Supersymmetry, naturalness and the “fine-tuning price” of the Very Large Hadron Collider

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Abstract

The absence of supersymmetry or other new physics at the Large Hadron Collider (LHC) has lead many to question naturalness arguments. With Bayesian statistics, we argue that natural models are most probable and that naturalness is not merely an aesthetic principle. We calculate a probabilistic measure of naturalness, the Bayesian evidence, for the Standard Model (SM) with and without quadratic divergences, confirming that the SM with quadratic divergences is improbable. We calculate the Bayesian evidence for the Constrained Minimal Supersymmetric Standard Model (CMSSM) with naturalness priors in three cases: with only the $M_Z$ measurement; with the $M_Z$ measurement and LHC measurements; and with the $M_Z$ measurement, $m_h$ measurement and a hypothetical null result from a $\sqrt{s} = 100$ TeV Very Large Hadron Collider (VLHC) with 3000/fb. The “fine-tuning price” of the VLHC given LHC results would be $\sim 400$, which is slightly less than that of the LHC results given the electroweak scale ($\sim 500$).
I. INTRODUCTION

Weak-scale supersymmetry (SUSY) [1–4] was supposed to solve the naturalness problem of the Standard Model (SM) [5, 6], but it was absent in the ATLAS [7] and CMS [8] searches at the Large Hadron Collider (LHC) in 20/fb with center-of-mass energies of $\sqrt{s} = 7\text{ TeV}$ and $\sqrt{s} = 8\text{ TeV}$. Although ATLAS and CMS will continue their searches for SUSY at $\sqrt{s} = 13\text{ TeV}$, a new $\sqrt{s} = 100\text{ TeV}$ Very Large Hadron Collider (VLHC) might be built [9].

There are numerous motivations for SUSY. The theoretical motivations for SUSY (see e.g., Ref. [10]) are, inter alia, that it completes the maximal symmetries of the $S$-matrix and connects with gravity and superstrings. The phenomenological and experimental motivations for SUSY (see e.g., Ref. [11]) are that it unifies the gauge couplings at the anticipated scale, that the lightest SUSY particle could explain the measured abundance of dark matter in the Universe and that it predicts that the mass of the lightest Higgs boson is $m_h \lesssim 135\text{ GeV}$. Perhaps the strongest motivation for SUSY, however, is that it solves the technical naturalness problem of the SM, if SUSY particles are sufficiently light. The LHC results, however, suggest that SUSY particles might not be sufficiently light [12, 13] and have lead many to question naturalness arguments [14–17].

We argue in Sec. II that the best measure of naturalness is Bayesian evidence and measure naturalness in the SM in Sec. III and in the Constrained Minimal Supersymmetric SM (CMSSM) [18–20] in Sec. IV by calculating their Bayesian evidences with “honest” or “naturalness” priors. We evaluate the consequences for naturalness of hypothetical null results from a $\sqrt{s} = 100\text{ TeV}$ VLHC with Bayesian statistics, i.e., the “fine-tuning price” of the VLHC [21, 23], by calculating the Bayesian evidence in this scenario. Learning this “price” could motivate building the VLHC [21]. We discuss the $\mu$-problem of the MSSM [25] in the context of Bayesian statistics in Sec. V and conclude in Sec. VI. For similar analyses, see e.g., Ref. [26–32].

