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# Accessing CKM suppressed top decays at the LHC

— Top23, 09/27/2023 —

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# This talk

Based on [recent work](#) by D. Faroughy, J.F. Kamenik, M.S. and J. Zupan

A **simple** extension of an existing strategy to measure  $|V_{td}|^2 + |V_{ts}|^2$  at the LHC

Main idea: Orthogonal  $b$ - and  $q$ -taggers define **complementary observables** that **increase the statistical power** of the analysis

This simple extension allows to **measure a non-null  $|V_{td}|^2 + |V_{ts}|^2$  at 95% CL at the HL-LHC**

# The CKM matrix

The CKM matrix encodes the flavor structure of the EW charged currents in the SM. Measuring the CKM → Very powerful precision tests of the SM (with potential sensitivity to BSM effects)

Specially true for its **third row** which is **indirectly** constrained by B-physics measurements. Global CKM fits yield estimates assuming unitarity

A strong **hierarchy** makes **off-diagonal elements** difficult to measure but also more sensitive to any BSM (also due to the large top mass)

$$|V_{tb}^{\text{SM}}| = 999.118_{-0.036}^{+0.031} \times 10^{-3}$$

$$|V_{ts}^{\text{SM}}| = 41.10_{-0.72}^{+0.83} \times 10^{-3}$$

$$|V_{td}^{\text{SM}}| = 8.57_{-0.18}^{+0.2} \times 10^{-3}$$

# Direct measurements

$|V_{tx}|$  can be obtained directly from on-shell top-quarks decays (for single-top see L. Pintucci's talk on Monday and J. Reidelstürz talk on Tuesday).

CMS coll. arxiv:1404.2292, provides the current best measurement using top pair production by measuring

$$\mathcal{R}_b \equiv \frac{\mathcal{B}(t \rightarrow bW)}{\sum_{j=d,s,b} \mathcal{B}(t \rightarrow jW)} > 0.955 \text{ @ 95\% C.L.}$$

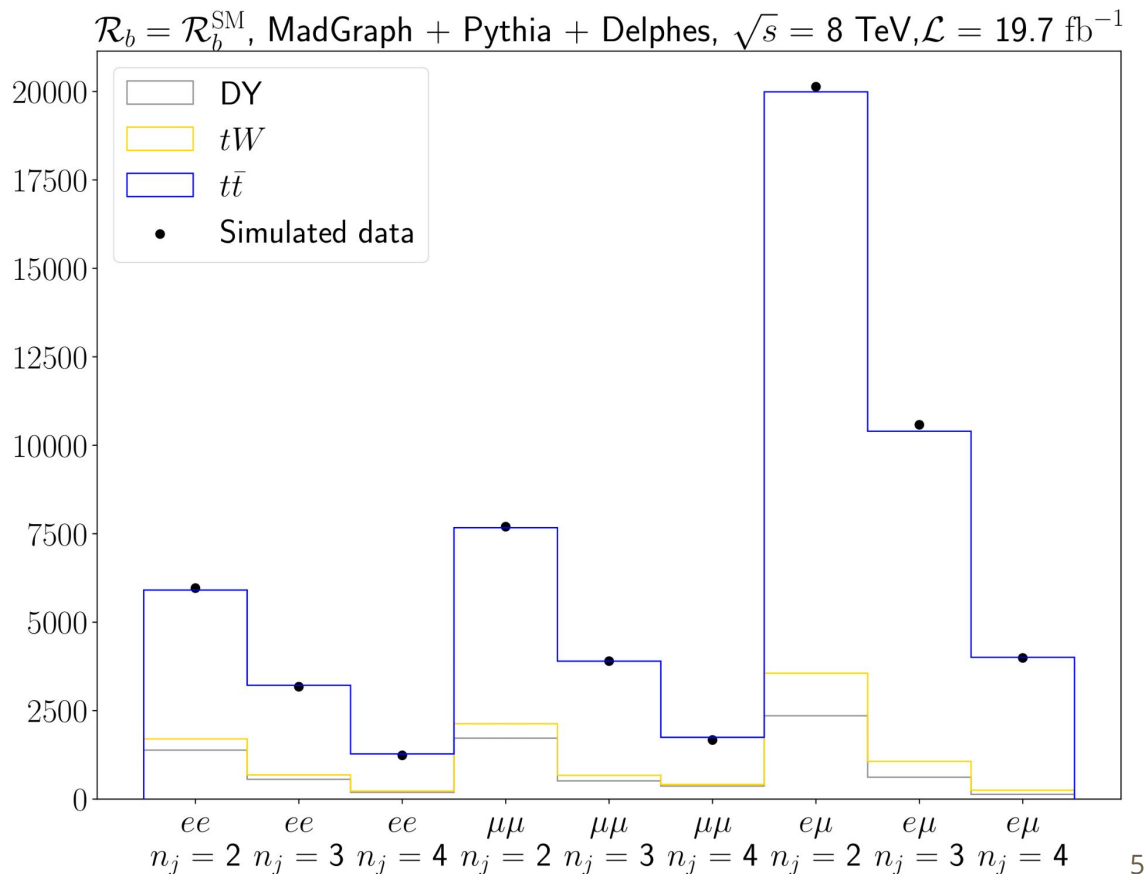
which is translated to

$$\sqrt{|V_{td}|^2 + |V_{ts}|^2} < 0.217 |V_{tb}|$$

# The starting point

This is the population for each **category** (number of jets  $n_j$  and dileptonic channel  $\ell\ell'$ )

Expected rates from Monte Carlo and pseudo-data per category sampled assuming Poisson distribution



# The CMS analysis

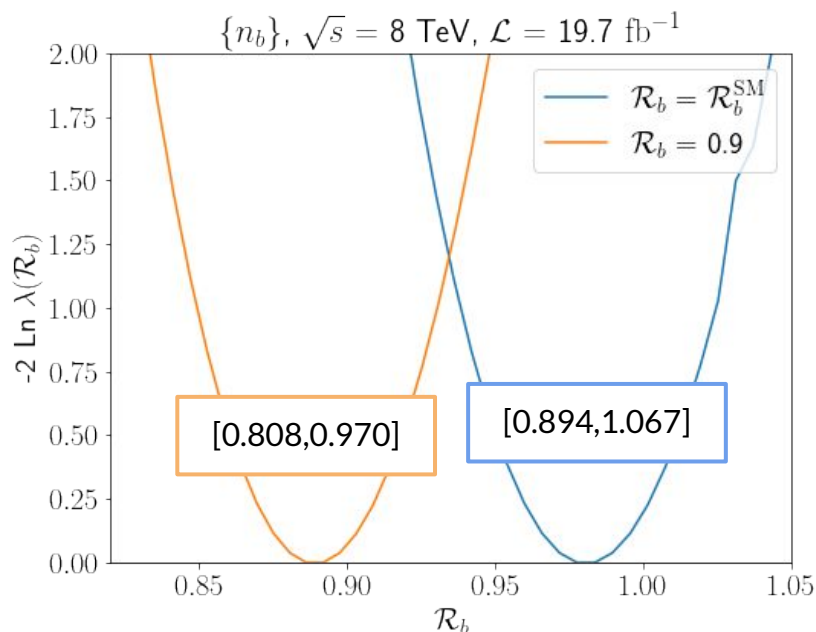
Model the expected number of events for **each possible number of b-tags** in a  $\{n_j, \ell\ell'\}$  category

$$\bar{N}_{\ell\ell'}(n_b|n_j) = P_{\ell\ell'}(n_b|n_j, \mathcal{R}_b, \theta_i) N_{\ell\ell'}$$

