Does η/s extracted from the data depend on the EoS?

Pasi Huovinen

Uniwersytet Wrocławski

CRC-TR 211 Transport meeting

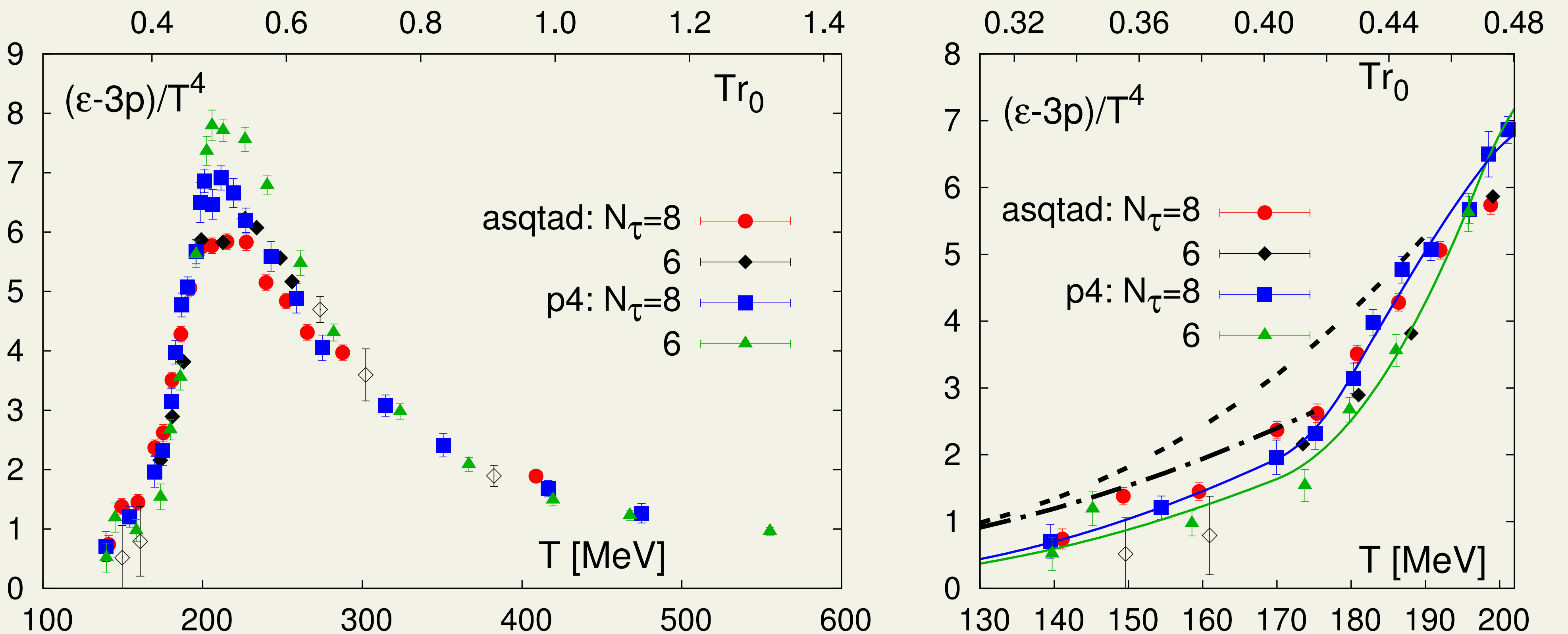
June 21, 2018, Institut für Theoretische Physik, Frankfurt

reporting work done by Jussi Auvinen and Harri Niemi

in collaboration with Kari J. Eskola, Risto Paatelainen, and Peter Petreczky

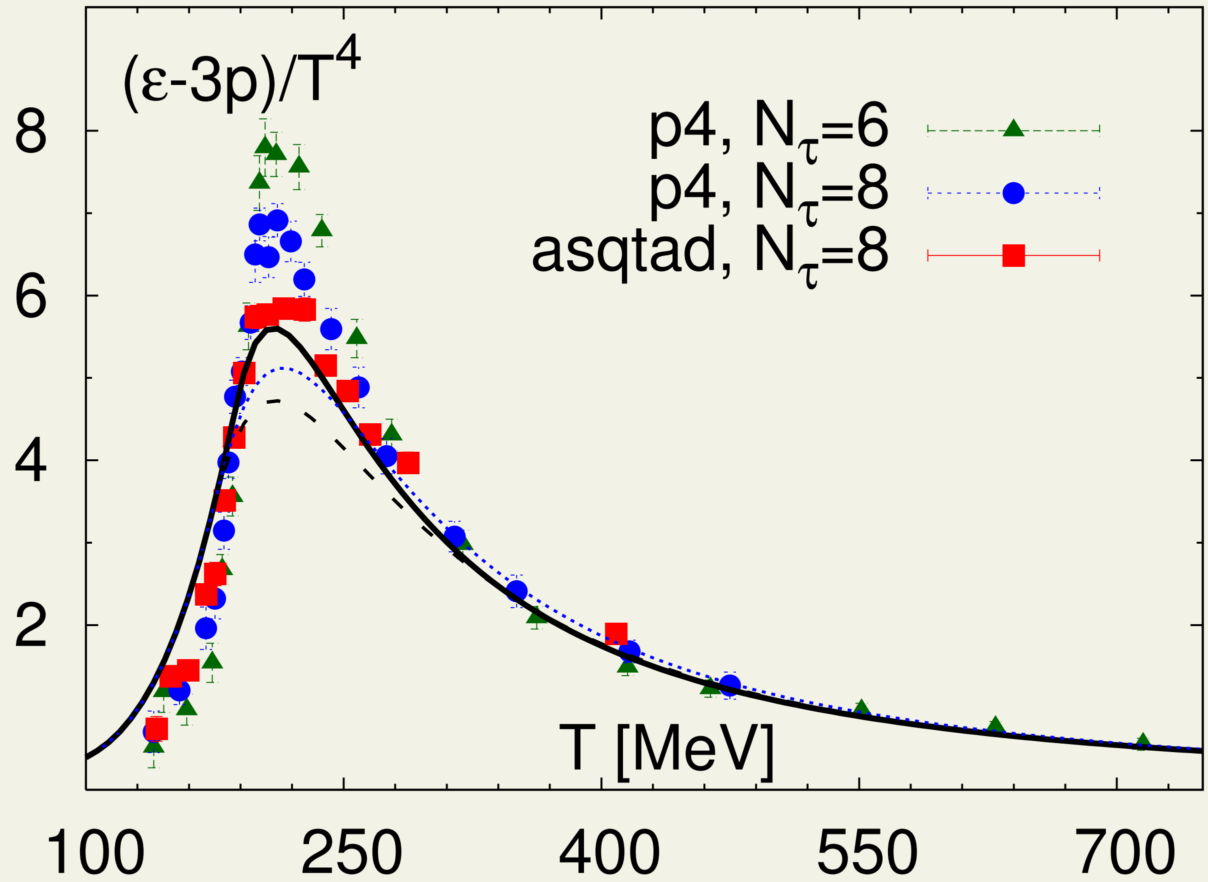
Lattice EoS at 2009

Bazavov *et al.* [hotQCD collaboration] arXiv:0903.4379 [hep-lat]