II. BAYESIAN EVIDENCE

For a pedagogical introduction to Bayesian statistics, see e.g., Ref. [33]. In Bayesian statistics, probability is a numerical measure of belief in a proposition. With Bayes’ theorem,
our belief in a model given experimental data is given by

\[ p(\text{model} | \text{data}) = \frac{p(\text{data} | \text{model}) \times p(\text{model})}{p(\text{data})}, \]  

(1)

where \( Z \equiv p(\text{data} | \text{model}) \) is the Bayesian evidence, \( p(\text{model}) \) is our prior belief in the model, and \( p(\text{data}) \) is a normalization constant. We can eliminate the normalization constant if we consider a ratio of probabilities for model \( a \) and model \( b \);

\[ \frac{p(\text{model}_a | \text{data})}{p(\text{model}_b | \text{data})} = \frac{p(\text{data} | \text{model}_a)}{p(\text{data} | \text{model}_b)} \times \frac{p(\text{model}_a)}{p(\text{model}_b)}. \]  

(2)

Our prior odds, \( \theta \), is a numerical measure of our relative belief in model \( a \) over model \( b \), before considering experimental data. The Bayes-factor, \( B \), updates our prior odds, \( \theta \), with the experimental data, resulting in our posterior odds, \( \theta' \). Our posterior odds is a numerical measure of our relative belief in model \( a \) over model \( b \), after considering experimental data.

The Bayes-factor is the ratio of the models’ evidences.

Let us make our discussion more concrete. From an experiment, one can construct a “likelihood function” giving the frequentist probability of obtaining the data, given a particular point, \( \vec{x} \), in a model’s parameter space,

\[ L(\vec{x}) = p(\text{data} | \vec{x}, \text{model}). \]  

(3)

The likelihood function for a measurement is typically a Gaussian function (by the central limit theorem). It could be, e.g., the probability of measuring a Higgs mass \( m_h = 125 \text{ GeV} \) given a particular parameter point \( \vec{x} \) in a SUSY model. With Bayes’ theorem, it can be readily shown that the evidence is an integral over the likelihood,

\[ Z = \int L(\vec{x}) \pi(\vec{x}) \prod dx, \]  

(4)

where \( \pi(\vec{x}) \equiv p(\vec{x} | \text{model}) \) is our prior; our prior belief in the model’s parameter space. Priors are somewhat subjective and there might exist a spectrum of assigned priors amongst investigators. All investigators, however, will make identical conclusions from the evidence, if the likelihood is sufficiently informative.

Because individual evidences are somewhat meaningless (e.g., the evidence has dimension \([1/\text{data}]\)), it is necessary to compare an evidence against that of a reference model with a Bayes-factor. If the Bayes-factor is greater than (less than) one, the model in the
numerator (denominator) is favored. The interpretation of Bayes-factors is somewhat subjective, though we have chosen the Jeffreys’ scale, Table I, to ascribe qualitative meanings to Bayes-factors. If a Bayes-factor is sufficiently large, all investigators will conclude that a particular model is favorable, regardless of their prior odds for the models. The Jeffreys’ scale is, however, only a guide for interpreting a Bayes-factor; the full result is the posterior odds found by multiplying the Bayes-factor by the prior odds in Eq. (2).

| Grade | Bayesian-factor, $B$ | Preference for model in numerator |
|-------|---------------------|----------------------------------|
| 0     | $B \leq 1$          | Negative                         |
| 1     | $1 < B \leq 3$      | Barely worth mentioning          |
| 2     | $3 < B \leq 20$     | Positive                         |
| 3     | $20 < B \leq 150$   | Strong                           |
| 4     | $B > 150$           | Very strong                      |

Table I: The Jeffreys’ scale for interpreting Bayes-factors [34], which are ratios of evidences. We assume that the favored model is in the numerator, though this could be readily inverted.

The Bayes-factor quantitatively incorporates a principle of economy widely-known as Occam’s razor and in physics as “fine-tuning” or “naturalness” [35–37]. It is insightful to consider the evidence $Z = p(\text{data} | \text{model})$ a function of the data normalized to unity, i.e., as a sampling distribution [38]. Natural models “spend” their probability mass near the obtained data, i.e., a large fraction of their parameter space agrees with the data. Complicated models squander their probability mass away from the obtained data. This is illustrated in Fig. 1. Bayesian statistics formalizes Occam’s razor, fine-tuning and naturalness arguments. Naturalness is no longer a nebulous, aesthetic criterion; it is formalized and justified by Bayesian statistics.

