EU Impact Assessments and Deep Uncertainty

COVID-19 Lessons for Better Regulation

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1. Introduction: Better Regulation framework did not help to be prepared

The European Commission has put in place an elaborate system of policy decision making procedures. Better Regulation aims to implement processes that ensure transparent, evidence-based policy making. Stakeholders are invited during a consultation process to express their views and have insight into how the services uses them in policy documents. The Commission has earned praise for Better Regulation, in the OECD´s Regulatory Policy Outlook (OECD, 2021) it earns high marks for how it organizes rulemaking, but it does not seem to have helped resilience when the Covid-19 pandemic emerged. The response of the Commission to the criticism of how it managed the pandemic had many aspects.[1] This paper argus that the experience of the pandemic suggests that Better Regulation can better contribute to being prepared for uncertain events. Specifically, the rules for preparing impact assessments lack provisions for deep uncertainty or ´ambiguity´ in the parlance of decision theory. It refers to situations where decision makers lack data to assign probabilities to future events. They are therefore unable to apply the textbook ¨decision making under uncertainty¨ methods.

The Better Regulation policy process is not prepared for dealing with unforeseen events. The regular policy cycle needs months of collecting data, mobilizing scientific advice, and consulting stakeholders. In cases where a rapid policy response is required, the Commission suspends the rules for decision making. In terms of the OECD Regulatory Policy and Governance indicators, the lack of ´systematic adoption´ is a reason the European Union does not rank first. Without contingency plans for emergencies, policy making is ad hoc and prone to make mistakes.

Much of the guidance for impact assessments assumes that there is a known unique best response to policy problems. During the pandemic expert dissensus between experts became obvious even in public discussions. It was often impossible to identify differences in recommendations with differences in epidemiological forecasts, as model-based predictions were combined with political value judgements how to solve trade-off between the

[1] See for example the leader of the Economist, *How Europe has mishandled the pandemic*, March 21st, 2021.

interests of different affected groups. Public disagreement between experts weakened the influence on policy making, which in many cases diverged from expert recommendations.

The lack of a process to learn from multiple sources of advice and to distinguish between the evidence-base and political judgement led to frequent policy changes. The changes were often contrasting expert advice, risking raising doubts on evidence-based policy making.

Even before the pandemic the European Commission had taken steps to counter built-in short-termism. It aims at creating Strategic Foresight Network to "explore different possible futures, alongside the opportunities and challenges they might present." The implementation is led by the Secretariat-General and the Joint Research Centre's foresight capacities. It seeks cooperation with other EU institutions, notably the European Strategy and Policy Analysis System (ESPAS). The network evolves through international partnerships, drawing also on the Member States' public foresight capabilities.[1]

Strategic foresight can help impact assessments by adopting systematic ways to account for deep uncertainty or ambiguity. The lack of such methods has become evident in the pandemic. It is a deficit that only concerns emergency measures in an emerging crisis. Before the pandemic, the need to account for ambiguity has been voiced for macro-policies and policy making in general.[2] The account for ambiguity would add a new dimension to the policy cycle that leads to a progressive improvement of policy advice.

2. Which Better Regulation method for impact assessments?

The Commission's guidance on how to do impact assessments allows for several methods.[3] With no constraints on data availability and technical means to monetize costs and benefits the preferred method is cost-benefit analysis. Cost-benefit analysis aspires to the ideal that all physical costs and benefits can be made commensurable and comparable by applying "willingness to pay" as monetary measuring unit. This is in line with the standards for example of the OECD (Atkinson *et al.*, 2018) and in the US (Sunstein, 2018) but it is at the same time at variance with the broader context of Better Regulation.

[1] Strategic foresight | European Commission (europa.eu).
[2] For prominent examples see Hansen's Nobel Prize lecture (2014) and Mervyn King's and John Kay's reflections on the practice of policy making (2020).
[3] See chapter eight of the Better Regulation Toolbox (European Commission, 2017b)

The better regulation agenda of the European Commission aims to counter complaints that decision-making processes are opaque and distant from the interest of the Europe's citizens, executed by "unelected bureaucrats". One of its main objectives was to create greater transparency.[1] The Juncker Commission, with Senior Vice President Timmermans in charge of the agenda has publicly emphasized this understanding of Better Regulation. The Better Regulation Guidelines are clear on the general objective of the agenda: "Better regulation is not about regulating or deregulating. It is a way of working to ensure that political decisions are prepared in an open, transparent manner, informed by the best available evidence and backed by the comprehensive involvement of stakeholders." (European Commission, 2017a)

