SDSS・すばるHSC銀河団の弱重力レンズ効果による可視光観測量と銀河団質量関係の導出

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(博士課程1年, Kavli IPMU)

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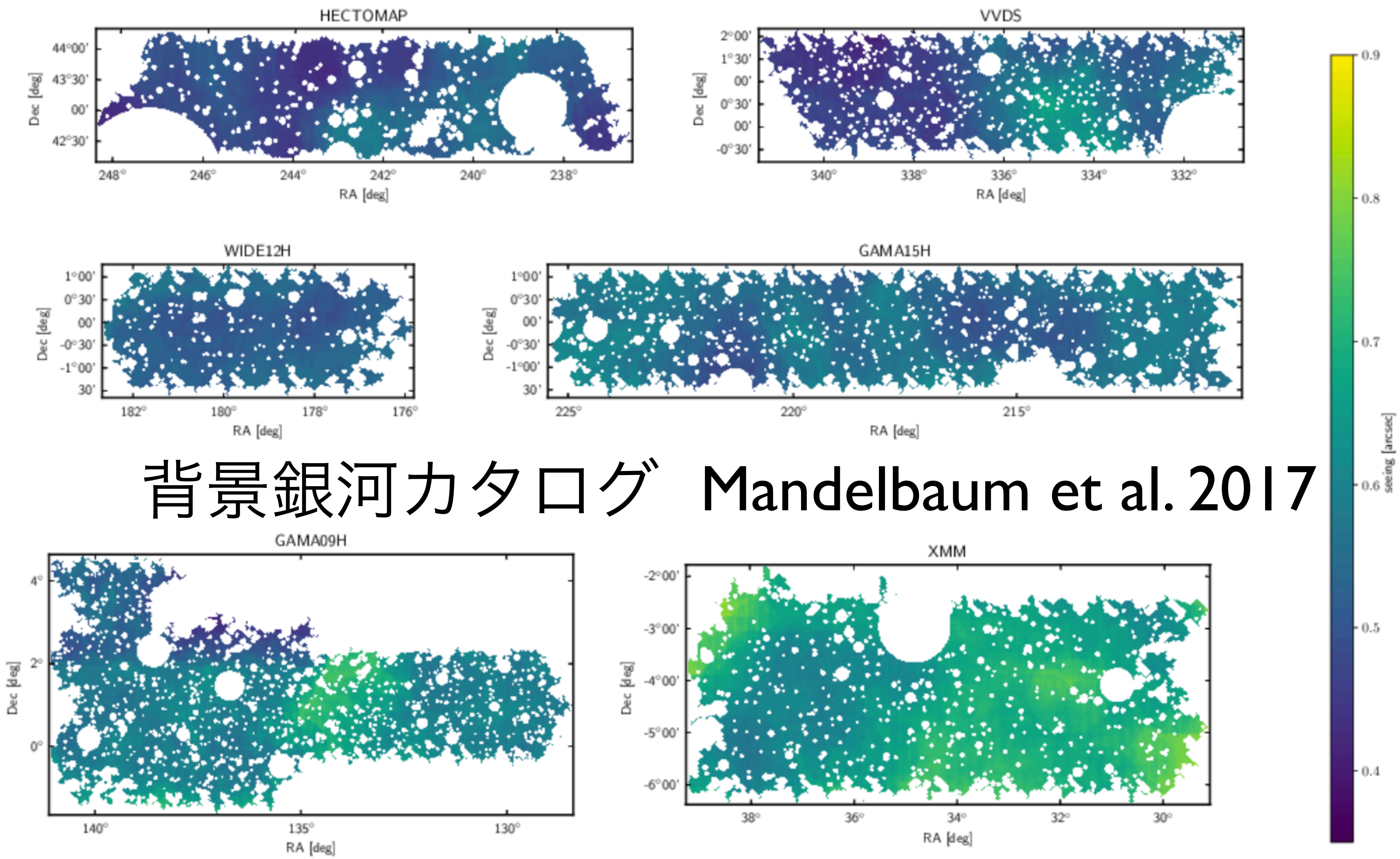
第6回観測的宇宙論ワークショップ@弘前大学, 10/25 2017

すばる望遠鏡 Hyper Suprime-Cam (HSC)



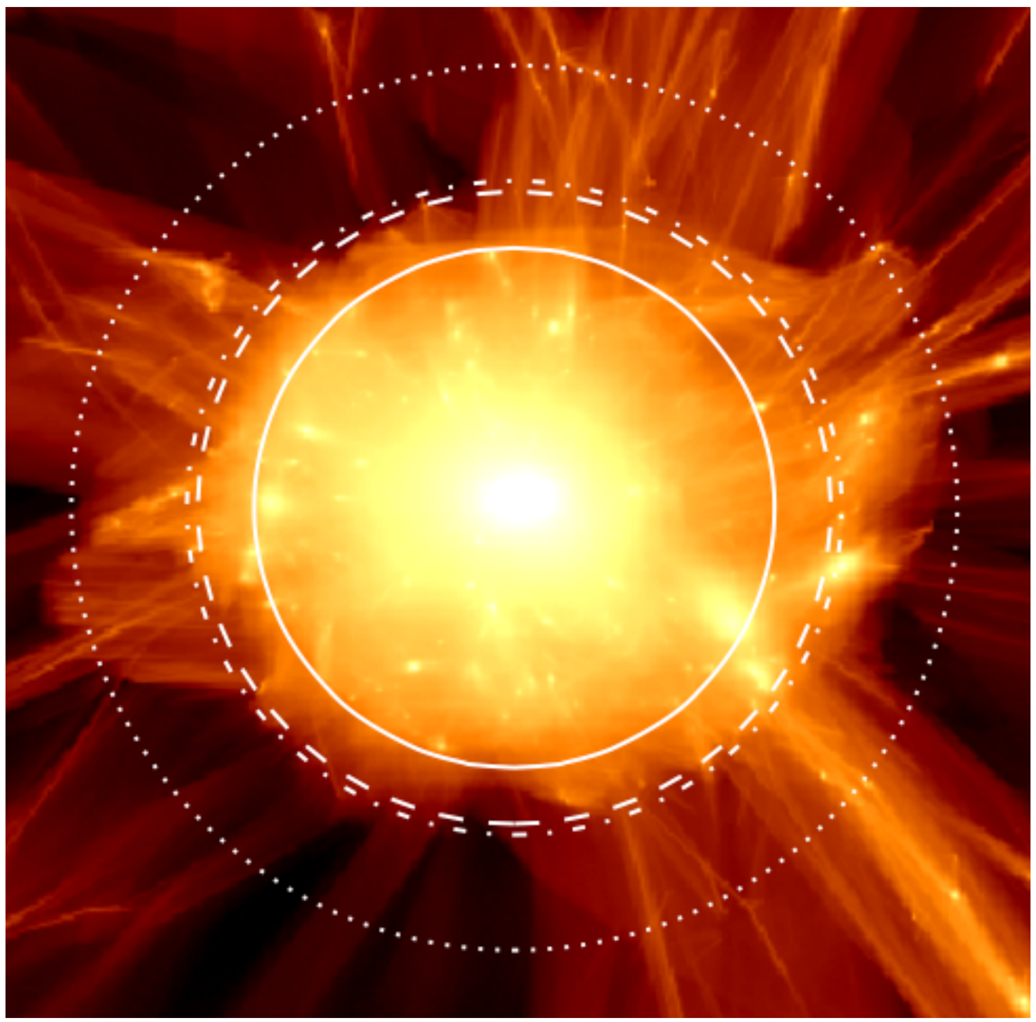
背景銀河カタログ Mandelbaum et al. 2017

More opportunities in these years!

Contents

可視光観測における銀河団

銀河団 “Dark matter halo”



More. S et, al.

