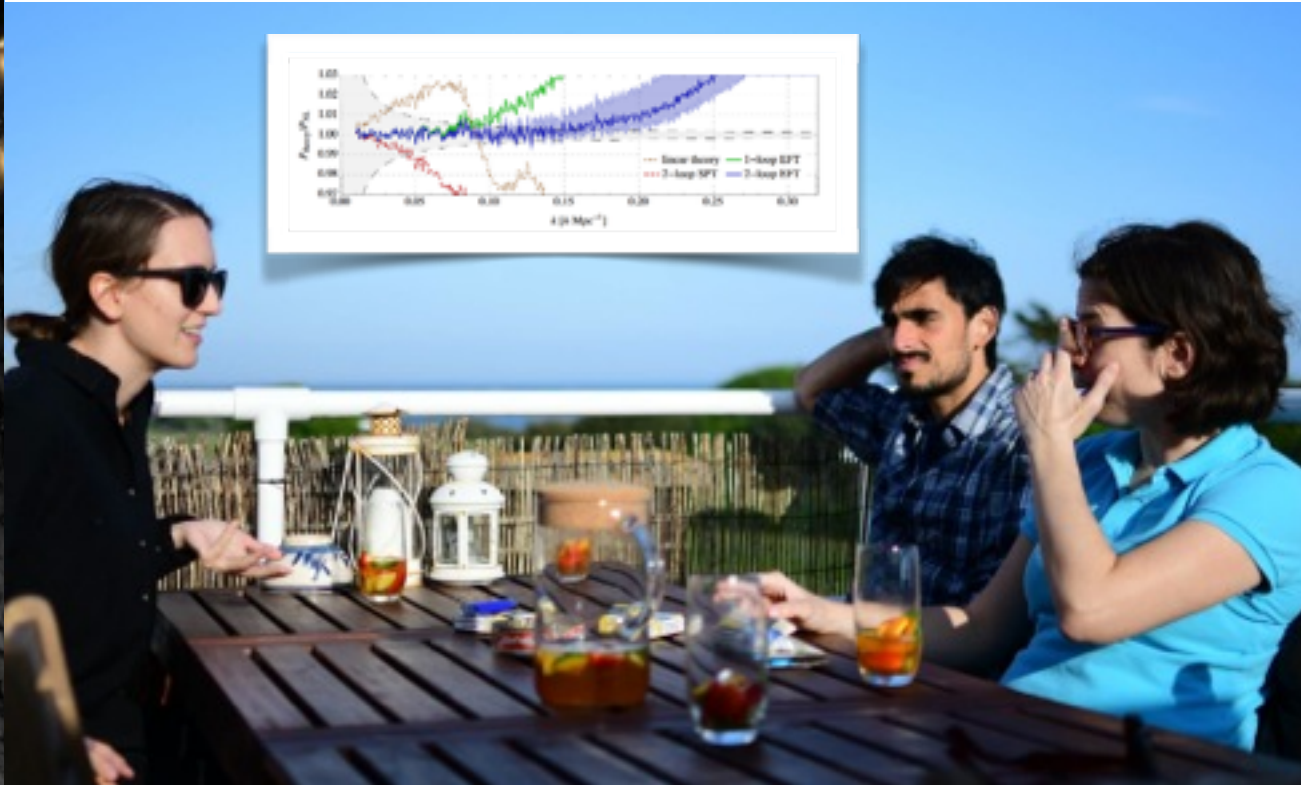
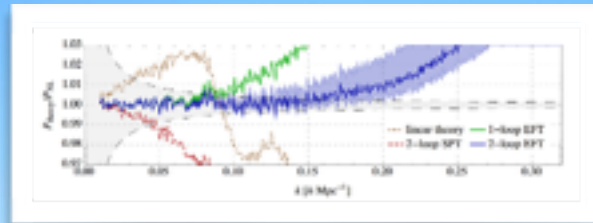


A visualization of the cosmic web, showing a complex network of dark matter filaments and nodes. The filaments are thin, dark lines that form a web-like structure, with nodes where they intersect. Small, bright yellow and orange spheres are scattered throughout the network, representing galaxies or galaxy clusters. The background is a dark, textured grey.

