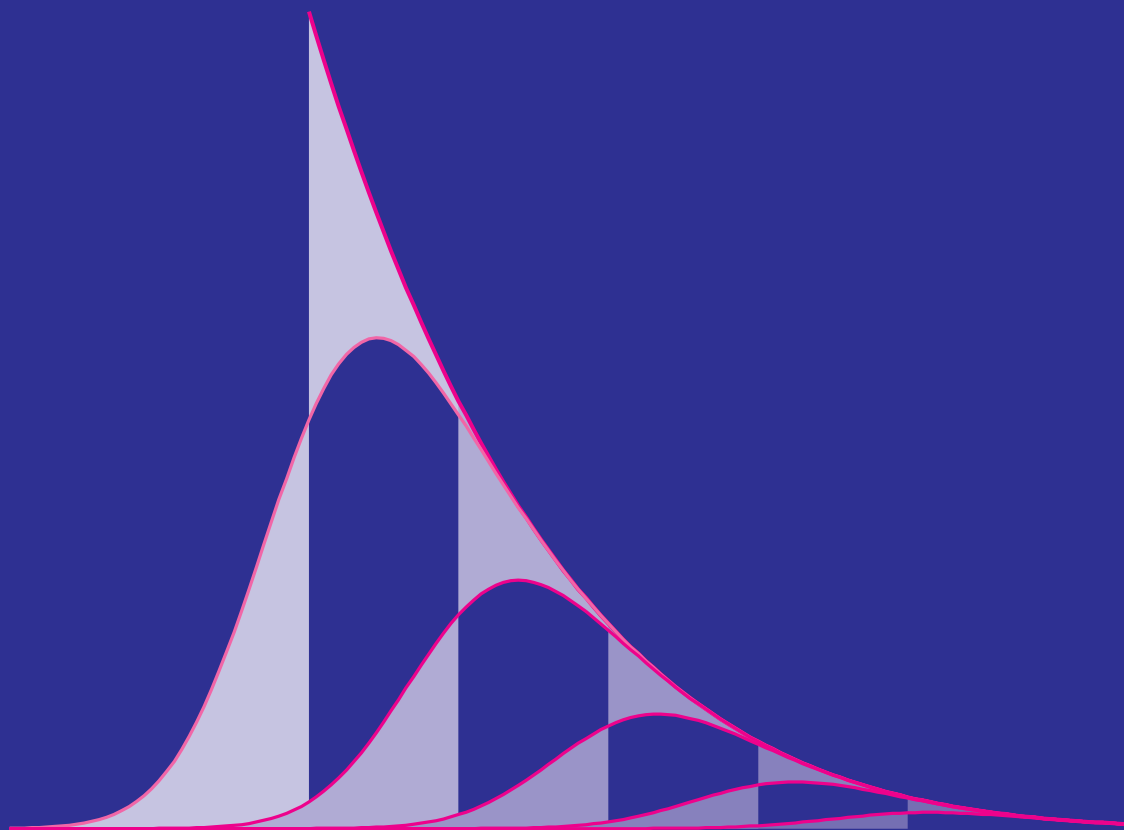


# Self Calibration of Cluster Counts:



Observable-Mass Distribution

*Wayne Hu*

Kona, March 2005

# Self Calibration of Cluster Counts:



## Observable-Mass Distribution

*Wayne Hu*

Kona, August 2004

# Scattered Forecasts

- Scatter, or a distribution in the observable mass, causes uncertainty in dark energy constraints at high  $z$
- Related work:
  - Holder et al (2000); Battye & Weller (2003): bias from scatter
  - Levine et al (2002): marginalization of constant M-T bias & scatter
- This work:
  - Lima & Hu (2005):

abstract/general analysis of the impact of scatter and bias in the distribution

prospects for self-calibration of a simple, Gaussian, mass independent distribution that evolves

shape: Hu (2003); power: Majumdar & Mohr (2003)

# Scattered Forecasts

- Scatter, or a distribution in the observable mass, causes uncertainty in dark energy constraints at high  $z$
- Related work:
  - Holder (2000): bias from scatter in noise cut
  - Levine (2001): 1-T bias & scatter

- This work:
  - Liu & Hu (2003): effect of scatter and bias in the

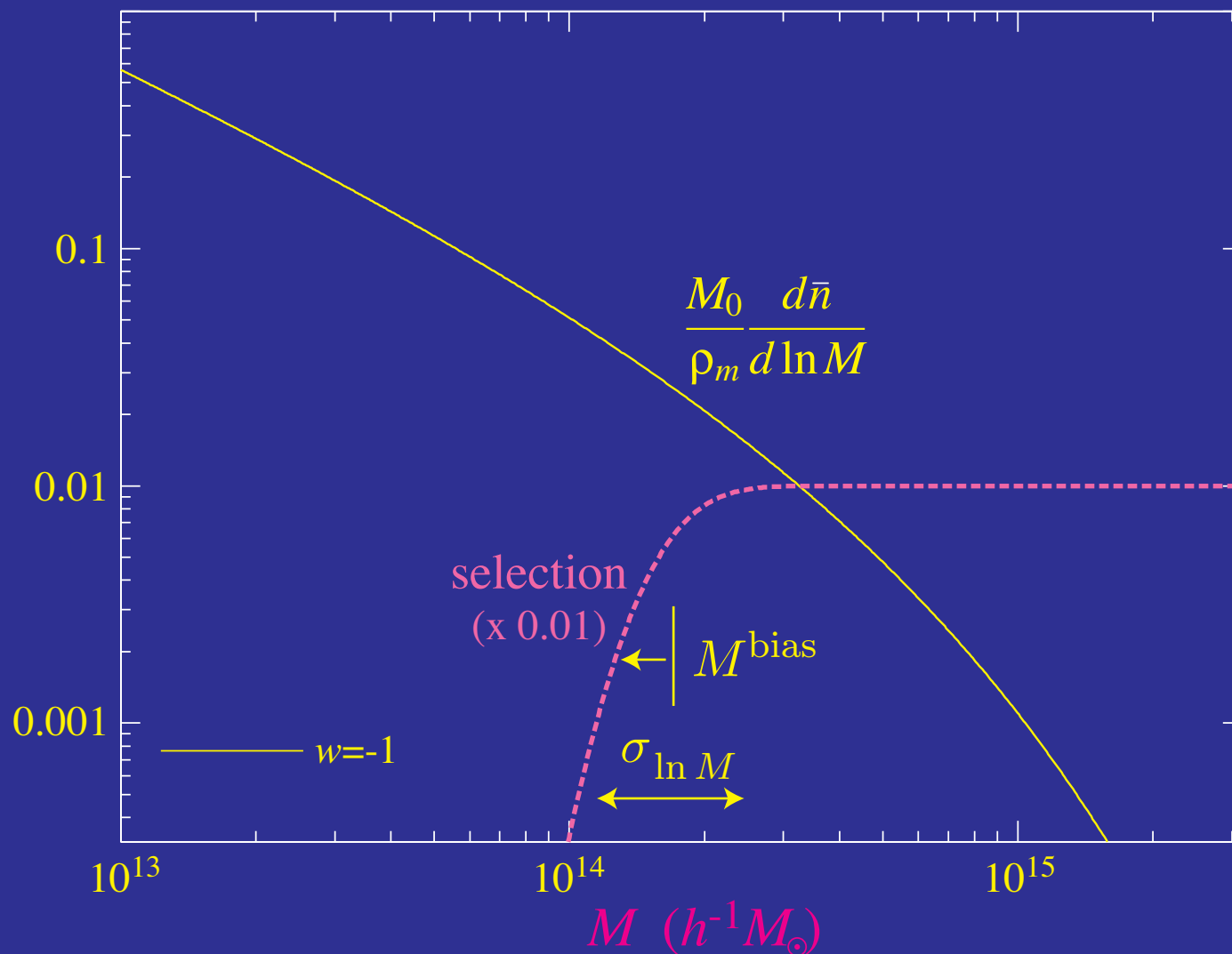
prospects for self-calibration of a simple, Gaussian, mass independent distribution that evolves

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# Observable Mass Distribution

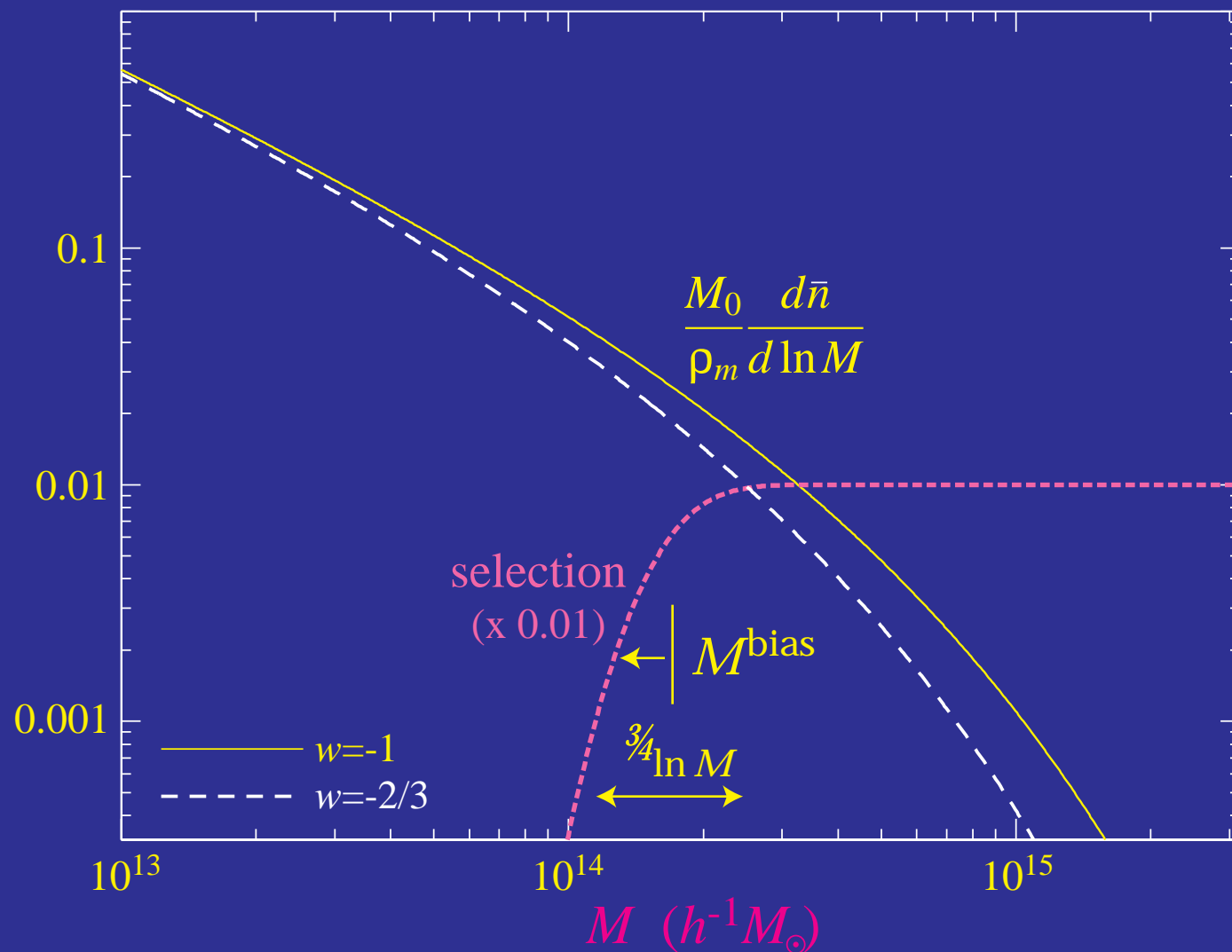
- Gaussian scatter and bias of a mass estimator

$$p(M^{\text{obs}}|M) = \frac{1}{\sqrt{2\pi\sigma_{\ln M}^2}} \exp \left[ -\frac{(\ln M^{\text{obs}} - \ln M - \ln M^{\text{bias}})^2}{2\sigma_{\ln M}^2} \right]$$



