

# Scalar dipole dynamical polarizabilities from proton real Compton scattering data



# Outline

## WHAT?

Extraction of dipole dynamical polarizabilities (DDPs) from proton RCS data

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Response of the nucleon to an external **dynamical** field  
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Dispersion Relation approach + data analysis

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Response of the nucleon to an external **dynamical** field (photon)

## HOW?

Dispersion Relation approach + data analysis

## WHY?

*“...sure, it may give some practical results, but that's not why we do it”* - R. P. Feynman

# SOME STATISTICS

# Complications

Gradient method to find the  $\chi^2$  minimum

**VERY high correlations** between parameters!

MINUIT WARNING IN HESSE

===== MATRIX FORCED POS-DEF BY ADDING  
0.13727E-01 TO DIAGONAL.

**VERY low sensitivity** of the data to dynamical polarizabilities

**NO WAY** to find the “right” minimum and to define “right” errors on fit parameters

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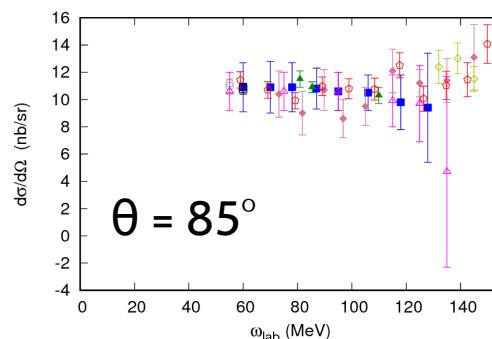
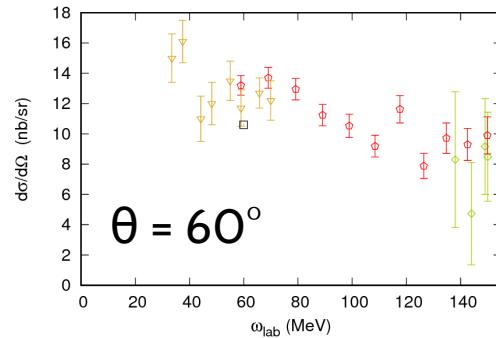
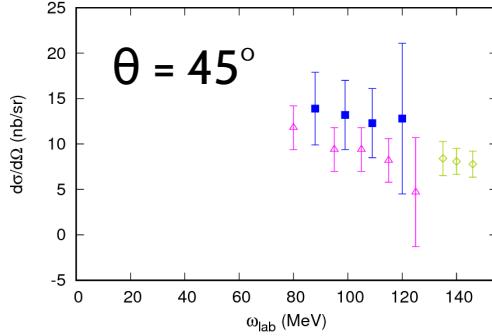
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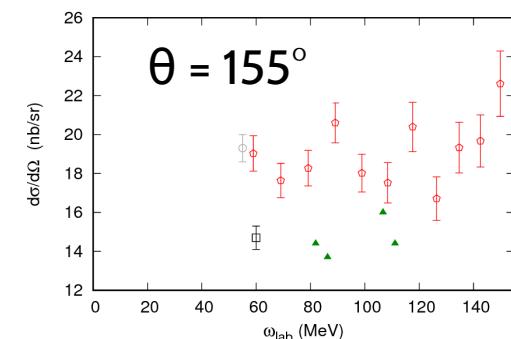
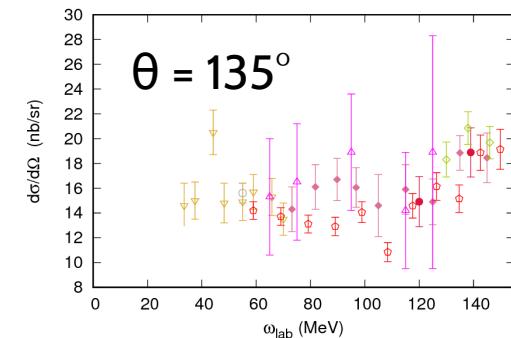
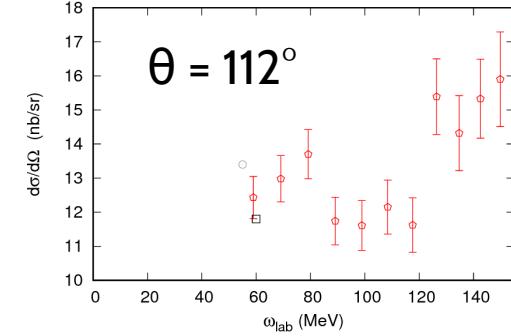
**NO WAY** to find the “right” minimum and to define “right” errors on fit parameters

Combination of **SIMPLEX** method and **BOOTSTRAP** technique

# The DATA set

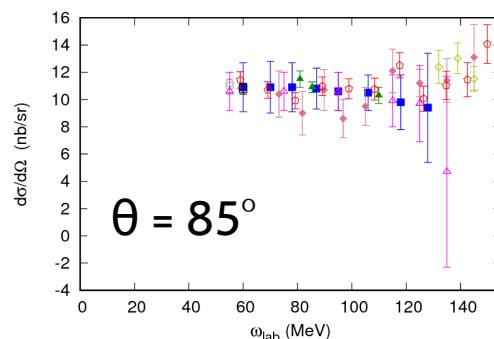
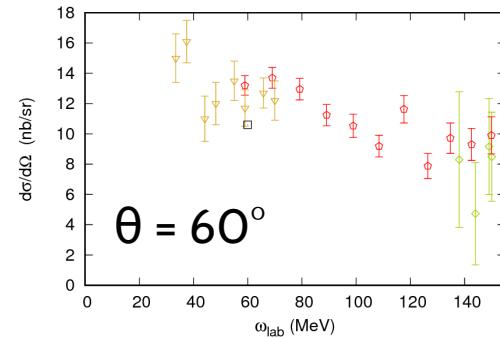
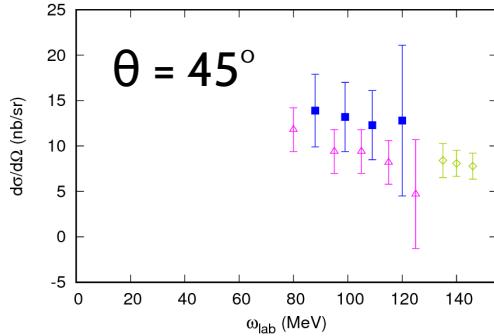


Symbol	Set	Ref
—○—	GOL 60	Goldansky et al.
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—▲—	BAR 74	Baranov et al.
—□—	OXL 58	Oxley
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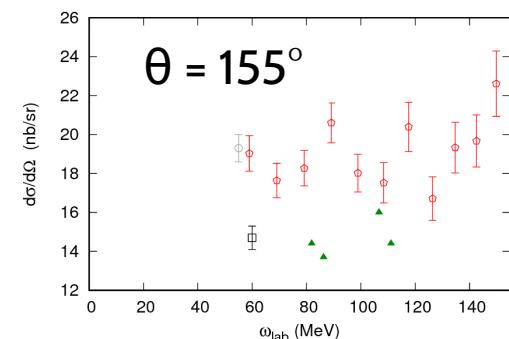
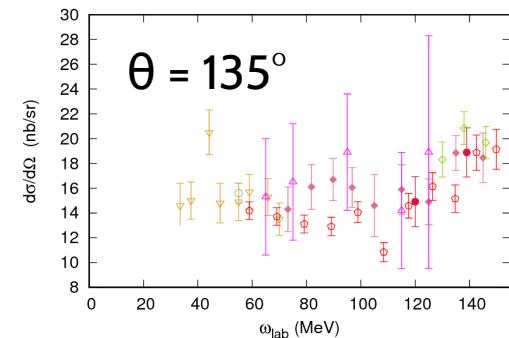
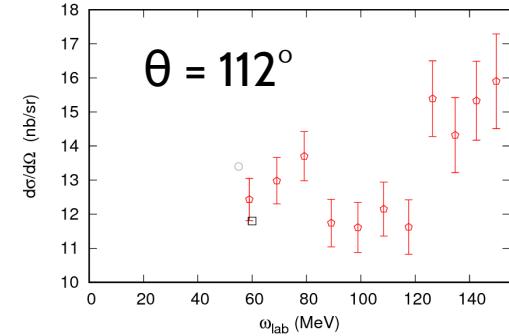


# The DATA set

***Half of the Spartans  
that King Leonidas led  
to the Battle of  
Thermopylae...***



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# Parametric bootstrap sampling and systematics

$$S_{i,\text{exp}}^{\text{boot}} = S_{i,\text{exp}} \pm \gamma \sigma_{i,\text{exp}}$$

Gaussian distributed

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Gaussian distributed

How can we include systematical errors?

$$\chi^2_{mod} = \sum_{i=1}^{N_{tot}} \left[ \frac{\mathcal{N}S_{i,\text{exp}} - S_{i,\text{theory}}}{\mathcal{N}\sigma_{i,\text{exp}}} \right]^2 + \left( \frac{\mathcal{N}-1}{\sigma_{i,\text{sys}}} \right)^2$$

...one normalization factor per data set is needed!

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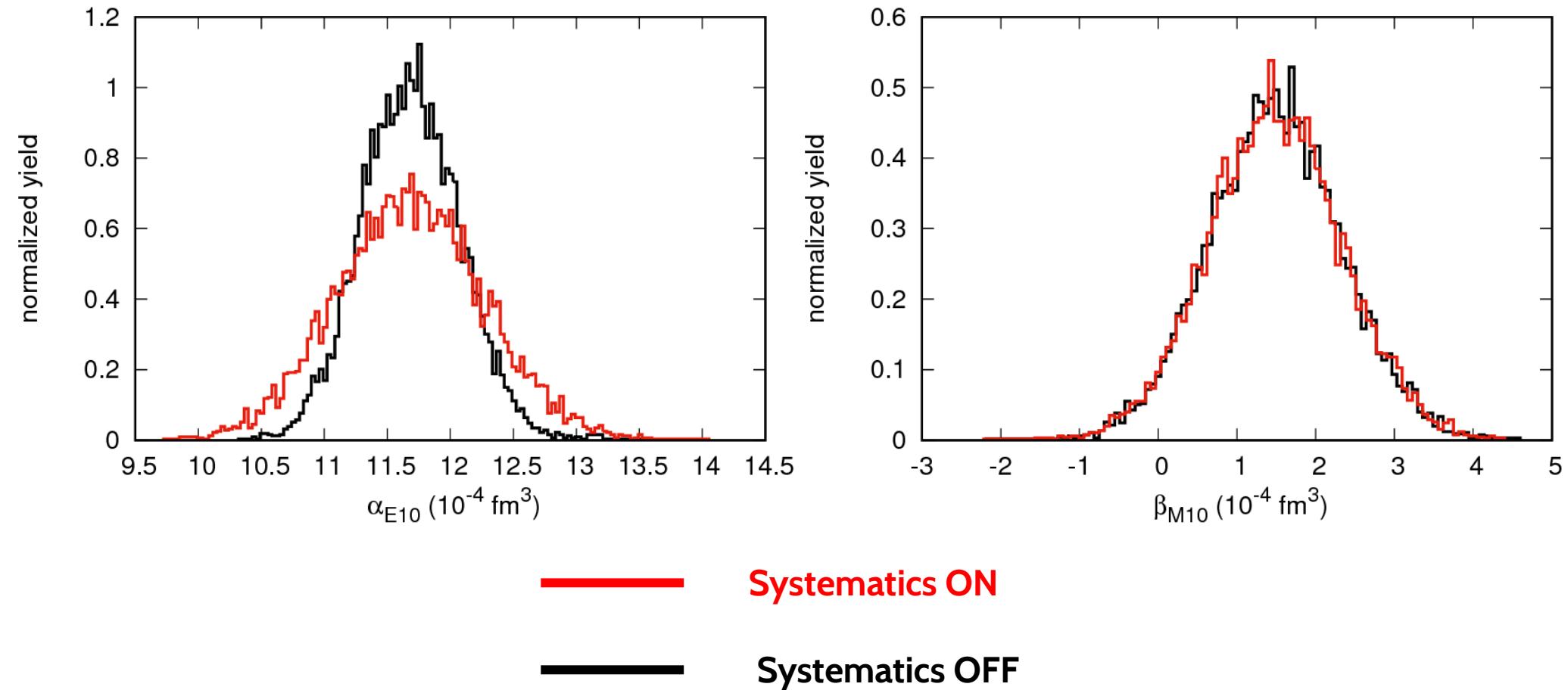
$$\chi^2_{\text{mod}} = \sum_{i=1}^{N_{\text{tot}}} \left[ \frac{\mathcal{N} S_{i,\text{exp}} - S_{i,\text{theory}}}{\mathcal{N} \sigma_{i,\text{exp}}} \right]^2 + \left( \frac{\mathcal{N} - 1}{\sigma_{i,\text{sys}}} \right)^2$$

...one normalization factor per data set is needed!

$$S_{i,\text{exp}}^{\text{boot}} = \xi [S_{i,\text{exp}} \pm \gamma \sigma_{i,\text{exp}}]$$

