tuning (model) parameters to data not corrected for acceptance

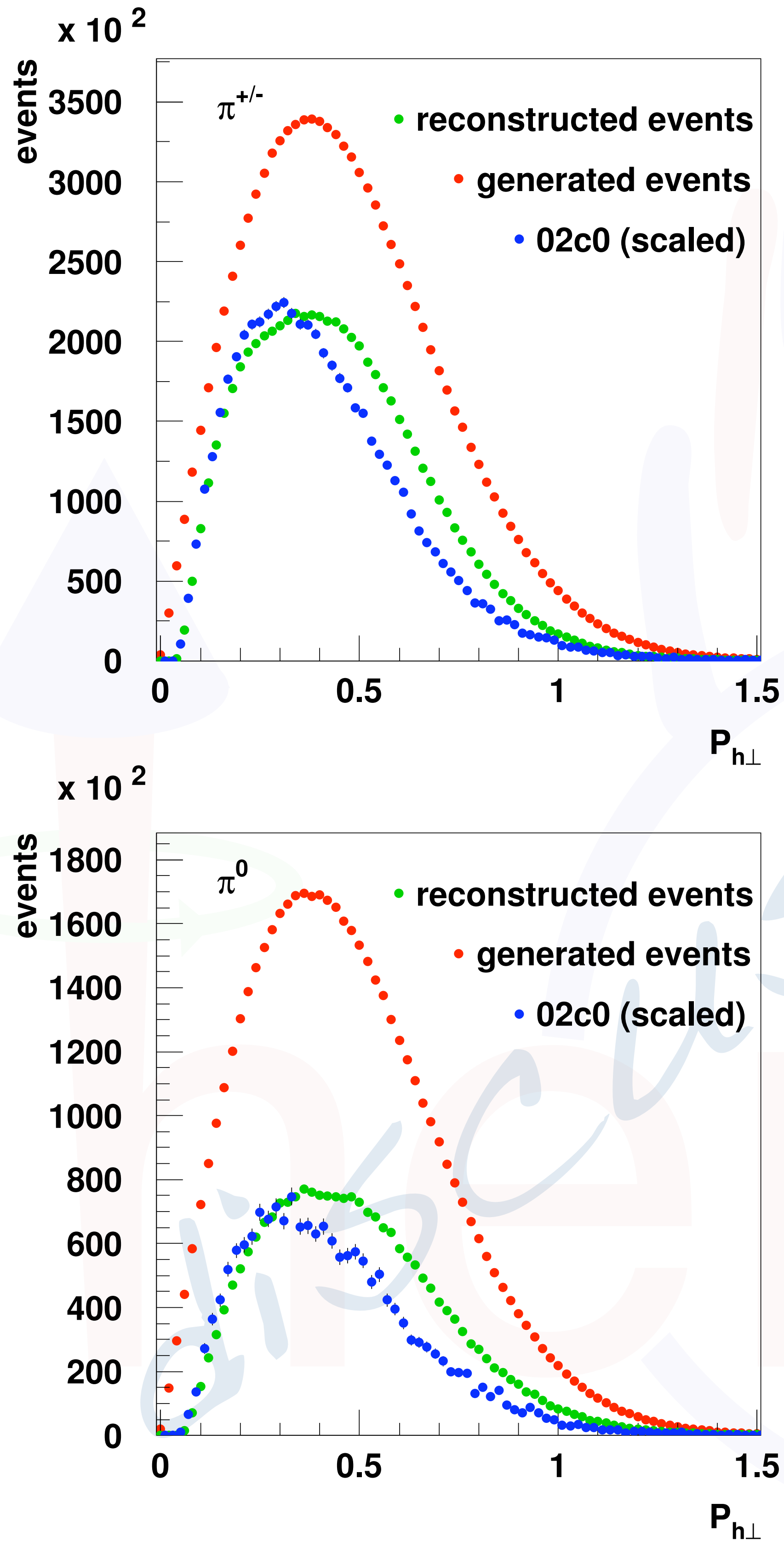
an alternative/complementary approach for extracting physics information from experimental data

tuning model parameters

Basic idea:

- traditionally, use experimental data corrected for all instrumental effects to extract physics, e.g., fit model parameters to experimental distributions
- for SIDIS, full unfolding of experimental data "expensive" as nominally differential in at least 5 kinematic variables
- alternatively, tune parameters using fully simulated events (i.e., physics model ⊗ detector simulation ⊗ reconstruction) and compare to real reconstructed experimental data