We measure the “fine-tuning price” of new experimental data with a partial Bayes-factor. A partial Bayes-factor, $P$, updates our relative belief in model$_a$ over model$_b$ with new experimental data,

$$P : \frac{p(\text{model}_a | \text{data})}{p(\text{model}_b | \text{data})} = \frac{p(\text{model}_a | \text{data + new data})}{p(\text{model}_b | \text{data + new data})}.$$ (5)
Observed data, $D$
Evidence, $Z = p(D|M)$
Good simple model:
concentrated
probability mass
at observed data.
Bad simple model:
probability mass
wasted here.
OK complicated model:
spreads probability
mass thinly.

"Naturalness" or Occam’s razor
Good simple model
Bad simple model
Complicated model

Figure 1: Illustration of the evidence, interpreted as a sampling distribution, originally from Ref. [38]. The observed evidence is the evidence evaluated at the observed data. The red line shows a model that concentrates its probability mass at the observed data: it is a good, simple model. The green line shows a model that concentrates its probability mass away from the observed data: it is a bad, simple model. The blue line shows a model that thinly spreads its probability mass around the observed data: it is an OK, complicated model.

It can be readily shown that a partial Bayes-factor is a ratio of Bayes-factors,

$$P = \frac{p(\text{data + new data} | \text{model}_a) \ p(\text{data} | \text{model}_b)}{p(\text{data + new data} | \text{model}_b) \ p(\text{data} | \text{model}_a)}. \quad (6)$$

See e.g., Ref. [32] for a comprehensive discussion of partial Bayes-factors. Having introduced our formalism, we are ready to calculate evidences in the SM and CMSSM.

III. BAYESIAN EVIDENCE FOR THE STANDARD MODEL

If the SM is coupled to the Planck scale, it suffers from a well-known fine-tuning problem, the “hierarchy problem” [5, 6]. The dimension-two coupling, $\mu^2$, in the Higgs potential,

$$V = \mu^2 \phi^2 + \lambda \phi^4, \quad (7)$$

must be incredibly fine-tuned. The dressed coupling must be $\sim -(100 \text{GeV})^2$, but the bare coupling receives a positive quadratic correction $\sim M_P^2$. Let us calculate the evidence for
the SM, given the electroweak scale and that the Higgs mass is \(\sim 125\) GeV. Whilst naively our Higgs potential is described by \(\mu^2\) and \(\lambda\), let us instead write the dressed dimension-two coupling as the sum of a bare coupling and a quadratic correction,

\[
\mu^2 = \mu_0^2 + \Delta \mu^2, \tag{8}
\]

and treat \(\mu_0^2\), \(\Delta \mu^2\) and \(\lambda\) as separate parameters. A priori, if the SM is coupled to the Planck scale, \(M_P\), we expect that \(\Delta \mu^2 \sim M_P^2\), and that \(\lambda \sim 1\), whereas we have no idea about the scale of \(\mu_0^2\). Let us formalize these thoughts with logarithmic, scale invariant priors \(\pi(x) \propto 1/x\);

\[
\Delta \mu^2 \text{ between } 10^{36} \text{ and } 10^{40} \text{ GeV}^2, \tag{9}
\]

\[
\mu_0^2 \text{ between } 10^0 \text{ and } 10^{40} \text{ GeV}^2, \tag{10}
\]

\[
\lambda \text{ between } 10^{-3} \text{ and } 10^1. \tag{11}
\]

We also note that a priori \(\mu_0^2\) could be positive or negative.