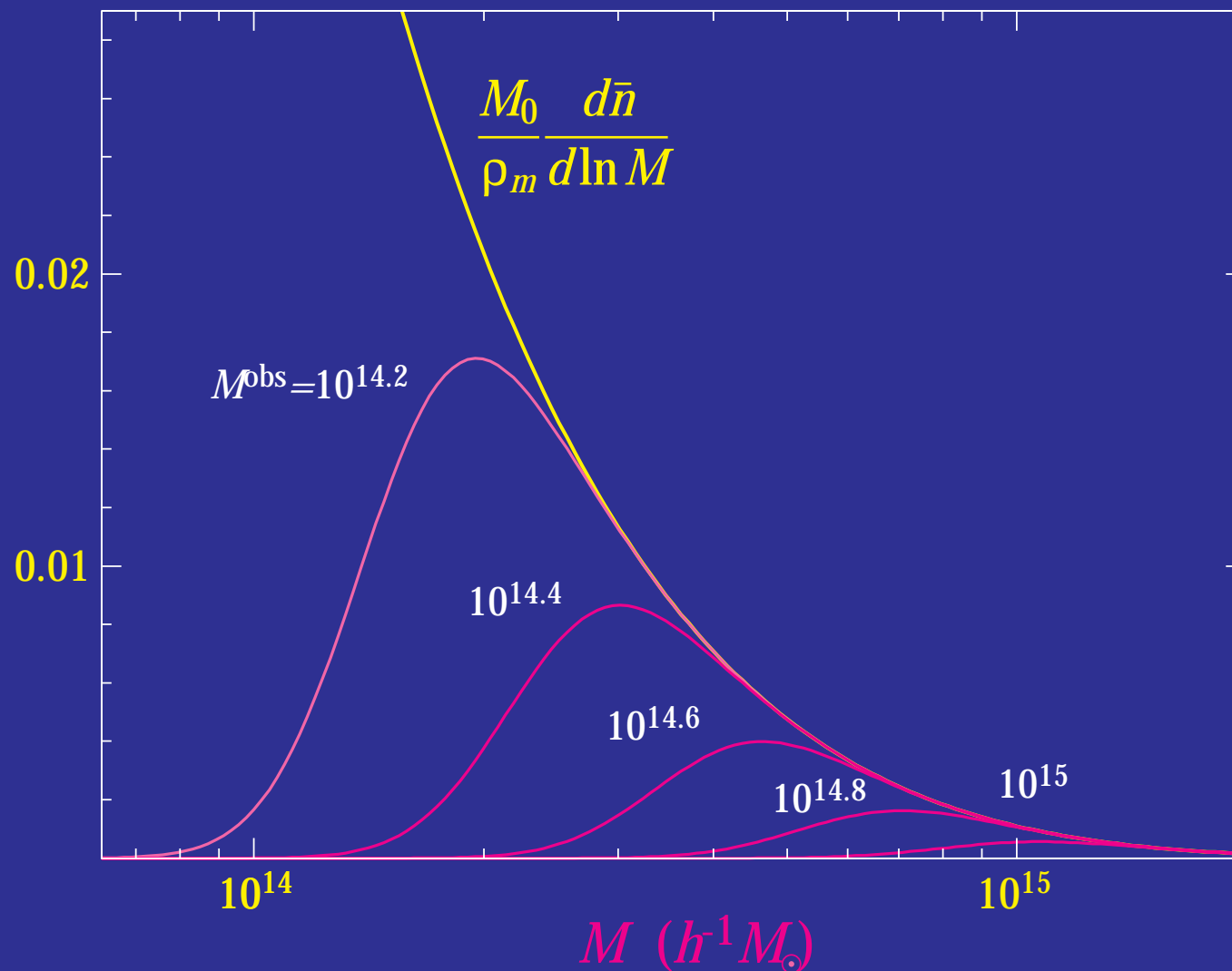
# Degeneracy

- Uncertainties in bias and scatter cause degeneracies with dark energy



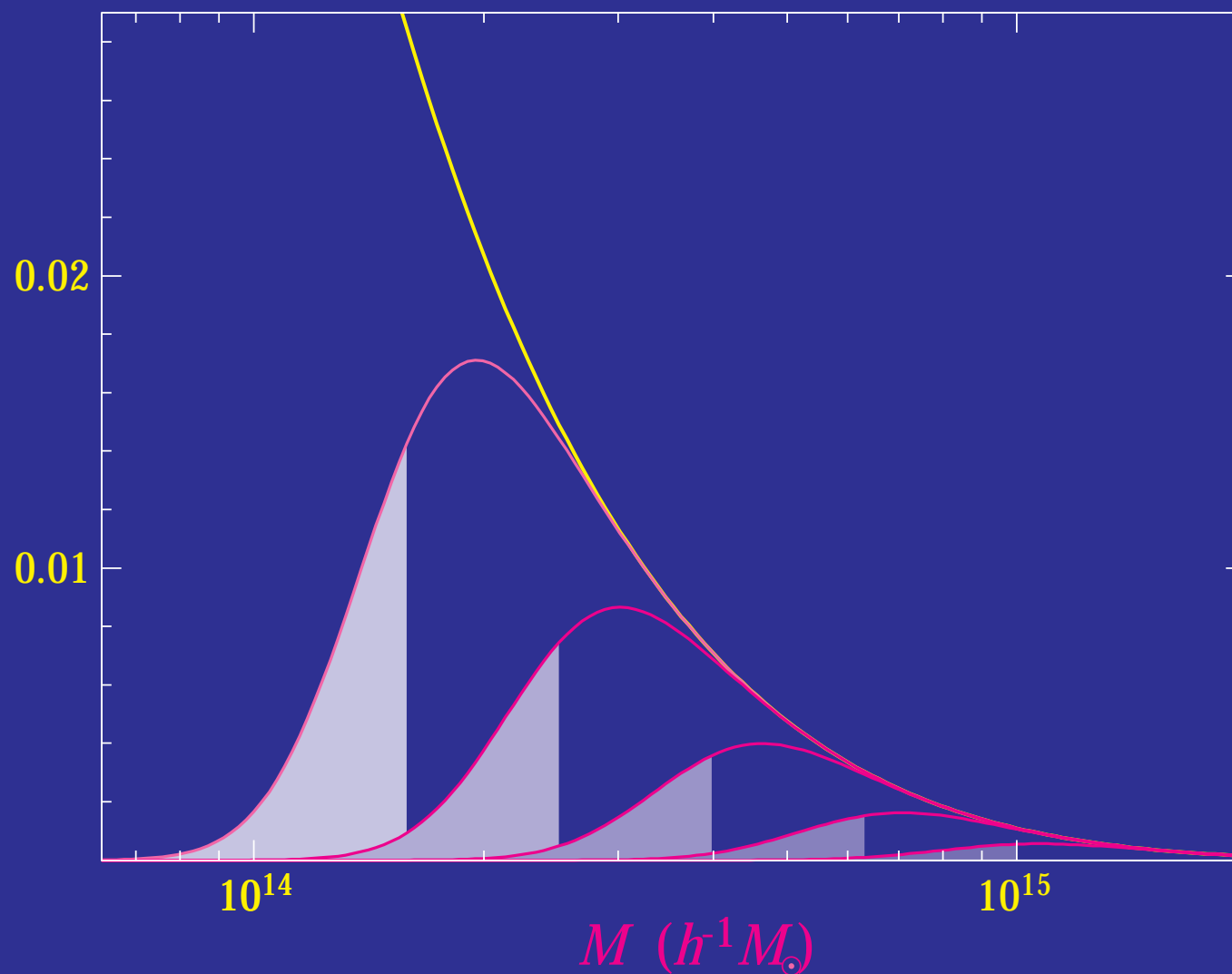
# Selection Bias

- Exponential tail of mass function
- Threshold cut in the observable mass



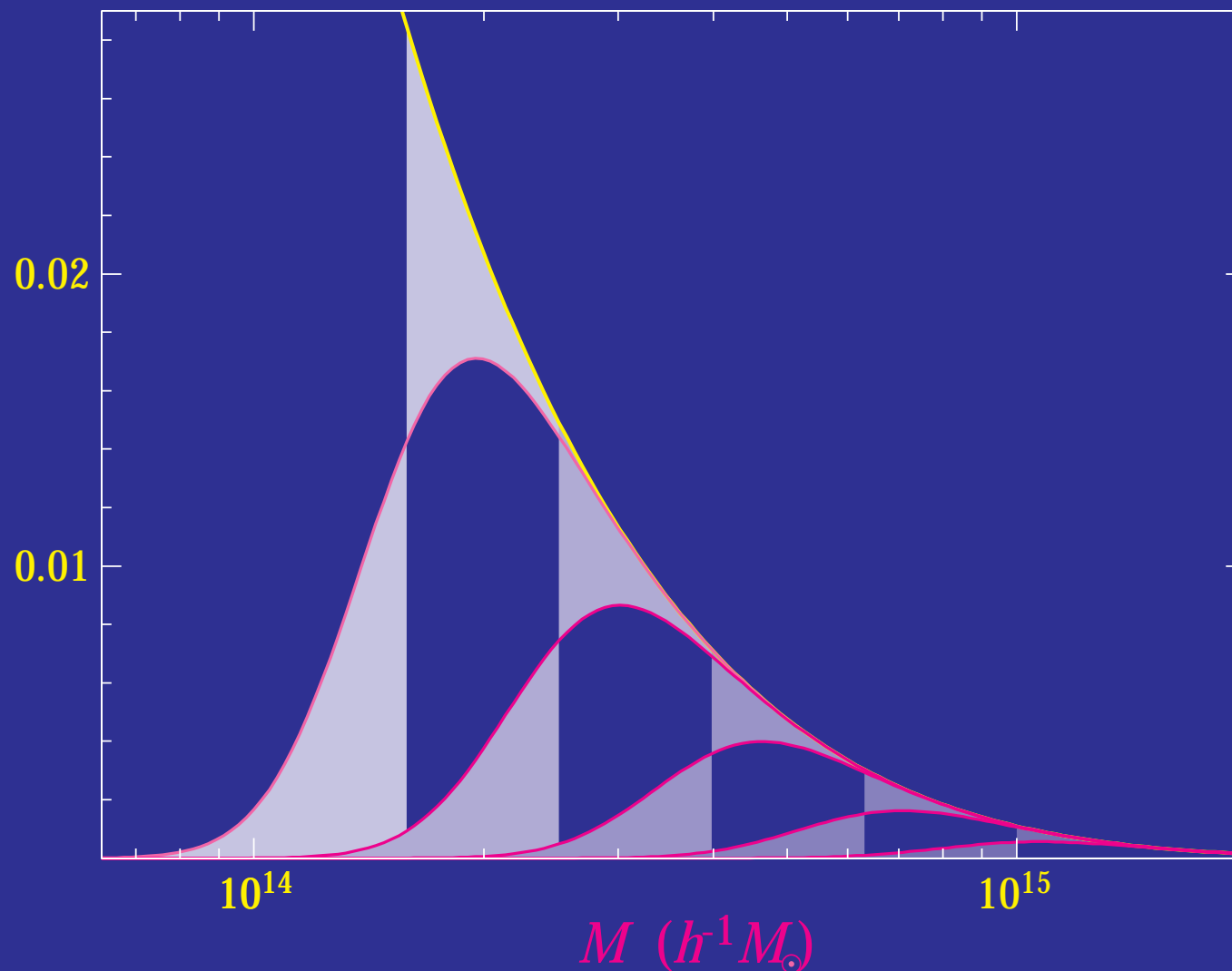
# Selection Bias

- Clusters **upscattered** into threshold



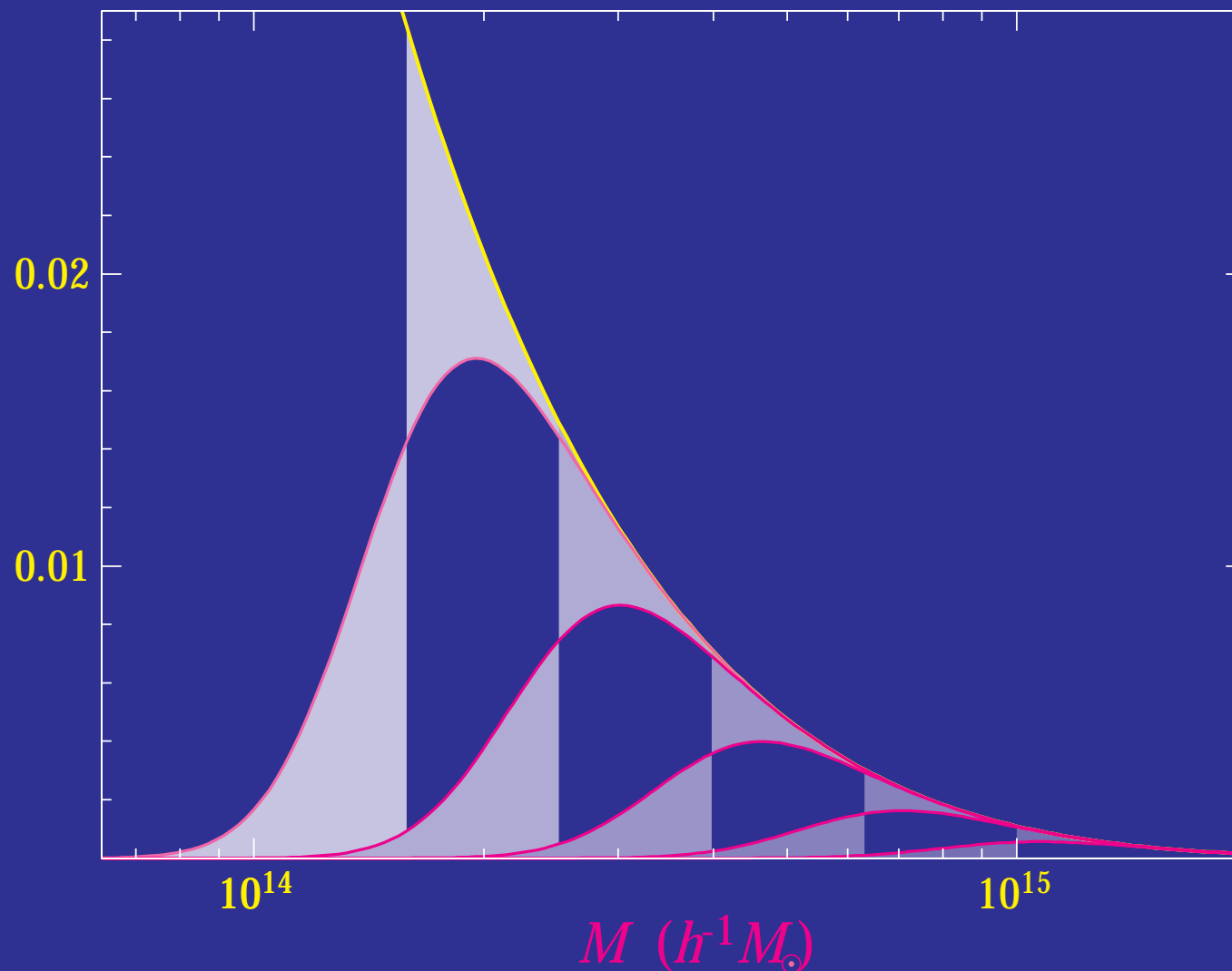
# Selection Bias

- Clusters **upscattered** into threshold
