Biasing and the distribution of dark matter haloes

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ABSTRACT
In hierarchical models of gravitational clustering, virialized haloes are biased tracers of the matter distribution. As discussed by Mo & White (1996), this bias is nonlinear and stochastic. They developed a model which allows one to write down analytic expressions for the mean of the bias relation, in the initial Lagrangian, and the evolved, Eulerian, spaces. We provide analytic expressions for the higher order moments as well.

In the initial Lagrangian space, each halo occupies a volume that is proportional to its mass. Haloes cannot overlap initially, so this gives rise to volume exclusion effects which can have important consequences for the halo distribution, particularly on scales smaller than that of a typical halo. Our model allows one to include these volume exclusion effects explicitly when computing the mean and higher order statistics of the Lagrangian space halo distribution. As a result of dynamical evolution, the spatial distribution of haloes in the evolved Eulerian space is likely to be different from that in the initial Lagrangian space. When combined with the Mo & White spherical collapse model, the model developed here allows one to quantify the evolution of the mean and scatter of the bias relation. We also show how their approach can be extended to compute the evolution, not just of the haloes, but of the dark matter distribution itself.

Biasing and its evolution depend on the initial power spectrum. Clustering from Poisson and white noise Gaussian initial conditions is treated in detail, since, in these cases, exact analytical results are available. We conjecture that these results can be easily extended to provide an approximate but accurate model for the biasing associated with clustering from more general Gaussian initial conditions. For all initial power spectra studied here, the model predictions for the Eulerian bias relation are in reasonable agreement with numerical simulations of hierarchical gravitational clustering for haloes of a wide range of masses, whereas the predictions for the corresponding Lagrangian space quantities are accurate only for massive haloes.

Key words: methods: analytical – galaxies: clusters: general – galaxies: formation – cosmology: theory – dark matter.

1 INTRODUCTION

In hierarchical models of gravitational clustering, it is possible to use the statistical properties of the initial density field, assumed to be Gaussian, to compute good approximations to the average number density of virialized objects at subsequent times (Press & Schechter 1974). In this paper, the number density of virialized objects will be called the unconstrained mass function. The statistical properties of the initial dark matter distribution can also be used to compute merger models which describe some aspects of how virialized haloes at a late time were assembled by mergers of smaller ones which, themselves, had virialized earlier (Bond et al. 1991). For example, the average number of $M_1$ haloes identified at $t_1$ that merged to form an $M_0$ halo by time $t_0$ can be computed (Lacey & Cole 1993, 1994). In this paper, this quantity will be called the constrained mass function.
white noise initial conditions (Sheth & Pitman 1997; Sheth & Lemson 1998).

In all these analyses, the number density of haloes was computed, but their spatial distribution was not. Recently, Mo & White (1996) described a model which uses the initial dark matter distribution to estimate the initial Lagrangian space distribution of dark matter haloes. Dynamical evolution is likely to modify this distribution, so that the distribution in the final Eulerian space is different from that initially. Mo & White also formulated a model for this evolution. In their model, statistical quantities in the Eulerian space are obtained by transforming the corresponding Lagrangian space quantities appropriately. In their model, then, the problem is to compute the Lagrangian space quantities, since, once these are known, the corresponding Eulerian quantities follow trivially.

In the Mo & White model, haloes are biased tracers of the underlying matter distribution, the bias between haloes and mass being, in general, nonlinear and stochastic. They showed that, on average, the bias relation depends only on the constrained and unconstrained mass functions, but that knowledge of the higher order moments of the merger history tree is required to compute the scatter around this mean correctly. Since they did not have an analytic model for the merger history tree, they were able to obtain analytic results for the scatter in the bias relation, or for the halo–halo correlation function, only in the limit of large separations. In this limit, the mean bias relation is linear, and the scatter around this relation is Poisson.

Since a halo in the Lagrangian space occupies a volume that is proportional to its mass, and since haloes do not overlap, the Lagrangian space halo distribution is a particular case of a hard-sphere model. As Mo & White discuss, the associated volume exclusion effects will introduce anticorrelations on scales smaller than that of a typical halo. On these scales, the scatter in the bias relation may well be less than Poisson. This paper combines some of the ideas contained in Mo & White (1996) with the analytic merger model of Sheth (1996) to provide a description of the evolution of the higher order moments of the halo distribution that incorporates these exclusion effects explicitly. Thus, within the context of the Mo–White model, the results presented here are valid even on the small scales where the mean bias relation is nonlinear.

Although the analytic merger tree described by Sheth (1996) was derived for the special case of Poisson initial conditions, it also describes the trees associated with white noise Gaussian initial conditions (e.g. Sheth & Pitman 1997). Sheth & Lemson (1998) showed that it could be used to derive reasonably accurate analytic approximations to the higher order moments of the merger tree distribution associated with more general Gaussian initial conditions. When combined with the Mo & White model, this allows us to write down analytic approximations for the higher order moments of, e.g. the bias relation, for more general Gaussian initial conditions, that should also be reasonably accurate.

This paper is organized as follows. The Lagrangian space halo distribution associated with white noise initial conditions is described in Section 2. This section also serves to set notation. The white noise results are extended to describe the Lagrangian space halo distribution in more general Gaussian random fields in Section 3. Section 4 contains a brief summary of the Mo & White spherical collapse model for computing Eulerian space quantities given the corresponding Lagrangian ones. It also shows how the model can be extended to compute the Eulerian space probability distribution function of the matter as well as the haloes. Section 5 shows the results of comparing the model predictions with the distribution of haloes identified in numerical simulations of gravitational clustering. This section also compares the model predictions for the stochasticity of the bias relation with what is measured in the simulations. A final section summarizes our results.

All the Lagrangian space results of this paper follow from results originally derived for haloes which form from Poisson initial conditions. Since these initial conditions are unfamiliar to most readers, the description of clustering from Poisson initial conditions is given in an Appendix. The Poisson case has the virtue that everything can be worked out rigorously, so readers interested in the various subtle issues involved in this approach are encouraged to read it.

2 WHITE-NOISE INITIAL CONDITIONS

This section provides a description of the initial halo distribution when the initial matter distribution is a white-noise Gaussian random field. Sections 2.1–2.3 summarize various known results. They are included to set notation, and to clarify the logic that leads to the final expressions. Section 2.4 provides analytic expressions for the higher order moments of the Lagrangian space halo distribution. These moments are related to the higher order moments of the bias relation, and are the principal new results of this paper.

2.1 Unconditional and conditional mass functions

To set notation it is useful to summarize various known results. Assume that the initial density field \( \delta \) is Gaussian, with power spectrum \( P(k) \). If the field is smoothed with a spherically symmetric filter of size \( V \), then the smoothed field \( \delta(V) \) is also Gaussian. This means that the one point probability distribution function is

\[
p(\delta, V) \, d\delta \equiv \frac{1}{\sqrt{2\pi S}} \exp \left( -\frac{\delta^2}{2S} \right) \, d\delta,
\]

where \( S \equiv \langle \delta(V)^2 \rangle \). That is,

\[
S \equiv \frac{1}{(2\pi)^2} \int_0^\infty 4\pi k^2 P(k) W^2(kR) \, dk,
\]

where \( W \) is the Fourier transform of the smoothing window, and \( V \propto R^3 \) with the constant of proportionality depending on the shape of the window. In this section we will mainly be concerned with a window which is a top hat in real space, for which \( W(x) = (3/x^3)[\sin(x) - x \cos(x)] \), and \( V = 4\pi R^3/3 \).

Let \( \bar{\rho} \) denote the average background density. If \( P(k) \propto k^n \), then \( S \propto (\bar{\rho}V)^{-n/3} \), where \( \alpha = (n + 3)/3 \). If \( n = 0 \) the random field is said to be white noise. The mass contained within the filter is \( M \equiv \bar{\rho}V (1 + \delta) \). Notice that when \( S \ll 1 \), then \( |\delta| \ll 1 \) almost surely. In this case, \( \delta < -1 \) is extremely unlikely, so there is no problem with defining the mass as was done above.

We will assume that \( S \ll 1 \) in the initial conditions, which we will sometimes call the Lagrangian space. Then, in
Lagrangian space, $|\delta| \ll 1$, so to lowest order in $\delta$, $M \equiv \bar{\rho}V$, and $S \propto M^{-\alpha}$. We will always be concerned with initial Gaussian fluctuation fields for which the relation between $S$ and $V$, and so the relation between $S$ and $M$ is monotonic. Thus, in Lagrangian space, $M$, $S$ and $V$ are all equivalent variables.

Most of the expressions associated with the excursion set approach concern properties of Gaussian random fields when they are smoothed on different scales. Here we will assume that the filter is a top hat in real space, and that the initial Lagrangian space distribution is Gaussian white noise. For white noise $\alpha = 1$, so $S = (\bar{\rho}V)^{-1}$, and the conditional probability that the field has value $\delta_1$ when smoothed on scale $V_1$, given that it had value $\delta_0$ when smoothed on scale $V_0$ is

$$p(\delta_1, V_1|\delta_0, V_0) = \frac{1}{\sqrt{2\pi(S_1 - S_0)}} \exp\left(-\frac{(\delta_1 - \delta_0)^2}{2(S_1 - S_0)}\right). \quad (3)$$

Let $q(\delta_1, \delta_0, V_0)$ denote the probability that, when smoothed on scale $V_0$, the density is $\delta_0$, and that it is less dense than $\delta_1$ for all $V > V_0$. Then

$$q(\delta_1, \delta_0, V_0) = p(\delta_0, V_0) \left[1 - \exp\left(-\frac{2\delta_1(\delta_1 - \delta_0)}{\delta_0}\right)\right], \quad (4)$$

provided $\delta_1 > \delta_0$, and it is equal to 0 otherwise (e.g. Chandrasekhar 1943). Of course, this means that $\delta < \delta_0$ as expected.

In the excursion set approach, virialized dark matter haloes are associated with isolated regions: these are those Lagrangian regions that, when smoothed on some scale $V$, are denser than some critical density, and when smoothed on still larger scales, are less dense than this (Bond et al. 1991). All the mass contained within this critically over-dense isolated $V$ is associated with a virialized halo. This required critical density is a function of time, but not of smoothing scale $V$. It decreases with increasing time: haloes that virialize at late times are associated with less dense isolated regions in Lagrangian space than haloes which virialize at early times. Let $\delta_\ast(z)$ denote this critical density, and let $f(M, \delta_\ast) dM$ denote the fraction of Lagrangian space that is taken up by volumes $V$ that have density $\delta_\ast(z)$ when smoothed on scale $V$, and are less dense on all larger scales, so that each such isolated $V$ is associated with a halo of mass $M$ that has just virialized at the epoch labelled by $z$. In Lagrangian space $S$, the mass $M$, and the associated volume $V$ are all equivalent variables, so $f(M, \delta_\ast) dM = f(S, \delta_\ast) dS$, and

$$f(S, \delta_\ast) dS = \frac{1}{\sqrt{2\pi S^{3/2}}} \exp\left(-\frac{\delta_\ast^2}{2S}\right) dS \quad (5)$$

(Bond et al. 1991). The associated number density of such isolated regions is the same as the number density of virialized objects, and is given by

$$n(M, \delta_\ast) dM = \frac{\bar{\rho}}{M} f(S, \delta_\ast) dS = \frac{\bar{\rho}}{M} f(M, \delta_\ast) dM. \quad (6)$$

This is sometimes called the unconstrained, or universal mass function (Press & Schechter 1974). Now, since $S$ and $M$ are equivalent variables, the integral of $f(S, \delta)$ over all $S$ is the same as the integral of $f(M, \delta)$ over all $M$. Equation (6) shows that this integral is unity. This can be interpreted as showing that associated with any given epoch $z$ is a partition of the total Lagrangian volume into isolated regions of volume $V$ and overdensity $\delta_\ast(z)$; the mass in each region $V$ first virializes to form a halo of mass $M = \bar{\rho}V$ at $z$.

Now consider some $\delta_1 \geq \delta_0$, where $\delta_1$ is a convenient notation for $\delta_\ast(z_1)$, and we have assumed that $z_1 > z_0$, so $z$ increases with decreasing epoch. Restrict attention to Lagrangian regions $V_0$ that are associated with $M_0$ haloes at the epoch $z_0$; i.e., isolated regions $V_0$. Consider one such isolated region. Suppose that when smoothed on the scale $V_1 \leq V_0$ this region is denser than $\delta_1$, and that it is less dense than this for all larger smoothing scales. Then $V_1$ is an isolated subregion within $V_0$; this isolated Lagrangian subregion $V_0$ can be associated with a subhalo $M_1$ of $M_0$; $M_1$ will first virialize at the epoch $z_1$. Let $f(M_1|M_0) dM_1$ denote the fraction of the mass of $M_0$ that, at the epoch $z_1$, is associated with subhalos $M_1$. Since $S$ and $M$ are equivalent variables, $f(M_1|M_0) dM_1 = f(S_1|\delta_0) dS_1$ where

$$f(S_1, \delta_1|\delta_0, \delta_0) dS_1 = \frac{1}{2\pi(S_1 - S_0)^{3/2}} \exp\left(-\frac{(\delta_1 - \delta_0)^2}{2(S_1 - S_0)}\right) dS_1 \quad (7)$$

(Bond et al. 1991; Lacey & Cole 1993). Integrating this over the range $0 \leq M_1 \leq M_0$ gives unity: all the mass of $M_0$ was in subclusters of some smaller mass at the earlier epoch $z_1 > z_0$. This fraction can be converted into a mean number of $M_1$ haloes within an $M_0$ halo:

$$N(M_1, \delta_1|M_0, \delta_0) = \frac{M_0}{M_1} f(M_1, \delta_1|M_0, \delta_0). \quad (8)$$

Since $M_0 = \bar{\rho}V_0$, we should divide $N(1|0)$ by $V_0$ to express it as a number density. Then comparison with equation (6) shows why this expression is sometimes called the constrained mass function. Equation (8) can also be understood as follows. For any given $z_1 > z_0$, the mass $M_0$ contained within an isolated Lagrangian region $V_0$ within which the average density is $\delta_0$, so the region first virializes at $z_0$, can be thought of as being partitioned into isolated subregions, each of slightly higher density $\delta_1$.

### 2.2 The first moment of the Lagrangian space halo distribution

The previous expressions mean that the mean number of $(M_1, \delta_1)$ haloes that are in randomly placed Lagrangian cells of size $V_0$ is $n(M_1, \delta_1) V_0$. Let $\bar{N}(M_1, \delta_1|\delta_0, \delta_0)$ denote the average number of $(M_1, \delta_1)$ haloes in a Lagrangian cell $V_0$ that has overdensity $\delta_0$. Then, by definition,

$$n(M_1, \delta_1) V_0 = \int_{-\infty}^{\infty} \bar{N}(M_1, \delta_1|\delta_0, \delta_0) p(\delta_0, V_0) d\delta_0. \quad (9)$$

Since mass and volume are equivalent variables, we will assume that $\bar{N}(1|0) = 0$ if $M_1 > M_0$. Below, we show that when $M_1 \leq M_0$, then $\bar{N}(1|0)$ is related to $\bar{N}(1|0)$, and that equation (8) is consistent with the results of the previous subsection.

Classify all cells $V_0$ by the overdensity within them. Each cell with density $\delta_0$ is either isolated or not. By definition, cells with $\delta_0 > \delta_1$ are not isolated. For cells that are not isolated, $\bar{N}(1|0) = 0$. Since there is no contribution from cells that are not isolated, to compute the average number.
of \((M_1, \delta_1)\) haloes, we now need to sum up the contribution from cells that are isolated.

If isolated, a cell can be partitioned into isolated subregions that are identified with \(\delta_1\) haloes. Label each such partition \(m\), where \(m\) lists the mass associated with each subregion. Let \(\pi(m)\) denote the set of all such partitions, and let \(p(m|M_0)\) denote the probability of having the particular partition \(m\) (we have not written explicitly that this probability will also depend on \(\delta_1\) and \(\delta_0\)). We must integrate over all partitions \(m\) of \((M_0, \delta_0)\) haloes, sum up the number \(n(M_1|m, M_0)\) of \((M_1, \delta_1)\) haloes in each partition, weight by the probability \(p(m|M_0)\) that that partition occurred, and then integrate over all values of \(\delta_0\), weighting by the probability that \(V_0\) with density \(\delta_0\) is isolated. The sum over partitions gives the average number of equation (8):

\[
\bar{N}(1|0) = \int_{\pi(m)} n(M_1|m, M_0) p(m|M_0) = \mathcal{N}(1|0),
\]

where the final equality follows because the integral over all partitions \(m\) of \(M\), so it is the definition of \(\mathcal{N}(1|0)\). This means that

\[
n(M_1, \delta_1) V_0 = \int_{-\infty}^{\delta_1} \bar{N}(1|0) \, q(\delta_1, \delta_0, V_0) \, d\delta_0,
\]

where the fact that only isolated cells give a nonzero contribution to the integral in equation (10) means that the upper limit in the integral over \(\delta_0\) must be \(\delta_1\), and that we must replace \(p(\delta_0, V_0)\) with \(q(\delta_1, \delta_0, V_0)\), the fraction of cells of density \(\delta_0\) that are isolated. Simple algebra shows that equations (8) and (10) when substituted into the right hand side of this expression, do satisfy this relation.

The main reason for writing this out explicitly is that it shows how one might begin to quantify the extent to which virialized haloes are biased tracers of the underlying matter distribution. We do this in the next section.

