Elemental Abundances of Kepler Objects of Interest in APOGEE DR17

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Abstract

The elemental abundances of planet host stars can shed light on the conditions of planet forming environments. We test if individual abundances of 130 known/candidate planet hosts in APOGEE are statistically different from those of a reference doppelgänger sample. The reference set comprises objects selected with the same \( T_{\text{eff}} \), \( \log \, g \), \([\text{Fe/H}]\), and \([\text{Mg/H}]\) as each Kepler Object of Interest (KOI). We predict twelve individual abundances (\( \mathbb{X} = \mathbb{C}, \mathbb{N}, \mathbb{O}, \mathbb{Na}, \mathbb{Al}, \mathbb{Si}, \mathbb{Ca}, \mathbb{Ti}, \mathbb{V}, \mathbb{Cr}, \mathbb{Mn}, \mathbb{Ni} \)) for the KOIs and their doppelgängers using a local linear model of these four parameters, training on ASPCAP abundance measurements for a sample of field stars with high-fidelity (signal-to-noise ratio > 200) APOGEE observations. We compare element prediction residuals (model–measurement) for the two samples and find them to be indistinguishable, given a high-quality sample selection. We report median intrinsic dispersions of \(~0.038\) dex and \(~0.041\) dex, for the KOI and doppelgänger samples, respectively, for these elements. We conclude that the individual abundances at fixed \( T_{\text{eff}}, \log \, g, [\text{Fe/H}], \) and \([\text{Mg/H}]\) are unremarkable for known planet hosts. Our results establish an upper limit on the abundance precision required to uncover any chemical signatures of planet formation in planet host stars.

Unified Astronomy Thesaurus concepts: Exoplanet astronomy (486); Exoplanet formation (492); High resolution spectroscopy (2096); Stellar abundances (1577)

1. Introduction

The elemental abundances of planet host stars bear the fingerprint of the processes governing planet formation and evolution. For example, it is well established that stars hosting giant planets often have enhanced iron abundances ([Fe/H]; Gonzalez 1997; Heiter & Luck 2003; Santos et al. 2004; Fischer & Valenti 2005). This is typically regarded as evidence for the core accretion model of planet formation (e.g., Rice & Armitage 2003; Ida & Lin 2004; Alibert et al. 2011; Mordasini et al. 2012; Maldonado et al. 2019); the host star [Fe/H] can be considered a proxy for the solid surface density of protoplanetary disks. In this context, more solids translates to rapid growth of planetary cores that can reach a critical mass of \( \sim 10 \, M_{\text{J}} \) before the disk gas dissipates. This enables accretion of a substantial gaseous envelope. The planet–[Fe/H] trend appears to weaken with decreasing planet mass/radius (Sousa et al. 2008; Ghezzi et al. 2010; Schlaufman & Laughlin 2011; Buchhave et al. 2012; Buchhave & Latham 2015; Wang & Fischer 2015; Ghezzi et al. 2018), but becomes stronger with decreasing orbital period, particularly in the \( P < \sim 10 \) days regime (Mulders et al. 2016; Narag et al. 2018; Petigura et al. 2018; Wilson et al. 2018; Sousa et al. 2019; Ghezzi et al. 2021). Thus, the distributions of planet masses, radii, and orbital periods are sculpted by the amount of available solids and therefore the host star metallicity and planet forming environment.

The connections between [Fe/H] and planet architectures are well studied because there are many strong iron absorption lines in the spectra of solar-like stars, making it a relatively easy abundance to constrain. High-precision abundances beyond iron are more challenging to measure, but can unveil more detailed relationships between host star chemistry and planet architectures. For example, Adibekyan et al. (2012b) found that Fe-poor \((-0.1 < [\text{Fe/H}] < 0.2 \) dex) hosts of small and giant planets exhibit enhanced \([\text{X/H}]\) ratios for Mg, Al, Si, Sc, and Ti. The authors later examined a sample of even more Fe-depleted \((-0.65 < [\text{Fe/H}] < -0.3 \) dex) stars that host small, rocky planets, and found strong enhancements in Ti (Adibekyan et al. 2012a). Similarly, Maldonado et al. (2018) found that Fe-poor host stars of cool Jupiters tend to be enhanced in alpha-elements. These results suggest that other refractory elements can compensate for low iron content during planet building block formation (e.g., Bashi & Zucker 2019).

Abundances beyond iron can also place constraints on planet formation locations and interior compositions. For example, the stellar C/O ratio characterizes the H2O, CO2, and CO ice lines in protoplanetary disks, and can be used as a sensitive tracer of formation location when compared to the C/O ratio of planetary atmospheres (Öberg et al. 2011); substellar and superstellar atmospheric C/O generally indicate planet formation within and beyond the H2O ice line, respectively. The host star C/O ratio can also dictate if planetary compositions will be dominated by carbonates or silicates, with further ratios like Mg/Si determining the types of silicates in low C/O regimes (e.g., Brewer & Fischer 2017).