2.1. Cost-benefit analysis if you can quantify?

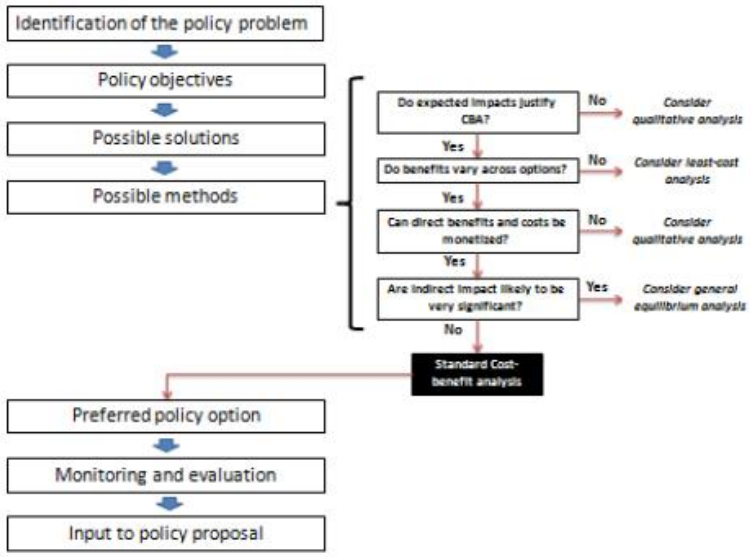
How to prepare policy decisions was formalised in detailed rules and procedures.[2] This differed markedly from the absence of such rules for other institutions for regulatory supervision in some other countries. It differed also from the prescription of cost-benefit analysis as the only method, like for example in the US.[3] The main principle of the Executive Order 12291 of the Reagan administration was that "Regulatory action should not be undertaken unless the potential benefits to society for the regulation outweigh the potential costs to society." To live up to this principal, each impact assessment must assess benefits and costs of an initiative and the former must exceed the latter. The Commissions toolbox is less prescriptive. It allows to choose from several methods, giving a degree of freedom on quantification and how to enter political value judgements.

The acceptance of methodological pluralism was first expressed in the 2002 Communication on Impact Assessment (European Commission, 2002), stating that "a number of analytical methods can be used to assess impacts. They differ in concept and coverage (e.g., cost-benefit analysis, cost-effectiveness analysis, compliance cost analysis, multi-criteria analysis and risk assessment)."[4] Which method to choose was left to the policy maker or analyst: "The choice of method and the level of detail will vary with the nature of the problem and judgements about feasibility."

[1] See the discussion in Iso-Markku (2020)
[2] See the Better Regulation "Toolbox". (European Commission, 2017b)
[3] See for example history of evaluation for secondary legislation in the US in Sunstein (2018).
[4] See the discussion in Renda (2020).

The methodological guidance became more prescriptive, giving greater weight to cost-benefit analysis, with its revision of 2009. It made the methodological choice dependent on the quantifiability of costs and benefits in impact assessments. If quantification of costs and benefits were possible, the justification of policy interventions should depend on positive net benefits. The Better Regulation Toolbox of 2015 reflected this position and is summarised in Figure 1.

Figure 1: Method choice for impact assessments as a matter of quantification



Source: Renda et al. (2013)

2.1.1. The practice of impact assessments deviates from the intentions of the rules

In the practice of impact assessments, cost-benefit analysis did not get a prominence that would see other methods only in cases of extraordinary quantification constraints. The feasibility of quantification did not determine whether cost-benefit analysis was the method used for an impact assessment.[1] That cost benefit analysis and general equilibrium analysis was infrequently used, and least cost analyses and qualitative analysis (presented as "multi-criteria analysis") was used more frequently than anticipated has to do with the rejection of its conceptual underpinnings. Least cost analysis and qualitative analysis were chosen not because benefits were equal across options or could not be monetised. The reasons for infrequent use of cost-benefit analysis lie elsewhere.

[1] See, for example, Regulatory Scrutiny Board (2018)

2.1.2. Cost-benefit analysis relies on discredited "revealed preference theory"

The prescription of cost-benefit analysis as the reference method for ex-ante policy evaluation follows from the normative position that only individual preferences should count. It excludes that group interests could differ from aggregates of the individual members' interests. Such representations of group interests should therefore play no role in policy analysis.