Tuning the Gaussians in gmc_trans



- gmc_trans: a TMD MC based on Gaussian Ansatz
- constant Gaussian widths, i.e., no dependence on x or z (inspired by Jetset):

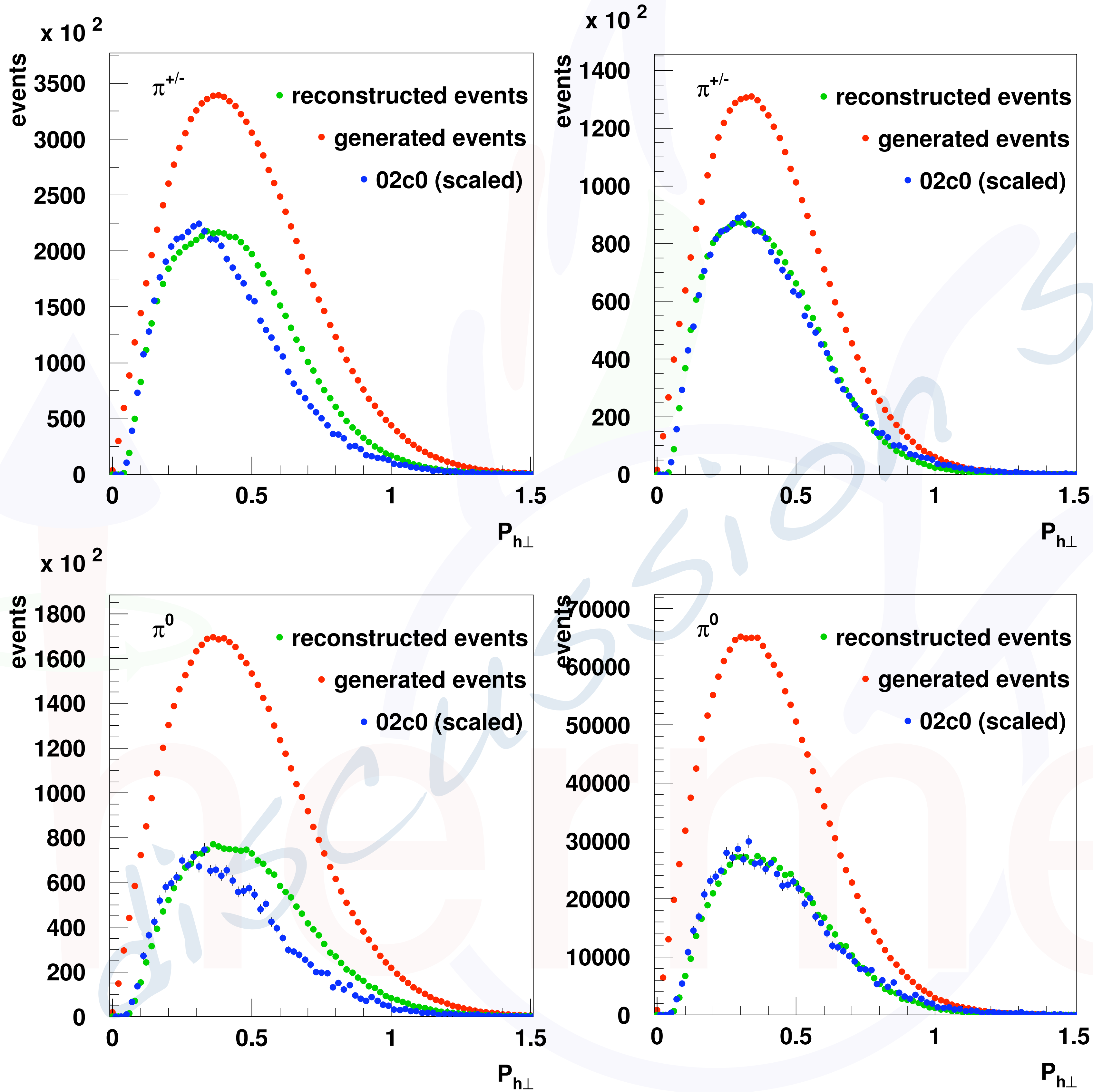
$$\langle p_T \rangle = 0.44$$

$$\langle K_T \rangle = 0.44$$

- tune to data integrated over whole kinematic range

- generated events "=" physics model
- reconstructed = model ⊗ experiment simulation
- 02c0 = real HERMES data

