Search for a resonance decaying to a scalar particle and a Higgs boson in the $b\bar{b}\gamma\gamma$ final state in *pp* collisions at $\sqrt{s}$ = 13 TeV with the ATLAS detector

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ATLAS EXPERIMENT

Outline

Observation of the Higgs boson by ATLAS and CMS ($H \to \gamma\gamma$ and $H \to ZZ^* \to 4l$ channels)

Ongoing campaign of **measurements** of the Higgs boson **properties**…

2012 — 2018 — Now

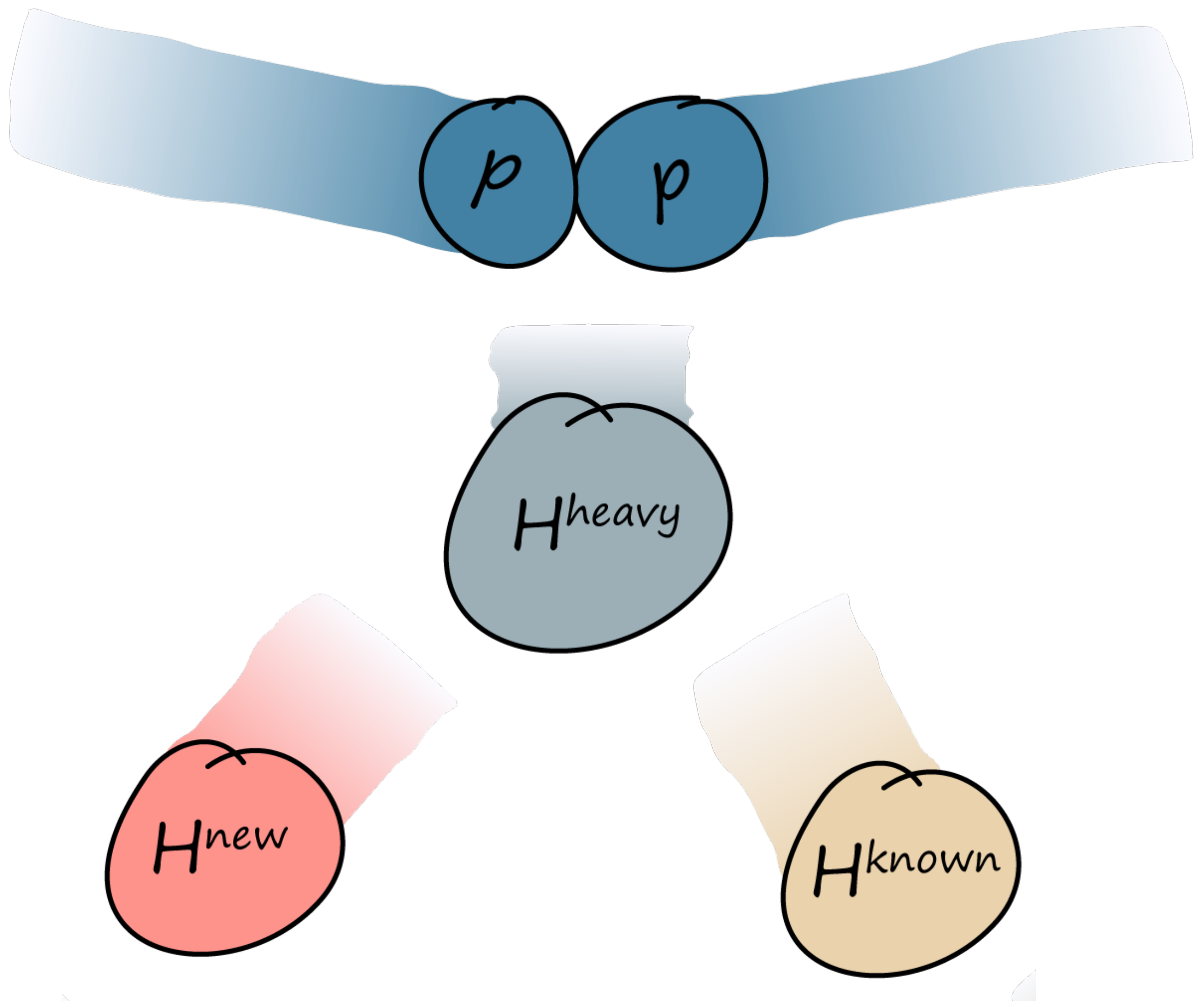
Observation of the $H \to b\bar{b}$ decay

Excellent agreement with the **Standard Model** (**SM**)!

Question: Is this observed Higgs boson (with $\mathbf{m_H = 125}$ GeV) the **only** Higgs boson?

- The SM is incomplete!
  - 2HDM, Next-to-Minimal Supersymmetric Standard Model, etc.
- **Many extensions** of the SM consider the observed Higgs boson as part of an **extended Higgs sector**, whose **additional scalar particles** still **remain to be found**.

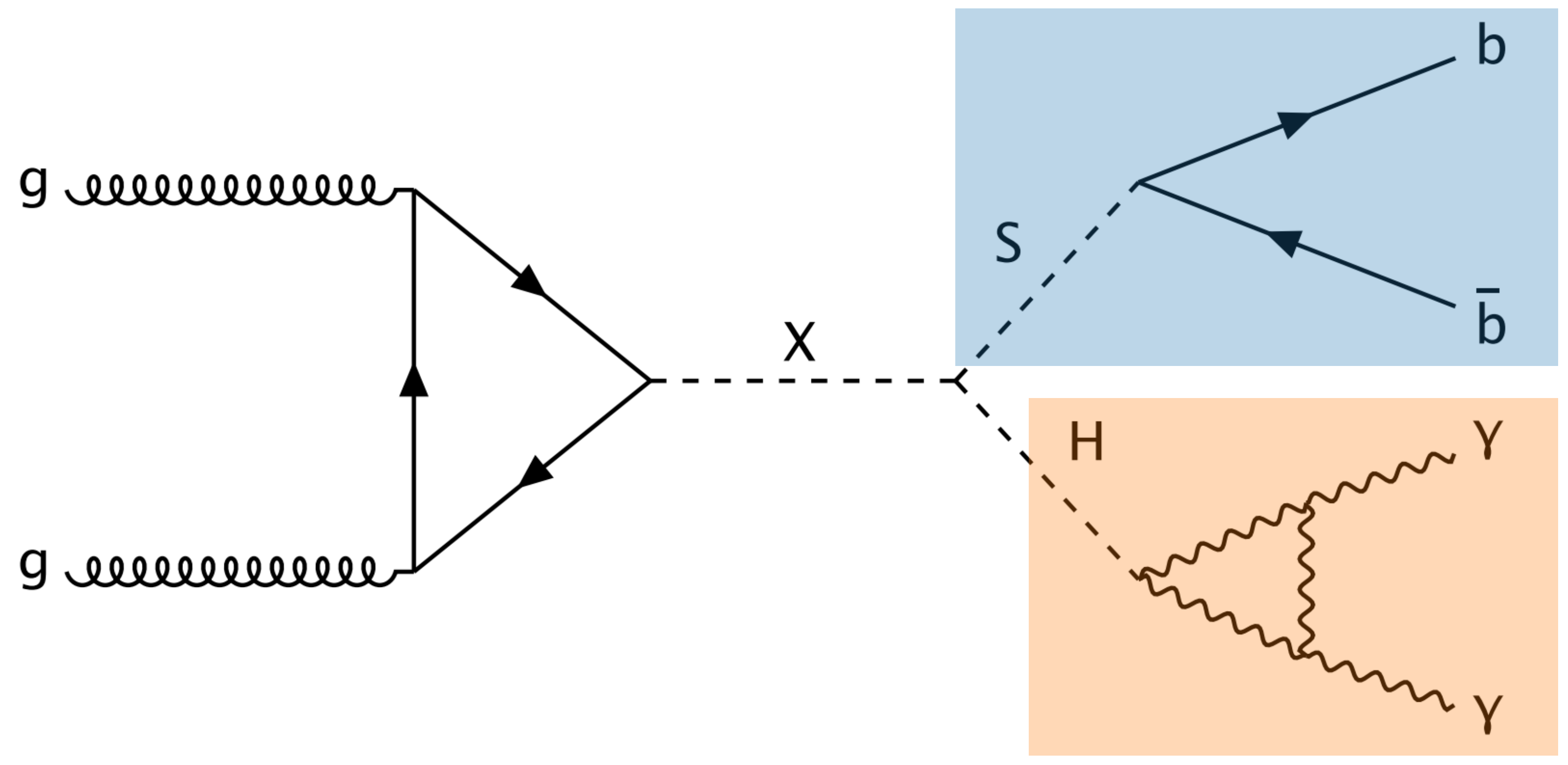
Could be produced in pp **collisions** at the LHC, like the **observed Higgs boson**!



Phenomenology: decay of a heavy scalar particle $\mathbf{X}$, decaying in a Higgs boson $\mathbf{H}$ and a lighter scalar particle $\mathbf{S}$, with $\mathbf{m_X > m_H + m_S}$.

Outline

This analysis searches for a **heavy resonance $\mathbf{X}$**, decaying in a Higgs boson $\mathbf{H}$ and a **lighter scalar particle $\mathbf{S}$**, in the final state with **two photons** and **two bottom quarks**.



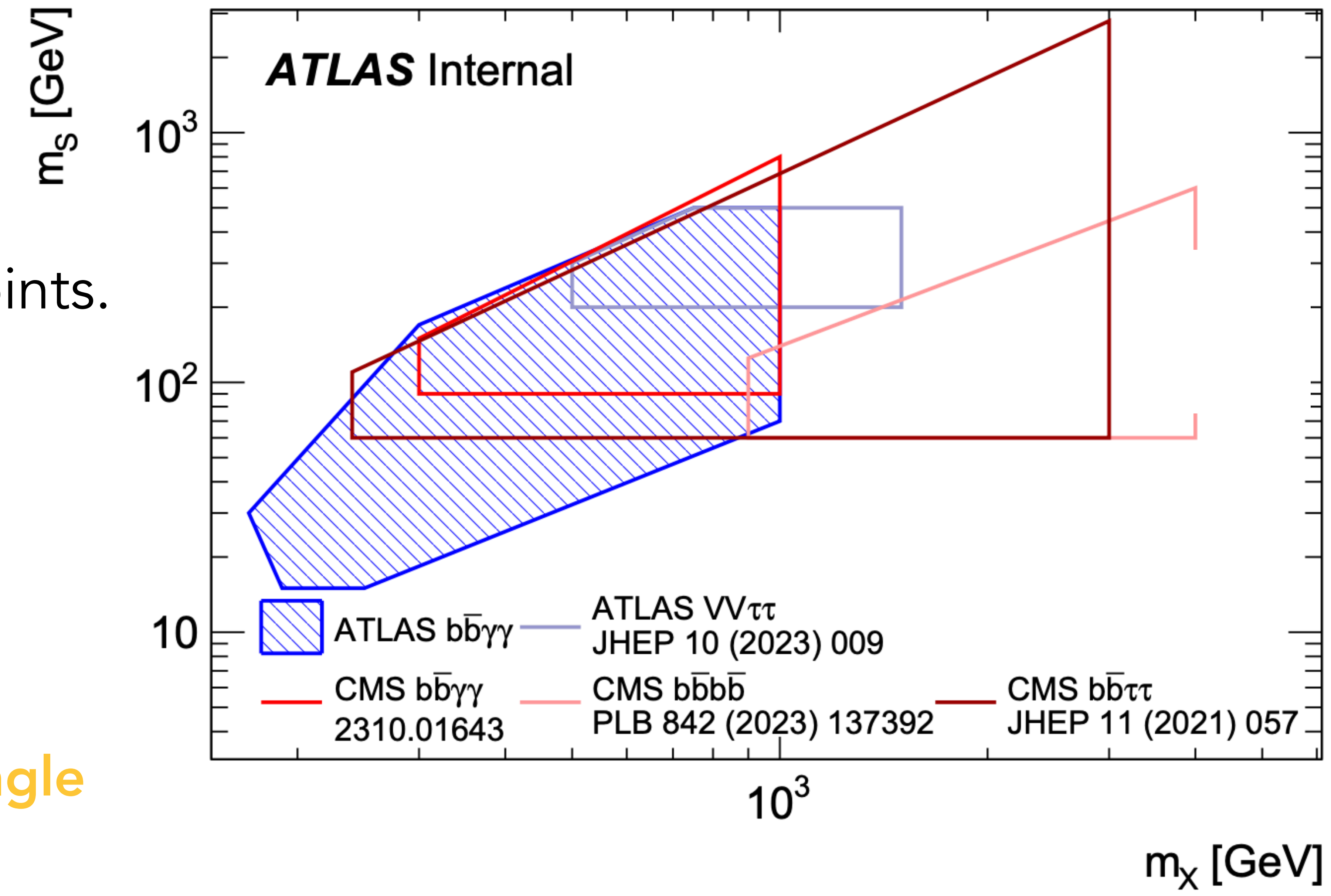
- The $\mathbf{S \to b\bar{b}}$ decay is strongly favored in a scenario where $\mathbf{S}$ is similar to the Higgs boson and $\mathbf{m_S < 130}$ GeV.
- The $\mathbf{S \to b\bar{b}}$ decay is **resolved** (**boosted**) for $\mathbf{m_S \sim m_X - m_H}$ ($\mathbf{m_S \ll m_X - m_H}$)!

Very low $H \to \gamma\gamma$ branching fraction, but:

- Excellent trigger and reconstruction efficiency for photons with the ATLAS detector.
- Excellent di-photon invariant mass resolution (1-2 GeV)!

- We explore a **wide range of masses** for the two scalars $\mathbf{m_X}$ and $\mathbf{m_S}$.

15 $\leq \mathbf{m_S} \leq$ 500 GeV × 170 $\leq \mathbf{m_X} \leq$ 1000 GeV! → Amounting to a total of **359** tested $\mathbf{(m_X, m_S)}$ points.



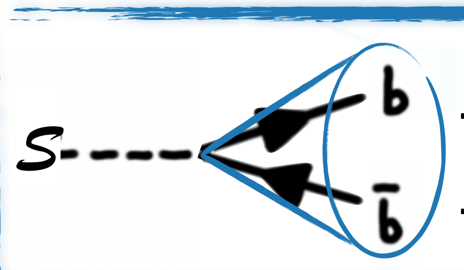
- For each tested $\mathbf{(m_X, m_S)}$ point, the $\mathbf{X \to S(\to b\bar{b})H(\to \gamma\gamma)}$ signal would give rise to **three resonances**:
  - Narrow $H \to \gamma\gamma$ peak around $\mathbf{m_H = 125}$ GeV.
  - Narrow $\mathbf{S \to b\bar{b}}$ resonance around $\mathbf{m_S}$.
  - Wider $X \to b\bar{b}\gamma\gamma$ peak around $\mathbf{m_X}$.

Key features for isolating the signal from the **non-resonant backgrounds**!

Non-resonant di-Higgs, **single Higgs** and **continuum**!

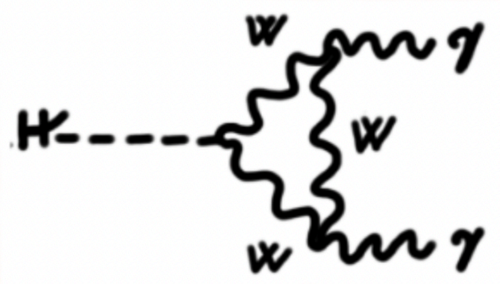
Summary of the analysis strategy

1. **Triggers & pre-selection.**
   - The $SH \rightarrow b\bar{b}\gamma\gamma$ analysis relies on a combination of **di-photon** and **single-photon** triggers.
   - A **pre-selection** targeting the $b\bar{b}\gamma\gamma$ **signature** is applied, depending on the **b-jet category**.



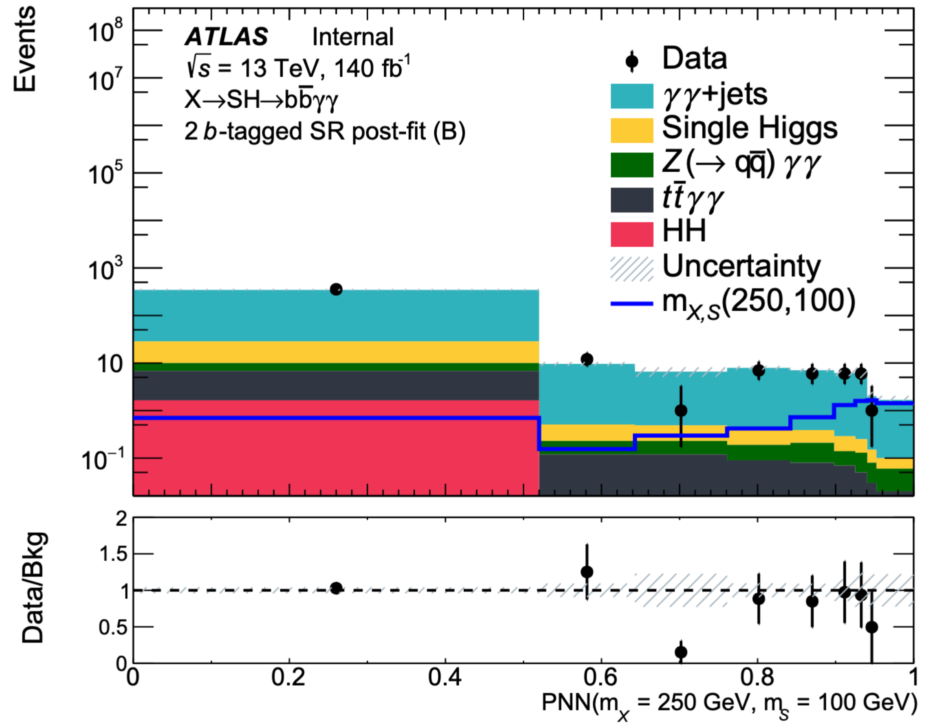
- **2 b-tagged**: Exactly 2 b-jets @ 77% WP.
- **1 b-tagged** : Exactly 1 b-jet @ 77% WP.

+



- **Two** tight and isolated **photons**.
- $p_T(\gamma_{1(2)})/m_{\gamma\gamma} > 0.35(0.25)$.
- $105 < m_{\gamma\gamma} < 160$ GeV.

Di-photon and b-jet selection



2. **Training of the Parametrized Neural Network (PNN).**

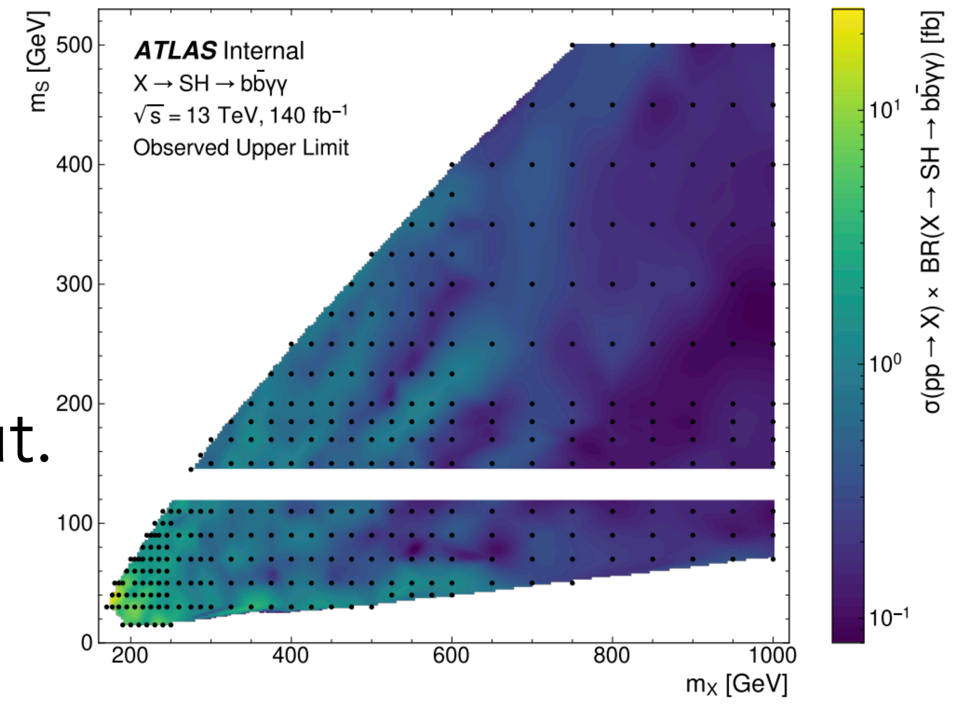
   A separate **PNN** is trained in both the **2 b-tagged** and the **1 b-tagged categories**, to isolate interesting $\mathbf{X \rightarrow SH \rightarrow b\bar{b}}\gamma\gamma$ events from the backgrounds! → The **PNNs** rely on $\mathbf{m_X}$ and $\mathbf{m_S}$ (or $\mathbf{m_X}$ only in the **1 b-tagged category**) as **parameters**!

3. **Signal & Background Modeling.**
   - The observable is the **output of the PNN** (in both the **2 b-tagged** and the **1 b-tagged categories**).
   - The processes are the $\mathbf{X \rightarrow SH \rightarrow b\bar{b}}\gamma\gamma$ signal, the **di-Higgs**, **single Higgs** and **continuum backgrounds** which are studied in a **SR** and a **CR**. → Defined using $m_{\gamma\gamma}$.

4. **Systematic uncertainties.**

   Evaluate the **systematic uncertainties** acting on the **signal** and **background** processes.

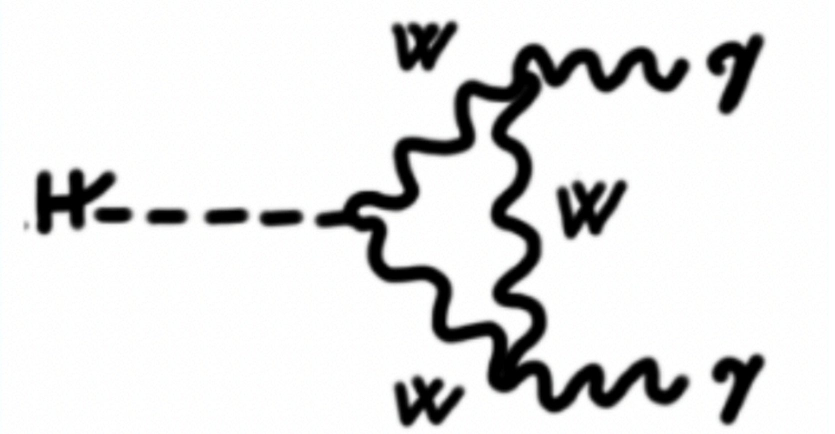
5. **Statistical interpretation & statistical results.**
   - The statistical results are extracted via a **binned maximum likelihood fit** on the distributions of the PNN output.
   - We would like to **quantify** the **excess over the expected background**, and set **upper limits** on the $X \rightarrow SH \rightarrow b\bar{b}\gamma\gamma$ **cross-section** across a fine grid in the **2-dimensional** (m_X, m_S) **plane**!



Event selection

Interesting events are selected if they fulfill the selection requirements **targeting** the $b\bar{b}\gamma\gamma$ **signature**.

Di-photon selection → Aimed at retaining **good $H \to \gamma\gamma$ decays**.



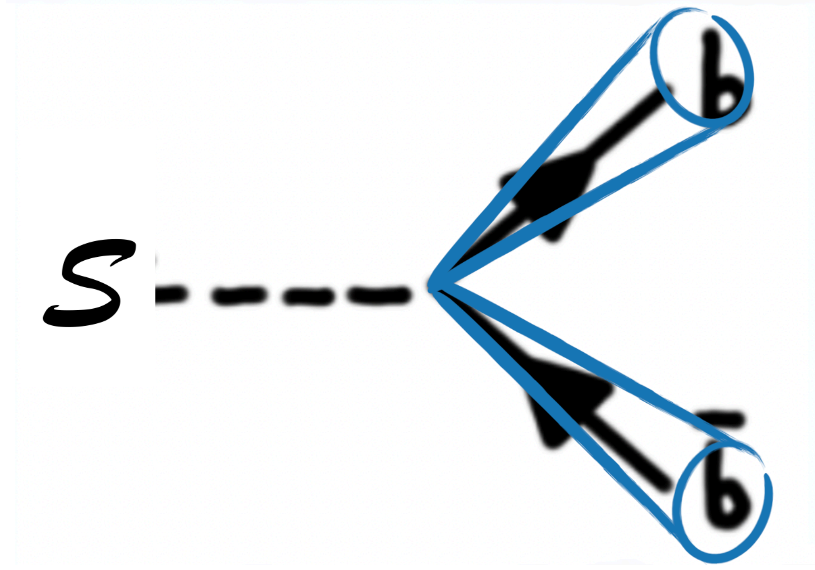
- **Two** tight and isolated **photons**.
- $p_T^{\gamma_{1(2)}}/m_{\gamma\gamma} > 0.35(0.25)$.
- $105 < m_{\gamma\gamma} < 160$ GeV.

+

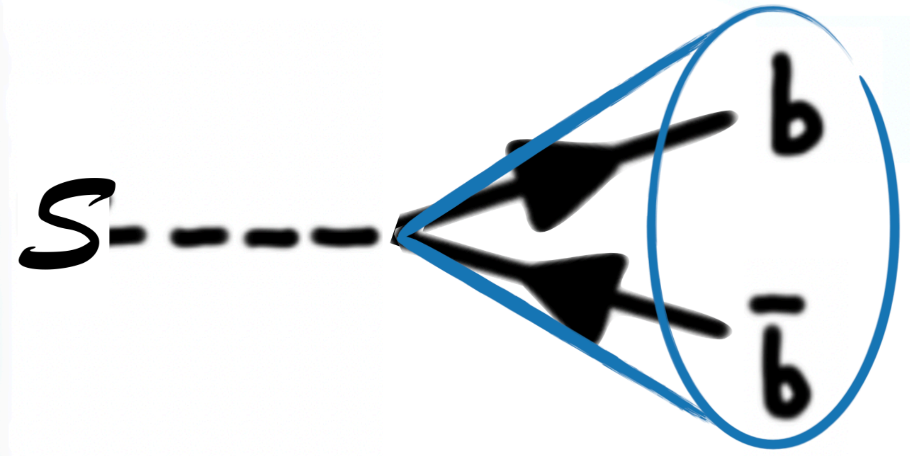
Additional requirements, aimed at suppressing the $t\bar{t}H$ background.