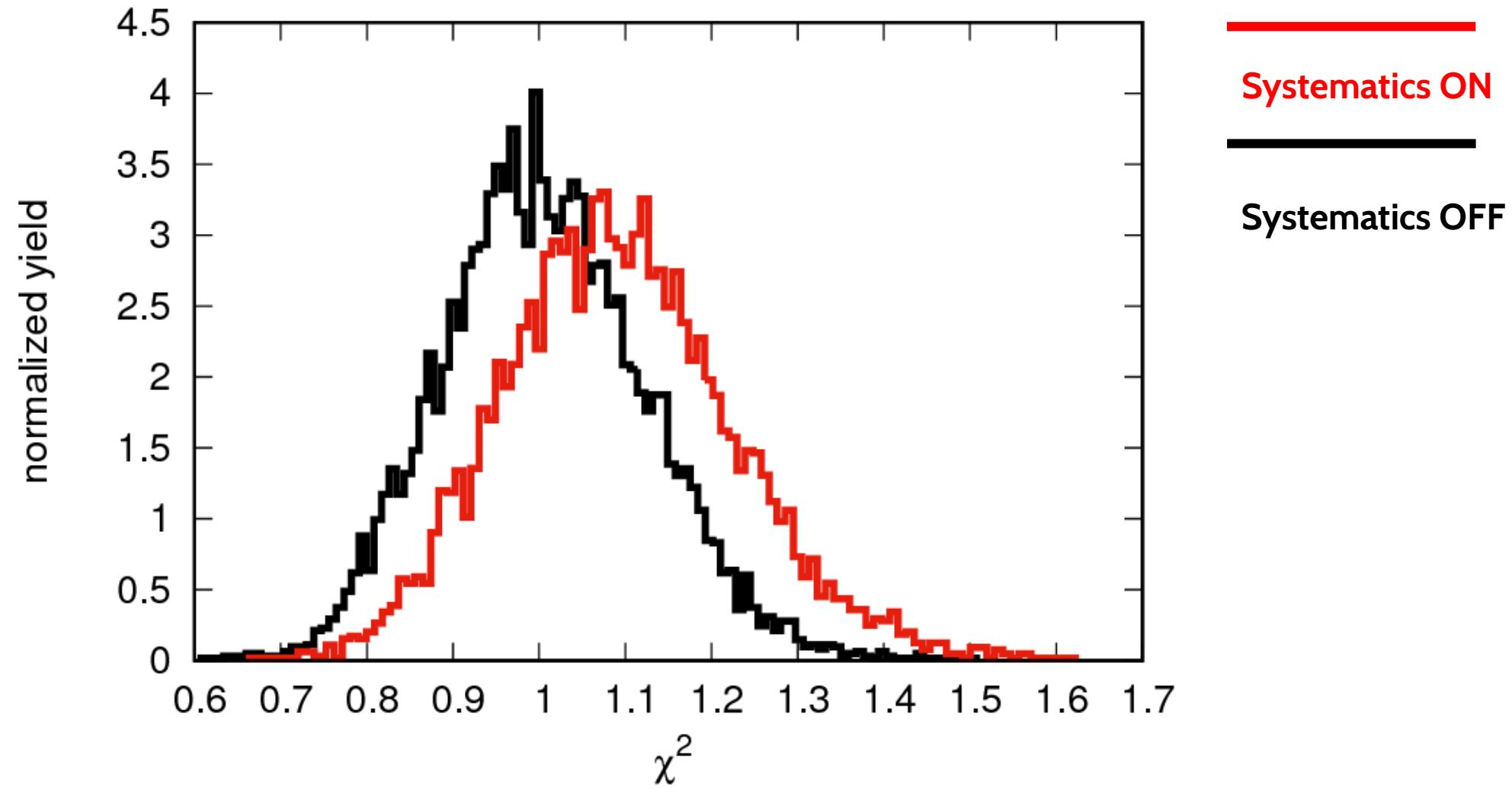
At every bootstrap cycle the systematical errors for each set can vary independently!

