Appendix A MCMC scheme

We use a Metropolis-within-Gibbs strategy with the following blocking:

Mixing parameters The individual mixing parameters $\omega_{i\,t}$ are drawn in a Gibbs step from a Gamma distribution.

Measurement precision A Gibbs step from a Gamma distribution for λ.

Initial values A random walk Metropolis step for $\boldsymbol{y}_0$, with a independent t_3 proposal, tuning the scale parameter as to achieve the desired acceptance rate.

Individual effects A random walk Metropolis step for $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_m)'$, with a independent t_3 proposal, tuning the scale parameter as to achieve the desired acceptance rate.

Individual effect parameters Both the precision parameter τ and β are drawn using a Gibbs step.

Covariate coefficients A random walk Metropolis step for $\boldsymbol{\mu}$, with a independent t_3 proposal, tuning the scale parameter as to achieve the desired acceptance rate.

Parameters of covariate coefficients A Gibbs step is used for $\boldsymbol{m}_\mu$, and a Metropolis-Hastings step for h_μ, using a Gamma-Gamma proposal with $n = 1$ and the mean at the previous draw and the free parameter tuned as to achieve the desired acceptance rate.

Skewness A Metropolis-Hastings step with a Gamma proposal for γ with mode at the previous drawn and the free parameter tuned as to achieve the desired acceptance rate.

Tails A Metropolis-Hastings step with a Gamma proposal for ν with mode at the previous drawn and the free parameter tuned as to achieve the desired acceptance rate.

Dynamics A Metropolis-Hastings step for α using a re-scaled Beta proposal with mode at the previous drawn and the free parameter tuned as to achieve the desired acceptance rate. The hyperparameters are drawn in the same way but with a Gamma proposal.

Appendix B Chain convergence

To assess the mixing and convergence of the chain, we first ran all the samplers for 8×10^4 iterations, discarding the first ten thousand and recording every fifth. This took around 25 mins for the OECD data and 15 for the earnings set. Visual inspection of the chains suggested good mixing and convergence. The result obtained are virtually identical to those obtained with the longer chains as in the paper, which took one hour for the earnings data and 1.5 hrs for the growth set.

Then we ran both Geweke (Geweke, 1992) and Heidelberger (Heidelberger and Welch, 1983) tests for most of the chains –at least for those that we report. We used the CODA software (Convergence Diagnostic and Output Analysis), which computes convergence diagnostics and statistical and graphical summaries for the samples produced by MCMC procedures. This software can be freely obtained from
`http://www.mrc-bsu.cam.ac.uk/bugs/classic/coda04/readme.shtml`,
where a detailed description is available.

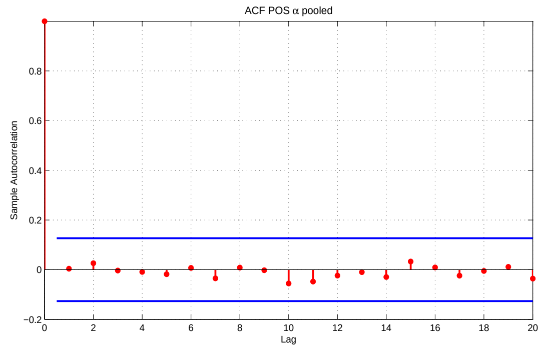
Our findings are as follows:

- For Tiao's data and both subsets all Heidelberger tests were passed, with p-values above 0.07. All Z stats of Geweke's test were $|Z| <= 1.6$

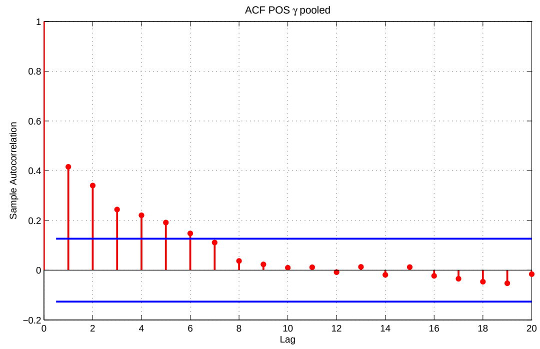
- For Hirano's data, all Heidelberger tests were passed, with p-values above 0.07. All Z stats of Geweke's test were $|Z| <= 1.8$