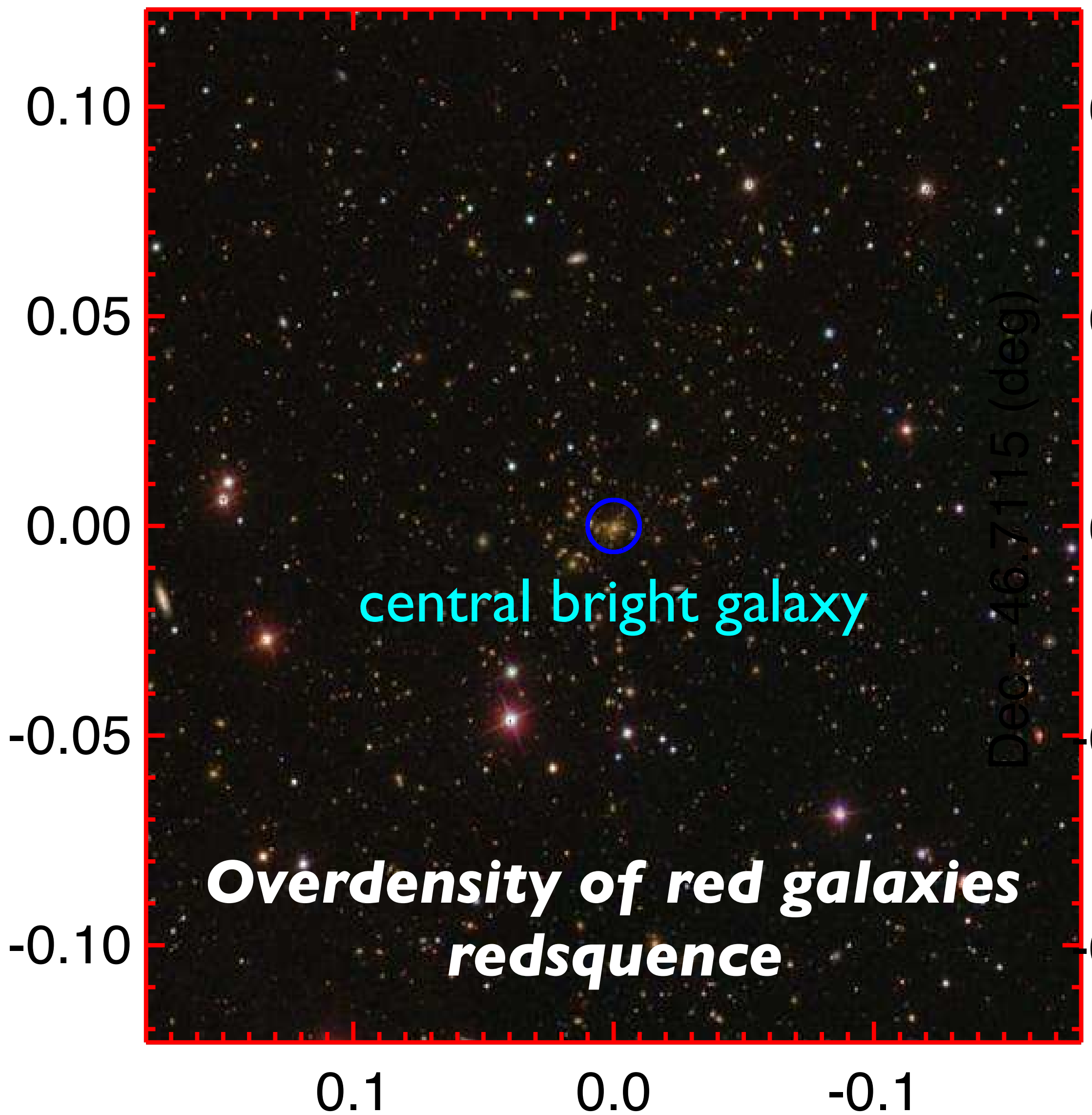
最大の自己重力束縛系

数密度とクラスタリングは
宇宙論に強く依存。

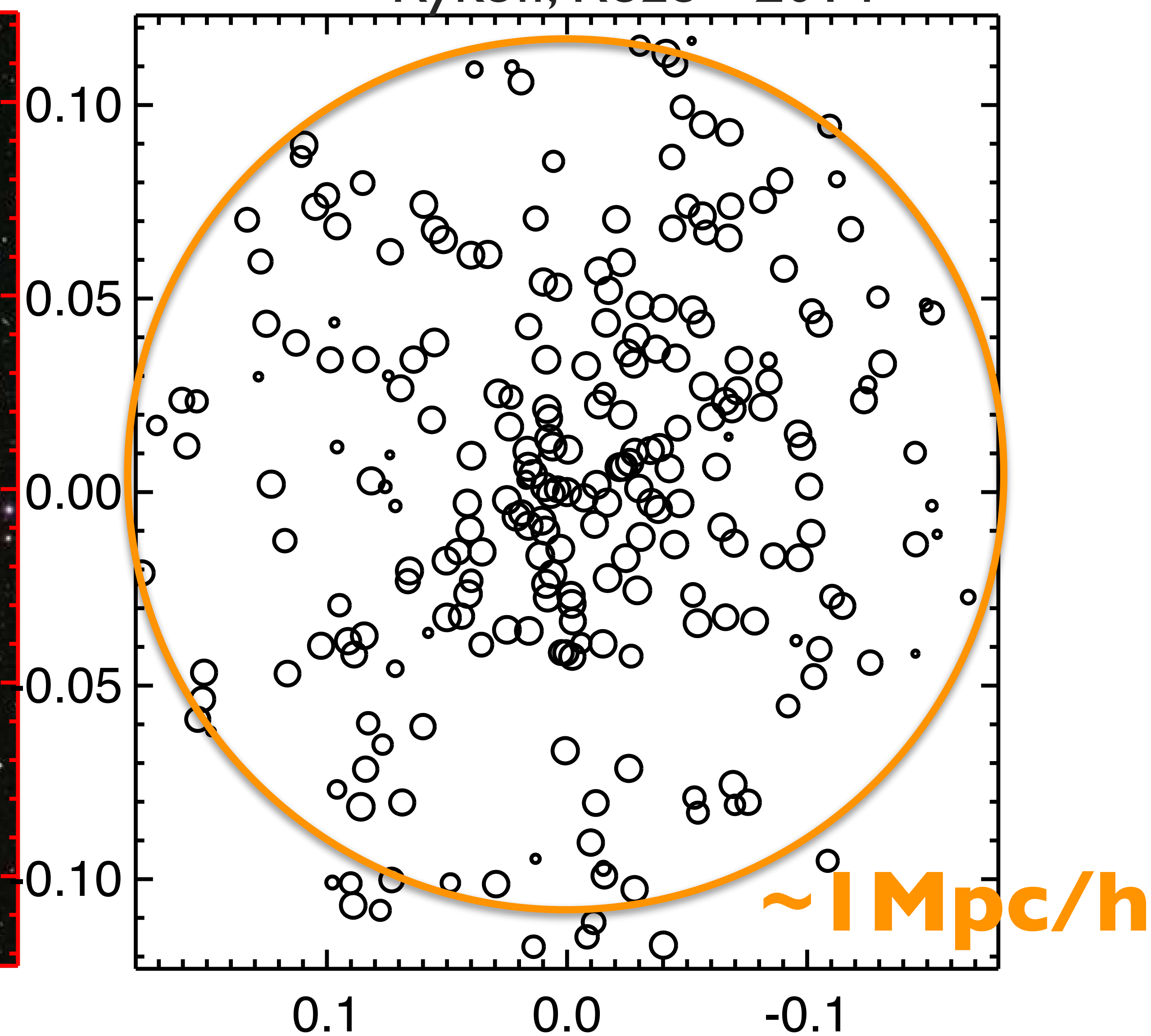
理論予測 (N体シミュレーション)は
銀河団質量と赤方偏移の関数。

銀河団における銀河進化

可視光における銀河団



Rykoff, Rozo+ 2014



$$\frac{\lambda}{S} = \sum_{\mathrm{gals}} p_{\mathrm{mem}}$$

マスクと深さの補正　　メンバー確率

可視光における観測量

richness λ=赤いメンバー銀河の数

Observational challenge

1) Mass-richness関係式

観測を理論モデルをつなげる。

$$\lambda \longleftrightarrow M_{\rm halo}$$

ばらつきも含めて

Very important to robustly compare observation with models!

Observational challenge

2) より詳細な系統誤差

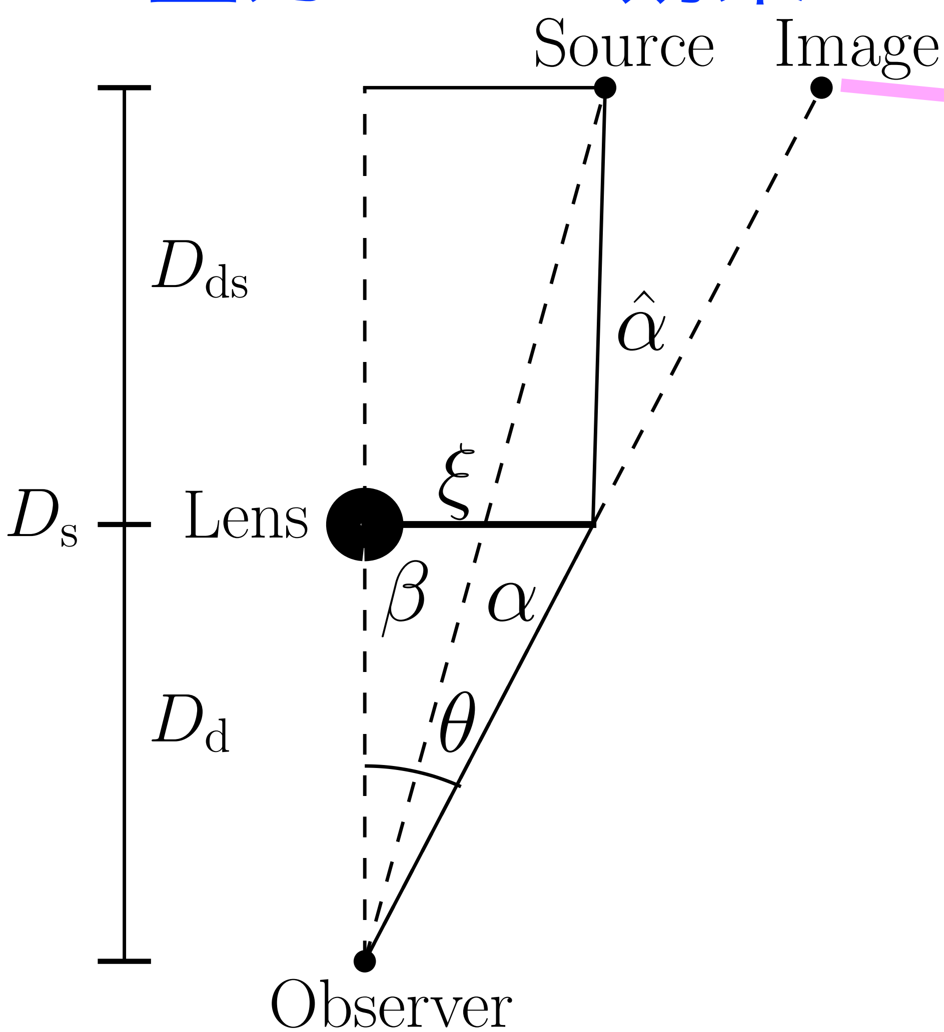
-Projection effect: misidentification of haloes as one cluster

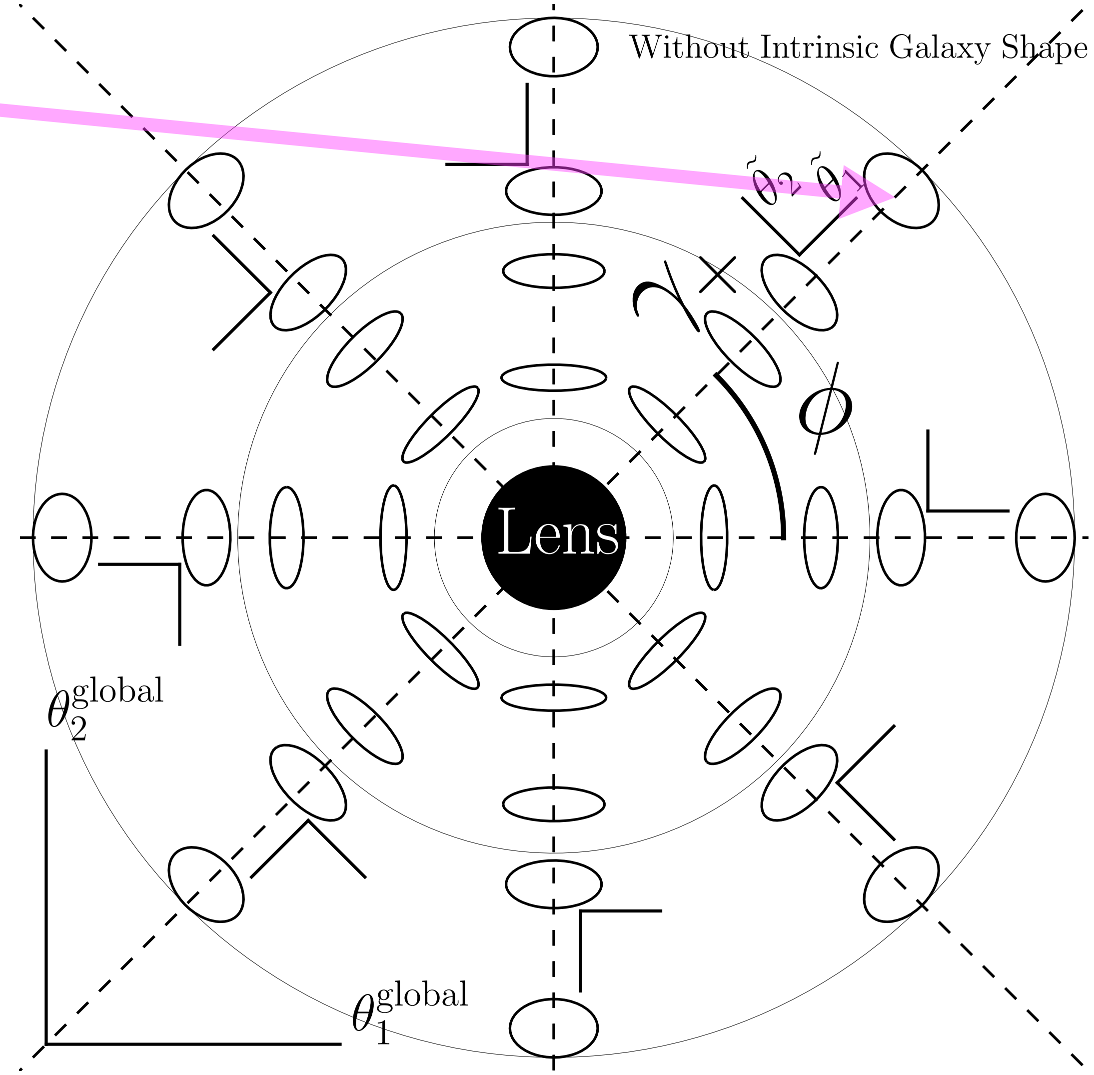
-Orientation selection bias: not spherical

Very important to robustly compare observation with models!