# The effect of systematics (static & spin-independent polarizabilities)

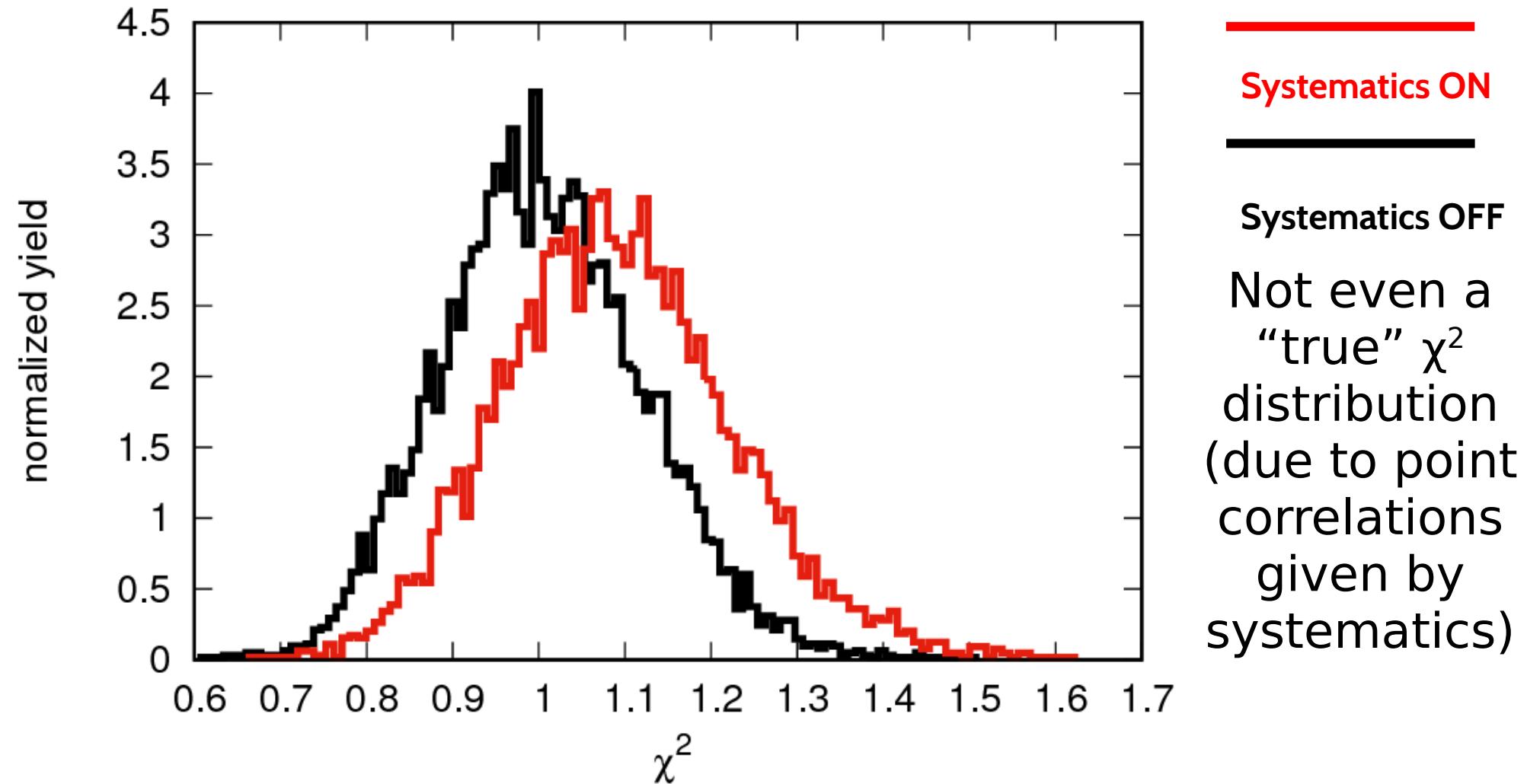


Expected Gaussian shape + systematics enlarging

# $\chi^2$ probability distribution in bootstrap framework (static pol.)

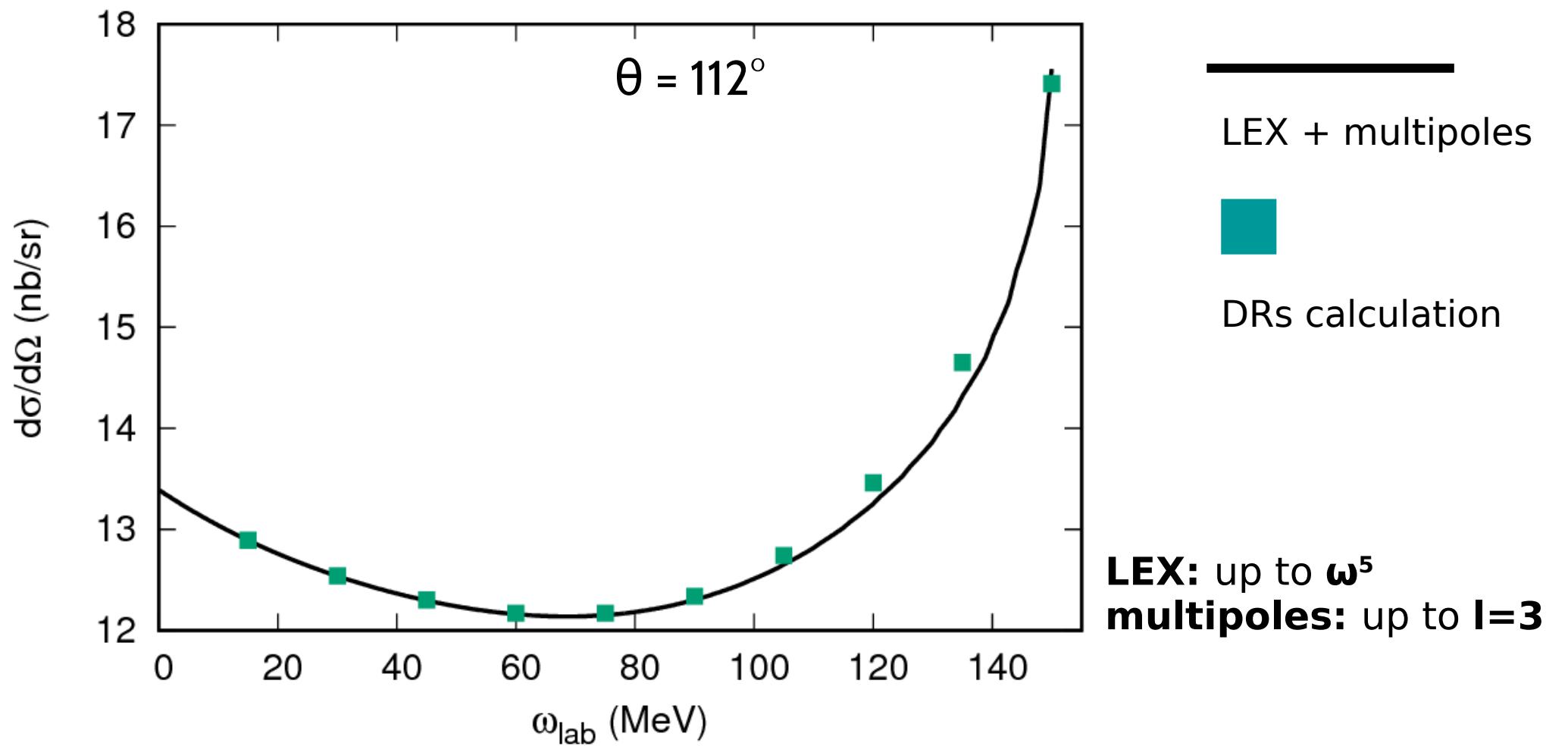


# “ $\chi^2$ ” probability distribution in bootstrap framework (static pol.)

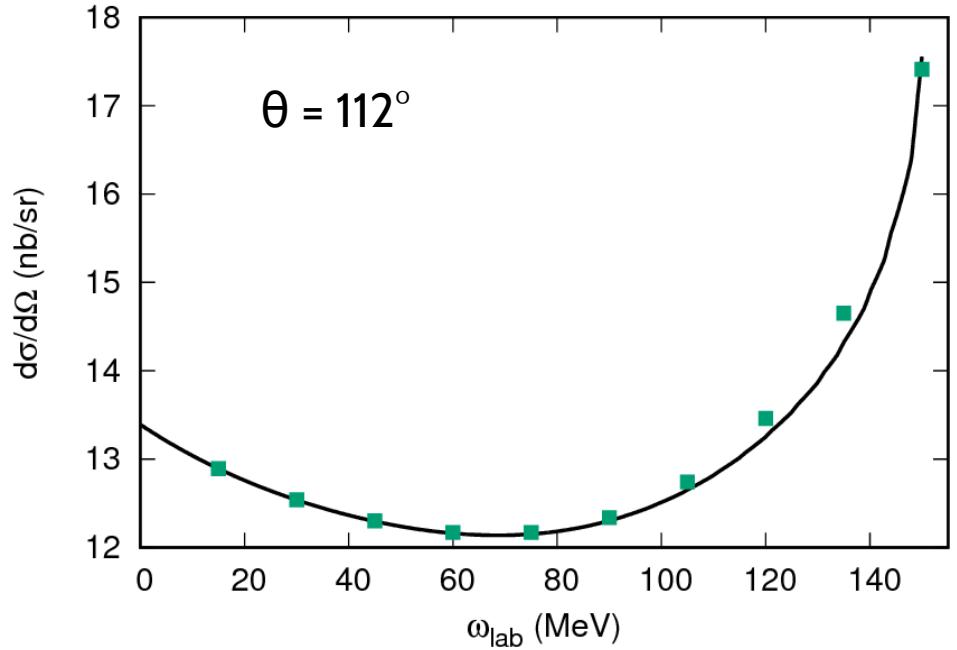


# DIPOLE STATIC POLARIZABILITIES

# DRs VS (*LEX* + *multipoles*)

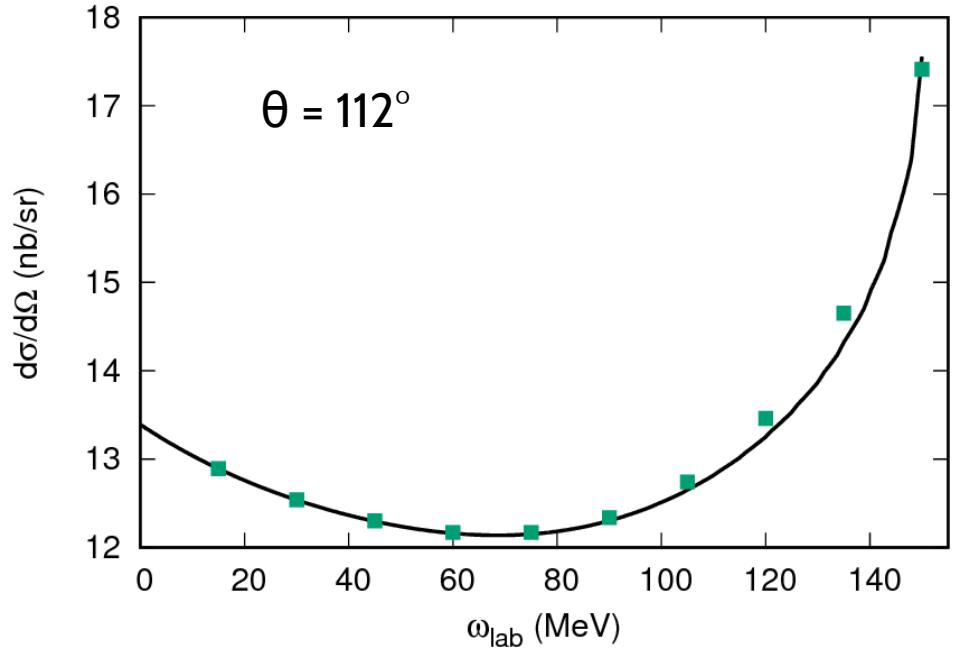


# DRs VS (*LEX* + *multipoles*): fit



FIRST cross check:  
comparison with  
***LEX + multipoles***  
and ***full DRs***

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$$\alpha_{E1} (10^{-4} \text{ fm}^3)$$

$$\beta_{M1} (10^{-4} \text{ fm}^3)$$

**full DRs**

**$11.9 \pm 0.2$**

**$1.9 \pm 0.2$**

**LEX + MULTIPOLES**

**$11.8 \pm 0.2$**

**$2.0 \pm 0.2$**

# Bootstrap VS gradient: systematics ON

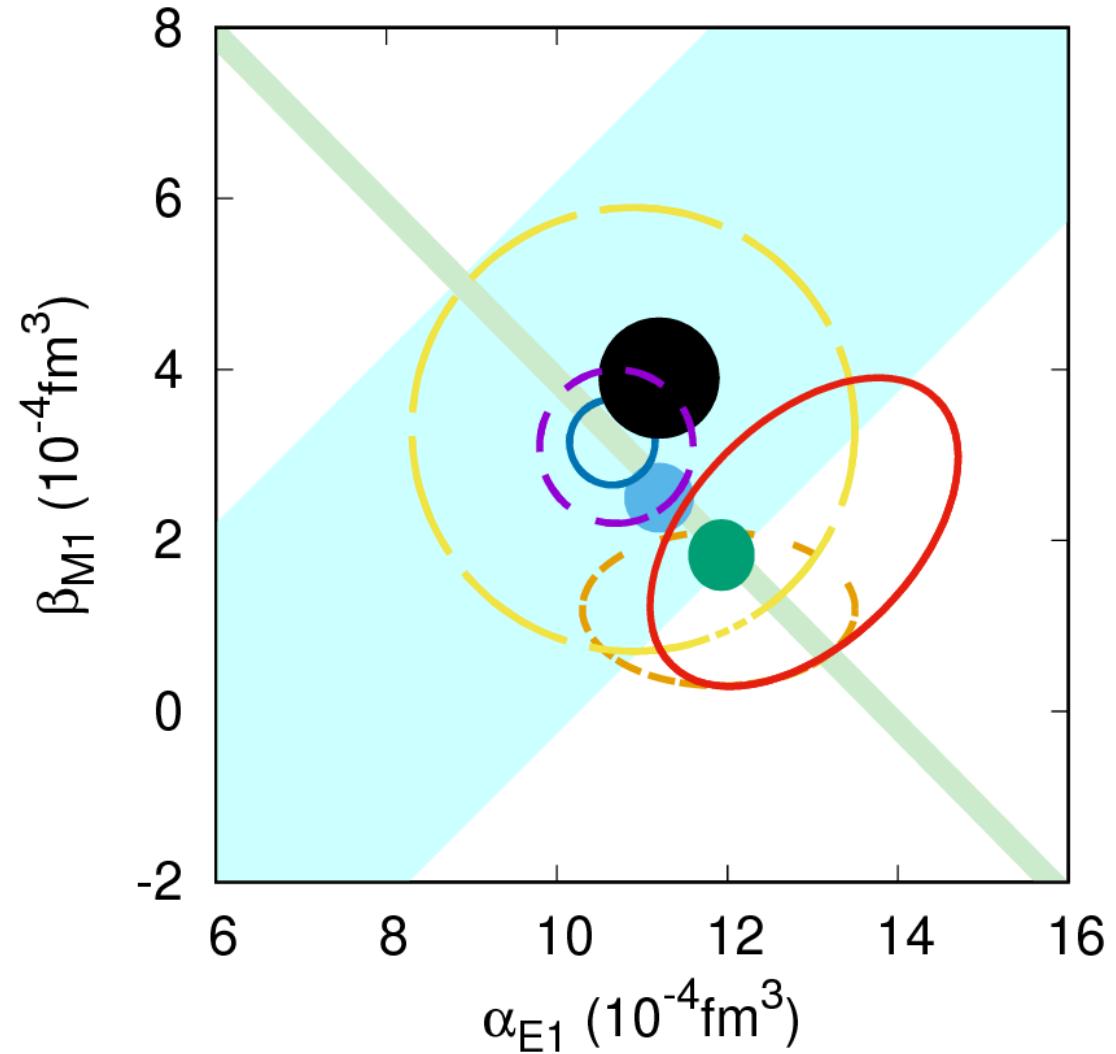
	$\alpha_{E1}$	$\beta_{M1}$
BOOTSTRAP	<b>11.8 ± 0.2</b>	<b>2.0 ± 0.2</b>
LEX + MULTipoles	<b>11.8 ± 0.2</b>	<b>2.0 ± 0.2</b>
BOOTSTRAP SYS ON	<b>11.8 ± 0.3</b>	<b>2.0 ± 0.3</b>

# Bootstrap VS gradient: systematics ON

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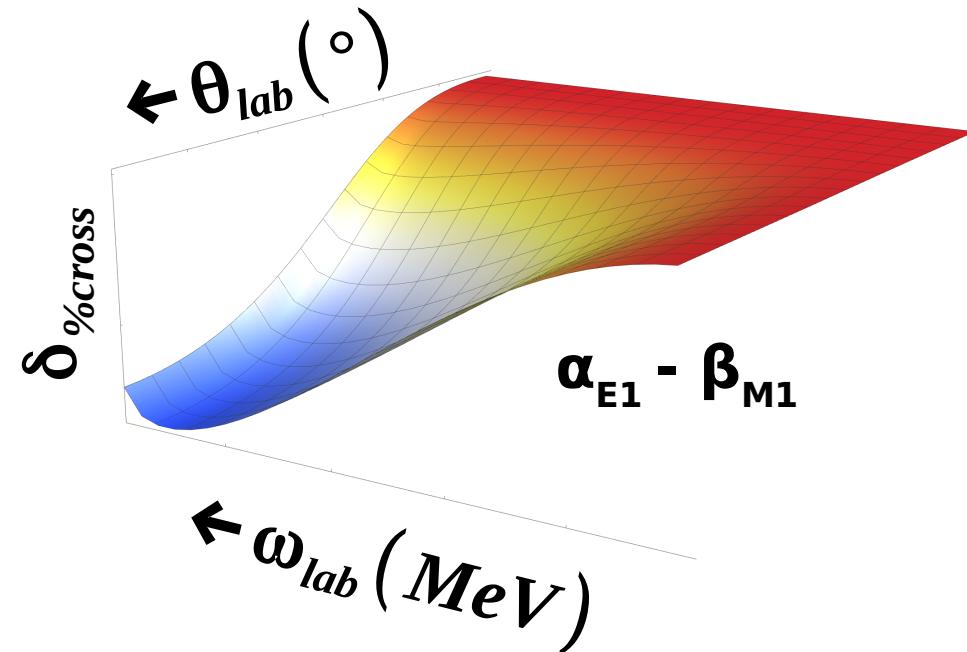
Systematical errors enlarge the error band of polarizabilities!

# Summary plot

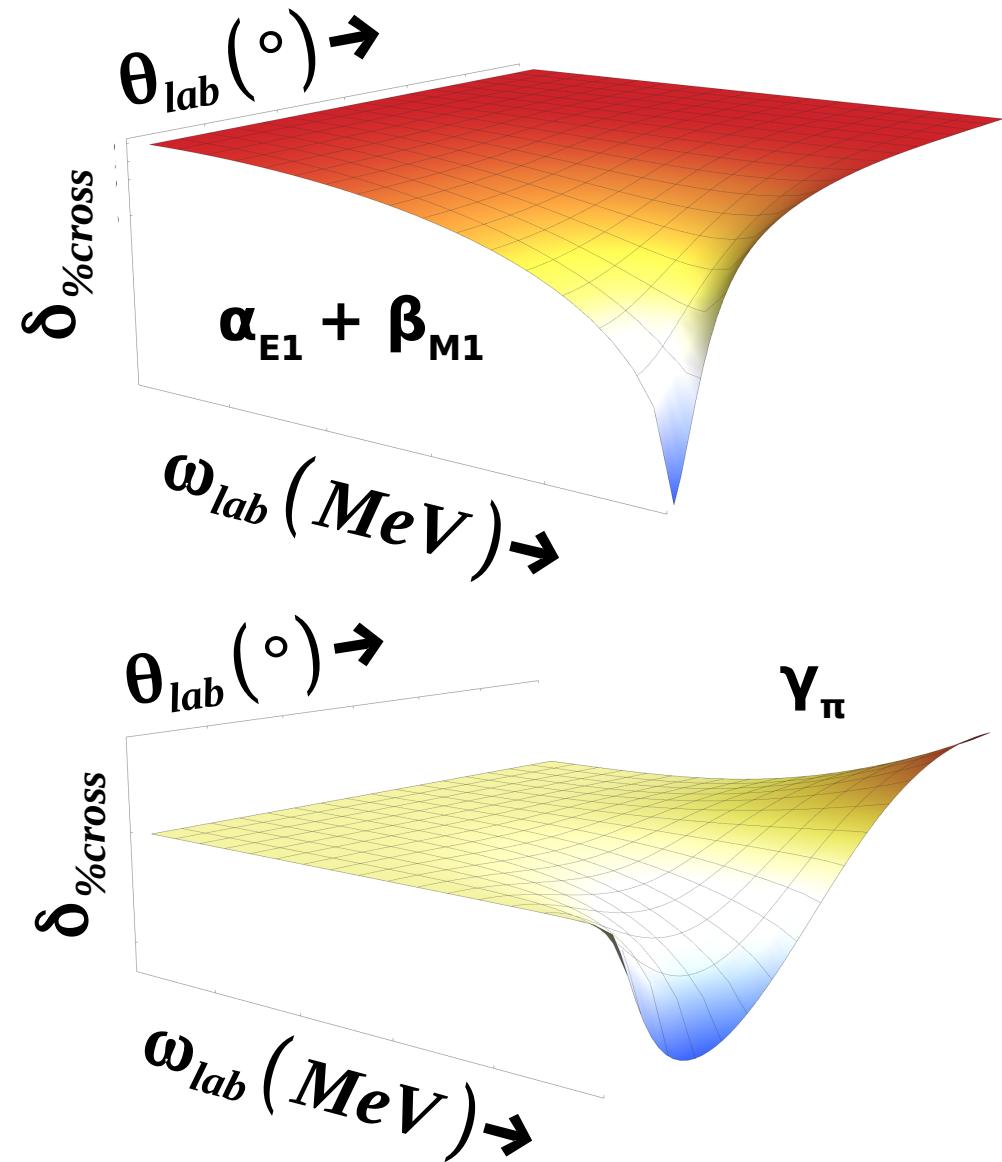


We include Baldin's  
uncertainty &  
systematic sources!

