

Mass and occupation fraction of dark matter halos hosting Lyman- α emitters at $z \sim 3$

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ABSTRACT

We derive constraints on the mass and occupation fraction of dark matter halos hosting Ly α Emitting galaxies (LAEs) at a redshift of $z = 3.1$ by matching the number density and the angular correlation function between mock and observed fields. We explicitly take into account the cosmic variance on the typical observed field size by constructing mock fields from a large cosmological N-body simulation matching the geometries of observed fields. To populate the halos in the simulation we use a model where a dark matter halo with mass in the range $M_{\min} < M_h < M_{\max}$ can only host one detectable LAE with a probability f_{occ} . The main motivation to build such a model is to avoid the large uncertainties in the estimation of Ly α luminosities. We find that the clustering and number density information are insufficient to impose a tight constraint on the escape fraction. On the other hand the minimum mass and maximum mass are tightly constrained to be $M_{\max} < 10^{12} h^{-1} M_\odot$ and $10^{10} h^{-1} M_\odot \leq M_{\min} \leq 10^{11.5} h^{-1} M_\odot$. We also find that all models have a narrow mass range $\Delta M \equiv \log_{10} M_{\max} - \log_{10} M_{\min}$ smaller than 1.0 dex, with the vast majority in the range $\Delta M < 0.5$ dex. Already published constraints on the mass range and occupation fraction are a sub-set of the models we report in this paper. Our results present an inconclusive response as to which is the occupation fraction for LAEs at $z = 3.1$. A precise answer requires robust physical models for the connection between dark matter, star formation and the escape of Ly α radiation. That kind of modelling should also be able to provide a plausible explanation for the narrow range in mass $\Delta M < 1.0$ dex derived here for the halos hosting LAEs at $z = 3.1$.

Key words: cosmology: theory cosmology: large-scale structure of universe galaxies: formation galaxies: high-redshift galaxies: statistics galaxy: haloes

1 INTRODUCTION

Lyman- α emitting galaxies (LAEs) have become in the last decade a central topic in studies of structure formation in the Universe. They are helpful in a diverse range of fields. LAEs can be used as probes of reionization (Dijkstra et al. 2011), tracers of large scale structure (Koehler et al. 2007), signposts for low metallicity stellar populations, markers of the galaxy formation process at high redshift (Dayal et al. 2009; Forero-Romero et al. 2012) and tracers of active star formation (Guaita et al. 2013).

At the same time, theoretical and observational developments have contributed to the emergence of a paradigm to describe structure formation in a cosmological context. In this context it is considered that the dominant matter content of the Universe is to be found in dark matter (DM), whereby each galaxy is hosted by larger dark matter structures known as a halo. (Peebles 1980; Springel et al. 2005).

Most models of galaxy formation find that halo mass can be used to predict galaxy properties such as the stellar mass and star formation rate (Behroozi et al. 2012). Processes that regulate the star formation cycle are also thought to be strongly dependent on its halo mass. For these reasons, finding the typical dark matter halo mass hosting LAEs represents a significant step forward to understand the nature of this galaxy population in the context of Lambda Cold Dark Matter (Λ CDM) paradigm.

Some theoretical approaches to this problem have been based on ab-initio approach. Starting from the DM halo population, the corresponding intrinsic star formation properties are inferred together with other statistics such as the luminosity function, the correlation function and the equivalent width distributions. Such modelling has been implemented from analytic considerations, semi-analytic models (Garel et al. 2012; Orsi et al. 2012) and full N-body hydrody-

nematical simulations (Laursen & Sommer-Larsen 2007; Dayal et al. 2009; Forero-Romero et al. 2011; Yajima et al. 2012; Walker-Soler et al. 2012).

In addition to the uncertainties in the astrophysical processes describing star formation in galactic populations, the calculation of the fraction of Ly α photons that escape the galaxy to the observer is another debated step. Given the resonant nature of the Ly α line, the radiative transfer of Ly α is sensitive to the density, temperature, topology and kinematics of the neutral Hydrogen in the interstellar medium (ISM). This problem can be tackled with Monte Carlo simulations for the radiative transfer, however the complexity of the relevant physical processes makes it difficult to achieve a robust consensus on what is the theoretical expected value for the Ly α escape fraction at high redshift (Neufeld 1991; Forero-Romero et al. 2011; Dijkstra & Kramer 2012; Laursen et al. 2013; Orsi et al. 2012).

Another approach to infer the typical DM halo mass of halos hosting LAEs is based on the clustering information. This uses the fact that in cold dark matter cosmologies the spatial clustering of galaxies on large scales is entirely dictated by the halo distribution (Colberg et al. 2000), which in turn has a strong dependence on halo mass. Using measurements of the angular correlation function of LAEs, observers have put constraints on the typical mass and occupation fraction of the putative halos hosting these galaxies (Hayashino et al. 2004; Gawiser et al. 2007; Nilsson et al. 2007; Ouchi et al. 2010). In this studies the observations were done on single fields of $\sim 1 \text{ deg}^2$ and the conclusions derived on the halo host mass from clustering information do not delve to deeply into the impact of cosmic variance.

Recently Yamada et al. (2012) observed a wide area a bit more than ten times the sky area covered so far by individual campaigns. The observations were done with the same instrument and same criteria to reduce the observational data and produce LAE catalogs. This large data-set allows us to make the first study on the expected cosmic variance effects in LAEs at $z = 3.1$ and its impact on the determination of the halo mass and occupation fraction.

In this paper we implement a method to populate the DM halos in cosmological simulations with LAEs that bypasses all the uncertainty involved in the estimation of star formation rates and Ly α escape fraction. The model only considers whether a DM can host a detectable LAE or not without predicting a Ly α luminosity. Once the mock catalogs are constructed we proceed with a direct comparison against the statistics derived from observations. This allows us to find the preferred mass range of DM halos hosting these galaxies and its occupation fraction.

This paper is structured as follows. In the next section we present the simulation and model used to produce the mock catalogs and the criteria we use to compare them against observations. In §3 we present the main results for the halo mass and occupation fraction. We continue with a discussion of these results under the light of other observational and theoretical results. Finally, we present our conclusions in §5.

Throughout this paper we assume a Λ CDM cosmology with the following values for the cosmological parameters, $\Omega_m = 0.27$, $\Omega_\Lambda = 0.73$ and $h = 0.70$, corresponding to the matter density, vacuum density and the Hubble constant in units of $100 \text{ km s}^{-1} \text{ Mpc}^{-1}$.

2 METHODOLOGY

Our method is based on the comparison of observations and mock catalogs. We use two different kinds of statistics to perform the comparison: (i) the distribution of the surface number density across fields fields and (ii) the angular correlation function measured in some fields.