- Out number **downscattered** across threshold



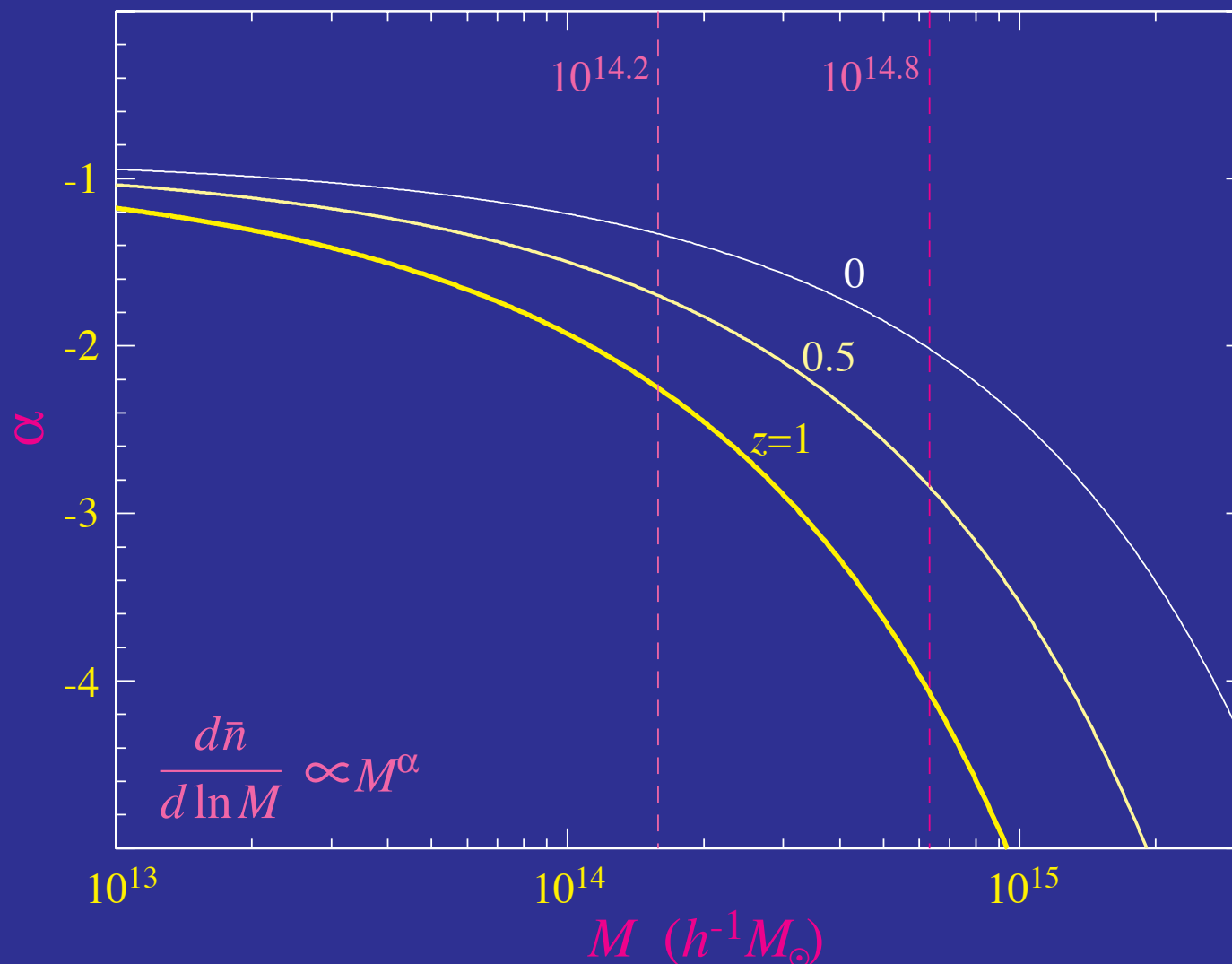
# Selection Bias

- Bias proportional to **variance** of distribution and **mass function slope**
- Introduces **trend in redshift** even if scatter is constant



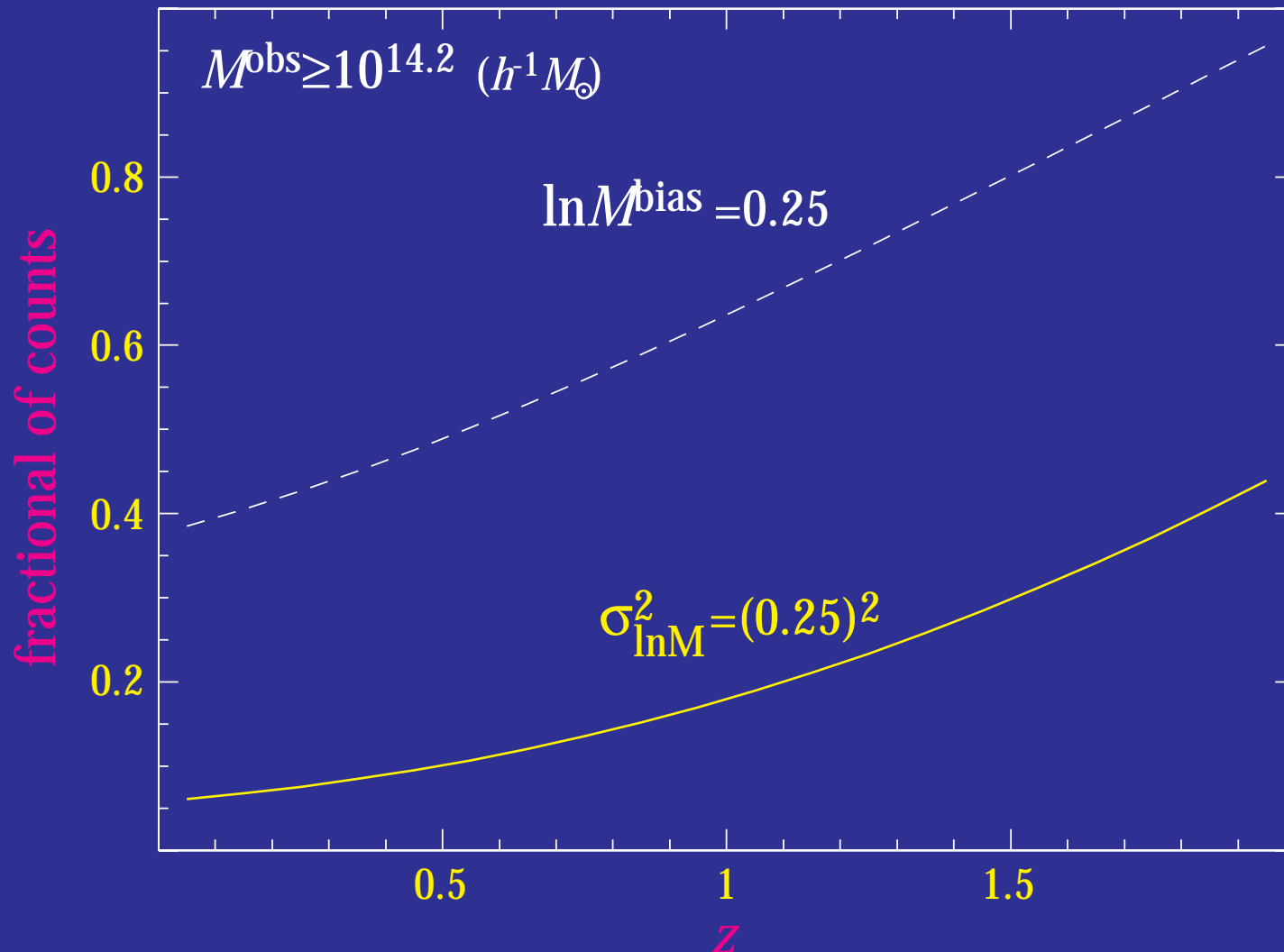
# Relative Importance of Scatter

- In the small scatter limit, relative importance of **variance** vs. **bias** proportional to local power law **slope** of **mass function**
- Increases with increasing mass or redshift



