Wagner legitimately calls his solution a "natural generalization of Jeffrey conditioning" [18] (p.250). There is, however, another natural generalization of Jeffrey conditioning, E.T. Jaynes' principle of maximum entropy in [24]. PME does not rest on JUP, but rather claims that one should keep one's entropy maximal within the constraints that the evidence provides (in the synchronic case) and one's cross-entropy minimal (in the diachronic case).

It is important to distinguish between type I and type II prior probabilities. The former precede any information at all (so-called ignorance priors). The latter are simply prior relative to posterior probabilities in probability kinematics. They may themselves be posterior probabilities with respect to an earlier instance of probability kinematics. Although Jaynes' original claims are concerned with type I prior probabilities, this paper works on the assumptions of Jaynes' later work focusing on type II prior probabilities. Some distinguish between MAXENT, the synchronic rule, and *Infomin*, the diachronic rule. The understanding here is that both operate on type II prior probabilities: MAXENT considers uniform prior probabilities (however this uniformity may have arisen) and a set of synchronic constraints on them; *Infomin*, in a more standard sense of updating, considers type II prior probabilities that are not necessarily uniform and updates them given evidence represented as new (diachronic) constraints on acceptable posterior probability distributions. Some say that MAXENT and *Infomin* contradict each other, but I disagree and maintain that they are compatible. I will have to defer this problem to future work, but a core argument for compatibility is already accessible in [21]

One advantage of PME is that it works on the wide domain of updating problems where the evidence corresponds to an affine constraint (for affine constraints see [25]; for problems with evidence not in the form of affine constraints see [26]). Updating problems where standard conditioning and Jeffrey conditioning are applicable are a subset of this domain. Some partial information cases (using the moment(s) of a distribution as evidence), such as Bas van Fraassen's *Judy Benjamin* problem and Jaynes' *Brandeis Dice* problem, are not amenable to either standard conditioning or Jeffrey conditioning. PME generalizes Jeffrey conditioning (and, a fortiori, standard conditioning) and therefore absorbs JUP on the more narrow domain of problems that we can solve using Jeffrey conditioning (for a proof see the appendix, although it can also be gleaned from [27]).

Wagner's contention is that on the wider domain of problems where we must use Wagner conditioning (and which he does not cast in terms of affine constraints), JUP and PME contradict each other. We are now in the awkward position of being confronted with two plausible intuitions, JUP and PME, and it appears that we have to let one of them go. Wagner adduces other conceptual problems for PME (see [13,28–30], [31] (p.270), [32] (p.107)) to reinforce his conclusion that PME is not a principle on which we should rely in general.

5. A Natural Generalization of Jeffrey and Wagner Conditioning

In order to show how PME generalizes Jeffrey conditioning (in the appendix) and Wagner conditioning to boot, I use the notation that I have already introduced for Jeffrey conditioning. We can characterize Wagner-type problems analogously to Jeffrey-type problems by a triple $(\kappa, \beta, \hat{\alpha})$. $\{\theta_j\}_{j=1,\ldots,n}$ and $\{\omega_i\}_{i=1,\ldots,m}$ now refer to independent partitions of Ω, *i.e.*, (1) need not be true. Besides the marginal