Clustering with JWST: Constraining Galaxy Host Halo Masses, Satellite Quenching Efficiencies, and Merger Rates at z=4-10

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ABSTRACT

Galaxy clustering measurements can be used to constrain many aspects of galaxy evolution, including galaxy host halo masses, satellite quenching efficiencies, and merger rates. We simulate JWST galaxy clustering measurements at z~4–10 by utilizing mock galaxy samples produced by an empirical model, the UniverseMachine. We also adopt the survey footprints and typical depths of the planned joint NIRCam and NIRSpec Guaranteed Time Observation program planned for Cycle 1 to generate realistic JWST survey realizations and to model high-redshift galaxy selection completeness. We find that galaxy clustering will be measured with z>5σ significance at z~4–10. Halo mass precisions resulting from Cycle 1 angular clustering measurements will be ~0.2 dex for faint (-18 ≳ M_UV ≳ -19) galaxies at z~4–10 as well as ~0.3 dex for bright (M_UV ≃ -20) galaxies at z~4–7. Dedicated spectroscopic follow-up over ~150 arcmin² would improve these precisions by ~0.1 dex by removing chance projections and low-redshift contaminants. Future JWST observations will therefore provide the first constraints on the stellar-halo mass relation in the epoch of reionization and substantially clarify how this relation evolves at z>4. We also find that ~1000 individual satellites will be identifiable at z~4–8 with JWST, enabling strong tests of satellite quenching evolution beyond currently available data (z≲ 2). Finally, we find that JWST observations can measure the evolution of galaxy major merger pair fractions at z~4–8 with ~0.1–0.2 dex uncertainties. Such measurements would help determine the relative role of mergers to the build-up of stellar mass into the epoch of reionization.

Key words: galaxies: high-redshift – cosmology: large-scale structure of the Universe – cosmology: dark ages, reionization, first stars

1 INTRODUCTION

Over the past decade, multiple observational programs have opened a window into the first billion years following the Big Bang (see Stark 2016 for a review). Ground and space-based photometric campaigns have revealed over one thousand galaxies at z≥6, enabling constraints on luminosity functions and star formation rate densities out to z~10 (e.g. Atek et al. 2015; Bouwens et al. 2015; Finkelstein et al. 2015a;Livermore et al. 2017; Ono et al. 2018; Oesch et al. 2018) as well as galaxy stellar mass functions out to z~8 (e.g. Stark et al. 2009; González et al. 2011; Grazian et al. 2015; Song et al. 2016). JWST promises to advance luminosity and stellar mass function constraints at high redshifts via detailed spectra and extremely deep (m ~ 29–30) photometry in the near to mid-infrared. However, less appreciated is JWST’s potential to place new constraints on early galaxy evolution via high-redshift galaxy clustering measurements.

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Galaxy clustering measurements are commonly used to infer halo masses by exploiting the strong relation between halo mass and clustering strength (e.g., Mo & White 1996; Tinker et al. 2010). These halo masses can then be used to infer the stellar-halo mass relation, a fundamental constraint on the connection between galaxies and their host halos (see Wechsler & Tinker 2018 for a review). Significant effort has been devoted to measuring $z\gtrsim 4$ galaxy clustering, revealing that the most UV luminous galaxies at $z\sim 4$–7 tend to reside in the most massive halos (Barone-Nugent et al. 2014; Harikane et al. 2016, 2018; Ishikawa et al. 2017; Hatfield et al. 2018). Combined with stellar mass constraints, high-redshift clustering results may already be signaling evolution in gas cooling efficiency, feedback efficiency, and merger rates from $z=4$ to $z=7$ (Harikane et al. 2016, 2018). However, stringent ($\lesssim 0.5$ dex error) halo mass constraints at $z=4$ are primarily limited to bright ($M_{\text{UV}} \sim -20$) galaxies at $z\lesssim 5$ (Barone-Nugent et al. 2014; Harikane et al. 2018). It therefore remains unclear how the stellar-halo mass relation evolves at $z\gtrsim 6$, leaving a gap in our understanding of galaxy evolution in the early Universe and, in particular, the epoch of reionization.

$JWST$’s greatly increased sensitivity is expected to significantly improve the precision of high-redshift clustering measurements. Deep ($m\gtrsim 29$-30) NIRCam photometry from Cycle 1 programs will enable the detection of $\sim$5000 galaxies at $z=6$ and $\sim$300 at $z=9$ (Mason et al. 2015; Williams et al. 2018). Such increased numbers will highly benefit clustering measurements because Poisson noise falls as the quadratic inverse of galaxy number density (Peebles 1980; Landy & Szalay 1993). Deeper imaging also enables the selection of lower mass halos which are less susceptible to cosmic variance (e.g., Somerville et al. 2004; Trenti & Stiavelli 2008).

$JWST$’s NIRSpec will also enable the first spatial galaxy clustering measurements at $z=4$ thanks to its multiplex capabilities and sensitivity to strong rest-optical lines at these redshifts (e.g., Hu and [OIII]; Chevalard et al. 2019; De Barros et al. 2019). These spatial clustering measurements will avoid chance projections as well as low-redshift contaminants present in angular clustering measurements.

All of these advancements should improve constraints on galaxy halo masses, and consequently, the stellar-halo mass relation at $z=4$. Recent studies have predicted the clustering of $z=8$–10 halos expected to host galaxies detectable with $JWST$ (Blomqvist et al. 2018; Zhang et al. 2019b). Adopting idealized assumptions, Zhang et al. (2019b) concluded that galaxy clustering should be measurable to $\sim 4$–5$\sigma$ significance at $z=10$. Here, we simulate $JWST$ galaxy clustering measurements at $z=4$–10, noting that our methodology provides more observationally realistic predictions compared to Zhang et al. (2019b) in the following ways. First, we model high-redshift galaxy selection completeness by adopting the typical depths of a planned Cycle 1 program, the $JWST$ Advanced Deep Extragalactic Survey (JADES; Williams et al. 2018), and utilizing an empirical model, the UniverseMachine (Behroozi et al. 2019), to assign galaxy properties to halos from a dark matter simulation. Second, we simulate clustering measurements over the exact survey footprint of the JADES program, including detector and pointing gaps, to accurately account for boundary effects. Third, we account for peculiar motion distortions in spatial clustering measurements. Fourth and finally, we include satellite galaxies in our simulated measurements, which can significantly impact the recovered clustering signal because clustering strengths are density dependent. We furthermore simulate the process of inferring halo masses from these clustering measurements to provide the first predictions of $z=4$–10 halo mass precisions resulting from future $JWST$ surveys.

We also investigate how $JWST$’s improved sensitivity and spectroscopic capabilities will enable studies of satellite quenching and merger rates in the early Universe. Results from ground-based facilities have shown that satellites out to $z=2$ are systematically more quenched than field galaxies at fixed stellar mass (e.g., van den Bosch et al. 2008; Kawanewnicki et al. 2016). These findings imply a strong environmental dependence on star-formation properties within the last $\sim 10$ Gyr, possibly driven by the presence of a hot circumgalactic medium surrounding the host halo. We therefore test how well $JWST$ will facilitate the identification of high-redshift satellites and thereby push satellite quenching efficiency measurements to earlier epochs. We also investigate how $JWST$ will improve galaxy pair fraction measurements at $z>4$. Galaxy pair fractions can be used to infer galaxy merger rates and thus the relative contribution of mergers to stellar mass buildup throughout cosmic time (e.g., Lotz et al. 2011; Mundy et al. 2017) as well as the AGN-merger connection (Kocevski et al. 2012).

In §2, we describe our methods for generating realistic mock $JWST$ survey realizations (§2.1), modeling high-redshift selection completeness (§2.2), calculating clustering strengths via the two-point correlation function (§2.3), and inferring halo masses from our simulated clustering measurements (§2.4). Our results are presented in §3 where we discuss the quality of our simulated $z=4$–10 galaxy clustering measurements (§3.1) and the halo mass uncertainties expected to result from these measurements (§3.2), concluding with a discussion of how $JWST$ will improve constraints on the stellar-halo mass relation at $z=4$. In §4, we discuss how well $JWST$ observations will enable the identification of individual satellites (§4.1) as well as measurements of galaxy major merger pair fractions (§4.2) at $z\gtrsim 4$. Our main conclusions are listed in §5.

All magnitudes are quoted in the AB system (Oke & Gunn 1983). Luminosity to stellar mass conversions assume a Chabrier (2003) stellar initial mass function. We adopt a flat, $\Lambda$CDM cosmology with parameters ($\Omega_m = 0.307$, $\Omega_{\Lambda} = 0.693$, $\Omega_b = 0.048$, $h = 0.678$, $\sigma_8 = 0.823$, $n_s = 0.96$) consistent with Planck results (Planck Collaboration et al. 2016). Halo masses follow the Bryan & Norman (1998) spherical overdensity definition and refer to peak historical halo masses extracted from the merger tree except where otherwise specified. All distances are quoted in comoving coordinates unless otherwise stated.

## 2 METHODS

In this section, we describe our methods for simulating $z=4$–10 $JWST$ galaxy clustering measurements and inferring halo masses from those measurements. We begin by detailing our procedure for generating realistic $JWST$ survey realizations based on a planned Cycle 1 GTO program, JADES (Williams et al. 2018), in §2.1. We then model the se-
lection of high-redshift galaxies to account for completeness, as well as low-redshift interlopers in the angular clustering measurements, as described in §2.2. Our methods for simulating galaxy clustering measurements are then detailed in §2.3, followed by a description of how we infer halo masses from these measurements in §2.4.

2.1 Generating Mock JWST Survey Realizations

Our approach to generating mock JWST survey realizations begins by taking halo positions from a dark matter simulation so that predicted clustering strengths arise from ΛCDM theory. Here, we use the Very Small MultiDark Planck (VSDMPL) dark matter simulation, which continues the series described in Klypin et al. (2016) to higher resolution. VSDMPL was run using GADGET-2 (Springel 2005) with a box size of (160 Mpc h^{-1})^3, containing 3840^3 particles with a high mass (6.2 × 10^9 M_⊙ h^{-1}) and force (1 kpc h^{-1}) resolution. The cosmological parameters adopted in VSDMPL are from Planck Collaboration et al. (2014) and listed in §1. Halos and sub-halos within VSDMPL were identified using the Rockstar algorithm (Behroozi et al. 2013a), and merger trees were constructed using the CONSISTENT TREES algorithm (Behroozi et al. 2013b).

We assign galaxy properties (including UV luminosities) to the VSMDPL halos using an empirical model, the UNIVERSE-MACHINE (hereafter referred to as the UM model; Behroozi et al. 2019). Briefly, the UM model utilizes observational constraints spanning z=0–10 to empirically infer halo star formation histories as a function of potential well depth, assembly history, and redshift. This procedure is performed using a Markov Chain Monte Carlo algorithm where each chain results in a mock catalog of galaxies paired with halos. In this work, we use the best-fitting catalog, hereafter referred to as the UM-VSMDPL mock catalog. Within the UM model, UV luminosities are computed from the star formation histories assigned to each halo using FSPS v3.0 (Conroy et al. 2009; Conroy & Gunn 2010) and a Chabrier (2003) stellar initial mass function, with dust attenuation scaled to match high-redshift observations (Bouwens et al. 2016b).