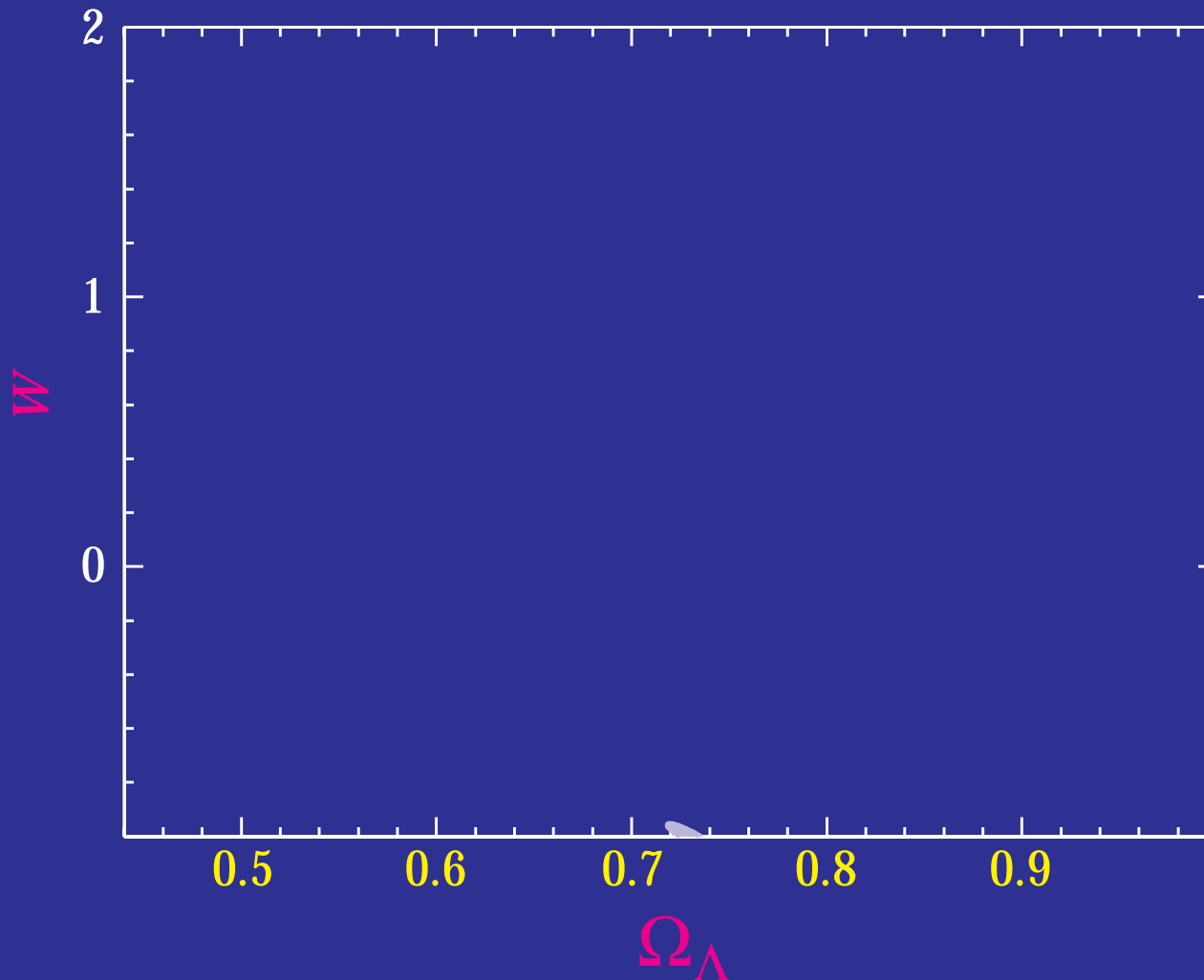
# Sensitivity to Uncertainties

- A **25% bias** would produce a **~100% change** in high- $z$  cluster counts
- A **25% scatter** a **~50% change** - but scales as **variance**



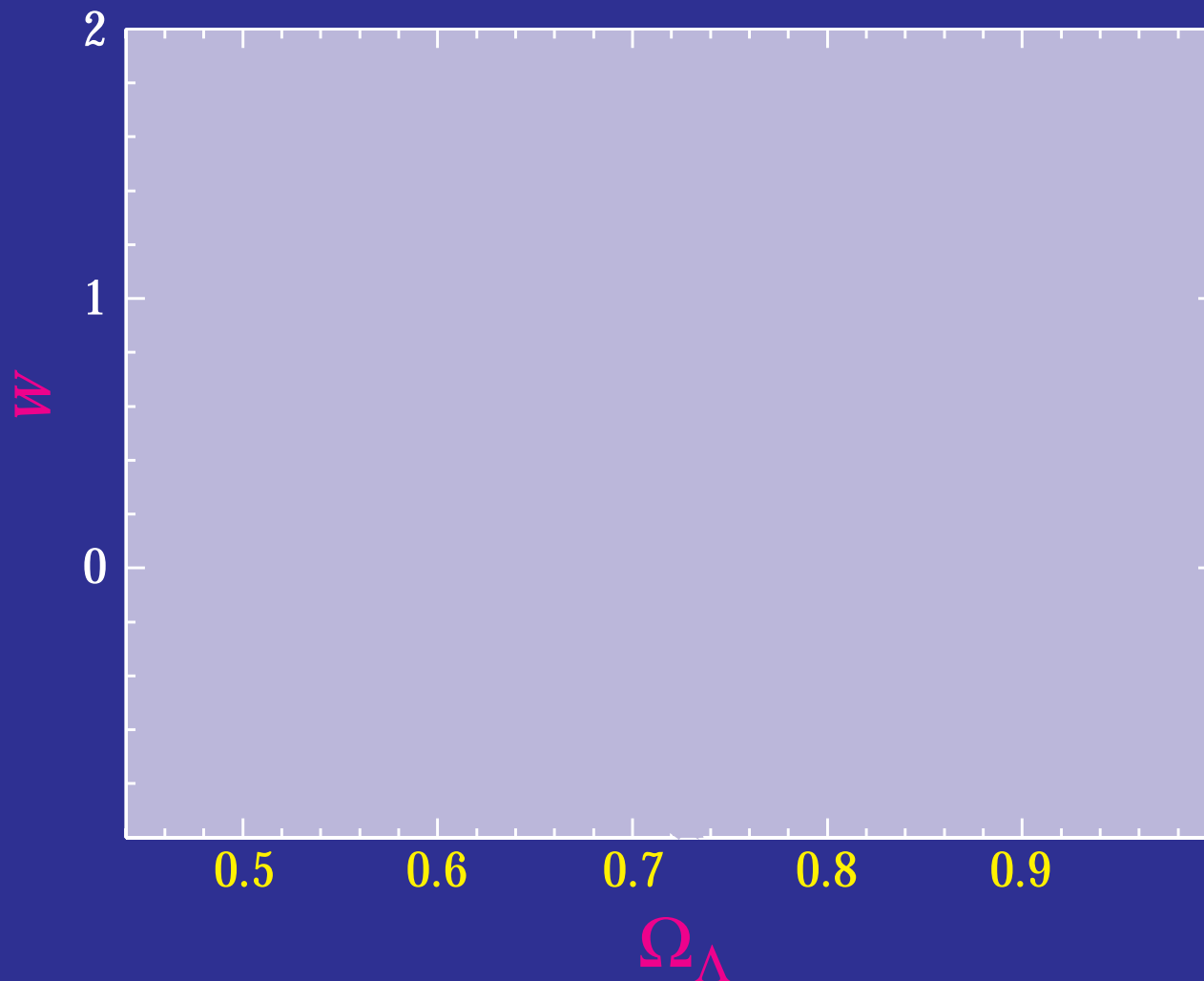
# Fully Calibrated

- Given a completely **known** observable-mass **distribution** dark energy **constraints** are quite **tight** (4000 sq deg,  $z < 2$ )



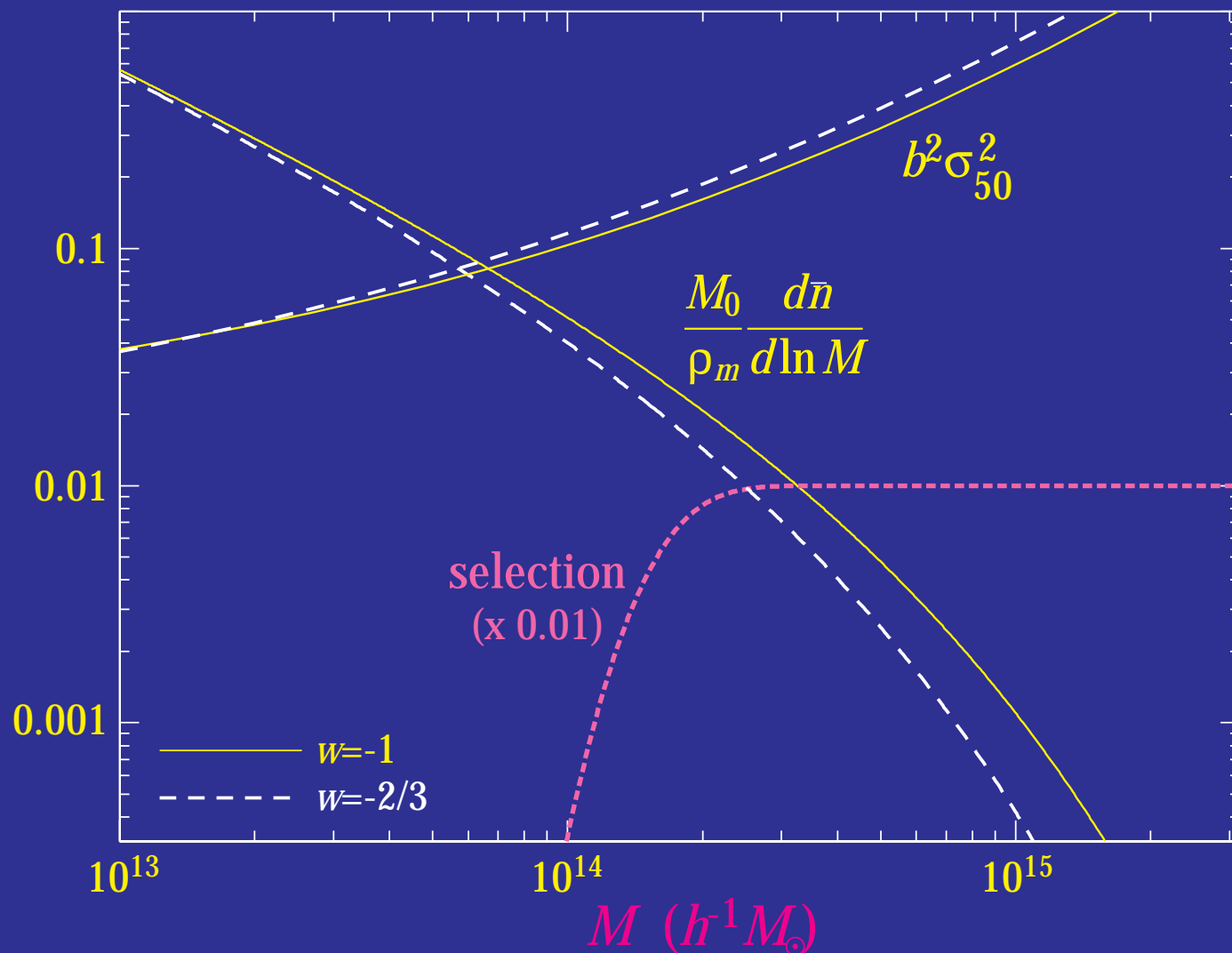
# Un-Calibrated

- Marginalizing **scatter** (linear  $z$  evolution) and **bias** (power law evolution) **destroys** all dark energy information



