FONDAZIONE ENI ENRICO MATTEI

NOTA DI LAVORO

13.2017

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Mitigation, Innovation & Transformation Pathways
Series Editor: Massimo Tavoni

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Keywords: Satisficing, Model Uncertainty, Climate Change, Computational Geometry

JEL Classification: C60, D81, Q42, Q48

The research leading to these results has received funding from the European Research Council under the European Community's Programme Ideas - Call identifier: ERC-2013-StG / ERC grant agreement n. 336703 project RISICO RISk and uncertainty in developing and Implementing Climate change policies.

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A simple framework for climate-change policy under model uncertainty

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November 2016

Abstract

We propose a novel framework for the economic assessment of climate-change policy. Our main point of departure from existing work is the adoption of a "satisficing", as opposed to optimizing, modeling approach. Along these lines, we place primary emphasis on the extent to which different policies meet a set of goals at a specific future date instead of their performance vis-a-vis some intertemporal objective function. Consistent to the nature of climate-change policy making, our model takes explicit account of model uncertainty. To this end, the value function we propose is an analogue of the well-known success-probability criterion adapted to settings characterized by model uncertainty. We apply this decision criterion to probability distributions constructed by Drouet et al. (2015) linking carbon budgets to future consumption. The main result that emerges is the superiority of "medium" carbon budgets in line with a 3°C target (i.e., 2000-3000 $GtCO_2$) in preventing large future consumption losses with high probability. Insights from computational geometry facilitate computations considerably, and allow for the efficient application of the model in high-dimensional settings.

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1 Introduction

Policy makers want direct answers to simple questions, yet such demands are frequently at odds with the complexity of economic analysis and forecasting. The economic assessment of climate change policy, an enterprise vexed by multiple layers of uncertainty, provides a salient case in point.

The economics of climate change are characterized by two fundamental challenges. First, there is deep uncertainty regarding the dynamic response of the climate to emissions, the damages higher temperatures will cause to economic activity, and the costs of climate-change mitigation and adaptation. The uncertainty surrounding these crucial modeling inputs falls under the category of *model uncertainty* (Marinacci [18]), meaning that it cannot be captured by unique Bayesian priors. Second, there is strong disagreement regarding the underlying *ethical objective* that policies should strive to meet. These are manifested in vigorous debates regarding the functional form of the objective function, its coefficients of intertemporal substitution and risk aversion, and the magnitude of future discount rates (for a particularly vehement exchange between two eminent economists see Roemer [23, 24] and Dasgupta [9, 10]). Preferences over such parameter values tend to reflect different fundamental ethical stances. As illustrated by the Roemer-Dasgupta conflict, adjudicating between them is a matter of subjective judgment and/or political debate that cannot be resolved via empirical analysis.

Despite these difficulties, the current paper rigorously engages with policy makers' concerns for clarity and simplicity. It does so by posing the following question, versions of which recur in the global negotiations regarding climate change: *Given the deep uncertainty surrounding climate-change estimates, which policy ensures that adverse future impacts are avoided with highest confidence?* To address this question, we adopt a so-called *satisficing*, as opposed to optimizing, modeling framework. First introduced by Herbert Simon in the nineteen-fifties [25, 26], satisficing models assume that people reason in terms of meeting a goal (or, alternatively, respecting a constraint), not of optimizing some objective. Over the years they have been shown to hold significant descriptive power [6] as well as normative appeal [7, 4, 17]. The specific decision-making criterion we propose can be viewed as an analogue of the well-known success-probability criterion [7, 4] adapted to settings characterized by model uncertainty. The uncertainty sets that form the backbone of our analysis are the *convex hulls* of already existing probability distributions, a choice that is suitable for our practical purposes and often discussed in the theoretical literature (e.g., Ahn [1], Olszweski [22], Danan et al. [8]). We exploit results from computational geometry [5, 15] to propose an efficient method of exactly computing the value function of this decision criterion. Under certain linearity assumptions on the constraint set, our geometric technique can accommodate high-dimensional problem domains and multiple goals and indicators.

In the paper's numerical section we apply our theoretical model to data by Drouet et al. [14]. Combining comprehensive data from the most recent IPCC AR5 reports with a novel statistical framework, these authors derived a range of plausible probabilistic estimates connecting carbon budgets to climate-change impacts given latest scientific knowledge. These differing estimates correspond to different, but plausible, assumptions regarding mitigation costs, climate dynamics, and climate damages. As such, they reflect the multiplicity of expert opinion on these issues, embodying the model uncertainty alluded to earlier. The main result which emerges from our analysis is the superior performance of middle-of-the-road carbon budgets (ranging from 2000 to 3000 $GtCO_2$) in containing future consumption losses to non-catastrophic levels with high probability.

Related work in environmental economics has applied satisficing concepts to dynamic models of sustainable resource management. De Lara and Martinet [11] proposed a stochastic, dynamic-satisficing (referred to also as "stochastic viability") framework for resource management and computed optimal control rules under an extensive set of monotonicity assumptions on dynamics and constraints. Beyond its adoption of a satisficing as opposed to optimizing framework, a distinctive feature of their model is its focus on multiple criteria of economic and environmental performance. Martinet [19] and Doyen and Martinet [12] made an explicit connection between stochastic-viability models and sustainability concepts such as the maximin criterion. Doyen et al. [13] and Martinet et al. [20] applied similar ideas to a setting of sustainable fishery management. In the stochastic component of this work, emphasis was placed on calculating the probability of different policies respecting the various sustainability constraints. Where applicable, this was done via Monte Carlo simulation.