- **Good at large T, not at low T**

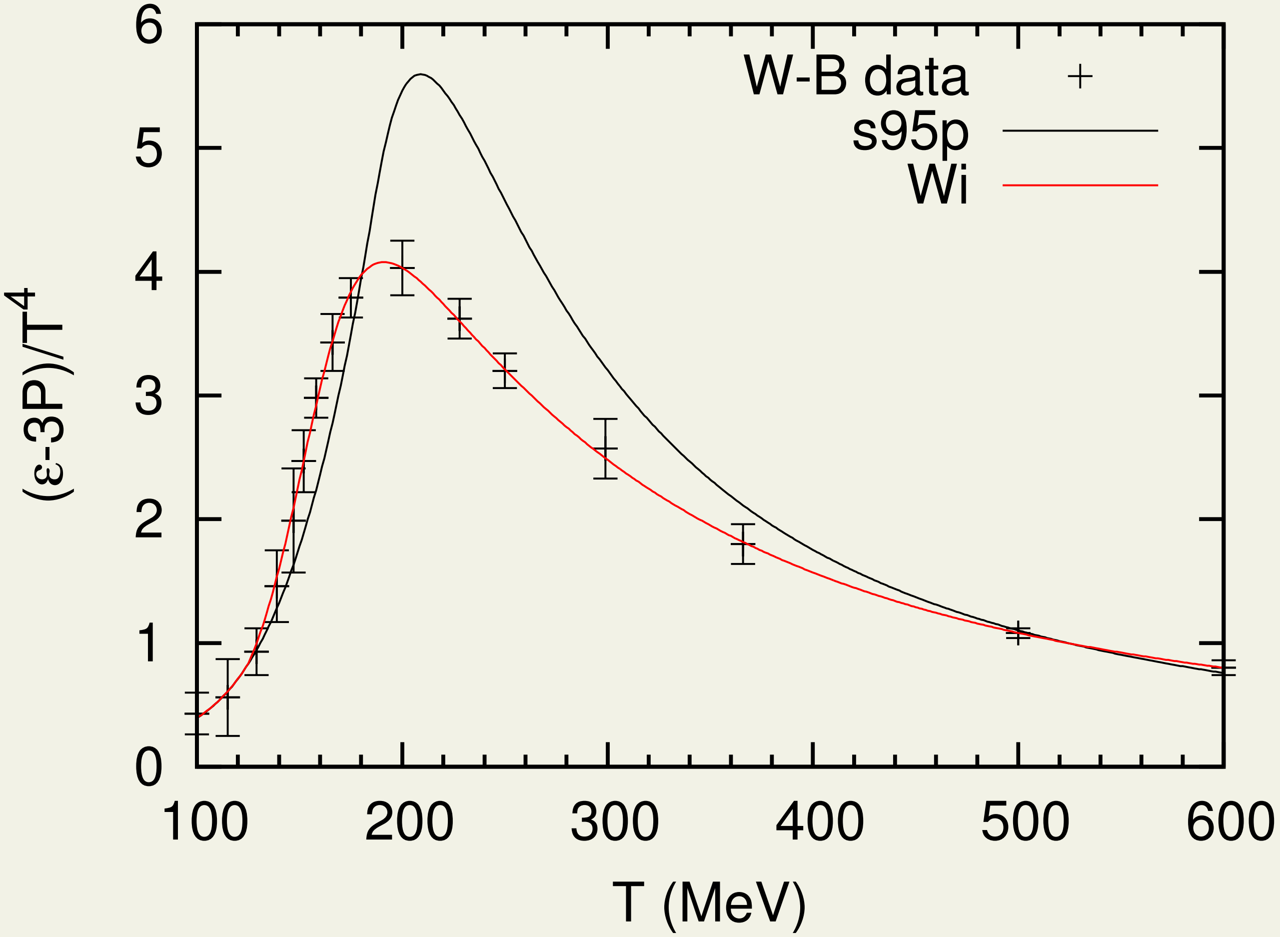
s95p



- **HRG below $T \approx 170$–190 MeV**
- **lattice above $T = 250$ MeV**
- **interpolate between**

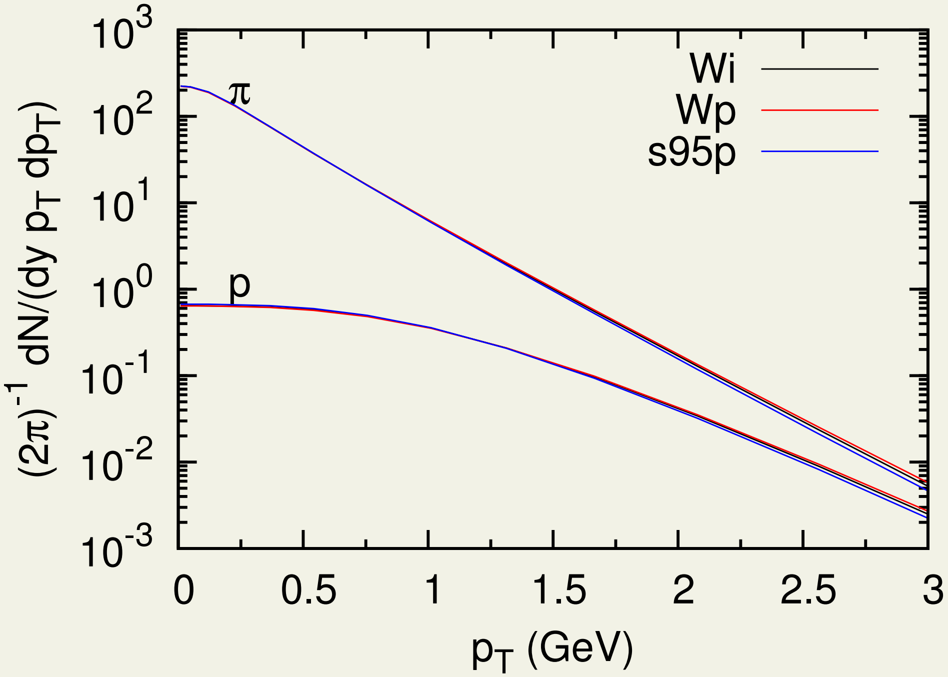
Budapest-Wuppertal trace anomaly

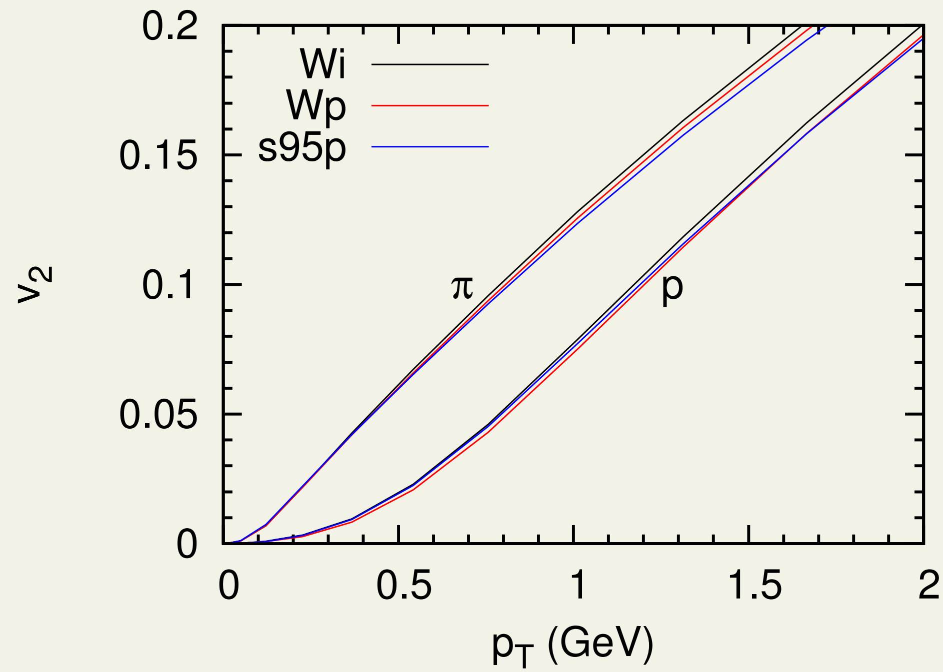
Borsanyi *et al.*, arXiv:1007.2580



Effect on distributions

- **ideal fluid**
- **Au+Au collision at RHIC, $\sqrt{s} = 200$ GeV, b=7 fm**
- $T_{\rm dec} = 124$ **MeV; all EoSs!**