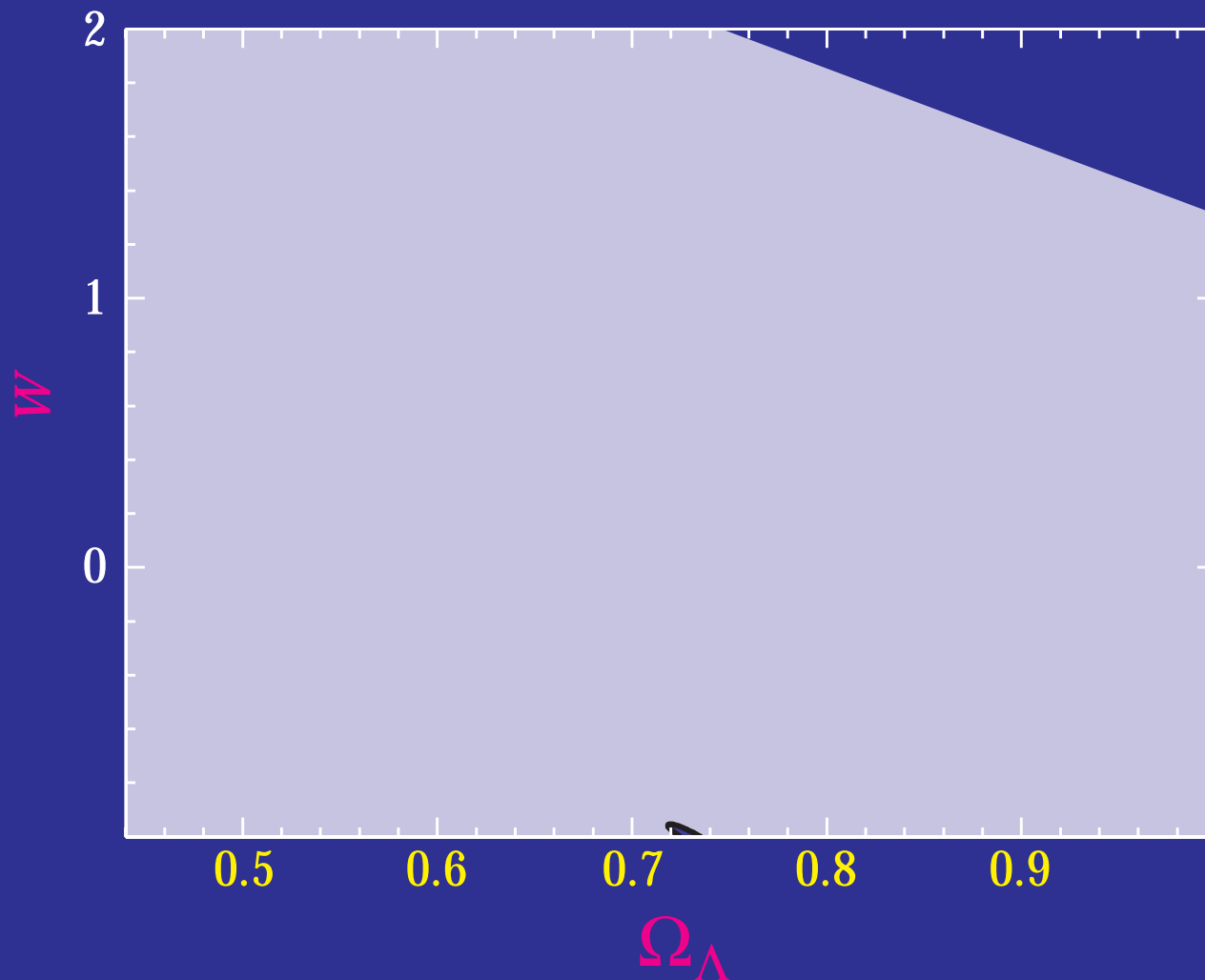
# Self-Calibration with Clustering

- Clustering bias as a function of mass is predicted in a cosmology
- Angular clustering of clusters or (co)variance of counts provides mass bias calibration but not jointly with scatter



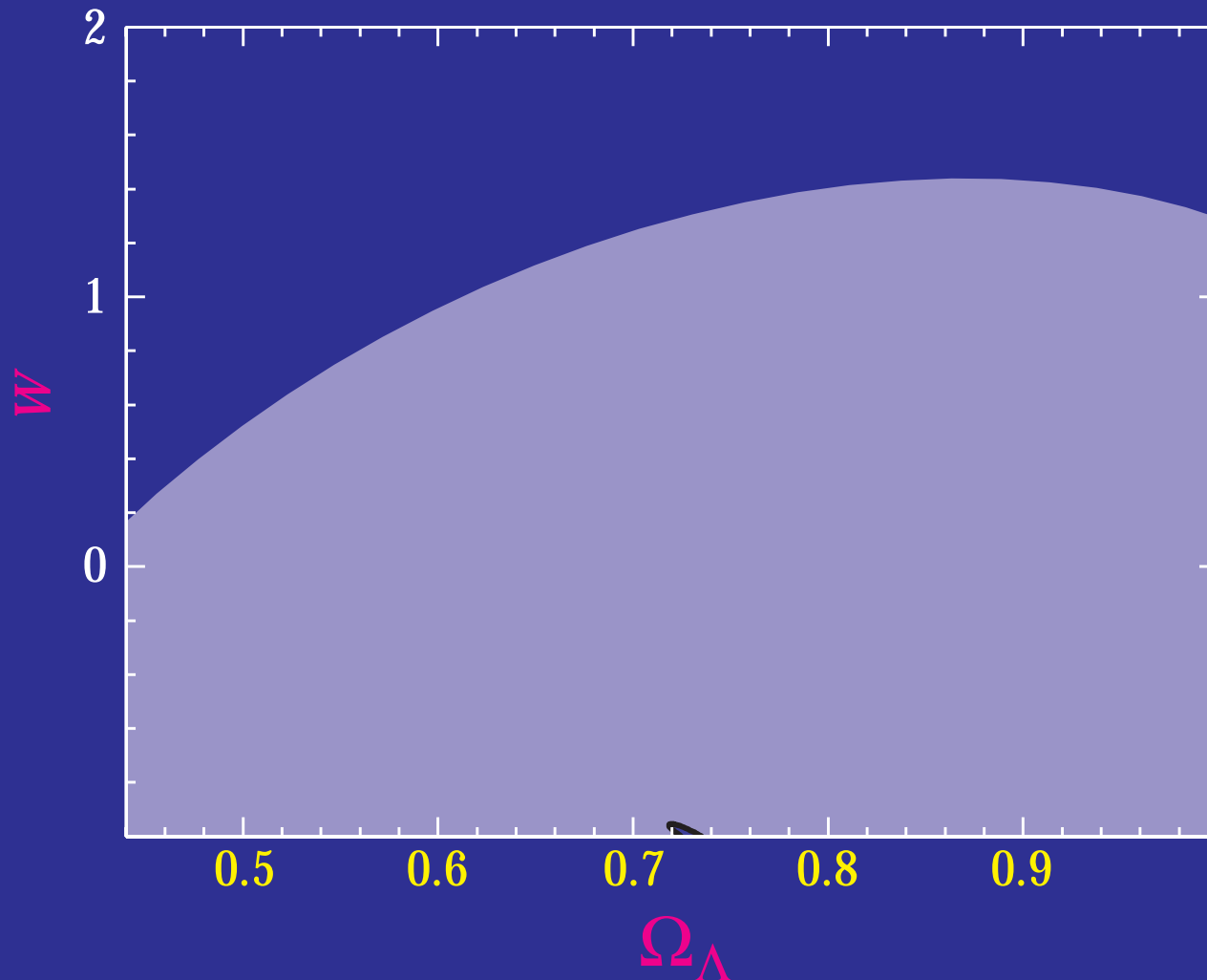
# Self-Calibration with Clustering

- Arbitrary evolution of bias and scatter in 20 bins of  $\Delta z=0.1$



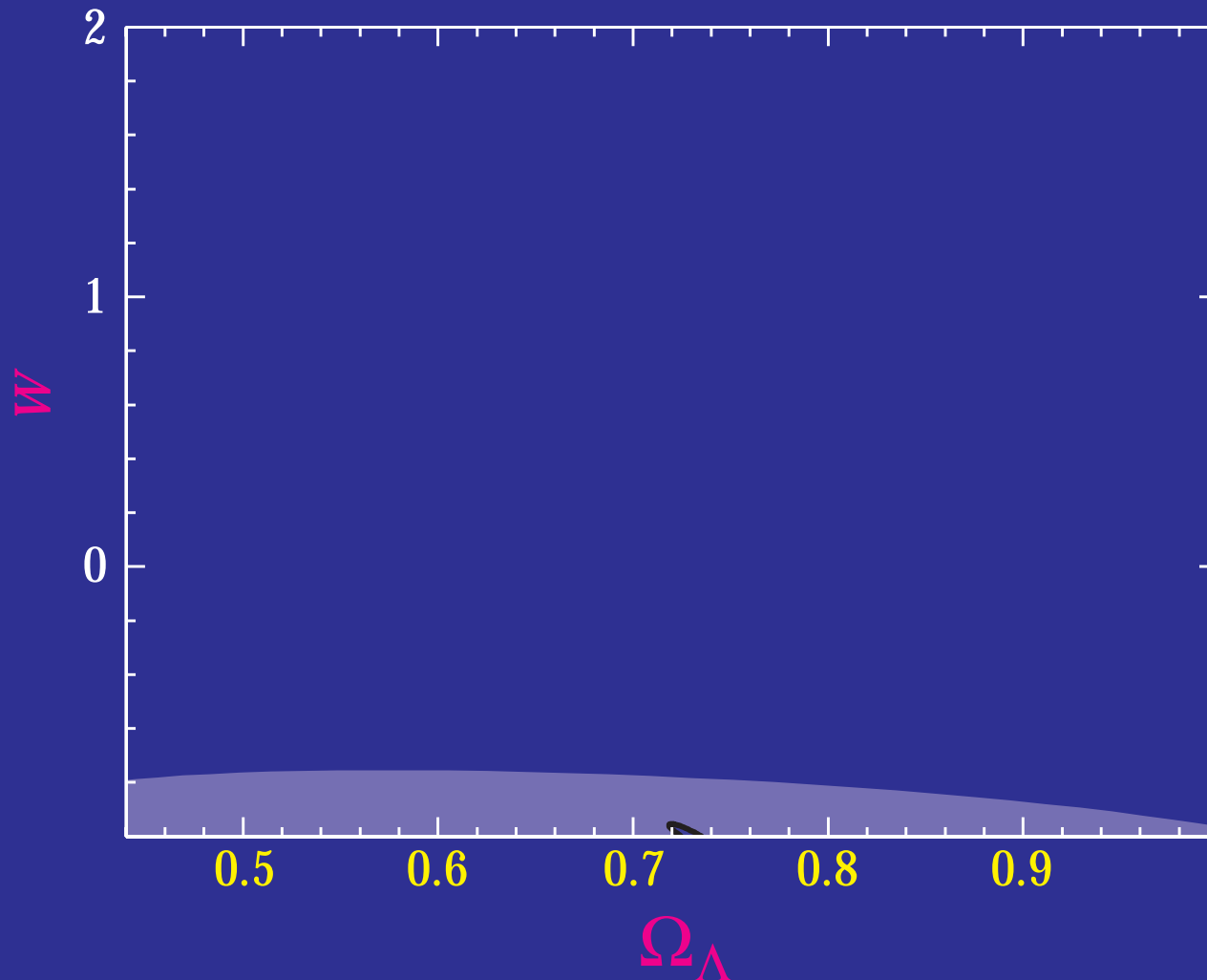
# Self-Calibration with Clustering

- Power law evolution of bias and arbitrary evolution of scatter in 20 bins of  $\Delta z=0.1$



