

Prompt A' Resonance Search with the Heavy Photon Search Experiment

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Stanford
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SLAC NATIONAL
ACCELERATOR
LABORATORY

Thermal Relic Dark Matter

Early Universe

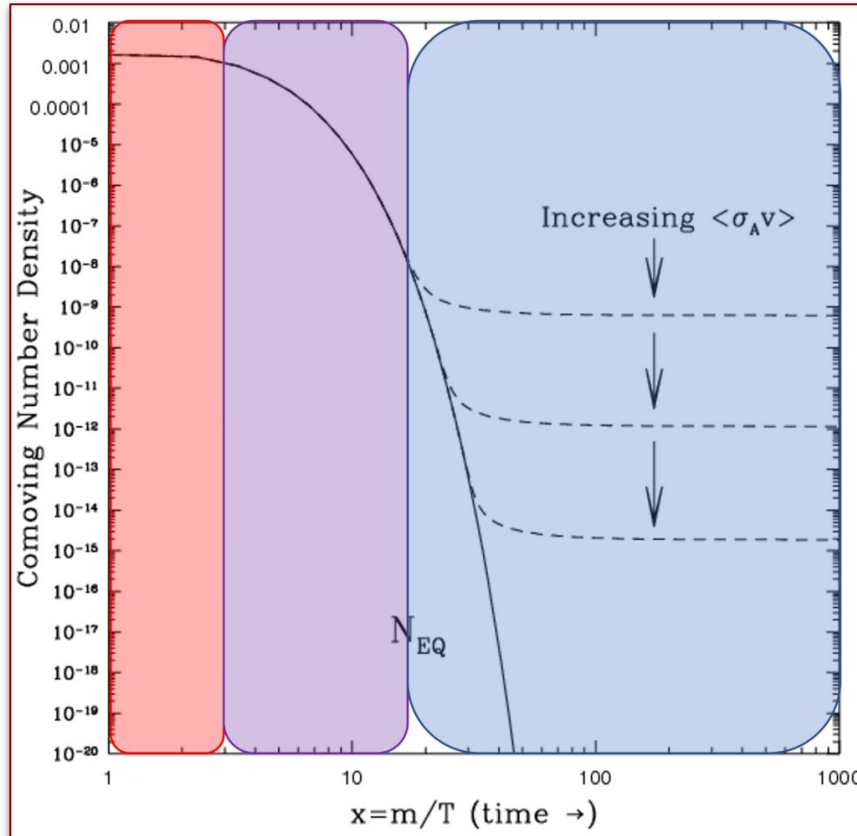
Production = Annihilation

Ended as universe cooled

Annihilation

Production < Annihilation

Ended as universe expanded



Now

Expansion cools off universe

Annihilation Stops

Relic Density Set by $\langle \sigma_A v \rangle$

$$\langle \sigma_A v \rangle \sim m_A$$

Kolb and Turner. The Early Universe
(ISBN: 978-0201626742). Colored by
Adam Green.

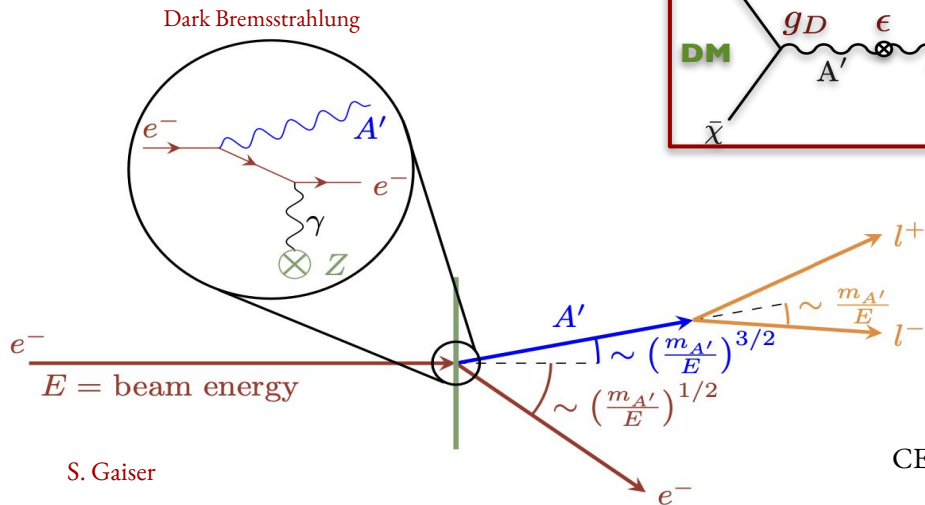
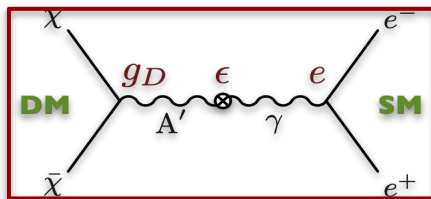
The Heavy Photon Search at JLAB

The Heavy Photon Search experiment is located at the Thomas Jefferson National Accelerator Facility in Virginia.

Engineering runs: 2015, 2016

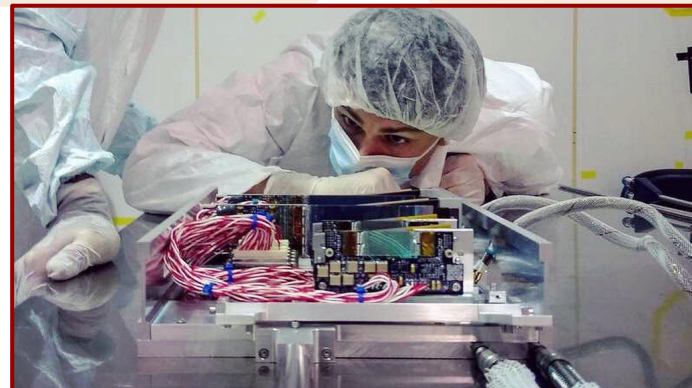
Physics Runs: 2019, 2021, 2025/2026 (planned)

