Stage-IV Cosmic Shear and the Curse of Covariate Shift

Cosmology from Home, 2022

Angus H Wright, 24.06.22

GERMAN CENTRE FOR COSMOLOGICAL LENSING

RUB

European Research Council
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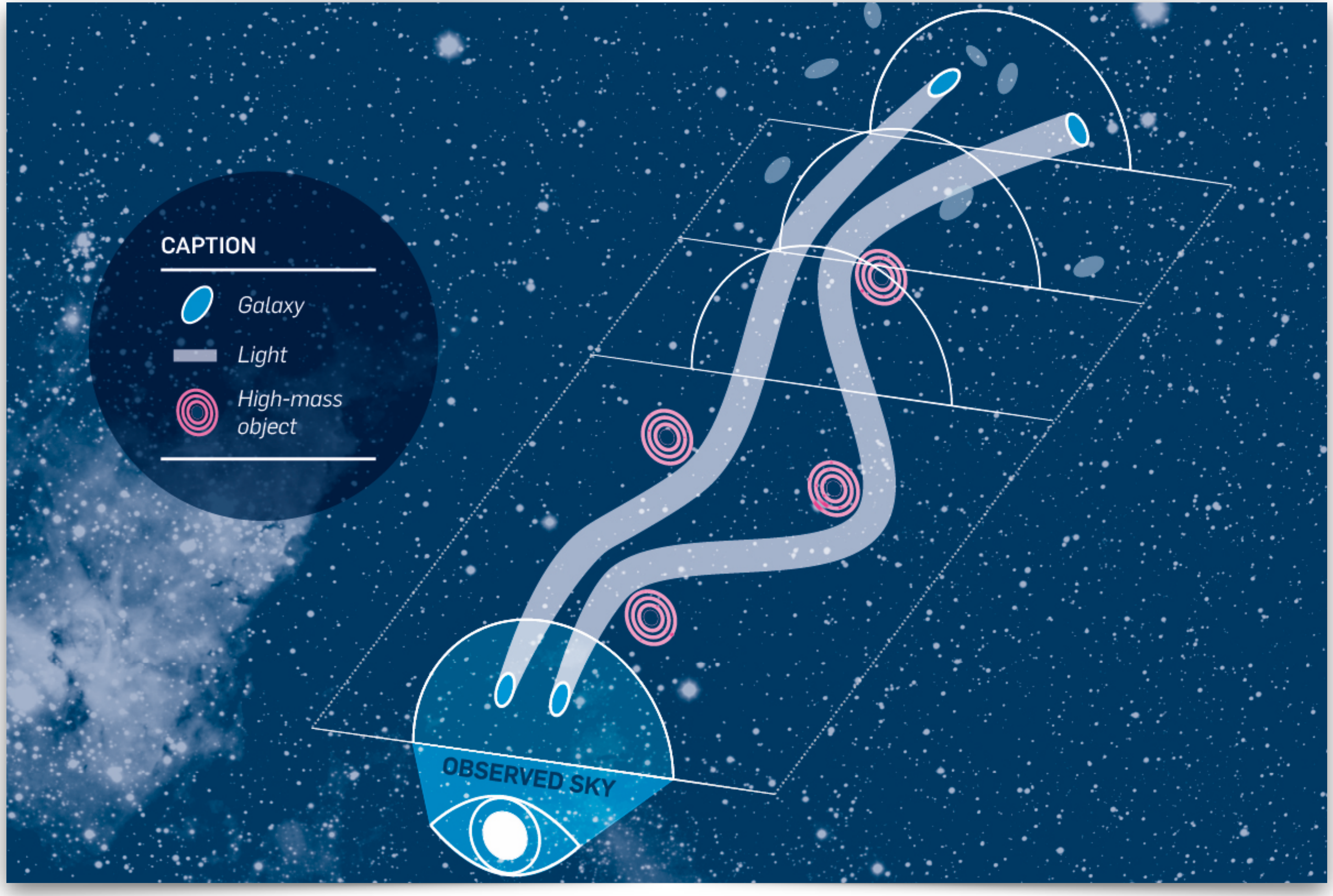
A brief reminder of cosmic shear

Fundamentals of Cosmic Shear

Lensing by large-scale structures



Galaxies in the distant universe have (mostly) randomly distributed shapes

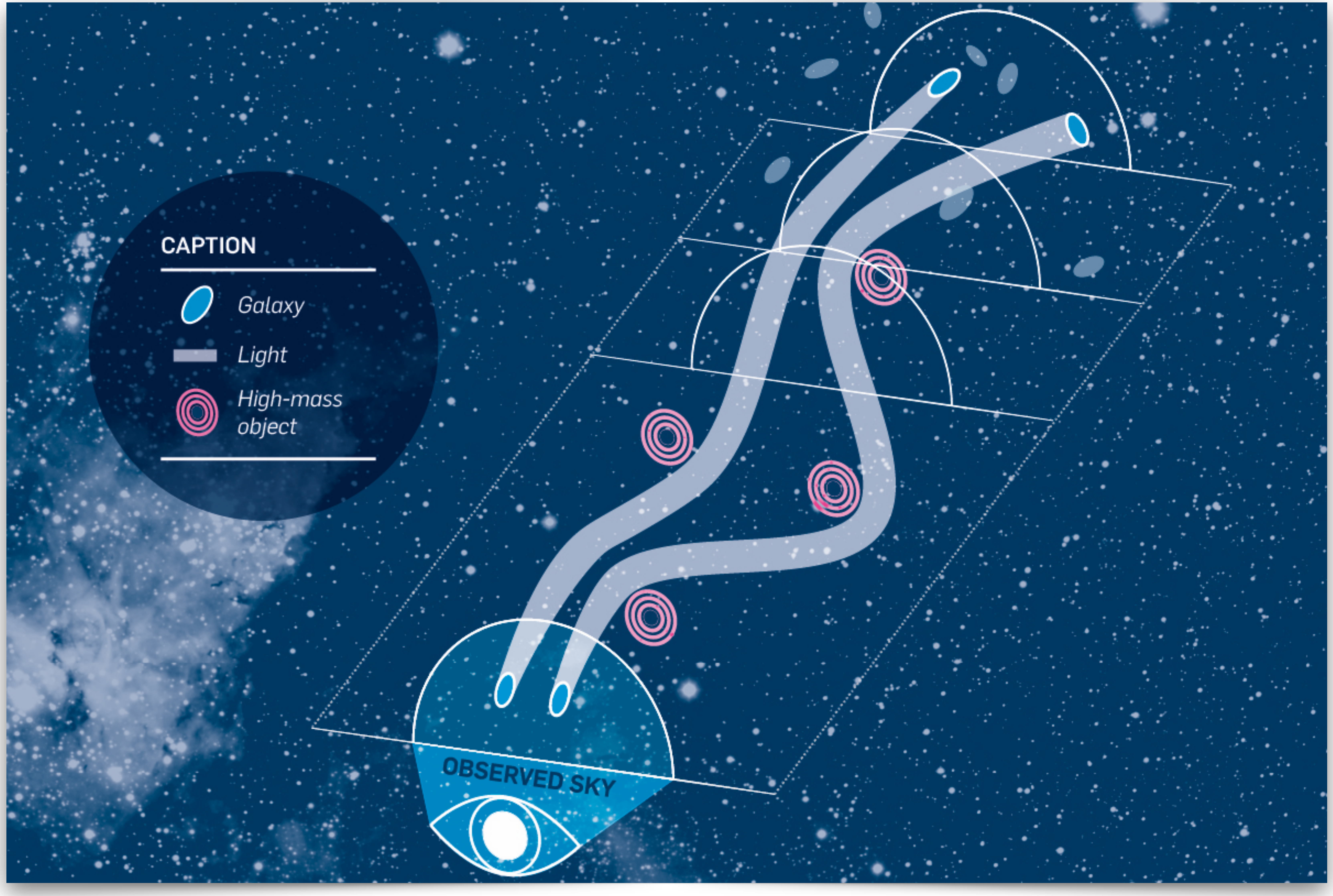
Light is distorted along the line-of-sight by massive structures

Propagation through similar structures imprints coherent distortions on galaxy shapes

Image Credit: Ruhr-University Bochum

Robust Cosmic Shear Requirements

What do you need to get right?



Shape Measurements

Source Redshift Distributions

Modelling of the Source galaxy population

Modelling of baryonic effects

Image Credit: Ruhr-University Bochum

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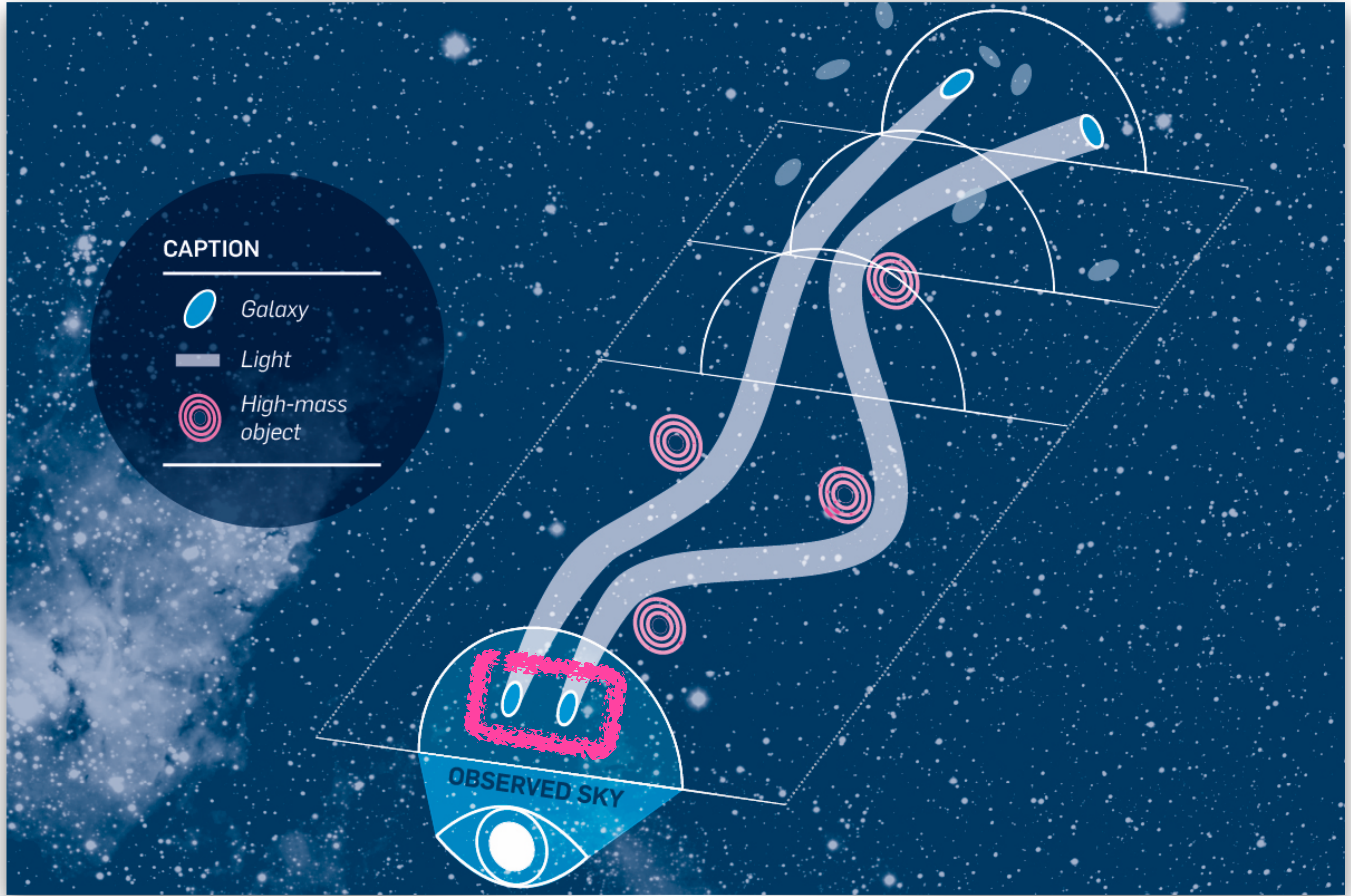