We calculate the evidence for the SM given the \(M_Z\) measurement [39] and the LHC \(m_h \sim 125\) GeV measurement [39–41]. We approximate the likelihood functions for the measurements of \(M_Z\) and \(m_h\) as Dirac delta functions;

\[
Z_{\text{only } M_Z} = \int \delta(M_Z - 91.1876 \text{ GeV}) \frac{d\mu_0^2}{\mu_0^2} \frac{d\lambda}{\lambda} \frac{d\Delta \mu^2}{\Delta \mu^2}, \tag{12}
\]

\[
Z_{m_h \text{ and } M_Z} = \int \delta(M_Z - 91.1876 \text{ GeV}) \delta(m_h - 125.9 \text{ GeV}) \frac{d\mu_0^2}{\mu_0^2} \frac{d\lambda}{\lambda} \frac{d\Delta \mu^2}{\Delta \mu^2}. \tag{13}
\]

The denominators normalize our logarithmic priors. We integrate the Dirac delta functions with tree-level formulas for the Higgs and Z-boson masses (see e.g., Ref. [42]),

\[
m_h = \sqrt{-2\mu_0^2}, \tag{13}
\]

\[
M_Z = g \sqrt{-\frac{\mu_0^2}{2\lambda}}. \tag{14}
\]

We calculate evidences by performing the integrals in Eq. [12] for two models:

1. The SM with quadratic divergences, \(\Delta \mu^2 \sim M_P^2\), and

2. The SM without quadratic divergences, \(\Delta \mu^2 = 0\).
The resulting evidences are in Table II. Unsurprisingly, the evidence for the SM with quadratic divergences is minuscule compared to that for the SM without quadratic divergences. The Bayes-factors in Table II are more than $10^{30}$ against the SM with quadratic divergences (150 is considered “very strong” on the Jeffreys’ scale).

Let us interpret the evidence as a sampling distribution for the expected $Z$-boson mass, i.e., plot the evidence as a function of $M_Z$ (Fig. 2). As expected, the SM with quadratic divergences squanders its prediction for the $Z$-boson mass near $M_P$, far away from the measured $M_Z$. The SM with quadratic divergences is unnatural. Because without quadratic divergences one can make no prediction for the magnitude of $M_Z$, the SM without quadratic divergences is somewhat unnatural and complicated.

![Distribution of $Z$-boson mass, Fowlie (2014)]

**Figure 2:** *The probability distribution of the $Z$-boson mass in the various models. The area under each plot is equal to one.*

Now that we have completed the somewhat trivial exercise of calculating the evidences for the SM, let us calculate the evidences for the CMSSM.
IV. BAYESIAN EVIDENCES FOR THE CMSSM

The $Z$-boson mass, or, equivalently, the scale of electroweak symmetry breaking, is predicted in the MSSM via radiative electroweak symmetry breaking. At tree-level \[4\],

\[
\frac{1}{2}M_Z^2 = -\mu^2 + \frac{m_{H_u}^2 - m_{H_d}^2 \tan^2 \beta}{\tan^2 \beta - 1}.
\]

(15)

This expression is problematic; it contains the “little-hierarchy problem” \[43\] and the related “$\mu$-problem” \[25\]. From experiments, we know that $M_Z$ is $\sim 100$ GeV. The MSSM predicts $M_Z$ via a cancellation between the SUSY breaking parameters, $m_{H_u}^2$ and $m_{H_d}^2$, and a SUSY preserving parameter in the superpotential, $\mu$. If the SUSY breaking scale is greater than the measured value of $M_Z$, a cancellation between such large numbers is somewhat miraculous. This is the little-hierarchy problem. This problem is statistical in nature; we are concerned that the MSSM is unlikely because its parameters must be fine-tuned, i.e., it might only agree with experiments in a small fraction of its parameter space.

We simplified Eq. (15) to find an analytic expression for the evidence from Eq. (4) as a function of $M_Z$ in the CMSSM with logarithmic priors. We plot this expression as a function of the $Z$-boson mass in Fig. 2. Whilst the CMSSM is somewhat fine-tuned, the fine-tuning of the SM with quadratic divergences is far worse. The SM dimension-two coupling is quadratically sensitive to the UV; the highest scales must enter our expression for $M_Z$. In the SM with quadratic divergences, the cancellation resulting in $M_Z$ must involve quantities $\sim M_P$. In the CMSSM, we require a cancellation, but the cancellation could be at any scale up to $M_P$.