- For the OECD set and four subsets all Heidelberger tests were passed, with p-values above 0.3. All Z stats of Geweke's test were $|Z| <= 1.4$

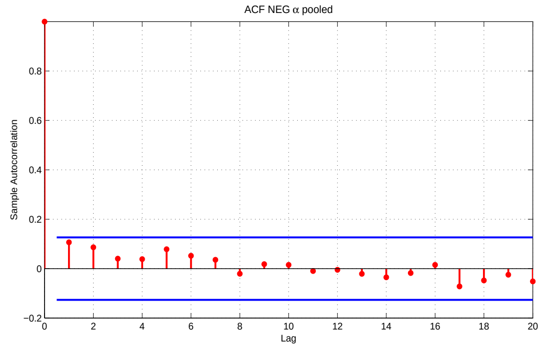
We also produced some ACF plots for different parameters/chains. The ones reported are chosen to be representative.



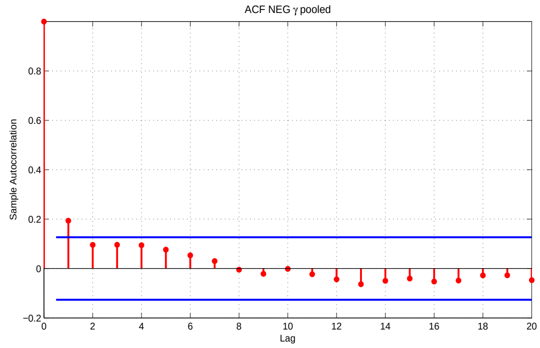
(a) *Average regional earnings. α POS*



(b) *Average regional earnings. γ POS*

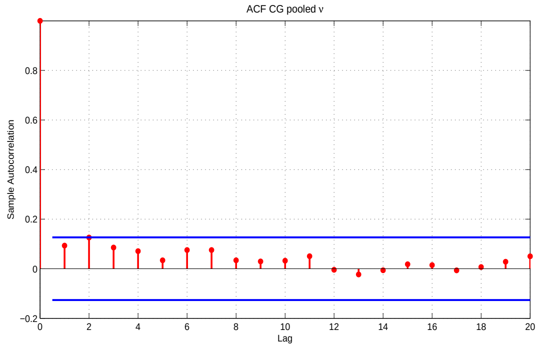


(c) *Average regional earnings. α NEG*

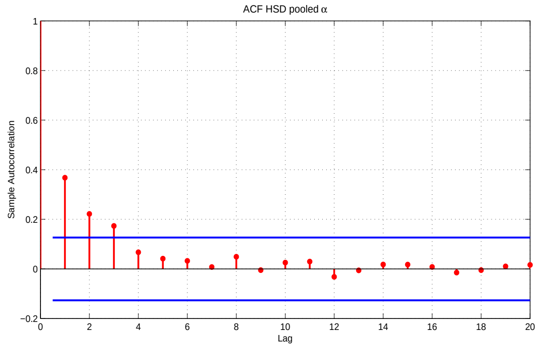


(d) *Average regional earnings. γ NEG*

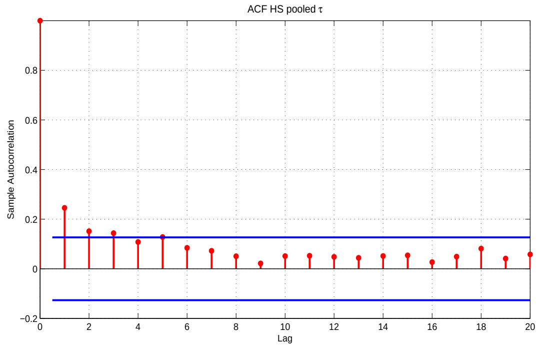
Figure 1. *Regional average earnings. Autocorrelation functions for α and γ in the POS and NEG subsets.*