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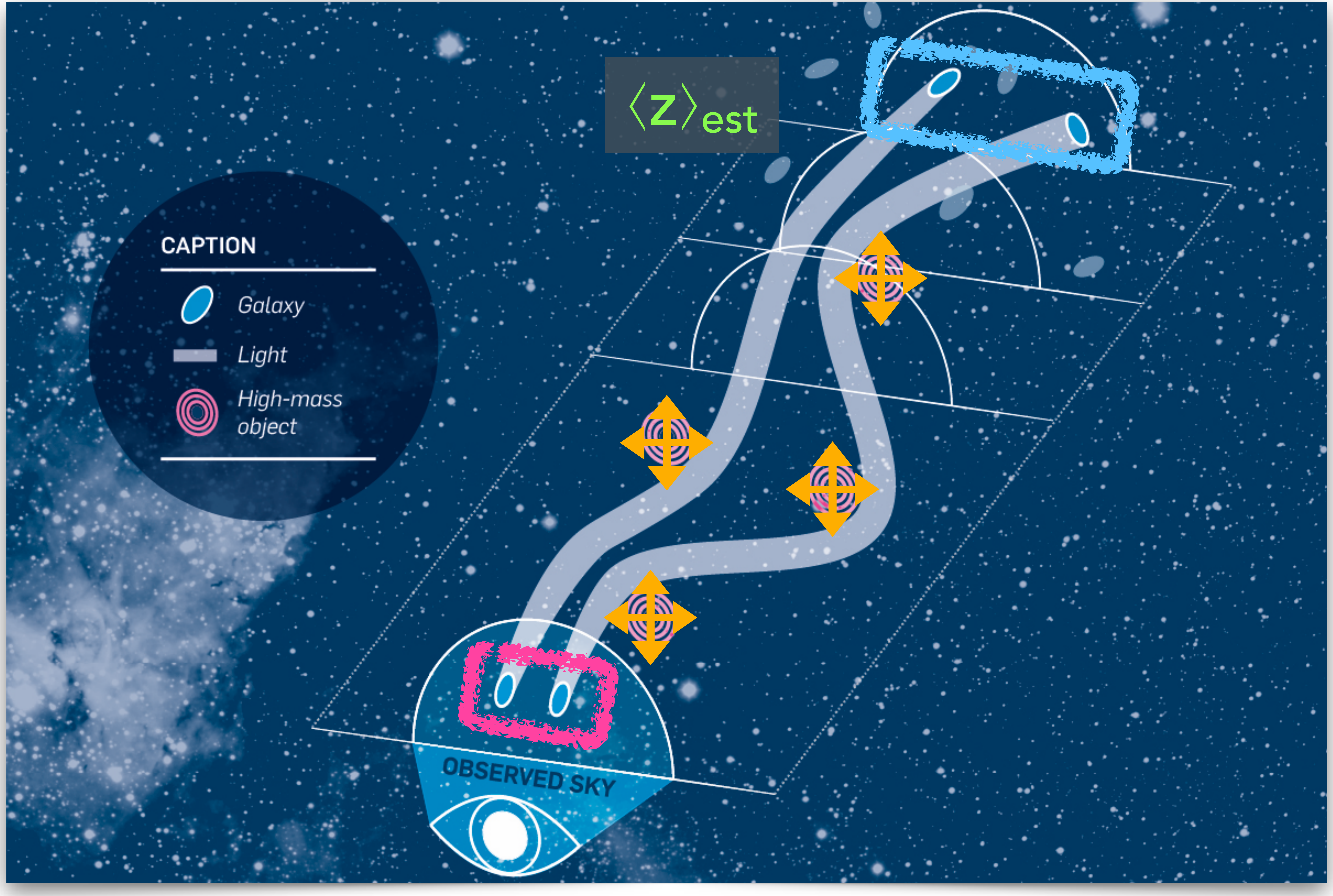

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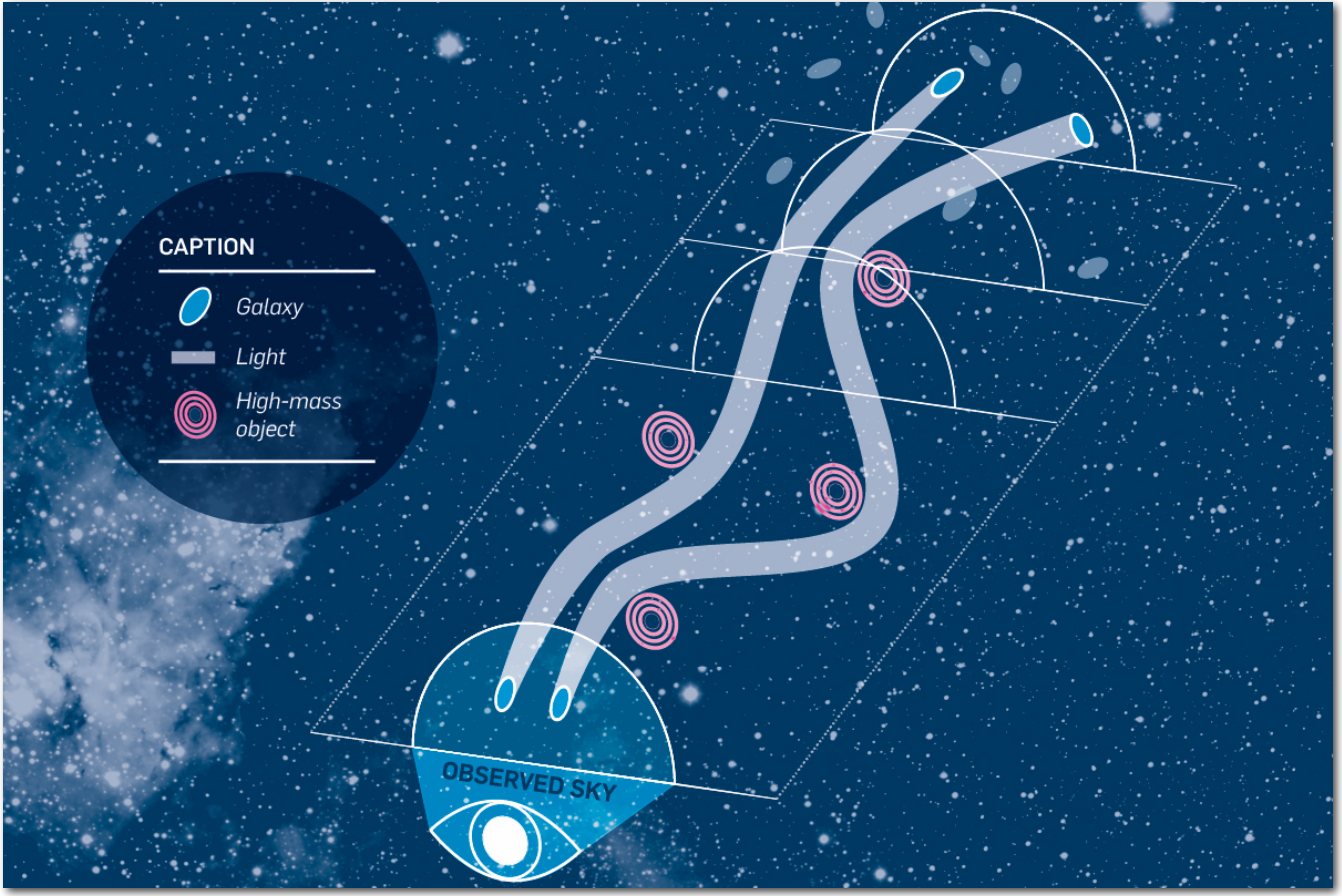
Why is redshift calibration important for cosmic shear?



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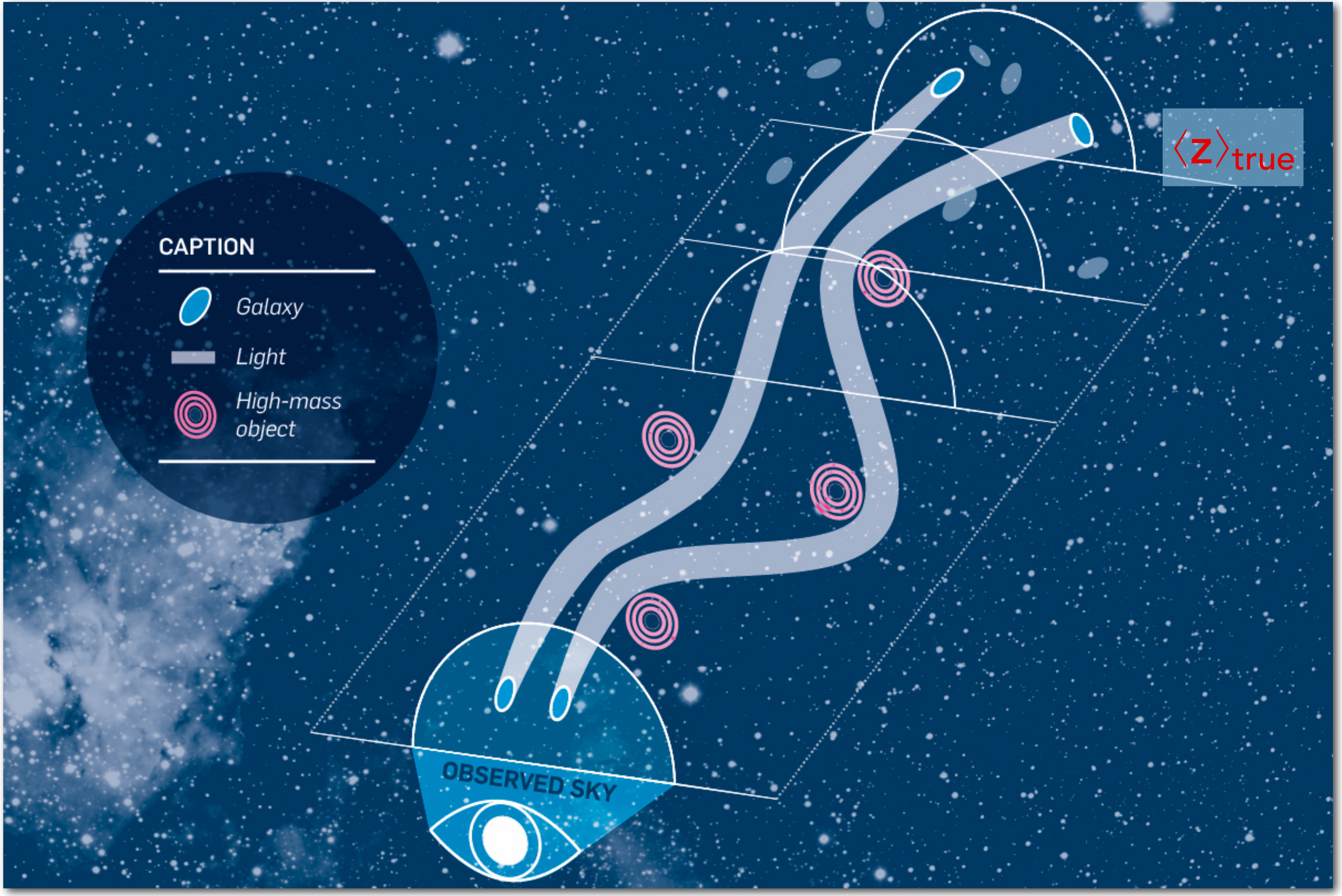