Fine-tuning is typically measured with a sensitivity, for example, that originally proposed in Ref. \[36\] \[37\], the Barbieri-Giudice measure,

\[
\Delta_i = \frac{x_i}{M_Z^2} \frac{\partial M_Z^2}{\partial x_i},
\]

(16)

where $x_i$ are the model’s parameters. The reciprocal of this measure is, indeed, similar to our Bayesian evidence, in that a small Barbieri-Giudice measure indicates that the model might spend its probability mass around the measured value of $M_Z$. This is illuminated by rewriting Eq. (16),

\[
\Delta_i^{-1} = \left[ \frac{\Delta M_Z^2}{M_Z^2} \frac{x_i}{\Delta x_i} \right]^{-1} \propto \frac{\Delta x_i}{x_i},
\]

(17)
The reciprocal of the Barbieri-Giudice measure is proportional to the local fraction of the model’s parameter space in which $M_Z$ varies by $\Delta M_Z$; in similarity, the evidence is a measure of the fraction of the model’s prior volume in which the model agrees with experiments [44–46]. The Barbieri-Giudice measure lacks, however, a formal interpretation and is, furthermore, a property of a point in the model’s parameter space, rather than of the model itself (c.f., the evidence).

Bayesian evidence automatically penalizes fine-tuning. Focusing mechanisms (e.g., the focus-point [47–49]) are automatically incorporated. We must, however, choose “honest” priors. In the CMSSM, we ought to formulate our prior beliefs in $\mu$ and $b$, the fundamental parameters, defined

$$W \supset \mu H_u H_d, \quad (18)$$

$$\mathcal{L}_{\text{Soft}} \supset -b^2 H_u H_d + c.c. \quad (19)$$

For pragmatism, however, we exchange $\mu$ and $b$ for $M_Z$ and $\tan \beta$ via e.g., Eq. (15). We ought to transform our priors with the appropriate Jacobian, resulting in effective priors for $M_Z$ and $\tan \beta$ [27, 28, 30, 44–46]. With logarithmic priors for $\mu$ and $b$, our effective priors are

$$\pi(M_Z) = \frac{\partial \mu}{\partial M_Z} \pi(\mu) = \frac{2\mu}{M_Z} \Delta^{-1}_\mu \pi(\mu) = \text{const.} \Delta^{-1}_\mu, \quad (20)$$

$$\pi(\tan \beta) = \frac{\partial b}{\partial \tan \beta} \pi(b) = \text{const.} \frac{\partial b}{b} \partial \tan \beta. \quad (21)$$

The effective prior for $M_Z$ reveals the formal relationship between Bayesian statistics and the Barbieri-Giudice measure [44–45]. With the Barbieri-Giudice measure, the statistical nature of the problem is latent [26, 50]; it is now manifest.

We calculated the evidence exactly in the CMSSM with “honest” priors. Let us make our prior choices clear, because it is a potential source of confusion. For the fundamental
CMSSM parameters and priors we pick\footnote{One might wonder whether we should pick, \textit{e.g.}, $m_0^2$ rather than $m_0$ as a fundamental parameter, since it is the square which appears in the soft-breaking Lagrangian. Because we pick logarithmic priors, however, the choice is irrelevant.}

\begin{align*}
m_0 & \text{ log prior between 1 GeV and } M_P, \\
m_{1/2}/m_0 & \text{ log prior between } 10^{-3} \text{ and } 10^3, \\
A_0/m_0 & \text{ linear prior between } -5 \text{ and } 5, \\
b/m_0 & \text{ log prior between } 10^{-3} \text{ and } 10^3, \\
\mu & \text{ log prior between 1 GeV and } M_P. \tag{22}
\end{align*}

We anticipate that a breaking mechanism might distribute the SUSY breaking masses about a common SUSY breaking scale \cite{43}, which we pick as $m_0$. We do not consider mechanisms in which SUSY breaking parameters are split into distinct groups separated by many orders of magnitude \cite{51,52}. We call this choice of priors and parameterization our \textit{de jure} priors.

