

Angular Observables Sensitive to NP in $\bar{B} \rightarrow D^* l^- \bar{\nu}_l$

Kilian Lieret

Ludwig Maximilian University of Munich

Advisers: Prof. Dr. Thomas Kuhr, Dr. Martin Jung, Prof. Dr. Gerhard Buchalla

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Bundesministerium
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Intro I

- Evidence for NP in $\bar{B} \rightarrow D^* \tau^- \bar{\nu}_\tau$ is mounting
 \implies Next question: *What kind of NP?*
 \implies **New observables!** (also good as cross checks)
- Here we consider the **angular distribution** of $\bar{B} \rightarrow D^*(\rightarrow D\pi) l^- \bar{\nu}_l$.
Example: Forward-backward asymmetry:

$$A_\theta := \left[\int_{-1}^0 - \int_0^1 \right] d\cos \theta_\ell \frac{d\Gamma}{d\cos \theta_\ell}$$

- Generalization: **Observables** \mathcal{O}_a built from *binned* measurements of $\frac{d^3 \Gamma}{d\chi d\theta_\ell d\theta_{D^*}}$
Similar to 12 observables constructed in [1602.03030](#)¹ (using polarizations in addition to angles)

¹Becirevic, Fajfer, Nisandzic, Tayduganov

Intro II

However (so far): Only proofs of concepts, **little experimental considerations!**

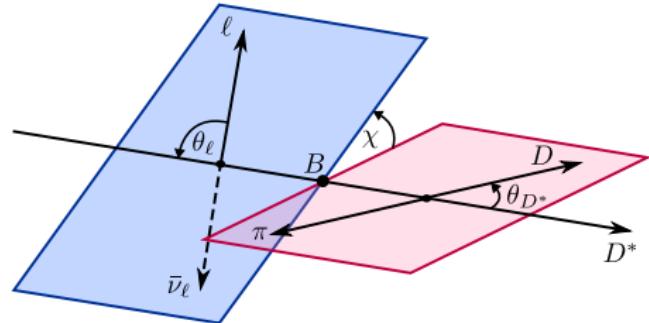
Aim:

- + Characterize **general form** of 12 observables \mathcal{O}_a
 - + Introduce **experimental error estimate**
 - + **Minimize expected errors** using d.o.f. in construction of \mathcal{O}_a
 - + Minimal **number of bins** required for construction of \mathcal{O}_a
 - + Optimal **bin spacing** for each \mathcal{O}_a
 - + Consider discriminatory power of observables on basis of operators corresponding to relevant NP mediators
- } **experimentally relevant!**

The Differential Cross Section

Slightly adapted² from 1405.3719³, we have⁴ (with (pseudo)scalar, (axial) vector and tensor NP operators, no CP average)

$$\frac{d^3\Gamma}{d\chi d\theta_\ell d\theta_{D^*}} = \sum_a \bar{W}_a B_a(\chi, \theta_\ell, \theta_{D^*})$$



With **12** different

- Angle dependencies
 $B_a(\chi, \theta_\ell, \theta_{D^*})$ (known)
e.g. $\cos(2\chi) \sin^3(\theta_{D^*}) \sin^3(\theta_\ell)$
- NP dependent coefficients
 \bar{W}_a (unknown)

Fig. 1: The decay angles $\chi, \theta_\ell, \theta_{D^*}$

²In relation to the V_a from 1405.3719: $W_1^0 := V_1^0 + V_2^0$, $W_1^T := V_1^T + V_2^T$, $W_2^0 := -2V_2^0$, $W_2^T := -2V_2^T$; for the rest $W_a := V_a$. Furthermore $\bar{W}_a := \int dq^2 W_a(q^2)$.

³Duraisamy, Sharma, Datta

⁴the kinematic variable q^2 will not be considered, i.e. the relevant quantities are integrated over q^2

The Idea (I)

Experimental measurements of $\frac{d^3\Gamma}{d\chi d\theta_\ell d\theta_{D^*}}$ will be (published) **binned**:

$$\text{bins: } U_i \subseteq [-\pi, \pi] \times [0, \pi] \times [0, \pi]$$

$$\begin{array}{ccc} \Psi & \Psi & \Psi \\ d\chi & d\theta_\ell & d\theta_{D^*} \\ \chi & \theta_\ell & \theta_{D^*} \end{array}$$

$$\begin{aligned} \text{bin content: } \Gamma(i) &:= \int_{U_i} d\chi d\theta_\ell d\theta_{D^*} \frac{d^3\Gamma}{d\chi d\theta_\ell d\theta_{D^*}} = \\ &= \sum_a \overline{W}_a \int_{U_i} d\chi d\theta_\ell d\theta_{D^*} B_a(\chi, \theta_\ell, \theta_{D^*}) = \\ &=: \sum_a \overline{W}_a \begin{array}{c} \text{unknown} \\ \text{NP-dependent} \\ \text{coefficient} \end{array} \overline{B}_a(i) \begin{array}{c} \text{known} \\ \text{"binned"} \\ \text{angle-dep.} \end{array} \end{aligned} \quad (1)$$

How to extract the \overline{W}_a ?

' Linear algebra: Eq. (1): N linear equations with 12 unknowns
 \implies there are **weights** $\omega_a(i)$ such that

$$\overline{W}_a \begin{array}{c} \text{unknown} \\ \text{NP-dependent} \\ \text{coefficient} \end{array} = \sum_i \omega_a(i) \begin{array}{c} \text{weights} \\ \text{measured} \\ \text{binned} \\ \text{CS} \end{array} \Gamma(i)$$

The Idea (I)

Experimental measurements of $\frac{d^3\Gamma}{d\chi d\theta_\ell d\theta_{D^*}}$ will be (published) **binned**:

$$\text{bins: } U_i \subseteq [-\pi, \pi] \times [0, \pi] \times [0, \pi]$$

$$\begin{array}{ccc} \Psi & \Psi & \Psi \\ d\chi & d\theta_\ell & d\theta_{D^*} \\ \chi & \theta_\ell & \theta_{D^*} \end{array}$$

$$\begin{aligned} \text{bin content: } \Gamma(i) &:= \int_{U_i} d\chi d\theta_\ell d\theta_{D^*} \frac{d^3\Gamma}{d\chi d\theta_\ell d\theta_{D^*}} = \\ &= \sum_a \overline{W}_a \int_{U_i} d\chi d\theta_\ell d\theta_{D^*} B_a(\chi, \theta_\ell, \theta_{D^*}) = \\ &=: \sum_a \overline{W}_a \overline{B}_a(i) \end{aligned} \quad (1)$$

\overline{W}_a
 unknown
 NP-dependent
 coefficient

$\overline{B}_a(i)$
 known
 "binned"
 angle-dep.

How to extract the \overline{W}_a ?

' Linear algebra: Eq. (1): N linear equations with 12 unknowns
 \implies there are **weights** $\omega_a(i)$ such that

$$\overline{W}_a = \sum_i \omega_a(i) \Gamma(i)$$

unknown
 NP-dependent
 coefficient

weights

measured
 binned
 CS

The Idea (II)

The observables

$$\mathcal{O}_a : \Gamma_{\text{measured binned CS}} \mapsto \sum_i \omega_a(i) \Gamma(i) \quad \text{such that} \quad \mathcal{O}_a(\Gamma_{\text{theo}}) = \overline{W}_a$$

unknown
NP-dependent
coefficient

Sensitivity

Expected uncertainty $\sqrt{\text{Var}(\mathcal{O}_a)}$ as figure of merit \rightarrow the smaller the better

(currently simplified setup with only statistical errors, studies of bin migration and flat systematics ongoing)

Degrees of freedom

If more bins than required

\implies DOFs in weights $\omega_a(i)$

\implies Use to improve sensitivity

Assumptions

1 “General bins”: Arbitrary subsets $U_i \subseteq [-\pi, \pi] \times [0, \pi] \times [0, \pi]$

2a “Product bins”: $U_{ijk} = U_i^\chi \times U_j^{\theta_\ell} \times U_k^{\theta_{D^*}}$