Set limits using

$$\mathcal{L}(\mathcal{R}_b, \theta_i) = \prod_{\ell\ell'} \prod_{n_j=2}^4 \prod_{n_b=0}^{n_j} \prod_{n_q=0}^{n_j-n_b} \mathcal{P}(N_{\ell\ell'}|\bar{N}_{\ell\ell'}) \prod_i \rho(\theta_i)$$

We are consistent with the CMS results with our set-up (simplified taggers but full Monte Carlo implementation)



# Our extension

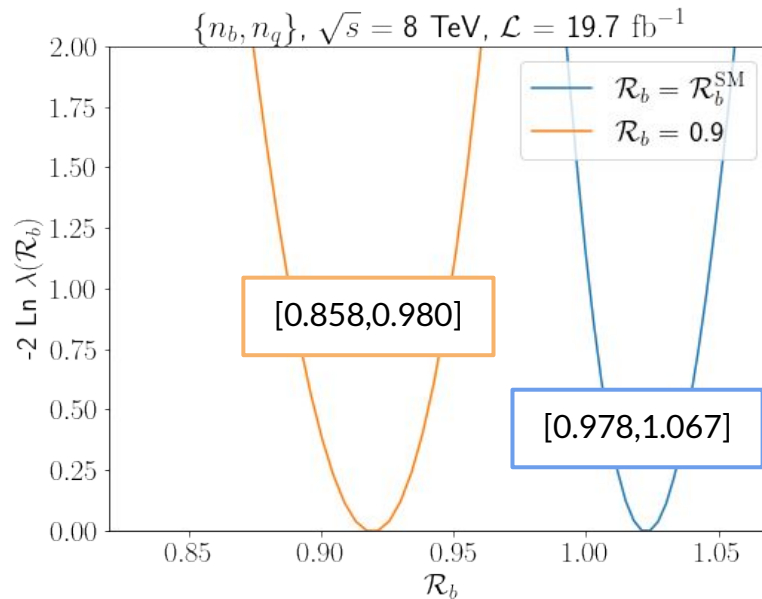
Let's incorporate more information

In addition to the number of  $b$ -tagged jets, we compute the number of  $q$ -tagged jets, creating **non-overlapping  $\{n_b, n_q\}$  bins**

$$\bar{N}_{\ell\ell'}(n_b|n_j) \rightarrow \bar{N}_{\ell\ell'}(n_b, n_q|n_j)$$

$$\bar{N}_{\ell\ell'}(n_b, n_q|n_j) = P_{\ell\ell'}(n_b, n_q|n_j, \mathcal{R}_b, \theta_i) N_{\ell\ell'}(n_j)$$

Already an improvement! Smaller CIs and larger discrimination even with suboptimal taggers + high uncertainties for  $q$ -tagger

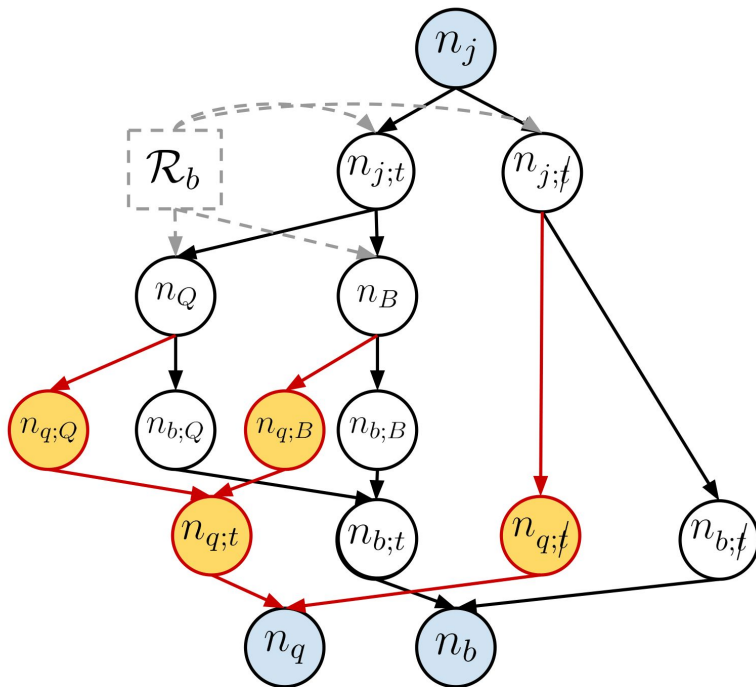


# Explicitly

This is the **probabilistic model** we propose for each  $\ell\ell'$  combination

Not shown are some nuisance parameters which need to be fitted from data and determine the probability distributions

Blue is **observed**, yellow and red are the **new additions**





# Projected sensitivity

We **first validate** the model through **consistency checks** using MC and **then** project its performance **assuming it is true**

→ We sample  $\{n_b, n_q, n_j, \ell\ell'\}$  counts using the probabilistic model, the simulated  $\{n_j, \ell\ell'\}$  event yields and specific choices for the parameters

We then re-do all our statistical analyses using this pseudo-data

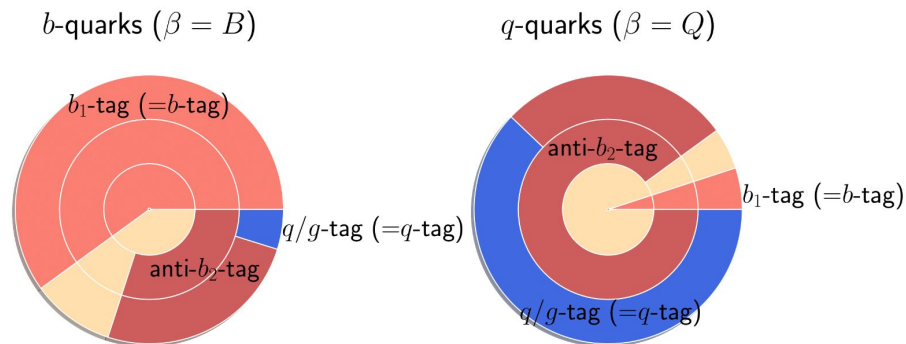
Two large speed-ups: we can incorporate any tagger we want without coding it at the ROOT level and we can explore different choices of  $R_b$  and other parameters

# Tagging strategy

We propose to mix state-of-the-art  $b$ -taggers and quark/gluon taggers to define complementary orthogonal regions.

We choose two Working Points of the former to define a  $b_1$ -tagger and an anti- $b_2$ -tagger. This anti- $b_2$ -tagger is combined with the quark/gluon tagger to define a  $q$ -tagger.

$$\epsilon_{\beta}^{b_1} \leq \epsilon_{\beta}^{b_2}$$
$$\epsilon_{\beta}^q = \epsilon_{\beta}^{\{\text{anti-}b_2\} \cap \{q/g\}}$$



# Reframing measurement as discovery

To compare Working Points in a simple way, we reframe the problem as a signal discovery.