Were we to numerically calculate the evidence for the CMSSM with our \textit{de jure} priors, we would waste CPU time considering parameter space with incorrect $M_Z$. For the purpose of our numerical calculation, we transform our \textit{de jure} priors into our equivalent \textit{de facto} priors,

\begin{align*}
m_0 & \text{ log prior between 1 GeV and 20 TeV,} \\
m_{1/2}/m_0 & \text{ log prior between } 10^{-3} \text{ and } 10^3, \\
A_0/m_0 & \text{ linear prior between } -5 \text{ and } 5, \\
\tan \beta & \text{ effective prior between 1 and 60,} \\
M_Z & \text{ effective prior, fixed } 91.1876 \text{ GeV,} \tag{23}
\end{align*}

where the effective priors are in Eq. \eqref{eq:20}. The “missing” parameter space in our \textit{de facto} priors at $M_{\text{SUSY}} \gg 20 \text{ TeV}$ is irrelevant in our calculation, because it contains negligible evidence. The “missing” parameter space, however, results in differences in normalization between our \textit{de jure} and \textit{de facto} priors, which we correct by hand. Fortunately, because the sign of $\mu$ is identical at the electroweak and $M_P$ scales, we require no Jacobian to transform our prior for sign $\mu$ from $M_P$ to the electroweak scale. We pick informative, Gaussian priors for the SM nuisance parameters $m_t$, $m_b$, $1/\alpha_{\text{em}}$ and $\alpha_s$ \cite{39}.\footnote{One might wonder whether we should pick, \textit{e.g.}, $m_0^2$ rather than $m_0$ as a fundamental parameter, since it is the square which appears in the soft-breaking Lagrangian. Because we pick logarithmic priors, however, the choice is irrelevant.}
We calculated the CMSSM’s mass spectrum and effective priors with \textsc{softsusy} [53]. We used \textsc{multinest} [54] with \textsc{pymultinest} [55] to perform the integral in Eq. (4). We found the evidence for three cases:

1. \( M_Z = 91.1876 \text{ GeV} \) [39] only in our likelihood (fixed by our \textit{de facto} priors),

2. \( M_Z, m_h = 125.9 \pm 0.4 \pm 2.0 \text{ GeV} \) [39–41, 56] and the null result from the LHC in 20/fb [7] in our likelihood, and

3. \( M_Z, m_h \) and a hypothetical null result from the VLHC in 3000/fb [57] in our likelihood.

In the first case, our likelihood for \( M_Z \) is a Dirac delta function. In the second case, our likelihood for \( m_h \) is a Gaussian with theoretical and experimental errors added in quadrature, and we veto points that are excluded by an ATLAS search for jets and missing energy [7]. In the last case, we consider the potential consequences of the \( \sqrt{s} = 100 \text{ TeV} \) VLHC, by vetoing points that would be excluded by a null result in 3000/fb [57], i.e., points with \( m_\tilde{g} \lesssim 16 \text{ TeV} \) and \( m_\tilde{q} \lesssim 16 \text{ TeV} \) or points with \( m_\tilde{g} \lesssim 13.5 \text{ TeV} \).