MODELLING NON-LINEAR SCALES FOR GALAXY CLUSTERING MEASUREMENTS

Alkistis Pourtsidou
Queen Mary University of London

Work with Ben Bose and Dida Markovic



WHY GO NON-LINEAR?

- ◆ **Because we can:** Future surveys (DESI, Euclid,...) will measure the small scales.
- ◆ **Because we need to:** For WL it is essential to probe up to $k=7h/\text{Mpc}$, and GC constraints can improve (in principle).
- ◆ **Theory needs to catch up:** We need to understand and model the behaviour of matter and galaxies in the non-linear regime.
Possible approaches include:
- ◆ Perturbation theory and EFT-like approaches (this talk).
- ◆ Simulations and emulators.
- ◆ **Chosen method will most certainly involve combinations of the above.**

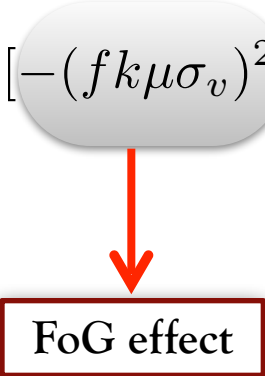
MODELLING THE GALAXY POWER SPECTRUM

- ◆ Ingredients:
- ◆ A model for the redshift space clustering
- ◆ A model for the bias
- ◆ In **BOSS** analyses (Beutler et al 2013, 2016) the Taruya-Nishimichi-Saito (TNS) model with bias given by the McDonald and Roy model has been used.

$$P_{TNS}^S(k, \mu) = \exp[-(fk\mu\sigma_v)^2] \left[P_{g,\delta\delta}(k) + 2f\mu^2 P_{g,\delta\theta}(k) + f^2\mu^4 P_{\theta\theta}^{1-\text{loop}}(k) + b_1^3 A(k, \mu) + b_1^4 B(k, \mu) + b_1^2 C(k, \mu) \right],$$

THE TNS MODEL

$$P_{TNS}^S(k, \mu) = \exp[-(fk\mu\sigma_v)^2] \left[P_{g,\delta\delta}(k) + 2f\mu^2 P_{g,\delta\theta}(k) + f^2\mu^4 P_{\theta\theta}^{1-\text{loop}}(k) + b_1^3 A(k, \mu) + b_1^4 B(k, \mu) + b_1^2 C(k, \mu) \right],$$



perturbative components

FoG effect

σ_v  free parameter, velocity dispersion

$A(k, \mu), B(k, \mu), C(k, \mu) :$ RSD correction terms

independent free bias parameters $\{b_1, b_2, N\}$

THE TNS MODEL: SUMMARY

$$P_{TNS}^S(k, \mu) = \exp[-(fk\mu\sigma_v)^2] \left[P_{g,\delta\delta}(k) + 2f\mu^2 P_{g,\delta\theta}(k) + f^2\mu^4 P_{\theta\theta}^{1-\text{loop}}(k) \right. \\ \left. + b_1^3 A(k, \mu) + b_1^4 B(k, \mu) + b_1^2 C(k, \mu) \right],$$

It is a Standard Perturbation Theory model combined with a bias model, having 4 free parameters in total:

$$\{b_1, b_2, N, \sigma_v\}$$

- ◆ The problem with SPT/TNS is that we can't trust it for $k_{\text{max}} > 0.25$ h/Mpc at $z=1$ (or $k_{\text{max}} > 0.1$ h/Mpc at $z=0$)
- ◆ SPT/TNS diverges from N-body results at larger k
- ◆ EFTofLSS allows us to go to larger k consistently, and it is “nicely convergent”

EFFECTIVE FIELD THEORY OF LARGE SCALE STRUCTURE

The main idea is that short-distance (UV) non-linearities affect long distance physics and therefore need to be parametrised with suitable counter-terms.