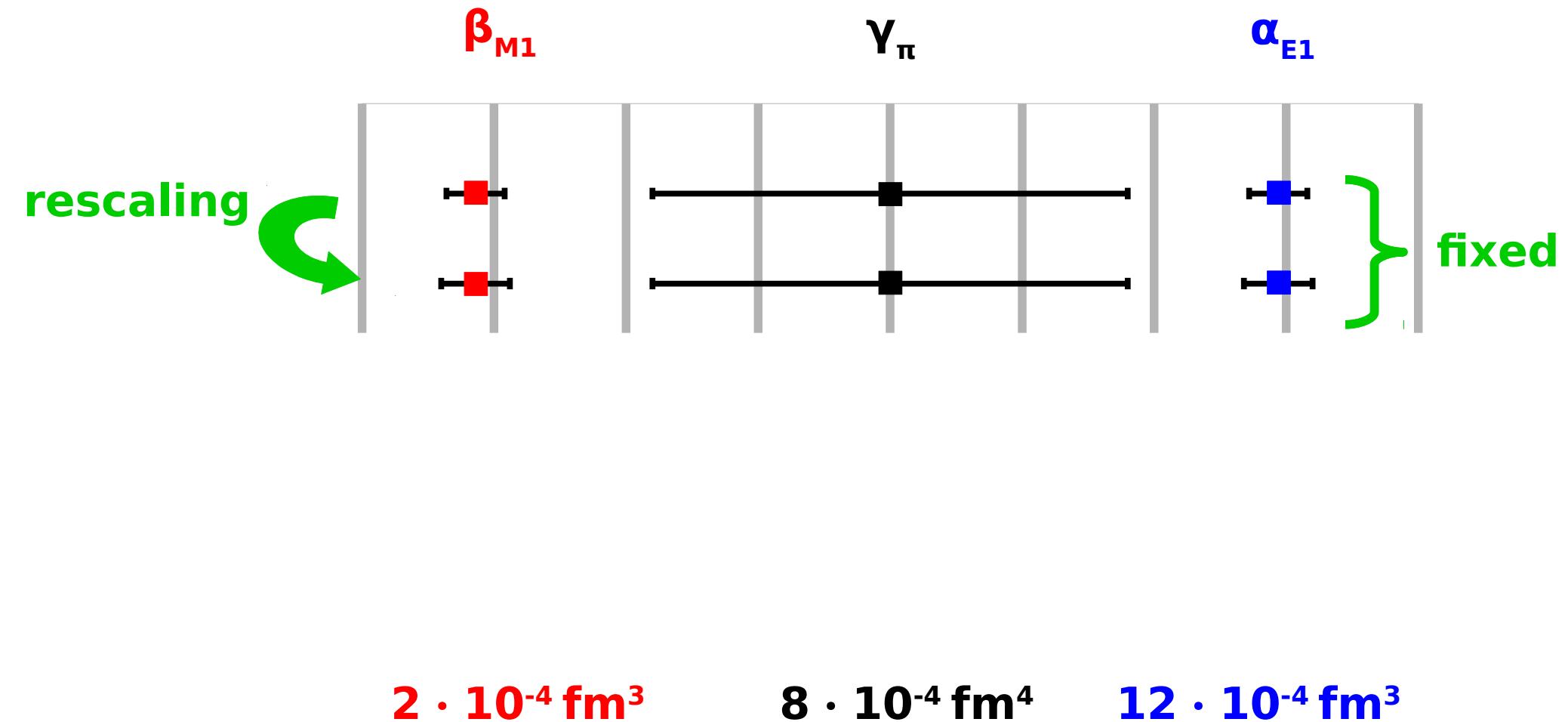
# Unpolarized differential cross section: sensitivity plots



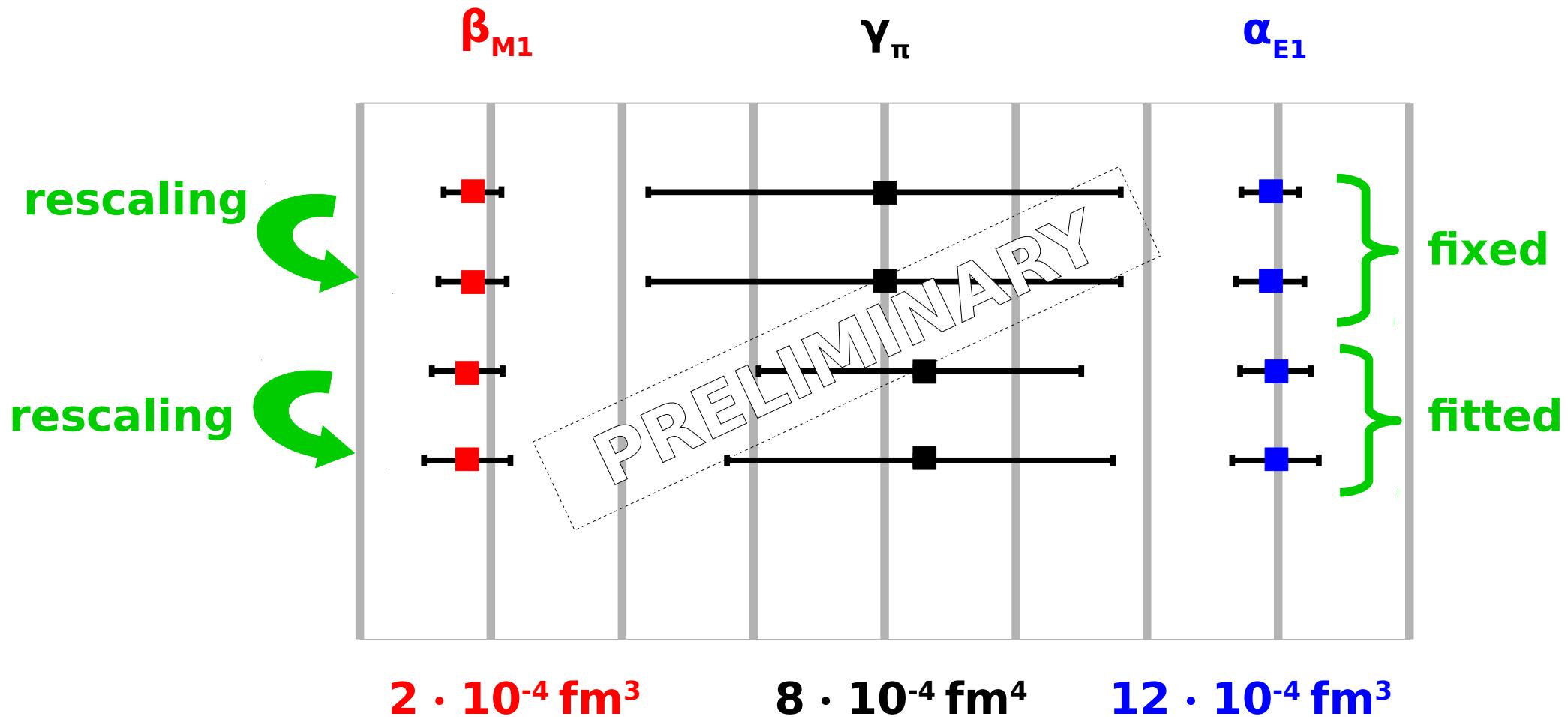
% variation of the  
observable when the  
particular polarizability is  
changed by a factor  $\pm 10\%$



# Static fit: $\gamma_\pi$ free parameter



# Static fit: $\gamma_\pi$ free parameter



Central values and uncertainties are almost the same!

# DIPOLE DYNAMICAL POLARIZABILITIES

# Fit conditions

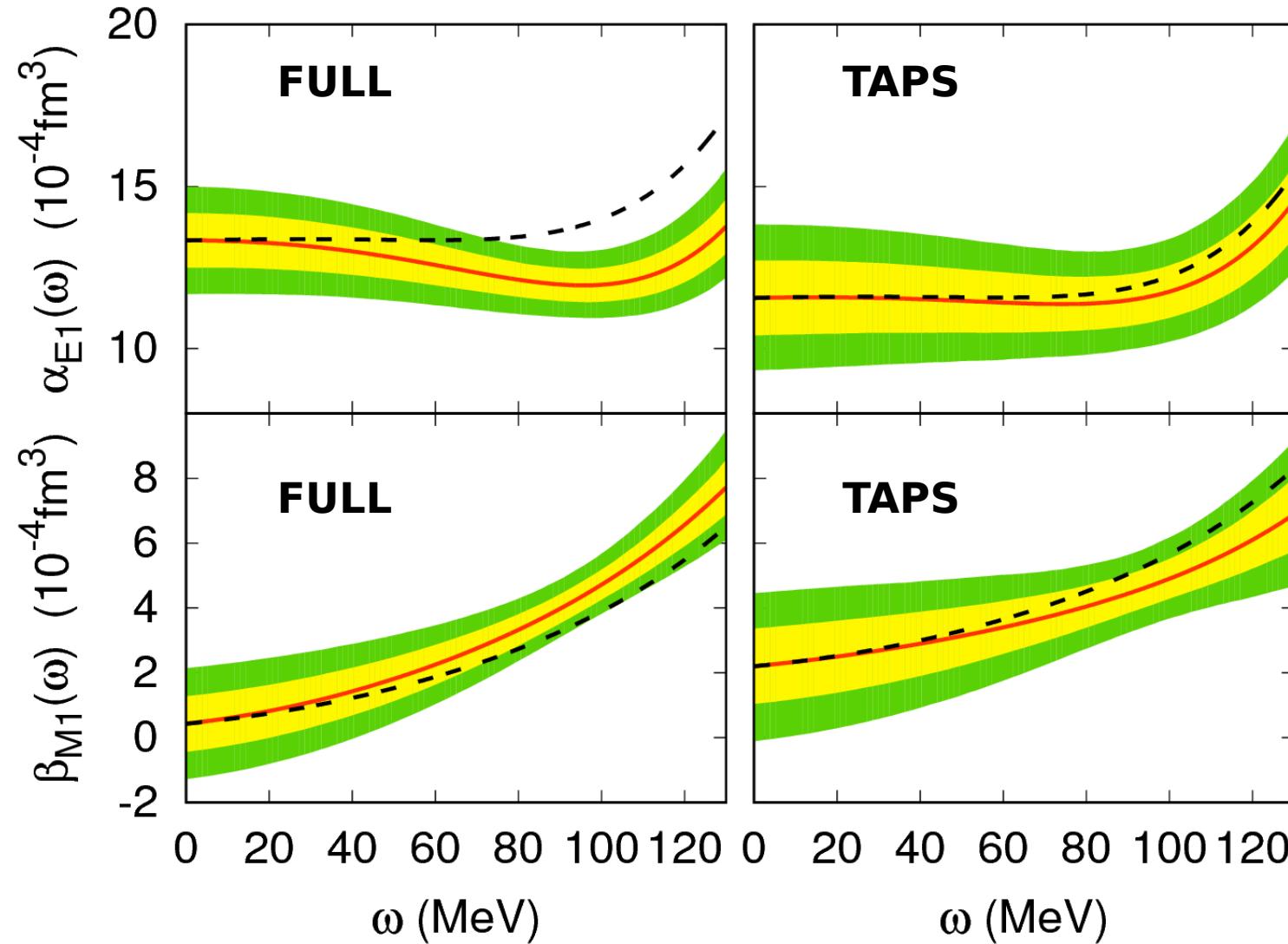
- ✓ Baldin's sum rule
- ✓ Systematical errors ON
- ✓ FULL data set (150 data)
- ✓ TAPS data set (55 data)
- ✓ Errors on Baldin's sum rule  
and  $\gamma_n$  included in the  
procedure