\begin{table}[h]
\centering
\begin{tabular}{lccc}
\hline
 & \( M_Z \) & \( M_Z, m_h \) and LHC & \( M_Z, m_h \) and VLHC \\
\hline
Evidences, \( Z \) & \( \text{GeV}^{-1} \) & \( \text{GeV}^{-2} \) & \( \text{GeV}^{-2} \) \\
SM with quadratic divergences & \( 9 \cdot 10^{-37} \) & \( 2 \cdot 10^{-40} \) & \( 2 \cdot 10^{-40} \) \\
SM no quadratic divergences & \( 1 \cdot 10^{-4} \) & \( 2 \cdot 10^{-7} \) & \( 2 \cdot 10^{-7} \) \\
CMSSM & \( 8 \cdot 10^{-5} \) & \( 3 \cdot 10^{-10} \) & \( 7 \cdot 10^{-13} \) \\
\hline
Bayes-factors, \( B = Z_a/Z_b \) & & & \\
CMSSM/SM with quadratic divergences & \( 9 \cdot 10^{31} \) & \( 2 \cdot 10^{30} \) & \( 4 \cdot 10^{27} \) \\
SM no quadratic divergences/CMSSM & \( 2 \cdot 10^{0} \) & \( 7 \cdot 10^{2} \) & \( 3 \cdot 10^{5} \) \\
Partial Bayes-factors, \( P = B_{i+1}/B_{i} \) & & & \\
SM no quadratic divergences/CMSSM & \( \sim 2 \) & \( \sim 500 \) & \( \sim 400 \) \\
\hline
\end{tabular}
\end{table}

\textbf{Table II:} \textit{Bayesian evidences and Bayes-factors for the SM with quadratic divergences, SM without quadratic divergences and CMSSM. The headings indicate which experimental results were included. The final column is the “fine-tuning price,” as measured by partial Bayes-factors.}

The evidences for the CMSSM in our three cases are shown are shown in Table II. Let us discuss the results case by case:
1. \( M_Z \) only in our likelihood. The Bayes-factor favors the CMSSM over the SM with quadratic divergences by \( \sim 10^{32} \); as anticipated, the CMSSM is favored by naturalness. The Bayes-factor favors the SM without quadratic divergences over the CMSSM by only \( \sim 2 \), which is “barely worth mentioning” on the Jeffreys’ scale in Table I. Prior to LHC experiments, the CMSSM was not unnatural.

2. \( M_Z, m_h \) and \( LHC 20/fb \) in our likelihood. The Bayes-factor favors the CMSSM over the SM with quadratic divergences by \( \sim 10^{30} \); the little-hierarchy problem in the CMSSM is minuscule compared with the hierarchy problem in the SM with quadratic divergences. The Bayes-factor favors the SM without quadratic divergences over the CMSSM by \( \sim 700 \) (150 is “very strong” on the Jeffreys’ scale). Relative to the SM without quadratic divergences, the evidence for the CMSSM diminishes by a factor of \( \sim 500 \); this is the “fine-tuning price” of the LHC.

3. \( M_Z, m_h \) and a hypothetical null result from VLHC 3000/fb in our likelihood. The Bayes-factor favors the SM without quadratic divergences over the CMSSM by \( \sim 10^5 \). Relative to the SM without quadratic divergences, the evidence for the CMSSM diminishes by a further factor of \( \sim 400 \). The “fine-tuning price” of null results from the VLHC (\( \sim 400 \)) would be similar to, though slightly less than that of the LHC (\( \sim 500 \)).

Note that in all cases, however, the Bayes-factors favor the CMSSM over the SM with quadratic divergences by \( \gtrsim 10^{27} \). The “fine-tuning prices” for the experiments in the CMSSM are illustrated in Fig. 3 by the logarithm of the Bayes-factor for the SM without quadratic divergences against the CMSSM.