In the next subsections we describe in detail the four key elements of this work-flow. First, we present the observations we take as a benchmark. Second, we describe the main characteristics of the N-body simulation and the halo catalogs we use. Third, we recount the important parameters of the simplified model that we use to populate the halo catalogs with LAEs. Finally we describe some of the statistical tests we adopt to compare observations and mocks.

2.1 Observational Constraints

The first observational constraint we use in this paper is the LAE number density information at $z = 3.1$ obtained by the panoramic narrow-band survey presented by Yamada et al. (2012) from a survey conducted with the Subaru 8.2m telescope and the Subaru Prime Focus Camera, which has a field of view covering $34 \times 27 \text{ arc-min}$, corresponding to a comoving scale of $46 \times 35 \text{ Mpc } h^{-1}$ at $z = 3.09$. The narrow band filter used in the survey is centered at 4977 \AA with 77\AA width, corresponding to the redshift range $z = 3.062 - 3.125$ and $41 \text{ Mpc } h^{-1}$ comoving scale for the detection of the Lyman- α line centered at $z = 3.09$. The authors reported a total 2161 LAEs with an observed equivalent width, in the observer frame, larger than 190\AA over a total survey area of 2.42 deg^2 that includes 12 sub-fields, this corresponds to average surface number density of $0.20 \pm 0.01 \text{ arcmin}^{-2}$.

The survey covered four independent fields. The first is the SSA22 field of 1.38 deg^2 with 1394 detected LAEs (7 sub-fields), this field has been known to harbor a region with a large density excess of galaxies. The second observed region is composed by the fields Subaru/*XMM-Newton* Deep Survey (SXDS)-North, -Center and -South, with a total of 0.58 deg^2 and 386 LAEs (3 sub-fields). The third and fourth fields are the Subaru Deep Field (SDF) with 0.22 deg^2 and 196 LAEs (1 sub-field), and the field around the Great Observatory Optical Deep Survey (GOODS-N) with 0.24 deg^2 and 185 LAEs (1 sub-field).

There is abundant observational work done on LAEs at redshift $z = 3.1$ (Kudritzki et al. 2000; Matsuda et al. 2005; Gawiser et al. 2007; Nilsson et al. 2007; Ouchi et al. 2008). However, we decide to focus on the data from Yamada et al. (2012) because it has the largest covered area with homogeneous instrumentation conditions (telescope, narrow band filter), data reduction pipeline and conditions to construct the LAE catalog. This ensures that the number density variations among fields are *not* due to different observational conditions or criteria to construct the catalogs.

The second constraint is the angular correlation function (ACF). Yamada et al. (2012) does not report an ACF measurement. Instead we use the results by Hayashino et al. (2004) and Ouchi et al. (2008, 2010). Hayashino et al. (2004) observed in the densest field of SSA22 while Ouchi et al. (2008) observed on a 1 deg^2 sky of the SXDS Field. There are some differences between these observations and those by Yamada et al. (2012). The details in the color selection,

corresponding limiting luminosities and EW thresholds are different in these references. Nevertheless we use these observations as additional constraints in spite of the fact that the first selected models are based only on the surface density statistics by (Yamada et al. 2012).

2.2 Simulation and Halo Catalogs

The Bolshoi simulation (Klypin et al. 2011) we use in this paper was performed in a cubic volume of $250 h^{-1}$ Mpc on a side. The dark matter distribution is sampled using 2048^3 particles, which translates into a particle mass of $m_p = 1.35 \times 10^8 h^{-1} M_\odot$. The cosmological parameters are consistent with a WMAP5 and WMAP7 data with a matter density $\Omega_m = 0.27$, cosmological constant $\Omega_\Lambda = 0.73$, dimensionless Hubble constant $h = 0.70$, slope of the power spectrum $n = 0.95$ and normalization of the power spectrum $\sigma_8 = 0.82$ (Komatsu et al. 2009; Jarosik et al. 2011).

We use halo catalogs constructed with a Friend-of-Friends (FOF) algorithm with a linking length of 0.17 times the inter-particle distance. The catalogs were obtained from the publicly available Multidark database¹ (Riebe et al. 2013). For each halo in the box we store its position in the box (3-D coordinates) and FOF mass. We focus our work on halos more massive than $1 \times 10^{10} h^{-1} M_\odot$ that are resolved with at least 70 particles, the reasons for this choice are explained in the next sub-section.

2.3 A Model to Populate Halos with LAEs

We assume that a dark matter halo can only host one detectable LAE at most. There are three parameters that decide whether a halo host a LAE: the lower and upper bounds for the mass range $M_{\min} < M_h < M_{\max}$ where LAEs reside and the fraction f_{occ} of such halos that host a detectable LAE. The reader must keep in mind that the physical interpretation of the occupation fraction f_{occ} convolves two phenomena: the presence of a star forming galaxy in a halo and its detectability as a LAE. We do not perform an explicit modeling for LAE detectability. Our model does not assign a luminosity or escape fraction to each LAE. We are only interested in constraining the halo mass range hosting detectable LAEs under the conditions defined by Yamada et al. (2012).

In what follows we note by the letter \mathcal{M} a model defined by a particular choice of the three scalar parameters M_{\min} , M_{\max} and f_{occ} . For each model \mathcal{M} we create a set of mock fields from disjoint volumes in the simulation. Each volume has the same geometry probed by Suprime-CAM and the narrow band filter, namely rectangular cuboids of dimensions $46 \times 35 \times 41 h^{-3}$ Mpc³ where the last dimension goes in the redshift direction. This corresponds to a total area of 880 arcmin² in each mock field. We construct a total $5 \times 7 \times 6 = 210$ of such volumes from a snapshot in the Bolshoi simulation. In each mock field a LAE is assigned to the position of a dark matter halo if the halo mass is in the range allowed by the model $M_{\min} < M_h < M_{\max}$ and

a random variable taken from an homogeneous distribution $0 \leq \xi < 1$ is smaller than the occupation fraction $\xi < f_{\text{occ}}$.

Next we construct mock surveys by making groups of 12 mock fields out of the 210 available volumes. In total 15 mock surveys are constructed for each model \mathcal{M} . The grouping of the 12 mock fields into a mock catalog is done in two different ways. The first is called `match`, it follows the clustering of the observational fields. From the 12 mock fields, 7 are constructed from contiguous fields in the simulation to mimic the SSA22 region, 3 are also contiguous between them but not to the first 7 fields to mimic the SXDS fields and finally 2 non-contiguous fields to imitate the SDF and GOODS-North field. The second way to group the mock fields is called `random`, whereby all the 12 fields are selected in such a way as to avoid that any two volumes are contiguous. In this paper we only report the results obtained by the `match` method and mention explicitly differences observed with the `random` selection.