- No electrons or muons.
- Less than 6 jets

***b*-jet selection** → **Two *b*-tag categories**, depending on the **kinematics** of the $S \to b\bar{b}$ **decay**!

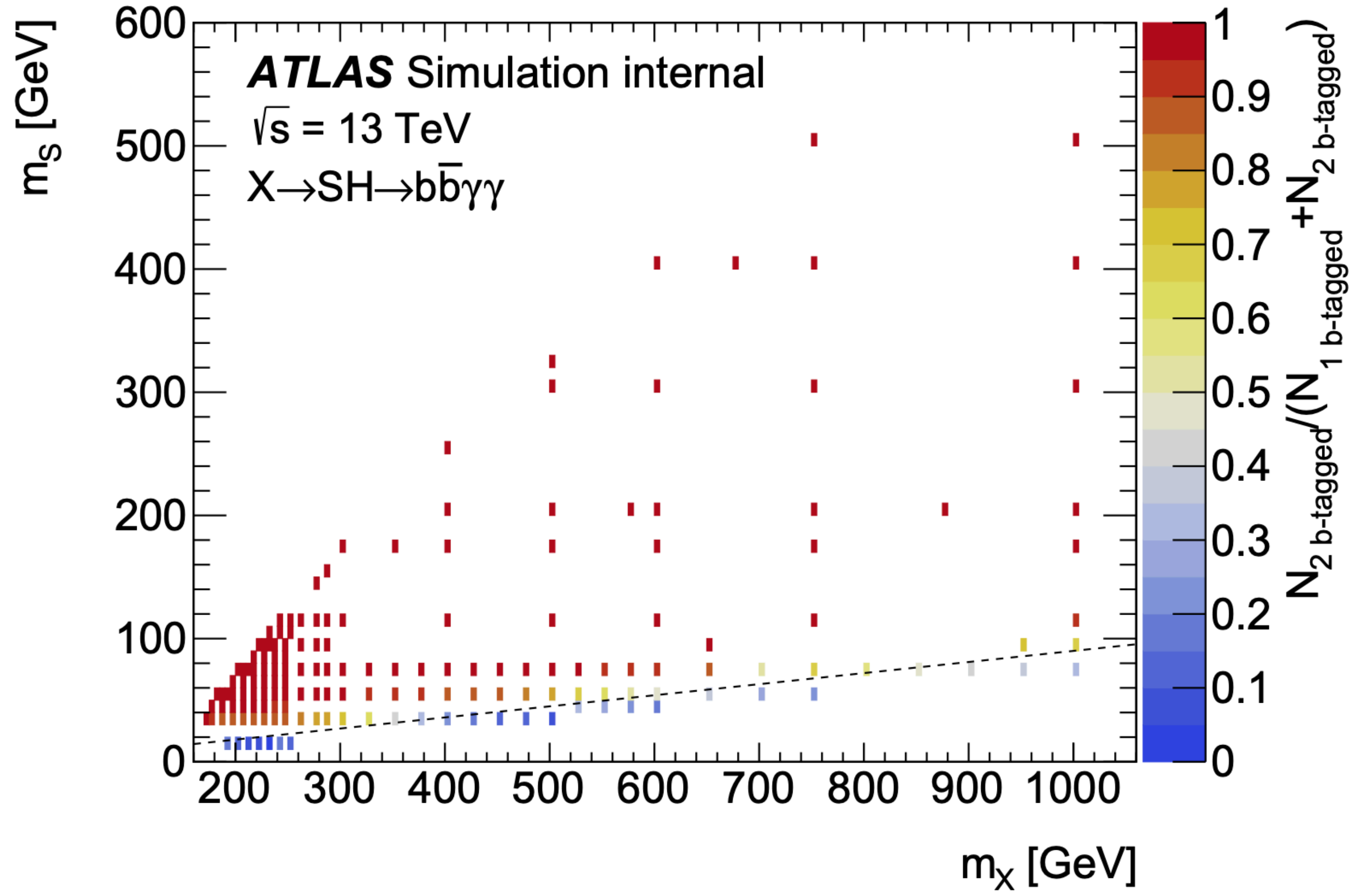


- For $m_S \sim m_X - m_H$, both the bottom quarks from the **resolved** S decay are reconstructed as two separate ***b*-jets.**
- **2 *b*-tagged category**: exactly 2 *b*-jets @ 77% WP.



- For $m_S \ll m_X - m_H$, the two bottom quarks from the **boosted** S decay are reconstructed within the same ***b*-jet.**
- **1 *b*-tagged category**: exactly 1 *b*-jet @ 77% WP.

The **2 *b*-tagged selection** and becomes very inefficient for (m_X, m_S) signals with $m_S/m_X < 0.09$ (= empirical threshold for the **2 *b*-tagged** / **1 *b*-tagged** separation)!



The **2 *b*-tagged** and **1 *b*-tagged** selections are not combined!

Building the PNN-based discriminant

Problem:

- This analysis is targeting the $X \to SH \to b\bar{b}\gamma\gamma$ signal in a **large domain in the 2-dimensional ($\mathbf{m_X}$, $\mathbf{m_S}$) plane**.
- The **characteristics** of the $X \to SH \to b\bar{b}\gamma\gamma$ signal **depend** non-trivially from the **masses** of the two resonances!

Solution:

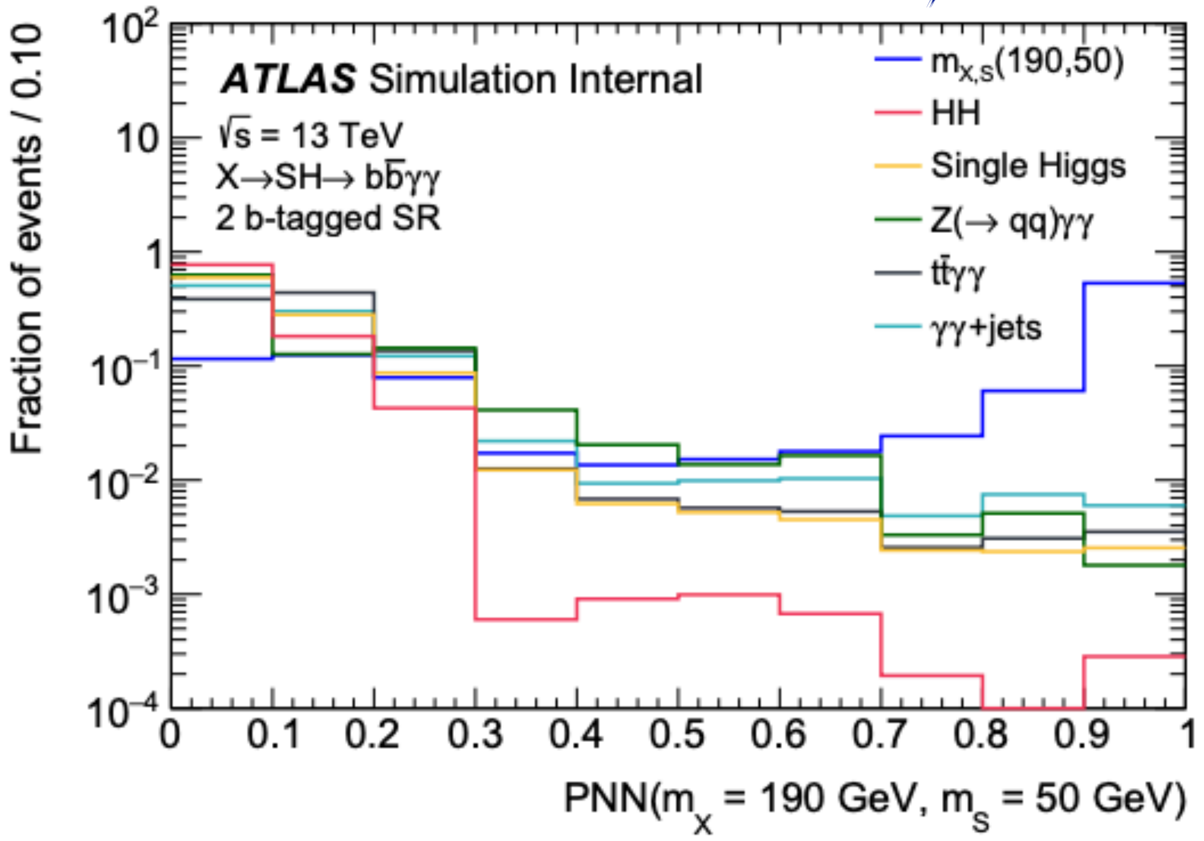
Parameterized Neural Networks (= **PNNs**) are used to **isolate interesting $X \to SH \to b\bar{b}\gamma\gamma$ signal events** from the backgrounds!

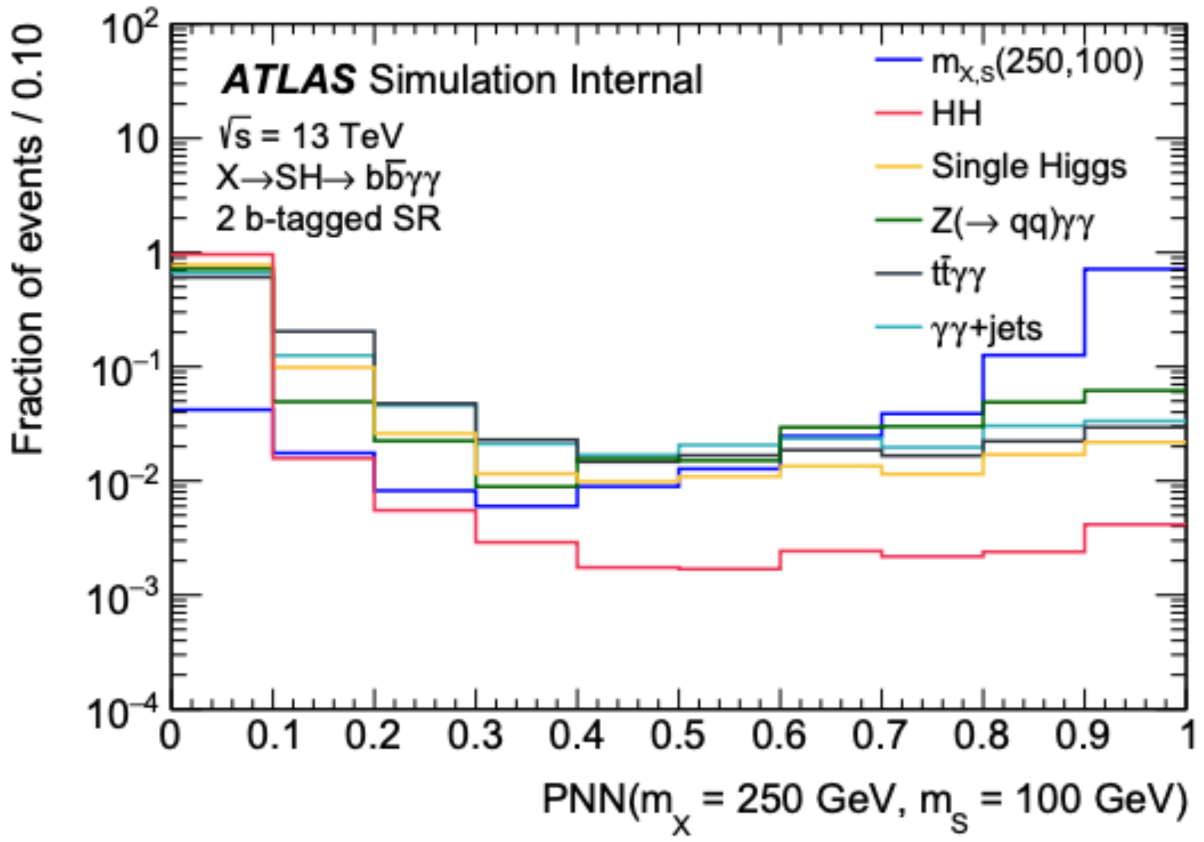
- Both **event-based kinematic quantities** $\vec{x}$ and **search parameters** $\vec{\theta}$ phase space are used as input for the PNNs. → Provides a response that is parameterized as a function of $\vec{\theta}$!
- Training a single network allows to have **continuous sensitivity** across the tested **($\mathbf{m_X}$, $\mathbf{m_S}$) domain**, allowing **signal interpolation** to parameters $\vec{\theta}$ not explicitly included in the training.

Two separate PNNs are trained in the **2 *b*-tagged category** and the **1 *b*-tagged category**.

	Input features	Parameters
2 *b*-tagged	$m_{bb\gamma\gamma^*}$, m_{bb}	m_X, m_S
1 *b*-tagged	$m_{b\gamma\gamma^*}$, p_T^b	m_X

With PNNs, also the shape of the backgrounds also depends from the ($\mathbf{m_X}$, $\mathbf{m_S}$) parameters!





Using PNN outputs as final discriminant

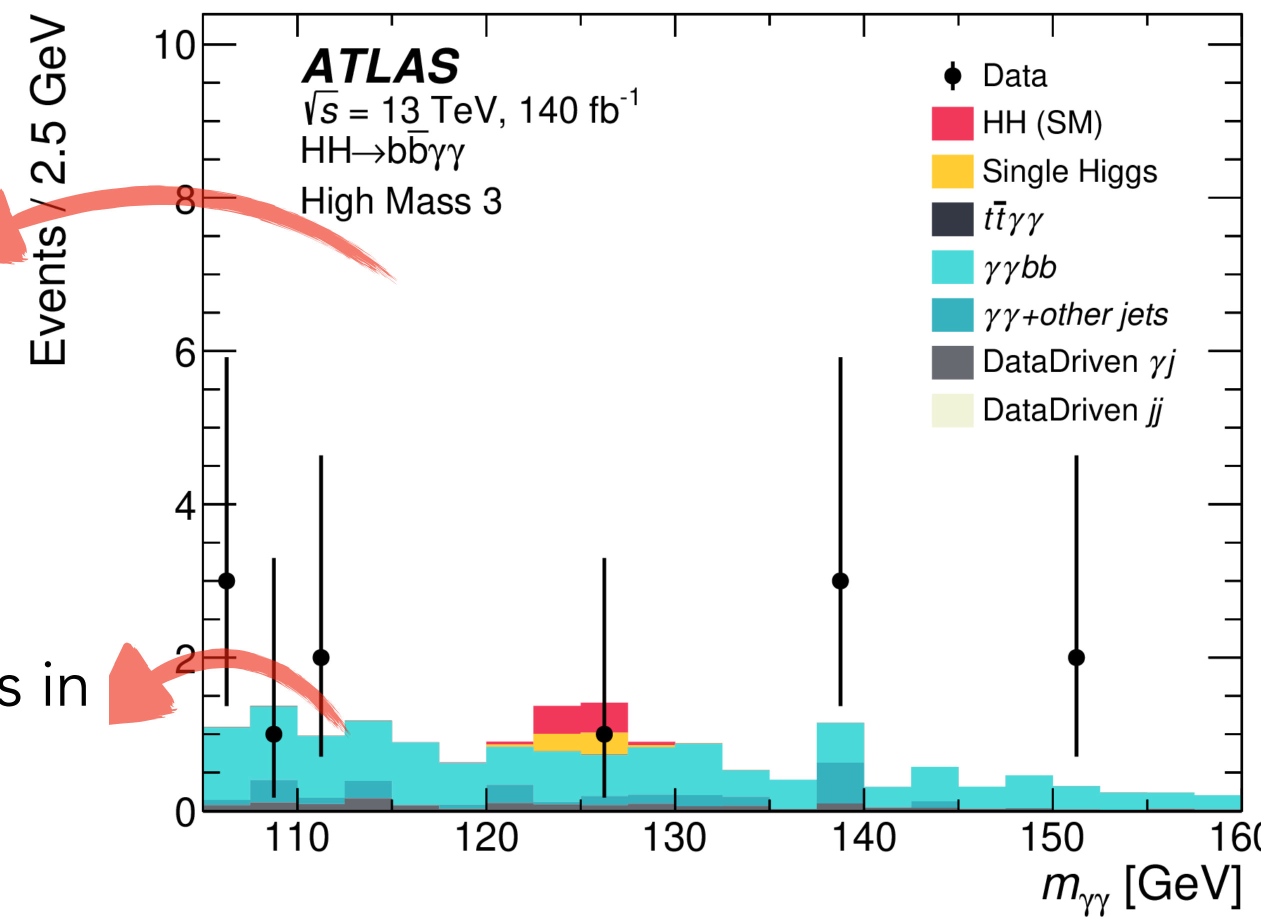
In the **traditional** $H \to \gamma\gamma$ analyses, the **di-photon invariant mass** $m_{\gamma\gamma}$ is typically used as **final discriminant** variable.

However, this choice has some **drawbacks**:

1. The background modeling strategy (= analytical function fitted on data) requires to have a **minimum number of events** in each category.
   - **Drives** the analysis **sensitivity** in **statistically limited** analyses!
2. The estimation of the only bkg. modelling systematic (= the spurious signal) is based on a **background-only MC template**, which may have very **poor statistics after** applying the **event selection**, leading to an **over-pessimistic estimation.**

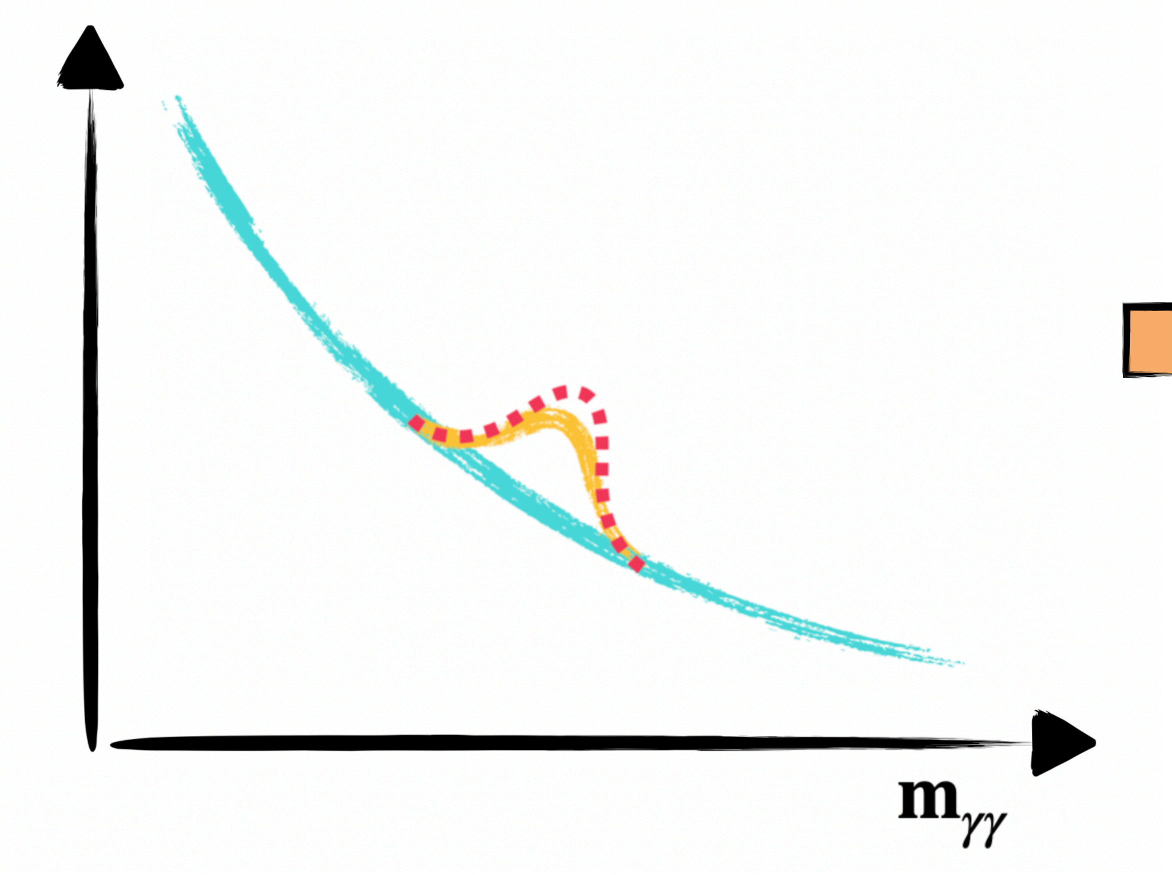
Very few data events!

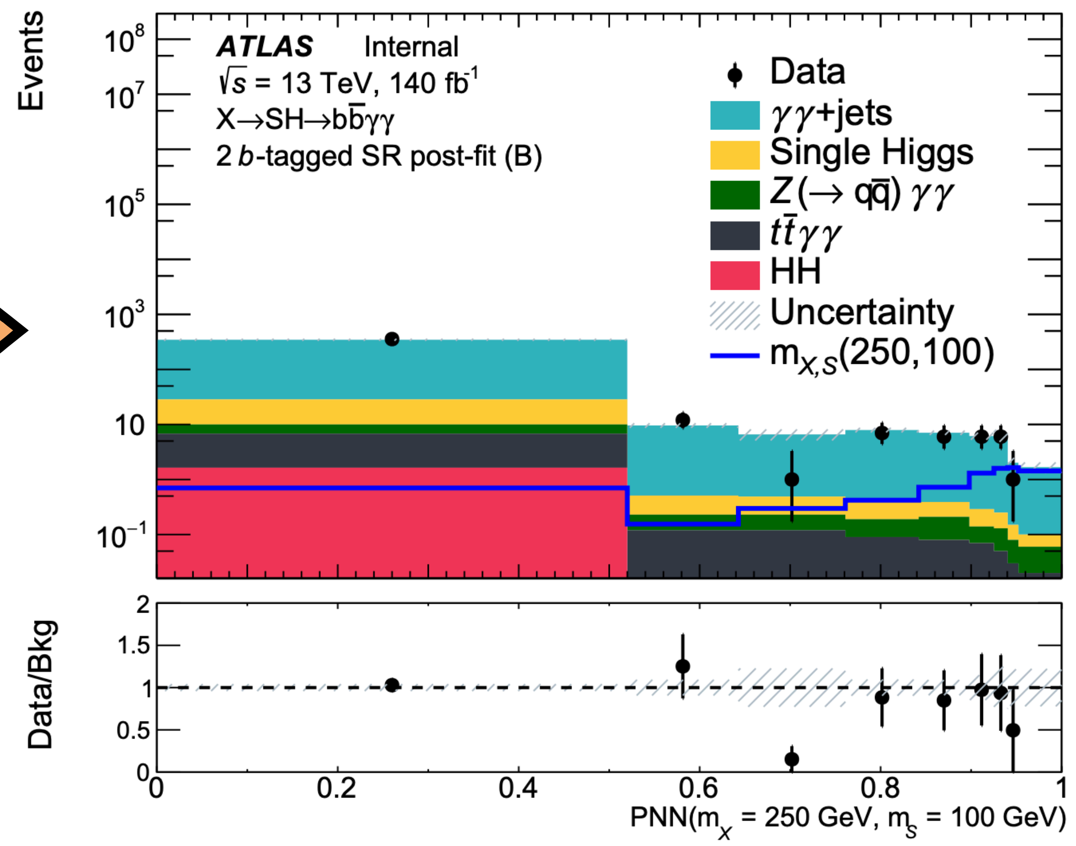
Large fluctuations in continuum bkg.!



Question: Can we address these drawbacks by experimenting with the analysis workflow?

From fitting on $\mathbf{m}_{\gamma\gamma}$ distributions… …to fitting on **PNN outputs**!





- Instead of applying cuts on the PNN discriminant to build analysis categories and fitting $m_{\gamma\gamma}$ in each category, we use the PNN output directly in the final fit. → The statistical results are derived via a binned maximum likelihood fit to the PNN distributions
- The $X \to SH \to b\bar{b}\gamma\gamma$ **signal** , the **SM HH**, the **single Higgs**, and the **continuum backgrounds** are **modelled** using **histograms** of the PNN **outputs** from the corresponding **MC** samples.
  - Completely **different modelling strategy**!
  - No need of requiring a minimum number of data events in each category, and **no spurious signal** is needed!