The posterior probability density (see e.g., Ref. 58 for an introduction) is a by-product of the MultiNest evidence calculation. With \( M_Z, m_h \) and null results from the LHC in our likelihood, the posterior probability density for \((m_0, m_{1/2})\) confirms that the focuspuntopt 47, 49 at \( m_0 \sim 8 \text{ TeV} \) and \( m_{1/2} \lesssim 2 \text{ TeV} \) is favored. With only \( M_Z \) in our likelihood, unsurprisingly, we find that \( M_{\text{SUSY}} \sim M_Z \) is favored by \( M_Z \), i.e., by naturalness.
Figure 3: The “fine-tuning prices” of the $M_Z$ measurement, LHC experiments and hypothetical null results from the VLHC. Our “fine-tuning prices” are the Bayes-factors for the SM without quadratic divergences against the CMSSM broken down by experiment. $M_Z$ indicates the measurement of the $Z$-boson mass, $m_h$ and LHC indicates the LHC Higgs mass measurement and null results from LHC, and VLHC indicates hypothetical null results in $3000/\text{fb}$ at $\sqrt{s} = 100$ TeV.

The logarithm is base 10.

V. THE $\mu$-PROBLEM

A problem emerges from our “honest” choice of prior for $\mu$, which aggravates the fine-tuning problem. The $\mu$-parameter is a symmetry conserving parameter in the superpotential. A priori, it is unrelated to a symmetry breaking scale. This is problematic; phenomenologically it must be that $\mu \sim M_{\text{SUSY}}$. The evidence for a model in which we expect $100 \text{ GeV} \lesssim \mu \lesssim M_P$ and observe $\mu \sim M_{\text{SUSY}}$ could be smaller than that for a model in which we expect $\mu \sim M_{\text{SUSY}}$ and observe $\mu \sim M_{\text{SUSY}}$. This is the “$\mu$-problem;” in our formulation, its statistical nature is manifest. Eq. (20) reveals the $\mu$-problem and the fine-tuning problem; the $\mu$-problem is that $\pi(\mu \approx M_{\text{SUSY}})$ is small and the fine-tuning problem is that $\partial \mu/\partial M_Z$ is small, resulting in a small prior belief in the observed electroweak scale, $\pi(M_Z)$. The ratio of evidences for a model that predicts $M_Z \lesssim \mu \lesssim M_P$ and an “almost-so” model
that predicts e.g., $10^{-1} M_{\text{SUSY}} \lesssim \mu \lesssim 10^3 M_{\text{SUSY}}$ is

\begin{equation}
\ln \left( \frac{10^3 M_{\text{SUSY}}}{10^{-1} M_{\text{SUSY}}} \right) \approx \ln \left( \frac{M_P}{M_Z} \right) \approx \frac{1}{5}.
\end{equation}

A similar result applies to SUSY models with a Giudice-Masiero mechanism [59].

The little-hierarchy problem in the CMSSM is $\sim 30$ times worse than the $\mu$-problem. The $\mu$-problem contributes a factor of only $\sim 5$ to a Bayes-factor for an “almost-so” model against the CMSSM. The Bayes-factor with $M_Z$, $m_h$ and null results from the LHC favors the SM without quadratic divergences over the CMSSM by $\sim 700$; the little-hierarchy problem contributes a factor of $\sim 150$ and the $\mu$-problem contributes a factor of $\sim 5$.

VI. CONCLUSIONS

The absence of SUSY or other new physics at the LHC has lead many to question naturalness arguments. Drawing upon the literature, we clarified the relationship between Bayesian statistics and naturalness, concluding that natural models are most probable and that naturalness is not merely an aesthetic principle. We calculated the Bayesian, probabilistic measure of naturalness, the evidence, for the SM with and without quadratic divergences, demonstrating that the SM with quadratic divergences is improbable. We calculated the evidence for the CMSSM in three cases: with only the $M_Z$ measurement; with the $M_Z$ measurement and LHC measurements; and with the $M_Z$ measurement and a hypothetical null result from the VLHC with 3000/fb. The latter allowed us to quantitatively understand the potential “fine-tuning price” of the VLHC. We found that the “fine-tuning price” of null results from the VLHC ($\sim 400$) would be slightly less than that of the LHC ($\sim 500$). We hope this result might help to inform preliminary discussions and plans for the VLHC.

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