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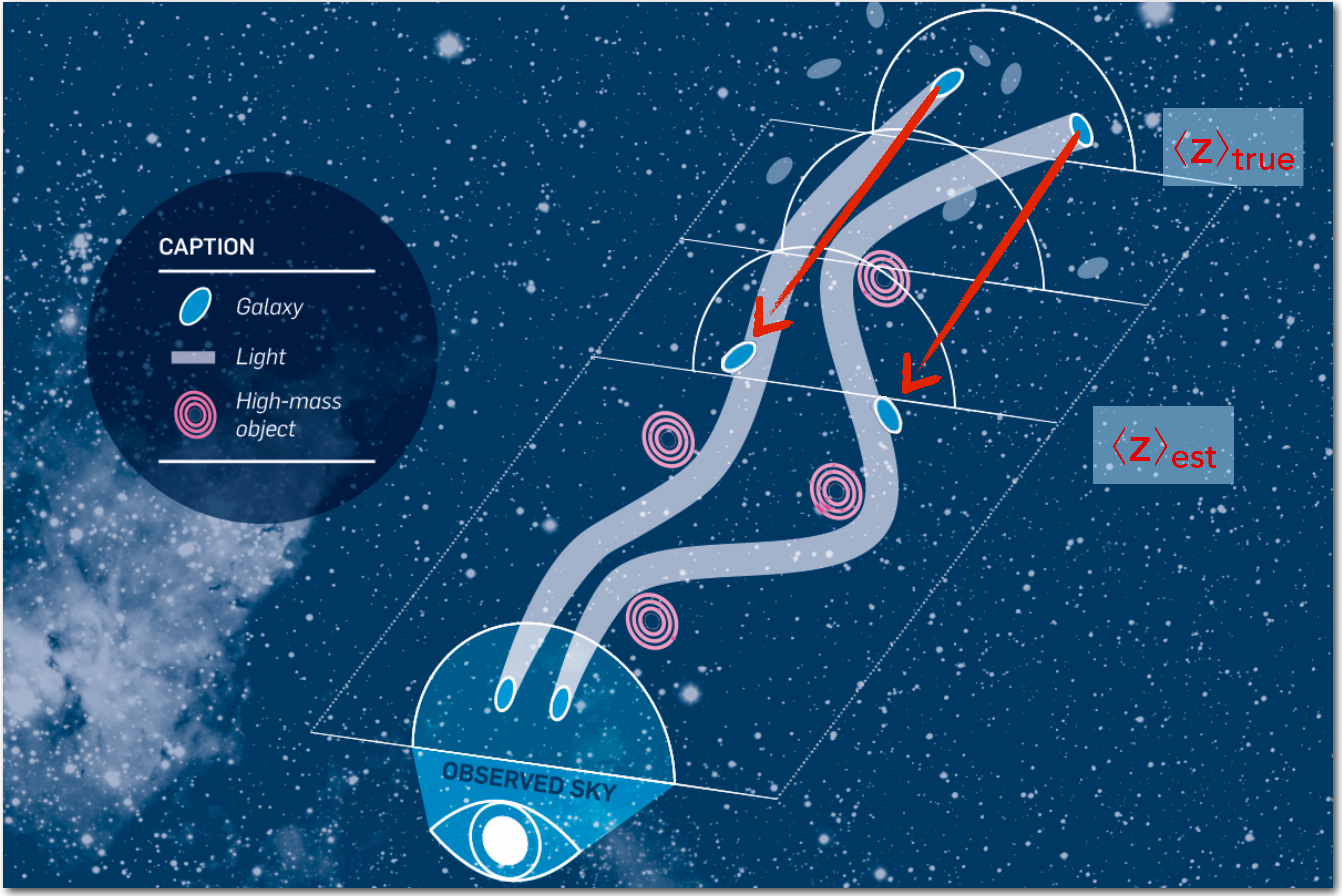

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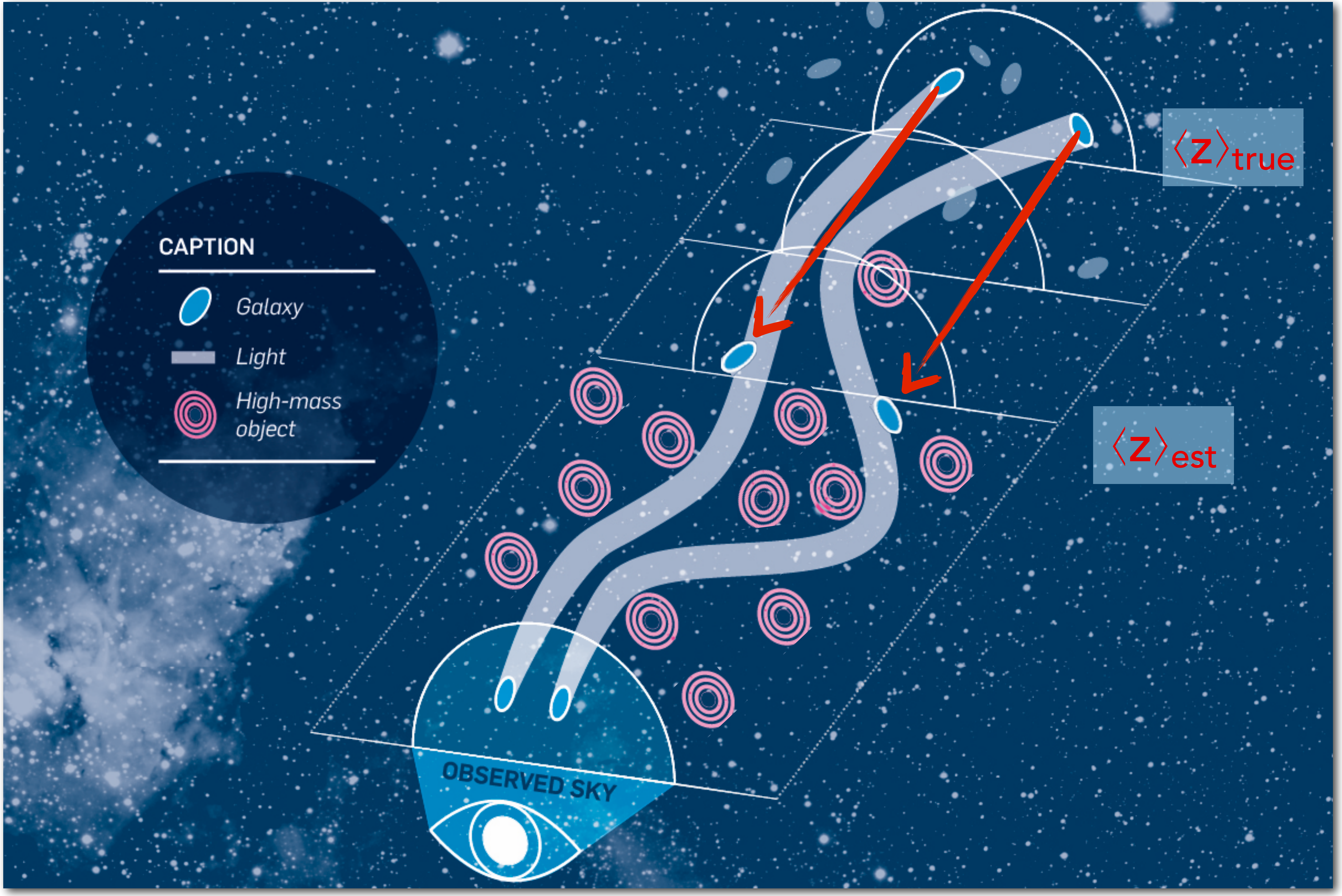


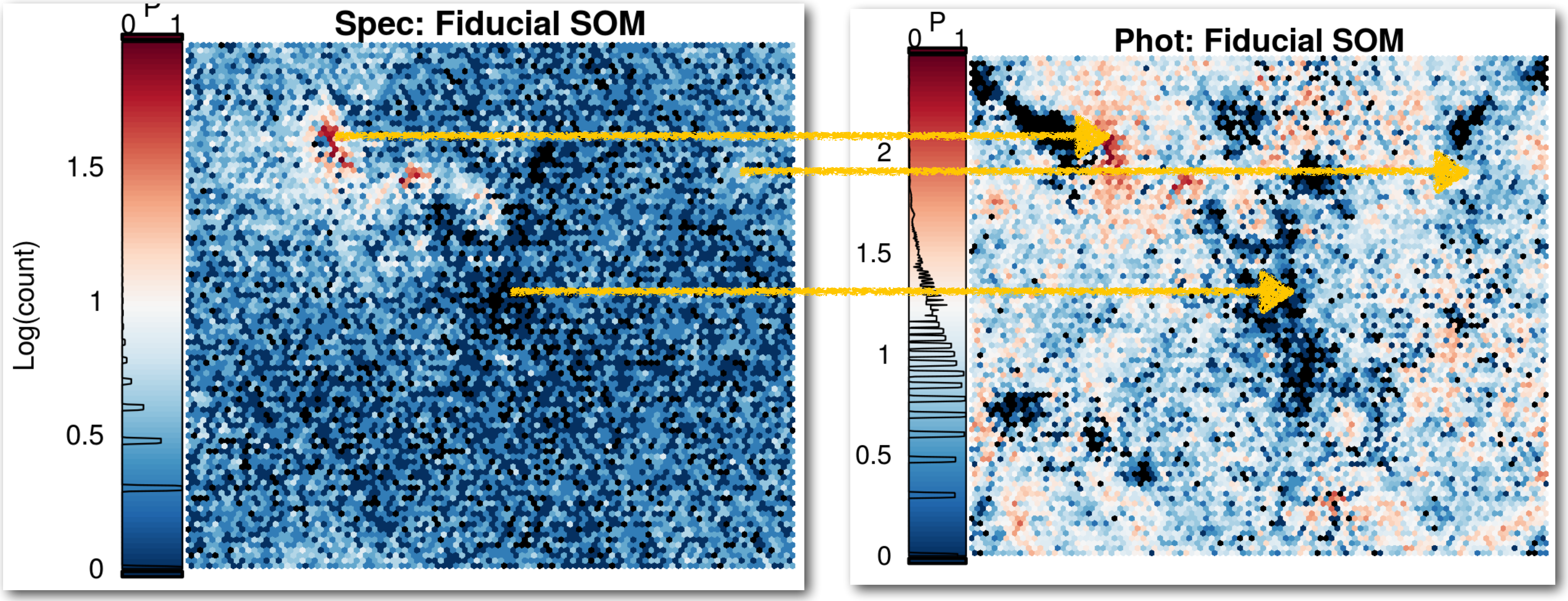
Image Credit: Ruhr-University Bochum

How are redshift distributions calculated?

SOM Redshift Distribution Calibration

Leverages unsupervised machine learning to map two samples together:

1. Spectroscopic “calibration sources” with known redshift, to
2. Wide-field “photometric sources” with unknown redshift



KiDS-1000

Wright et at 2020a

A ML classification problem

We use unsupervised machine learning to associate sources into cells c, and compute the target-sample redshift-distribution $p_{\rm tg}(z)$:

$$\begin{aligned} p_{\rm tg}(z) &= \sum_c p_{\rm tg}(z\,|\,c)p_{\rm tg}(c) \\ &\approx \sum_c p_{\rm tr}(z\,|\,c)p_{\rm tg}(c) \end{aligned}$$

The conditional probability of redshift given a cell (i.e. colour) $p(z\,|\,c) = p(c\,|\,z)p(z)/p(c)$ is dependent on:

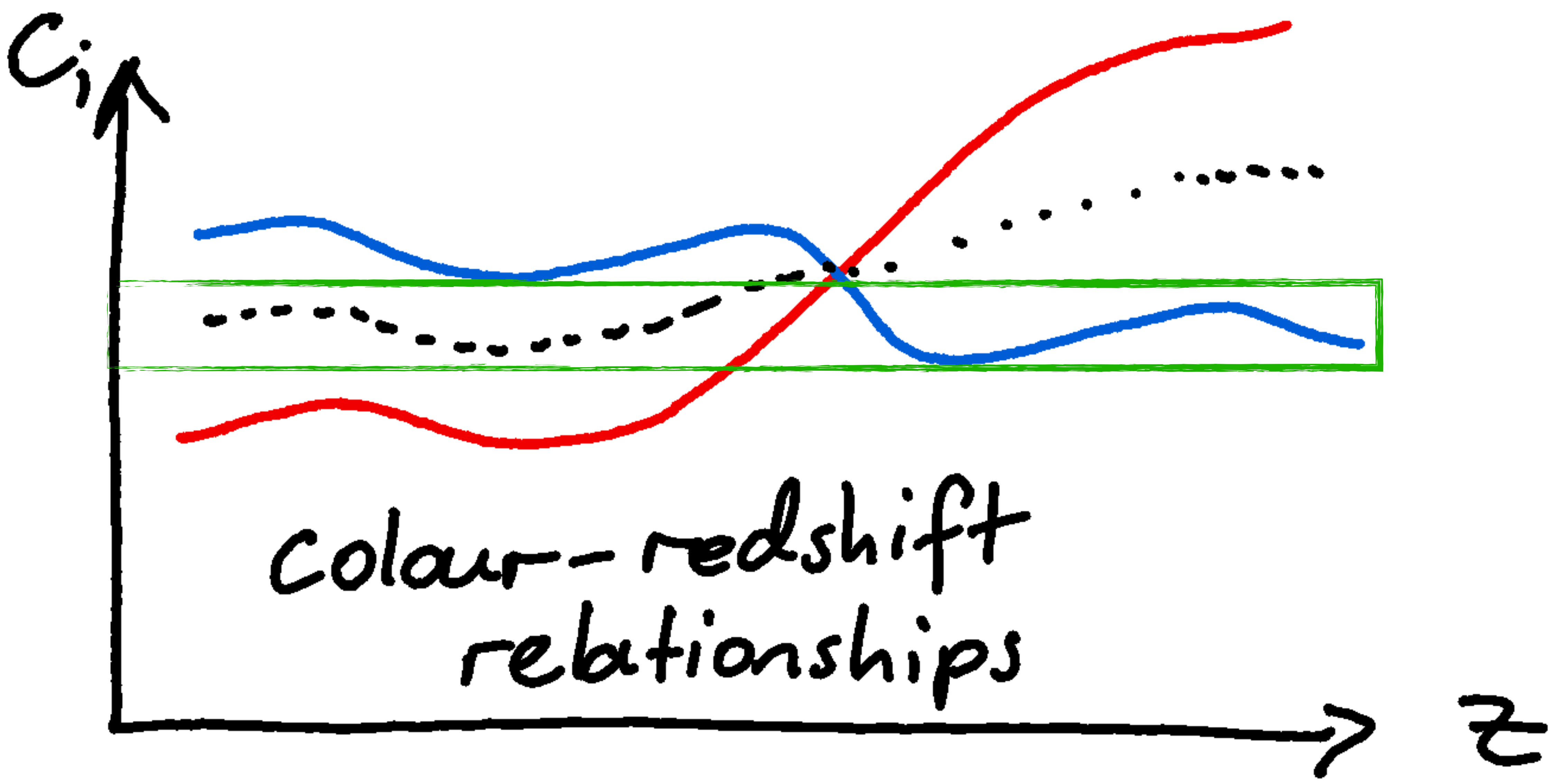
1. the likelihood of observing particular colours at a given redshift;
2. the “prior probability” of the sample as a function of redshift; and
3. the “covariate” probability distribution of the sample as a function of colour.