Our work differs from the above papers in substantive ways. First, our model accounts for model uncertainty by considering multiple probability distributions that link policy choices to future economic and environmental outcomes. Second, it does not rely on simulation as a tool for calculating success probabilities, as it exploits the problem's structure to provide exact numbers for these probabilities. Along related lines, the geometric techniques we employ allow us to efficiently study the implications of an (uncountably) infinite set of plausible probability distributions linking current policies to future impacts. Another important difference is our work's primary focus on one-shot future goals (e.g., sustainability guarantees for the year 2100) as opposed to dynamic constraints in optimal-control settings.

The paper is organized as follows. Section 2 introduces the model and formally defines the decision making criterion we adopt. It also discusses the suitability of convex hulls to the economic assessment of climate change and addresses important issues having to do with computation. Section 3 applies the model to climate-change data by Drouet et al [14]. Section 4 concludes and an Appendix collects all Figures and supplementary analyses.

2 Theoretical Model

The model's decision variable is the *carbon budget*, which we define as cumulative CO_2 emissions up to and including year 2100, indexed by b. Carbon budgets enjoy favor within the climate-modeling community for their robust statistical relation to global warming [21] and clear translation into policy [16].

There are $m = 1, 2, ..., M$ different *models* linking carbon budgets to future consumption, and we denote this set of models by $\mathcal{M}$. Conditional on carbon budget b, model m implies a probability distribution $\pi_t^m(\cdot|b)$ on relative consumption losses in year t compared to a world in which there are no climate damages. Collecting these distributions across models we define the set[1]

$$\Pi_b \equiv \{\pi^m(\cdot|b) : \ m \in \mathcal{M}\}, \tag{1}$$

summarizing the uncertainty of future consumption losses conditional on carbon budget b, as captured by all available models.

Convex hulls. In the analysis we pursue, we go beyond set Π_b by considering not only the distributions that make it up, but also the set of all their *convex combinations.* That is, for each carbon budget b we introduce and focus on the *convex hull* of Π_b, which we denote by CH_b. Formally,

$$CH_b \equiv \left\{ \sum_{m=1}^{M} \lambda_m \pi^m(\cdot|b) : \ \boldsymbol{\lambda} \geq \mathbf{0}, \ \sum_{m=1}^{M} \lambda_m = 1 \right\}. \tag{2}$$

We assume that the set CH_b encapsulates the entire universe of uncertain beliefs regarding the effect of carbon budget b on future consumption losses. Is this a sensible choice? An oblique way of addressing this question is to imagine examples in which the consideration of convex combinations is problematic. Such examples tend to involve cases in which there is some prior knowledge restricting the range of the "true" distribution. For instance, suppose we wish to make a decision on the basis of our shower's temperature. There are two experts, one of which claims that the water is freezing and the other that it is boiling hot. Suppose, further, that we *know* that one of the two experts *must* be correct (this may be because our water mixer is broken and unable to modulate between the two extremes). Then it is clear that if we consider the set of convex combinations of the two experts' beliefs, we will be taking into account a whole set of estimates implying that the water is tepid, in clear contrast to the binary nature of the true temperature. In such cases the use of convex hulls of probability distributions is ill-advised and should be avoided.

Do the socio-economic effects of climate change policy fall into the above category? We do not see how they could. Probabilistic projections of consumption losses are such that no expert (or model, or set of assumptions) is expected to be exactly "right". Like most questions in social science, the economic impact of carbon budgets

[1]Since the analysis will concentrate on year 2100, in what follows we omit the subscript t.

on future consumption patterns cannot be neatly summarized with unique probability distributions, even if the latter are updated over time with Bayesian methods. Instead, it seems reasonable to assume that the truth lies in some middle-of-the-road estimate that splits the difference between the various existing probabilistic models. If we accept this proposition, then it makes sense to consider the convex hull of all probability distributions as defining a probabilistic "realm of the possible" that can be used to guide decision-making.[2]

A satisficing framework. A recurring feature of climate-change negotiations is policy makers' reluctance to engage with traditional economic analysis. The intertemporal optimization models used by economists are deemed esoteric and overly dependent on assumptions that laymen cannot fully grasp. In addition, the false sense of determinism that a single optimal solution provides may be a source of well-justified suspicion. Still, as alluded to in the Introduction, policy makers seek simplicity. In the context of our paper's focus on carbon budgets as instruments for climate change policy, we translate this need into the following question:

> **Q1:** *If carbon budget b is chosen, is the probability that future consumption losses are no greater than $L\%$ at least p?*

In climate negotiations, policy makers tend to gravitate towards this kind of goal-oriented mindset when weighing the relative merits of different policies. Indeed, the much vaunted 2°C target is an example of a non-optimized goal policy makers seek to meet. It satisfies some requirements on the prevention of major natural disasters, but certainly it is not the result of any conscious optimization effort.

For any given distribution of future consumption losses, we can definitely answer the above question with a simple yes or no. Such clarity is impossible in an environment of model uncertainty where multiple distributions of future consumption losses conditional on b need to be taken into account. This means that the preceding question must be modified to reflect probabilistic ambiguity. We propose the following

[2] Note that such polyhedral uncertainty sets are often encountered in the decision-theoretic literature (e.g., Olszewski [22], Danan et al. [8]) and its applications to environmental policy (Athanassoglou and Bosetti [3], Danan et al. [8]).

adaptation:

> **Q2:** *If carbon budget b is chosen, what proportion of distributions in CH_b keep future consumption losses to at most $L\%$ with probability at least p?*

The parameters L and p are real numbers satisfying $L \in [0, 100]$ and $p \in [0, 1]$.