We note that we use $15 \times 12 = 144$ mock fields out of the total of 210 available sub-volumes. The reason is that the `match` method imposes constraints on the way the 7 fields mimicking the SSA22 can be distributed. This restriction makes unusable some of the sub-volumes in the box. We decide to keep the number of mock surveys fixed to 15 also for the `random` method in order to allow a fair comparison between the two methods.

2.4 Exploring and Selecting Good Models

We make a thorough exploration of the parameter space for the models \mathcal{M} . $\log_{10} M_{\min}$ takes 30 values from 10.0 up to 12.9 with an even spacing of 0.1 dex. $\log_{10} M_{\max}$ takes values in the same range as $\log_{10} M_{\min}$ only with a displacement of 0.1 dex in the whole range. The occupation fraction f_{occ} takes 10 different values from 0.1 to 1 regularly spaced by 0.1. In total the number of different models \mathcal{M} that are explored is $30 \times 30 \times 10 = 9000$.

The lower limit for the parameter M_{\min} is set by the minimum occupation fraction we are able to consider. At $M_{\min} = 10^{10} h^{-1} M_\odot$ the halo number density is already ~ 10 times higher than the observational constraints for LAEs. This means that models in that mass range and an occupation fraction $f_{\text{occ}} = 0.1$ have the possibility to be compatible with observations. Lower values for M_{\min} require $f_{\text{occ}} < 0.1$, which are not considered in this paper.

For each mock survey generated in a given model \mathcal{M} we compute the surface density in the 12 mock fields. We perform a Kolmogorov-Smirnov (KS) to compare this mock data against the 12 observational values. From this test we obtain a value $0 < P < 1$ to reject the null hypothesis, namely that two data sets come from the same distribution. In this paper we consider that for values $P > 0.05$ the two distributions can be thought as coming from the same distribution.

We begin by considering that a model \mathcal{M} that has at least one mock survey (out of 15) consistent with the observed distribution of LAE number densities has viable parameters that deserve to be considered for further analysis. Later on we impose harder constraints to reduce the number of models by asking that all the 15 mocks to be consistent with observations.

The second constraint comes from the angular correla-

¹ <http://www.multidark.org/MultiDark/>

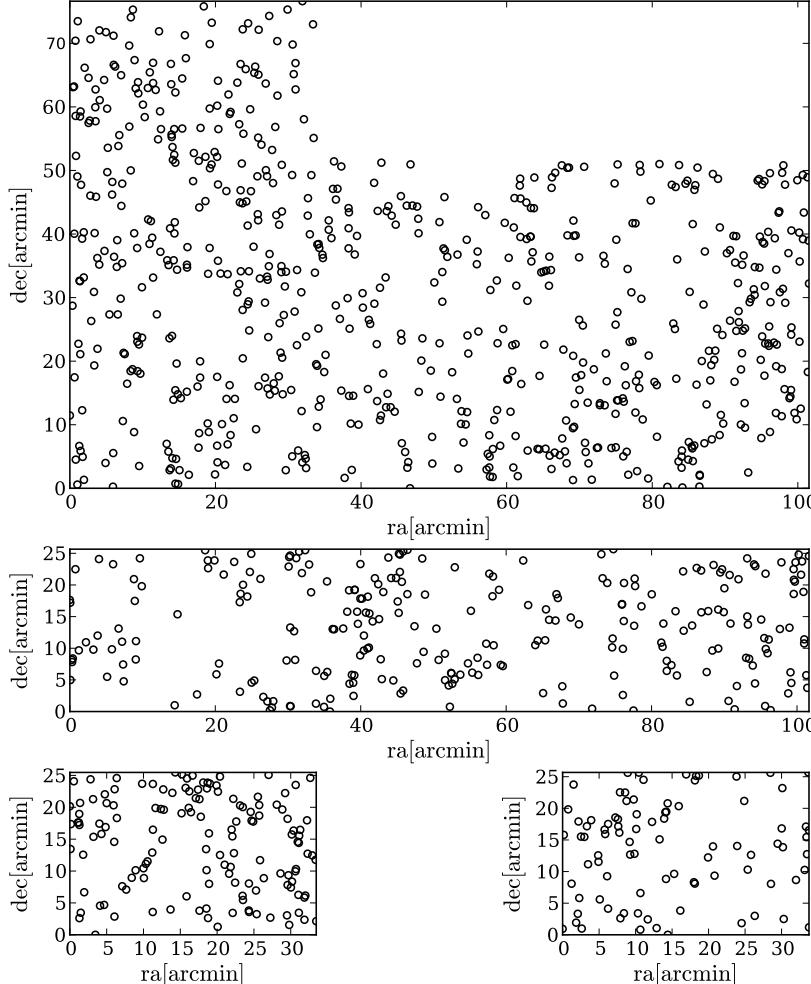


Figure 1. Spatial distribution of a LAEs mock survey for a model with parameters $\log_{10} M_{\min} = 10.4$, $\log_{10} M_{\max} = 10.5$ and $f_{\text{occ}} = 0.1$ for the match method. The larger panel shows 7 mock fields together mimicking the SSA22 region. The intermediate panel shows 3 mock fields corresponding to the SXDS region. The lower panels represent the SDF and GOODS-North fields. The same model has another 14 associated mock surveys build from different regions in the simulation, but constructed following the same pattern in the match method.

tion function (ACF) for all the models having the 15 mock surveys consistent with observations . The ACF is computed (using the Landy & Szalay estimator (Landy & Szalay 1993)) on two kinds of fields in the mock survey: the densest and one corresponding to the average density. The first with the Hayashino et al. (2004) and Ouchi et al. (2010) ACFs respectively.

The observational ACF and the mock ACF of the models are compared in terms of the correlation length (θ_0) by fitting them to a power-law function:

$$\omega(\theta) = \left(\frac{\theta}{\theta_0} \right)^{-\beta} \quad (1)$$

Both mock and observational ACF are derived by a least square minimization procedure. For each mock we obtain a covariance matrix that gives us the uncertainty in the parameters β and θ_0 . We compute a mean value for the parameters and its associated uncertainty as the quadratic average of the uncertainties in the fitting procedure. We con-

sider that a model is consistent with observations if the two parameters β and θ_0 are equal within a $1-\sigma$ range.

3 RESULTS

The main purpose of this section is to show how different observational constraints narrow down the parameters space of allowed models. Each sub-sections presents the effect of adding new pieces of observational or statistical evidence.

