Comments on "Locally time-varying parameter regression", submitted to *Econometric Reviews*

Summary This is an interesting paper that makes several contributions in the context of time-varying parameter (TVP) models which became an indispensable and valuable tool for modelling economic time series in the past decade. The main contribution of the paper is two-fold (see below). The paper is well motivated and solidly executed and I have only a few, specific comments how to improve this interesting paper further:

(1) The author introduces a new method of dynamic variance selection in TVP models, relying on the idea of latent thresholding introduced by Nakajima and West (2013) who applied this idea directly to each time-varying regression coefficient β_{jt} which was assumed to follow an AR process. Building upon this literature, Huber et al. (2019) apply the idea of latent thresholding to the innovations $\Delta\beta_{jt} = \beta_{jt} - \beta_{j,t-1}$ in random walk process for β_{jt} which makes much more sense. The author of the present paper follows this later lead and makes the following improvements.

(2) First, through thresholding, the innovations are shrunken to exact zeros, allowing the coefficient β_{jt} to remain perfectly constant for some time periods, while a (mild) shrinkage prior on $v_j = \sqrt{w_j}$ adjusts the variance and controls how much flexibility is needed during non-constant periods of β_{jt}. This is an important improvement, since Huber et al. (2019) shrink toward a small, but non-zero variance $\theta_{j0} << w_j$ if thresholding becomes active, which has the disadvantage that the coefficient β_{jt} never is exactly constant.

(3) Second, thresholding is triggered by a continuous latent variable z_{jt} that follows an AR process, similar in spirit to Nakajima and West (2013). Also this assumption is an important improvement compared to Huber et al. (2019), who assume that the latent thresholding variable z_t simply is an iid binary variable.

(4) Shrinking the innovations toward zero and allowing z_{jt}s to be a latent AR process are important improvements, but make estimation much more challenging compared to Huber et al. (2019). Hence, as a second main contribution of the paper, an efficient MCMC algorithm is developed to estimate this new thresholding model, using update-to-date techniques such as working with the non-centered parametrization of the model and applying an ASIS strategy.

(5) As mentioned above, the paper by Huber et al. (2019) is very closely related to this paper, however as far as I could see, it is not included in Section 2.2, discussing related literature. Also, it is not among the TVP models included in Section 4.4., comparing the suggested model with existing TVP models.

(6) No guidance is given how well the MCMC sampler is performing. It would be interesting to see MCMC posterior sampling paths and, in particular, inefficiency factors and effective sampling size also for the empirical data (it is only mentioned that IFs are below 100 for the simulated data).

References

Huber, F., G. Kastner, and M. Feldkircher (2019). Should I stay or should I go? A latent threhold approach to large-scale mixture innovation models. *Journal of Applied Econometrics 34*, 621–640.

Nakajima, J. and M. West (2013). Bayesian analysis of latent threshold dynamic models. *Journal of Business* & *Economic Statistics 31*, 151–164.