A' is a **vector mediator**

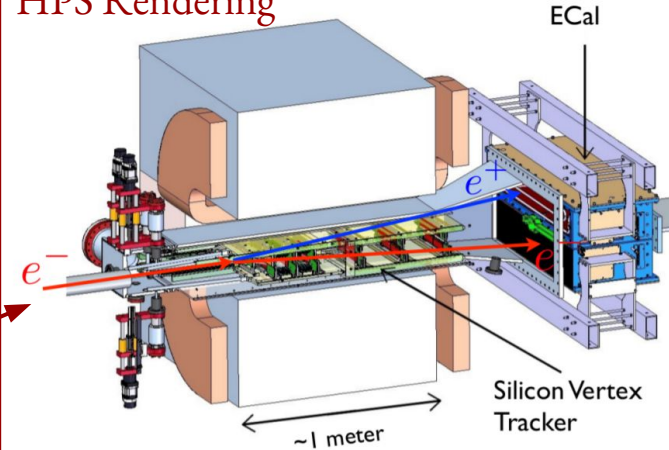


S. Gaiser

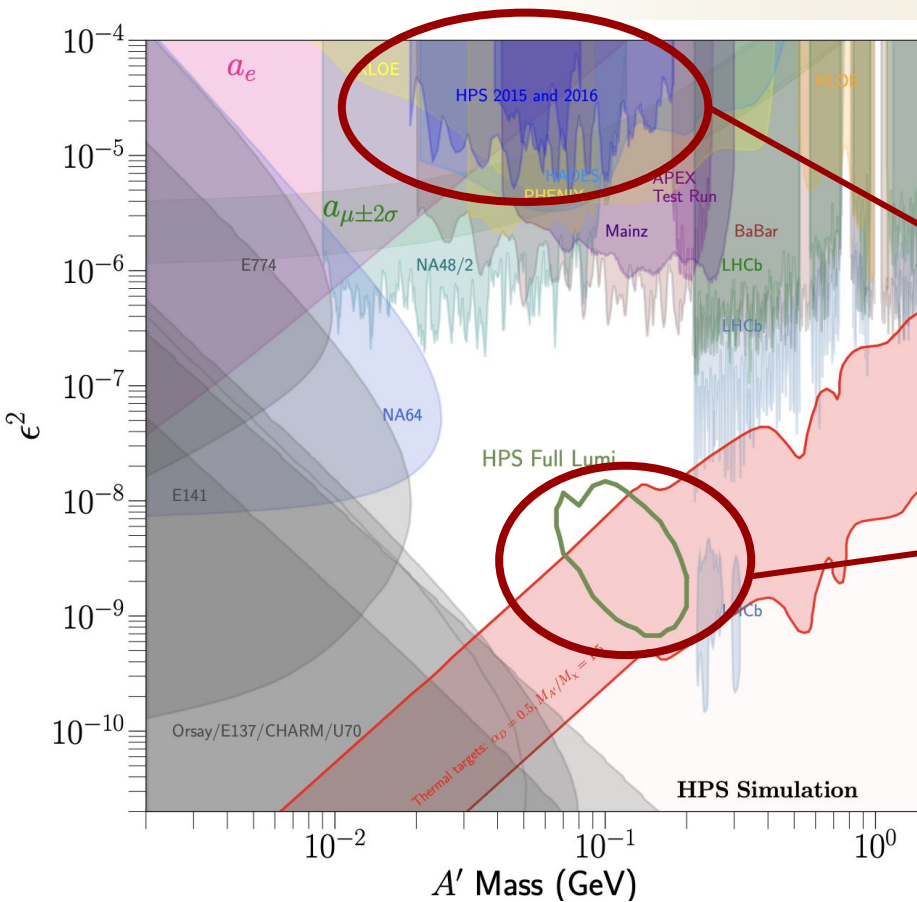
CEBAF accelerator



HPS Rendering



Physics Sensitivity of HPS



HPS has two primary search strategies for the A' depending on the lifetime / kinetic mixing, or coupling strength, (ϵ^2).

HPS Prompt Resonance Search Result

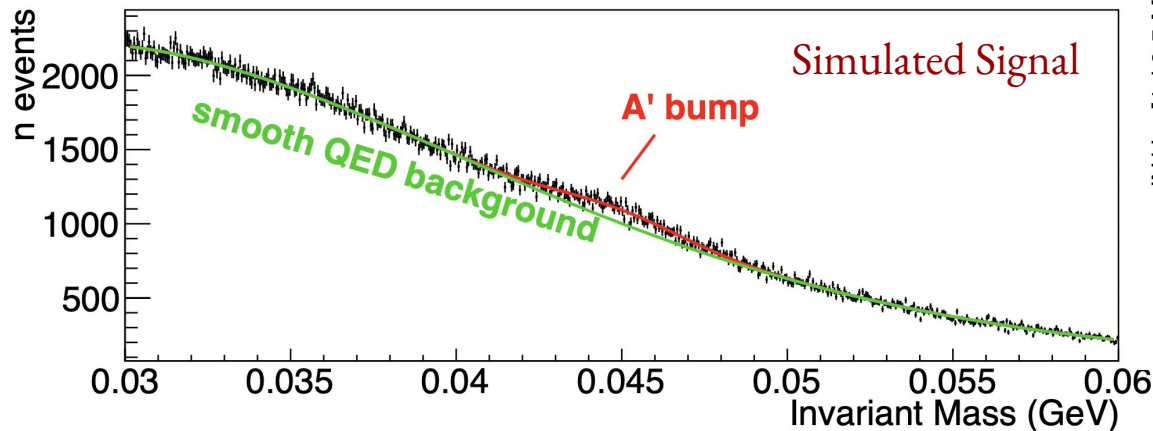
For higher coupling strengths (lower lifetime), A' 's are expected to decay extremely fast at the target and a signal is expected as a “bump” in the reconstructed e^+e^- invariant mass distribution (**IMD**).

HPS Displaced Vertex Search Reach Estimate

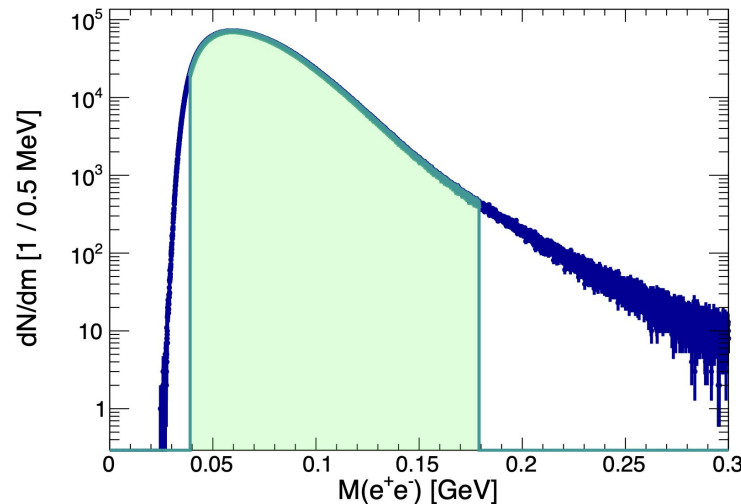
For lower coupling strengths, A' 's have a longer lifetime and the e^+e^- pairs are expected to be generated at characteristic distances away from the target.

Prompt A' Signal Model

If A' exists within the acceptance of HPS, it will present itself as a **gaussian excess above background** in the IMD.