At high redshifts, the galaxy-halo connection set by the UM model is primarily governed by the input empirical UV luminosity functions. These are taken from Finkelstein et al. (2015a) and Bouwens et al. (2016a) at z=4–8 and z=9–10, respectively. As shown in Figure 1, the UV luminosity functions from the UM-VSMDPL mock catalog used in this work match the input constraints as expected. Additional high-redshift empirical constraints input into the UM model include UV-stellar mass relations (z=4–8), specific SFRs (z=0–8), and cosmic SFRs (z=0–9). See Behroozi et al. (2019) for additional details of the UM model including the calculation of UV luminosities.

In Appendix A, we test how our results change if we instead adopt an abundance matching approach to assign UV luminosities to halos, finding no strong dependence. We also check whether our conclusions are dependent on the choice of empirical z=4–10 luminosity functions used to set the galaxy-halo connection at high redshifts. The only substantial difference occurs when adopting published z=10 luminosity functions that are ~0.3 dex lower than those adopted by the UM model. This choice leads to significantly larger cosmic and Poisson variance in pair counts at this redshift, discussed further in Appendix B.

To incorporate realistic sample variance into our simulated clustering measurements, we seek to only use mock galaxies that fall within the footprints of a planned Cycle 1 GTO program, the JWST Advanced Deep Extragalactic Survey (JADES; Williams et al. 2018). Briefly, JADES will observe the GOODS-S and GOODS-N HST Legacy fields with both photometry via NIRCam over 236 arcmin^2 and multi-object spectroscopy via NIRSpec over 142 arcmin^2. We therefore overlay the JADES footprints (including detector and pointing gaps) on mock survey volumes (i.e., lightcones) extracted from the UM-VSMDPL catalog.

We choose to use only mock survey volumes that best match observed high-redshift galaxy number densities within the two GOODS fields to be observed by JADES. Our reasons for doing so are twofold. First, this procedure ensures our simulated clustering measurements will possess realistic Poisson variance which is of particular importance for the brightest and highest redshift samples. Secondly, it anchors the intrinsic clustering strengths of high-redshift galaxies within the GOODS fields because it has been shown that clustering strengths correlate with number density (i.e., environment; Croton et al. 2007; Zehavi et al. 2018). We generated 500 mock survey volumes in total by first extracting 100 lightcones from the UM-VSMDPL catalog, each spanning z=0–20 and subtending 50 arcminutes in right-ascension by 25 arcminutes in declination. Because each lightcone is large enough to encompass multiple JADES footprints for either field, we choose to extract five mock survey volumes from each lightcone centered at five evenly spaced RA positions.
within the lightcone. These mock volumes span an area of 0.4x0.4 deg$^2$ to ensure that each can host a full footprint for either field.

We select the best matching mock survey volumes by first calculating the UV luminosity functions within each mock volume and then performing $\chi^2$ fits against observed luminosity functions within the two GOODS fields. Specifically, we adopt the luminosity functions reported by Finkelstein et al. (2015a) at $z\sim4$–8 and Oesch et al. (2014) at $z\sim10$. To avoid fitting incomplete data, we only fit to the bright-end ($M_{UV} \leq -20$) luminosity function data points which are $\gtrsim 50\%$ complete (see Figure 9 in Finkelstein et al. 2015a). We perform the fitting procedure for each GOODS field and each redshift interval individually. We also only use the central 0.2x0.2 deg$^2$ of each mock volume as that better approximates the area covered by HST in each GOODS field$^2$.

One of the primary goals of this work is to determine 68% confidence interval statistics for both clustering measurement completeness and inferred halo masses. We find that generating 100 JADES realizations is sufficient for this purpose. Generating more realizations would require us to use mock survey volumes that are a poorer match to the empirical luminosity functions. To generate 100 realizations of the JADES program, we take the 10 best-fit mock survey volumes (out of 500) for each GOODS field and generate one realization for every possible pair of GOODS-N and GOODS-S volumes. The ten best-fit volumes for each field and redshift interval have reduced $\chi^2$ values less than three in all cases and are often $\lesssim 1$.

### 2.2 Modeling Selection of High-Redshift Galaxies

We now determine which mock galaxies would be used for high-redshift clustering measurements by simulating the selection of $z\sim4$–10 galaxies. In doing so, we adopt typical depths of the planned Cycle 1 program, JADES, and utilize empirically calibrated mock galaxy photometry and spectra produced by the JAdes extraGalactic Ultradeep Artificial Realizations (JAGUAR) package$^3$ (Williams et al. 2018). The overall goal here is to determine, as a function of redshift and UV magnitude, the photometric and spectroscopic selection completeness for angular and spatial clustering measurements, respectively.

For the angular clustering measurements, we assume that high-redshift galaxies will be photometrically selected using color cuts as commonly done with HST imaging (e.g., Stark et al. 2011; González et al. 2012; Oesch et al. 2014; Bouwens et al. 2015, 2019). The color cuts adopted in this work are detailed in Appendix C1 and are designed to separate galaxies into photometric redshift intervals of $z\sim[3.7,4.4], [4.4,5.5], [5.5,6.7], [6.7,7.7], [7.7,9.0], \text{and } [9.0,11.0]$. We will hereafter refer to these as the $z=4, 5, 6, 7, 8, \text{and } 10$ intervals, respectively.

The photometric selection completeness, $\mathcal{C}_P(z, M_{UV})$, is calculated as the fraction of mock JAGUAR galaxies (as a function of redshift and UV magnitude) that are selected to lie within the redshift interval of interest. Prior to this mock selection process, we add noise to the photometry of each JAGUAR galaxy 50 times with noise set equal to the medium JADES/NIRCam depths (Williams et al. 2018) for JWST photometry and deep GOODS/ACS depths (Bouwens et al. 2015) for optical HST photometry$^4$. We find that $>50\%$ of $z\sim4, 5, 6, 7, 8, 10$ galaxies with apparent rest-UV magnitudes of $m_{UV} = 28.0, 28.5, 28.8, 29.2, 29.5$, and 29.5, respectively, are selected to lie within the correct photometric redshift interval. We further find that only using galaxies brighter than these magnitude restricts the low-redshift ($z<3$) contamination fraction to reasonably small values ($\lesssim 15\%$) within the context of JAGUAR. Therefore, mock galaxies in the UM-VSMDPL catalog fainter than the above magnitudes are ignored while brighter galaxies are selected at random for the simulated angular clustering measurements with probability equal to $\mathcal{C}_P(z, M_{UV})$.

Because NIRSpec micro-shutter assembly (MSA) targets must first be photometrically identified, the overall spectroscopic completeness, $\mathcal{C}_S(z, M_{UV})$, is determined by the spectroscopic redshift completeness, the photometric selection completeness, and the availability of MSA slits for targets. We assume that spectroscopic redshifts can be obtained from galaxies with at least one emission line detected at $\gtrsim 5\sigma$. Therefore, spectroscopic redshift completeness is calculated as the fraction of JAGUAR mock galaxies (as a function of redshift and UV luminosity) that have at least one emission line brighter than the $5\sigma$ flux limit set by the planned medium JADES/NIRSpec depths. For the low-resolution ($R\sim100$) prism, the $5\sigma$ limiting flux is $1.4\times 10^{-18}$ erg/s/cm$^2$ at 2.5 $\mu$m. The medium-resolution ($R\sim1000$) G235M and G395M grisms are approximately twice as sensitive with $5\sigma$ flux limits of 0.8 and $0.5\times 10^{-18}$ erg/s/cm$^2$ at 2.5 $\mu$m and 4.5 $\mu$m, respectively. Flux limits at other wavelengths are computed using the online sensitivity curves$^5$ for each disperser. We note that [OIII]+H$\beta$ equivalent widths in the JAGUAR catalog are consistent with inferences from observations (e.g. Labbé et al. 2013).

We assume that MSA targets will only include $z\gtrsim 4$ photometric candidates that have an estimated $>50\%$ spectroscopic redshift completeness and are brighter than the limiting photometric magnitudes summarized in Table 1. As detailed in Appendix D, we find that the number of $z\gtrsim 4$ photometric candidates will not exceed the number of available MSA slits assuming that the $z=4$–6 candidates will be targeted with the R$\sim 100$ prism while the $z\gtrsim 7$ candidates will be targeted with the R$\sim 1000$ G235M and G395M grisms. Adopting those dispersers, we infer that $z=4, 5, 6, 7, 8, 10$ galaxies with $m_{UV} = 28.0, 28.5, 28.8, 29.2, 29.5, \text{and } 29.8$ are $>50\%$ likely to have at least one emission line detection with NIRSpec. We therefore adopt these as the limiting magnitudes for simulating spatial clustering measurements where brighter galaxies are selected with probability equal to $\mathcal{C}_S(z, M_{UV})$. This net spectroscopic completeness is calculated as the convolution of the spectroscopic detection completeness and photometric selection completeness, both as a

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2 Each mock survey volume has an area of $0.4\times 0.4$ deg$^2$ because parallel observations with JADES lead to more extended coverage relative to HST.

3 We use the JAGUAR package because the UM model currently does not directly calibrate mock galaxy photometry and spectra.

4 Such HST coverage is expected over a large fraction of the two GOODS fields to be imaged by JADES.

5 https://jwst-docs.stsci.edu/display/JTI/NIRSpec+Sensitivity
function of redshift and UV luminosity. This assumes that every \(z \geq 4\) photometric candidate in a given NIRSpec pointing can eventually be placed on an MSA mask. In practice, it is likely that only \(-50\%\) of such sources can be placed on MSA masks in the Cycle 1 JADES program alone to avoid overlapping spectra. We discuss how a \(50\%\) slit placement efficiency would impact our simulated spatial clustering measurements at \(z \sim 10\) because of the low spectroscopic completeness expected in this regime.

We do not consider spectroscopic samples at \(z > 10\) because the very strong rest-optical lines such as [OIII] and H\(\alpha\) are no longer accessible to NIRSpec at \(z \geq 9\), suggesting low spectroscopic completeness in this regime. While moderately strong lines such as [OII]3729 and [NeIII]\(\lambda 3869\) are still accessible to NIRSpec out to \(z \sim 12\), these lines are expected to be \(\geq 3\times\) weaker than [OIII] at these redshifts (Tang et al. 2018). As such, we do not expect a sufficient number of \(z \sim 10\) galaxies to be spectroscopically detectable for spatial clustering measurements, at least within the medium JADES/NIRSpec survey. We discuss ways to address this challenge in §3.1.