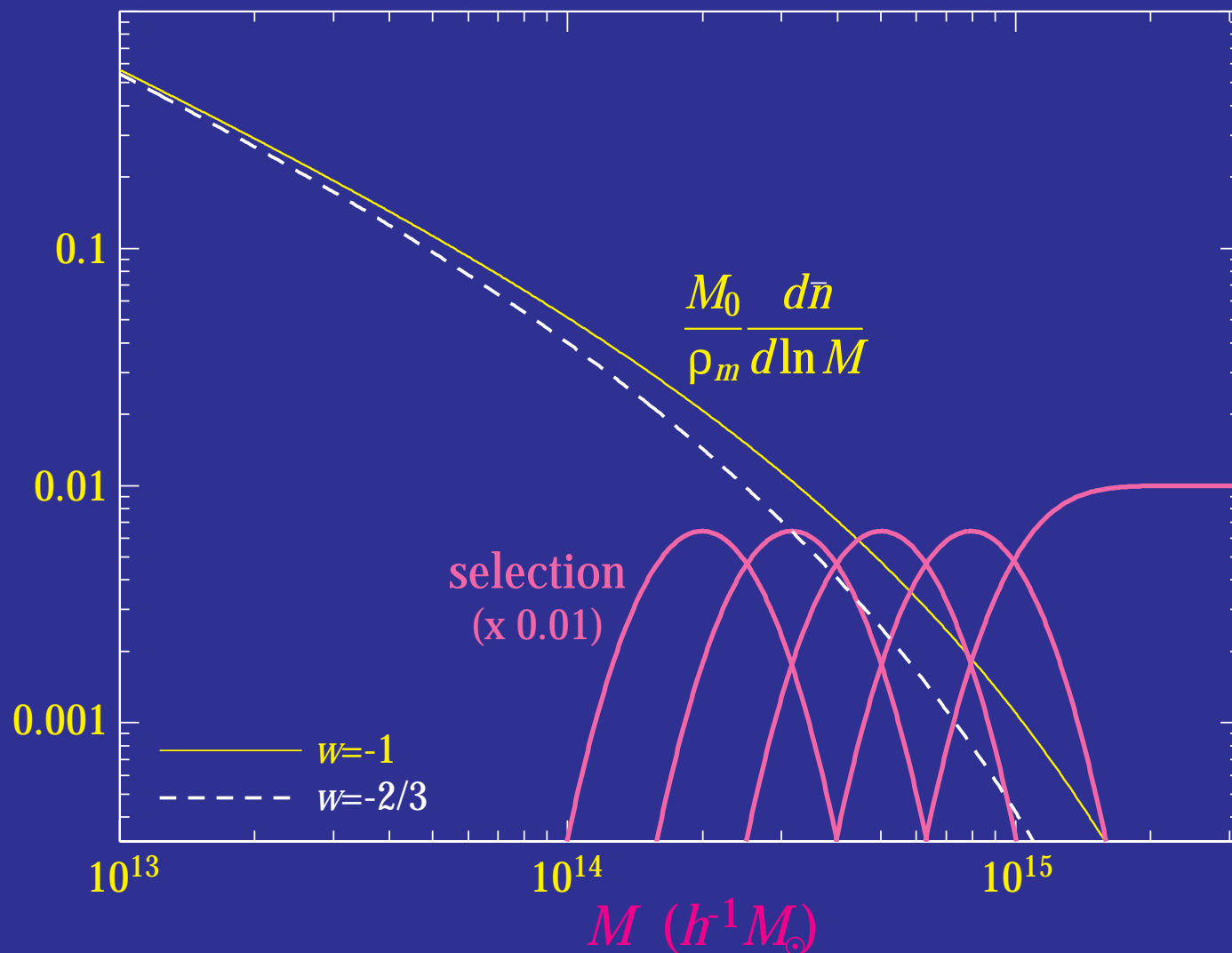
# Self-Calibration with Clustering

- Power law evolution of bias and cubic evolution of scatter in  $z$



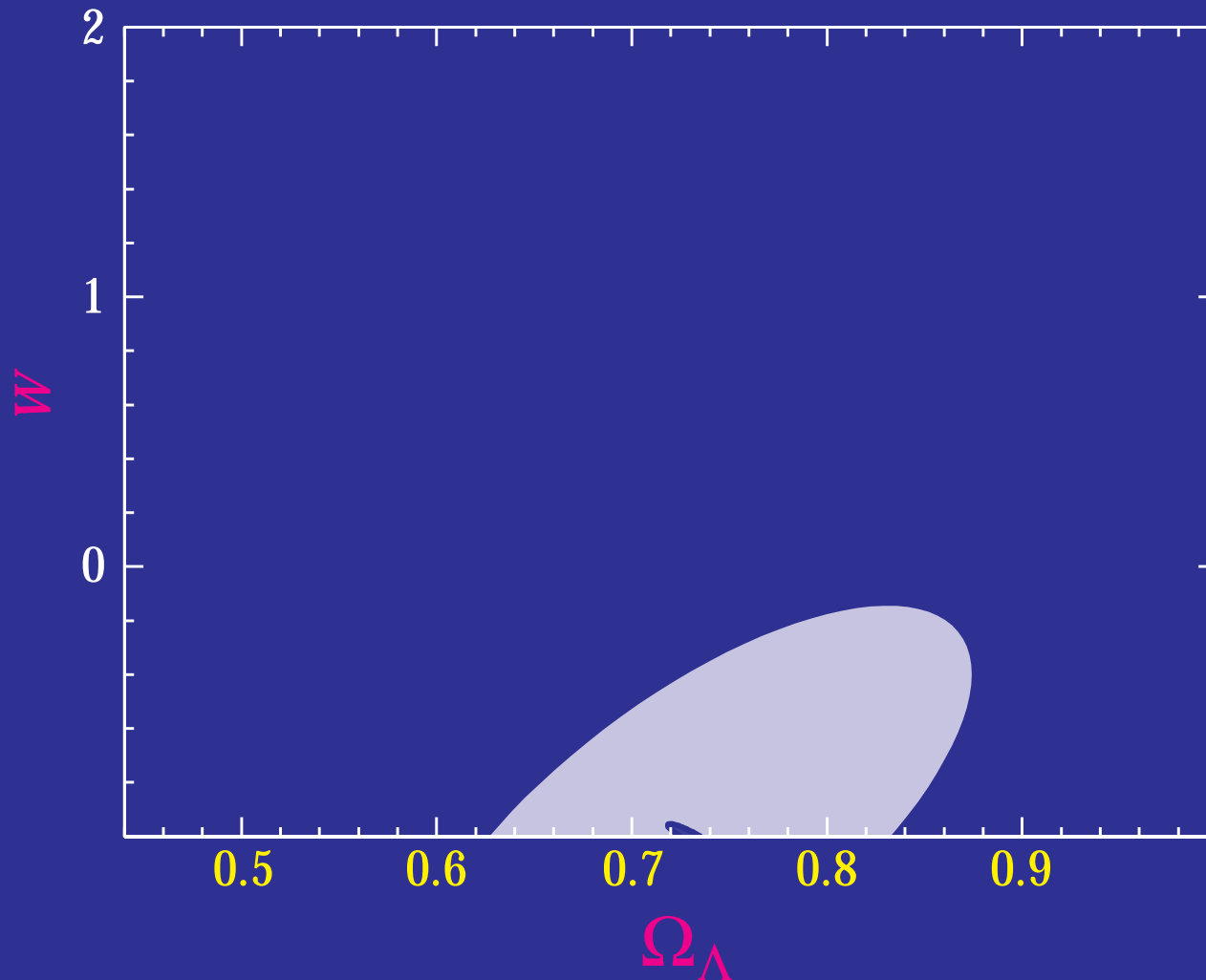
# Observable Mass Bins

- Exploit knowledge by **breaking sample into observable mass bins**
- Demand **consistent count ratio** to solve for **bias** and **scatter**



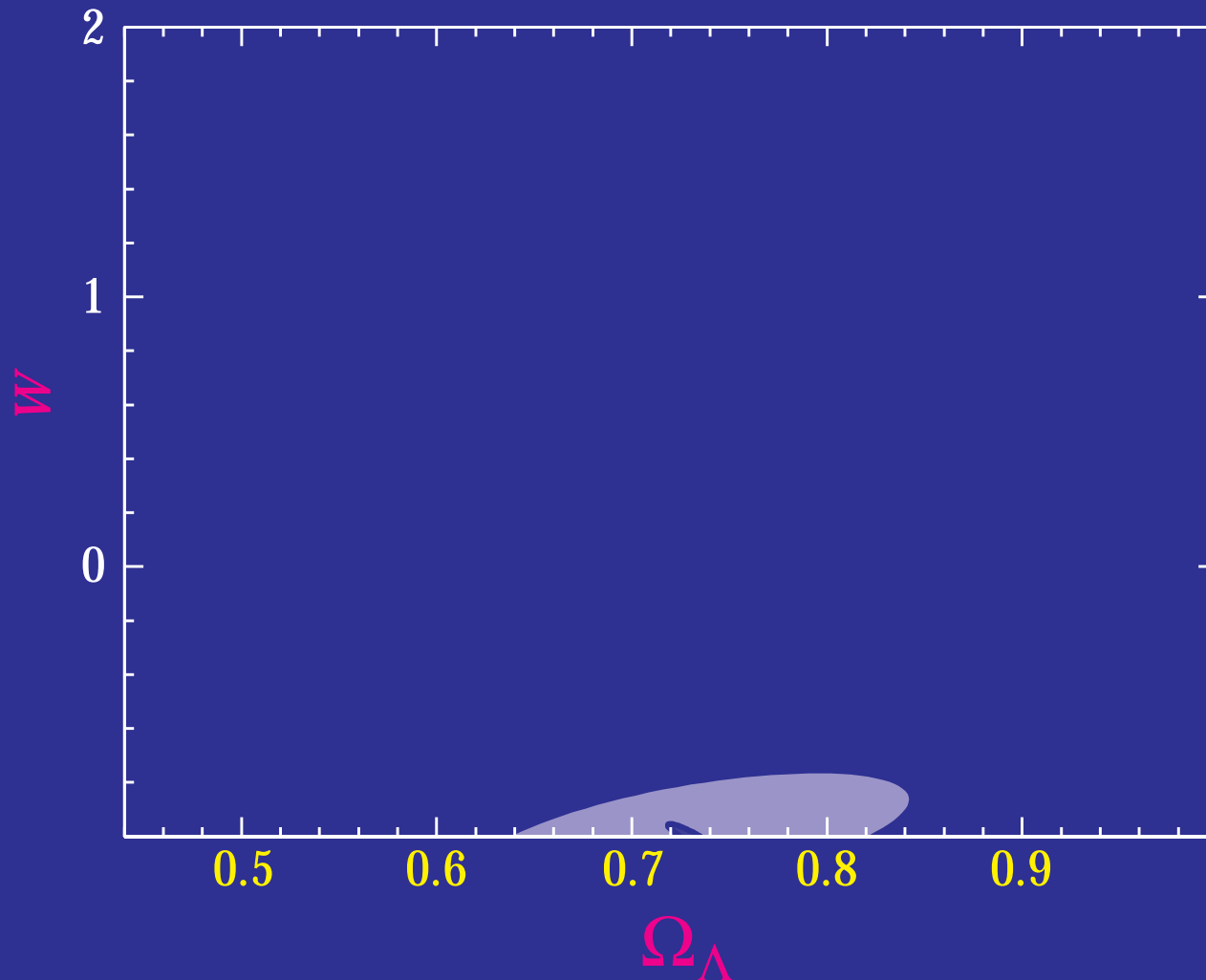
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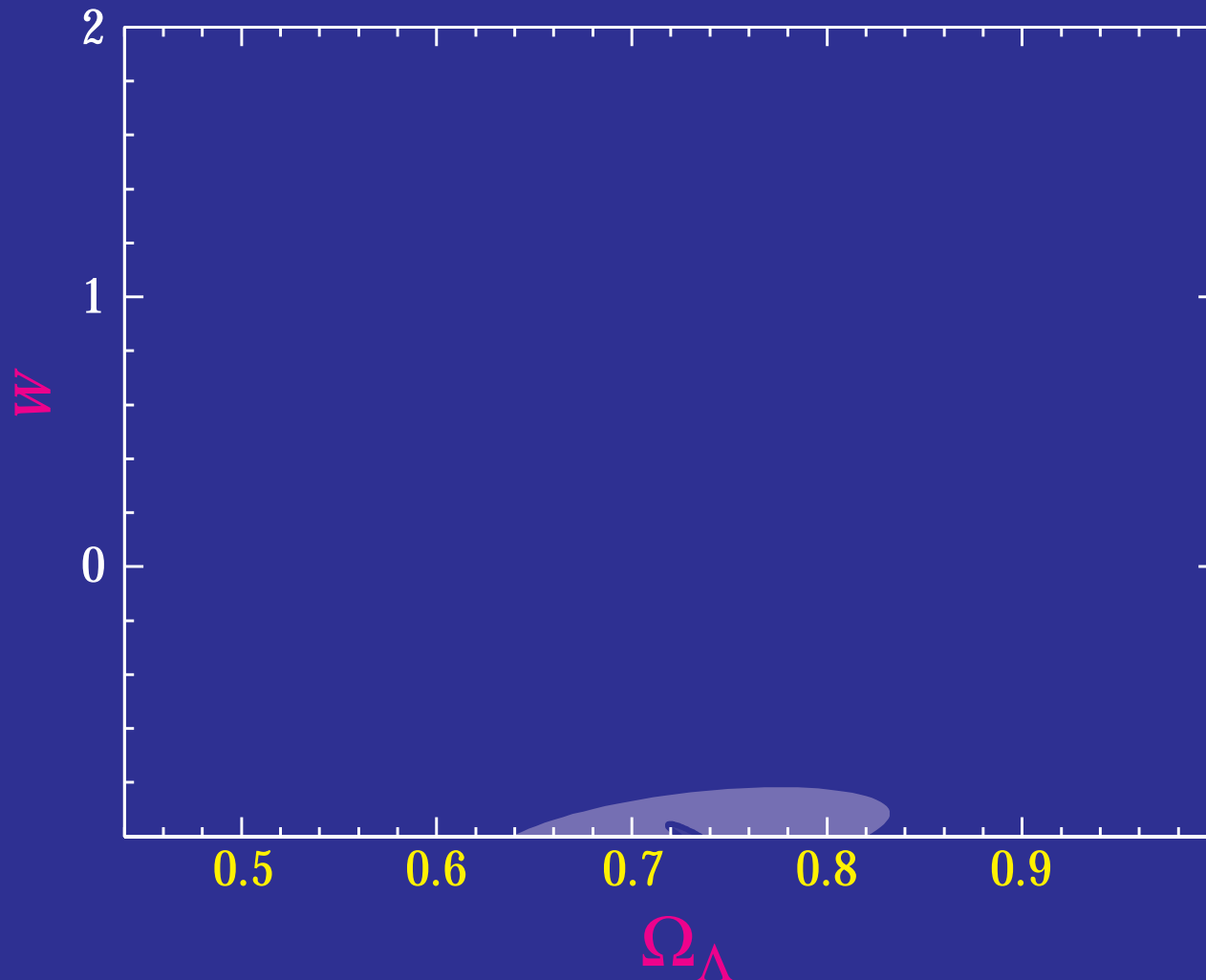
# Self-Calibration with Binning