**Null hypothesis  $R_b = 1$  vs  
Alternative hypothesis  $R_b = SM$**

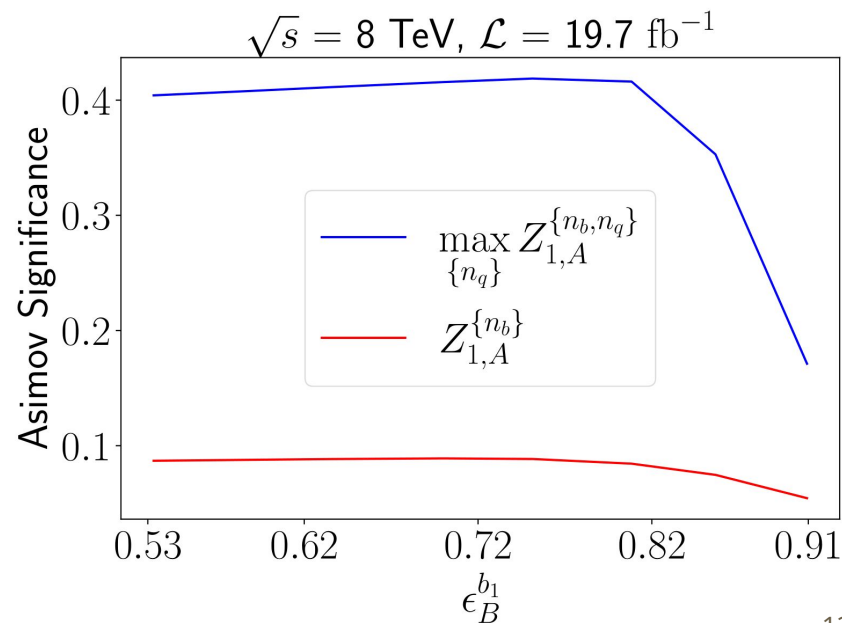
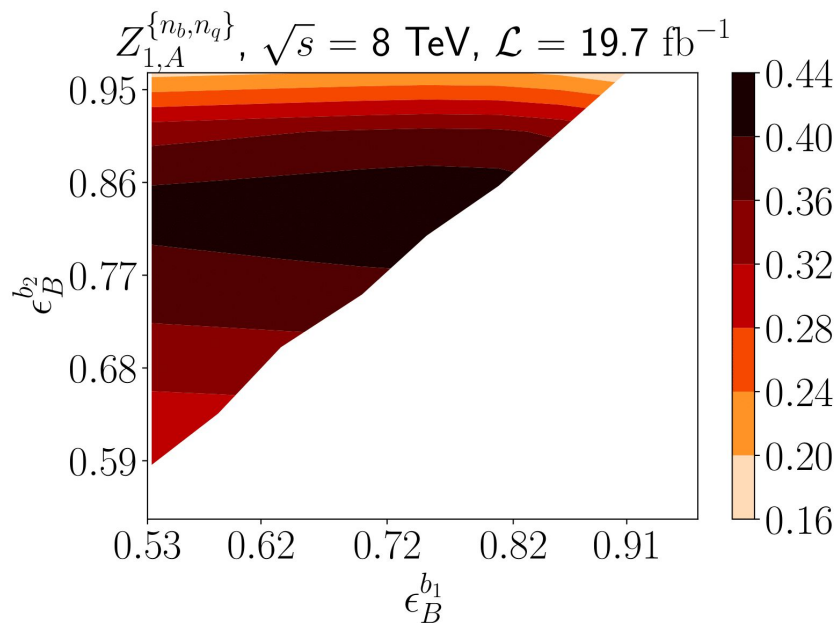
New test statistic + Asimov dataset  $\rightarrow$   
**expected discovery significance of  
the SM hypothesis**

$$\tilde{\lambda}(R_b) = \begin{cases} \mathcal{L}(R_b, \hat{\theta}_i(R_b)) / \mathcal{L}(\hat{R}_b, \hat{\theta}_i), & \text{if } \hat{R}_b \leq 1, \\ \mathcal{L}(R_b, \hat{\theta}_i(R_b)) / \mathcal{L}(1, \hat{\theta}_i(1)), & \text{if } \hat{R}_b > 1. \end{cases}$$

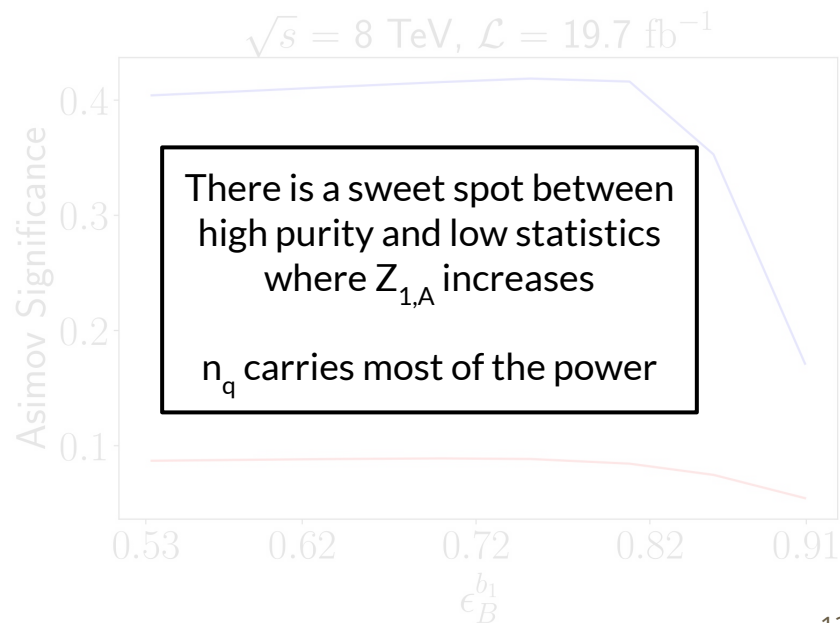
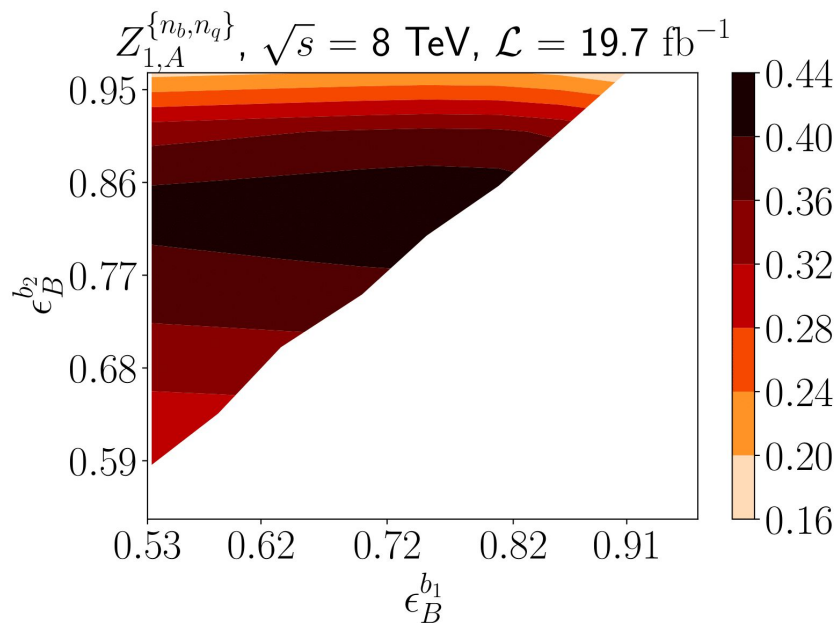
$$q_1 = \begin{cases} -2 \text{Ln } \lambda(1) & \text{if } \hat{R}_b \leq 1, \\ 0 & \text{if } \hat{R}_b > 1. \end{cases}$$