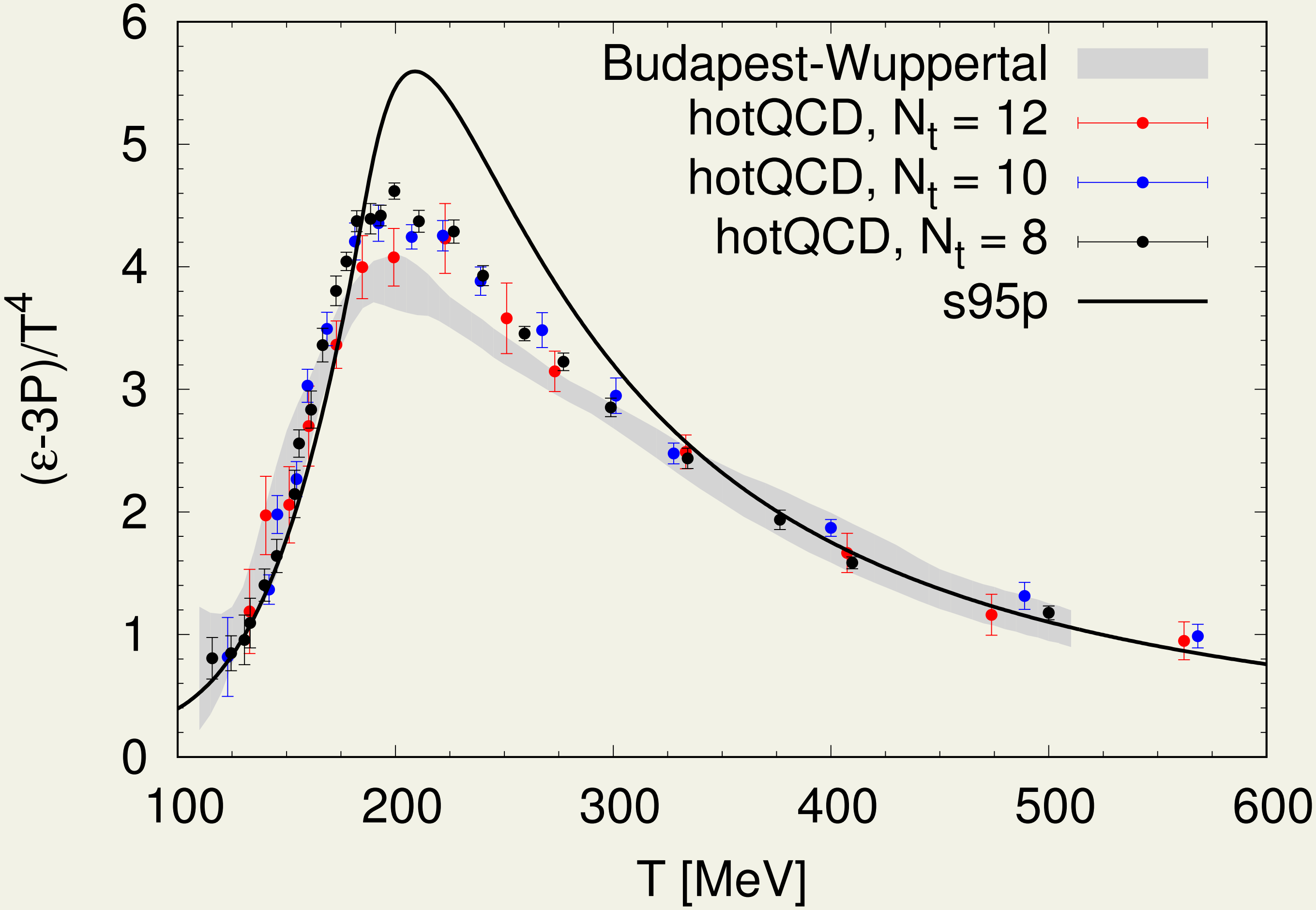




Effect on η/s

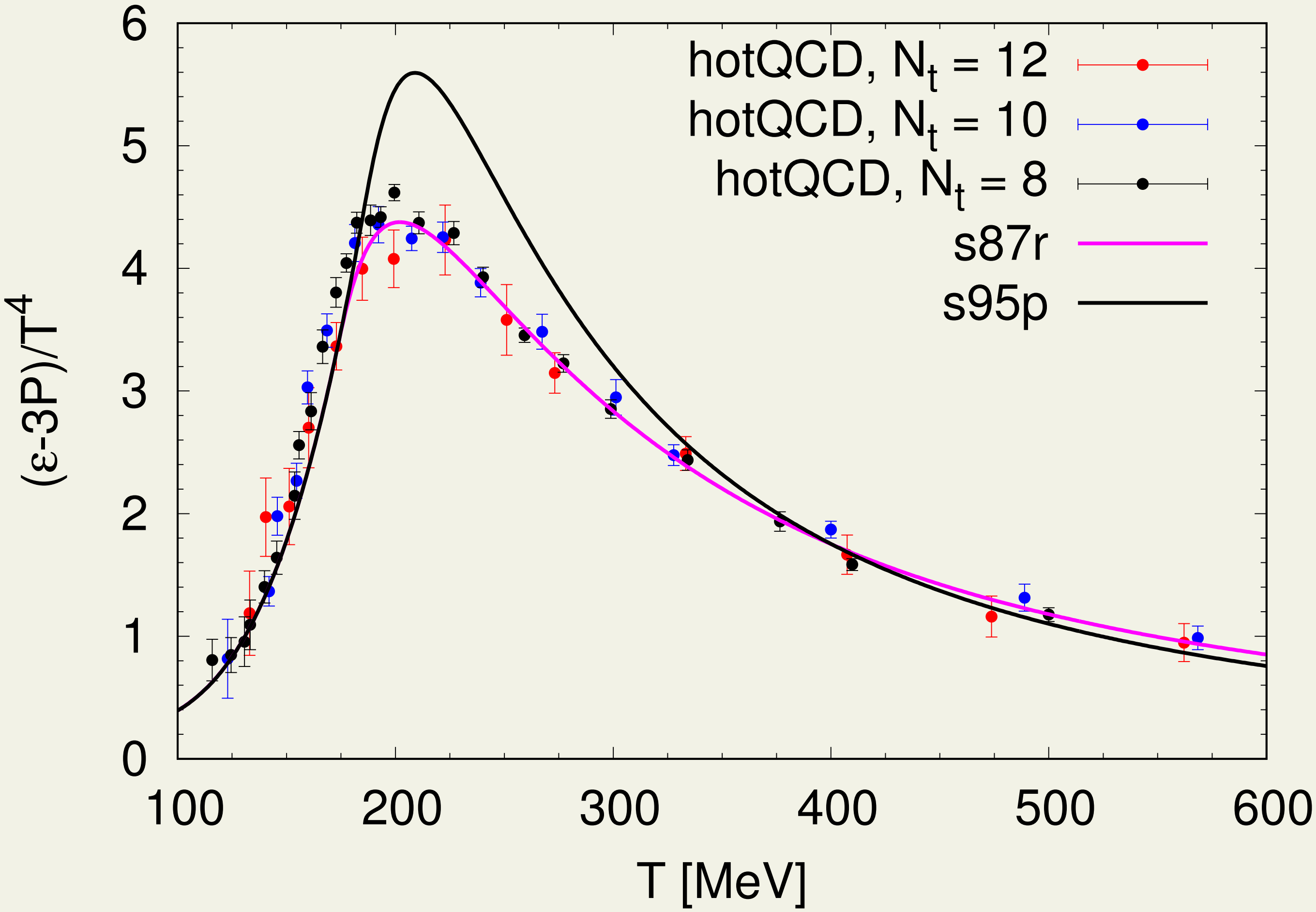
- **Alba** $et\ al.$**, arXiv:1711.05207**
  - **s95p:** $\eta/s = 0.025$
  - **B-W:** $\eta/s = 0.047$