### 2.3 The mean bias relation and the cross correlation between haloes and mass

Let

\[
\Delta_m(1|0) = \frac{n(M_1|m, M_0)}{n(M_1, \delta_1)} V_0 - 1
\]

(12)

denote the average overdensity of \(M_1\) haloes within a \(M_0\) halo that is known to be partitioned into the haloes \(m\). Integrating this over all partitions gives

\[
\delta^L_{\delta_1}(1|0) = \int_{\pi(m)} d\Delta_m \, \Delta_m(1|0) \, p(m|M_0) = \frac{\mathcal{N}(1|0)}{n(M_1, \delta_1)} V_0 - 1.
\]

(13)

This gives the mean overdensity of \((M_1, \delta_1)\) haloes that are within \((M_0, \delta_0)\) haloes. It can also be understood as the mean overdensity of isolated \((M_1, \delta_1)\) regions that are within isolated \((M_0, \delta_0)\) regions in the Lagrangian space. In regions that are not isolated, (e.g., if \(\delta_0 > \delta_1\)) \(\delta^L_{\delta_1}(1|0) = -1\). Thus, \(\delta^L_{\delta_1}(1|0)\) is the same as the mean bias relation of equation (12) in Mo & White (1996). The peak background split (their equation 13) is obtained in the limit in which the cell size \(V_0\) is much larger than the Lagrangian size of an \(M_1\) halo (e.g. Bardeen et al. 1986).

\[
\delta^L_{\delta_1}(1|0) \to \frac{\nu^2}{\delta_1} - 1 \quad \delta_0 \equiv B(1|0) \delta_0,
\]

(14)

where \(\nu^2 = \delta_1^2 / S_1\), and the final equality defines \(B(1|0)\).

Notice that the mean overdensity of the halo distribution is a linear function of the mass overdensity only in the limit of equation (13). Equation (13) shows that, in general, this mean bias relation is nonlinear. Just as the mean bias relation depends on the mean number of haloes in Lagrangian cells \((M_0, \delta_0)\), the higher order moments of the Lagrangian bias relation depend on the higher order moments of the Lagrangian space halo distribution. We will compute these higher order moments in the next subsection. If these higher order moments are nonzero, then there will be some scatter around this mean bias relation: in addition to being nonlinear, the bias will be stochastic.

Before doing so, we will first calculate the Lagrangian space cross correlation between haloes and mass, averaged over all randomly placed Lagrangian cells \(V_0\). This is

\[
\xi_{\delta m}(M_1, \delta_1|V_0) = \left< \left( \frac{N(1|0)}{n(M_1, \delta_1) V_0} - 1 \right) \delta_0 \right> = \int_{-\infty}^{\delta_1} \mathcal{N}(1|0) \, \delta_0 \, p(\delta_0, V_0) \, d\delta_0.
\]

(15)

In the first line, the integral is over all Lagrangian cells, so the second equality follows since \(\delta_0 \equiv 0\). This integral is the sum of two terms, the first due to those Lagrangian cells that are isolated, and the second due to those that are not. However, \(\mathcal{N}(1|0) = 0\) for cells that are not isolated. For isolated cells, the contribution is computed by a double average, one over all values of \(\delta_0\) with the substitution \(p(\delta_0) \to q(\delta_0)\), and the other over all partitions of \(m\). The integral over partitions gives \(\mathcal{N}(1|0) = \mathcal{N}(1|0)\), so

\[
\xi_{\delta m}(M_1, \delta_1|V_0) = \int_{-\infty}^{\delta_1} \frac{\mathcal{N}(1|0)}{n(M_1, \delta_1)} \delta_0 \, q(\delta_1, \delta_0, V_0) \, d\delta_0.
\]

(16)

This expression for the cross correlation between haloes and mass is the same as equation (15) in Mo & White (1996), but with a difference in interpretation. As we have shown, the average is to be understood as being over all randomly placed Lagrangian cells \(V_0\), not just those that are less dense than \(\delta_1\).

The integral in (16) can be done analytically:

\[
\xi_{\delta m}(1|0) \equiv \frac{\xi_{\delta m}(1|0)}{S_0} = \frac{\delta_1}{S_0} - \frac{\nu^2 + 1}{\delta_1} \mathrm{erf} \left( \frac{\nu_0}{\sqrt{2}} \right) - \sqrt{\frac{2\nu_0}{\pi}} e^{-\nu^2/2} \delta_1,
\]

where

\[
\nu^2 = \frac{\delta_1^2 (S_1 - S_0)}{S_0 S_1}.
\]

(17)

When \(S_0 \ll 1\), then the error function tends to unity and the third term tends to zero. Thus,

\[
\xi_{\delta m}(1|0) \to \frac{1}{\delta_1} \left( \frac{\delta^2}{S_0} - \nu^2 - 1 \right) = B(1|0).
\]

(18)

This is consistent with using equation (14) for \(\delta^L_{\delta_1}(1|0)\) in equation (13) and substituting in (15).
2.4 Higher order moments of the bias relation and halo halo correlations

Suppose that there are \( n \) \( \delta_1 \) haloes within an \( \delta_0 \) halo. The Lagrangian volume associated with these haloes is \( n V_l \). The average overdensity of the remaining volume is

\[
1 + \delta^{(n)} = \frac{M_0 - nM_1}{V_0 - nV_l}, \quad \text{where} \quad \delta^{(n)} = \delta_0.
\]

(19)

Since \( M_1 = V_l (1 + \delta_1) \),

\[
\delta_1 - \delta^{(n)} = (\delta_1 - \delta_0) \frac{M_0}{M_0 - nM_1}
\]

(20)
to lowest order in the \( \delta \) terms. With this definition, the \( i \)th factorial moment is

\[
\phi_i(M_1, \delta_1 | M_0, \delta_0) = \prod_{n=0}^{i-1} N(M_1, \delta_1 | M_0 - nM_1, \delta^{(n)}),
\]

(21)

provided \( iM_1 \leq M_0 \), and it is zero otherwise. This formula is essentially a reworking of results originally in Sheth (1996). See Appendix A of this paper or Sheth & Lemson (1998) for details. Following the same logic as for the mean (the case \( i = 1 \)), the \( i \)th factorial moment of the corresponding halo counts in cells distribution is

\[
\int_{-\infty}^{\delta_1} \phi_i(M_1, \delta_1 | M_0, \delta_0) q(\delta_1, \delta_0, V_0) \, d\delta_0
\]

\[
\equiv \left( n(M_1, \delta_1, V_0) \right)^{i} \left( 1 + \Xi(M_1, \delta_1, V_0) \right),
\]

(22)

where the final equality defines \( \Xi(M_1, \delta_1, V_0) \). If the scatter of halo counts were Poisson, then \( \Xi = 0 \). For \( i > 1 \), equation (22) can be solved analytically. For example, when \( i \) is even, then it reduces to a sum of incomplete Gamma functions. Thus, it is possible to show explicitly that the scatter is not Poisson.

Recall that the scatter in the bias relation is related to the higher order moments of the halo distribution. For example, the variance in the bias relation is essentially the same as the variance in the halo distribution. In general, this variance is neither zero, nor is it the same as the mean. In other words, the mean bias is non-linear, it is stochastic, and the rms scatter around the mean is not the canonical square-root-of-the-mean value that is typical of a Poisson distribution. To see why, we turn now to a more detailed study of the halo halo correlation functions.

Define

\[
\omega \equiv \frac{\nu_{\text{rem}}}{2s_0}, \quad \text{where} \quad \nu_{\text{rem}} \equiv 1 - \frac{S(M_0)}{S(M_1)} \quad \text{and} \quad s_0 \equiv \frac{\delta_1^2}{S_0},
\]

(23)

with \( S_0 \equiv S(M_0) \). These two parameters have simple physical interpretations. An \((M_1, \delta_1)\)-halo occupies a volume \( V_l \) in the initial Lagrangian space, and, by assumption, all the mass within \( V_l \) is associated with \( M_1 \). That is, haloes are spatially exclusive; they do not overlap with other. If a randomly placed \( V_0 \) contains \( i \) haloes, each of initial size \( V_l \), then \( \nu_{\text{rem}} \) is related to the fraction of \( V_0 \) that is not occupied by these haloes. Since \( M_0 \propto V_0 \), \( S_0 \) expresses the cell size \( V_0 \) in units of the (Lagrangian) size of typical haloes at time \( \delta_1 \), since the usual definition of a typical \( M_1 \) halo is that \( \delta_1 \equiv S_1 \) is associated with a typical \( M_1 \) halo that is \( \delta_1/S_1 \equiv \delta_1/S(M_1) \equiv 1 \).

For white noise, \( \Xi(M_1, \delta_1, V_0) \) is not a function of \( M_1 \), \( \delta_1 \), and \( V_0 \), individually, but only of \( \nu_{\text{rem}} \) and \( s_0 \). Thus, \( \Xi(M_1, \delta_1, V_0) \) has a self-similar form; for haloes defined at a given \( \delta_1 \), it depends only on the cell size relative to the size of typical objects with the same \( \delta_1 \), and on the size of the objects being measured relative to the cell size. Let \( \tilde{\xi}_{\text{hh}}^{\perp}(11|0) \equiv \Xi_2(M_1, \delta_1, V_0) \). Note that this means that \( \tilde{\xi}_{\text{hh}}^{\perp}(11|0) \) denotes the volume average of the halo-halo correlation function. It is related to \( \xi_{\text{hh}}^{\perp} \) itself by the relation

\[
\tilde{\xi}_{\text{hh}}^{\perp}(11|0) = \frac{3}{R_0^2} \int_0^{R_0} \xi_{\text{hh}}^{\perp}(r) r^2 \, dr.
\]

This volume average is the variance of halo counts in Lagrangian cells of size \( V_0 \) divided by the square of the mean number of halo counts, minus the shotnoise contribution, \( 1/M_0 \) which accounts for the fact that the haloes are discrete objects. Equation (22) implies that

\[
1 + \tilde{\xi}_{\text{hh}}^{\perp}(11|0) = \frac{2s_0}{\sqrt{\pi} \omega} \left[ \sqrt{\omega} e^{-\omega} + \frac{[\omega + 0.5] \gamma (0.5, \omega)}{\gamma (0.5, \omega)} \right].
\]

(24)

If \( c(M_1, M_2, \delta_1 | M_0, \delta_0) \) denotes the cross correlation between \( M_1 \) and \( M_2 \) haloes, each with initial overdensity \( \delta_1 \), that are both within the same \( M_0 \) halo of initial overdensity \( \delta_0 \), then the same logic that led to equation (2) implies that

\[
c(M_1, M_2, \delta_1 | M_0, \delta_0) \equiv \left( n(M_1, \delta_1, V_0) \right)^{M_1} \left( n(M_2, \delta_1, V_0) \right)^{M_2} q(\delta_1, \delta_0, V_0) \, d\delta_0.
\]

(25)

where \( \delta^{(1)} \) was defined earlier (equation [2]). The volume averaged cross correlation function is got by averaging \( c(12|0) \) over all isolated volumes \( V_0 \):
large, they are not affected by the fact that some of the volume is excluded. Suppose that, on scales larger than $2V$, these haloes were uncorrelated with each other. Then $\xi_{hh}^L = -1$ on small scales, and $\xi_{hh}^L = 0$ on larger scales, so that on large scales the volume average is $\bar{\xi}_{hh}^L(m|V_0) \propto -2V/V_0$. This gives approximately the same qualitative behaviour as the limiting relation (24). Namely, $\xi_{hh}^L$ is always negative, and it becomes less negative with increasing scale $\nu$.

Less massive haloes have $w < 1$. These haloes are affected by the excluded volume, since a large fraction of the volume they could have occupied is now excluded. This means that they must all be crowded into the remaining volume, so over a range of scales, they will appear to be correlated with each other. Thus, for white noise initial conditions, volume exclusion produces two effects. Firstly, all haloes are anti-correlated on scales smaller than that which they occupy. Secondly, less massive haloes are positively correlated on intermediate scales, whereas more massive haloes are essentially uncorrelated on all scales larger than those which they occupy. Thus, on small scales, and for less massive haloes, volume exclusion gives rise to effects which are in the opposite sense to the commonly held view that less massive haloes are also less correlated.

2.5 The large-volume limit

Before moving on to consider more general initial conditions than white-noise, it is useful to write down the large scale limits of the Lagrangian space halo-halo correlation functions.

When $M_0 \gg (M_1 + M_2)$ and $\delta_0 < \delta_1$, then use of the asymptotic expansion of the error function reduces equation (24) to

$$\xi_{hh}^L(12(0)) \rightarrow \left[ B(1|0) B(2|0) - \frac{\nu_1^2 \nu_2^2}{\delta_1^2} \right] S_0,$$

where $\nu_2^2$ and $B(2|0)$ are defined similarly to $\nu_1^2$ and $B(1|0)$ (cf. equation 14). Since the factor $(\nu_1 \nu_2 / \delta_1)^2$ is not necessary small, this limiting form shows that volume exclusion effects are important, even on large scales, for massive haloes. In fact, in this limit $\xi_{hh}^L(12(0))/S_0 \rightarrow (1 - \nu_1^2 - \nu_2^2)/\delta_1^2$, so massive haloes are less clustered than less massive haloes on all scales.

For $n > 2$, define

$$H_n \equiv \bar{\xi}_n^{L-1}, \quad \text{where } \bar{\xi}_2 \equiv \xi_{hh}^L,$$

and $\bar{\xi}_n$ denotes the volume average of the $n$-point Lagrangian space correlation function of haloes that have the same mass. It is usual to use $S_n$ to denote the corresponding ratios of the mass correlation functions; for a Gaussian random field, $S_n = 0$. In the large volume limit, $\bar{\xi}_2 = (S_0/\delta_1^4) (1 - 2\nu^4)$, where $\nu$ is related to the halo mass (equation 14). In this limit, equation (22) with the asymptotic expansion of the error function yields

$$H_3 \rightarrow \frac{9\nu^2 (\nu^2 - 1)}{(1 - 2\nu^2)^2},$$

$$H_4 \rightarrow \frac{4\nu^4 (-3 + 24\nu^2 - 16\nu^4)}{(1 - 2\nu^2)^4},$$

$$H_5 \rightarrow \frac{125\nu^4 (3 - 10\nu^2 + 5\nu^4)}{(1 - 2\nu^2)^6}.$$

For massive haloes in this large cell limit

$$H_n \rightarrow (n/2)^{n-1} \quad \text{when } \nu \gg 1.$$

These values are smaller than those associated with high peaks in a Gaussian random field, for which $H_n = n^{n-2}$. This is a consequence of volume exclusion. (For volume exclusion effects associated with peaks, see Coles 1986 and Lumsden, Heavens & Peacock 1989.) It is interesting that these values are just those associated with the Poisson limit of the Generalized Poisson distribution (see, e.g., Saslaw & Sheth 1993). Thus, equation (30) shows that, when smoothed on large scales, the Lagrangian space distribution of massive haloes is Poisson.

3 GENERIC GAUSSIAN INITIAL CONDITIONS

Section 2 provided expressions for the constrained and unconstrained halo mass functions, and for the moments of the halo counts in cells distribution, for the special case of white noise initial conditions. It is known that for more general Gaussian initial conditions [i.e., the initial power spectrum differs from $P(k) \propto k^n$], the constrained and unconstrained mass functions have the same form as the white noise functions, provided that all quantities are written in terms of the variance, defined by equation (9). That is, the unconditional and conditional mass functions for different initial power spectra differ only because the transformation from variance to mass depends on the initial power spectrum. For example, if $P(k) \propto k^n$, then $S(M) \propto R^{-n+3} \propto M^{-(n+3)/3}$, where we have used the additional fact that in Lagrangian space $M$ and $V$ are equivalent variables. Recall that white noise has $n = 0$, so in the previous section $S \propto 1/M$.

This section assumes that what works for the mass functions works for the counts in cells distributions also. That is, expressions for the moments of halo distribution, when

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written in terms of the variance, are assumed to have the same form for all power spectra. There is no compelling reason why this should be so. For example, the form of equation (23) follows from the mutual independence of disconnected subvolumes. While this is a reasonable assumption for white noise initial conditions, it is almost certainly wrong for other power spectra. Nevertheless, the hope is that those correlations between neighbouring volumes which are ignored when using equation (23) to estimate halo-halo correlations will not make a crucial difference to the final answer, for reasons discussed by Bower (1991). Moreover, Sheth & Lemson (1998) showed that this simple model for the higher order moments associated with the forest of merger history trees is in reasonably good agreement with the results of numerical simulations, even when the initial distribution is quite different from white noise. Since it is these same higher order moments that one uses to estimate halo-halo correlations, their results suggest that this simple model should be reasonably accurate here as well.

Another way to see why this conjecture should be accurate is the following. The correlation function of haloes of two different masses is the product of the mean number of haloes of each of the two mass ranges times one plus the halo-halo correlation function. In principle, all three terms depend on power spectrum, although we only know this dependence for the two mean terms, and not for the correlation function. In the white-noise case, were it not for volume exclusion, this correlation term would be zero. For other initial power spectra, our conjecture means that we adjust the two mean terms correctly, and assume that most of the contribution to the correlation term comes from volume exclusion effects. This means that our conjecture does correctly account for some, if not most, of the dependence of the correlation function and other higher order moments on the initial power spectrum. 

The integral (equation (26)) for the cross correlation between haloes of mass $M_1$ and $M_2$, that one obtains by ignoring these correlations can be solved analytically. The final expression is lengthy, so we have not written it out below. In the limit of large cells, i.e., $M_0 \gg (M_1 + M_2)$,

$$\bar{\xi}_{hh}(12(0)) \to B(1|0)B(2|0) S_0 + \text{correction terms, } (31)$$

provided $\delta_1 > \delta_0$. In general, the correction terms are not as simple as in the white noise case, so we have not written them down explicitly.