$$Z_{1,A} = \sqrt{q_{1,A}}$$

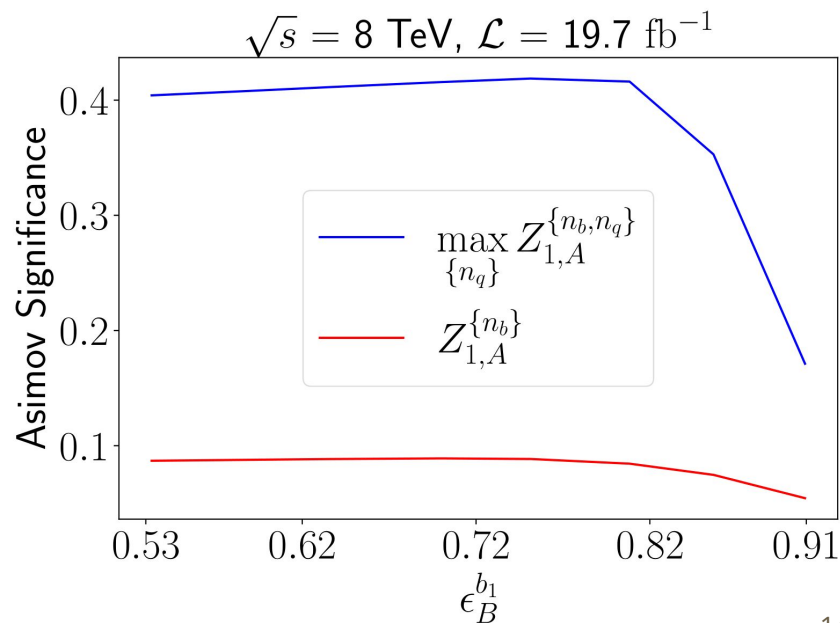
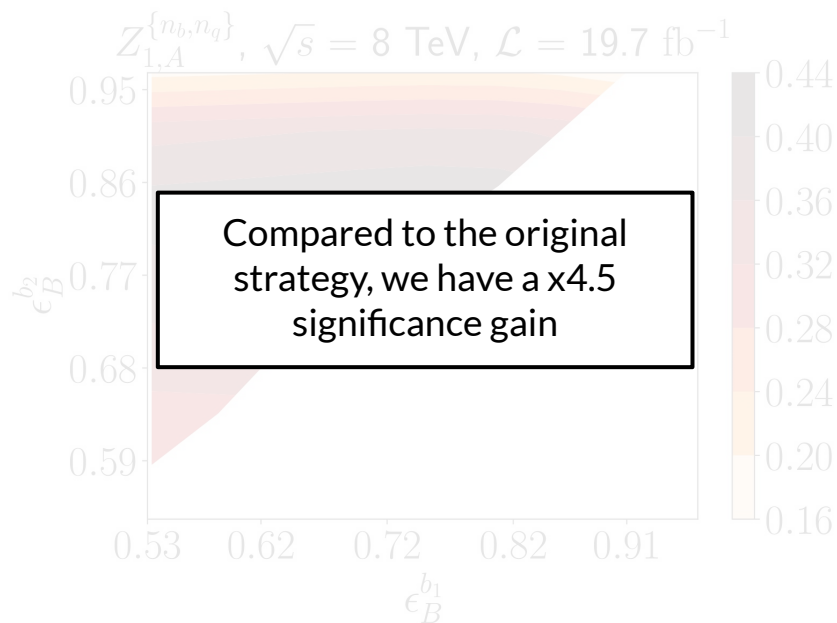
# Results: original benchmark



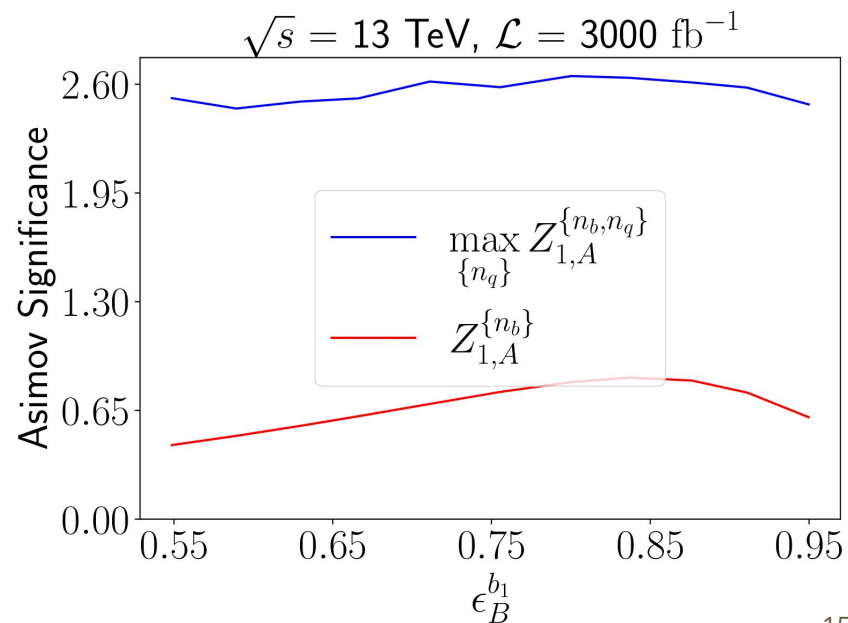
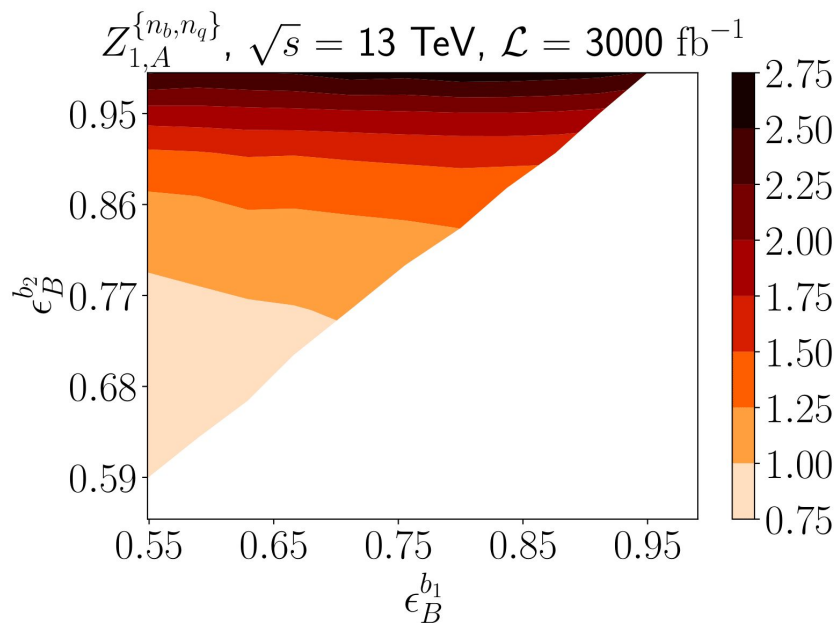
# Results: original benchmark