$$\delta \equiv \delta\rho/\rho, \quad v^i, \quad \theta \equiv \partial_i v^i$$

$$\nabla^2 \Phi_l = \frac{3}{2} H_0^2 \frac{a_0^3}{a} \delta_l$$

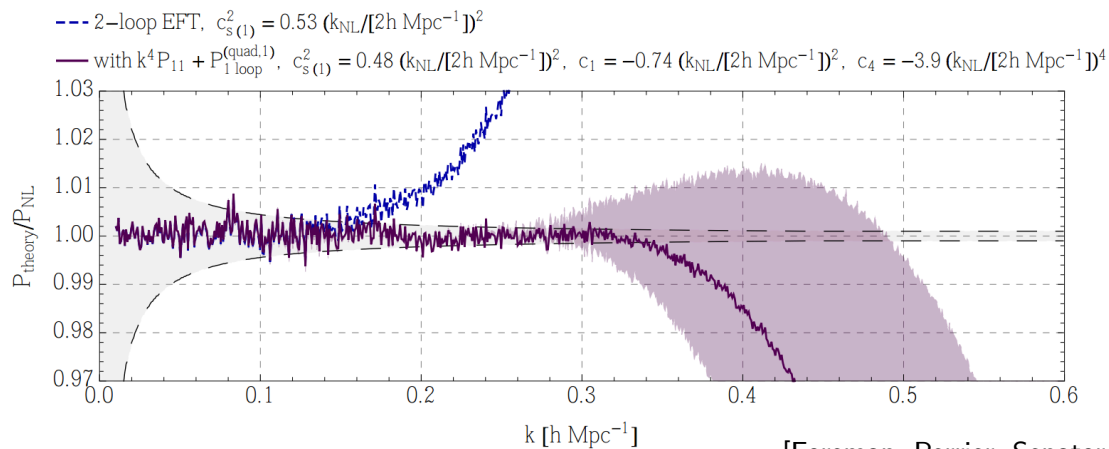
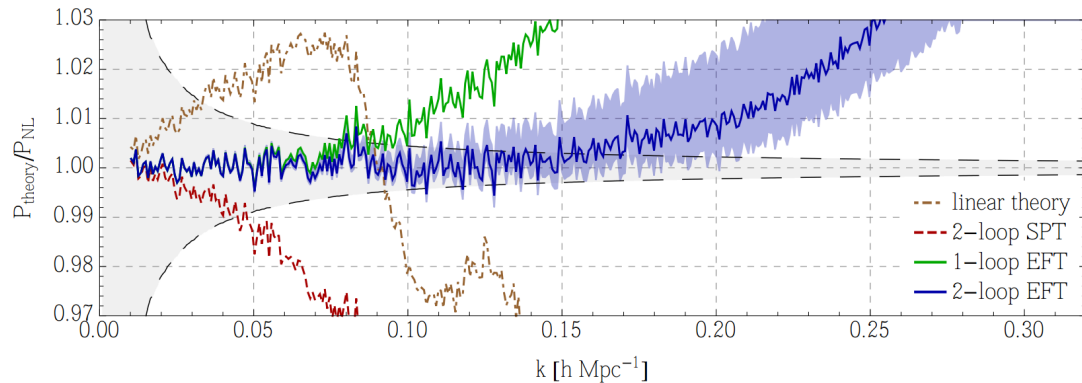
$$\dot{\delta}_l + \frac{1}{a} \partial_i ((1 + \delta_l) v_l^i) = 0$$

$$\begin{aligned} a\dot{\theta}_l + aH\theta_l + \partial_i (v_l^j \partial_j v_l^i) + \nabla^2 \Phi_l &\sim -\partial_i (v_s^j \partial_j v_l^i) - \partial_i (v_l^j \partial_j v_s^i) \\ &= -\partial_i (\partial_j \tau_s^{ij} / \rho) \\ &\rightarrow c_s^2 H^2 \left(\frac{k}{k_{\text{NL}}} \right)^2 \delta_l + \dots \end{aligned}$$

Work by Angulo, Carrasco, de la Bella, Fasiello, Foreman, Lewandonski, Perko, Perrier, Senatore, Vlah, et al.

EFFECTIVE FIELD THEORY OF LARGE SCALE STRUCTURE

The main idea is that short-distance (UV) non-linearities affect long distance physics and therefore need to be parametrised with suitable counter-terms.



[Foreman, Perrier, Senatore]

EFFECTIVE FIELD THEORY OF LARGE SCALE STRUCTURE

In terms of describing the observed power spectrum, our EFTofLSS modelling is TNS with a modified FoG effect + the EFT counter terms.

