# Digging with care

## Systematic analysis of subtle microlensing features

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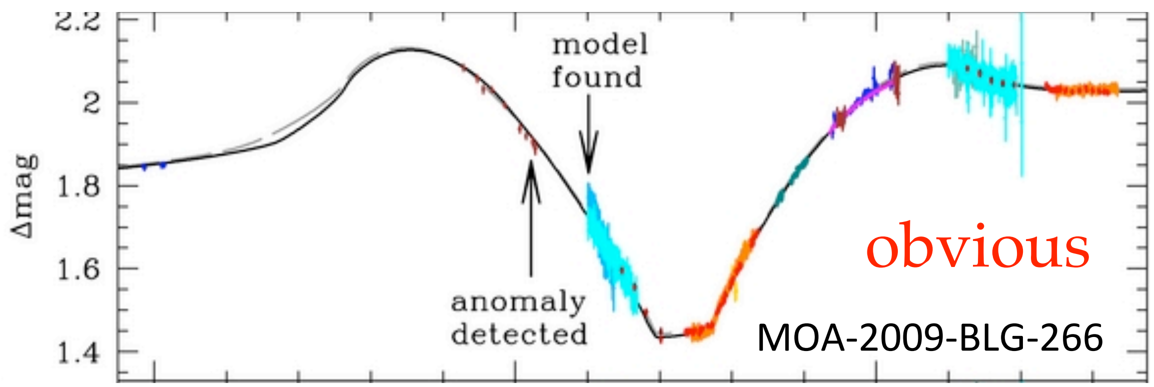
*with support from*

RoboNet team
MiNDSTEp team
OGLE team

# Obvious detections vs subtle features




but: $\mathcal{P}(\chi^2_4 \geq 20) = 4 \times 10^{-4}$

(e.g. 5 points at $2\sigma$)

***low***
***detection threshold***

↕

***false positives***

get high number statistics

be sensitive to low-mass companions

avoid wasting telescope resources

high detection threshold no insurance against false positives

correlated noise can produce "pseudo-detections" at large $\Delta\chi^2$
on just high enough cadence

cannot hang detection on to points
that show similar deviations as other points considered "noise"

"*we need to understand our error bars*"

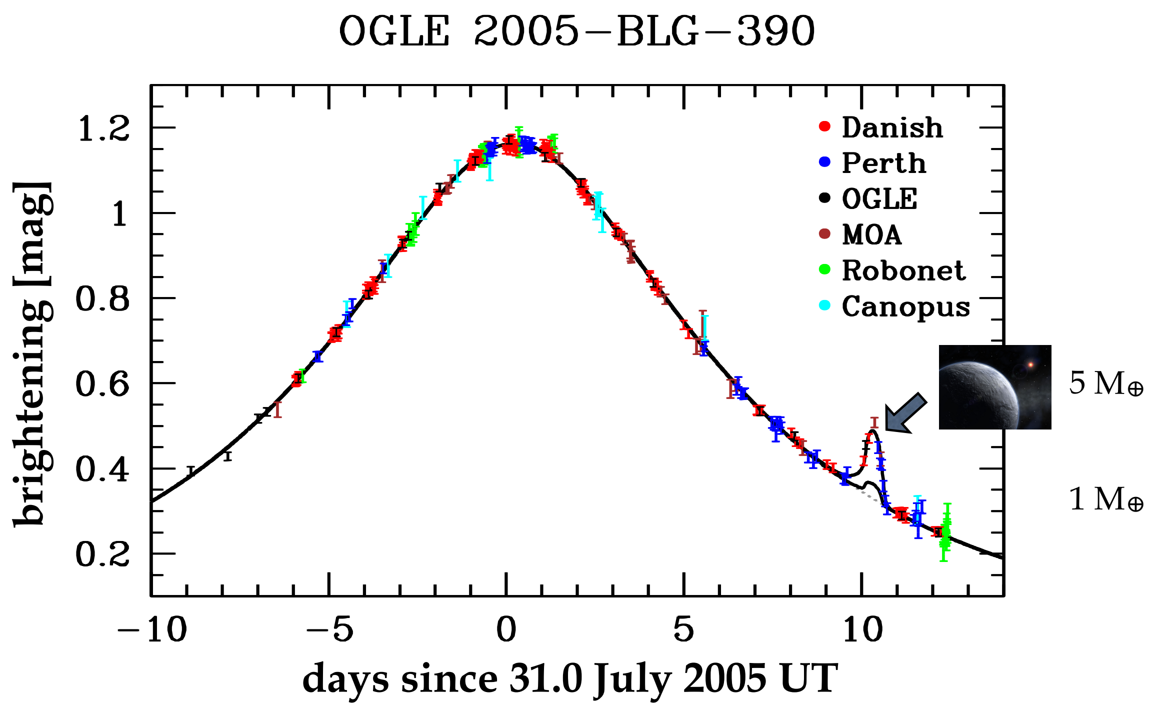
(Penny D. Sackett, 1995)

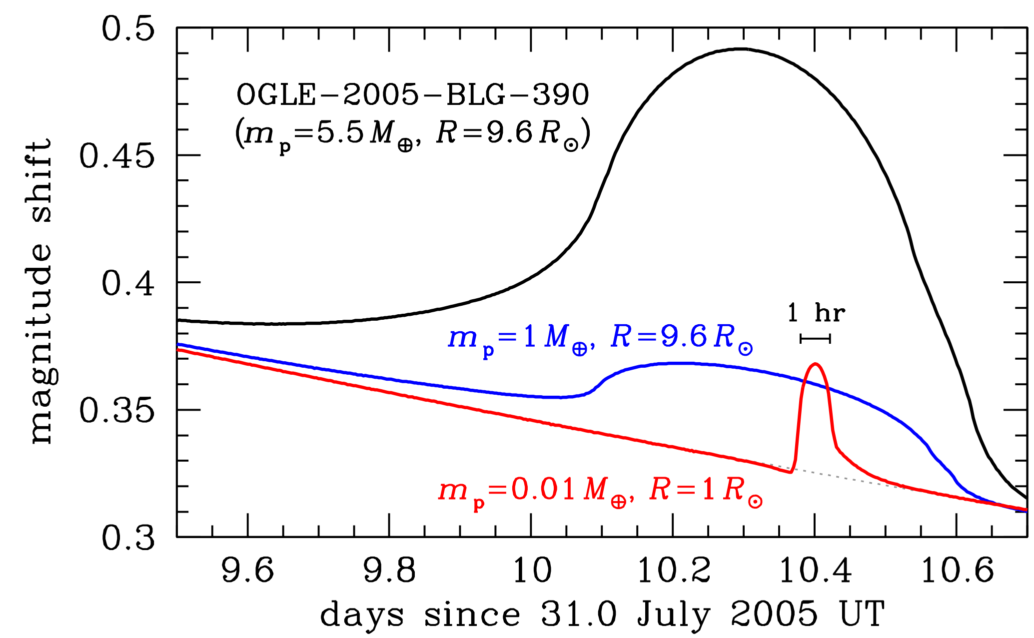
consistent interpretation of data

establish "noise" model and estimate "noise" statistics

# Low-mass planets and satellites

signals may be subtle, but are ***well localised***




model parameters describing anomaly $\not\leftarrow$ vast majority of photometric data

other parameters can be well determined from photometric data outside anomaly

parameter hierarchy / disentaglement of subspaces $\mathfrak{P} \sim \mathfrak{P}_{\mathrm{N}} \otimes \mathfrak{P}_{\mathrm{A}}$

$$D = D_{\mathrm{N}} \cup D_{\mathrm{A}} \qquad D_{\mathrm{N}} \cap D_{\mathrm{A}} = \varnothing$$

avoid misestimation / check consistency: (no) effect of anomaly region on $\mathfrak{P}_{\mathrm{N}}$

estimate of noise statistics that does not depend on putative anomaly
(assuming everything else is regular)

# Obtain "noise" statistics

M data sets with $N^{[m]}$ data points

$$\left(F_n^{[m]}, \sigma_n^{[m]}, t_n^{[m]}\right)$$

$$F^{[m]}(t) = F_{\text{base}}^{[m]}\, A(t) - F_{\text{B}}^{[m]}\left[A(t) - 1\right]$$

$$\tilde{\sigma}_n^{[m]}\left(\sigma_n^{[m]}, \kappa^{[m]}, s_0^{[m]}\right) = \sqrt{\left(\kappa^{[m]}\sigma_n^{[m]}\right)^2 + \left(s_0^{[m]} F_n^{[m]}\right)^2}$$