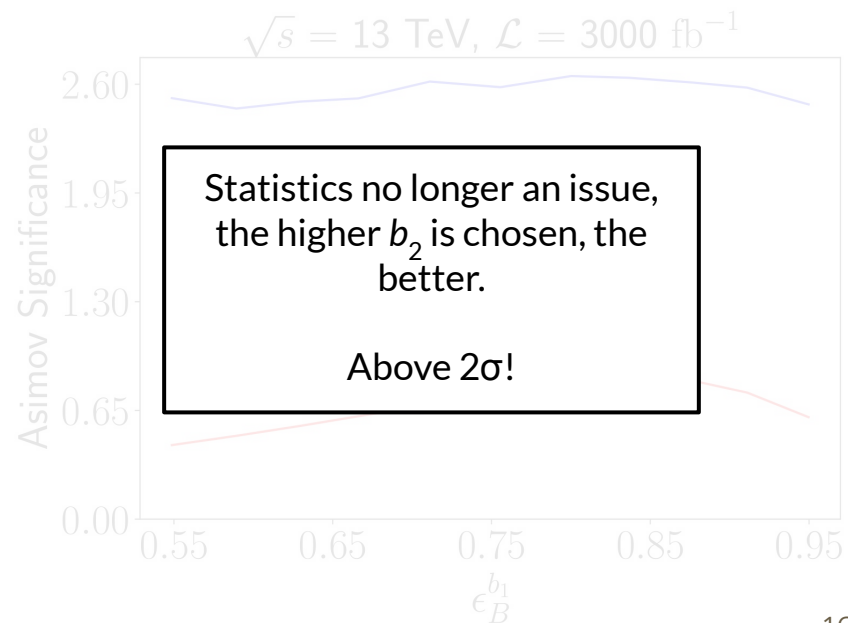
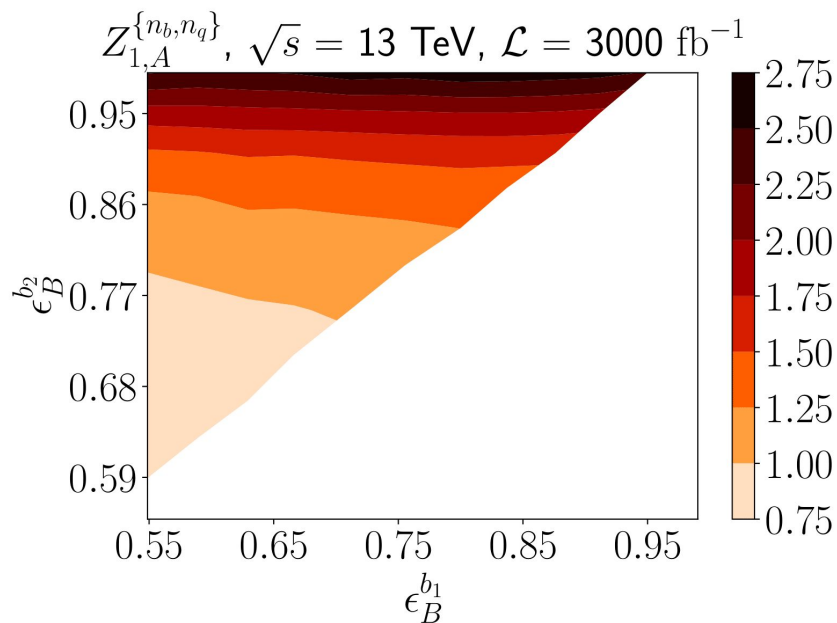
# Results: original benchmark



# Results: ~HL-LHC projection

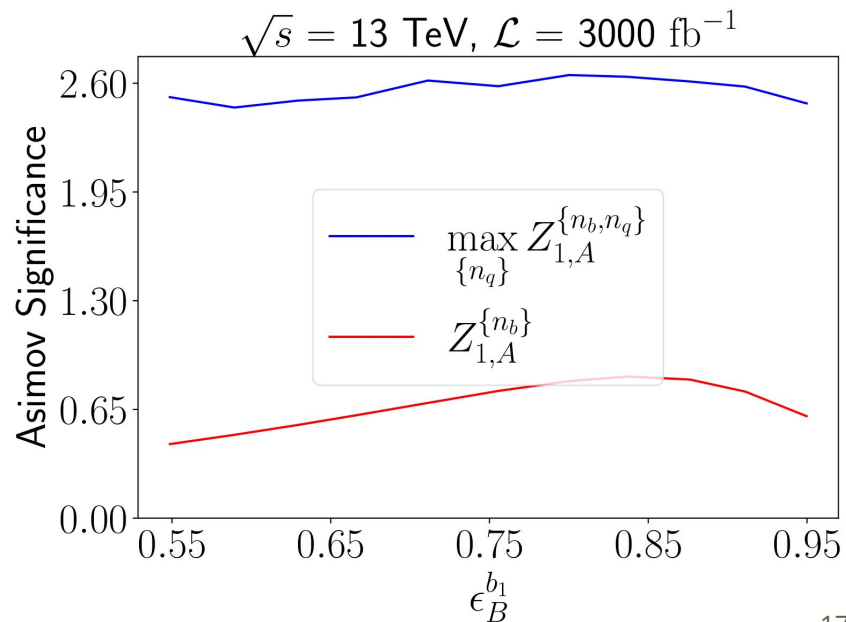
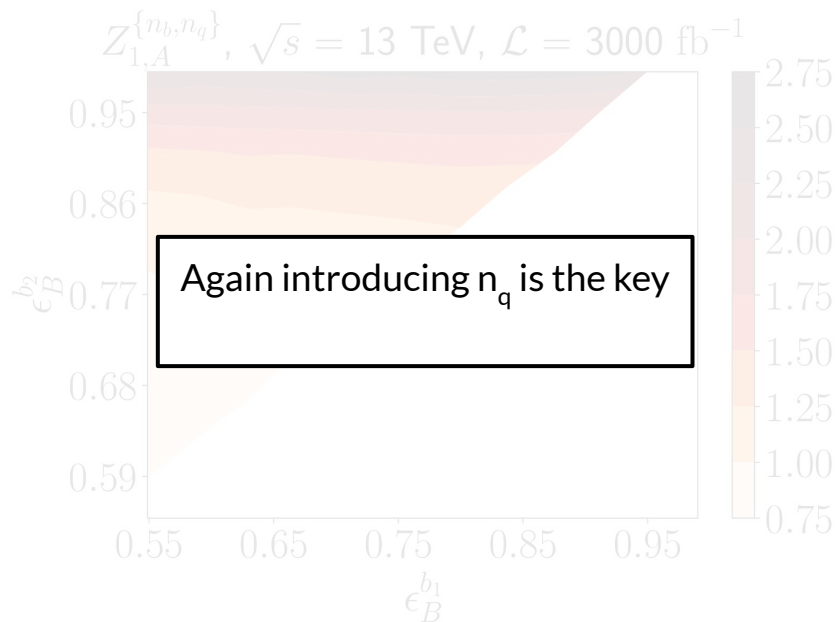