Let's now add some formalism to make the above a little more precise. We focus on future consumption losses with respect to a world without any climate change damages. This is clearly a continuous random variable with support $[0, 1]$. For tractability we discretize consumption losses in intervals of length $1/I$ where I is a natural number. Let Δ^{I-1} denote the $(I-1)$-dimensional simplex, i.e. $\Delta^{I-1} = \{\boldsymbol{\pi} \in \Re^I : \boldsymbol{\pi} \geq \mathbf{0},\ \boldsymbol{e}'\boldsymbol{\pi} = 1\}$.[3] Given a distribution $\boldsymbol{\pi} \in \Delta^{I-1}$, let $\pi(i)$ denote the probability of a consumption loss of $i\%$. Then, the set of distributions satisfying the sustainability requirement outlined above is given by the following expression:

$$\Pi(L, p) = \left\{ \boldsymbol{\pi} \in \Re^I : \boldsymbol{\pi} \geq \mathbf{0},\ \sum_{i=1}^{I} \pi(i) = 1,\ \sum_{i \leq L} \pi(i) \geq p \right\}. \tag{3}$$

The intersection of CH_b with $\Pi(L, p)$, denoted by $CH_b(L, p)$ includes all distributions of CH_b satisfying the constraint of set (3). Formally, it is given by:

$$CH_b(L, p) \equiv \left\{ \boldsymbol{\pi} \in \Re^I : \boldsymbol{\pi} \in CH_b,\ \sum_{i \leq L} \pi(i) \geq p \right\}. \tag{4}$$

With the above definitions and Eqs. (2) and (4) in place, we assume that the performance of a carbon budget b is measured by the following ratio:

$$V_L^p(b) \equiv \frac{\int_{\Re^I} \mathbf{1}\{\boldsymbol{\pi} \in CH_b(L, p)\}\, \mathrm{d}\boldsymbol{\pi}}{\int_{\Re^I} \mathbf{1}\{\boldsymbol{\pi} \in CH_b\}\, \mathrm{d}\boldsymbol{\pi}} \equiv \frac{Vol(CH_b(L, p))}{Vol(CH_b)}, \tag{5}$$

where Vol denotes volume in I-dimensional space.

Thus, given a carbon budget b, the quantity $V_L^p(b)$ calculates the *proportion* of distributions belonging to CH_b that ensure consumption losses of *no more* than $L\%$ with probability *at least* p. The greater this quantity is the better, for any choice of L and p.

[3] $\boldsymbol{e}$ is an I-dimensional vector of all 1's.

The decision-making criterion of Eq. (5) is a particular kind of satisficing criterion adapted to a setting of model uncertainty. The goal that decision-makers want to meet (or, alternative, the constraint they want to satisfy) is that of ensuring that consumption losses do not exceed a threshold L. Translated to an environment with multiple probability distributions, this requirement is recast as a lower bound on the proportion of such "virtuous" probability distributions. As such, it is similar to satisficing measures that focus on so-called success probabilities [7, 4, 17]. In addition, this criterion can be viewed as an approximate special case of the one proposed and axiomatized by Ahn [1].

Computation. Granting that criterion V_L^p provides a sound basis for comparing alternative carbon budgets, is it computationally tractable? In engaging with this question, it is immediately clear that the high-dimensional integrals in Eq. (5) pose a formidable challenge. The usual way of proceeding is via approximations based on Monte Carlo simulation. This approach however can be both computationally costly as well as inaccurate, especially when working in high-dimensional settings such as ours.[4]

We thus take a different approach that draws on results from computational geometry (Bueler et al. [5]). This enables us to efficiently calculate the *exact* value of $V_L^p(b)$, without resorting to any approximations whatsoever. The key trick is to exploit the uncertainty sets' CH_b and $CH_b(L,p)$ polyhedral structure and reduce the computation of Eq. (5) to a smaller problem, which in turn can be tackled by standard volume-computation algorithms. Essential to this result is the linearity of the constraint in Eq. (3).

To this end, suppose that $I \geq M$, i.e. that the dimension of the consumption space is greater than the number of models. This is an innocuous assumption since consumption losses are a continuous variable, typically discretized in intervals of (arbitrarily) small length (e.g., intervals of 1%), and the number of climate models is generally no more than 10 or 20.[5] Define the $I \times M$ matrix (the $\pi^i(\cdot|b)$'s are implicitly

[4]Any meaningful discretization of consumption losses -a continuous variable- will be high-dimensional.

[5]If for some reason we wanted to impose $M > I$ (so that our problem is effectively already

assumed to be column vectors)

$$\mathbf{\Pi}_b \equiv \left[\pi^1(\cdot|b), \pi^2(\cdot|b), ..., \pi^M(\cdot|b)\right]$$

collecting all the distributions in set $\mathcal{P}_b$. We assume the matrix $\mathbf{\Pi}_b$ has full column rank, i.e., that the elements of Π_b are linearly independent (if this is not the case, we drop one of the linearly dependent distributions at random and continue). Let us define now the linear transformation $T_b : \Re^M \mapsto \Re^I$, where

$$T_b(\boldsymbol{x}) = \mathbf{\Pi}_b \cdot \boldsymbol{x} = \sum_{m=1}^{M} \pi^m(\cdot|b)x_m.$$

Now, consider the sets

$$\begin{aligned} \Lambda &= \left\{ \boldsymbol{\lambda} \in \Re^M : \boldsymbol{\lambda} \geq \mathbf{0}, \sum_{m=1}^{M} \lambda_m = 1 \right\}, \\ \Lambda_b(L,p) &= \left\{ \boldsymbol{\lambda} \in \Re^M : \boldsymbol{\lambda} \in \Lambda, \sum_{m=1}^{M} \lambda_m \left(\sum_{i \leq L} \pi^m(i|b) \right) \geq p \right\}. \end{aligned}$$