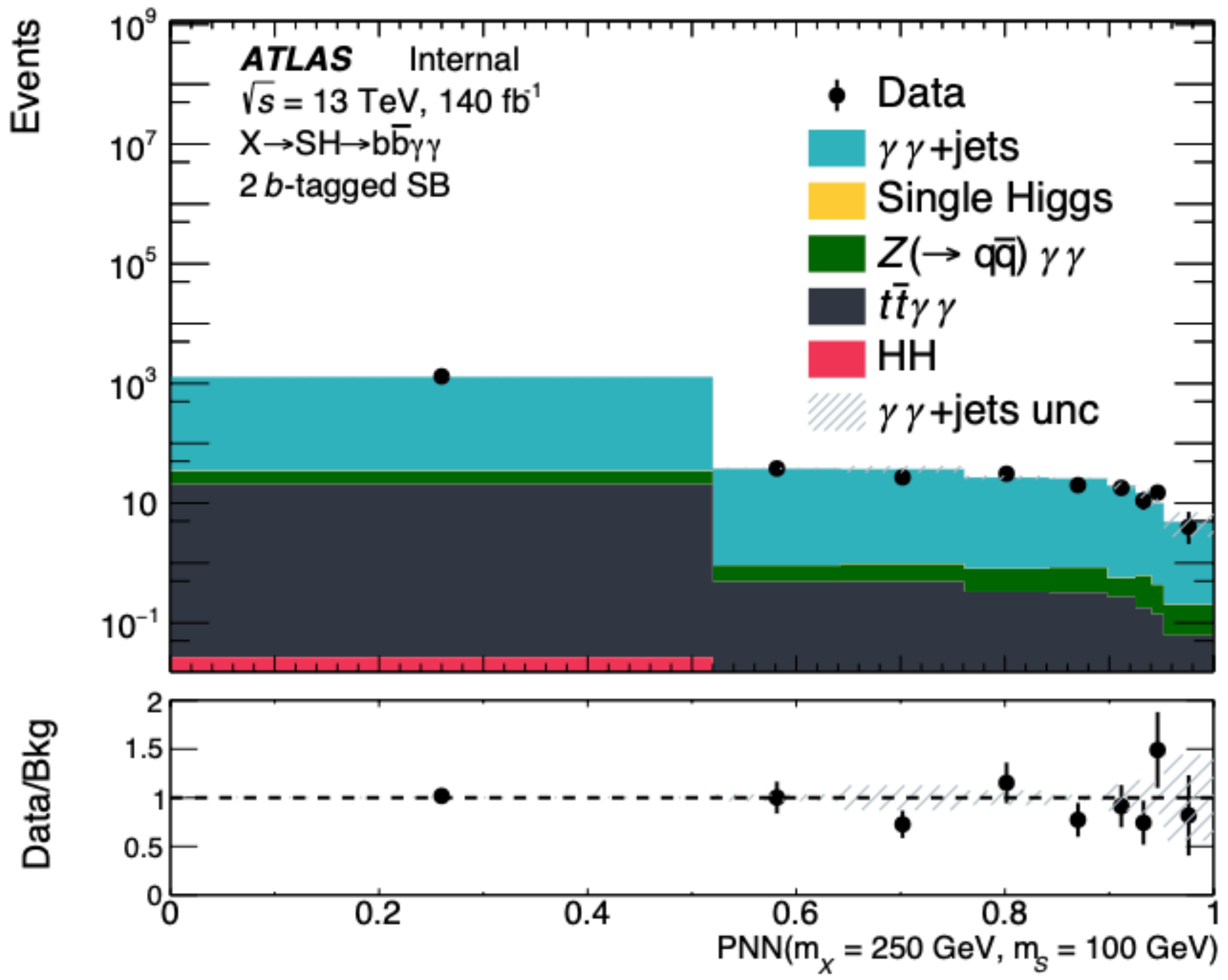
Background estimation

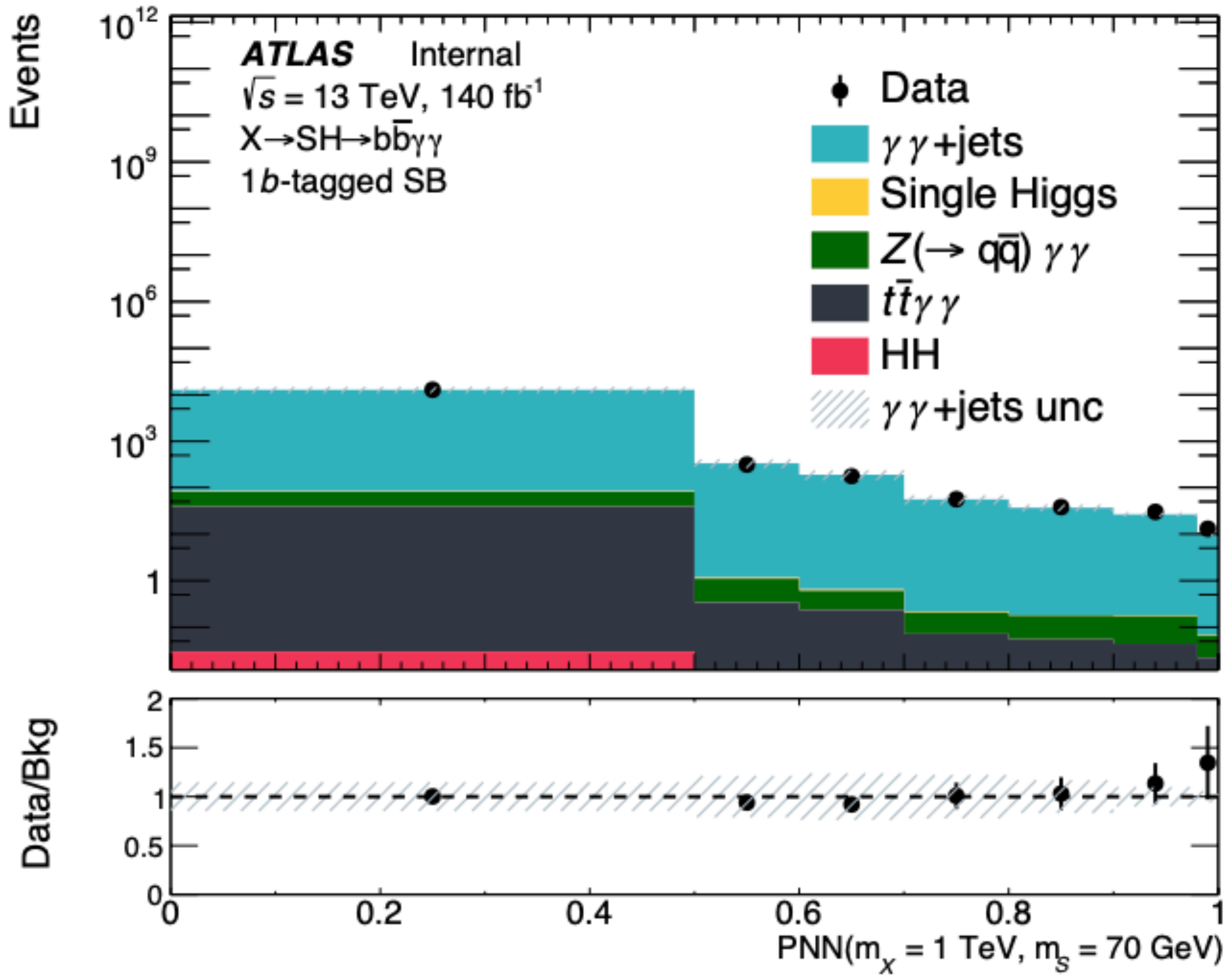
Continuum background

With this **new analysis workflow** adopted by the $SH \to b\bar{b}\gamma\gamma$ analysis, we need to **completely rethink** the **modelling** of the **continuum bkg.**, w.r.t. the traditional $H \to \gamma\gamma$ analyses.

$\gamma\gamma$ **component** = 85% of the continuum bkg., measured with the ABCD method.

Instead of having a **data-driven bkg. estimation**, we rely on the $\gamma\gamma$+jets MC sample for building **histograms of the PNN output**, to use directly in the fit.





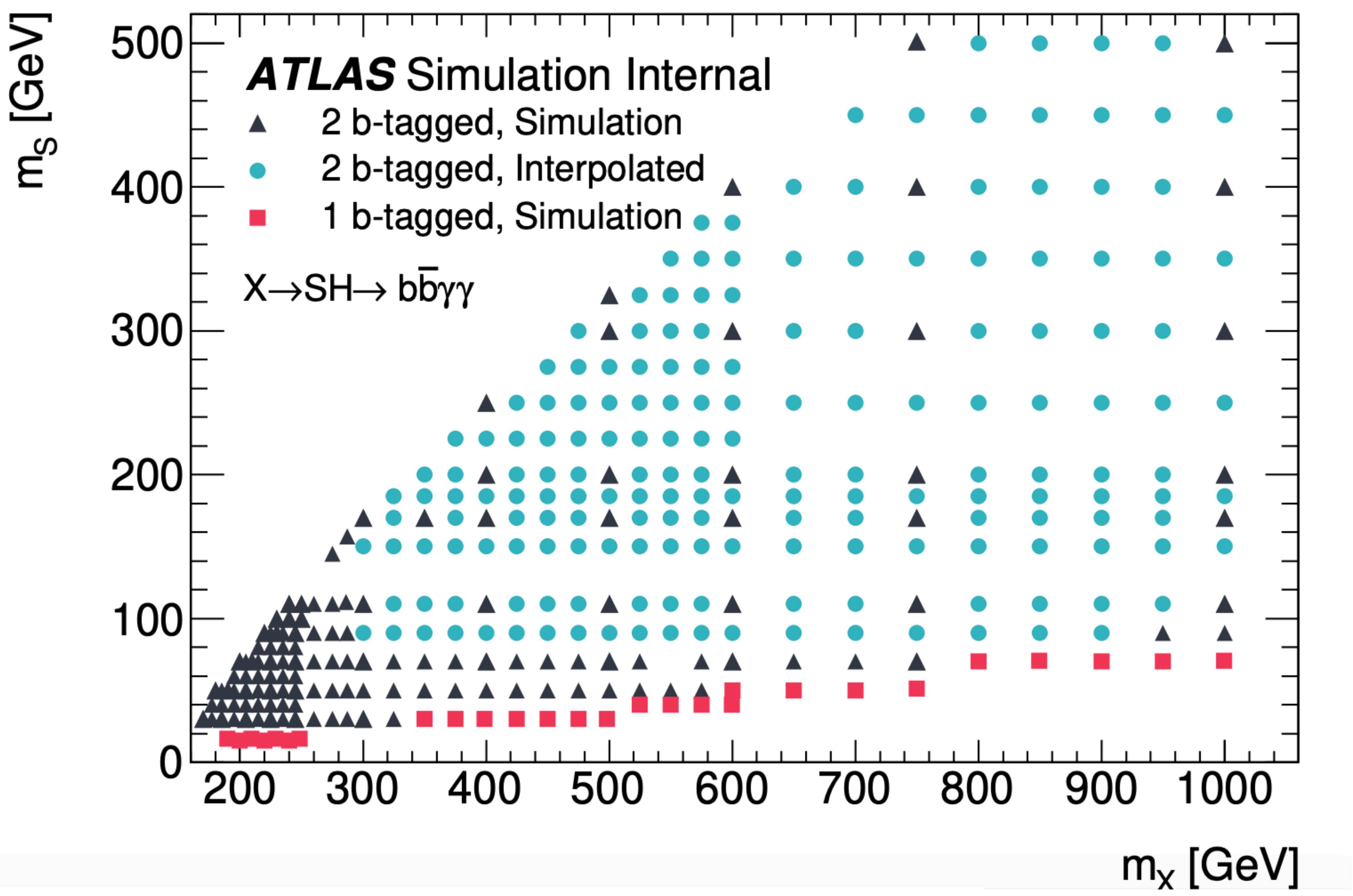
- The data / MC agreement in the spectrum of the PNN output was checked in the $m_{\gamma\gamma}$ sidebands (= CR), where the contribution of the **other resonant backgrounds** (SM HH and single Higgs) is negligible.
- A good agreement between the PNN shape in real data and $\gamma\gamma$+jets MC is found!
  - The impact on the **shape** of the continuum bkg. in the spectrum of the PNN output from the **reducible** γj **and** jj **components** can then safely be **neglected**.
  - Their contribution to the **overall normalization is adjusted during the fit**, thanks to a $\gamma\gamma$ **K-factor**.
  - The new **continuum bkg. modelling is** solid!

Non-resonant SM HH and single Higgs backgrounds

- Minor backgrounds!
- Well modeled by MC simulations.

Both the **normalization** and the **shapes** are modeled using **MC samples**, normalized to the most accurate available **theoretical cross-section**.

Signal interpolation in the (m_X, m_S) plane



- To fully exploit the discriminating power of the PNN across the 2-dimensional $(\mathbf{m_X}, \mathbf{m_S})$ plane, we would like to search for $\mathbf{X} \rightarrow \mathbf{S}(\rightarrow \mathbf{b\bar{b}})\mathbf{H}(\rightarrow \gamma\gamma)$ signals in intermediate $(\mathbf{m_X}, \mathbf{m_S})$ points, where a dedicated MC sample was not simulated.
- A **signal interpolation interpolation** procedure is applied, in order to define a **finer search grid** in the $(\mathbf{m_X}, \mathbf{m_S})$ plane.
  - ➡ The step of the grid is chosen such that the PNN (evaluated for the tested $(\mathbf{m_X}, \mathbf{m_S})$ points) would not miss a signal "in-between".
    - ➡ - ~ 5 GeV step in the densest (= low mass) region.
    - - ~ 50 GeV step in the less granular (= high mass) region.

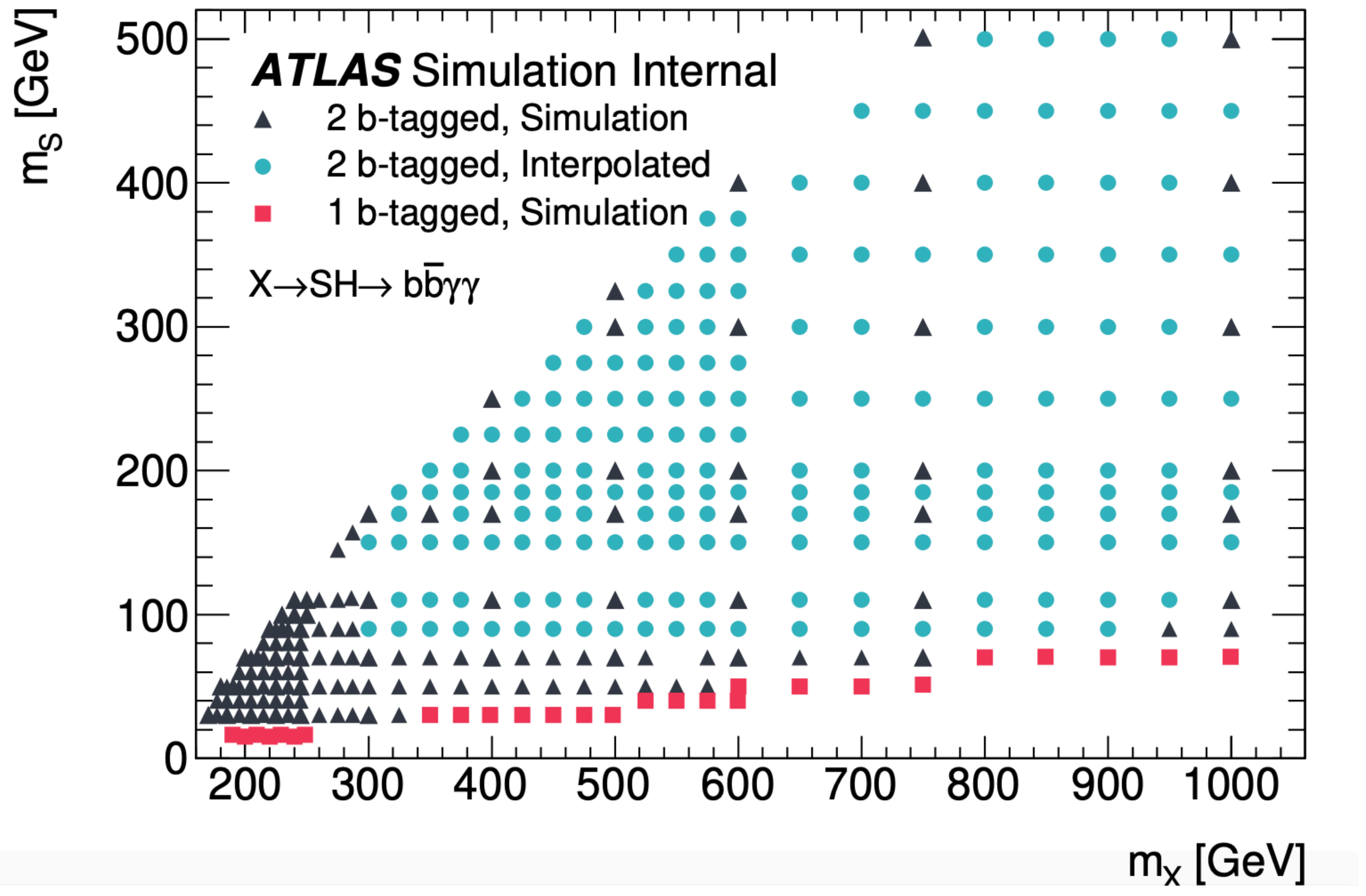
Recipe of the interpolation procedure

1. The 4-vectors of the particles $\mathbf{X}$, $\mathbf{S}$, and $\mathbf{H}$ are measured using the reconstructed kinematics of the two selected photons and b-jets, and recomputed in the rest frame of $\mathbf{X}$, where the 4-vector only depend from $\mathbf{m_X}$, $\mathbf{m_S}$, and $\mathbf{m_H}$.

   ➡ Only possible in the **2 *b*-tagged category**, where both the b-jets are reconstructed.

2. The interpolated signal is then reweighted, such that the resolution of the two resonances $\mathbf{X}$ and $\mathbf{S}$ matches the expected resolution from experimental effects in the new nearby $(\mathbf{m_X}, \mathbf{m_S})$ point.

Signal interpolation in the (m_X, m_S) plane



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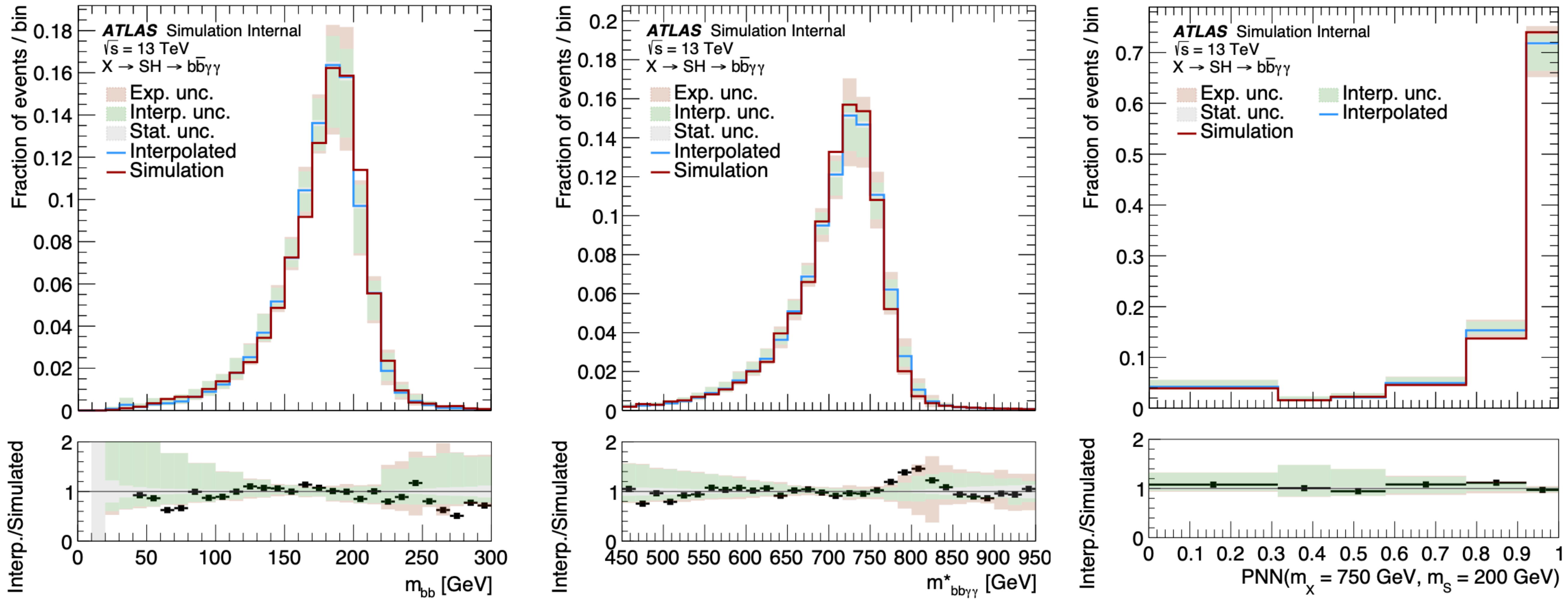
Validation of the interpolation procedure



- Good closure for the interpolation procedure for the high mass region (where the two b-jets are well resolved).
- An additional uncertainty (up to $\sim 10\,\%$) is assigned to the interpolated signals in the fit.

Systematic uncertainties

		Signal X→SH→bbγγ	ggF HH	VBF HH	Single Higgs	γγ+jets
Theory	Cross section and branching fraction	-	• BR(γγ) (2.9%) and BR(bb) (1.7%) • PDF + α_S (3%) • Scale + mtop ($^{+6\%}_{-23\%}$)	• BR(γγ) (2.9%) and BR(bb) (1.7%) • PDF + α_S (2.1%) • Scale (0.04%)	• BR(γγ) (2.9%) • Heavy Flavor uncertainty (100%, only for ggF, VBF, and WH)	-
Theory	Acceptance	-	Scale, PDF + α_S (ready for main single H bkg.)			-
Theory	Yield + Shape	Scale, PDF + α_S, Parton Shower	Parton Shower			Scale, PDF + α_S, PDF set, Modeling
Theory	Yield + Shape	Interpolation in the (m_X, m_S) plane.	-			
Exp.	Yields + Shape	• Pile-up modelling; • Di-photon trigger efficiency; • Photon identification and isolation efficiency; • Photon energy scale and resolution; • Jet energy scale and resolution; • Jet vertex tagger efficiency; • Flavour tagging efficiencies.				

- The impact of each source of **systematic uncertainty** has to be quantified and included when performing the **statistical analysis**.

  Providing **varied templates**, where theoretical and experimental systematics are propagated.

- The **modelling uncertainty** for the **$\gamma\gamma$+jets MC sample** is implemented by providing **alternative background template**, from an **alternative $\gamma\gamma$+jets MC sample** that relies on a **different generator for the ME and the PS (MG + Py8)** w.r.t. the nominal sample (Sherpa 2.2.12).

  Driven by the limited statistics of the MG + Py8 alternative sample!

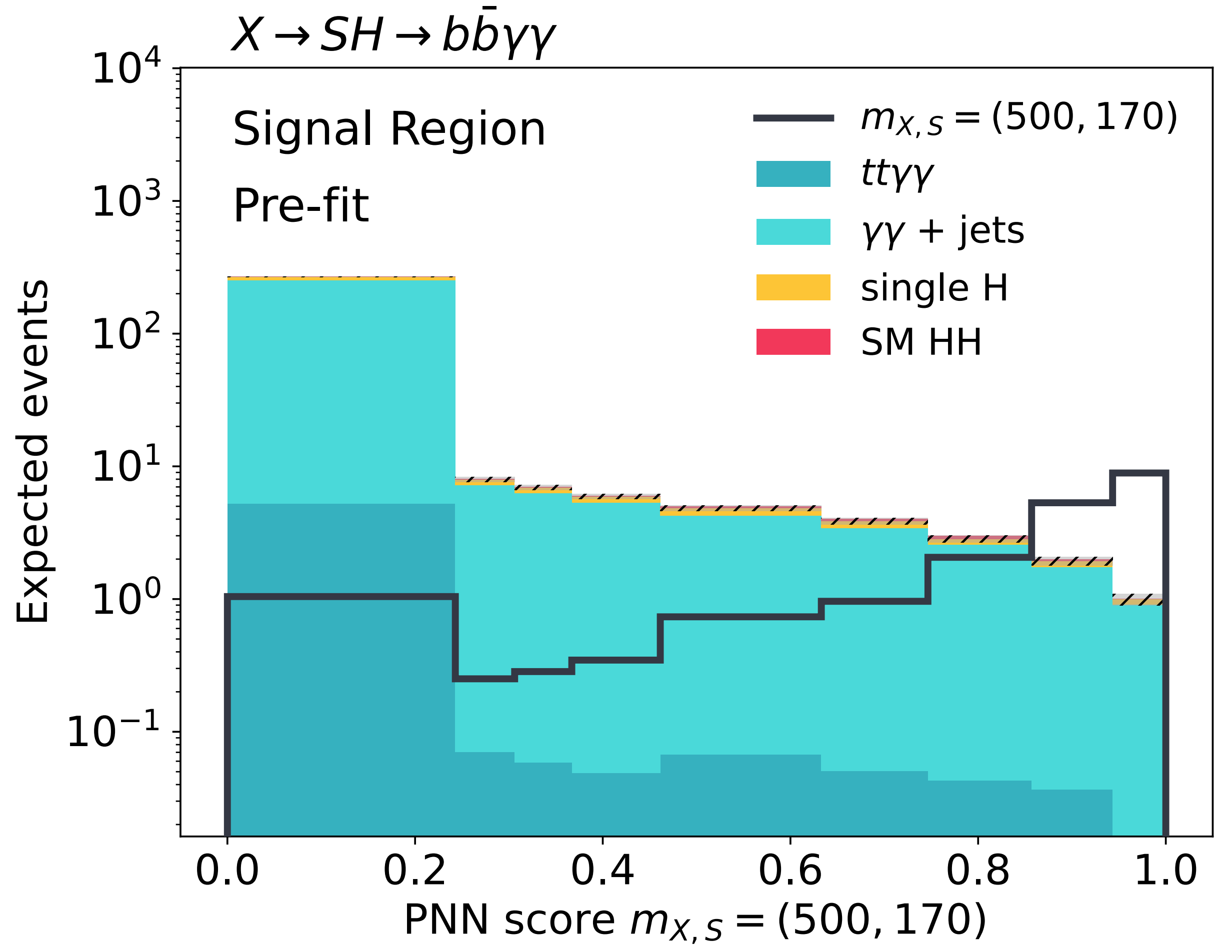
Analysis regions & modeling strategy

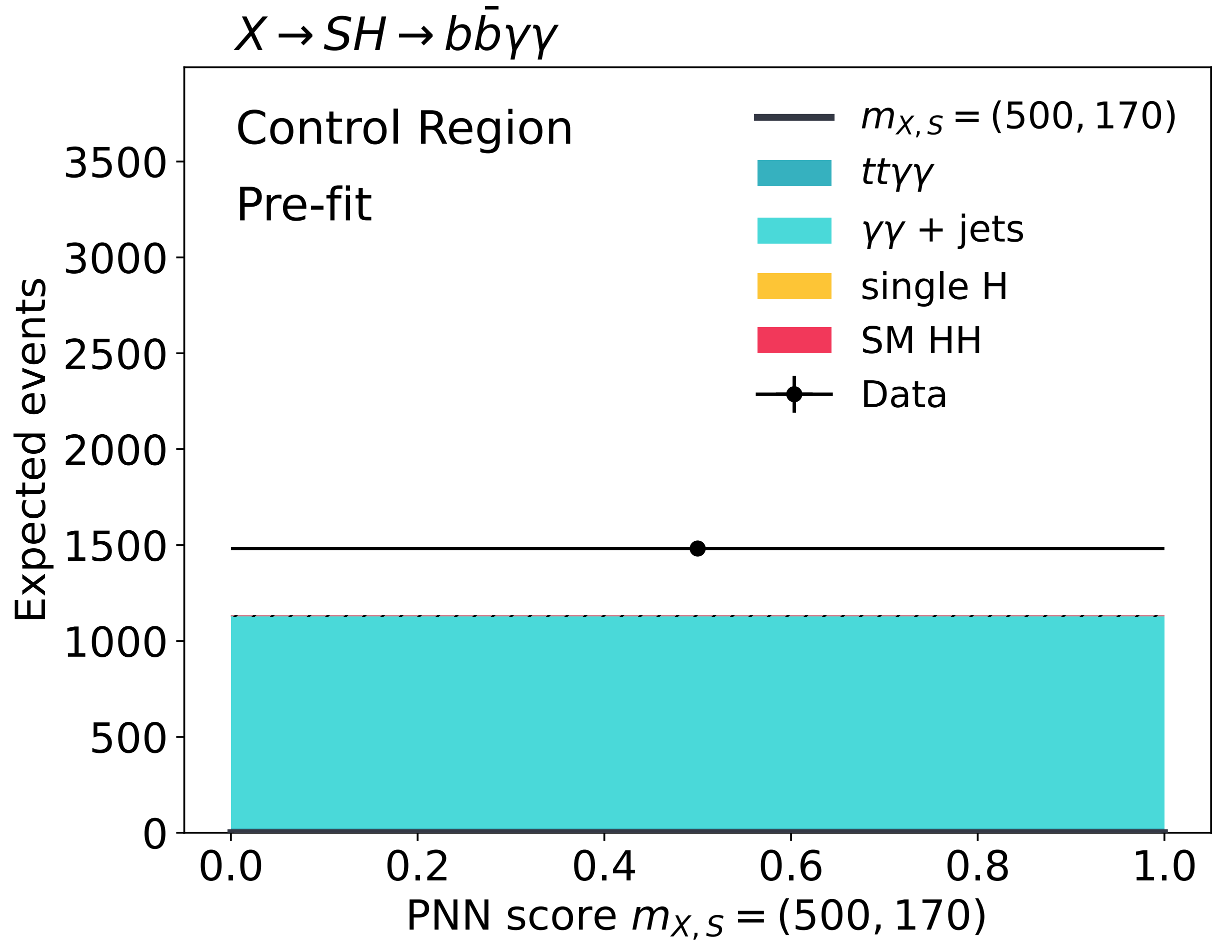
Two orthogonal analysis regions are defined, based on the variable $\mathbf{m}_{\gamma\gamma}$. → We still rely on the discriminating power of $\mathbf{m}_{\gamma\gamma}$!