Particular abundance patterns are also thought to be indicative of planet formation, as suggested by measured individual abundance trends with element condensation temperature \( (T_c) \). This is based on the premise that rocky planet forming material more readily incorporates elements with high \( T_c \) (e.g., Ti, Al, Y) that reside in the solid phase throughout most of the disk. Conversely, low \( T_c \) elements (e.g., C, N, O) are more likely to remain in the gas phase. Planet compositions
are thus characterized by larger abundances in order of increasing $T_e$. It follows that adding planetary material to host stars will create refractory enhancements in stellar photospheres and a positive abundance gradient with $T_e$. This could result from processes such as planet engulfment, or steady accretion of solids during Late Heavy Bombardment-like events. Depletion trends in order of $T_e$ could likewise result from an absence of planetary material in host star photospheres. This could result from solids getting locked up in rocky planets and subsequent accretion of dust-depleted gas onto the host star (Meléndez et al. 2009), or from gaps in protoplanetary disks created by forming giant planets that prevent host star accretion of refractory material (Booth & Owen 2020). Such trends with $T_e$ have been observed in the differential abundances of several binary systems (Ramírez et al. 2011; Mack et al. 2014; Tucci Maia et al. 2014; Biazzo et al. 2015; Ramírez et al. 2015; Teske et al. 2015; Adibekyan et al. 2016; Saffe et al. 2016; Teske et al. 2016; Saffe et al. 2017; Oh et al. 2018; Maia et al. 2019; Ramírez et al. 2019; Nagar et al. 2020; Galarza et al. 2021; Jofré et al. 2021), and in larger samples. For example, Nibauer et al. (2021) analyzed 1700 solar analogs from the Apache Point Galactic Evolution Experiment (APOGEE), and found that 70%–90% of solar analogs appear depleted in refractory elements in order of $T_e$. Thus, there is ample evidence that abundance alteration via planet formation processes is common.

Stellar elemental abundances beyond iron are therefore important for understanding planet formation and evolution. Drawing connections between abundances and planet architectures require sufficiently large stellar samples to establish statistically significant correlations, as well as high-precision ($\sim 0.01$ dex uncertainties) abundance measurements (Meléndez et al. 2009; Ramírez et al. 2014; Schuler et al. 2015). Here, we utilize the latest APOGEE data release (DR17), which provides high-resolution spectra ($R \approx 22,500$) and derived parameters for $> 650,000$ stars (Abdurro’uf et al. 2022). This enormous sample will boost abundance pattern statistics, making it possible to compromise on individual abundance precisions. The APOGEE DR17 parameters include individual abundances for 20 species, measured with the APOGEE Stellar Parameter and Chemical Abundances Pipeline (ASPCAP) pipeline that achieves typical abundance precisions of $< 0.1$ dex (García Pérez et al. 2016). The full second generation APOGEE sample observed at the Apache Point Observatory (APOGEE-2N) contains 2098 stars also observed by Kepler, where 824 are confirmed planet hosts. This makes APOGEE DR17 an excellent sample for exploring connections between host star chemistry and planet formation. We describe our data selection further in Section 2.

Our goal is to examine individual abundances in planet hosts in isolation of other parameters, such as evolutionary state and overall metallicity. We want to determine if the individual abundances are differentiable in any way from the underlying field population (where planet membership is unknown). To this end, we take the Kepler Objects of Interest (KOIs, defined as stars that host confirmed or candidate planets) observed in APOGEE, and construct a reference set of doppelgängers with identical $T_{eff}$, $\log g$, [Fe/H], and [Mg/H] from the APOGEE field. This reference set corresponds to one doppelgänger per KOI. Recent work has demonstrated that (Fe, Mg) alone capture the majority of abundance dimensionality for stars more metal-rich than [Fe/H] $> -1.0$ dex with surprising predictive power (Weinberg et al. 2019; Griffith et al. 2021; Ness et al. 2022; Weinberg et al. 2022). This is because these elements are fiducial tracers of two primary production sources, specifically core collapse supernovae and low-mass stellar explosions. However, small individual abundance variations at fixed (Fe, Mg) may represent (at least in part) key additional information on stellar birth and evolutionary histories (Ness et al. 2022; Ting & Weinberg 2022; Weinberg et al. 2022). Individual abundances are inherited from birth and can be modified as a consequence of both internal (e.g., dredge-up; Souto et al. 2019) and external evolution (e.g., planet engulfment; Oh et al. 2018). Therefore, abundance scatter in absence of (Fe, Mg) and evolutionary state contributions may encode abundance deviations from birth. Stars with planets may furthermore be born with different abundance distributions at fixed (Fe, Mg) compared to stars without.

Rather than simply comparing the individual elemental abundance distributions of our KOI and doppelgänger samples, we use a four-parameter ($T_{eff}$, $\log g$, [Fe/H], [Mg/H]) model to predict the individual abundances of both the doppelgänger and KOI sets. This approach enables a quantitative exploration of the relative predictive power these four parameters hold for abundances of KOI stars compared to those of the field population. It also allows us to examine element correlations if there are clear discrepancies between the KOI and doppelgänger samples. Our model is detailed in Section 3. The stars we use to build our model are effectively drawn from the same underlying population as our doppelgängers in that none are confirmed/candidate planet hosts; we do not know their planet memberships. This enables us to examine how well we can predict each individual element while only considering our four predictors. We present the results of our abundance residual analysis in Section 4, and discuss these results in the context of potential planet host star chemistry and planet formation connections in Section 5.