2b “Product weights”: Product bins with weights in product form

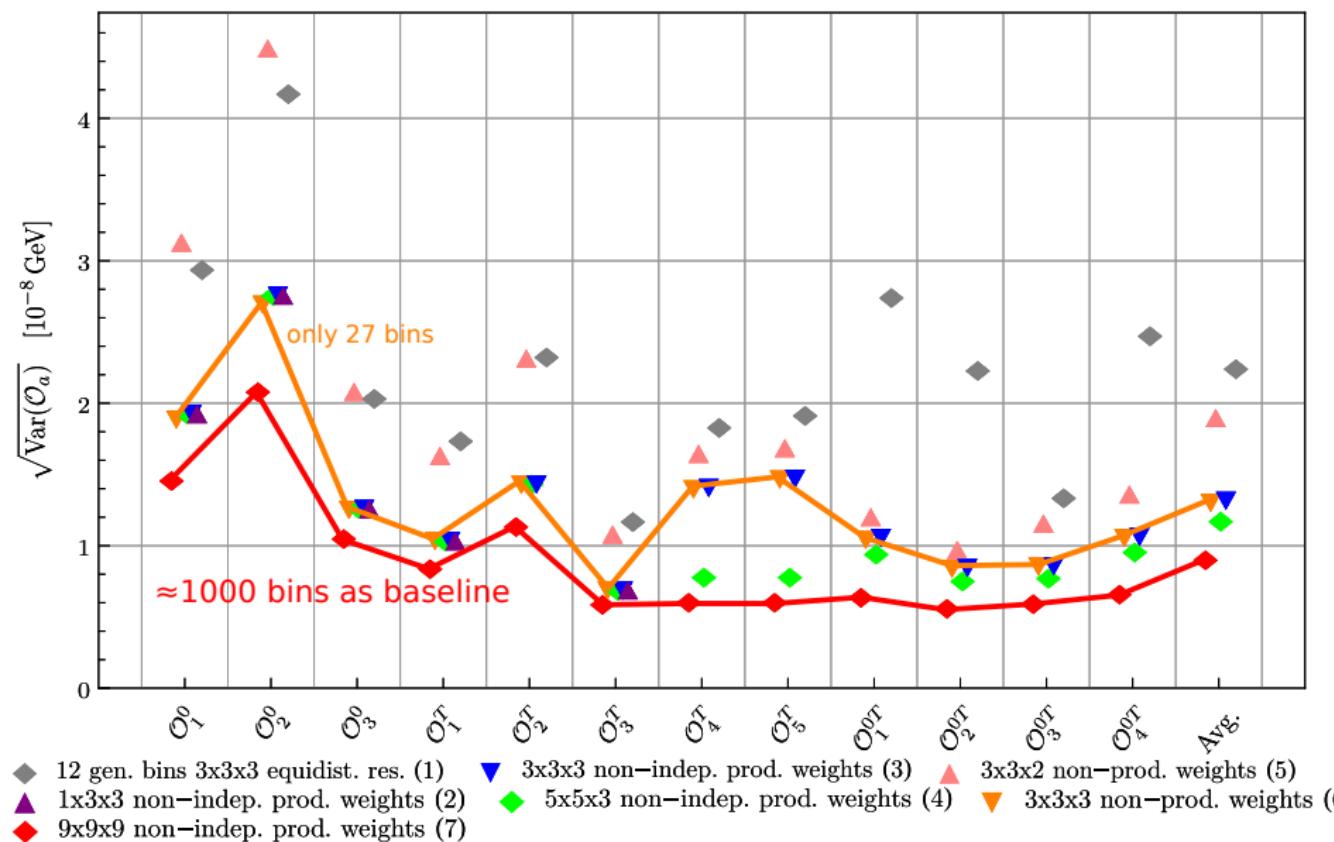
Minimal number of bins ($l = \tau$)

(under conservative assumptions for the binning)

Min. number of bins in $\chi \times \theta_\ell \times \theta_{D^*}$ required to construct \mathcal{O}_a

\mathcal{O}_a	$\mathcal{O}_1^0, \mathcal{O}_2^0, \mathcal{O}_3^0, \mathcal{O}_1^T, \mathcal{O}_3^T$	\mathcal{O}_2^T	$\mathcal{O}_4^T, \mathcal{O}_5^T$	$\mathcal{O}_1^{0T}, \mathcal{O}_2^{0T}, \mathcal{O}_3^{0T}, \mathcal{O}_4^{0T}$
Minimal # bins	$1 \times 3 \times 3$	$3 \times 3 \times 2$	$3 \times 1 \times 2$	$2 \times 2 \times 3$
	$1 \times 5 \times 2$		$3 \times 3 \times 1$	$2 \times 5 \times 1$
	$3 \times 3 \times 2$		$5 \times 1 \times 1$	$3 \times 2 \times 2$
				$3 \times 3 \times 1$
				$5 \times 2 \times 1$

All observables can be constructed for $3 \times 3 \times 2$ binning.

Performance Comparison ($l = \tau$)

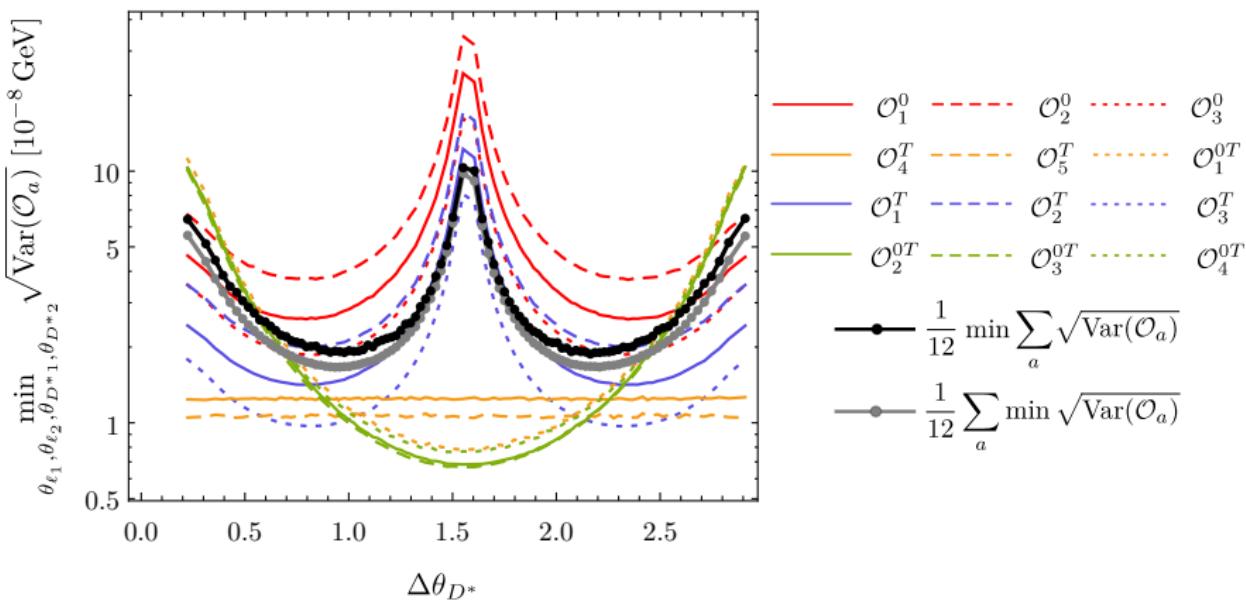
Finding optimal bin edges (example)

Example: $3 \times 3 \times 2$ bins (prod bins, gen. weights) with edge points

$$\{-\pi, \chi_1, \chi_2, \pi\}_{\chi} \times \{0, \theta_{\ell 1}, \theta_{\ell 2}, \pi\}_{\theta_{\ell}} \times \{0, \Delta\theta_{D^*}, \pi\}_{\theta_{D^*}}$$

⇒ How does the optimal achievable sensitivity depend on $\Delta\theta_{D^*}$?