Clearly, CH_b and $CH_b(L,p)$ are equal to the images under T_b of Λ and $\Lambda_b(L,p)$, respectively.[6] Since matrix $\mathbf{\Pi}_b$ is assumed to have full column rank, elementary linear algebra implies:

$$Vol(CH_b) = \sqrt{\det[\mathbf{\Pi}_b' \cdot \mathbf{\Pi}_b]}\, Vol(\Lambda) \tag{6}$$

$$Vol(CH_b(L,p))) = \sqrt{\det[\mathbf{\Pi}_b' \cdot \mathbf{\Pi}_b]}\, Vol(\Lambda_b(L,p)). \tag{7}$$

As a result, Eqs. (6)-(7) yield

$$V_L^p(b) = \frac{Vol(\Lambda_b(L,p))}{Vol(\Lambda)}. \tag{8}$$

This is very good news because it means that the problem's dimensionality has been reduced from I, typically a large number, to M, the number of different models. Since $\Lambda = \Delta^{M-1}$, where Δ^{M-1} denotes the $(M-1)$-dimensional simplex, we have $Vol(\Lambda) = \frac{\sqrt{M}}{(M-1)!}$. Furthermore, we can use the equality constraints in Λ and $\Lambda_b(L,p)$ to eliminate a variable and reduce their dimension to $M-1$. After this elimination,

low-dimensional), we would proceed directly without reducing Eq. (5) to Eq. (8).

[6]Note how $\sum_{i \leq L} \left(\sum_{m=1}^{M} \lambda_m \pi^m(i|b) \right) = \sum_{m=1}^{M} \lambda_m \left(\sum_{i \leq L} \pi^m(i|b) \right)$.

the denominator of Eq. (8) becomes $\frac{1}{(M-1)!}$. Conversely, we can compute the value of the numerator using insights from computational geometry and volume computation (see Bueler et al. [5]). In this paper's numerical exercise, we use an efficient Matlab implementation of state-of-the-art volume computation algorithms due to Herceg et al. [15].

Extensions. The power and efficiency of the volume-computation algorithms we employ mean that the decision-making criterion of Eq. (5) can be extended in a number of meaningful directions. In particular, the following enhancements can be made to the basic model of Section 2:

(i) *multiple linear (in $\boldsymbol{\pi}$) constraints.* For instance, we could add to set $CH_b(L,p)$ a constraint imposing that the expected value of future consumption losses not exceed some limit. Analogously, we could include similar bounds on higher moments of future consumption losses.[7] In addition, if we had data on the distribution of consumption across and within countries, we could have used them to impose "equity" requirements of various types. As long as the additional constraints are linear in $\boldsymbol{\pi}$, the underlying structure of the problem does not change. We can perform a similar reduction of the problem's dimensionality as in Eq. (8) and subsequently use the same algorithm as before to calculate volumes.

(ii) *multiple indicators.* For example, staying within the climate-change setting, we could consider not only probability distributions on future consumption but also on pure temperature increase. Setting bounds on the latter could be considered a sort of "ecological" constraint, similar in spirit to the ones considered in the stochastic viability literature (e.g. [11, 19, 20]). Such an operation would increase the problem's dimensionality considerably, but it can be addressed, so long as the total number of distributions across indicators is not excessive.

[7] Note that moment constraints can be made linear by raising both sides of the inequality to the corresponding inverse power.

3 Application

In this section we apply the decision-theoretic criterion of Eq. (5) to climate-change data from Drouet et al. [14]. Using the most recent modeling output from the three IPCC AR5 working groups, Drouet et al. developed a novel statistical framework to derive a *set* of probability distributions linking carbon budgets to future damages, consumption, and welfare. These probability distributions are built on the basis of different (but plausible) modeling assumptions regarding (i) mitigation costs, (ii) temperature dynamics, and (iii) climate damages. For the purposes of our analysis we disregard uncertainty in temperature dynamics and retain six of Drouet et al.'s [14] modeling assumptions corresponding to the different combinations of mitigation costs (top-down and bottom-up) and climate damages (quadratic, exponential, and sextic damage function).[8] We do so because we find that the latter two factors account for a much greater proportion of the variation in 2100 consumption levels.[9]

In the present paper we draw from the part of Drouet et al.'s analysis that connects carbon budgets to consumption losses in year 2100. To be clear, we are referring to per capita consumption as defined in the second page of the Methods section of Drouet et al. [14]. This formulation is standard in the climate-change economics literature. We focus on year 2100 because of its symbolic and substantive status as a future date in which the effects of climate change will begin to be seriously felt. Furthermore, 2100 is the farthest in the future that integrated assessment models can reasonably reach. Finally, carbon budgets (i.e., our model's decision variable) are defined as total greenhouse-gas emissions up to year 2100 so our emphasis on 2100 is appropriate in this sense as well.

Consistent with the range of carbon budgets examined by Drouet et al., we examine nine carbon budgets ranging from 1000 to 5000 $GtCO_2$ in increments of 500. A carbon budget of 1000 $GtCO_2$ represents the adoption of an extremely stringent policy that rapidly accomplishes a complete transition from fossil fuels to renewable

[8]Specifically, looking at Section S12 of Drouet et al.'s supplementary information, we assume temperature is fixed to "climate-all" and consider all combinations of {mitigation-BU, mitigation-TD} and {damage sextic, damage quadratic, damage exponential}.

[9]Details available upon request.

energy sources. Conversely, a carbon budget of 5000 $GtCO_2$ represents a business-as-usual energy trajectory that takes no special measures to reduce fossil-fuel use.

We start by focusing on 2100 global consumption losses that are between 5 and 20 percent, i.e. we consider $L \in [5, 20]$. Losses in this range are considered very grave, to the extent that they are comparable to major economic calamities such as the Great Recession of 2008 and the Great Depression of the United States in the 1930's. As such, policy makers should seek to avoid them with high probability, which is why we focus on high values for p, namely $p \in [.8, 1]$.