# Results: ~HL-LHC projection





# Results: ~HL-LHC projection



# Outlook

We propose to extend a previous analysis strategy by incorporating additional information in the form of the number of  $q$ -tagged jets  $n_q$ . We have verified that the probabilistic model captures dileptonic top pair production events appropriately

The proposed strategy allows to measure non-null  $|V_{tx}|$  at the  $1\sigma$  level during Run 2 and at the  $2\sigma$  level at the HL-LHC

However the probabilistic model is incomplete and additional NPs should be included. It could also be extended to be more physical. For example, the model could incorporate jet kinematics by conditioning on  $p_T$

We have treated tagger efficiency estimation and  $R_b$  determination as separate problems. However, they are related and could be treated at the same time



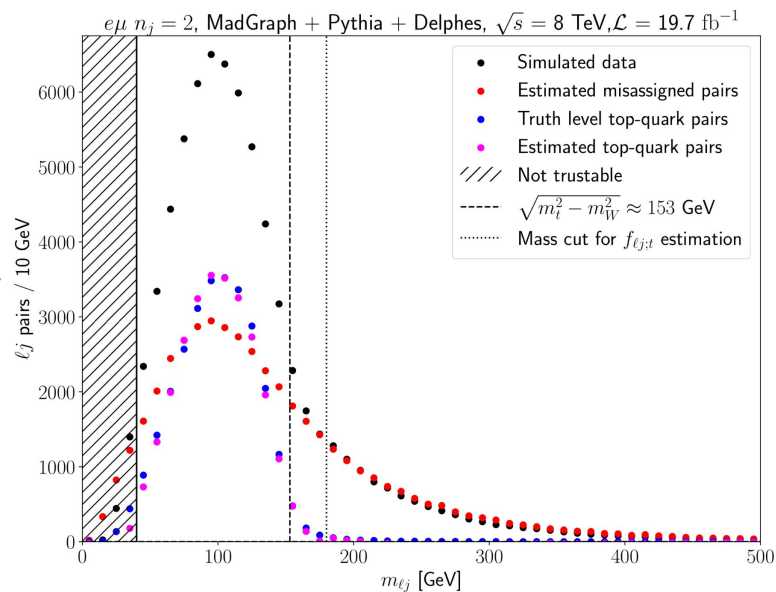
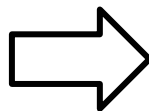
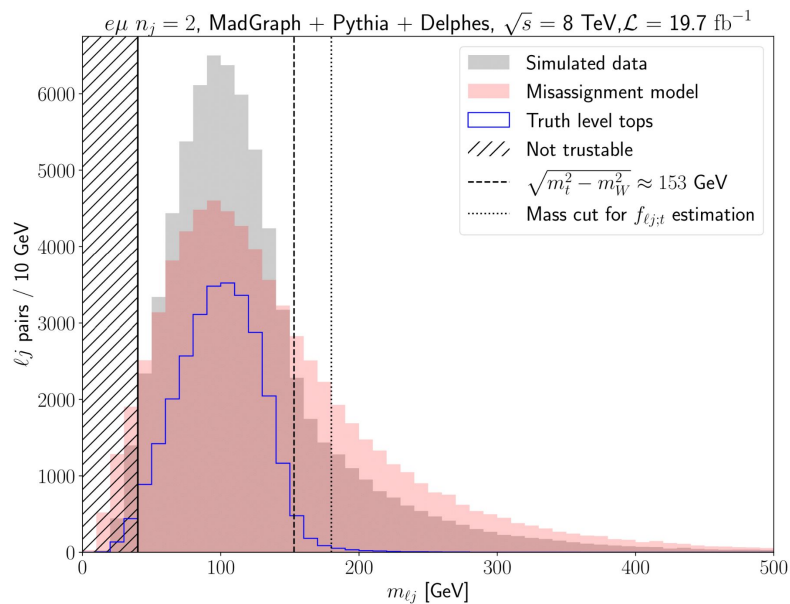
# Backup slides

# What about other direct measurements?

All other approaches (t-channel single top production, tW associated production, s-tagging the top decay products) suffer from low statistics due to the smallness of  $|V_{td}|^2 + |V_{ts}|^2$  and cannot match the CKM global fits

The CMS analysis does not suffer so badly from low statistics, as it considers dileptonic top pair production with no tag requirement on the jets but it lacks discriminating power between SM values and  $R_b = 1$

# Top fraction determination



# Model validation

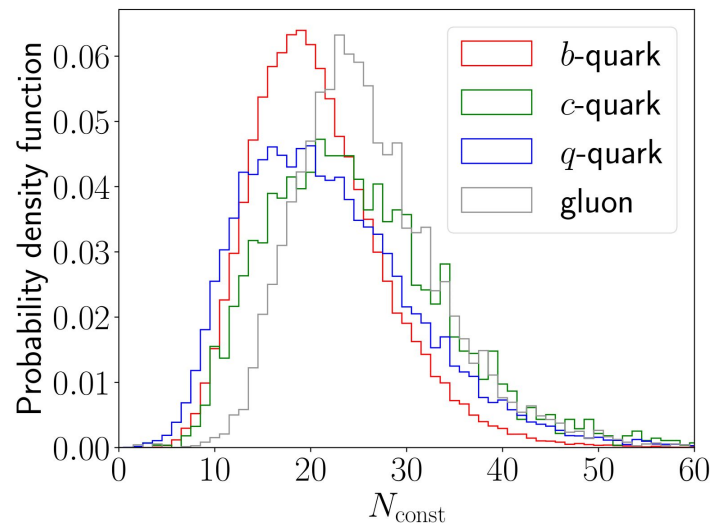
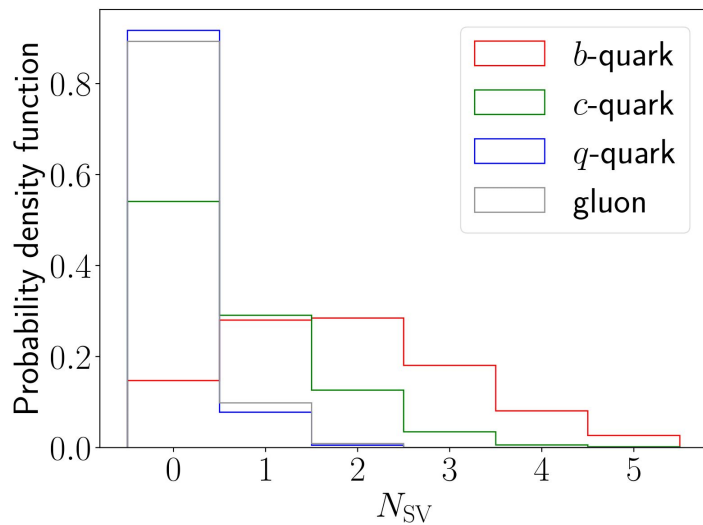
We first want to assess how good the probabilistic model is at capturing the true physics