3.1 Dark Matter Halo Number Density

In Figure 2 we present the results for the integrated dark matter halo surface density as a function of halo mass. Each line corresponds to one of the 210 sub-volumes in the Bolshoi simulation. The gray band indicates the surface density values for LAEs allowed reported in observations (Yamada et al. 2012).

This result provides the basis to understand why only a specific range of models \mathcal{M} can be expected to be consistent

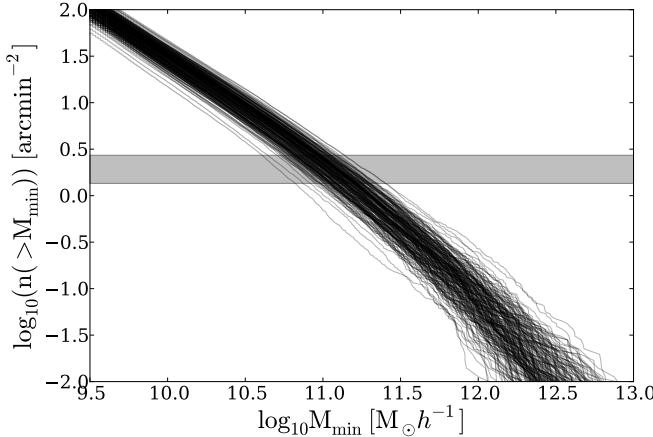


Figure 2. Surface density of dark matter halos as a function of a minimum halo mass to count the total number of elements in a volume. Each line represents one of the 210 volumes of dimensions $46 \times 35 \times 41 \text{ h}^{-3}\text{Mpc}^3$ in the Bolshoi simulation. The horizontal gray band represents the range of surface densities observed for LAEs at $z = 3.1$ as reported by (Yamada et al. 2012).

with observations. From Figure 2 we can read that models with a minimum mass $\log_{10} M_{\min} > 11.5 h^{-1} M_{\odot}$ will always have a surface number density lower than the observational constrain. This makes impossible that models in that range can be compatible with observations, there are simply too few halos compared to observed LAEs.

The opposite is true in models with $\log_{10} M_{\min} < 10.5$ that have a surface number density larger than observations. In those cases the occupation fraction $f_{\text{occ}} < 1.0$ can be tuned in order to lower the halo number density to match observations.

Figure 2 also illustrates the impact of cosmic variance. At fixed mass there is a scatter of 0.3–0.6 dex in the mass range $10^{10} h^{-1} M_{\odot} < M_{\min} < 10^{11} h^{-1} M_{\odot}$. A consequence of this variation is that models with the same mass range and occupation fraction can have mock fields with number densities varying up to a factor of $\sim 2 - 5$. Also, the scatter in mocks across the simulation is comparable to the 0.3 dex scatter in observations.

In the same Figure 2 we see that at fixed number density, around the range allowed by observations, there is an scatter in the masses of 0.4–0.5 dex. This intrinsic scatter in the masses with a given number density adds is also included in the mock construction process, enlarging the range of possible models consistent with observations.

3.2 Models consistent with the surface density distributions

Figure 3 presents regions in parameter space $M_{\min} - M_{\max}$, $M_{\min} - f_{\text{occ}}$ where the KS test yields values of $P > 0.05$ at least for one mock survey, which is the most conservative assumption for agreement between a model and observations. For those models it is not possible reject the hypothesis that the simulated and observed data for the surface number density come from the same parent distribution. In total, there are between 550 to 600 models out of the original

9000 models that have at least one mock survey consistent with observations. By inspection of Figure 3 we see that the halo number abundance is able to constraint the minimum mass M_{\min} to a narrow range, while M_{\max} and f_{occ} remain unconstrained.

In Figure 3 there are three regions of parameter space that can be clearly distinguished. The first region corresponds to models where the minimum mass is high $\log_{10} M_{\min} > 11.5$. None of these models is compatible with observations as expected from the arguments presented in the previous subsection. For these models the number density of LAEs is too low compared to observations.

The second region corresponds to an intermediate range for the minimum mass $10.5 < \log_{10} M_{\min} < 11.5$ where, regardless of the value of the maximum mass M_{\max} , it is possible to tune the occupation fraction f_{occ} to bring some of the mock observations into good agreement with observations. In this region of parameter space one can find two extreme kinds of models. One kind where the mass interval $\Delta M \equiv \log_{10} M_{\max} - \log_{10} M_{\min}$ is narrow with $\Delta M < 1.0$ dex, others where the mass interval is extended $\Delta M > 1.0$ dex going up to the maximum halo mass present in the simulation at that redshift, up to $\Delta M = 2.5$ dex in some cases.

The third region in parameter space corresponds to $\log_{10} M_{\min} < 10.5$. In this case only models with a very narrow mass interval of at most 0.5 dex ($\log_{10} M_{\max} < 11.0$) and low occupation fractions $f_{\text{occ}} < 0.3$ are allowed.

Without any additional information our method allows us to infer that most of the successful models are found in the second and third regions of parameter space. This result was already expected from halo abundance calculations shown in Figure 2 and discussed in the previous subsection.

However, the additional information we gain with this test is the relative abundance of models in the parameter space. Not all the models in the second region have an equal abundance. By inspection of Figure 3 it seems that models with $\log_{10} M_{\min} \sim 10^{11.3} h^{-1} M_{\odot}$ and low occupation fraction $f < 0.3$ are preferred. In the next sub-section we explore in detail the models in this region, imposing tighter constraints on the KS test results and exploring the mocks' consistency with the angular correlation function.

3.3 Models with the largest number of consistent mock surveys

In the previous Section we present a conservative criterion of agreement by selecting the models that had at least one mock survey with $P > 0.05$ in the KS test. Now we turn to a more strict selection by requiring all constructed mock surveys to be consistent with observations.

Figure 4 shows the number of models that have at least $N_{\text{high-}P}$ mocks with $P > 0.05$. For each model \mathcal{M} there are 15 different mock surveys. We discard the models that have 14 mocks or less consistent with observations. With this cut we find ~ 100 models with all the 15 mock survey realizations with $P > 0.05$. This cut represents a reduction by a factor of ~ 6 with respect to the total number of models with at least one consistent mock.