Tuning the Gaussians in gmc_trans



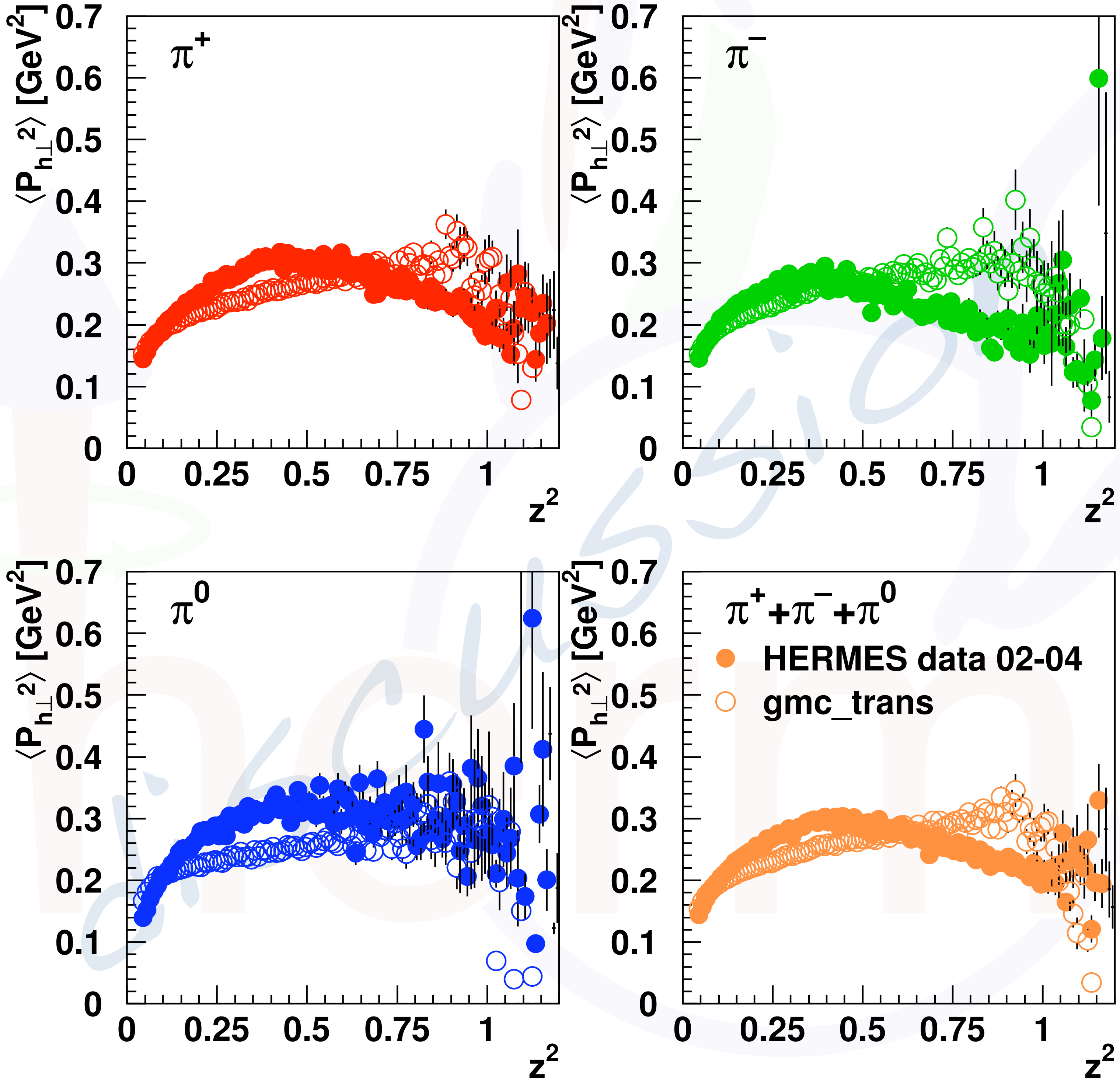
Better:

$$\langle p_T \rangle = 0.38$$

$$\langle K_T \rangle = 0.38$$

Tuning the Gaussians in gmc_trans

so far: $\langle P_{h\perp}^2(z)\rangle = z^2\,\langle p_T^2\rangle + \langle K_T^2\rangle$



