The Clustering of High-redshift \((2.9 \leq z \leq 5.1)\) Quasars in SDSS Stripe 82

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Abstract

We present a measurement of the two-point autocorrelation function of photometrically selected high-z quasars over \(\sim 100\) deg\(^2\) in the Sloan Digital Sky Survey Stripe 82 field. Selection is performed using three machine-learning algorithms in a six-dimensional optical/mid-infrared color space. Optical data from the Sloan Digital Sky Survey are combined with overlapping deep mid-infrared data from the Spitzer IRAC Equatorial Survey and the Spitzer-HETDEX Exploratory Large-Area survey. Our selection algorithms are trained on the colors of known high-z quasars. The selected quasar sample consists of 1378 objects and contains both spectroscopically confirmed quasars and photometrically selected quasar candidates. These objects span a redshift range of \(2.9 \leq z \leq 5.1\) and are generally fainter than \(i = 20.2\), a regime that has lacked sufficient number density to perform autocorrelation function measurements of photometrically classified quasars. We compute the angular correlation function of these data, marginally detecting quasar clustering. We fit a single power law with an index of \(\delta = 1.39 \pm 0.618\) and amplitude of \(b_0 = 0.271 \pm 0.546\). A dark matter model is fit to the angular correlation function to estimate the linear bias. At the average redshift of our survey \((z) = 3.38\), the bias is \(b = 6.78 \pm 1.79\). Using this bias, we calculate a characteristic dark matter halo mass of \(1.70 \times 10^{12} M_\odot\). Our bias estimate suggests that quasar feedback intermittently shuts down the accretion of gas onto the central supermassive black hole at early times. If confirmed, these results hint at a level of luminosity dependence in the clustering of quasars at high-z.

Key words: large-scale structure of universe – quasars: general – quasars: supermassive black holes

1. Introduction

In the present-day universe, supermassive black holes (SMBHs) reside at the center of most, if not all, galaxies with \(M_\bullet \gtrsim 10^{10} M_\odot\), in which star formation has almost completely ceased (e.g., Bell 2008; Bower et al. 2017). It is commonly accepted that every massive galaxy has undergone at least one quasar phase within its lifetime (Soltan 1982; Richstone et al. 1998). In this quasar phase, baryons in an accretion disk lose angular momentum through mechanisms such as viscous transfer and eventually are accreted by the SMBH (Salpeter 1964; Lynden-Bell 1969; Rees 1984). The friction in the disk heats the baryons, causing the disk to shine in the optical, ultraviolet (UV), and X-ray.

Quasars, defined here as luminous active galactic nuclei (AGNs) with bolometric luminosity \(L_{\text{bol}}\) above \(\sim 10^{45}\) erg s\(^{-1}\), are among the most luminous objects in the universe and therefore can trace the large-scale structure out to high redshift. Galaxies are thought to reside in the peaks in the dark matter (DM) distribution and are generally biased tracers of the underlying DM (e.g., Dekel & Lahav 1999; Peacock 1999; Sheth & Tormen 1999). This relationship can be quantified by measuring the linear bias parameter, \(b\). As an initial guide, we define \(b\) as

\[
\delta_Q = b \delta_{\text{DM}}.
\]

where \(\delta_Q\) is the quasar density contrast and \(\delta_{\text{DM}}\) is the mass density contrast. Defining the two-point autocorrelation function (2PCF) as \(\xi(r) = \langle \delta_Q(x) \delta_Q(x + r) \rangle\), where \(r\) is the separation between two local overdensities, leads to

\[
\xi_Q(r) = b_Q^2 \xi_{\text{DM}}(r),
\]

where \(\xi_Q\) is the quasar two-point correlation function and \(\xi_{\text{DM}}\) is the DM correlation function. The 2PCF is defined as the joint probability of finding a pair of objects having a particular separation in two volume elements (Totsuji & Kihara 1969; Peebles 1980) and is a statistic commonly employed to measure the spatial distribution of galaxies (e.g., Zehavi et al. 2011), hydrogen gas in absorption (e.g., Bautista et al. 2017), and, in this case, quasars. In practice, the 2PCF is calculated as the excess probability, above a random Poisson distribution, of finding a pair of objects within an annulus between \(r\) and \(r + \delta r\) (Peebles 1980; Martinez & Saar 2002; Feigelson & Babu 2012).

The 2PCF and the corresponding bias have been measured for quasars as a function of different observable properties, including redshift, luminosity, and color; Table 1 presents a summary of recent results. Studies of quasar clustering as a function of luminosity (da Ângela et al. 2008; Shen et al. 2009;...
Table 1: Selected Quasar Clustering Measurements

| Survey                  | Area / deg² | NQ | Magnitude Selection | z Range | Type | References            |
|-------------------------|-------------|----|---------------------|---------|------|-----------------------|
| NDWFS+AGES              | 7.9         | 585| $l \leq 21.5, [3.6] = 6.4 \mu m$ | X+R+MIR | 0.25 < z < 0.8 | C/s | Hickox et al. (2009) |
| NDWFS+AGES              | 9           | 924| $R \sim 25.0, [3.6] = 6.4 \mu m$ | opt+MIR | 0.7 < z < 1.8 | C/b | Hickox et al. (2011) |
| PRIMUS+DEEP2            | ~10         | ~1,000 | $m_A \sim 23.5$ | X+R+MIR | 0.2 < z < 1.2 | C/s | Mendez et al. (2016) |
| SpiEsb+SHELAe           | 100         | 1,378 | $i \sim 23.5, [3.6] = 6.1 \mu m$ | opt+MIR | z > 2.9 | A/b | This study |
| 2SLAQ                   | 150         | 6,374 | 20.85 < g < 21.85 | ch/UVX | 0.3 < z < 2.9 | A/s | da Angela et al. (2008) |
| HSC                     | 172         | 901 | 21.0 < i < 23.5 | opt+MIR | 3.4 < z < 4.6 | C/s | He et al. (2018) |
| ACTxSDSS                | 118         | 7,600 | $g \leq 22.0$ or $r < 22.0$ | XDQSO | 0.9 < z < 2.1 | A/s | Rodríguez-Torres et al. (2016) |
| 2QZ                     | 445         | 13,989 | $18.25 < h_y < 20.85$ | ch/UVX | 0.3 < z < 2.2 | A/s | Croom et al. (2005) |
| 2QZ                     | 721         | 22,655 | $18.25 < h_y < 20.85$ | ch/UVX | 0.3 < z < 2.2 | A/s | Croom et al. (2005) |
| eBOSS Y1Q               | 118         | 7,600 | $g \leq 22.0$ or $r < 22.0$ | XDQSO | 0.9 < z < 2.2 | A/s | Rodríguez-Torres et al. (2016) |
| eBOSS                   | 1200        | ~69,000 | $g < 22.0$ or $r < 22.0$ | XDQSOz | 0.9 < z < 2.2 | A/p | Laurent et al. (2017) |
| eBOSS BAO               | 2044        | 147,000 | $g < 22.0$ or $r < 22.0$ | XDQSOz | 0.9 < z < 2.2 | A/p | Atpa et al. (2018) |
| SPTxWISE                | 2500        | 107,469 | W2 < 15.05 | IR | z ~ 1 | C/p | Geach et al. (2013) |
| BOSSsLyC                | 3275        | 61,342 | $g < 22.0$ or $r < 21.5$ | XDQSO | 2.0 < z < 3.5 | C/s | Font-Ribera et al. (2013) |
| WISE                    | 3363        | 176,467 | W2 < 15.05 | IR | z ~ 1 | A/p | Donoso et al. (2014) |
| WISE                    | 3422        | 175,911 | W2 < 15.05 | IR | z ~ 1 | A/C/P | DiPompeo et al. (2016) |
| BOSS DR9                | 3600        | 27,129 | $g < 22.0$ or $r < 21.5$ | XDQSO | 2.2 < z < 2.8 | A/s | White et al. (2012) |
| SDSS DR5                | ~4000       | 38,208 | $i < 19.1$ | eb | 0.1 < z < 5.0 | A/C/P | Shen et al. (2009) |
| SDSS DR5                | 4013        | 30,239 | $i < 19.1$ | eb | 0.3 < z < 2.2 | A/s | Ross et al. (2009) |
| SDSS DR5                | 4041        | 4,426 | $i < 20.2$ | eb | 2.9 < z < 5.4 | A/s | Shen et al. (2007) |
| SDSS DR4                | ~6670       | ~300,000 | $g < 21$ | KDE eb | 0.75 < z < 2.28 | A/p | Myers et al. (2007) |
| BOSS DR12               | 6950        | 55,826 | $g < 22.0$ or $r < 21.5$ | XDQSO | 2.2 < z < 2.8 | A/s | Eftekhari-zadeh et al. (2015) |

Notes.

- Measurement of the autocorrelation function (A) and cross-correlation function (C) using photometric (p)/spectroscopic (s) redshifts or a combination of both (b).
- The study table advantage take advantage of the properties of quasars in the X-ray (X), radio (R), mid-infrared (MIR), near-infrared (NIR), and optical (opt) wavelengths and use color boxes (cb) and/or machine-learning techniques for selection.
- The Spitzer IRAC Equatorial Survey.
- The Spitzer HETDEX Exploratory Large-Area Survey.
- “Extreme Deconvolution”; see Bovy et al. (2011).
- DiPompeo et al. (2014, 2015) performed similar analyses on earlier WISE data sets.
- Kernel density estimator; see Richards et al. (2009).
- Myers et al. (2006) performed a similar analysis on SDSS DR1 data.

Eftekharzadeh et al. 2015; Chehade et al. 2016) have shown that the bias is very weakly, if at all, dependent on absolute quasar UV/optical luminosity. In fact, both Shen et al. (2013) and Krolewski & Eisenstein (2015) found no luminosity dependence of quasar clustering at low $z$ by studying the cross-correlation between galaxies and quasars. This result implies that quasars all live in the most massive DM halos, regardless of how bright the quasar shines. Aird et al. (2018), however, suggested that the observed lack of luminosity dependence on quasar clustering may be due to a selection effect depending on the type of galaxy in which the AGN resides (star-forming or quiescent).