Figure 1 summarizes the value of V_L^p for this range of L and p for the nine carbon budgets under consideration. A clear pattern emerges. High carbon budgets (especially those equaling or exceeding 4000 GtCO2) do uniformly worse for all values of L and p. The best-performing carbon budget is among the middle-of-the-road choices, ranging from 2000 to 3000 GtCO2.

Table 1 provides additional evidence of this finding. It compares the performance of three carbon budgets (1000-3000-5000 $GtCO_2$), representing stringent, "medium", and business-as-usual climate policies, across a range of L and p.

$L \setminus p$	.80	.85	.90	.95	.99
5	[0, .01, 0]	[0, 0, 0]	[0, 0, 0]	[0, 0, 0]	[0, 0, 0]
10	[1,1,.63]	[.66, 1, .32]	[0, .96, .07]	[0, .29, 0]	[0, 0, 0]
15	[1, 1, 1]	[1, 1, .91]	[1,1,.58]	[.32, 1, .12]	[0, .28, 0]
20	[1, 1, 1]	[1, 1, 1]	[1, 1, .96]	[1, 1, .46]	[0, 1, 0]
25	[1, 1, 1]	[1, 1, 1]	[1, 1, 1]	[1, 1, .82]	[.45, 1, .03]

Table 1: $\left[V_L^p(1000\ GtCO_2), V_L^p(3000\ GtCO_2), V_L^p(5000\ GtCO_2)\right]$ evaluated at different levels of L and p (truncated at two significant digits). A medium carbon budget of 3000 $GtCO_2$ uniformly outperforms its very stringent (1000 $GtCO_2$) and business-as-usual (5000 $GtCO_2$) counterparts. Moreover, business-as-usual is by far the worst option.

It becomes clear that a medium carbon budget uniformly outperforms the two extremes, occasionally significantly so. In fact, for all the $L-p$ combinations appearing in Table 1, it is the *highest-performing* carbon budget among the nine examined (oftentimes uniquely so). This is because its middle-of-the-road approach guards against consumption losses that are due both to high mitigation costs and high climate damages. The differences can occasionally be striking: consider for instance $L = 10$ and $p = .9$. Here, a medium carbon budget does exceedingly well, as 96% of all pdfs in CH_{3000} manage to contain losses at 10% with probability at least .9. The corresponding figures for the very stringent and business-as-usual policies are 0 and 7% respectively. Finally, it should be mentioned, even though it does not appear in the Table, that a carbon budget of 2500 $GtCO_2$ is always at least the second-best choice after 3000 $GtCO_2$ (occasionally tying for first), for these combinations of L and p.

The dominance of medium carbon budgets is borne out even more strongly when we take a closer look at the results. Table 2 reports the results of direct head-to-head comparison for all pairs of carbon budgets. That is, given a pair of carbon budgets (b_i, b_j), it reports the proportion of $(L, p) \in [5, 20] \times [.8, 1]$ for which $V_L^p(b_i) > V_L^p(b_j)$. In other words, it calculates the percentage area within the $L - p$ rectangle $[5, 20] \times [.8, 1]$ in which carbon budget b_i *strictly outperforms* b_j according to criterion $V_L^p(\cdot)$. Formally, given $\mathcal{L} \subseteq [0, 100]$ and $P \subseteq [0, 1]$, we are referring to this quantity

$$E_{b_i b_j}(\mathcal{L}, P) = \frac{\int_{(L,p)\in\mathcal{L}\times P} \mathbf{1}\{V_L^p(i) > V_L^p(j)\} \mathrm{d}L \, \mathrm{d}p}{\int_{(L,p)\in\mathcal{L}\times P} \mathrm{d}L \, \mathrm{d}p}.$$

Table 2 summarizes the values of $E_{b_i b_j}([5, 15], [.8, 1])$ for all pairs of carbon budgets considered in this analysis.[10] If $E_{b_i b_j} > E_{b_j b_i}$, then the former appears in bold. Clearly, $E_{b_i b_j} + E_{b_j b_i} \leq 1$ with equality if and only if the two carbon budgets yield equal values of V_L^p over a region of zero Lebesgue measure.[11] A cursory look at Figure 1, with its sizable 0-1 regions shows this not to be the case, so that $E_{b_i b_j} + E_{b_j b_i} < 1$ for all pairs of carbon budgets. Table 2 provides additional evidence for the qualitative results that were discussed earlier. A carbon budget of 3000 $GtCO_2$ is shown to dominate all others, while the situation is completely reversed for a choice of 5000 $GtCO_2$.

[10] To reduce clutter from now on we drop the argument of $E_{b_i b_j}(\cdot)$, unless necessary.

[11] We note in passing that the pairwise-dominance information encoded in the E matrix can be used to determine an optimal policy via the application of methods from the social-choice literature (see, e.g., Athanassoglou [2]).

carbon budget	1000	1500	2000	2500	3000	3500	4000	4500	5000
1000	0	0	0	0	0	0	0.11	0.33	**0.49**
1500	**0.43**	0	0	0	0	0.07	0.29	**0.55**	**0.71**
2000	**0.53**	**0.44**	0	0.02	0.04	0.25	**0.55**	**0.73**	**0.84**
2500	**0.58**	**0.49**	**0.42**	0	0.08	**0.53**	**0.65**	**0.79**	**0.90**
3000	**0.59**	**0.50**	**0.41**	**0.37**	0	**0.54**	**0.66**	**0.79**	**0.90**
3500	**0.58**	**0.46**	**0.28**	0	0	0	**0.65**	**0.78**	**0.89**
4000	**0.51**	**0.33**	0.08	0	0	0	0	**0.76**	**0.86**
4500	**0.39**	0.17	0.01	0	0	0	0	0	**0.82**
5000	0.29	0.07	0	0	0	0	0	0	0

Table 2: $E_{b_i b_j}(\mathcal{L}, P)$ for all pairs of carbon budgets and $\mathcal{L} = [5, 20]$ and $P = [.8, 1]$ (truncated at two significant digits). "Winning" performances are highlighted in bold. The dominance of the medium carbon budget of 3000 $GtCO_2$ becomes apparent.