2. Data

We assemble a high-fidelity sample of APOGEE DR17 stars with abundance measurements for twelve elements ($X = C, N, O, Na, Al, Si, Ca, Ti, V, Cr, Mn, Ni$). These abundances are determined by the ASPCAP pipeline (García Pérez et al. 2016), and are reported with respect to Fe. Because we are interested in abundance patterns resulting from planet formation with respect to hydrogen rather than enhancements with respect to iron, we convert the abundances as relative to hydrogen ($[X/H] = [X/Fe] + [Fe/H]$). We then apply the following quality cuts, which leaves a sample of $\sim 129,000$ stars (Figure 1):

- $T_{eff} = 4500–5500$ K
- $\log g > 1.8$ dex
- signal-to-noise ratio (SNR) $> 80$
- $[X/Fe]_{\text{error}} < 0.1$ dex
- Flag ASPCAPFLAGS not set to STAR_BAD, M_H_BAD, ALPHA_M_BAD
- Flag STARFLAGS not set to VERY_BRIGHT_NEIGHBOR

We then cross-match the sample with a catalog of 2098 KOIs observed by APOGEE-2N (C. Cañas 2022, private communication), resulting in 220 high-fidelity KOI stars from APOGEE DR17. We cross-match the resulting sample with the final Kepler planet candidate catalog data release (DR25, Coughlin et al. 2017) to obtain up-to-date candidate dispositions and planetary parameters. We subsequently remove all KOIs marked as “False Positive,” which indicates that the
detected signals are due to events other than exoplanet transits, e.g., eclipsing binaries. This cut leaves 128 confirmed planets and 56 planet candidates hosted by 131 APOGEE DR17 stars. As expected, the KOI-APOGEE DR17 sample is dominated by “Kepler-like” architectures. That is, planets characterized as super-Earths or sub-Neptunes (e.g., Winn & Fabrycky 2015; Yang et al. 2020): ~92% of the KOIs fit this category by hosting confirmed/candidate planets with orbital periods and planet radii of $P < 400$ days and $R < 4 R_\oplus$, respectively (Figure 2).

Next, we construct a set of doppelgänger stars to our KOI-APOGEE DR17 sample. The doppelgängers are drawn from the ~129,000 high-fidelity stars selected from the APOGEE field, and have unknown planet membership. We select doppelgängers by defining a similarity metric between two stars:

$$D^2 = \left( \frac{\Delta T_{\text{eff}}}{\sigma_{T_{\text{eff}}}} + \frac{\Delta \log g}{\sigma_{\log g}} \right)^2 + \frac{\Delta [\text{Fe}/\text{H}]}{\sigma_{[\text{Fe}/\text{H}]}},$$

which incorporates the relative $T_{\text{eff}}$, $\log g$, $[\text{Fe}/\text{H}]$, and $[\text{Mg}/\text{H}]$ between the two stars, and their associated errors added in quadrature. These parameters are ideal for selecting doppelgängers because $T_{\text{eff}}$ and $\log g$ describe the stellar evolutionary state, while $[\text{Fe}/\text{H}]$ and $[\text{Mg}/\text{H}]$ represent fiducial contributions from supernovae as mentioned earlier. Together, these parameters effectively create a four-dimensional reference frame to examine variance in individual elements. We select one doppelgänger per KOI, defined as the high-fidelity non-KOI star drawn from the APOGEE field with the smallest $D^2$ metric value relative to that KOI and SNR matching to within 20 pix$^{-1}$. This SNR condition cannot be met for one KOI and any other star in the high-fidelity sample, so we remove it and are left with a final KOI sample of 130 stars (Figure 1, colored circles).

Because we select our doppelgängers on KOI $[\text{Fe}/\text{H}]$, there is a concern that our doppelgänger sample may have a higher rate of planet occurrence compared to field stars due to the known $[\text{Fe}/\text{H}]-$planet occurrence relation. To test this, we compare the $[\text{Fe}/\text{H}]$ distributions of our KOI and doppelgänger samples with that of a field star sample drawn from the Kepler field that lack planets (“False Positive” candidates). The $[\text{Fe}/\text{H}]$ distributions of these three samples all span approximately the same $[\text{Fe}/\text{H}]$ range and roughly peak at the same $[\text{Fe}/\text{H}]$ value ($\sim 0.1$ dex; Figure 3, left panel). We conclude that our doppelgänger sample is not significantly more $[\text{Fe}/\text{H}]-$rich that a sample of non-planet hosting field stars, and thus do not expect our doppelgängers to have a higher rate of planet occurrence compared to field stars based on $[\text{Fe}/\text{H}]$.

Because we select our doppelgängers on KOI $[\text{Mg}/\text{H}]$ as well, we also test if $[\text{Mg}/\text{H}]$ correlates with planet occurrence independent of $[\text{Fe}/\text{H}]$. To do this, we construct another field star sample by drawing with replacement from all non-planet hosting Kepler field stars, with each draw pulling a field star with the closest $[\text{Fe}/\text{H}]$ to that of each KOI. We then examine the $[\text{Mg}/\text{H}]$ distributions of our KOI and doppelgänger samples, as well as that of the new KOI $[\text{Fe}/\text{H}]-$matching non-planet host Kepler field star sample (Figure 3, right panel). All three $[\text{Mg}/\text{H}]$ distributions are quite similar, indicating that our selection on $[\text{Mg}/\text{H}]$ does not significantly bias the doppelgänger sample relative to field stars without known planets. Thus, our doppelgänger sample does not have a higher rate of planet occurrence compared to field stars due to selection on KOI $[\text{Mg}/\text{H}]$.

The $\Delta T_{\text{eff}}$, $\Delta \log g$, $\Delta [\text{Fe}/\text{H}]$, and $\Delta [\text{Mg}/\text{H}]$ distributions for all KOI-doppelgänger pairs are provided in Figure 4. These distributions are centered on zero, which indicates that there are no systematic biases. The average associated errors added in quadrature (for KOIs and doppelgängers) for each parameter across all pairs are marked in the dashed red lines, which contain $\sim 77\%$, $\sim 85\%$, $\sim 78\%$, and $\sim 81\%$ of the $\Delta T_{\text{eff}}$, $\Delta \log g$, $\Delta [\text{Fe}/\text{H}]$, and $\Delta [\text{Mg}/\text{H}]$ for KOIs and doppelgängers.
\( \Delta[\text{Fe/H}] \) and \( \Delta[\text{Mg/H}] \) distributions, respectively. Thus, the differences in parameters between KOIs and their respective doppelgängers are largely contained within their typical errors. There are 14 KOI-doppelgänger pairs that have [Fe/H] and [Mg/H] abundance differences far from the typical error boundaries (which we define as \( \Delta[\text{Fe/H}] \) or \( \Delta[\text{Mg/H}] \) less than \(-0.03 \text{ dex}\) or greater than \(0.03 \text{ dex}\); see Figure 4). We remove these outlier KOI-doppelgänger pairs and recompute the intrinsic dispersion of our abundance predictions (see Section 4 for a full description of our intrinsic dispersion analysis). We find that the intrinsic dispersion results do not change outside of our reported precision, and thus determine that the inclusion of these KOI-doppelgänger outlier pairs does not affect our abundance prediction results.