HPS 2016 e^+e^- IMD

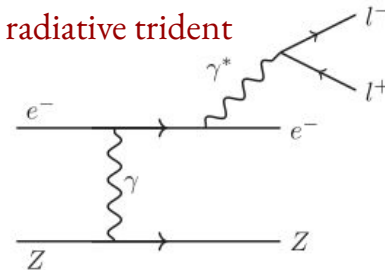


Natural width of A' \ll detector resolution
→ observed signal width is that of experimental mass resolution

Primary Backgrounds

- radiative, Bethe-Heitler tridents
- converted wide angle Bremsstrahlung

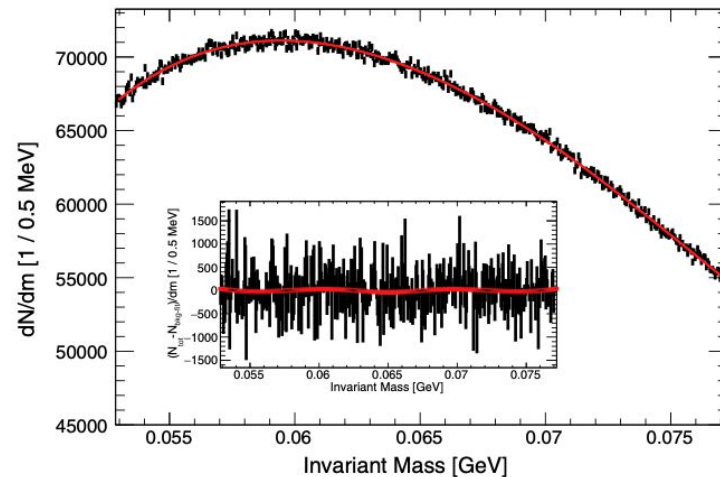
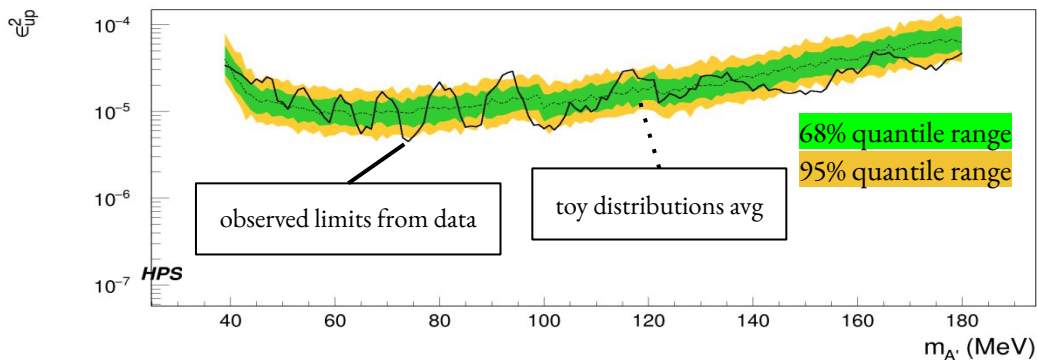
radiative trident



Improving the Background Model

As published in *Phys. Rev D*, the HPS resonance search was conducted over the (e^+e^-) invariant mass distribution **between 39 MeV and 179 MeV**, and found, in agreement with other searches, an exclusion limit of $\epsilon^2 \geq 10^{-5}$.

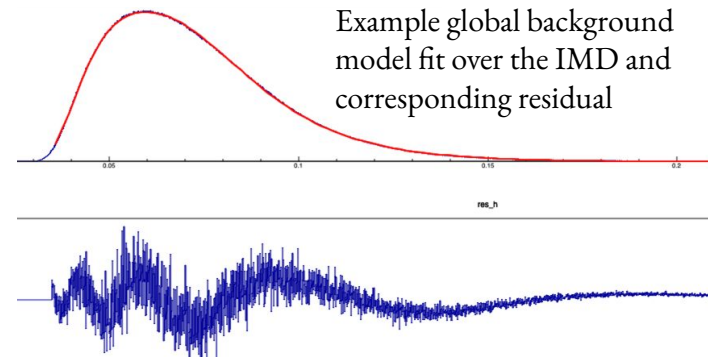
ϵ^2 Upper Limit Published Result



This method used a background model **centered around each mass hypothesis** with a window width determined by the respective mass resolution.

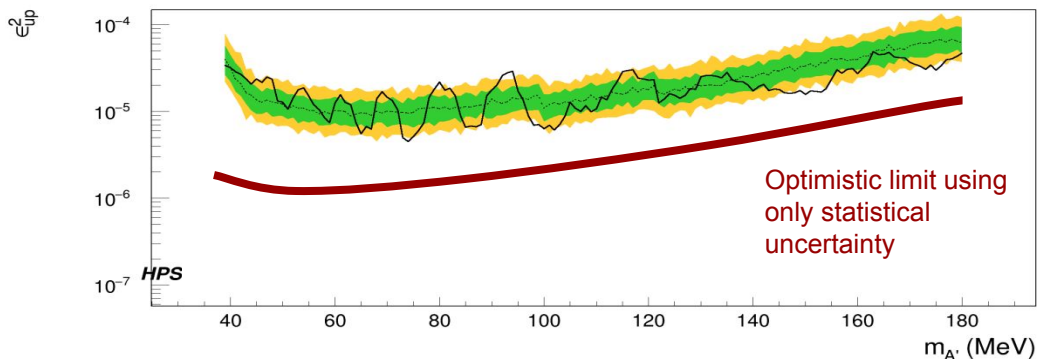
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Example global background model fit over the IMD and corresponding residual

ϵ^2 Upper Limit Published Result



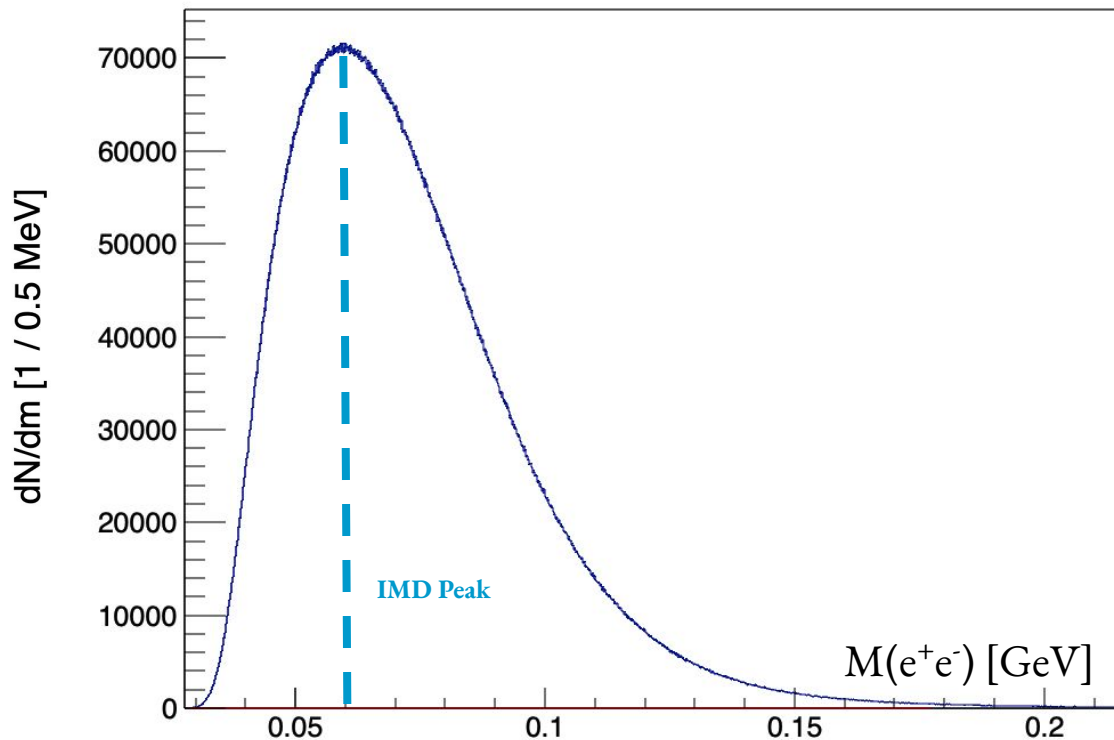
A **global background model** fit over the entire IMD is being investigated in order to reduce background shape uncertainty and improve the exclusion limit.