Mapping between Colour and Redshift

Made possible because of the colour-redshift relation

$P_{v}(z/\underset{\sim}{c})$

The probability of a source being at redshift z given its observed colours c



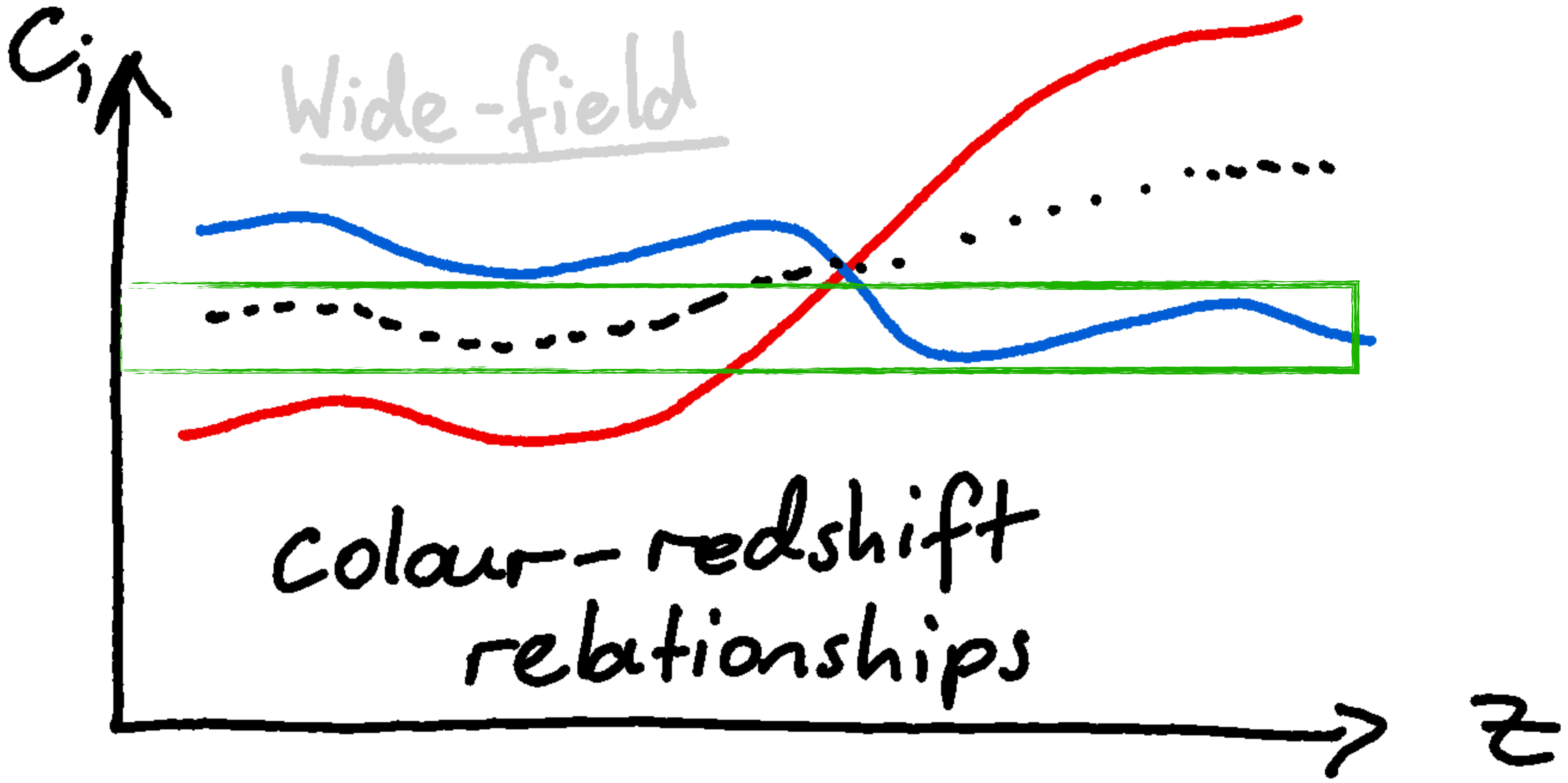
"Red" galaxy SED

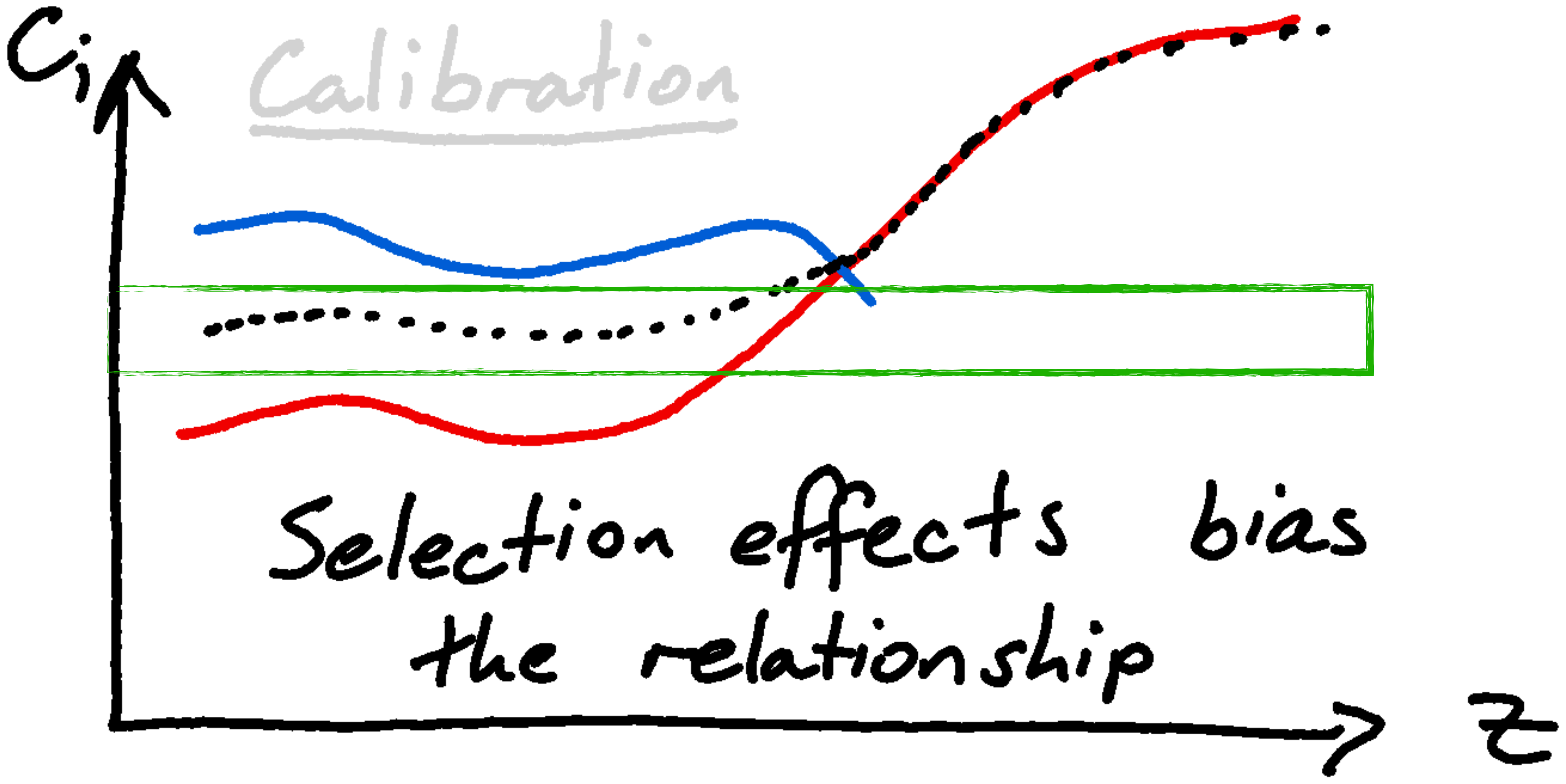
"Blue" galaxy SED

One colour cell

The Problem: Covariate & Prior Probability Shift

Within a SOM cell, the distribution of redshift & colour differs between the calibration and wide-field samples