$\kappa^{[m]}$ scaling factor

$s_0^{[m]}$ systematic uncertainty

simple effective error bar model

$$r_n^{[m]}\left(F^{[m]}(t), F_n^{[m]}, \tilde{\sigma}_n^{[m]}\right) = \frac{F_n^{[m]} - F^{[m]}(t)}{\tilde{\sigma}_n^{[m]}}$$

$$w_n^{[m]} = \begin{cases} \left[1 - \left(\dfrac{r_n^{[m]}}{K\tilde{r}^{[m]}}\right)^2\right]^2 & \text{for } \left|r_n^{[m]}\right| < K\tilde{r}^{[m]} \\ 0 & \text{for } \left|r_n^{[m]}\right| \geq K\tilde{r}^{[m]} \end{cases}$$

robust fitting, bi-square weight function

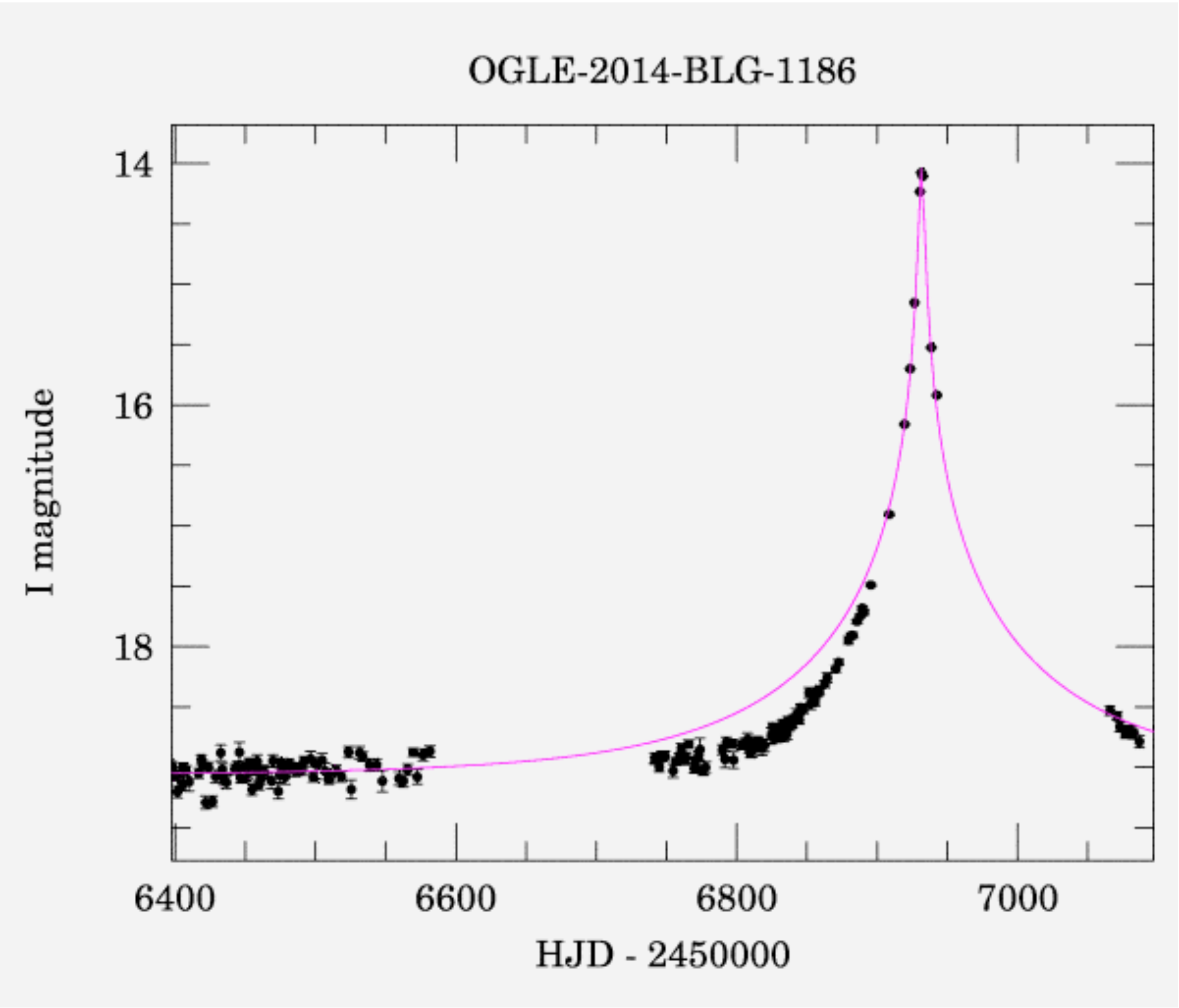
(accounting for "outliers" and non-Gaussian tail)

"pseudo-Gaussian", alternatives: more elaborate models such as Student's t etc.

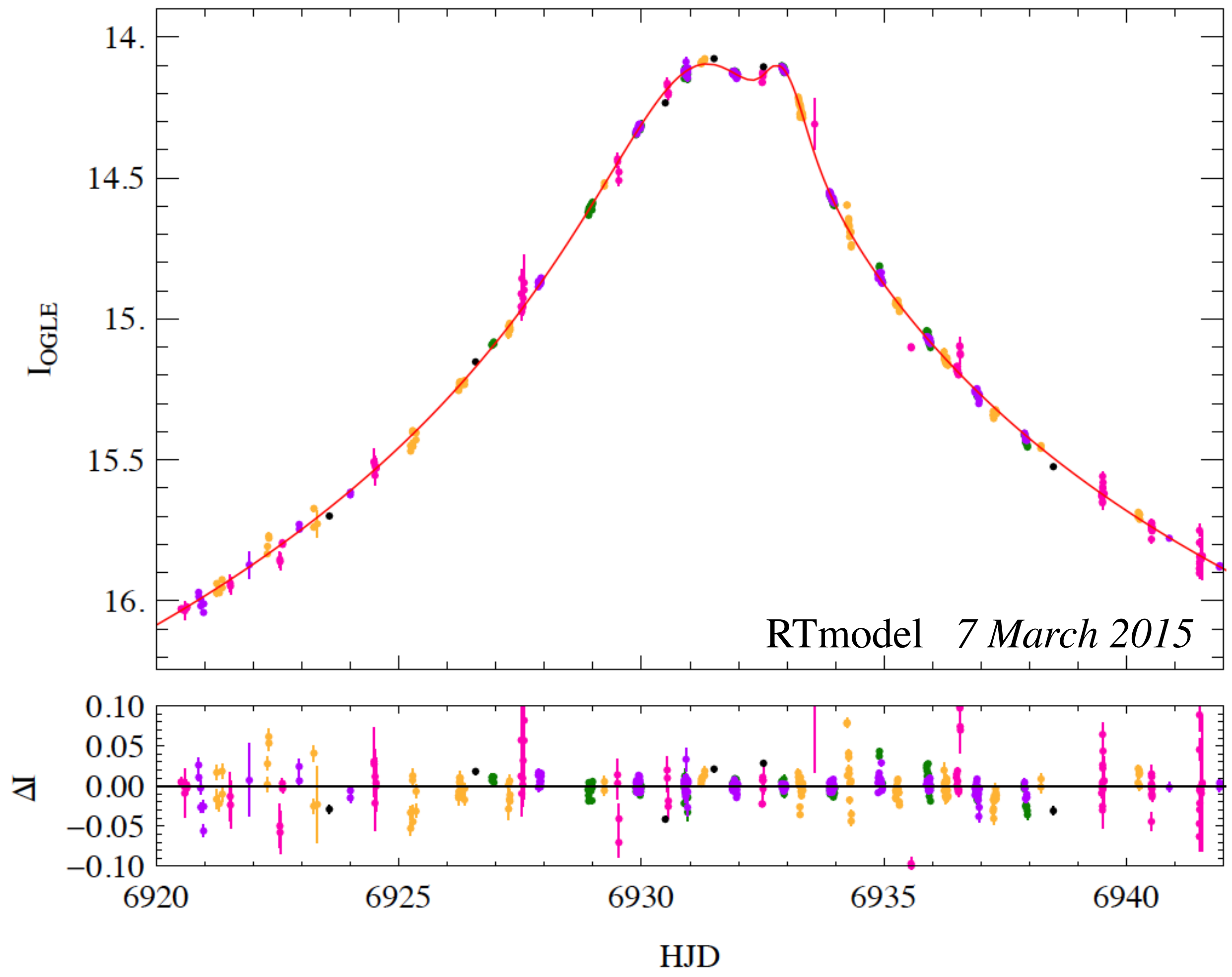
$$\tilde{\chi}^2 = \sum_{m=1}^{M} w_n^{[m]} \left[\sum_{n=1}^{N^{[m]}} \left(r_n^{[m]}\right)^2 + 2\sum_{n=1}^{N^{[m]}} \ln\, \tilde{\sigma}_n^{[m]}\right]$$

modified $\chi^2$, counting data points with weight $0 \leq w_n^{[m]} \leq 1$

# OGLE-2014-BLG-1186: a 2013–2016 event




http://ogle.astrouw.edu.pl/ogle4/ews/2014/blg-1186.html




light curve substantially affected by parallax

model does not work well with OGLE data?
OGLE and RoboNet data telling different stories?

reported uncertainties very small
What is signal, what is systematic uncertainty?