FoG effect

$$P_{eft}^S(k, \mu) = \{1 - (D_1^2 f k \mu \tilde{\sigma}_v)^2\} \left[P_{g,\delta\delta}(k) + 2f\mu^2 P_{g,\delta\theta}(k) + f^2\mu^4 P_{\theta\theta}^{1-loop}(k) \right. \\ \left. + b_1^3 A(k, \mu) + b_1^4 B(k, \mu) + b_1^2 C(k, \mu) \right] \\ - 2b_1^2 D_1^2 P_L(k) \left[\bar{c}_{s,0}^2 + \bar{c}_{s,2}^2 \mu^2 + \bar{c}_{s,4}^2 \mu^4 + \mu^6 (f^3 \bar{c}_{s,0}^2 - f^2 \bar{c}_{s,2}^2 + f \bar{c}_{s,4}^2) \right],$$

EFT counter terms

- ◆ This expression is motivated by arguing that the bias is well described by McDonald and Roy and so we are just missing an extra suppression of power coming from UV physics described by EFTofLSS.

THE EFTOFLSS MODEL: SUMMARY

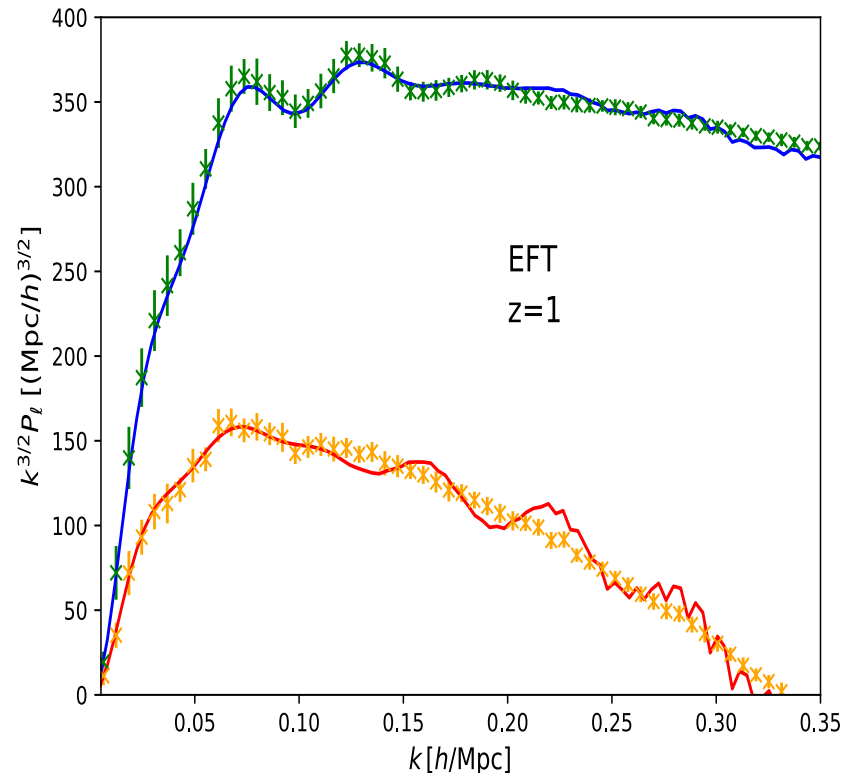
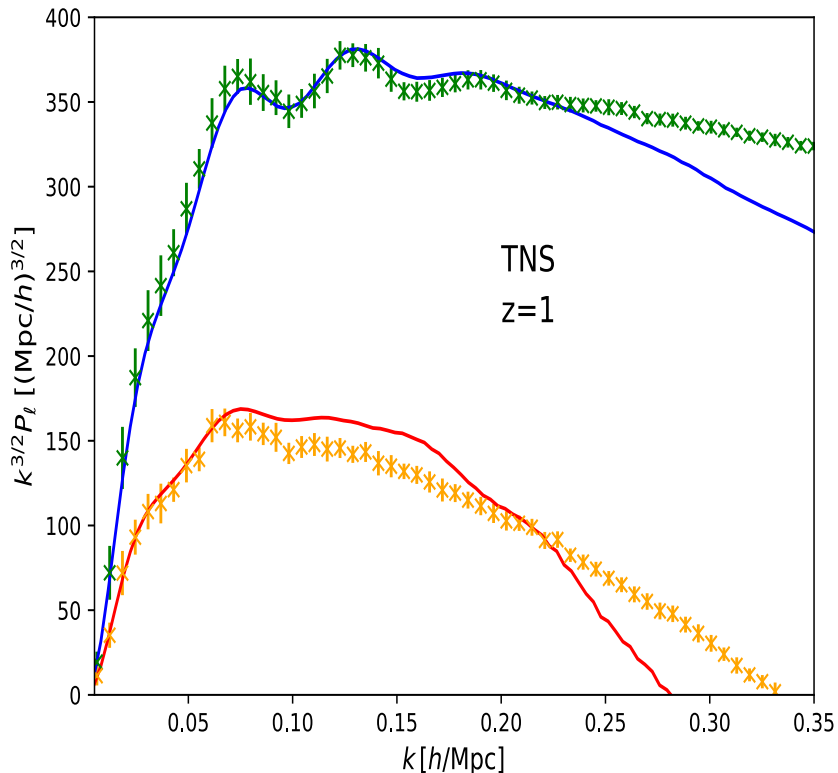
$$P_{eft}^S(k, \mu) = \{1 - (D_1^2 f k \mu \tilde{\sigma}_v)^2\} \left[P_{g,\delta\delta}(k) + 2f\mu^2 P_{g,\delta\theta}(k) + f^2 \mu^4 P_{\theta\theta}^{1-\text{loop}}(k) \right. \\ \left. + b_1^3 A(k, \mu) + b_1^4 B(k, \mu) + b_1^2 C(k, \mu) \right] \\ - 2b_1^2 D_1^2 P_L(k) \left[\bar{c}_{s,0}^2 + \bar{c}_{s,2}^2 \mu^2 + \bar{c}_{s,4}^2 \mu^4 + \mu^6 (f^3 \bar{c}_{s,0}^2 - f^2 \bar{c}_{s,2}^2 + f \bar{c}_{s,4}^2) \right],$$