We constructed another doppelgänger sample also selected on \( K \)-band extinction \( A_K \) as provided by the \( \text{AK}_\text{TARG} \) column in APOGEE DR17. The similarity metric is modified to include the \( A_K \) term as follows:

\[
D^2_{\text{AK}} = \left( \frac{\Delta T_{\text{eff}}}{\sigma T_{\text{eff},1} + \sigma T_{\text{eff},2}} \right)^2 + \left( \frac{\Delta \log g}{\sigma \log g,1 + \sigma \log g,2} \right)^2 + \left( \frac{\Delta[\text{Fe/H}]}{\sigma[\text{Fe/H}],1 + \sigma[\text{Fe/H}],2} \right)^2 + \left( \frac{\Delta[\text{Mg/H}]}{\sigma[\text{Mg/H}],1 + \sigma[\text{Mg/H}],2} \right)^2 + \left( \frac{\Delta A_K}{\sigma A_K,1 + \sigma A_K,2} \right)^2 .
\]

The \( K \)-band extinction characterizes the strength of absorption features in the optical and near-infrared wavelength range, e.g., diffuse interstellar bands (DIBs). These spectral features probe dusty regions of the interstellar medium (ISM), which is valuable from a planet formation perspective as planet occurrence is enhanced in metal-rich environments. We thus include this additional doppelgänger sample criterion for conducting a stricter test of similarity by also considering the line-of-sight ISM.

3. Regression Model

We construct a local linear model for each KOI to determine how well we can predict abundances from our four parameters of interest \( (T_{\text{eff}}, \log g, \text{[Fe/H]}, \text{[Mg/H]}) \). We note that including the evolutionary state parameters accounts for any systematic changes in abundance with \( T_{\text{eff}} \) or \( \log g \). The local linear models employ simple linear regression (Hastie et al., 2001), where each individual model is constructed from a training set specific to that KOI drawn from the high-fidelity APOGEE DR17 sample of \( \sim129,000 \) stars. The training sets are selected by defining a region around each KOI in parameter space (e.g., Sayeed et al. 2021; Ness et al. 2022). We outline the steps of our approach below, where the parameters selected as predictors are \( Y = (T_{\text{eff}}, \log g, \text{[Fe/H]}, \text{[Mg/H]}) \), and the twelve predicted abundances are \( X = (\text{C}, \text{N}, \text{O}, \text{Na}, \text{Al}, \text{Si}, \text{Ca}, \text{Ti}, \text{V}, \text{Cr}, \text{Mn}, \text{Ni}) \):

1. We standardize the parameters used as predictors across the entire high-fidelity sample. This is done for each star by subtracting the mean and dividing by the standard deviation: \( y = (y - \bar{y})/\sigma_y \).
2. For each star in our high-fidelity sample, we identify the nearest \( k \) neighbors in predictor parameter space according to the Euclidean distance. We carried this out with the scikit-learn (sklearn) package implemented in Python (specifically sklearn.neighbors.KDTree).
3. We construct a local model for each KOI from the \( k \) nearest non-KOI neighbors. We select \( k = 100 \) but note that the model appears insensitive to the choice of \( k \); \( k = 50–300 \) produces comparable results (Ness et al. 2022). The 100 nearest neighbor training sets for each KOI include the KOI’s corresponding doppelgänger, but not the KOI itself.
4. We use linear regression, again applied via the sklearn package, to train each local linear model. This modeling step elucidates the relationships between the predictor parameters \( Y = (T_{\text{eff}}, \log g, \text{[Fe/H]}, \text{[Mg/H]}) \), and each of the twelve abundances \( [X/H], \) separately. Each local model includes five coefficients constrained from linear regression, corresponding to the intercept and one for each predictor parameter.
5. We predict a new set of twelve abundances for each KOI from their individual local linear models. The predicted \([X/H]\) can be compared with the measured \([X/H]\) from ASPCAP.

6. We carry out this procedure for (i) our KOI-APOGEE DR17 sample and (ii) our corresponding doppelgänger samples. The 100 nearest neighbor training sets for each doppelgänger do not include the doppelgänger itself. The result is a set of local linear models with one model per star for every star in each sample. We subsequently use these models for abundance prediction.

The average parameter space size spanned by the 100 nearest neighbors of all KOIs and doppelgängers can be likened to the average difference in each parameter between the KOIs/doppelgängers and their nearest neighbors. The average \(\Delta T_{\text{eff}}, \Delta \log g, \Delta [\text{Mg/H}], \text{and} \Delta [\text{Fe/H}]\) for all KOIs and their neighbors range from 11.5 to 190 K, 0.011 to 0.358 dex, 0.007 to 0.107 dex, and 0.013 to 0.111 dex, respectively. The scatter in average \(\Delta T_{\text{eff}}, \Delta \log g, \Delta [\text{Mg/H}], \text{and} \Delta [\text{Fe/H}]\) across all KOIs are 46.4 K, 0.063 dex, 0.028 dex, and 0.024 dex.