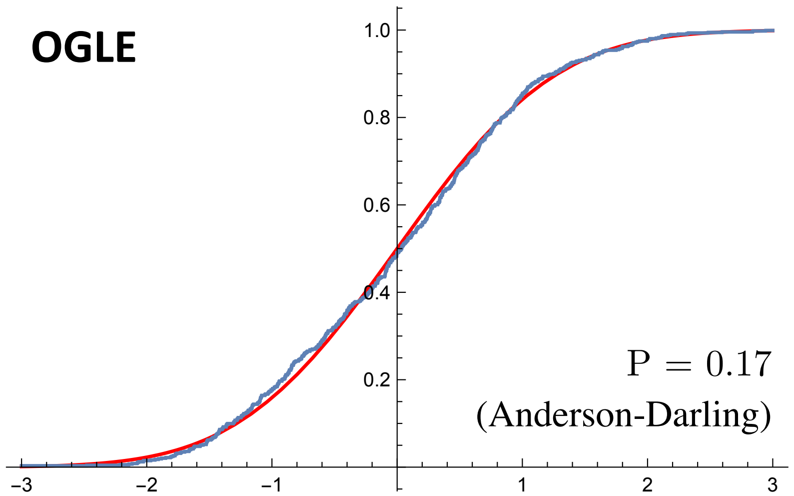
→ noise statistics

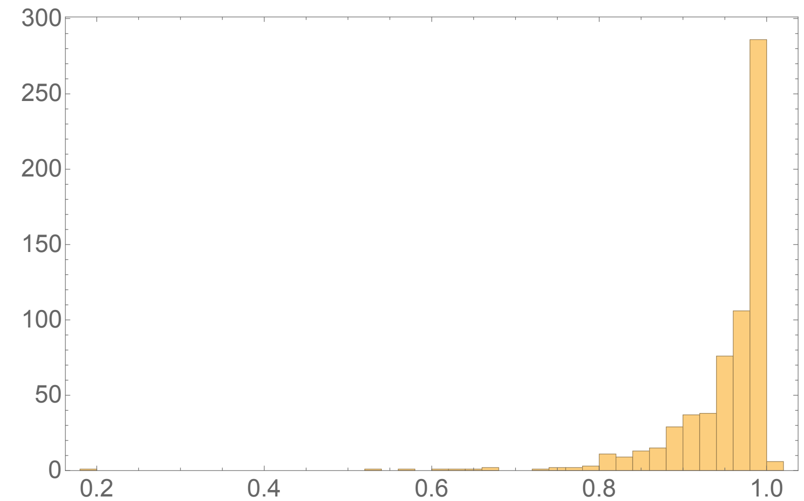
# OGLE-2014-BLG-1186 residuals

weighted CDF

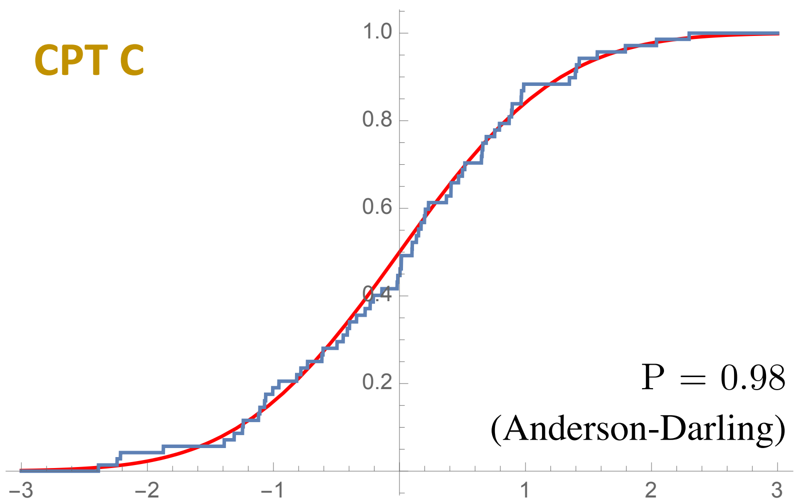
weight distribution

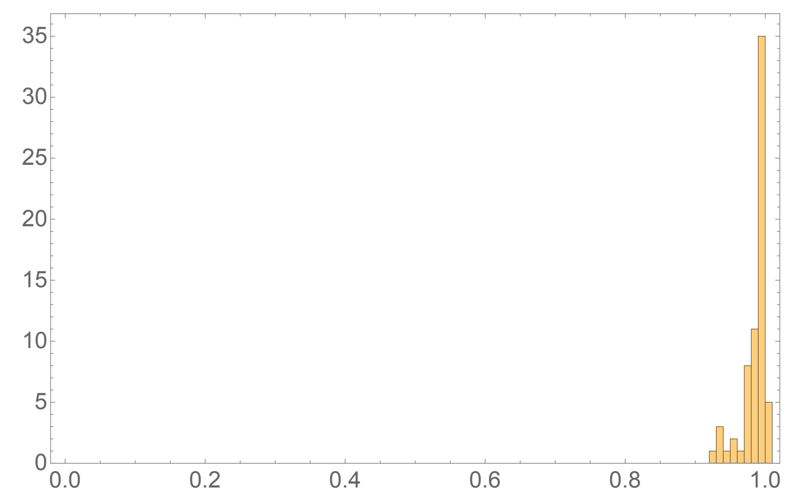
**OGLE**



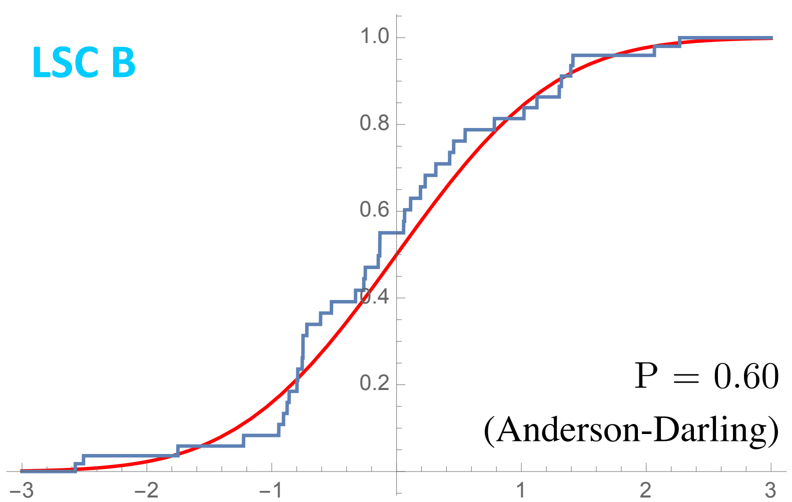



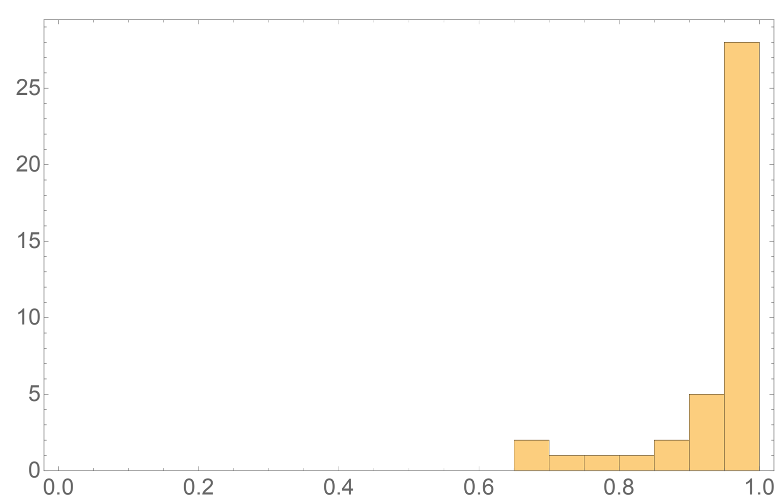
**CPT C**



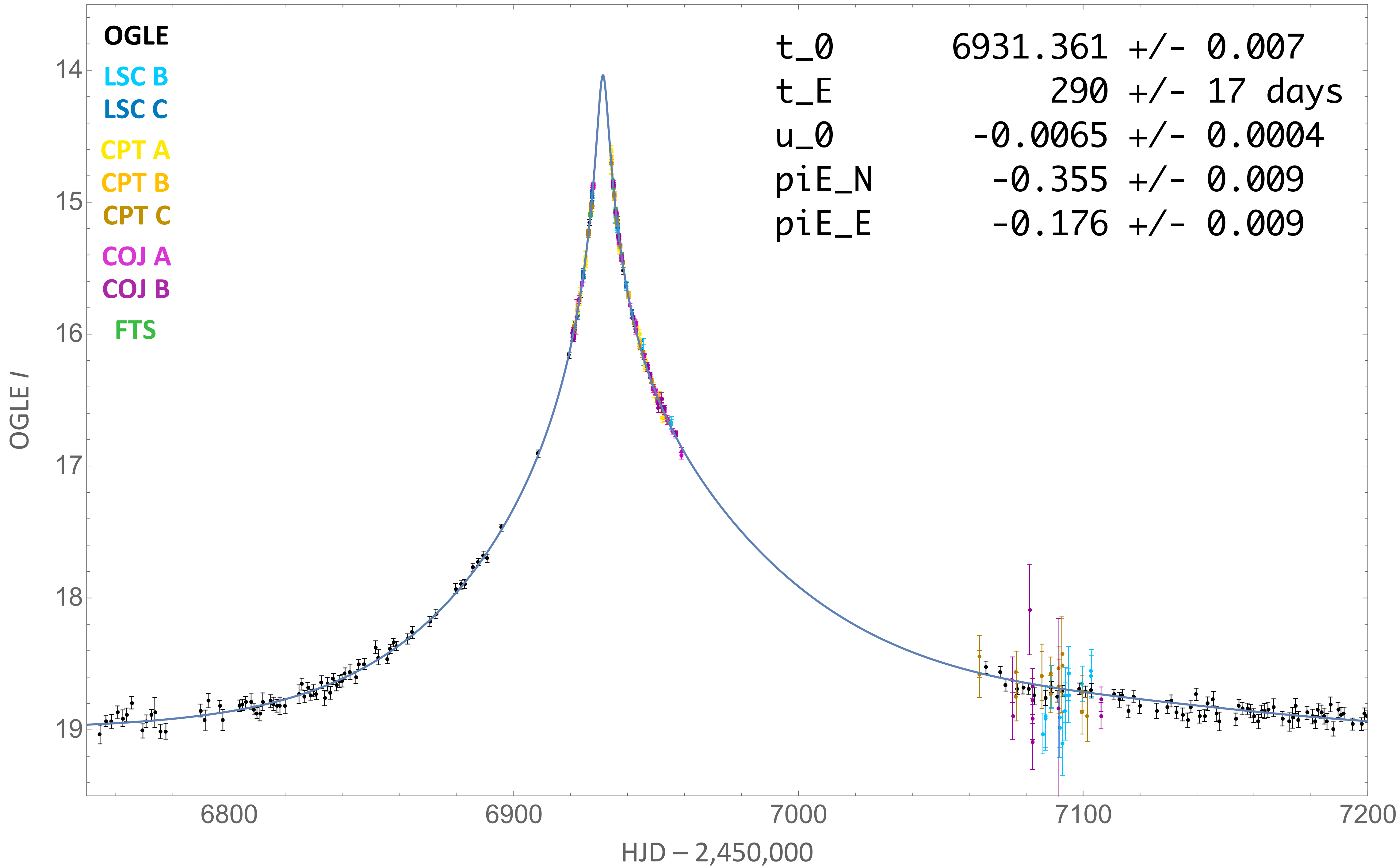
**LSC B**



*without putative anomaly*
($6928.8 \leq t \leq 6934.0$)