It is a Standard Perturbation Theory model combined with a bias model and EFTofLSS counter terms, having 6 free parameters in total:

$$\{b_1, b_2, N, \bar{c}_{s,0}, \bar{c}_{s,2}, \bar{c}_{s,4}\}$$

FIDUCIAL PARAMETERS: FITS TO SIMULATIONS

We want to perform forecasts for Stage IV surveys (TNS vs EFT), and try to understand the EFT parameters. We use fits to simulations (COLA). We have $z=1$ and $z=0.5$ results. I'll stick to $z=1$ for this talk.



simulations data from Hans Winther - thanks Hans!

FORECASTS FOR STAGE IV SURVEYS

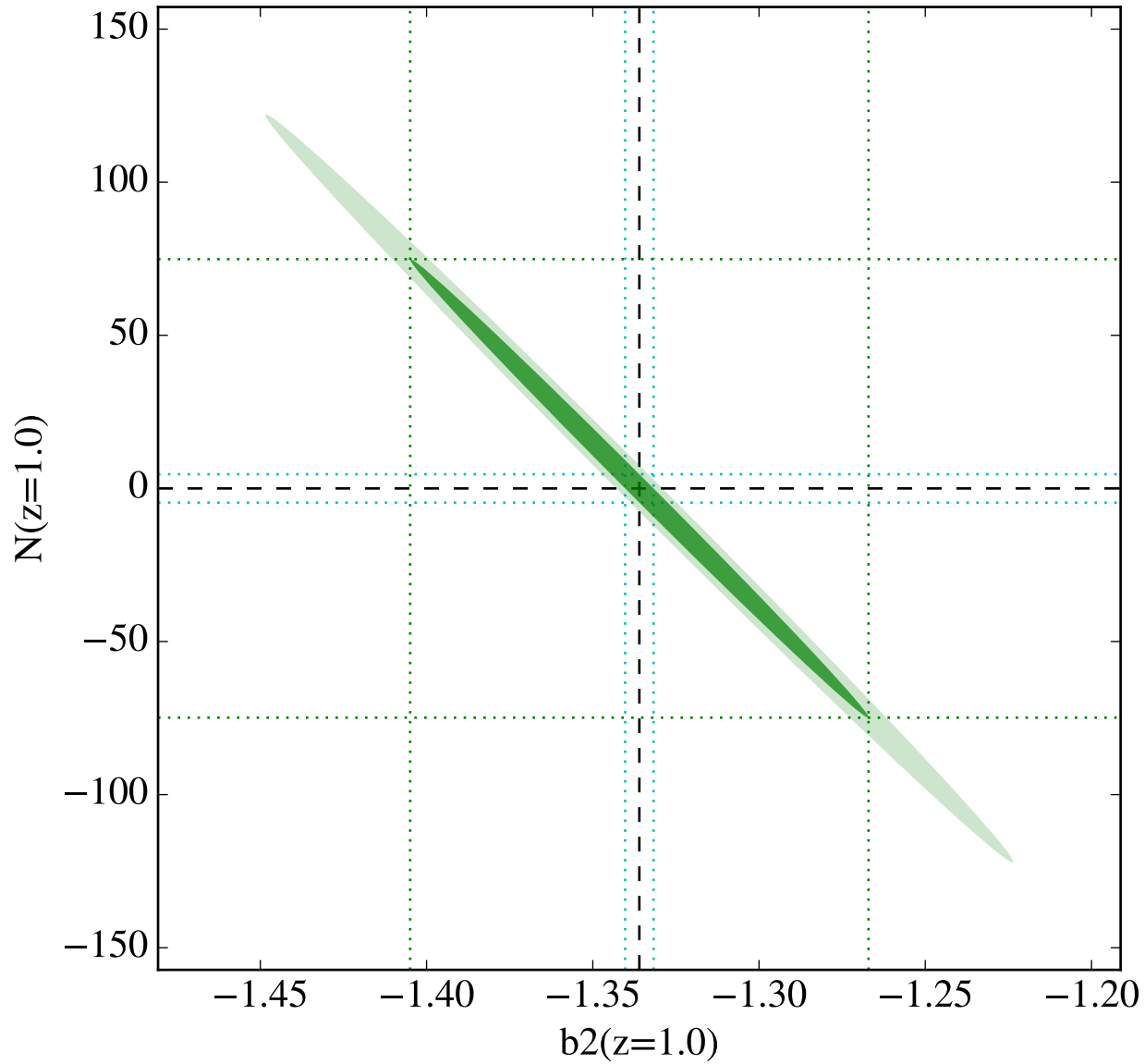
We have written a fast, user-friendly Python code (in the form of a Jupyter notebook) to forecast constraints using the TNS and EFTofLSS models. Paper in preparation, code will be publicly available (and hopefully useful for Euclid's IST:non-linear).

TNS VS EFT: FITS RESULTS (FIDUCIAL VALUES)