In general, the full expression for halo-halo correlations differs from the white-noise expression in three significant ways. Firstly, $N(2|0)N(1|0) = N(1|20)N(2|0)$ only when $M_0$ is much greater than either $M_1$ or $M_2$. This implies that, in general, equation (23) should be replaced with either $c(2|10) = \bar{N}(2|10)\bar{N}(1|0)$, or $c(1|20)$, where $N(2|10)$ is understood as the average number of $M_2$ haloes within those $M_0$ haloes that are known to have an $M_1$ halo in their central volume element. The lack of spatial correlations for a white-noise spectrum meant that there, this restriction was irrelevant. Here, however, this means that $\bar{\xi}_{bh}(12(0))$ and $\bar{\xi}_{bh}(21|0)$ computed using equation (24) are no longer equivalent.

Secondly, the halo-halo correlations depend on the masses of the haloes themselves, rather than just their sum. This suggests that volume exclusion effects are not the sole cause of halo correlations. Thirdly, provided $S$ varies as some inverse power of scale, then, in the limit of large separations, sufficiently high mass haloes are more correlated than low mass haloes. The correlation function of peaks in Gaussian random fields is known to depend exponentially on peak height (e.g., Bardeen et al. 1986; Jensen & Szalay 1986; Lumsden, Heavens & Peacock 1989; Regös & Szalay 1995). If high mass haloes correspond to high peaks in the initial density field, then this result is qualitatively similar to that for peaks. The agreement with the peaks results is only qualitative. For example, just as in the white-noise case, the higher-order moments of the spatial distribution of massive haloes is different from that of high peaks.

Figures 2 and 3 show the volume average of the halo-halo correlation function, $\xi_{hh}^{CL}(11|0)$, given by equation (24), as a function of cell size $V_0$, when the initial power spectrum has slope $n = -1$. The different curves are for haloes with mass $m_1 = s_1^{-3/2}$, and $s_1 = 2^{-1.6}, 2^{-1.66}, 2^{1.33}, 1, 2^{-1.33}$ and $2^{-2.66}$, respectively.
haloes less massive than \(M\) are positively correlated on intermediate scales, and on scales larger than about 4 \(v_1\), \(\xi_{\text{bh}}^\ell(11|0)/s_0 \approx \) constant. On sufficiently large scales, haloes that are more massive than \(\sim M\) are more correlated than less massive haloes.

4 THE HALO DISTRIBUTION IN EULERIAN SPACE

The previous sections showed how to quantify the difference between the halo and matter distributions in Lagrangian space. Dynamical evolution changes these distributions, so the bias between haloes and mass in Eulerian space is likely to be different from that initially.

Mo & White (1996) argued that the bias relation in Eulerian space, i.e., the mean overdensity of \(\delta_1\)-haloes that are more massive than \(\sim M\), are in spheres with comoving volume \(V\) which contain mass \(M_0\) at \(z\), so they have Eulerian overdensity

\[
\Delta \equiv 1 + \delta \equiv M_0 / \rho V, \tag{32}
\]

should be

\[
\delta_{\text{E}}(1|0) = \frac{\bar{N}(M_1, \delta_1|M_0, \delta_0)}{n(M_1, \delta_1)V} - 1, \tag{33}
\]

where \(\bar{N}(1|0)\) is given by the (Lagrangian) equation \(\xi_{\text{bh}}\), but with

\[
\delta_0 = \frac{1}{1 + z'} = 1.65 - \frac{1.35}{\Delta_2^3} + 0.78 \frac{1.124}{\Delta_2^{1.5}}. \tag{34}
\]

Therefore, in their model, expressions for the higher order moments of the bias relation in the Eulerian space can be obtained by transforming the corresponding Lagrangian expressions similarly. We will use this fact below.

Let \(p(M_0|V, z)\) denote the probability that an Eulerian cell \(V\) contains mass in the range \(dM_0\) of \(M_0\) at \(z\). We will sometimes call this the Eulerian probability distribution function. Of course, \(p(M_0|V, z)\) d\(M_0\) = \(p(\Delta|V, z)\) d\(\Delta\) and

\[
\int_0^\infty p(\Delta|V, z)\ d\Delta = \int_0^\infty \Delta \ p(\Delta|V, z)\ d\Delta = 1. \tag{35}
\]

Let \(\bar{N}(M_1, \delta_1|M_0, V, z)\) denote the average number of \((M_1, \delta_1)\)-haloes in such a cell. Then the average number of haloes in Eulerian cells of size \(V\) is

\[
n(M_1, \delta_1)V \equiv \int_0^\infty \bar{N}(M_1, \delta_1|M_0, V)\ p(M_0|V)\ dM_0, \tag{36}
\]

where we have not bothered to write the dependence on \(z\) explicitly. This is the analogue of the Lagrangian relation \(\xi_{\text{bh}}\).

Suppose we assume that

\[
\bar{N}(M_1, \delta_1|M_0, V, z) = \bar{N}(M_1, \delta_1|M_0, \delta_0), \tag{37}
\]

where \(\delta_0\) is given by equation (34). That is, the average number of haloes in Eulerian cells of size \(V\) that contain mass \(M_0\) is assumed to be the same as the average number of haloes in Lagrangian cells \(M_0\) that, because they originally had overdensity \(\delta_0(\Delta)\), have size \(V\) at \(z\). Then equation (36) implies that

\[
f(M_1, \delta_1) = \int_{M_1}^\infty f(M_1, \delta_1|M_0, \delta_0) \ \Delta \ p(M_0|V)\ dM_0, \tag{38}
\]

where \(\delta_0\) is given by equation (34), and again, we have not written the \(z\) dependence explicitly. The lower limit of the integral has been set to \(M_1\) since, in the spherical collapse model which gives equation (34), the Eulerian radius of a collapsed halo is zero. This means that if an Eulerian cell \(V\) contains an \((M_1, \delta_1)\)-halo, then it must contain all of the halo’s mass, so it must have \(M_0 \geq M_1\).

Equation (38) is interesting for the following reason. The term on the left hand side, \(f(M_1, \delta_1)\) is known. If the Eulerian cell size \(V\) is given, then \(f(M_1, \delta_1|M_0, \delta_0)\) is also known, for all \(M_0\). Only the Eulerian probability distribution \(p(M_0|V)\) is not known. Therefore, equation (38) is an integral equation of the first kind, so it can be solved numerically to yield \(p(M_0|V)\) d\(M_0\).

That is, for any Eulerian cell size \(V\), the assumption (37) allows one to solve for the Eulerian probability distribution function that is associated with the spherical collapse model as parametrized by equation (34). Once \(p(M_0|V)\) is known, repeated use of the assumption (37) allows one to compute

\[
\xi_{\text{bh}} E(M_1, \delta_1|V) = \left< \delta_{\text{E}}(1|0) \right>^\ell
\]

\[
= \int_0^\infty \delta_{\text{E}}(1|0) \ \delta p(M_0|V)\ dM_0, \tag{39}
\]

where \((1 + \delta) \equiv M_0/\rho V\). Notice that this resembles the Lagrangian relation (16). Similarly,

\[
1 + \xi_{\text{bh}} E(M_1, M_2, \delta_1|V) = \int_0^\infty \frac{c(M_1, M_2, \delta_1|M_0, \delta_0)}{n(M_1, \delta_1) V n(M_2, \delta_1) V} \ p(M_0|V)\ dM_0, \tag{40}
\]

where \(c(12) = N(1|0) N(2|10)\) is the Lagrangian relation (24), with \(\delta_0\) given by equation (34).

Our approach extends that of Mo & White (1996). They wrote down equations (30) and (40), though they did not have an expression for \(c(12)\). However, they did not write down equation (38), so they did not know how to solve for the Eulerian \(p(M_0|V)\). Therefore, they assumed that they could use the one measured in their simulations. Strictly speaking, this is not permitted, since there is no guarantee that then equation (38) is satisfied, as it should. Indeed, if one substitutes the Lognormal distribution for \(p(M_0|V)\) (as Mo & White did) into this formula, then one finds that, in general, this normalization requirement is not satisfied (though Mo & White do not mention this). Nevertheless, if the spherical model is a good approximation to what actually happens in the simulations, then there is some hope that using the actual \(p(M_0|V)\) distribution measured in the simulations will, indeed, give the correct normalization. (Also see Sheth 1998 for more discussion of this point.)

Below, when we compare our results with simulations, we will show that the Mo & White approach is reasonably well normalized on large scales. So, although we should first determine the Eulerian \(p(M_0|V)\) using the integral equation (38), and then we should use it to compute \(\xi_{\text{bh}} E\) and \(\xi_{\text{bl}}\) self-consistently, in what follows, we will not.

Mo & White mainly considered the case in which the time at which the haloes first virialized \(a_1\), and that when their spatial distribution was studied \(a_0\), were the same. They also studied the spatial distribution of haloes at epochs later than those at which the haloes had virialized \((a_0 \geq a_1)\). In both these cases, the previous formulae are correct if
\[ \delta_1 = 1.68647 \left( \frac{a_0}{a_1} \right) \] and \( \delta_0 \) is given by equation (12) with \( z = 0 \). Thus, \( \delta_1 > \delta_0 \) is always satisfied.

In principle, it should also be possible to use the spherical model to describe the distribution of the haloes at high redshift, prior to virialization. The spatial distribution at some early time \( z_1 \) of haloes that will virialize at the present \( z = 0 \), is described by the previous expressions, but with the appropriate value of \( z = z_1 \) in equation (12). This means that we need to know the Eulerian distribution function as a function of \( z \). For example, for haloes that virialize at \( z = 0 \), \( \delta_1 = 1.68647 \), so it is possible that \( \delta_0 > \delta_1 \). In the language of the previous sections, such Eulerian cells are not isolated. So, in principle, we need to be able to compute the probability that an Eulerian cell is isolated. In general, this is difficult. Fortunately, things simplify when \( z \gg 1 \): in this limit \( S \ll 1 \), most fluctuations are small \( \langle |\delta| \rangle \ll 1 \), and the Eulerian distribution function tends to a Gaussian. So, in this limit, this procedure reduces to the Lagrangian description of the previous sections. It is also reassuring that, in this limit, the spherical model expressions reduce to those expected using linear theory (Section 19 in Peebles 1980). We will use this fact below.

5 COMPARISON WITH SIMULATIONS

This section shows the results of comparing the model predictions obtained in the previous sections to the halo distributions measured in numerical simulations of clustering. This is done in two steps. First, the theoretical bias relation, \( \delta_0(1)(0) \), and the scatter around this relation, are compared with those found in the simulations. Then the theoretical halo-mass and halo-halo correlation functions are compared with those in the simulations, since these are essentially weighted integrals over the bias relations. We do this in Lagrangian space, and then in Eulerian space.

The simulations used here are the same as those used by Mo & White (1996), where they are described in more detail. They follow the evolution of \( 10^5 \) identical particles in a cubic box with periodic boundary conditions. If the volume \( L^3 \) of the box, the mass \( m \) per particle, and the initial expansion factor \( a \) are all set to unity, then the simulations are normalized so that \( S(M) = M^{-(n+3)/3} \) initially, where \( n \) is the initial slope of the power spectrum. The characteristic mass \( M_s(a) \) at the expansion time \( a \) is given by \( S(M_s) = (\delta_c/a)^2 \), for some \( \delta_c \) which is determined by fitting the unconditional mass function of equation (1) to the mass function of bound objects identified in the simulations. The group identification algorithm used here is the same friends-of-friends algorithm used by Mo & White, as are the methods for assigning Lagrangian and Eulerian positions to a group identified at any given time. As for the simulations studied by Lacey & Cole (1994), the mass function of bound objects in these simulations is fit, to within a factor of two or so, by equation (12) with \( \delta_c = 1.7 \). This value is used to compute all the theoretical curves shown below.

The main complication in comparing the theory to simulations is that of the finite mass resolution in the simulations. This means that, in practice, correlations between haloes are measured for a range of masses. This has an important consequence, since now, the distribution of isolated regions is different from that of the centre-of-mass distri-

![Figure 4](image-url) The Lagrangian space probability distribution function \( P(\delta) \) as a function of overdensity \( \delta \). Each panel shows four choices of scale \( R/L = 0.02 \) (broadest curves), 0.4, 0.8 and 0.16 (narrowest curves). Histograms show the distribution measured in the simulations; thin dashed curves show Gaussian distributions, and thicker solid curves show Generalized Inverse Gaussian fitting functions (equation 4), that have the same variance.

This means that the mean bias relation is

\[ \delta_0(> m|0) \equiv N(> m, \delta_1 | M_0, \delta_0) / n(> m, \delta_1) V_0 = 1, \] (41)

where

\[ n(> m, \delta_1) = \int_m^{\infty} n(M_1, \delta_1) \, dM_1, \]
and

\[ N(> m, \delta_1 | M_0, \delta_0) = \int_m^{M_1} N(M_1, \delta_1 | M_0, \delta_0) \, dM_1, \]

provided \( M_1 \leq M_0 \) and \( \delta_1 \geq \delta_0 \). In the Eulerian space, \( M_0 \) and \( \delta_0 \) are obtained from \( V \) and \( \delta \) as described in Section 4.

This quantity depends only on the first moment of the subclump distribution. Although it could have been computed by Mo & White (1996), they did not show it. The scatter in this relation depends on the second order moment, so, although they were unable to compute it, we can.

There are additional reasons why it is not entirely straightforward to compare the theory with simulations. For example, the average number density of haloes (the unconditional mass function), and the average number of subhaloes within haloes (the conditional mass function) in the simulations are, typically, described by the theory only to within a factor of two or so. Also, on small scales in particular, the initial particle distribution in the simulations is not par-
particularly Gaussian when the initial power on large scales is significant (see Fig. 4). Since the bias relations are essentially the ratio of the conditional to the unconditional mass functions, they are sensitive to the first of these discrepancies. The integrals which define $\delta_{\text{lin}}$ and $\delta_{\text{GIG}}$ are also sensitive to the shape of the initial probability distribution function, so they are sensitive to both these discrepancies.

Finally, there is some uncertainty regarding how the initial particle load in the simulations should be treated. This freedom arises because the initial particle distribution is not the true Lagrangian distribution, but a linearly evolved version of it. This means that, when comparing the Lagrangian theory with the simulations, we must account for the fact that cell sizes in the initial distribution are not the same as the associated Lagrangian size. Though they do not say so in their paper, Mo & White (1996) treated this problem as follows (private communication). They used equation (32) to rescale the size of each cell in the simulations, and then used this rescaled size in the denominator that defines $\delta_{\text{lin}}$, but nowhere else. They then used this value of $\delta_{\text{lin}}$ when averaging over all cells to determine what they called the Lagrangian $\delta_{\text{lin}}$.

We have chosen the following procedure. We treat the initial particle distribution no differently from any other output time in the simulations. This means that we plot the simulation results exactly as measured, with no rescaling. We then compare these to our theoretical Eulerian expressions, transformed according to the spherical model to the appropriate redshift. Recall that, in the limit of small initial fluctuations, this is the same as using linear theory to make the necessary corrections (Section 19 of Peebles 1980). The complication is that, in this case, the associated $p(\delta)$ distribution is no longer Gaussian, so the distribution corresponding to $q$ is no longer known. Nevertheless, if $p(\delta)$ is sufficiently close to Gaussian, then using $q$ should be a good approximation. We find that the Generalized Inverse Gaussian distributions (described in Section 5.3 below) provide reasonable fits to the counts in cells distributions measured in the simulations for a wide range of scales and output times, so we use them for $p(\delta)$.

5.1 Biasing in Lagrangian space

This subsection compares the bias relation between haloes and mass measured in the simulations in the Lagrangian space with the theoretical model developed in the previous sections.

Figs. 5, 6, 7 show the bias relation for haloes containing more than $m = 32$ particles, identified in simulations with initial power spectra having slope $n$ at an expansion factor $a$ since the initial time, and for four representative choices of the spherical cell radius: $R/L = 0.02$, 0.04, 0.08, and 0.16. For each cell size, statistics were averaged over 27,000 spherical cells. The histogram which rises from the bottom left to the top right of each panel shows the cumulative distribution function of the matter fluctuation $\delta_m$. This curve is intended to show the range of $\delta_m$ over which the simulations are able to provide a good test of the theory. The thin solid line through each histogram shows the corresponding Generalized Inverse Gaussian. The large filled circles show the mean bias relation measured in the simulations, smaller filled circles show the rms fluctuations around this mean, and the open circles show the expected Poisson fluctuation given the mean. In most cases, the rms fluctuations are smaller than the Poisson value; this shows that volume exclusion effects are important. The thickest solid curve shows the mean bias relation predicted by the model, the less thick solid curves show the theoretical rms fluctuation around this mean, and the dashed curves show the value if the fluctuations were Poisson.

Fig. 5 is extremely encouraging. The theory is able to describe the mean bias relation, $\langle \delta_h(\delta_m) \rangle$, as well as the scatter in this relation well, even when the scatter is less than Poisson (though, for haloes of this mass range, the difference from Poisson scatter is small). That is, the theory appears to describe the effects of volume exclusion on the halo distribution well. Figs. 6 and 7 are intended to show that the theory must be used with some caution. These figures show the bias relation associated with haloes identified at a later time than those in Fig. 5. Since $M_* \equiv (a/\delta)^3$ for white noise, $M_* \approx 13$ for the haloes in Fig. 5, whereas $M_* \approx 470$ for the haloes in Figs. 6 and 7. At the later output time, the theory gets the mean of the Lagrangian bias relation wrong, although the scatter around the mean is still qualitatively correct, when the minimum mass $m = 32$. For haloes more

![Figure 5. The Lagrangian space bias relation for haloes which contain more than $m = 32$ particles that form from white noise initial conditions. Plot shows the mean overdensity of haloes $\delta_h(\delta_m)$ as a function of the overdensity of mass $\delta_m$ in spherical cells of radius $R$, as well as the scatter around the mean. Symbols show quantities measured in the simulations: large filled circles show the mean, smaller filled circles show the rms scatter, and open circles show the scatter if the halo counts were Poisson. Solid curves show the model predictions, dashed curves show the Poisson scatter corresponding to the theoretical mean. Haloes were identified at an expansion factor of $a = 6.1$; the bias relation was computed from the halo-centre-of-mass and mass distributions at the initial time $a = 1$. The histograms that rise from left to right in each panel show the cumulative counts-in-cells distribution. The simulations provide a good test of the theory only in the range where this cumulative curve is steep.](image-url)
Biasing and the distribution of dark matter haloes

Figure 6. The same as the previous Figure, i.e., $n = 0$ and $m = 32$, but now $a = 36.9$.