Croom et al. (2005), Myers et al. (2007), and Ross et al. (2009) demonstrated that the bias evolves with redshift, increasing at higher redshift until the peak of quasar activity at $z \sim 2.5$. These studies were performed with large number densities of either spectroscopically confirmed or photometrically selected quasars, driving down Poisson noise in the clustering measurement (see Table 1). Interestingly, however, due to the evolution of the underlying DM density field, the masses of the halos that quasars inhabit remains approximately constant at $M_{\text{halo}} \sim 2-3 \times 10^{12} M_{\odot}$, from redshifts $z \sim 2.5$ to the present day. Shen et al. (2007) performed a similar analysis of the luminous, high-$z$ ($2.9 < z < 5.4$) confirmed quasars from the Sloan Digital Sky Survey (SDSS; York et al. 2000) Data Release 5. Despite having low number densities ($\sim 1$ quasar deg$^{-2}$), their study detected a large clustering signal, which implied that the bias increases rapidly beyond $z \sim 2.5$, yielding a large increase in the DM halo mass estimate with redshift.

Clustering has also been studied as function of quasar color, which is a proxy for quasar type. Here the results are not so definitive. Hickox et al. (2011) measured the clustering of both obscured and unobscured quasars, as defined by an optical-to-IR flux ratio (specifically, $R_{\lambda AB} - [4.5]_{\text{Vega}} = 6.0$; Hickox et al. 2007), with bluer objects being classed as unobscured quasars. Hickox et al. (2011) reported “marginally stronger clustering” for the obscured quasars compared to the unobscured population, with the consequence that dust-obscured quasars tend to reside in more massive DM halos than “dust-free” quasars. Donoso et al. (2014), using a similar selection to Hickox et al. (2011), similarly found that obscured AGNs inhabit denser environments than unobscured AGNs. DiPompeo et al. (2014, 2015, 2016), in finding a less significant difference between the clustering of obscured and unobscured quasars, noted that Donoso et al. (2014) discounted
several critical systematics that affect the amplitude of quasar clustering measurements.

Linking the measurements of the 2PCF and corresponding bias to quasar and host galaxy physical parameters is paramount in understanding the relationship between the observable universe and the underlying DM distribution. These observables can then be used to direct theories and models of galaxy and quasar formation and evolution. One model that links the DM distribution, quasar activity, and the associated environment was presented in Hopkins et al. (2007). The simulations in that investigation predicted the clustering of the quasar population through the implementation of three different quasar feedback models. Quasar feedback works against gravity by forcing material away from the SMBH through radiation pressure, thus limiting the material that can accrete onto and increase the mass of the SMBH. This process can ultimately shut down the quasar phase and cause the SMBH to cease growing. Measuring the spatial distribution of quasars, particularly in the early universe, can test the predictions made by Hopkins et al. (2007).

Testing these models requires surveys to push beyond the redshift peak in the quasar epoch (2 < z < 3; Schmidt et al. 1995; Boyle et al. 2000) and delve further down the quasar luminosity function (QLF). Current surveys are underway to address this question—for example, the extended Baryon Oscillation Spectroscopic Survey (eBOSS; Dawson et al. 2016), which will be able to select quasars out to z ~ 3.5 (Myers et al. 2015)—however, the majority of existing quasar surveys are designed to observe rest-frame UV-bright quasars and/or are focused on z < 2; thus, new data and analysis are needed.

In this paper, we present the first measurements of the autocorrelation function of optical+infrared-selected quasars at z > 2.9 with the 2PCF. This approach is made possible by the combination of deep optical data from the SDSS Stripe 82 coadded catalog (Annis et al. 2014; Jiang et al. 2014) and new deep overlapping Spitzer coverage from the Spitzer IRAC Equatorial Survey (SpIES; Timlin et al. 2016) and the Spitzer-HETDEX Exploratory Large-Area (SHELA; Papovich et al. 2016) survey. Following the work of Richards et al. (2015), we combine the color information from the optical and mid-infrared (MIR) and employ machine-learning algorithms to classify faint, high-z quasar candidates using their photometric colors.

Traditionally, large numbers of quasars have been detected from Spitzer surveys alone. Quasars tend to lie in a specific location in MIR color space, so selection can be performed through various color cuts (Lacy et al. 2004; Stern et al. 2005). These constraints, while effective, lead to an increasing amount of contamination, particularly at high-z, where quasar colors overlap with the stellar locus, resulting in a higher level of incompleteness in the selection (Assef et al. 2010; Donley et al. 2012). Donley et al. (2012) added a power-law selection requirement for classification, which significantly reduced contamination; however, quasar spectra are not necessarily power laws in the MIR (Richards et al. 2015). Similarly, optical-only selections have found a large number of new quasars in the SDSS alone; however, these techniques suffer from incompleteness at z ~ 3.5 (Richards et al. 2006; Worseck & Prochaska 2011), where quasars have colors near that of the stellar locus. The combination of optical and infrared colors allows for more robust classifications, particularly at high-z, which is essential for this study (see Section 2.2).

In this paper, we measure the clustering strength of photometrically selected quasar candidates. We compare these measurements to the theoretical predictions for DM clustering to draw inferences on various physical parameters, such as DM halo mass and AGN feedback mechanisms in the early universe. In Section 2, we discuss the data used in this study, as well as the techniques to select quasar candidates. Section 3 provides further details about the 2PCF definition and uses. We present our results in Section 4 and discuss the implications of our results, comparing to several quasar feedback models, in Section 5. We summarize and conclude in Section 6. The Appendices give further relevant and supplemental information. Throughout this paper, we assume a spatially flat ΛCDM model, consistent with the latest cosmic microwave background (CMB; Planck Collaboration et al. 2016) and BOSS (Alam et al. 2017) data sets: \( \Omega_m = 0.275 \), \( H_0 = 70 \text{ km s}^{-1} \text{ Mpc}^{-1} \), and \( \sigma_8 = 0.77 \), unless otherwise stated. All colors and magnitudes in this data set were corrected for Galactic extinction using the parameters (for \( R_V = 3.1 \)) given in Table 6 of Schlafly & Finkbeiner (2011). We calculate magnitudes on the AB scale, which has a flux density zero point of 3631 Jy (Oke & Gunn 1983).

2. Data and Selection

In this section, we describe our data sets, including the SpIES and SHELA surveys and the optical data on SDSS Stripe 82. Following that, we describe our “test” and “training” sets required to classify our data. Finally, we present the classification algorithms. The final sample of quasar candidates we generate is given in Section 2.5.

2.1. SpIES, SHELA, and SDSS Stripe 82

Covering approximately a third of S82 (\( -60^\circ \leq \alpha \leq 60^\circ; -1^\circ25 \leq \delta \leq 1^\circ25 \)), the SpIES survey was designed to span a large area (~100 deg² centered at \( \delta = 0 \); see Figure 1) and probe sufficiently deep to select faint high-z quasars, which were undetected by the Wide-field Infrared Survey Explorer (WISE; Wright et al. 2010). The SpIES catalogs reported the photometry and photometric errors for ~5.4 million objects at 3.6 and 4.5 μm. Using SpIES, we are able to detect quasars as faint as \( i ~ 22 \) with high reliability (Timlin et al. 2016). SpIES is also optimally located to surround existing Spitzer data from SHELA (Papovich et al. 2016), forming a long stripe of deep MIR coverage on S82 (see Figure 1).

The SHELA survey was designed to be used alongside the Hobby-Eberly Dark Energy Experiment (HETDEX;
Hill et al. (2008) to perform dark energy measurements requiring deep infrared data. With depths greater than that of SpIES, SHELA provided an additional ~24 deg² of deep infrared coverage on S82 (see Figure 1). In total, SHELA detected ~2 million objects down to Spitzer magnitude depths of [3.6] = 22.0 and [4.5] = 22.6 (compared to 21.9 and 22.0, respectively, for SpIES). In tandem, SpIES and SHELA provide ~120 deg² (accounting for overlapping coverage; Figure 1) of deep MIR data on S82—data necessary to, along with optical colors, select faint, high-z quasars.

Optical photometric data come from the full SDSS-II/II (York et al. 2000) data release, as well as the SDSS-III/BOSS (Eisenstein et al. 2011; Dawson et al. 2013). Of particular interest for this study is the S82 coadded catalog (Annis et al. 2014; Jiang et al. 2014). Imaged with the five optical SDSS filters (ugriz; Fukugita et al. 1996), S82 was the target for recurring observations to detect variable objects and obtain deep optical photometry. When the images are stacked, S82 has an optical i-band magnitude limit of $i \sim 24.1$ (Jiang et al. 2014), which is significantly deeper than the rest of the SDSS survey.

Spectroscopically confirmed quasar data come from the composite quasar catalog of Richards et al. (2015). This catalog is a compilation of spectroscopic quasars from large surveys such as SDSS (York et al. 2000; Eisenstein et al. 2011) and the 2QZ project (Croom et al. 2004), as well as from smaller surveys such as Hectospec (Fabricant et al. 2005). In total, they compiled ~2 million quasars and quasar candidates (including ~437,000 spectroscopically confirmed quasars) that span a large range in both redshift and $i$ magnitude. The catalog encompasses faint, high-z quasars from BOSS (Pâris et al. 2014), which are key to defining the quasar color space used to classify the photometric objects.

Richards et al. (2015) also matched their catalog to infrared catalogs such as AllWISE$^{12}$ and various overlapping Spitzer surveys to investigate the MIR colors of these known quasars in the full SDSS field. MIR color–color diagrams have been particularly useful in quasar classification, as shown in Lacy et al. (2004), Stern et al. (2005), and Donley et al. (2012), among others. The addition of this MIR data in classification allows for higher number densities of detected quasars, particularly at high $z$ ($z \geq 2.9$).