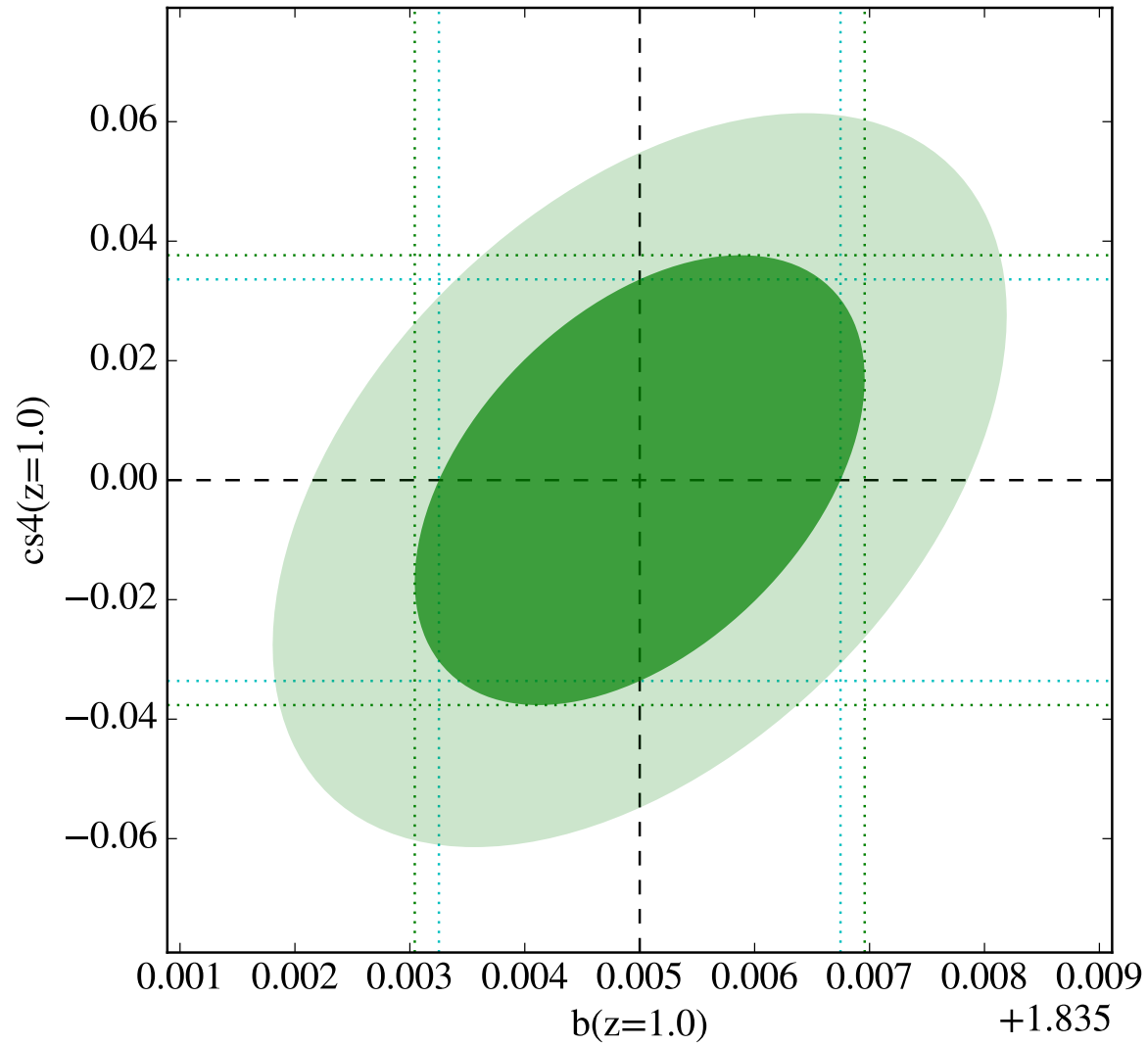
Model	TNS		EFT	
z	0.5	1	0.5	1
N_{bins}	43	40	35	52
k_{max}	0.264	0.245	0.215	0.32
b_1	1.362	1.788	1.450	1.840
b_2	-1.435	-1.854	-0.7924	-1.336
N	2461	2060	1089	1226
σ_v	6.306	5.132	-	-
$c_{s,0}^2$	-	-	0.6100	0
$c_{s,2}^2$	-	-	6.959	0
$c_{s,4}^2$	-	-	10.64	11.29

For our forecasts we vary (f , s_8 , DA , H), the shape parameters (w_m, h, w_b, n_s), and the TNS/EFT parameters. We then project to (fs_8) and show full marginalised errors, with and without priors.