### 4. Results

#### 4.1. Local Linear Model Predictions

Our local linear model-predicted abundances are plotted against ASPCAP abundances for the twelve considered elements in Figure 5. The doppelgänger sample, doppelgänger sample also selected on \(A_K\), and KOI sample are shown in the panels from left to right. We calculated the intrinsic dispersion of the abundance predictions from the rms difference between the model—measurement abundances, and the average ASPCAP abundance uncertainty (which can be assumed as the same for each star): \(\sigma_{\text{intrinsic}} = \sqrt{\sigma_{\text{rms}}^2 - \sigma_{\text{measurement}}^2}\). For the KOIs, the intrinsic dispersion values across all elements range from \(\sigma_{\text{intrinsic}} = 0.019\) to 0.167 dex, with Na and Ca exhibiting the highest and lowest values, respectively. In other words, the measured Na abundances tend to deviate most significantly from the model and the measured Ca abundances the least. If we group the abundances into light (C, N, O, Na, Al, V), alpha (Si, Ca), and iron-peak (Ti, Cr, Mn, Ni) element groups, the median intrinsic dispersion values are 0.060 dex, 0.021 dex, 0.0146 to 0.133 dex. The scatter in average differences are 46.4 K, 0.063 dex, 0.028 dex, and 0.024 dex.
and 0.040 dex, respectively. For the doppelgängers, the intrinsic dispersion values range from 0.017 to 0.128 dex, with Na also exhibiting the highest value, but Si exhibiting the lowest value. The light, alpha, and iron-peak element groups have median intrinsic dispersion values of 0.053 dex, 0.017 dex, and 0.036 dex, respectively. While the majority of our

Figure 5. Local linear model-predicted vs. ASPCAP abundances of the doppelgänger (left), doppelgänger $A_K$ (middle), and KOI (right) samples for the twelve elements considered. The points are colored by log g. The rms difference between the ASPCAP and predicted abundances, intrinsic dispersions, and bias measurements are provided in the upper left corners of each panel. A dashed 1-to-1 line is plotted in all panels for comparison.
sample is dominated by “Kepler-like” super-Earth/sub-Neptune architectures, we examine if other planet architectures result in different intrinsic dispersions. We divide the KOI sample into four architecture categories, namely hot/warm Jupiters ($R > 8 R_\oplus$ and $P < 100$ days), hot/warm sub-Saturns ($4 R_\oplus < R < 8 R_\oplus$ and $P < 100$ days), cold Jupiters ($R > 8 R_\oplus$ and $P > 100$ days), and super-Earths/sub-Neptunes ($R < 4 R_\oplus$). There are eight hot Jupiters, 17 sub-Saturns, and five cold Jupiters among the KOI sample, with the remaining classified as super-Earths/sub-Neptunes. The average intrinsic

**Figure 5.** (Continued.)

![Graphs showing [Al/H], [Si/H], [Ca/H], and [Ti/H] relationships with $\text{[A/H]}_{\text{predict}}$ for doppelgangers, KOIs, and Kepler-like super-Earths/sub-Neptunes. Each graph includes error bars and the corresponding intrinsic dispersions ($\sigma_{\text{rms}}$ and $\sigma_{\text{intrinsic}}$) along with bias values. The color scale represents $\text{log} g$. The scatter plots show a linear relationship with no significant deviation from the line indicating a system of planetary architectures.
dispersions are 0.033 dex, 0.056 dex, 0.037 dex, and 0.046 dex for the hot/warm Jupiters, hot/warm sub-Saturns, cold Jupiters, and super-Earths/sub-Neptunes, respectively. Thus, the intrinsic dispersion values do not change much as a function of planet architecture, and are well within the intrinsic dispersion range of the entire KOI sample. We conclude that
architecture differences do not change the deviations between predicted and ASPCAP abundances, though larger samples of non-“Kepler-like” systems are needed to further investigate this.

We calculate the error on intrinsic dispersion \( \sigma_{\text{intrinsic}} \) by sampling all abundances from their distributions 20 times, running the local linear models, then taking the scatter of the resulting \( \sigma_{\text{intrinsic}} \) values as the error on \( \sigma_{\text{intrinsic}} \). We also calculate the abundance prediction bias as the difference of the average predicted and ASPCAP abundances for each element. The bias is approximately zero for the doppelgänger and KOI samples across all twelve abundances, which indicates that our predicted abundances are unbiased. The rms difference and intrinsic dispersion measurements are approximately equal across all abundances except for Na; for the KOIs, \( \sigma_{\text{intrinsic}} \approx 0.17 \) dex, while for the doppelgänger and \( \text{AK} \) doppelgänger samples, \( \sigma_{\text{intrinsic}} \approx 0.13 \) dex and 0.12 dex, respectively. We plot the intrinsic dispersion measurements for all abundances and samples in order of their condensation temperature \( T_c \) in Figure 6. There is no apparent \( T_c \) trend, and the largest difference between the intrinsic dispersion values of the KOI and doppelgänger samples for \([\text{Na}/H]\) is apparent.