Figure 5 presents the locii of these models in the parameter space $M_{\min} - M_{\max}$ and $M_{\min} - f_{\text{occ}}$. With this constraints the number of consistent models with $10.5 <$

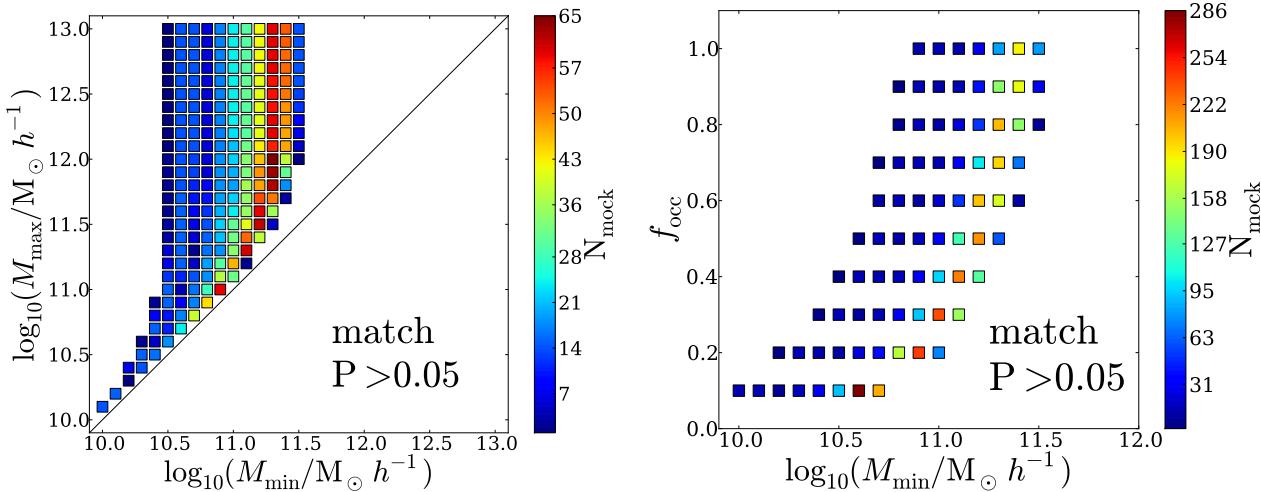


Figure 3. M_{\min} - M_{\max} (left) and M_{\min} - f_{occ} (right) planes for all models with KS test values $P > 0.05$. The color code corresponds to the number of mock surveys compatible with observations. Only regions of parameter space with at least one consistent mock survey are included.

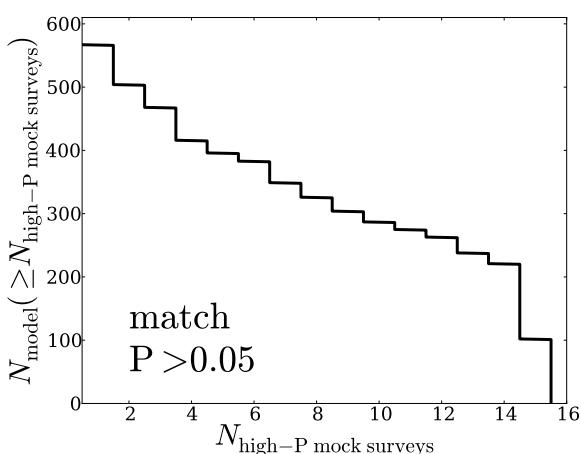


Figure 4. Number of models with at least $N_{\text{high}-P}$ mock surveys consistent with the observed surface number density distribution in terms of the KS-test values $P > 0.05$. Only ~ 100 models have all their mocks consistent with observations.

$\log_{10} M_{\min} < 11.0$ are greatly reduced. This corresponds to the regions in the parameter space in Figure 3 that already had a low number of consistent mock surveys. On the other hand, from the right panel in Figure 5 one can see that there is not a strong reduction on the favored values for the occupation fraction f_{occ} .

We conclude that conditions on the number density statistics, even if they are very strict, only put strong constraints on the minimum mass M_{\min} but not on the other two parameters of the model M_{\max} and f_{occ} . In the next section we use additional observational information to constrain these parameters.

3.4 Consistency with the Angular Correlation Function

Figure 6 shows the main results in a $\theta_0 - \beta$ plane where the average and standard deviation over the mocks is shown in comparison with the result derived from observations. The error bars in this Figure represents the standard deviation of the ACF over all the 15 mock fields used to make the computation. These error bars are larger than the statistical uncertainty from the fitting procedure on a single field.

In the left panel Figure ?? we see how the observational ACF measured by Hayashino et al. (2004) (green dot) is successful in reducing the total number of possible models. Only those with angular-correlation length within $15'' < \theta_0 < 23''$ are considered to reproduce observations. The right panel of Figure ?? shows the results for fields in the mock catalog that have an average number density that are compared against the fit of the data reported by Ouchi et al. (2010). In this case we find that there are large uncertainties in the observational data, however it is possible to discard a fraction of the models.

In Figure 7 we present the preferred models in the planes $M_{\min} - M_{\max}$ and $M_{\min} - f_{\text{occ}}$ both for the comparison against Hayashino et al. (2004) and Ouchi et al. (2010). To make this selection we consider that a model is consistent with observations if there is a $1 - \sigma$ overlap between both the correlation length θ_0 and the power β . We clearly see from this Figure that the conditions imposed by Hayashino et al. (2004) are the tightest. Comparing this Figure with the results shown in Figure 5 we see that practically all models with $M_{\max} > 10^{12}$ are removed. On the other hand the comparison against Ouchi et al. (2010) does not substantially reduce the number of models.

At this point we take the most strict selection criterion and keep the models that are consistent with both observational constraints. This basically reduces the selection to the models already restricted by the data in Hayashino et al.

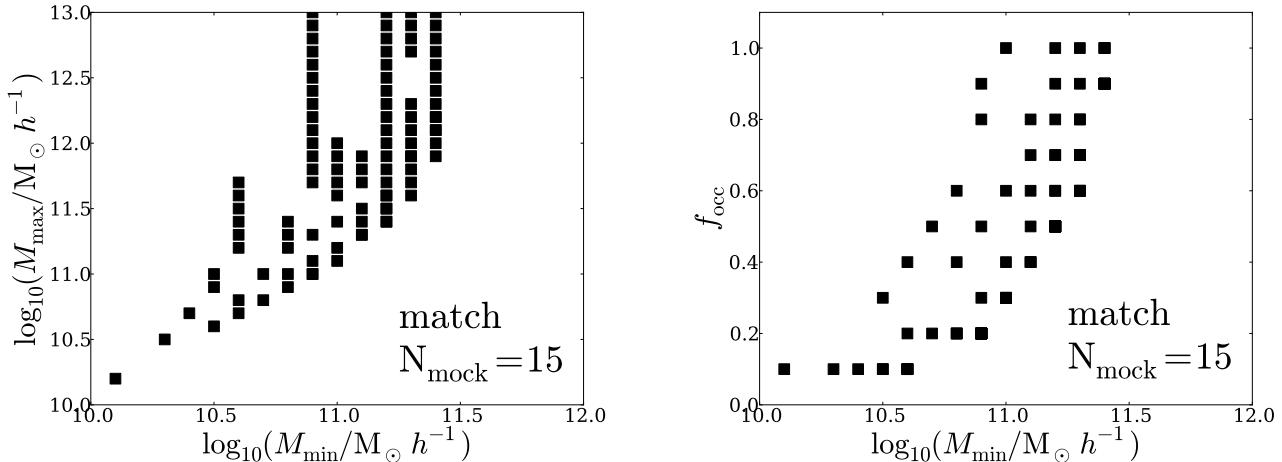


Figure 5. Favored regions in parameter space when the constraints on the maximal number of consistent mocks is imposed. Only the results for the match method are shown.