→ Generate sample of **toy binnings** (i.e. random values $\chi_1, \chi_2, \theta_{\ell 1}, \theta_{\ell 2}, \Delta\theta_{D^*}$)



What can we conclude about NP contributions? (I)

Suppose we can extract all \overline{W}_a from the angular distribution

$$\Gamma(i) = \sum_a \begin{array}{c} \overline{W}_a \\ \text{unknown} \\ \text{NP-dependent} \\ \text{coefficient} \end{array} \begin{array}{c} \overline{B}_a(i) \\ \text{known} \\ \text{"binned"} \\ \text{angle-dep.} \end{array}$$

Want to extract c_i given \overline{W}_a :

- System of linear equations
- Sometimes $\overline{W}_a \propto c_i \implies$ easy!
- Generally hard \implies additional assumptions for NP coefficients

Split up \overline{W}_a :

$$\overline{W}_a = \sum_{i=1}^{13} \begin{array}{c} \overline{W}_a^{(i)} \\ \text{known} \\ \text{coeff} \in \mathbb{R} \end{array} \begin{array}{c} c_i(g_A, g_V, g_S, g_P, T_L) \\ \text{unknown} \\ \text{quadratic in NP coupl.} \end{array}$$

Effective Lagrangian:

$$\mathcal{H}_{\text{eff}} = \frac{4G_F V_{cb}}{\sqrt{2}} \left[\begin{aligned} & (1 + \mathcal{C}_{V_L} [\bar{c} \gamma_\mu P_L b] [\bar{l} \gamma^\mu P_L \nu_l] + \mathcal{C}_{V_R} [\bar{c} \gamma^\mu P_R b] [\bar{l} \gamma_\mu P_L \nu_l] + \\ & + \mathcal{C}_{S_L} [\bar{c} P_L b] [\bar{l} P_L \nu_l] + \mathcal{C}_{S_R} [\bar{c} P_R b] [\bar{l} P_L \nu_l] + T_L [\bar{c} \sigma^{\mu\nu} P_L b] [\bar{l} \sigma_{\mu\nu} P_L \nu_l]) , \end{aligned} \right]$$

With $g_{V,A} = \mathcal{C}_{V_R} \pm \mathcal{C}_{V_L}$, $g_{S,P} = \mathcal{C}_{S_R} \pm \mathcal{C}_{S_L}$, $T_L = \mathcal{C}_T$, $P_{L/R} := (1 \mp \gamma_5)/2$, $\sigma_{\mu\nu} := i(\gamma_\mu \gamma_\nu - \gamma_\nu \gamma_\mu)/2$.

What can we conclude about NP contributions? (I)

Suppose we can extract all \overline{W}_a from the angular distribution

$$\Gamma(i) = \sum_a \begin{array}{c} \overline{W}_a \\ \text{unknown} \\ \text{NP-dependent} \\ \text{coefficient} \end{array} \begin{array}{c} \overline{B}_a(i) \\ \text{known} \\ \text{"binned"} \\ \text{angle-dep.} \end{array}$$

Split up \overline{W}_a :

$$\overline{W}_a = \sum_{i=1}^{13} \begin{array}{c} \overline{W}_a^{(i)} \\ \text{known} \\ \text{coeff} \in \mathbb{R} \end{array} \begin{array}{c} c_i(g_A, g_V, g_S, g_P, T_L) \\ \text{unknown} \\ \text{quadratic in NP coupl.} \end{array}$$

Effective Lagrangian:

$$\begin{aligned} \mathcal{H}_{\text{eff}} = & \frac{4G_F V_{cb}}{\sqrt{2}} \left[(1 + \mathcal{C}_{V_L} [\bar{c}\gamma_\mu P_L b][\bar{l}\gamma^\mu P_L \nu_l] + \mathcal{C}_{V_R} [\bar{c}\gamma^\mu P_R b][\bar{l}\gamma_\mu P_L \nu_l] + \right. \\ & \left. + \mathcal{C}_{S_L} [\bar{c}P_L b][\bar{l}P_L \nu_l] + \mathcal{C}_{S_R} [\bar{c}P_R b][\bar{l}P_L \nu_l] + T_L [\bar{c}\sigma^{\mu\nu} P_L b][\bar{l}\sigma_{\mu\nu} P_L \nu_l]) \right], \end{aligned}$$

With $g_{V,A} = \mathcal{C}_{V_R} \pm \mathcal{C}_{V_L}$, $g_{S,P} = \mathcal{C}_{S_R} \pm \mathcal{C}_{S_L}$, $T_L = \mathcal{C}_T$, $P_{L/R} := (1 \mp \gamma_5)/2$, $\sigma_{\mu\nu} := i(\gamma_\mu \gamma_\nu - \gamma_\nu \gamma_\mu)/2$.

Want to extract c_i given \overline{W}_a :

- System of linear equations
- Sometimes $\overline{W}_a \propto c_i \implies$ easy!
- Generally hard \implies additional assumptions for NP coefficients

What can we conclude about NP contributions? (II)

c_i	In terms of coupling constants
c_1	$ 1 - g_A ^2$
c_2	$ g_V + 1 ^2$
c_3	$ g_P ^2$
c_4	$ T_L ^2$
c_5	$\text{Re}((1 - g_A)(g_V^* + 1))$
c_6	$\text{Re}((1 - g_A)g_P^*)$
c_7	$\text{Re}((1 - g_A)T_L^*)$
c_8	$\text{Re}((g_V + 1)T_L^*)$
c_9	$\text{Re}(g_P T_L^*)$
c_{10}	$\text{Im}((1 - g_A)(g_V^* + 1))$
c_{11}	$\text{Im}((1 - g_A)T_L^*)$
c_{12}	$\text{Im}((g_V + 1)g_P^*)$
c_{13}	$\text{Im}(g_P T_L^*)$

$\left. \begin{array}{l} \\ \\ \\ \\ \end{array} \right\} \text{drop out in } CP \text{ average}$

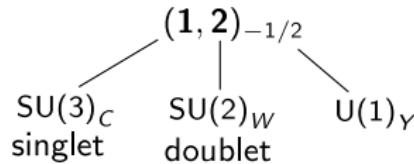
Fig. 2: $c_i \rightarrow$ coupling constants

What can we conclude about NP contributions? (III)

Consider base of operators with⁵

- Renormalizable couplings relevant for $\bar{B} \rightarrow D^* l^- \bar{\nu}_l$
- Dimension 4 or 6
- Non-flavor universal couplings \Rightarrow right-handed vector current not considered

Denote operators by transformation under $SU(3)_C \times SU(2)_W \times U(1)_Y$:



⁵source: Freytsis, Ligeti, Ruderman 1506.08896

What can we conclude about NP contributions? (IV)

Considering base of operators corresponding to relevant mediators

	SM	All NP	$(\mathbf{1}, \mathbf{3})_0,$ $(\mathbf{3}, \mathbf{3})_{2/3},$ $(\bar{\mathbf{3}}, \mathbf{3})_{1/3}$	$(\mathbf{1}, \mathbf{2})_{1/2},$ $(\bar{\mathbf{3}}, \mathbf{2})_{5/6}$	$(\mathbf{3}, \mathbf{1})_{2/3}$	$(\mathbf{3}, \mathbf{2})_{7/6}$	$(\bar{\mathbf{3}}, \mathbf{1})_{1/3}$
W_1^0		c_1, c_3, c_4, c_6, c_7	c_1	c_3, c_6	c_1, c_3, c_6	c_3, c_6	c_1, c_3, c_6
W_2^0		c_1, c_4	c_1		c_1	c_3	c_1, c_3
W_3^0		c_1, c_6, c_7, c_9	c_1	c_6	c_1, c_6	c_6, c_3	c_1, c_6, c_3
W_1^T		c_1, c_2, c_4, c_7, c_8	c_1		c_1	c_3, c_6	c_1, c_3, c_6
W_2^T		c_1, c_2, c_4	c_1		c_1	c_3	c_1, c_3
W_3^T		c_4, c_5, c_7, c_8	c_1		c_1	c_3, c_6	c_3, c_1, c_6
W_4^T		c_1, c_2, c_4	c_1		c_1	c_3	c_1, c_3
(W_5^T)		c_{10}					
W_1^{0T}		c_1, c_4	c_1		c_1	c_3	c_1, c_3
W_2^{0T}		$c_1, c_4, c_5, c_6, c_7, c_8, c_9$	c_1	c_6	c_1, c_6	c_3, c_6	c_1, c_3, c_6
(W_3^{0T})		$c_{10}, c_{11}, c_{12}, c_{13}$		c_{12}	c_{12}	c_{11}	c_{11}
(W_4^{0T})		c_{10}					

Colors: $W_a = 0$ W_a c_i -indep. $W_a \propto c_i$ $(W_a - \text{const.}) \propto c_i$ Multiple c_i

Bold: Contributes to fully integrated CS; **Parenthesized:** Drops out in CP average

Fig. 3: All operators with dim. 4 or 6 and renormalizable non-flavor universal couplings relevant for $\bar{B} \rightarrow D^* l^- \bar{\nu}_l$ (cf. [1506.08896](#)) applied to observables for $l = \tau$.