Similarly, cost-benefit analysis purists would argue that policy analysis for evidence-based policy making can and should be independent of the policy process. Policy decisions should be solely based on the choice behaviour of individual members of society. This choice behaviour would reveal the value policy initiatives create for society. It could be identified from observed behaviour revealing "willingness to pay" also for services that are not subject to market transactions.[1]

Behavioural economics has shown that choices do not necessarily reveal preferences. (Smith and Moore, 2010; Bernheim and Rangel, 2009) There is then no basis for the claim that individual preferences can be identified from observed behaviour. This has weakened the conviction that cost-benefit analysis is the only ideal method for policy analysis.

2.1.3. Cost-benefit analysis abstracts from the political process

One main reason for the infrequent use of cost-benefit analysis in EU impact assessments is that the individualistic norm leaves little room for genuine policy decisions. *The determination of distributional weights is the only decision left to policy makers.*[2] *In contrast to cost-benefit analysis, policy makers and bureaucrats understand the quality of outcomes and the quantity of benefits as something that should be in the domain of politics rather than expert analysis.* According to its assumptions, decision-makers follow expert advice without the constraints of electorate expectations, stakeholder views or discretionary powers of bureaucrats. This metaphor of an independent policy decision maker following

[1] See the critical discussion of other valuation methods in Diamond and Hausman (1994) and Hausman (2012).
[2] See for example the interactive process between analyst and policy makers in the UNIDO guidelines for policy evaluation (Dasgupta, Marglin and Sen, 1972) and OECD (Atkinson *et al.*, 2018). Most cost-benefit analyses do not consider even distributional issues, implicitly assuming that they should be addressed by distributional fiscal policies.

the expert advice formalised in a cost benefit analysis is rooted in a strict individualistic value judgement presented above.[1]

This normative foundation in welfare economics has been rejected by public choice theory, arguing that a welfare economic optimum may differ from the outcomes of political processes in a democratic society and therefore be of limited relevance for decision-making. (Besley and Coate, 2003; Acemoglu and Robinson, 2013; Zingales, 2020)

That the process of political decision making has a major influence on political outcomes has been confirmed, for example, by the empirical literature on infrastructure investment that identifies systematic biases in cost benefit analyses. Costs are underestimated and benefits overestimated to ensure "political success". (Flyvbjerg, Bruzelius, and Rothengatter, 2003; Priemus, Flyvbjerg, and van Wee, 2008)

Interpretable as a response to political economics' criticism of traditional policy evaluation tools and constraining the discretionary powers of the executive to exercise subjective judgements on the benefits of policy initiatives, the better regulation agenda included an obligatory consultation process. The better regulation guidelines require consultation with relevant stakeholders and the public for all impact assessments, evaluations, fitness checks and green papers. (European Commission, 2017a)

The process would start out from the publication of a consultation strategy, including a targeted consultation, identifying, and addressing concerns of relevant stakeholders, and an internet-based 12-week open consultation. The Directorates General must publish the overall consultation results on the dedicated website and add them in general as an annex to the impact assessment or evaluation report.

In this view, benefits are not to be measured against the individual preferences. For the EU, the conditional prescription of cost-benefit analysis as the central instrument for evidence-based policymaking has not led to a "triumph of the technocrat". (Sunstein, 2018) The results of the consultation process are processed for the impact assessment and to be published in an annex. The better regulation guidelines do not detail how the services should process the consultation outcomes for the impact assessments.

[1] Cost-benefit analysis is seen as applied welfare economics. See Just, Hueth and Schmitz (2004).

2.2 Multi-criteria analysis in case of restrictions on quantification

Standards in line with the Better Regulation Toolbox

The aim of all literature on multi-criteria analysis is to establish preferences for a set of options. It is supposed to ensure transparency of the data used, the options considered, and the criteria used to rank the options. (Dodgson, 2009) It details analytical steps to arrive at policy decisions and offers the opportunity to make expert and stakeholder contributions explicit. While there are many ways to arrive at a ranking of options (Keeney and Raiffa, 1976**;** Kourtit, Macharis, and Nijkamp, 2014**;** Govindan and Jepsen, 2016; Lode et al., 2021) they follow the same steps of analysis, like the 2017 Better Regulation Toolbox (European Commission, 2017b):

1. Establish what problem the analysis should address. Who is/are the decision maker(s)?
2. Establish a performance matrix
    a. Identify the objectives and specific variables that reflect the target achievement. (columns)
    b. Identify the options, based on an intervention logic. Which actions are expected to contribute to the specific target variables? (rows)
    c. Describe the expected impacts of the potential actions with respect to the specific target variables. (cell entries)
3. Make the impacts comparable by translating the physical outcomes into "values". This usually requires the scoring the outcomes.
4. Weight the criteria columns. Assign weights to reflect the relative importance of the specific outcome dimensions of the decision.
5. Aggregate the impact scores or values using the target weights and rank the overall impacts of the options.

