

Bayesian approach and Naturalness in MSSM forecast for the LHC

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arXiv:0911.4686v1 [hep-ph]

- The start of the LHC!!
- The present experimental data are not powerful enough to select a small region of the parameter space for SUSY models.
- We perform a MSSM forecast for the LHC based on an improved Bayesian analysis.

References of recent works

- B. C. Allanach and C. G. Lester, Phys. Rev. D 73 (2006) 015013 [arXiv:hep-ph/0507283].
- B. C. Allanach, Phys. Lett. B 635 (2006) 123 [arXiv:hep-ph/0601089].
- R. R. de Austri, R. Trotta and L. Roszkowski, JHEP 0605 (2006) 002 [arXiv:hep-ph/0602028].
- B. C. Allanach, K. Cranmer, C. G. Lester and A. M. Weber, JHEP 0708 (2007) 023 [arXiv:0705.0487 [hep-ph]].
- L. Roszkowski, R. Ruiz de Austri and R. Trotta, JHEP 0707, 075 (2007) [arXiv:0705.2012 [hep-ph]].
- O. Buchmueller et al., JHEP 0809 (2008) 117 [arXiv:0808.4128 [hep-ph]].
- R. Trotta, F. Feroz, M. P. Hobson, L. Roszkowski and R. Ruiz de Austri, arXiv:0809.3792 [hep-ph].
- J. Ellis, Eur. Phys. J. C 59 (2009) 335 [arXiv:0810.1178 [hep-ph]].
- S. S. AbdusSalam, B. C. Allanach, F. Quevedo, F. Feroz and M. Hobson, arXiv:0904.2548 [hep-ph].
- O. Buchmueller et al., Eur. Phys. J. C 64 (2009) 391 [arXiv:0907.5568 [hep-ph]].
- ...

The posterior probability density function (pdf), $p(p_i^0|\text{data})$, is given by

Theorem

$$p(p_i^0|\text{data}) = \frac{p(\text{data}|p_i^0) p(p_i^0)}{p(\text{data})}$$

where $p(\text{data}|p_i^0)$ is the likelihood, $p(p_i^0)$ is the prior, $p(\text{data})$ is the evidence.

From **the minimization of the tree-level form of the scalar potential**

$$M_Z^2 = 2 \frac{m_{H_1}^2 - m_{H_2}^2 \tan^2 \beta}{\tan^2 \beta - 1} - 2\mu_{low}^2 .$$

Barbieri-Giudice fine-tuning parameters

$$c_i = \left| \frac{\partial \ln M_Z^2}{\partial \ln p_i} \right|,$$

The global measure of the fine-tuning is taken as $c \equiv \max\{c_i\}$ or $c \equiv \sqrt{\sum c_i^2}$.

Bayesian approach and Naturalness

Separate M_Z from the rest of experimental data,

$$p(\text{data}|s, m, M, A, B, \mu) \simeq \delta(M_z - M_z^{\exp}) \mathcal{L}_{\text{rest}} ,$$

Use M_Z to marginalize μ

$$\begin{aligned} p(s, m, M, A, B | \text{data}) &= \int d\mu \, p(s, m, M, A, B, \mu | \text{data}) \\ &\simeq \int dM_Z \left[\frac{d\mu}{dM_Z} \right] \delta(M_z - M_z^{\exp}) \mathcal{L}_{\text{rest}} \, p(s, m, M, A, B, \mu) \\ &\sim \left[\frac{d\mu}{dM_Z} \right]_{\mu_0} \mathcal{L}_{\text{rest}} \, p(s, m, M, A, B, \mu_0) \end{aligned}$$

then

$$p(s, m, M, A, B | \text{data}) = 2 \frac{\mu_0}{M_Z} \frac{1}{c_\mu} \mathcal{L}_{\text{rest}} \, p(s, m, M, A, B, \mu_0) !!!$$