Summary

$$\mathcal{O}_a : \underset{\substack{\text{measured} \\ \text{binned} \\ \text{CS}}}{\Gamma} \mapsto \sum_i \underset{\substack{\text{weights}}}{\omega_a(i)} \underset{\Gamma(i)}{\Gamma(i)} \quad \text{such that} \quad \mathcal{O}_a(\Gamma_{\text{theo}}) = \underset{\substack{\text{unknown} \\ \text{NP-dependent}}}{{\overline{W}}_a}$$

Some key points

- Can construct some of the observables even for very coarse binnings (especially relevant for the experimentally challenging $l = \tau$ case)
- The same strategies have been applied to $l = e, \mu$ (both experimentally and theoretically easier, but less suspicious of NP so far)
- Can also consider the same observables with q^2 dependency (but will need a new figure of merit to optimize against and discriminating between NP models will be more complex)
- To cancel systematics: Consider ratios of observables or use a normalization mode

Summary

$$\mathcal{O}_a : \underset{\substack{\text{measured} \\ \text{binned} \\ \text{CS}}}{\Gamma} \mapsto \sum_i \underset{\text{weights}}{\omega_a(i)} \underset{\Gamma(i)}{\Gamma(i)} \quad \text{such that} \quad \mathcal{O}_a(\Gamma_{\text{theo}}) = \underset{\substack{\text{unknown} \\ \text{NP-dependent} \\ \text{coefficient}}}{W_a}$$

Literature⁶

- Some simple expression of weights to extract (combinations of the) W_a (on a “proof of concept” base)
- Studied the NP dependency by considering the q^2 distribution of $W_a(q^2)$, considering only one of g_A, g_V, g_S, g_P, T_L to be non-vanishing

New results

- Characterized the construction of the observables \mathcal{O}_a for several assumptions on binning and weights
- Determined the **min. number of bins** to construct each \mathcal{O}_a
- Introduced a **figure of merit** for the obtainable sensitivity
- Used degrees of freedom in the weights to **optimize sensitivity**
- Studied the **influence of bin widths** on the sensitivity
- Studied the **NP dependency** of \overline{W}_a based on a base of operators *corresponding to relevant mediators* (better physical motivation)

⁶Becirevic, Fajfer, Nisandzic, Tayduganov 1602.03030 (ref. closest to our work to best knowledge)

Backup Slides

Backup slides overview

- General bins
- The angular functions B_a
- Correlation
- Plots $3 \times 3 \times 2$ edges
- Plots $3 \times 3 \times 3$ edges

General binning

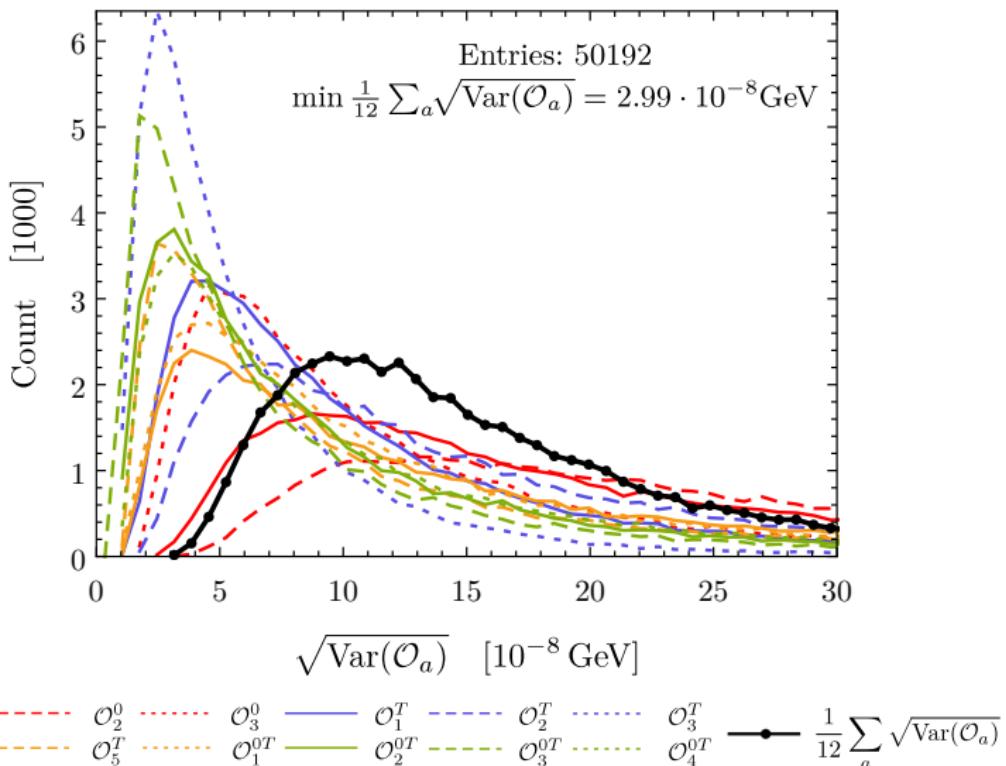


Fig. 4: 12 bins, $3 \times 3 \times 3$ cubes

General binning

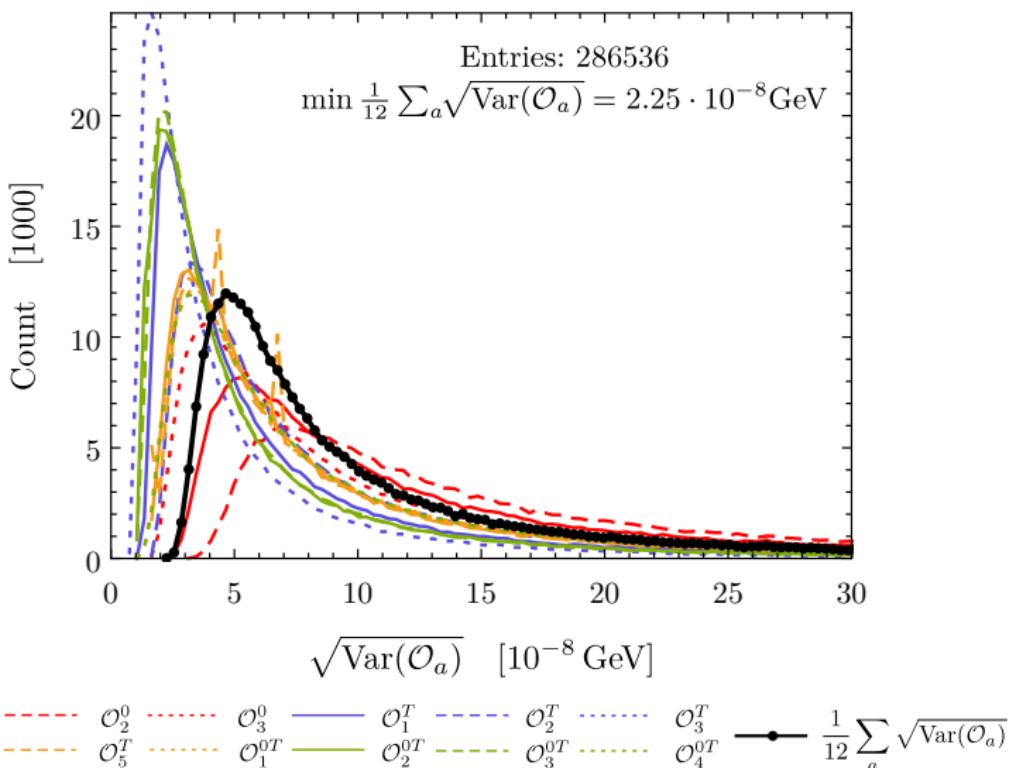


Fig. 4: 12 bins, $3 \times 3 \times 3$ cubes (equidistant)