- Power law evolution of bias and arbitrary evolution of scatter in 20 bins of  $\Delta z=0.1$



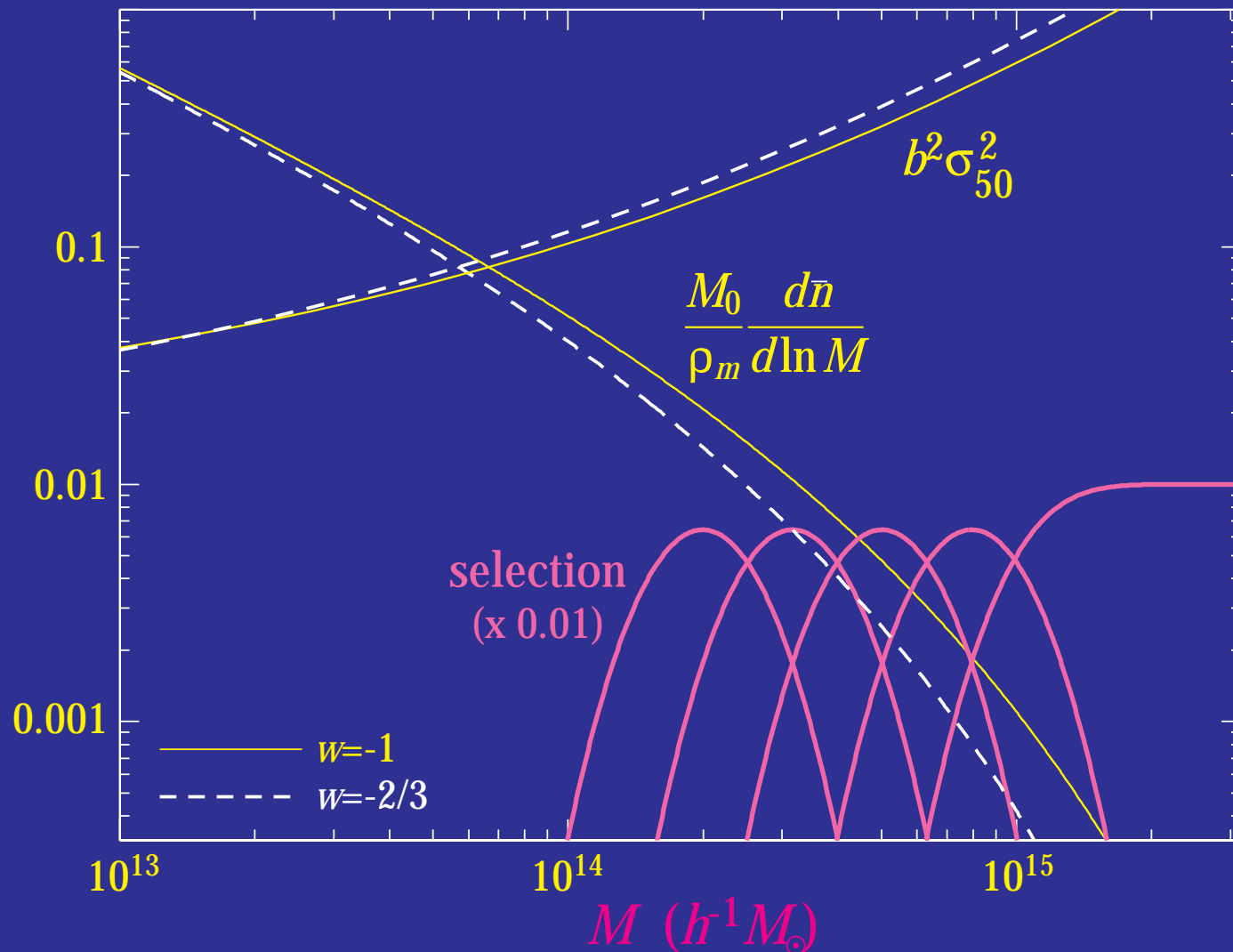
# Self-Calibration with Binning

- Power law evolution of bias and cubic evolution of scatter in  $z$



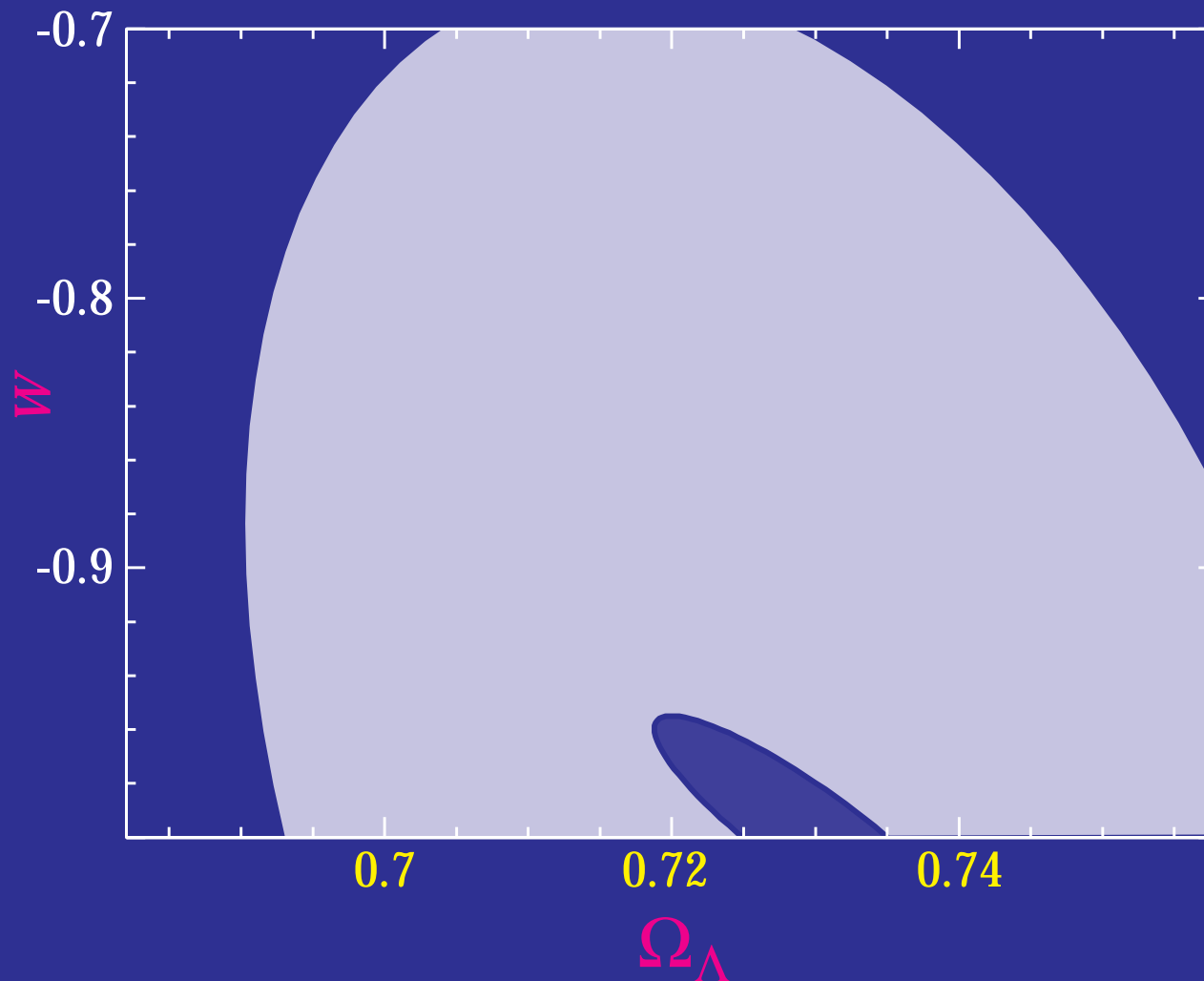
# Joint Self-Calibration

- Both **counts** and their **variance** as a function of **binned observable**
- Many observables allows for a **joint solution** of a mass independent bias and scatter with cosmology