### 2.3 Measuring Clustering Strengths Via the Two-Point Correlation Function

We simulate galaxy clustering measurements using the two-point correlation function as it allows us to consider the spatial two-point correlation function, \(\xi(\mathbf{r})\), which quantifies the excess pair counts at a given 3D separation distance, \(r\), compared to pair counts for randomly-distributed galaxies (e.g., Peebles 1980):

\[
dP = n [1 + \xi(\mathbf{r})] dV.
\]

where \(dP\) is the number of excess pairs, \(n\) is the galaxy number density, and \(dV\) is the volume element. Because peculiar motions distort the observed line-of-sight distance, we instead measure the projected spatial correlation function,

\[
w_p(\theta_p) = \int_{-\pi_{\text{max}}}^{\pi_{\text{max}}} \xi(\theta_p, \pi) \ d\pi.
\]

Adopted Limiting Rest-UV Apparent Magnitudes

| Redshift Interval | Targeted Angular Clustering | Spatial Clustering |
|-------------------|-----------------------------|-------------------|
| \(z \sim 4\)     | 3.7–4.4                     | 28.0              | 28.0              |
| \(z \sim 5\)     | 4.4–5.5                     | 28.5              | 28.5              |
| \(z \sim 6\)     | 5.5–6.7                     | 28.8              | 28.8              |
| \(z \sim 7\)     | 6.7–7.7                     | 29.2              | 29.0              |
| \(z \sim 8\)     | 7.7–9.0                     | 29.2              | 28.7              |
| \(z \sim 10\)    | 9.0–11.0                    | 29.5              | -                 |

Table 1. The limiting rest-UV apparent magnitudes used to select high-redshift galaxies when simulating JWST clustering measurements. All of the angular apparent magnitudes correspond to Table 1.

Here, the 3D separation distance, \(r\), has been split into a projected 2D distance, \(\theta_p\), and a line-of-sight distance, \(\pi\), that includes peculiar motion distortions. We adopt \(\pi_{\text{max}}\) values of 10, 7, 5, 5, and 8 bins, respectively. These values were chosen to encompass the majority of peculiar motion distortions, calculated via the halo velocity information in the UM-VSMIDPL mock catalog. Our adopted \(\pi_{\text{max}}\) values also satisfy the resolution limitations of each NIRSpec disperser (see §2.2), assuming that emission line wavelength measurements can be made to within \(\sim 1/4\) of the resolution element.

We calculate \(w_p(\theta_p)\) using the Landy & Szalay (1993) estimator:

\[
w(\theta_1, \theta_2) = \frac{1}{\theta_1 \theta_2} \left[ D(\theta_1, \theta_2) - 2 \times D(\theta_1, \theta) + D(\theta_2, \theta) \right],
\]

where \(D(\theta_1, \theta_2)\) is the number of pairs between two galaxy samples (\(D(1)\) and \(D(2)\)) at a given projected separation distance (\(\theta_p\)) and \(D(\theta_2)\) are the number of data-random (random-random) pairs, appropriately normalized (see Landy & Szalay 1993). To ensure that our random samples contribute negligible Poisson noise, we generate them using a surface density of \(10^5\) objects per arcmin\(^2\) which is more than \(1000\times\) that of our most populated mock galaxy sample.

We simulate angular clustering measurements using the angular two-point correlation function, \(w(\theta)\). For this, we again use the Landy & Szalay (1993) estimator and a random sample with surface density of \(10^5\) objects per arcmin\(^2\). Because low-redshift galaxies contaminate high-redshift photometrically selected samples, we account for the resulting reduction in measured angular two-point correlation functions (at most \(50\%\)) via the methods described in Appendix C2.

We assume that galaxy clustering will be observationally measured in samples binned by redshift and threshold apparent rest-UV magnitudes, \(m_{\text{UV}}\) (e.g., \(m_{\text{UV}} = 29\) means that only \(m_{\text{UV}} < 29\) galaxies are included in the sample). Such binning is common in observational clustering studies at high redshifts (e.g., Harikane et al. 2016, 2018; Hatfield et al. 2018). First, we adopt a threshold magnitude equal to the limiting magnitude at each redshift (see Table 1). These mock galaxy samples are auto-correlated (\(D(1) = D(2)\) and simply correspond to the entire sample used for our simulated clustering measurements at their respective redshift. We also consider galaxy samples with threshold magnitudes one or two magnitudes brighter than the limiting magnitude for redshifts where sufficient numbers of such bright galaxies are expected to lie within our adopted survey area. These brighter samples are cross-correlated with the entire galaxy sample at their respective redshift to minimize Poisson noise in pair counts. Table 2 shows the full list of our adopted threshold magnitudes.

We simulate correlation function measurements for each JWST survey realization described in §2.1. Because Poisson error can be significant in any single mock clustering measurement, we also simulate correlation function measurements using all twenty mock survey volumes adopted for each redshift (see §2.1). These ‘true’ correlation functions are used to assess the accuracy of simulated JADES
clustering measurements via the $\chi^2$ statistic,

$$\chi^2 = \sum_i \frac{(w_{i,\text{meas}} - w_{i,\text{true}})^2}{\sigma_i^2}. \quad (4)$$

Here, $w_{i,\text{meas}}$ is the simulated two-point correlation function measurement for a separation bin $i$, $w_{i,\text{true}}$ is the ‘true’ two-point correlation function at that separation, and $\sigma_i$ is the simulated jackknife error for $w_{i,\text{meas}}$. We use jackknife errors because they are commonly adopted in observational clustering studies (e.g., Harikane et al. 2016, 2018; Coil et al. 2017) and we find that they will reasonably approximate a Gaussian error distribution (Appendix F). These errors are calculated from 10 jackknife samples of roughly equal area split by constant right-ascension over the JADES survey footprint.

We also assess the significance of each simulated clustering measurement by comparing it to the null result ($w = 0$). When calculating accuracy and significance, we exclude the innermost distance bin (i.e., the intrahalo term) which is dominated by satellite clustering. Satellite clustering, particularly for faint samples at high redshifts, remains highly uncertain in dark matter simulations due to the artificial loss of low-mass satellites (e.g., van den Bosch et al. 2018; van den Bosch & Ogiya 2018). While the UM model compensates for these effects (see Appendix E), we choose to exclude the intrahalo term to reduce any potential bias introduced by this correction method.

We also report how the significances of our simulated clustering measurements change when instead utilizing a covariance matrix. As in Zhang et al. (2019b), we calculate covariance matrices by computing correlation function measurements across 100 randomly selected mock survey volumes. While the covariance matrix provides a better representation of the true significance, it will likely not be possible to quantify this with JWST observations as doing so requires observing a large number (>10) of independent fields. Here, we report both significances so that those obtained from a jackknife approach can be compared with those derived from a covariance matrix.

To avoid imposing artificial clustering signals, we ensure that the number densities of random samples, $n_R$, used for spatial clustering measurements follow the redshift and luminosity evolution of galaxy number densities and their selection completeness:

$$n_R(z) \propto \int_{M_L}^{M_H} \phi(z,M_{1\text{UV}}) \chi_S(z,M_{1\text{UV}}) \ dM_{1\text{UV}}. \quad (5)$$

Here, $\phi(z,M_{1\text{UV}})$ is the luminosity function taken from the best-fit redshift evolution reported by Finkelstein et al. (2015a), $\chi_S(z,M_{1\text{UV}})$ is the spectroscopic completeness as a function of redshift and luminosity (see §2.2), and $M_{1\text{UV}}$ is the corresponding value of $M_{\text{halo}}$ at a given redshift, $z$.

2.4 Inferring Halo Masses

We now simulate the process of inferring halo masses from our simulated galaxy clustering measurements. By comparing these inferred halo masses to the true values in the UM-VSDPL mock catalog, we are able to predict the precisions that will result from future JWST clustering measurements. Specifically, we infer halo masses by fitting our simulated galaxy two-point correlation function measurements to a grid of correlation functions expected from halos at different masses. The inferred halo mass is then taken as the median value from the likelihood function, $L \propto \exp(-\chi^2/2)$, where this process is performed for each mock galaxy sample and each survey realization separately.

We first generate a grid of auto-correlation functions for halos of different masses. Here, we use halo mass grid points between $\log (M_{\text{halo}}/M_\odot) = 9.50 - 12.75$ with a spacing of 0.01 dex. To calculate correlation functions for each halo mass grid point, we auto-correlate samples of halos drawn from the twenty mock survey volumes used to simulate galaxy clustering measurements at the redshift of interest (see §2.1). Halos are selected such that the typical (i.e., median) halo mass is equal to the grid point value of interest. They are also selected such that the resulting mass distribution is log-normal with 0.25 dex scatter, as this well-approximates the true halo mass distribution shape of all the $z=4-10$ mock galaxy samples considered in this work (see Figure 2 for examples). To account for the partially random selection necessary to force this desired distribution, we perform the halo selection process ten times for each grid point and average the correlation functions from the ten selections. Halos are only selected if they lie within the redshift interval of interest (see Table 1). For each survey realization, we infer halo masses for the faintest galaxy sample in each redshift interval by fitting its simulated auto-correlation function with these gridded halo auto-correlation functions.

To infer halo masses for the brighter galaxy samples, we generate a grid of halo cross-correlation functions to match the procedure for simulating correlation function measurements of these brighter samples (§2.3). In this case, the halo samples D1 and D2 are selected to have different median masses $M_1$ and $M_2$, with the same 0.25 dex scatter as for the halo auto-correlation functions. $M_2$ is fixed to the inferred halo mass of the faintest galaxy sample for the redshift interval and survey realization of interest. The $M_k$ values (representing the brighter sample) are binned between $M_2$ minus 0.25 dex and $\log (M_{\text{halo}}/M_\odot) = 12.75$, again with a spacing

![Figure 2. Comparison of the true halo mass distribution of mock galaxy samples used to simulate JWST clustering measurements (blue) and our adopted approximation to that distribution (red). As examples, we show this comparison for $z=5$ and 10 galaxy samples with $m_{1\text{UV}} < 28.5$ and 29.5, respectively.](image-url)
of 0.01 dex. As in the auto-correlation grid case, we average the correlation functions resulting from ten selections. We then fit for the value of $M_1$, which is taken as the inferred halo mass of the brighter sample.

Finally, we determine the true 68% confidence interval halo mass precisions for each galaxy sample resulting from this simulated procedure. Specifically, the true halo mass precision, $\sigma_{\text{halo}}$, is defined such that the inferred halo mass is within $\sigma_{\text{halo}}$ dex of the true typical halo mass for each mock galaxy sample (taken from the UM-VSMDPL catalog) in 68 of the 100 mock survey realizations. These halo mass precisions are therefore not necessarily equal to the halo mass uncertainties that would be inferred directly from observations. We find that observationally inferred halo mass uncertainties (68% confidence intervals from the $\chi^2$ distribution using jackknife errors) can underestimate the true precision by up to a factor of $\sim$2 in dex. This is largely due to the systematic uncertainty imposed by the requisite assumption of the true halo mass distribution for the observed galaxy sample (see §3.2) since we find that jackknife errors reasonably well capture the 68% confidence interval from statistical fluctuations in the galaxy correlation function (Appendix F).

As motivated in §2.3, we use simulated jackknife errors when computing $\chi^2$ values because it will not be possible to derive accurate covariance matrices from observations alone. We do not calculate errors in our modeled halo mass-selected clustering strengths because the area from which these halos are selected is $10\times$ larger than the mock observed fields thereby substantially reducing Poisson error. Furthermore, we exclude the intrahalo term when calculating $\chi^2$ values due to the model dependency of satellite clustering strengths (see §2.3).