The new infrared SpIES and SHELA surveys provide a much larger area where deeper infrared data overlap the optical, providing the necessary information to classify objects as type-1 quasars; the challenge becomes selecting a clean sample of quasar candidates. However, using the machine-learning techniques demonstrated in Richards et al. (2015), selection of high-z quasar candidates has become much more complete. To generate a final catalog of high-z quasars, we must first assemble a complete sample of all detected objects (i.e., photometric and spectroscopic) to form the test set. This test set is then reduced to a subset containing the known (spectroscopically confirmed) high-z quasars used to define the color spaces that train the algorithms, along with a fraction of the unknown (photometric) objects (the training set). Test objects are then fit using the trained algorithm and assigned a classification. Presented in Table 2 are the demographics of the test and training sets used in this study, as well as the final selected type-1 quasar candidates.

### Notes

$^{12}$ [http://wise2.ipac.caltech.edu/docs/release/allwise/](http://wise2.ipac.caltech.edu/docs/release/allwise/)

$^{13}$ [http://ned.ipac.caltech.edu/forms/und.html](http://ned.ipac.caltech.edu/forms/und.html)
Additionally, we add to the training set nonquasar sources ("stars"), which do not have spectroscopic information, randomly selected from the full test set. As described in Richards et al. (2015), the "stars" in the training set can also include previously unclassified quasars, stellar sources, and compact galaxies. The additional "star" information is important in the classification because it defines the color-space boundaries around the high-z quasars in the machine-learning algorithms. The full training set is comprised of \(\sim 700,000\) "stars" and confirmed quasars in the SDSS footprint that are as faint as \(i \sim 23\) and observed to \(z \sim 6\). In this investigation, we split the training set into two redshift ranges for selection: a lower-z \((2.9 \leq z < 3.5)\) and a higher-z \((3.5 \leq z \leq 5.2)\) range. The colors of the higher-z objects are much more distinct from low-z "stars" compared to the objects in the lower-z range; thus, the selection is much more efficient in the higher-z range. Figure 2 depicts the colors of extended and point sources in the training set and highlights the colors of the known high-z quasars in each color space used to classify the test objects. We also provide the demographics for both the testing and training sets in Table 2.

2.3. Classification Algorithms

The colors of confirmed high-z quasars in the training set (shown in Figure 2) are used to teach the machine-learning algorithms where high-z quasars lie in multidimensional color space. The colors of the photometric objects in the S82 test set are then input into the trained algorithms to classify them as high-z quasars. For this analysis, we utilize three classification algorithms: random-forest (RF) classification, support-vector classification (SVC), and bootstrap aggregation (bagging) on K-nearest neighbors (KNN), which we define below. All of these algorithms are openly available in the Scikit-Learn\(^{14}\) Python package used in this study.

The RF classifier\(^{15}\) creates a set of \(N\) random decision trees that split the training quasars by their colors into different branches, with each branch returning a classification (in this case, high-z or not). The colors of the test objects are then subject to the splitting that each tree has created, and each of the trees assigns a classification based on the conditions that the

\(^{14}\) [http://scikit-learn.org/stable/]

\(^{15}\) [http://scikit-learn.org/stable/modules/ensemble.html#forest]
test objects satisfy. The mode result of all of the trees is used as the final classification for each of the test objects.

We also employ the SVC algorithm,\(^{16}\) which defines an optimal hyperplane that separates two populations of objects by the largest margin. In this case, the training-set objects create the six-dimensional color space, and the hyperplane is defined by the plane that maximally separates the known high-\(z\) quasars from the “stars” in the training set. Classification of the test objects is based on the side of the hyperplane they lie on in this multidimensional color space.

Finally, we use “bagging” with a KNN algorithm,\(^{17}\) where bagging is the process of splitting the training set into \(N\) different subsets of randomly chosen training objects (with replacement). Each of those subsets is used to train the machine-learning algorithm (KNN, in this case), resulting in \(N\) trained KNN algorithms. The KNN algorithm assembles the training-set color information and classifies the test data by analyzing the closest “\(k\)” training objects in color space. Similar to a majority rule, the test object is classified based on the type of the closest “\(k\)” training object (in this case, high-\(z\) quasar or not). This analysis is done in all of the bagging subsets, and the mean result from all of the bags is chosen as the final classification.

To measure the effectiveness of each algorithm, we compute the two key selection parameters: efficiency and completeness. The efficiency of an algorithm relates the number of objects it classifies correctly to the total number of objects it classifies and can be used to estimate the contamination of the classified sample by taking the difference from unity. Completeness is a measure of how many quasars are properly classified compared to the total number of known quasars in the data set.

Estimation of the completeness and efficiency of our algorithms requires the full training set to be split into two subsets for cross-validation (CV): a subset with 75% of the data to be used as a CV “training set” and a subset with 25% of the data to be used as CV “test” objects. These sets are input into the classification algorithms discussed above. Since the CV test objects contain known quasars, completeness and efficiency can be calculated using the classification results of the known quasars from the CV test set. Ideally, both completeness and efficiency should be maximized to recover all of the high-\(z\) quasars, and only the high-\(z\) quasars. Practically, however, quasar colors can overlap with stars and low-\(z\) galaxies, so contamination and missed classifications are inevitable.

We compare our algorithms to the kernel density estimation (KDE) used in Richards et al. (2015). This study classified photometric objects in the SDSS footprint using optical data along with infrared data from WISE. The KDE method used in Richards et al. (2015) first defined a color “bandwidth” for each class of object (quasar or nonquasar), which acts to smooth the color distributions, and a Bayesian stellar prior, which defines the percentage of objects in the test sets thought to be “stars” (i.e., nonquasars). A probability density function (PDF) is then defined in color space for a class of object, and the likelihood that a test object with certain photometric colors belongs to a class is computed using the bandwidth and a kernel function. The posterior probability that an object is a quasar given its color is computed by applying Bayes’ theorem using the defined priors and likelihoods for each test object (see Richards et al. 2009 for details). This study classified objects over a wide range of redshifts; however, we will compare the performance of our algorithms to their highest redshift classification (\(3.5 \leq z \leq 5\)).

In our investigation, we split the classification of quasar candidates into lower-\(z\) (\(2.9 \leq z < 3.5\)) and higher-\(z\) (\(z \geq 3.5\)) bins. We found that the classification algorithms performed better at higher-\(z\) compared to lower-\(z\), as reported in Table 3. This is mainly because quasars begin to drop out of the SDSS \(u\)-band filter at \(z \sim 3.5\), which significantly alters the \(u-g\) color space and helps the machine-learning algorithms efficiently select these objects. The colors of \(z \sim 3\) quasars are very similar to those at \(z \sim 2.2\); therefore, the algorithms tend to confuse low-\(z\) quasars with higher-redshift quasars. Through CV, we found that the “bagging” algorithm performed the best at lower-\(z\), and all three perform equally well at higher-\(z\), as reported in Table 3. More details are presented in Section 2.5, where we describe our final candidate selection.

2.4. Photometric Redshifts

The photometric redshifts of our candidates were estimated with Nadaraya–Watson (NW) kernel regression.\(^{18}\) The NW algorithm is a natural extension of more familiar regression techniques. Linear regression fits a line to 2D data. Polynomial regression instead fits a higher-order curve. Basis-function regression (of which polynomial regression is an example) uses a predetermined “basis” function to fit the data. The NW algorithm is just basis-function regression using a Gaussian kernel (Ivezić et al. 2014).

The NW algorithm defines the multidimensional color space of the training objects with spectroscopic redshifts, then builds a kernel matrix, \(K\), that measures the pairwise distance between the colors of the test objects and training objects, where \(K\) is the Gaussian kernel:

\[
K = \exp\left(\frac{1}{2\sigma^2} \left\| d_{\text{test}} - d_{\text{train}} \right\|^2 \right).
\]

Here \(\left\| d_{\text{test}} - d_{\text{train}} \right\|\) is the Euclidean distance between the colors of the test objects and training objects, and \(\sigma\) is the bandwidth of the kernel (\(\sigma = 0.05\) produced the best self-validation results in this study). From Equation (3), if a test object is close to a training object (i.e., if the 6D colors are very similar), the kernel approaches 1; however, the further the colors are from each other, the smaller the Gaussian kernel becomes. Therefore, the kernel matrix is used as weights in the estimate of the photometric redshift, defined by

\[
z_{\text{phot}} = \frac{\sum K_{i} \cdot z_{\text{spec},i}}{\sum K_{i}}.
\]

where the kernel element in \(K\) is multiplied by the spectroscopic redshift corresponding to the training quasar input into Equation (3). The final photometric redshift result for a candidate object is then the weighted sum over all of the spectroscopic redshifts of the training objects.

To test the effectiveness of this method, we calculate the photometric redshifts of the spectroscopic quasars on S82 over all redshift ranges using the same training set we use for the candidates. Additionally, we split the quasars into bright and

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16. http://scikit-learn.org/stable/modules/svm.html#svm

17. http://scikit-learn.org/stable/modules/neighbors.html#classification

18. http://www.astroml.org/modules/generated/astroML.linear_model.NadarayaWatson.html
faint subsets, where we differentiate between bright and faint at $i = 20.2$. The results in Figure 3 show that there is a tight correlation between the spectroscopic redshift of the quasar and its estimated photometric redshift for both subsets. In both cases, $\sim 93\%$ of the photometric redshifts differ from the spectroscopic redshifts by no more than $|\delta z| \leq 0.1$. These results are similar to the findings for the highest redshift bin in Richards et al. (2015), who used an empirical method outlined in Richards et al. (2001) and Weinstein et al. (2004).

Using the NW regression algorithm, each candidate quasar selected with the aforementioned algorithms was assigned a photometric redshift. A comparison of the candidate redshifts to the spectroscopic redshifts is displayed in Figure 4. With candidates selected and their photometric redshifts computed, we now create a final sample of candidates with which to compute the correlation function.

### 2.5. Clustering Sample

Although classification was performed on all of the S82 test objects, and photometric redshifts were computed for all candidates that were selected, we further restricted the data set to create the cleanest sample of faint, high-$z$ quasars with which to compute the 2PCF. First, to retain the faintest objects with the deepest photometry, we required that the objects lay within the SpIES/SHELA footprint, where the deep MIR data exist, and that they were sufficiently far away from bright stellar sources that contaminate the photometry (see Timlin et al. 2016 for more details). Additionally, candidates were required to have photometric redshifts in the range $2.9 \leq z \leq 5.1$, enabling us to compare our results with Shen et al. (2007), the most recent wide-area spectroscopic study of quasar clustering at redshifts as high as $z \sim 4$.