# OGLE-2014-BLG-1186 without putative anomaly

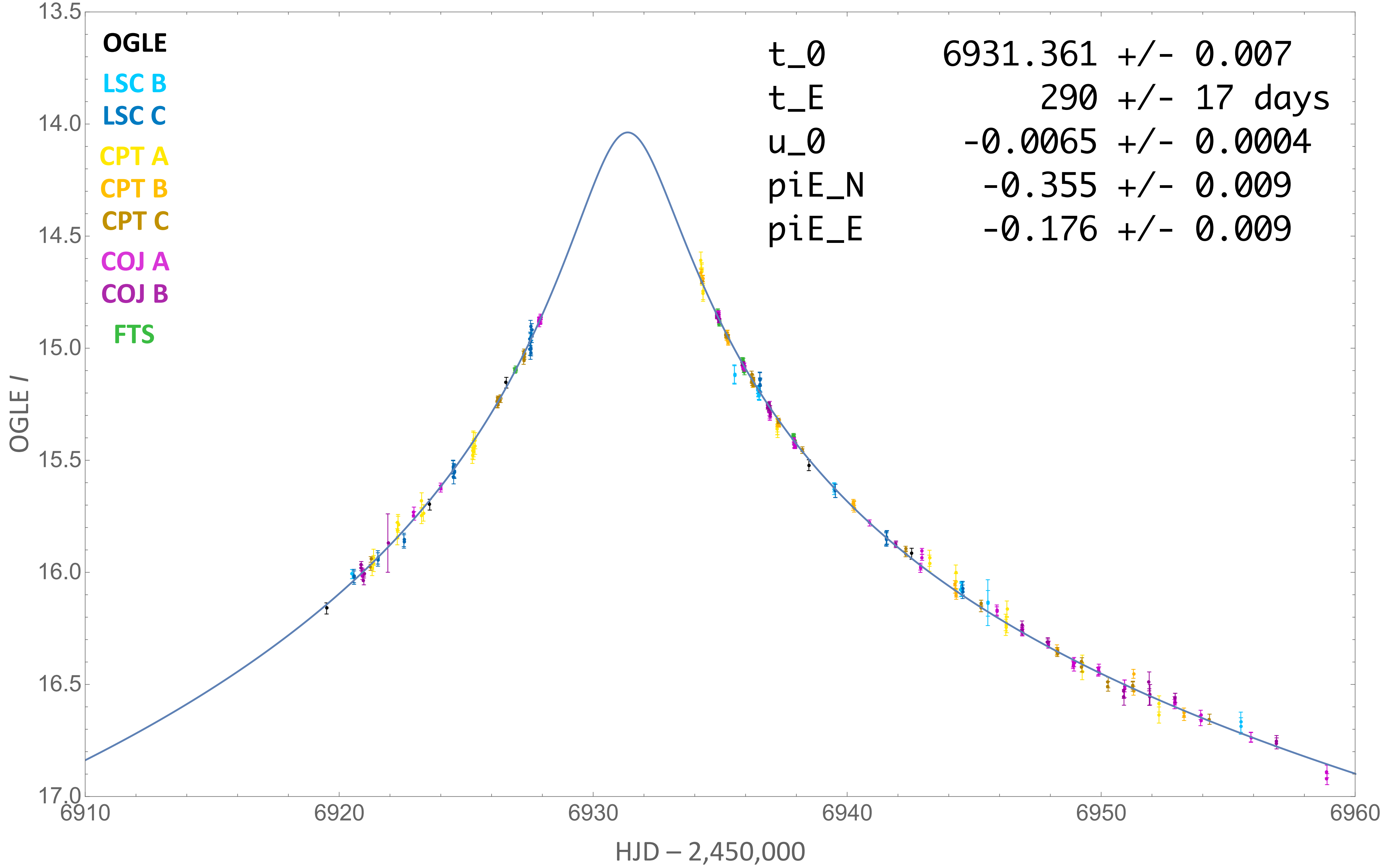



very robust measurement of parallax

time-scale uncertainty related to blend uncertainty

similar estimates for OGLE only, but uncertainties larger

# OGLE-2014-BLG-1186 without putative anomaly

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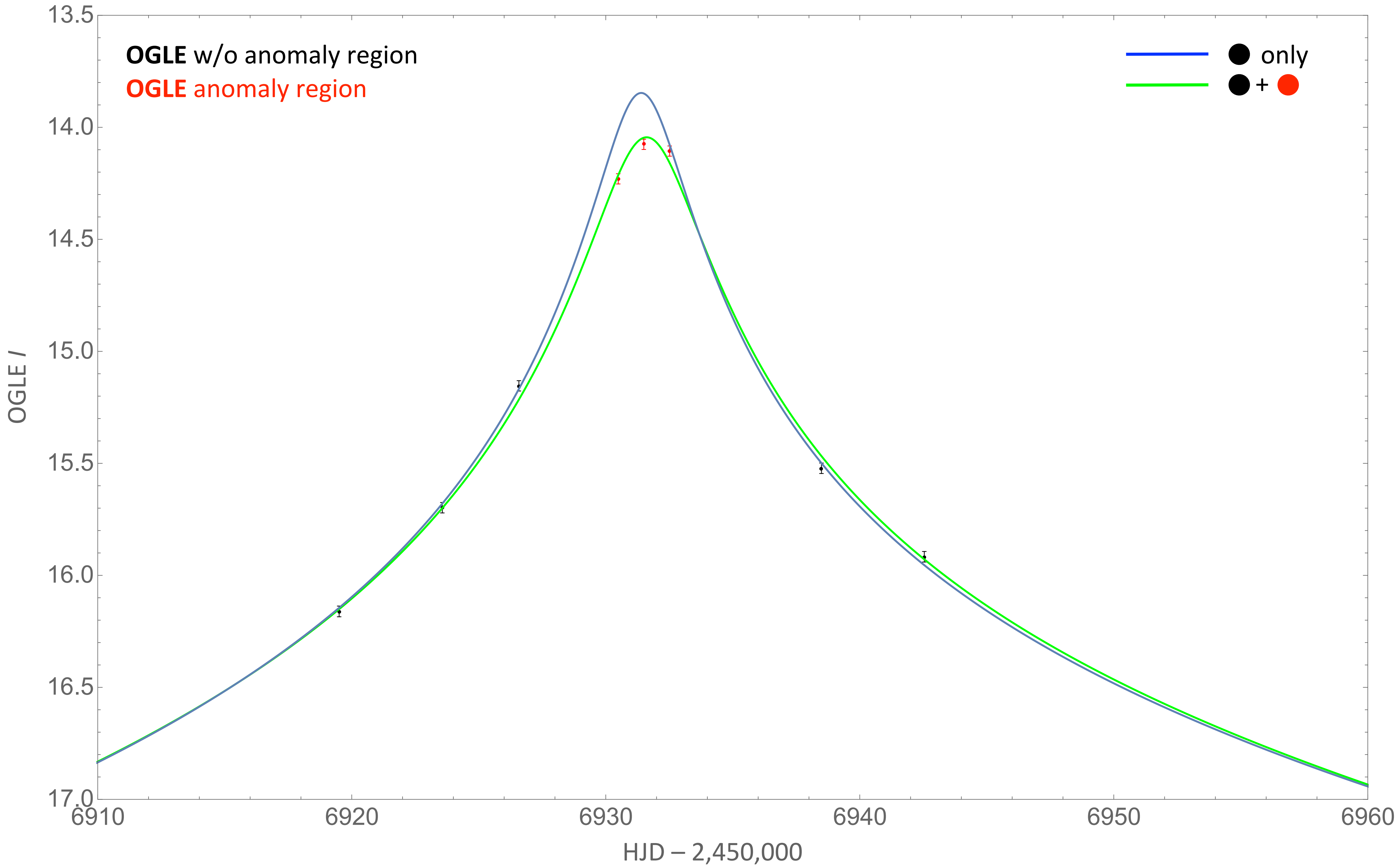
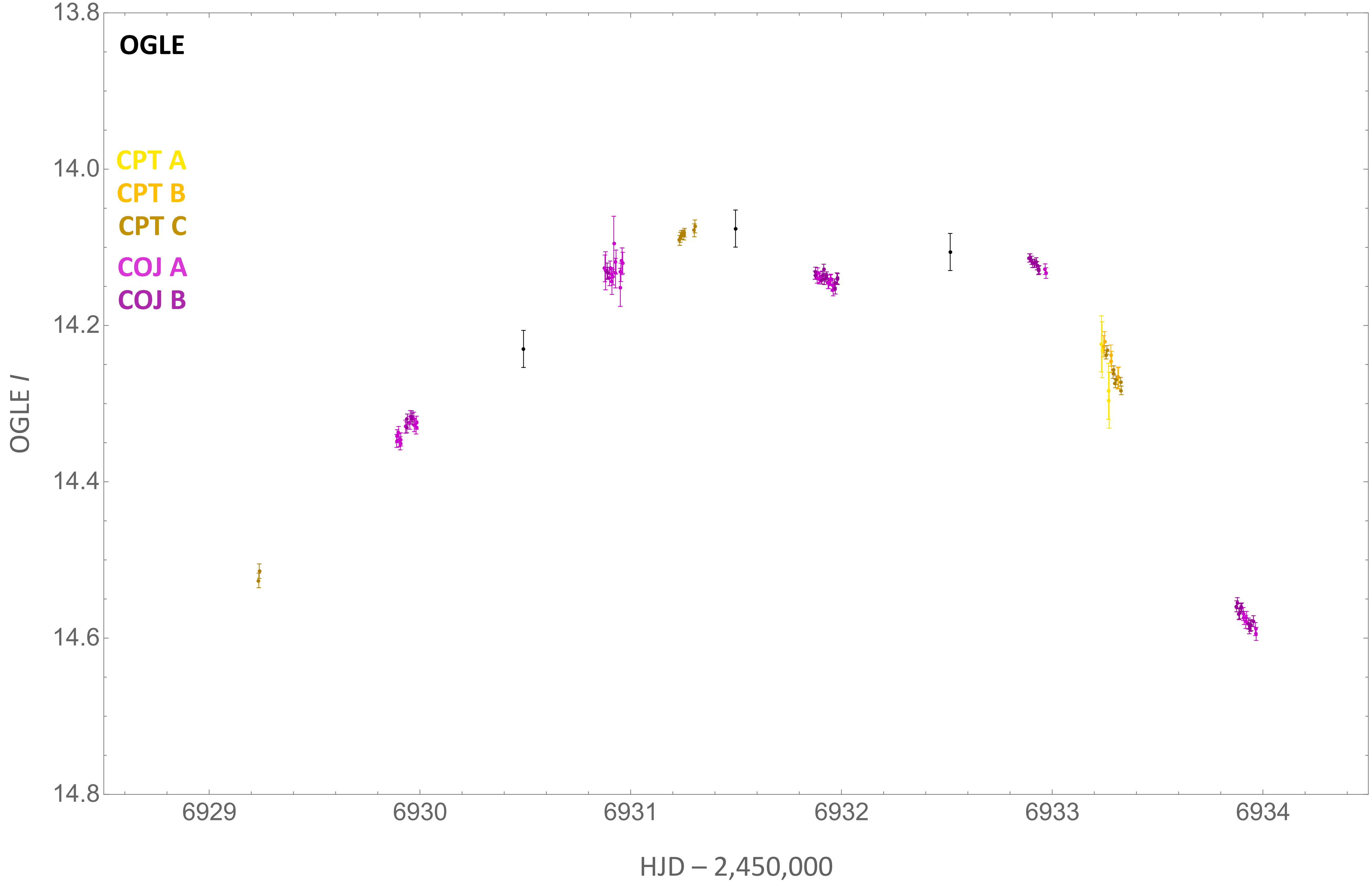
# no anomaly in OGLE-2014-BLG-1186?