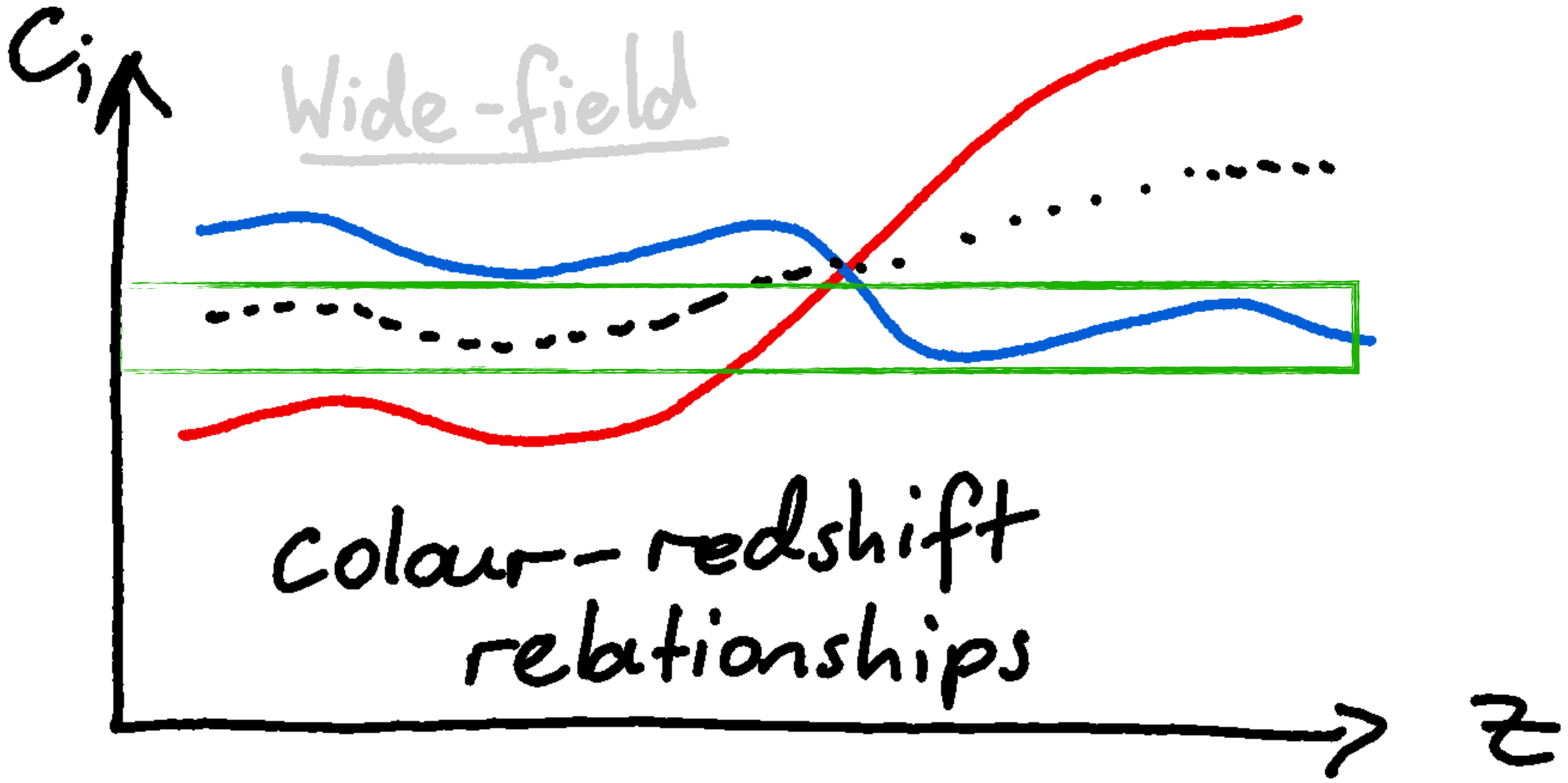


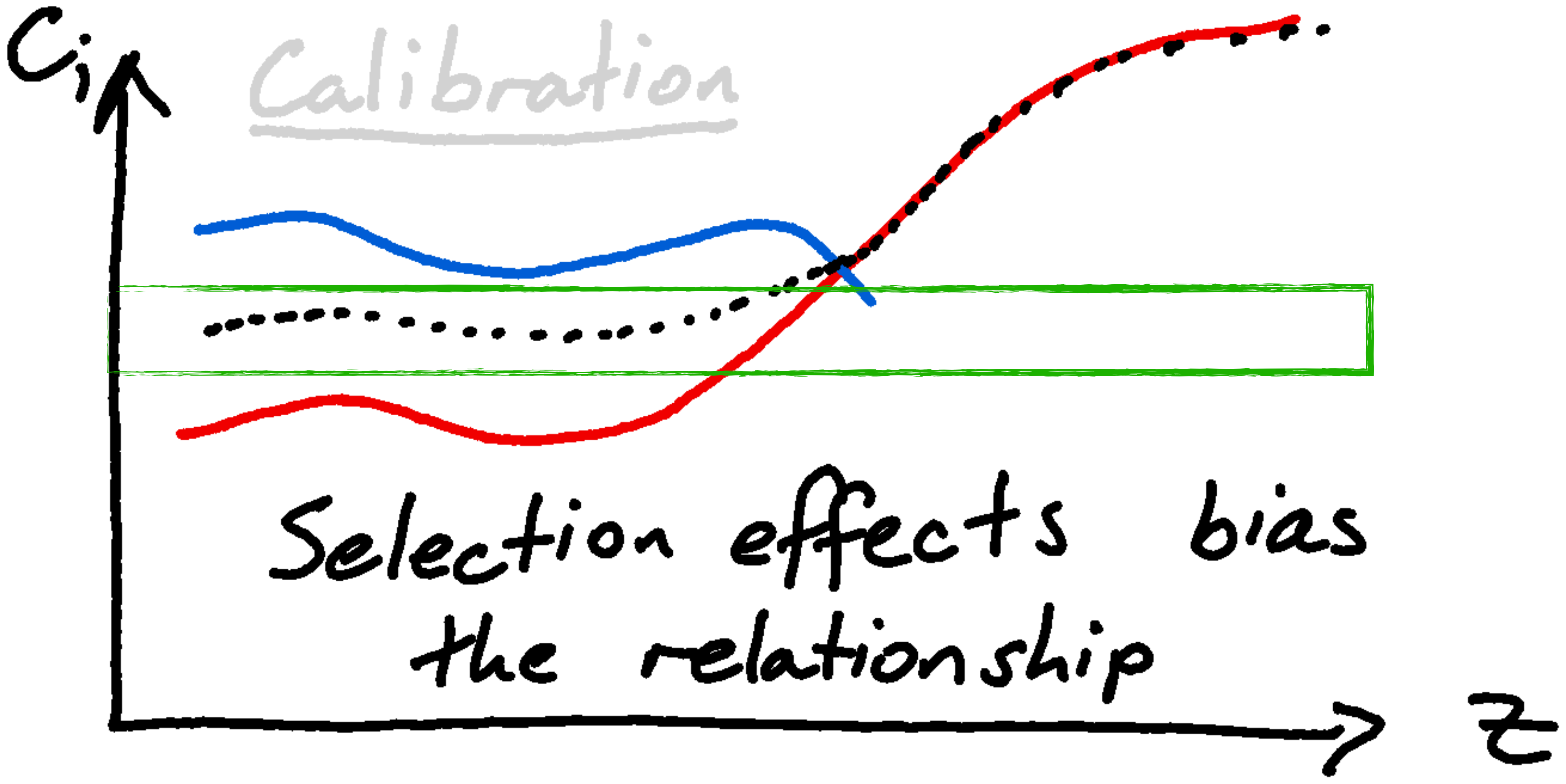
The Problem: Covariate & Prior Probability Shift

Within a SOM cell, the distribution of redshift & colour differs between the calibration and wide-field samples

$$p_t(z) \neq p_v(z)$$

The overall distribution of redshift differs between the samples, so the mapping at fixed colour becomes biased





The Problem: … ability Shift

Within a SOM … & colour differs
betwee … samples

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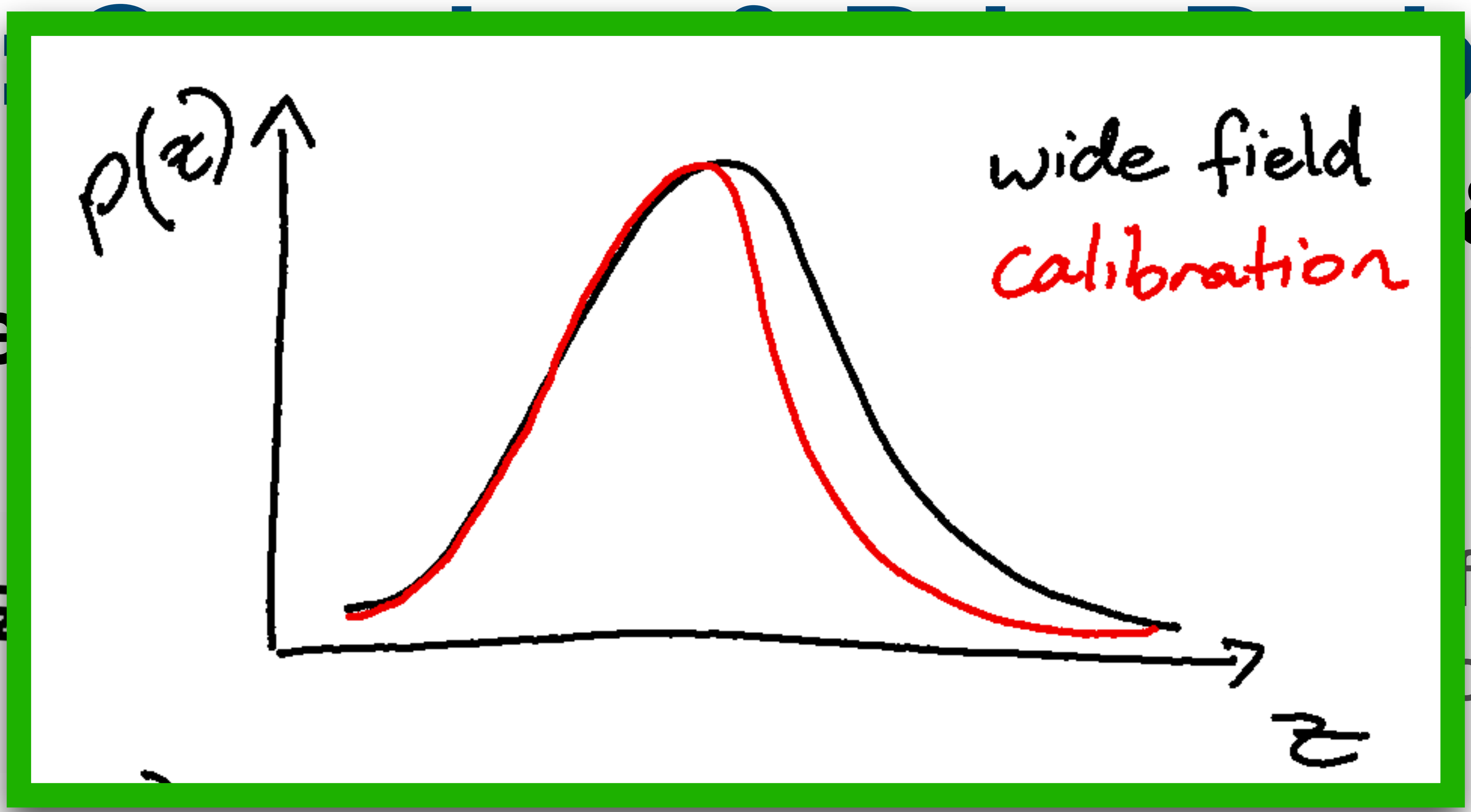