Based on the statistical uncertainty only limit, there is room for improvement in our background model.

Looking for a Global Background Model

The general strategy for finding functions to fit the IMD is modeling the **detector acceptance threshold (AT)**.

2016 Invariant Mass Distribution

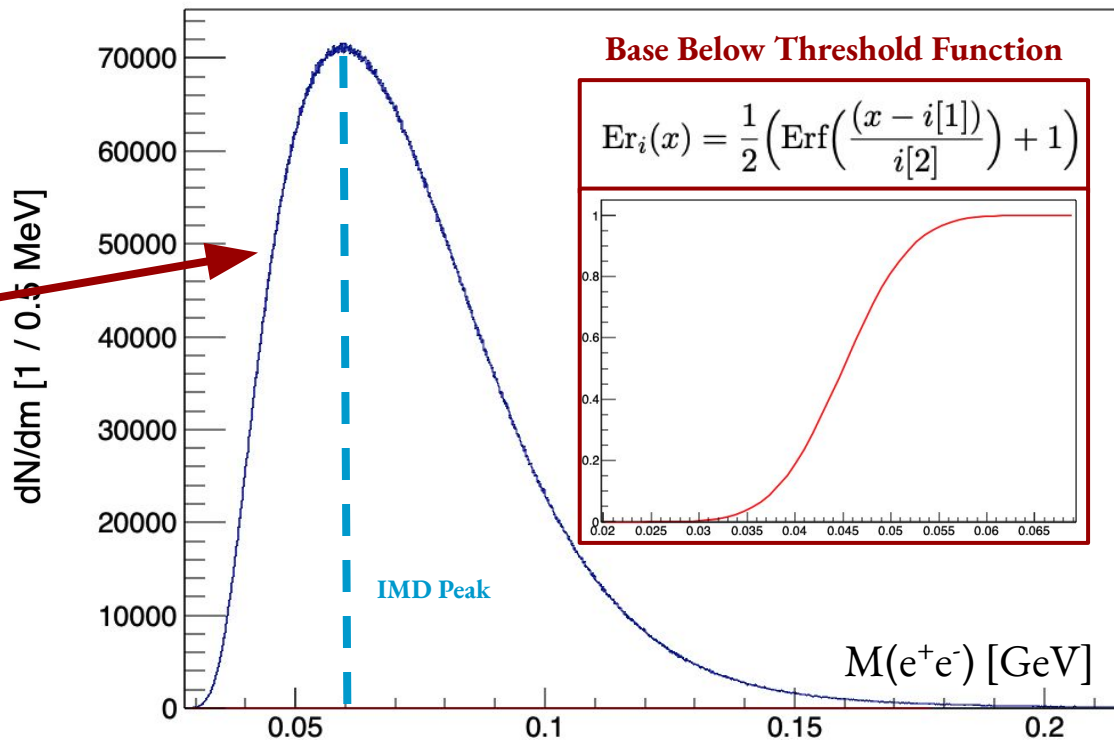


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Invariant Masses **Below** Acceptance Threshold
Fit with monotonically increasing functions to approximate acceptance of the lower energy electrons and positrons.

2016 Invariant Mass Distribution

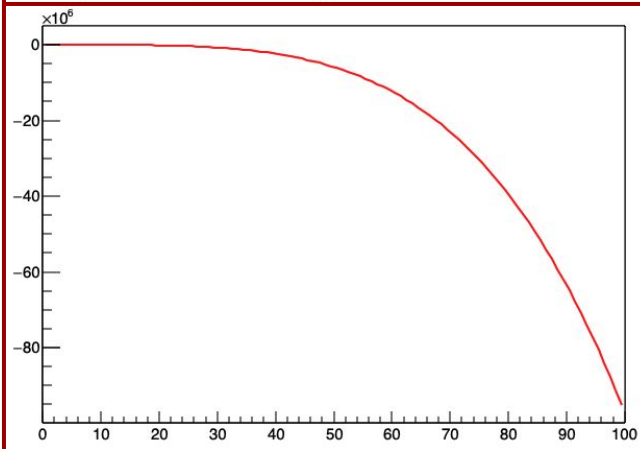


Looking for a Global Background Model

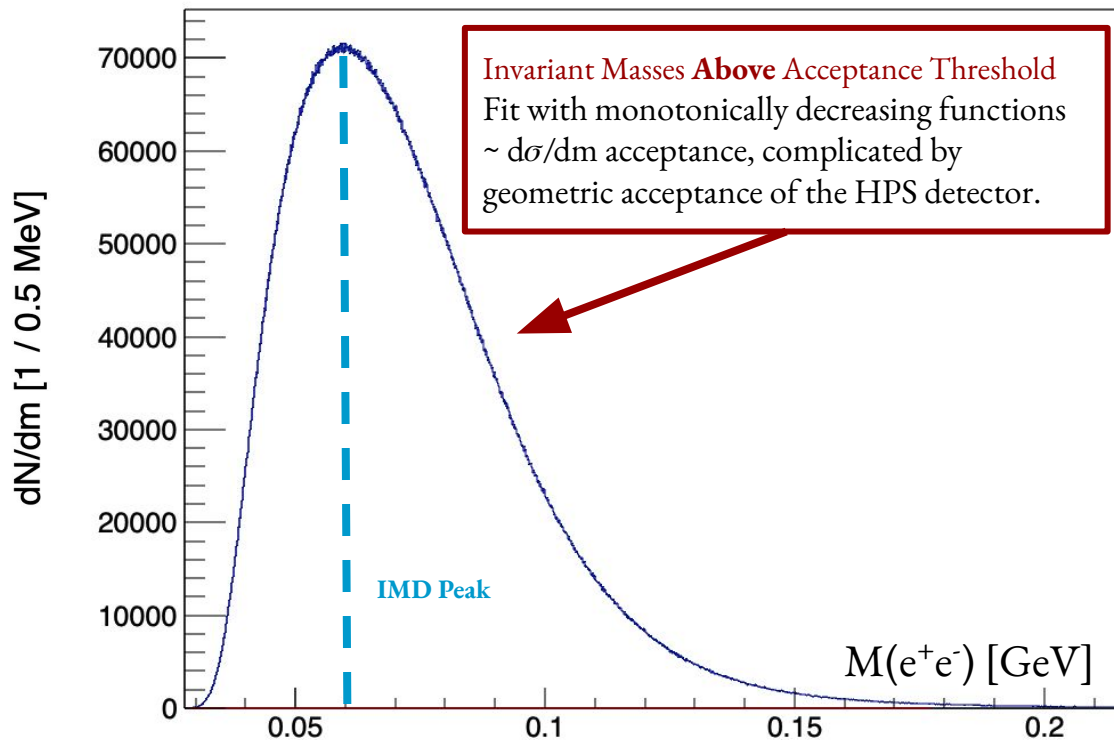
The general strategy for finding functions to fit the IMD is modeling the **detector acceptance threshold (AT)**.