# Reviewing the putative anomaly



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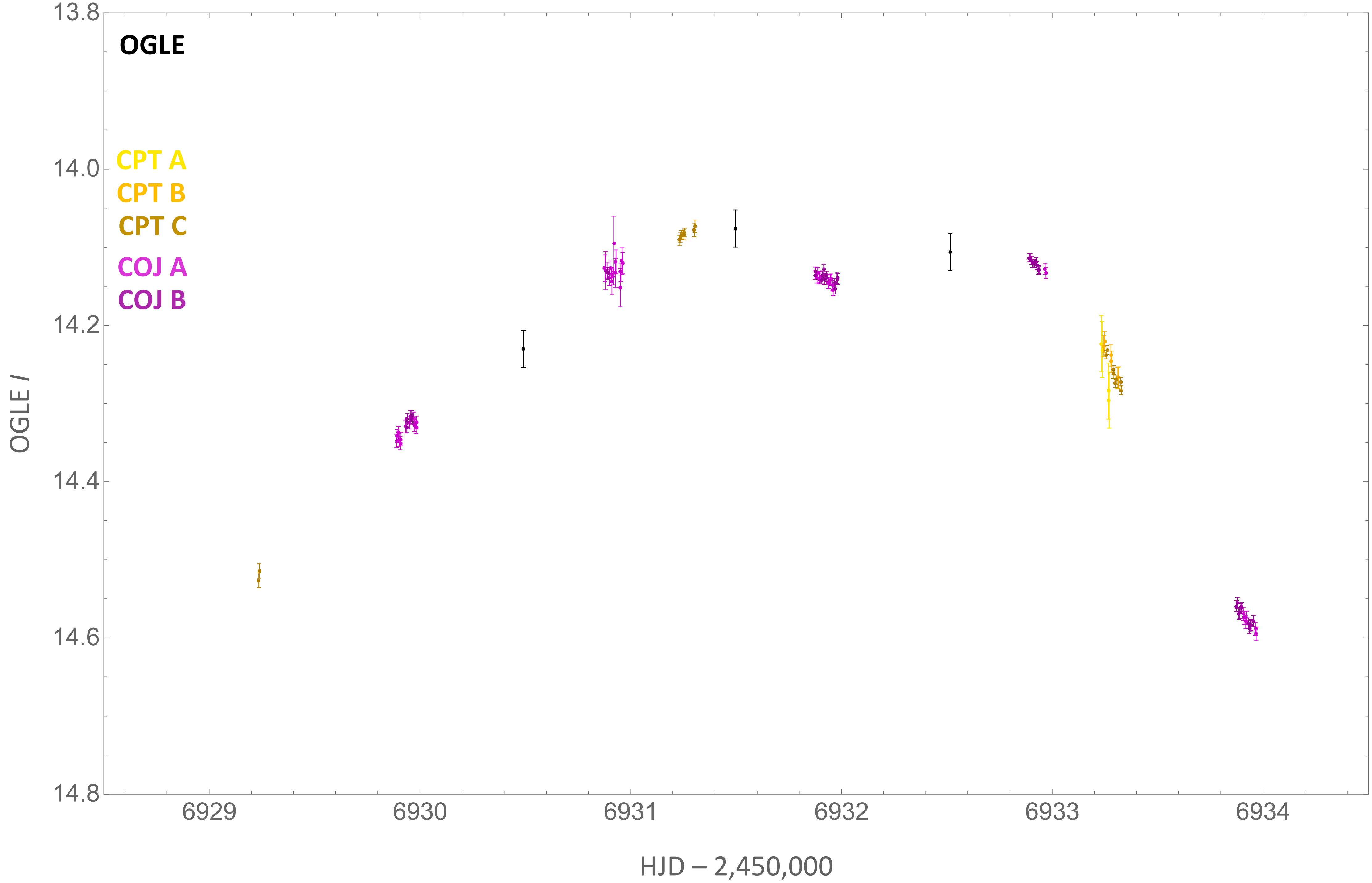
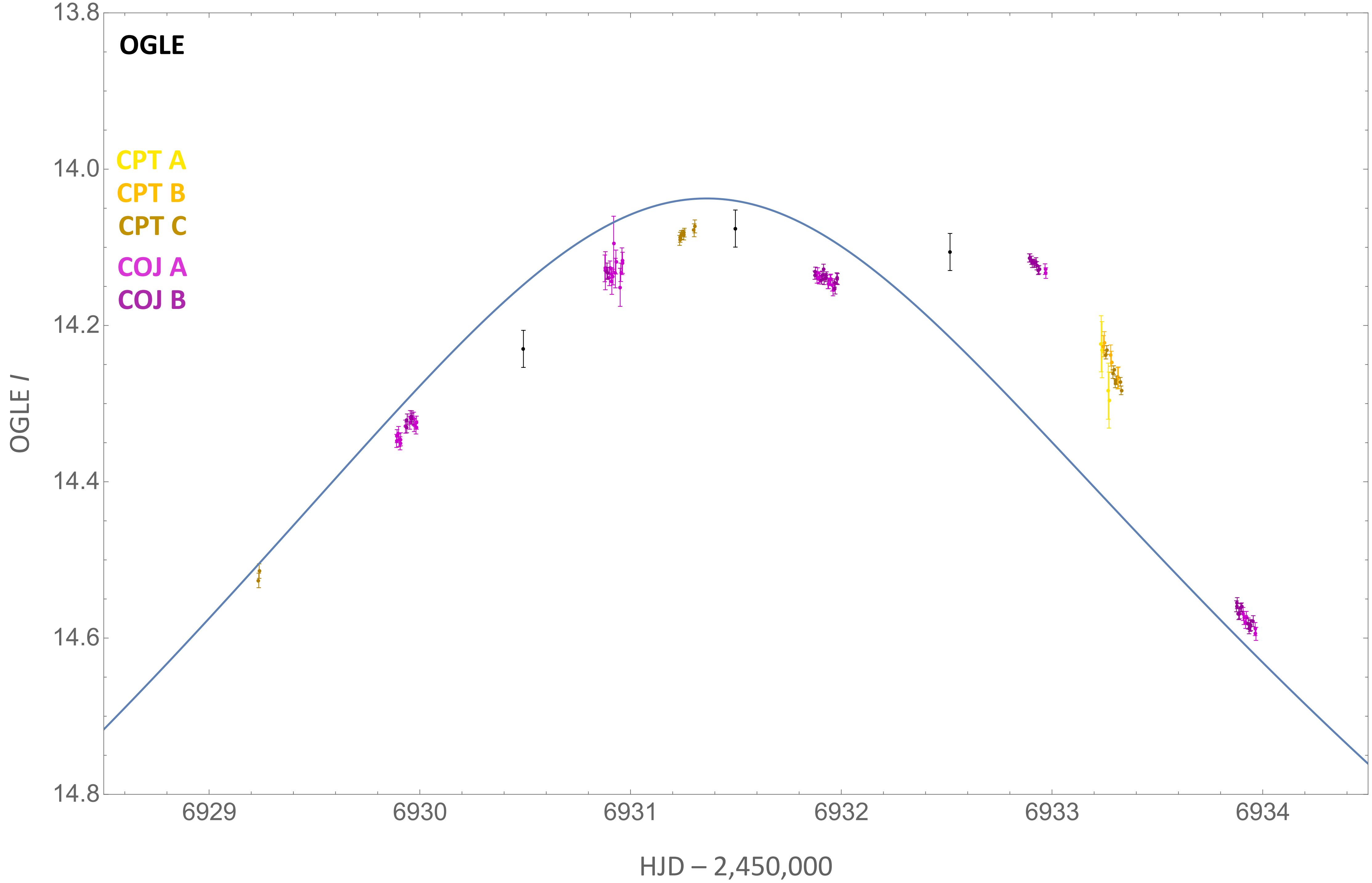