Figure 7. The same as the previous Figure, i.e., $n = 0$ and $a = 36.9$, but now $m = 256$.

Figure 8. The same as the previous Figure, but for $n = -1.5$, $m = 32$ and $a = 6.07$.

Figure 9. The same as the previous Figure, i.e., $n = -1.5$ and $a = 6.07$ but now $m = 256$.

massive than $m = 256$, however, the theory is accurate, in the mean, and for the scatter.

Thus, these figures show that the theory is relatively accurate when describing the distribution of haloes more massive than $\sim M_\star$, but not of less massive haloes. This suggests that the spherical model is a good description of the collapse of massive haloes, but that the formation and evolution of less massive haloes may be more complicated.

Figs. 6 and 7 show that the theory works even when the initial conditions are different from white noise. These figures were constructed from haloes identified at an expansion factor $a = 6.1$ in a simulation in which the initial power spectrum had slope $n = -1.5$. So, for these figures, $M_\star \approx 163$. Again, the bias relation associated with massive haloes is well described by the theory (Fig. 9), whereas that of the less massive haloes is not (Fig. 8).

Before concluding this subsection, it is worth noting that the theoretical curves for the mean bias relation become increasingly different from the simulation results as $R$ decreases. Although the mean relation on these smaller scales is different, the predicted scatter around the mean shows the same qualitative behaviour as that measured. We have not shown curves for smaller $R$ here, since on these smaller scales it is not clear how much of the discrepancy in the mean is due to limitations associated with the finite number of particles in the numerical simulations.
5.2 Lagrangian space halo correlation functions

The cross correlation between haloes and mass is essentially a weighted integral over the bias relations shown in the previous subsection. In this sense, \( \xi_{\text{hm}}(\text{mass}) \) is a slightly less fundamental quantity than \( \delta_{\text{c}} \). The cross correlation between haloes with mass larger than \( m \), whose centres-of-mass are within a cell \( V_0 \), and the mass within that cell, is

\[
\bar{\xi}_{\text{hm}}(> m | 0) = \int_{m}^{\infty} \frac{n(M_1, \delta_1)}{n(> m, \delta_1)} \bar{\xi}_{\text{hm}}(1 | 0) \, dM_1 + \delta_1 \int_{\mu}^{\infty} \frac{n(M_1, \delta_1)}{n(> m, \delta_1)} \, dM_1 \tag{42}
\]

where \( n(M_1, \delta_1) \) and \( \bar{\xi}_{\text{hm}}(1 | 0) \) were defined earlier, \( \mu = \text{max}(m, M_0) \), and the convention is that, in the first term, \( \bar{\xi}_{\text{hm}}(1 | 0) = 0 \) if \( M_1 > M_0 \). The second term accounts for the difference between counting haloes instead of isolated regions. This is the analogue of equation (40). In general, these integrals over the range of halo masses must be done numerically.

Figure 10 shows equation (42) for white noise initial conditions, for haloes identified at a range of output times, and minimum mass cutoffs, as a function of scale. The plots are for the Lagrangian space distribution of haloes identified at the epoch \( a \), and the four curves in each plot are (from bottom to top) for \( m = 32, 64, 128 \), and 256 particles, respectively. The figure actually shows \( \bar{\xi}_{\text{hm}} / \bar{\xi}_m \), where \( \bar{\xi}_m \equiv a^2 / M^2 \), and \( S_n(a) \equiv \delta^2 \), with \( \delta_c = 1.7 \) as required by the spherical model. The two panels show the difference between averaging over all Lagrangian cells (right) and averaging only over those Lagrangian cells which are not too overdense (left). Thus, the panels on the left are the same quantity computed by Mo & White (1996).

Typically, the fits in the panels on the left are better than those shown in the panels on the right, and, typically, the fit is usually better on larger than on smaller scales. On large scales, the number of cells in the two panels is almost the same anyway.) This suggests that the way in which the model assigns haloes to Lagrangian cells that are not isolated is not quite correct. In the panels on the right, the model systematically underestimates \( \bar{\xi}_{\text{hm}}(> m | V) \) on small scales. Comparison with Fig. 11 shows that the discrepancy increases as the initial power on large scales increases (\( n \) becomes more negative). This is not unexpected. The assumption that the centre-of-mass particle is a random one of a halo’s particles is likely to be less accurate as \( n \) becomes more negative. On the other hand, some of the discrepancy on small scales may be spurious. These are measurements in Lagrangian space, and the initial inter-particle spacing was on the order of \( R/L \sim 0.01 \), so it is not clear that differences on these small scales are significant. Moreover, recall that when \( n = -1.5 \), then the initial particle distribution on small scales is far from Gaussian (Fig. 9).

Figs. 10 and 11 appear to show that the theory describes the simulation results better for small values of the expansion factor \( a \). This is a consequence of one of the results of the previous subsection: when the mass of a halo identified at time \( a \) is expressed in units of \( M_0(a) \), then the theory describes the distribution of massive haloes better than less massive ones. At some small \( a \), haloes with more than, say, 64 particles are larger relative to an \( M_0 \) halo at that time, than they are at some later time. So, in Figs. 10 and 11, the theory appears to work better at small \( a \) than large.

Before considering the halo–halo correlation function we think it worth remarking that some of the agreement between theory and simulation is a consequence of showing the ratio \( \bar{\xi}_{\text{hm}}(> m | V) / \bar{\xi}_{h} \), rather than \( \bar{\xi}_{\text{hm}} \) and \( \bar{\xi}_m \) themselves. On small scales \( \bar{\xi}_m \gg 1 \), so the ratio tends to zero. Had we shown \( \bar{\xi}_{\text{hm}} \) only, then the theory and the simulation curves

\[ Figure 10. \] The volume average of the Lagrangian space halo–mass cross correlation function, \( \bar{\xi}_{\text{hm}}(> m | R) \), equation (43), as a function of cell size \( R \), when the initial power spectrum has slope \( n \), for haloes identified at a range of output times, labelled by the expansion factor \( a \). Panels on the left show the result of computing the average by using only those cells whose initial density was less than \( \delta_c / a \). Panels on the right show the result of averaging over all Lagrangian cells, whatever their density. Symbols show the model predictions (made using the value of \( \delta_c \) shown). From bottom to top in each panel, the different curves are for haloes with \( m = 32 \) (circles), 64 (triangles), 128 (squares), and 256 (stars) particles.

\[ Figure 11. \] The same as the previous figure, but now \( n = -1.5 \). The theory describes the simulation results reasonably well for massive haloes, and rather poorly for less massive haloes, where massive and less massive are defined relative to \( M_0(a) \).
Figure 12. The volume average of the Lagrangian space halo-halo correlation function, $\bar{\xi}_{hh}(>|m|,R)$, equation (43), as a function of cell size $R$, for the same haloes that were used to make Fig. 10. Panels on the left show the result of computing the average by using only those cells whose initial density was less than $\delta_c/n$. Panels on the right show the result of averaging over all Lagrangian cells, whatever their density. Symbols show this quantity measured in the simulations; curves show the model predictions, with the value of $\delta_c$ shown.

Figure 13. The same as the previous figure, but now $n = -1.5$. The correlation function between haloes with mass greater than $m$, averaged over Lagrangian cells of size $V_0$, is

$$1 + \bar{\xi}_{hh}(>|m|) = \int_0^\infty dM_1 \int_0^\infty dM_2 \frac{n(M_1, \delta_1) n(M_2, \delta_1)}{n^2(>|m|, \delta_1)} \times \left[ 1 + \bar{\xi}_{hh}(12|0) \right],$$

(43)

where $\bar{\xi}_{hh}(12|0)$ is given by equation (23), and the convention is that $\bar{\xi}_{hh}(12|0) = -1$ if $M_1 + M_2 > M_0$. This is the analogue of equation (A72).

Figs. 12 and 13 show that, as a result of volume exclusion effects, $\bar{\xi}_{hh}(>|m|)$ is likely to be negative for all except large values of $V_0$. Since halo correlations increase as $n$ decreases, this effect will be weaker as $n$ becomes more negative. Thus, when $n \sim 0$, then $\bar{\xi}_{hh}(>|m|)$ will almost always be negative. Only when $n \sim -1$ or so will it become positive, and then, only when $m$ is large compared to $M_*(z)$. The distribution of haloes measured in the simulations show that this is true.

Fig. 14 shows equation (A43), for a range of output times and minimum mass cutoffs, as a function of scale. The plots are for the Lagrangian space distribution of the same haloes that were used to produce Fig. 10. Notice that more massive haloes are always less clustered than less massive haloes, in agreement with the white-noise result (equation 27). This would not have been expected from the Mo & White (1996) formulae. Again, this suggests that our model for halo exclusion effects is reasonably accurate. Figure 15 shows that our model is also reasonably accurate when the initial conditions differ from white noise.

There are, of course, some systematic differences. The theoretical curves fit the data in the panels on the left better than the data shown on the right, and the discrepancy is more obvious for $n = -1.5$ than for $n = 0$. This simply reflects the fact that our model, in which the centre-of-mass particle of a halo is a random one of its constituent particles, is not very realistic (though it is a better approximation in the white noise case). Also, on small scales, the simulation haloes are systematically less anti-correlated than the model predictions, suggesting that they are affected less strongly by volume exclusion effects than in the model. This is a consequence of at least two facts. The first is that, in the simulations, small haloes in particular are not necessarily spherical, so the excluded volume associated with them is not necessarily spherical. Thus, in the simulations, it is possible for two centre-of-mass particles, associated with haloes of mass $M_1$ and $M_2$, to fall in the same spherical Lagrangian region $M_0$, even if $M_1 + M_2 > M_0$, since not all their associated particles actually fall in $M_0$. In the model this never happens. The second is that, in fact, the number density of haloes described by the model (the denominator in equation 13) is, in general, only within a factor of two or so of the actual number density of haloes measured in the simulations. Since the halo–halo correlation function is normalized by the square of this number density, this relatively minor discrepancy may still be important. Finally, recall that when $n = -1.5$, then the initial distribution on small scales was not particularly Gaussian (Fig. 4).

5.3 The Eulerian probability distribution function

We argued (Section 4) that, in principle, the Mo & White model for transforming Lagrangian space statistics into Eulerian space ones can be used to derive the Eulerian space dark matter distribution function. To do so, we showed that one must solve the integral equation (23). However, not only must the resulting distribution be correctly normalized (to unity), but $\langle \Delta \rangle = 1$ as well (cf. equation 27). There is no guarantee that, in general, the solution to the integral equation will meet both normalization conditions. Therefore, we have chosen to stick with the approach used by Mo & White (1996). Namely, when the Eulerian distribution function is required, we will simply use the one measured in the simulations, since it is guaranteed to satisfy (23). Whenever we do so, we will also show the extent to which this is self-
The Eulerian space probability distribution function $p(\delta)$ as a function of overdensity $\delta$, for clustering from white noise initial conditions. Each panel shows four choices of scale $R/L = 0.02$ (broadest curves), 0.4, 0.8 and 0.16 (narrowest curves). Histograms show the distribution measured in the simulations; thicker, smoother curves show Generalized Inverse Gaussian distributions that have the same variance.

consistent by showing the ratio of the left hand side to the right hand side of equation (36).

Figs. 14 and 15 show the Eulerian space probability distribution function for a range of cell sizes. The histograms show the $p(\delta)$ distribution measured in the simulations. Solid curves show Generalized Inverse Gaussian distributions (e.g. Sheth 1998) that have the same variance:

$$p(\delta) \, d\delta = \frac{s^{-\lambda}}{2K_\lambda(\omega)} \exp\left(-\frac{s^{(1+s-1)}}{s}\right) \, ds,$$  \hspace{1cm} (44)

where $s = 1/(1+\delta)^{(n+3)/3}$, $K_\lambda(\omega)$ is a modified Bessel function of the third kind, and $\lambda = -3/[2(n+3)]$, if the initial power spectrum had slope $n$. The parameter $\omega$ is related to the variance by the relation

$$\langle (1+\delta)^2 \rangle \equiv 1 + \bar{\xi}_m = K_\lambda(\omega)/K_\lambda(\omega)$$  \hspace{1cm} (45)

(since $\langle \delta \rangle = 0$, and $K_\lambda = K_{-\lambda}$). For the curves shown, the values of $\bar{\xi}_m$ are as follows: when $n = 0$ and $a = 6.1$, then $\bar{\xi}_m = 0.62$, 0.1, 0.01, and 0.002 for $R/L = 0.02$, 0.04, 0.08 and 0.16, respectively. When $n = 0$ and $a = 37$, then the corresponding values of $\bar{\xi}_m$ have grown to 10.9, 2.1, 0.4 and 0.07. When $n = -1.5$ and $a = 6.07$, then $\bar{\xi}_m = 14$, 3.6, 0.98, and 0.26. Thus, on small scales, the clustering is reasonably well evolved. The figures show that the analytic formulae provide a reasonably good, but by no means perfect, fit to the simulation data on all scales. The fit appears better on a log scale than on a linear scale. Nevertheless, they will be used as convenient fitting functions to the Eulerian space distributions when they are used in Section 5.6.

5.4 Biasing in Eulerian space

This subsection compares the bias relation between haloes and mass measured in the simulations in the Eulerian space with the theoretical model developed in the previous sections. The theoretical model combines the Lagrangian expressions derived in Sections 2 and 3 with the Mo & White (1996) model of Eulerian evolution discussed in Section 4.

However, it is independent of the Eulerian space dark matter distribution function.

Figs. 16—18 show the bias relation for the same haloes as in previous figures, but now the mean and the scatter are measured in Eulerian space. The histograms show the cumulative Eulerian space distribution function, and the solid lines through the histograms show the cumulative Generalized Inverse Gaussians that have the same variance. As in the Lagrangian case, these cumulative curves are included.
shows that the unconditional, universal mass function is reasonably accurate. Equation (36) is also encouraging, since there the scatter is significantly less than Poisson. This shows that our model is able to account correctly for volume exclusion effects. The agreement between theory and simulation when \( n = -1.5 \) is also encouraging. It suggests that our simple analytic model for quantifying the effects of volume exclusion is reasonably accurate even when the initial conditions are significantly different from white noise.

5.5 Dependence of the mass function on local overdensity

There is another way to show that the Mo & White Eul-erian space bias model is reasonably accurate. Equation (36) shows that the unconditional, universal mass function \( n(M) \) is simply related to the conditional mass function \( N(M|\delta) \) of haloes that are known to be in Eulerian cells \( V \) which have overdensity \( \delta \) averaged over all values of \( \delta \). In the Mo & White model, \( N(M|\delta) \) is given by equation (37), in general, it is different from \( (1 + \delta) n(M)V \). In particular, in the model, the shape of the mass function depends on the Eulerian overdensity: the ratio of massive haloes to less massive haloes is larger in dense regions than in less dense regions. Figs. 18 and 19 show that this is consistent with what is measured in the simulations.

These figures are similar to Fig. 1 of Lemson & Kauflmann (1999). They show the conditional mass function \( N(M|\delta) \) for haloes in Eulerian cells \( V \) that have overdensity \( \delta \), for a range of choices of \( \delta \) and \( V \). The top left panel shows the range \(-0.8 \leq \delta \leq -0.4 \), the top right shows \(-0.5 \leq \delta \leq -0.1 \), bottom left shows \(0.3 \leq \delta \leq 0.7 \) and bottom right shows \(1.2 \leq \delta \leq 1.8 \). The three sets of curves in each panel show different cell sizes: \( R/L = 0.04 \) (bottom), 0.08 and 0.16 (top). The histograms show \((1 + \delta)V \) times the Press–Schechter formula for the unconditional mass function measured in the simulations. The associated dashed curves show \((1 + \delta)V \) times the Press–Schechter formula for the universal unconditional mass function with \( \delta_c = 1.7 \). The dashed curves provide good but not perfect fits to the histograms. Changing the cell size on a log-log plot simply changes the amplitude of the curves, so for smaller cell sizes we only show the analytical formula. The solid symbols show the actual conditional mass function measured in the simulations and the bold curves show the conditional mass function of equation (37). The symbols differ from the histograms in the same way that the solid curves differ from the dashed curves. (The bottom right panel has only two sets of symbols because there were no large cells with the given range in \( \delta \).) This shows explicitly that, just as the Press–Schechter formula provides a reasonable fit to the unconditional mass function averaged over all Eulerian cells, the Mo & White model provides a reasonable fit to the mass function if only cells of a certain density range are used when computing the average.

The data points show the mean number of haloes in cells \( V \) that are known to have overdensity \( \delta \). Since not all cells have the same number of haloes, there is some scatter around this mean. Our extension of the Mo & White model allows us to predict the rms ‘error bars’ on the data points. We have not shown them here.

5.6 Eulerian space halo correlation functions

This subsection compares the Eulerian space halo–mass and halo–halo correlations measured in the simulations with the theoretical model developed in the previous sections. To do this requires knowledge of the distribution function of the
probability that a randomly placed Eulerian cell of size $V$ contains mass $M$. Although Section 4 discussed how the Mo & White approach can be extended to derive this distribution self-consistently, here we simply follow the approach used by Mo & White. Namely, we will use the Eulerian probability distribution functions measured in the simulations themselves (and, in fact, we will use the Generalized Inverse Gaussian fits to these distributions), rather than the ones required by self-consistency. Recall that this means that there is no longer any guarantee that the model gives the correct number density of haloes. Below, we will show explicitly that the model is not self-consistent on small scales.