Next, we investigate these nine carbon budgets' potential of meeting stronger guarantees on consumption losses. In particular, we zero in on losses ranging from 1 to 5 percent. Containing losses to such modest levels would represent a very good outcome for the world. Yet, current estimates suggest it may be too late to attain, at least with a reasonable degree of confidence.

Figure 2 depicts the relevant results and Table 3 summarizes a set of corresponding V_L^p values for the same three carbon budgets (very stringent, medium, and business-as-usual) mentioned before. The patterns previously observed in Figure 1 are still present in Figure 2. It is evident that middle-of-the-road carbon budgets (2000-3000 GtCO2) offer the best chance of containing consumption losses to modest levels. The only exception to this statement applies to very low damages. For example, in Table 3 we see that a little more than a fifth of the pdfs in CH_b for $b = 1000$ $GTCO_2$ imply losses of $L \leq 1$ with probability at least .05, whereas no other carbon budget achieves losses this low with probability at least .05. That said, $p = .05$ is a low probability offering little insurance against such losses, so it would be wise not to make too much of this fact.

$L \setminus p$	.05	.10	.20	.40	.60	.80
1	[.21, 0, 0]	[0, 0, 0]	[0, 0, 0]	[0,0,0]	[0, 0, 0]	[0, 0, 0]
2	[.95, 1, .92]	[.72, .80, .32]	[.10, .03, 0]	[0, 0, 0]	[0, 0, 0]	[0, 0, 0]
3	[1, 1, 1]	[1, 1, 1]	[.95, 1, .59]	[.02, .10, 0]	[0, 0, 0]	[0, 0, 0]
4	[1, 1, 1]	[1, 1, 1]	[1, 1, 1]	[.87, .98, .25]	[0, .10, 0]	[0, 0, 0]
5	[1, 1, 1]	[1, 1, 1]	[1, 1, 1]	[1, 1, .93]	[.22, .87, .03]]	[0, .01, 0]

Table 3: $\left[V_L^p(1000\text{ GtCO}_2), V_L^p(3000\text{ GtCO}_2), V_L^p(5000\text{ GtCO}_2)\right]$ evaluated at different levels of L and p (truncated at two significant digits).

4 Conclusion

This paper has presented a model for decision-making under model uncertainty. Its main conceptual departure from existing work is the integration of ideas from the literature on satisficing (Simon [25, 26]) into an ambiguity-aversion framework. The value function that we propose is an adaptation of the success-probability criterion (Castagnoli and LiCalzi [7]) to a setting of non-unique probability distributions linking actions to consequences. This connection between the model-uncertainty and satisficing literatures is (to the best of our knowledge) novel, as is the application of results from computational geometry to facilitate calculations.

We apply our decision criterion to a set of distributions derived by Drouet et al. [14] linking carbon budgets to future consumption losses. The main finding of our analysis is the superiority of medium carbon budgets (2000-3000 GtCO_2) in preventing grave consumption losses with high probability. Such medium-sized carbon budgets also perform best when imposing more stringent consumption-loss targets. The intuition for this result is that medium carbon budgets are able to significantly decrease climate damages without imposing very high mitigation costs.

Appendix

A1 Comparison with Monte Carlo simulation based on Latin hypercube sampling

It is reasonable to ask how our geometric technique compares to the results of an equivalent simulation exercise. To answer this question we performed the exact same computations by using Latin Hypercube sampling to sample 10000 points in the 5-dimensional simplex. This leads to roughly similar running time. Figure 3 summarizes the relevant results. Comparing it to Figure 1, we notice qualitatively similar patterns regarding the superior performance of medium carbon budgets and poor performance of business-as-usual scenarios. However, we also see that the simulation-based method doesn't fully capture the true range of the V_L^p criterion, as it tends to expand the area of the $L - p$ graphs with binary 0-1 values. This imprecision is relatively harmless in the current example but could become problematic when there is greater divergence between the pdfs whose convex hull we are considering. Higher dimensionality could also pose significant hurdles for a pure simulation-based approach due to the "curse of dimensionality".