To ameliorate potential sources of contamination yet select as many true high-$z$ quasars as possible, we combined the results of each of the selection algorithms (see Table 3). At low-$z$ ($2.9 \leq z < 3.4$), we chose to only employ the “bagging” classifier because of its high efficiency. While including the results from the other two classifiers would have made our sample more complete, it also would have added a large amount of contamination. At high-$z$ ($3.4 \leq z \leq 5.2$), however, we combined the selection results of the three algorithms, since they all have low contamination, as shown in Table 3.

Despite combining the classification results in this manner, the sample still contained contamination from low-$z$ galaxies.

### Table 3

| Algorithm | Completeness | Efficiency | Contamination |
|-----------|--------------|------------|---------------|
| RF        | 83/78/80     | 43/93/86   | 57/7/14       |
| SVC       | 82/79/79     | 40/95/86   | 60/5/12       |
| Bagging KNN | 83/80/80     | 85/95/88   | 15/5/12       |
| KDE       | –/78/-       | –/97/-     | –/3/-         |

Note. Estimated completeness, efficiency, and contamination measured for the three algorithms used in this study compared to the KDE method used in Richards et al. (2015). The first three rows report our algorithms when selecting in a lower redshift range ($2.9 \leq z < 3.5$; left), higher redshift range ($3.5 \leq z \leq 5.2$; middle), and broader redshift range ($2.9 \leq z \leq 5.2$; right). The values in the middle are used to compare to Richards et al. (2015). These values are estimates, since the actual test set probes slightly fainter than the validation set.

To eliminate the obvious galaxies, we restricted our data to point-like sources only. We generated our own metric for high-$z$ quasar point sources by taking the difference between the PSFMAG and cMODELmag ($\delta_{\text{mag}}$) in the SDSS DR10 $i$ band. A difference of $\delta_{\text{mag}} \leq 0.145$ is used in the SDSS catalogs to label an object as a point source. We found that the known quasars in our lower-$z$ range ($2.9 \leq z < 3.4$) had $\delta_{\text{mag}} = 0.2$, whereas the known higher-$z$ ($z \geq 3.4$) quasars had $\delta_{\text{mag}} = 0.15$. We applied this morphology cut to the selected objects in the appropriate redshift range after the selection had been performed. This cut eliminated a significant fraction of...
Table 4
Quasar Candidate Table

| α2000 (deg) | δ2000 (deg) | u | g | r | i | z | zspec | zbest |
|-------------|-------------|---|---|---|---|---|-------|-------|
| 31.92786    | −0.04275    | 0.15 | 2.17 | 0.933 | 0.277 | 0.203 | 0.811 | 0.329 | 21.00 | −999.0 | 3.89 | 3.89 |
| 12.30498    | 0.69156     | 0.14 | 0.23 | 2.04 | 0.113 | 0.030 | 0.631 | −0.543 | 22.10 | −999.0 | 3.90 | 3.90 |
| 27.56491    | 0.76547     | 0.14 | 1.84 | 1.50 | 0.205 | 0.283 | 0.600 | 0.143 | 20.76 | 3.90 | 3.90 |

Notes. List of all candidates selected by the three algorithms. Along with positional information, we record the i-band AB magnitude, its u-band extinction parameters, and the optical/infrared color of each object. We also report the spectroscopic redshift if the quasar is a confirmed object (a value of −999.0 indicates that there is no spectroscopic redshift). The photometric redshift estimate from the NW regression algorithm is recorded in the next column, followed by the “best” redshift estimate (records the spectroscopic redshift instead of the photometric estimate, when available). The full version of this catalog can be found at https://github.com/JDTimlin/QSO_Clustering/tree/master/highz_clustering/clustering/Data_Sets.

extended sources, which we consider to be contaminants in our sample (confirmed using visual inspection; see Appendix A).

Another source of contamination that we account for is high Galactic extinction objects, which can cause low-z objects to be mistaken for high-z quasars (Myers et al. 2006). Removal of these highly extincted objects is particularly important in this study, since the eastern edge of the SpIES field overlaps with the Galactic plane (330° < α<sub>2000</sub> < 344°). To remove the contamination due to these objects, we elect to cut out this region from our final analysis (see Appendix A for more details). While this process eliminates some area over which we can perform the clustering analysis, it also removes contaminants that are confused for high-z quasars in the machine-learning algorithms (despite the extinction-corrected magnitudes).

Differences in the angular mask of the data and randoms can also affect our clustering measurement. The edges of the SHELA field are not uniformly covered in the mask, requiring that we cut in declination (−1°2 < δ<sub>2000</sub> < 1°2) to ensure that the densities of the data and randoms were approximately the same across the field. After cutting out the extinction region and these underdense regions, our final footprint covers 102 deg<sup>2</sup> on Stripe 82.

Finally, every candidate object (before and after the morphology cut) was visually inspected using the stacked g, r, z images from the Dark Energy Camera Legacy Survey (DECaLS<sup>20</sup>) image cutout tool.<sup>20</sup> DECaLS images to similar depths as the SDSS S82 coadded catalog (r = 23.4 compared to r = 24.6 on S82) but uses the Dark Energy Camera (DECam<sup>21</sup>), which has a finer resolution than the SDSS (0″26 compared to 0″39 pixel<sup>−1</sup>). This added resolution enabled us to visually eliminate a small number of obvious low-redshift galaxies that share color spaces with high-z quasars (see examples in Appendix A).

After the cuts and visual inspection, 1378 objects remain as high-z quasars (see Table 4). Of these, 726 are spectroscopically confirmed from the Richards et al. (2015) comprehensive catalog, and we select 652 new high-z quasar candidates with which we can measure the 2PCF. None of the quasars or candidates used in this study were used in the Shen et al. (2007) study. The colors of our selected quasars are presented in Figure 5 and compared to the colors of the training objects. The majority of the selected quasars share the same color space as the high-z quasars whose colors were used to train the algorithms, but as our candidates delve fainter than the majority of the training objects, there is some scatter in their colors. While there is stellar contamination in the sample (which we will model in Section 4), some of the scatter in the colors could be due to contamination from objects such as compact galaxies, which are more difficult to identify from colors alone.

Using the redshifts and i-band apparent magnitudes, we compute the absolute magnitudes of these quasar candidates and compare them to the spectroscopic sample from Shen et al. (2007) (renormalized to z = 2 after K-correcting using the model in Richards et al. 2006) in the top panel of Figure 6. The majority of the photometric candidates are fainter than both the Shen et al. (2007) quasars and i = 20.2 (shown in the bottom panel of Figure 6), which is necessary to break the degeneracy in the bias as a function of redshift. This investigation contains a small number of objects brighter than i := 20.2 compared to Shen et al. (2007) because it covers a smaller area (∼100 deg<sup>2</sup> versus ∼4000 deg<sup>2</sup>, respectively).

3. Clustering

3.1. Two-point Correlation Function

Spatial clustering of a population of objects is quantified using the 2PCF, which is the joint probability of finding an object in two volume elements, dV<sub>1</sub> and dV<sub>2</sub>, at some separation r<sub>12</sub> (Peebles 1980). This quantity can be expressed as

\[ dP = n^2 [1 + \langle \xi(r_{12}) \rangle] dV_1 dV_2, \]

(5)

where \( n \) is the mean number density and \( \langle \xi(r_{12}) \rangle \) is the correlation function. In this equation, if the 2PCF is zero, the probability shows no excess compared to a Gaussian random distribution.

We can derive this statistic for a distribution of objects in a density field, \( \rho \), where the probability of finding an object in that field is \( dP = \langle \rho(r) \rangle dV \) (Peebles 1980). The probability of finding a pair of objects in two density fields \( \rho_1, \rho_2 \) separated by a distance \( r \) is

\[ dP = \langle \rho_1(r) \rangle \langle \rho_2(r) \rangle dV_1 dV_2. \]

(6)

The density in an expanding universe is modeled with a linear perturbation \( \rho(r) = \bar{\rho} (1 + \delta(r)) \), so Equation (6) becomes

\[ dP = \bar{\rho}^2 [1 + \langle \delta_1(r) \delta_2(r) \rangle] dV_1 dV_2. \]

(7)

\[ dP = \bar{\rho}^2 [1 + \langle \delta_1(r') \delta_2(r) \rangle] dV_1 dV_2. \]

(8)

Comparing with Equation (5), we see that the correlation function is the ensemble average of the perturbations, \( \langle \delta_1(r') \delta_2(r) \rangle \). The density field can also be expressed...
in Fourier space (Bonometto et al. 2002):

$$\delta(r) = \frac{1}{(2\pi)^3} \int \delta(k) e^{-ikr} dk.$$  \hspace{1cm} (9)

Taking the Fourier transform of the correlation function yields

$$\langle \delta_1(r') \delta_2(r) \rangle = \frac{1}{(2\pi)^3} \int \langle \delta(k) \delta^*(k) \rangle e^{-ikr} dk,$$  \hspace{1cm} (10)

where the ensemble average of the density modes, $\langle \delta(k) \delta^*(k) \rangle$, is the definition of the power spectrum, $P(k)$. The correlation function is, therefore, the Fourier transform of the power spectrum. We relate our clustering results to the theoretical clustering of DM, which will be obtained through calculation of the DM power spectrum. In this paper, we compute the angular projected correlation function, $\omega(\theta)$, which is a projection from three-dimensional (3D) volume space into two-dimensional (2D) angular space.

3.2. Estimating the Correlation Function

To estimate the correlation function, one needs to compare the data set to a set of randomly distributed points. To compute the correlation function, we use the estimator from Landy & Szalay (1993),

$$\omega(\theta) = \frac{\langle DD \rangle - 2\langle DR \rangle + \langle RR \rangle}{\langle RR \rangle},$$  \hspace{1cm} (11)

where $\langle DD \rangle$, $\langle DR \rangle$, and $\langle RR \rangle$ are the data–data, data–random, random–random pair counts within an angular separation of $\theta$ (to measure the 3D correlation function, $\xi(s)$, one simply counts pairs within a 3D comoving separation distances). The pair counts are normalized by the ratio of the number of objects in the data and random sets. To reduce the shot noise in the measurement, we use $\sim 100$ times the number of points as the data catalog. The normalization of the pair counts reconciles that there are more random points to match than data.