General binning

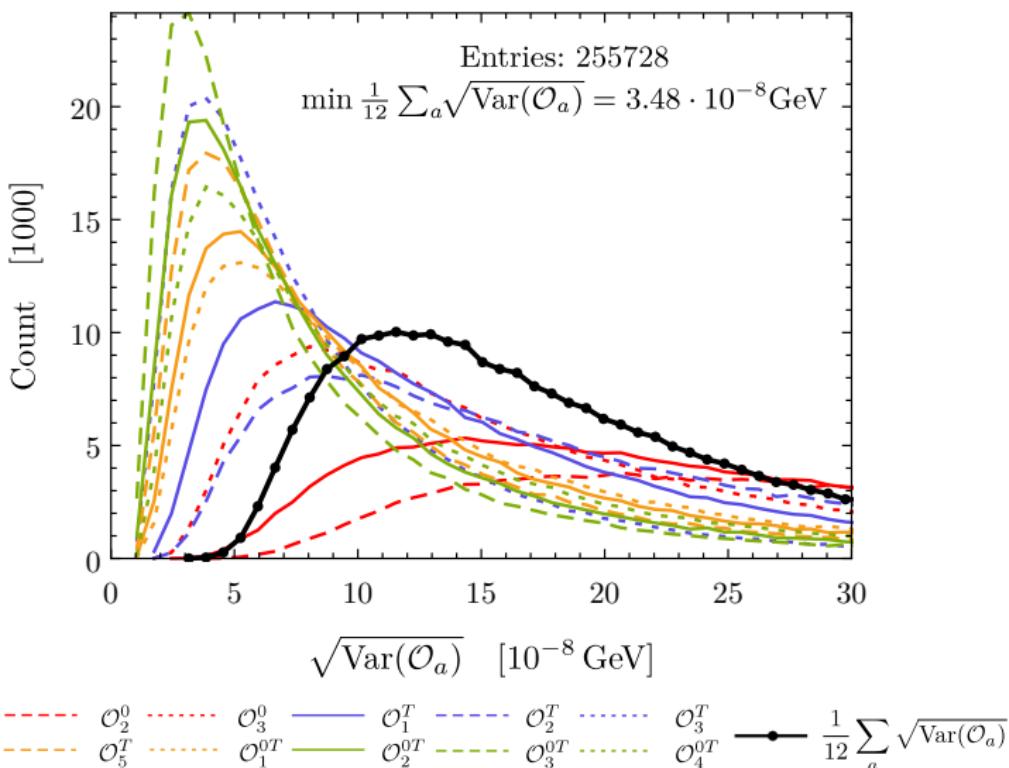


Fig. 4: 12 bins, $5 \times 5 \times 5$ cubes

General binning

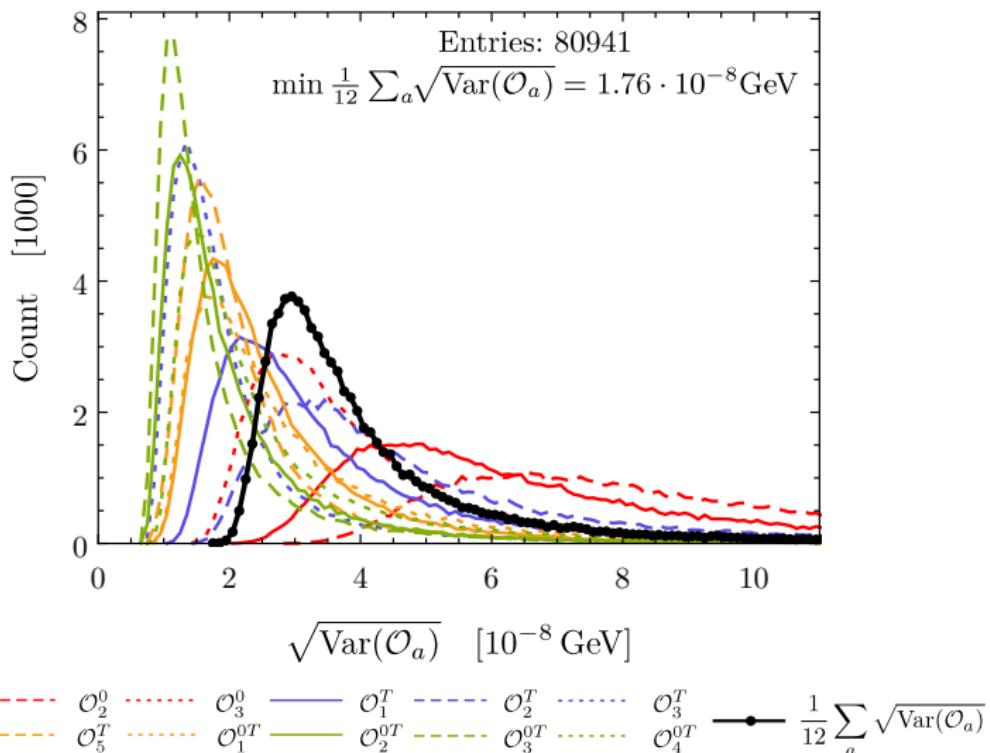


Fig. 4: 27 bins, $5 \times 5 \times 5$ cubes

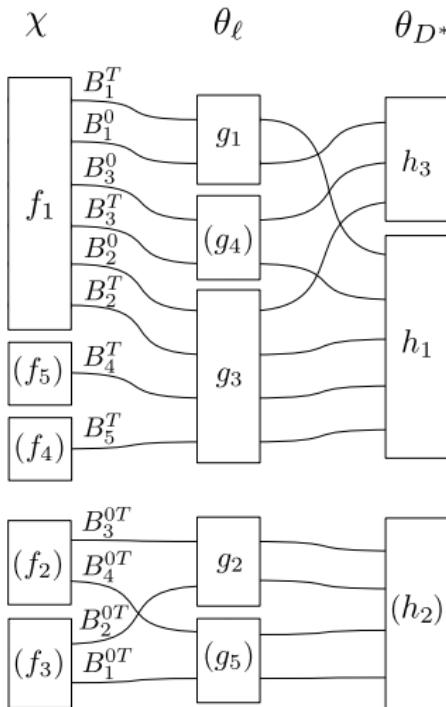
The angular functions B_a (I)

$$\begin{aligned}
 B_1^0 &= \sin(\theta_{D^*}) \cos^2(\theta_{D^*}) \sin(\theta_\ell) & B_1^T &= \sin^3(\theta_{D^*}) \sin(\theta_\ell) \\
 B_2^0 &= \sin(\theta_{D^*}) \cos^2(\theta_{D^*}) \sin^3(\theta_\ell) & B_2^T &= \sin^3(\theta_{D^*}) \sin^3(\theta_\ell) \\
 B_3^0 &= \sin(\theta_{D^*}) \cos^2(\theta_{D^*}) \sin(\theta_\ell) \cos(\theta_\ell) & B_3^T &= \sin^3(\theta_{D^*}) \sin(\theta_\ell) \cos(\theta_\ell) \\
 B_4^0 &= \cos(2\chi) \sin^3(\theta_{D^*}) \sin^3(\theta_\ell) & B_4^T &= \cos(2\chi) \sin^3(\theta_{D^*}) \sin^3(\theta_\ell) \\
 B_5^0 &= \sin(2\chi) \sin^3(\theta_{D^*}) \sin^3(\theta_\ell)
 \end{aligned}$$

$$\begin{aligned}
 B_1^{0T} &= \cos(\chi) \sin(\theta_{D^*}) \sin(2\theta_{D^*}) \sin(\theta_\ell) \sin(2\theta_\ell) \\
 B_2^{0T} &= \cos(\chi) \sin(\theta_{D^*}) \sin(2\theta_{D^*}) \sin^2(\theta_\ell) \\
 B_3^{0T} &= \sin(\chi) \sin(\theta_{D^*}) \sin(2\theta_{D^*}) \sin^2(\theta_\ell) \\
 B_4^{0T} &= \sin(\chi) \sin(\theta_{D^*}) \sin(2\theta_{D^*}) \sin(\theta_\ell) \sin(2\theta_\ell)
 \end{aligned}$$

Table 1: The functions $B_a(\chi, \theta_\ell, \theta_{D^*})$

The angular functions B_a (II)

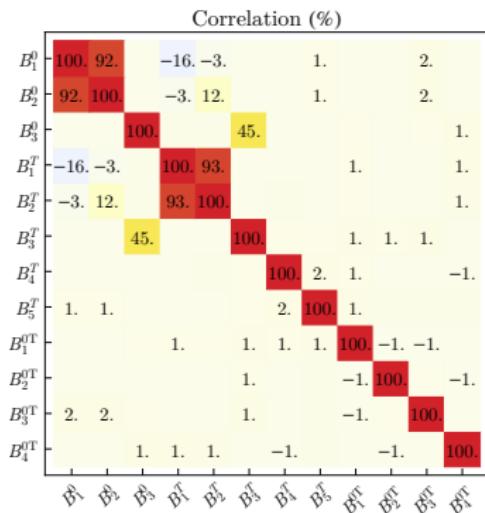


$$\begin{aligned}f_1(\chi) &:= 1, \\f_2(\chi) &:= \sin(\chi), \\f_3(\chi) &:= \cos(\chi), \\f_4(\chi) &:= \sin(2\chi), \\f_5(\chi) &:= \cos(2\chi),\end{aligned}$$

$$\begin{aligned}g_1(\theta_\ell) &:= \sin(\theta_\ell), \\g_2(\theta_\ell) &:= \sin^2(\theta_\ell), \\g_3(\theta_\ell) &:= \sin^3(\theta_\ell), \\g_4(\theta_\ell) &:= \sin(\theta_\ell) \cos(\theta_\ell), \\g_5(\theta_\ell) &:= \sin(\theta_\ell) \sin(2\theta_\ell), \\h_1(\theta_{D^*}) &:= \sin^3(\theta_{D^*}), \\h_2(\theta_{D^*}) &:= \sin(\theta_{D^*}) \sin(2\theta_{D^*}), \\h_3(\theta_{D^*}) &:= \sin(\theta_{D^*}) \cos^2(\theta_{D^*}).\end{aligned}$$

Fig. 5: Combinations of the angle functions.