Signal Region ⟷ (Norm. factor) ⟷ **Control Region**

Signal Region: $120 < \mathbf{m}_{\gamma\gamma} < 130$ GeV

Control Region: $105 < \mathbf{m}_{\gamma\gamma} < 120$ GeV or $130 < \mathbf{m}_{\gamma\gamma} < 160$ GeV



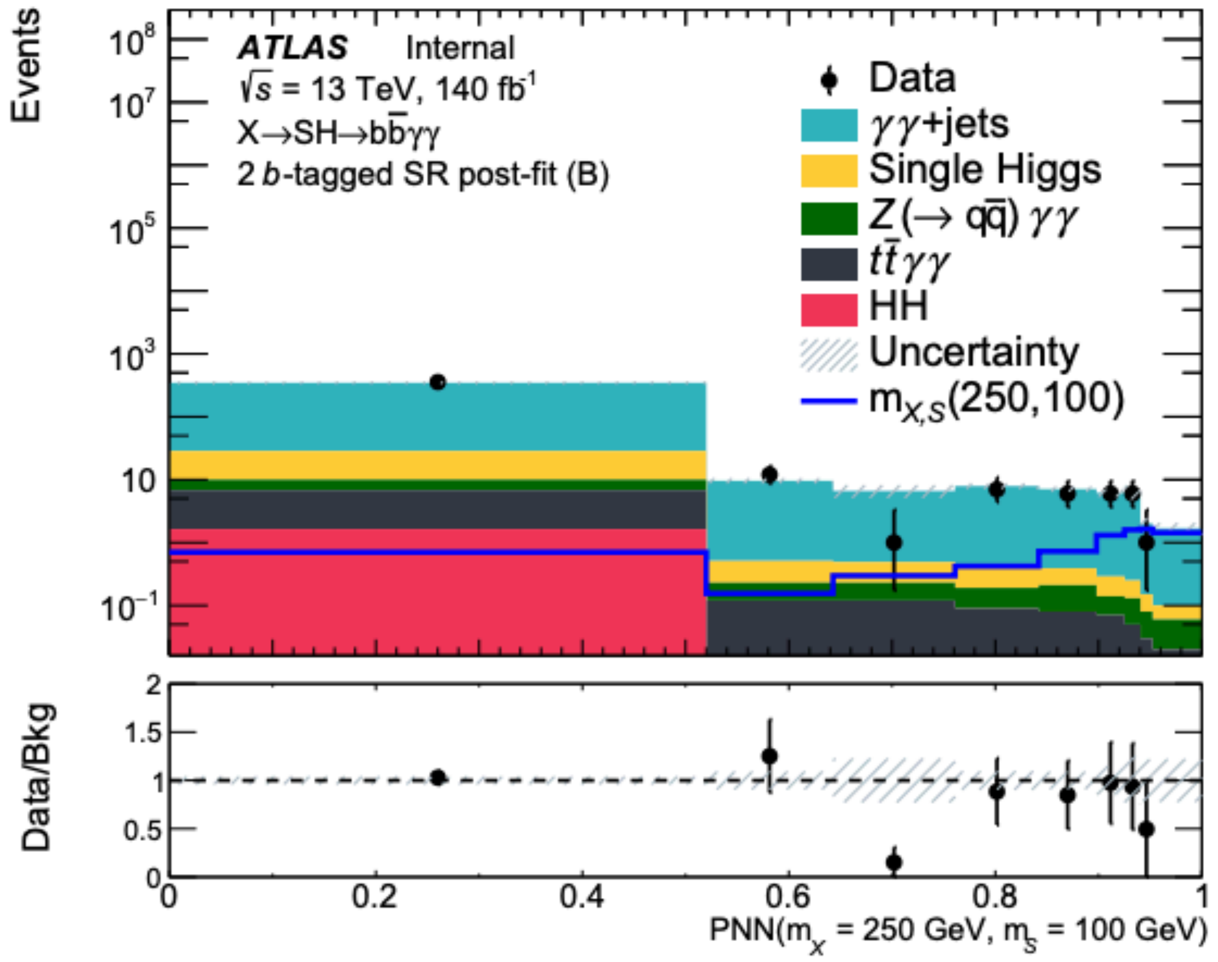


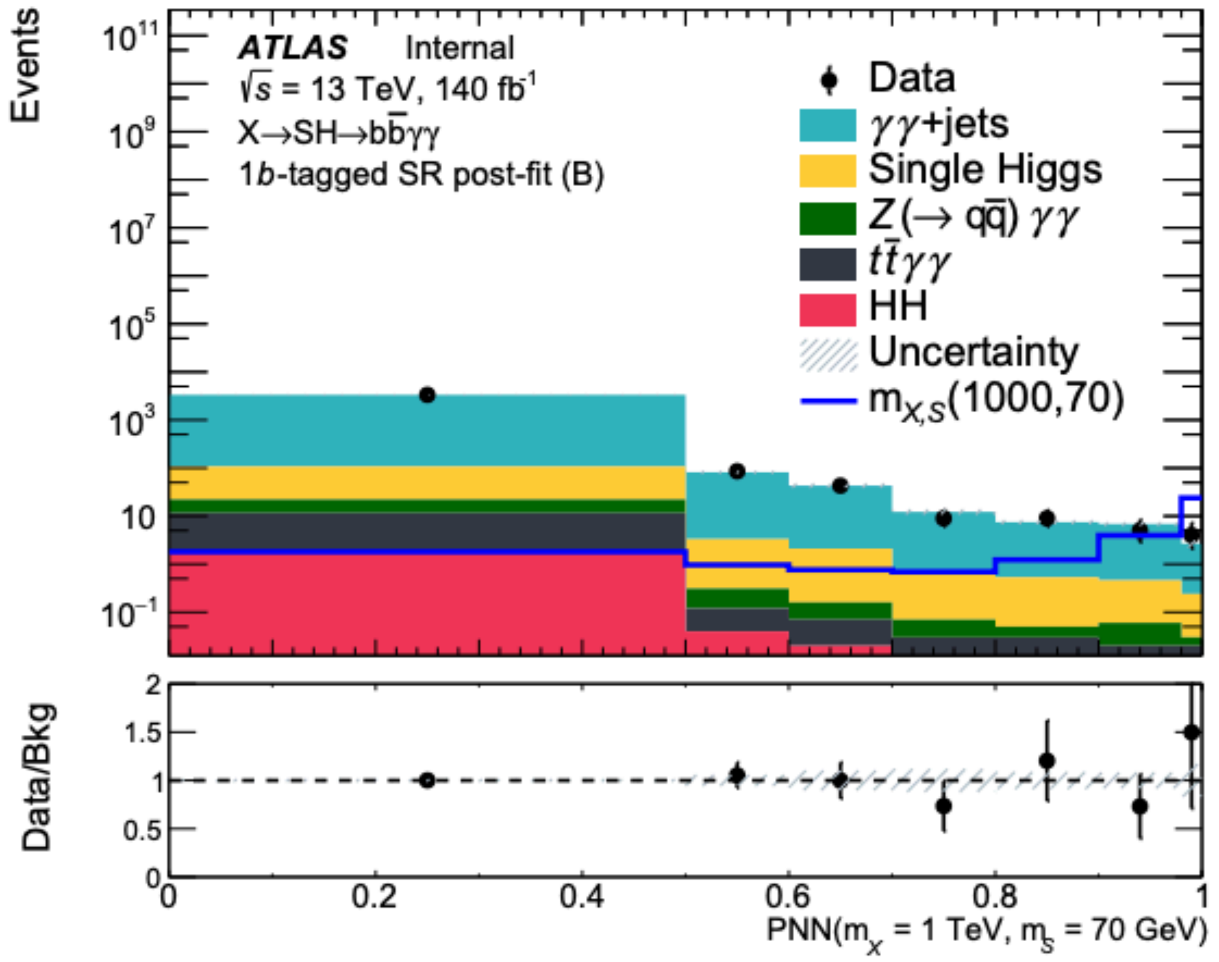
- The **normalization** of the continuum background template relies on a **normalization factor (=** $\gamma\gamma$ **K-factor)**, extracted directly from the fit to data.
- The $\gamma\gamma$ **K-factor is mainly constrained in the Control Region (CR)**.
  - ➡ **Very low contamination** from **signal**, non-resonant SM HH, and single Higgs processes.
    - ➡ - **Resonant** in the $m_{\gamma\gamma}$ spectrum, around $\mathbf{m_H = 125}$ GeV!
    - - Their contribution is only relevant in the SR.

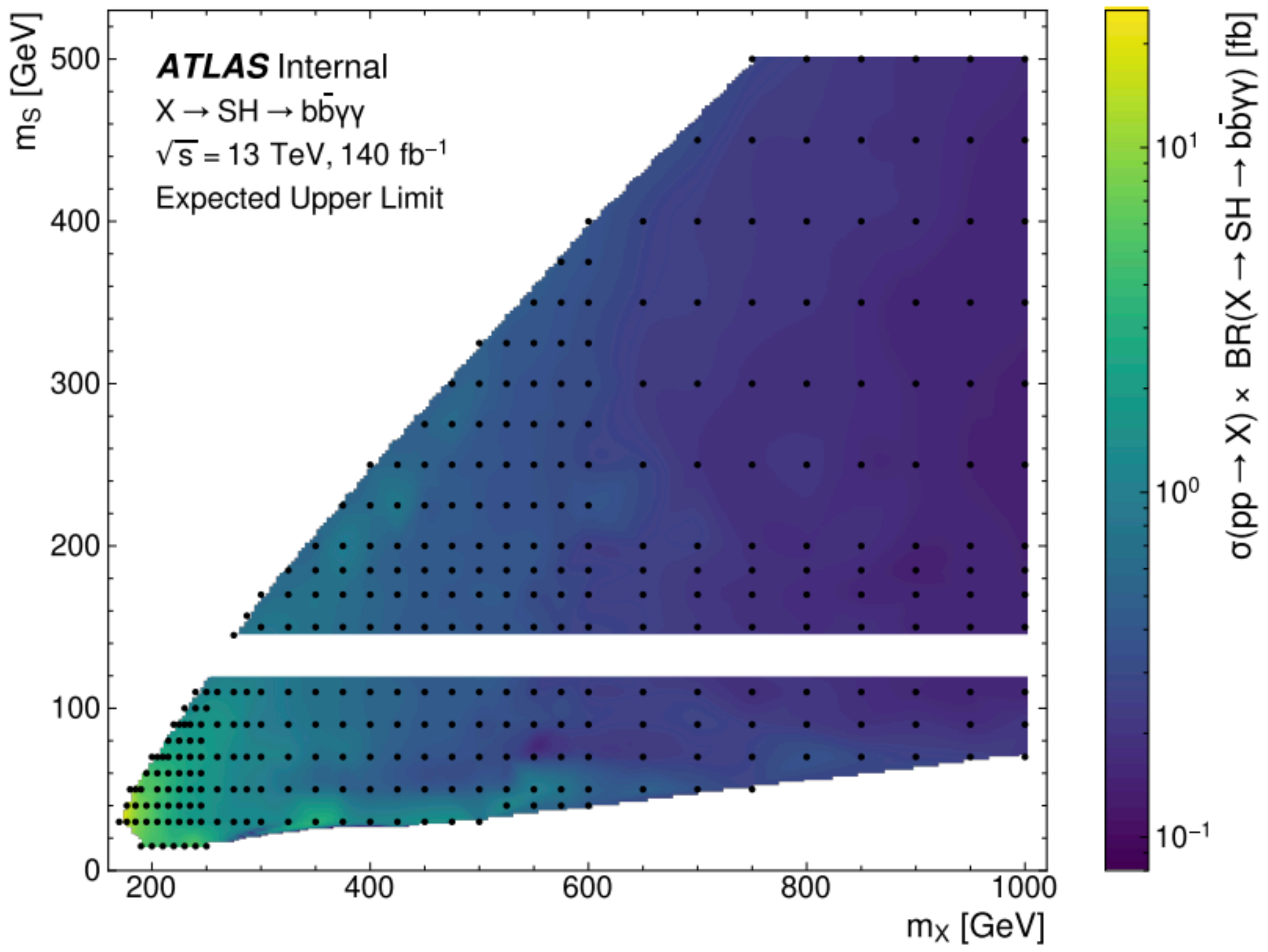
	Signal Region	Control Region
Modelling in the spectrum of the PNN output	**Finely binned histograms** are defined, to extract the best possible sensitivity to the SH signals. ➡ The **bins** in the PNN output **depend** on the **particular** (m_X, m_S) **point**, and we require to have at least **1 expected bkg event in each bin**.	The main role of the CR is to **normalize** the **continuum background** to **data**. ➡ **Single-bin histograms** are used.

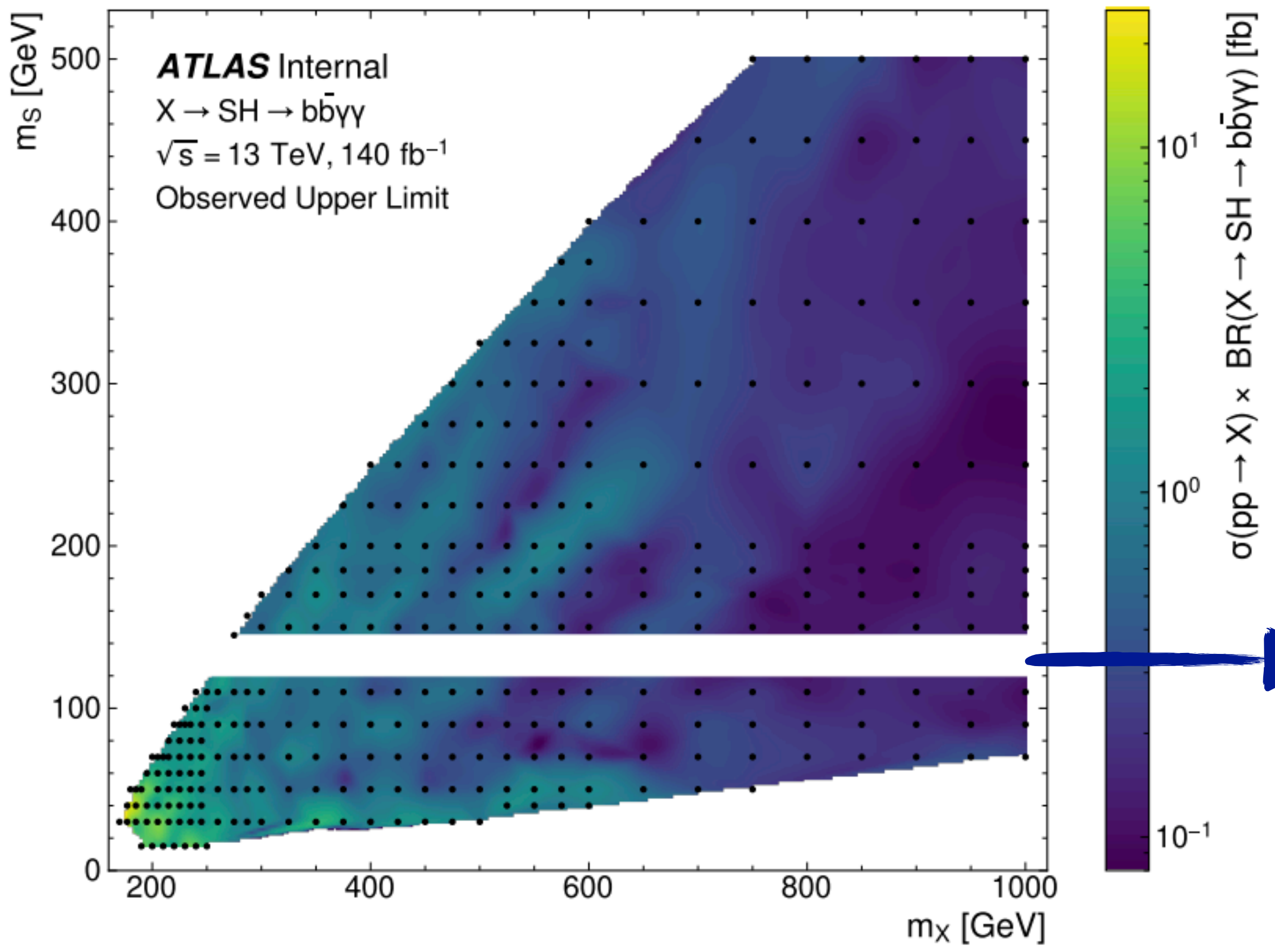
Statistical results

Given a tested $(\mathbf{m_X}, \mathbf{m_S})$ signal, the final results are extracted via a **binned maximum likelihood fit** to the **PNN output**, performed **simultaneously** in the **SR** and the **CR**.









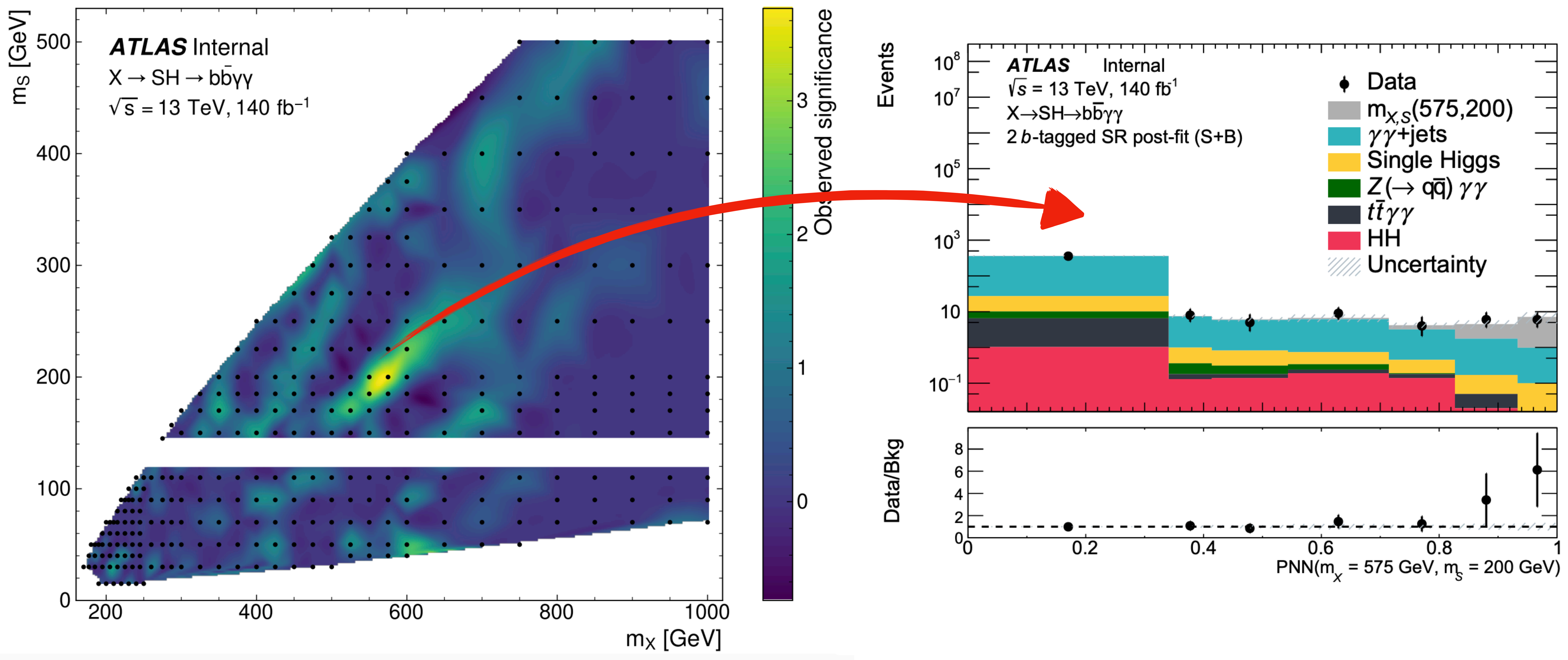
- For most $(\mathbf{m_X}, \mathbf{m_S})$ points, a **good agreement** is observed between the data and the **background only expectation**.
- The largest **deviation** is observed for $(\mathbf{m_X}, \mathbf{m_S}) =$ **(575, 200) GeV**.

Interesting excess, with a **local significance of 3.5σ**!

- The results are interpreted in terms of **upper limits** on the the $X \to SH \to b\bar{b}\gamma\gamma$ **cross-section** across the **2-dimensional** $(\mathbf{m_X}, \mathbf{m_S})$ plane!

The band where $\mathbf{m_S} \approx \mathbf{m_H} = \mathbf{125}$ GeV is excluded, since it was **already covered** by the previous Run 2 $X \to HH \to b\bar{b}\gamma\gamma$ analysis!

Investigation of the excess: evaluation of the global significance



- A **interesting excess** emerges from the signal+background fit, with a **maximum** of the **local significance** at $(\mathbf{m_X}, \mathbf{m_S})$ = **(575, 200) GeV (= 3.5σ)!**
- However, since we are looking for a $X \to SH \to b\bar{b}\gamma\gamma$ **signal** in a **wide range** of **masses** for the two resonances, we need to take into account the **"look elsewhere effect"** for evaluating the significance of our excess.

  ➡ **= evaluate the global $\mathbf{p_0}$ / significance!**

Recipe for evaluating the global significance

- Definition of the global $\mathbf{p_0}$:

  Global $\mathbf{p_0} = \mathbb{P}\,(\max_{\theta\in\mathcal{M}} q(\theta) > q_{obs}\,|\,\mu = 0)$ ⟶ ➡

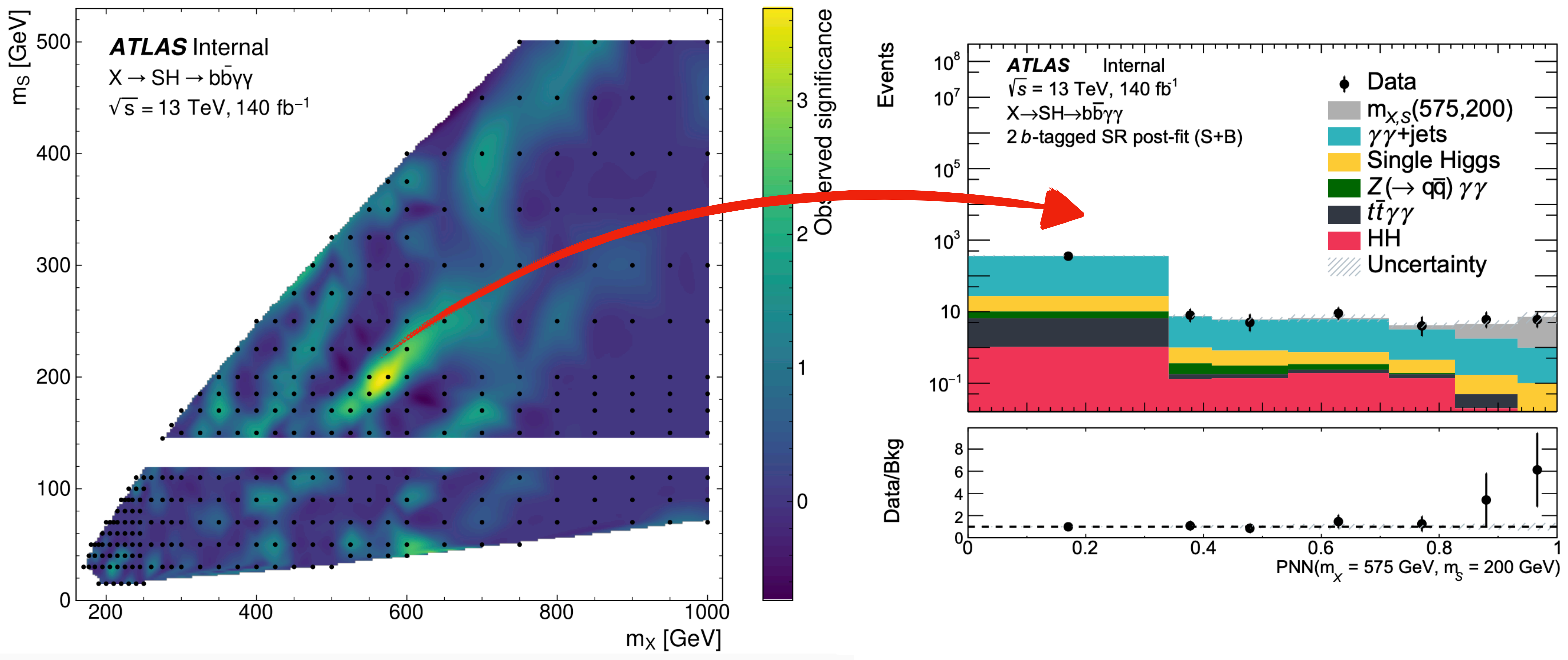
  Unfeasible to evaluate directly, because it requires to estimate the distribution of the maximum of the test statistic $\max_{\theta\in\mathcal{M}} q(\theta)$.

