It is common practice in Markov chain Monte Carlo to update the simulation one variable (or sub-block of variables) at a time, rather than conduct a single full-dimensional update. When it is possible to draw from each full-conditional distribution associated with the target this is just a Gibbs sampler. Often at least one of the Gibbs updates is replaced with a Metropolis-Hastings step yielding a Metropolis Hastings-within-Gibbs algorithm. Strategies for combining component-wise updates include composition, random sequence and random scans. While these strategies can ease MCMC implementation and produce superior empirical performance compared to full-dimensional updates, the theoretical convergence properties of the associated Markov chains have received limited attention. We present conditions under which component-wise Markov chains converge to the stationary distribution at a geometric rate. We pay particular attention to the connections between the convergence rates of the various component-wise strategies. This is practically relevant since it ensures the existence of tools that an MCMC practitioner can use to be as confident in the simulation results as if they were based on independent and identically distributed samples. We illustrate our results in several examples including a Bayesian version of a linear mixed model and an example involving maximum likelihood estimation for a generalized linear mixed model.