$\langle p_T\rangle = 0.38$

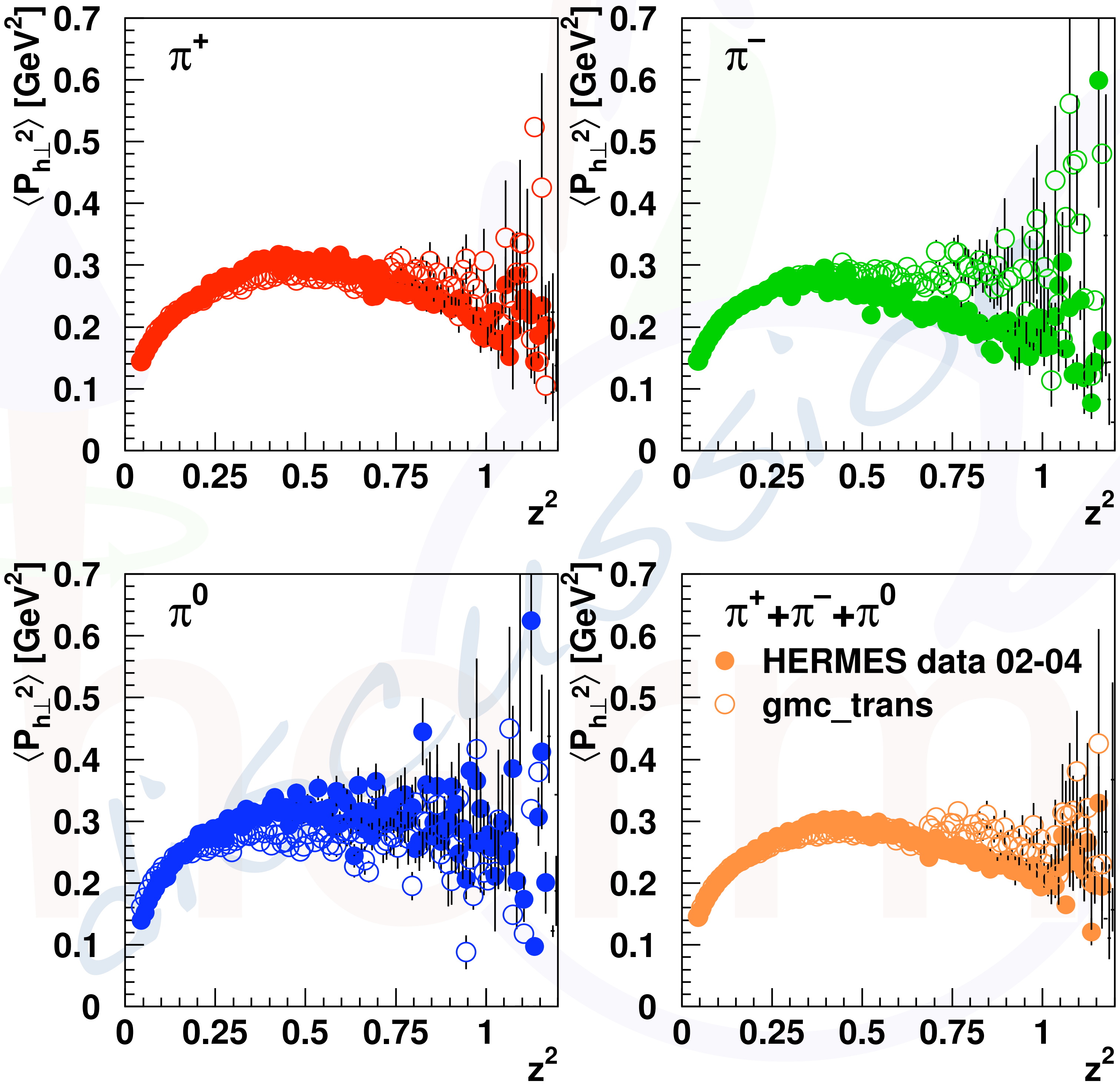
$\langle K_T\rangle = 0.38$

$\langle p_T^2\rangle \simeq 0.185$

$\langle K_T^2\rangle \simeq 0.185$

Tuning the Gaussians in gmc_trans

$$\left\langle P_{h\perp}^2(z) \right\rangle = z^2 \left\langle p_T^2 \right\rangle + \left\langle K_T^2(z) \right\rangle$$

