Abstract: Various tasks in statistics involve numerical integration, for which Markov chain Monte Carlo (MCMC) methods are state-of-the-art. MCMC methods yield estimators that converge to integrals of interest in the limit of the number of iterations. This iterative asymptotic justification is not ideal; first, it stands at odds with current trends in computing hardware, with increasingly parallel architectures; secondly, the choice of "burn-in" and of the total number of iterations are difficult. This talk will describe recently proposed estimators that are exactly unbiased for the expectations of interest, while having an almost surely finite computing cost and a finite variance. They can thus be generated independently in parallel and averaged over. We argue that the removal of the "burn-in" bias can be done for many MCMC algorithms of practical interest without inflating the variance by much. The core idea is to use coupled pairs of Markov chains with a time lag, following the pathbreaking work of Peter Glynn & Chan-Han Rhee. The method also provides practical upper bounds on some distances between the marginal distribution of the chain at a finite step and its invariant distribution. This talk will provide an overview of this line of research, joint work with John O'Leary, Yves Atchadé and many others.

Bio: I have graduated from Université Paris-Dauphine in 2012, my PhD on Bayesian computation was supervised by Christian P. Robert. Then I did postdocs at the National University of Singapore and the University of Oxford. I am now tenure-track faculty at Harvard. I develop methods for statistical inference, time series analysis, Monte Carlo. My research is supported by an NSF Career award.