Correlation



(a) Unbinned angle functions

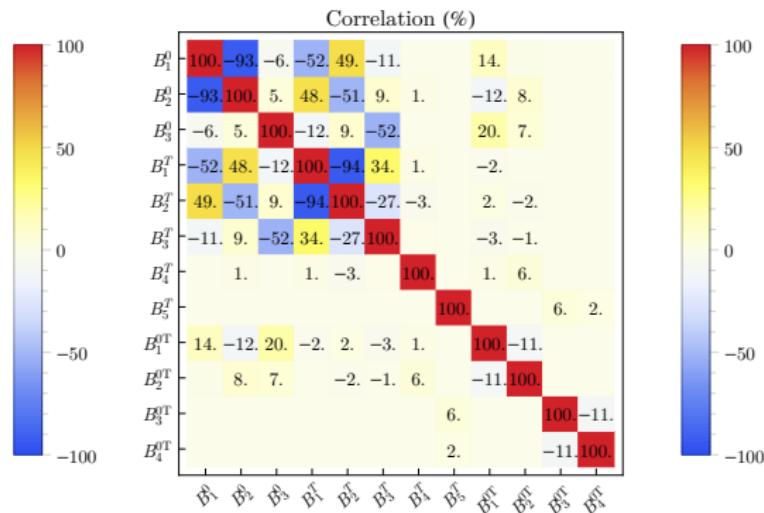
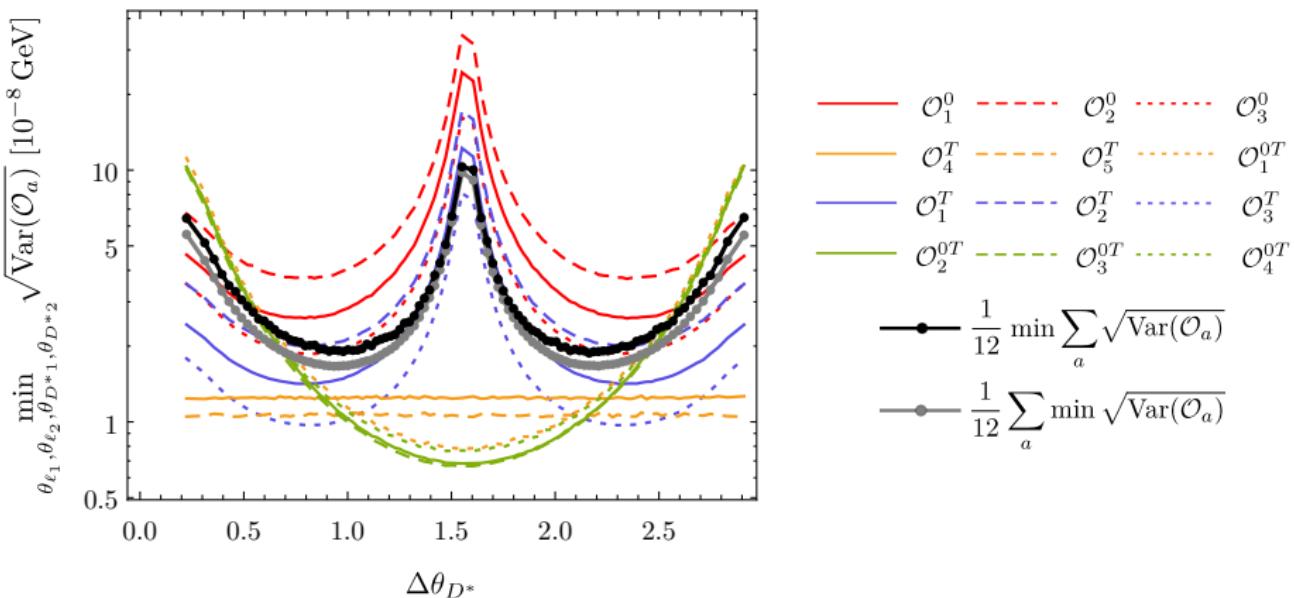
(b) Optimal observables $3 \times 3 \times 3$

Fig. 6: Correlation of angle functions resp. observables

$3 \times 3 \times 2$ (prod bins, gen. weights)

$$\{-\pi, \chi_1, \chi_2, \pi\}_{\chi} \times \{0, \theta_{\ell 1}, \theta_{\ell 2}, \pi\}_{\theta_{\ell}} \times \{0, \Delta\theta_{D^*}, \pi\}_{\theta_{D^*}}$$

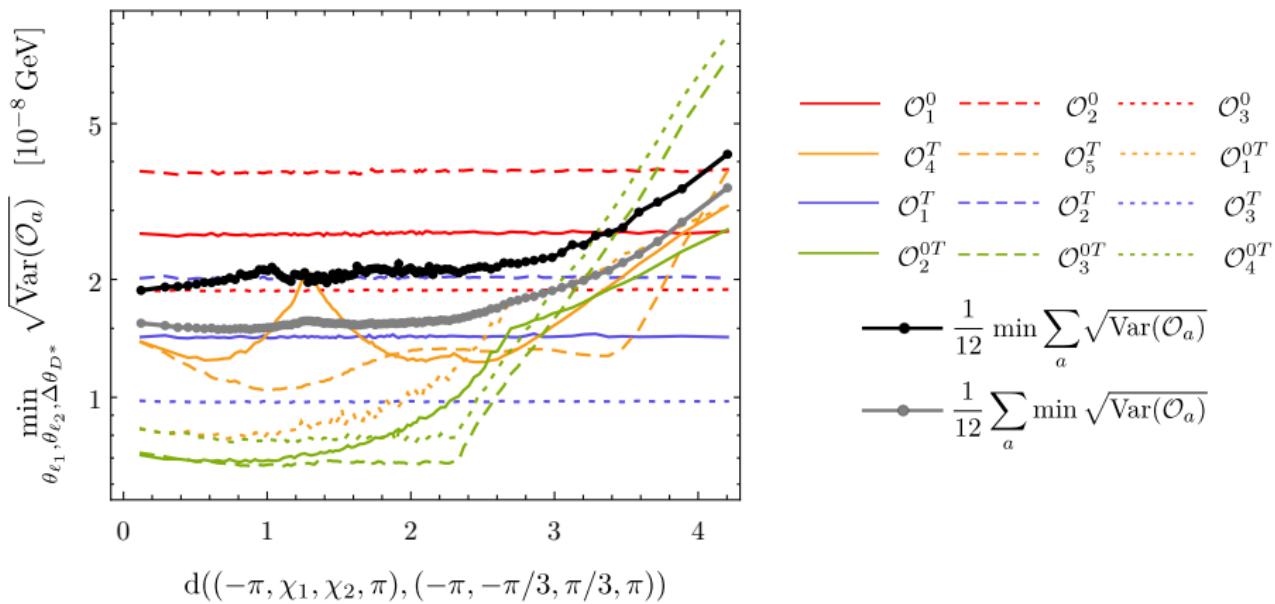
→ Generate sample of **toy binnings** (i.e. random values $\chi_1, \chi_2, \theta_{\ell 1}, \theta_{\ell 2}, \Delta\theta_{D^*}$)



$3 \times 3 \times 2$ (prod bins, gen. weights)

$$\{-\pi, \chi_1, \chi_2, \pi\}_{\chi} \times \{0, \theta_{\ell 1}, \theta_{\ell 2}, \pi\}_{\theta_{\ell}} \times \{0, \Delta\theta_{D^*}, \pi\}_{\theta_{D^*}}$$