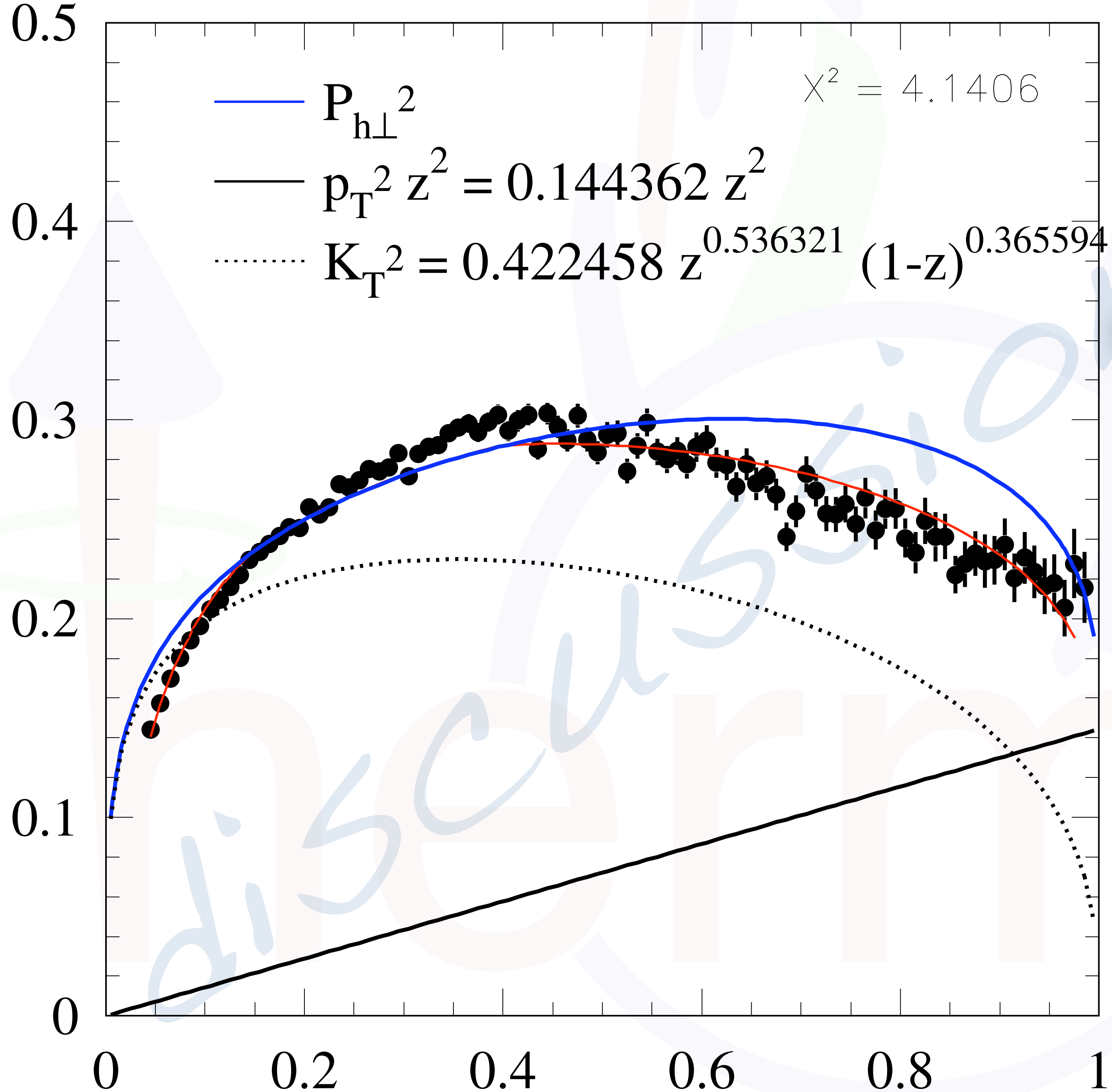


z-dependent!

"Hashi set"

Tuning the Gaussians in gmc_trans

now: $\langle P_{h\perp}^2(z)\rangle = z^2 \langle p_T^2\rangle + \langle K_T^2(z)\rangle$