The large intrinsic dispersion value for predicted \([\text{Na}/H]\) exhibited by the KOI sample appears to be driven by five outlier stars that lie anomalously far from the 1-to-1 trend (Figure 5, [\text{Na}/H] KOI panel). We examine the spectra of these outlier stars near the Na spectral features used to derive \([\text{Na}/H]\) in the ASPCAP pipeline (window centered on 16378.276 Å; Feeney et al. 2021), shown in Figure 7. There are no obvious differences between the Na features of the KOIs and their corresponding doppelgängers. Thus, we propose that the differences in intrinsic dispersion values between the KOIs and doppelgängers are due to poorly measured Na values rather than any real astrophysical differences between the samples. We calculate the average abundance error of our twelve considered elements for the sample of high-fidelity (SNR > 200) field stars, and find that \([\text{Na}/\text{Fe}]\) exhibits an average error of 0.060 dex, the second-to-largest among these elements after \([\text{V}/\text{Fe}]\) (0.073 dex). For comparison, the typical average error of these twelve abundances is \( \sim 0.03 \) dex. We conclude that Na is generally poorly measured by the ASPCAP pipeline.

We also examine the heliocentric velocity \( V_{\text{helio}} \) as Ness et al. (2022) found abundance residual trends with \( V_{\text{helio}} \) that indicate contamination from ISM features. Our \([\text{Na}/H]\) residuals do not display such trends, so we conclude that the intrinsic dispersion differences between KOIs and doppelgängers are not due to ISM contamination.

### 4.2. Higher Quality Sample

We examine if the KOI \([\text{Na}/H]\) intrinsic dispersion remains much larger than those of the doppelgänger samples with more stringent cuts on \([\text{X}/\text{Fe}]_{\text{error}}\). To investigate this, we construct a higher quality sample with cuts on \([\text{X}/\text{Fe}]_{\text{error}} < 0.07 \) dex rather than 0.1 dex. This results in a substantial sample size decrease, from 130 to 27 KOIs. The five outlier stars in predicted and ASPCAP \([\text{Na}/H]\) abundance space are removed (Figure 8). The new \([\text{Na}/H]\) intrinsic dispersion measurement for the KOIs is \( \sigma_{\text{intrinsic}} \approx 0.062 \) dex, compared to those of the doppelgänger and \( \text{AK} \) doppelgänger samples, \( \sigma_{\text{intrinsic}} \approx 0.085 \) dex and 0.054 dex, respectively. Median intrinsic dispersions across all abundances are \( \sim 0.038 \) dex and \( \sim 0.041 \) dex for the KOI and doppelgänger samples, respectively. This constitutes further evidence that there is likely no systematic difference between the KOI and doppelgänger samples, and the initial differences in \([\text{Na}/H]\) intrinsic dispersion were driven by targets with large abundance uncertainties.

![Figure 6. Intrinsic dispersion measurements \( \sigma_{\text{intrinsic}} \) for all \( T_c \) ordered abundances, for the KOI sample (red), doppelgänger sample (navy), and \( \text{AK} \) doppelgänger sample (light blue). There are no apparent trends with \( T_c \), but the KOI \([\text{Na}/H]\) prediction intrinsic dispersion is noticeably larger than those of the doppelgänger samples.](image)

![Figure 7. Spectra of the five KOIs that appear to be outliers in predicted and ASPCAP \([\text{Na}/H]\) space (red), zoomed into the region with Na spectral features used to derive \([\text{Na}/H]\) abundances with the ASPCAP pipeline (window center at 16378.276 Å; Feeney et al. 2021), marked by the dashed line). The spectra of the corresponding outlier doppelgängers are shown in black.](image)
4.3. Sensitivity to Training Set

We are interested in testing how sensitive our abundance predictions are to the local linear model training sets. Instead of selecting the nearest \( k = 100 \) neighbors in predictor parameter \( Y = (T_{\text{eff}}, \log g, [\text{Fe}/\text{H}], [\text{Mg}/\text{H}]) \) space as training sets, we took a more generous approach by using a random selection of 100 stars from our high-fidelity APOGEE DR17 sample. We did this because we suspect that using even a random selection of stars to construct the local linear models will do not change the results significantly; we assume that the relationships between each element we predict for and the four parameters of our models ([Fe/H], [Mg/H], \( T_{\text{eff}} \), \( \log g \)) are fairly similar from star to star.

After using a random selection of 100 high-fidelity APOGEE DR17 stars for our local linear model construction, we find that the intrinsic dispersion results change only slightly overall. The average intrinsic dispersion across all elements for the KOIs increase from 0.055 dex to 0.080 dex, at most increasing by a factor of \( \sim 2.2 \) for the most precisely predicted elemental abundances. The intrinsic dispersion range for the KOIs shift from \( \sigma_{\text{intrinsic}} = 0.019-0.167 \) dex to 0.036-0.195 dex, and from \( \sigma_{\text{intrinsic}} = 0.017-0.128 \) dex to 0.032-0.173 dex for the doppelgängers. The intrinsic dispersion errors also do not change within our reported precision. We conclude that local linear models provide better fits to the data, but linear models whose training sets span the full range of our parameter space also well describe how abundance labels vary with our four predictive labels. The good performance of the global model is presumably because \([X/Fe]\) varies reasonably linearly, conditioned on the labels, over the full range of our sample. This is true for the Galactic disk, but not similarly true for the Galactic halo (i.e., Ness et al. 2022; D. H. Weinberg et al. 2023, in preparation). Thus, if there are interesting/ significantly nonlinear variations in the individual abundances at fixed (Fe, Mg), they must be below the APOGEE abundance measurement precision. We conclude that our results will not meaningfully change if we adopt the global model, which is reassuring. The local linear model is however preferable and generalizes well to larger parameter spaces, where the global model would presumably deteriorate as the data parameter space increases.

4.4. Condensation Temperature Trends

We further explore possible \( T_c \) patterns by fitting linear trends to the \( T_c \)-ordered abundances of each KOI and doppelgänger star, respectively. We carry this out for the model-predicted and ASPCAP-provided abundances. The distributions of the linear trend slopes are shown in Figure 9.
Both distributions are centered on approximately zero, which indicates that there is no excess of $T_c$-dependent enrichment or depletion trends.