The first two steps resonate closely with the general steps for impact assessments prescribed by the Better Regulation Guidelines, the problem analysis, and the identification of general and specific objectives. In a first step, in each cell of the performance matrix a physical variable would measure the impact of an option to the specific objective.

As these physical outcome values lack commensurability, like the monetary "willingness to pay" metric in cost-benefit analysis, the physical values must be transferred into a metric that indicates the relative contribution of an option to a specific objective.

For much of the literature on multi-criteria analysis this is a merely technical exercise.[1] Finding the weights for the criteria columns follows a procedure that aims to normalize the cell entries. [2] In this literature there is no discussion of how the values for the cell entries are identified. In the practice of the European Commission's impact assessments, the scoring of the options and the weighting of the 'criteria' corresponding to the specific objectives appears often only loosely related to the problem analysis and the stakeholder views elicited in the consultation process.

Guidance of the new Better Regulation Toolbox

The new Better Regulation Toolbox (2021) differs from much of the decision theoretic literature. The normative basis for the multi-criteria analysis is established in a three-step procedure:

> 1. *"Selection of the relevant social actors for the problem at hand.*
> 2. *Definition of social actors' values, desires, and preferences. Stakeholder consultation methods described in Chapter 7 can be used to deal with both steps 1 and 2. 3.*
> 3. *Generation of evaluation criteria to represent social actors' needs, preferences and desires." (p. 548)*

The impact assessment using multi-criteria analysis processes stakeholder views to select evaluation criteria. Evaluation criteria are defined as "an empirical indicator that associates each policy option with a variable indicating its desirability according to its expected real-world consequences." (European Commission, 2021, p.547) Scoring of criteria to make contributions to one criterion commensurable, is left to the analyst:

> *"Criterion scores can be both qualitative and quantitative; uncertainty can also be included. These assessments are the ones presented in the elements of the impact matrix." (p. 547)*

[1] This holds also for the methodology set out in the 2021 version of the Better Regulation Toolbox. (European Commission, 2021)

[2] The most prominent ones are the Analytical Hierarchy Process (AHP) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) (Brans and Vincke, 1985)

But scoring and the usual step to achieve commensurability is presented as unnecessary, scoring and weighting of different criteria is solved by a mathematical procedure in step 6:

> 6. *"Application of a mathematical procedure to rank all the policy options in a consistent way. Multi-criteria mathematics solves the standard objection that the aggregation of apples and oranges is impossible in a definitive way." (p. 548)*

The Toolbox suggests that these steps are done by a software SOCRATES, which has been developed by the Competence Centre on Modelling of the European Commission's Joint Research Centre.

Even if the cell entries and the weighting of the criteria do not involve political judgement, the algorithmic ranking exercise is open to pitfalls: (French, 1988)

- Scoring can easily be inconsistent. Pairwise comparisons lead to valuing the options that violate the transitivity requirement.
- The weighting of the criteria is often done with no or imperfect knowledge on the impacts and is revised when impact values are revealed.
- The introduction of new options can change the original ranking of options. The rank reversal phenomenon results from the fact that scoring and weighting of criteria are not independent of each other. (Belton and Gear, 1983)
- Information on the expected physical impacts will depend on expert information. The translation into scores and the weights will depend on preferences of policy makers and stakeholders. None of these procedures is unambiguously rooted in a value theory like the microeconomics of cost benefit analysis or statistical decision analysis.