A2 Figures

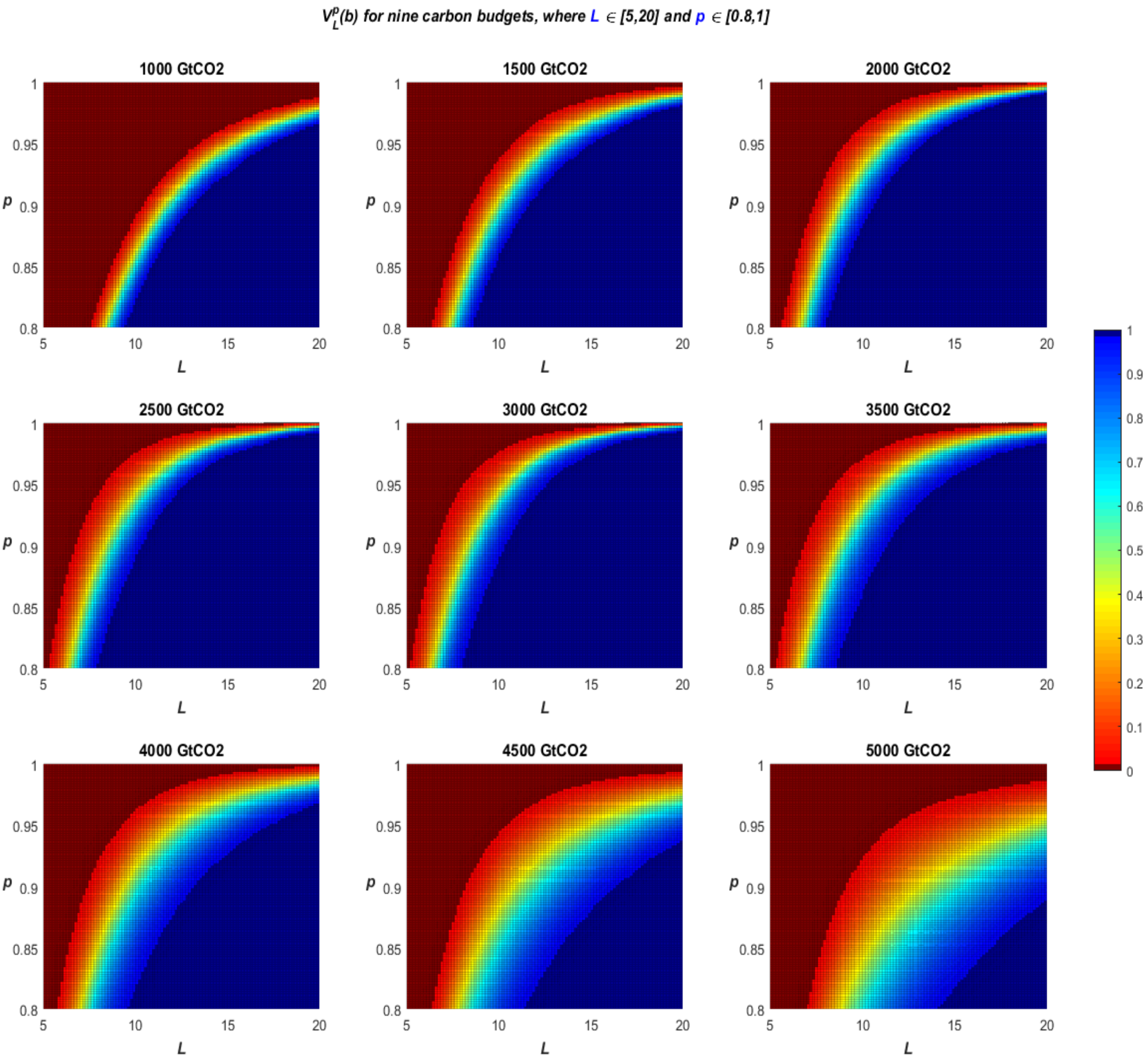

Figure 1: Applying criterion $V_L^p(b)$ to nine carbon budgets using the data of Drouet et al. [14], in the range $L \in [5, 20]$ and $p \in [0.8, 1]$. Medium carbon budgets (2000-3000 $GtCO_2$) are shown to be superior in containing catastrophic consumption losses with high probability.