Improved Bayesian approach

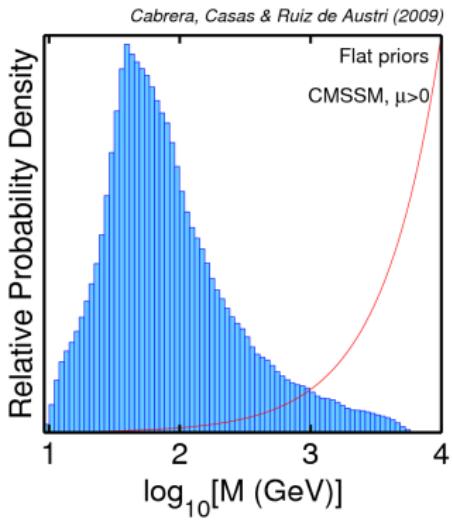
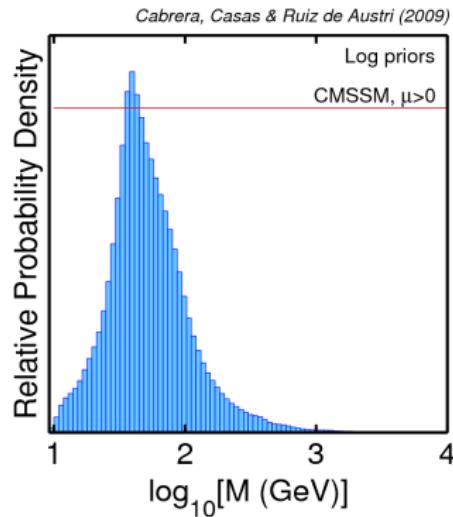
- Fine-tuning penalization arises from the Bayesian analysis itself.
- Rigorous treatment of the nuisance variables.
- We use an efficient set of variables to scan the MSSM
 $\{m, M, A, B, \mu, y_t\} \rightarrow \{m, M, A, \tan \beta, M_Z, m_t\}$,

$$p(g_i, m_t, m, M, A, \tan \beta | \text{data}) = \mathcal{L}_{\text{rest}} J|_{\mu=\mu_0} p(g_i, y_t, m, M, A, B, \mu = \mu_0)$$

$$\text{where } J \sim \frac{1}{4}(g^2 + g'^2)^{1/2} \left[\frac{E}{R_\mu^2} \right] \frac{B_{\text{low}}}{\mu} \frac{t^2 - 1}{t(1+t^2)} \left(\frac{y_t}{y_t^{\text{low}}} \right)^2 s_\beta^{-1}$$

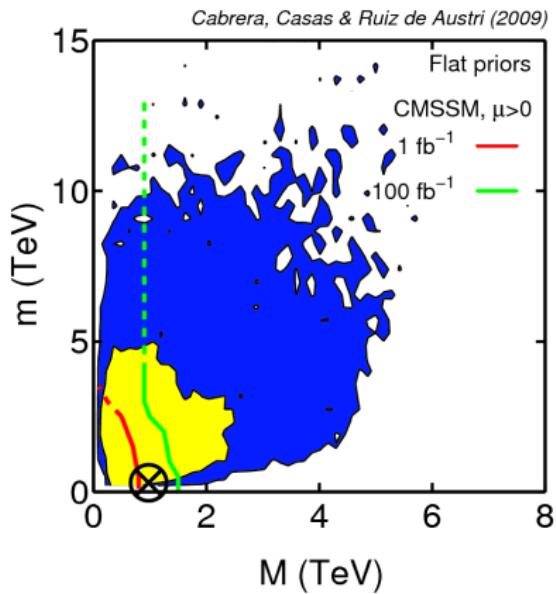
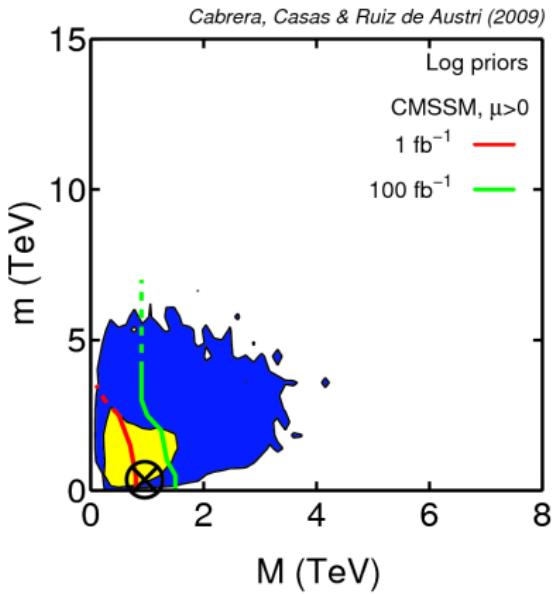
- We have developed sensible priors.