The Multi Actor Multi Criteria Analysis

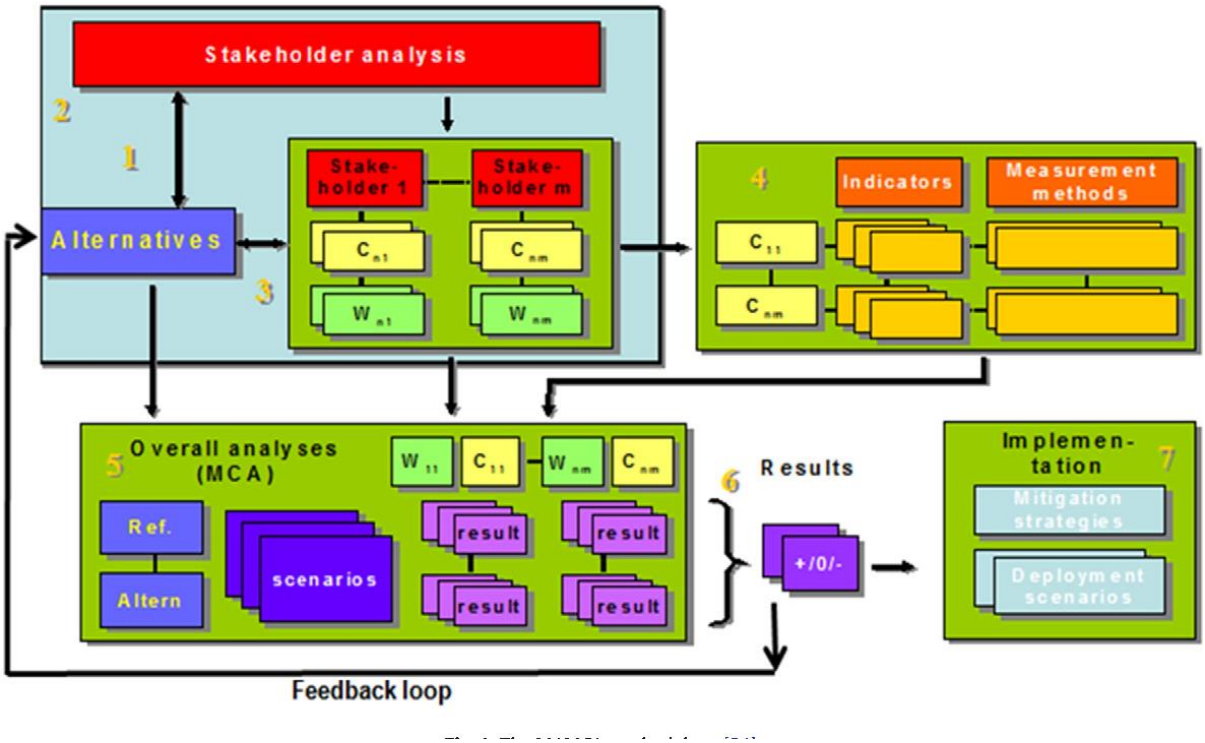
The political character of the multi-criteria analysis is recognized in the Multi Actor Multi Criteria Analysis (MAMCA). (Macharis, 2005; Lode *et al.*, 2021) It combines many of the general steps of an impact assessment.

It starts with a problem definition and the development of a baseline. It defines the specific objectives of policy options as "criteria". It foresees the elaboration of policy options as alternative scenarios, including the weighting of the criteria, the selection of performance

variables, data to be used and measurement methods. The ranking of the alternatives is done by the Analytic Hierarchy Process or outranking methods.

The MAMCA gives a lot of room to stakeholder involvement to evaluate objectives, measurement methods, scenarios, and analytics. It allows the organizers of the process a large degree of freedom in mobilisation evaluative inputs of interested parties. (Lode *et al.*, 2021) It lacks a clear view on the separation of technical expert inputs and the signalling of political positions by interested parties,

Figure 2: The process of the Multi Actor Multi Criteria Analysis



Source: Machairs (2005)

3. The COVID emergency was different

Policy making was very different when the crisis emerged. (Renda and Castro, 2020) It was not following the usual pattern of rapid decision making that had no obvious way of collecting and using data for decision making. It could not isolate itself from intense public policy debate. The actual process of decision making was, however, very different from what Better Regulation foresees. The rules showed deficits that bear on the regular policy-making cycle

3.1 Seeking an evidence-base for decision-making was not suspended as usual in cases of urgency

One reason why existing impact assessment rules failed to help respond to the Covid-19 shock is the fact that the rules for ex ante evaluation do not foresee shortcut processes in case of emergencies. Instead, governments can often suspend formal decision-making processes altogether.[1]

Interestingly, the common and accepted response to urgency was not to suspend seeking expert advice and public consultation altogether. In the COVID-19 crisis, decision makers, the media and public at large had a strong interest in data and sought an evidence-base for opinion formation and decision making. Rather than following the formalized decision-making, health agencies and statistical offices set up data dashboards in much shorter time than allotted in the regular decision processes.[2] Quantitative data on infection rates, the R-factor, and mortality rates were updated and reported in high frequency. They played a key role in public debates.