弱重力レンズ効果

重力レンズ効果　　天球面上での銀河団周りの*shear*





銀河団質量に依存する。

SN比を上げるために、銀河団をrichnessビンで (e.g. 20<λ<30)

をstackする必要がある。

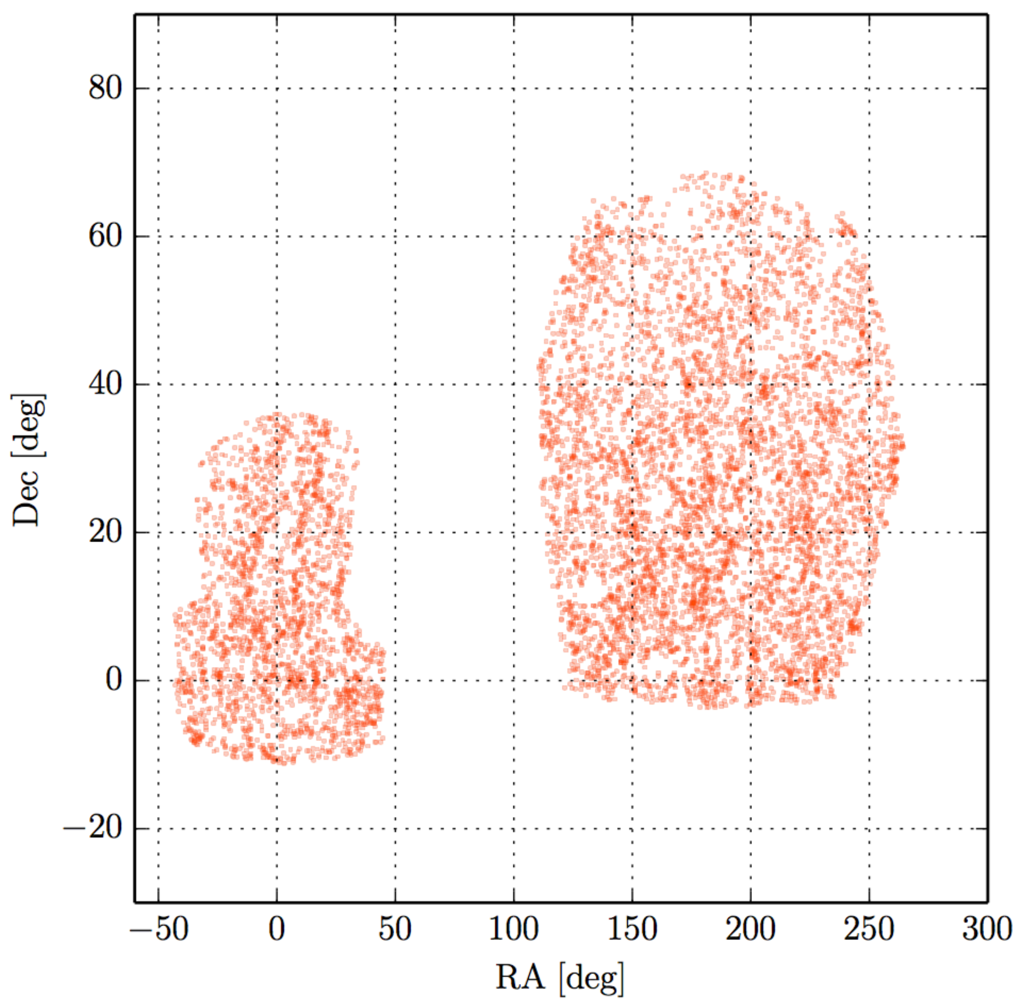
SDSSデータ

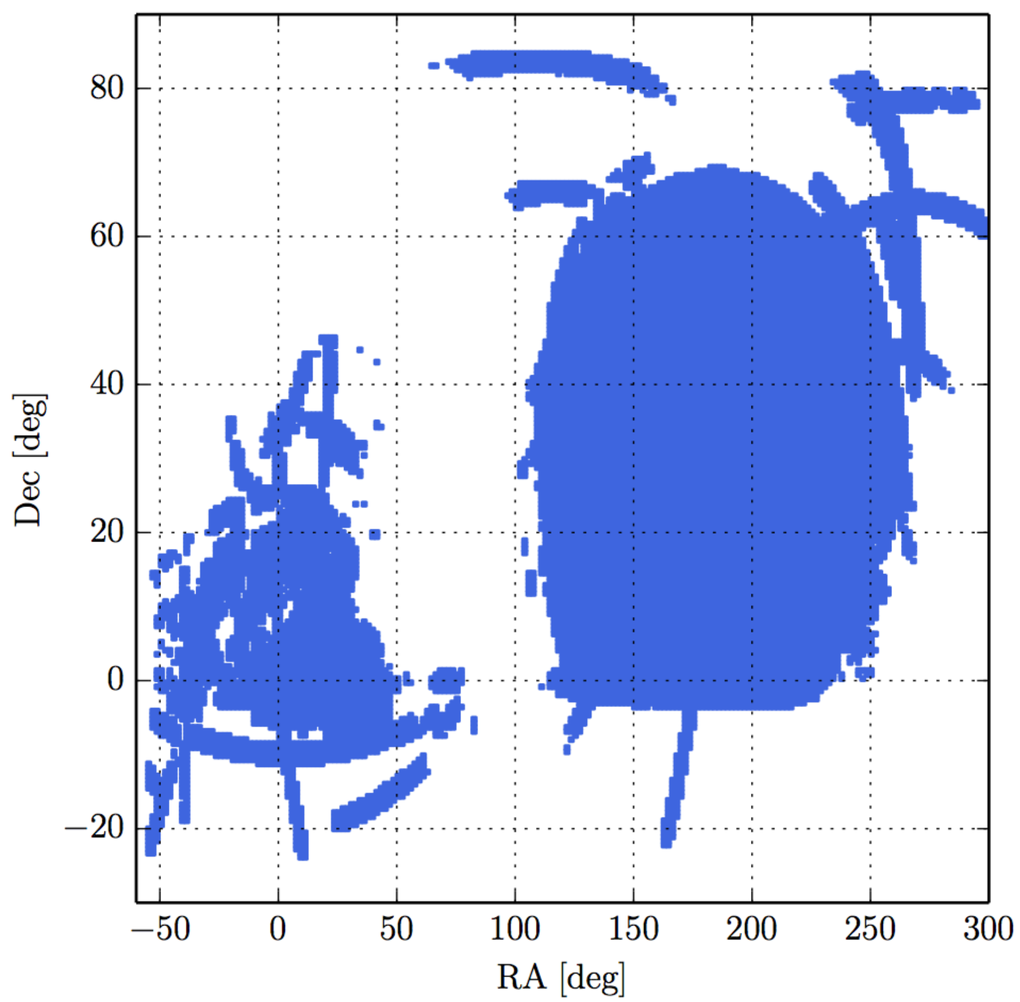
SDSSデータ 天球の~25%

宇宙論解析はまだ行われて**いない**

redMaPPer銀河団カタログ
Rykoff et. al. (2013, 2016)

背景銀河重力レンズカタログ
Mandelbaum et. al. (2013)





Richnessと赤方偏移
8,312個の銀河団
(0.1<z<0.33, 20<λ<100)

銀河形状と赤方偏移
3,900万個の銀河

Richnessビン

Four richness bins for **lensing**
Eight richness bins for **abundance**

Table 1
Binning scheme for the redMaPPer clusters and characteristics in each bin

bin index (abundance)	bin index (lensing)	λ_{min}	λ_{max}	$\langle\lambda\rangle$	z_{min}	z_{max}	$\langle z_\lambda \rangle$	$\langle p_{cen} \rangle$	$N^{raw}_{\lambda_\alpha}$	$N^{corr}_{\lambda_\alpha}$
1	1	20.0	25.0	22.3	0.10	0.33	0.25	0.87	3133	3488.4 (11.3%)
2	1	25.0	30.0	27.2	0.10	0.33	0.24	0.86	1762	1790.8 (1.6%)
3	2	30.0	35.0	32.3	0.10	0.33	0.24	0.86	1146	1164.1 (1.6%)
4	2	35.0	40.0	37.4	0.10	0.33	0.24	0.86	734	745.7 (1.6%)
5	3	40.0	47.5	43.5	0.10	0.33	0.24	0.87	596	605.2 (1.5%)
6	3	47.5	55.0	51.0	0.10	0.33	0.24	0.88	381	386.8 (1.5%)
7	4	55.0	77.5	63.6	0.10	0.33	0.24	0.87	434	440.4 (1.5%)
8	4	77.5	100	85.8	0.10	0.33	0.23	0.89	126	127.8 (1.4%)

Cluster observables

Weak gravitational lensing

Halo clustering

Abundance

Cluster observables

Weak gravitational lensing

This work

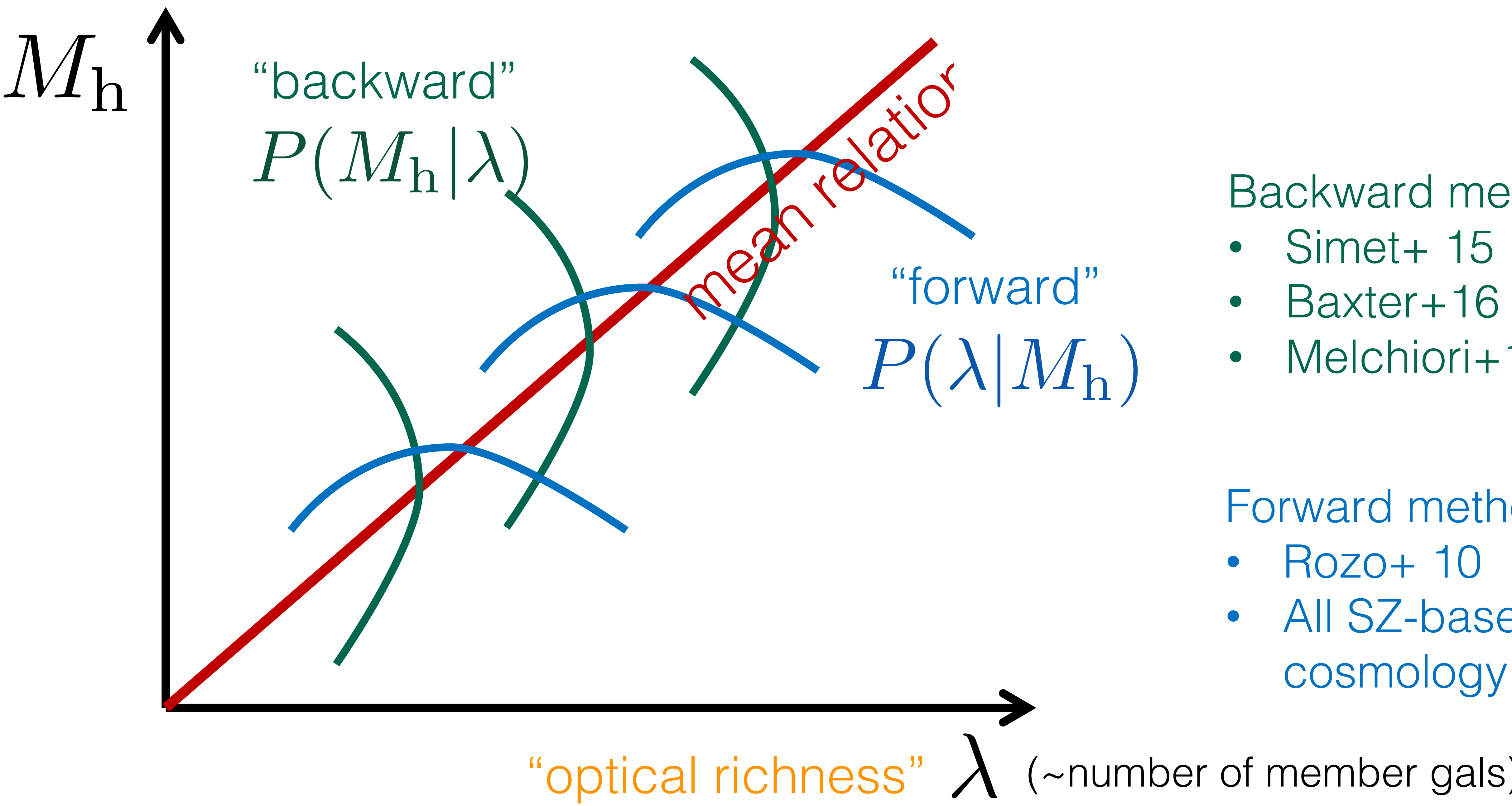
Halo clustering

Abundance

For future *cosmological* analysis

Mass-richness関係式のモデリング

Two modeling approaches



Backward method:

- Simet+ 15
- Baxter+16
- Melchiori+16

Forward method:

- Rozo+ 10
- All SZ-based cosmology papers

We use "forward" modeling!