Lattice EoS at 2018



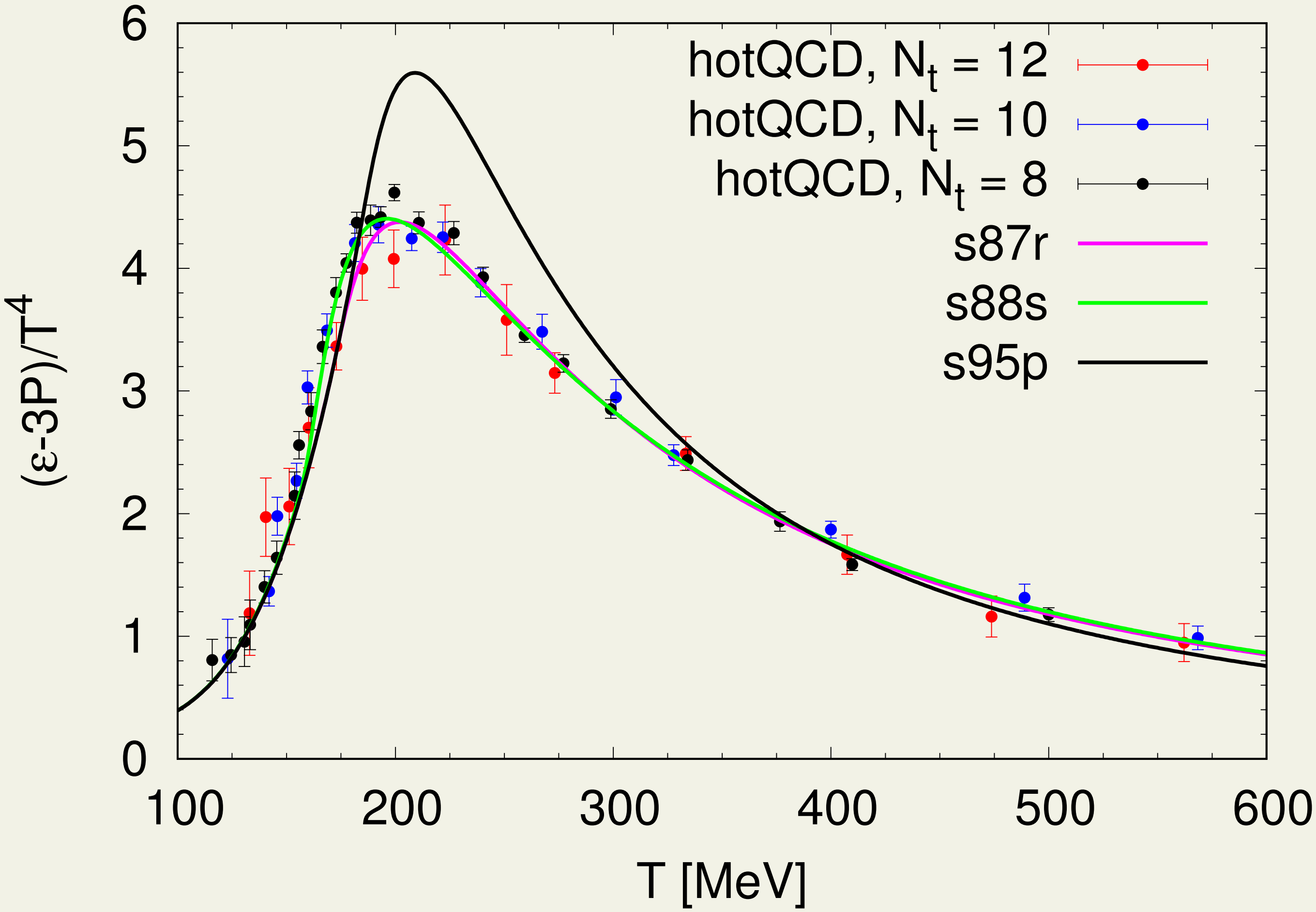
- **s95p: PDG 2005, hotQCD 2008**

New EoSs



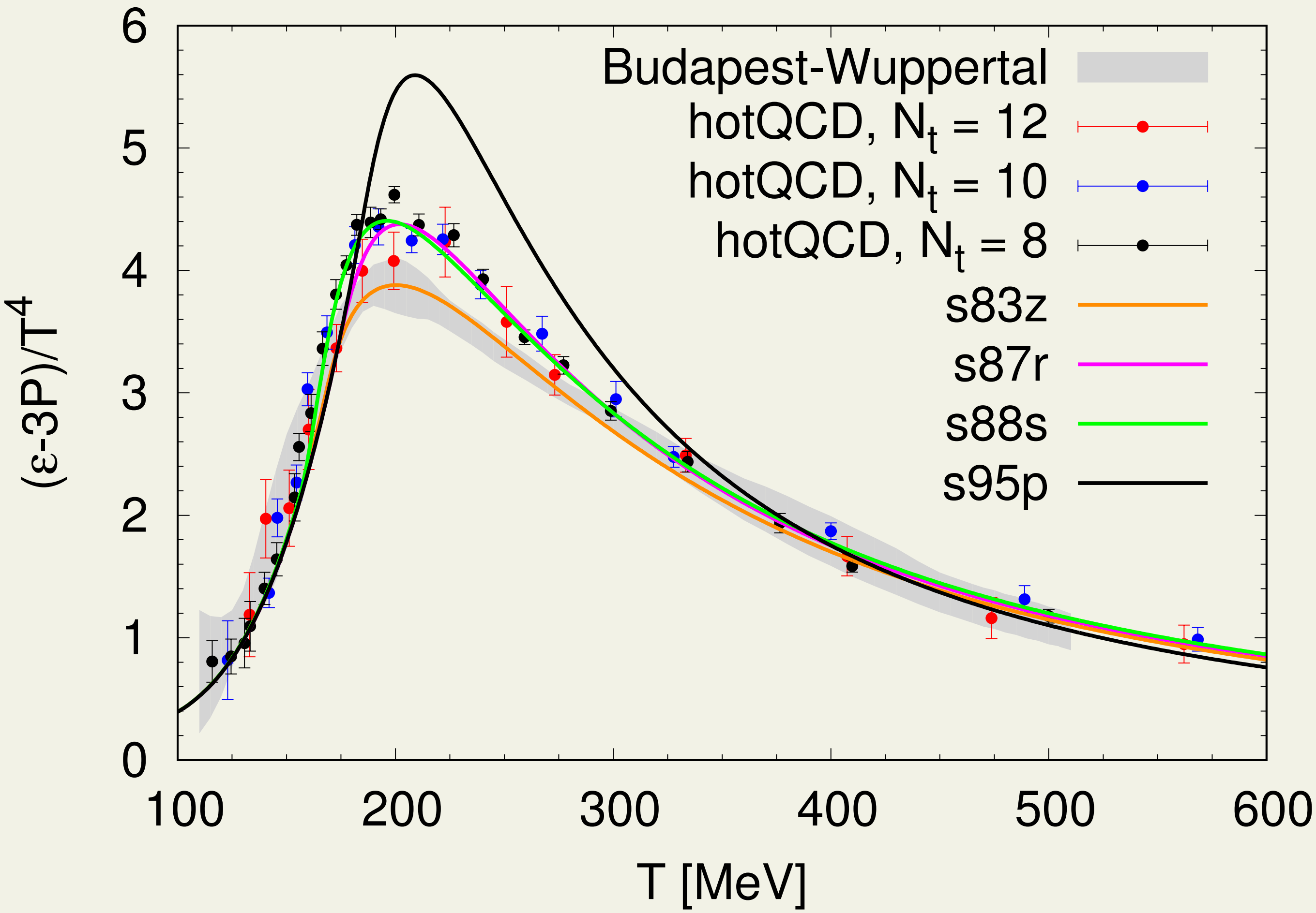
- **s87r: PDG 2005, latest hotQCD data**
- **s95p: PDG 2005, hotQCD 2008**

New EoSs



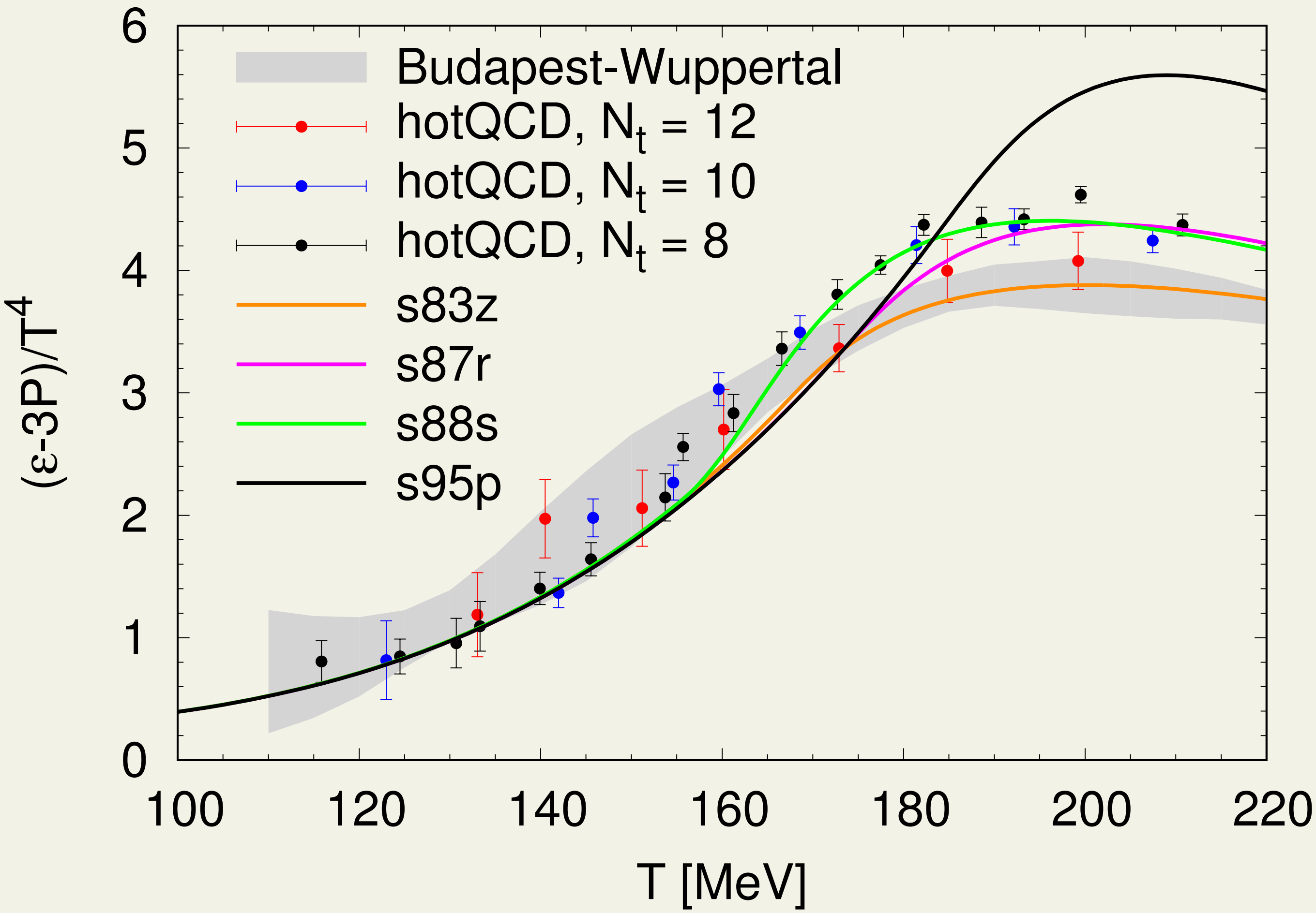
- s87r: PDG 2005, latest hotQCD data
- s88s: PDG 2017, latest hotQCD data
- s95p: PDG 2005, hotQCD 2008

New EoSs



- **s83z: PDG 2017, latest B-W data**
- **s87r: PDG 2005, latest hotQCD data**
- **s88s: PDG 2017, latest hotQCD data**
- **s95p: PDG 2005, hotQCD 2008**

New EoSs



- **s83z: PDG 2017, latest B-W data**
- **s87r: PDG 2005, latest hotQCD data**
- **s88s: PDG 2017, latest hotQCD data**
- **s95p: PDG 2005, hotQCD 2008**

The model

- **2+1D viscous hydro with shear viscosity only**
  - **EKRT initialisation, normalisation parameter** $K_{\rm sat}$
  - $T_{\rm dec} = 120$ **MeV fixed**
  - $\tau_0 = 0.2$ **fm fixed**
  - **initial** $v_r = 0$ **and** $\pi^{\mu\nu} = 0$

- $(\eta/s)(T)$ **of the form**

$$
\begin{aligned}
(\eta/s)(T) &= S_{\rm HG}(T_{\rm min} - T) + (\eta/s)_{\rm min}, \qquad T < T_{\rm min} \\
(\eta/s)(T) &= S_{\rm QGP}(T - T_{\rm min}) + (\eta/s)_{\rm min}, \qquad T > T_{\rm min}
\end{aligned}
$$