various data sets appear to give consistent picture

# Reviewing the putative anomaly




various data sets appear to give consistent picture

anomaly apparent

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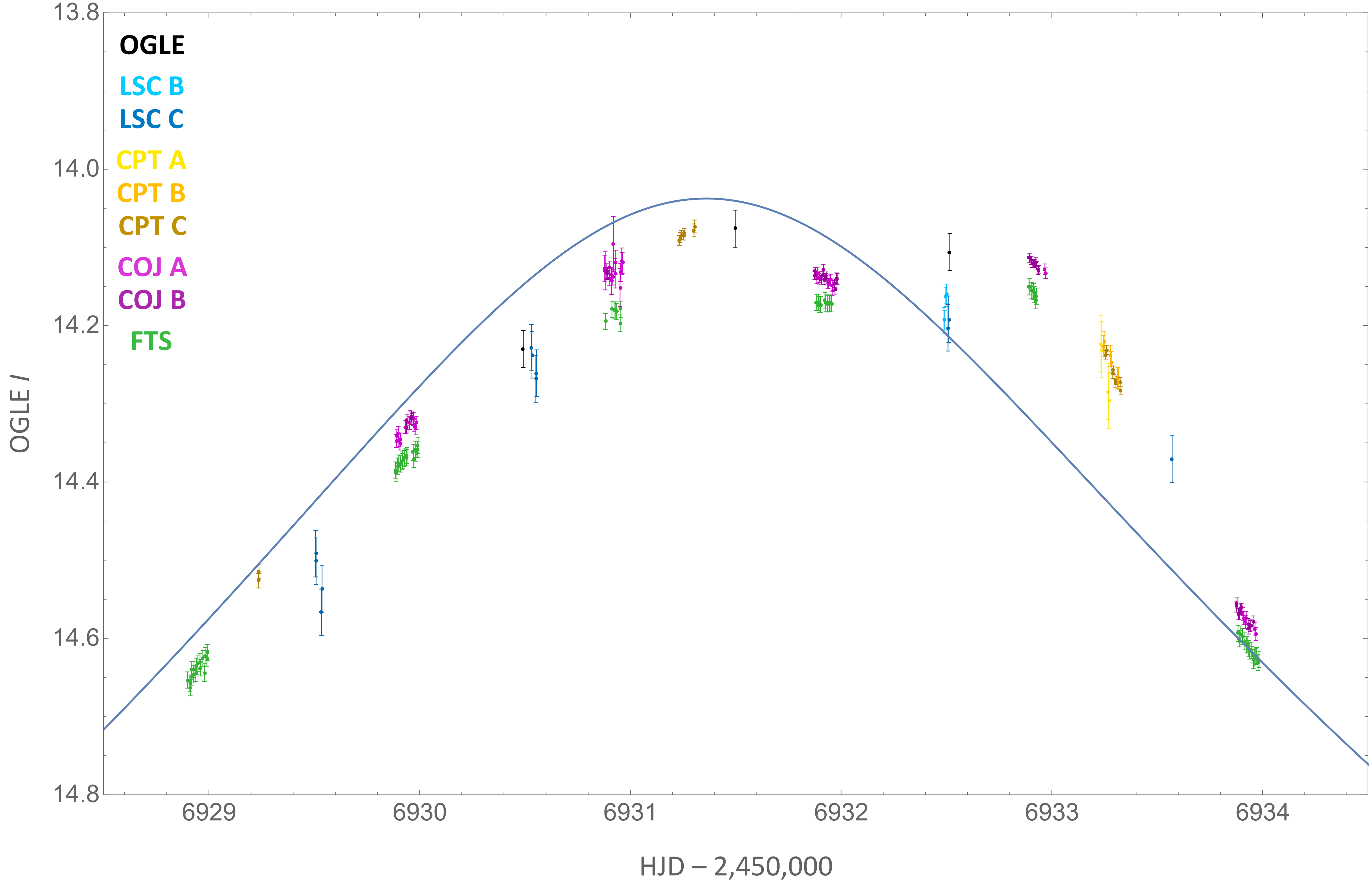
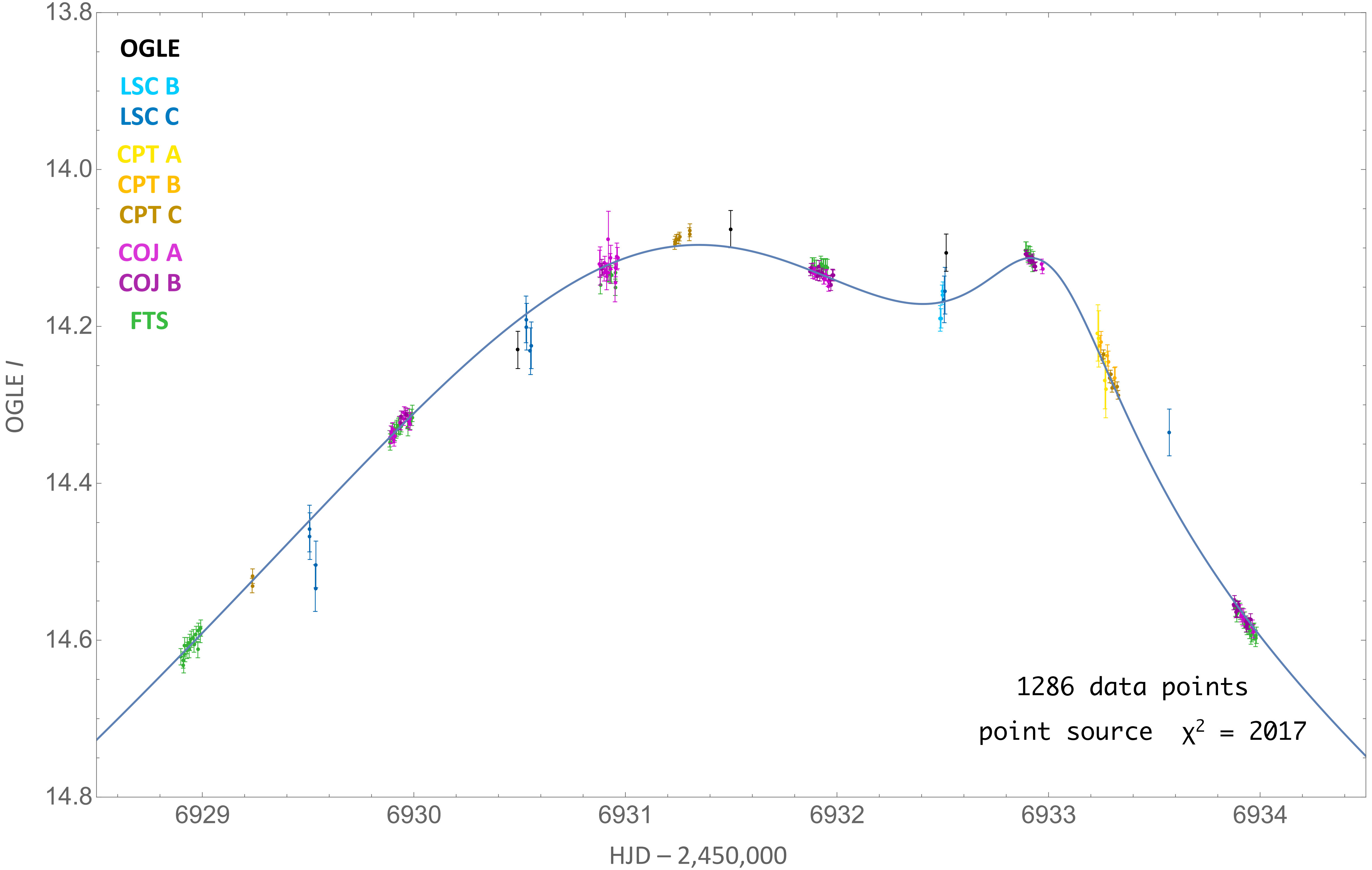