  - Would need to **generate** $\sim 10^4$ **toy MC experiments**, and perform the full $X \to SH \to b\bar{b}\gamma\gamma$ analysis for each of them to obtain a value for $\max_{\theta\in\mathcal{M}} q(\theta)$.
  - 359 tested $(\mathbf{m_X}, \mathbf{m_S})$ signals $\times\ 10^4$ toys = **too many fits**!

- **Solution**: we relied on the asymptotic method described in this paper.

  ➡ Still requires to generate a limited number of bkg. only toys, but feasible! ⟶ 359 tested $(\mathbf{m_X}, \mathbf{m_S})$ signals × 20 toys = 7180 fits!

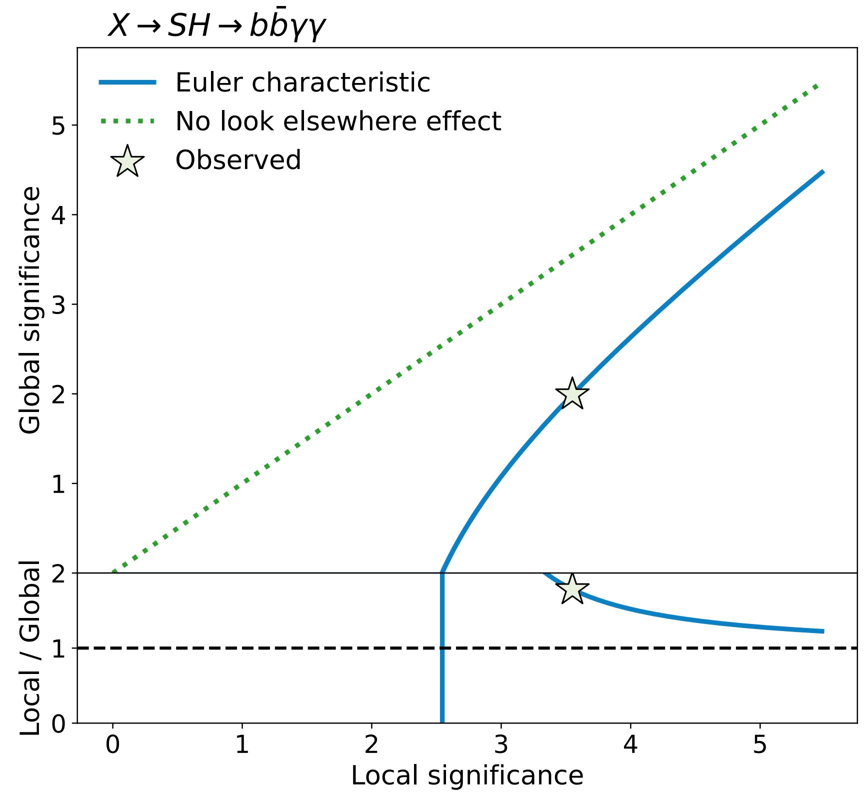
Investigation of the excess: evaluation of the global significance



- A **interesting excess** emerges from the signal+background fit, with a **maximum** of the **local significance** at $(\mathbf{m_X}, \mathbf{m_S})$ = **(575, 200) GeV (= 3.5σ)!**
- However, since we are looking for a $X \to SH \to b\bar{b}\gamma\gamma$ **signal** in a **wide range** of **masses** for the two resonances, we need to take into account the **"look elsewhere effect"** for evaluating the significance of our excess.

= evaluate the global $\mathbf{p_0}$ / significance!

Global significance: results



The asymptotic method that we adopted allowed us to estimate the global significance as a function of the maximum value of the local significance for the $SH \to b\bar{b}\gamma\gamma$ analysis, together with an uncertainty!

Max. of the local significance	3.5
Global significance	1.992 +/- (-0.016, +0.021)

Summary

- We presented a **search** for a heavy scalar resonance $\mathbf{X}$, decaying in a Higgs boson $\mathbf{H}$ and an additional lighter scalar $\mathbf{S}$ in the $b\bar{b}\gamma\gamma$ final state, using data collected by ATLAS during the full Run 2.

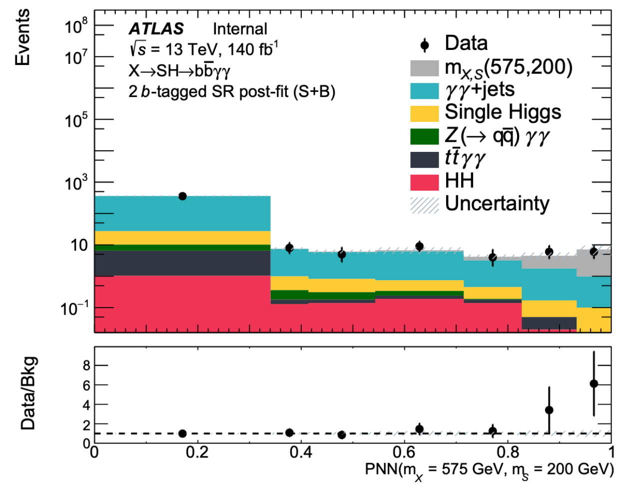
  The $X \to SH \to b\bar{b}\gamma\gamma$ phenomenology at the LHC is predicted by **many extensions of the SM**, describing an **extended Higgs sector** with many scalar particles, which (aside from the SM Higgs boson), still r**emain to be discovered**.

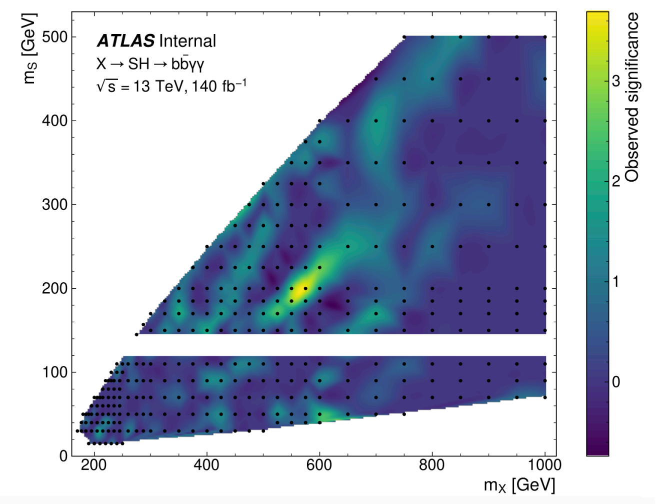
- The search is conducted in a wide range of masses for the two resonances $\mathbf{m_X}$ and $\mathbf{m_S}$, covering the plane **$15 \leq \mathbf{m_S} \leq 500$ GeV** $\times$ $170 \leq \mathbf{m_X} \leq 1000$ GeV, with $\mathbf{m_X} \geq \mathbf{m_S} + \mathbf{m_H}$, where the $\mathbf{X} \to \mathbf{SH}$ decay is kinematically allowed.

Push the searches for new physics in **previously uncovered** regions of the phase space!

- The analysis relies on a **new and creative modelling strategy** w.r.t. the traditional $H \to \gamma\gamma$ analyses, based on using **PNN output directly in the final fit**.

Di-photon and b-jet selection





- For most of the tested $(\mathbf{m_X}, \mathbf{m_S})$ a good agreement is found between the data and the background-only hypothesis.

  The results are interpreted in terms of upper limits on the $X \to SH \to b\bar{b}\gamma\gamma$ **cross-section** across the **2-dimensional** $(\mathbf{m_X}, \mathbf{m_S})$ plane.

- An **interesting excess** ⚠️ was found around $(\mathbf{m_X}, \mathbf{m_S})$ = (575, 200) GeV, with a **maximum of the local significance of 3.5σ**, where the corresponding **global significance is $\approx$ 2.0 σ**!

This is a brand new result! 🎉

Currently in ATLAS Circulation, and it is expected to be **public** for the **Moriond EW Conference**!

Thank you for your attention!

Backup

The look elsewhere effect and the global significance

- For our $X \to SH \to b\bar{b}\gamma\gamma$ analysis, we are searching for a **resonant signal** in the parameter space of the masses of the **two resonances** X and S. → (m_X, m_S)!
- We have found an excess of events above the background only expectations, where the maximum of the local significance is 3.6σ.

⇒ However, the large statistical significance might be just a fluctuation, due to the very large number of (m_X, m_S) points that we are testing. → **Look elsewhere effect**!

- To evaluate the significance of our excess by taking into account the look elsewhere effect, we need to evaluate the **global significance** (or **global** p_0) across all the tested (m_X, m_S) space.

⇒ **Global $\mathbf{p_0}$** = $\mathbb{P}\left(\max_{\theta \in \mathcal{M}} q(\theta) > q_{obs} \,|\, \mu = 0\right)$

→ $q(\theta)$ is our test statistic (which is different for every point in the parameter space θ).

→ The probability is evaluated under the background only hypothesis.

→ q_{obs} is the maximum of our test statistic across the parameter space evaluated on our data.

→ θ represents the parameters of the search (in our case, the masses (m_X, m_S)) that vary in the parameter space $\mathcal{M}$.

The **global $\mathbf{p_0}$** quantifies the **probability** that our **excess** seen in a specific (m_X, m_S) point is just a **statistical fluctuation** of the background.

The asymptotic method for evaluating the global significance

Recipe for the global significance

> **Reference**: *Estimating the "look elsewhere effect when searching for a signal* paper.

- Given a certain level u, the **set** of the parameters θ where $q(\theta) > u$ is called **excursion set** A_u.

  $A_u = \{\theta \in \mathcal{M} \text{ where } q_\theta > u\}$

  For large enough values of the **test statistic threshold** u.

- **Asymptotically** the expectation value of the so-called "**Euler characteristic**" of the excursion set (= $\phi(A_u)$) can be used as an approximation of the global $\mathbf{p_0}$.

  $\mathbb{E}[\phi(A_u)] \approx \mathbb{P}\,(\max_{\theta \in \mathcal{M}} q(\theta) > u).$ → For evaluating the global $\mathbf{p_0}$ we would need to calculate $\mathbb{E}[\phi(A_{q_{obs}})]$ under the background only hypothesis!

- It can be shown that, under the background-only hypothesis, with a 2-dimensional parameter space,

  $\mathbb{E}[\phi(A_u)] = \mathbb{P}(\chi^2 > u) + e^{-u/2} \cdot (\mathcal{N}_1 + \sqrt{u}\mathcal{N}_2)$ [★] → $\mathbb{P}(\chi^2 > u)$ = χ^2 probability distribution!

  This equation holds for **every threshold of the test statistic** u, with the **same** $\mathcal{N}_1$ **and** $\mathcal{N}_2$ constants!

- We can use **convenient thresholds** u for estimating $\mathbb{E}[\phi(A_u)]$, and **inverting** the Equation [★] for determining $\mathcal{N}_1$ and $\mathcal{N}_2$.

- Once we have $\mathcal{N}_1$ and $\mathcal{N}_2$, we can use the same formula [★] for evaluating $\mathbb{E}[\phi(A_u)]$ with $\mathbf{u} = \mathbf{q_{obs}}$, and thus have an **estimation** of the **global** $\mathbf{p_0}$.

Why do we need toys for the asymptotic method?

Also for **convenient thresholds u of the test statistic**!

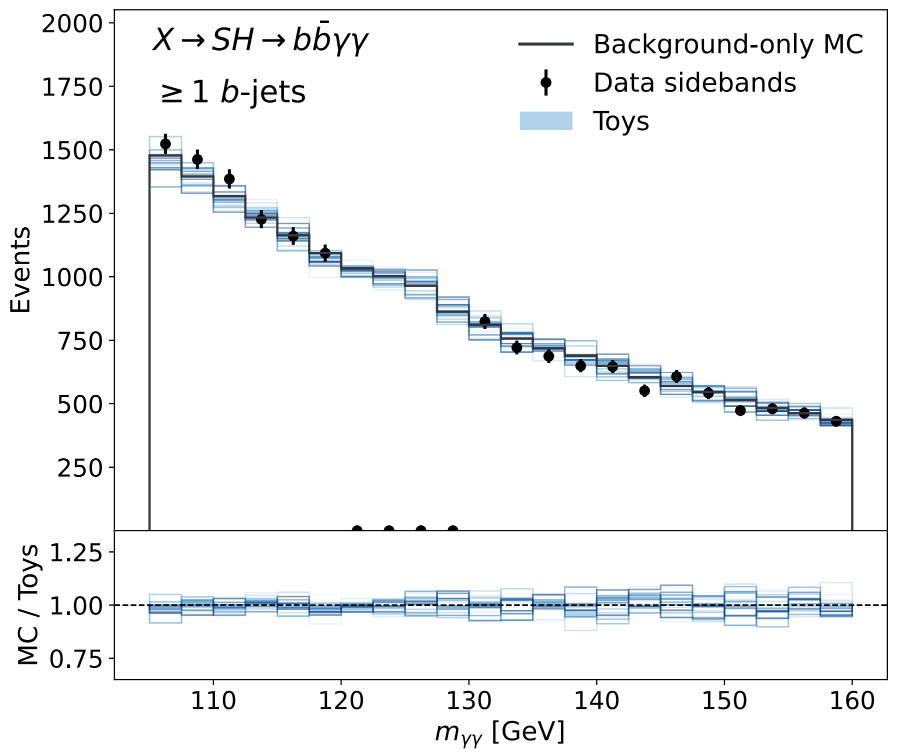
- The **estimation** of the **expectation value** of the Euler characteristic $\mathbb{E}[\phi(A_u)]$ requires a **certain (limited) number of background-only toys**, for computing the statistical uncertainty on $\mathcal{N}_1$ and $\mathcal{N}_2$.
- We need to generate $N_{\textbf{toys}}$ **background-only toys**!

We can use the **standard deviation of the mean** as an **uncertainty** on $\mathbb{E}[\phi(A_u)]$.

➡ Given a threshold u, $\mathbb{E}[\phi(A_u)]$ comes from the **average across the $N_{\textbf{toys}}$ toys**.

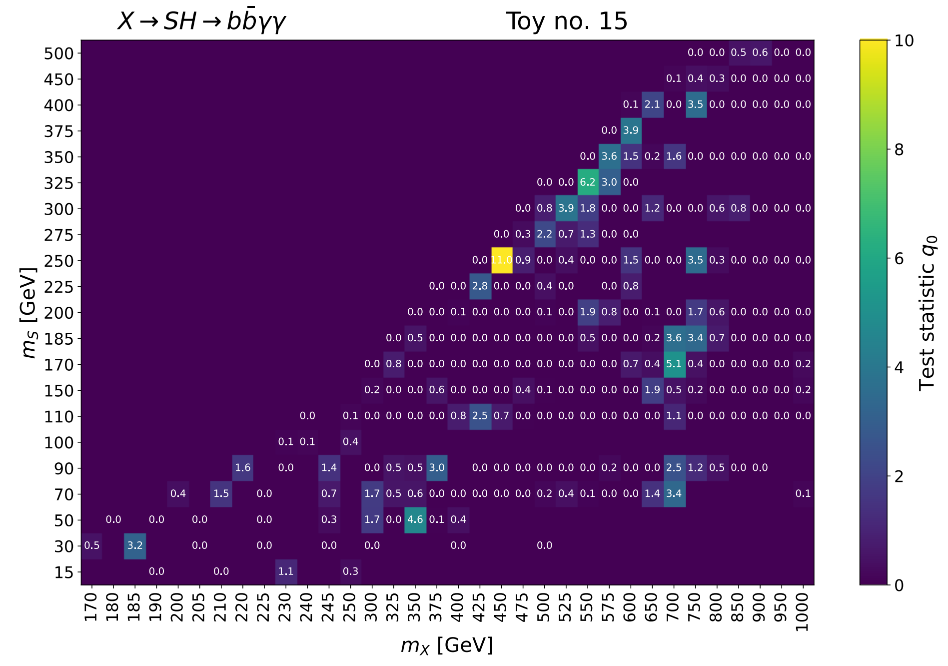
1. Generating $N_{\text{toys}} = 20$ background-only toys.

   ➡ Not trivial, because the analysis selection depends from the search parameters θ (=(m_X, m_S)). Hence, the toys need to be generated at a common preselection level!



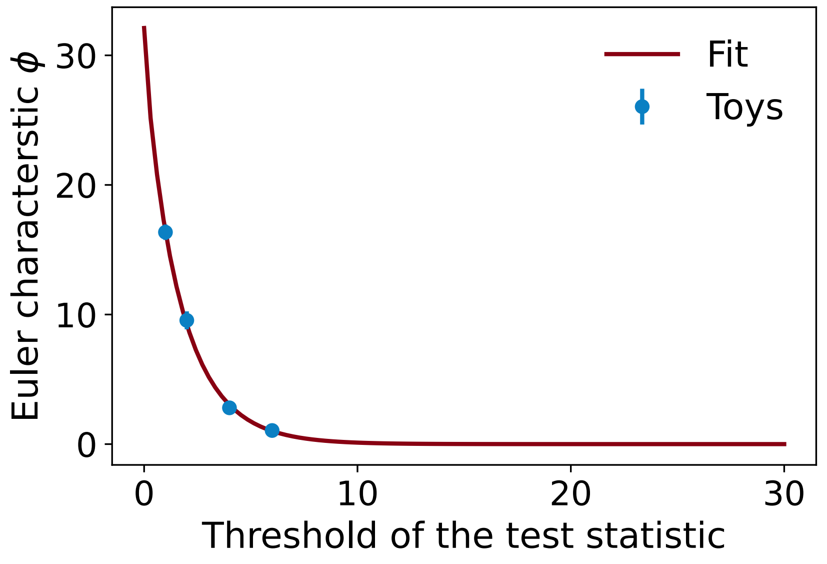
2. Performing the $SH \to b\bar{b}\gamma\gamma$ analysis for each toy.

   ➡ The goal is obtaining N 2-dimensional maps of the test statistic q_0 as a function of the search parameters θ (=(m_X, m_S)).

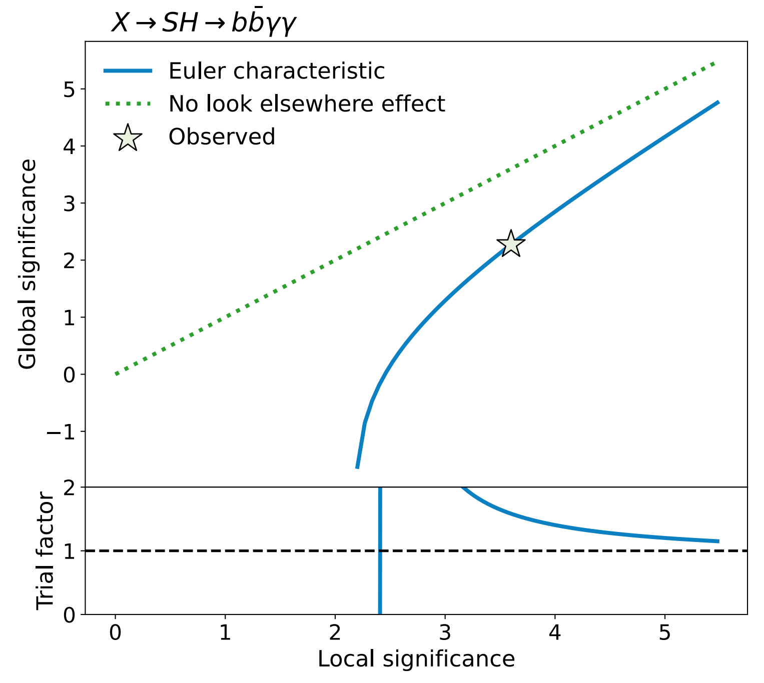


3. Estimating the $\mathcal{N}_1$ and $\mathcal{N}_2$ constants.

   ➡ From fitting $(u, \mathbb{E}[\phi(A_u)])$ points evaluated from toys with Equation [★].



4. Evaluating the trial factor and the global significance!



Toy generation

Background modelling

Generating background-only toys with a PNN-based analysis

- Generating **a background-only toy** for all the values of the search parameters θ **(=(m_X, m_S))** is **not trivial** for the $SH \rightarrow b\bar{b}\gamma\gamma$ analysis.

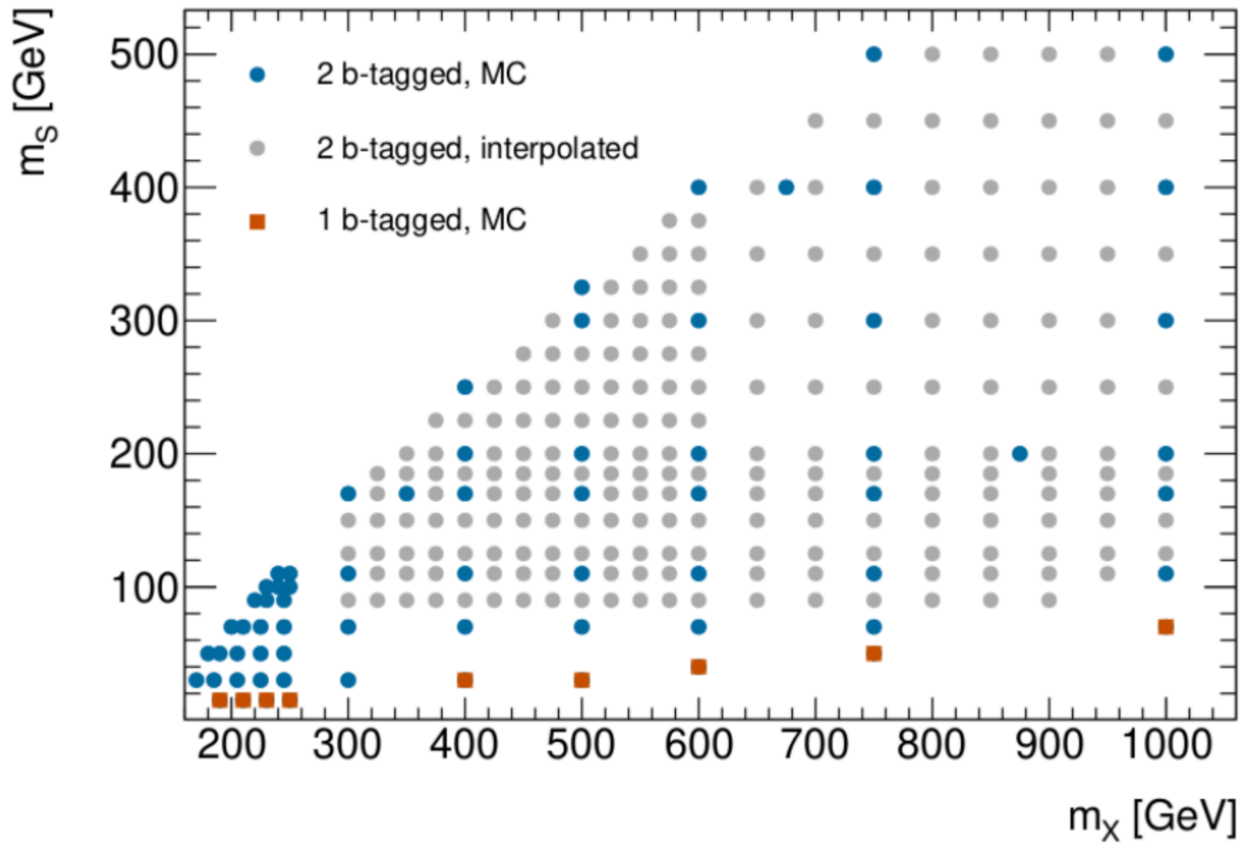
  For our analysis, **also** the **background-only p.d.f.** (and not only the signal) **depends from the search parameters** θ!

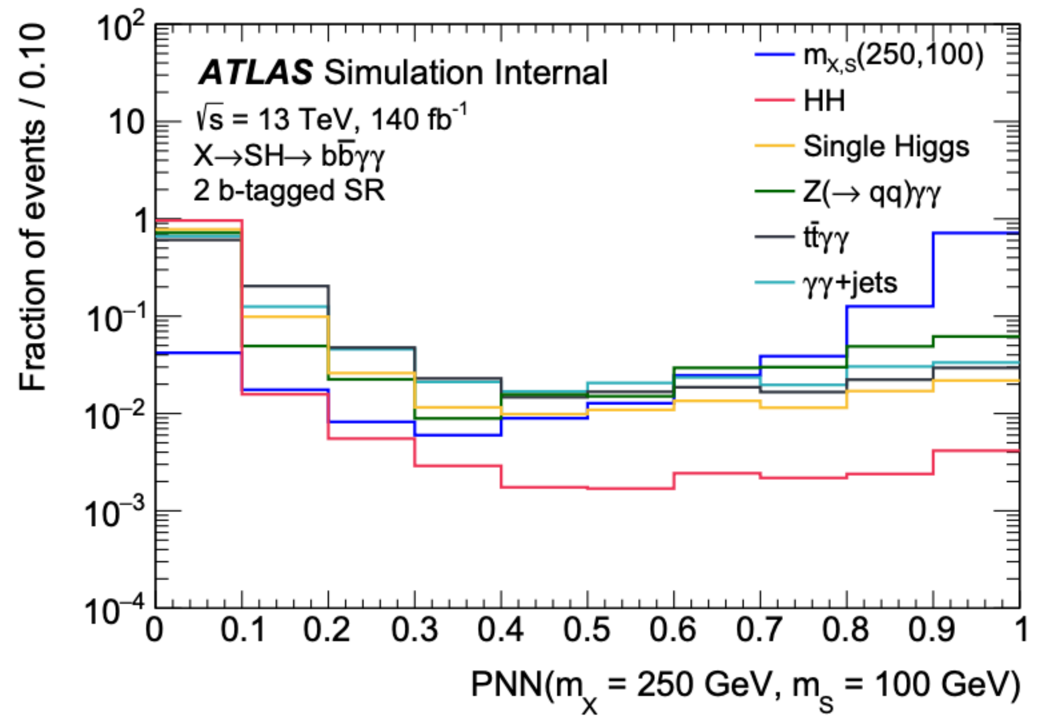
  1. We have **two categories** with a **different selection**, that is applied depending on the (m_X, m_S) signal.
     - 1 b-tagged category: applied to (m_X, m_S) signals where $m_S/m_X < 0.09$.
     - 2 b-tagged category: applied to all the other (m_X, m_S) signals.
  2. Since our discriminant variable is based on **PNNs**, whose parameters are m_X (and also m_S for the 2 b-tagged category), the shape of the background depends from the search parameters m_X and m_S.