3.2 Expert advice was sought from many sources

How policymakers received expert advice remarkably differed from the usual acquisition of knowledge support for policy initiatives in formalised decision cycles. Responding to health system shocks, policymakers must take actions to protect their population from the emergence of yet unknown threats, lacking information for example about a virus and its transmission mechanism, on the effectiveness of feasible actions, and their health consequences and economic fallout. Policy makers tried to combine what they hold to be the best available scientific evidence, usually expert opinions, and modelling studies. It became obvious that there was no single best model to guide policies, not even in the narrow field of virology or epidemiology. In the US, for example, the CDC based its forecasts on ongoing work in health research institutes who had to coordinate in the Covid-19 ScenarioModeling Hub, with 9 models of 12 institutions being involved.[3] In the early phase

[1] This holds also for the European Commission, see BR-GL-Chapter 1-BR in the Commission (europa.eu)
[2] For the European Centre for Disease Prevention and Control (ECDC) see Download COVID-19 datasets (europa.eu), as an example for a national statistical office see All data related to coronavirus (covid-19) - Office for National Statistics (ons.gov.uk)
[3] Home - COVID 19 scenario model hub (covid19scenariomodelinghub.org) and GitHub - midas-network/covid19-scenario-modeling-hub: COVID-19 Scenario Modelling Hub and April 30 MIDAS Webinar - COVID-19 Scenario Modelling Hub - YouTube

of the outbreak views on pertinent information changed rapidly and was highly fluid. Individual sources of advice made claims that soon proved to be untenable. (Manski, 2020)

The diversity of advice got lost in the efforts to set up "integrated assessment models" that combined the epidemiological models with models to forecast the economic impact of the pandemic.[1] The integrated assessment models relied heavily on the SIR model, predicting the spread of a disease by the dynamic development of the number of people susceptible to the disease (S), the number of the infected (I) and the number of recovered patients (R).[2]

3.3 Policy advice and public debate did not distinguish between expertise and political judgement

The advice of virologists and epidemiologists was made public and led to controversies about mitigation measures. These debates suffered from uncertainties about what could be inferred from the data. The public debate blurred the boundaries between expert advice and judgements on how to balance policy trade-offs. This problem was exacerbated by a polarizing amplification by the media. For example, whether and for how long schools should be closed, or how many job losses in the hospitality sector should be accepted to reduce risks for the elderly required genuine policy decisions that are not a matter of epidemiological expertise. Faced with a high level of uncertainty, policy makers tend to adopt a particular representation of the pandemic and are led to misrepresent the situation. (Chater, 2020)

4. How to take policy decisions under ambiguity

The major deficit in the Better Regulation decision-making process that has become obvious in the COVID-19 crisis is the lack of a systematic way to address uncertainty. A traditional and most immediate approach to account for uncertainty would be to integrate expected utility theory into cost-benefit analysis. Outcomes of different policy options of impact assessments are no longer certain, but probabilities can be attached to potential impacts. Probability distributions can be used if they are based on regular mechanisms like flipping a coin or rolling dice, with full confidence in the probabilistic outcomes. With risk neutral decision makers, outcomes are ex ante evaluated as

[1] See the examples Eichenbaum et al. (2020) and Gollier (2021), and the review in Guerreri et al. (2020).
[2] The SIR Model for Spread of Disease - The Differential Equation Model | Mathematical Association of America (maa.org)

expected values, the sum of potential outcome values multiplied with the known probabilities. Policy makers select the option with the highest expected outcome value.

For most impact assessments the probability distributions are not known. Policy makers take decisions under "ambiguity" (Manski, 2007, ch. 11), "ignorance" (Arrow and Hurwicz, 1972; Maskin, 1979) or "Knightian uncertainty" (Knight, 1921). For most policies there is no history of interventions that would allow to find out the relative frequencies of observed policy outcomes. Policy problems are often unique and causally independent, leaving little opportunity to compute probabilities as empirical frequencies.

Ambiguity excludes that policy makers can optimise their decisions. Policy makers can discard some choice options if they are dominated, i.e., inferior to other options under all possible probability distributions. They cannot discriminate between undominated options because different distributions may lead to different rankings.