The model

- **2+1D viscous hydro with shear viscosity only**
  - **EKRT initialisation, normalisation parameter** $K_{\rm sat}$
  - $T_{\rm dec} = 120$ **MeV fixed**
  - $\tau_0 = 0.2$ **fm fixed**
  - **initial** $v_r = 0$ **and** $\pi^{\mu\nu} = 0$

- $(\eta/s)(T)$ **of the form**

$$
\begin{aligned}
(\eta/s)(T) &= S_{\rm HG}(T_{\rm min} - T) + (\eta/s)_{\rm min}, \qquad T < T_{\rm min} \\
(\eta/s)(T) &= S_{\rm QGP}(T - T_{\rm min}) + (\eta/s)_{\rm min}, \qquad T > T_{\rm min}
\end{aligned}
$$

- **Free parameters** $K_{\rm sat}$, $(\eta/s)_{\rm min}$, $S_{\rm HG}$, $S_{\rm QGP}$, $T_{\rm min}$

The data

- **Au+Au at $\sqrt{s_{\rm NN}} = 200$ GeV (RHIC)**
  - N_{ch} **in $|\eta| < 0.5$ in 0-5%, 5-10%, 10-20%, 20-30%, and 30-40% centrality [STAR]**
  - $v_2\{2\}$ **in 0-5%, 5-10%, 10-20%, 20-30% and 30-40% centrality [STAR]**

- **Pb+Pb at $\sqrt{s_{\rm NN}} = 2.76$ TeV (LHC)**
  - N_{ch} **in $|\eta| < 0.5$ in 5-10%, 10-20%, 20-30% and 30-40% centrality [ALICE]**
  - $v_2\{2\}$ **in 5-10%, 10-20%, 20-30% and 30-40% centrality [ALICE]**

- **Pb+Pb at $\sqrt{s_{\rm NN}} = 5.02$ TeV (LHC)**
  - N_{ch} **in $|\eta| < 0.5$ in 10-20%, 20-30% and 30-40% centrality [ALICE]**
  - $v_2\{2\}$ **in 10-20%, 20-30% and 30-40% centrality [ALICE]**

The task

What is the most probable set of parameters to reproduce the data as well as possible?

Bayesian analysis

Model parameters (input): $\vec{x} = (x_1, ..., x_n)$

$(K_{\rm sat}, (\eta/s)_{\rm min}, T_{\rm min}, S_{\rm HG}, S_{\rm QGP},)$

$\Downarrow$

Model output $\vec{y} = (y_1, ..., y_m) \Leftrightarrow$ **Experimental values** $\vec{y}^{\rm exp}$

$(N_{ch}(\sqrt{s_{\rm NN}}, {\rm centrality}), v_2(\sqrt{s_{\rm NN}}, {\rm centrality}))$

Bayes' theorem:

Posterior probability $\propto$ **Likelihood** $\cdot$ **Prior knowledge**

Bayesian analysis

Model parameters (input): $\vec{x} = (x_1, ..., x_n)$

$(K_{\text{sat}},\ (\eta/s)_{\text{min}},\ T_{\text{min}},\ S_{\text{HG}},\ S_{\text{QGP}},)$

$\Downarrow$

Model output $\vec{y} = (y_1, ..., y_m) \Leftrightarrow$ **Experimental values** $\vec{y}^{\text{exp}}$

$(N_{ch}(\sqrt{s_{\text{NN}}}, \text{centrality}),\ v_2(\sqrt{s_{\text{NN}}}, \text{centrality}))$

Bayes' theorem:

Posterior probability $\propto$ **Likelihood** $\cdot$ **Prior knowledge**

- **Prior knowledge: Range of parameter values**

$$
\begin{aligned}
0.2 < &\ K_{\text{sat}} < 2 \\
0 < &\ (\eta/s)_{\text{min}} < 0.3 \\
0.14 < &\ T_{\text{min}} < 0.2 \\
0 < &\ S_{\text{HG}} < 4 \\
0 < &\ S_{\text{QGP}} < 2
\end{aligned}
$$

Bayesian analysis

Model parameters (input): $\vec{x} = (x_1, ..., x_n)$

$(K_{\rm sat},\ (\eta/s)_{\rm min},\ T_{\rm min},\ S_{\rm HG},\ S_{\rm QGP},)$

$\Downarrow$

Model output $\vec{y} = (y_1, ..., y_m) \Leftrightarrow$ **Experimental values** $\vec{y}^{\,\rm exp}$

$(N_{ch}(\sqrt{s_{\rm NN}}, \text{centrality}),\ v_2(\sqrt{s_{\rm NN}}, \text{centrality}))$

Bayes' theorem:

Posterior probability $\propto$ **Likelihood** $\cdot$ **Prior knowledge**

- **Likelihood:** $\mathcal{L}(\vec{x}) \propto \exp\left(-\frac{1}{2}(\vec{y}(\vec{x}) - \vec{y}^{\,\rm exp})\Sigma^{-1}(\vec{y}(\vec{x}) - \vec{y}^{\,\rm exp})^T\right)$, where Σ is the covariance matrix

Bayesian analysis

Model parameters (input): $\vec{x} = (x_1, ..., x_n)$

$(K_{\rm sat}, (\eta/s)_{\rm min}, T_{\rm min}, S_{\rm HG}, S_{\rm QGP},)$

$\Downarrow$

Model output $\vec{y} = (y_1, ..., y_m) \Leftrightarrow$ **Experimental values** $\vec{y}^{\rm exp}$

$(N_{ch}(\sqrt{s_{\rm NN}}, \text{centrality}), v_2(\sqrt{s_{\rm NN}}, \text{centrality}))$

Bayes' theorem:

Posterior probability $\propto$ **Likelihood** $\cdot$ **Prior knowledge**

- **Likelihood:** $\mathcal{L}(\vec{x}) \propto \exp\left(-\frac{1}{2}(\vec{y}(\vec{x}) - \vec{y}^{\rm exp})\Sigma^{-1}(\vec{y}(\vec{x}) - \vec{y}^{\rm exp})^T\right)$, where Σ is the covariance matrix
- evaluation of the likelihood function $\mathcal{O}(10^6)$ runs. . .
- use Gaussian emulator instead
  = stochastic, non-parametric interpolation of the model

Bayesian analysis

Model parameters (input): $\vec{x} = (x_1, ..., x_n)$

$(K_{\rm sat},\ (\eta/s)_{\rm min},\ T_{\rm min},\ S_{\rm HG},\ S_{\rm QGP},)$

$\Downarrow$

Model output $\vec{y} = (y_1, ..., y_m) \Leftrightarrow$ **Experimental values** $\vec{y}^{\,\rm exp}$

$(N_{ch}(\sqrt{s_{\rm NN}}, \text{centrality}),\ v_2(\sqrt{s_{\rm NN}}, \text{centrality}))$

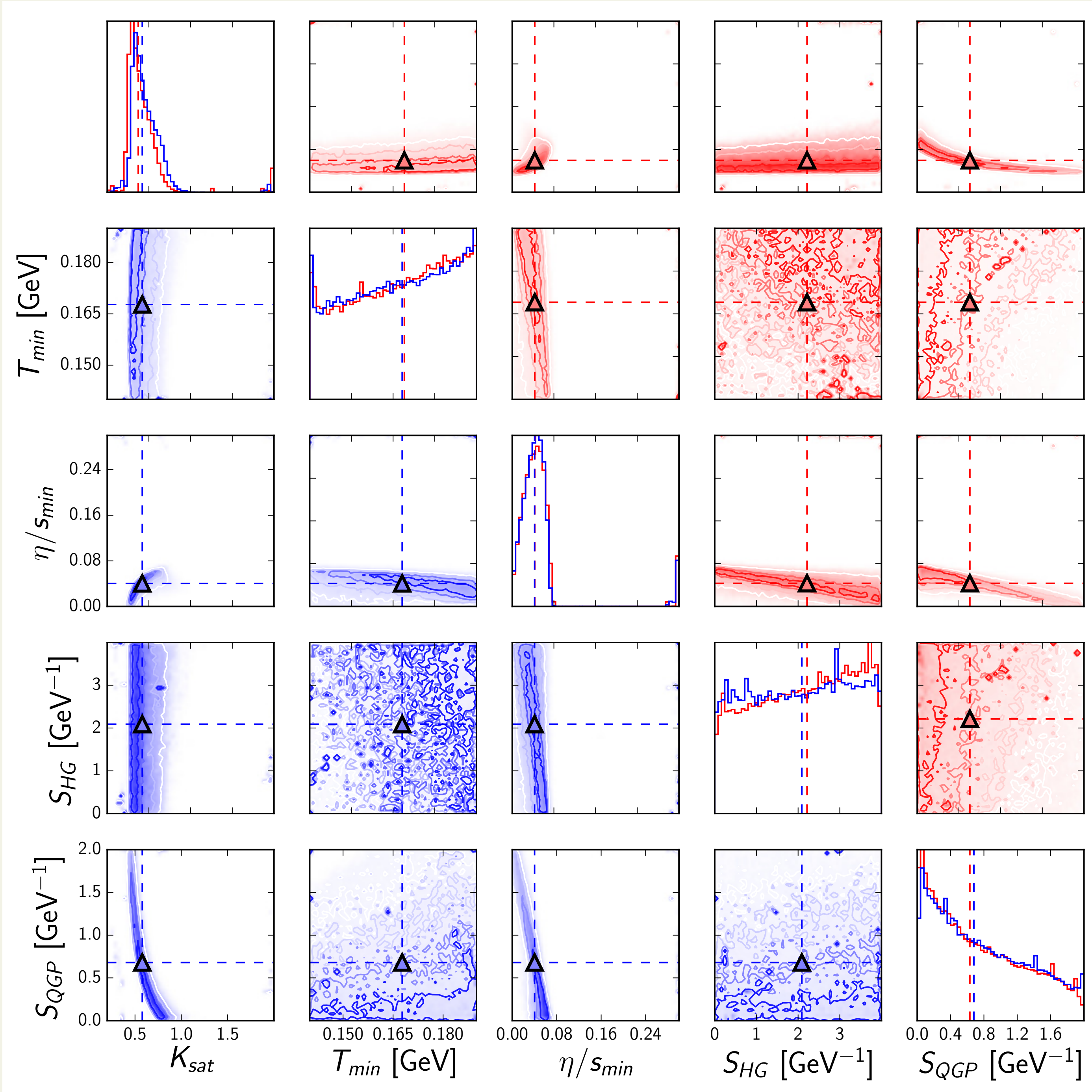
Bayes' theorem:

Posterior probability $\propto$ **Likelihood** $\cdot$ **Prior knowledge**

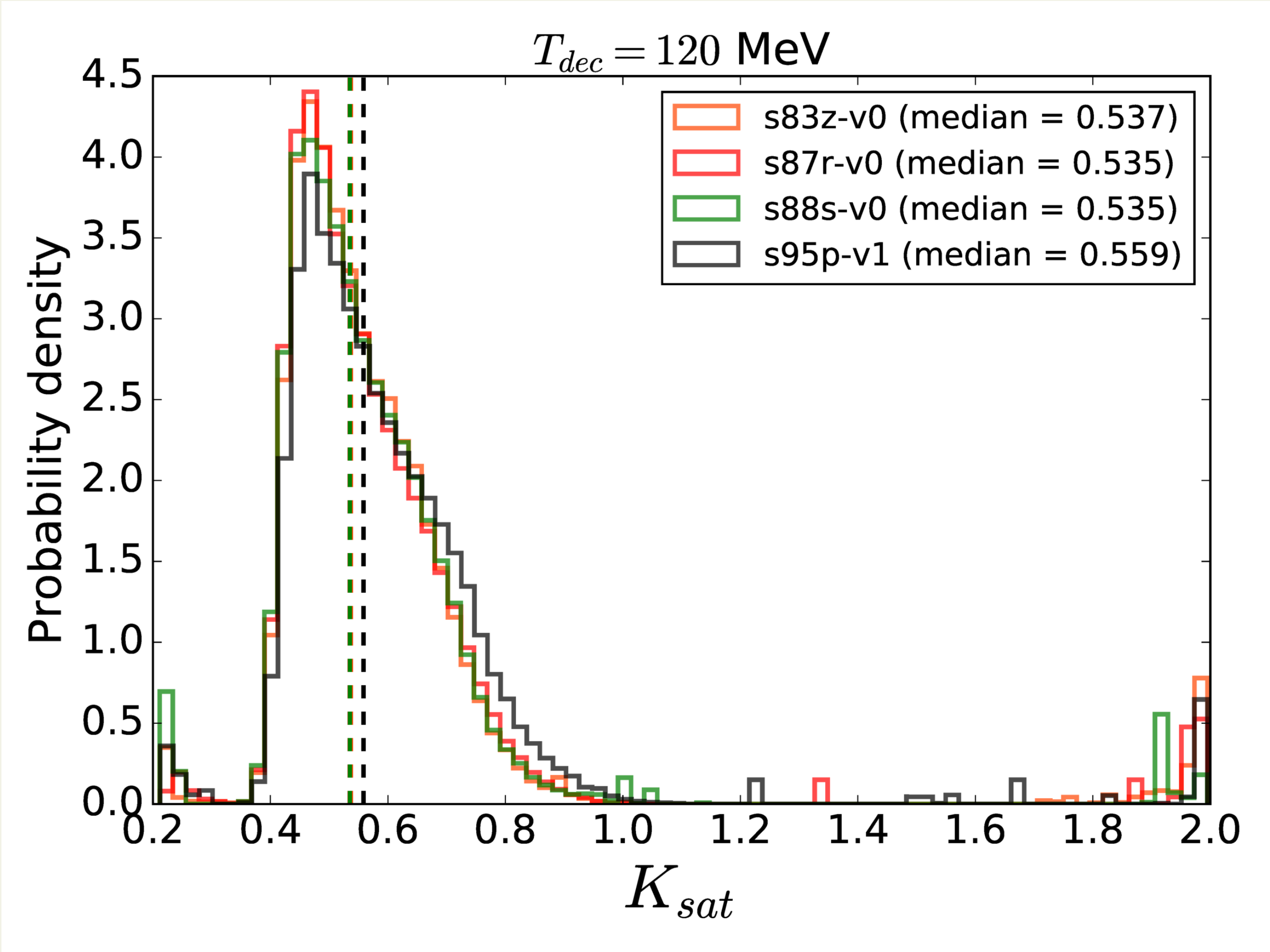
- **Likelihood**: $\mathcal{L}(\vec{x}) \propto \exp\left(-\frac{1}{2}(\vec{y}(\vec{x}) - \vec{y}^{\,\rm exp})\Sigma^{-1}(\vec{y}(\vec{x}) - \vec{y}^{\,\rm exp})^T\right)$, where Σ is the covariance matrix
- evaluation of the likelihood function $\mathcal{O}(10^6)$ runs. . .
- use Gaussian emulator instead
  = stochastic, non-parametric interpolation of the model
- Sample the likelihood function using Markov chain Monte Carlo
  = random walk in parameter space constrained to favour high likelihood

$\rightarrow$ distribution of Markov chain steps $\equiv$ probability distribution