Mass-richness relation in forward modeling

$$P(\lambda|M_{\rm h})$$

Assume
log-normal distribution:

$$P(\ln\lambda|M)\mathrm{d}\ln\lambda \equiv \frac{1}{\sqrt{2\pi}\sigma_{\ln\lambda|M}}\exp\left(-\frac{x(\lambda,M)^2}{2\sigma^2_{\ln\lambda|M}}\right)\mathrm{d}\ln\lambda,$$

where

$$x(\lambda,M) \equiv \ln\lambda - \left[A + B\ln\left(\frac{M}{M_{\rm pivot}}\right)\right]$$

$$M_{\rm pivot} = 3\times 10^{14} M_{\odot}/h$$

Mean relation:

$$\langle\ln\lambda\rangle(M) = \underline{A} + \underline{B}\ln\left(\frac{M}{M_{\rm pivot}}\right)$$

Scatter relation:

$$\sigma_{\ln\lambda|M} = \underline{\sigma_0} + \underline{q}\ln\left(\frac{M}{M_{\rm pivot}}\right)$$

In this work, a simple model with **four** free parameters

Model: abundance ***in richness bin***

richness range

$$N_{\lambda_\alpha} \equiv \Omega_{\rm tot} \int_{z_{\rm min}}^{z_{\rm max}} {\rm d}z \, \frac{{\rm d}^2 V}{{\rm d}z {\rm d}\Omega} \int_{M_{\rm min}}^{M_{\rm max}} {\rm d}M \, \frac{{\rm d}n}{{\rm d}M} \int_{\ln \lambda_{\alpha,{\rm min}}}^{\ln \lambda_{\alpha,{\rm max}}} {\rm d} \ln \lambda \; P(\ln \lambda | M)$$

$$= \Omega_{\rm tot} \int_{z_{\rm min}}^{z_{\rm max}} {\rm d}z \, \frac{\chi(z)^2}{H(z)} \int_{M_{\rm min}}^{M_{\rm max}} {\rm d}M \, \frac{{\rm d}n}{{\rm d}M} \, \underline{S(M | \lambda_{\alpha,{\rm min}}, \lambda_{\alpha,{\rm max}})}$$

total area — volume — Prediction — Mass-richness relation

Mass selection function in richness bin

$$\underline{S(M | \lambda_{\alpha,{\rm min}}, \lambda_{\alpha,{\rm max}})} \equiv \int_{\ln \lambda_{\alpha,{\rm min}}}^{\ln \lambda_{\alpha,{\rm max}}} {\rm d} \ln \lambda \; \underline{P(\ln \lambda | M)}$$

$$= \frac{1}{2} \left[{\rm erf} \left(\frac{x(\lambda_{\alpha,{\rm max}}, M)}{\sqrt{2} \sigma_{\ln \lambda | M}} \right) - {\rm erf} \left(\frac{x(\lambda_{\alpha,{\rm min}}, M)}{\sqrt{2} \sigma_{\ln \lambda | M}} \right) \right]$$

Model: lensing ***in richness bin***

Normalization

volume

$$\Delta\Sigma_{\lambda_\beta}(R) \equiv \frac{1}{N_{\Delta\Sigma}(\lambda_{\beta,\min}, \lambda_{\beta,\max})} \int_{z_{\min}}^{z_{\max}} \mathrm{d}z \int_{M_{\min}}^{M_{\max}} \mathrm{d}M \, \frac{\chi(z)^2}{H(z)} w_l(z;R)$$

weight

$$\times \underbrace{\frac{\mathrm{d}n}{\mathrm{d}M}}_{\text{Prediction}} \underbrace{S(M|\lambda_{\beta,\min}, \lambda_{\beta,\max})}_{\text{Mass-richness relation}} \underbrace{\Delta\Sigma(R;M,z)}_{\text{Prediction}}$$

In addition to mass-richness relation parameters,
we need accurate prediction of mass function and lensing!

Advantages of **forward** modeling over backward modeling

$P(\lambda|M_{\rm h})$ $P(M_{\rm h}|\lambda)$

1) Can use **abundance** measurement -> **stronger constraint**

Backward modeling: **cannot** use abundance.

Advantages of **forward** modeling over backward modeling

$P(\lambda|M_{\rm h})$ $P(M_{\rm h}|\lambda)$

2) With mass function P(M), **can get P(M|λ) from P(λ|M).**

Backward modeling: **difficult** to get P(λ|M) from P(M|λ).

Advantages of **forward** modeling over backward modeling

$P(\lambda|M_{\rm h})$ $P(M_{\rm h}|\lambda)$

3) We **can** **populate richness** in simulation from P(λ|M).

Backward modeling: **difficult**

Halo emulator for signal

In this work, we fix cosmology to Planck cosmology.

Halo mass function

Lensing profile

We now can calculate model predictions *in richness bins* with mass-richness parameters.

Full-sky lensing mock catalogs for covariance

We also need *realistic covariance* for MCMC analysis.

$$\chi^2 = \sum_{i,j} \left[\mathbf{D} - \mathbf{D}^{\rm model}\right]_i \left(\mathbf{C}^{-1}\right)_{ij} \left[\mathbf{D} - \mathbf{D}^{\rm model}\right]_j$$

-2x log(Likelihood)

Measurement - Model

Model=Forward modeling with emulator

Covariance

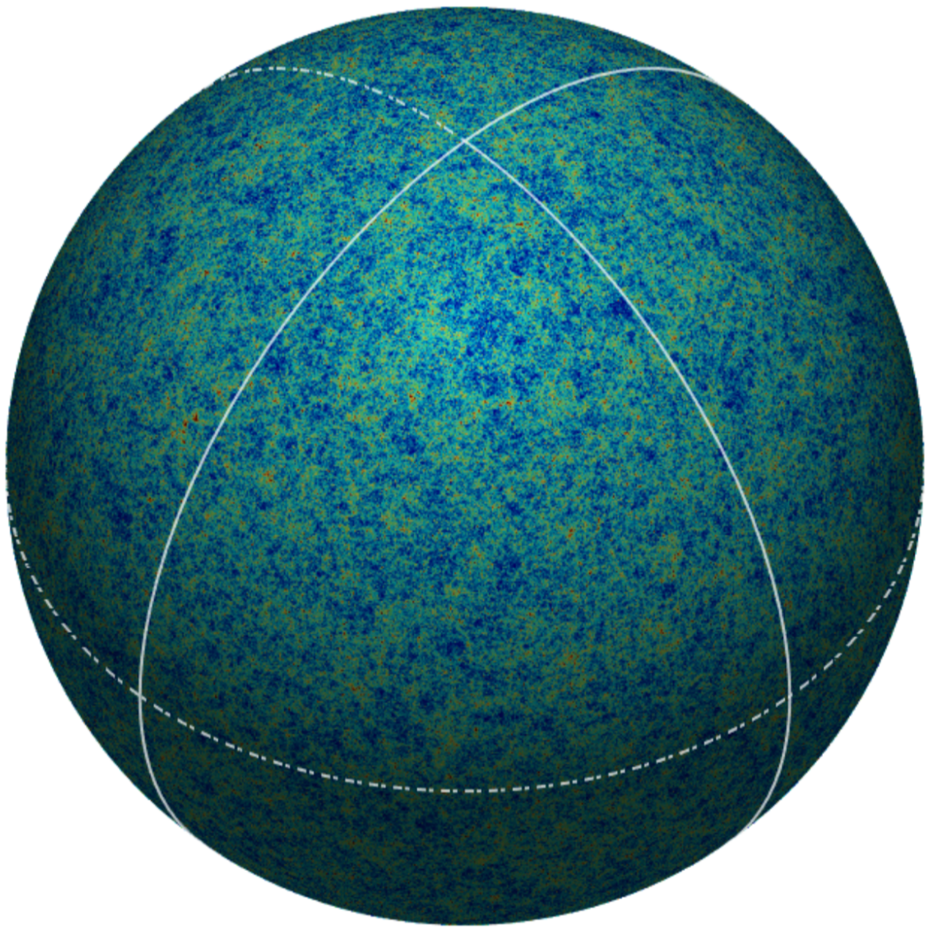
Including:

1) Shape noise (lensing)

2) Poisson noise (abundance)

3) Sample covariance

We used 108 realizations of
full-sky lensing maps and halo catalogs
in *Shirasaki et al. 2017, Takahashi et al. 2017*.



Lensing maps from Shirasaki et al. 2015

Realistic setup for covariance estimation of SDSS data,
including RA&Dec, redshift, survey boundary and richness distributions.

Covariance estimation results

Correlation matrix:

$$r_{ij} \equiv \frac{\mathbf{C}(D_i, D_j)}{\sqrt{\mathbf{C}(D_i, D_i)\mathbf{C}(D_j, D_j)}}$$