Experimental Constraints: M_Z^{exp}



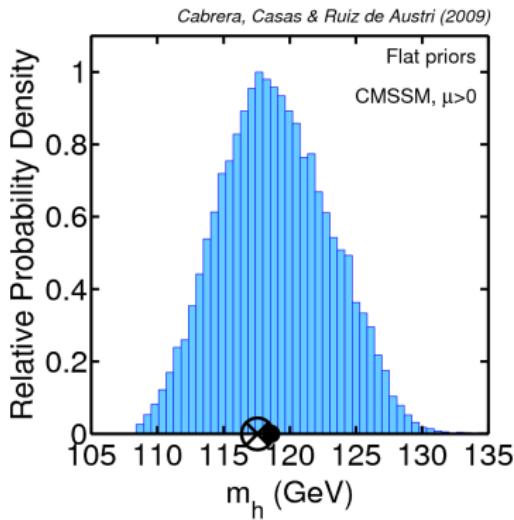
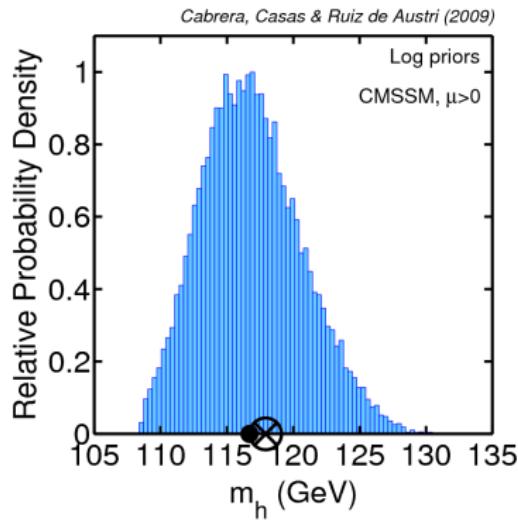
SuperBayeS: SoftSusy, FeynHiggs, SuperIso, SusyBSG,
MicrOMEGAs

Experimental Constraints: EW + Bounds + B-Physics

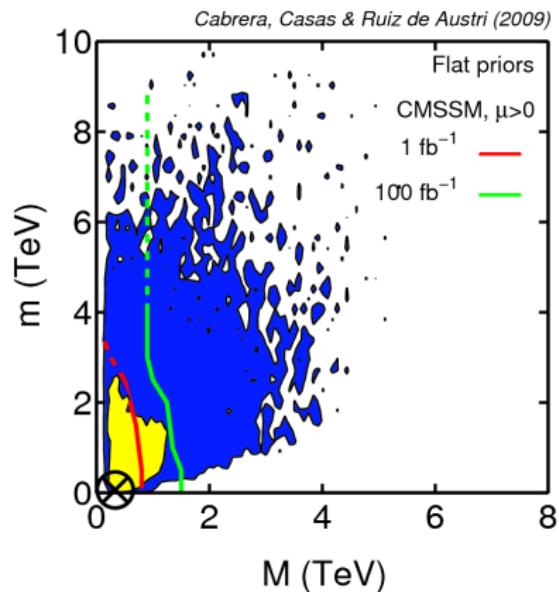
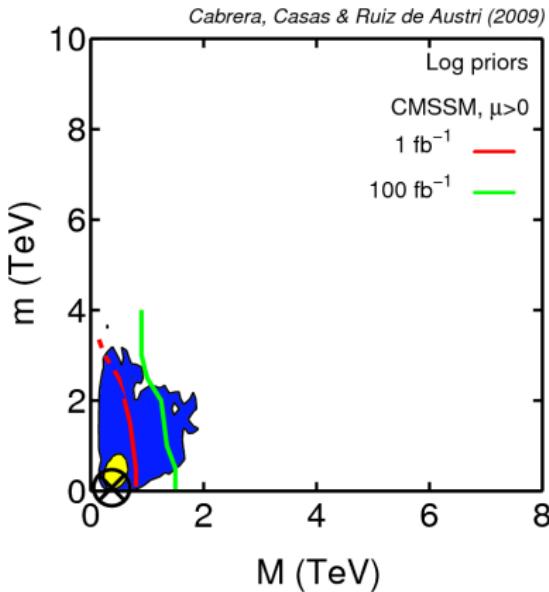