Example Falling Function

$$FF_j = (1 - x)^{j[1]} \cdot e^{j[2] \cdot \log(x)}$$



2016 Invariant Mass Distribution



Looking for a Global Background Model

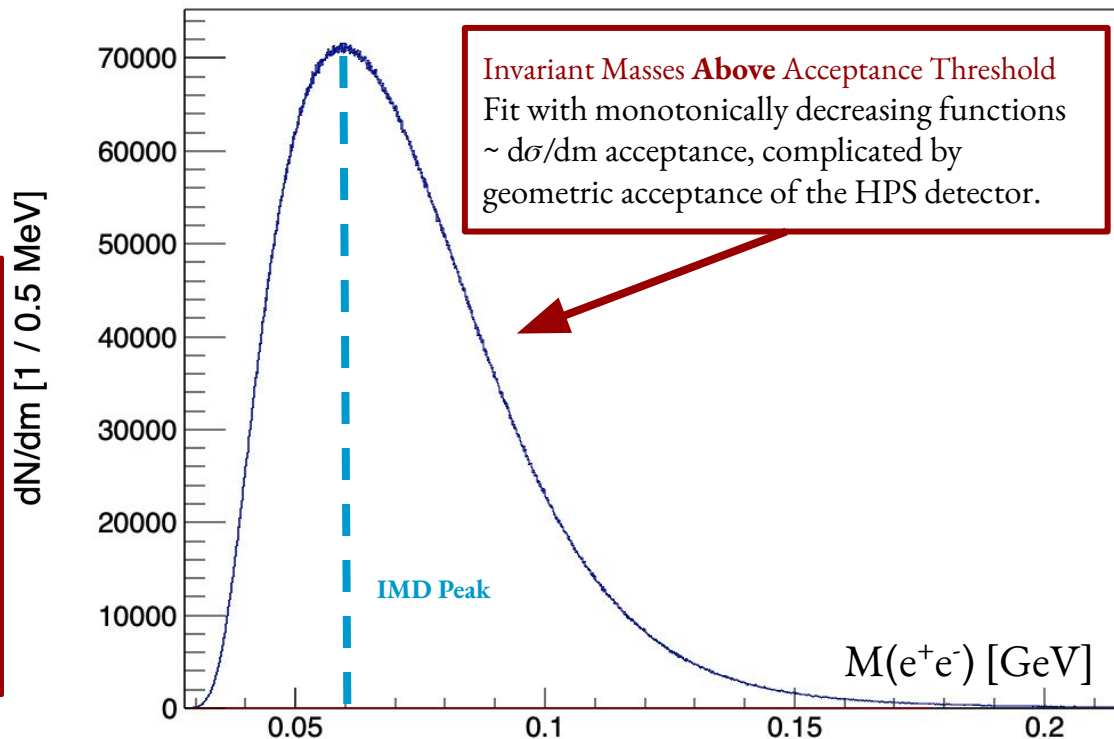
The general strategy for finding functions to fit the IMD is modeling the **detector acceptance threshold (AT)**.

Initial Falling Functions

$f_{dijet1}(x) = \frac{p_0(1-x)^{p_1}}{x^{p_2}}$	$f_{dijet2}(x) = \frac{p_0(1-x)^{p_1}}{x^{p_2+p_3 \log(x)}}$
$f_{dijet3}(x) = \frac{p_0(1-x)^{p_1}}{x^{p_2+p_3 \log(x)+p_4 \log^2(x)}}$	$f_{ATLAS1}(x) = \frac{p_0(1-x^{1/3})^{p_1}}{x^{p_2}}$
$f_{ATLAS2}(x) = \frac{p_0(1-x^{1/3})^{p_1}}{x^{p_2+p_3 \log^2(x)}}$	$f_{UA2_1}(x) = p_0 x^{p_1} e^{p_2 x}$
$f_{UA2_2}(x) = p_0 x^{p_1} e^{p_2 x + p_3 x^2}$	$f_{UA2_3}(x) = p_0 x^{p_1} e^{p_2 x + p_3 x^2 + p_4 x^3}$
$f_{cmsBH1}(x) = \frac{p_0(1+x)^{p_1}}{x^{p_2 \log x}}$	$f_{cmsBH2}(x) = \frac{p_0(1+x)^{p_1}}{x^{p_3+p_2 \log x}}$
$f_{ATLASBH1}(x) = p_0(1-x)^{p_1} x^{p_2 \log(x)}$	$f_{ATLASBH2}(x) = p_0(1-x)^{p_1} (1+x)^{p_2 \log(x)}$
$f_{ATLASBH3}(x) = p_0(1-x)^{p_1} e^{p_2 \log(x)}$	$f_{ATLASBH4}(x) = p_0(1-x^{1/3})^{p_1} x^{p_2 \log(x)}$
$f_{ATLASBH5}(x) = p_0(1-x)^{p_1} x^{p_2 x}$	$f_{ATLASBH6}(x) = p_0(1-x)^{p_1} (1+x)^{p_2 x}$