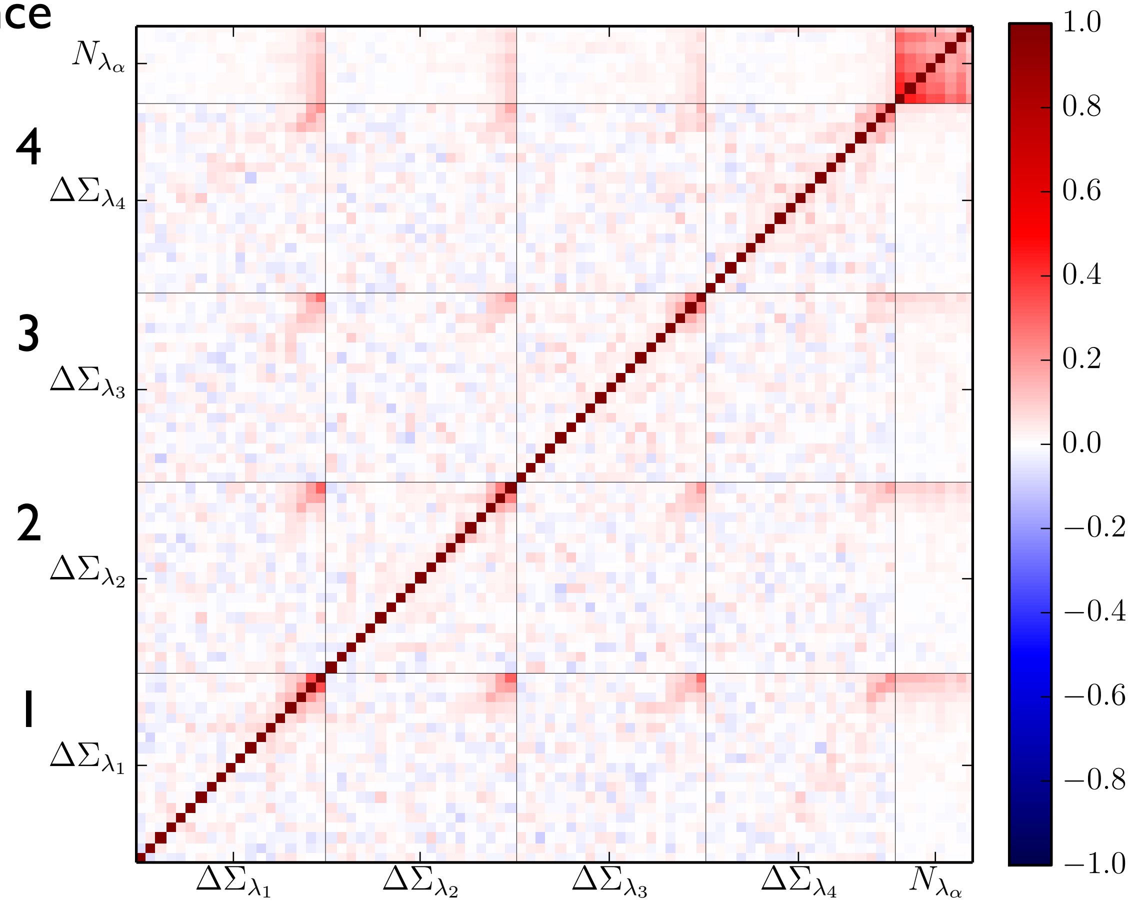
Abundance

Lens bin 4

Lens bin 3

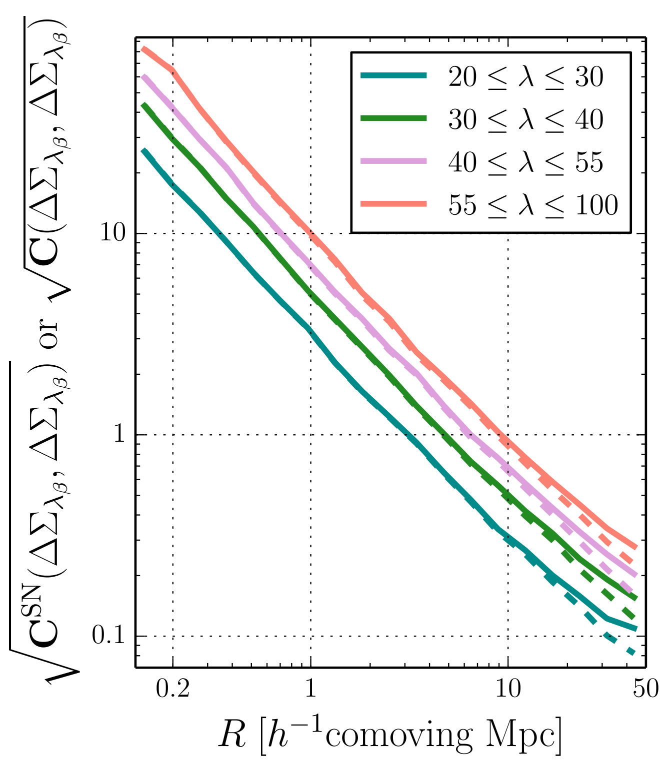
Lens bin 2

Lens bin 1

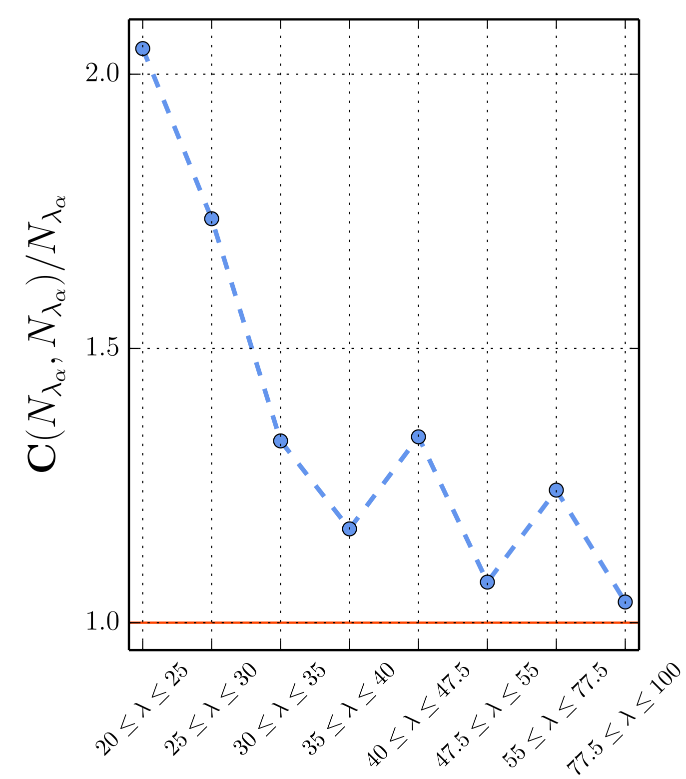


Diagonal part:

Lensing

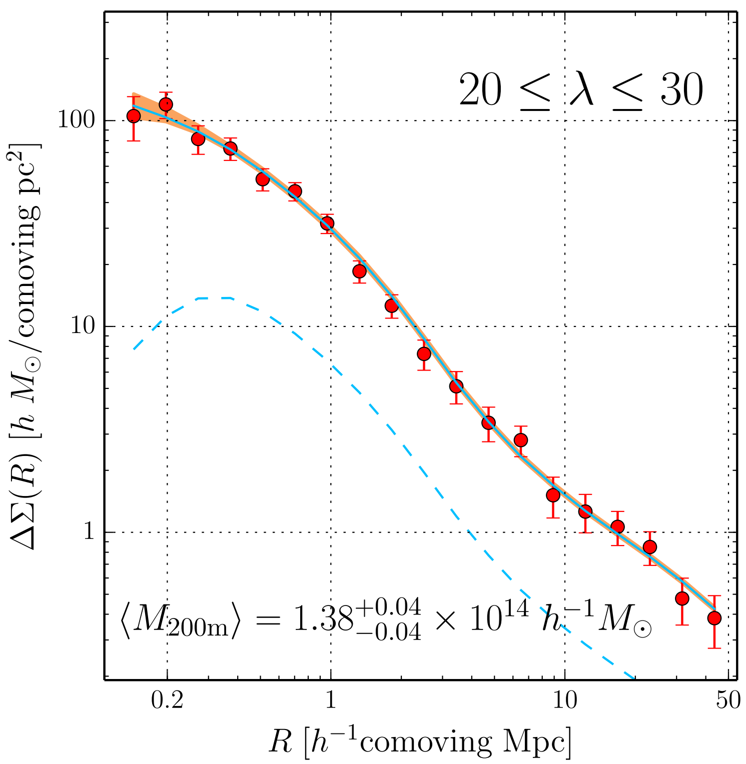


Abundance

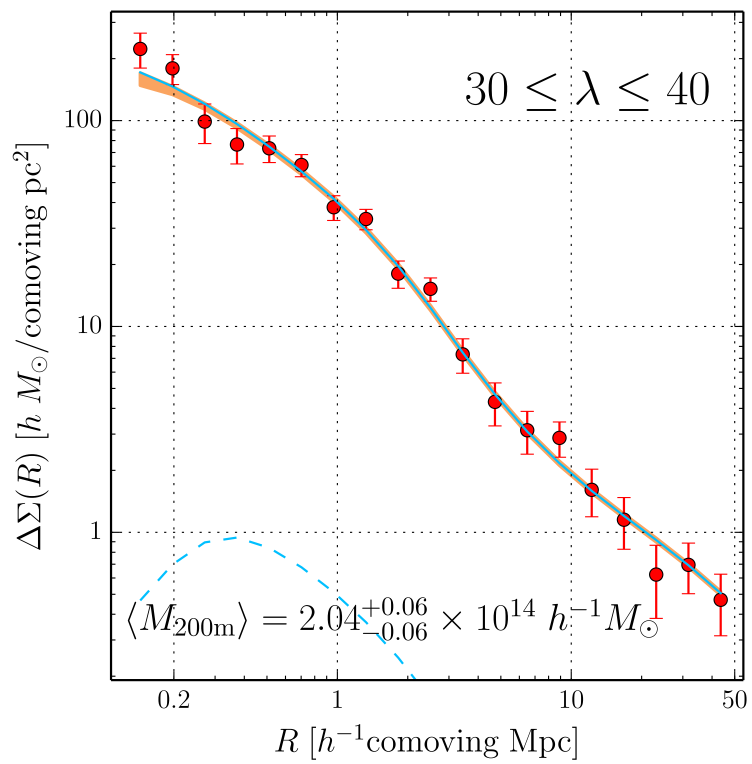


SDSSの銀河団での解析結果

Lens richness bin 1



bin 2

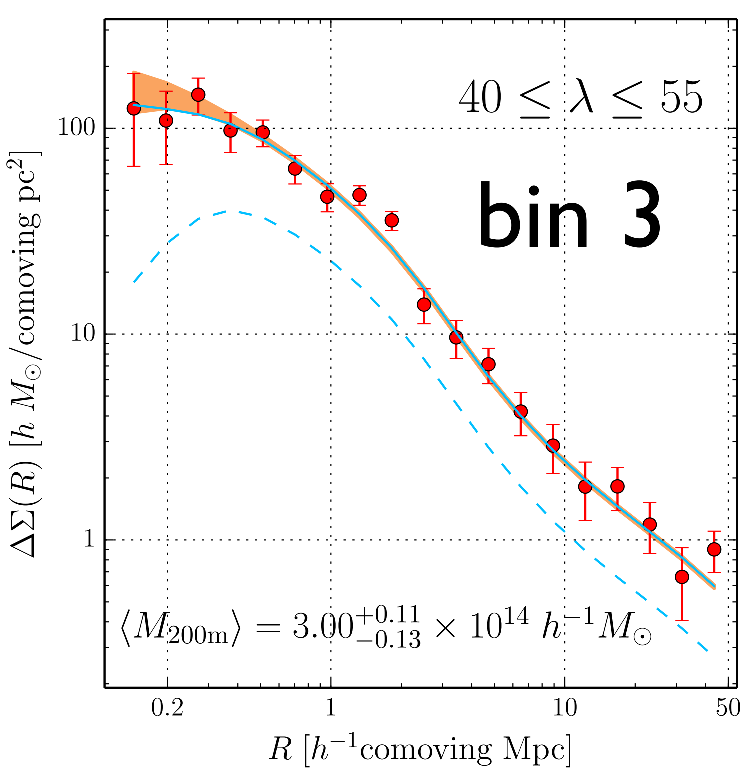


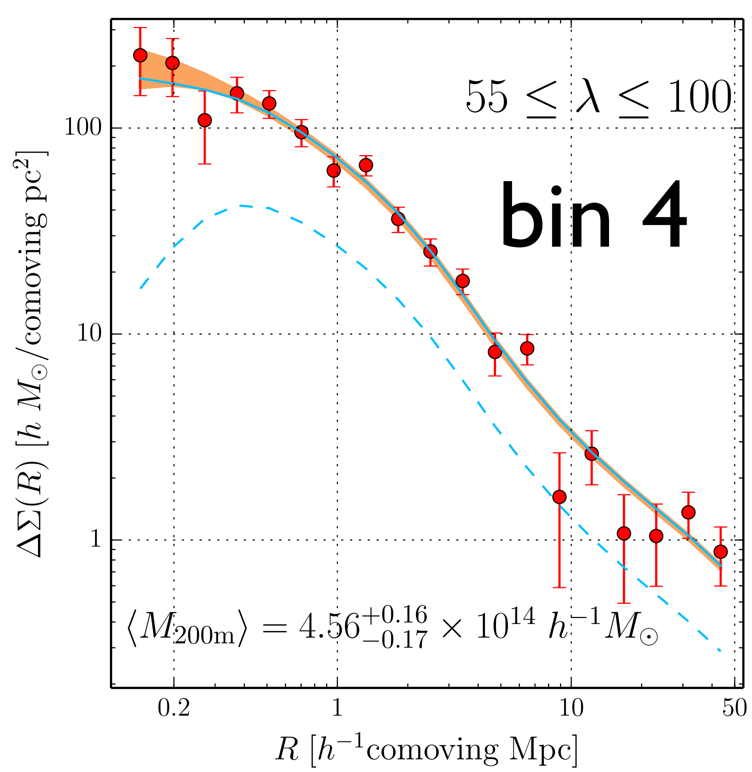
20<λ<100

$\chi^2_{\rm min}/{\rm dof} = 79.5/75$ **Good fit**

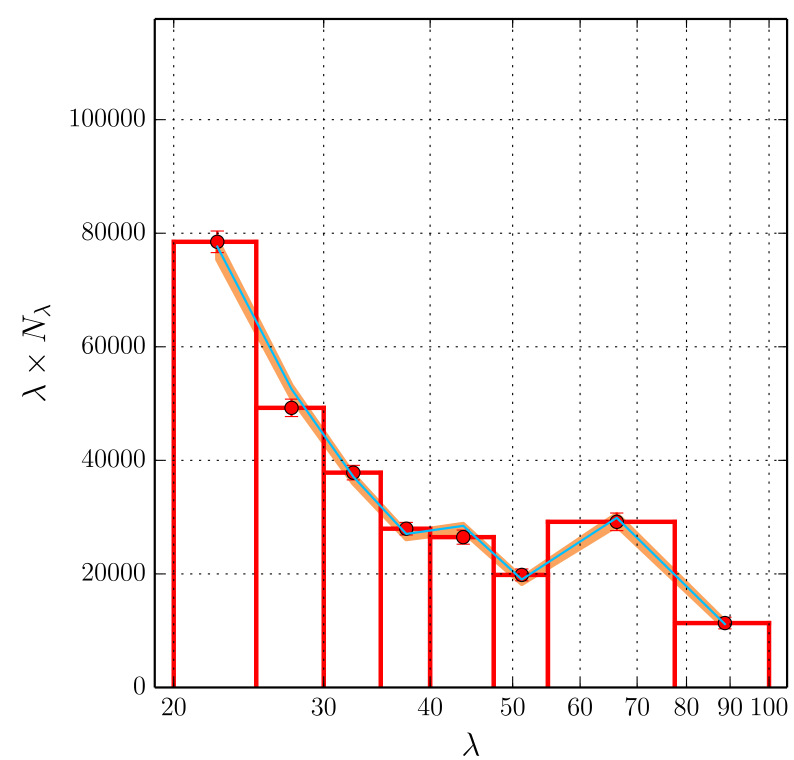
$\langle M_{200m,\ 20\leq\lambda\leq100} \rangle = 1.91^{+0.05}_{-0.05} \times 10^{14}\ h^{-1} M_\odot$

