

# Constraining mixed dark matter models with the Lyman- $\alpha$ forest

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Small-scale structure problems in the standard  $\Lambda$ CDM model could potentially be solved in a hybrid dark matter model that allows for a fraction of dark matter to be warm with a mass in the keV range: **Cold+Warm Dark Matter (CWDM)**. This model could further reconcile the measurements giving rise to the  $S_8$  tension. This project builds upon the work presented in [1].

In the CWDM paradigm, structure growth is affected by the free-streaming of dark matter at the small non-linear scales probed by the Lyman- $\alpha$  (Ly- $\alpha$ ) forest, the main observable of the IGM. To investigate this feature, it is important to first characterize the thermal state of the IGM and its effect on the Ly- $\alpha$  forest.



The IGM contains most of the neutral hydrogen that gives rise to the Ly- $\alpha$  forest, which, from Fig.1, mainly dominates the cosmic gas (baryon) distribution and clusters around dark matter, resulting in high-density regions, filaments and voids. Fig.1 shows a slice through a cosmological box of size  $20 \text{ h}^{-1} \text{ Mpc}$  with  $2 \times 10^{12}$  dark matter and gas particles at  $z = 4.2$  using the Sherwood-Relics simulations with the P-Gadget3 code [2]. Top: Hydrogen distribution with bright (left) and neutral hydrogen with darker (right) high density regions. Bottom: Dark matter distribution in the standard CDM model (left) compared to a 2 keV WDM model (right).

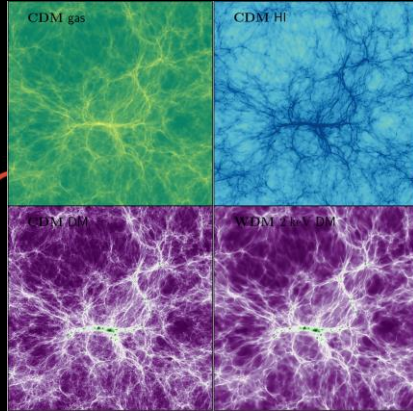


Figure 1. Credit: Vid Iršič.

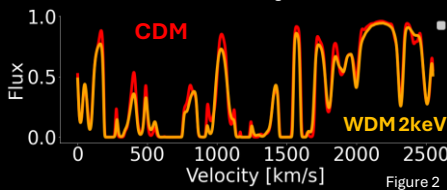
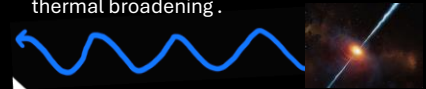


Figure 2

After reionization, the IGM approaches asymptotically the relation:  $T = T_0 \Delta^{\gamma-1}$ , with  $T_0$  the gas temperature at mean density ( $\Delta = 1$ ), and  $\gamma - 1$  a power-law index [3].  $T$  affects the Ly- $\alpha$  forest through thermal broadening.



The Ly- $\alpha$  forest is further sensitive to pressure smoothing, parameterized via the cumulative energy deposited into gas per proton,  $u_0$ , which depends on the prior IGM thermal history [4].

**Marginalizing over the effects of  $T_0$ ,  $\gamma$  and  $u_0$  on the Ly- $\alpha$  forest is fundamental to constrain dark matter models.**

Fig. 2 shows the transmitted flux  $F$  along a random LOS at  $z = 4.2$  for standard CDM and for a 2 keV WDM model, related to the deficit of photons  $\tau$  travelling through e.g. the box in Fig. 1 by  $F = e^{-\tau}$ .

## Effect of DM free-streaming

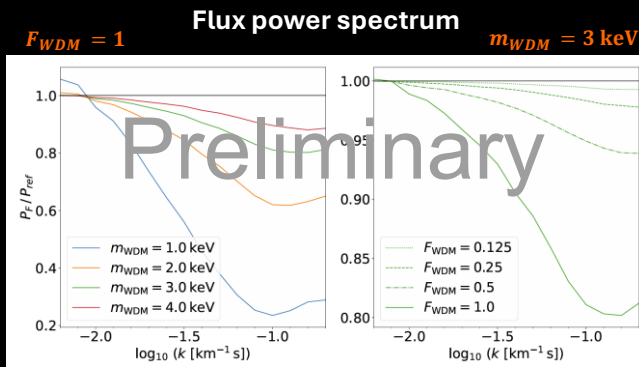


Figure 3: Flux power spectrum ratio of simulated CWDM models to the reference CDM model showing the small-scale power suppression due to dark matter free-streaming. Large-scale power enhancement is also visible due to effective optical depth  $\tau_{eff}$  rescaling used to calibrate simulations against measurements.