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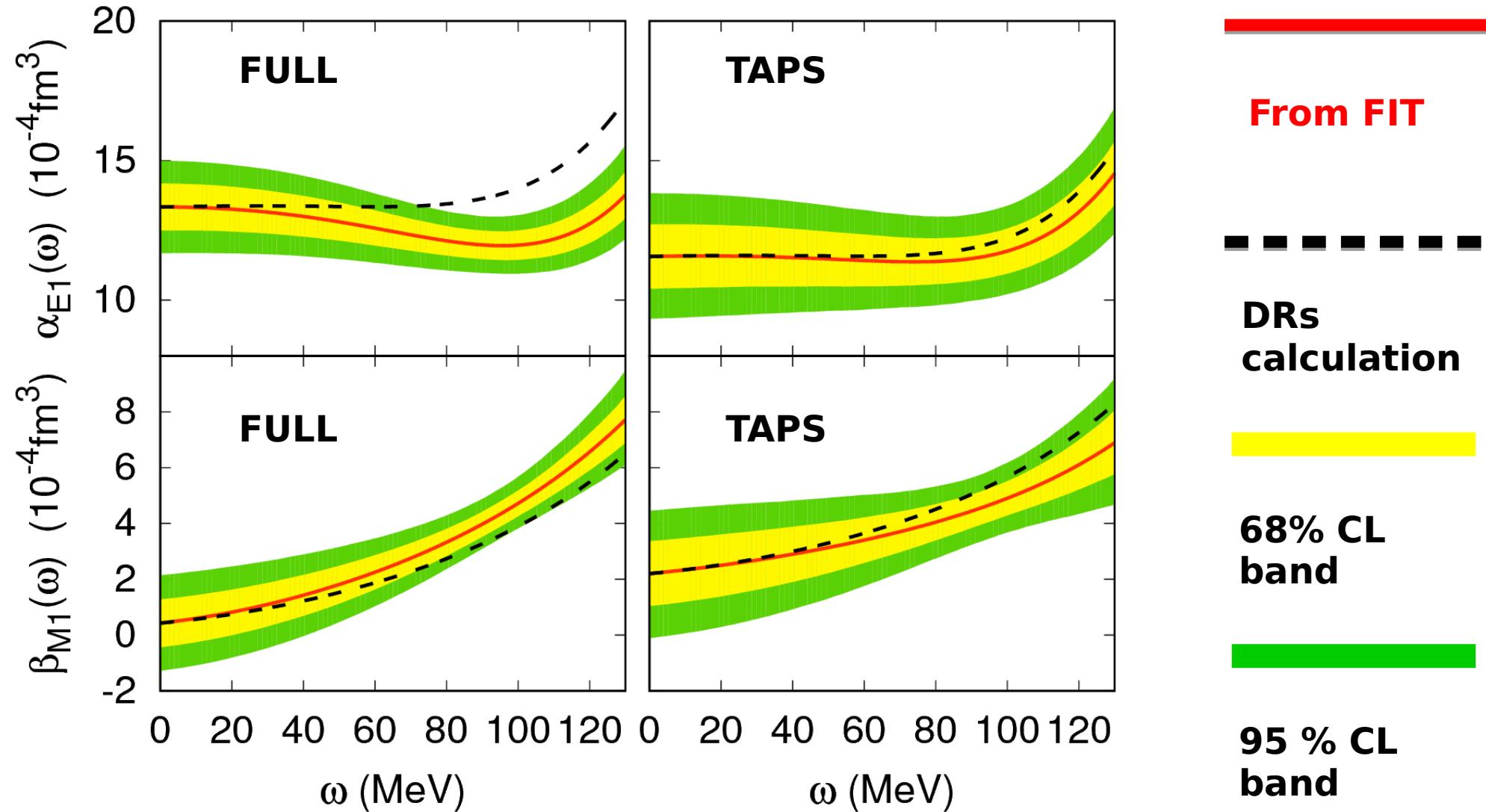
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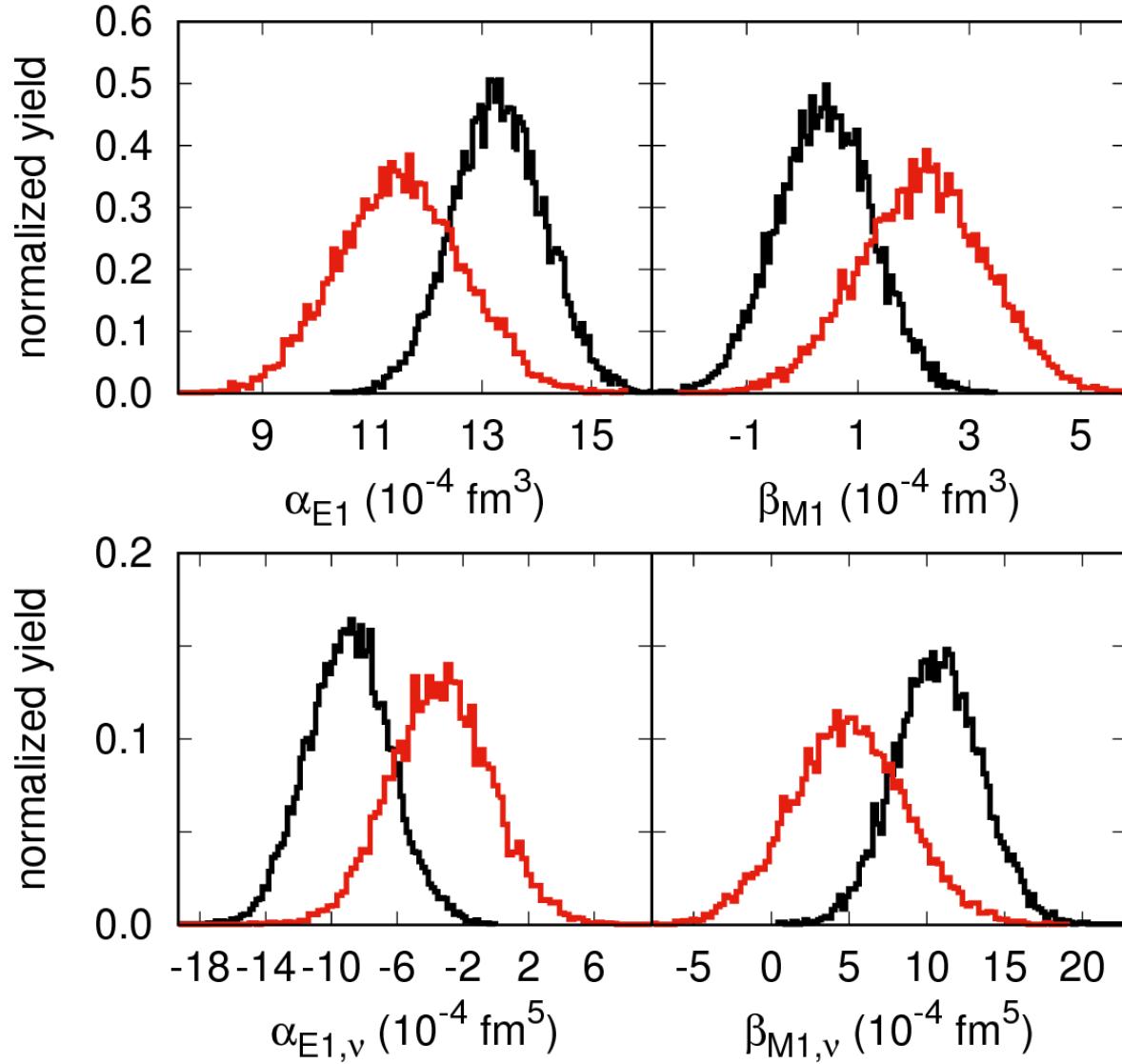
# DDPs from the fit



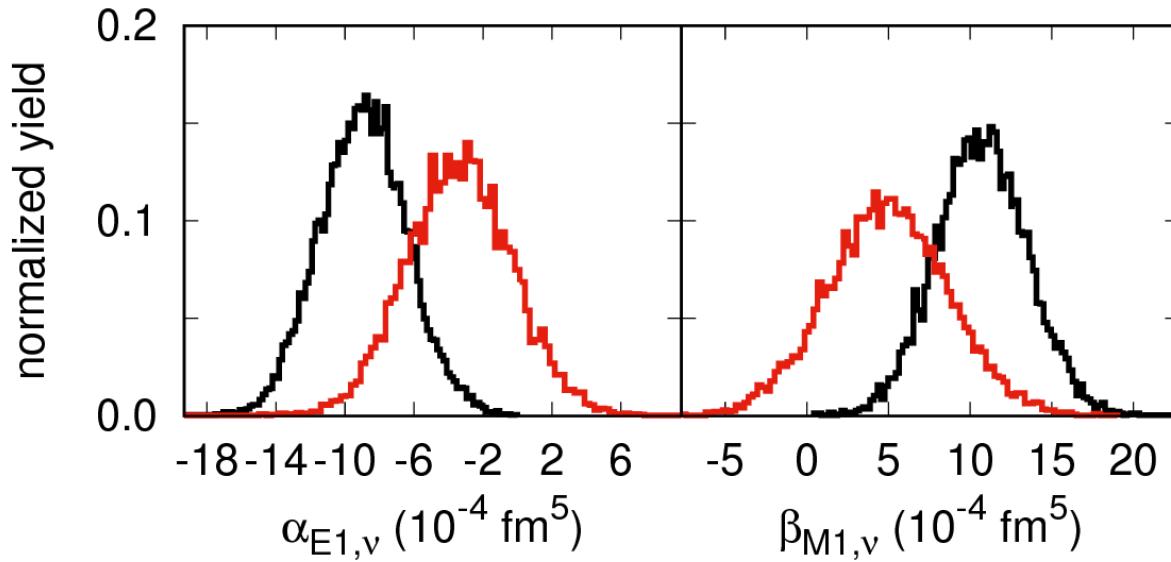
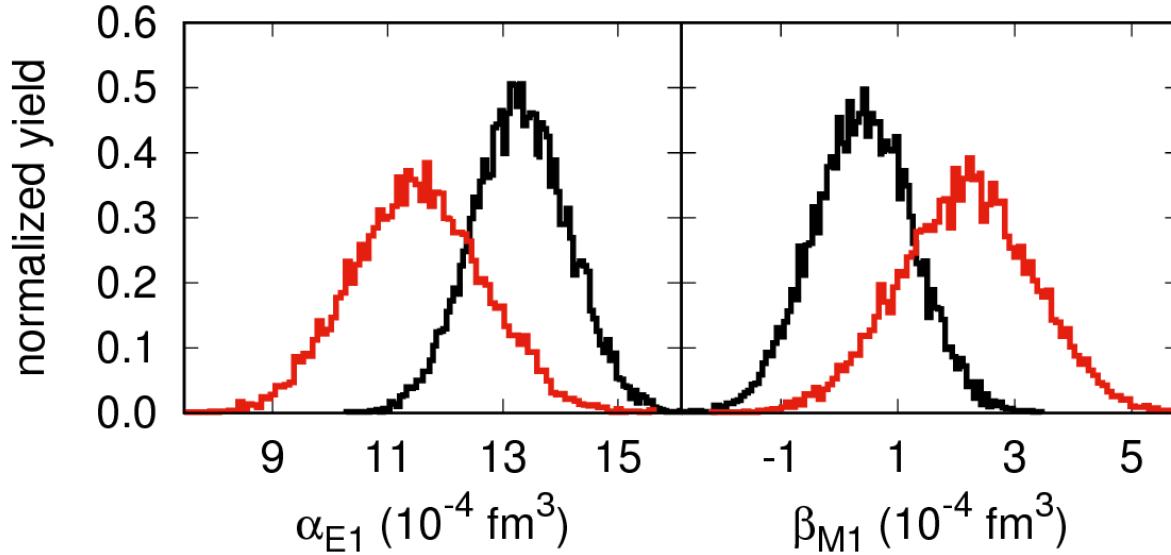
# DDPs from the fit



# DDPs from the fit: probability distributions



# DDPs from the fit: probability distributions



— TAPS data set

— FULL data set

Probability  
distributions given  
by our technique  
**(not** assumed a  
priori)

# Global results: numerical values

		FULL	TAPS
$\alpha_{E1}$	$(10^{-4}\text{fm}^3)$	$13.3 \pm 0.8$	$11.6 \pm 1.1$
$\alpha_{E1,\nu}$	$(10^{-4}\text{fm}^5)$	$-8.8 \pm 2.5$	$-3.2 \pm 3.1$
$\beta_{M1}$	$(10^{-4}\text{fm}^3)$	$0.4 \mp 0.9$	$2.2 \mp 1.1$
$\beta_{M1,\nu}$	$(10^{-4}\text{fm}^5)$	$10.8 \pm 2.8$	$5.1 \pm 3.7$