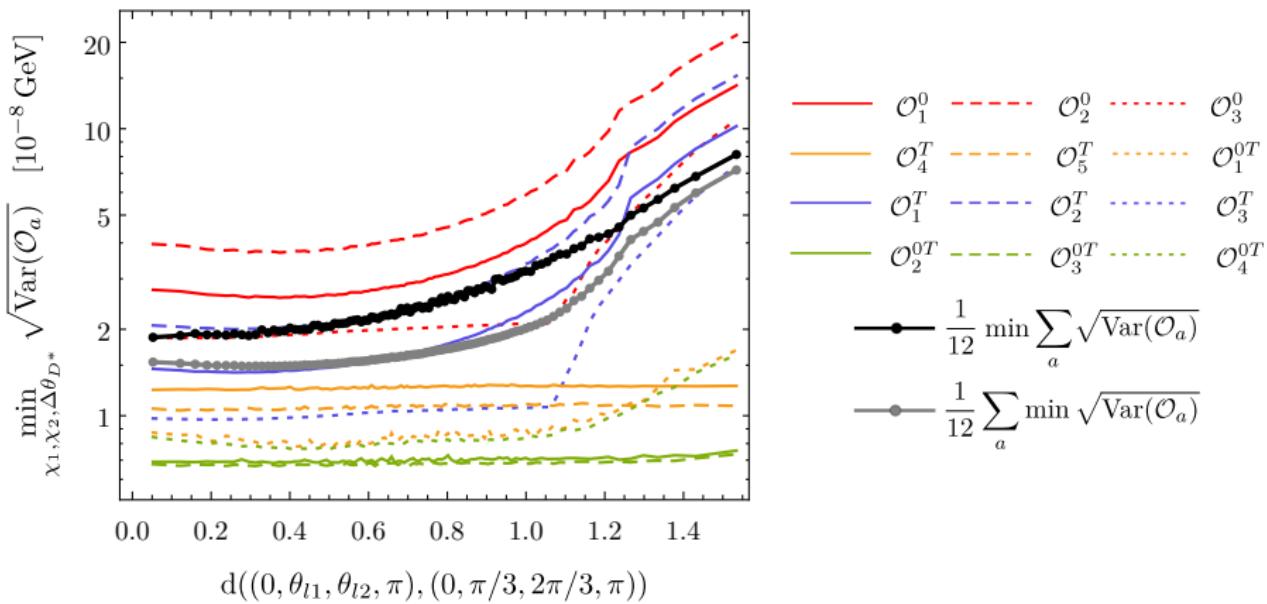
→ Generate sample of **toy binnings** (i.e. random values $\chi_1, \chi_2, \theta_{\ell 1}, \theta_{\ell 2}, \Delta\theta_{D^*}$)



$3 \times 3 \times 2$ (prod bins, gen. weights)

$$\{-\pi, \chi_1, \chi_2, \pi\}_{\chi} \times \{0, \theta_{\ell 1}, \theta_{\ell 2}, \pi\}_{\theta_{\ell}} \times \{0, \Delta\theta_{D^*}, \pi\}_{\theta_{D^*}}$$

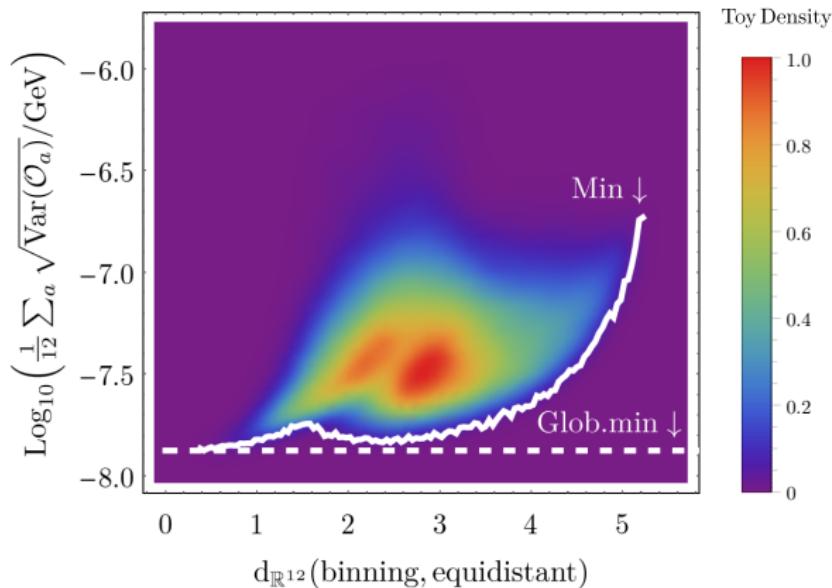
→ Generate sample of **toy binnings** (i.e. random values $\chi_1, \chi_2, \theta_{\ell 1}, \theta_{\ell 2}, \Delta\theta_{D^*}$)



$3 \times 3 \times 2$ (prod bins, gen. weights)

$$\{-\pi, \chi_1, \chi_2, \pi\}_{\chi} \times \{0, \theta_{\ell 1}, \theta_{\ell 2}, \pi\}_{\theta_{\ell}} \times \{0, \Delta\theta_{D^*}, \pi\}_{\theta_{D^*}}$$

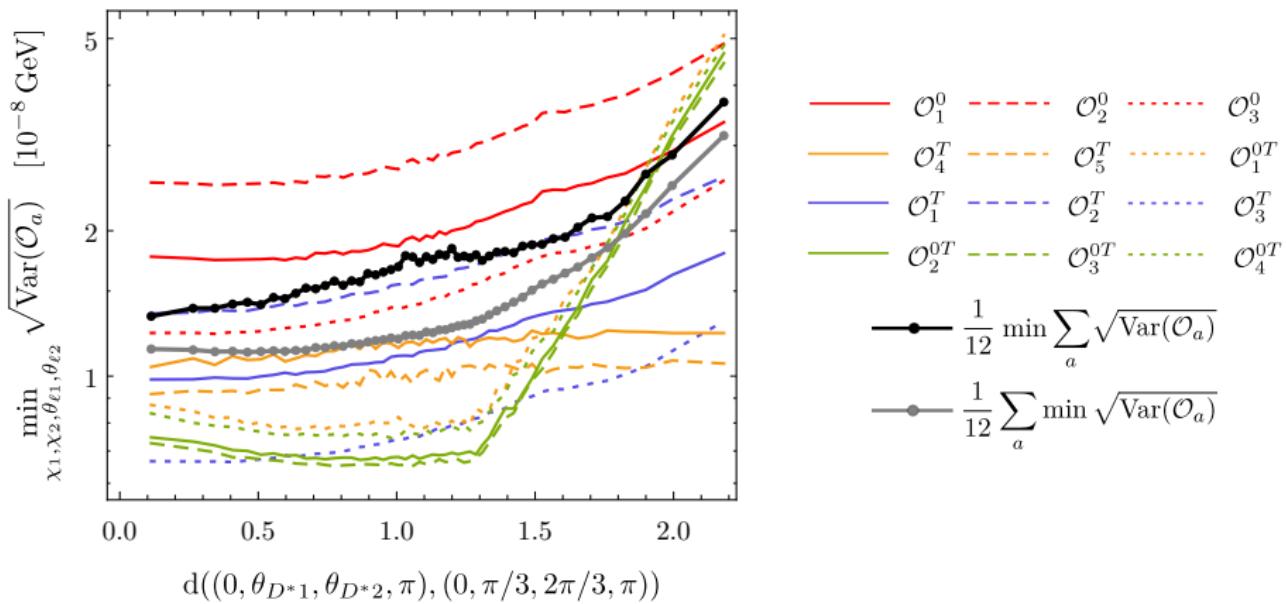
→ Generate sample of **toy binnings** (i.e. random values $\chi_1, \chi_2, \theta_{\ell 1}, \theta_{\ell 2}, \Delta\theta_{D^*}$)



$3 \times 3 \times 3$ (prod bins, gen. weights)

$$\{-\pi, \chi_1, \chi_2, \pi\}_{\chi} \times \{0, \theta_{\ell 1}, \theta_{\ell 2}, \pi\}_{\theta_{\ell}} \times \{0, \theta_{D^* 1}, \theta_{D^* 2}, \pi\}_{\theta_{D^*}}$$