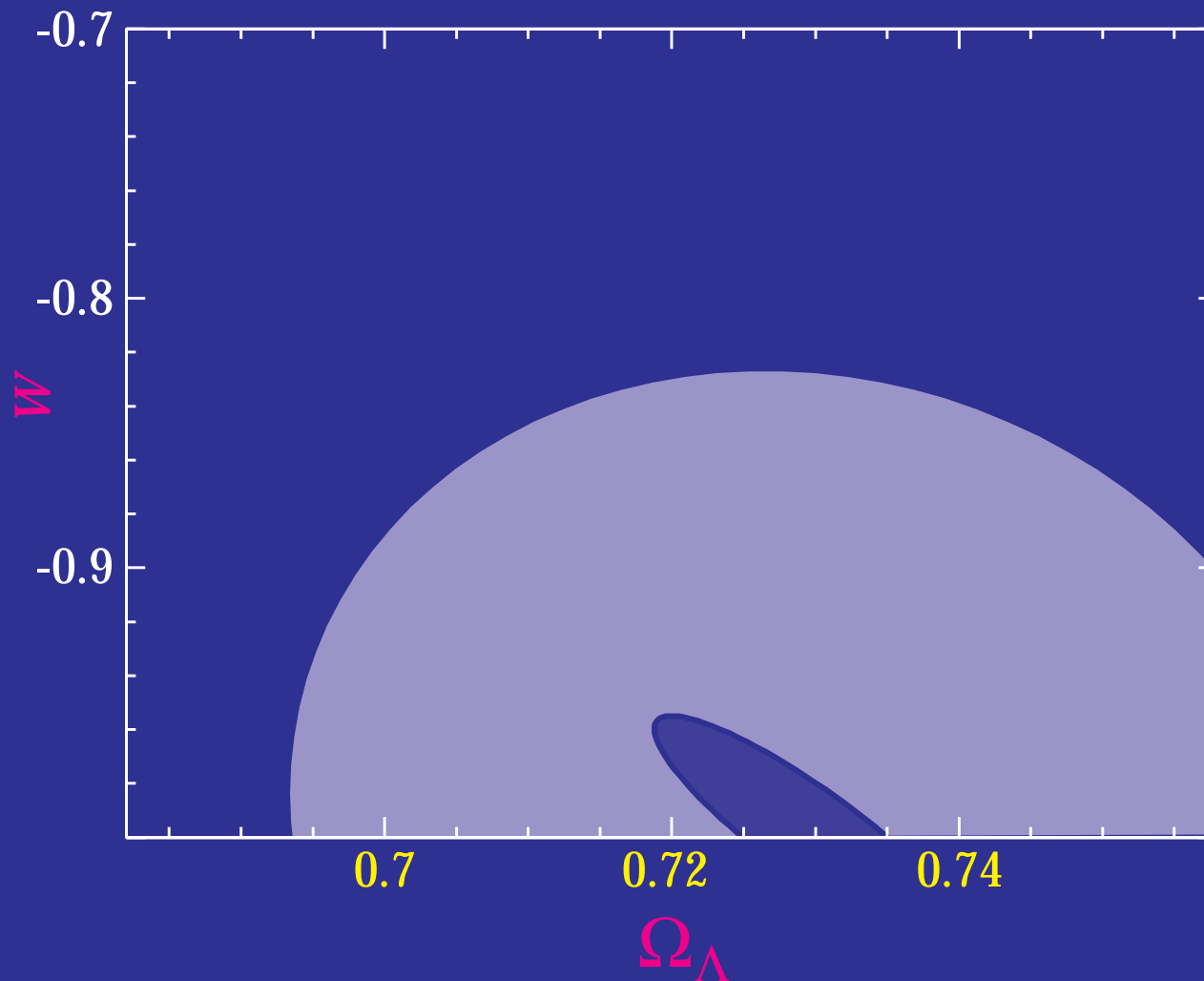
# Joint Self Calibration

- Arbitrary evolution of bias and scatter in 20 bins of  $\Delta z=0.1$



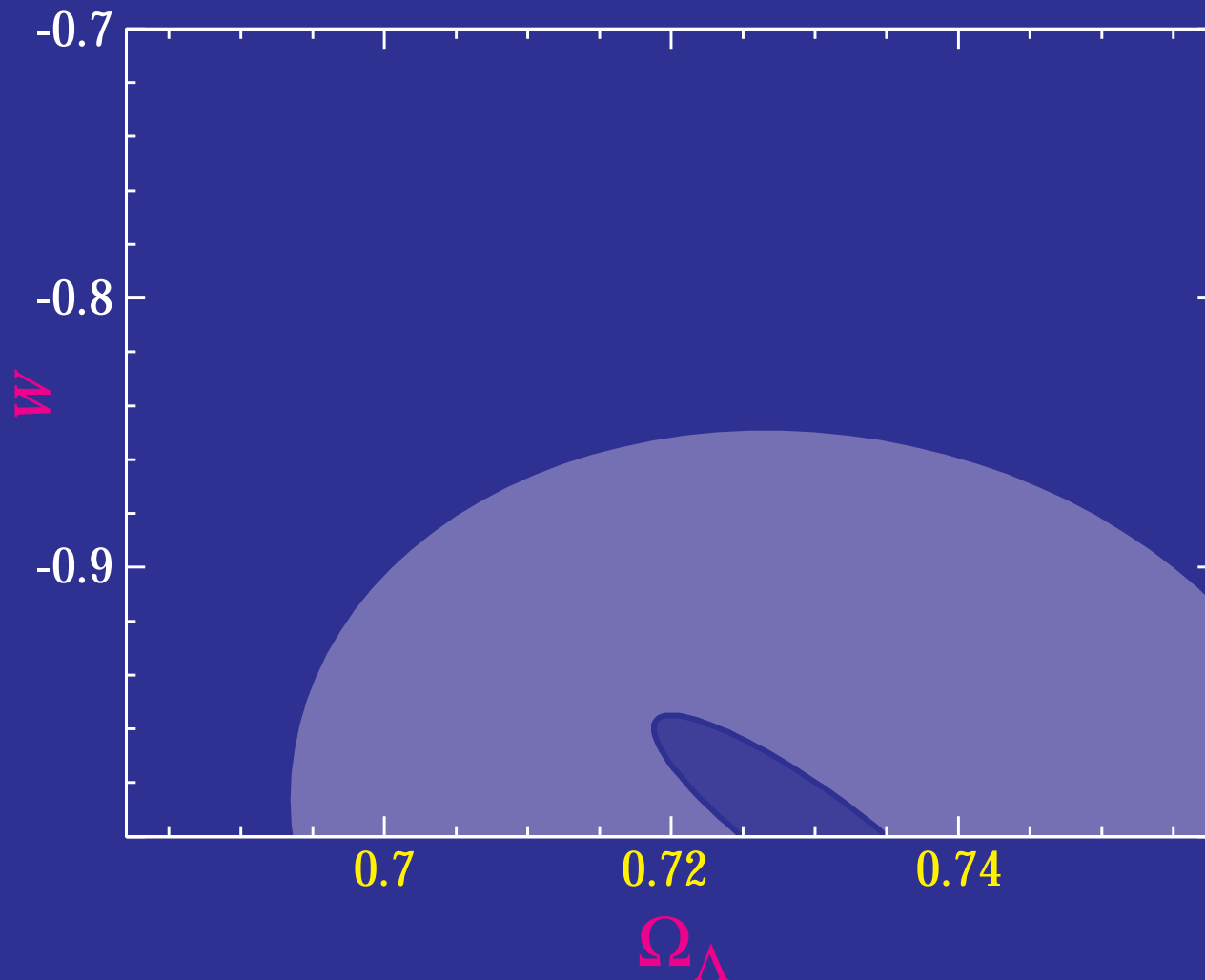
# Joint Self Calibration

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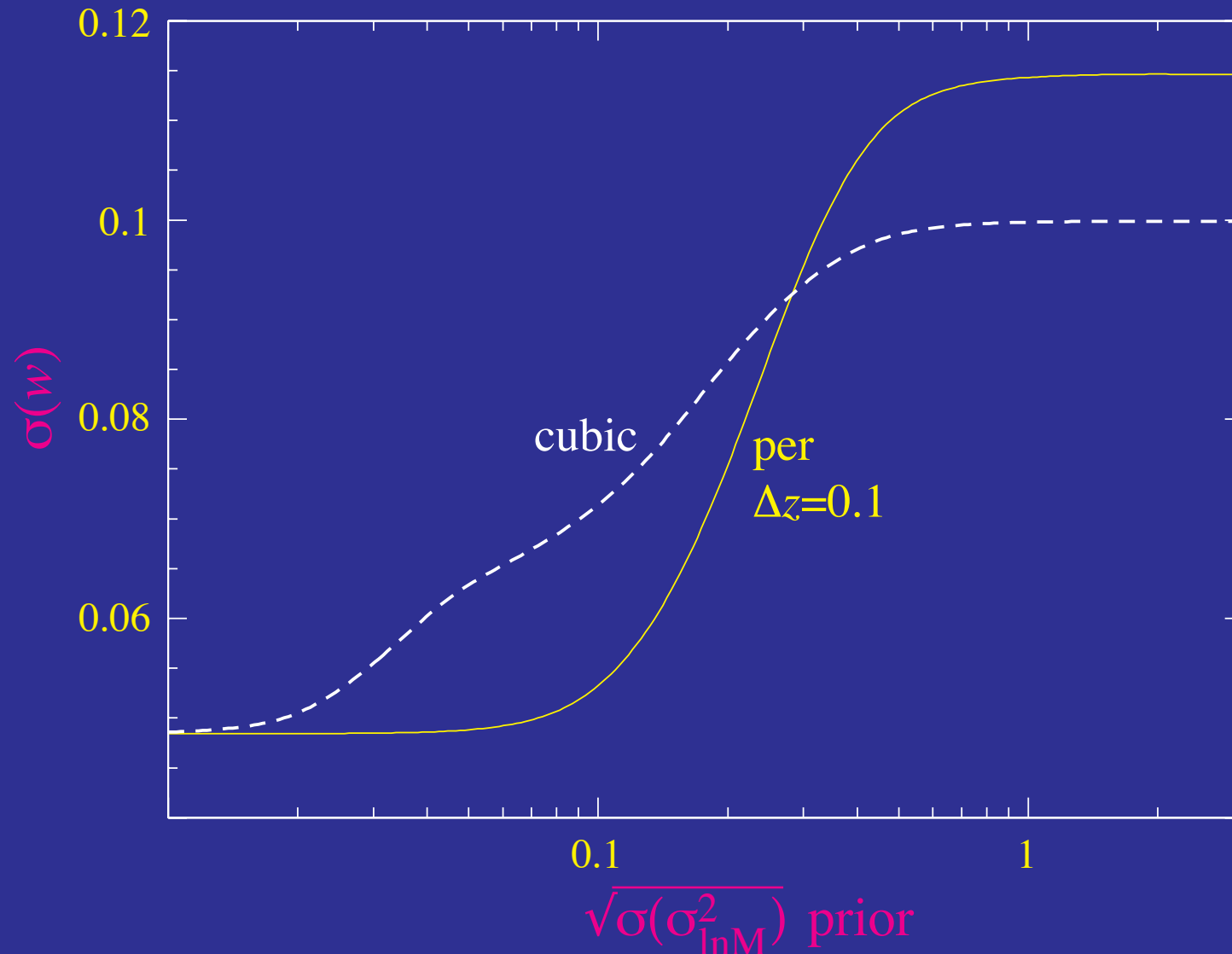
# Joint Self Calibration

- Power law evolution of bias and cubic evolution of scatter in  $z$



# Prior Knowledge of Scatter

- Priors on the 20 independent scatter parameters of 10% each
- Or 2% on the evolution of scatter to  $z \sim 1$  improves constraints x2 beyond self-calibration



# Forecasts: Scatters with Partial Clearing

- Unknown scatter at the 10% level at  $z > 1$  will significantly degrade the cosmological utility of such clusters
- Self-calibration from the power spectrum or clustering of clusters alone is insufficient to solve internally for both a bias and a scatter
- Self-calibration from the shape of the counts in the observable can jointly provide for calibration with a sufficiently deep sample
- External calibration will assist self calibration at the level of 2-10% scatter uncertainties at  $z \sim 1$

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- Self-calibration from the shape of the counts in the observable can jointly provide for calibration with a sufficiently deep sample
- External calibration will assist self calibration at the level of 2-10% scatter uncertainties at  $z \sim 1$
- Caveats:
  - trends in the distribution versus the mass must be known and taken out
  - non-Gaussian tails in the distribution must be understood
  - self calibration  $\leftrightarrow$  self consistency
  - divide up data in as many ways as possible, check assumptions!