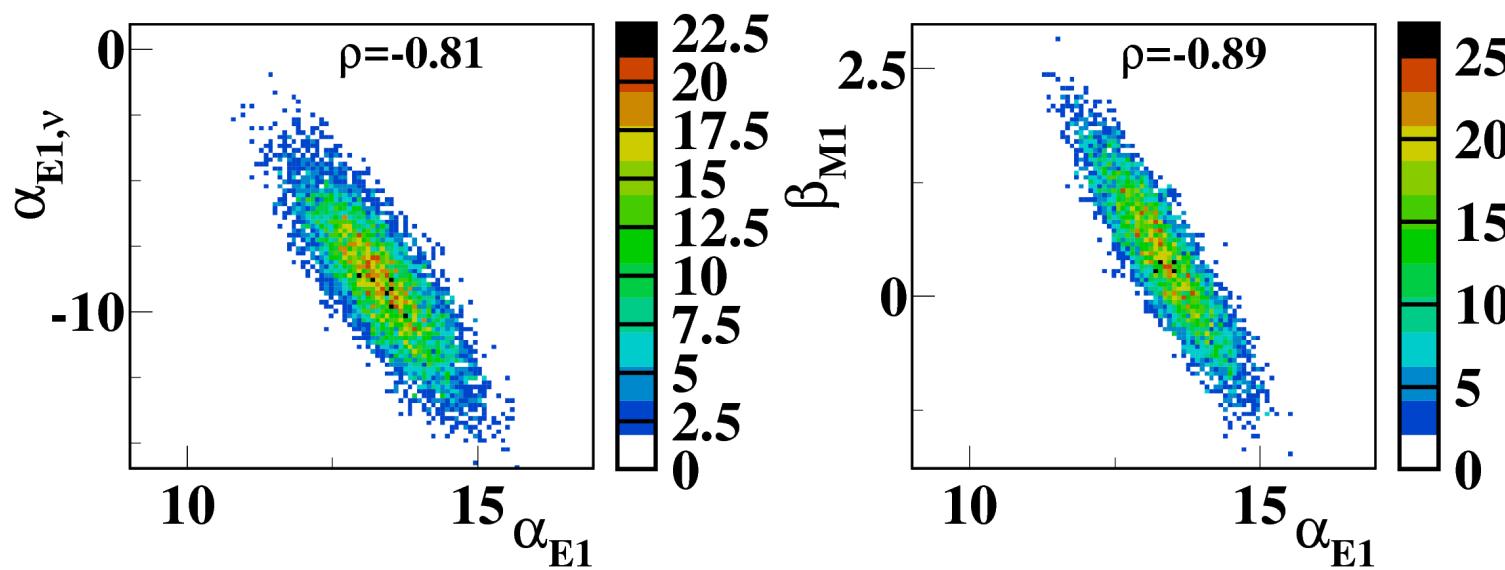
Very STRONG dependence on  
data set (maybe due to  
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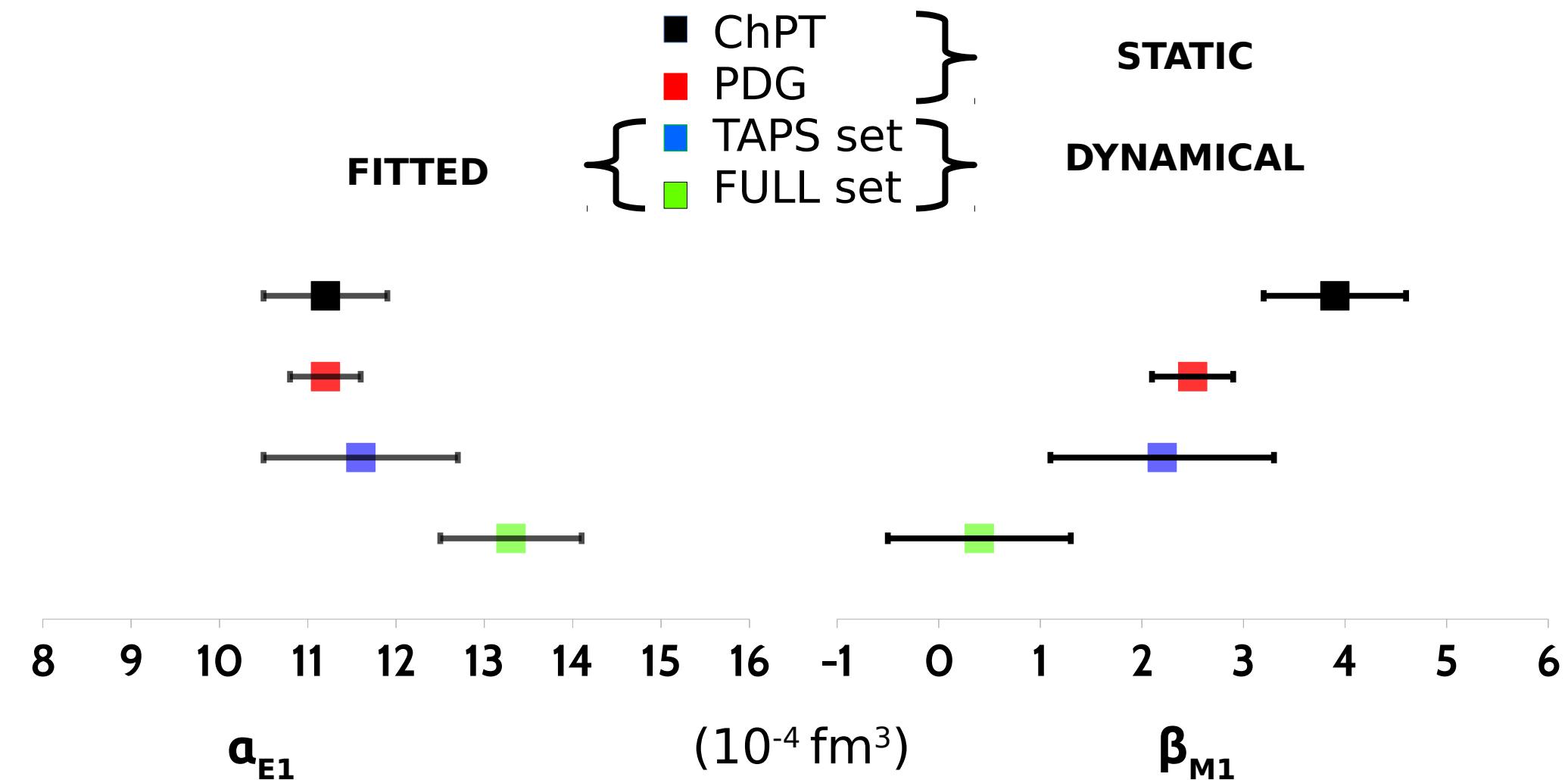
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Very STRONG dependence on data set (maybe due to different angular regions...)

Very HIGH correlations among parameters



# Global results: $\alpha_{E1}$ & $\beta_{M1}$

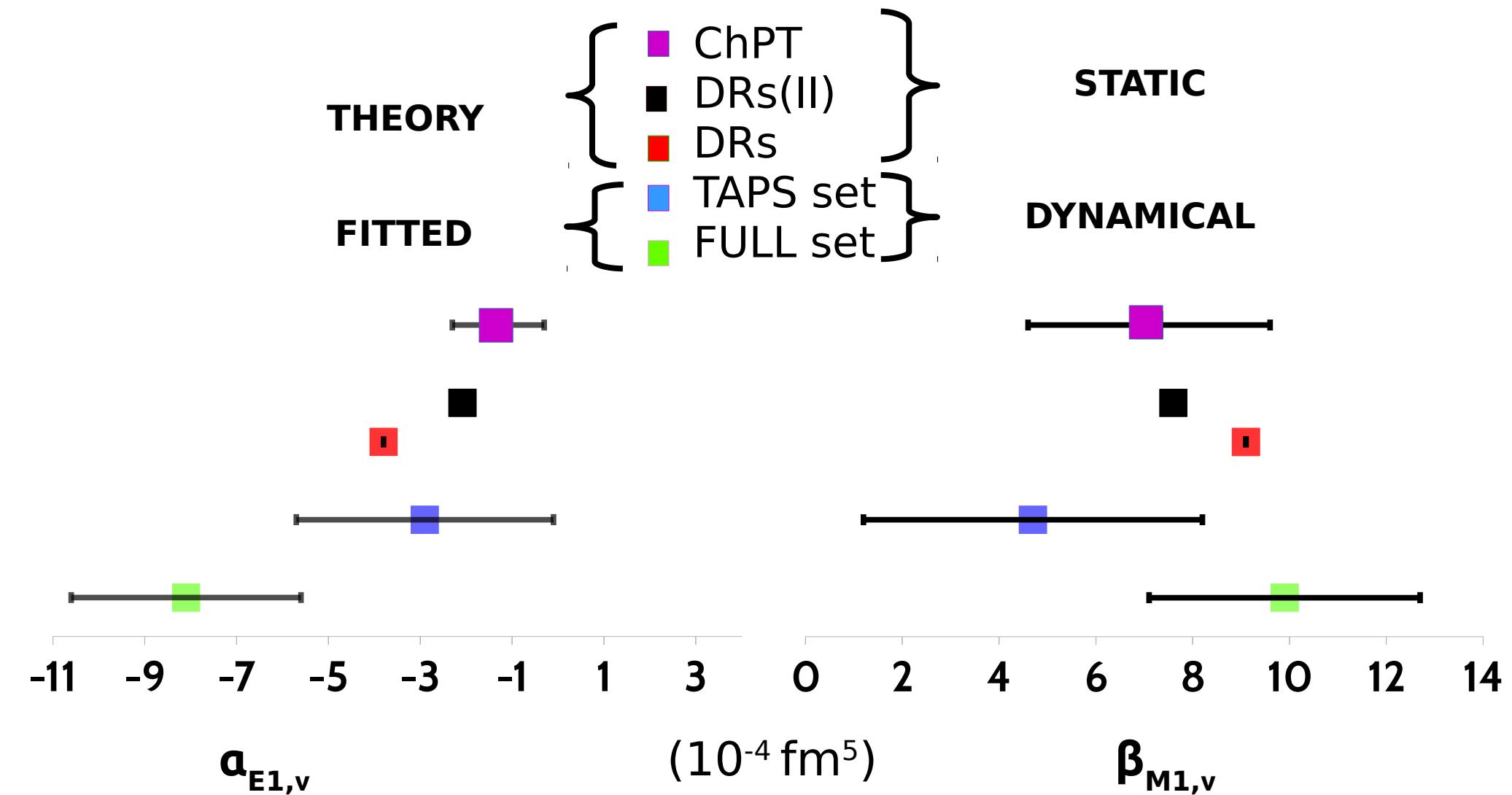


PDG: C. Patrignani et al. (Particle Data Group), Chin. Phys. C, 40, 100001 (2016) and 2017 update

ChPt: V. Lensky, J. McGovern, and V. Pascalutsa, Eur. Phys. J. C75, 604 (2015)

B. Pasquini, P. Pedroni, S. Sconfietti, Phys. Rev. C 98, 015204 (2018)

# Global results: $\alpha_{E1,v}$ & $\beta_{M1,v}$



DRs (I): B. R. Holstein, D. Drechsel, B. Pasquini, M. Vanderhaeghen. Phys.Rev. C61 (2000) 034316

DRs (II): B. Pasquini, D. Drechsel, M. Vanderhaeghen. Phys.Rev. C76 (2007) 015203

ChPt: V. Lensky, J. McGovern, and V. Pascalutsa, Eur. Phys. J. C75, 604 (2015)

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# Problems with the data set (what we could do)

Very strong dependence of polarizabilities on the specific data set!

Outliers → rescaling of all the statistic uncertainties by a factor

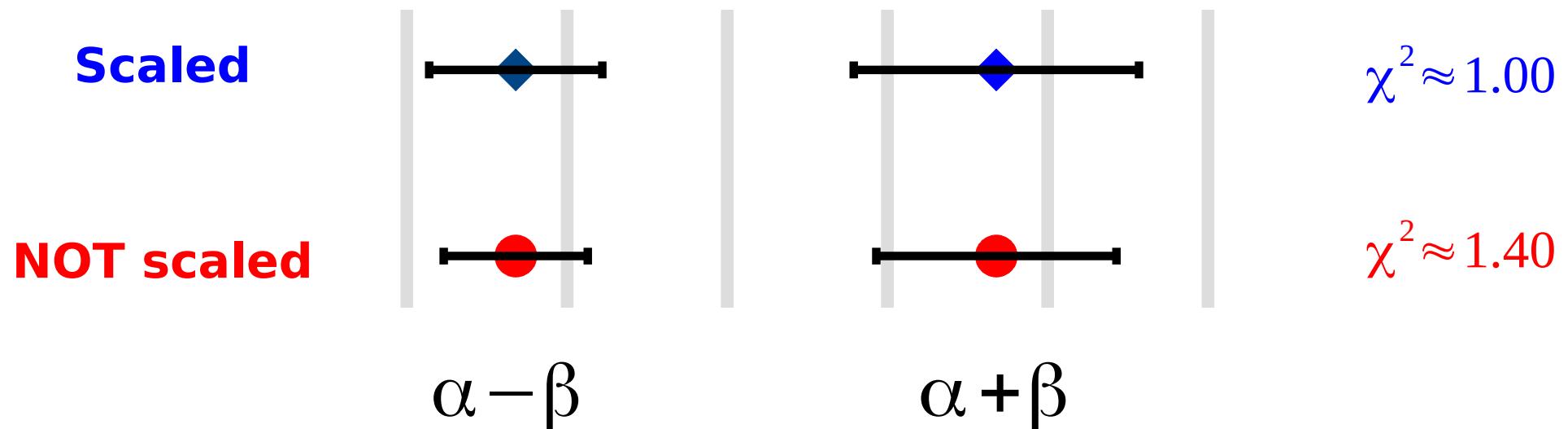
$$\sqrt{\chi^2}$$

# Problems with the data set (what we could do)

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$$\sqrt{\chi^2}$$



Effect: enlarging of errors on fitted parameters ( $\sim 20\%$ )

# Conclusions & perspectives

Very useful and versatile technique for data analysis

Effect of systematic sources of uncertainties on the fitted parameters

Waiting for new data in order to reduce the uncertainties of the fitted parameters (MAMI)

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Very useful and versatile technique for data analysis