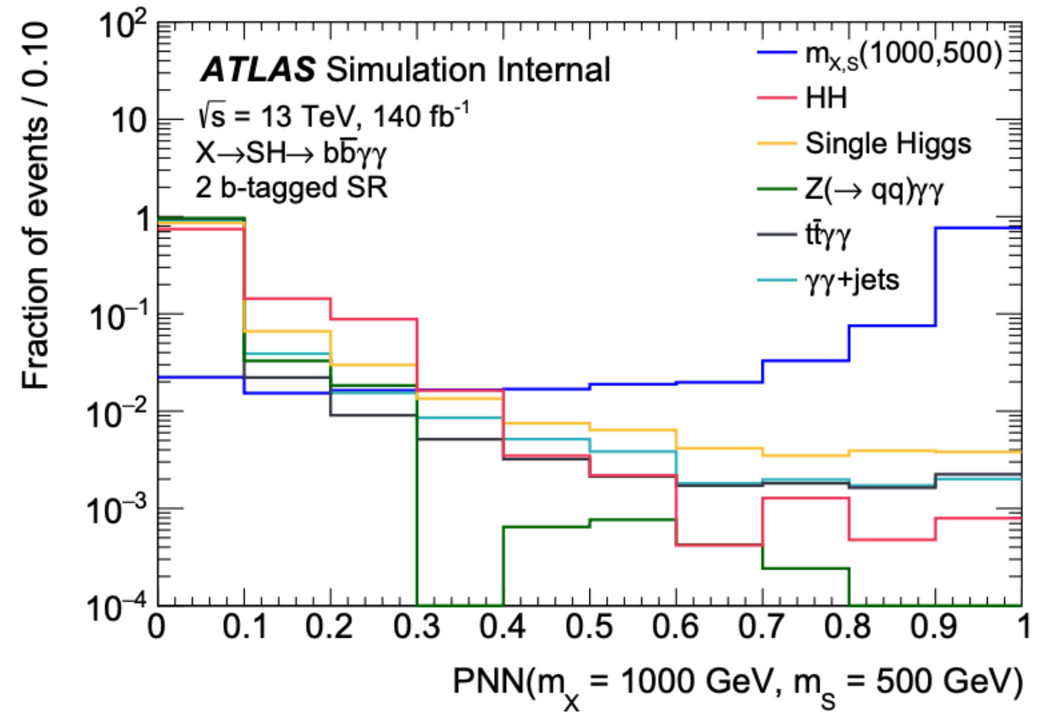
  We can't generate a **single background-only toy** on which to perform the analysis for the **full search space** by sampling from the **p.d.f. of the PNN for the background after the analysis selection**, since this **p.d.f. is different** for each (m_X, m_S) tested signal!

- Instead of generating toys by sampling the p.d.f. after the analysis selection, we start directly from **background MC events at a common preselection level**.

  We generate the **background-only toys** by combining **events picked from the background MC samples**.







Recipe for the toy generation: main idea

- First, a **common preselection** (including both the 1 b-tagged and the 2 b-tagged category) is applied to the background MC samples.

	Common presel.	2 b-tagged	1 b-tagged
Number of 'tight' and isolated photons	≥ 2		
$m_{\gamma\gamma}$ [GeV]	$\in [105, 160]$		
Number of leptons	$= 0$		
Number of central jets	$\in [2, 5]$		
Number of b-tagged jets @ 77% WP	≥ 1	$= 2$	$= 1$

The common preselection corresponds to merging the 1 b-tagged and the 2 b-tagged categories.

They only differ on the requirement on the number of b-jets @ 77% WP.

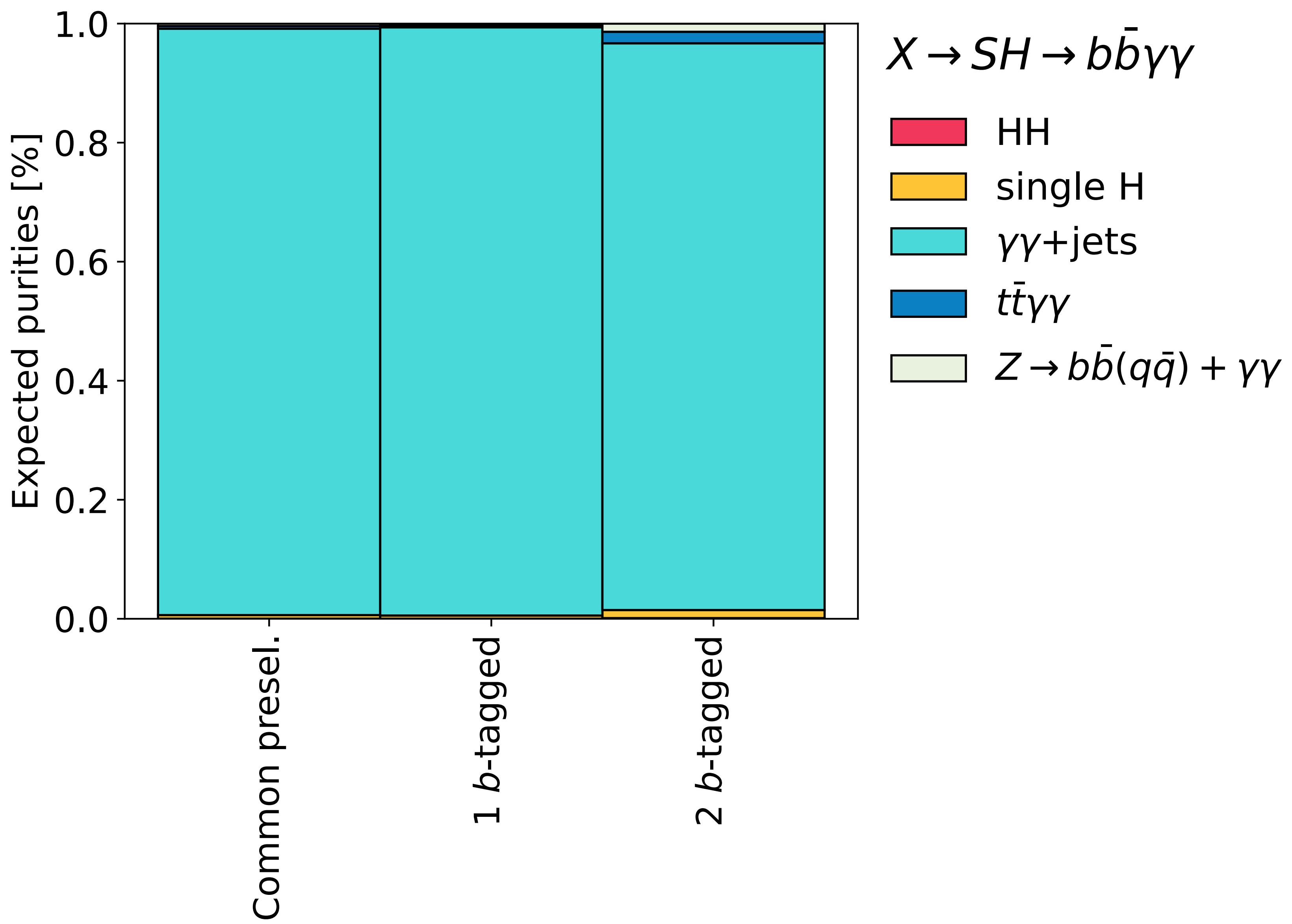
- We evaluate, for each background b, the number of expected events n_b at the common preselection level.

Main idea:

Combine random MC events picked from each background sample b, such that their number follows a Poisson distribution centered in n_b.

- Additional layers of complications are needed, in order to take into account the fact that **MC events are weighted**, and can also have **negative weights**.

We should come up with a procedure that takes into account **MC weights** when **picking the events** from the MC samples, and also the **fraction of negatively weighted events without introducing any bias** in the toys generation!



Recipe for the toy generation: considering MC (negative) weights

- We split each background sample (after the common preselection) in two subsamples.

  1. Sample $(b, +)$ → Events with positive weights.
  2. Sample $(b, -)$ → Events with negative weights.

  We also evaluate the fraction of events with negative weights $(= f_b)$ from the statistics of these two subsamples.

- We define two positive quantities, n_b^+ and n_b^-, that satisfy the following requirements:

$$\begin{cases} n_b^+ - n_b^- = n_b \\ n_b^- = f_b \cdot (n_b^+ + n_b^-) \end{cases} \quad [\star]$$

- We define two independent Poisson p.d.f.s, centered in n_b^+ and n_b^- respectively, that we use for sampling N_{toys} integers $x_1^{b,+}, x_2^{b,+}, \ldots, x_N^{b,+}$ and $x_1^{b,-}, x_2^{b,-}, \ldots, x_N^{b,-}$, where:

$$\begin{cases} x_i^{b,+} \sim \text{Pois}\,(x \,|\, n_b^+) \\ x_i^{b,-} \sim \text{Pois}\,(x \,|\, n_b^-) \end{cases}$$

- For generating the i^{th} toy, we will pick $x_i^{b,+}$ MC events from the subsample Sample $(b, +)$, and $x_i^{b,-}$ MC events from the subsample Sample $(b, -)$.

  - When picking the events from the two subsamples, we use the absolute value of their MC weight (normalizing their sum to unity) as probability of being extracted.
  - For building the distribution of any observable using toys, we assign a weight = +1 (-1) to the MC events picked from Sample $(b, +(-))$.

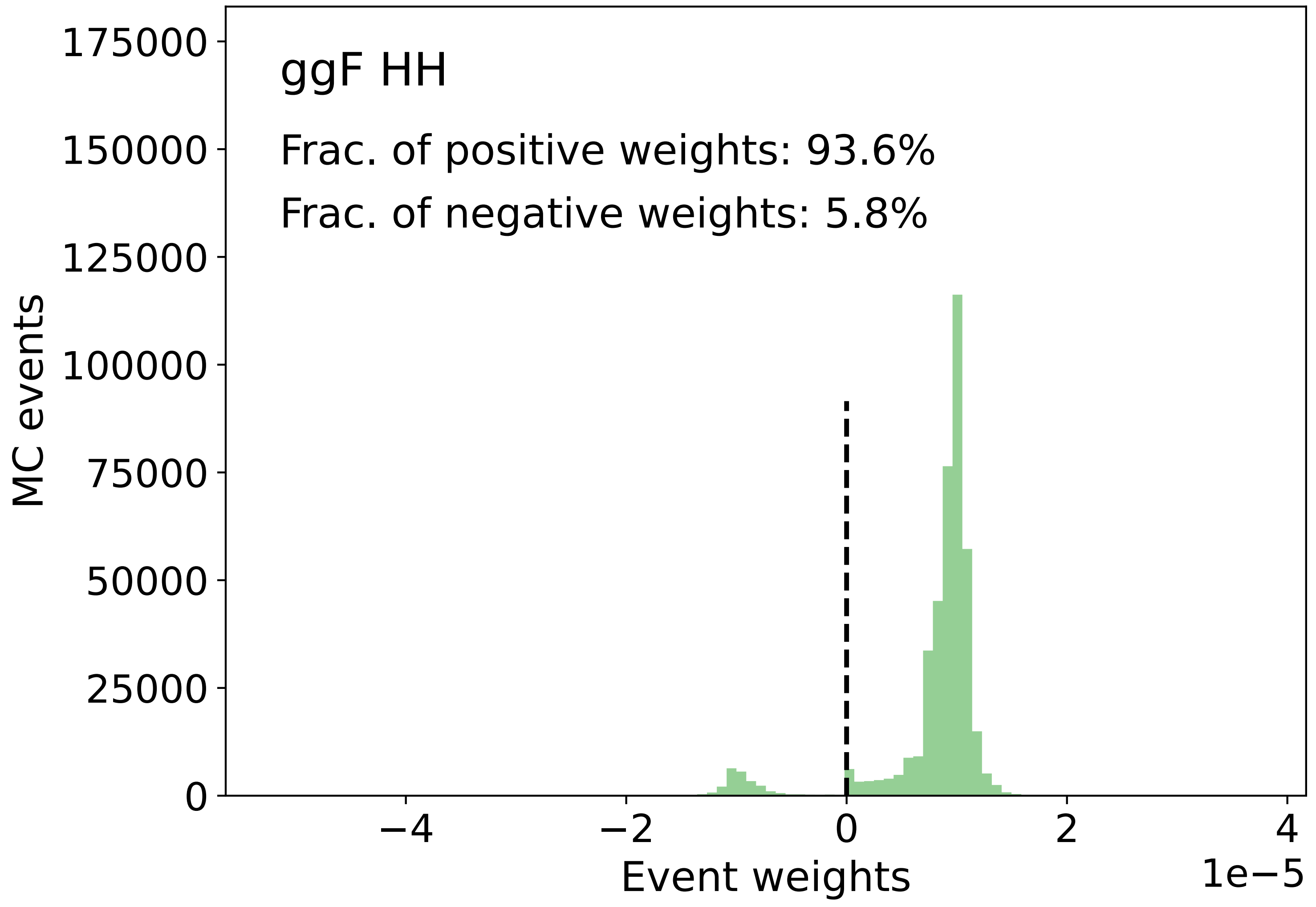
Recipe for the toy generation: example

Example: The **ggF HH background**.

- $n_b = 3.37$ after preselection @ 140 fb^{-1}.
- The fraction of negatively weighted events is $f_b = 5.8\,\%$.

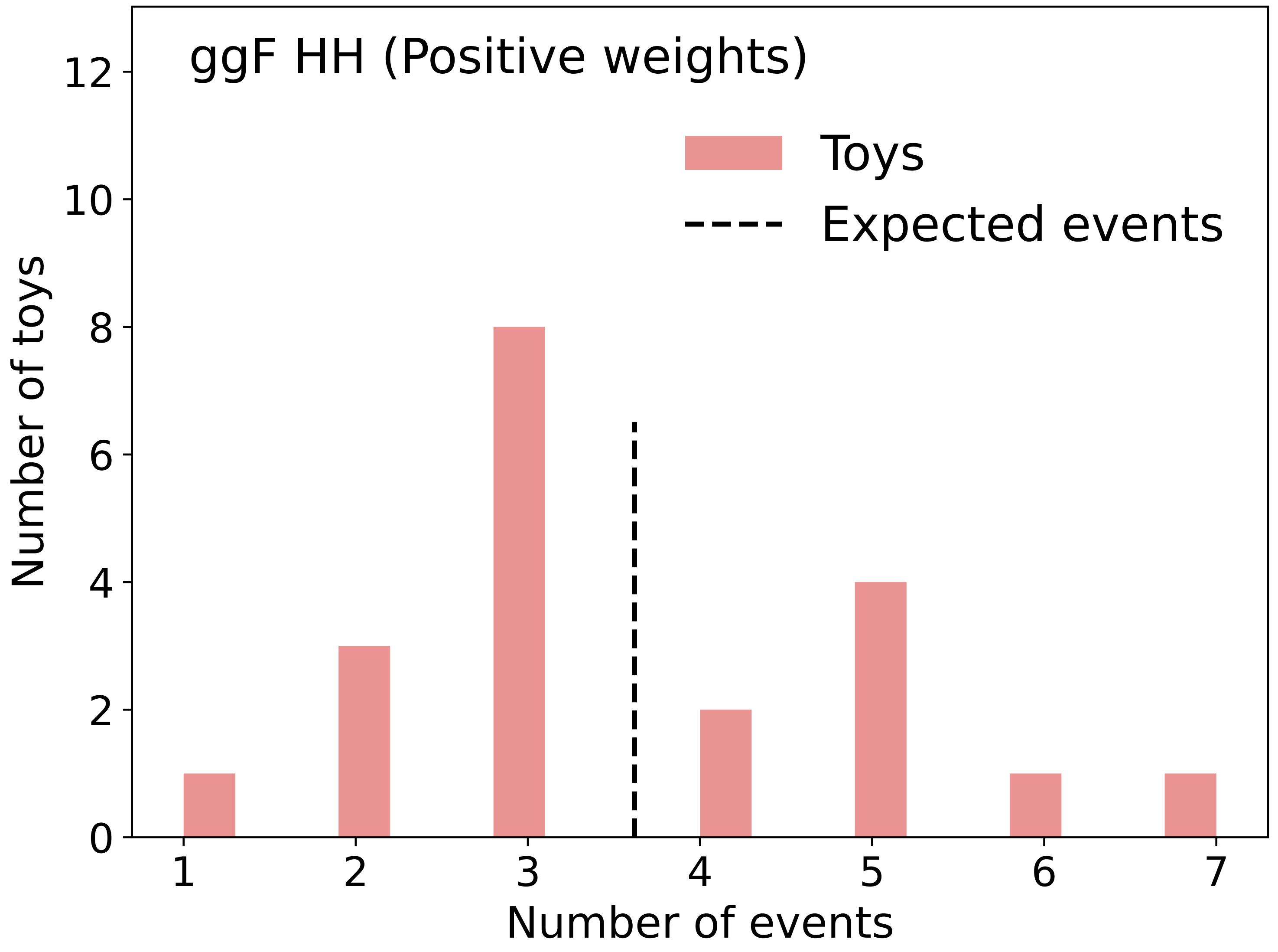
By solving Equation [★], we find:

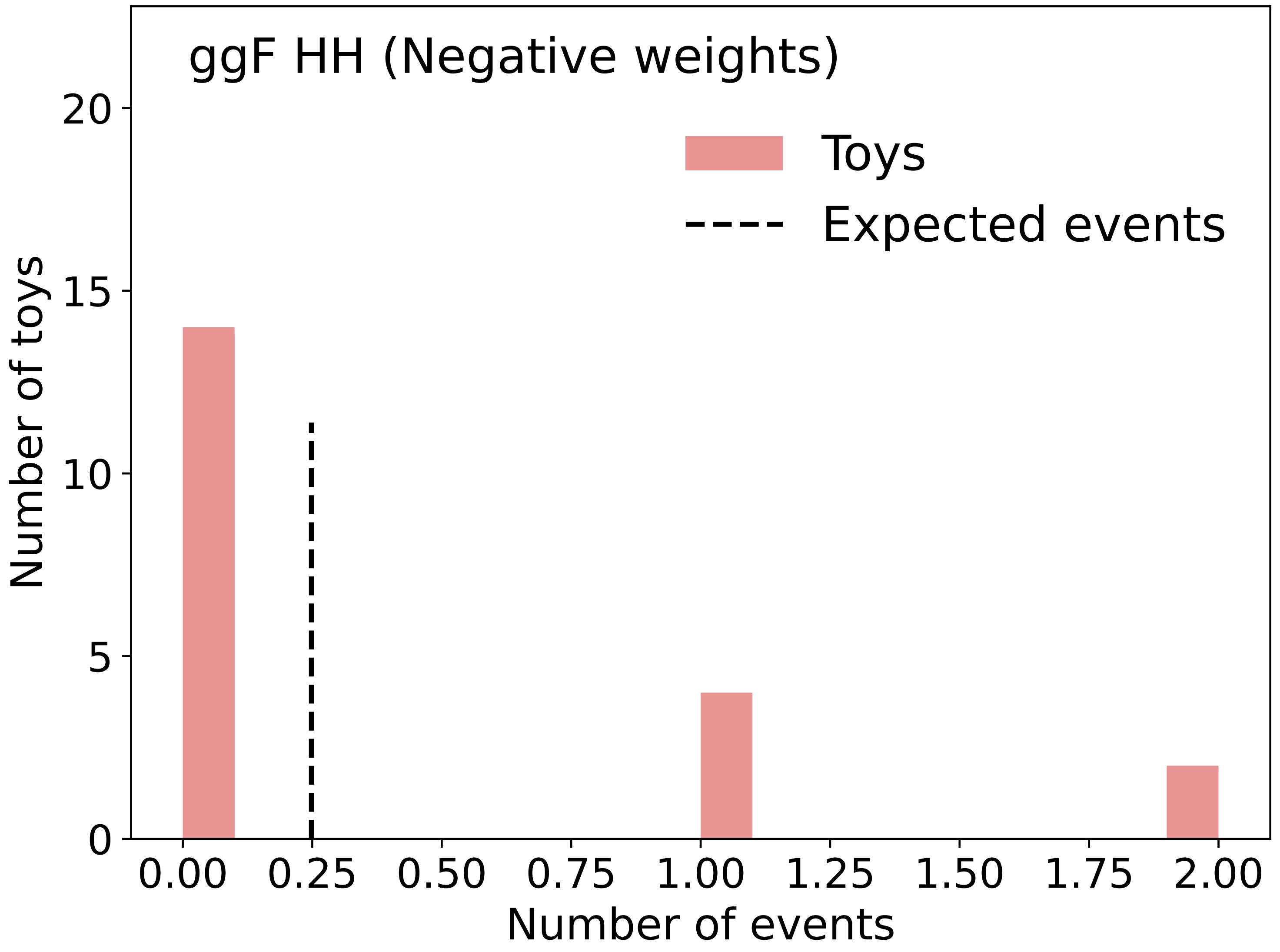
$$\begin{cases} n_b^+ = 3.59 \\ n_b^- = 0.22 \end{cases}$$



The histograms of the event weights for each background sample at preselection level are available here.

$N_{\text{toys}} = 20$ integers are sampled from the two Poisson p.d.f.s Pois $(x\,|\,3.59)$ and Pois $(x\,|\,0.22)$.





- Each toy will include a certain number of ggF HH MC events from the subsample with positive weights, distributed $\sim$ Pois $(x\,|\,3.59)$.
- Similarly, the number of ggF HH MC events in each toy that originally had negative weights follows Pois $(x\,|\,0.22)$.

Recipe for the toy generation: cross-check

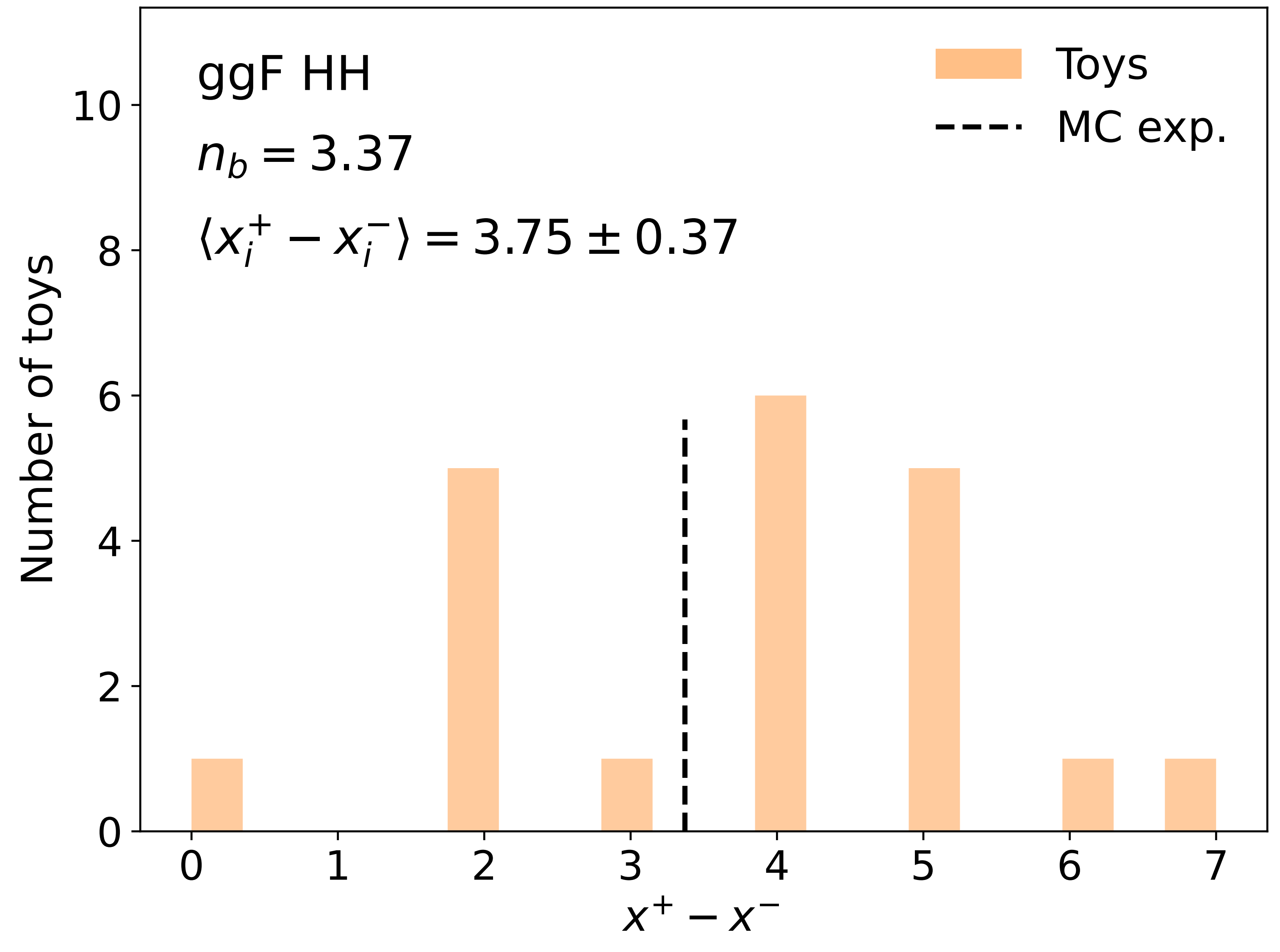
We would like to cross-check that, the number of (weighted with +1 or -1) events for each process b present in our toys corresponds, in average, to the expectation n_b.