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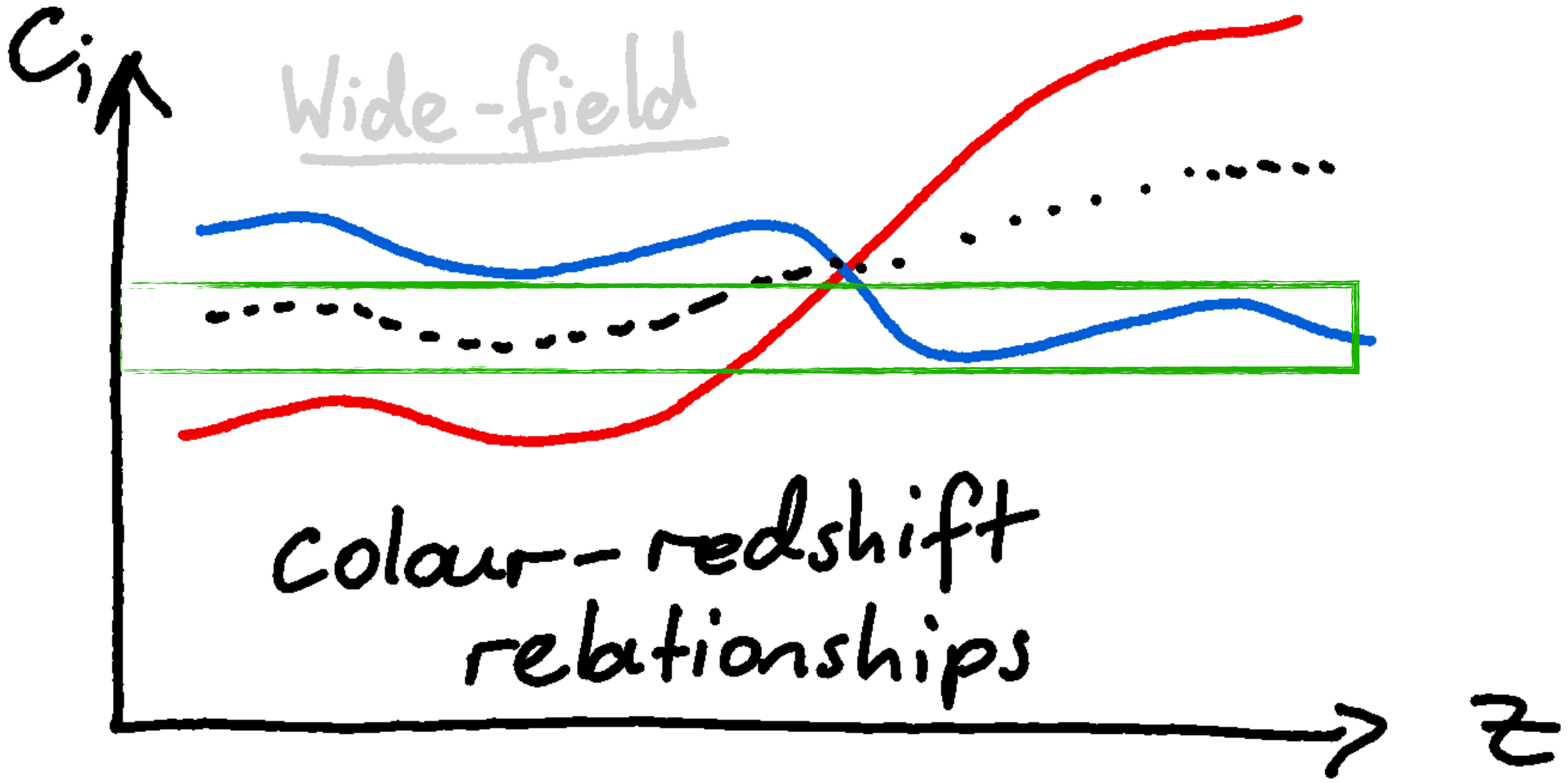
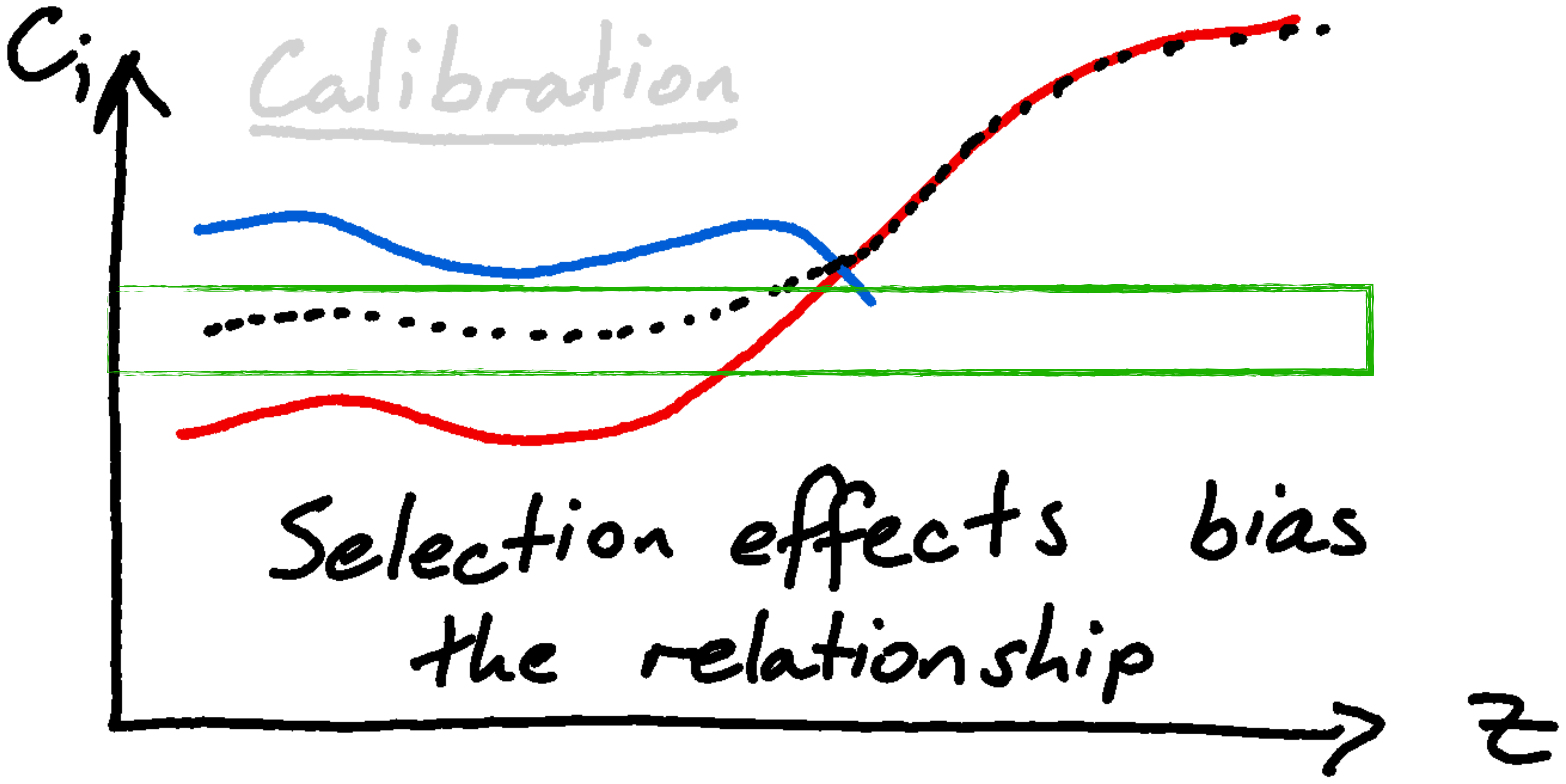




So: essentially a ML classification problem

There are three classic failure modes in ML regression/classification problems:

1. Covariate shift: $p_{\rm tr}(z\,|\,c) = p_{\rm tg}(z\,|\,c)$ & $p_{\rm tr}(c) \neq p_{\rm tg}(c)$
2. Prior Probability shift: $p_{\rm tr}(c\,|\,z) = p_{\rm tg}(c\,|\,z)$ & $p_{\rm tr}(z) \neq p_{\rm tg}(z)$
3. Concept drift: $p_{\rm tr}(z\,|\,c) \neq p_{\rm tg}(z\,|\,c)$

These all affect redshift calibration in various ways.

1. Targeting in spectroscopy differs from photometry
2. Redshift success and confidence is systematic
3. SOM cells have non-zero size

➡ the above effects persist below the cell level

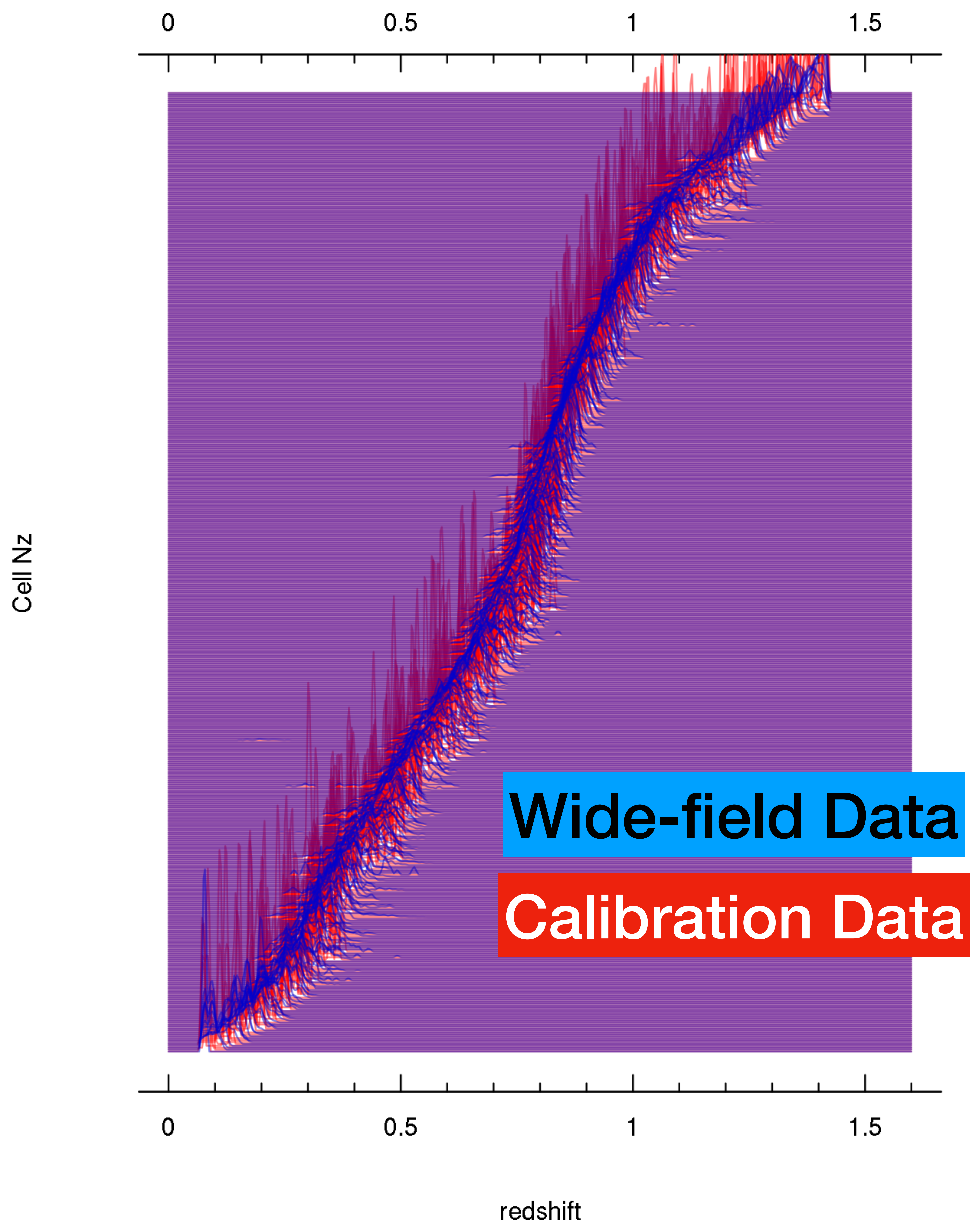
Are our methods sufficient for Stage-IV (e.g. Euclid)?

No

- Here I construct two simulated samples:
  1. A realistic spec-z calibration sample;
  2. A realistic wide-field shear sample
- And I **assume perfect photometry**

- Cells are **not delta-functions in redshift**:
  - Non-zero width allows selections at the within-cell level to play a role
  - Wider/more complex cells require more spectra to fairly sample the full Nz

- Cells are not **sparse-sampled** by spectra:
  - spec-z targeting, success, confidence selections all contribute