Finally, throughout this work, we use the peak halo mass (i.e., the maximum halo mass throughout that halo’s lifetime prior to the redshift of interest) rather than the current halo mass. We do so because peak halo masses better predict halo clustering strengths (e.g., Reddick et al. 2013; Guo et al. 2016). As such, when calculating projected spatial halo correlation functions, we use random samples ($R_1$ and $R_2$) with number densities that follow the redshift evolution of the $z=4-10$ peak halo mass function from the UM-VSMDPL catalog (Appendix C). The peak halo mass is on average $<0.05$ dex higher than the current halo mass for the $z=4-10$ mock galaxy samples used in this work.

3 RESULTS

We now present $z\sim4-10$ galaxy clustering measurements and halo mass precisions expected to result from future JWST observations. In §3.1, we discuss the quality of simulated $z\sim4-10$ galaxy clustering measurements which adopt the footprints and typical depths of a planned Cycle 1 GTO program, JADES. Halo mass precisions resulting from these simulated clustering measurements are presented in §3.2, followed with a discussion of how JWST will improve constraints on the evolution of the stellar-halo mass relation at $z>4$.

3.1 $z\sim4-10$ Galaxy Clustering Measurements with JWST

We begin by investigating the quality of $z\sim4-10$ galaxy clustering measurements expected from future JWST surveys. Figure 3 shows simulated angular (left) and projected spatial (right) two-point correlation function measurements utilizing the footprint and depths of the planned Cycle 1 GTO program JADES (Williams et al. 2018). The median measurement significance from 100 survey realizations is shown in the lower left of each panel, one for each redshift bin. We find that Cycle 1 observations will enable $\gtrsim5$ sigma clustering measurements at $z=4-10$.

Figure 3 shows examples of typical measurements expected with the JADES program. Specifically, we plot measurements from realizations with significances within 0.5 of the median significance and $\chi^2$ values (relative to the true clustering strengths; see §2.3) within unity of the median $\chi^2$. The median $\chi^2$ lies between 2.4–3.9 for the angular measurements and 2.7–7.7 for the spatial measurements, resulting in median reduced $\chi^2$ values that are less than two in all cases.

The high quality of $z\sim4-10$ angular clustering measurements expected from Cycle 1 observations are the result of NIRCam’s $\sim50\times$ improved sensitivity relative to WFC3/HST. Such capabilities will enable surveys that cover $\gtrsim100$ arcmin$^2$ regions with depths similar to Hubble ultra-deep fields (m$\sim29.5$; Bouwens et al. 2015). Access to galaxies $\sim2$ magnitudes further down the luminosity function will significantly reduce Poisson noise due to the steep faint-end slope (e.g., Bouwens et al. 2015; Finkelstein et al. 2015a), and weaken cosmic variance because fainter galaxies reside in lower mass halos (e.g., Somerville et al. 2004; Trenti & Stiavelli 2008; Moster et al. 2011).

As shown in Figure 3, we find that the precision of Cycle 1 angular clustering measurements will gradually evolve with redshift. Specifically, the typical measurement significance will increase from $\sim7\sigma$ at $z=4$ to $\sim9\sigma$ at $z=6$, then decrease at higher redshifts to $\sim5\sigma$ at $z=10$. This evolution is caused by two sources of noise that have opposite trends with redshift. In general, Poisson noise increases with redshift because galaxy number densities approximately halve per unit redshift, at least out to $z=8$ (e.g., Bouwens et al. 2015; Finkelstein et al. 2015a). Conversely, the noise caused by chance projections decreases with redshift because galaxies are more sparse and more strongly clustered at higher redshifts. Noise from chance projections dominates at $z<6$ while Poisson noise begins to take over at higher redshifts.

JWST’s NIRSpec will greatly reduce the impact of chance projections by efficiently delivering precise redshifts out to $z=9$ via the detection of strong rest-optical lines such as Hα and [OIII] (e.g., Chevallard et al. 2019; De Barros et al. 2019). This is of particular importance for the crowded $z\sim4-5$ samples where chance projections over hundreds of Mpc dilute strong clustering signals on sub-Mpc scales. Figure 3 illustrates that NIRSpec is capable of delivering $\sim15\sigma$ spatial clustering measurements at $z=4-5$ over the $142$ arcmin$^2$ JADES spectroscopic area, double the significance expected from angular measurements over the $236$
Figure 3. Typical simulated angular (left) and projected spatial (right) galaxy two-point correlation function measurements at \(z=4-10\) using the footprints and depths of the planned JWST Cycle 1 GTO program JADES. Measurements (markers) are the result of auto-correlating the entire mock galaxy sample selected to lie within the redshift interval of interest. The typical significance (using jackknife errors) from 100 simulated survey realizations is listed in the lower left of each panel (one per redshift bin). The true correlation functions (see §2.3) are shown with a solid line to illustrate accuracy. We do not consider spatial clustering measurements at \(z>10\) due to the low spectroscopic completeness expected in this regime (§2.2). The quality of spatial clustering measurements shown may require spectroscopic follow-up in addition to Cycle 1 observations due to possible target placement restrictions (see Appendix D).

arcm\(^2\) JADES NIRCam area. The spatial clustering measurements and significances shown in Figure 3 assume spectroscopic follow-up of every \(z\geq 4\) candidate brighter than the limiting magnitudes listed in Table 1. As discussed in Appendix D, it is likely that only \(\sim 50\%\) of such candidates can be targeted in Cycle 1 to avoid overlapping spectra. However, we choose to show results assuming 100\% follow-up completeness to illustrate results possible with dedicated spectroscopy in future cycles. These results are also possible with 50\% follow-up completeness given \(\approx 4\times\) the coverage\(^7\).

We expect that angular clustering measurements will be more precise than spatial at \(z\geq 8\) for the following three reasons. First, chance projections occur less often at higher redshifts because number densities drop and clustering strengths increase. Secondly, angular clustering measurements will suffer less Poisson and cosmic variance because of wider coverage. Finally, spectroscopic completeness declines at \(z\geq 8\) as NIRSpec becomes less sensitive to strong \([\text{OIII}]\) emission. We do not consider spatial clustering measurements at \(z>10\) because NIRSpec’s sensitivity to strong lines stops at \(z=9\), suggesting low spectroscopic completeness in this regime as discussed in §2.2. It is possible that dedicated deep spectroscopic follow-up of \(z>10\) photometric candidates would enable spatial clustering measurements at this redshift.

Notably, we find that angular clustering measurements will reach \(\sim 5\sigma\) significance at \(z=10\) within Cycle 1, rivaling current clustering measurements at \(z=7\) (Barone-Nugent et al. 2014). This conclusion persists even when adopting the most pessimistic \(z=10\) luminosity functions yet published so long as we take into account other planned Cycle 1 surveys. As detailed in Appendix B, adopting the \(-0.3\) dex lower \(z=9-10\) luminosity functions reported by Bouwens et al. (2019) and Oesch et al. (2018) (relative to Bouwens et al. 2016a, used for the UM model) decreases the typical \(z=10\) angular clustering measurement significance from \(4.9\sigma\) to \(3.0\sigma\). However, this ignores the \(-0.8\) mag increased depths within the \(46\) arcmin\(^2\) deep JADES region (Williams et al. 2018). Cycle 1 observations will also include the \(100\) arcmin\(^2\) Cosmic Evolution Early Release Science (CEERS; P.I. S. Finkelstein) program with NIRCam depths \(-0.4\) mags shallower than those adopted in this work. Assuming \(z=10\) Schechter parameters of \(M_{\text{lim}}^{\text{JWST}} = -20.60\) and \(\alpha = -2.3\) (Oesch et al. 2018), we estimate that combining all of these Cycle 1 observations will decrease Poisson noise by \(-60\%\) relative to the medium JADES program alone. Additional coverage provided by the CEERS program will also reduce cosmic variance. We therefore estimate that \(z=10\) angular galaxy clustering will be measured at \(\sim 5\sigma\) significance with Cycle 1 surveys, even assuming low galaxy number densities at this redshift.

When calculating the significances quoted above, we have omitted intrahalo clustering strength measurements due to model uncertainties in satellite clustering strengths (see Appendix E). Including the intrahalo term generally boosts the predicted significances by \(-2\rightarrow 3\sigma\). On the other hand, adopting a covariance matrix to remove correlations between different separation distances lowers our reported jackknife significances down to \(-6\rightarrow 7\sigma\) at \(z=4-6\) and \(-3\rightarrow 5\sigma\) at \(z=7-10\). This, however, does not impact our conclusions below on halo mass inferences because we adopted jackknife errors for this procedure.

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\(^7\) Poisson noise is proportional to \(1/\sqrt{D1D2}\) (Landy & Szalay 1993). Doubling galaxy number densities quadruples \(D1D2\) and therefore reduces Poisson noise by a factor of 2. However, doubling the coverage with fixed number density only reduces Poisson noise by \(1/\sqrt{2}\).
3.2 Inferred Halo Mass Precision with JWST

Here, we predict the halo mass precisions that will result from JWST galaxy clustering measurements at z~4–10 using the procedure outlined in §2.4. To briefly review, we define halo mass precisions, σ_halo, such that the inferred halo mass is within σ_halo dex of the true typical halo mass of the mock galaxy sample of interest in 68 of the 100 mock survey realizations. These values therefore represent the true errors in recovering halo masses, as opposed to the error estimates that would be obtained by marginalizing over observationally measured correlation function uncertainties obtained using, e.g., a jackknife approach.

In general, we find that z~4–10 halo mass precisions will be ≤0.25 dex. The implications of this precision are illustrated in Figure 4 where we compare the inferred M_UV−M_halo relations (markers) with the true relation (line) taken from the entire UM-VSMDPL mock catalog. Halo masses within the UM-VSMDPL catalog decline by ~1 dex from z~4 to z~10 at fixed UV luminosity. If such a strong evolution does indeed exist in the real Universe, our results suggest that it will be easily possible to measure this evolution from future JWST observations.