Posterior probabilities

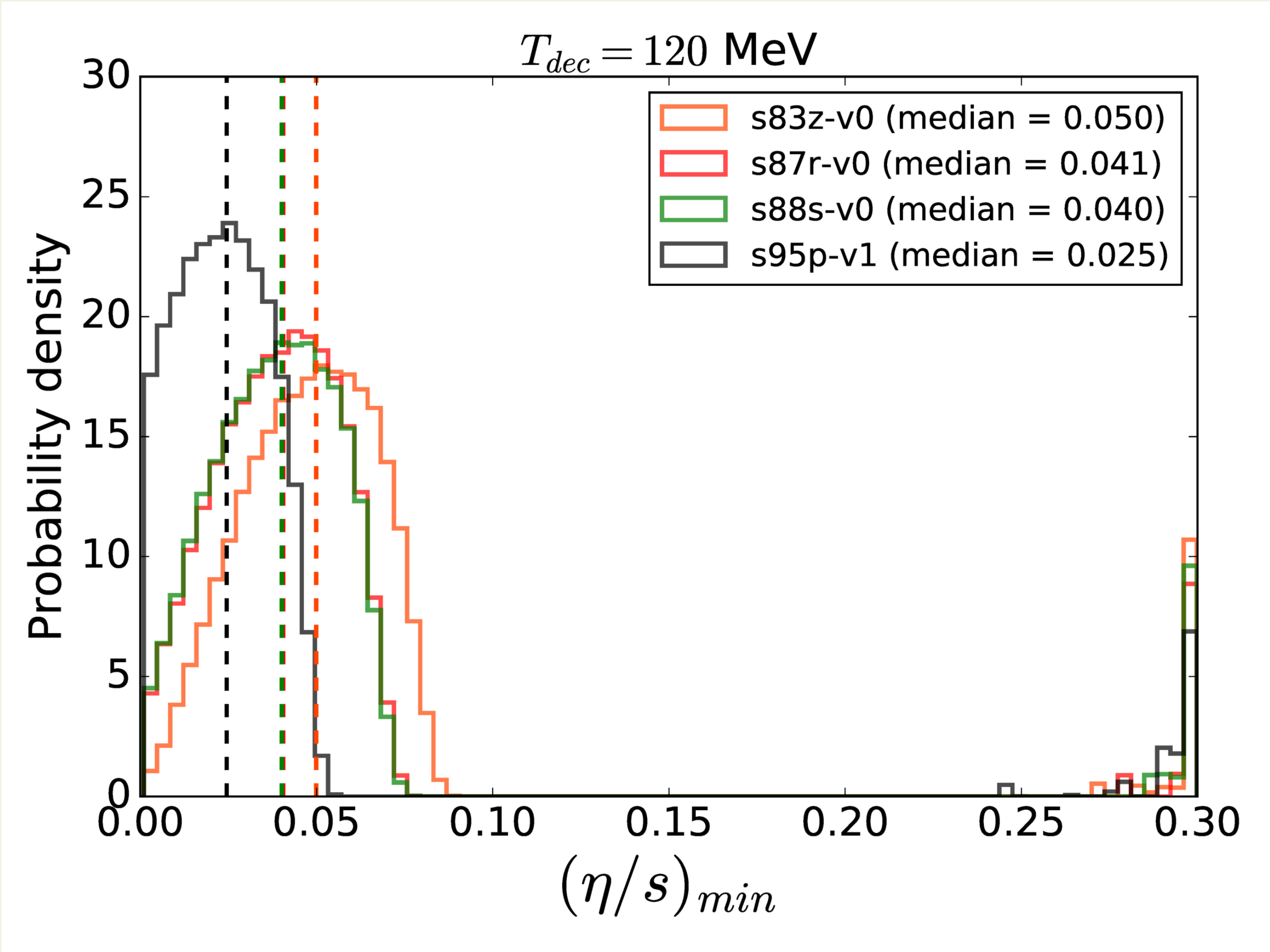


K_{sat}



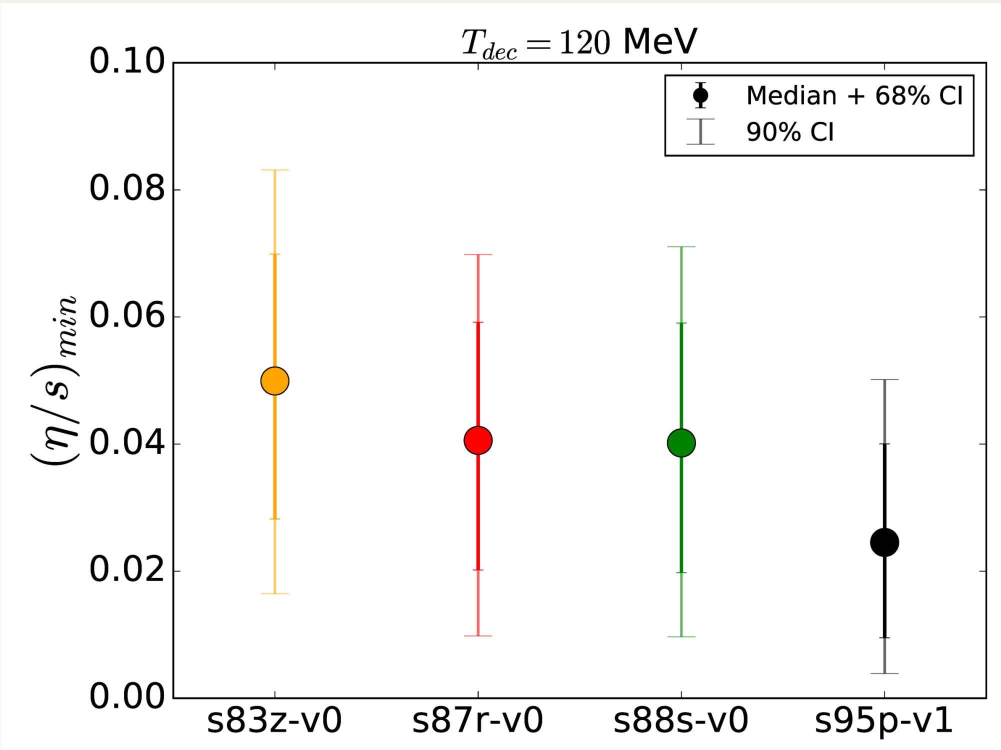
- **consistent with previous calculations**