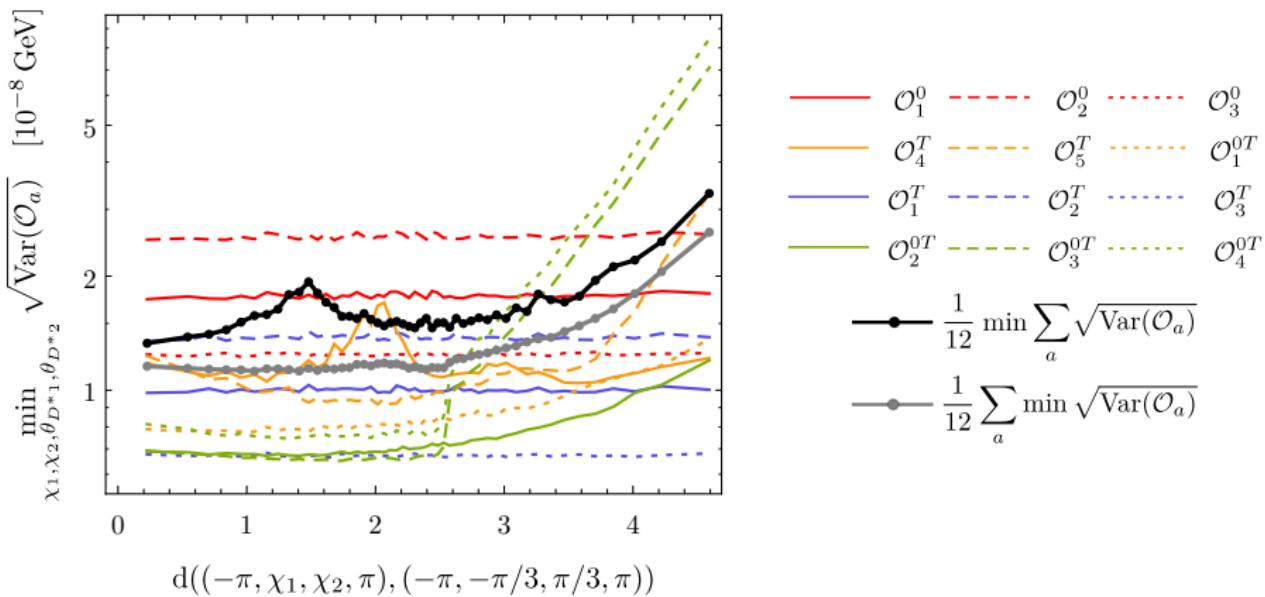
→ Generate sample of **toy binnings** (i.e. random values $\chi_1, \chi_2, \theta_{\ell 1}, \theta_{\ell 2}, \Delta_{\theta_{D^*}}$)



$3 \times 3 \times 3$ (prod bins, gen. weights)

$$\{-\pi, \chi_1, \chi_2, \pi\}_{\chi} \times \{0, \theta_{\ell 1}, \theta_{\ell 2}, \pi\}_{\theta_{\ell}} \times \{0, \theta_{D^* 1}, \theta_{D^* 2}, \pi\}_{\theta_{D^*}}$$

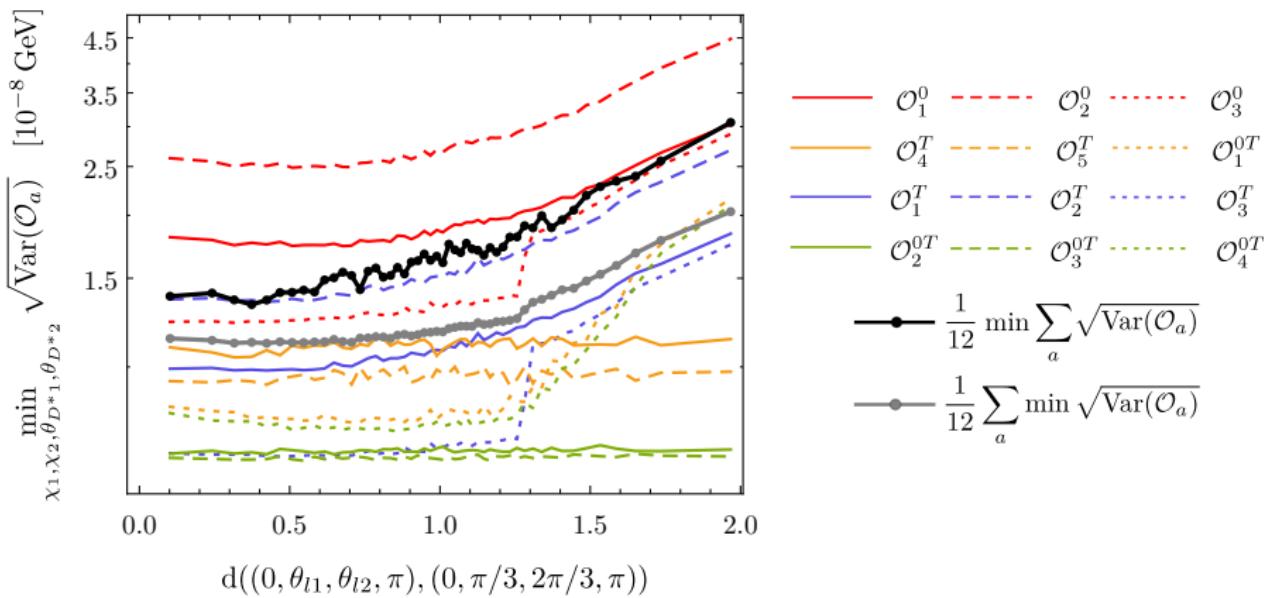
→ Generate sample of **toy binnings** (i.e. random values $\chi_1, \chi_2, \theta_{\ell 1}, \theta_{\ell 2}, \Delta_{\theta_{D^*}}$)



$3 \times 3 \times 3$ (prod bins, gen. weights)

$$\{-\pi, \chi_1, \chi_2, \pi\}_{\chi} \times \{0, \theta_{\ell 1}, \theta_{\ell 2}, \pi\}_{\theta_{\ell}} \times \{0, \theta_{D^* 1}, \theta_{D^* 2}, \pi\}_{\theta_{D^*}}$$

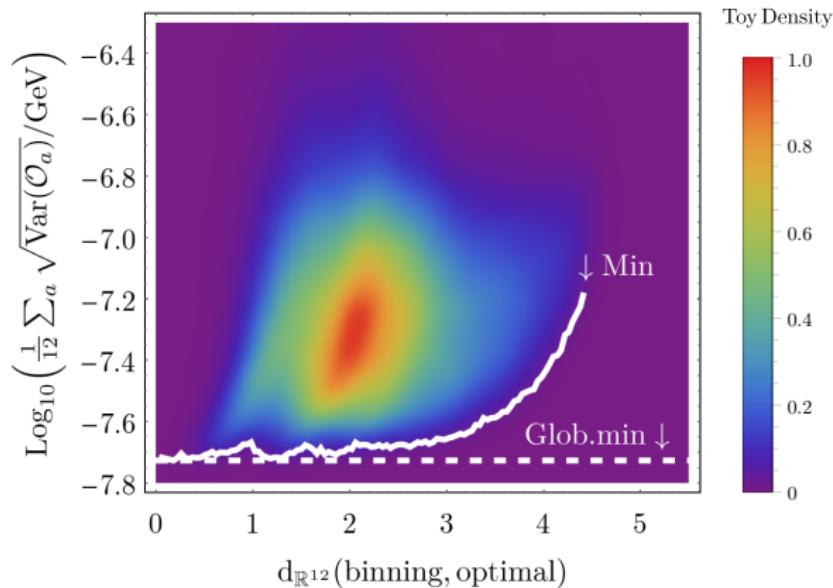
→ Generate sample of **toy binnings** (i.e. random values $\chi_1, \chi_2, \theta_{\ell 1}, \theta_{\ell 2}, \Delta_{\theta_{D^*}}$)



$3 \times 3 \times 3$ (prod bins, gen. weights)

$$\{-\pi, \chi_1, \chi_2, \pi\}_{\chi} \times \{0, \theta_{\ell 1}, \theta_{\ell 2}, \pi\}_{\theta_{\ell}} \times \{0, \theta_{D^* 1}, \theta_{D^* 2}, \pi\}_{\theta_{D^*}}$$

→ Generate sample of **toy binnings** (i.e. random values $\chi_1, \chi_2, \theta_{\ell 1}, \theta_{\ell 2}, \Delta_{\theta_{D^*}}$)



Backup slides

Backup slides overview

- General bins
- The angular functions B_a
- Correlation
- Plots $3 \times 3 \times 2$ edges
- Plots $3 \times 3 \times 3$ edges