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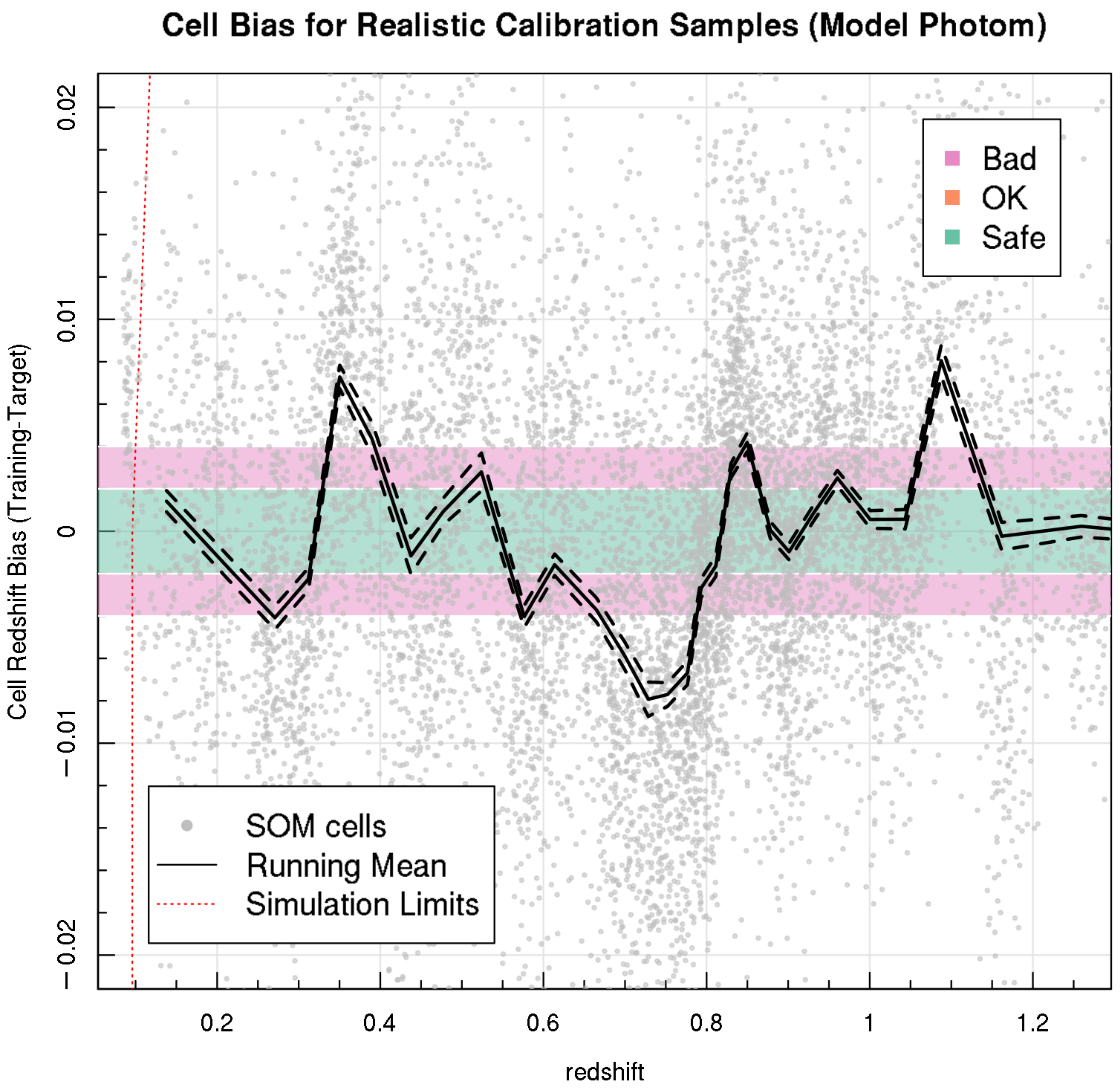
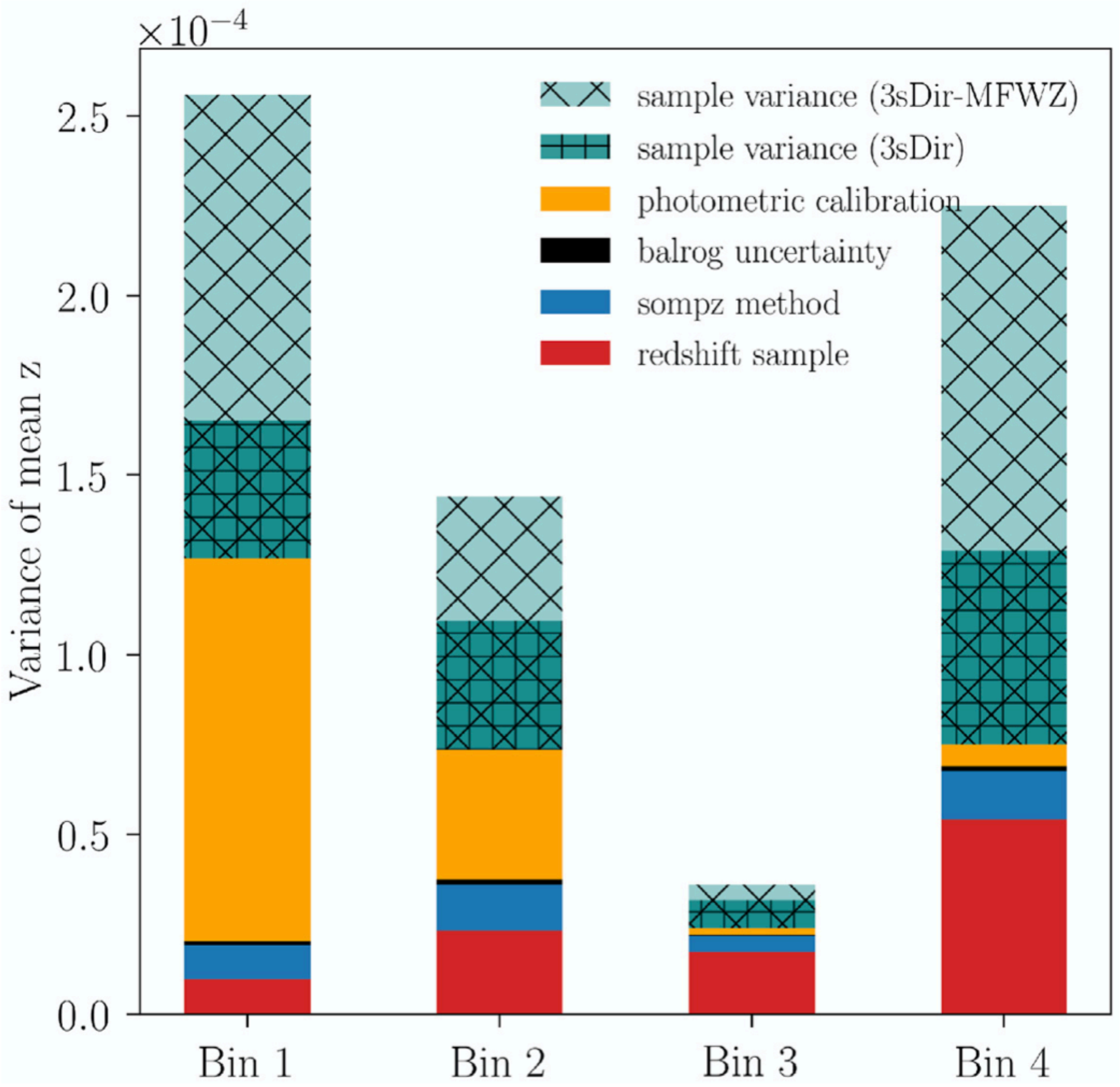
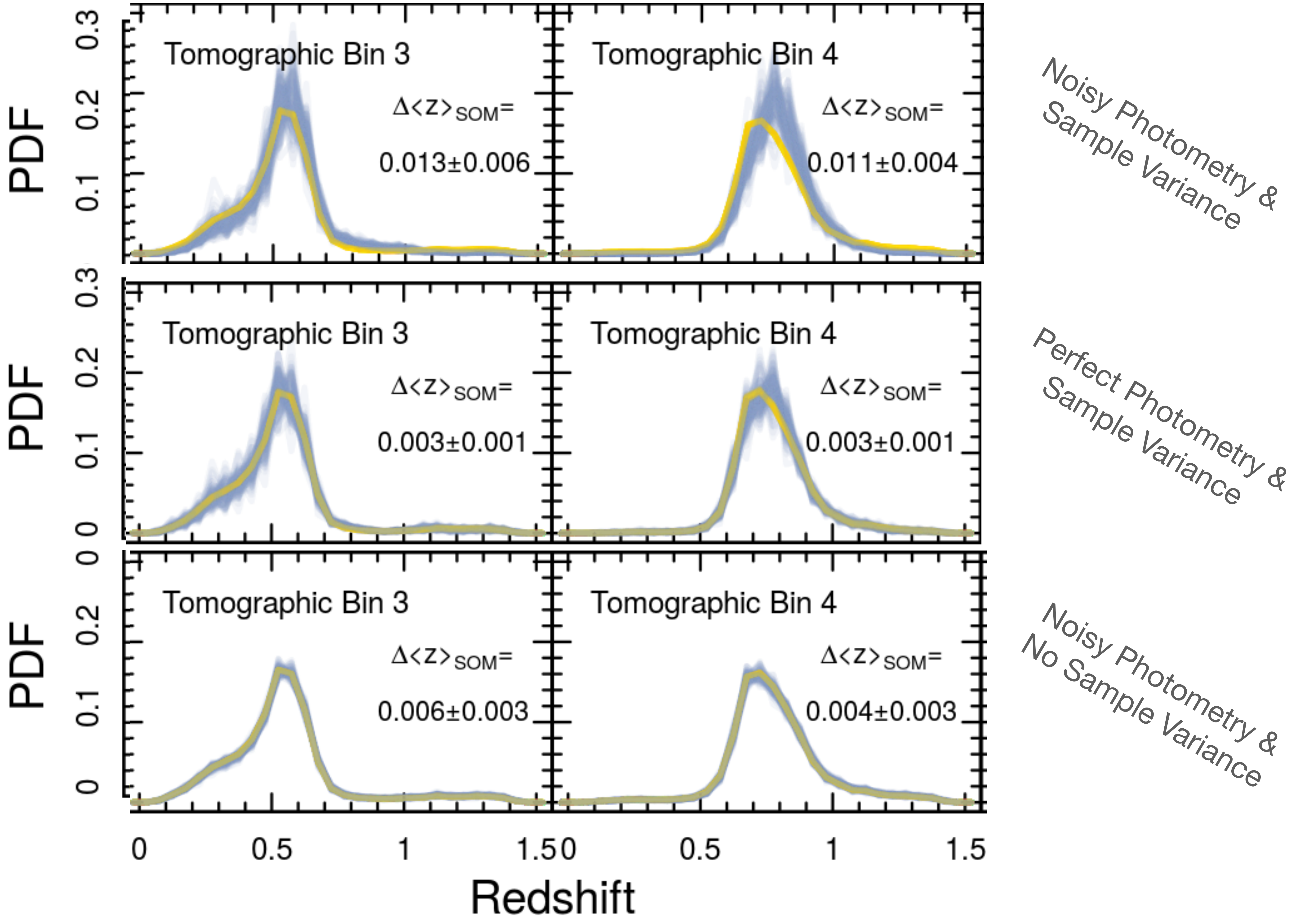
- At the requirements of Euclid: these selection effects alone **exceed** the allowed error budget



What can we do?

Forward Modelling





DESY3
Myles et al (2021)

KiDS-1000
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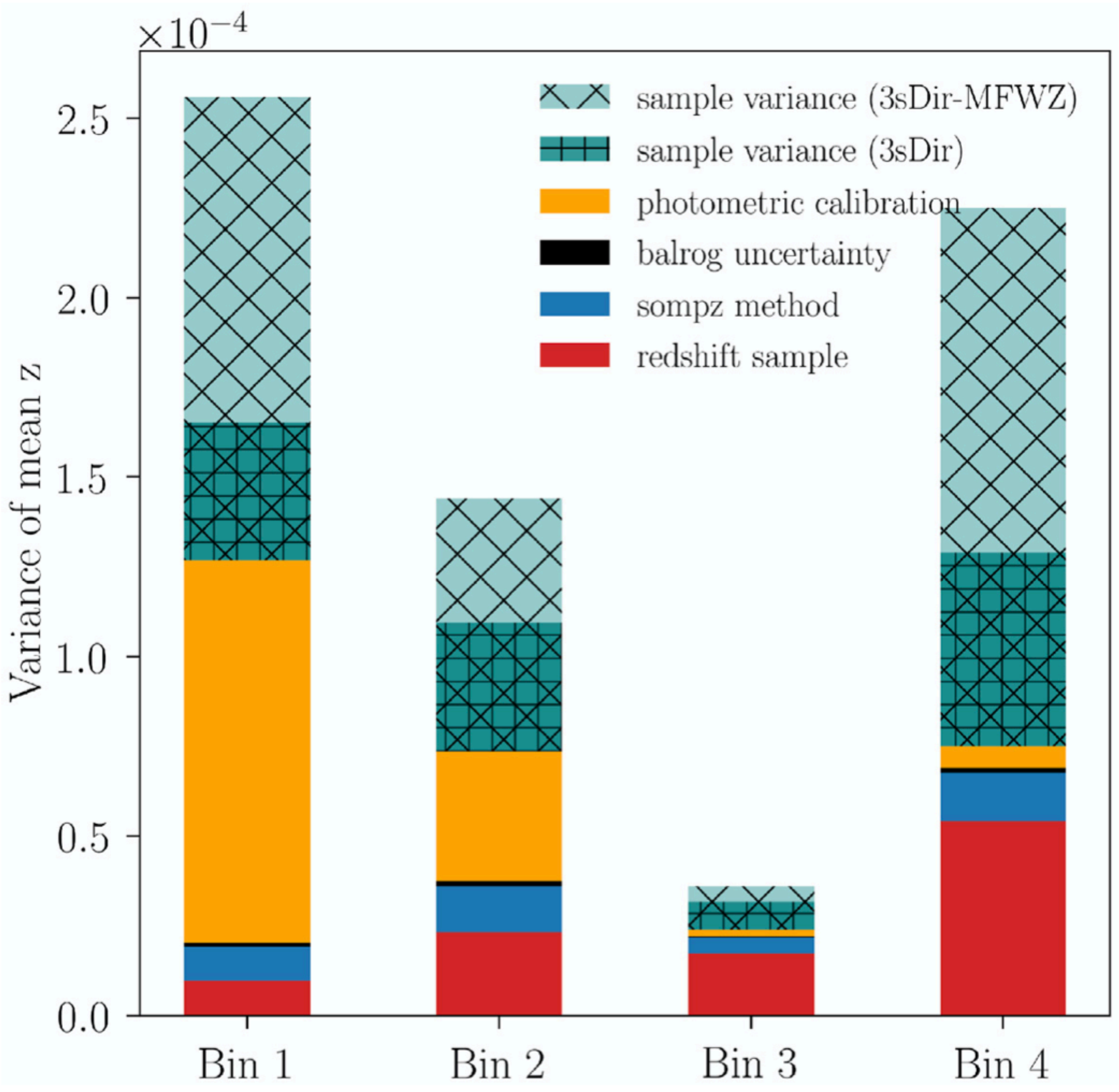
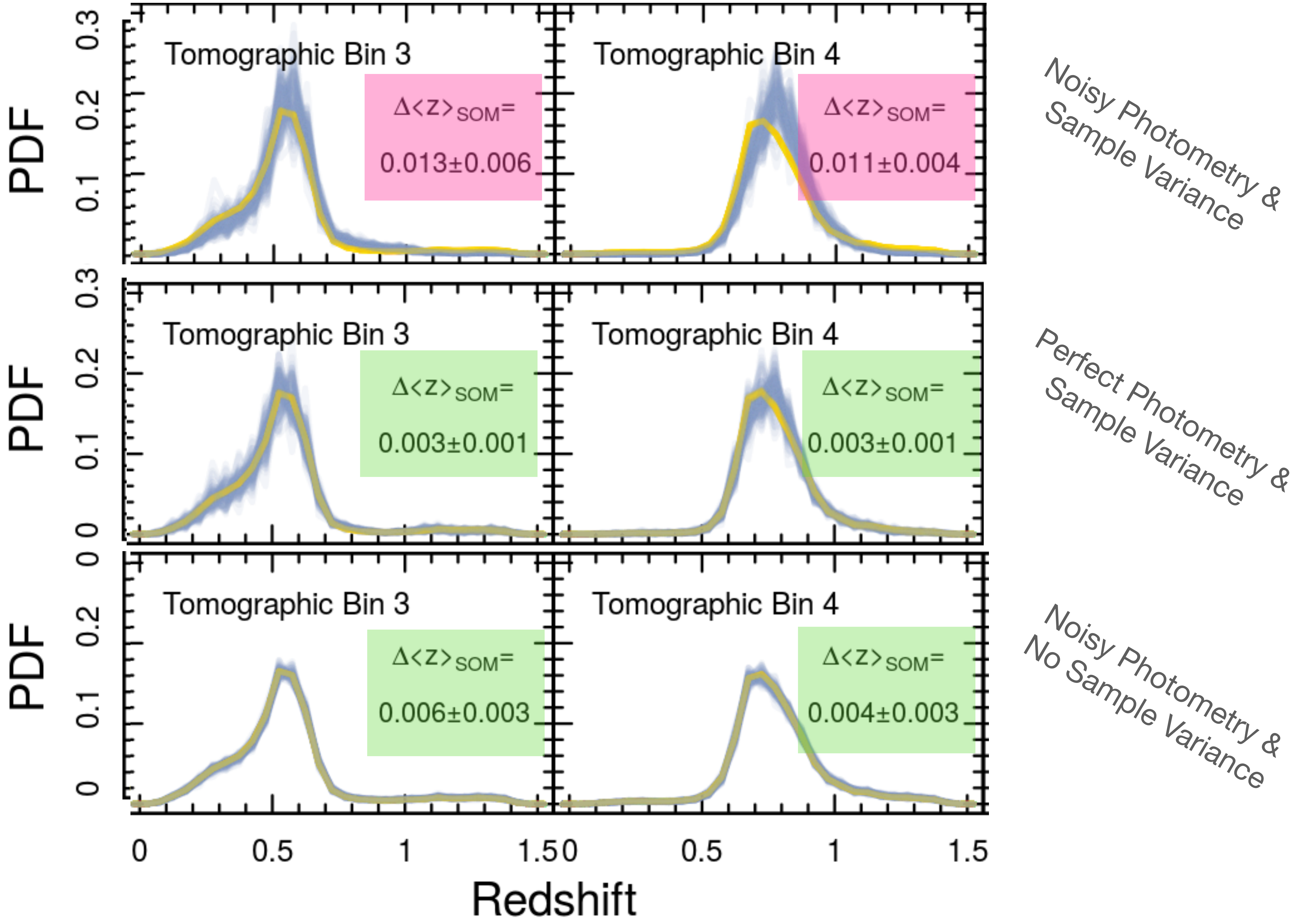
Forward Modelling