The random data must lie on an identical angular mask as the data. To generate the random catalog for our candidates, we first construct the angular mask using the MANGLE2 software (Swanson et al. 2008). This package allows a user to combine polygons from telescope observations to create a continuous mask with accurate boundaries and holes on the surface of a sphere. We combine the fields from the SpIES and SHELA surveys (see Figure 1) and remove circular

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**Figure 5.** Optical and infrared colors of the selected quasars (orange contours). The other contour colors are the same as in Figure 2. These panels demonstrate that the location of the candidates in color space overlaps with the colors on which they were trained (dark blue contours).
regions of varying radii around bright stars from the 2MASS Point Source Catalog as outlined in Timlin et al. (2016). Objects in these regions were excluded from the selection of quasars because they are contaminated by the excess flux from the bright star, so we mask them using MANGLE. Random positions are chosen across the full field, avoiding masked areas, to form the random mask, which is used in the Landy & Szalay estimator in Equation (11). Figure 7 compares the data to the random catalogs within a sample of the field created in MANGLE.

3.3. Measuring Bias

The linear bias in Equation (1) is used as a measure of the clustering strength of the population of quasars and has been related to many physical parameters of quasars, as well as their DM environments.

Estimating the bias, however, requires that we relate the projected correlation function to the 3D power spectrum. To perform this task, we use Limber’s approximation, which projects the 3D correlation function to two dimensions (Limber 1953) for objects with small separations ($\theta \ll 1$ rad; Simon 2007). Projecting the correlation function requires that we integrate the 3D correlation function along the line of sight of two objects,

$$\omega(\theta) = \int \int \xi(r_1, r_2) |r_1|^2 |r_2|^2 \phi(r_1) \phi(r_2) dr_1 dr_2,$$

(12)

where $|r_1|, |r_2|$ are the magnitudes of the two distance vectors and $\phi(r)$ is a radial selection function. The selection function acts as a probability distribution where the integral of $r^2 \phi(r) dr$ is normalized to unity (Brewer 2008). Shifting the coordinate system to one where the unit vectors are along the line of sight, $u = r_1 - r_2$, and across the line of sight, $r = \frac{1}{2}(r_1 + r_2)$, Equation (12) can be rewritten as

$$\omega(\theta) = \int_0^\infty r^4 \phi(r)^2 dr \int_0^\infty \xi(\sqrt{u^2 + r^2 \theta^2}) du,$$

(13)

where, for small $u$, $r_1 \approx r_2$, and for small angles, $\cos(\theta) \approx 1 - \frac{\theta^2}{2}$ (see Peebles 1980; Brewer 2008 for more details). Equation (13) is the functional form of Limber’s equation to project the 3D correlation function into two dimensions.

We transform Limber’s equation into familiar cosmological parameters. For instance, the observed number of objects in radial shells can be described in terms of the redshift...
distribution of a sample of objects by
\[
\phi(r)r^2 dr = \frac{dN}{dz} dz.
\]  
(14)
Solving for \( \phi \) and incorporating into Limber’s equation, we get
\[
\omega(\theta) = \int_0^\infty \left( \frac{dN}{dz} \right)^2 \left( \frac{d\chi}{dr} \right) dz \int_0^\infty \xi(\sqrt{u^2 + r^2 \theta^2}) \ du,
\]  
(15)
with the variable \( r \) defined as the comoving distance \( \chi \) (Brewer 2008). Assuming a flat universe,
\[
dr = d\chi = \frac{c}{H_0 E_z} \ dz,
\]  
(16)
where \( E_z = [\Omega_m(1 + z)^3 + \Omega_\Lambda]^{\frac{1}{2}} \). Thus, Equation (13) transforms to
\[
\omega(\theta) = \int_0^\infty \left( \frac{dN}{dz} \right)^2 \frac{H_0 E_z}{c} \ dz \int_0^\infty \xi(\sqrt{u^2 + r^2 \theta^2}) \ du.
\]  
(17)
Using the fact that the correlation function is the Fourier transform of the power spectrum, and since we know that \( u \) is small, we can employ the Hankel transform on the second integral to obtain Limber’s equation in terms of the quasar power spectrum,
\[
\omega(\theta) = \frac{H_0 \pi}{c} \int \left( \frac{dN}{dz} \right)^2 E_z \frac{\Delta_\phi^2(k, z)}{k^2} J_0(k\theta \chi(z)) \ du dz,
\]  
(18)
where \( \Delta_\phi^2 \) is the dimensionless quasar power spectrum \( \left( \Delta^2 = \frac{k^3 P(k)\Omega_{\text{b}}}{2\pi^2} \right) \) and \( J_0 \) is the zeroth-order Bessel function of the first kind (Bonometto et al. 2002; Myers et al. 2007; Brewer 2008). This formula relates the 3D quasar power spectrum to the 2D correlation function.

Equation (1) can now be written in a similar fashion by replacing the correlation functions with the dimensionless power spectra of quasars and DM. \( \Delta_\phi^2 = b^2 \Delta_{\text{DM}}^2 \). We substitute this relation into Equation (18), which allows us to cast this equation as a function of bias directly,
\[
\omega(\theta) = b^2 \frac{H_0 \pi}{c} \int \left( \frac{dN}{dz} \right)^2 E_z \frac{\Delta_{\text{DM}}^2(k, z)}{k^2} J_0(k\theta \chi(z)) \ du \ dz,
\]  
(19)
where we assume that, for our samples of interest, bias does not evolve strongly with redshift or scale (e.g., Myers et al. 2007).

Using Equation (19), we can fit a bias value using the measurement of the projected correlation function and the 3D dimensionless DM power spectrum.

To compute the DM power spectrum, we use the Code for Anisotropies in the Microwave Background (CAMB24), which is a general cosmology package that creates a model cosmography. CAMB has the functionality to compute the DM power spectrum, including the nonlinear corrections from the halo model in Smith et al. (2003). Combining the DM power spectrum (which is a function of wavenumber, \( k \), and redshift, \( z \)) with the redshift selection function for our candidates (blue curve in Figure 8), we Monte Carlo integrate Equation (19) and generate a theoretical model for the projected clustering of DM. Finally, we fit the DM clustering model to the measurement from our sample and obtain a bias.

\[\text{http://camb.info}\]

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**Figure 8.** Photometric redshift distribution of the quasar candidates. The blue curve was determined from KDE using the “epanechnikov” kernel with a bandwidth = 0.1. This curve is used in Limber’s equation to estimate the bias by comparing the projected correlation function to the 3D DM power spectrum. The red histogram depicts the distribution of the photometric redshifts in the data set.

**4. Results**

**4.1. Projected Clustering**

The measured SpIES/SHELA angular projected 2PCF of the quasars in this sample is shown in Figure 9. We estimate the errors on these points using both the Poisson approximation (see Equation (27) in Appendix A.3) and the jackknife resampling technique (Scranton et al. 2002; Myers et al. 2007; Ross et al. 2009; Eftekharzadeh et al. 2015), where a subset of the data (and the randoms) is removed from the full set, and the clustering analysis is performed on the remaining objects. In this investigation, the data sample was split into 10 declination slices, resulting in 10 separate clustering measurements, each excluding a different region. Using the 10 jackknife clustering measurements and their RR pair counts, we compute the full covariance matrix by

\[
C_{ij} = \sum_L \left[ \frac{\text{RR}_L(\theta_i)}{\text{RR}(\theta_i)} \left[ \omega_L(\theta_i) - \omega(\theta_i) \right] \right] \times \frac{\text{RR}_L(\theta_j)}{\text{RR}(\theta_j)} \left[ \omega_L(\theta_j) - \omega(\theta_j) \right],
\]  
(20)
where \( L \) denotes the removal of one of our 10 regions to form a jackknife sample comprising the other nine regions, and \( \theta_i, \theta_j \) represent the clustering result at different separation values. The error bars on the orange points in Figure 9 show the standard deviations of the full measurement, computed by taking the square root of the main diagonal of the covariance matrix (Myers et al. 2007; Ross et al. 2009; Eftekharzadeh et al. 2015). We take Poisson errors to be the minimum error of the data; therefore, we replace any jackknife error with a value less than the Poisson estimate with the Poisson error value (see Appendix A.3).
where $\theta_0$ is the angular separation over which objects are correlated, and $\delta$ defines the degree of clustering as a function of angular scale.

Using the measurement and errors of the 2PCF (see Table 5) and the DM model estimated using Limber’s equation, we can determine the bias that best relates the measurement and the theory. Similar to the fit in Myers et al. (2007), the bias was fit on scales with sufficient data—data pairs ($\theta \geq 1'$) and before the stellar correlation function dominates the quasar clustering signal ($\theta \leq 30'$). In principle, stellar contamination does not greatly change the correlation function at small scales (Myers et al. 2006). However, photometrically selected samples inevitably contain some level of contamination; thus, it is imperative that we incorporate an estimation of contamination in our model.

We fit the bias value, $\delta$, as well as the cross-correlation, $\epsilon$, over the range of $1'-30'$ (removing the negative value points) using Equation (21). The best-fit bias value is $b = 6.78 \pm 1.79$ and $\epsilon = -0.010 \pm 0.018$ for the full sample of 1378 quasar candidates, which have an average redshift of $\langle z \rangle = 3.38$. Using a simple $\chi^2$ goodness-of-fit test, $\chi^2 = 1.73$ over 5 degrees of freedom (DOF), which corresponds to a $p$-value of $p = 0.885$ on the fitting scales. Our model is also consistent, within the errors, with the data at larger scales despite fitting over the range of $1'-30'$. This behavior reveals the effect that the stellar contaminants have and suggests that our larger-scale correlation function is contaminated with stellar sources.