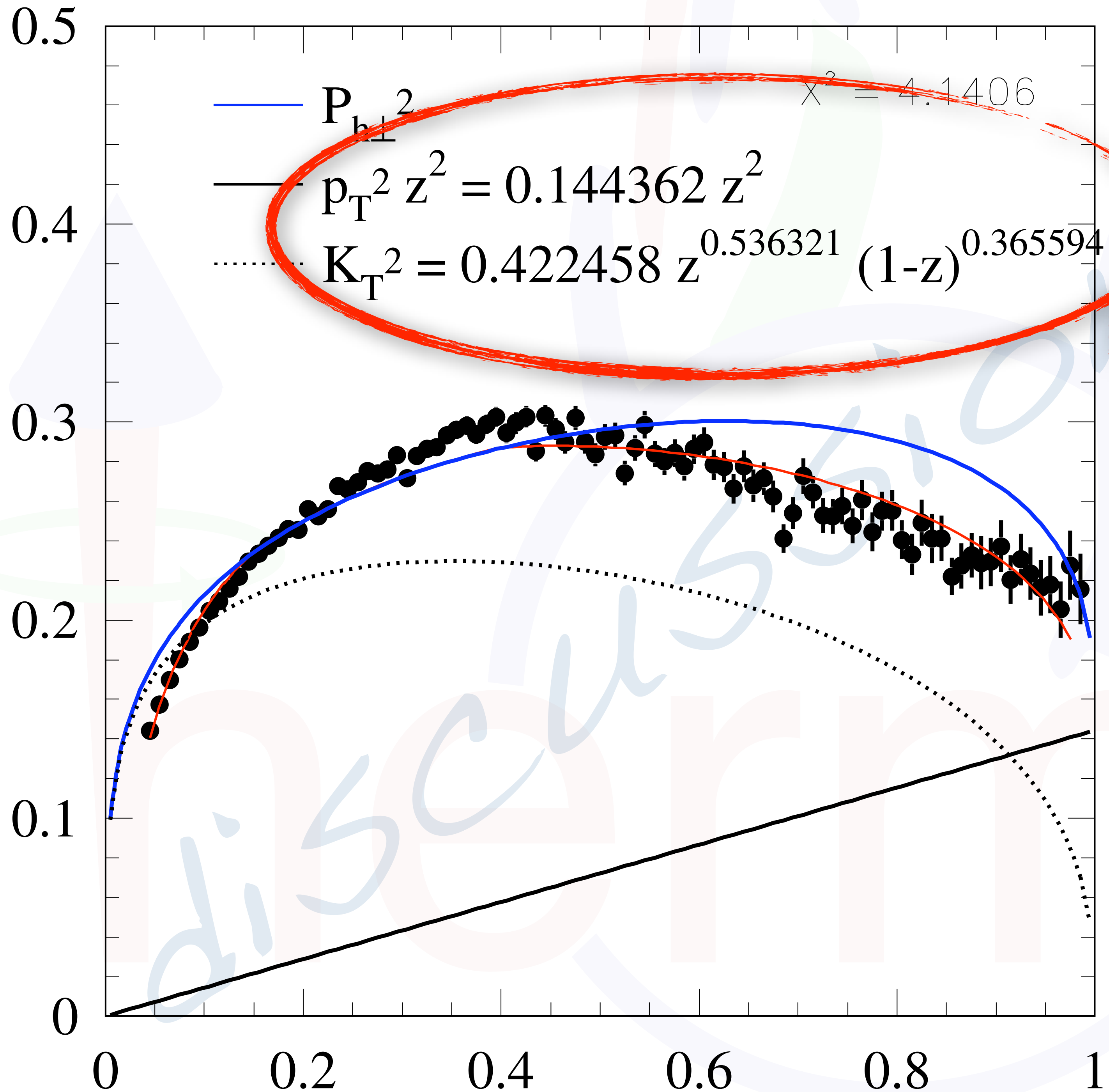
z-dependent!

"Hashi set"

tuned to HERMES data in acceptance

Tuning the Gaussians in gmc_trans

now: $\langle P_{h\perp}^2(z)\rangle = z^2\,\langle p_T^2\rangle + \langle K_T^2(z)\rangle$



z-dependent!

