For this exercise we tried to change \lambda\_1 holding \lambda\_2 constant, then varying \lambda\_2 holding lambda\_1 and then varying both \lambda\_1 and \lambda\_2. For each of those, we compare 6 different values of lambda. The corresponding coefficients are depicted in first 3 figures in Appendix.

Changes in the estimated AR coefficients:

For small values of \lambda\_1 given \lambda\_2 we see that all AR coefficients except constant are pushed towards their expectation given by \underbar{A} strongly. For each variable its first lag is close to one and all other coefficients are close to 0. For high values of \lambda\_1 the distinction between the coefficients of own first lags and others gets less pronounced. This was expected since in Minnesota prior \lambda\_1 induces global shrinkage for all parameters except the constant term.

Low value of \lambda\_2 pushes the cross-variable coefficients to 0, while the own-variable coefficients have more freedom given by medium value of \lambda\_1. For high values of \lambda\_2 the cross variables coefficients fluctuate more freely around 0.

Varying \lambda\_1 and \lambda\_2 combines these two effects.

Changes in the estimated IRFs (we use Cholesky for illustration):

Low \lambda\_1 pushes all median IRFs to a constant response, since all coefficients except for constant are pushed strongly to 0. Low \lambda\_2 pushes the cross-variable responses to a constant. High \lambda\_1 and \lambda\_2 lets the data speak. Notice that in Cholesky right-upper triangle of IRFs starts at 0 by definition, thus they are pushed towards 0.

Changes in forecast:

Low \lambda\_1 makes the forecasts to see more like random walk. Low \lambda\_2 not necessarily, since the dependence on own lags and constant seem to cause substantial variation in the forecasts.