We construct similar distributions of linear trend slopes resulting from fits to $T_c$-ordered abundances, but only considering elements with $T_c > 1000$ K (Mn, Cr, Si, Ni, V, Ca, Ti, Al). Elements are refractory rather than volatile above this temperature, and populate the steepest regions of abundance versus $T_c$ trends in patterns exhibiting refractory enhancement or depletion (Meléndez et al. 2009; Ramírez et al. 2009; Bedell et al. 2018). This is similar to the analysis presented in Nibauer et al. (2021), which assessed $T_c$ trends of elements with $T_c > 900$ K. The resulting slope distributions for the predicted and ASPCAP abundances are shown in Figure 10. Both the ASPCAP and predicted abundance distributions for the KOI and doppelgänger samples exhibit a tail of slopes toward the right of the distribution center that appears to peak at $\approx 4 \times 10^{-4}$ dex K$^{-1}$. A similar secondary peak was found by Nibauer et al. (2021) in their $T_c$ slope distribution for $> 900$ K elements from APOGEE DR16 data.

This indicates that our data reproduce the $T_c$ patterns in field stars, which is reassuring. However, we find fewer stars in the secondary peak at positive gradients compared to Nibauer et al. (2021). This is potentially explained by our different stellar samples that span different evolutionary states; Nibauer et al. (2021) examined stars across a narrow range of the main sequence whereas we study stars across the main sequence and red giant branch.

Another interesting feature in our ASPCAP abundance distributions is a small tail toward negative slopes that stretches beyond $-2 \times 10^{-4}$ dex K$^{-1}$ (Figure 10, left panel). This tail of negative slope values is not apparent in our predicted abundance distributions (Figure 10, right panel), or the Nibauer et al. (2021) results. We calculate that $\approx 10\%$ and $\approx 7.7\%$ of the KOI and doppelgänger ASPCAP distributions are below $-2 \times 10^{-4}$ dex K$^{-1}$, respectively, and therefore compose the negative slope tail. The presence of this tail in the ASPCAP abundance distribution but not the predicted abundance distribution may indicate that there is abundance information not fully captured by (Fe, Mg) alone that may alter dex versus $T_c$ trends at the most negative slope regions. The absence of this tail in the Nibauer et al. (2021) abundances, which are comparable to ASPCAP abundances, may again be due to evolutionary state differences in our respective stellar samples. $T_c$ patterns can also be examined by splitting abundances into volatile and refractory groups, and fitting individual linear trends to both sets. This was done by Bedell et al. (2018) for a sample of solar twins (see their Figure 4). Stars with enrichment trends will exhibit steeper linear fits to abundances with $T_c > 1000$ K compared to abundances with $T_c < 1000$ K, while the opposite will be true for depletion trends. We carry out this analysis for our KOIs and their doppelgängers, and provide examples of our linear trend fits in Figure 11. Because strong enrichment results in steeper refractory trends, the linear fits will have lower intercept values. Thus, enrichment pattern strength can be likened to the difference in volatile and refractory linear fit intercepts. We plot the distributions of these intercept differences in Figure 12. The distribution corresponding to ASPCAP abundances exhibits a tail toward higher intercept differences that is not present in the distribution derived from predicted abundances. We examine the ASPCAP $T_c$ trends for the KOIs with the top five largest intercept differences, and find that they have anomalously low measured [Na/H] (ranging from $-0.23$ dex to $-1.29$ dex) that are $> 0.2$ dex below the other measured abundances. The associated errors on measured [Na/H] are large (0.074–0.94 dex). In addition, four out of the five KOIs with largest intercept differences overlap with the five KOIs that are outliers in predicted and ASPCAP [Na/H] space (Figure 5, [Na/H] KOI panel). This is further evidence that the [Na/H] intrinsic dispersion differences in the initial sample selected on $[X/Fe]_{\text{error}} < 0.1$ dex are the result of large abundance uncertainties. We conclude that if there are underlying differences in the individual abundance $T_c$ trends for the KOI and doppelgänger samples at fixed evolutionary state, [Fe/H], and [Mg/H], they are marginal. To be detected, these differences must exceed the sensitivity of our predicted abundances, which is typically $\sigma_{\text{intrinsic}} \approx 0.038$ dex and 0.041 dex for the KOIs and doppelgängers, respectively.

5. Discussion

The planet–metallicity correlation remains the only proven connection between host star chemistry and planet properties. We demonstrate that after removing the effects of evolutionary
state and metallicity from two primary sources (Fe, Mg), the individual abundances of confirmed/candidate planet hosts (KOIs) and a reference doppelgänger set with unknown planet membership are indistinguishable. More specifically, we compute model–measurement abundance residuals from ASPCAP and predicted abundances using a four-parameter model ($T_{\text{eff}}$, $\log g$, $[\text{Fe}/\text{H}]$, $[\text{Mg}/\text{H}]$), and find that there are no differences in residual structure between the KOI and doppelgänger samples. We calculate the median intrinsic dispersion across all analyzed elements other than (Fe, Mg) to be $\sigma_{\text{intrinsic}} \approx 0.038$ dex and 0.041 dex for the KOI and doppelgänger samples, respectively, which can be taken as the minimum abundance precision required for discerning individual abundance signatures related to planet formation.