Orange: 68% region



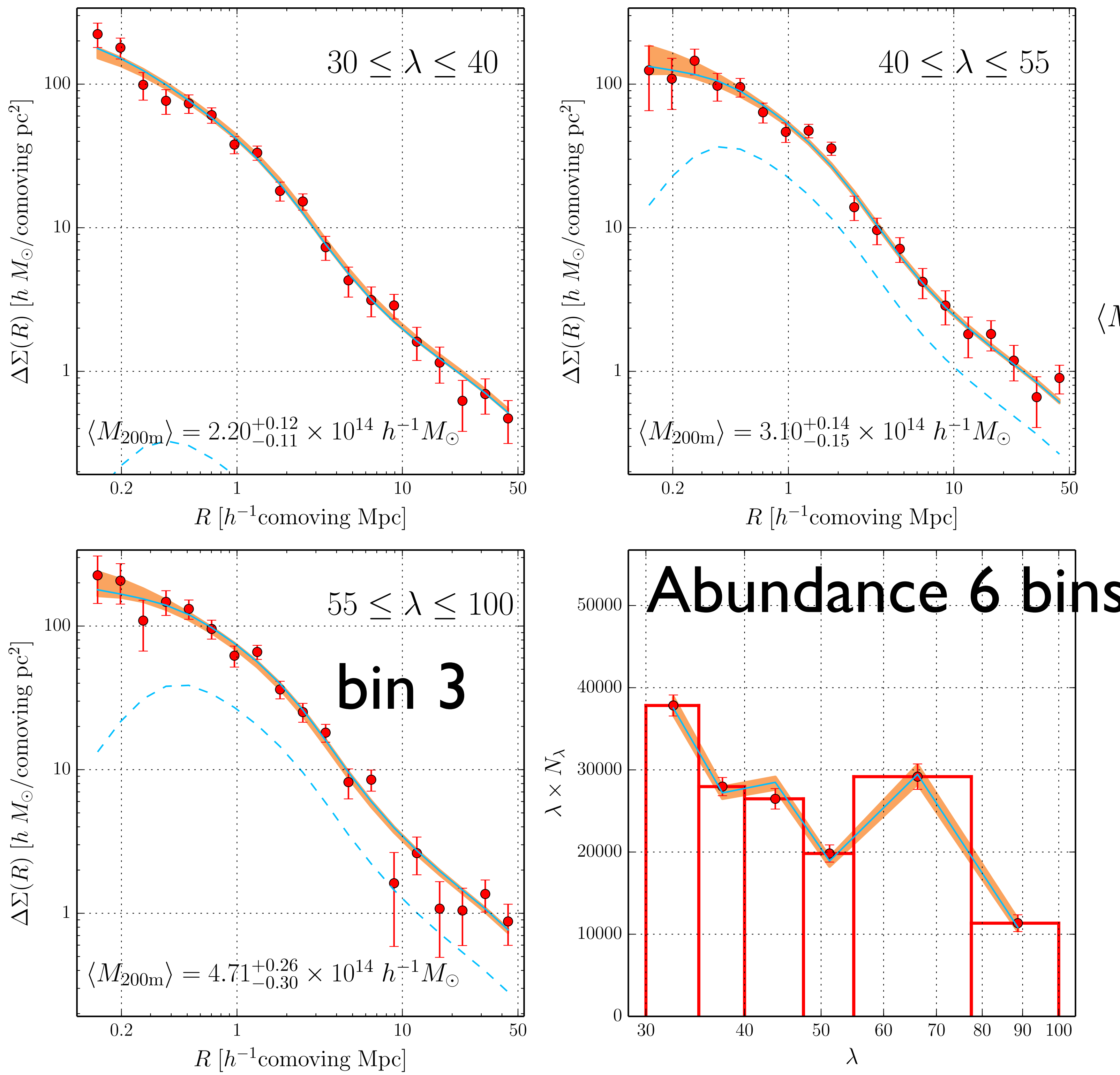


Abundance 8 bins



Reproduce lensing and abundance *simultaneously*

Lens richness bin 1 bin 2



30<λ<100

$\chi^2_{\mathrm{min}}/\mathrm{dof} = 60.3/55$

Good fit

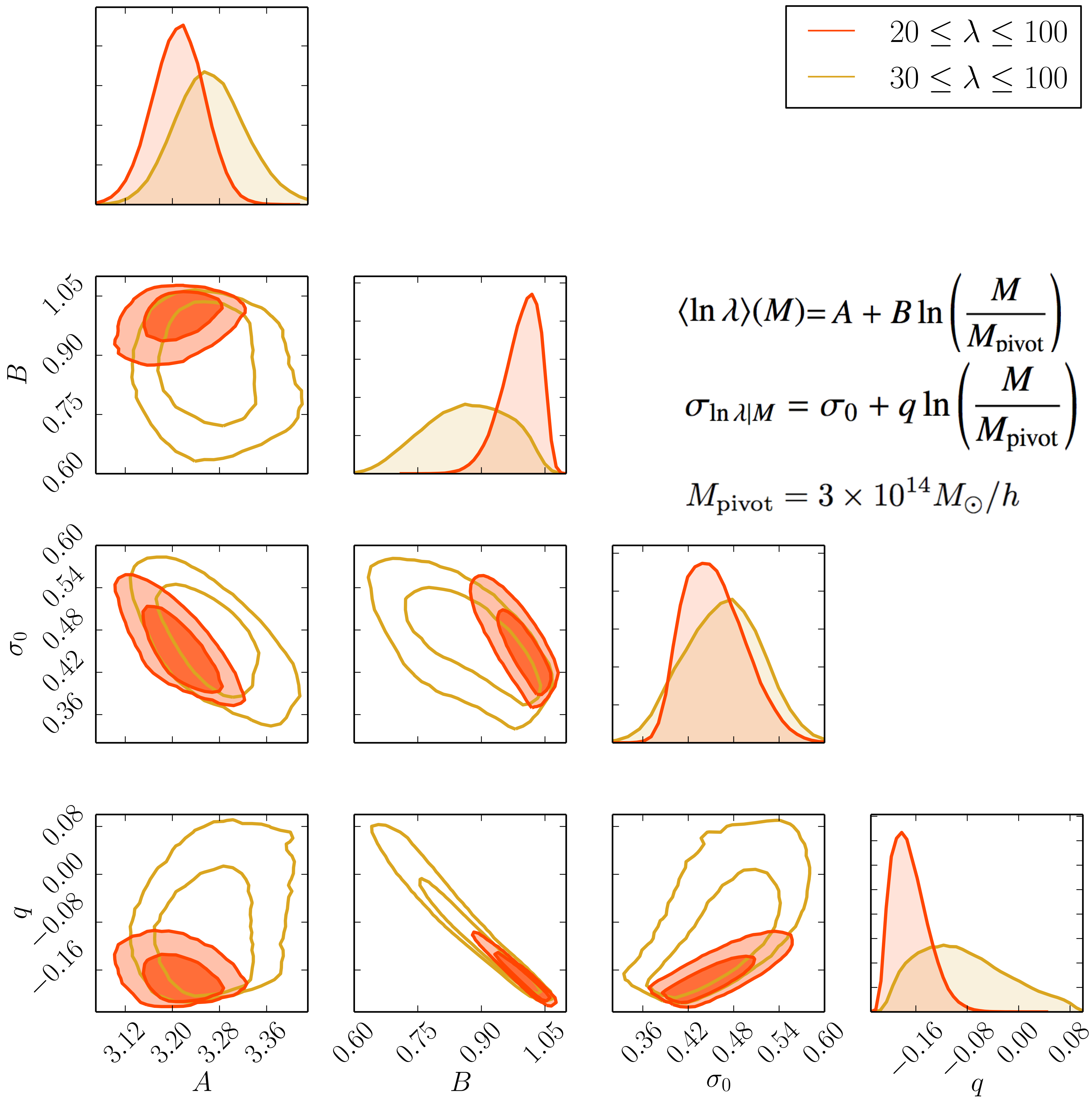
$\langle M_{200\mathrm{m},\ 30\leq\lambda\leq 100} \rangle = 2.02^{+0.10}_{-0.09} \times 10^{14}\ h^{-1} M_\odot$

Orange: 68% region

Reproduce lensing and abundance *simultaneously*

MCMC results

Flat priors



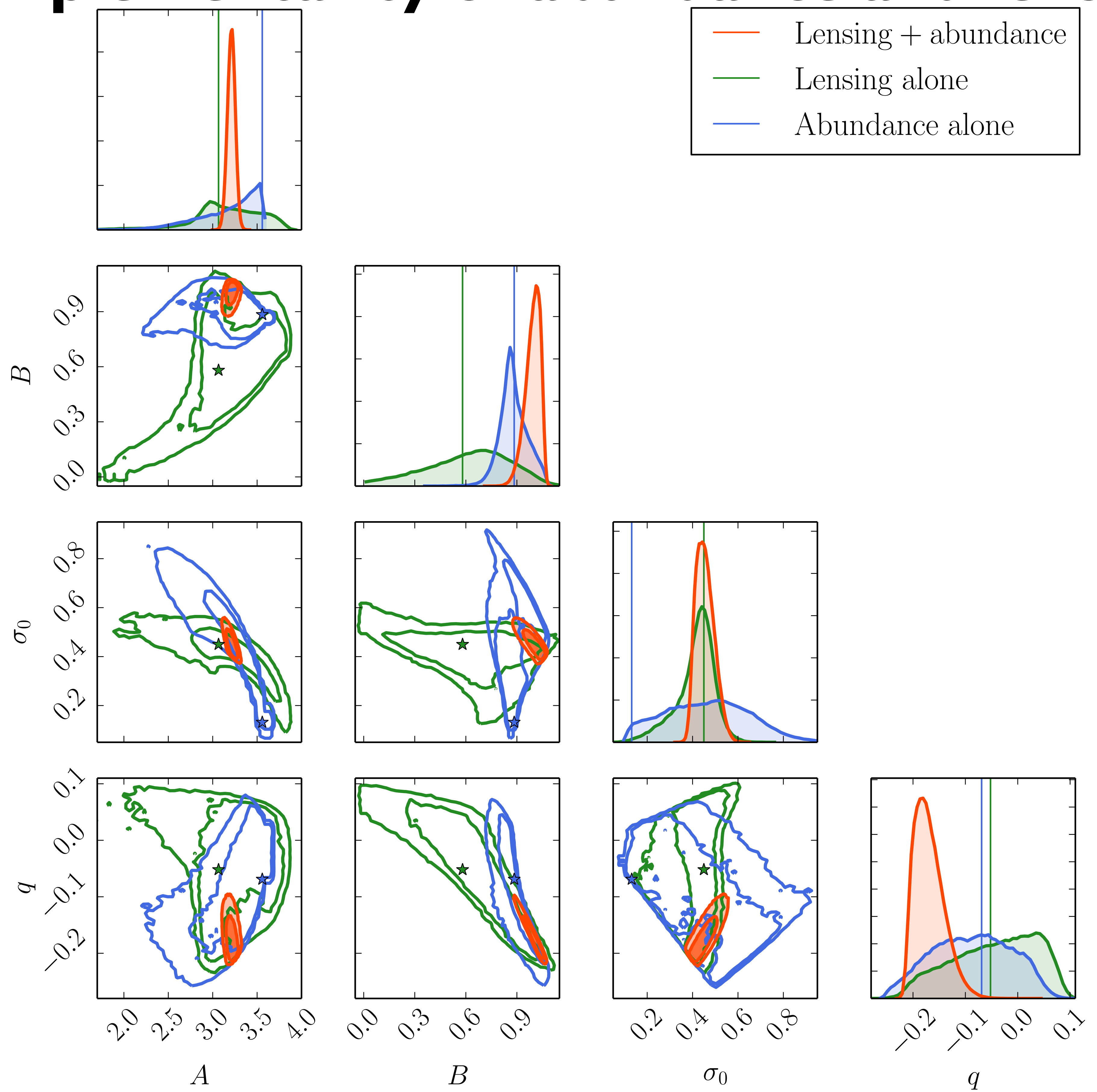
$$\langle \ln \lambda \rangle (M) = A + B \ln \left(\frac{M}{M_{\mathrm{pivot}}} \right)$$

$$\sigma_{\ln \lambda | M} = \sigma_0 + q \ln \left(\frac{M}{M_{\mathrm{pivot}}} \right)$$

$$M_{\mathrm{pivot}} = 3 \times 10^{14} M_{\odot}/h$$

Mean and scatter are well constrained!