As noted above, our reported precisions include both statistical and systematic components. The statistical component results from Poisson noise as well as field-to-field density fluctuations which alter the intrinsic clustering strengths at fixed halo mass. Angular clustering measurements also possess increased statistical uncertainties due to redshift contamination and chance projections. Combined, these statistical components contribute ~0.05–0.15 dex to the halo mass uncertainties. Systematic uncertainty arises from the required assumption of the true halo mass distribution of the entire UM-VSMDPL mock catalog. The volume of the UM-VSMDPL mock catalog is ~500x that to be observed with the JADES program at each redshift.
Table 2. Estimates of the true halo mass precisions, \( \sigma_{\text{halo}} \), (in dex) expected to result from future JWST clustering measurements at \( z \approx 4 \). Each row shows the predicted precision for a given galaxy sample selected by redshift and threshold rest-UV magnitude, \( m_{\text{UV}} \). These precisions are defined to reflect true 68% confidence intervals (see §2.4) and result from adopting the footprints and typical depths of the JWST Cycle 1 GTO program JADES. We do not consider spatial clustering measurements at \( z > 10 \) due to the low spectroscopic completeness expected in this regime (§2.2).

| Redshift | \( m_{\text{UV}} \) | \( \sigma_{\text{halo}} \) | \( m_{\text{UV}} \) | \( \sigma_{\text{halo}} \) |
|----------|-----------------|-----------------|-----------------|-----------------|
| \( z \approx 4 \) | 28.0 | 0.21 | 28.0 | 0.10 |
| 27.0 | 0.21 | 27.0 | 0.15 |
| 26.0 | 0.31 | 26.0 | 0.21 |
| 28.5 | 0.23 | 28.5 | 0.10 |
| 27.5 | 0.15 | 27.5 | 0.13 |
| 26.5 | 0.14 | 26.5 | 0.15 |
| \( z \approx 6 \) | 28.8 | 0.12 | 28.8 | 0.10 |
| 27.8 | 0.17 | 27.8 | 0.17 |
| 26.8 | 0.38 | 26.8 | 0.29 |
| \( z \approx 7 \) | 29.2 | 0.16 | 29.0 | 0.24 |
| 28.2 | 0.21 | 28.0 | 0.30 |
| 27.2 | 0.21 | 27.0 | 0.39 |
| \( z \approx 8 \) | 29.2 | 0.22 | 28.7 | 0.36 |
| 28.2 | 0.21 | 27.7 | 0.38 |
| \( z \approx 10 \) | 29.5 | 0.22 | - | - |
| 28.5 | 0.29 | - | - |

observed galaxy sample. An incorrect assumption of the distribution may bias the observationally inferred halo masses. To estimate the resulting systematic halo mass uncertainties, we compare the true correlation functions (§2.3) of each mock galaxy sample with the correlation functions of halos with a mass distribution following our adopted prescription (log-normal with 0.25 dex scatter) and median mass equal to that of the mock galaxy sample. These two correlation functions tend to differ by \( \lesssim 0.1 \) dex for both our simulated angular and spatial clustering measurements, translating to \( \sim 0.05-0.15 \) dex systematic uncertainties in the inferred halo masses of our galaxy samples.

Table 2 lists our predicted true halo mass precisions for each galaxy sample at \( z \approx 4-10 \). In summary, we find that Cycle 1 angular clustering measurements will yield \( \sim 0.2 \) dex halo mass precisions for faint \( (M_{\text{UV}} \gtrsim 19) \) galaxies at \( z \approx 4-10 \) as well as \( \sim 0.3 \) dex precisions for bright \( (M_{\text{UV}} \lesssim 20) \) galaxies at \( z \approx 4-7 \). Dedicated spectroscopic follow-up of \( z \approx 4-6 \) photometric candidates over the JADES/NIRSpec footprint would improve halo mass precisions by \( \sim 0.1 \) dex at these redshifts. Specifically, spatial clustering measurements can yield high halo mass precision \( \sim 0.10-0.15 \) dex for faint galaxies as well as moderate precision \( \sim 0.2 \) dex for bright galaxies at \( z \approx 4-6 \).

Precisely inferring halo masses at high redshifts is of particular interest for settling the debate surrounding the evolution of the stellar-halo mass relation. This relation constrains the relative importance of various baryonic effects impacting galaxy evolution throughout cosmic time. Quantifying the evolution of this relation at high redshifts not only provides vital insight on the processes governing the early stages of galaxy evolution, but also the processes driving the ionizing output from galaxies during reionization. Many recent models have used observational data to infer the \( z \approx 4 \) evolution of the stellar-to-halo mass relation with differing conclusions. Significant (Behroozi et al. 2013c; Behroozi & Silk 2015; Finkelstein et al. 2015b; Harikane et al. 2016, 2018; Sun & Furlanetto 2016), moderate (Moster et al. 2018), and little evidence of evolution (Rodríguez-Puebla et al. 2017; Stefanon et al. 2017) have all been claimed. This discrepancy is largely due to currently poor empirical constraints on both halo and stellar masses at high redshifts.

Current halo mass uncertainties from clustering measurements (and independent of galaxy number density measurements) are \( \gtrsim 0.5 \) dex at \( z \approx 6-7 \) (Barone-Nugent et al. 2014) while no halo mass constraints yet exist at \( z > 8 \). Our results therefore imply that future JWST observations will provide markedly improved halo mass constraints at \( z \approx 6-7 \) as well as the first constraints at \( z \approx 8-10 \). We also expect \( z \approx 4 \) stellar mass measurements to improve with JWST. Such measurements currently suffer from poor sensitivity (\( m > 25-26 \); Bouwens et al. 2015), significant confusion (e.g., González et al. 2011; Song et al. 2016; Stefanon et al. 2017), and systematic uncertainties due to nebular contamination (e.g., Stark et al. 2013; Song et al. 2016) in mid-infrared Spitzer/IRAC photometry. NIRCam’s \( \sim 100 \) fold increase in mid-infrared sensitivity and greatly improved point-source resolution (\( \sim 0.1 \) arcsec vs. \( \sim 2 \) arcsec) will eliminate the first two challenges while NIRSpec spectroscopy and NIRCam medium band photometry will mitigate the last. We thus conclude that future JWST observations will provide the first picture of the stellar-halo mass relation in the reionization era and substantially clarify how this relation evolves with redshift at \( z > 4 \).

4 ADDITIONAL APPLICATIONS WITH JWST

High-redshift clustering measurements will enable many other studies relevant to understanding early galaxy evolution. In §4.1, we discuss how well JWST will enable inferences on satellite fractions and the identification of satellites and satellite-host pairs at \( z \gtrsim 4 \). Such studies can be applied to inform models of sub-halo occupation and the environmental dependence on star formation in the early universe. In §4.2, we simulate Cycle 1 measurements of \( z \gtrsim 4 \) galaxy pair fractions to assess how well JWST will provide insight on galaxy merger rates and the relative role of mergers to stellar mass build-up throughout cosmic history.

4.1 Constraining Galaxy Satellite Fractions and Quenching Efficiencies at \( z \gtrsim 4 \)

Small-scale (\( \lesssim 5 \) arcsec) galaxy clustering measurements can be used to infer galaxy satellite fractions. Inferences from current clustering measurements suggest that galaxy satellite fractions at \( z \approx 4-6 \) increase from \( \lesssim 1\% \) for very bright \( (M_{\text{UV}} \lesssim -21) \) galaxies to \( \sim 5\% \) for bright \( (M_{\text{UV}} \lesssim -20) \) galaxies (Ishikawa et al. 2017; Harikane et al. 2018; Hatfield et al. 2018). They also suggest that \( z \approx 4-6 \) galaxy satellite fractions decrease with redshift at fixed UV luminosity (e.g., Harikane et al. 2018). As illustrated in Figure 3, our results suggest that JWST will deliver high-precision (\( \sim 5-10\)r) small-scale galaxy clustering measurements for faint \( (M_{\text{UV}} \gtrsim -19) \) galaxies at \( z \approx 4-10 \). The satellite fractions
of these samples are assumed to be 10–15% from the UM model (including orphan satellites; Appendix E) with lower values at higher redshifts. We therefore predict that upcoming JWST surveys will soon make it possible to verify that satellite fractions decrease at earlier times and increase in fainter samples at z ∼ 4–10.

In addition to quantifying the overall fraction of satellites, JWST's spectroscopic capabilities will make it possible to determine, with high confidence, which z ≥ 4 galaxies are satellites and which are hosts. This capability is of particular interest for testing the influence of environment on star formation in the early Universe. Studies at z < 2 have found that satellites are systematically more quenched than field galaxies at fixed stellar mass where the quenching efficiency decreases with redshift (e.g., Kawinwanichakij et al. 2016). Empirically constraining satellite quenching efficiencies at z ≥ 4 would test model predictions of when environment begins to strongly influence galaxy evolution and how rapidly this dependence sets in.

To assist future studies in these endeavors, we provide optimal parameters for selecting z ≥ 4 satellites and their hosts from future JWST surveys. We assume that satellites and centrals will be observationally selected using an isolation criteria commonly adopted in lower-redshift studies (e.g., Tal et al. 2013; Kawinwanichakij et al. 2014). Specifically, we assume that a galaxy will be observationally identified as a central if it is the brightest galaxy (in the rest-UV) out to a specified maximum angular distance, θ_{max}, and inferred line-of-sight distance r_{max}. We further assume that galaxies will be identified as satellites if they lie within θ_{max} and r_{max} of an inferred central galaxy brighter than some limiting magnitude, m_{UV}^{lim}, where that central is inferred to be the satellite's host.

We simulate this selection process using mock galaxies from the UM-VSMDPL catalog (§ 2.1) and compare the resulting satellite and host galaxy populations to the true populations within that catalog. Because the most significant impact of the host circumbulgalactic medium occurs within the virial radius (Zhang et al. 2019a), UM-VSMDPL halos are defined as true satellites if they reside within the virial radius of a more massive halo which is defined as the true host. We account for spectroscopic completeness as described in § 2.2 only considering mock galaxies brighter than the limiting spectroscopic magnitudes listed in Table 1. We fix r_{max} values to 10, 7, 5, 5, and 3 Mpc h^{-1} at z ∼ 4, 5, 6, 7, and 8, respectively (§ 2.3), corresponding to a redshift uncertainty of σ_{z} = 0.02. Because it will be likely difficult to observationally distinguish faint satellites from their hosts at separations of ≤ 2kpc in the host half-light radius, we conservatively ignore all potential satellites within 0.5" of a brighter neighbor. This threshold value was chosen assuming a typical half-light radii of 0.15" for very bright (M_{UV} = -21) galaxies at z ∼ 4 (Shibuya et al. 2015).

For each redshift interval, we test various maximum angular separations, θ_{max}, and central galaxy limiting magnitudes, m_{UV}^{lim}, seeking to optimize the number of correctly identified satellite and satellite-host pairs while keeping the fraction of contaminants to < 20%. We find that the parameter values listed in Table 3 are optimal. We choose a threshold 20% contamination fraction because it is close to the lowest value that our mock procedure suggests will be possible with JWST (particularly for satellite-host identification) while still providing large samples of true satellites and satellite-host pairs. Statistical background subtraction procedures utilized in lower redshift studies (e.g., Tal et al. 2012; Kawinwanichakij et al. 2014) can be used to correct for contaminants.

Using the parameters listed in Table 3, we find that, on average, ±0.65, 1.05, 0.45, 0.15, and 0.05 true satellites will be identifiable per arcmin^{2} at z ∼ 4, 5, 6, 7, and 8, respectively. We also find that ±0.30, 0.75, 0.35, 0.15, and 0.05 true satellite-host pairs will be identifiable per arcmin^{2} at z ∼ 4, 5, 6, 7, and 8, respectively, again on average. The number of identifiable true satellite-host pairs is lower than the number of identifiable true satellites because a galaxy can be the satellite of another, more massive halo that may not necessarily be the brightest due to scatter in the observed M_{UV}−M_{halo} relation.