Over the same scales ($1'-30'$), we fit the 2D power-law model in Equation (22) to the data. The best-fit values from this two-parameter model are $b_0 = 0.71 \pm 0.0546$ and $\delta_0 = 1.39 \pm 0.618$. Using only the best-fit amplitude of the power-law model, we estimate that the significance of this clustering result is $\sim 1.3\sigma$ above the null hypothesis of an unclustered sample (i.e., $\theta_0 = 0$ at all scales). Reducing the error bars inherent to our selection technique is not practical in the near future, given the depth of WISE and the limited mapping capability of Spitzer; however, the combination of other deep and wide-area optical and infrared data in the near future, such as the Dark Energy Survey (DES; Diehl et al. 2014) and Euclid (Racca et al. 2016), should allow further progress.

### 4.2. Faint Quasar Clustering

The results in Figure 9 show the clustering strength of all of our candidate quasars, both bright ($i < 20.2$; 252 objects) and faint ($i \geq 20.2$; 1126 objects). In this analysis, we remove the bright quasars and cluster only the 1126 faint objects to directly test the degeneracy in the models of Hopkins et al. (2007). The computation of the correlation function and bias is the same as the previous section; we simply change the redshift selection function in Limber’s equation to match the new distribution. We find a best-fit bias of $b = 6.64 \pm 2.23$ and $\epsilon = 0.005 \pm 0.022$ for this faint sample with an average redshift of $\langle z \rangle = 3.39$. The $\chi^2$ test results in $\chi^2 = 0.45$, again over 5 DOF, which corresponds to a $p$-value of $p = 0.994$ on the fitting scales. The results of this analysis are shown in Figure 10. The error in this fit is much larger than that in the full sample, which we attribute to the size of the error bar at $\sim 5'$ and the difference in value at $\sim 30'$, which are both likely due to a smaller number density of objects. Despite this difference, the biases between this sample and the full sample are consistent; however, we focus on the full sample results in the next section.
Table 5
Pair Counts Results

| $\theta$ (') | DD | DR | RR | $\omega(\theta)$ | $\sigma_{\rm JK}(\theta)$ | $\sigma_{\nu}(\theta)$ |
|------|---|---|---|-----------------|-----------------|-----------------|
| 0.076 | 0  | 7  | 828 | -0.754 | 0.5038 | ... |
| 0.116 | 0  | 17 | 1980 | -0.781 | 0.5074 | ... |
| 0.175 | 0  | 37 | 4370 | -0.756 | 0.2472 | ... |
| 0.266 | 2  | 116 | 10432 | 0.756 | 2.7091 | 1.7556 |
| 0.403 | 2  | 268 | 23350 | -0.459 | 0.8997 | 0.5406 |
| 0.611 | 8  | 542 | 53470 | 0.507 | 0.6561 | 0.7534 |
| 0.927 | 12 | 1162 | 120784 | 0.073 | 0.5107 | 0.4381 |
| 1.405 | 32 | 2652 | 273444 | 0.247 | 0.3623 | 0.3118 |
| 2.131 | 74 | 6022 | 619802 | 0.269 | 0.2385 | 0.2086 |
| 3.231 | 156 | 13782 | 1403064 | 0.158 | 0.1461 | 0.1312 |
| 4.899 | 324 | 30643 | 3191350 | 0.100 | 0.0680 | 0.0865 |
| 7.428 | 692 | 69474 | 7209140 | 0.034 | 0.0398 | 0.0556 |
| 11.262 | 1506 | 155010 | 16201178 | 0.015 | 0.0295 | 0.0370 |
| 17.075 | 3226 | 343452 | 36027696 | -0.014 | 0.0239 | 0.0245 |
| 25.889 | 7104 | 747011 | 78725889 | 0.002 | 0.0116 | 0.0168 |
| 39.253 | 14932 | 1581774 | 166710784 | -0.005 | 0.0088 | 0.0115 |
| 59.516 | 29674 | 3141776 | 330927082 | -0.005 | 0.0058 | 0.0082 |
| 90.237 | 53028 | 5579277 | 583004272 | -0.007 | 0.0067 | 0.0061 |
| 136.818 | 75010 | 7795784 | 815069184 | 0.006 | 0.0048 | 0.0052 |
| 207.443 | 100858 | 10584579 | 1113270342 | 0.002 | 0.0050 | 0.0045 |

**Notes.** Pair counts and correlation function measurements within increasing separations on the sky. Also recorded are the error estimates from the main diagonal of the covariance matrix (see Equation (20)) estimated using jackknife resampling, as well as Poisson errors (see Equation (27)). In this investigation, jackknife errors are replaced with Poisson errors where the ratio of jackknife to Poisson is less than unity (see Appendix A.3). In this table, we report DD and RR as double-counted pairs.

However, there are other measurements of quasar clustering with which we can compare across our redshift range of interest. Here we examine the techniques and results of the surveys in the literature to those in our study.

We first compare our results to the results of the BOSS survey from Eftekharzadeh et al. (2015). This study examined the redshift-space correlation function of spectroscopically confirmed quasars in the SDSS field in the redshift range 2.2 $\leq z \leq 2.8$. For a more direct comparison with our angular projected correlation function, we compute the angular correlation function of the BOSS data from Eftekharzadeh et al. (2015) using their NGC CORE sample and a random catalog with five times the data (shown in the top panel of Figure 11). Despite spanning slightly disjoint redshift ranges, the two correlation functions agree on scales before contamination dominates the signal ($\sim 25$ $h^{-1}$ Mpc or $\sim 20$; Eftekharzadeh et al. 2015). Since these correlation functions have similar power in the clustering signal yet are at different redshifts, the best-fit bias values are different (see Figure 12).

Next, we compare with the results of He et al. (2018), who computed the quasar cross-correlation function (as opposed our measurement of the autocorrelation function; ACF) for photometrically selected quasars in the redshift range $3 \leq z \leq 4$. In the He et al. (2018) investigation, quasars are selected using optical and near-infrared colors from the Hyper Suprime-Cam25 (HSC). In total, they selected 1023 quasars as candidates across 172 deg$^2$, 901 of which were both faint ($i \geq 21$) and high-$z$. Using these candidates, they computed the cross-correlation function (CCF) between their candidates and Lyman-break galaxies at $z \sim 4$. Figure 11 (middle panel) depicts the results from the CCF analysis compared to our study. Since the measurement is performed with two different statistics, the amplitudes of the two $\omega(\theta)$ should not be directly

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Footnote 25: [https://www.naoj.org/Projects/HSC/surveyplan.html](https://www.naoj.org/Projects/HSC/surveyplan.html)
compared; however, the bias measurements from these two surveys can be compared, despite being computed with different statistics (CCF and ACF). Our ACF measurements find a bias of $b = 6.78 \pm 1.79$, and the bias from the CCF of He et al. (2018) is $b = 5.93 \pm 1.43$; both results are displayed in Figure 12. The biases of these two studies overlap within their measurement errors and can be interpreted using a similar physical model. We will discuss the physical implications of this model in Section 5.3. A larger sample of spectroscopic high-$z$ quasars is needed to reduce the uncertainties in the bias measurement of high-$z$ quasars.

We also compare our study over the full redshift range to the results of Shen et al. (2007), who investigated the clustering properties of spectroscopically confirmed high-$z$ quasars from the SDSS DR5. These DR5 quasars span a redshift range of $2.9 \leq z \leq 5.4$ and are bright ($i \leq 20.2$; see Figure 6). With spectroscopic redshifts, Shen et al. (2007) present a measurement of the 3D redshift-space correlation function, so to compare their results to ours, we compute the angular projected correlation function using their data and the DR5 mask from Ross et al. (2009). The results are shown in the bottom panel of Figure 11. The correlation function is, in general, higher in amplitude for the objects in DR5 than our candidates over the relevant scales ($\sim 30''$); however, we find a slightly smaller bias value than Shen et al. (2007).

The Shen et al. (2007) quasar sample has an $i$-band limiting magnitude of $M_i = -26.5$ (their Table 6) and is thus only sampling the very bright end of the QLF. By contrast, our data, as well as the data from He et al. (2018), have an $i$-band limiting magnitude of $M_i \simeq -24.0$. A direct comparison of the bias values (see Figure 12) between Shen et al. (2007), He et al.
We estimate the matter power spectrum, $P(k, z)$, using CAMB and our adopted cosmology, where $\hat{W}(k, R)$ is the spherical top-hat window function:

$$\hat{W}(k, R) = \frac{3}{(kR)^3}(\sin(kR) - kR \cos(kR)).$$  \hfill (25)

The parameters $A$, $a$, $B$, $b$, $C$, and $c$ in Equation (23) are adopted from Table 2 of Tinker et al. (2010) for $\Delta = 200$, where $\Delta$ is the ratio of mean density to background density (similarly used in Eftekharzadeh et al. 2015; DiPompeo et al. 2016; He et al. 2018):

$$y = \log_{10}(\Delta)$$

$$A = 1 + 0.24 \text{ye}^{-(4/\nu)^d}$$

$$a = 0.44a - 0.88$$

$$B = 0.183$$

$$b = 1.5$$

$$C = 0.019 + 0.107y + 0.19\text{e}^{-(4/\nu)^d}$$

$$c = 2.4.$$  \hfill (26)

Using the measured bias values in Equation (23), the power spectrum from CAMB, and the parameters defined above, we can solve for the characteristic halo mass (see Table 6). For our measured bias over the full redshift range of $b = 6.78 \pm 1.79$, the characteristic halo mass ranges between 1.70 and 9.83 $\times 10^{11}h^{-1}M_\odot$. Computing the halo mass from the bias estimated using only the faint quasars yields 1.04–10.56 $\times 10^{11}h^{-1}M_\odot$, where the large mass ranges in both estimates are a direct result of the large uncertainty in the bias values.

We compare our estimated halo masses to the masses found in Chen et al. (2007), who computed the minimum halo mass that is slightly different from our computation in that an estimate of the luminosity function is required. Over the redshift range $2.9 \leq z \leq 3.5$, Shen et al. (2007) found a minimum halo mass of $(2.3-3)\times 10^{12}h^{-1}M_\odot$, and in the redshift range $z \geq 3.5$, Shen et al. (2007) estimated a minimum halo mass of $(4-6)\times 10^{12}h^{-1}M_\odot$.