Complementarity of abundance and lensing



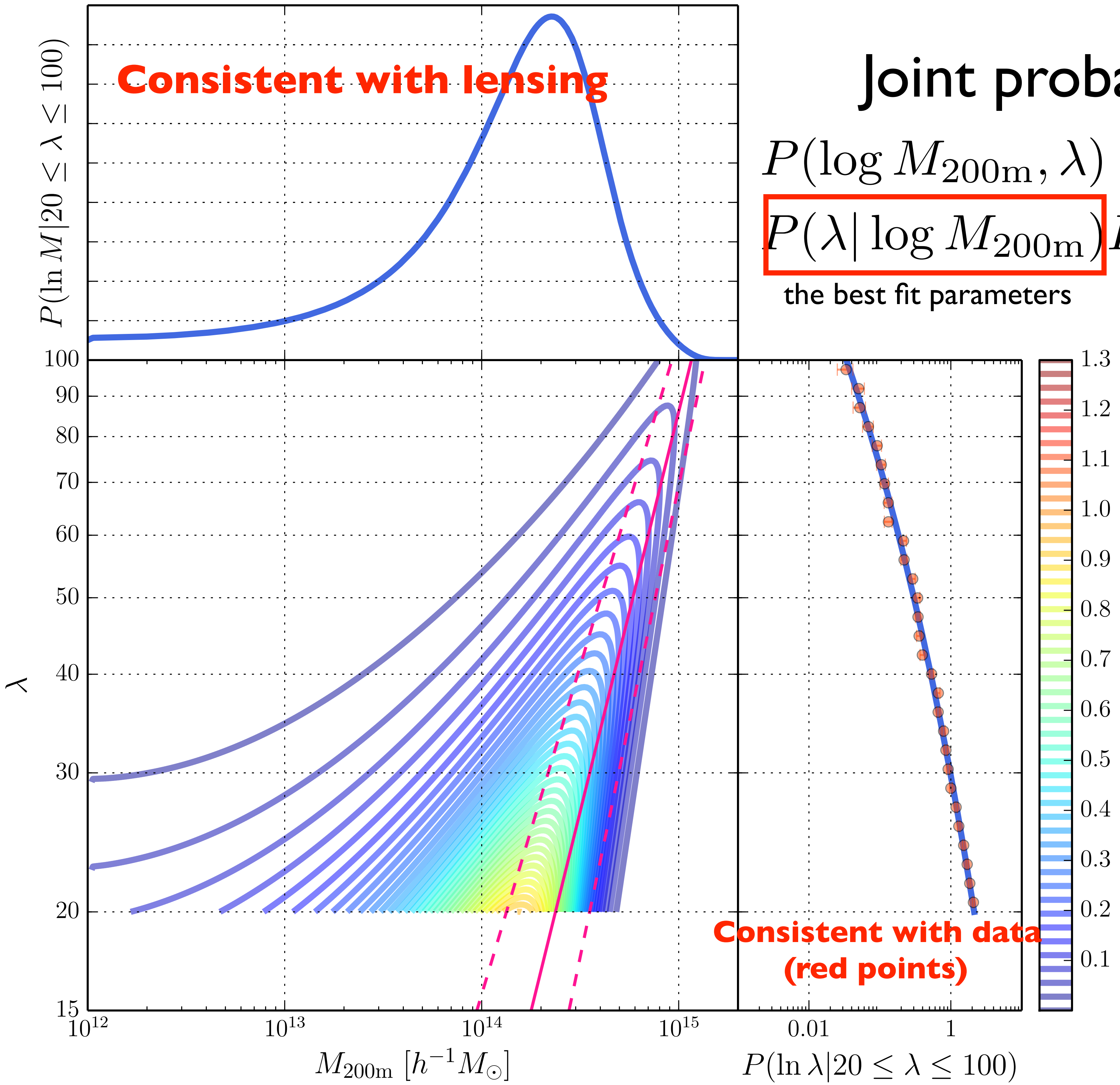
Efficiently break the degeneracy of mass-richness relation!

20<λ<100

Joint probability

$$P(\log M_{200m}, \lambda) = P(\lambda | \log M_{200m}) P(\log M_{200m})$$

the best fit parameters — mass function



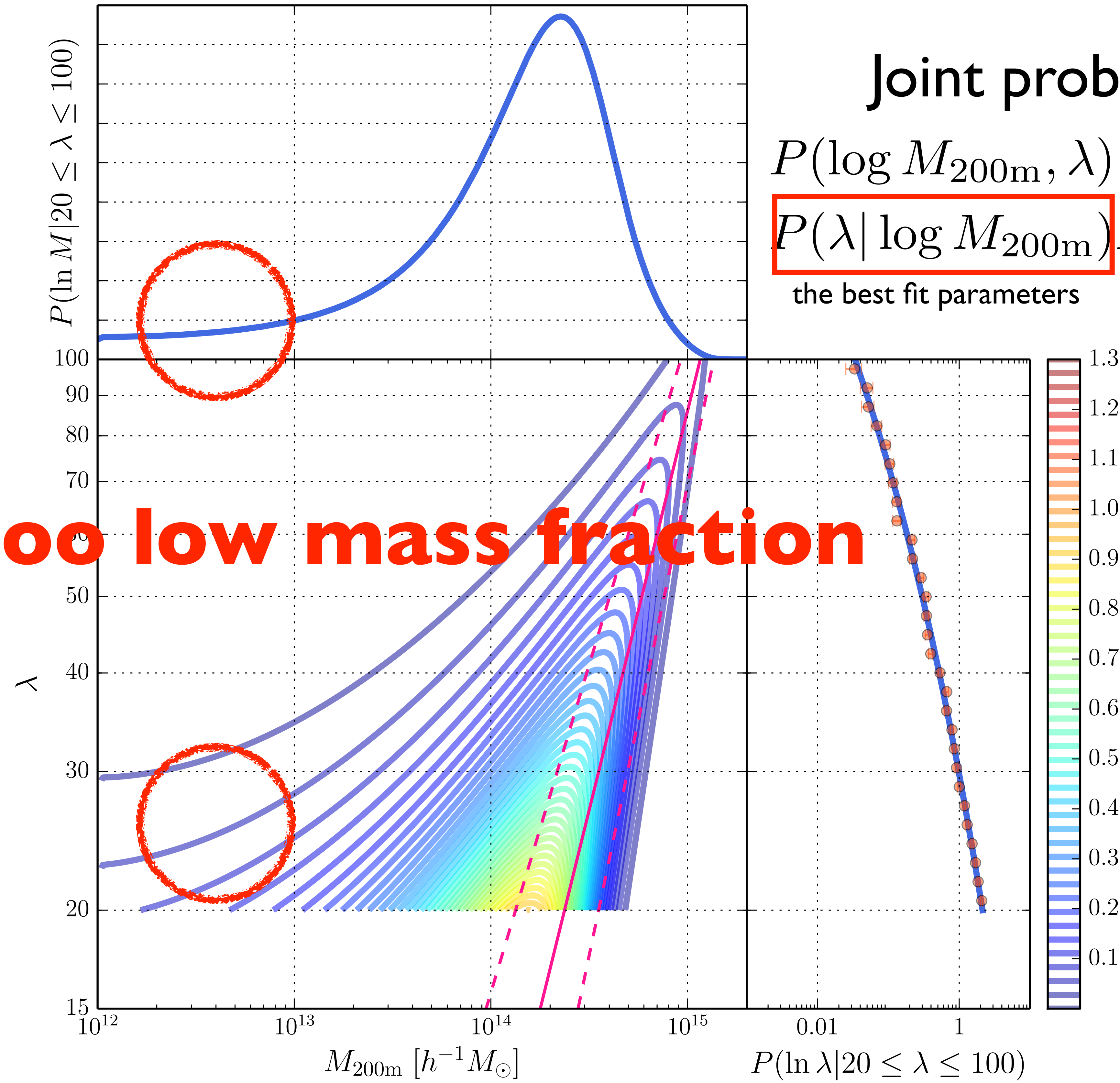
20<λ<100

Joint probability

$$P(\log M_{200\mathrm{m}}, \lambda) = P(\lambda | \log M_{200\mathrm{m}}) P(\log M_{200\mathrm{m}})$$