These numbers suggest that Cycle 1 observations from the JADES and CEERS programs (~200 arcmin^{2} of photometric and spectroscopic coverage) will enable the identification of ~200 satellites in z ∼ 4–5. Studies of satellite quenching efficiencies at z ∼ 2 have used ~450 satellites (Kawinwanichakij et al. 2014, 2016), suggesting that Cycle 1 observations will begin pushing constraints on the environmental impact of star formation (e.g., Kawinwanichakij et al. 2016). Furthermore, given that current extragalactic HST legacy surveys cover ~750 arcmin^{2} (Grogin et al. 2011), our results suggest that comprehensive follow-up of these regions with JWST would provide z ∼ 6–8 satellite quenching constraints comparable to what is currently available at z ∼ 2. We conclude that JWST is capable of testing how satellite quenching efficiencies continue to evolve with both redshift and host star formation efficiency at z ∼ 4 and into the epoch of reionization.

It is worth discussing model dependencies of these conclusions. The UM model introduces orphan satellites (galaxies which no longer have an identifiable host halo in a dark matter simulation; Wang et al. 2006) to correct for the artificial disruption of low-mass satellites in simulations (Appendix E). Because orphan satellites constitute approximately 50% of satellites at z ∼ 4–8 within the UM-VSMDPL catalog, the accuracy of this satellite correction method impacts the numbers quoted above. In the worst-case scenario that no orphans should be introduced, we would overestimate the number of identifiable z ≥ 4 satellites and satellite-host pairs by a factor of 2. Fortunately, independent empirical constraints of z ∼ 4–5 galaxy major merger pair fractions suggest that the high-redshift orphan populations introduced by the UM model are reasonable (Appendix E). It is also possible that z ∼ 4–8 galaxy number densities are underestimated in the UM-VSMDPL catalog due to the empirical luminosity functions adopted by the UM model (Appendix B). If this is the case, we would expect the number of identifiable z ≥ 4 satellites and satellite-host pairs quoted above to rise.
fractions measurements at $z \gtrsim 4$. We test this hypothesis directly by simulating $z \gtrsim 4$ galaxy pair fraction measurements using the same mock volumes and survey footprints described in §2.1 which reflect the planned Cycle 1 program, JADES (Williams et al. 2018). We also account for spectroscopic completeness using the methods outlined in §2.2.

We assume that galaxy pair fractions will be measured with JWST in a similar manner as described in Ventou et al. (2017), hereafter V17, which follows the methodology of de Ravel et al. (2009) and López-Sanjuan et al. (2013). Specifically, we identify a close pair as a system of two mock galaxies within a projected distance range of $r_p^{\text{min}} \leq r_p \leq r_p^{\text{max}}$ and a rest-frame relative velocity of $\Delta v \leq \Delta v_{\text{max}}$. As in V17, we adopt $r_p^{\text{max}} = 25$ kpc. The $r_p^{\text{min}}$ value is set equal to the projected distance corresponding to 0.5″ at the redshift of interest to account for the fact that it will be difficult to distinguish faint galaxies within ~2 half-light radii of a very bright neighbor (c.f. the 0.15″ half-light radii of extremely luminous $z$–4 galaxies; Shibuya et al. 2015). Rather than use the $\Delta v_{\text{max}} = 500$ km $s^{-1}$ value from V17, we adopt $\Delta v_{\text{max}} = 1000$ km $s^{-1}$ guided by the expected resolving power of JADES NIRSpec observations\textsuperscript{11}. We do not expect that this increased choice of $\Delta v_{\text{max}}$ will significantly impact the fraction of identified close pairs that will eventually merge (see, e.g., Figure 5 of Patton et al. 2000). For comparison, $\Delta v_{\text{max}} = 10000$ km $s^{-1}$ corresponds to $r_p^{\text{max}} \approx 8$ and 6 Mpc $h^{-1}$ at $z$=4 and 8, respectively.

We further consider only major mergers, which we define as galaxy pairs with a stellar mass ratio $\leq 1/4$ to keep in convention with many other pair fraction studies (e.g., Man et al. 2016; Snyder et al. 2017; Mantha et al. 2018; Duncan et al. 2019). Observed stellar masses are calculated by perturbing the true stellar mass of each mock galaxy (computed from the full star formation histories of the halo from the UM model) with a fixed scatter reflecting observational uncertainties. We assume that stellar mass uncertainties with JWST will be 0.2 dex at $z$–4–8 though our conclusions are not significantly altered if we instead adopt an 0.3 dex uncertainty.

Similar to V17, we compute the major merger pair fraction, $f_{\text{MM}}$, as

$$f_{\text{MM}}(z) = \frac{N_{p}^{\text{Corr}}}{N_{p}} = \frac{\sum_{i=1}^{N_{p}} C_{i}^{-1} C_{i}^{-1} \omega_{K}}{\sum_{i=1}^{N_{p}} C_{i}^{-1}}. \tag{6}$$

Here, $N_{p}$ is the number of galaxies in the parent sample, $N_{p}$ is the number of close pairs, $C_{i}$ is the spectroscopic completeness of each mock galaxy as a function of magnitude and redshift where $i=1,2$ corresponds to each galaxy in an observed pair $K$, and $\omega_{K}$ is the area correction factor accounting for both survey boundaries and the minimum projected distance. That is

$$\omega_{K} = \pi \left( \frac{r_{p}^{\text{max}}}{r_{p}} \right)^{2} \left( \frac{r_{p}^{\text{max}}}{r_{p}} \right)^{2} \times \frac{\pi (r_{p}^{\text{max}})^{2}}{A_{\text{JWST}}} \tag{7}$$

where $A_{\text{JWST}}$ is the survey area enclosing the circle of radius $r_{p}^{\text{max}}$ centered on the more massive source in pair K. $N_{p}^{\text{Corr}}$ and $N_{p}$ are then the completeness corrected number of parent

\textsuperscript{11}As noted in §2.2, we assume $R$=100 at $z$–4–6 and $R$=1000 at $z$–7–8. The MUSE resolving power is $R$=3000 for Ly$\alpha$ at $z$–4–6.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|}
\hline
Redshift & $\theta_{\text{max}}$ ($^\circ$) & $m_{\text{UV}}^{\text{cen}}$ & $\#$ per arcmin$^2$ & $\theta_{\text{max}}$ ($^\circ$) & $m_{\text{UV}}^{\text{cen}}$ & $\#$ per arcmin$^2$ \\
\hline
$z$=4 & 4.25 & 27.5 & 0.65 & 3.50 & 26.0 & 0.30 \\
$z$=5 & 3.75 & 28.0 & 1.05 & 3.25 & 27.0 & 0.75 \\
$z$=6 & 3.50 & 28.3 & 0.45 & 3.00 & 27.3 & 0.35 \\
$z$=7 & 2.75 & 28.5 & 0.15 & 2.25 & 28.0 & 0.15 \\
$z$=8 & 2.50 & 28.2 & 0.05 & 2.50 & 27.7 & 0.05 \\
\hline
\end{tabular}
\caption{Optimal parameters ($\theta_{\text{max}}$ and $m_{\text{UV}}^{\text{cen}}$; defined in §4.1) to use when identifying satellites and satellite-host pairs (both the satellite and its specific host galaxy) at $z$–4–8 with $>80\%$ confidence from spectroscopic JWST surveys. We also show the expected surface number of true identifiable satellites and satellite-host pairs using these parameters. Here, we have modeled spectroscopic completeness using the methods described in §2.2.}
\end{table}
galaxies and major merger galaxy pairs, respectively. We compute pair fraction uncertainties via a jackknife approach to account for sample variance. As with the simulated clustering measurements, ten jackknife samples are obtained by splitting the footprints of each JADES field into 5 roughly equal-area regions split by constant right ascension.

We show the simulated JADES/NIRSpec major merger pair fraction measurements at $z \sim 4-8$ in Figure 5. We also plot for comparison the MUSE measurements from V17 at $z \sim 0-6$. We find that future JWST surveys will substantially improve current galaxy pair fraction measurements at $z \sim 4-6$ and establish the first measurements at $z \sim 7-8$. Specifically, we find that errors on measured major merger pair fractions will be $\lesssim 0.1$ dex from $z \sim 4-6$ and $\sim 0.1-0.2$ dex from $z \sim 7-8$, made possible by the much wider coverage enabled by JWST/NIRSpec ($\gtrsim 100$ arcmin$^2$) relative to MUSE ($\sim 10$ arcmin$^2$). Given that we have not considered contributions from the JADES deep field nor pair fraction measurements made via photometry alone (c.f., Duncan et al. 2019), it is plausible that $z \sim 10$ measurements will be possible within the first few cycles. We conclude that JWST will clarify the importance of major mergers at $z \gtrsim 4$ and into the epoch of reionization.

5 CONCLUSIONS

We have simulated JWST galaxy clustering measurements at $z \sim 4-10$ by adopting footprints and typical depths of the planned Cycle 1 GTO program, JADES (Williams et al. 2018), and utilizing an empirical model, the UNIVERSEMA-Chine (Behroozi et al. 2019), to assign galaxy properties to halos from a dark matter simulation. We have also assessed the ability of future JWST surveys to quantify galaxy satellite fractions, identify individual satellites, and measure galaxy major merger pair fractions at $z \gtrsim 4$. Conclusions from this study include:

(i) Planned Cycle 1 JWST surveys will measure galaxy angular clustering with $\gtrsim 5\sigma$ significance at $z \sim 4-10$. Dedicated spectroscopic follow-up over $\sim 150$ arcmin$^2$ will enable $\sim 10-15\sigma$ spatial clustering measurements at $z \sim 4-6$ and $\sim 8\sigma$ measurements at $z \sim 7$.

(ii) Halo mass uncertainties resulting from Cycle 1 angular clustering measurements will be $\sim 0.2$ dex for faint ($\gtrsim M_{\text{UV}} \gtrsim -20$) galaxies at $z \sim 4-10$ as well as $<0.3$ dex for bright ($M_{\text{UV}} \sim -20$) galaxies at $z \sim 4-7$. Dedicated spectroscopic follow-up over $\sim 150$ arcmin$^2$ would yield $\sim 0.10-0.15$ dex halo mass uncertainties for faint galaxies as well as $\sim 0.2$ dex uncertainties for bright galaxies at $z \sim 4-6$. Future JWST observations will therefore provide the first constraints on the stellar-halo mass relation in the epoch of reionization and substantially clarify how this relation evolves with redshift at $z \sim 4$.

(iii) Cycle 1 observations will allow precise inferences on galaxy satellite fractions at $z \sim 4-10$ by enabling high-precision ($\sim 5-10\sigma$) small-scale galaxy clustering measurements at these redshifts. JWST observations will therefore soon test sub-halo occupation models in the early Universe.

(iv) It will be possible to identify $\sim 200$ individual satellites at $z \sim 4-5$ from Cycle 1 surveys. Furthermore, comprehensive follow-up of HST legacy surveys with NIRSpec would enable the identification of $\sim 500$ satellites at $z \sim 6-8$. JWST will therefore be able to test the environmental dependence of star formation in the early Universe.

(v) Future JWST surveys can substantially improve current galaxy major merger pair fraction measurements at $z \sim 4-6$ and establish the first measurements at $z \gtrsim 7$. Specifically, we find that dedicated NIRSpec follow-up over $\sim 150$ arcmin$^2$ would yield $\lesssim 0.1$ dex errors at $z \sim 4-6$ and $\sim 0.1-0.2$ dex at $z \sim 7-8$. Such measurements can be used to quantify galaxy major merger rates and determine the relative role of mergers to the build-up of stellar mass into the epoch of reionization.