The low-z halo mass estimate from Eftekharzadeh et al. (2015) of $\sim 0.66 \times 10^{12}h^{-1}M_\odot$ over the redshift range $2.64 \leq z \leq 3.4$ (their Table 7) is a factor of 10 smaller than our results; however, they also reported halo masses on the redshift range $2.20 \leq z \leq 2.80$ of $\sim 1.2-2.8 \times 10^{12}h^{-1}M_\odot$, which is $\sim 3 \times$ smaller than our result. This difference arises from the different redshifts, as well as the large difference in bias. The high-z estimate of the He et al. (2018) less-luminous sample is $\sim 2 \times 10^{12}h^{-1}M_\odot$. Again, the difference here is mainly due to the difference in bias between the two studies. However, if we take these results at face value, it does imply that less-luminous quasars tend to have smaller halo masses at high $z$. A larger sample of spectroscopically confirmed faint high-z quasars is needed to answer this question with greater certainty. If we could increase the number of pair counts along the fitting scales by 50%, we estimate that the error bars would decrease by $\sim 20\%$ (using the Poisson error estimate, which scales as $D^2$). More data would reduce the error on the bias, which, in turn, leads to a tighter constraint on the DM halo masses.

5.3. Implications for Feedback

The measurement of the 2PCF and bias of the faint, high-z quasars in this study is ideal information to constrain the feedback mechanisms presented in Hopkins et al. (2007). The Hopkins et al. (2007) study compared the clustering of quasars

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**Figure 12.** Evolution of the bias with redshift. We show the bias result for our full candidate sample (orange diamond). Also displayed are the feedback models from Hopkins et al. (2007), as well as the low- and intermediate-redshift measurements from Ross et al. (2009); dark blue circles) and Eftekharzadeh et al. (2015); light blue triangles), respectively. Finally, we show the high-z bias of the bright quasars from Shen et al. (2007; red squares) and the new HSC study from He et al. (2018; purple triangle). The bias increases with redshift in our sample and tends to agree with the “inefficient feedback” model; however, we cannot rule out the “maximal growth” model.
and galaxies as a function of different intrinsic properties (e.g., mass, luminosity, redshift) to investigate triggering mechanisms and the growth of the quasar and galaxy populations. Included in this study was an analysis of how different quasar feedback mechanisms affect their clustering strength. These models were designed to fit the measured results at low \( z \) (e.g., Croom et al. 2005, among others), which we represent using the Ross et al. (2009) results, yet vary at high \( z \) (\( z \geq 3 \)). This study highlighted three feedback scenarios: “efficient” and “inefficient” feedback and a “maximal growth” model. We depict the clustering predictions from these three models as the solid line in Figure 12 and provide a brief explanation below.

The solid line in Figure 12 depicts the clustering evolution with redshift if BH growth shuts down after the quasar epoch. This is the “efficient” feedback model in Hopkins et al. (2007) and assumes that quasars represent a single short-lived phase in the growth of the central BH. Here feedback efficiently terminates the quasar phase, and the central BH ceases its growth. This model assumes that the observed properties of quasars at \( z \lesssim 2 \) are the same as at higher redshifts; thus, the predicted clustering strength weakens at high \( z \) to reflect observations at low \( z \).

Additionally, Hopkins et al. (2007) presented a model in which quasars and their central BHs grow intermittently until \( z \sim 2.5 \), when “downsizing” begins (the dashed line in Figure 12). In this model, the quasar grows with the luminosity function, and the evolution of the luminosity function is dictated by the same objects growing hierarchically. Thus, feedback is “inefficient,” since the BH continues to grow over various epochs, as opposed to the first model, where, after the initial quasar phase, BH growth ends. This also means that brighter quasars live in very massive DM halos and fainter quasars would live in smaller DM halos at early times.

The “maximal growth” model postulates that the central BHs continue to grow proportionally with the DM halo until \( z \sim 2 \). This model assumes that quasars are continually accreting at their Eddington rates. Here feedback is not only inefficient prior to \( z \sim 2 \) but is not sufficient to stop the BH from growing at its most maximal rate. These quasars live in the highest-mass DM halos, which accumulate gas unimpeded by the radiation from the central quasar. Therefore, the predicted clustering is very high from this model and is shown by the dot-dashed line in Figure 12.

At low \( z \), the three models are designed to match the measurements of the 2PCF (Croom et al. 2005; Myers et al. 2007; Ross et al. 2009), but beyond \( z \sim 3 \), the models diverge. Additionally, the three models become degenerate for a sample of quasars with \( i \lesssim 20.2 \) (Hopkins et al. 2007), all taking the form of the “maximal growth” model. Our study, however, examines quasars fainter than the limit at high \( z \), thus breaking the degeneracy between the models in the redshift range \( 3 \lesssim z \lesssim 4 \).

Figure 12 displays the best-fit bias result over all of our candidates over the full redshift range in this study (orange diamond). The bias of the faint candidates (\( i \geq 20.2 \)) is not depicted; however, it is consistent with the full result. Also depicted in Figure 12 is the error in both the bias, which is a result from fitting the DM model, and the redshift, where, since our redshift distribution is not Gaussian, we depict the first and third quartile of the redshifts (as opposed to the standard deviation). Within the error of these results, the bias in our study overlaps both the “maximal growth” model and the “inefficient feedback” model, as shown in Figure 12, for the full sample of candidates in this analysis. The “maximal growth” model is also consistent with the results of Shen et al. (2007); however, we remind the reader that our investigation clustered a different population of quasars than Shen et al. (2007). We analyzed the clustering of faint quasars and are therefore capable of breaking the degeneracy limit noted in Hopkins et al. (2007). As shown in Figure 12, our result deviates from the “maximal growth” model toward the “inefficient feedback” model, which coincides with the result from He et al. (2018) at \( z \sim 4 \). The “inefficient feedback” model predicts that feedback from the central BH intermittently shuts down the accretion of gas onto the BH at early times. This model also suggests a degree of luminosity dependence of quasar clustering at high \( z \) and that fainter quasars live in less massive DM halos as compared to bright quasars. To better understand these models at \( z \sim 3.4 \) will likely require a larger sample of spectroscopically confirmed quasars that are both faint and high-redshift.

At first glance, it may appear that the findings of Eftekharzadeh et al. (2015) contradict our results; however, a significant difference in the bias measurements between our study and Eftekharzadeh et al. (2015) can be attributed to the difference in the redshift selection functions. While Figure 11 shows that we report a larger sample and the angular correlation function Eftekharzadeh et al. (2015) have a similar amplitude, the DM model is strongly dependent on the redshift selection function. Lower redshift ranges result in larger power in the angular correlation function model, which, in turn, results in a smaller bias fit (i.e., decreasing redshift in the model shifts the orange curve in Figure 11 to the right). As a result, we expect Eftekharzadeh et al. (2015) to have a lower bias than our

| Measurement | \( z \) Interval \( \langle z \rangle \) | \( N_{\text{qso}} \) | Bias \( \delta \) | \( \delta \) | \( M_{\text{fill}} \) | \( M_{\text{DM}} \) |
|-------------|-------------------|----------|--------|--------|-----------|-----------|
| This work (all) | 2.90, 5.10 | 3.48 | 1378 | 6.78 ± 1.79 | 0.710 ± 0.546 | 1.39 ± 0.618 | −23.80, −27.50 | 1.70±9.83 |
| This work (faint) | 2.90, 5.10 | 3.49 | 1260 | 6.64 ± 2.23 | 0.420 ± 0.582 | 0.99 ± 0.502 | 23.60, −26.40 | 1.04±10.6 |
| He et al. (2018) | 3.00, 4.00 | 3.80 | 901 | 5.93 ± 1.43 | 0.148 ± 0.050 | 0.86 | 23.70, −25.86 | 1.00±2.00 |
| Eftekharzadeh et al. (2015) | 2.64, 3.40 | 2.97 | 24724 | 3.57 ± 0.09 | 0.00 ± 0.000 | 0.00 | 24.40, −29.31 | 0.60±0.72 |
| Shen et al. (2007) | 2.90, 3.50 | 3.20 | 2651 | 7.90 ± 0.80 | 0.00 ± 0.000 | 0.00 | −26.00, −30.00 | 2.00±3.00 |
| Shen et al. (2007) | 3.50, 5.40 | 4.00 | 1775 | 14.0 ± 2.00 | 0.00 ± 0.000 | 0.00 | −26.50, −30.00 | 4.00±6.00 |

Notes: Bias estimates for selected surveys of comparable redshifts to our study.

a Cross-correlation of the faint sample. The power-law index is held fixed at \( \delta = 0.86 \) in this study.

b Redshift-space estimate, thus no angular power-law information is given.

c Shen et al. (2007) results split into two redshift bins to reflect the bias values shown in Figure 12.
investigation despite having similar amplitudes in angular correlation space. Taking these bias values at face value shows a rapid change in the bias at \( z \sim 3.1 \). Understanding this jump in bias at this particular redshift will be the topic of future work.

6. Summary

In this investigation, we have determined the 2PCF of 1378 photometrically selected, faint \((i \geq 20.2)\), high-z \((2.9 \leq z \leq 5.1)\) quasars across \( \sim 100 \) deg\(^2\) on SDSS S82. Details about this catalog, as well as our main findings, are as follows:

1. We combine the deep optical photometry on S82 from SDSS with new deep NIR information from the SpIES and SHELA surveys to form a comprehensive catalog of photometric objects. Utilizing their optical/MIR colors and the colors of known high-z quasars from the Richards et al. (2015) composite catalog (see Figure 2), we use three machine-learning algorithms to select 1378 faint, high-z quasar candidates.

2. We estimate the photometric redshifts of these candidates using NW kernel regression. When tested on spectroscopic quasars, this algorithm predicts photometric redshifts within a range of \( z_{\text{phot}} - z_{\text{spec}} = 0.1 \) for 93% of the quasars (Figure 3). The overlap in color-redshift space between the photometric candidates and the known quasars with which they were selected is presented (Figure 4).