We know it is approximate (all jets have the same efficiencies regardless of kinematics!) but we want to know if it is expressive enough

We build  $b$ - and  $q$ -taggers, apply them to Monte Carlo data at the ROOT level and check if the fitted model presents good coverage around the true  $R_b$  value

As a bonus, we obtain a first example of how  $n_q$  improves the determination of  $R_b$

# Validation: Homemade $b$ - and $q$ -taggers





# Validation: Homemade $b$ - and $q$ -taggers

High sample purity for  $n_b$ , but intermediate for  $n_q$

$\alpha$ -tagger	Cuts	$\epsilon_Q^\alpha$	$\epsilon_B^\alpha$
$b$ -tagger	$N_{SV} \geq 2$	$0.002^{+10\%}_{-10\%}$	$0.49^{+5\%}_{-5\%}$
$q$ -tagger	$N_{SV} = 0 \ \& \ N_{\text{const}} < 20$	$0.69^{+20\%}_{-20\%}$	$0.16^{+10\%}_{-10\%}$

# Validation: Defining a test statistic

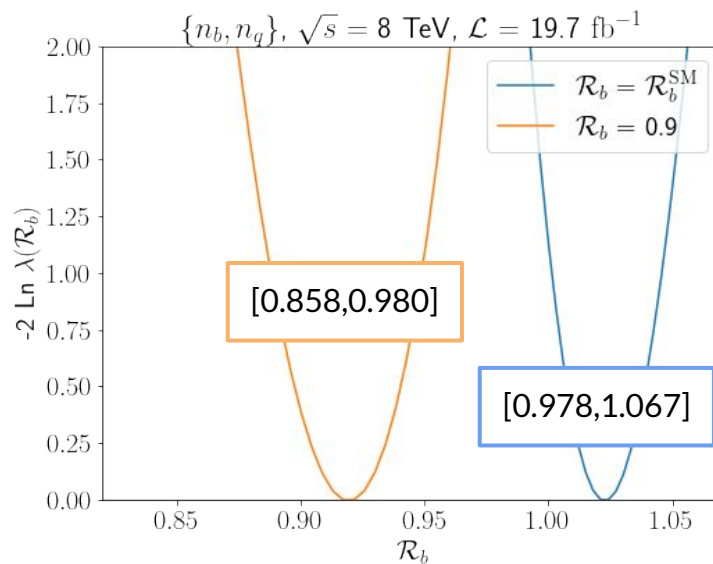
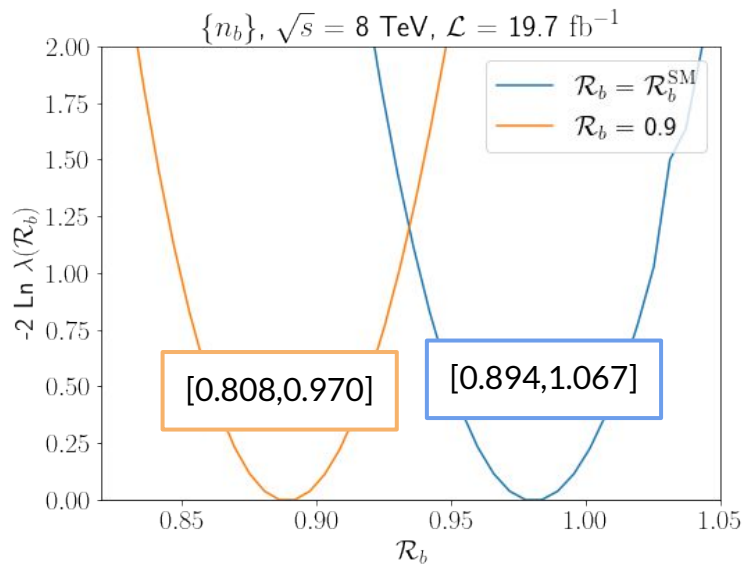
To measure a parameter in presence of systematic uncertainties, we define the Profile Likelihood Ratio

$$\lambda(\mathcal{R}_b) = \frac{\mathcal{L}(\mathcal{R}_b, \hat{\hat{\theta}}_i(\mathcal{R}_b))}{\mathcal{L}(\hat{\mathcal{R}}_b, \hat{\theta}_i)}$$

and the associated test statistic, which helps us compute the 95% Confidence Intervals

$$-2 \text{ Ln } \lambda(\mathcal{R}_b)$$

# Validation: It already improves the results!



# Validation: Results

The model is able to capture the essential features of the data

It is able to differentiate between different values of  $R_b$

The addition of the number of  $q$ -tagged jets considerably improves the fit by tightening the Confidence Intervals even with large systematic uncertainties

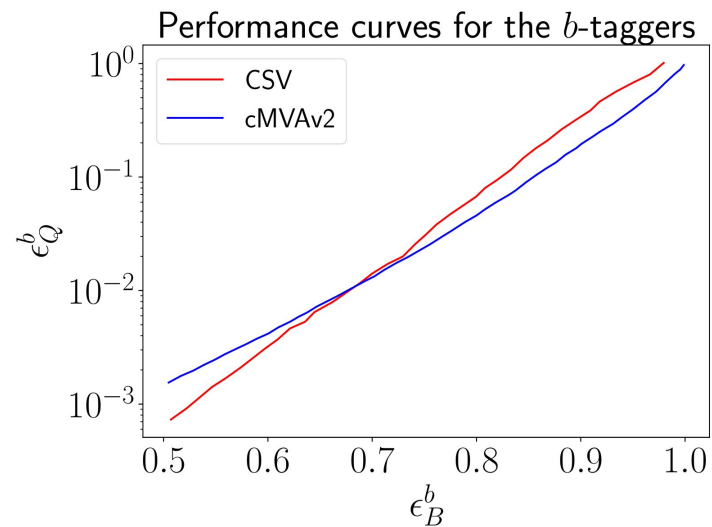
# Validation: Results

Observables	$\mathcal{R}_b = \mathcal{R}_b^{\text{SM}}$	$\mathcal{R}_b = 0.9$
$\{n_b\}$	[0.894, 1.067]	[0.808, 0.970]
$\{n_b, n_q\}$	[0.978, 1.067]	[0.858, 0.980]

# Incorporating state-of-the-art $b$ -taggers

We digitalize two state-of-the-art  $b$ -taggers, one for 8 TeV and another for 13 TeV

We explore different Working Points to assess the difference trade-offs between sample purity and sample statistics



# Arbitrary $q$ -taggers

We chose the following definition.