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This research made use of Astropy, a community-developed core Python package for Astronomy (Astropy Collaboration et al. 2013; Price-Whelan et al. 2018); Matplotlib (Hunter 2007); NumPy (Van Der Walt et al. 2011); and SciPy (Jones et al. 2001).

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Here, we investigate how the clustering results shown in Figure 3 would change if we instead used abundance matching to assign UV luminosities to halos within the UM-VSMDPL.
match to the same empirical high-redshift UV luminosity functions as those adopted by the UM model, namely the Finkelstein et al. (2015a) luminosity functions at \(z \sim 4-8\) and the Bouwens et al. (2016a) luminosity functions at \(z \sim 9-10\). We use the best-fit analytic Schechter form at each redshift to generate the galaxy counts as a function of \(M_{UV}\) and follow the abundance matching with scatter algorithm described in Allen et al. (2018). Here, we order halos in the UM-VSMDPL mock catalog by their peak mass and adopt a fixed scatter in \(M_{UV}\) of \(\sigma = 0.5\) mags for simplicity. This value was chosen to be consistent with the scatter inferred by the UM model at high redshifts. All other methods for simulating clustering measurements remain as described in §2 with the exception that the best-fit mock survey volumes (see §2.1) are re-chosen using the UV luminosities assigned via abundance matching. While these best-fit volumes were originally selected using the same luminosity functions, the UV magnitudes assigned to each mock galaxy are different with abundance matching so we re-select the volumes for consistency.

As shown in Figure A1, the typical clustering measurements and significances (again determined using simulated jackknife errors and ignoring the 1-halo term) obtained using abundance matching are consistent with those obtained using the UM model. The only particularly notable changes are at \(z \sim 8\) and \(z \sim 10\) where the measurement significances are \(\sim 5\sigma\). At \(z \sim 8\), the abundance matching approach yields slightly more optimistic measurement significances, moving from 5.0\(\sigma\) to 5.6\(\sigma\) for angular clustering and from 4.5\(\sigma\) to 4.9\(\sigma\) for spatial clustering. At \(z \sim 10\), the UM model approach yields a slightly higher typical measurement significance (4.9\(\sigma\)) than abundance matching (4.2\(\sigma\)). This is because the \(z \sim 10\) luminosity function inferred by the UM model is slightly higher than the best fit reported by Bouwens et al. (2016a), thereby lowering Poisson noise in pair counts.

We choose to emphasize results using the UM model for two reasons. First, our abundance matching approach does not account for possible evolution in the scatter of the \(M_{UV}-M_{\text{halo}}\) relation with redshift or halo mass. Secondly, abundance matching does not account for the expectation that satellites have systematically lower star formation rates than centrals at fixed halo mass due to environmental quenching (e.g., van den Bosch et al. 2008; Kawasaki et al. 2016). This means that satellites are less likely to be detected when using the UM model and explains why clustering strengths obtained via the UM model tend to be lower. The exception to this trend is at \(z \sim 5\). At this redshift, the UV luminosity function inferred by the UM model is systematically lower than that reported by Finkelstein et al. (2015a) (see Figure 1) meaning that the UM model is assigning fixed \(M_{UV}\) values to higher mass halos which are more strongly clustered.

APPENDIX B: THE IMPACT OF Z≥4 UV LUMINOSITY FUNCTION UNCERTAINTIES

We also test how our inferred clustering measurement significances depend on the \(z \geq 4\) luminosity functions adopted by the UM model. Rather than re-run the UM model with different input luminosity functions, we use the abundance matching with scatter approach described in Appendix A. This approach is justified by the similar results obtained between the two methods (Appendix A).

At \(z \geq 4\), the Bouwens et al. (2015) luminosity functions are also commonly adopted in the literature. Galaxy number densities implied by this work are typically higher than those reported by Finkelstein et al. (2015a) which was adopted by the UM model. This suggests that using the Bouwens et al. (2015) luminosity functions will result in lower clustering strengths because galaxies at fixed UV magnitude are being assigned to lower mass halos. However, we also expect cosmic variance to decrease for the same reason. Finally, Poisson noise should decrease due to higher overall pair counts. In the end, we find that \(z \sim 4-8\) clustering measurements significances either remain at very similar values or are boosted by \(\sim 1\sigma\).

We re-simulate the \(z \sim 10\) clustering strength measurements using the Bouwens et al. (2019) and Oesch et al. (2018) luminosity functions at \(z \sim 9\) and \(z \sim 10\), respectively. These luminosity functions are \(-0.3\) dex lower than those reported by Bouwens et al. (2016a) so we expect higher clustering strength measurements with larger cosmic and Poisson variance. We find that the typical \(z \sim 10\) clustering measurement significance drops to 3.0\(\sigma\) as a result. While these luminosity functions give more pessimistic results, we still find that Cycle 1 surveys are likely to enable \(\sim 5\sigma\) clustering measurements at \(z \sim 10\) (§3.1).

APPENDIX C: MODELING PHOTOMETRIC SELECTION OF HIGH-REDSHIFT GALAXIES

C1 Determining Optimal Color Cuts

To ensure that our simulated high-redshift galaxy clustering measurements are realistic, we account for selection completeness. We assume that high-redshift galaxies will be photometrically selected with JWST using color cuts as commonly done with HST imaging (e.g., Stark et al. 2011; González et al. 2012; Oesch et al. 2014; Bouwens et al. 2015, 2019). To determine the most optimal color cuts for \(z \geq 4-10\) galaxy selection, we utilize the JAdes extraGalactic Ultra-deep Artificial Realizations (JAGUAR; Williams et al. 2018) package which provides HST and JWST broadband photometry for mock galaxies from \(z=0.2\) to \(z=15\). The properties of the high-redshift JAGUAR mock galaxies are empirically constrained by stellar mass functions, stellar mass to UV luminosity relations, and UV luminosity to UV slope relations. See Williams et al. (2018) for further details.

We first add noise to JAGUAR mock galaxy photometry 50 times for each source using the medium JWST depths listed in Table 5 of Williams et al. (2018) and the deep GOODS-S HST’ depths listed in Table 1 of Bouwens et al. (2015). Specifically, these \((5\sigma)\) depths are \(m = 28.8, 29.4, 29.5, 29.7, 29.8, 29.4, 28.8, 29.4, 28.9, 29.1\) for the F070W, F090W, F115W, F150W, F200W, F277W, F335M, F356W, F410M, and F444W JWST bands, respectively, and \(m = 28.7, 28.0, 27.5\) for the F435W, F606W, and F775W HST bands, respectively. We then iterate through potential photometric redshift selection criteria in various redshift intervals at \(z \sim 4-10\) using a combination of Lyman-break, rest-UV continuum, rest-optical emission line, and Balmer-break color cuts, seeking to maximize selection completeness and minimize the fraction of low-redshift contaminants.
Figure A1. Same as Figure 3 except that we show typical simulated JWST clustering measurements using $M_{\text{UV}}$ values assigned via abundance matching with scatter with diamond markers. Original data points using $M_{\text{UV}}$ values from the UniverseMachine model are shown with empty markers and are slightly offset to the right for clarity. In the lower left of each panel, we display typical measurement significances using $M_{\text{UV}}$ values from abundance matching where it can be seen (by comparing to Figure 3) that these significances remain approximately the same between the two methods. Simulated clustering measurements are often lower when adopting the UniverseMachine model as satellites are assigned systematically fainter $M_{\text{UV}}$ values relative to abundance matching.

| Redshift | Color Cuts | Non-Detection Criteria |
|----------|------------|------------------------|
| $z\sim10$ | F115W−F150W>1.6 ∧ 2.15<F150W−F200W<0.55 ∧ F115W−F150W>0.1(F150W−F200W)+1.6 | SN(F090W)<2 ∧ SN(F070W)<2 ∧ SNw(F435W<350,607,775)<2.5 |
| $z\sim8$ | F090W−F115W<2 ∧ F150W−F200W<0.4 ∧ F090W−F115W<2.6(F090W−F115W)+2 ∧ F410M−F444W>0 | SN(F070W)<2 ∧ SNw(F435W<350,607,775)<2.5 ∧ Not in z<10 selection |
| $z\sim7$ | F090W−F115W<1.3 ∧ F150W−F200W<0.4 ∧ F090W−F115W<2.6(F090W−F115W)+1.3 | SN(F070W)<2 ∧ SNw(F435W<350,607,775)<2.5 ∧ Not in z<8-10 selection |
| $z\sim6$ | F070W−F090W>2.4(F070W−F090W)+1 ∧ F410M−F444W<0.1 ∧ F410M−F444W>1.16(F200W−F277W)+0.28 | SN(F435W)<2 ∧ SN(F606W)<2 ∧ Not in z<7-10 selection |
| $z\sim5$ | F090W−F115W<0.24 ∧ F200W−F277W>0.28 ∧ F410M−F444W>1.06(F200W−F277W)+0.34 ∧ F410M−F444W>0.1 | SN(F435W)<2 ∧ SN(F555W)<2 ∧ Not in z<6-10 selection |
| $z\sim4$ | F115W−F150W<0.25 ∧ F355M−F555W<1.92(F150W−F200W)+0.52 | SN(F435W)<2 ∧ SN(F555W)<2 ∧ Not in z<5-10 selection |

Table B1. Photometric redshift color cuts and non-detection criteria designed to be used with medium depth JWST photometry along with deep optical HST photometry. The SNw(F435W<350,607,775) values are the inverse-variance weighted signal-to-noise values of the F435W, F606W, and F775W optical HST filters. All galaxies are also required to have a $\chi^2 > 25$ using all filters redder than and including F200W.

We find that the color cuts listed in Table B1 are optimal. These color cuts classify galaxies into approximate photometric redshift bins of [3,7,4,4.4,4.5,5,5.5,6,6.7,7,7.7,9,9,10] which we refer to as the $z\sim4$, $z\sim5$, $z\sim6$, and $z\sim7$ intervals, respectively. Within the context of JAGUAR, they successfully select >50% of galaxies at apparent rest-UV magnitudes of $m_{\text{UV}} = 28.0$, 28.5, 28.8, 29.2, 29.2, and 29.5 at $z\sim4$, $z\sim5$, $z\sim6$, $z\sim7$, $z<8$, and 10, respectively, while simultaneously introducing only 2-15% fractions of low-redshift contaminants. We use these color cuts to simulate both photometric and spectroscopic completeness as described in §2.2.

C2 Accounting for Contaminants in Angular Clustering Measurements

After applying color cuts to the JAGUAR catalog (Williams et al. 2018), we find that low-redshift ($z<3$) contaminants will comprise ~2-15% of the photometrically selected $z\sim4$-10 galaxy samples used for simulated angular clustering measurements. We assume that these low-redshift contaminants will not be clustered with one another because none of the low-redshift contaminant distributions are sharply peaked in redshift space within the context of JAGUAR. We therefore insert a sample of randomly positioned objects into the angular clustering measurements so that they populate a fixed fraction of the total sample equal to our estimated low-redshift contamination fractions (Williams et al. 2011). Specifically, these fractions are 2.4%, 9.1%, 2.1%, 5.3%, 1.8%, and 16.3% at $z_{\text{phot}}=4$, 5, 6, 7, 8, and 10, respectively. Because the vast majority of these contaminants are within one magnitude of our adopted limiting magnitudes (listed in Table 1), we do not introduce these random points in the brighter threshold samples.