3. Figure 6 demonstrates that our candidates are generally fainter than the objects used in the Shen et al. (2007) study. This aspect of our sample helps to break the degeneracy between the feedback models studied in Hopkins et al. (2007).

4. Utilizing the estimator from Landy & Szalay (1993), we compute the angular 2PCF of our faint high-z quasars, where a random mask is generated using MANGLE (Figure 7). The correlation function result is presented in Figure 9.

5. We estimate a linear bias using the method of Limber (1953), which relates the 3D DM power spectrum to the angular correlation function. We compute the 3D power spectrum using CAMB and our fiducial cosmology. Over the full redshift range of our sample \((\langle z \rangle = 3.38)\), the bias is \( b = 6.78 \pm 1.79 \). The best-fit values from the power-law model are \( \theta_0 = 0.71 \pm 0.546 \) and \( \delta = 1.39 \pm 0.618 \).

6. In Figure 10, we remove the bright objects and recompute the correlation function of 1126 faint quasar candidates. We find that the faint quasars have a bias of \( b = 6.64 \pm 2.23 \), similar to the full study. The agreement in bias demonstrates that the bright quasars in the sample do not skew the bias result of the faint objects. We compare the results of our full study with other surveys in Figure 11.

7. Using the estimates of bias, we compute characteristic DM halo masses using the formalism of Tinker et al. (2010). Our quasars inhabit DM halos with masses of 1.70–9.83 \( \times 10^{13} h^{-1} M_{\odot} \). This mass estimate covers a wide range due to the large uncertainty in the bias.

8. We use our bias estimate to constrain the feedback models of Hopkins et al. (2007) in Figure 12. Our data are consistent with both the “maximal growth” model, which assumes that the central quasar is not powerful enough to shut down accretion of material onto the BH, and the “inefficient feedback” model, which suggests that feedback from the central source intermittently shuts down accretion of the central BH. The “inefficient feedback” model, however, also coincides with the bias of faint quasars at \( z \sim 4 \) found in He et al. (2018). Finally, the “inefficient feedback” model suggests that fainter quasars sit in smaller DM halos.

Further studies of the 2PCF of faint, high-z quasars will benefit from the new optical and infrared surveys on the horizon. Surveys performed with the Large Synoptic Survey Telescope (LSST; LSST Science Collaboration et al. 2009) in the optical and the Wide-Field Infrared Survey Telescope (WFIRST; Spergel et al. 2013) and, to an extent, the James Webb Space Telescope (JWST; Gardner et al. 2006) in the infrared will be able to observe fainter than what we have now. These surveys will add an immense amount of data to our sample and a significant amount of area, which, in turn, increases the significance of the results. Similarly, spectroscopic investigation of the candidates will allow us to add to the high-z training data, as well as make the necessary corrections to our photometric redshifts to compute the redshift-space 2PCF. In this investigation, however, we have demonstrated that, using machine-learning techniques, we can both select faint, high-z quasars cleanly and compute the 2PCF on these samples. These techniques will be crucial in the next phase of astronomy, which will be dominated by photometric data that lacks detailed spectroscopic follow-up.

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We make our full data sets, analysis codes, and methodologies available at https://github.com/JDTimlin/QSO_Clustering/tree/master/highz_clustering.

For this research, we use the Python language and Astropy\(^{26}\) (Astropy Collaboration et al. 2013), TOPCAT\(^{27}\) (Taylor 2005). We thank Michael DiPompeo and Ryan Hickox for their correspondence and advice on both our contamination checks and our interpretations of the feedback models. We also thank Yao-Yuan Mao for the DECaLS image list tool (https://github.com/yymao/decauls-image-list-tool) used in this study.

Appendix A

Contamination Checks

Contamination in any clustering sample can drastically change the correlation function and the resulting bias. We carefully define our sample in this study to avoid contamination

\(^{26}\) astropy.org

\(^{27}\) http://www.star.bristol.ac.uk/~mbt/topcat/
as much as possible. As part of this work, we also performed a clustering analysis using the selection results without restricting to the point sources alone. We found that, if we just use color selection and do not check for low-$z$ contamination, we get a bias value of $b \sim 5$ instead of $b \sim 6.5$, which would lead us to different conclusions in Figure 12. It is therefore very important that we eliminate as much contamination as possible in this study.

While we explicitly model stellar contamination in this study, there are other forms of contamination that dilute the clustering signal. The two main sources of additional contamination are misidentification of objects in the classification algorithms and regions where the angular mask of the random objects is not identical to the data. Here we describe our methods to identify and reduce contamination from galaxies in our analysis.

### A.1. Extinction Cut

As mentioned in Section 2.5, we cut the overlapping region between SpIES and the outskirts of the disk of the Milky Way ($330 \leq \alpha_{2000} \leq 344.4$, which corresponds to a galactic latitude of $-51.5 \leq b_{\text{gal}} \leq -41.5$) to eliminate highly extincted objects from the analysis that act as contaminants in the clustering signal. Figure 13 depicts the clustering result before (green circles) and after (orange diamonds) this extinction cut, as well as their best-fit DM models (which have slightly different redshift selection functions). These models are fit as before using an efficiency of $e = 0.86$, which means that 14% of the sample are stellar contaminants. At large scales, the model (green curve) lies below the measured clustering strength, which implies that there are more contaminants than estimated using just stellar contamination. After the extinction cut is performed, however, there is much better agreement between the model and the data (in fact, it appears that the model overestimates the contamination at large scales). Deep infrared spectra are required to determine the particular type of object contaminating the sample; however, it is most likely stars that were reddened by Galactic dust, such as late-type M-dwarf stars. These objects would not appear in optically selected samples; however, since we include the infrared colors in our selection, they could be selected as quasars.

While the extinction cut resulted in a loss of $\sim 20$ deg$^2$, it also significantly decreased the power of the correlation function at larger scales (see Figure 13). There were, however, objects in that field with lower extinction measurements that were also cut. Ideally, we would keep these objects to use in our correlation function measurements, but cutting on the extinction value causes the density to drop significantly in this area, which affects the correlation function if not properly accounted for in the angular mask. Our future work to remedy this problem is to change the density of the random mask in this field to reflect the data.
A.2. Visual Inspection

Visual inspection using the DECam Legacy Survey image cutout tool (see footnote 21) enabled us to examine the classified objects and eliminate obvious sources of contamination. The superior depth and resolution of DECam is crucial for the follow-up visual inspection of the candidates that were selected in each algorithm. This inspection also drove the need to create the point-source metric we used to cut all extended objects in this study. We note that fainter quasars are more likely to be classified as extended emission; thus, spectroscopic follow-up is needed on all faint candidates, not just the point sources used in this study.

Figure 14 depicts three types of objects that passed the high-z quasar selection algorithms (in either redshift range). In the left panel, we show local galaxies \((z \sim 0.3)\), which, as a result of the 4000 Å break in their spectra, can be mistaken for the Ly\(\alpha\) forest from high-z quasars (at \(z \sim 3.5\)). This confusion causes the low-z galaxies to pass the machine-learning selection. These are obvious contaminants that were easily detected and removed by hand.

We also selected objects that appeared to have extended emission, an example of which is shown in the middle panel of Figure 14. While these objects could be galaxies at higher redshift (e.g., Lyman-break galaxies; He et al. 2018), it is also possible that they could be faint quasars at high-z whose emission from the central engine is not bright enough to outshine the host galaxy. For the faint quasars in our study, this could certainly be the case. These objects did not pass our final point-source metric and thus were removed from our final analysis.

Finally, in the right panel of Figure 14, we show a known high-z quasar at redshift \(z \sim 3.7\) that our machine-learning algorithm also classifies as a high-z quasar. This object passes the point-source metric and is thus included in this study. Most of the objects that we call point-like have similar profiles to this object (albeit some are much fainter). Once again, spectroscopic follow-up is needed on these objects for a combination of testing the classification and the redshift estimates from our machine-learning algorithms.

A.3. Error Estimates and Fitting Parameters

To ensure that we obtain reasonable jackknife errors, we compare our errors in Table 5 to the Poisson errors (Peebles 1973) defined as

\[
\sigma_{\text{Poisson}} = \frac{1 + \omega(\theta)}{\sqrt{\text{DD}}}. \tag{27}
\]

Poisson error is a measure of the noise due to the number of pairs in the sample (Ross et al. 2009) and is most valid at smaller scales, where pairs of objects are independent of each other (Shanks & Boyle 1994). We depict the ratio of our jackknife errors to the Poisson errors in Figure 15. Poisson errors represent a minimum standard deviation in a clustering measurement, particularly on the smallest scales; thus, the ratio of the jackknife to Poisson errors should be of order unity. In
this investigation, we replace the jackknife errors with Poisson errors wherever the ratio of the two in Figure 15 is less than 1.

We also test the best-fit parameters from both the power-law model and the DM model by generating $\chi^2$ maps for each space. We compute the $\chi^2$ as

$$\chi^2 = \sum \frac{(\omega_{\text{measured}}(\theta) - \omega_{\text{model}}(\theta))^2}{\sigma^2}.$$  

(28)

For our power-law model, we iterate the power-law index over the range $0.5 \leq \delta \leq 2.2$ in 300 steps and the correlation angle $0 \leq \theta_0 \leq 1.2$ in 400 steps and compute the $\chi^2$ value. Figure 16 depicts the results of this analysis for the full sample of quasar candidates (left) and the faint sample (right). In both cases, we find that the best-fit parameters given in Table 6 (represented by black crosses) lie in the region of the minimum $\chi^2$. We also plot the $1\sigma$ region and find that it is consistent with the ranges given in Table 6.

Figure 17 depicts the $\chi^2$ map of the DM model and is computed in a similar manner as before. Here we iterate both the bias values over a range of $3 \leq b \leq 9$ in 300 steps and the cross-correlation term over a range $-0.03 \leq \epsilon \leq 0.01$ in 600 steps. Again, we find that the values reported in Table 6 are consistent with the minimum $\chi^2$ value, and the errors span an appropriate range.

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