Figs. 21–23 show the result of comparing the Mo & White model with the Eulerian space distributions measured in the simulations. The top panels in each figure show $N(m|V)/n(m|V)$, the middle panels show $\xi_{\text{lin}}(m|V)/\xi_{\text{lin}}(V)$, and the bottom panels show $\xi_{\text{inh}}(m|V)/\xi_{\text{inh}}(V)$ as a function of Eulerian scale. The symbols show the quantities measured in the simulations, and are coded similarly to those in the corresponding Lagrangian space plots. The solid curves show the theoretical quantities.

If the Mo & White model were self-consistent, then the theoretical curves in the top panels of each figure would be unity on all scales. Thus, the figures show that the Mo & White model is inconsistent on small scales. The middle panels show that, despite this inconsistency, the model provides a good fit to the Eulerian space cross correlation between haloes and mass. This is primarily a consequence of the fact that the mean Eulerian bias is well reproduced by the Mo & White model (Figs. 16–18). These curves are similar to those shown in Fig. 4 of Mo & White (1996). The bottom panels should be compared with Fig. 5 of Mo & White (1996). Whereas their model curves increase as $R/L$ decreases, ours do not. Thus, our model for the volume averaged halo–halo correlation function works significantly better than the one they used. This is to be expected, since our model explicitly takes account of volume exclusion effects, whereas theirs did not. The bottom panels also show that, on sufficiently large scales, one consequence of dynamical evolution is to make massive haloes more strongly clustered than less massive ones. This is in agreement with earlier predictions (Cole & Kaiser 1989; Mo & White 1996) as well as with the model developed here.

6 DISCUSSION

Numerical simulations show that haloes are biased tracers of the matter distribution. This bias depends nonlinearly on scale and on halo mass, and the bias on any given scale is stochastic. This paper describes an analytic model which describes this nonlinear, stochastic biasing, as well as its evolution, reasonably accurately.

The model is consistent with the assumption that disconnected volumes in the initial Lagrangian space may be treated as being mutually independent. This assumption allows one to use quantities associated with the merger histories of dark haloes to estimate the Lagrangian space correlation functions of these haloes. The assumption of independence is most likely to be accurate if the initial distribution was Poisson or Gaussian white noise. The Poisson model is described in detail in Appendix A, where various subtle issues involved in this approach are discussed rigorously. In the limit of small fluctuations and large numbers of particles, statements about clustering from Poisson initial con-
biasing and the distribution of dark matter haloes

Various Eulerian space quantities as a function of Eulerian cell size. Top panel shows $N(\geq m|V)/n(\geq m) V$, middle panel shows $\xi_{hm}(\geq m|V)/\xi_m$, and bottom panel shows $\xi_{hh}(\geq m|V)/\xi_m$. Filled circles, triangles, squares and stars show results for haloes in the simulations that contain more than 32, 64, 128, and 256 particles, respectively. Solid curves show the model predictions.

Same as the previous figure, but for haloes identified at a later output time.

Sections are easily related to those that describe clustering from white noise initial conditions (Sheth 1995, 1996).

Section 3 showed these expressions for the mean and higher order moments of the halo distribution, for white noise initial conditions. The final expressions compliment and extend those derived by Mo & White (1996). In particular, the results of this section allow one to account for volume exclusion effects which arise from the fact that haloes initially occupy a volume that is proportional to their mass.

These effects were described, but not quantified by Mo & White. Our results also include the effects of the scatter among different formation histories of individual regions in the initial conditions on the statistics of the halo distribution in space—another effect that was described, but not quantified, by Mo & White.

Whereas disconnected volumes are mutually independent in the white noise case, this is not true for more general Gaussian initial conditions. However, Sheth & Lemson (1998) showed that it is possible to provide a good approximate description of the forest of merger history trees associated with haloes which form from initial conditions with large scale correlations by simply ignoring these correlations. In the Mo & White model, knowledge of the merger history trees is equivalent to knowledge of the spatial distribution of dark haloes. Section 3 used this fact to argue that the white noise results could be used to provide simple analytic approximations for the higher order moments of the Lagrangian space halo distribution even when the initial power on large scales is substantial. The Sheth & Lemson merger tree results suggest that these analytic approximations should also be reasonably accurate.

As a result of dynamical evolution, the evolved halo distribution is different from that in the initial Lagrangian space. To describe the evolved distribution we used the spherical model, in the way suggested by Mo & White, to relate the initial halo distribution described above to the final evolved one. We showed that in addition to allowing one to estimate the evolved halo–mass and halo–halo correlation functions, the Mo & White model could have been used to compute the Eulerian space probability distribution function of the dark matter itself. This is a potentially useful extension of their model.

Once the model had been fully specified, we compared it with numerical simulations of hierarchical gravitational clustering. Comparison with the halo distribution in the simulations (Section 3) showed that while the Mo & White bias model is reasonably accurate when describing the mean Lagrangian space bias relation of massive haloes, it predicts the wrong mean value for less massive objects. Our extension of the Mo–White model allows us to compute the higher order moments of the bias relation. For massive objects (those for which the Mo–White mean is accurate), it describes the scatter around the mean well. For less massive objects, when the Mo–White model gets the mean value wrong, our model for the scatter around the mean is still in qualitative agreement with the simulations.

Results for the halo distribution in Eulerian space were more encouraging. The Mo & White model describes the mean properties of the bias relation in Eulerian space well, for a larger range of masses than in the Lagrangian space,
and our extension of the model is able to describe the scatter around this mean well. Our model works even on scales where volume exclusion effects are important. This is very encouraging, since our model provides simple, analytic expressions for these higher order moments. Although our simulations do not have the dynamic range to investigate a large mass range, those of Jing (1998) do. Jing finds that on large scales where $E_{h}^k / E_0$ is constant, the Eulerian space low-mass halo distribution is more clustered than the Mo & White model predicts. In other words, he finds that the large scale mean bias relation between low-mass haloes and the mass is larger than the mean bias relation that the Mo & White model predicts. It is interesting that this is the same trend we found in our study of the Lagrangian space halo distribution. This has an important consequence.

The Mo & White model has two parts: the first is a model of the initial number density and spatial distribution of haloes, and the second models their subsequent dynamical evolution. Given only Jing’s result, one might have thought that the Mo & White fails only in the second step; that using the spherical model to translate from Lagrangian to Eulerian space is inaccurate. If so, one might have thought that the Zel’dovich approximation, or variants of it, could be combined with the initial distribution described here to derive accurate estimates of the evolution of the spatial distribution of massive as well as less massive haloes. This is the sort of approach taken by Catelan, Mataresse & Porciani (1998). To date, they have only studied the halo distribution on scales larger than that of a typical halo, since their approach does not allow them to account for the effects of volume exclusion. Since we are able to account for volume exclusion, it may be interesting to combine some of the results presented here with their work.

However, our results show that the Mo & White model fails in Lagrangian space: it does not describe the initial spatial distribution of low mass haloes correctly. This is not so surprising, since it is well known that the spherical model for the collapse of haloes, on which the first step of the Mo & White model is based, is more likely to be accurate for massive objects than for less massive ones (e.g. Bernardeau 1994). If it is not so much the spherical model of the evolution of the halo distribution, but rather the spherical collapse model for the formation of small mass haloes itself that is wrong, then we expect the discrepancy Jing measures for the Eulerian space distribution of the haloes in his simulations to be reflected in the shape of the unconditional mass function. The mass function in the simulations does indeed differ from the Press–Schechter function, and this difference is in the correct sense: whereas the theory predicts approximately the correct number of massive haloes, there are fewer low mass haloes in the simulations than the Press–Schechter formula predicts. Quantifying this relation between the unconditional mass function and the large scale bias relation is the subject of ongoing work.

In this paper we have gone to a fair amount of trouble to derive a realistic, accurate, analytic model for the scatter in the halo-to-mass bias relation. This is because knowledge of this scatter allows one to address a number of interesting problems, some of which we list briefly below. To relate these results to the observed distribution of galaxies is complicated. Galaxies are thought to form inside dark matter haloes (White & Rees 1978; White & Frenk 1991). Semi-analytic models of this galaxy formation process (e.g. Kauffmann, White & Guiderdoni 1993) show that the number of galaxies which form in a given dark matter halo is stochastic. Lemson & Kauffmann (1999) showed that most of the physical parameters of a dark matter halo on which galaxy formation processes are expected to depend, while they may depend on the halo mass, are independent of the halo’s environment. Thus, their results suggest that quantities like the average number, or the scatter in this number, of galaxies in a dark matter halo ultimately depend on the halo mass. So it should be possible to provide semi-analytic estimates of the mean galaxy-number-to-halo-mass bias relation, as well as the scatter in this relation. When combined with our results for the mean and higher order moments of the bias between dark matter haloes and the underlying matter distribution, such a relation would allow one to relate the observed galaxy distribution to that of the underlying dark matter distribution. Thus, our expressions for the scatter in the halo-dark matter bias relation can be used to extend the results of Kauffmann, Neistein & Steinmetz (1997) to smaller scales. In addition, combining the galaxy number to halo mass bias relation with the dark halo to dark matter bias relation may allow one to compute estimates of the expected scatter in the Tully-Fisher relation, to study the bias associated with estimating $\Omega_0$ from redshift distortions (Pen 1998; Dekel & Lahav 1998), to evaluate the compatibility between observations of the number density and correlation functions of objects at high redshift and various cosmological models (Mo, Mao & White 1998), and to model the evolution of the cluster–cluster correlation function in different cosmological models (Mo, Jing & White 1997).

This paper has dealt primarily with the problem of quantifying the mean and higher order moments of the halo bias given the matter fluctuation field (e.g. $\langle \delta_h | \delta_m \rangle$). The inverse problem is equally, if not more, interesting. The problem of estimating the mean and higher order moments of the matter fluctuation field given the halo distribution (e.g. $\langle \delta_m | \delta_h \rangle$) is the subject of ongoing work.

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APPENDIX A: POISSON INITIAL CONDITIONS

In this Appendix the excursion set approach is used to derive expressions for the unconstrained mass function, and then for the constrained mass function and associated merger probabilities. The approach follows and extends that of Epstein (1983) and Sheth (1995) in the following way. These earlier analyses considered spherical collapse around particles in the initial Poisson distribution. However, in this paper we want to compute averages over all randomly placed cells in the initial distribution, not just those that are centred on particles. So, in the next few subsections, we derive expressions for the constrained and unconstrained mass functions where the restriction to volumes centred on particles is dropped. It turns out that the modification to the previously derived expressions is trivial. Therefore, the first two subsections may seem a little pedagogical—we have included them to set notation. Readers familiar with the Poisson excursion set analysis may prefer to skip directly to Section A3.

The spatial distribution of these haloes, in the initial Lagrangian space, is described in Sections A2. Comparison of these results with numerical simulations is often done for haloes having a range of masses. There is some subtlety in doing this correctly—this is discussed in Section A4. That all these Poisson results are easily extended to describe clustering from white noise initial conditions is shown in Section A4. Essentially, those statements about clustering from white noise initial conditions which are known (e.g., the conditional and unconditional mass functions, and the mean bias relation), can be derived by taking appropriate limits of the corresponding Poisson statements. The same limiting procedure can be used to derive statements about the higher order moments of the Lagrangian space halo distribution. It is these expressions that are presented in the main text.

A1 The unconstrained mass function

Consider a Poisson distribution of particles with mean density $\bar{n}$. This means that a volume of size $V$ placed at a random position in this distribution will contain exactly $N$ particles with probability

$$p(N,V) = \frac{(\bar{n}V)^N e^{-\bar{n}V}}{N!}.$$  \hfill (A1)

Furthermore, if it is known that there are $N$ particles in $V_2$, then the probability that there are $j$ particles in $V_1$ placed randomly within $V_2$ is

$$p(j|N,V_1,V_2) = \frac{p(j,V_1)p(N-j,V_2-V_1)}{p(N,V_2)} = \frac{\binom{N}{j} \frac{V_1}{V_2}^j \left(1 - \frac{V_1}{V_2}\right)^{N-j}}. \hfill (A2)$$

Now choose a random position in the distribution, and compute the density within concentric spheres centred on this position. Call the curve traced out by the number of particles contained within a sphere $V$ centred on this point, as a function of the sphere size $V$, a trajectory. Then each position in the Poisson distribution has its associated trajectory. Let $f^*(\delta_1)$ denote the probability that, for all concentric spheres centred on a randomly chosen position, the density never exceeds the threshold value $\bar{n}(1 + \delta_1)$. One way to compute this probability is to compute the fraction of trajectories for which $N(V) < nV(1 + \delta_1)$ for all $V$, where $N(V)$ is the number of particles within $V$. This quantity can be computed as follows.

Start with an arbitrarily small sphere centred at the chosen position, and consider successively larger concentric spheres. As the volume increases by an infinitesimal amount, the number of particles contained within the current sphere either remains the same, or increases by one (Strictly speaking, the probability that the number of particles increases by one is an infinitesimal, the probability that the number increases by two is an infinitesimal of higher order, an increase by three particles is an infinitesimal of still higher order, and so on.) Therefore, a given value of $\delta_1$ defines a series of volumes $V_1 < V_2 < \ldots$ for which

$$j/V_j = \bar{n}(1 + \delta_1) \equiv \bar{n}/b_1. \hfill (A3)$$

The final equality defines $b_1 = 1/(1 + \delta_1)$, a parameter which will be useful later. The quantity of interest, $f^*(\delta_1)$, is one minus the probability that $V_j$ is the largest sphere centred at the chosen position that has density $\bar{n}(1 + \delta_1)$, summed over all $V_j$. That is,

$$1 - f^*(\delta_1) = \sum_{j=1}^{\infty} p(j,V_j) f^*(\delta_1|j,V_j), \hfill (A4)$$
where the first term in the sum is the probability that $V_j$ contains exactly $j$ particles, and the second term expresses the probability that, given that $V_j$ contains exactly $j$ particles, no concentric sphere larger than $V_j$ is denser than it. Epstein (1983) shows that

$$f^o(\delta_1|j, V_j) = \frac{\delta_1}{1 + \delta_1} = 1 - b_1,$$

and he discusses why it is independent of $j$. Thus,

$$1 - f^o(\delta_1) = (1 - b_1) \sum_{j=1}^{\infty} p(j, V_j) = b_1,$$  \hfill (A6)

where the sum is simplified by recognizing that it is $b_1$ times the first moment of the Borel distribution (Borel 1942). This shows that $f^o(\delta_1) = 1 - b_1$, so that it is the same as $f^o(\delta_1|j, V_j)$. This is simply a consequence of the fact that, since the distribution is Poisson, the probability that all larger volumes containing a given volume are less dense than a given value depends only on the density within the volume, and not on the number or the distribution of the particles within it.

The expression above implies that the probability that at least one sphere centred on a randomly chosen position in a Poisson distribution is denser than $\bar{n}(1 + \delta_1)$ is $b_1$. In other words, of the infinity of spatial positions in a Poisson distribution, and, of the infinity of associated trajectories, only a fraction $b_1$ are at the center of at least one sphere that is denser than $\bar{n}(1 + \delta_1)$. That is, only a fraction $b_1$ of the trajectories ever have $N(V) \geq \bar{n}V(1 + \delta_1)$ for at least one value of $V$. Let $F(j, b_1)$ denote the fraction of trajectories for which $N(V_j) = j$, and for which $N(V_k) < k$ for all $V_k > V_j$. Then

$$F(j, b_1) = p(j, V_j) f^o(\delta_1|j, V_j),$$  \hfill (A7)

where the first term gives the probability that a trajectory has $N(V_j) = j$, and the second term gives the probability that $V_j$ is the largest volume at which the trajectory exceeds the threshold $\bar{n}(1 + \delta_1)$.

There is a useful relation between equations \(A1\) and \(A2\). Let $\mathcal{V}_k \equiv k b_2 / \bar{n}$. Then

$$p(j, V) = \sum_{k=j}^{\infty} p(j, V|k, \mathcal{V}_k) F(k, b_2),$$  \hfill (A8)

provided $\bar{n}V \geq \bar{n}$, and $b_2 \leq b_1 \equiv \bar{n}/j$. To see this, note that the left hand side includes all trajectories that have value $j$ at $V$. Suppose each trajectory is labelled by the value of $k$ for which $\mathcal{V}_k$ is the largest volume at which that trajectory crossed the line $\bar{n}(1 + \delta_2)$. Trajectories which cross the line for the final time with value less than $j$ cannot also pass through $V$ with value $j$. Therefore, the sum on the right hand side is only over those trajectories that cross the line $\bar{n}(1 + \delta_2)$ for the final time with $k \geq j$, and also pass through $V$ with value $j$. Clearly, the left hand side must equal the right. Direct substitution shows that equations \(A1\) and \(A2\) and \(A3\) satisfy this relation. The normalization and first moment of Consul's (1989) generalized Poisson distribution aid in proving this result.

Define an isolated region as a spherical region within which the average density is $\bar{n}(1 + \delta_1)$, and for which the average density within all larger concentric spheres is less than this. Then $F(j, b_1)$ denotes the fraction of space that is associated with isolated $(j, b_1)$-volumes. If $N(j, b_1)$ denotes the number of such volumes, and $V_U$ denotes the total volume, then

$$F(j, b_1) = N(j, b_1) \frac{V_j}{V_U} = \frac{N(j, b_1) \, j b_1}{\bar{n}},$$

so that the number density $\bar{n}(j, b_1)$ of such isolated volumes is

$$\bar{n}(j, b_1) \equiv \frac{\bar{n}}{j b_1} F(j, b_1) = \bar{n}(1 - b_1) \frac{(j b_1)^{j-1} e^{-j b_1}}{j!} = \bar{n}(1 - b_1) \eta(j, b_1),$$  \hfill (A9)

where $\eta(j, b_1)$ is the Borel$(b_1)$ distribution. Thus, the Borel$(b_1)$ distribution gives the probability that an isolated region contains exactly $j$ particles [since $\sum_j \eta(j, b_1) = 1$, and $\sum_j j \eta(j, b_1) = 1/(1 - b_1)$].

