young Massive Star Clusters. *ARA&A*, 48:431–493, September 2010. doi: 10.1146/annurev-astro-081309-130834.
- [150] Natalie Price-Jones and Jo Bovy. Blind chemical tagging with DBSCAN: prospects for spectroscopic surveys. *MNRAS*, 487(1):871–886, July 2019. doi: 10.1093/mnras/stz1260.
- [151] Arumalla B. S. Reddy, David L. Lambert, and Sunetra Giridhar. The evolution of the Milky Way: new insights from open clusters. *MNRAS*, 463(4):4366–4382, December 2016. doi: 10.1093/mnras/stw2287.
- [152] George R. Ricker, Joshua N. Winn, Roland Vanderspek, David W. Latham, Gáspár. Á. Bakos, Jacob L. Bean, Zachory K. Berta-Thompson, Timothy M.

- Brown, Lars Buchhave, Nathaniel R. Butler, R. Paul Butler, William J. Chaplin, David Charbonneau, Jørgen Christensen-Dalsgaard, Mark Clampin, Drake Deming, John Doty, Nathan De Lee, Courtney Dressing, E. W. Dunham, Michael Endl, Francois Fressin, Jian Ge, Thomas Henning, Matthew J. Holman, Andrew W. Howard, Shigeru Ida, Jon Jenkins, Garrett Jernigan, John A. Johnson, Lisa Kaltenegger, Nobuyuki Kawai, Hans Kjeldsen, Gregory Laughlin, Alan M. Levine, Douglas Lin, Jack J. Lissauer, Phillip MacQueen, Geoffrey Marcy, P. R. McCullough, Timothy D. Morton, Norio Narita, Martin Paegert, Enric Pallé, Francesco Pepe, Joshua Pepper, Andreas Quirrenbach, S. A. Rinehart, Dimitar Sasselov, Bun'ei Sato, Sara Seager, Alessandro Sozzetti, Keivan G. Stassun, Peter Sullivan, Andrew Szentgyorgyi, Guillermo Torres, Stephane Udry, and Joel Villaseñor. Transiting Exoplanet Survey Satellite (TESS). In Jr. Oschmann, Jacobus M., Mark Clampin, Giovanni G. Fazio, and Howard A. MacEwen, editors, *Space Telescopes and Instrumentation 2014: Optical, Infrared, and Millimeter Wave*, volume 9143 of *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*, page 914320, August 2014. doi: 10.1117/12.2063489.
- [153] L. Sánchez-Menguiano, S. F. Sánchez, I. Pérez, R. García-Benito, B. Husemann, D. Mast, A. Mendoza, T. Ruiz-Lara, Y. Ascasibar, J. Bland-Hawthorn, O. Cavichia, A. I. Díaz, E. Florido, L. Galbany, R. M. González Delgado, C. Kehrig, R. A. Marino, I. Márquez, J. Masegosa, J. Méndez-Abreu, M. Mollá, A. Del Olmo, E. Pérez, P. Sánchez-Blázquez, V. Stanishev, C. J. Walcher, Á. R. López-Sánchez, and CALIFA Collaboration. Shape of the oxygen abundance profiles in CALIFA face-on spiral galaxies. *A&A*, 587:A70, March 2016. doi: 10.1051/0004-6361/201527450.
- [154] Robyn E. Sanderson, Andrew Wetzel, Sarah Loebman, Sanjib Sharma, Philip F. Hopkins, Shea Garrison-Kimmel, Claude-André Faucher-Giguère, Dušan Kereš, and Eliot Quataert. Synthetic Gaia Surveys from the FIRE Cosmological Simulations of Milky Way-mass Galaxies. *ApJS*, 246(1):6, January 2020. doi: 10.3847/1538-4365/ab5b9d.
- [155] R. Schödel, D. Merritt, and A. Eckart. The nuclear star cluster of the Milky