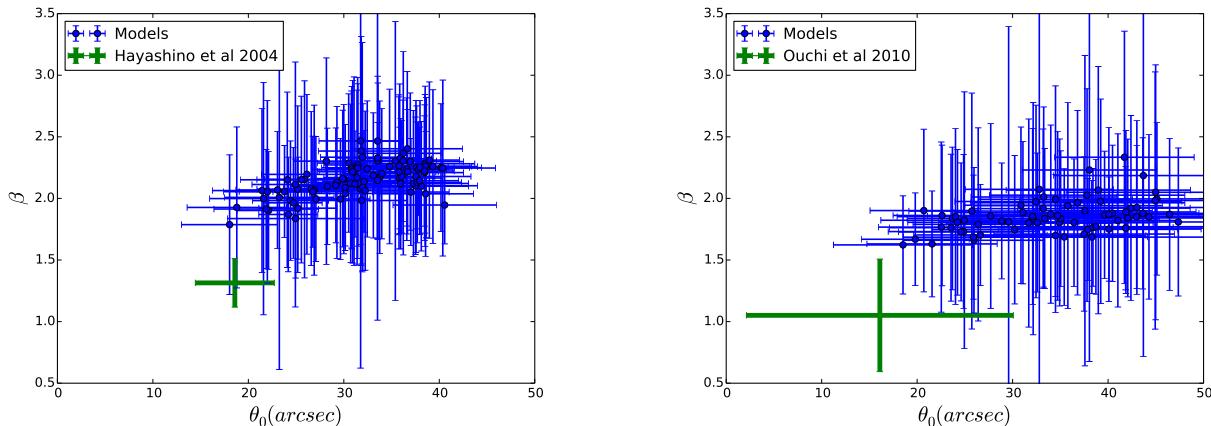


Figure 6. Left: Values for the free parameters (θ_0 vs β) in the fitting formula (Eq. 1) for the angular correlation function. Blue dots correspond to simulations and the green cross to observations by Hayashino et al. (2004) and Ouchi et al. (2010). The error bars in the theoretical data correspond to the standard deviation from the different mocks surveys.

(2004) as presented in the lower panels of Figure 7. Our main conclusions after this comparison is that clustering information is able to put meaningful constraints on the values of M_{\max} . However, the possible values for the occupation fraction are still in the initial range $0.1 \leq f_{\text{occ}} \leq 1$.

4 DISCUSSION

In the Results Section we start by matching the rough numbers for the galaxy surface number density. This sets the median mass of all successful models to the broad range $(10^{10} - 10^{12}) h^{-1} M_{\odot}$ for M_{\min} and M_{\max} . We include additional criteria on the number of mock surveys that must be consistent observations and the information from the angular correlation function, reducing the number of feasible models. We end up with ~ 25 models out of the initial 9000 possible combination of parameters.

In order to make a physical interpretation of these

models we use the halo mass range, defined as $\Delta M = \log_{10} M_{\max} - \log_{10} M_{\min}$, together with the occupation fraction f_{occ} to classify all the successful models into two families:

- (1) Low $f_{\text{occ}} \leq 0.3$, $M_{\min} \leq 10^{10.8} h^{-1} M_{\odot}$ and low $\Delta M \leq 1.0$ dex: 12 models.
- (2) High $f_{\text{occ}} > 0.3$, $M_{\min} \geq 10^{10.8} h^{-1} M_{\odot}$ and low $\Delta M \leq 1.0$: 11 models

The full list of parameterer in the two families is summarized in Table 1 and Table 2. We do not have a clear majority of any family. This leads us to the following two conclusions. First, the occupation fraction cannot be constrained based on clustering analysis. Second, the halos hosting LAEs have a narrow mass range.

The existence of a narrow mass rango for halo masses has different possible explanations. A cut at the low mass end M_{\min} can be interpreted in terms of the minimal halo star formation rate needed to produce the minimal Ly α lu-