4.1.1. Bayesian decision making

As one way out, a branch of decision theory follows a Bayesian approach.[1] Bayesian decision analysis does not provide tools to identify priors. The unknown probabilities are replaced by subjective probabilities, indicating personal beliefs of the decision maker. In repeating decision situations, the subjective distributions are updated in the light of new data. The resulting posterior distributions are used for future decisions. Under certain axioms concerning the environment and behaviour of the decision maker, Bayesian decision making can be considered to be "rational". It does not exclude that it leads to bad decisions. (Berger, 1993, p. 121)

In many applications priors are not subjective values of decision makers but imposed for the sake of modelling convenience.[2] A frequent rationale for restricting the set of priors is the sensitivity to model predictions to the priors.

Another way of optimising on priors is to consider multiple priors, from different experts or different stakeholders, and evaluate them, making next period's priors a function of the current environment and current actions. The uncertainty about which of the multiple models should guide policies, model ambiguity, is solved by applying dynamic programming methods. (Hansen and Marinacci, 2016)

[1] See the Appendix for a simple example to distinguish the decision theoretic methods for deep uncertainty.
[2] See, for example, the critique of prominent macroeconomic models in Canova and Sala (2009), Blanchard (2016) and Romer (2016).

Robust decision making introduces a function to assess a decision maker's response to ambiguity about the prior. It associates a penalty with the choice of the priors. (Maccheroni, Marinacci and Rustichini, 2006) It maximises an objective function regarding policies, picking priors that imply pessimistic expectations to reflect the ambiguity aversion. The approach aims to avoid the sensitivity of outcomes to priors, which characterises the standard Bayesian decision making approach. Hansen and Sargent (2001) use a formulation with a reference prior and a relative entropy penalty.

To what extent can such methods guide policy decisions with deep uncertainty? All of them suffer from the critique of behavioural economics. (Gilboa, Rouziou and Sibony, 2018) p. 6 ff.

- Policy makers, experts and stakeholders tend to make systematic mistakes in scoring options of outcomes. (Kahneman and Tversky, 1979)
- Even when there is a frequentist basis for assigning probabilities for repeated events that occur conditional on known factors, like the frequency of fires or floods depending on measures to protect houses, the probabilities cannot be determined because there is no history of relevant data. In such cases, decision makers may find their subjectively perceived probabilities too vague and too ill-structured to be useful for decision theory tools. Beliefs are likely to differ between experts and stakeholders. The choice of probabilities may then be considered a matter of how politically opportune they appear. It may give reason to policy makers not to pick a particular prior.
- In considering potential negative outcomes decision makers have systematic difficulties to assign values to perceived losses. They are subject to loss aversion, a sunk cost error and an endowment bias. (Kahneman, Knetsch and Thaler, 1991)
- What is particularly problematic for a Bayesian view of decision-making under uncertainty is the fact that decision-makers make systematic mistakes in quantifying probabilities. (Tversky and Kahneman, 1982) They strongly overestimate the probability of salient but infrequent and hold conjunctions of events to be more probable than its components. The problem definition has an influence on how options are valued. (Tversky and Simonson, 2000) The way analysts frame the problem definition will lead to different rankings of policy options. Similarly, if decision makers anticipate and account for the regular ex post evaluation, that credit and blame will be attributed after the fact, they will be reluctant to take decisions under deep uncertainty. (Tversky and Kahneman, 1982)
- Related to the last point is a general bias towards the status quo. Critical reflection of what seem to be immediate options is avoided by disregarding negative data, following from a general confirmation bias. (Dean, Ozgur and Masatlioglu, 2017)

4.1.2. Maximin Criterion

The maximin criterion helps decision makers to hedge against the risk of overlooking events that could negatively impact on policy outcomes.[1] It focuses attention of decision makers on the effectiveness of intended policies. It asks how many members of the target population will benefit from an intended policy associated with conceivable pessimistic expectations concerning the policy outcomes, and what difference the policy makes to the baseline. The attention to the downside risks helps to contain the optimism bias identified by behavioural economics and increasingly recognized in policy making.[2]

For each of the options presented in an impact assessment, the experts and policy makers would consider a scenario with pessimistic assumptions on the occurrence of events that constrain or counter the effectiveness of the policy. Against the background of this min part of the decision-making process, the policy maker will select best (max) responses to the pessimistic expectations concerning the covariates of the policy action.

The maximin criterion will always lead to a singleton policy rule, that is, the same policy rule will apply for the entire population.

4.1.3. Minimax-regret criterion

The minimax-regret criterion avoids to base policy decisions only on pessimistic scenarios like the maximin criterion. It considers both optimistic and pessimistic expectations concerning the determinants of the effectiveness of policy options.[3] The potential regret associated with pessimistic expectations decreases with a greater policy intensity. It increases with the policy intensity in case of optimistic assumptions. The minimax-regret criterion tries to identify the option that balances these forces.