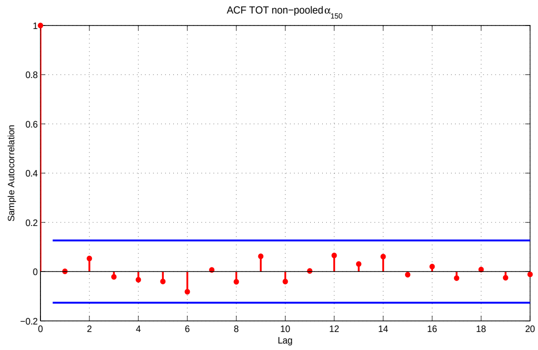
(a) *Individual earnings. ν CG subset, pooled model*



(b) *Individual earnings. α HSD subset, pooled model*

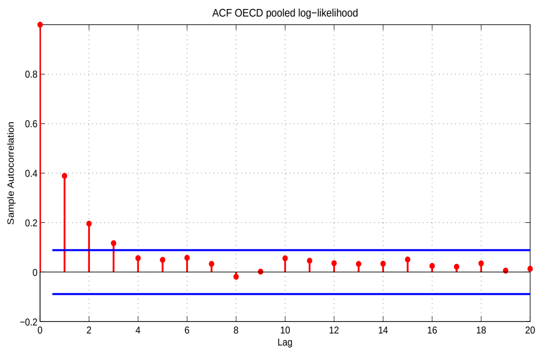


(c) *Individual earnings. τ HS subset, pooled model*

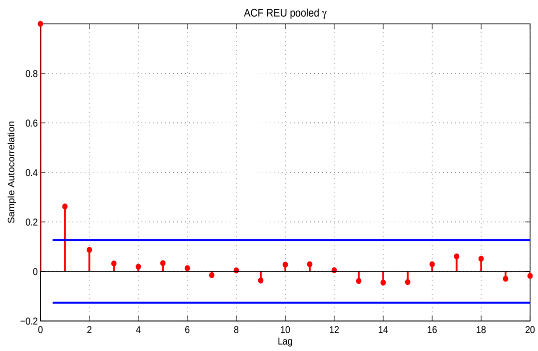


(d) *Individual earnings. α_{150} TOT set, non-pooled model*

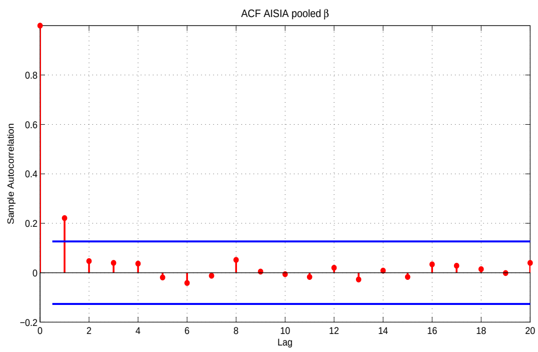
Figure 2. *Individual earnings. Autocorrelation functions for α and γ in the HSD subset.*



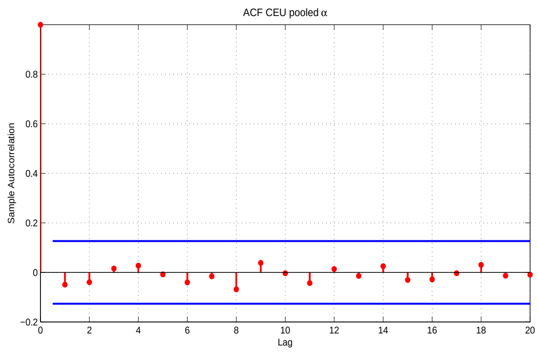
(a) *OECD data. Pooled model, loglikelihood*



(b) *OECD data. Pooled model, γ REU subset*



(c) *OECD data. Pooled model, β Asia subset*



(d) *OECD data. Pooled model, α CEU subset*

Figure 3. *OECD data. Autocorrelation functions for different parameters-subsets.*

References

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to calculating posterior moments, *Bayesian Statistics 4* (J. Bernardo, J. Berger, A. Dawid and A. Smith, eds.), Oxford: Oxford University Press, pp. 69–194.

Heidelberger, P. and Welch, P. (1983). Simulation run length control in the presence of an initial transient, *Operations Research*, **31**, 1109–1145.

Meng, X.-L. and Schilling, S. (2002). Warp bridge sampling, *Journal of Computational and Graphical Statistics*, **11**, 552–586.