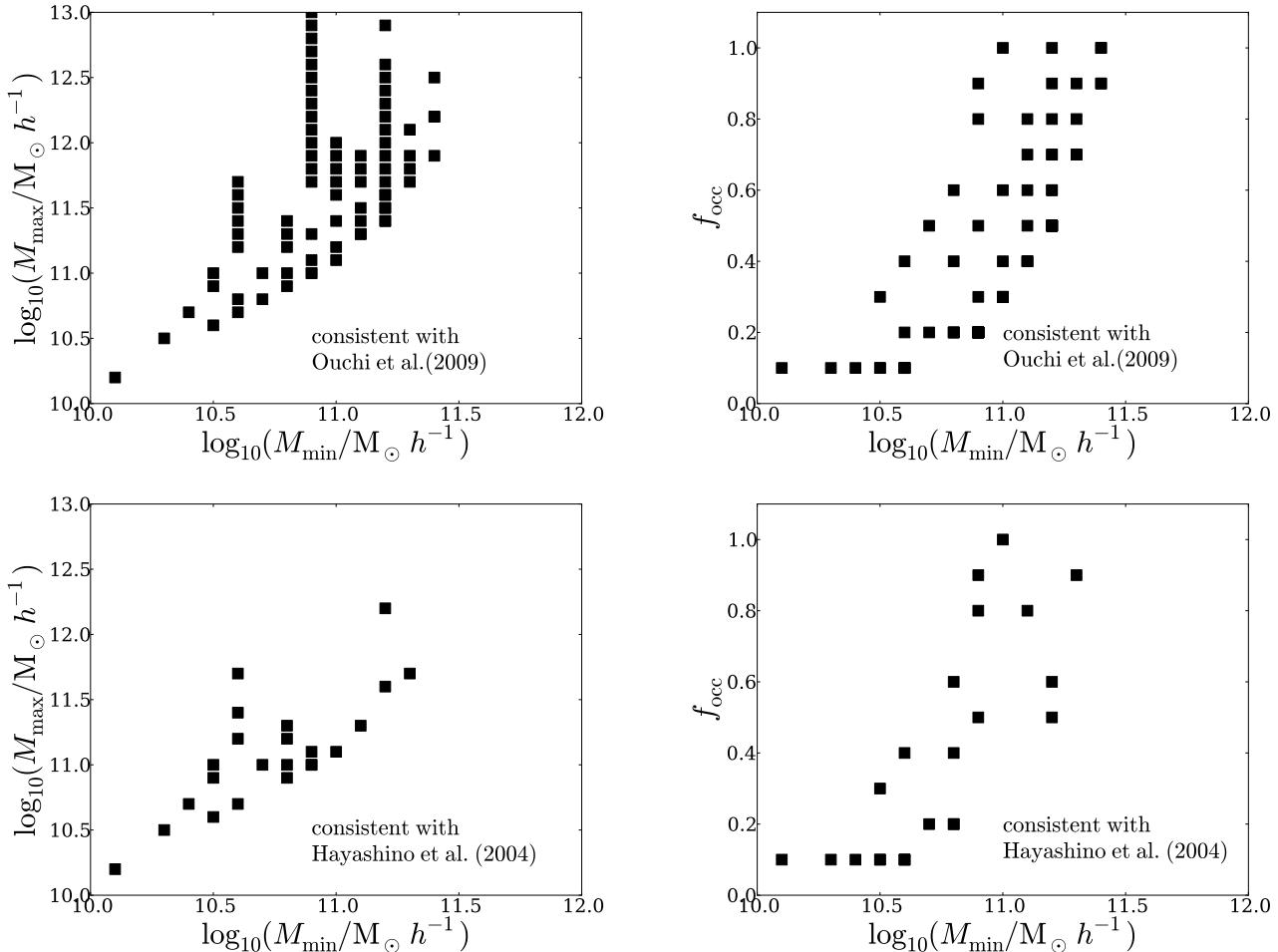


Figure 7. Planes M_{\min} vs M_{\max} (left), M_{\min} vs f_{occ} (right). The squares represent the models when both constraints on the maximal number of consistent mocks and the angular correlation function are included. Upper panels correspond checks the consistency against the observational data of Ouchi et al. (2010), while lower panels show results for Hayashino et al. (2004)

minosity to be above a given detection threshold. However, under the reasonable assumption of star formation rate increasing with halo mass, the cut at higher halo masses requires a different justification. There are two complementary physical scenarios that can provide it.

One scenario can be presented in terms of a decreasing escape fraction of Ly α radiation in massive systems. There are detailed models for radiative transfer that support the idea that massive galaxies with higher metallicities have larger dust contents and less concentrated ISM than lower mass systems. Due to the resonant nature of the Ly α line the probability of absorption of Ly α photons increases in massive systems, producing high absorption of Ly α photons but not of continuum or other non-resonant lines (Laursen et al. 2009; Forero-Romero et al. 2011).

A second scenario is that larger systems have more extended gaseous envelopes which due to resonance effects of the Ly α line, can induce a low surface brightness and a broader line, making these systems less observable in narrow band filter surveys (Laursen et al. 2009; Zheng et al. 2010).

The preference for narrow ΔM ranges to host LAEs and the small presence of reasonable models with $M_{\max} >$

$10^{12} h^{-1} M_{\odot}$ also follows theoretical and observational insights for high-z galaxies where the most massive systems are not bright Ly α sources (Forero-Romero et al. 2012; Shapley et al. 2003).

4.1 Comparison against results from galaxy surveys

Theoretical interpretations of blind galaxy surveys at $z = 2.2$ find a volume weighted escape fraction $f_{\text{esc}} \sim 0.1 - 0.2$ Hayes et al. (2010), similar results are obtained in a recent theoretical study of observational data in a wide redshift range $0 < z < 6$ (Dijkstra & Jeeson-Daniel 2013).

Hayes et al. (2010) showed that the luminosity function for LAEs at $z = 2.2$ is consistent with the escape fraction being constant for every galaxy regardless of its luminosity. From this results they derive that almost 90% of the star forming galaxies emit insufficient Lyman α to be detected, effectively setting the occupation fraction to be $f_{\text{occ}} = 0.10$. Dijkstra & Jeeson-Daniel (2013) uses similar methods to find an average Ly α escape fraction in high-z galaxies, they conclude that there is a range in luminosity where the escape

fraction they derive at $z \sim 3.0$, $f_{\text{esc}} = (17 \pm 5)\%$, could be interpreted as an occupation fraction $f_{\text{occ}} \sim 0.2$.

We consider a success that our model indeed includes such low occupation fraction models. The observational evidence from galaxy surveys seem to disfavor the second family of models with high occupation fractions. Nevertheless, it remains a task for galaxy formation models to explain the mass range $\Delta M < 0.5$ in the models.

4.2 Comparison to other clustering estimates

Observational based on the ACF inferred from photometric measurements in the Extended Chandra Deep Field South have shown that the median dark matter masses of h los hosting LAEs is $\log_{10} M_{\text{med}} = 10.9^{+0.5}_{-0.9} M_{\odot}$, with a corresponding occupation fraction of $1 - 10\%$ (Gawiser et al. 2007). Our results are in a general good agreement with those estimates for the host mass. This is not completely unexpected given that we have also required consistency with ACF measurements.

The novelty in our approach is that we have a detailed estimate for host halo mass range together with the escape fraction. This allows us to demonstrate that the halo mass range could be very narrow $\Delta M < 0.2\text{dex}$, something that cannot be inferred from ACF analysis alone.

We also find that an ACF analysis on a single data-set is not enough to rule out models with a high occupation fraction $f_{\text{occ}} > 0.3$, which represent half of our best models. These models cannot be considered unfavorable based on a clustering analysis only, it requires additional information from galaxy surveys, as we have presented in the previous section.

Ouchi et al. (2010) presents an analysis of LAE observations in the redshift interval $3.1 < z < 7.0$. At $z = 3.1$ They quote an average mass for the host dark matter halos of $M_h = 2.9^{+24.0}_{-2.9} \times 10^{10} h^{-1} M_{\odot}$ with a corresponding duty cycle of 0.008 ± 0.03 . This broadly matches the expectations from the first family of models, also summarized in Table 1. In particular it seems to favor only the very low occupations fractions.

We conclude this section by noting that the uncertainties on the preferred masses in (Gawiser et al. 2007) and Ouchi et al. (2010) are found with in the intervals M_{min} and M_{max} of our models.