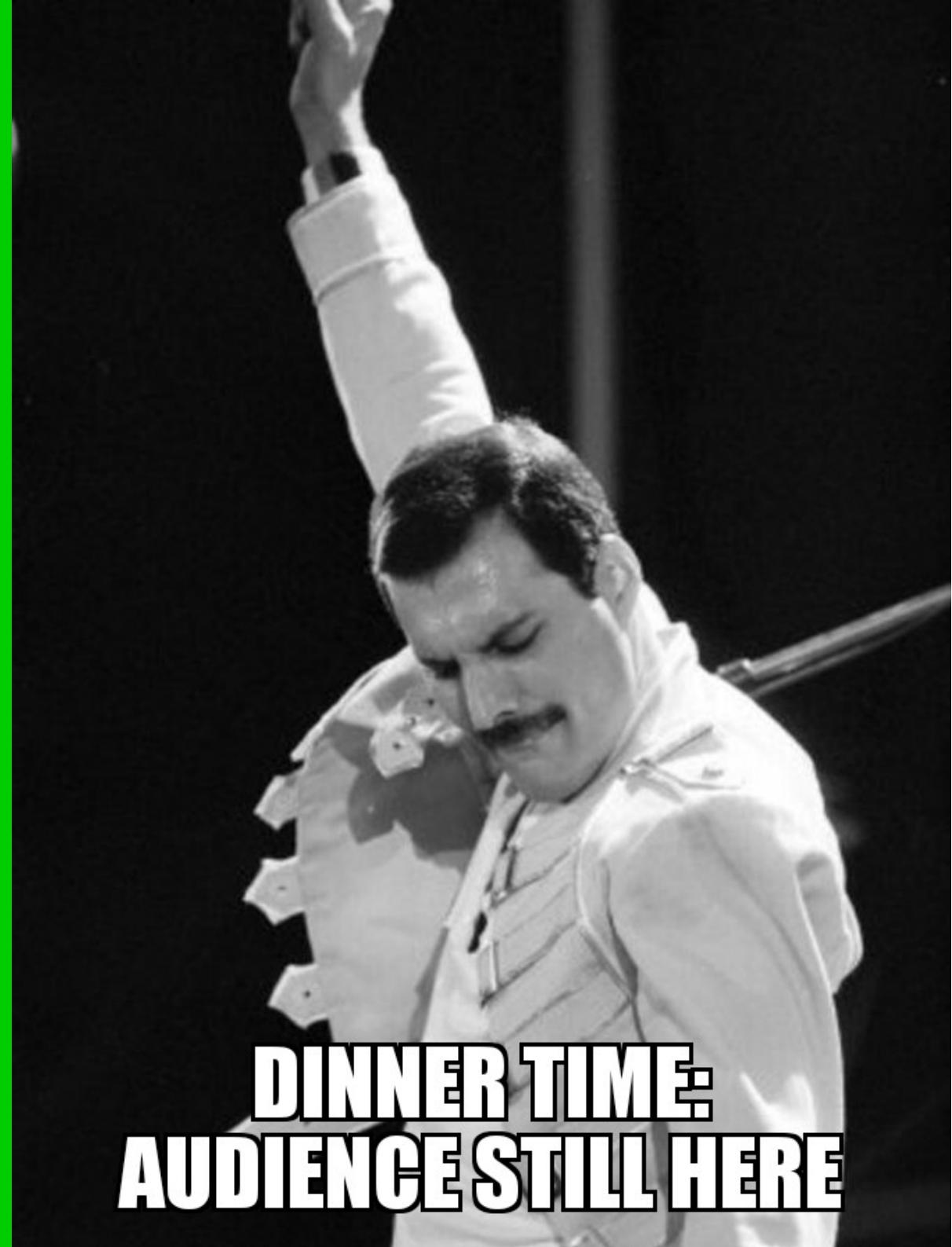
Effect of systematic sources of uncertainties on the fitted parameters

Waiting for new data in order to reduce the uncertainties of the fitted parameters (MAMI)

DDPs without LEX (double subtraction in DRs)

Fit of polarized observables in RCS with the same technique

Thank you!

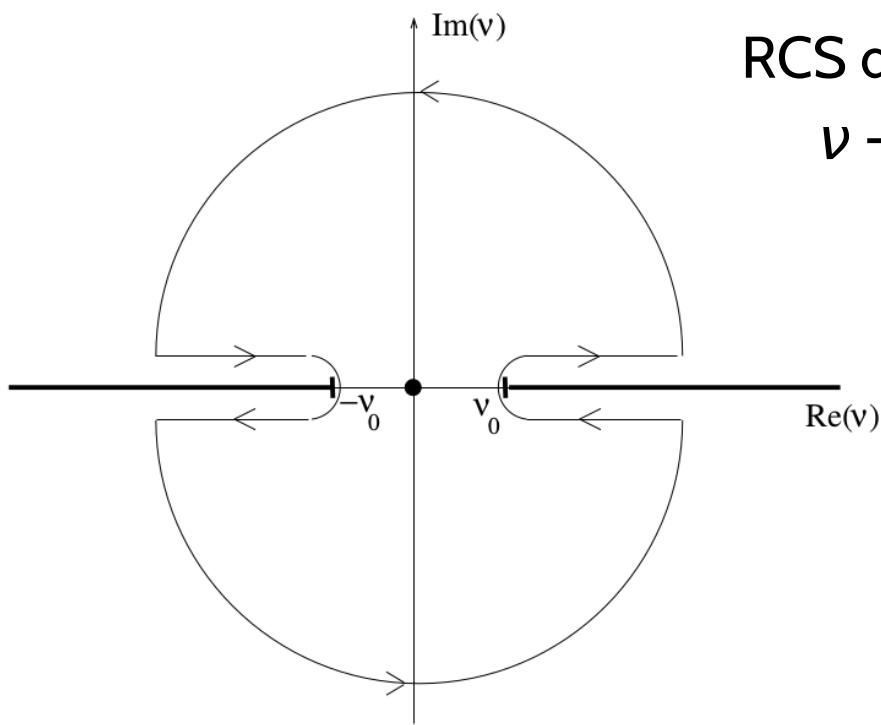
A black and white photograph of Freddie Mercury, the lead singer of Queen. He is shown from the chest up, wearing a light-colored, button-down shirt. His right arm is raised high above his head, with his hand clenched in a fist. He has a mustache and dark hair. The background is dark and out of focus.

**DINNER TIME:  
AUDIENCE STILL HERE**

# Backup slides



# Dispersion relations and RCS (I)



RCS differential cross section  $\rightarrow$  6 amplitudes  $A_i$ ,  
 $\nu \rightarrow \text{energy}$        $t \rightarrow \text{transferred momentum}$

$$A_i(\nu, t) = A_i^B(\nu, t) + \int_{\nu_{thr}}^{\nu_{MAX}} \dots + \int_{\nu_{thr}}^{\nu_{MAX}} \dots$$

For  $i=3, \dots, 6$ : “good” behavior

$$A_i(\nu, t) = A_i^B(\nu, t) + \int_{\nu_{thr}}^{\infty} \dots + 0$$

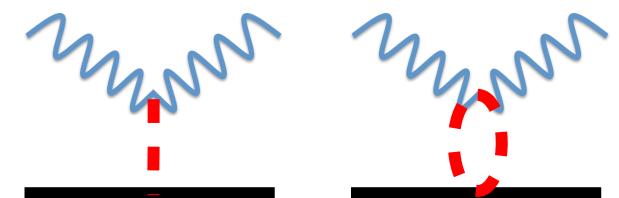
For  $i=1, 2$ : “bad” behavior

$$A_i(\nu, t) = A_i^B(\nu, t) + \int_{\nu_{thr}}^{\nu_{MAX}} \dots + A_i^{AS}$$

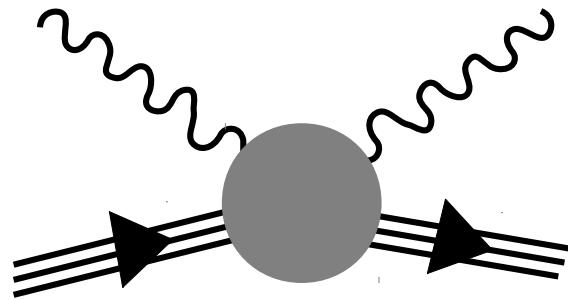
Asymptotic contribution  $\rightarrow$  meson exchange

Contour behavior: that's the problem!  $\rightarrow$  faster convergence is needed...

## SUBTRACTED DISPERSION RELATIONS



# Dispersion relations and RCS (II)



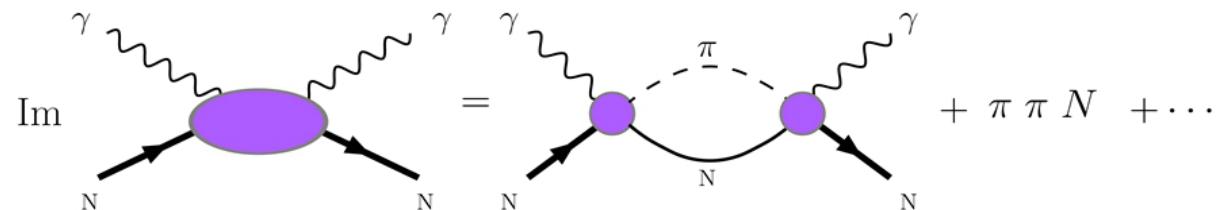
$A_i(0,0) = a_i \longrightarrow$  Static polarizabilities

$$A_i(\nu, t) = A_i^s(\nu, 0) + A_i^t(0, t) + A_i(0, 0)$$

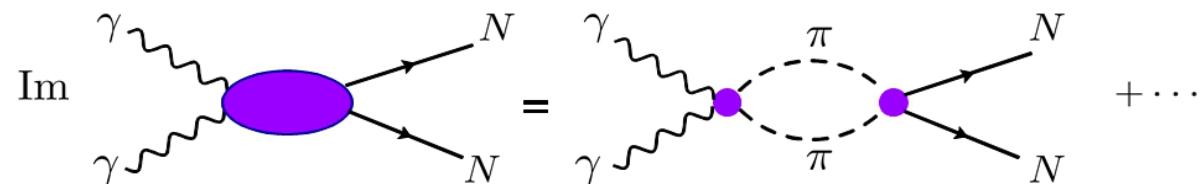
Subtracted Dispersion Relations (s-channel)

$$A_i^s(\nu, 0) = \frac{2}{\pi} \nu^2 P \int_{\nu_{thr}}^{\infty} \text{Im}_s A_i(\nu', t) \frac{d\nu'}{\nu'(\nu'^2 - \nu^2)}$$

s-CHANNEL



t-CHANNEL



# Multipoles expansion and DYNAMICAL polarizabilities

$$R_1 = \sum_{l \geq 1} \{ [(l+1)f_{EE}^{l+} + lf_{EE}^{l-}] (lP'_l + P''_{l-1}) - [(l+1)f_{MM}^{l+} + lf_{MM}^{l-}] P''_l \}$$

$$R_2 = \sum_{l \geq 1} \left\{ [(l+1)f_{MM}^{l+} + lf_{MM}^{l-}] (lP'_l + P''_{l-1}) - [(l+1)f_{EE}^{l+} + lf_{EE}^{l-}] P''_l \right\}$$

## DYNAMICAL POLARIZABILITIES

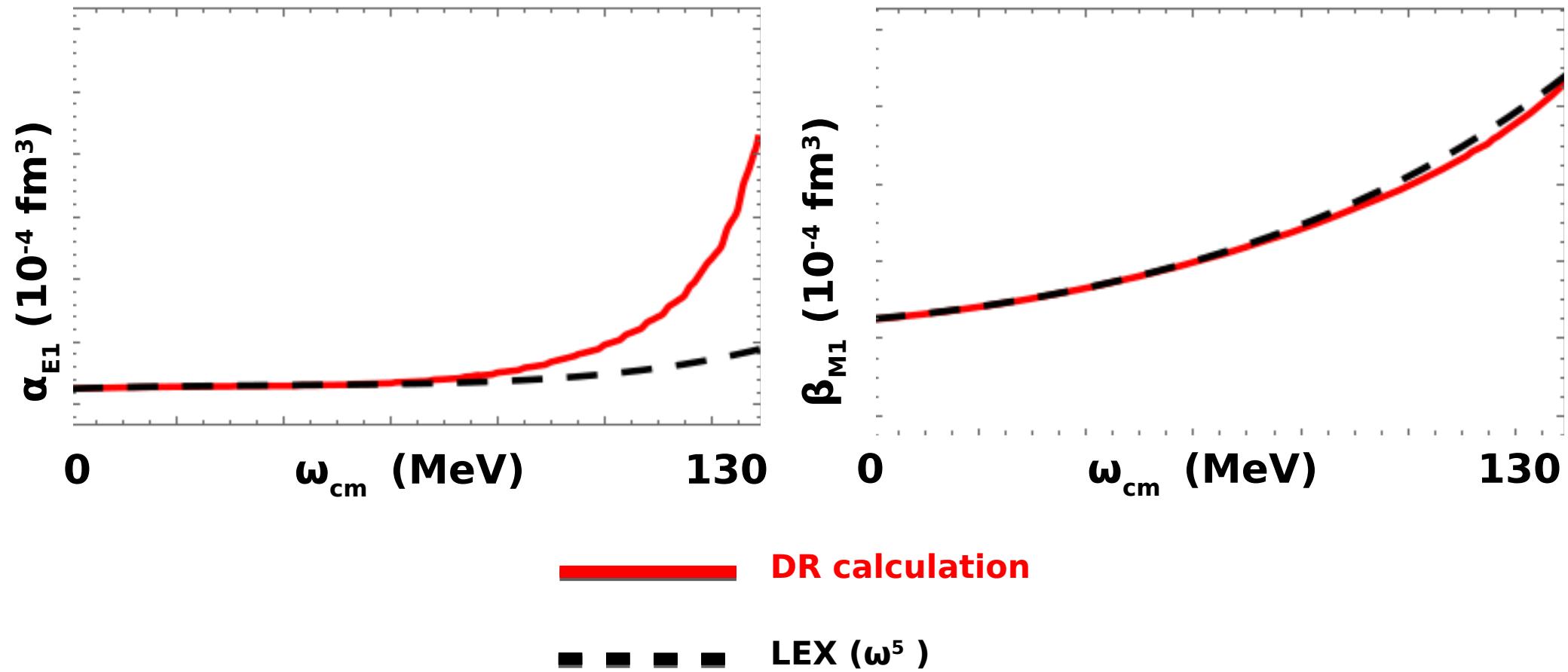
$$\alpha_{El} = a(l) \frac{(l+1)f_{EE}^{l+} + lf_{EE}^{l-}}{\omega^{2l}} \quad \beta_{Ml} = a(l) \frac{(l+1)f_{MM}^{l+} + lf_{MM}^{l-}}{\omega^{2l}}$$