Following Bond et al. (1991), it will be convenient to associate these isolated regions with collapsed haloes. Then equation \(A3\) is the unconditional mass function, since it gives the number density of collapsed objects that contain exactly $j$ particles.

It is interesting to compare equations \(A7\) and \(A9\) with the results of Epstein (1983). In his analysis, Epstein only considered those trajectories that were certainly centred on particles of the Poisson distribution. Here, that restriction has been dropped. Let $f(j, b_1)$ denote the fraction of trajectories that are centred on particles and are associated with isolated regions containing exactly $j$ particles. Epstein's expression for $f(j, b_1)$ implies that

$$F(j, b_1) = b_1 f(j, b_1),$$  \hfill (A10)

Thus, the effect of considering the set of all trajectories, rather than the subset that are centred on particles, is simply to introduce the $b_1$ term. This is sensible. In the limit in which the threshold $\delta_1 \to \infty$, $b_1 \to 0$. In this limit, the only trajectories that ever exceed the threshold are those that are centred on particles, and they exceed the threshold only when the volume is vanishingly small. In this limit, $f(j, b_1) \to 1$ if $j = 1$, and it is zero otherwise. On the other hand, the subset of trajectories that are centred on particles is a vanishingly small fraction of the set of all trajectories, so that, as $\delta_1 \to \infty$, the fraction of all trajectories that ever exceed $\delta_1$ tends to zero. So, in this limit, $F(j, b_1) \to 0$ for all $j$.

### A2 The constrained mass function

The probability that a randomly placed volume $V_j$ contains exactly $j$ particles and has density $\bar{n}(1 + \delta_1)$, and that the larger volume $\mathcal{V}_k > V_j$, including $\mathcal{V}_j$ contains exactly $k$ particles, has density $\bar{n}(1 + \delta_2)$, and is isolated, is

$$p(j, V_j) \, p(k - j, \mathcal{V}_k - V_j) f^o(\delta_2|k_2, V_k),$$

Equation \(A3\) shows that $f^o(\delta_2|k_2, V_k) = (1 - b_2)$. The probability $F(j, b_1|k, b_2)$ that $\mathcal{V}_j$ is itself isolated within the isolated region $\mathcal{V}_k$ [that is, the average density within all volumes $V$ that include $\mathcal{V}_j$ and are within $\mathcal{V}_k$ is less than $\bar{n}(1 + \delta_1)$] satisfies a recursion relation:

$$F(j, b_1|k, b_2) = \frac{p(j, V_j, k, \mathcal{V}_k) \, f^o(\delta_2|k_2, V_k)}{F(k, b_2)}$$
The numerator in the first term on the right is the joint probability above, in which \( V_j \) is not necessarily isolated. The denominator is included since it is known that \( V_k \) is isolated. From this first term, we must subtract the probability that a volume \( V_m \) containing \( V_j \) was itself the largest isolated region within \( \mathcal{M}_k \). This is just the product of the probability \( F(m, b_1 | k, b_2) \) times the probability \( p(j, V_j | m, V_m) \) that there were exactly \( j \) particles within \( V_j \) given that they were within the isolated region \( V_m \), summed over all \( m \) larger than \( j \). Now,

\[
p(j, V_j | m, V_m) \equiv \frac{p(j, V_j) p(m - j, V_m - V_j)}{p(m, V_m)}
\]

\[
= \left( \frac{m}{j} \right) \left( \frac{V_j}{V_m} \right)^j \left( 1 - \frac{V_j}{V_m} \right)^{m-j}
\]

\[
= \left( \frac{m - 1}{j - 1} \right) \left( \frac{V_m}{V_j} \right)^{j-1} \left( 1 - \frac{j}{m} \right)^{m-j}
\]

(A12)

since \( V_k = \frac{kb}{\bar{n}} \). This binomial-like term is necessary because not all configurations of particles that contribute to \( F(m, b_1 | k, b_2) \) will have had exactly \( j \) particles within \( V_j \). Appendix C shows that

\[
F(j, b_1 | k, b_2) = k \left( 1 - \frac{b_1}{b_2} \right) \left( \frac{j}{k} \right) \left( \frac{b_1}{b_2} \right)^{k-j-1}
\]

(A13)

satisfies the recursion relation given above.

Let \( f(j, b_1 | k, b_2) \) denote the corresponding expression for volumes \( V_j \) that are known to certainly be centred on a particle. Then \( f(j, b_1 | k, b_2) \) is given by equation (40) of Sheth (1995), and

\[
F(j, b_1 | k, b_2) = \frac{b_1}{b_2} f(j, b_1 | k, b_2).
\]

(A14)

Thus, as with the statements \( F(j, k) \), the expressions for randomly placed volumes are easily related to those for volumes that are centred on particles. The \( (b_1/b_2) \) factor here plays the same role as the factor \( b_1 \) in equation (A10). It simply reflects the fact that, for a Poisson distribution, the particles within \( \mathcal{M}_k \) are distributed as though they are part of a Poisson distribution with average density \( \bar{n}(1 + \delta_2) \), rather than \( \bar{n} \). Moreover, the discussion in the final paragraph of section A applies to the limiting behaviour of \( F(j, b_1 | kb_2) \) as \( \delta_1 \to \infty \), i.e., as \( b_1 \to 0 \), just as it did for the limiting behaviour of \( F(j, b_1) \).

The similarity between \( F(j, k) \) and \( F(j | k) \) can be made still more striking. Suppose there are \( k \) particles in the volume \( \mathcal{M}_k \) and \( j \leq k \) particles in the subvolume \( V_j \) within it. Then \( \bar{n}(1 + \delta^*) = \bar{n}(k - j)/(kb_2 - j b_1) \) is the density in the remaining volume \( \mathcal{M}_k - V_j \), and

\[
F(j, b_1 | k, b_2) = \left( \frac{\bar{n}(1 + \delta^*)}{\bar{n}} \right) p(j, V_j | k, \mathcal{M}_k),
\]

(A15)

where \( p(j | k) \) is given by equation (A3). Equation (A7) shows that \( F(k, b_1) \) is given by an analogous expression; there, the remaining volume is infinite, so that the overdensity in it, \( \delta^* \), is 0 by definition. Thus, \( F(j | k) \) is related to \( p(j | k) \) in the same way that \( F(j) \) is related to \( p(j) \).

Recall that, although \( F(j, b_1) \) differed from \( f(j, b_1) \), the final expression for the number density of isolated \( (j, b_1) \) volumes was the same for randomly placed volumes as for volumes centred on a particle (equation A1). The same is true here. If \( N(j, b_1 | k, b_2) \) denotes the average number of isolated \( (j, b_1) \)-volumes within a randomly placed \( (k, b_2) \)-volume, then

\[
F(j, b_1 | k, b_2) = \mathcal{N}(j, b_1 | k, b_2) \frac{V_j}{\mathcal{V}_k} = \mathcal{N}(j, b_1 | k, b_2) \frac{jb_1}{kb_2}
\]

so that

\[
\mathcal{N}(j, b_1 | k, b_2) = \frac{kb}{j b_1} F(j, b_1 | k, b_2) = \frac{k}{j} f(j, b_1 | k, b_2).
\]

(A16)

The final expression is the same as equation (45) of Sheth (1995). Thus, equation (A16) shows that the average number of \( (j, b_1) \)-volumes that are within a \( (k, b_2) \)-volume is the same when \( \mathcal{M}_k \) is placed randomly in the Poisson distribution as when it is centred on a particle. In terms of collapsed haloes, this expression is similar to equation (A9), except that here the \( (j, b_1) \)-halo is constrained to be within a \( (k, b_2) \)-halo.

Thus, this expression gives the conditional mass function.

Notice that

\[
\mathcal{N}(j, b_1 | k, b_2) \to \langle k/j \rangle f(j, b_1 | b_2) \quad \text{when} \quad k \gg j.
\]

(A17)

Comparison with equation (A9) shows that, in this limit, the number density of \( (j, b_1) \)-volumes that are within a \( (k, b_2) \)-volume is the same as in the unconstrained case, the only difference is that \( b \to b_1/b_2 \), which reflects the fact that the background density within \( \mathcal{M}_k \) is \( \bar{n}(1 + \delta_2) \), rather than \( \bar{n} \).

All the arguments above were phrased entirely in terms of volumes that were concentric spheres. This was done with a view to improving the clarity of the presentation—the entire analysis applies unchanged for arbitrarily shaped volumes. This is because the underlying distribution is Poisson, so that all statements depend only on volumes \( V \) and not their shapes, and all volumes can be broken up into mutually independent sub-volumes. This is also why the dimensionality of the point distribution does not enter into the analysis anywhere. Appendix C here shows this explicitly. In this respect, the statements above are obtained by an averaging process that is similar in spirit to that described in the Appendix of Bower (1991).

### A3 Clustering of haloes in Lagrangian space: the mean number of haloes

This section derives the first moment of the distribution of halo counts in randomly placed cells. The following sections describe the distribution of haloes in randomly placed cells when the halo mass is specified, and Section A6 considers the distribution for a range of masses.

To compute the mean number of haloes in randomly placed cells, it is useful to consider another way of computing \( F(j, b_1) \). This alternative method also shows that dropping the Epstein (1983) and Sheth (1995) restriction (to only those volumes that are centred on particles) makes only a trivial difference to the final expression for \( F(j, b_1) \).

Let \( f^t(N, V_0) \) denote the probability that there are exactly \( N \) particles within the sphere \( V_0 \), given that \( V_0 \) is centred on a randomly chosen particle in the Poisson distribution. Then
\[ f^i(N, V_0) = p(N - 1, V_0), \]  
where \( p(k, V_0) \) is given by equation \( \text{(A1)} \). The probability that there are \( j \) particles in the sphere \( V_j \) centered on the chosen particle, and all concentric spheres \( V \) satisfying \( V_j < V < V_0 \) are less dense than \( V_j \), given that there are \( N \) particles in the concentric sphere \( V_0 > V_j \) is \( f(j, b_1|N, b_0) \), where \( 1 \leq j \leq N, b_1 \) was defined above, and \( b_0 \equiv \bar{n}V_0/N \).

Let \( N_0 \) denote the largest integer less than \( \bar{n}V_0/b_1 \); it is the maximum number of particles that may be in \( V_0 \), if \( V_0 \) is to be concentric to and less dense than \( V_j \). Also, let \( f^i(b_1|N, V_0) \) denote the probability that no sphere \( V > V_0 \) is concentric to and denser than the sphere \( V_j \), given that there are exactly \( 1 \leq N \leq N_0 \) particles within \( V_0 \). This quantity is just one minus the probability that there exists a sphere \( V_0 > V \) which is the largest sphere concentric to and having the same density as \( V_j \), given that there are \( N \) particles within \( V_0 \). Then,

\[ f^i(b_1|N, V_0) = 1 - \sum_{k > N_0} p(k - N, V_k - V_0) f^i(b_1|k, V_k), \]  
and equation \( \text{(A3)} \) shows that we can replace \( f^i(b_1|k, V_k) \) with \( (1 - b_1) \). Define

\[ Q(b_1, N, V_0) = p(N, V_0) - \sum_{k > N_0} p(N, V_0|k, V_k) F(k, b_2). \]  
Equations \( \text{(A2)}, \text{(A7)} \) and \( \text{(A13)} \) imply that

\[ Q(b_1, N, V_0) = p(N, V_0) - \sum_{k > N_0} p(N, V_0|k, V_k) F(k, b_2). \]  
This, with equation \( \text{(K8)} \), shows that \( Q = 0 \) when \( N > N_0 \).

In terms of these quantities,

\[ f(j, b_1) = \sum_{N=j}^{N_0} F(j, b_1|N, b_0) \cdot \bar{f}^i(N, V_0) \cdot f^i(b_1|N, V_0). \]  
Now, equation \( \text{(A3)} \) implies that \( b_0 = \bar{n}V_0/N \), so this sum expresses \( f(j, b_1) \) in terms of volumes \( V_0 \) that are certainly centred on a particle. However, equations \( \text{(A1)} \) and \( \text{(A18)} \) show that

\[ \bar{f}^i(N, V_0) = p(N - 1, V_0) = \frac{N}{\bar{n}V_0} p(N, V_0) = p(N, V_0)/b_0, \]  
so

\[ F(j, b_1) = \sum_{N=j}^{N_0} F(j, b_1|N, b_0) p(N, V_0) f^i(b_1|N, V_0). \]  
This final expression is written entirely in terms of randomly placed volumes, since \( f^i(b_1|N, V_0) \) depends only on the fact that there are exactly \( N \) particles within \( V_0 \), and not on whether or not one of those particles is at the centre. Straightforward but tedious algebra shows that this sum is consistent with the expressions for \( f(j, b_1) \) and \( F(j, b_1) \) derived earlier.

This calculation can be easily manipulated to give the average number of isolated \( (j, b_1) \)-volumes that are in randomly placed cells of size \( V_0 \). It is

\[ \bar{n}(j, b_1)V_0 \equiv \sum_{N=j}^{N_0} N(j, b_1|N, b_0) Q(b_1, N, V_0). \]  
The sum on the right is \( \bar{n}V_0/\bar{n}b_1 \) times the one in equation \( \text{(A23)} \), so it is equal to \( \bar{n}V_0 f(j, b_1)/j \). Comparison with equation \( \text{(A4)} \) shows that the average number of isolated \( (j, b_1) \)-volumes that are in randomly placed cells of size \( V_0 \) is \( \bar{n}V_0 \) times the average density of these haloes, as required.

### A4 Cross correlation between haloes and mass

It is also straightforward to compute a measure of the cross correlation between \( (j, b_1) \)-haloes and the total number of particles that are in randomly placed cells of size \( V_0 \).

Recall that \( \mathcal{N}(j, b_1|N, b_0) \) denotes the average number of \( (j, b_1) \)-haloes within an \( (N, b_0) \)-halo. This expression also represents the average number of \( (j, b_1) \) isolated regions that are within isolated regions \( V_0 \) which each have density \( N/V_0 \). Since these regions are isolated, they are different from a random region of size \( V_0 \) containing \( N \) particles; recall that only a fraction \( f^i(b_1|N, V_0) \) of such random regions may contain a \( b_1 \)-halo (and, of course, the number of particles in the \( b_1 \)-halo may not exceed \( N \)). The average number of \( (j, b_1) \)-haloes in the remaining \( V_0 \) cells (those that contain exactly \( N > j \) particles and are not isolated) is zero.

Thus, the average overabundance of \( (j, b_1) \)-haloes within the fraction \( f^i(b_1, N, V_0) \) of randomly placed \( V_0 \) that are isolated is

\[ \delta_b^i(j, b_1|N, b_0) = \frac{\mathcal{N}(j, b_1|N, b_0)}{\bar{n}(j, b_1)V_0} - 1 \]  
(Mo & White 1996), and \( \delta_b^i = -1 \) in the remaining \( V_0 \). The superscript \( L \) represents the fact that this expression defines a bias relation that is associated with randomly placed regions \( V_0 \) in the initial Lagrangian space. As Mo & White (1996) note, in general, dynamical evolution will result in a bias relation in Eulerian space that is different from this one in the Lagrangian space. Notice that, because \( \delta_b^i \) is the average overabundance of haloes, it depends only on the first moment of the halo distribution. To compute the rms scatter around this mean value requires knowledge of the higher order moments of the halo distribution. We will compute this scatter later in this paper.

When \( N \gg j \), \( f(j, b_1|N, b_0) \to f(j, b_1/b_0) \) (Appendix B in Sheth 1996), and \( f^i(b_1|N, V_0) \to 1 \), so

\[ \delta_b^i(j, b_1|N, b_0) \to \frac{N}{\bar{n}V_0} \cdot f(j, b_1/b_0) - 1. \]  
This relation will be useful later.

Define

\[ \bar{\xi}_{\text{bin}}(j, b_1|V_0) \equiv \langle \delta_b^i(1|0) \delta_0 \rangle \]  
where \( \delta_b^i(1|0) \) is given by equation \( \text{(A25)} \),

\[ \delta_0 = \frac{N}{\bar{n}V_0} - 1, \]  
and the average above is over all randomly placed \( V_0 \). Writing all the terms out explicitly gives

\[ \bar{\xi}_{\text{bin}}(j, b_1|V_0) = \left< \frac{N(1|0)}{\bar{n}(j, b_1)V_0} \right> - \left< \frac{N}{\bar{n}V_0} \right> - \left< \frac{N(1|0)}{\bar{n}(j, b_1)V_0} \right>, \]  
where \( \bar{n}(j, b_1) \) is given by equation \( \text{(A0)} \), and \( N(1|0) \) by equation \( \text{(A1)} \). The second term in this expression is
where \(N/b_0 \equiv \bar{n}V_0\). This is the overdensity of \((j, b_1)\)-haloes in the partition \(n\) of \(N\), relative to the average density of such haloes. This, averaged over all partitions, gives the average bias relation of equation (A25):
\[
\delta^{j_\|}_{(j, b_1\mid N, b_0)} \equiv \sum_{n\mid[n]} \bar{\Delta}_j(b_1, n, N, b_0) \ p(n, b_1\mid N, b_0).
\] (A33)

The variance in this bias relation is
\[
\text{Var}(\Delta_j) = \left\langle \frac{n_j}\{n_j - \alpha\}! \right\rangle_{b_1}^{N(b_0 - b_1) / \eta(n, b_0)} \ ,
\] (A34)
where the averages are over all partitions \(n\) of \(N\). This is the same as
\[
\text{Var}(\Delta_j) = \left\langle \frac{n_j^2(b_1, n, N, b_0)}{\bar{\nu}(j, b_1)|V_0|^2} - \left\langle \frac{n_j(b_1, n, N, b_0)}{\bar{\nu}(j, b_1)|V_0|^2} \right\rangle^2, \tag{A35}
\]

where \(mB \equiv (N - \alpha\beta_j)B \equiv N b_0 - \alpha\beta_j b_1\) (Appendix B of Sheth 1996). Similarly, cross–moments are given by
\[
\left\langle \frac{n_i!}{(n_i - \alpha\beta_j)!} \right\rangle_{b_1}^{N(b_0 - b_1)} \equiv \left[ N(b_0 - b_1) \right]^{\alpha + \beta} \eta^n(i, b_1) \eta^\beta(j, b_1) \eta(m, B) / \eta(n, b_0),
\] (A37)
where
\[
mB \equiv (N - \alpha\beta_j)B \equiv N b_0 - \alpha\beta_j b_1. \tag{A38}
\]

These formulae for the higher order moments were obtained after using equation (A31) for the partition formula. Sheth & Lemson (1998) show that this formula arises naturally as a consequence of the fact that disconnected volumes in a Poisson distribution are mutually independent. This allows a simple interpretation of equation (A35).