4.3 In the context of abundance matching models

The abundance matching methods are based on observational results for Lyman Break Galaxies (Behroozi et al. 2013b,a) (LBG). In the case of Behroozi et al. (2013b) the minimum halo mass considered to be relevant in their analysis is $10^{11.4} h^{-1} M_{\odot}$. They report stellar mass mass around $(1.0 \pm 0.3) \times 10^{9.0} h^{-1} M_{\odot}$, while their star formation rate is in the range $0.6 \pm 0.2 \text{ Msun yr}^{-1}$, which nevertheless are close to the lower bound of values inferred for LAEs at high redshift (Gawiser et al. 2007; Nilsson et al. 2009; Pentericci et al. 2009).

In our results, all the preferred models have a halo mass range lower than the minimum of $M_{\text{min}} < 10^{11.4} h^{-1} M_{\odot}$ considered in abundance matching at $z = 3$. This confirms once more the expectations that most of LAEs

$\log_{10} M_{\text{min}}$	$\log_{10} M_{\text{max}}$	f_{occ}	ΔM
10.1	10.2	0.1	0.1
10.3	10.5	0.1	0.2
10.4	10.7	0.1	0.3
10.5	10.6	0.3	0.1
10.5	10.9	0.1	0.4
10.5	11.0	0.1	0.5
10.6	11.2	0.1	0.6
10.6	11.4	0.1	0.8
10.6	11.7	0.1	1.1
10.7	11.0	0.2	0.3
10.8	11.2	0.2	0.4
10.8	11.3	0.2	0.5

Table 1. List of parameters for the first family of models. Narrow mass range $\Delta M \leq 1.0\text{dex}$ and low occupation fraction $f_{\text{occ}} \leq 0.3$.

$\log_{10} M_{\text{min}}$	$\log_{10} M_{\text{max}}$	f_{occ}	ΔM
10.6	10.7	0.4	0.1
10.8	10.9	0.6	0.1
10.8	11.0	0.4	0.2
10.9	11.0	0.8	0.1
10.9	11.0	0.9	0.1
10.9	11.1	0.5	0.2
11.0	11.1	1.0	0.1
11.1	11.3	0.8	0.2
11.2	11.6	0.6	0.4
11.2	12.2	0.5	1.0
11.3	11.7	0.9	0.4

Table 2. List of parameters for the second family of models. Narrow mass range $\Delta M \leq 1.0\text{dex}$ and high occupation fraction $f_{\text{occ}} > 0.3$.

are to be found in less massive halos LBG hosts. A detailed analysis of the spectral and photometric properties of LAEs coupled to the kind of analysis performed in this paper can be a guide in the study of the properties of low mass dark matter halos at $z = 3.1$, extending the capabilities of abundance matching methods.

4.4 Caveats of our method

There are two important caveats for the work presented here. The first is the assumption of a single LAE per dark matter halo. This contradicts the general expectation of dark matter sub-halos in the simulation to host satellite galaxies. However, it has been found in analysis based on the shape of the correlation function (Jose et al. 2013) that satellite galaxies are not a dominant population, making our initial approximation a reasonable one. Therefore we think that it is not crucial to include the effect of satellites in the model.

The second caveat are the precise values for the mass intervals. These numbers are defined from the halos defined in using the BDM halo finder with a density threshold of 200 times the critical density. Different halo finders and definitions for the detection density threshold can yield different masses up to a factor. For instance a Friends-of-Friends algorithm with linking lenght $l = 0.20$ times the average

interparticle distance finds halos on average 1.4 times more massive than BDM halos (Klypin et al. 2011). Therefore, the mass values for M_{\min} and M_{\max} should not be considered exact within less than ~ 0.2 dex.

4.5 On the reproducibility of our results

All the software, raw and processed data to produce the results and plots in this paper are publicly available in a github repository². Most of the code to produce the plots can be found as an Ipython notebook (Pérez & Granger 2007) in the same repository.

5 CONCLUSIONS

In this paper we look for constraints on the preferred mass and occupation fraction of dark matter halos hosting Lyman Alpha Emitters at redshift $z = 3.1$ in a Λ CDM cosmology. We perform this study paying special attention to the impact of cosmic variance on these results. To this end we build a large number of mock catalogs matching observational geometries. The mocks are constructed from a N-body simulation following a simple recipe to assign a single LAE to each halo. Only a fraction f_{occ} of halos with a mass range $M_{\min} < M_h < M_{\max}$ can host a LAE. We proceed with a thorough exploration of the space of free parameters M_{\min} , M_{\max} and f_{occ} to find mocks that are consistent with two observational constraints: the surface number density and the angular correlation function. Out of the initial 9000 combinations of parameters in the model we find 23 arrangements consistent with observations.

We find that the observational information we use is insufficient to impose a tight constraint on the escape fraction. On the other hand the minimum mass and maximum mass are tightly constrained as follows $M_{\max} < 10^{12} h^{-1} M_{\odot}$ and $10^{10} h^{-1} M_{\odot} \leq M_{\min} \leq 10^{11.5} h^{-1} M_{\odot}$. Furthermore, we find that the mass range defined as $\Delta M = \log_{10} M_{\max} - \log_{10} M_{\min}$ is always $\Delta M \leq 1.0$.

The wide range in solutions is facilitated by the large dispersion in the statistics derived from the mocks. Nevertheless, all the halo mass ranges and occupation fractions deduced previous analysis (i.e. Gawiser et al. 2007; Ouchi et al. 2010) are a subset of the models we find in this paper. All of our models support the notion that the most massive halos at $z = 3.1$ do not host the brightest LAEs.

The existence of a narrow mass range for halos hosting LAEs, $\Delta M \leq 1.0$ dex, has two different explanations at least. The first is having LAEs with a decreasing Ly α escape fraction with increasing mass, the second is having larger screening effects by neutral Hydrogen around the most massive systems (Laursen et al. 2009; Forero-Romero et al. 2011).

However, there are extreme cases with a very narrow $\Delta M < 0.3$, meaning that there is barely a factor of ~ 2 between the minimum and halo mass. If these models turn out to be confirmed, this would be a great challenge for galaxy formation models to explain how is that LAEs can be hosted in such a narrow range of halo mass.

In summary, we show how spatial information of LAEs cannot put a tight constraint on their host halos and occupation fraction. We foresee that the new observations with new instruments (such as MUSE, Hyper SuprimeCam and HETDEX) covering larger fields and a wider range of luminosities will be key in imposing tighter constraints on the properties of dark matter halos hosting LAEs. At the same time, additional modeling for Ly α radiation transfer, is needed to put a tighter constrain on the Ly α escape fraction in high redshift galaxies.

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² <https://github.com/forero/CosmicVarianceLAES>

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