- Way: proper motions and mass. *A&A*, 502(1):91–111, July 2009. doi: 10.1051/0004-6361/200810922.
- [156] J. A. Sellwood and A. Wilkinson. Dynamics of barred galaxies. *Reports on Progress in Physics*, 56(2):173–256, February 1993. doi: 10.1088/0034-4885/56/2/001.
- [157] P. Sestito, A. Bragaglia, S. Randich, R. Pallavicini, S. M. Andrievsky, and S. A. Korotin. Open clusters as key tracers of Galactic chemical evolution. III. Element abundances in Berkeley 20, Berkeley 29, Collinder 261 and Melotte 66. *A&A*, 488(3):943–958, September 2008. doi: 10.1051/0004-6361:200809650.
- [158] Anil C. Seth, Nadine Neumayer, and Torsten Böker. The properties of nuclear star clusters and their host galaxies. In Angela Bragaglia, Melvyn Davies, Alison Sills, and Enrico Vesperini, editors, *Star Clusters: From the Milky Way to the Early Universe*, volume 351, pages 13–18, January 2020. doi: 10.1017/S1743921319007117.
- [159] Sanjib Sharma, Michael R. Hayden, Joss Bland-Hawthorn, Dennis Stello, Sven Buder, Joel C. Zinn, Lorenzo Spina, Thomas Kallinger, Martin Asplund, Gayandhi M. De Silva, Valentina D’Orazi, Ken C. Freeman, Janez Kos, Geraint F. Lewis, Jane Lin, Karin Lind, Sarah L. Martell, Katharine J. Schlesinger, Jeffrey D. Simpson, Daniel B. Zucker, Tomaž Zwitter, Boquan Chen, Klemen Cotar, Prajwal R. Kafle, Shourya Khanna, Thor Tepper-Garcia, Purmortal Wang, and Rob A. Wittenmyer. The GALAH Survey: dependence of elemental abundances on age and metallicity for stars in the Galactic disc. *MNRAS*, 510(1):734–752, February 2022. doi: 10.1093/mnras/stab3341.
- [160] Frank H. Shu, Fred C. Adams, and Susana Lizano. Star formation in molecular clouds: observation and theory. *ARA&A*, 25:23–81, January 1987. doi: 10.1146/annurev.aa.25.090187.000323.
- [161] L. Spina, Y. S. Ting, G. M. De Silva, N. Frankel, S. Sharma, T. Cantat-Gaudin, M. Joyce, D. Stello, A. I. Karakas, M. B. Asplund, T. Nordlander, L. Casagrande, V. D’Orazi, A. R. Casey, P. Cottrell, T. Tepper-García, M. Baratella, J. Kos,

- K. Čotar, J. Bland-Hawthorn, S. Buder, K. C. Freeman, M. R. Hayden, G. F. Lewis, J. Lin, K. Lind, S. L. Martell, K. J. Schlesinger, J. D. Simpson, D. B. Zucker, and T. Zwitter. The GALAH survey: tracing the Galactic disc with open clusters. *MNRAS*, 503(3):3279–3296, May 2021. doi: 10.1093/mnras/stab471.
- [162] L. Spina, L. Magrini, G. G. Sacco, G. Casali, A. Vallenari, G. Tautvaisienė, F. Jiménez-Esteban, G. Gilmore, S. Randich, S. Feltzing, R. D. Jeffries, T. Bensby, A. Bragaglia, R. Smiljanic, G. Carraro, L. Morbidelli, and S. Zaggia. The Gaia-ESO Survey: Chemical tagging in the thin disk. Open clusters blindly recovered in the elemental abundance space. *arXiv e-prints*, art. arXiv:2203.14991, March 2022.
- [163] Lorenzo Spina, Parth Sharma, Jorge Meléndez, Megan Bedell, Andrew R. Casey, Marília Carlos, Elena Franciosini, and Antonella Vallenari. Chemical evidence for planetary ingestion in a quarter of Sun-like stars. *Nature Astronomy*, 5:1163–1169, November 2021. doi: 10.1038/s41550-021-01451-8.
- [164] Lorenzo Spina, Laura Magrini, and Katia Cunha. Mapping the Galactic Metallicity Gradient with Open Clusters: The State-of-the-Art and Future Challenges. *Universe*, 8(2):87, January 2022. doi: 10.3390/universe8020087.
- [165] Letizia Stanghellini and Misha Haywood. Galactic Planetary Nebulae as Probes of Radial Metallicity Gradients and Other Abundance Patterns. *ApJ*, 862(1):45, July 2018. doi: 10.3847/1538-4357/aacaf8.
- [166] Kung-Yi Su, Philip F. Hopkins, Christopher C. Hayward, Claude-André Faucher-Giguère, Dušan Kereš, Xiangcheng Ma, and Victor H. Robles. Feedback first: the surprisingly weak effects of magnetic fields, viscosity, conduction and metal diffusion on sub- L^* galaxy formation. *MNRAS*, 471(1):144–166, October 2017. doi: 10.1093/mnras/stx1463.
- [167] Yuan-Sen Ting, Gayandhi M. De Silva, Kenneth C. Freeman, and Stacey Jo Parker. High-resolution elemental abundance analysis of the open cluster IC 4756. *MNRAS*, 427(1):882–892, November 2012. doi: 10.1111/j.1365-2966.2012.22028.x.