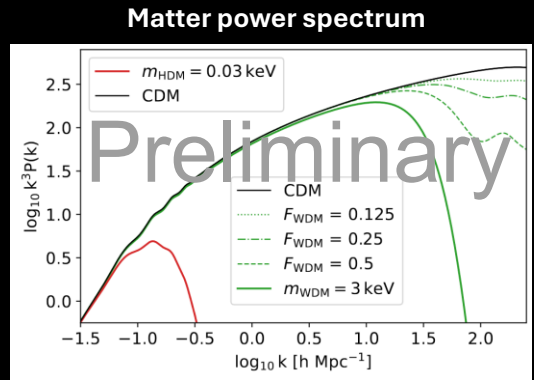


Figure 4: Linear matter power spectrum at  $z = 0$  in CDM, CWDM, WDM and HDM models using CLASS [5].

## Effect of thermal parameters and preliminary analysis

We extract the flux power spectra from the simulated Ly- $\alpha$  forest using Sherwood-Relics simulations spanning different cosmologies and thermal histories to constrain CWDM models. We first set up the Bayesian inference analysis framework to constrain a subset of the model parameters ( $T_0$ ,  $\gamma$ ,  $u_0$ ,  $\tau_{eff}$ ) using the high signal-to-noise ratio and high redshift spectra samples observed by the UVES and HIRES spectrographs [6]. We speed up the parameter recovery by incorporating a neural network emulator into the MCMC code.

The neural network emulator is trained on 90% of the total dataset, and its performance is validated on the remaining 10%. We then test the precision of the model using k-cross fold validation following [6]. Fig. 5 shows the predicted power spectra by our emulator, varying one parameter a time while keeping the remaining three fixed to fiducial values in the CDM simulation.

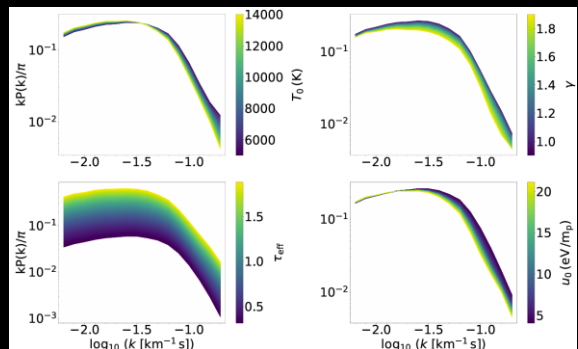


Figure 5.

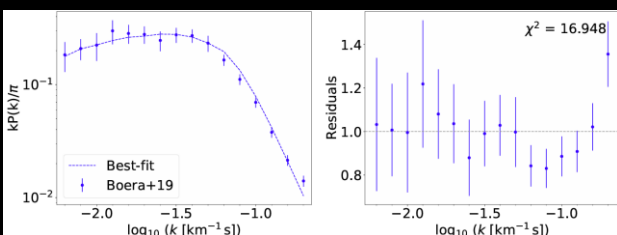


Figure 6.

We run the MCMC with the neural network emulator and obtain best-fit values for  $T_0$ ,  $\gamma$ ,  $u_0$  and  $\tau_{eff}$ . Fig. 6 shows the best-fit model predicted by the neural network to the data (left) and corresponding residuals and  $\chi^2$  (d.o.f = 15) value (right). The model represents the data well across all scales and resembles the best-fit from [1]. Discrepancies at large  $k$  values, especially in the last bin, highlight potential limitations of the model: the neural network's performance and not including instrumental and mass resolution correction to the mock spectra. The fit will fundamentally improve by incorporating thermal priors on  $T_0$  and  $u_0$ , and by expanding the current parameter subset to include CWDM model parameters.