C. Bravo.

2016 Invariant Mass Distribution



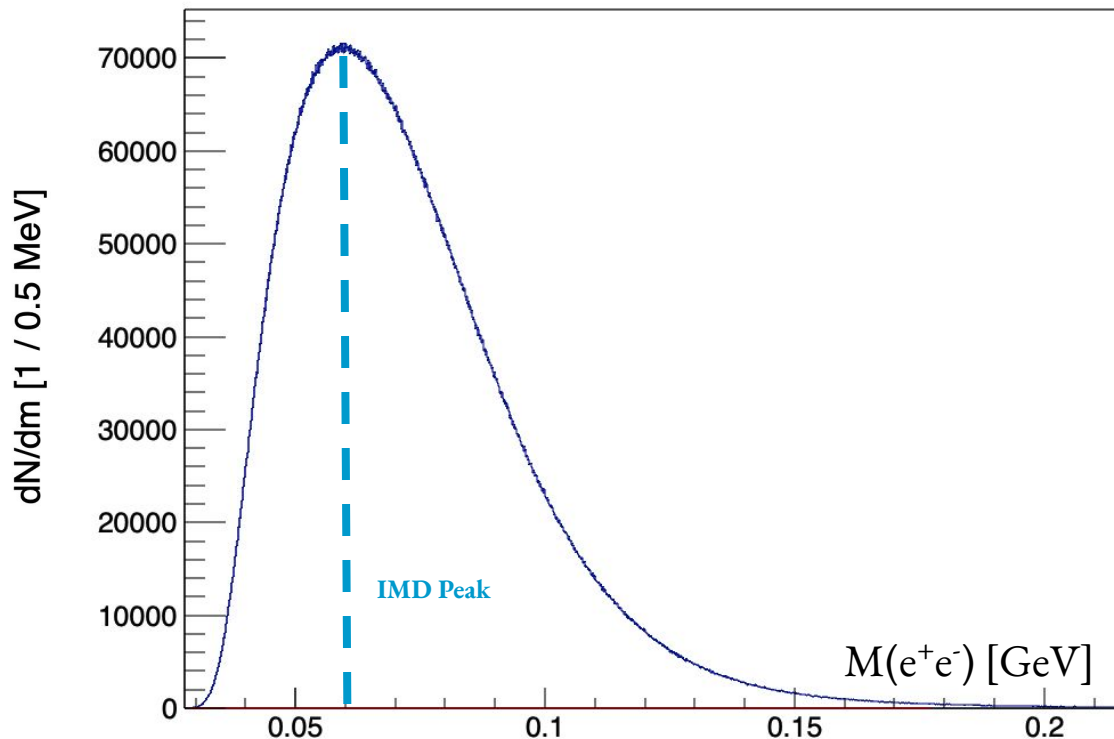
Looking for a Global Background Model

The general strategy for finding functions to fit the IMD is modeling the **detector acceptance threshold (AT)**.

Generic Functional Form

$$\mathcal{F} = \sum_i \left(E r_i \cdot F F_i \right)$$

2016 Invariant Mass Distribution



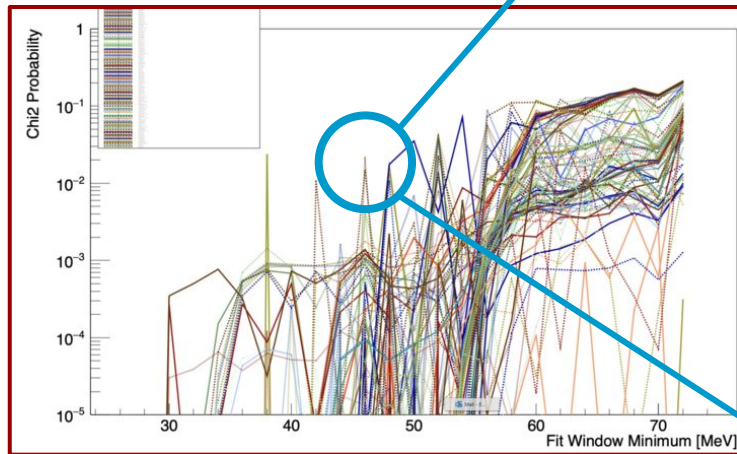
Function Selection Procedure (1/3)

Proof of concept conducted from multi stage fitting and selection procedure.

Prototyping Stage

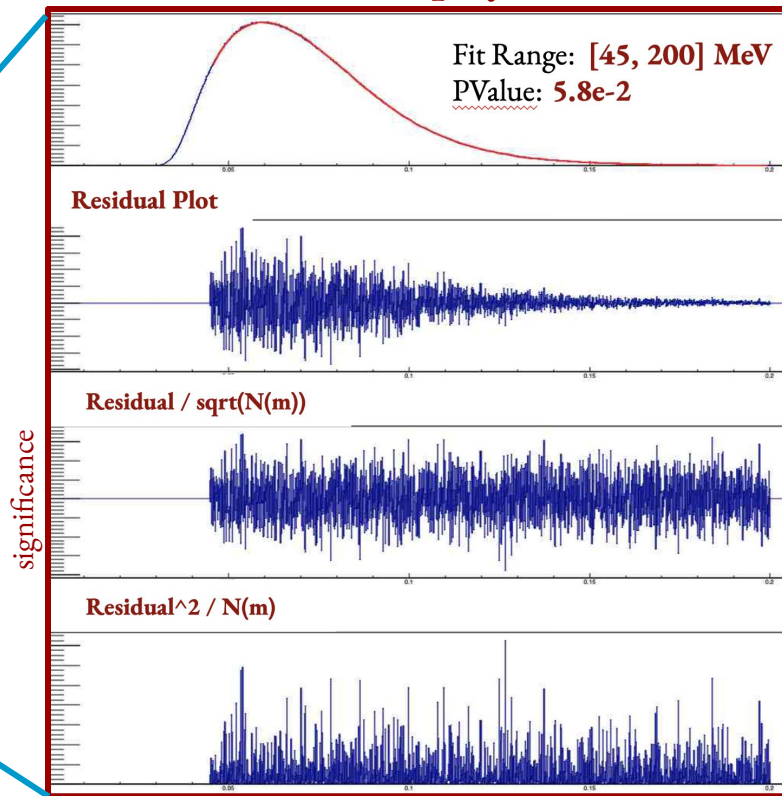
- construct and test functions + displays
- use MINUIT to find rough initial parameters
- develop global fitting analysis infrastructure

χ^2 Probability Compilation



Display tool used to compare function performances across a range of fit windows.

Fit Displays

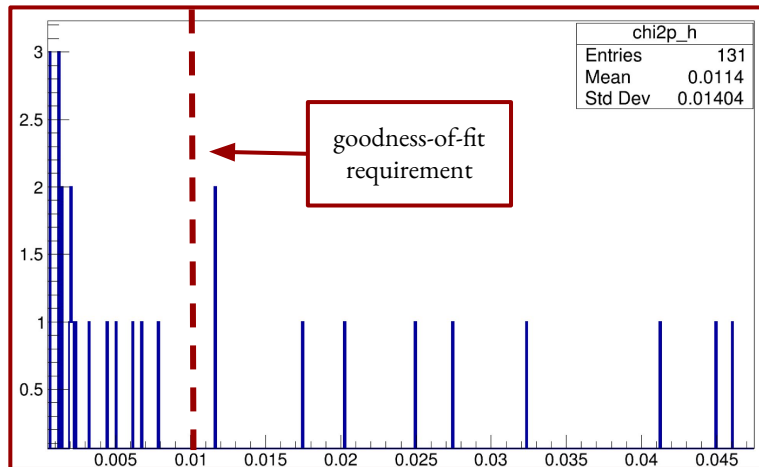


Function Selection Procedure (2/3)

Preliminary Fitting and Filtering

- All functions are fit over a single invariant mass range with dynamic changes in seeding of initial function parameters.
- Store results of all functions meeting a goodness-of-fit requirement.
- Initial study conducted by storing all fits with **pvalue greater than 1E-2**.