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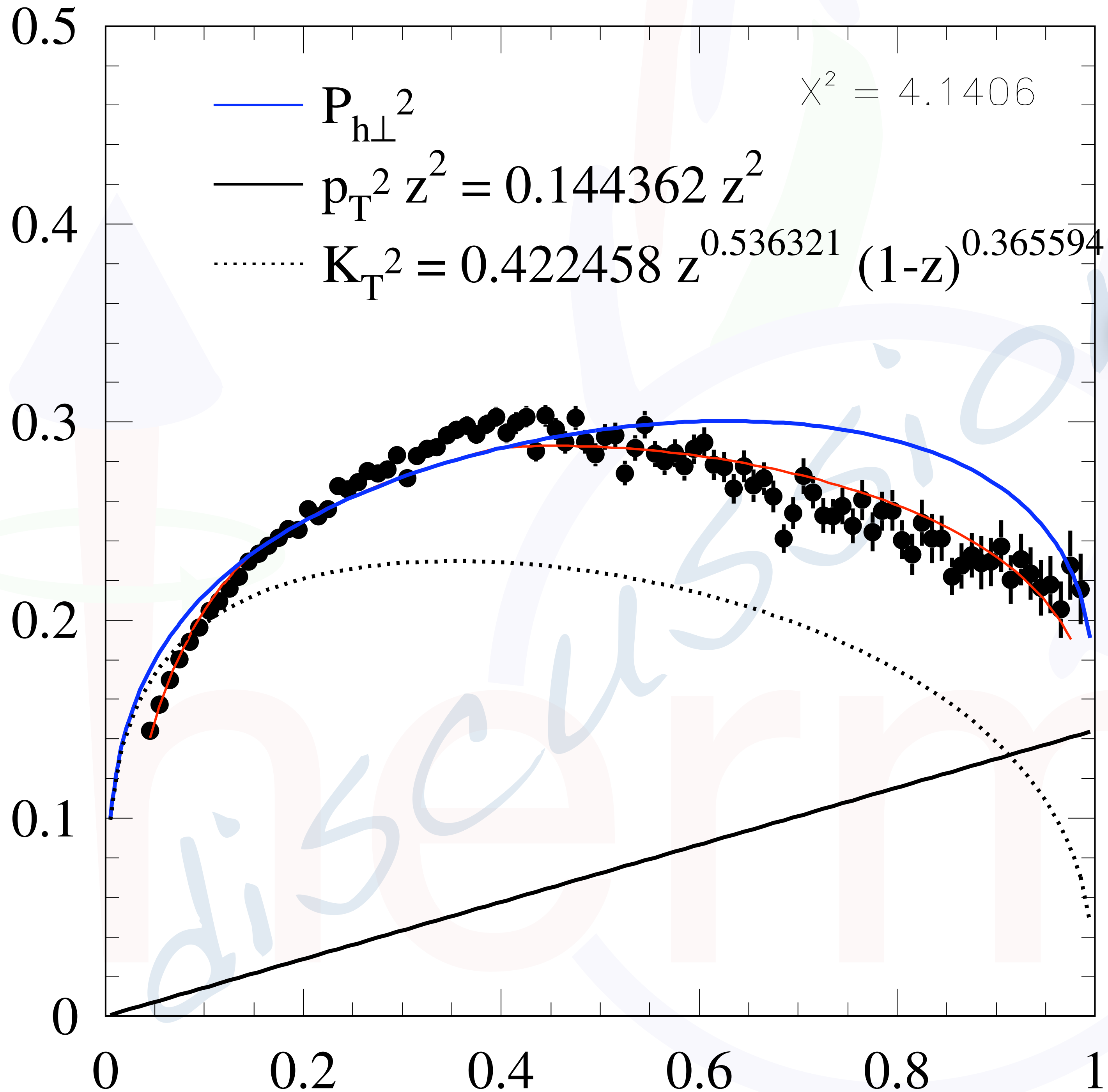
Tuning the Gaussians in gmc_trans

now: $\langle P_{h\perp}^2(z)\rangle = z^2 \langle p_T^2\rangle + \langle K_T^2(z)\rangle$



z-dependent!

"Hashi set"