various data sets appear to give consistent picture

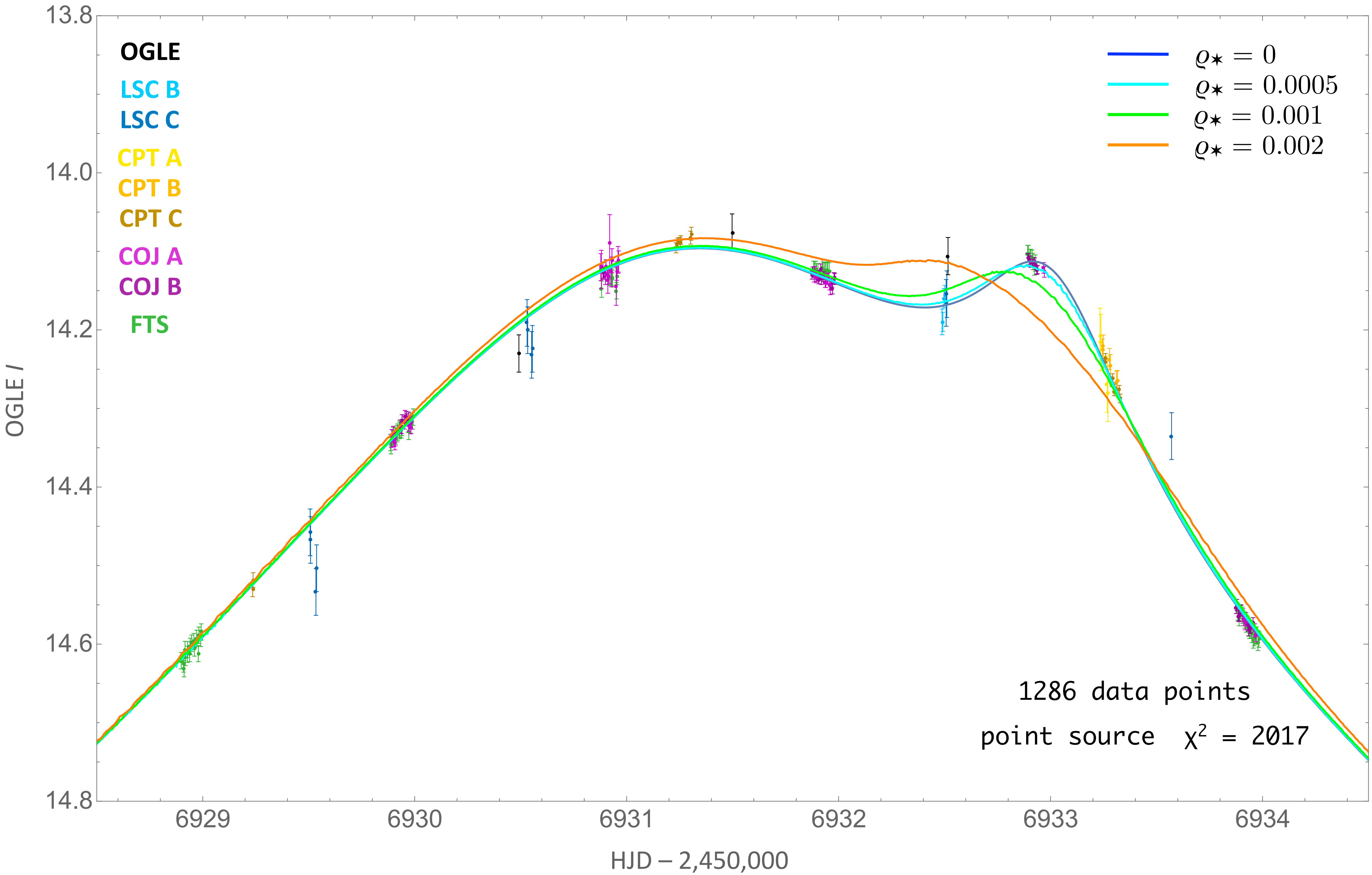
anomaly apparent

baseline/blending less well defined for some data sets

# Modelling the OGLE-2014-BLG-1186 anomaly



# Modelling the OGLE-2014-BLG-1186 anomaly



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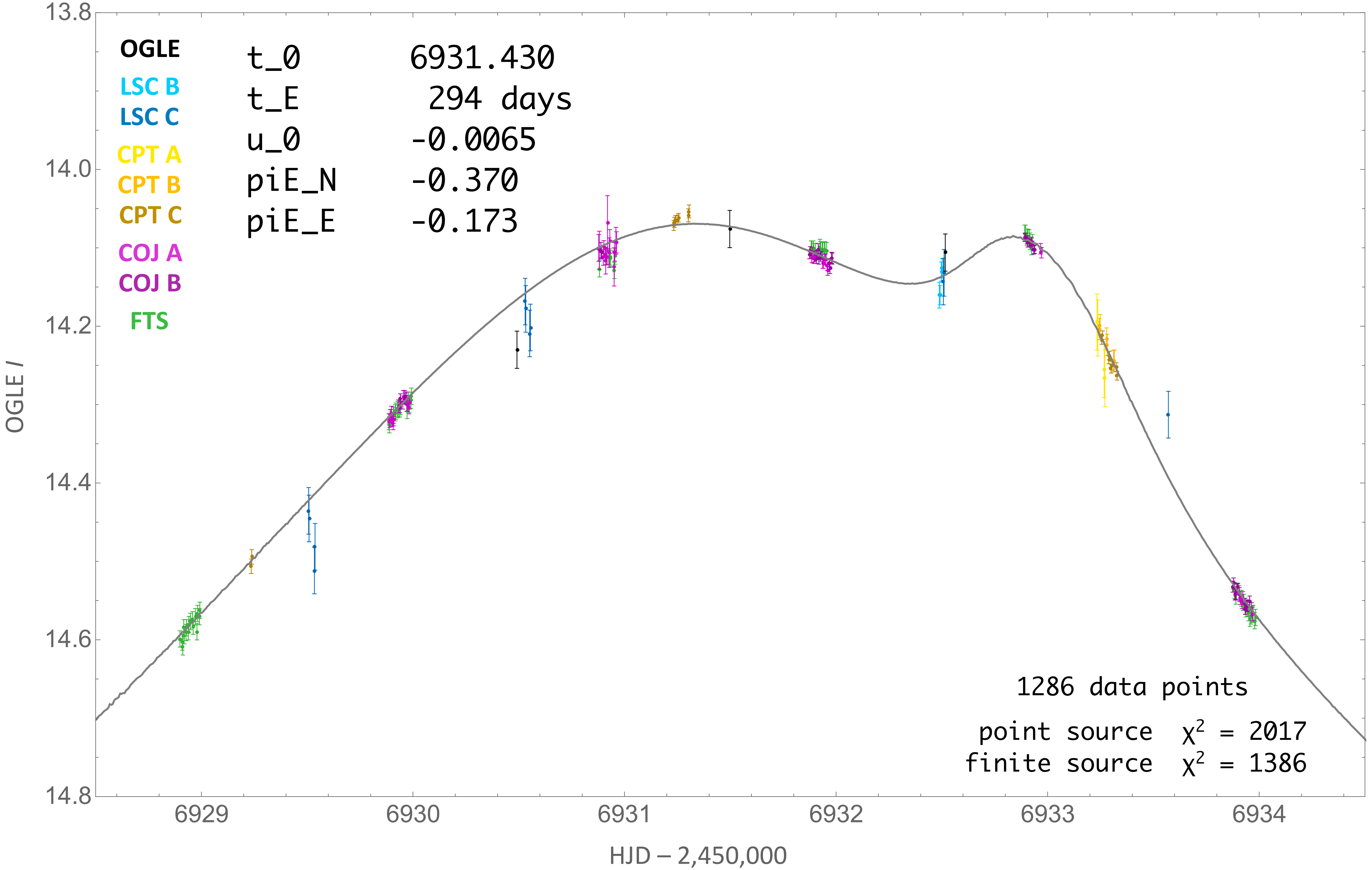
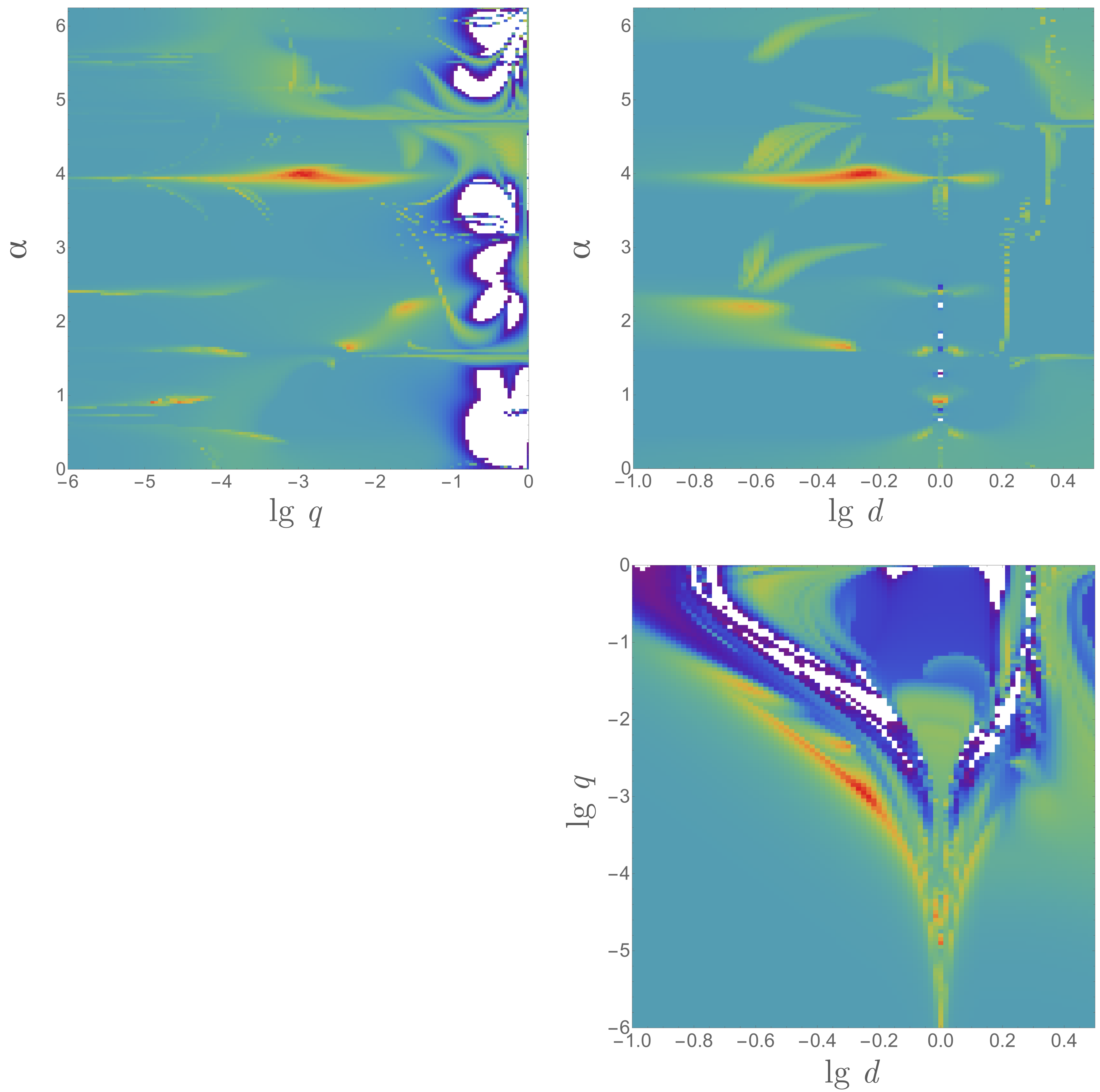



binarity not affecting parallax measurement

# Which model?



# Which model?

## planetary vs non-planetary "solutions"

$\chi^2(\boldsymbol{p}_i) \quad \not\Rightarrow$ probability for true parameters $\boldsymbol{p}_0$ being in vicinity of $\boldsymbol{p}_\mathrm{i}$

$\Delta\chi^2(\boldsymbol{p}_1, \boldsymbol{p}_2) \equiv \chi^2(\boldsymbol{p}_1) - \chi^2(\boldsymbol{p}_2) \quad \not\Rightarrow$ probability for $\boldsymbol{p}_1$ being "preferred" over $\boldsymbol{p}_2$

can use $\chi^2$ test: $\mathcal{P}[\chi_N^2 \geq \chi^2(\boldsymbol{p}_i)]$

applicable regardless of model being linear in $\boldsymbol{p}$ or not

normally-distributed uncertainties: $\chi^2$ follows $\chi^2$-distribution

$$\mathrm{PDF}(\sqrt{2\chi_N^2}) \sim \mathcal{N}(\sqrt{2N-1}, 1)$$

otherwise: evaluate distribution of $\chi^2$ based on non-normal $\sigma$

**does not work without consistent model for measurement uncertainties!**

# special thanks to...

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