1D Pvalue Distribution: Fit Range[45, 200 MeV]



Promising Functions

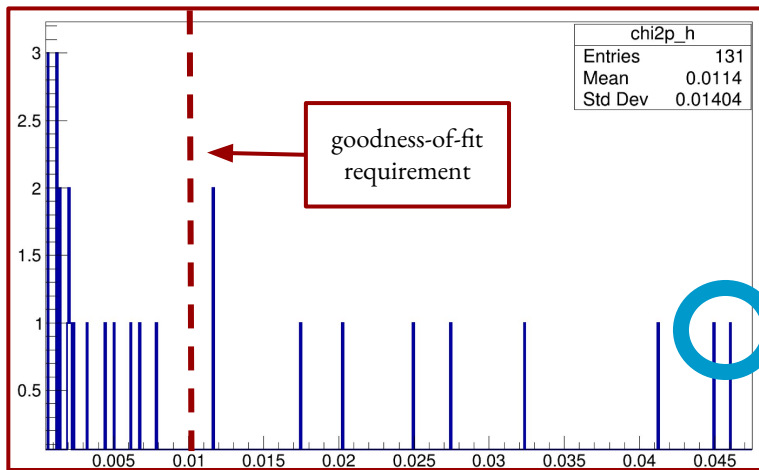
Function Name	Number of Fits	Chi2/Ndf	PValue
las3_plus_las6	1217	1.044	4.606E-02
las3_plus_las3	22667	1.045	4.498E-02
ua23_nolin_plus_las1	2531	1.046	4.128E-02
ua23_nolin_plus_las3	126	1.049	3.231E-02
ua23_nolin_plus_las2	2986	1.051	2.747E-02
las2_plus_las6	1148	1.052	2.496E-02

Function Selection Procedure (3/3)

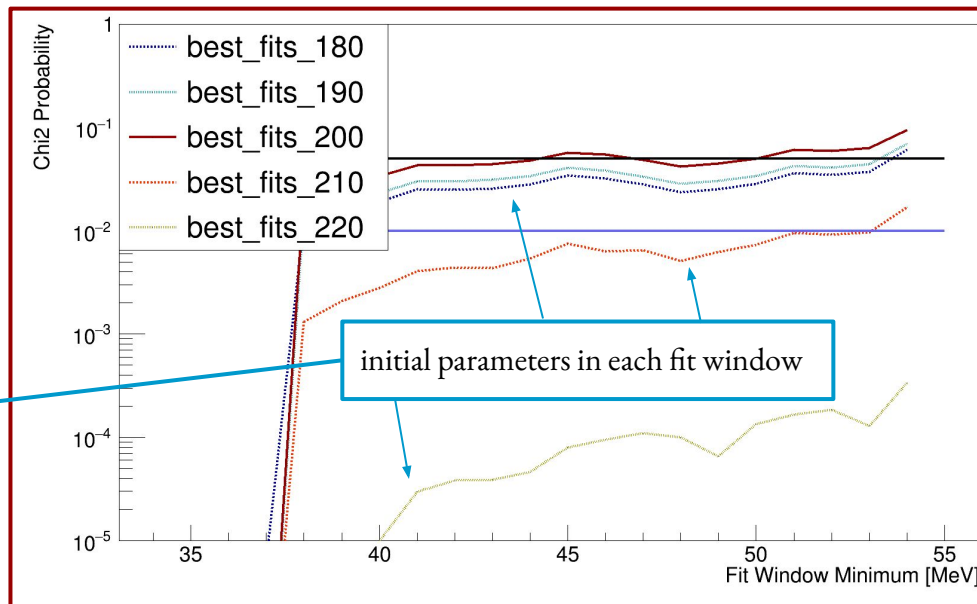
Iterative Fit Window Scanning

- Use parameters saved from previous stage as parameter seeds and fit across varying window ranges for candidate functions.

1D Pvalue Distribution: Fit Range[45, 200 MeV]



Candidate Function χ^2 Probability Compilation



Preliminary ϵ^2 Upper Limit Results

Candidate Functional Form

$$\mathcal{F} = \mathcal{C} \cdot \sum_i \left(E r_i \cdot FF_i \right)$$

Global Normalization Constant

Once candidate function has been determined

Fit over full IMD using HPS Analysis Software

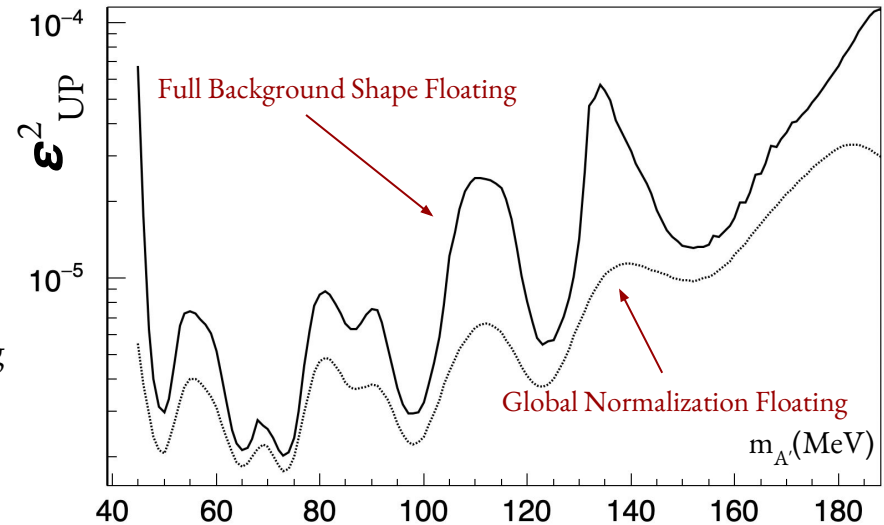
Study 1: all background parameters are floating

Study 2: only the global normalization constant is floating

Compute observed upper limits on signal yield and incorporate background + radiative fraction to determine ϵ^2 .

$$\epsilon^2 = \frac{2\alpha N_{\text{sig}}^{\text{up}}}{3\pi m_{A'} f_{\text{rad}} \frac{dN_{\text{bkg}}}{dm}}$$