Define
\[
c(i, j, b_1|k, b_0) \equiv N(j, b_1|k, b_0) N(i, b_1|k - j, b') = \langle n_j, b_1|k, b_0 \rangle \langle n_i, b_1|k - j, b' \rangle, \tag{A39}
\]
where
\[
\bar{n} \equiv \frac{k - j}{\bar{\nu}(j, b_1)} \equiv \bar{n}(1 + \delta_j).
\] (A40)

The halo containing \(j\) particles can be thought of as occupying \(V_j\) of the total volume \(\bar{\nu}\). Thus, \(\delta_j\) parametrizes the
density in the remaining volume $\delta V_k - v_j$, which contains $(k - j)$ particles. Thus, $c(i, j; k)$ is the product of the mean number of $(j, b_j)$-haloes within the volume associated with the $(k, b_k)$-halo and the mean number of $(i, b_i)$-haloes in the remaining volume, given that there is a $(j, b_j)$-halo within $\delta V_k$. Now, equation (A31), implies that
\[ c(i, j, b_j | k, b_k) = \frac{k}{j} f(j, b_j | k, b_k) \left( \frac{k - j}{i} \right) f(i, b_i | k - j, b') \]
\[ = k(b_0 - b_1) \frac{\eta(j, b_j \eta(k - j, b'))}{\eta(k, b_k)} \]
\[ \times (k - j)(b' - b_1) \]
\[ \times \frac{\eta(i, b_i) \eta(k - j - i, b'')}{\eta(k - j, b')}, \]
(A41)

where $b''$ is defined similarly to $b'$. That is,
\[ \frac{\bar{n}}{b''} = \frac{k - j - i}{\delta k - iv_j - iv_i}. \]
(A42)

However,
\[ (k - j)(b' - b_1) = (k b_0 - j b_1) - (k - j)b_1 = k(b_0 - b_1), \]
(A43)

so that
\[ c(i, j, b_j | k, b_k) = \frac{(k b_0 - b_1)^2}{\eta(k, b_0)} \eta(j, b_j) \eta(i, b_i) \eta(k - j - i, b''). \]
This expression is symmetric in $i$ and $j$, and it is easy to see that it is the same as
\[ c(i, j, b_j | k, b_k) = \mathcal{N}(i, b_i | k, b_0) \mathcal{N}(j, b_j | k - i, b'), \]
(A44)

with the appropriate redefinition of $b'$. Simple algebra shows that
\[ c(i, j, b_j | k, b_k) = \left\langle n_i n_j, b_i | k, b_0 \right\rangle, \]
(A45)

where the right hand side is equation (A33) with $\alpha = \beta = 1$. This shows explicitly that
\[ \left\langle n_i n_j, b_i | k, b_0 \right\rangle = \left\langle n_j, b_j | k, b_0 \right\rangle \left\langle n_i, b_i | k - j, b' \right\rangle, \]
(A46)

and that it was obtained by treating the volumes $V_j$ and $\delta V_i - v_j$ as being disconnected from, and independent of, each other.

This argument can be generalized to the higher order moments. For example, if
\[ (k - nj)b^{(n)} = kb_0 - nb_1, \]
with $b^{(0)} = b_0$, (A47)

then
\[ (k - nj)(b^{(n)} - b_1) = k(b_0 - b_1). \]
(A48)

So equation (A33) is also equal to
\[ \mu_{ij}(j, b_j | N, b_0) = \frac{\alpha - 1}{n = 0} \left\langle n_j, b_1 | k - nj, b^{(n)} \right\rangle \]
\[ = \prod_{n = 0}^{\alpha - 1} \mathcal{N}(j, b_j | k - nj, b^{(n)}). \]
(A49)

Thus, the higher order moments described by equation (A33) are consistent with the fact that disconnected volumes in a Poisson distribution are mutually independent. The cross correlation moments of equation (A37) can be interpreted similarly. Thus, for example, the variance in the bias relation above is
\[ \text{Var}(\Delta_j) = \frac{c(j, j, b_j | N, b_0) + \mathcal{N}(j, b_j | N, b_0)}{\bar{n}(j, b_j | V_0)^2} - \frac{\mathcal{N}(j, b_j | N, b_0)^2}{\bar{n}(j, b_j | V_0)^2}. \]
(A50)

Equation (A31) in (A24) implies that
\[ \bar{n}(j, b_j | V_0) = \sum_{N - j}^{N_0} (n_j, b_1 | N, b_0) Q(b_1, N, V_0). \]
(A51)

This shows how the average number of isolated regions, each with average internal density $\bar{n}(1 + b_i)$ and each containing $j$ particles, that are within randomly placed volumes $V_0$, can be obtained from the partition formula of equation (A30).

The main reason for writing this expression explicitly is that it shows clearly how to compute the higher order moments associated with the model of equation (A34).

Let $M_{ij}(j, b_j)$ denote the $\alpha$-th factorial moment of the distribution of $(j, b_j)$-regions that are within spheres of size $V_0$. It is obtained by a similar average to that for the mean:
\[ M_{ij}(j, b_j | V_0) = \sum_{N = j}^{N_0} \mu_{ij}(j, b_j | N, b_0) Q(b_1, N, V_0). \]
(A52)

When $\alpha = 1$, this is the same as equation (A51).

Let $\xi_{hh}(ij | 0)$ denote the correlation between isolated $(i, b_i)$- and $(j, b_j)$-regions, averaged over Lagrangian cells of size $V_0$. Then
\[ M_{ij}(j, b_j | V_0) = \left( \bar{n}(j, b_j | V_0) \right)^{\alpha - 1} (1 + \xi_{hh}(ij | 0)). \]
(A53)

Similarly, when the $b_i$-isolated regions do not have the same number of particles,
\[ 1 + \xi_{hh}(ij | 0) = \sum_{N = i + j}^{N_0} \frac{c(i, j, b_j | N, b_0)}{\bar{n}(i, b_i | V_0) \bar{n}(j, b_j | V_0) Q(b_1, N, V_0)}. \]
(A54)

with the understanding that $c(i, j | N) = 0$ if $(i + j) > N$, so that $\xi_{hh}(ij | 0) = -1$ if $(i + j) > N_0$.

Suppose that each isolated $b_i$-region within $V_0$ is represented by (a randomly chosen) one of its constituent particles. This defines a point process, for which statistics such as the distribution of halo counts-in-cells can be computed. Since $(j, b_j)$-regions are associated with $(j, b_j)$-haloes, it is convenient to call the randomly chosen representative point of such a halo its centre-of-mass. The expressions above give the higher order moments of the distribution of counts of haloes in randomly placed cells $V_0$. Halo–halo correlations can be computed from these moments. For example, equation (A54) gives the volume averaged correlation function of $(i, b_i)$- and $(j, b_j)$-haloes. All the necessary sums can be evaluated analytically.

A6 Statistics for a range of halo masses

The previous subsections considered the halo distribution when the halo mass was specified. This subsection shows how to compute correlations between haloes that have a range of masses. This is necessary, since comparison with simulations is typically done by considering averages over a range of masses, and, as we discuss below, the transition to
considering a range of masses is not completely straightforward. That is, simply integrating the previous expressions over the relevant mass range, weighted by the unconditional mass function, is not entirely correct. It turns out that, over a large range of scales, the correct expression yields only a minor correction to the naive expression, so readers interested only in results may prefer to skip this section.

So far, the distribution of isolated regions and that of the centre-of-mass distribution of collapsed haloes were assumed to be the same. However, there is an important difference between haloes and isolated regions. Namely, by definition, a Lagrangian volume \( V_0 \) with overdensity \( \delta_0 \) cannot contain an isolated \( V_1 < V_0 \) region of overdensity \( \delta_1 < \delta_0 \), nor can it contain an isolated region of density \( \delta_1 \leq \delta_0 \) if its size is \( V_1 > V_0 \). Thus, the number of such isolated regions within an overdense or non-isolated cell \( V_0 \) is zero.

However, since a collapsed halo is represented only by the volume element associated with its centre-of-mass, haloes are said to lie within a cell if their centre-of-mass falls inside it; in the model, the centre-of-mass of the halo falls inside it; in the model, the centre-of-mass is a randomly chosen volume element, so this happens with probability \( \frac{V_1}{V_0} \). Thus, a cell \( V_0 \) that is either overdense or not isolated may contain a halo, whereas, by definition, it cannot contain an isolated region. Previously, this difference between haloes and isolated regions was unimportant. Now, however, since we must integrate over a range of halo masses, it can be important.

Consider the set of \( V_0 \) cells placed randomly in the Lagrangian space. Suppose we wish to count up the number of \( b_1 \)-haloes that are more massive than \( m \), that are in such cells. Given a value of \( b_1 \), these cells can be divided into two classes: those that are isolated and those that are not. Those that are isolated can be classified by the number \( N \) of particles within the cell. All isolated cells that contain \( N \) particles can be further classified by the way in which the particles are divided into \( b_1 \)-haloes. Consider an isolated cell \( V_0 \) that is known to contain exactly \( N \) particles which are partitioned into \( b_1 \)-haloes. As before, denote the particular partition by the vector \( \mathbf{n} \). Let \( N_0(j, b_1 | \mathbf{n}, b_0) \) denote the number of \( (j, b_1) \)-haloes that are within such a cell. The number of \( b_1 \)-haloes more massive than \( m \) that are within such cells is

\[
N_{\text{isal}}(> m, b_1 | V_0) = \sum_{j > m} N_0(j, b_1 | \mathbf{n}, b_0). \tag{A55}
\]

Equation (A31) shows that this quantity, averaged over all partitions of \( N \), is

\[
\sum_{\mathbf{n} | N} N_{\text{isal}}(> m, b_1 | \mathbf{n}, V_0) p(\mathbf{n}; b_1 | N, b_0) = \sum_{j > m} \langle n_j, b_1 | N, b_0 \rangle. \tag{A56}
\]

This, averaged over all values of \( N \), is

\[
\bar{N}_{\text{isal}}(> m, b_1 | V_0) = \sum_{j > m} Q(b_1, N, V_0) \sum_{j > m} \langle n_j, b_1 | N, b_0 \rangle, \tag{A56}
\]

since \( Q(b_1, N, V_0) \) denotes the fraction of the total number of cells that are isolated. This sum is zero when \( N \leq m \), because if the cell \( V_0 \) is isolated, then all the particles associated with a halo within \( V_0 \) must be contained in \( V_0 \), and we are only counting haloes more massive than \( m \). The definition of \( Q \) (equation A21) insures that the sum is also zero when \( N > N_{\text{isal}} \). This is because, when \( N > N_{\text{isal}} \), then the cell is denser than \( b_1 \), so it is not isolated on the scale \( V_0 \).

The order of the sums above can be interchanged to yield

\[
\bar{N}_{\text{isal}}(> m, b_1 | V_0) = \sum_{j > m} N_0 \sum_{N=j} Q(b_1, N, V_0) \bar{N}(j, b_1 | N, b_0)
= \sum_{j > m} \bar{n}(j, b_1) V_0, \tag{A57}
\]

where the final equality follows from equation (A24).

Cells that are not isolated on scale \( V_0 \) can be classified by the scale \( V_j \) at which they first become isolated. They can be further classified by the number of particles \( N < j \) they actually contain on scale \( V_0 \). The probability that a cell first becomes isolated on scale \( V_j \), given that it contains \( N \) particles on scale \( V_0 < V_j \) is

\[
P(j, b_1 | N, V_0) \equiv \frac{p(N, V_0 | j, V_j) F(j, b_1)}{p(N, V_0)}. \tag{A58}
\]

Recall that \( F(j, b_1) \) is the probability that randomly placed particles are inside \( V_j \) and are not isolated by \( j \), so the expression above follows from Bayes’ rule. The region \( V_0 \) is a subregion of the isolated region \( V_j \). Since \( V_j \) is isolated, it can be thought of as a \( (j, b_1 \)-halo. The subregion \( V_0 \) is said to contain this \( (j, b_1 \)-)halo only if it contains the randomly chosen centre-of-mass particle of the halo. This happens with probability \( V_0 / V_j \). Therefore, the average number of \( b_1 \)-haloes that are in cells which are not isolated on scale \( V_0 \) is

\[
N_{\text{other}}(> m, b_1 | V_0) = \sum_{N=0}^{\infty} p(N, V_0) \sum_{j=j_{\text{min}}}^{\infty} \frac{V_0}{V_j} P(j, b_1 | N, V_0), \tag{A59}
\]

where \( j_{\text{min}} = (m+1) \) if \( m > N_{\text{isal}} \). Otherwise, \( j_{\text{min}} = (N_{\text{isal}} + 1) \). Since \( V_0 < V_j \), \( p(N, V_0 | j, V_j) = 0 \) if \( N > j \). With this in mind, the order of the sums can be interchanged:

\[
N_{\text{other}} = \sum_{j=j_{\text{min}}}^{\infty} \sum_{N=0}^{\infty} \frac{V_0}{V_j} P(j, b_1 | N, V_0) \sum_{N=0}^{\infty} p(N, V_0 | j, V_j) \tag{A60}
\]

The sum over \( N \) is unity, so the average number of \( b_1 \)-haloes more massive than \( m \) that are within such \( V_0 \) cells is

\[
N_{\text{other}} = \sum_{j=j_{\text{min}}}^{\infty} \frac{V_0}{V_j} F(j, b_1) \sum_{j=j_{\text{min}}}^{\infty} \bar{n}(j, b_1) V_0. \tag{A60}
\]

The final equality follows from equation (A31).

On average, the number of \( b_1 \)-haloes that are more massive than \( m \), that are within randomly placed \( V_0 \) cells, is given by adding the contribution from the two types of cells—those that are isolated on scale \( V_0 \) and those that are not. Thus, when \( m < N_{\text{isal}} \), then the average over all \( V_0 \) cells, \( \bar{N}_{\text{isal}} + \bar{N}_{\text{other}} \), is

\[
\bar{n}(> m, b_1) V_0 \equiv \sum_{j>m} \bar{n}(j, b_1) V_0. \tag{A61}
\]
If \( m > N_{01} \), then \( \bar{N}_{\text{isol}}(> m, b_1|V_0) = 0 \), and the average is simply \( \bar{N}_{\text{other}}(> m, b_1|V_0) \) which is the same as the expression above.

As before, define
\[
\Delta_h(> m, b_1|n, V_0) \equiv \frac{N_h(> m, b_1|n, V_0)}{\bar{n}(> m, b_1)V_0} - 1. \tag{A62}
\]
The cross correlation between haloes and mass, averaged over all cells \( V_0 \), is
\[
\bar{\xi}_{\text{hm}}(> m, b_1|V_0) \equiv \left\langle \Delta_h(> m, b_1|n, V_0) \delta_0 \right\rangle
= \frac{\langle N_h(> m, b_1|n, V_0) \delta_0 \rangle}{\bar{n}(> m, b_1)V_0}, \tag{A63}
\]

since \( \delta_0 = (N - \bar{N}_{01})/\bar{N}_{00} \).

For isolated cells, this average can be computed in two steps. The first is to average over all partitions \( \pi[n] \) of \( N \). The second is to average over all values of \( N \). If \( m \leq N_{01} \), then the contribution from isolated cells is
\[
\left\langle \bar{N}_{\text{isol}} \delta_0 \right\rangle = \sum_{j > m} \sum_{N = j}^{N_{01}} \bar{n}(j, b_1)V_0 \bar{\xi}_{\text{hm}}(j, b_1|V_0), \tag{A64}
\]
where the first equality arises from the average over partitions of \( N \) (equation [A56]), and the second equality follows from using equation (A59). The contribution from the other cells is
\[
\left\langle \bar{N}_{\text{other}} \delta_0 \right\rangle = \sum_{j > N_{01}}^{N_{01}} \frac{V_0}{V_j} \Gamma(j, b_1) \sum_{N = 0}^{j} \delta_0 p(N, V_0|j, V_j). \tag{A65}
\]

Since \( \delta_0 = (N - \bar{N}_{01})/\bar{N}_{00} \), the sum over \( N \) is
\[
\frac{j}{\bar{N}_{00} V_j} - 1 = 1 - \frac{b_1}{b_1} = \delta_1,
\]
so the contribution from these other cells is
\[
\left\langle \bar{N}_{\text{other}} \delta_0 \right\rangle = \delta_1 \sum_{j > N_{01}}^{N_{01}} \bar{n}(j, b_1)V_0. \tag{A66}
\]
The cross correlation function averaged over all cells is the sum of these two terms divided by \( \bar{n}(> m, b_1)V_0 \):
\[
\bar{\xi}_{\text{hm}}(> m, b_1|V_0) = \sum_{j > m}^{N_{01}} \bar{n}(j, b_1)V_0 \bar{\xi}_{\text{hm}}(j, b_1|V_0)
+ \delta_1 \sum_{j > N_{01}}^{N_{01}} \frac{\bar{n}(j, b_1)V_0}{\bar{n}(> m, b_1)V_0}. \tag{A67}
\]

There is no contribution from isolated cells, and the remaining cells yield
\[
\bar{\xi}_{\text{hm}}(> m, b_1|V_0) = \delta_1, \quad \text{if } m > N_{01}.
\]

Auto-correlations between haloes can be computed similarly. Define
\[
\bar{\xi}_{hh}(> m, b_1|V_0) \equiv \langle \Delta_h^2(> m, b_1|n, V_0) \rangle - \frac{1}{\bar{n}(> m, b_1)V_0}. \tag{A68}
\]
The second term is the shot-noise term. It accounts for the fact that the halo distribution is discrete.