Because we do not know the planet membership of our doppelgänger sample, some doppelgänger stars may be planet hosts. This is plausible because large planet discovery surveys such as the Kepler and the Transiting Exoplanet Survey Satellite (TESS) missions have revealed that planets are common. Using Kepler DR25, Hsu et al. (2019) recently calculated an upper limit occurrence rate of 0.27 planets per star for 0.5–16 $R_{\oplus}$ planets around FGK dwarfs. Breaking occurrence rates by planet architectures reveals that the majority of these planets are small ($R = 1$–4 $R_{\oplus}$) and generally classified as super-Earths and sub-Neptunes (e.g., Burke et al. 2015; Zhu et al. 2018; Bryson et al. 2021). If a significant fraction of our doppelgänger set consists of planet hosts, it makes sense that the abundance distributions of our KOI and doppelgänger samples are indistinguishable at fixed (Fe, Mg) and evolutionary state.

To reliably examine abundance differences between planet hosts and reference doppelgänger stars drawn from the field, none of the reference stars should host planets. Unfortunately, constructing a reference sample of doppelgänger stars that we know lack planets is difficult. This would require extensive monitoring of targets with Doppler planet search surveys to ensure that there are no radial velocity signals indicative of planets. Carrying out such observations for an entire reference set of stars would be time and resource intensive. However, certain planet populations can be ruled out with minimal telescope time; close-in giant planets are more easily detected in radial velocity and transit data without long cadence compared to smaller planets on longer orbits. In addition, close-in giants are intrinsically rare. Radial velocity surveys produce hot Jupiter ($P < 10$ days) occurrence rates of $\sim 0.8$–$1.2\%$ around solar-like stars (e.g., Mayor et al. 2011; Wright et al. 2012; Wittenmyer et al. 2020), and transit surveys yield even smaller occurrence rates of $\sim 0.4$–$0.6\%$ (Howard et al. 2012; Fressin et al. 2013; Petigura et al. 2018; Kunimoto & Matthews 2020). These rates are still small for warm Jupiters ($P < 50$ days), with estimates of $\sim 1.3\%$. They remain small for hot and warm sub-Saturns ($R = 4$–$8 R_{\oplus}$) as well, which have occurrence rate estimates of $\sim 0.4\%$ and $\sim 2.3\%$, respectively (Howard et al. 2012). Thus, constructing a reference sample without close-in giant hosts is
feasible. We hope to examine close-in giants in future studies, but this will require another planet host sample, as only 18 of our KOIs host confirmed/candidate hot/warm sub-Saturn to Jupiter-sized planets according to the standard definition ($R > 4 R_\oplus$ and $P < 100$ days).

Previous studies have found interesting abundance differences between stars that host and do not host close-in giants. For example, Meléndez et al. (2009) determined that the Sun exhibits a refractory depletion trend with $T_\text{eff}$ relative to eleven solar twins from the Hipparcos catalog, as well as four solar analogs with close-in giant planets. However, six other solar analogs lacking close-in giants as verified by radial-velocity monitoring show the solar depletion trend 50%–70% of the time. One potential explanation for the solar pattern is sequestration of rocky material in the terrestrial planets, and late (10–25 Myr) accretion of dust-depleted gas once the solar convective zone began shrinking to its current mass fraction (~2%, Hughes et al. 2007). Another explanation is that all solar twins and most solar analogs lacking close-in giants engulfed planetary material at late times (>25 Myr), once their convective zones were thin. This scenario would produce refractory enrichment in stellar photospheres. However, it assumes that most solar-like stars are depleted in refractories (at least in the absence of events like planet engulfment), and more recent abundance studies of larger Sun-like samples show that this is not the case (e.g., Bedell et al. 2018). Either way, the findings of Meléndez et al. (2009) suggest that close-in giant planets play a role in altering host star abundances. While their results defy a clear explanation, a larger sample of close-in giant hosts and reference stars lacking close-in giants could be leveraged to examine these trends more closely.

The KOI and doppelgänger median abundance prediction intrinsic dispersions are ~0.038 dex and ~0.041 dex, respectively. These values can be considered the upper limit of abundance precision needed to discern planet formation signatures in the elemental abundance patterns of host stars. Planet formation processes can exceed these levels in rare cases, such as the reported planet engulfment detection in the HD 240429-30 system (~0.2 dex; Oh et al. 2018). Planet hosts may also be born with different abundances compared to stars without planets. The planet–metallicity correlation indicates that this is true for at least [Fe/H]. Such primordial abundance deviations must also exceed our intrinsic dispersion levels to be detectable.

Our KOI and doppelgänger residual abundance distributions are indistinguishable, which yields two possibilities: (1) our reference doppelgänger set includes too many planet hosts, or (2) primordial or post-birth abundance patterns related to planet formation in our samples are below detectable levels. We can tackle the first possibility by focusing on more easily detectable planet architectures, namely close-in giants as discussed earlier. The second possibility could be addressed with higher-precision abundances from advances in spectral synthesis pipelines and/or line lists (e.g., Schuler et al. 2011; Bedell et al. 2014; Liu et al. 2018), or from spectrographs with higher resolving power (e.g., Adibekyan et al. 2020). Many stars in our KOI and doppelgänger samples have abundance uncertainties that exceed our intrinsic dispersion values. Large uncertainties are the root cause of the particularly poorly measured Na abundances for the five outlier stars in our initial sample selected on [X/H]$_{\text{err}} < 0.1$ dex. Upgrades to the ASPCAP pipeline, such as improved line lists and advances to the spectral synthesis pipeline, may improve APOGEE abundance precisions in the years to come.

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Software: numpy (Harris et al. 2020), matplotlib (Hunter 2007), pandas (Wes McKinney 2010), scipy (Virtanen et al. 2020), scikit-learn (Pedregosa et al. 2011), astropy (Astropy Collaboration et al. 2013, 2018).