DESY3
Myles et al (2021)

One only sees these biases when you **jointly** simulate all expected systematic effects

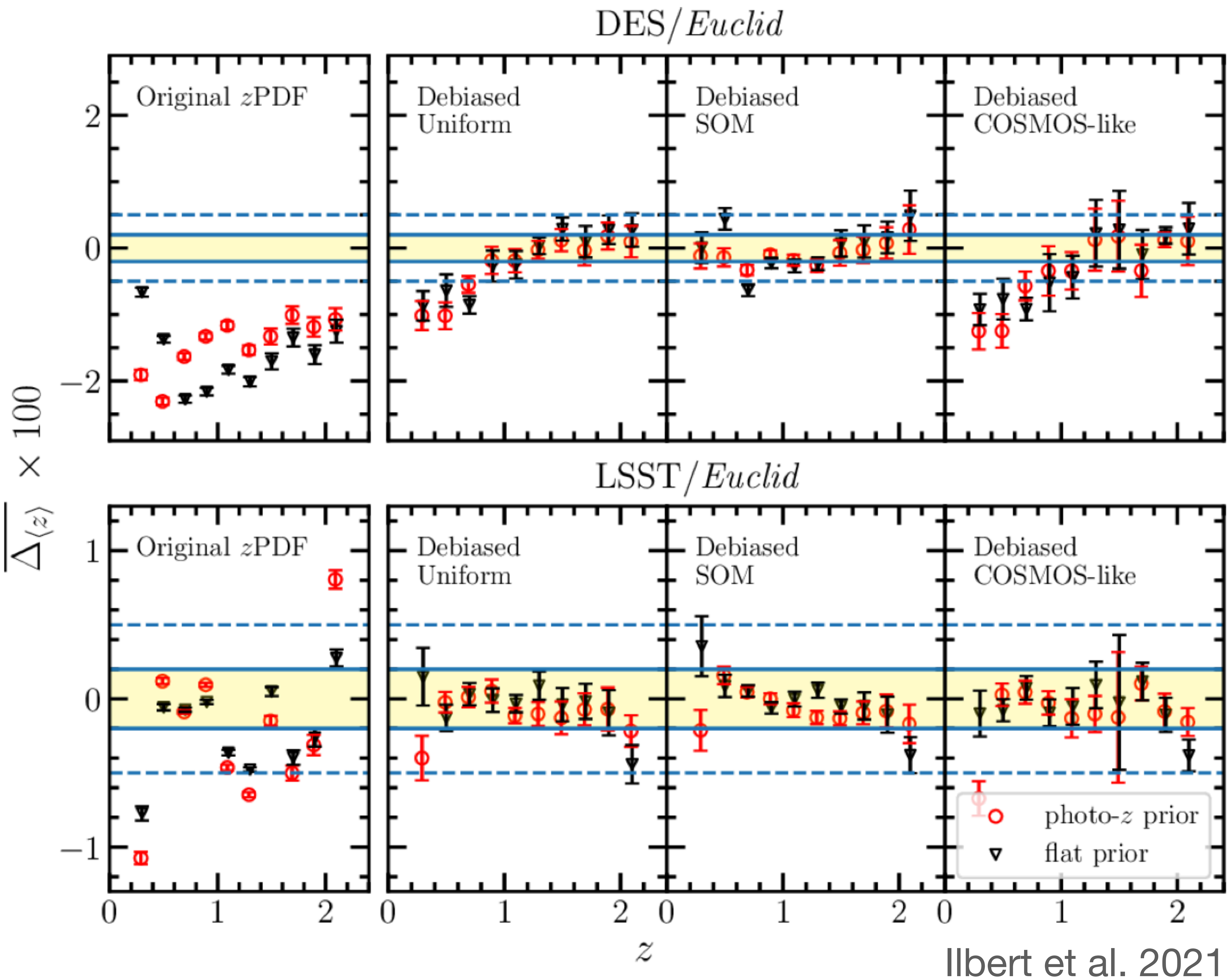
KiDS-1000
Wright et at 2020a

Use population statistics to de-bias cells

Requires population statistics to be robust per cell (or group of cells).

Is more robust to failures of the calibration sample (which is good!)

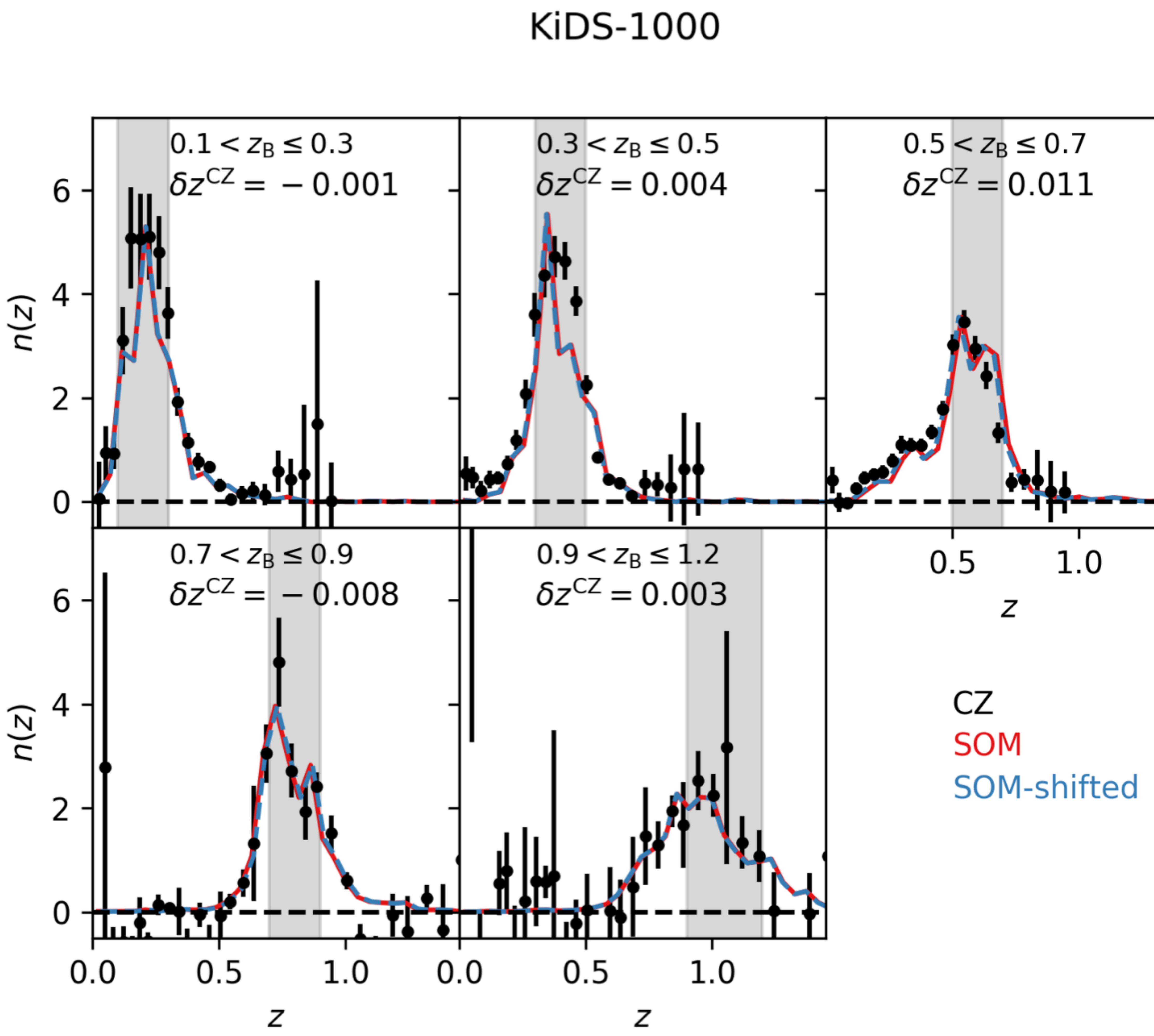
Requires high-quality initial photo-z (DES not sufficient)



Ilbert et al. 2021

Leverage multiple estimation techniques

Clustering-based estimation methods have different selections



Uses the spatial cross correlation with a reference sample to produce Nz

Reference sample is generic: need not be matched to the colour/magnitude range of the target sample

Marginalisation over evolution of galaxy bias is a complication

Summary

- Cosmic shear is a valuable tool for exploring the matter power spectrum
- Machine learning estimation of source redshift distributions is a valuable tool
- But sampling and selection biases in spec-z samples lead to significant covariate shift within individual SOM cells.
- For Stage-III surveys, mitigation methods are currently suitable.
- For Stage-IV surveys like Euclid, they are not.
- Accurate cosmology with Euclid will require development of more comprehensive methods, such as combined clustering and colour-based approaches.