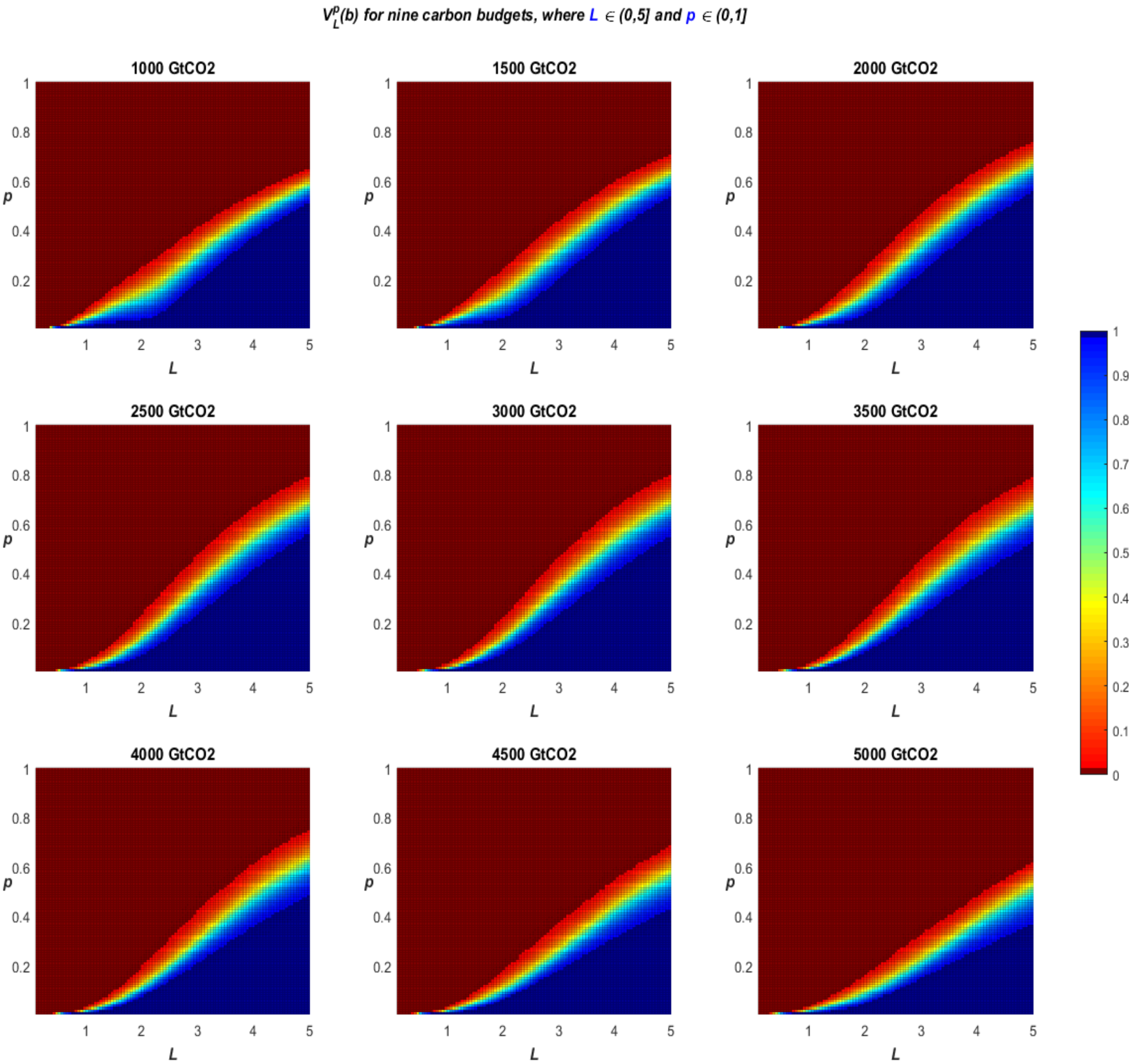

Figure 2: Applying criterion $V_L^p(b)$ to nine carbon budgets using the data of Drouet et al. [14], in the range $L \in [1, 5]$ and $p \in (0, 1]$. Medium carbon budgets (2000-3000 $GtCO_2$) are shown to be superior in containing mild consumption losses with low, but non-zero, probability.

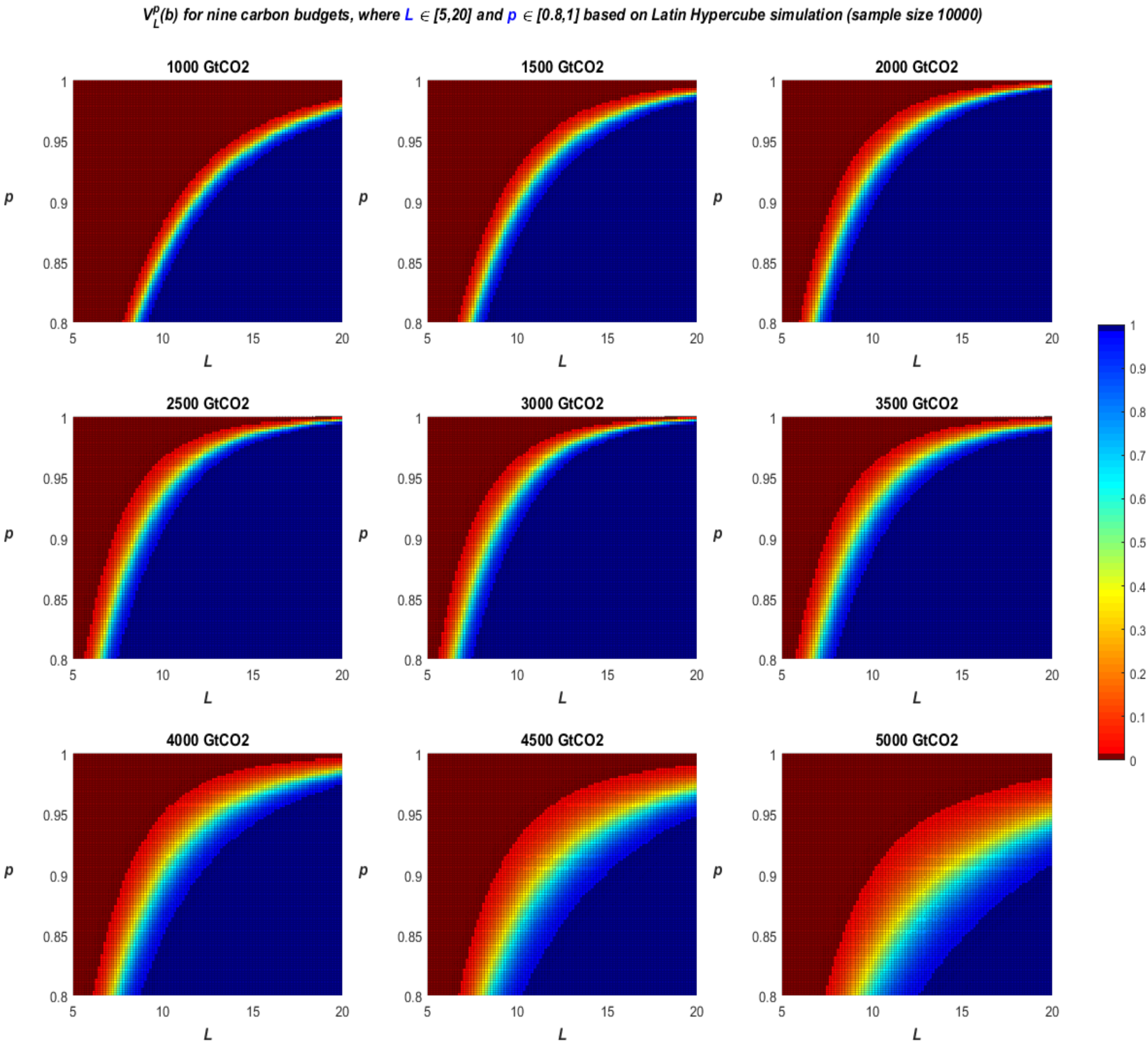

Figure 3: Monte Carlo simulation estimates (using Latin Hypercube sampling) of V_L^p for nine carbon budgets using the data of Drouet et al. [14], in the range $L \in [5, 20]$ and $p \in [0.8, 1]$. Compared to Figure 1, some of the true uncertainty has been suppressed, with a greater proportion of 0-1 values appearing in the graphs.

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