- [168] Yuan-Sen Ting, Charlie Conroy, and Alyssa Goodman. Prospects for Chemically Tagging Stars in the Galaxy. *ApJ*, 807(1):104, July 2015. doi: 10.1088/0004-637X/807/1/104.
- [169] Bruce A. Twarog, Keith M. Ashman, and Barbara J. Anthony-Twarog. Some Revised Observational Constraints on the Formation and Evolution of the Galactic Disk. *AJ*, 114:2556, December 1997. doi: 10.1086/118667.
- [170] L. B. van den Hoek and M. A. T. Groenewegen. New theoretical yields of intermediate mass stars. *A&AS*, 123:305–328, June 1997. doi: 10.1051/aas:1997162.
- [171] Eugene Vasiliev. AGAMA: action-based galaxy modelling architecture. *MNRAS*, 482(2):1525–1544, January 2019. doi: 10.1093/mnras/sty2672.
- [172] Pauli Virtanen, Ralf Gommers, Travis E. Oliphant, Matt Haberland, Tyler Reddy, David Cournapeau, Evgeni Burovski, Pearu Peterson, Warren Weckesser, Jonathan Bright, Stéfan J. van der Walt, Matthew Brett, Joshua Wilson, K. Jarrod Millman, Nikolay Mayorov, Andrew R. J. Nelson, Eric Jones, Robert Kern, Eric Larson, C J Carey, İlhan Polat, Yu Feng, Eric W. Moore, Jake VanderPlas, Denis Laxalde, Josef Perktold, Robert Cimrman, Ian Henriksen, E. A. Quintero, Charles R. Harris, Anne M. Archibald, Antônio H. Ribeiro, Fabian Pedregosa, Paul van Mulbregt, and SciPy 1.0 Contributors. SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods*, 17:261–272, 2020. doi: 10.1038/s41592-019-0686-2.
- [173] M. D. Weinberg. Evolution of barred galaxies by dynamical friction. *MNRAS*, 213:451–471, March 1985. doi: 10.1093/mnras/213.3.451.
- [174] Andrew Wetzel and Shea Garrison-Kimmel. GizmoAnalysis: Read and analyze Gizmo simulations, February 2020.
- [175] Andrew Wetzel and Shea Garrison-Kimmel. HaloAnalysis: Read and analyze halo catalogs and merger trees, February 2020.

- [176] Andrew Wetzel, Christopher C. Hayward, Robyn E. Sanderson, Xiangcheng Ma, Daniel Anglés-Alcázar, Robert Feldmann, T. K. Chan, Kareem El-Badry, Coral Wheeler, Shea Garrison-Kimmel, Farnik Nikakhtar, Nondh Panithanpaisal, Arpit Arora, Alexander B. Gurvich, Jenna Samuel, Omid Sameie, Viraj Pandya, Zachary Hafen, Cameron Hummels, Sarah Loebman, Michael Boylan-Kolchin, James S. Bullock, Claude-André Faucher-Giguère, Dušan Kereš, Eliot Quataert, and Philip F. Hopkins. Public Data Release of the FIRE-2 Cosmological Zoom-in Simulations of Galaxy Formation. *ApJS*, 265(2):44, April 2023. doi: 10.3847/1538-4365/acb99a.
- [177] Andrew R. Wetzel, Philip F. Hopkins, Ji-hoon Kim, Claude-André Faucher-Giguère, Dušan Kereš, and Eliot Quataert. Reconciling Dwarf Galaxies with Λ CDM Cosmology: Simulating a Realistic Population of Satellites around a Milky Way-mass Galaxy. *ApJ*, 827(2):L23, August 2016. doi: 10.3847/2041-8205/827/2/L23.
- [178] Lawrence M. Widrow and John Dubinski. Equilibrium Disk-Bulge-Halo Models for the Milky Way and Andromeda Galaxies. *ApJ*, 631(2):838–855, October 2005. doi: 10.1086/432710.
- [179] Robert P. C. Wiersma, Joop Schaye, Tom Theuns, Claudio Dalla Vecchia, and Luca Tornatore. Chemical enrichment in cosmological, smoothed particle hydrodynamics simulations. *MNRAS*, 399(2):574–600, October 2009. doi: 10.1111/j.1365-2966.2009.15331.x.
- [180] David Yong, Bruce W. Carney, and Eileen D. Friel. Elemental Abundance Ratios in Stars of the Outer Galactic Disk. IV. A New Sample of Open Clusters. *AJ*, 144(4):95, October 2012. doi: 10.1088/0004-6256/144/4/95.
- [181] HanYuan Zhang, Vasily Belokurov, N. Wyn Evans, Jason L. Sanders, Yuxi, Lu, Chengye Cao, GyuChul Myeong, Adam M. Dillamore, Sarah G. Kane, and Zhao-Yu Li. Radial migration in the Galactic disc driven by a slowing bar. *arXiv e-prints*, art. arXiv:2502.02642, February 2025. doi: 10.48550/arXiv.2502.02642.