ϵ^2 Upper Limit Comparison



Preliminary ϵ^2 Upper Limit Results

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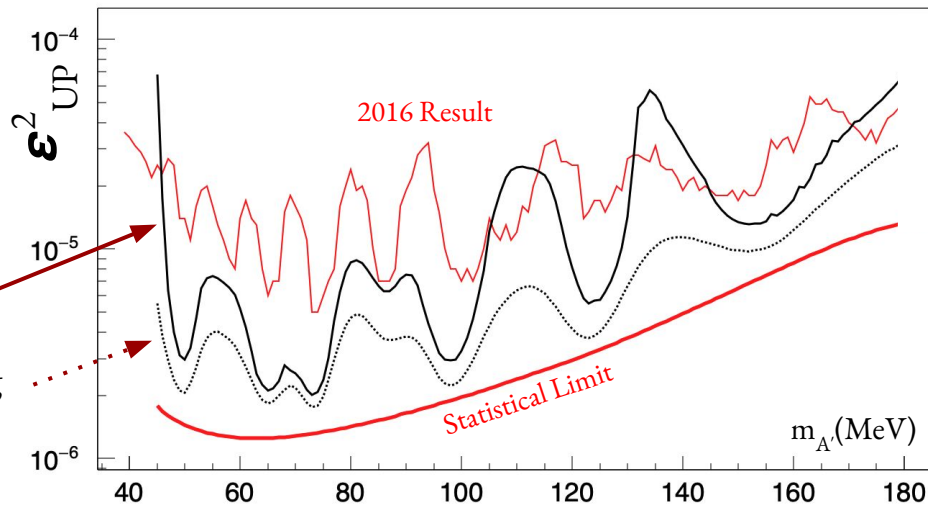
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ϵ^2 Upper Limit Comparison



Conclusions and Analysis Framework Moving Forward

We have demonstrated proof of principle that changing background parameterization can improve exclusion results for prompt A's and have found promising global background model candidates.

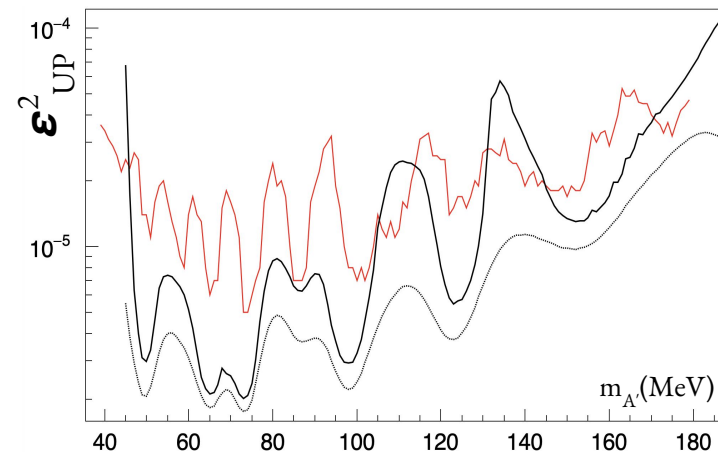
Next Steps

Develop process to determine background parameterizations in a blind procedure.

Calibrations are being finalized for the HPS Physics Runs of 2019/2021.

Acknowledgements: Special thanks to Cameron Bravo, Tim Nelson, Sarah Gaiser, Rory O'Dwyer for feedback, plots, and support. This work was conducted in coordination with the Dark Sectors group at SLAC and the HPS Collaboration.

ϵ^2 Upper Limit Comparison



Luminosity of Datasets

2016 Luminosity: 10 pb^{-1}
2019 Luminosity: 110 pb^{-1}
2021 Luminosity: 160 pb^{-1}

Additional Slides

- Full Candidate Functional Form
- Radiative Fraction and Primary Backgrounds
- Analysis Types Overview

Full Candidate Functional Form

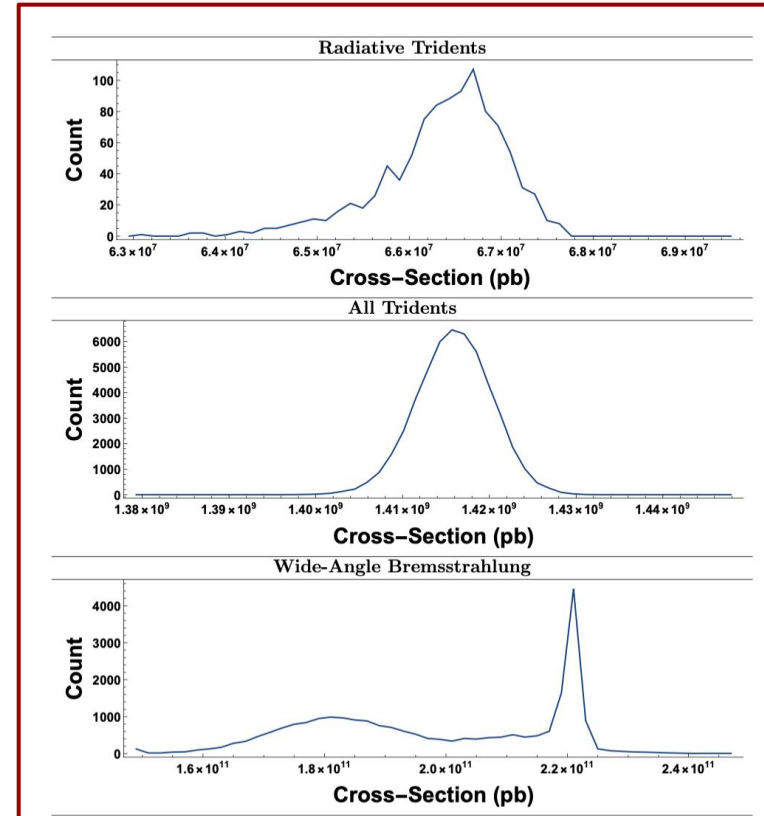
$$\mathcal{C} \cdot \left[\text{Er}_1 \cdot (1 - x)^{p[1]} \cdot e^{p[2] \cdot \log(x)} + \text{Er}_2 \cdot q[1] \cdot (1 - x)^{q[2]} \cdot (1 + x)^{q[3] \cdot x} \right]$$

Radiative Fraction and Primary Backgrounds

$$\epsilon^2 = \frac{2\alpha N_{\text{sig}}^{\text{up}}}{3\pi m_{A'} f_{\text{rad}} \frac{dN_{\text{bkg}}}{dm}}$$

$$f_{\text{rad}} = \frac{\frac{dN_{\gamma^*}}{dm}}{\frac{dN_{\text{bkg}}}{dm}} = \frac{\frac{dN_{\gamma^*}}{dm}}{\frac{dN_{\text{tri}}}{dm} + \frac{dN_{\text{WAB}}}{dm}}$$

Radiative fraction is defined as the ratio of differential rate of radiative tridents to differential bkg rate. Relative rates determined in MC.



I. Iterative Mass Window Fitting

Fit shape of background with 100% of the data by ignoring data near mass hypothesis in initial fit and freezing parameters and fitting a second time without blinding data near mass hypothesis

II. Parameter Fixing Approach

Using 10% of a dataset determine which parameters to freeze and which to float for 100% of the data set, then generate limit bands using toy MC and determine the validity of background models using signal injection studies.