- The quantity $x_i^{b,+} - x_i^{b,-}$ for each background b is evaluated for each toy i, and then averaged.
- We compare $\langle x_i^{b,+} - x_i^{b,-} \rangle$ with the number of expected events n_b for the considered background process at preselection level.

	$\langle x_i^{b,+} - x_i^{b,-} \rangle$	Expected events n_b
ggF HH	3.75 ± 0.37	3.37
VBF HH	0.20 ± 0.09	0.15
ggH	52.65 ± 1.39	54.00
VBF H	8.70 ± 0.62	9.02
W^+H	3.80 ± 0.39	3.56
W^-H	2.30 ± 0.38	2.62
$qq \to ZH$	8.50 ± 0.69	8.76
$gg \to ZH$	2.55 ± 0.25	2.45
$t\bar{t}H$	19.00 ± 1.00	20.00
tHjb	3.80 ± 0.73	3.65
tWH	0.55 ± 0.32	0.70
$b\bar{b}H$	3.25 ± 0.50	3.59
$\gamma\gamma$+jets	18482.05 ± 25.66	18525.05
$t\bar{t}\gamma\gamma$ (no all had)	41.85 ± 1.43	40.96
$t\bar{t}\gamma\gamma$ (all had)	37.75 ± 1.45	37.52
$Z \to b\bar{b} + \gamma\gamma$	24.95 ± 0.86	23.34
$Z \to q\bar{q} + \gamma\gamma$	55.70 ± 1.50	50.73

The quantities $\langle x_i^{b,+} - x_i^{b,-} \rangle$ and n_b seem to be compatible within the uncertainties!

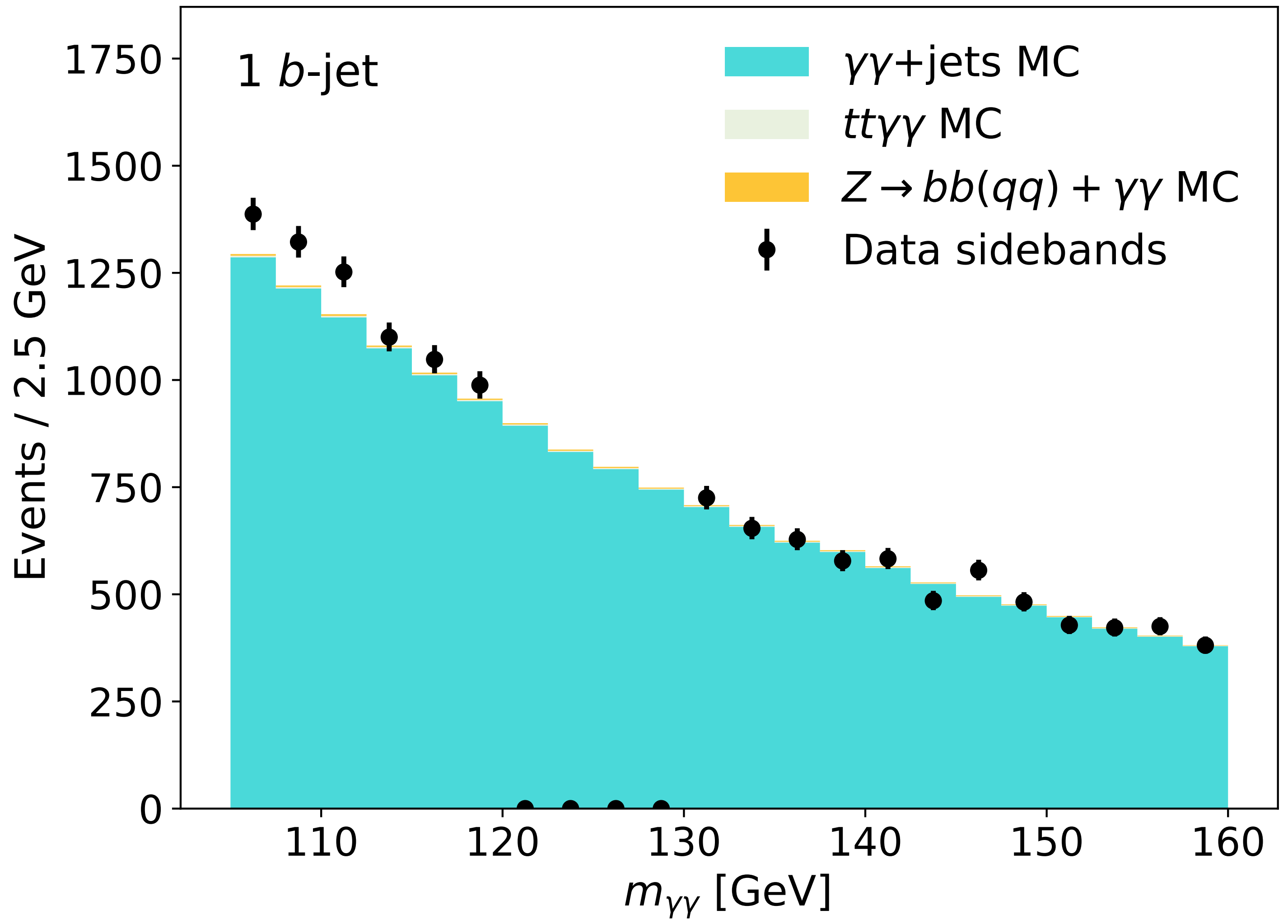
Example: Distribution of $x_i^{b,+} - x_i^{b,-}$ for the **ggF HH background**.

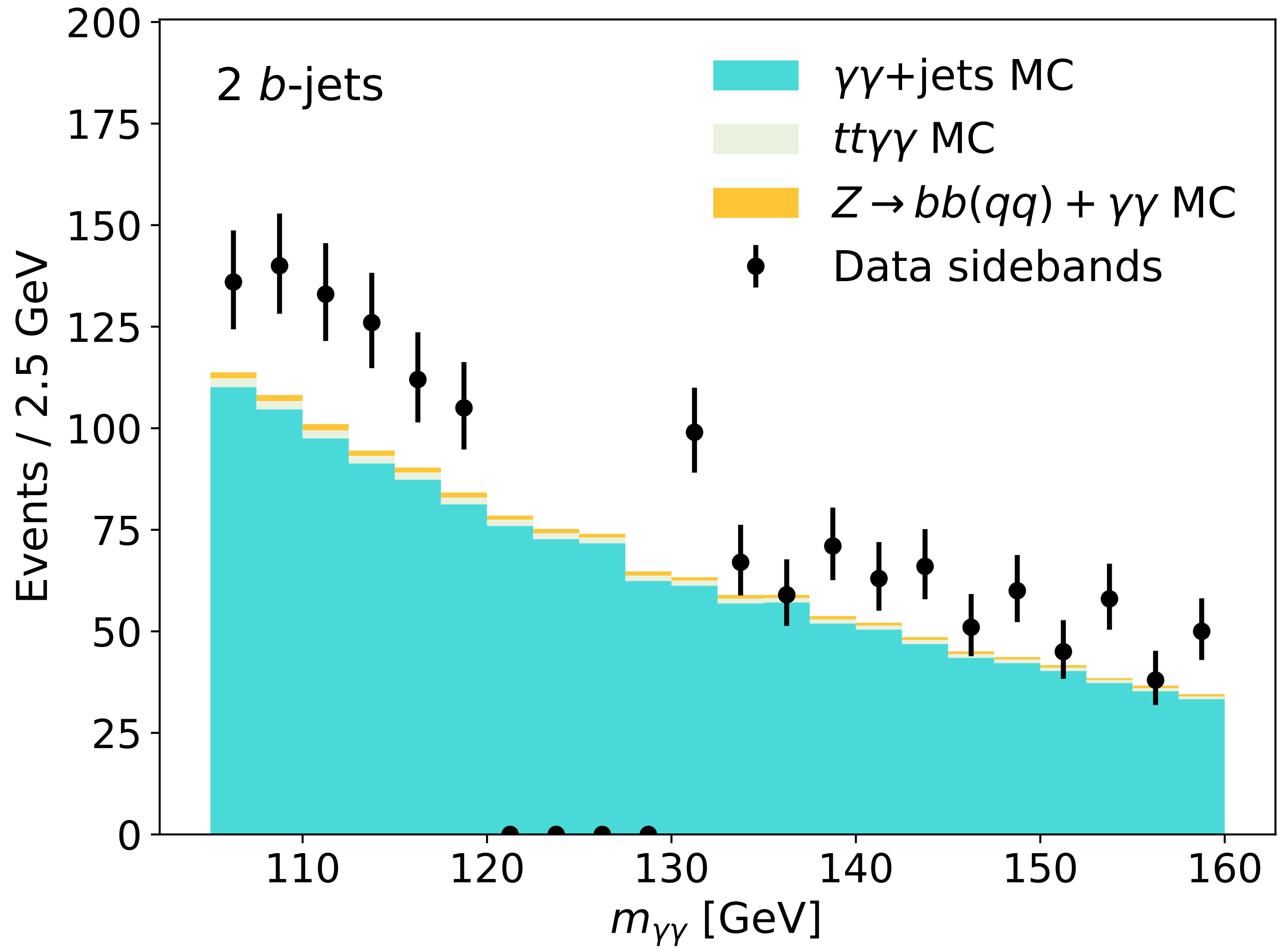


Special treatment for the $\gamma\gamma$+jets sample

The $\gamma\gamma$ K-factor!

- In the $SH \to b\bar{b}\gamma\gamma$ analysis, a **normalization factor** is applied to the $\gamma\gamma$+jets template in the final fit.
  - Used to match the overall normalization of the **non-resonant backgrounds** to data.
    - Including the $\gamma\gamma$+jets, the $t\bar{t}\gamma\gamma$, and the $Z \to b\bar{b}(q\bar{q})$ processes.
  - In the analysis, the $\gamma\gamma$ K-factor is obtained independently for each $(\mathbf{m_X}, \mathbf{m_S})$ point from a SR + CR simultaneous fit to data.
    - The exact values can be slightly different for each $(\mathbf{m_X}, \mathbf{m_S})$ signal, and are mainly constrained in the CR and (partially) in the most background-like bin of the SR!
- The typical values of the $\gamma\gamma$ K-factor are quite different between the 1 b-tagged category and the 2 b-tagged category.
  - 1 b-tagged category → $\gamma\gamma$ K-factor ≈ 1.0.
  - 2 b-tagged category → $\gamma\gamma$ K-factor ≈ 1.3.





- Two separate K-factors are defined:

$K_1(\gamma\gamma)$	1.03	Applied to γγ+jets events that pass the 1 b-tagged selection
$K_2(\gamma\gamma)$	1.27	Applied to γγ+jets events that pass the 2 b-tagged selection

  - Taken into account when picking the MC events for the toys!

- Hence, the background only-toys should match data in the sidebands region (=CR), where we do not expect signal, in both categories simultaneously!

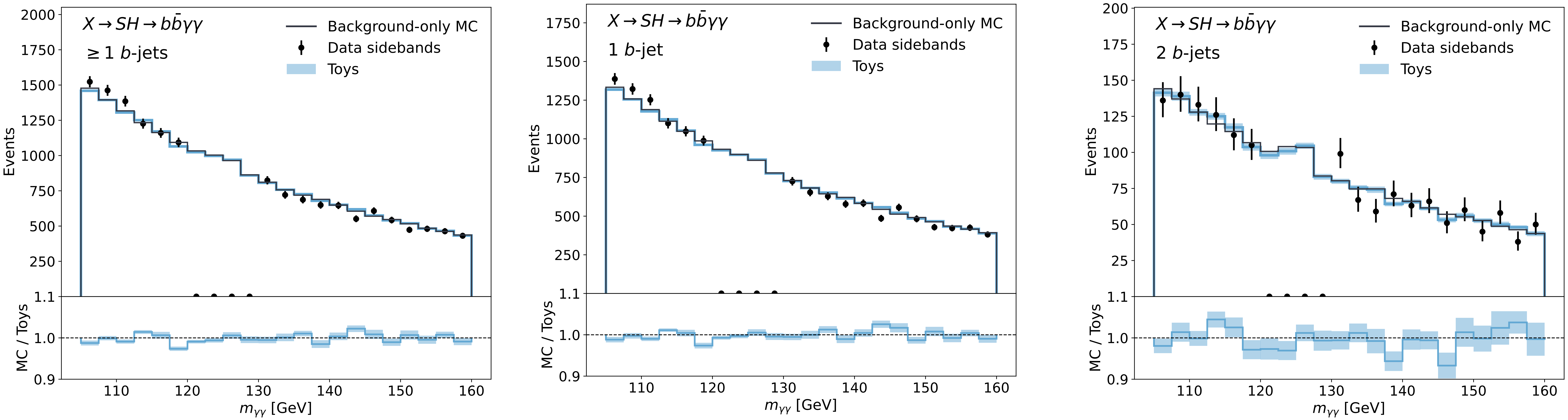
Background-only toys for the $SH \to b\bar{b}\gamma\gamma$ analysis

- Using this procedure, we generated $N_{\text{toys}} = 20$ background-only toys at preselection level.

➡ Each event in each toy contains all the variables that are needed to perform the full $SH \to b\bar{b}\gamma\gamma$ analysis.

$m_{\gamma\gamma}$	For applying the selection for the SR and CR.
m_{jj} and $m_{\gamma\gamma jj}$*	For evaluating the PNN in the 2 b-tagged category
$p_T(j_1)$ and $m_{\gamma\gamma j}$*	For evaluating the PNN in the 1 b-tagged category
Event weight	+1 or -1, depending if the event had originally a positive weight or a negative weight.
Selection flags	For applying the selection of the 1 b-tagged or the 2 b-tagged category.

- **Cross-check**: distributions of $m_{\gamma\gamma}$ averaged across toys, compared with data and the background MC samples.



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Selection flags	For applying the selection of the 1 b-tagged or the 2 b-tagged category.

- **Cross-check**: distributions of $m_{\gamma\gamma}$ averaged across toys, compared with data and the background MC samples.

  ⇨ ○ The fluctuations of the toys (= measured using the std. dev. of the mean for the toys in each bin):

  ⇨ 1. Are centered around the distribution for the background-only MC sample.

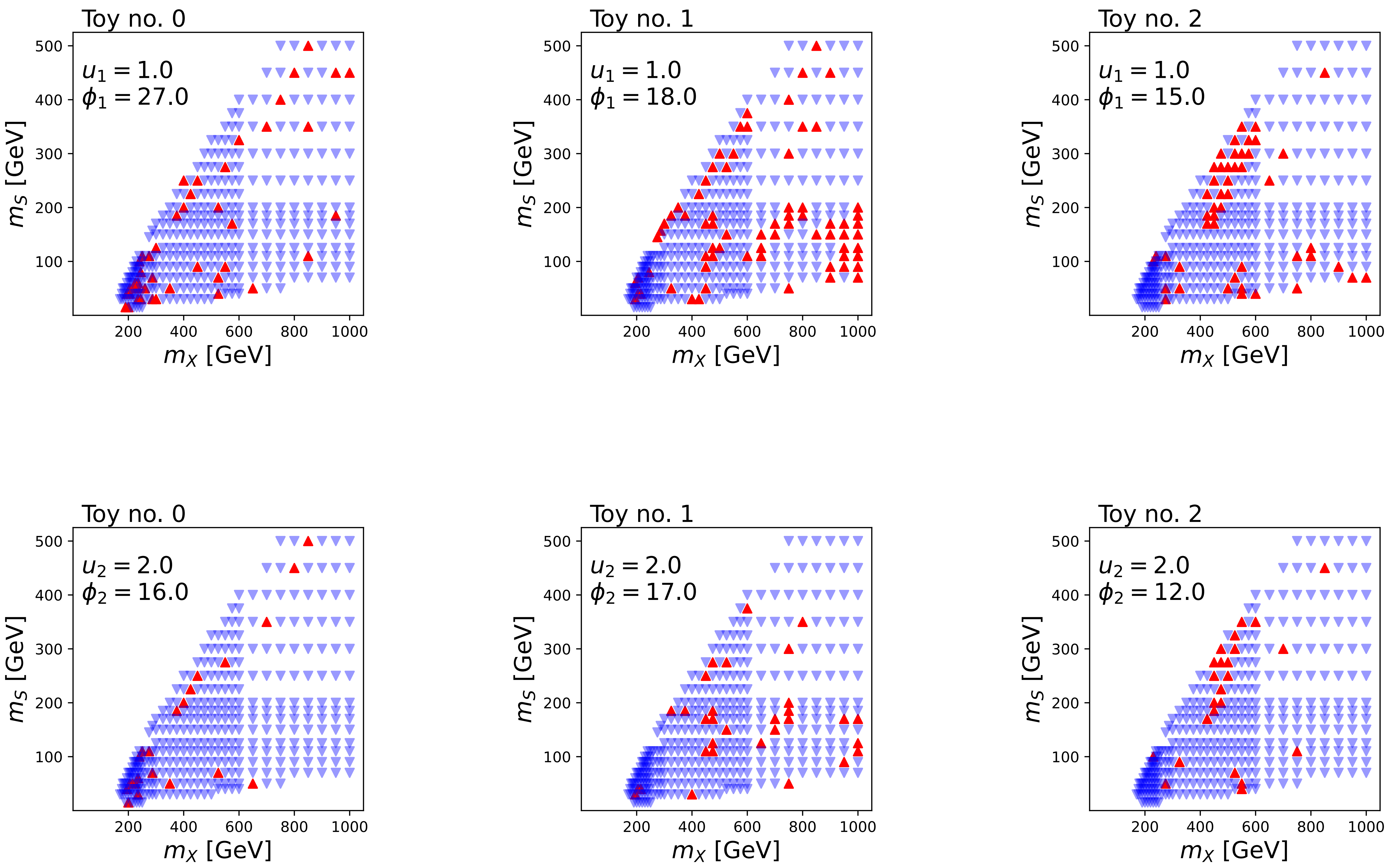
  → Used as a starting point for the toy generation.

  2. Seem to reflect the statistical fluctuations that we see in data.

  ○ The normalization of the background-only toys matches data in the CR (= sidebands region) after the common preselection and in both the 1 b-tagged and 2 b-tagged categories simultaneously.

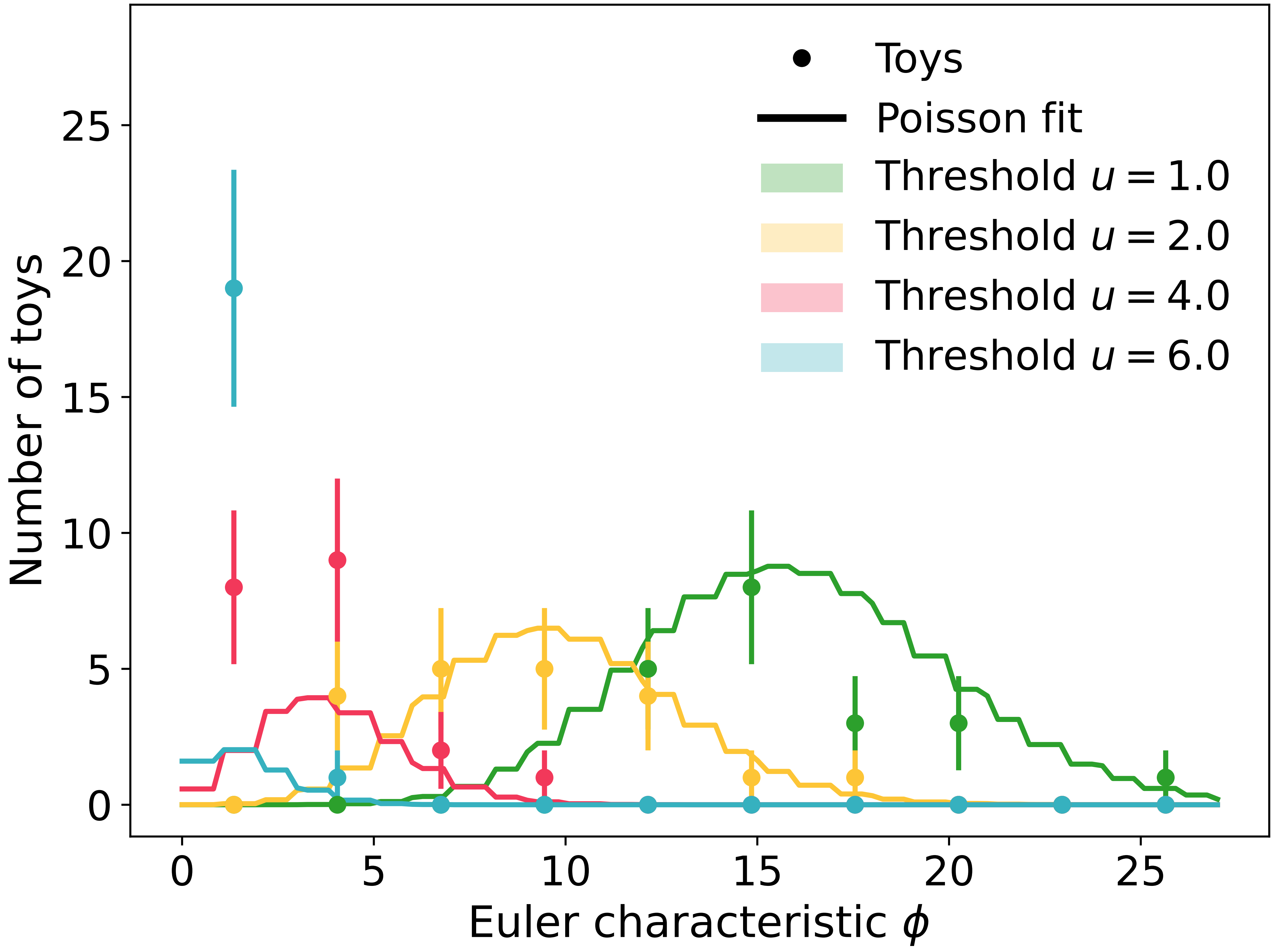
The $m_{\gamma\gamma}$ distribution for each of the $N_{\text{toys}} = 20$ toys is available in backup slides.

Evaluation of the Euler characteristics for the toys



- For each $\mathbf{q_0(m_X, m_S)}$ map extracted from each toy, we evaluate the Euler characteristic of the excursion sets corresponding to the thresholds $\mathbf{u} = 1.0$, 2.0, 4.0, and 6.0.
- Evaluating the Euler characteristics means counting the islands made of points above threshold.
  - An **island** = a group of neighboring $\mathbf{(m_X, m_S)}$ points with $\mathbf{q_0}$ value above the threshold.
  - $\mathbf{(m_X, m_S)}$ points that are neighbours in the diagonal directions are also considered connected to the same island.
- In this plot, the red $\mathbf{(m_X, m_S)}$ points corresponds to the $\mathbf{q_0}$ value above the threshold, while the blue points correspond to those with the $\mathbf{q_0}$ value below the threshold.
- All the neighbouring red points are connected within the same island.