Experimental Constraints: EW + Bounds + B-Physics

Higgs Mass



Experimental Constraints: EW + Bounds + B-Physics + $(g - 2)_\mu$ from e^+e^-

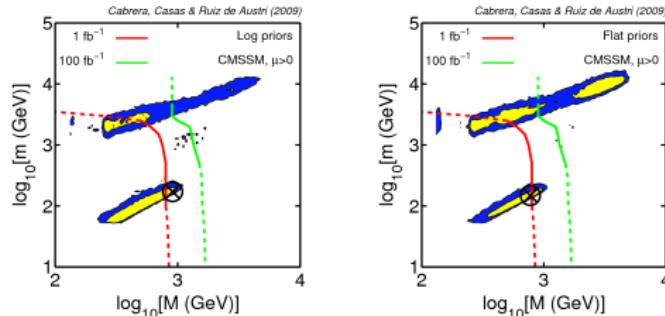


Experimental Constraints: + Dark Matter

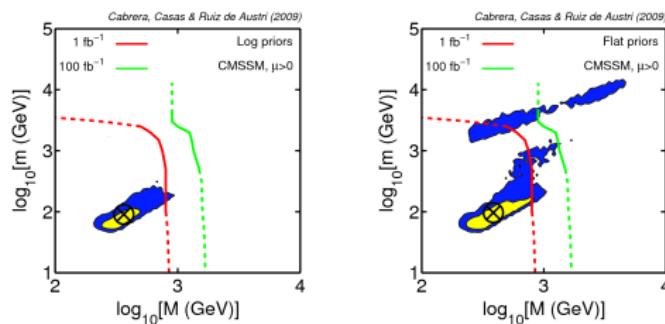
EW + Bounds + B-phys + Ω_{DM}

Regions of CDM candidate:

- Co-annihilation
- Bulk
- Higgs funnel
- Focus Point



EW + Bounds + B-phys + $(g - 2)_\mu$ + Ω_{DM}



Positive versus Negative μ

We perform the analysis also for $\mu < 0$ and made the comparison,

Observables	Evidence (flat)	Evidence (log)
EW + Bounds + B-phys	Inconclusive	Inconclusive
EW + Bounds + B-phys + $(g - 2)_\mu$	Inconclusive	Weak
EW + Bounds + B-phys + Ω_{DM}	Inconclusive	Inconclusive
EW + Bounds + B-phys + $(g - 2)_\mu + \Omega_{DM}$	Weak	Moderate

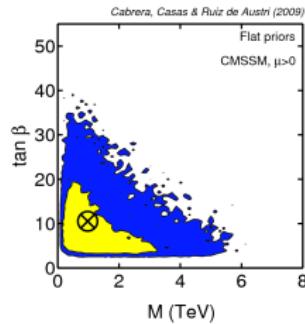
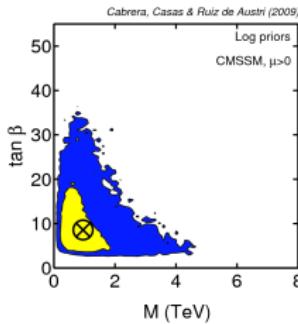
Where red means it prefers $\mu > 0$ and blue means it prefers $\mu < 0$

Thanks!