## DIPOLE DYNAMICAL POLARIZABILITIES (DDPs)

$\alpha_{E1}(\omega)$

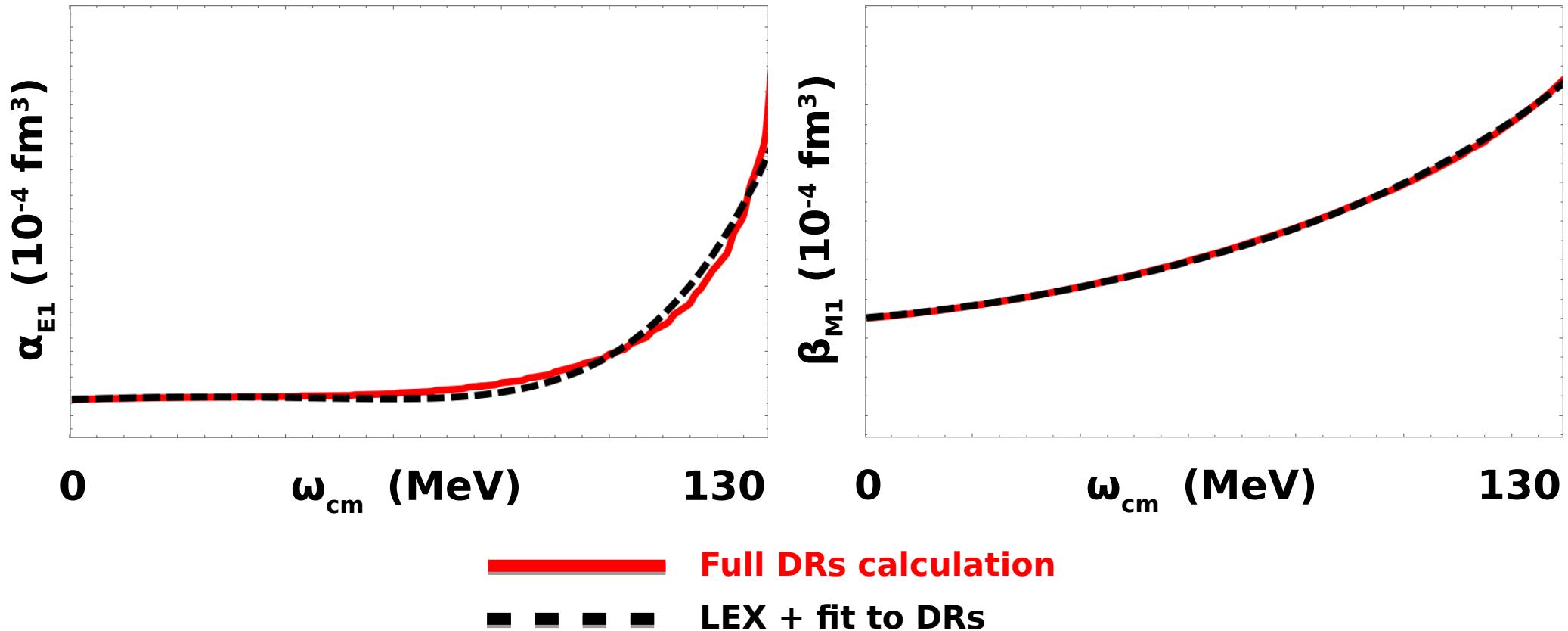
$\beta_{M1}(\omega)$

# LEX is *very* low ...



# LEX + residual functions

$$DDP(\omega) = DDP_{LEX}(\omega) + f_R(\omega)$$



# Some comments on the data set

Strong correlation between parameters

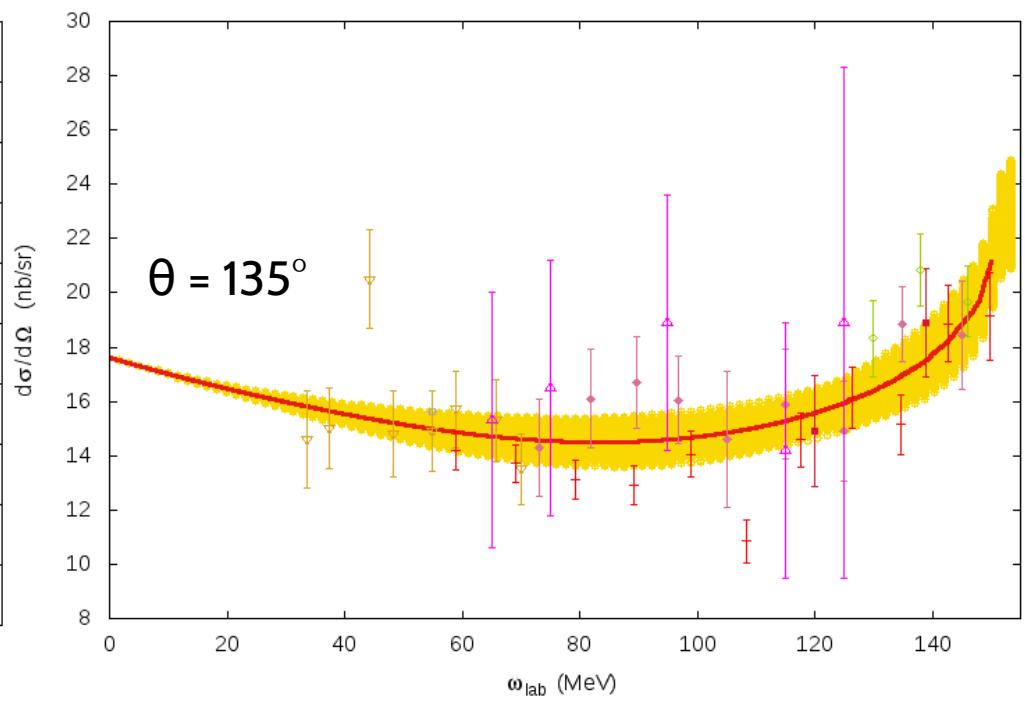
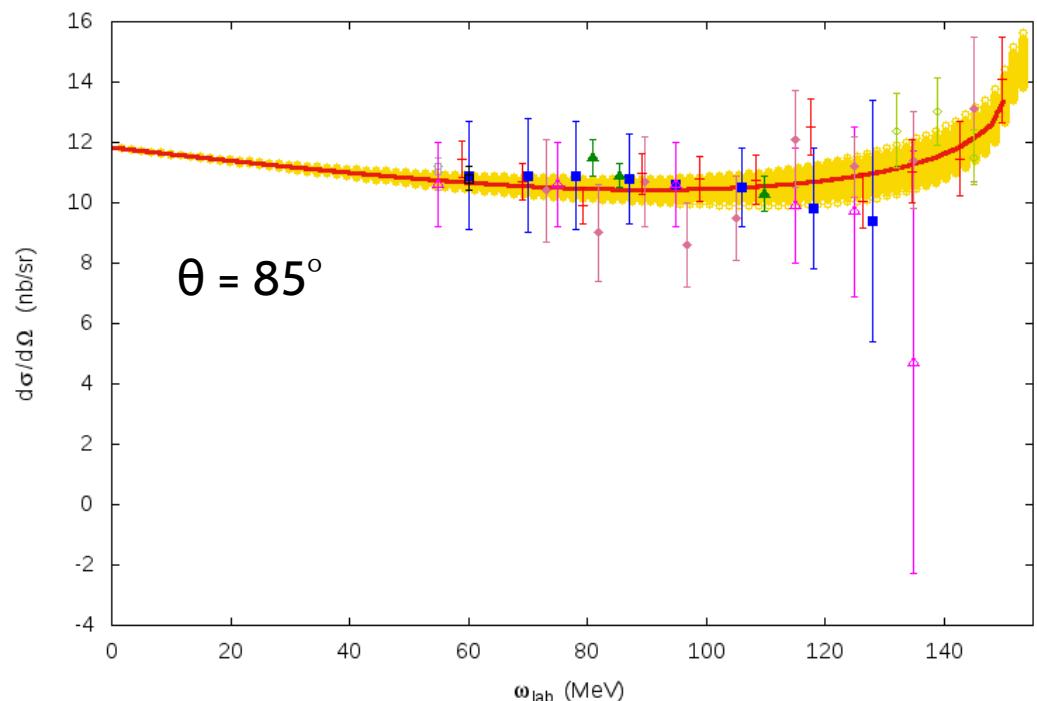
Reduction of parameters number thanks to sum rules

Identifications of the *outliers* (rescaling for statistic errors?)

The  $\chi^2$  is not the only *quality indicator* → no “definition” of data set

Waiting for new data (MAMI)

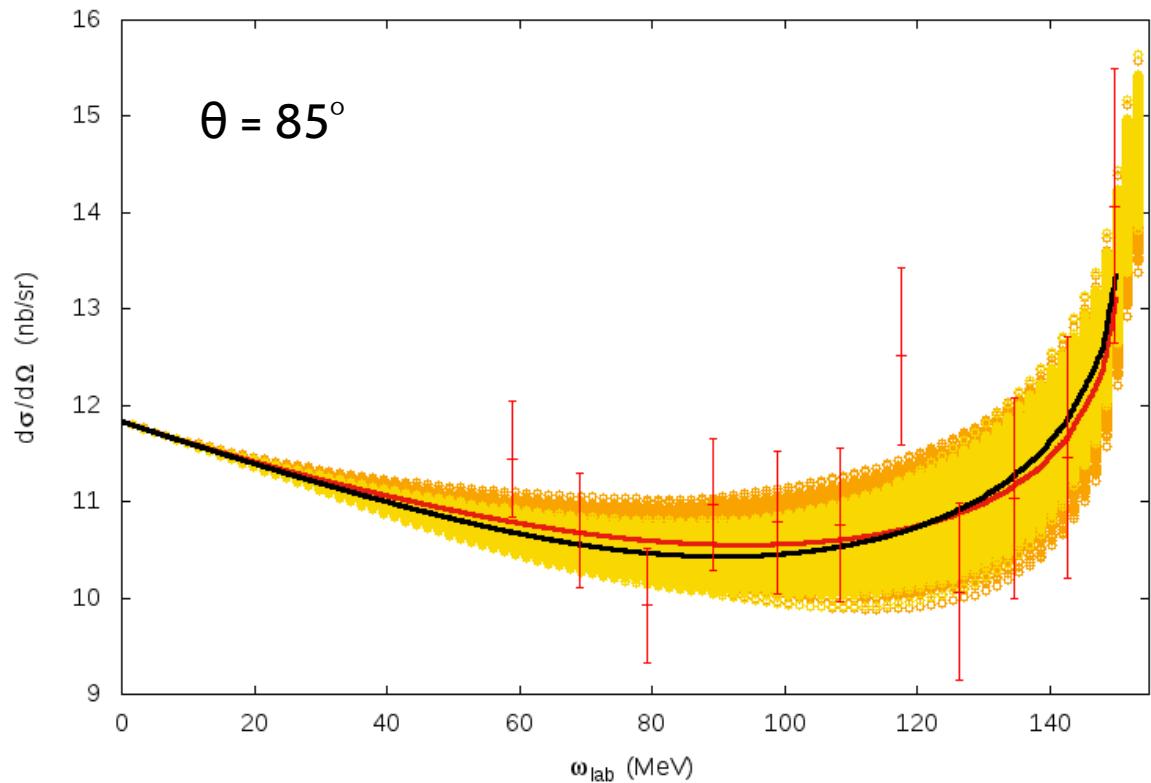
# Differential cross section



$d\sigma/d\Omega$  VS lab energy

100% error band from the bootstrap fit

# TAPS vs FULL data set



— TAPS —

— FULL —

— TAPS 100% error band —

— FULL 100% error band —

VERY small difference both in calculation and in error band

# $\chi^2$ curvature close to its minimum