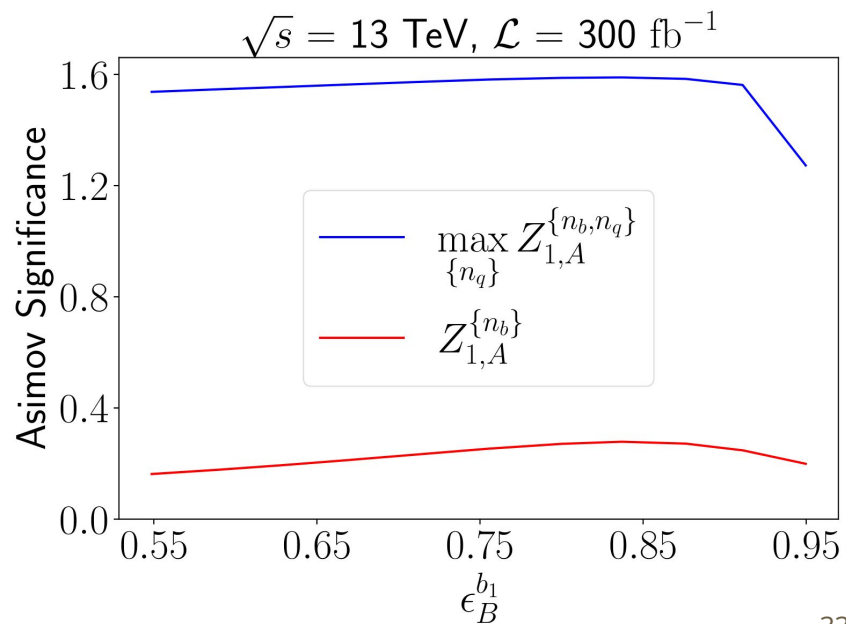
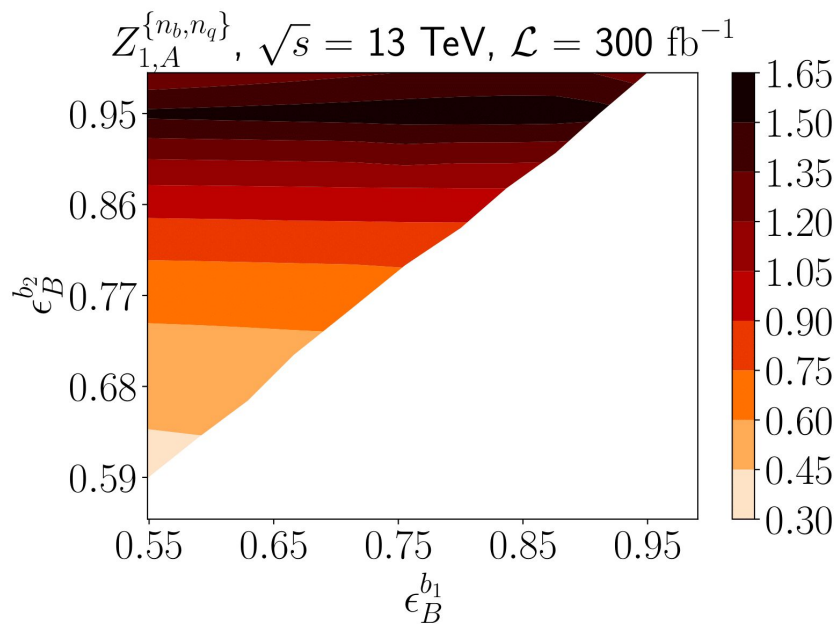
$$\begin{aligned}\epsilon_B^q &= 0.16(1 - \epsilon_B^{b_2}) \\ \epsilon_Q^q &= 0.69(1 - \epsilon_Q^{b_2}) & \epsilon_{j;\neq}^\alpha &= 0.85\epsilon_Q^\alpha\end{aligned}$$

# Systematic uncertainties

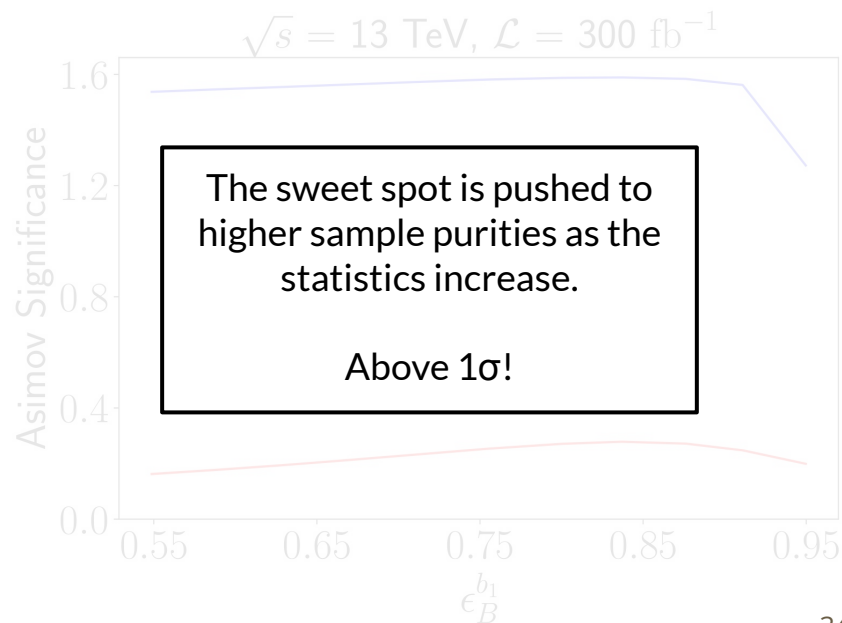
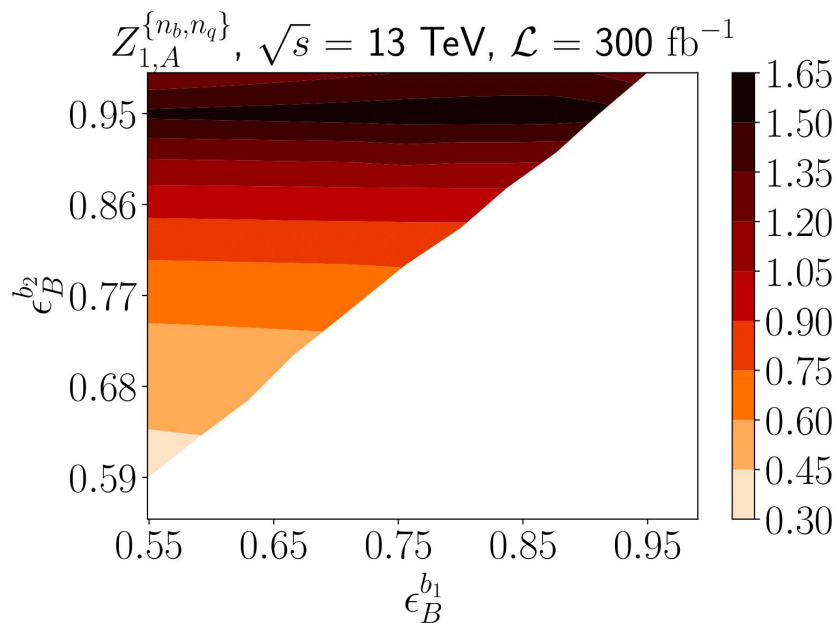
Nuisance Param.	Uncertainty
$\epsilon_{B}^{b_1}$	2%
$\epsilon_{Q}^{b_1}$	11%
$\epsilon_{B,Q}^q$	5%



# Results: Run 2 projection



# Results: Run 2 projection



# Results: Run 2 projection