There will also be high-redshift contaminants which lie slightly outside the targeted redshift interval in photometri-
physically selected samples. These sources may be clustered with each other and galaxies which lie inside the targeted redshift interval. We therefore select high-redshift contaminants according to modeled photometric selection completeness as a function of redshift and magnitude using the color cuts in Table B1.

Unclustered contaminants decrease measured angular clustering strengths. For the case of low-redshift contaminants where each galaxy is completely unclustered relative to all other galaxies in the sample, auto-correlation clustering strengths are reduced by a factor of \((1 - f_{\text{low}})^2\) where \(f_{\text{low}}\) is the low-redshift contamination fraction. However, for the case of high-redshift contaminants, some of these sources may be clustered. We therefore treat the effective fraction of high-redshift contaminants as \(f_{\text{high, eff}} = X_{\text{eff}} \times f_{\text{high}}\) where \(f_{\text{high}}\) is the inferred fraction of high-redshift contaminants and \(X_{\text{eff}}\) is some value between 0 and 1. Adopting \(X_{\text{eff}} = 0\) assumes that the high-redshift contaminants are as equally clustered as the intended galaxy sample. Conversely, adopting \(X_{\text{eff}} = 1\) assumes that every high-redshift contaminant is completely unclustered with all other galaxies in the sample. We find that fixing \(X_{\text{eff}} = 0.75\) leads to angular clustering strength measurements that best match the ‘true’ clustering strengths (§2.3) which only include galaxies inside the targeted redshift interval. Therefore, we take the total contamination fraction of each galaxy sample as \(f_{\text{low}} + 0.75 \times f_{\text{high}}\).

It will, in principle, be possible to more accurately forward model these effects once JWST begins to supply a large sample of spectroscopic redshifts at \(z > 4\).

APPENDIX D: ACCOUNTING FOR SPECTROSCOPIC FOLLOW-UP EFFICIENCY

In our simulated clustering measurements, we adopt the survey design of the planned Cycle 1 JADES (Williams et al. 2018) program which includes 26 NIRSpec micro-shutter assembly (MSA) pointings. Every MSA pointing will be comprised of R=100 prism exposures as well as exposures with the R=100 G235M and G395M grisms. Each R=100 MSA pointing can hold ~200 sources (NIRSpec team private communication). Using the JAGUAR mock catalog (Williams et al. 2018), we find that the typical JADES R=100 prism depths will provide \(\geq 50\%\) spectroscopic redshift completeness for \(z \sim 4-6\) galaxies brighter than the limiting magnitudes set by our modeled photometric selection (Table 1). Applying this photometric selection to the UM-VSMDPL catalog (§2.1), we expect that ~5300 galaxies will be photometrically selected to be at \(z \sim 4-6\) over the 142 arcmin\(^2\) of JADES/NIRSpec coverage. Therefore, the 26 MSA pointings are sufficient to follow-up nearly every \(z \sim 4-6\) candidate with R=100 spectroscopy assuming that each MSA pointing is completely filled with high-redshift galaxies.

Due to the smaller dispersion, each R=1000 pointing will likely only be able to hold ~75 sources (NIRSpec team private communication) suggesting a maximum of ~2000 sources over 26 pointings. The JADES R=1000 depths will provide \(\geq 50\%\) spectroscopic redshift completeness for \(z \sim 7\) and 8 galaxies brighter than \(m_{\text{UV}} = 29.0\) and 28.7, respectively, within the context of JAGUAR. Applying modeled photometric selection to the UM-VSMDPL mock catalog, we expect ~800 such \(z \sim 7-8\) candidates to be photometrically selected over the 142 arcmin\(^2\) of JADES/NIRSpec coverage, well below the maximum ~2000. We therefore assume that every \(z \sim 7\) and 8 photometric candidate brighter than our assumed spectroscopic limiting magnitudes (see Table 1) will also be spectroscopically followed up with NIRSpec.

While the above calculations show that the 26 JADES MSA pointings can, in principle, hold targets equal to the number of \(z \geq 4\) photometric candidates, we have not accounted for target placement restrictions to avoid overlapping spectra. Based on our experience with ground-based spectroscopy, a maximum of ~50\% of available targets can plausibly be placed on a multi-object mask. We therefore discuss how the spatial clustering results presented in §3.1 would change if we assume a 50\% spectroscopic follow-up efficiency for the JADES Cycle 1 program. Assuming that targets of different magnitudes are assigned the same follow-up priority, cosmic variance will not be altered. However, Poisson error will approximately double as a result because \(\sigma_{\text{Poisson}} \propto 1/\sqrt{D_{\text{ IDs}}} \times 1/\Sigma\) (Landy & Szalay 1993) where \(\Sigma\) is galaxy surface density. This suggests that spatial clustering will be measured with similar \((z \sim 4-5)\) or weaker \((z \geq 6)\) precision relative to angular clustering with the Cycle 1 JADES program alone. Additional dedicated spectroscopic follow-up will be necessary to achieve the ~15\% precisions quoted in Figure 3. Nonetheless, spatial clustering measurements are more desirable (if measured with similar significance) as they remove the systematic uncertainty associated with redshift contamination.

APPENDIX E: SATELLITE EVOLUTION IN THE UNIVERSEMACHINE MODEL

The UniverseMachine (hereafter UM; Behroozi et al. 2019) model accounts for both satellite and central halo evolution, allowing us to investigate not only central galaxy clustering, but satellite-satellite and satellite-central clustering as well. During the halo identification process, halos are identified as true satellites if they reside within the virial radius of a more massive halo. It is well known that multiple systematic effects lead to the premature disruption of low-mass satellites within dark matter simulations (e.g., van den Bosch et al. 2018; van den Bosch & Ogiya 2018). The UM model compensates for these effects by allowing disrupted satellites to continue orbiting their host as orphan galaxies (Wang et al. 2006) until their expected mass loss (computed via Jiang & van den Bosch 2016) reaches a preset threshold. This threshold is tuned to match zero-1 clustering constraints for star-forming and quiescent galaxies and it is assumed not to evolve with redshift. The net effect is to extend satellite lifetimes by ~25\% at all redshifts; however, the total satellite fraction is always \(\leq 15\%\) at \(z \sim 4\).

We note that our simulated galaxy major merger pair fraction measurements (§3.2) are sensitive to the orphan populations introduced by the UM model. Ignoring all orphans reduces the measured pair fractions by 0.3 dex at \(z \sim 4\) and 0.2 dex at \(z \sim 5\), which would make our simulated measurements less consistent with observations (Figure 5). This suggests that the satellite correction methodology adopted by the UM model is reasonable at high redshifts and we therefore adopt this model as a plausible representation of satellite behavior at \(z \geq 4\) even as we acknowledge that clus-
tering constraints from JWST will inform better models in the future.

**APPENDIX F: JACKKNIFE ERRORS ON THE TWO-POINT CORRELATION FUNCTION WITH JWST**

Jackknife and bootstrap methods are commonly used to determine the error on observationally measured two-point correlation functions. However, it is known that these errors should be interpreted with caution as they do not necessarily follow a Gaussian error distribution nor are they necessarily accurate (Norberg et al. 2009). On one hand, this is because clustering depends not only on halo mass but also environment, halo formation time, concentration, and subhalo occupation (e.g. Sheth & Tormen 2004; Gao et al. 2005; Wechsler et al. 2006; Pujol & Gaztañaga 2014). This phenomenon is broadly referred to as ‘assembly bias’ and can be particularly strong in the narrow pencil-beam fields JWST is designed to survey. Thus, if JWST survey volumes are not sufficiently large to capture the full extent of clustering variations for a given galaxy sample, clustering strength errors will be underestimated. Furthermore, the number of subsamples into which the observational data are split must be sufficiently large to accurately derive the true errors.

We test whether these concerns apply to future JWST surveys by asking how often the ‘true’ two-point correlation functions (§2.3) are enclosed by jackknife errors for the 100 simulated clustering measurement realizations for each galaxy sample (§2.1). Jackknife errors are calculated by dividing each of the two GOODS fields into 5 roughly equal area segments split by constant right ascension for a total of 10 jackknife samples. We find that these jackknife errors have typical 1σ and 2σ confidence intervals of ∼70% (i.e., jackknife errors enclose the true correlation functions in 70 of the 100 realizations) and 94%, respectively, with JADES angular clustering measurements and ∼62% and 88%, respectively, with JADES spatial clustering measurements. Because these confidence intervals are not highly different from those expected of a Gaussian distribution and because we wish to predict observational clustering measurements, we adopt jackknife errors throughout this work.

**APPENDIX G: EVOLUTION OF PEAK HALO MASS FUNCTION AT Z=3.5-10**

Here, we derive a smooth analytic fit to the redshift evolution of the peak halo mass function from z=3.5-10. We calculate the intrinsic peak halo mass function at snapshot redshifts spanning z=3.5-10 from the VSMPL dark matter simulation (§2.1) using only halos with masses of log_{10} (M_{peak}/M_\odot) > 9.5. After experimentation with various functional forms, we find that the following form best matches the intrinsic evolution over these redshifts:

\[
\log_{10} \phi \left( M_{\text{peak}}, z \right) = \log_{10} \phi^* + a \left( x - M^* \right) - \log_{10} (e) 10 \theta(x-M^*). \tag{G1}
\]

Here \( x = \log_{10} \left( M_{\text{peak}} / M_\odot \right) \). We find that it is not necessary to leave \( a \) (which represents the faint-end slope) as a free parameter and fix it at \( a = -0.95 \). The evolutionary forms of the other parameters are found to be:

\[
\beta(z) = -0.0185 z + 0.488 \tag{G2}
\]

\[
M^*(z) = 10^{9.44} - 0.652(z - 4.558) + 0.204 \log_{10} \left( 1 + 10^{0.820(z-4.558)} \right) \tag{G3}
\]

\[
\log_{10} \phi^* (z) = -1.361 + 0.533(z - 4.690) - 0.0714 \log_{10} \left( 1 + 10^{1.722(z-4.690)} \right) \tag{G4}
\]

This analytic evolutionary form agrees with the VSMPL data at z=3.5-10 to within either 2σ (Poisson) or 0.10 dex at each data point (binned by 0.05 dex in M_{peak}). These data points and the fit from Equation G1 at each redshift are shown in Figure F1.

We note that these halo mass functions include the contribution from satellites identified by our adopted halo finder (ROCKSTAR; Behroozi et al. 2013a) as well as orphan satellites that have been introduced to account for the premature disruption of low-mass satellites within dark matter simulations (Appendix E). Excluding orphan satellites would have a very small impact on the intrinsic peak halo mass function at z=3.5-10, decreasing it by at most 0.04 dex.

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