tuned to HERMES data in acceptance

tuning Jetset

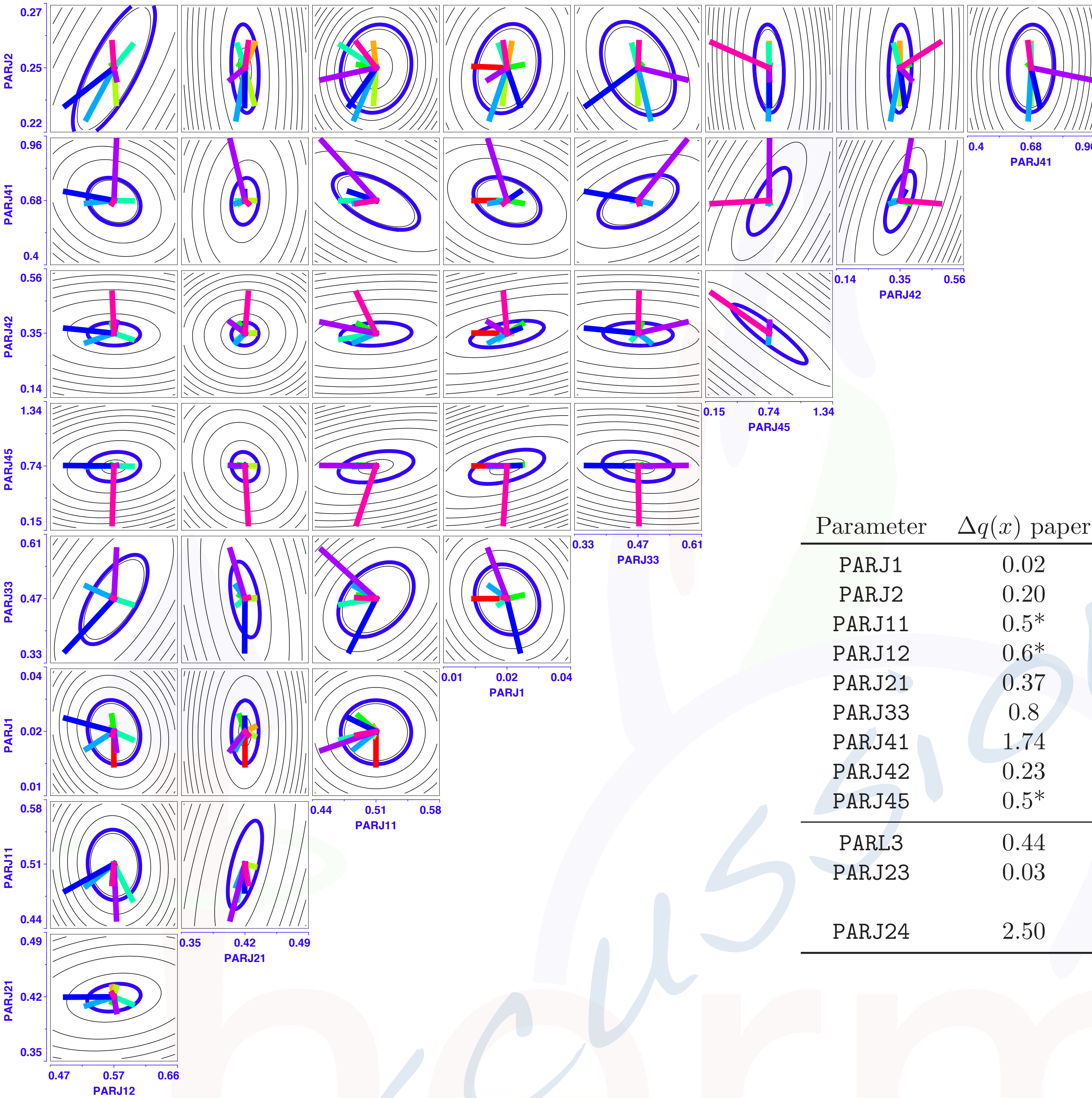


Figure 5.5: Contour plots of two-dimensional cross sections of the quadratic fit function in nine JETSET parameters to the $\chi^2_{\rm tune}$ surface produced by comparing Monte Carlo to data multiplicities ($\chi^2_{\rm fit}/195\text{DoF} = 0.82$). Most panels contain contours with elliptical axes which are to some degree diagonal. This indicates correlation between the JETSET parameters. The blue band represents 2D slices of the hyper-ellipsoid that has a 68% likelihood of containing the true best tune. This band was expanded to compensate for the fact that the χ^2 minimum was still considerably greater than the number of degrees of freedom ($\chi^2_{\rm tune}/224\text{DoF} = 12.2$). The colored lines represent the nine uncorrelated parameter axes produced by diagonalizing the Hessian matrix and terminate where they intersect the 68% hyper-ellipsoid.

Parameter	$\Delta q(x)$ paper	2004c	"Lund-scan"	Parameter Description
PARJ1	0.02	0.029	0.02	Diquark suppression
PARJ2	0.20	0.283	0.25	Strange quark suppression
PARJ11	0.5*	0.5*	0.51	Vector meson suppression (light mesons)
PARJ12	0.6*	0.6*	0.57	Vector meson suppression (strange mesons)
PARJ21	0.37	0.38	0.42	Width of Gaussian $p_{h\perp}$ distribution [GeV]
PARJ33	0.8	0.8	0.47	String breaking mass cutoff
PARJ41	1.74	1.94	0.68	Lund-String "a" parameter
PARJ42	0.23	0.544	0.35	Lund-String "b" parameter
PARJ45	0.5*	1.05	0.74	"a" adjustment for diquark
PARL3	0.44	0.44	(0.44)	Gaussian width of intrinsic k_T [GeV]
PARJ23	0.03	0.01	(0.01)	Fraction of $p_{h\perp}$ distribution to have additional non-Gaussian tails
PARJ24	2.50	2.0	(2.0)	Strength of non-Gaussian $p_{h\perp}$ tails

[J. Rubin, PhD thesis UIUC]