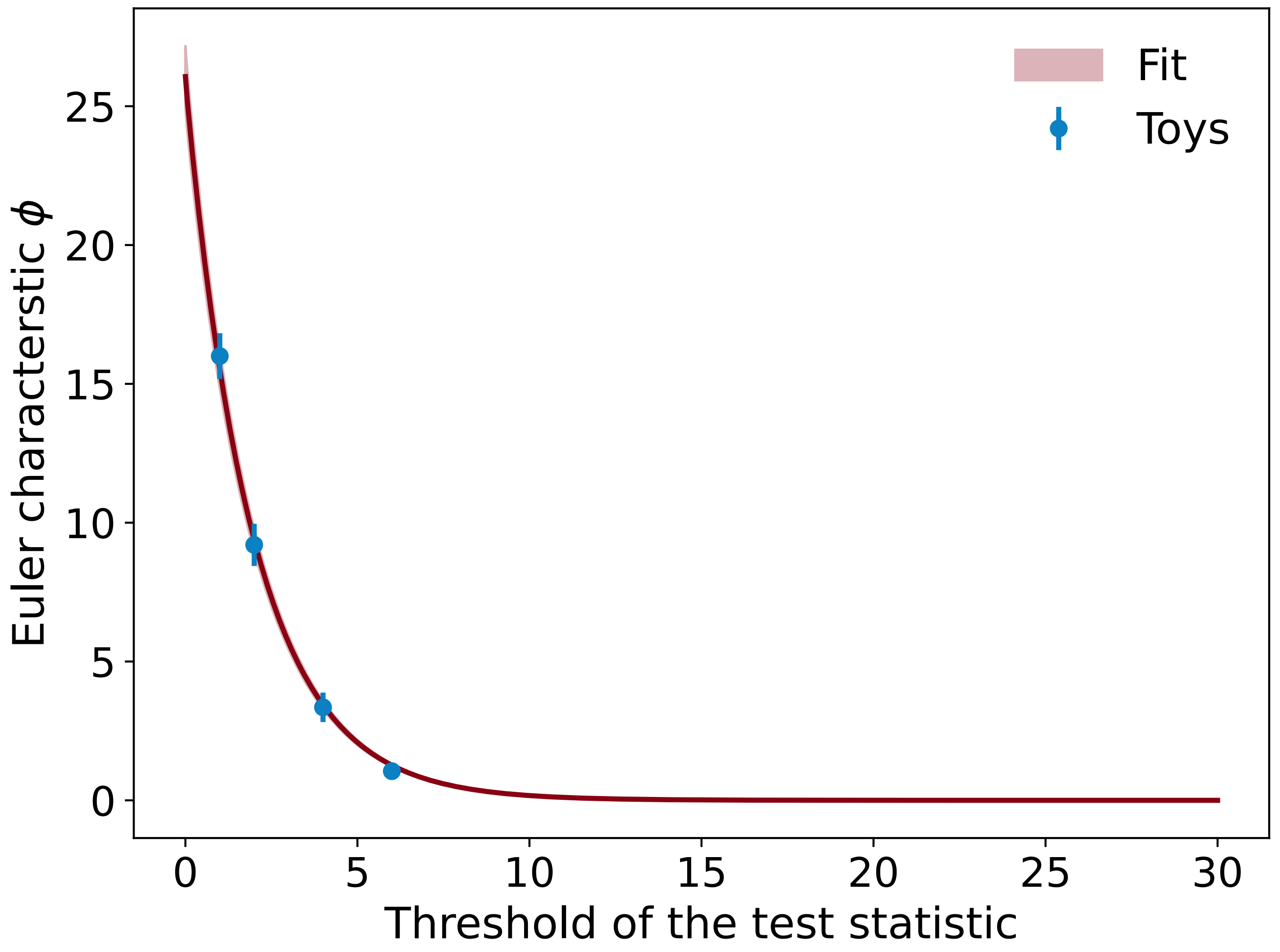
Fit of the $\mathcal{N}_1$ and $\mathcal{N}_2$ values

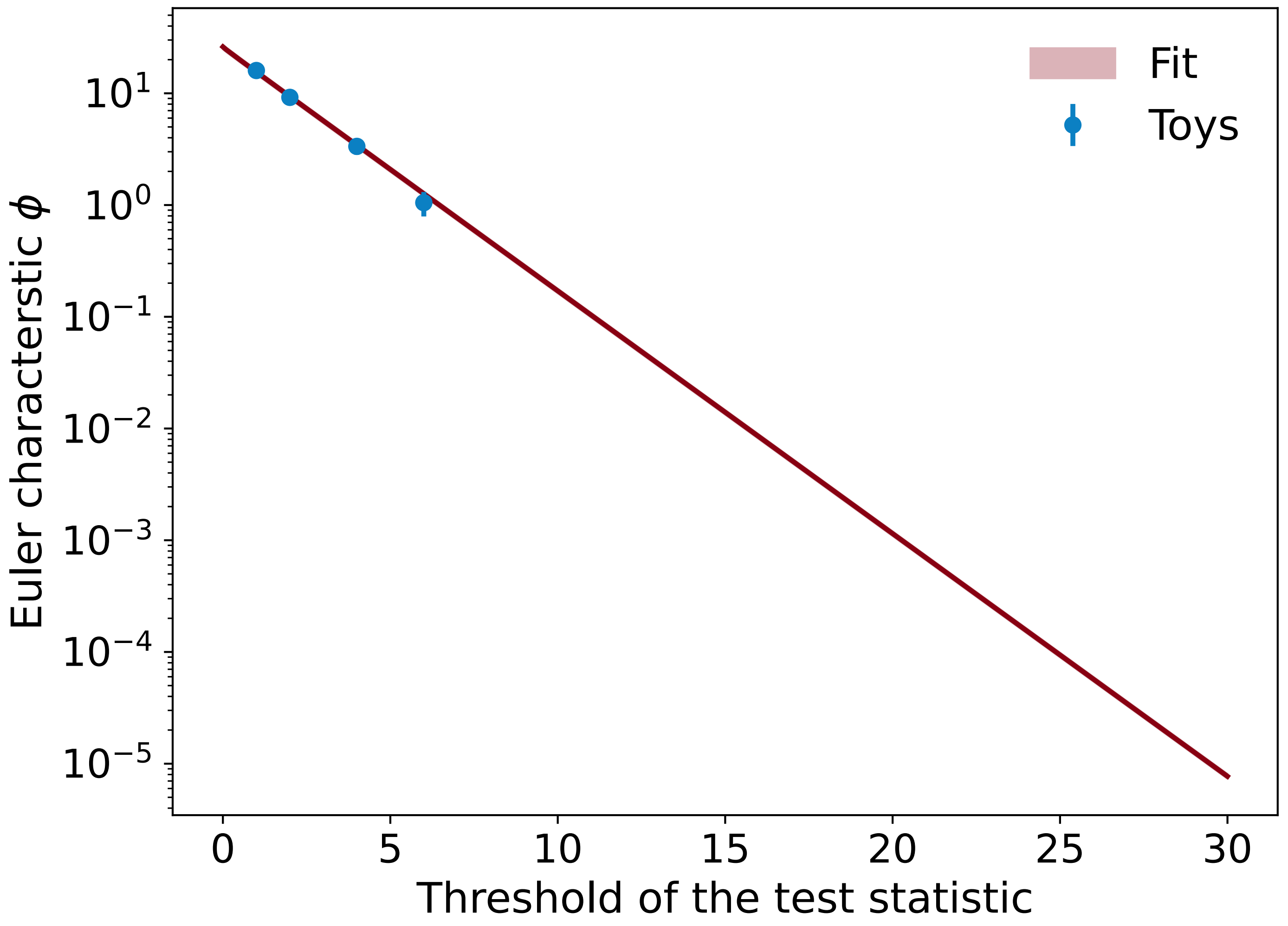


- The $\mathcal{N}_1$ and $\mathcal{N}_2$ values are extracted via a simultaneous fit to the distributions of the Euler characteristics for each toy and for each threshold.
- Given a threshold $\mathbf{u_i}$, the Euler characteristics from the $\mathbf{N}_{\text{toys}} = \mathbf{20}$ toys are described by a poisson distribution with average $\lambda_\mathbf{i}$.
- The averages $\lambda_\mathbf{i}$ are not independent, but are described by the equation [★] as a function of $\mathbf{u}$, where $\mathcal{N}_1$ and $\mathcal{N}_2$ are considered as free parameters in the fit.
- In the fit, the range of $\mathcal{N}_2$ is constrained to non-negative values only.

Fit of the $\mathcal{N}_1$ and $\mathcal{N}_2$ values

- These plots show the fitted curve [★] , where the uncertainty on the Euler characteristic is propagated from the uncertainty on $\mathcal{N}_1$ and $\mathcal{N}_2$ from the fit.
- The blue points represent the arithmetic averages of the Euler characteristics calculated across the $\mathbf{N}_{\text{toys}} = \mathbf{20}$ toys for each threshold, and the error bar corresponds to the standard deviation.





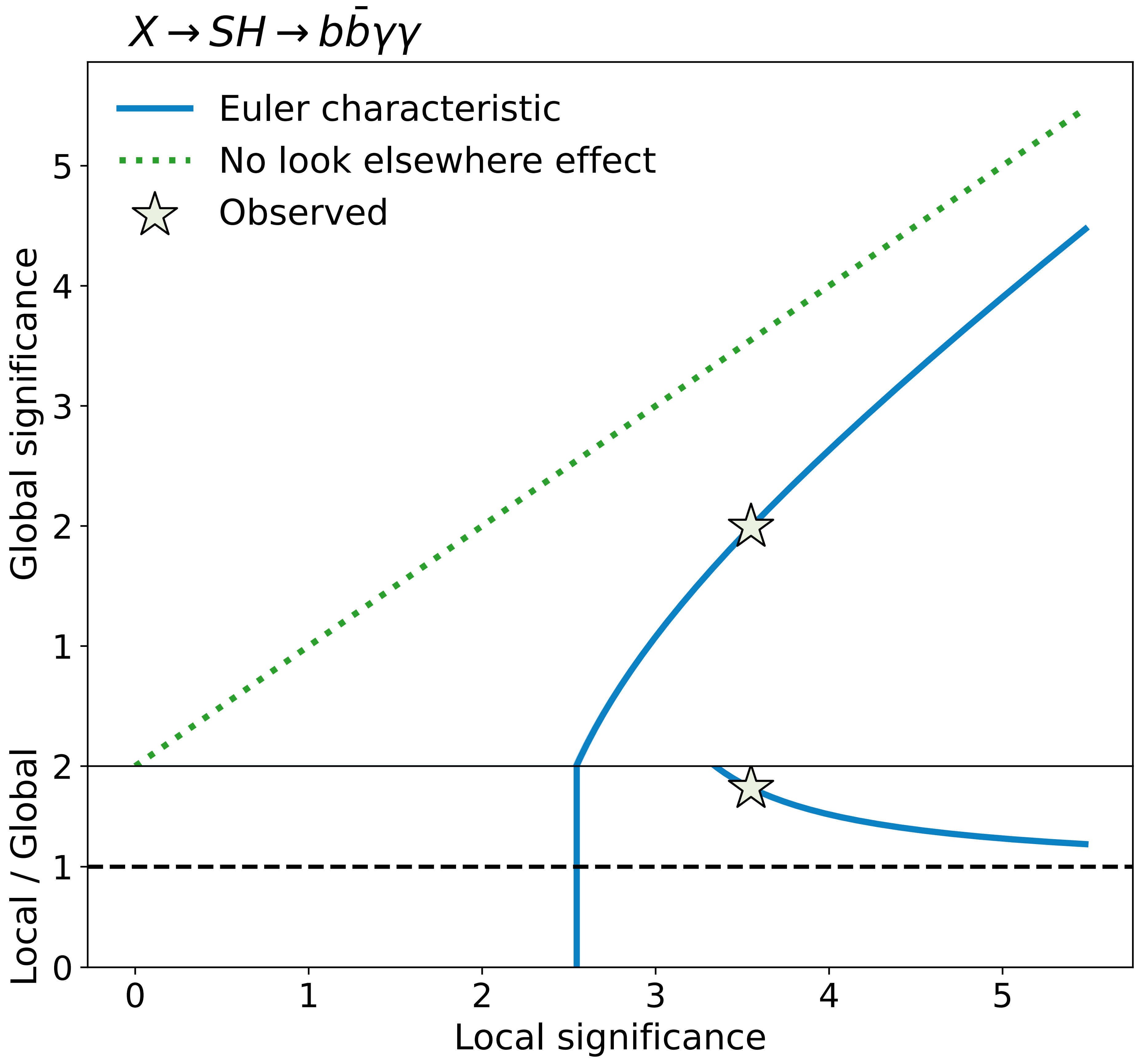

```
 Floating Parameter    FinalValue +/-  Error
--------------------  --------------------------
                  n1    2.5067e+01 +/-  1.10e+00
                  n2    0.0000e+00 +/-  8.33e-12


2x2 matrix is as follows

     |      0    |      1    |
-------------------------------
   0 |      1.208 -9.154e-12
   1 | -9.154e-12   6.936e-23
```

Global significance

- We can convert the Euler characteristic (= global $\mathbf{p_0}$) in a global significance, and the threshold of the test statistic $\mathbf{q_0}$ in a (local) significance value.
- We can obtain the global significance as a function of the maximum of the local significance.
- The global significance has also an uncertainty, propagated from the fit results.



Max. of the local significance	3.55
Max. of the local q0	12.6025
Max. of the local p0	0.000385
Global significance	1.992 +/- (-0.016, +0.021)
Global p0	0.046358
Trial factor (local p0 / global p0)	240.678

➡ Same result as last computation, with a less granular signal grid!

➡ Expected, since the size of the grid did not change (only the granularity did).

Global significance

We repeated the evaluation of the global significance twice:

- Allowing $\mathcal{N}_2$ to assume negative values.
- Setting a non-negative fit range for $\mathcal{N}_2$.

Floating $\mathcal{N}_2$

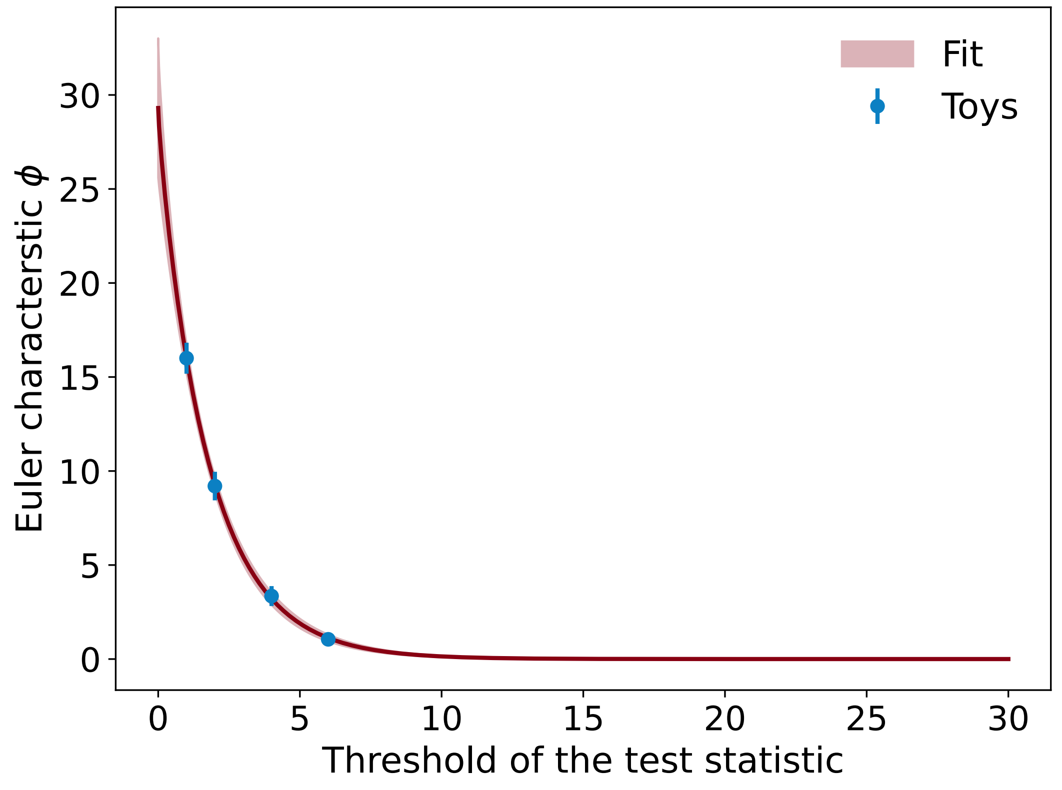
Fit results

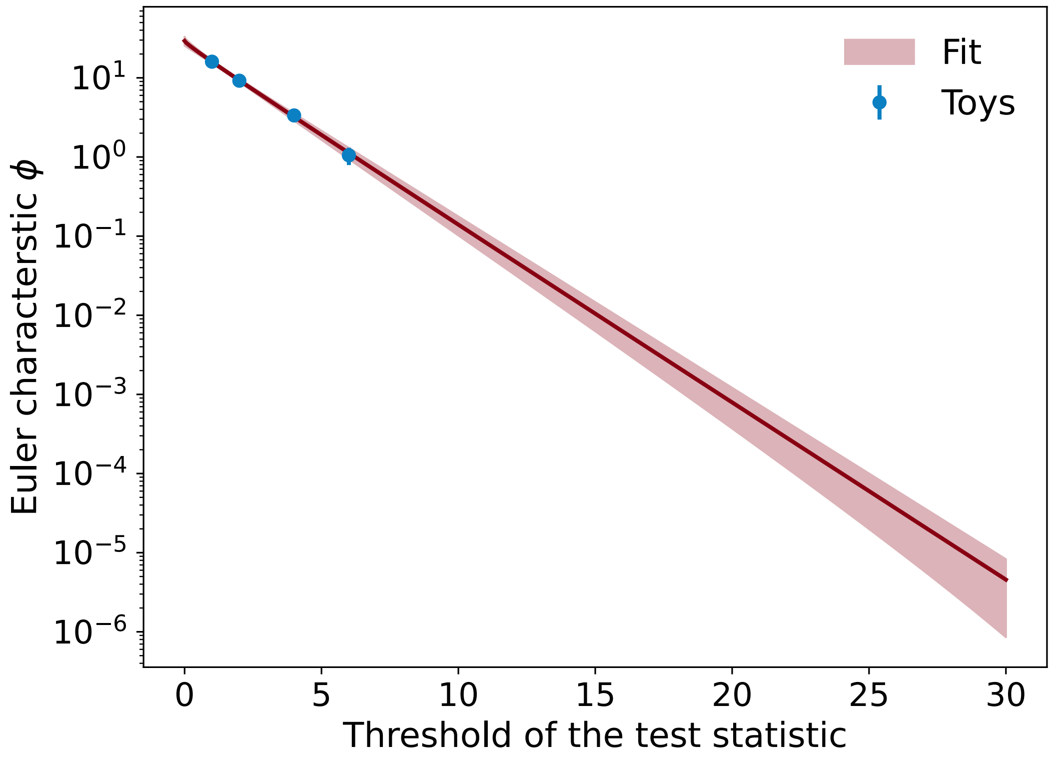
```
 Floating Parameter    FinalValue +/-  Error
--------------------  --------------------------
                  n1    2.8305e+01 +/-  3.71e+00
                  n2   -2.4716e+00 +/-  2.85e+00
```

Cov. matrix

```
2x2 matrix is as follows

     |      0    |      1    |
--------------------------------
   0 |      13.75      -10.11
   1 |     -10.11       8.124
```





Non-negative $\mathcal{N}_2$ (nominal result)

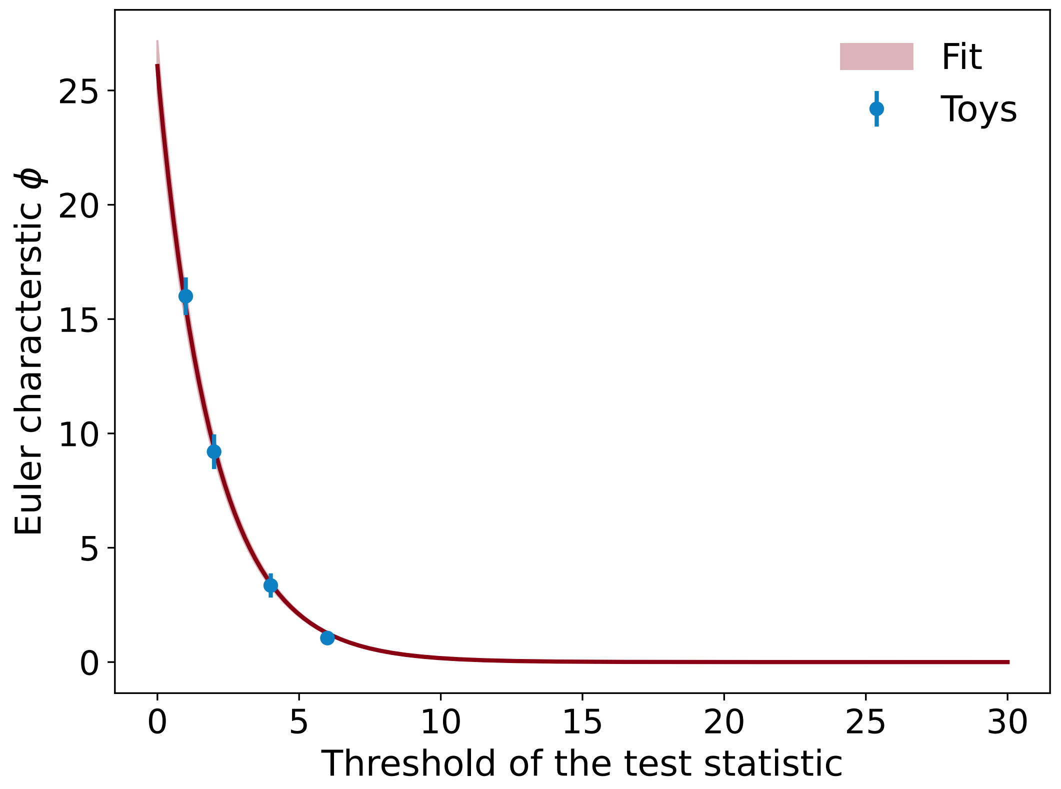
Fit results

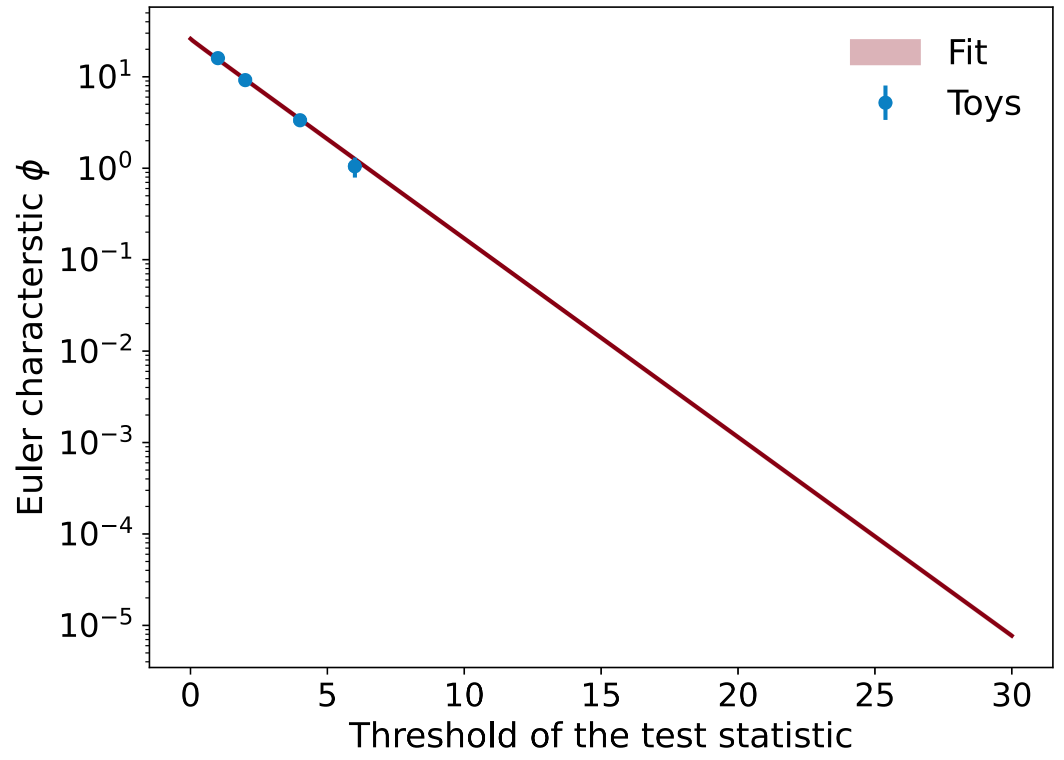
```
 Floating Parameter    FinalValue +/-  Error
--------------------  --------------------------
                  n1    2.5067e+01 +/-  1.10e+00
                  n2    0.0000e+00 +/-  8.33e-12
```

Cov. matrix

```
2x2 matrix is as follows

     |      0    |      1    |
--------------------------------
   0 |      1.208  -9.154e-12
   1 | -9.154e-12   6.936e-23
```

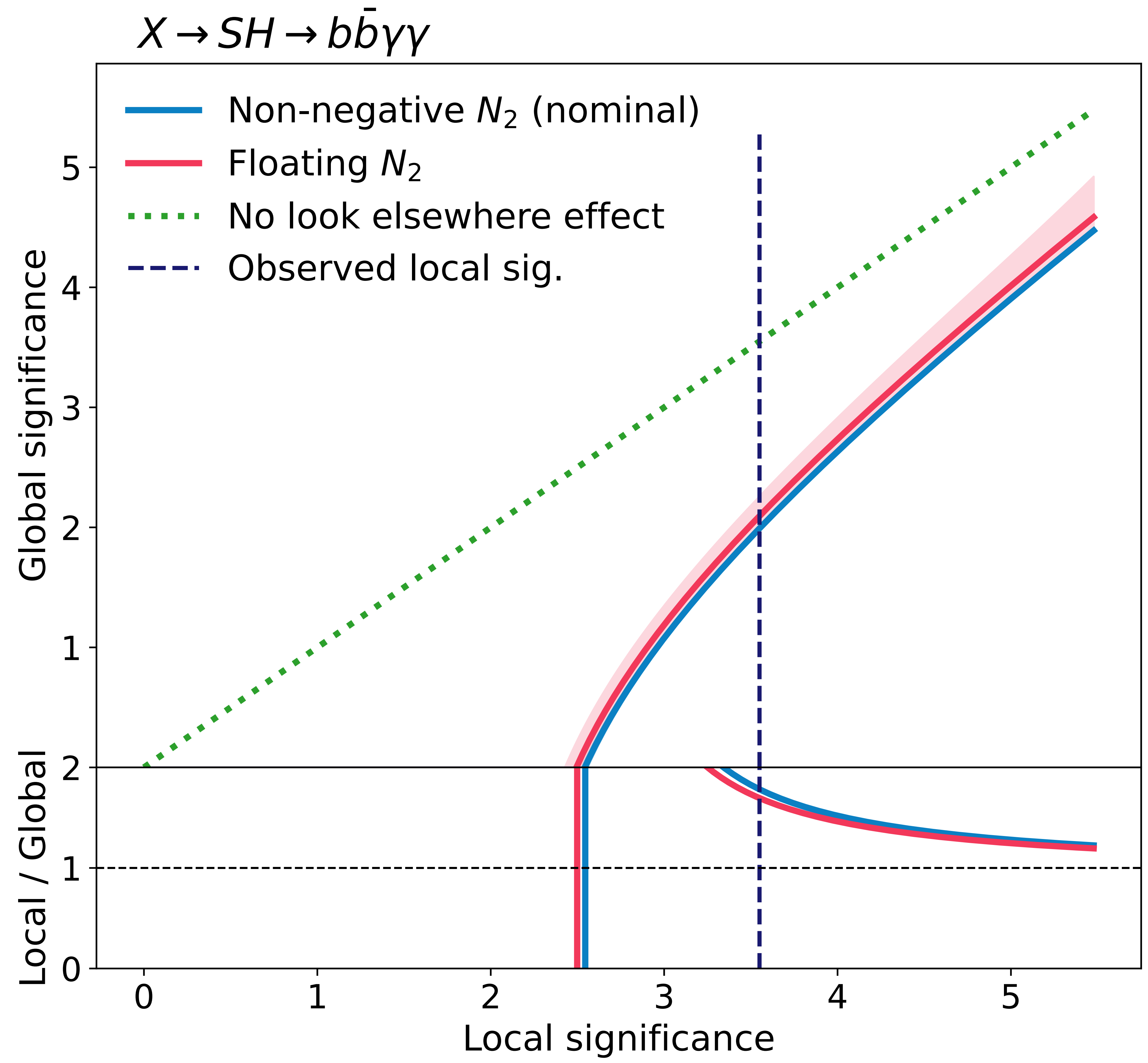




Global significance

We repeated the evaluation of the global significance twice:

- Setting a non-negative fit range for $\mathcal{N}_2$.
- Allowing $\mathcal{N}_2$ to assume negative values.



Non-negative N_2 (nominal)	1.992 +/- (-0.016, +0.021)
Floating N_2	2.094 +/- (-0.119, +0.165)