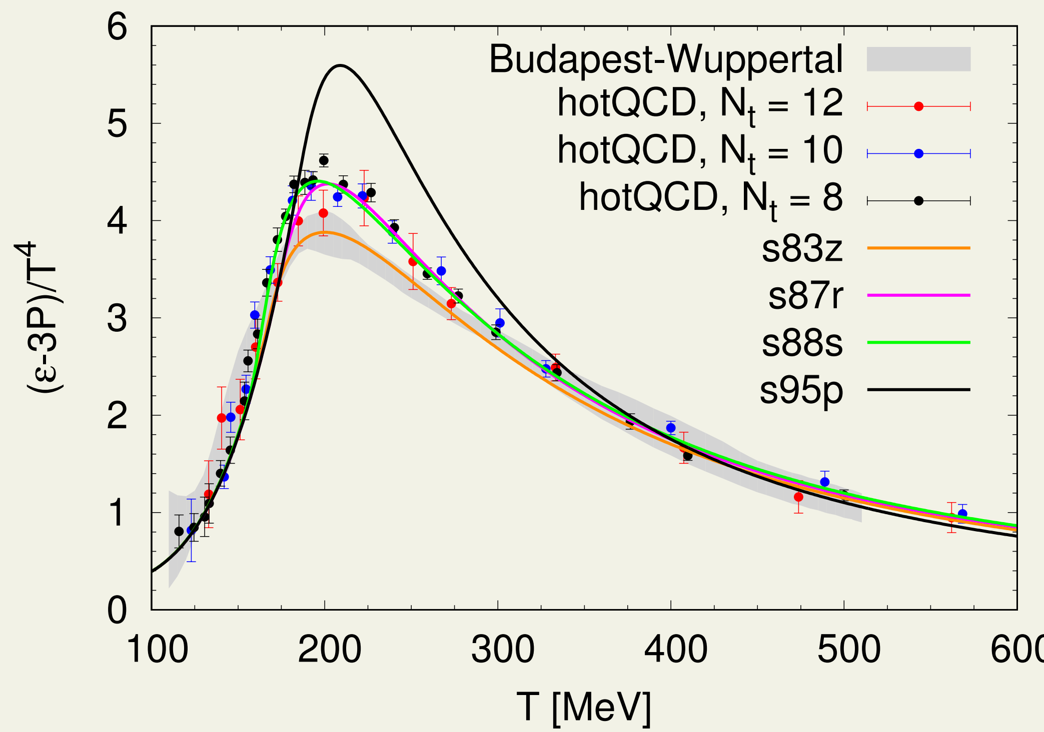
$(\eta/s)_{\rm min}$



- **median affected by EoS**
- **widths overlap**

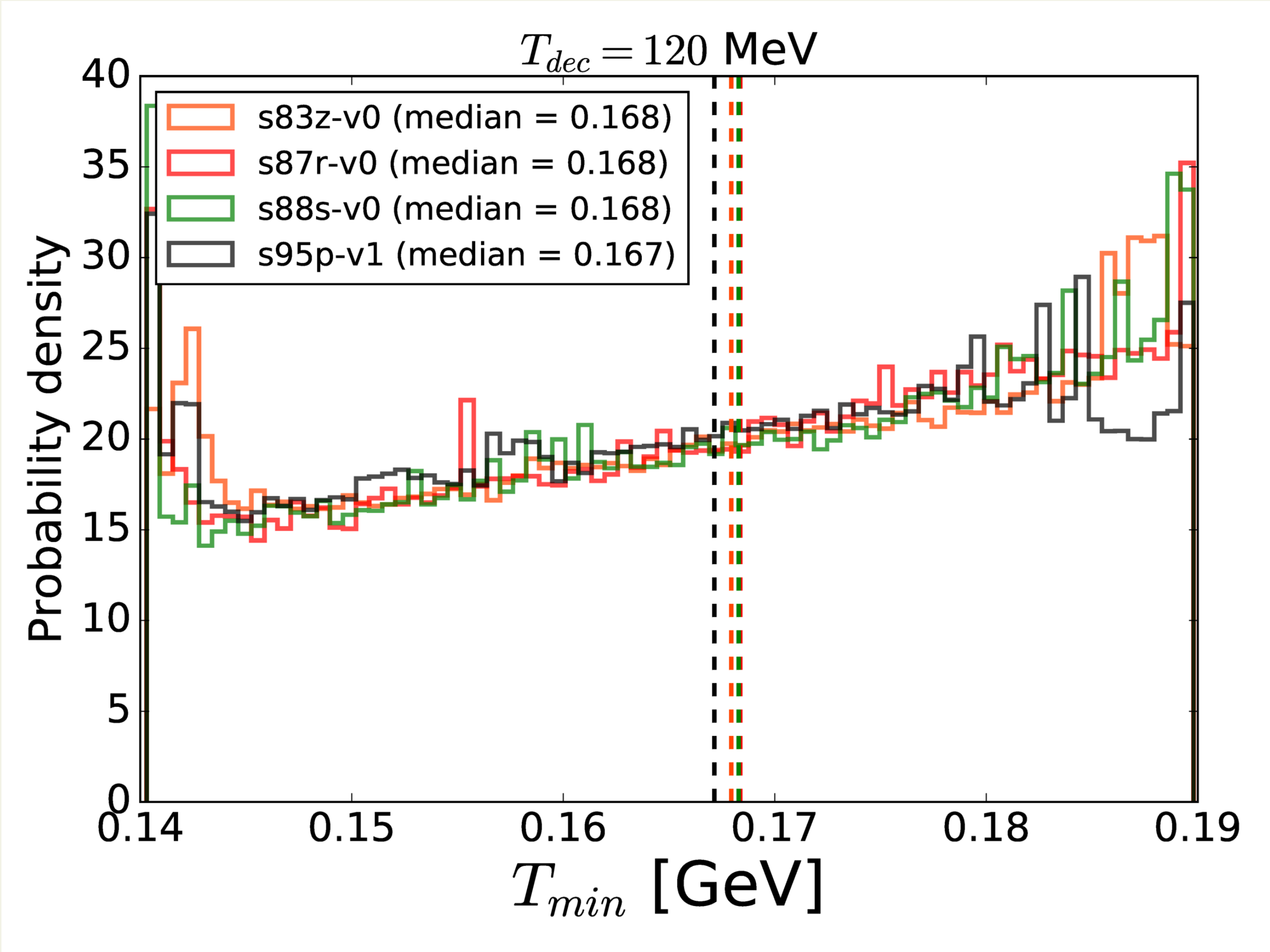
$(\eta/s)_{\rm min}$





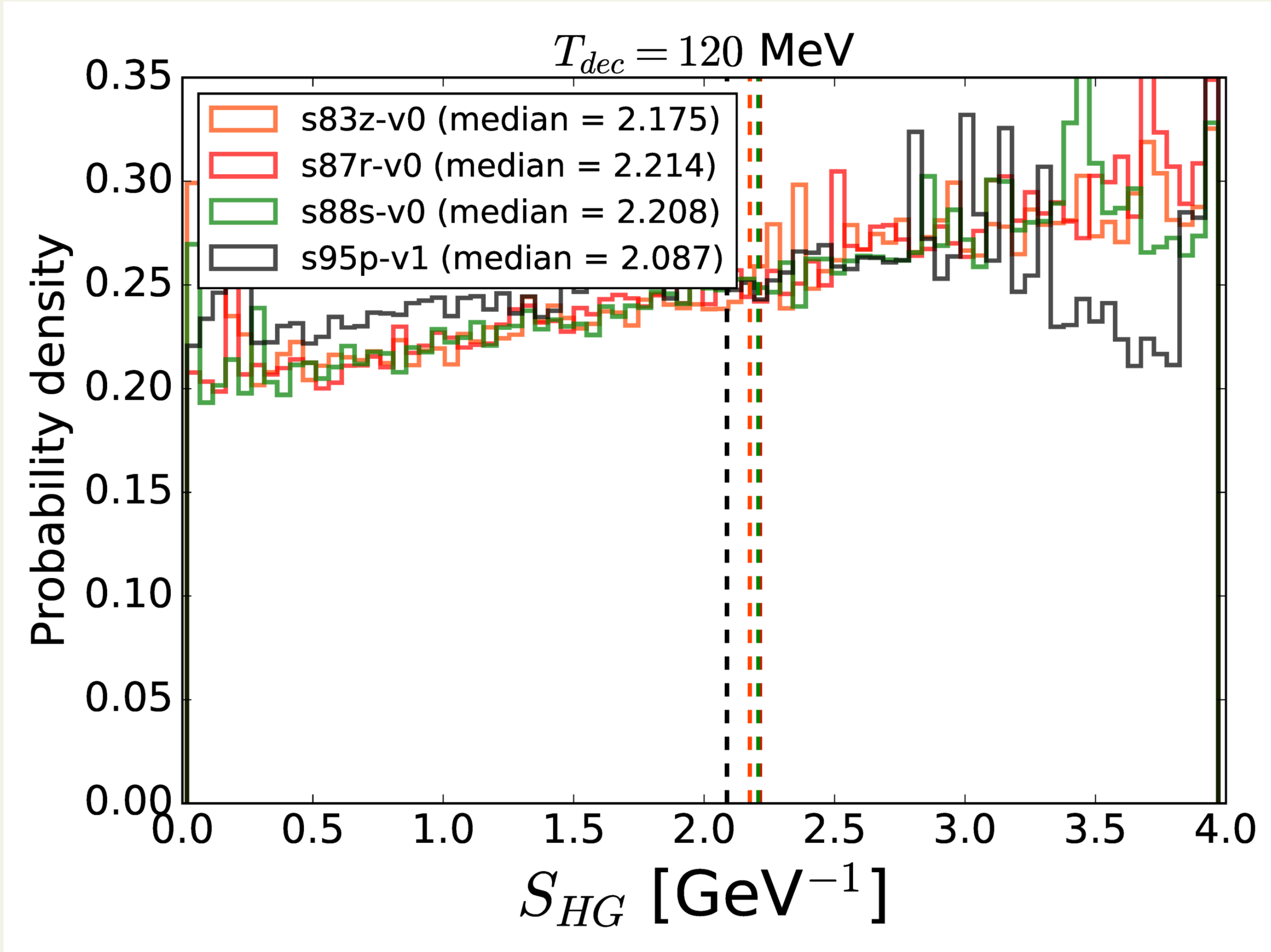
- **median affected by EoS**
- **widths overlap**

$T_{\min}$



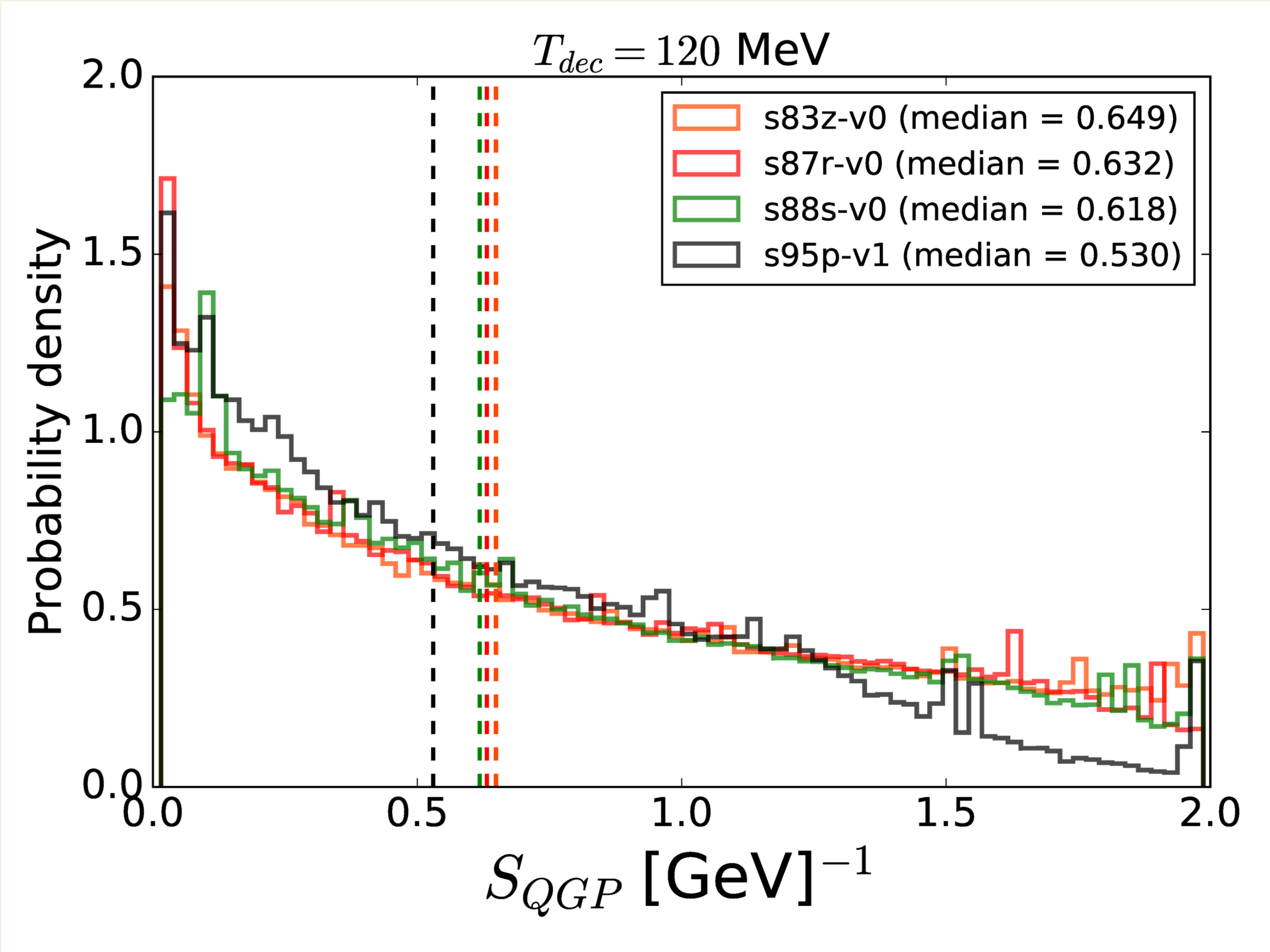
- **not constrained**

S_{HG}



- **not constrained**

S_{QGP}



- **weakly constrained**

Does η/s depend on EoS?

- **yes, it does**

Does η/s depend on EoS?

- **yes, it does**
- **but very weakly, effect within the confidence limits**

Does η/s depend on EoS?

- **yes, it does**
- **but very weakly, effect within the confidence limits**
- $(\eta/s)(T)$ **not constrained**
- **where** η/s **has its minimum is not constrained**

The speaker has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 665778 via the National Science Center, Poland, under grant Polonez DEC-2015/19/P/ST2/03333