First consider the case when \( m \leq N_{01} \), so isolated cells may contain more than one halo in the mass range of interest. For isolated cells, correlations arise as a result of two averages. The first is over all partitions of \( N \). The second is over all values of \( N \). Given a partition \( n \) of \( N \),
\[
N_{\text{isol}}^2 = (n_{m+1} + \cdots + n_k)^2 \sum_{i > m}^{N} \sum_{j > m}^{N} n_i n_j.
\]

Equations (A33) and (A34) show how to compute these averages over the set of partitions \( \pi[n] \). Notice that when \( i = j \), then \( (A37) \) for \( \langle n_i n_j \rangle \), is the same as \( (A33) \) for \( \langle n_i (n_i - 1) \rangle \). Therefore, if we use (A37) even when \( i = j \), and write it using (A45), then the average over \( N \) is
\[
\langle N_{\text{isol}}^2 \rangle = \sum_{N} Q(b_1, N, V_0) \sum_{i > m}^{N_{01}} \sum_{j > m}^{N_{01}} c(i, j, b_1|N, b_0)
+ \sum_{N} Q(b_1, N, V_0) \sum_{j > m}^{N_{01}} \langle n_j, b_1|N, b_0 \rangle \tag{A69}
\]

where \( c(i,j)|N \rangle = \langle n_i n_j|N \rangle = 0 \) if \( (i + j) > N \). Equation (A57) shows that the second term is just \( \bar{N}_{\text{isol}}(> m, b_1|V_0) \).

Cells \( V_0 \) that are not isolated either contain one or no haloes. So, the contribution from these cells is just \( \bar{N}_{\text{other}}(> m, b_1|V_0) \) of equation (A54). The contribution from these cells, plus the second term from the isolated cells equals \( \bar{n}(> m, b_1)V_0 \). Together, they cancel the shot noise term in the definition of \( \bar{\xi}_{\text{hm}} \). The order of the sums in the remaining first term of (A66) can be rearranged to yield
\[
1 + \bar{\xi}_{\text{hm}}(> m, b_1|V_0) = \sum_{i > m}^{N_{01}} \sum_{j > m}^{N_{01}} \frac{\bar{n}(i, b_1)V_0 \bar{n}(j, b_1)V_0}{\bar{n}(> m, b_1)V_0^2}
\times \sum_{N = i + j}^{N_{01}} \frac{c(i, j, b_1|N, b_0)}{\bar{n}(j, b_1)V_0} Q(b_1, N, V_0). \tag{A70}
\]

where \( c(i,j)|N \rangle = 0 \) if \( (i + j) > N \). If \( m > N_{01} \), there are no isolated cells which contain haloes in the mass range of interest. All other cells either contain one or no haloes, so, for these cells \( \bar{N}_{hh}(> m, b_1|V_0) = \bar{n}(> m, b_1)V_0 \). This term cancels the shot noise term, so that
\[
\bar{\xi}_{hh}(> m, b_1|V_0) = -1, \quad \text{if } m > N_{01}. \tag{A71}
\]

Comparison with equation (A54) shows that
\[
1 + \bar{\xi}_{hh}(> m, b_1|V_0) = \sum_{i > m}^{N_{01}} \sum_{j > m}^{N_{01}} \frac{\bar{n}(i, b_1)V_0 \bar{n}(j, b_1)V_0}{\bar{n}(> m, b_1)V_0^2}
\times \left[ 1 + \bar{\xi}_{hh}(i, j|0) \right], \tag{A72}
\]
with the convention that \( 1 + \bar{\xi}_{hh}(ij|0) = 0 \) if \( (i + j) > N_{01} \).

A7 Clustering from white noise as a limit of the Poisson model

This subsection shows explicitly that, in the limit of small fluctuations and large numbers of particles, all the statements about clustering from white noise initial conditions presented in the main text can be derived from the Poisson statements derived above by using Stirling’s approximation
for all the factorials, and writing all expressions to lowest order in \( \delta \).

Let \( N = \bar{n}V(1 + \delta) \), and let \( S \equiv \langle \delta^2 \rangle = 1/\bar{n}V \) denote the mean square fluctuation of \( \delta = (N - \bar{n}V)/\bar{n}V \) in cells of size \( V \). Then \( dN/d\delta = \bar{n}V \), and, when \( \delta \ll 1 \), then use of Stirling’s approximation for the factorial reduces equation (A3) for \( p(M, V) \) to equation (1). Similarly, equation (A2) tends to equation (A4). Furthermore, \( f(M, b) \rightarrow f(S, \delta) \delta^M/dM \delta^M/dM \) of equation (1) (e.g. Epstein 1983) and \( f(M_1, b_1|0, b_0) \rightarrow f(S_1, \delta_1|0, \delta_0) |dS_1|/dM_1 \delta_1^M/dM_1 \) of equation (3) (Sheth 1995), since \( b = 1/(1 + \delta) \approx (1 - \delta) \), and \( 1 - (b_1/b_0) \approx (\delta_1 - \delta_2) \). Simple algebra shows that equations (3) and (4) satisfy a recursion relation that is similar to the one in the discrete Poisson case (and solved in Appendix B). Namely,

\[
p(S_1, \delta_1|S_0, \delta_0) = \int_{S_0}^{S_1} f(S', \delta_1|S_0, \delta_0)p(S_1, \delta_1|S', \delta_1) dS'. \tag{A73}
\]

By considering the statistics of trajectories that are analogous to those considered in the Poisson case, Bond et al. (1991) have shown that these expressions can be derived directly from the white noise field itself.

The virtue of using the trajectory description is that it allows one to see the correctness of many statements that are otherwise tedious to compute. For example, suppose we label each trajectory by the value \( S' \), which is the smallest value of \( S \) at which it has overdensity density \( \delta ' \). If \( \delta \geq \delta ' \geq 0 \), then

\[
p(S, \delta) = \int_0^S p(S, \delta|S', \delta') f(S', \delta') dS'. \tag{A74}
\]

The left hand side of this expression is the set of all trajectories that pass through \( \delta > 0 \). The right hand side is the set of all trajectories that first pass through \( \delta ' \leq \delta \) at \( S' < S \), and then pass through \( \delta > 0 \). Since trajectories that first pass through \( \delta ' \) on scale \( S' > S \) have certainly not passed through \( \delta > \delta ' \) at \( S \). Clearly, the left hand side equals the right. When \( \delta = \delta ' \), then direct substitution shows that this is correct. Otherwise, direct substitution is not the easiest way to see that this must be correct. This equation is the analogue of equation (A3).

Notice that

\[
\frac{d}{d\delta} p(S, \delta) = f(S, \delta), \tag{A75}
\]

and

\[
\frac{d}{d\delta} p(S, \delta|S', \delta') = f(S, \delta|S', \delta'). \tag{A76}
\]

These relations, with equation (A74), imply that

\[
\frac{d}{d\delta} p(S, \delta) = \frac{d}{d\delta} \int_0^S p(S, \delta|S', \delta') f(S', \delta') dS' = \int_0^S f(S, \delta|S', \delta') f(S', \delta') dS' = f(S, \delta) \tag{A77}
\]

as required by equation (A73).

The number density of \( M_1 \) haloes, that is, the unconstrained mass function, is \( \bar{p}(M_1, \delta_1) \) which is the same as equation (1). Similarly, the conditional mass distribution is \( \bar{p}(M_0, \delta_0) = f(M_1, \delta_1|M_0, \delta_0) \) which is the same as equation (A8). These are the analogues of equations (A9) and (A10).

The limit of equation (A20) is

\[
Q(b_1, M_0, 0) \rightarrow q(\delta_1, 0, V_0) \equiv p(S_0, \delta_0) - \int_0^{S_0} p(S_0, \delta_0|S_1, \delta_1) f(S_1, \delta_1) dS_1. \tag{A78}
\]

If \( \delta_0 > \delta_1 \), then equation (A74) shows that \( q = 0 \). When \( \delta_0 > \delta_1 \), then the integral above can be solved to yield equation (1). Bond et al. (1991) discuss Chandrasekhar’s derivation of \( q(\delta_1, 0, V_0) \). Their discussion of excursion set trajectories associated with Gaussian random fields shows, with no calculation, that the expression above is correct.

The excursion set approach of Bond et al. (1991) also shows why equation (1) must be correct. Consider the set of all excursion set trajectories, and label each trajectory by its value of \( \delta(V_0) \equiv \delta_0 \) on scale \( V_0 \). Now, \( q(\delta_1, 0, V_0) \) gives the probability that such a trajectory lies below \( \delta_1 \) for all \( V > V_0 \), and \( f(M_1, \delta_1|M_0, \delta_0) \) gives the fraction of trajectories that first cross the value \( \delta_1 \) on scale \( V_1 \), given that they have value \( \delta_0 \) on scale \( V_0 \). Integrating the product of these two expressions over all \( \delta_0 \leq \delta_1 \) gives the fraction of trajectories that first cross the value \( \delta_1 \) on scale \( V_1 \), which is the same as equation (1). The extra factor of \( M_0/M_1 \) on the left hand side above is \( \rho V_0/M_1 \) when written on the right hand side, which is consistent with equation (1).

Expressions for the mean bias between haloes and mass can be obtained by taking similar limits. A little algebra shows that the peak background split of equation (3) could have been obtained directly from the corresponding Poisson limit, equation (A20).

Expressions for the cross correlation between haloes and mass transform similarly, as well as for the higher order moments of the halo distribution all transform similarly. For example, equation (A21) could have been derived by taking the limit of equation (A49), etc.

APPENDIX B: SOLUTION TO THE RECURSION RELATION

This Appendix shows, by direct substitution, that equation (A13) for \( F(j|k) \) in the main text solves the recursion relation given in equation (A11).

Equation (A11) can be rearranged to read

\[
\sum_{m > j} F(m, b_1|k, b_2) p(j, \nu_j|m, \nu_m) = \frac{p(j, \nu_j, k, \nu_k)}{F(k, b_2)} f(\delta_2|k, V_k) - F(j, b_1|k, b_2). \tag{B1}
\]

Equation (A7) shows that the right hand side of this expression is

\[
\text{RHS} = \frac{p(j, \nu_j)}{p(k, \nu_k)} f(\delta_2|k, V_k) - F(j, b_1|k, b_2), \tag{B2}
\]

where all the \( p(n, V) \)s are Poisson, so they are given by equation (A11). If equation (A13) for \( F(j|k) \) is correct, then

\[
\text{RHS} = (k - j) \left( \frac{j}{k} \right) \left( \frac{b_1}{b_2} \right)^{j+1} \left( \frac{k - b_1}{b_2} \right)^{k-j-1}. \tag{B3}
\]
Substituting equation (A12) for \( p(j, v_j|m, \nu_m) \) in the left hand side gives
\[
k \left( 1 - \frac{b_1}{b_2} \right) \left( \frac{m}{k} \right) m^m \left( \frac{b_1}{b_2} \right)^m (k-m) \left( \frac{b_1}{b_2} \right)^{k-m-1} \times \left( \frac{m-1}{j} \right) (\frac{j}{m})^{j-1} (1 - \frac{j}{m})^{m-j}
\]
summed over all \( j < m \leq k \). This reduces to
\[
(k-j) \left( \frac{k}{j} \right) k^{j+1} \left( \frac{b_1}{b_2} \right)^{j+1} (k-1) \left( \frac{b_1}{b_2} \right)
\]
\[\times \sum_{n=0}^{N} \left( \frac{N}{n} \right) \left( \frac{b_1}{b_2} + \frac{n b_1}{b_2} \right)^n \left( k - (j+1) \frac{b_1}{b_2} - n \frac{b_1}{b_2} \right)^{N-n-1}
\]
which \( N = (k-j-1) \). Abel’s generalization of the binomial theorem
\[(x+y)^N = \sum_{m=0}^{N} \left( \frac{N}{m} \right) x(x-mz)^{m-1}(y+mz)^{N-m}, \quad \text{(B6)}
\]
with \( m = N-n \), \( x = k(b_2-b_1)/b_2 \), \( y = (k-j)(b_1/b_2) \), and \( z = -(b_1/b_2) \), reduces this to equation (B3).

A similar recursion relation is satisfied by \( f(j, b_1|k, b_2) \). Namely,
\[
\sum_{m>j} f(m,b_1|k,b_2) \frac{p(j, v_j|m, \nu_m)}{f(k,b_2)} = \frac{p(j-1, v_j)}{f(k,b_2)} - f(j, b_1|k, b_2).
\]
Since now trajectories are known to be centred on particles,
\[p(j, v_j | k, \nu_k) = \frac{p(j-1, v_j)}{f(k,b_2)} = \frac{p(j,v_j)}{b_1} p(j-k, \nu_k - v_j).
\]
Since \( F(k,b_2) = b_2 f(k,b_2) \) (equation A10), the right hand side of equation (B7) is \((b_2/b_1)\) times that in equation (B1).

Similarly, since now trajectories are centred on particles,
\[p(j, v_j | m, \nu_m) = \frac{p(j-1, v_j)}{f(m-1, \nu_m)} \frac{p(m-j, v_m - v_j)}{f(m-1,b_2)}.
\]
This is the same as equation (A12). Therefore, if the left hand side of equation (B3) is to equal \((b_2/b_1)\) times the left hand side of equation (B1), then it must be that \( f(j, b_1|k, b_2) = (b_2/b_1) F(j, b_1|k, b_2) \). This is just what is required by equation (A14). Thus, if \( f(j,k) \) is given by equation (A14), then it satisfies the recursion relation (B7).

**APPENDIX C: AVERAGING OVER ALL VOLUMES**

This Appendix shows that the expressions for the conditional and unconditional mass functions are obtained by an averaging process envisaged by Bower (1991). Namely, the averaging is over all possible subvolumes, not necessarily connected, that are contained entirely within a parent volume.

Suppose space is divided up into a large number \( C \) of infinitesimally small cells, each of volume \( v \). The cells are sufficiently small that each cell is either empty, or it contains one and only one particle. Suppose that there are \( N \) particles distributed in this space. This means that \( N \) of the \( C \) cells are occupied. Now choose \( c \) cells in random order without replacement from the total set of \( C \) cells. The probability that \( n \) of these \( c \) cells are occupied is
\[
p(n,c) = \binom{c}{n} \frac{(N-1) \cdots (N-n+1)}{(C-1) \cdots (C-n+1)} \times \frac{(C-n) \cdots (C-c+1)}{(c-n) \cdots (c+1)}
\]
When \( C \gg n \), Stirling’s approximation for all the factorials except \( n! \) reduces this to
\[
p(n,c) = \frac{1}{n!} \left( \frac{cN}{C} \right)^n e^{-cN/C}.
\]

Now, \( C_v \) is the total volume, so \((N/C_v)N/C_v \) is the average number density of particles; denote it by \( \bar{n} \). The parameter \( cN/C_v \) is the size of the cell made of \( c \) infinitesimal cells; set \( cN/C_v \equiv V \). Then \((cN/C_v) = nV \) and this expression is the same as equation (A4). This shows explicitly how the Poisson distribution is obtained by choosing, in random order without replacement, a series of volume elements of the total space, and weighting each series of choices with the probability that it occurs. Since \( F(j,b) \) is simply the product of \( p(j,v_j) \) with a quantity that depends on \( b \) but not \( V \), the argument above applies to \( F(j,b) \) also. In particular, since the volume elements \( c \) are chosen at random from the full space, there is no requirement that they be adjacent.

A similar argument can be used to derive equation (A2). Namely, suppose \( V_2 \), containing exactly \( N \) particles is divided up into a large number \( C \) of small volumes \( v \). Then, the probability that in \( c \) volumes, chosen randomly without replacement from \( C \), there are exactly \( n \) occupied volumes, when it is known that there are exactly \( N \) occupied volumes in \( C \), is given by the same expression (C1) as before. When \( C \gg n \), \( N \gg n \), Stirling’s approximation for all the factorials except \( n! \) term reduces this to
\[
p(n,c|N,C) \rightarrow \binom{N}{n} \left( \frac{c}{C} \right)^n \left( 1 - \frac{c}{C} \right)^{N-n}.
\]

With \( cV \equiv V_1 \), this is the same as equation (A4), since \( C_v \equiv V_2 \). Again, the only constraint on the volume elements \( c \) is that they lie entirely within \( V_2 \). There is no requirement that they be adjacent.

What remains to be shown is that \( F(j|k) \) is also obtained by a sampling process in which the different volume elements which make up \( v_j \) are chosen randomly without replacement from \( \nu_k \), so, in particular, they are not necessarily adjacent to each other. This follows from the original derivation, or from the fact that the derivative of \( p(j|k) \) is so easily related to \( F(j|k) \), or from the derivation of \( f(j|k) \) given in Sheth (1995).