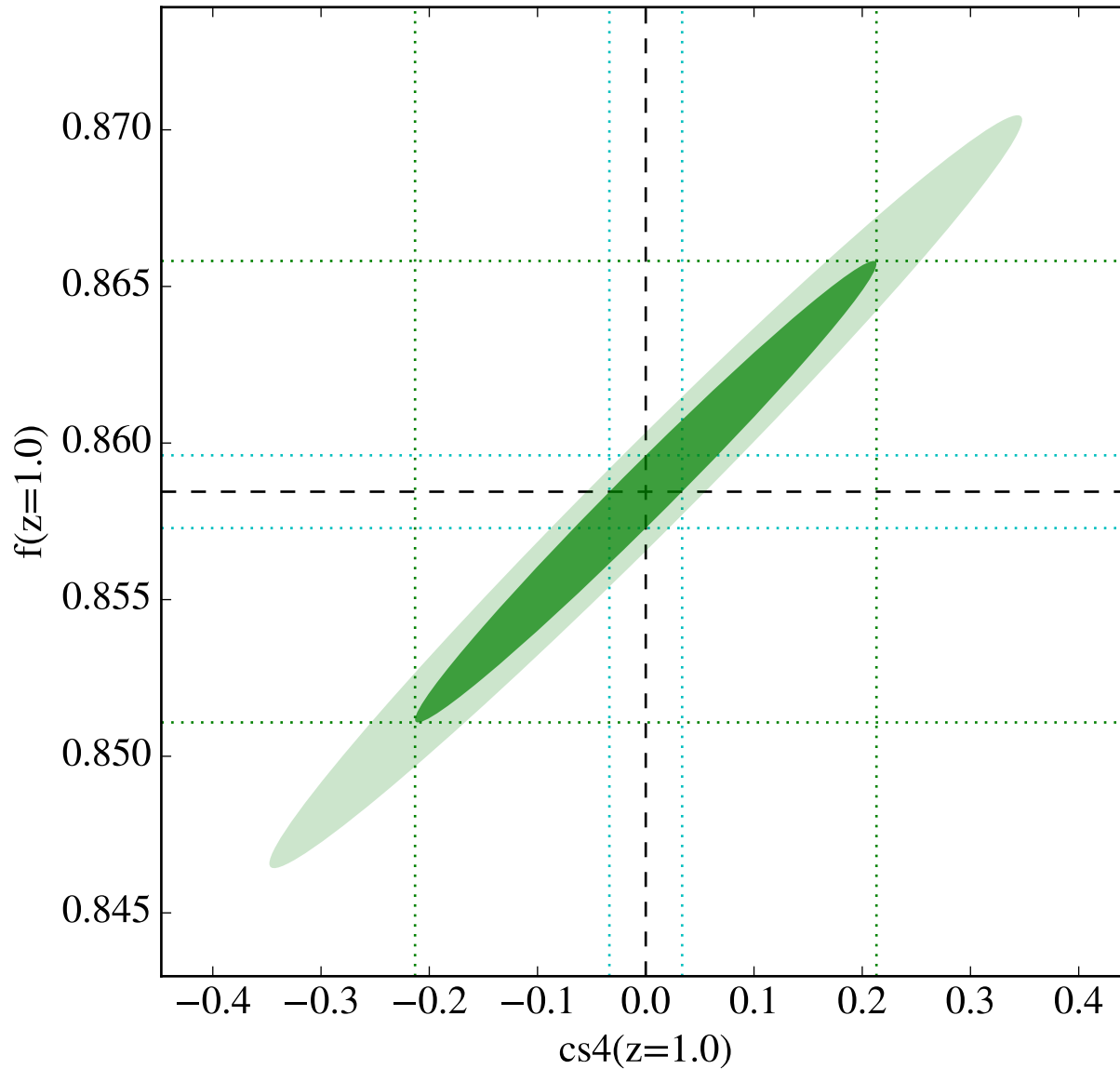
EFTOFLSS: CORRELATIONS/DEGENERACIES



EFTOFLSS: CORRELATIONS/DEGENERACIES



EFTOFLS: CORRELATIONS/DEGENERACIES



GROWTH CONSTRAINTS RESULTS (PRELIMINARY)

- ◆ **TNS:** gives a Euclid-like marginalised 6.8% error on (fs8) at $z=1$ with $k_{\max}=0.25$, going to 5.2% using Planck priors.
- ◆ **EFTofLSS:** gives a Euclid-like marginalised marginalised 6.2% error at $z=1$ with $k_{\max}=0.32$, which only slightly improves using Planck priors.
- ◆ If (wrongly!) you use TNS until $k_{\max}=0.32$, you get a factor of 3 better constraints on (fs8) than with EFTofLSS.
- ◆ **So there is a tradeoff** between the gain from larger k_{\max} and the loss from extra parameters that have to be marginalised over (not surprising).
- ◆ Adding strong priors -basically fixing- the EFT parameters the (fs8) error improves considerably, down to 4.5%.
- ◆ Simulations very important. Different (non-GR) models can have very different EFT parameters best-fit.
- ◆ We need to test a few exotic models using proper simulations. We also need fast emulators.