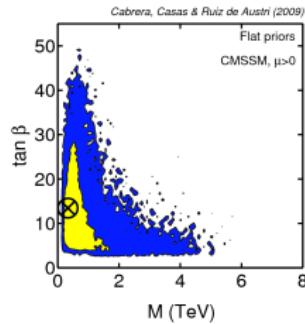
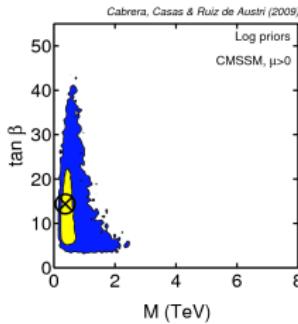
BACKUP SLIDES

Experimental Constraints

EW + Bounds + B-phys

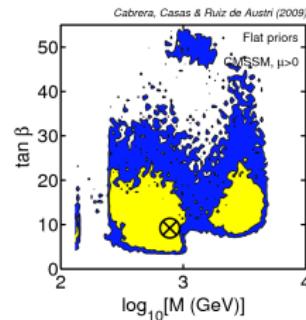
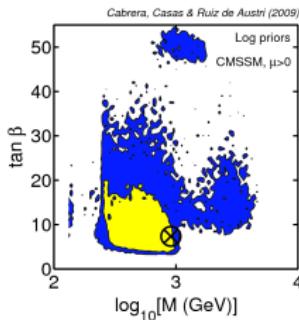


EW + Bounds + B-phys + $(g - 2)_\mu$

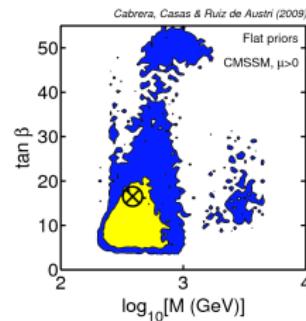
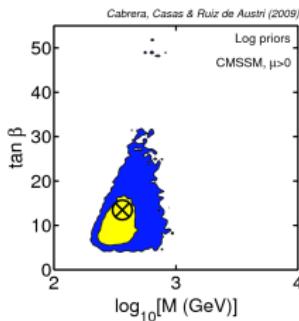


Experimental Constraints

EW + Bounds + B-phys + Ω_{DM}



EW + Bounds + B-phys + $(g - 2)_\mu$ + Ω_{DM}



Taking the typical size of the soft terms as M_S

$$-qM_S \leq B \leq qM_S$$

$$-qM_S \leq A \leq qM_S$$

$$0 \leq m \leq qM_S$$

$$0 \leq M \leq qM_S$$

$$0 \leq \mu \leq qM_S$$

where $M_S^0 \leq M_S \leq M_X$, $M_S^0 \sim 10$ GeV.

We are going to assume **Flat Priors for the soft parameters inside the ranges.**

Priors: Logarithmic Prior

Logarithmic Prior in M_S : $p(M_S) = N_{M_S} \frac{1}{M_S}$

$$\begin{aligned} p(m, M, A, B, \mu) &= \frac{N_{M_S}}{4} \int_{\max\{m, M, |A|, |B|, \mu, M_S^0\}}^{M_X} \frac{1}{M_S^6} dM_S \\ &= \frac{N_{M_S}}{20} \left[\frac{1}{[\max\{m, M, |A|, |B|, \mu, M_S^0\}]^5} - \frac{1}{M_X^5} \right] \end{aligned}$$

$$p(m, M, A, B, \mu) \simeq \frac{1}{[\max\{m, M, |A|, |B|, \mu, M_S^0\}]^5}$$

The **Logarithmic Prior** of the gaugino mass will be

$$P(M) \propto \frac{1}{\max\{M, M_S^0\}}$$

Priors: Flat Prior

Flat Prior in M_S : $p(M_S) = N_{M_S}$.

$$\begin{aligned} p(m, M, A, B, \mu) &= \frac{N_{M_S}}{4} \int_{\max\{m, M, |A|, |B|, \mu, M_S^0\}}^{M_X} \frac{1}{M_S^5} dM_S \\ &= \frac{N_{M_S}}{16} \left[\frac{1}{[\max\{m, M, |A|, |B|, \mu, M_S^0\}]^4} - \frac{1}{M_X^4} \right] \end{aligned}$$

$$p(m, M, A, B, \mu) \simeq \frac{1}{[\max\{m, M, |A|, |B|, \mu, M_S^0\}]^4}$$

The **Flat prior** of the gaugino mass will be

$$P(M) \sim \log \frac{M_X}{\max\{M, M_S^0\}}$$