the best fit parameters — mass function

~10% too low mass fraction

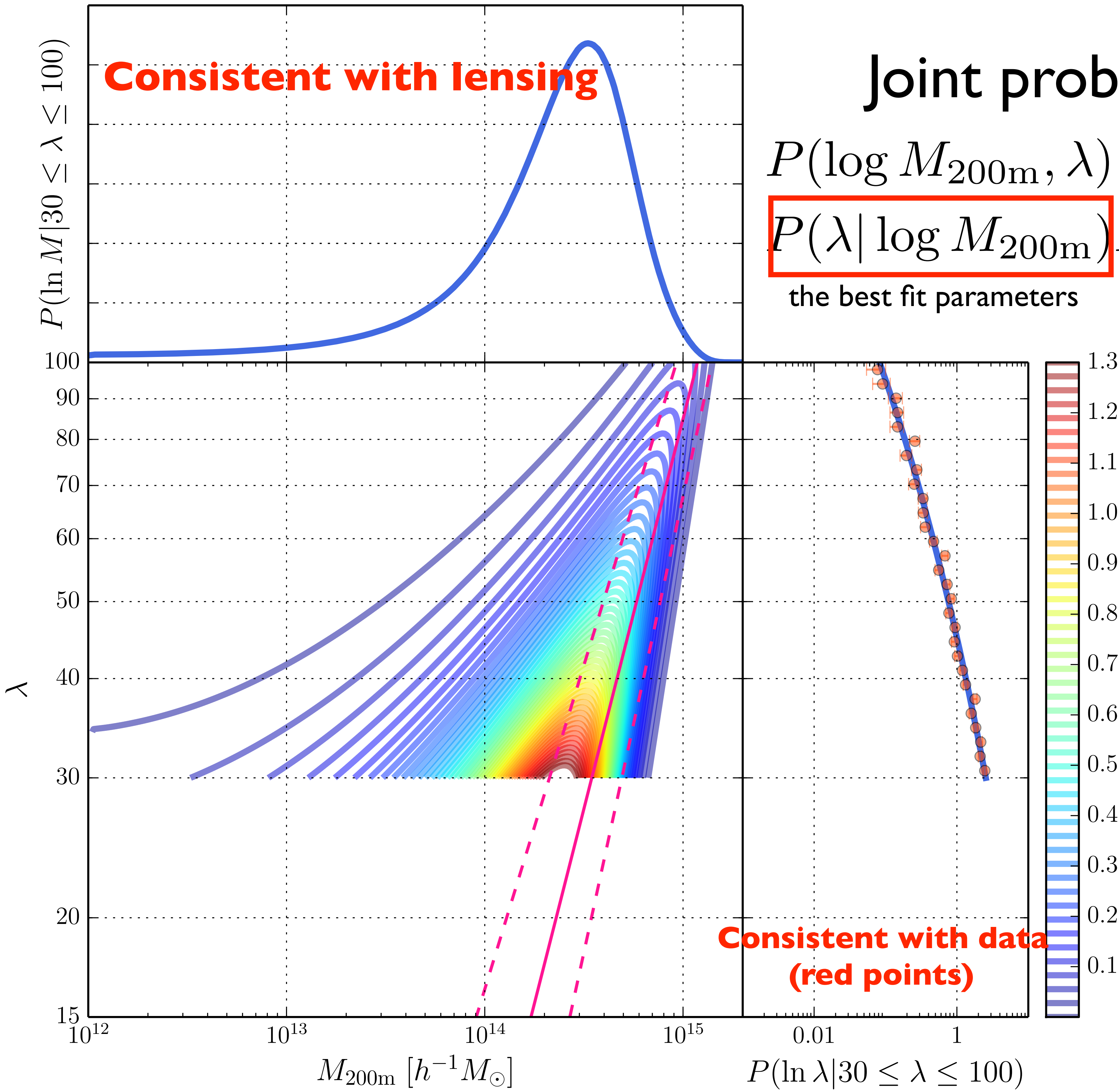


30<λ<100

Joint probability

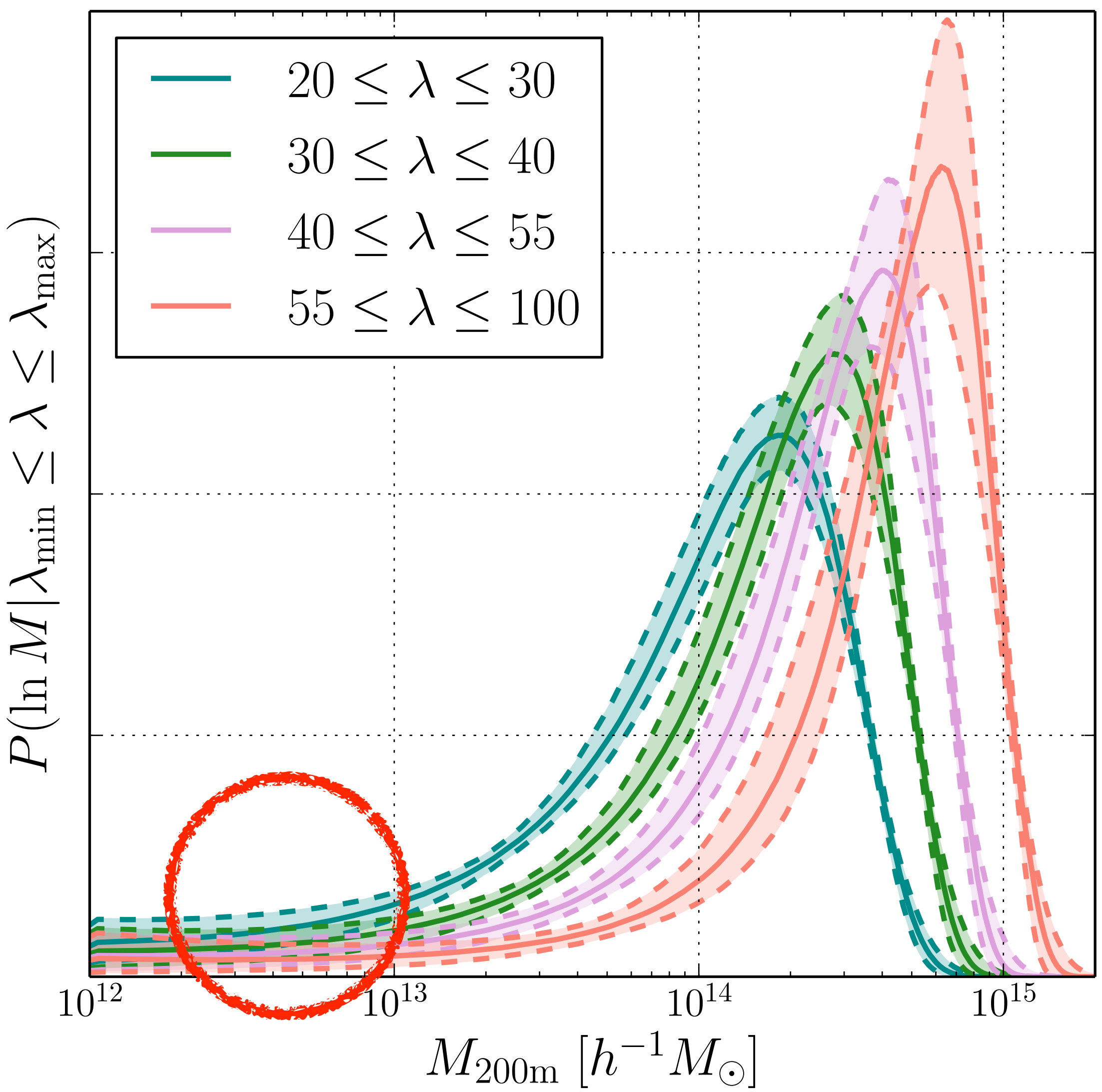
$$P(\log M_{200\mathrm{m}}, \lambda) = P(\lambda | \log M_{200\mathrm{m}}) P(\log M_{200\mathrm{m}})$$

the best fit parameters — mass function

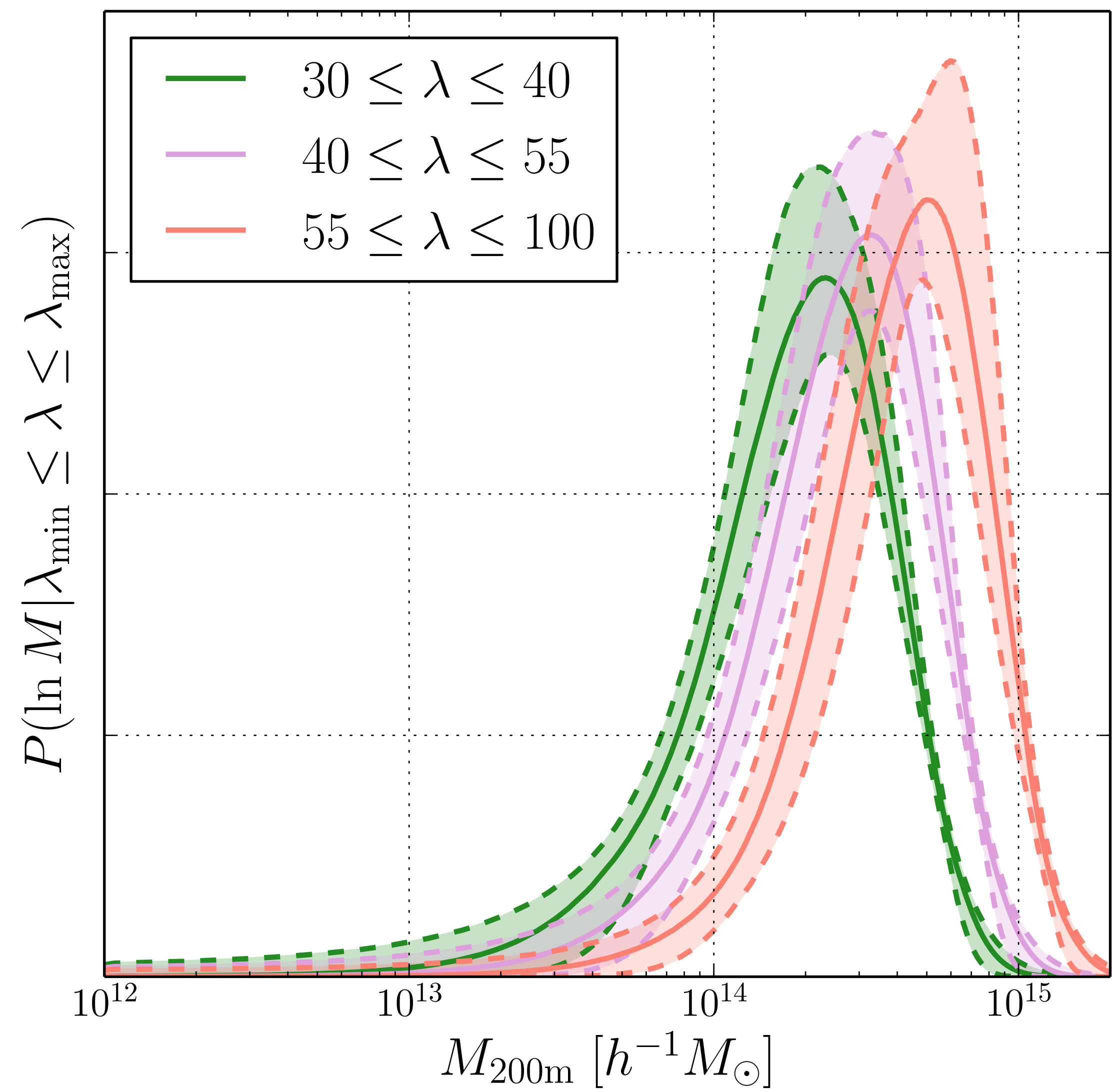


Mass distribution in each richness bins

20<λ<100



30<λ<100



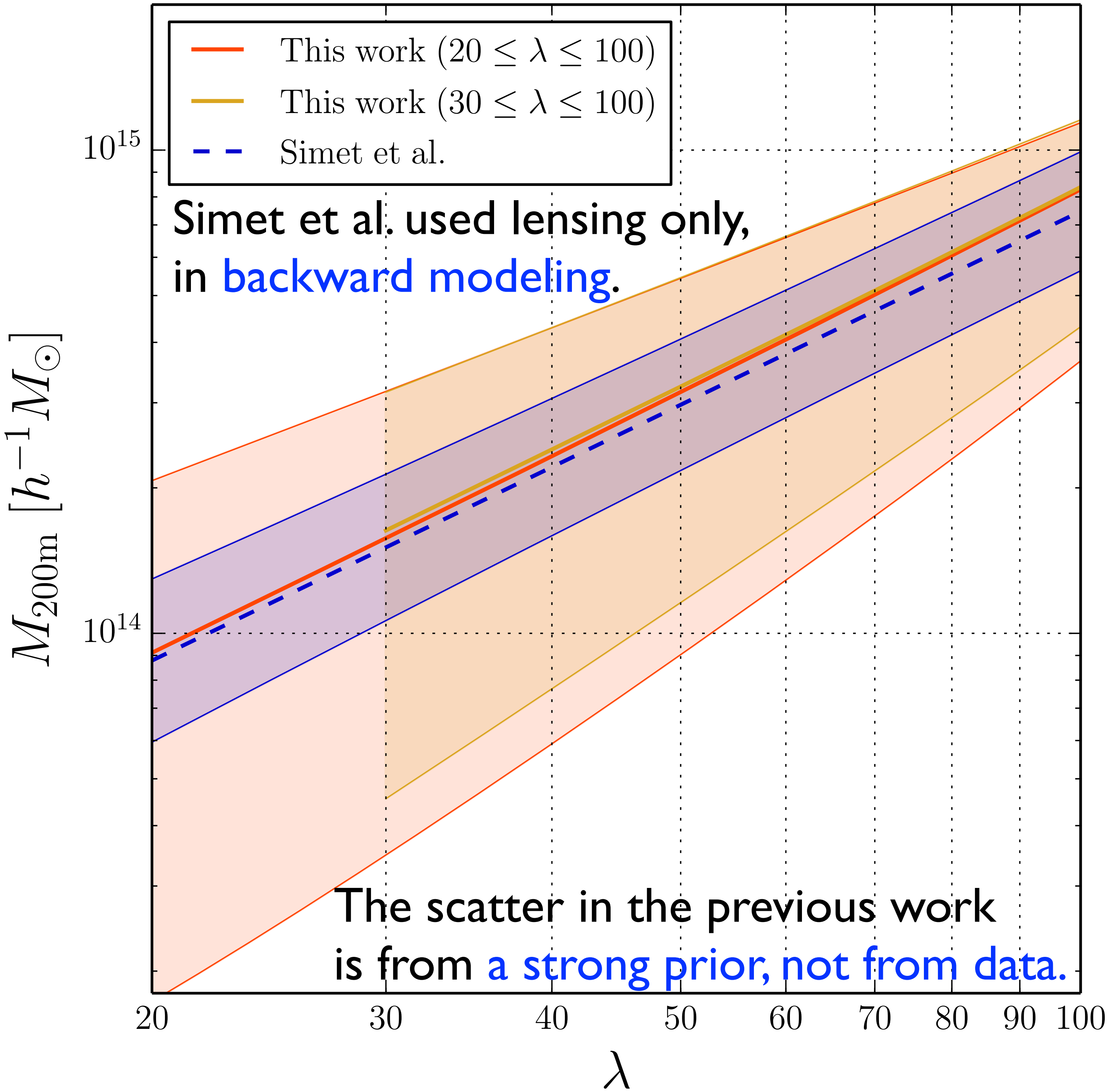
"*Projection effect*" for 10% contamination?

Identifying more than two haloes along line of sight as **one cluster**. (e.g. Cohn et al. 2007)

We will check this **systematics effect** in simulation box.

Comparison with previous work

$$P(M|\lambda) = \frac{P(\lambda|M)P(M)}{P(\lambda)}$$



Median relation is consistent.

But, scatter in this work is larger.

Summary

We have developed forward modeling method.
Joint fitting of abundance and lensing.

Simulation based signal and covariance.

We have applied this for SDSS clusters.

Next steps:
1) Projection effect test in simulation box
2) Add clustering to determine cosmology
3) Apply for *HSC* CAMIRA clusters (z~1)