It is important to note that, in contrast to the maximin criterion, the minimax regret criterion does in general not lead to a singleton policy recommendation. It leads to policy proposals that try different policies for homogeneous groups of affected people to diversify the risk of policy mistakes. (Manski, 2007, pp. 237-238)

[1] See the Appendix for a simple example to distinguish the decision theoretic methods for deep uncertainty.
[2] See for example HM Treasury (2013).
[3] The Appendix shows that deep uncertainty and how to respond to it would even concern randomized control trials.

This characteristic lends itself, for example to the recommendation of "adaptive diversification" of Covid policies (Manski, 2020) or more general demands for regulatory experimentation (Greenstone, 2009), that have also become prominent in academic work on Better Regulation (Ranchordas, 2021) and debates in the relevant committee of the European Council.

5. Adapting to lessons for Better Regulation

The first lesson is a generalization of the early phase of the pandemic to similar, more general decision situations: Policy makers were confronted with little pertinent data, had no information on how applicable epidemiological model that had been tested in other outbreaks would be for COVID-19, and were confronted with fragments of ad hoc expert advice. This situation occurs in general when fast policy action is required with scant data, on determinants of policy outcomes and no information on the likelihood of policy success. The rules for Better Regulation allow to suspend impact assessments in those cases. (European Commission, 2017, tool # 9) The reasons for not requiring an impact assessment include that "Impacts cannot be clearly identified ex ante…". This may have contributed to the fact that for 2015 to 2018 8.5 % of the initiatives announced in the Commission work programme did not have an impact assessment. (European Commission, 2019) In these cases policy makers resort to intuition or perceived political preferences of stakeholders.

5.1. Strengthening Foresight

The European Commission has made efforts counter short-termism by establishing Strategic Foresight in EU policy making. It aims to anticipate "trends, risks, emerging issues, and their potential implications and opportunities in order to draw useful insights for strategic planning, policy making and preparedness."[1] It aspires to alert policy making by scanning upcoming changes that will impact on policy outcomes. It is supposed to identify megatrends that frame current and future policy making. And it is to develop scenarios that should help policy makers to predict longer term effects of policies.

Strategic Foresight aims to capture the need to integrate multiple sources of expertise by building on collective intelligence. The Commission builds "close foresight cooperation and

[1] Strategic foresight | European Commission (europa.eu)

alliances with other EU institutions, notably in the context of the European Strategy and Policy Analysis System (ESPAS). It also works with international partners, and develops partnerships that draw on Member States' public foresight capabilities through the EU-wide Foresight Network."

Strategic Foresight has been added to the revised Better Regulation Toolbox (European Commission, 2021, tool #20), indicating that it should become an integral part of impact assessments and evaluations.

The advice of the new toolbox could help to maintain more rapid and shorter impact assessment processes as in the regular policy cycle by activating ongoing research of partners in the networks. This could help to avoid that decision-making support and transparency is suspended altogether when urgent decisions are required.

Impact assessments could make explicit how the scenarios shape the options that are presented in the decision matrix in impact assessments today.

Whether and how it will work is still to be seen. The tool presents a set of 14 megatrends without arguing their importance. It is only emerging, how scenarios will be developed, how they are linked to the megatrends and what role they will play for impact assessments.

The toolbox does not discuss how the foresight work could help to respond to uncertainty. Without an explicit account of the uncertainty associated with the scenarios, they may create a welcome certitude that does not help to be prepared for unforeseen events.

5.2. Separation of technical advice and eliciting of political preferences as part of the decision-making process

Like all evidence-based policy making, Better Regulation foresees analytical input. In contrast to many decision-making models, it also accounts for an eliciting of political preferences of stakeholders in the consultation process. For now, consultancy input does not demand a review of multiple scientific or statistical positions. The consultation combines the functions of obtaining data from stakeholder sources and learning about policy positions of affected parties. In both, the consultation, and the processing of stakeholder inputs, it is not always clear what is what.

The process is geared to serve substantive rationality and could be adapted to better take into account of inputs reflecting the interests of participating parties and the cognitive limitations of decision makers pointed out by behavioural economics. (Simon, 1978)

As shown in Figure 2, the process could start with consulting multiple sources of scientific/engineering or social science advice. The multiple sources can be integrated by policy makers or by joint activities of the expert networks. This could be paralleled by a peer reviewing of experts outside the established network. The expert advice should include a communication of the uncertainties associated with the advice.

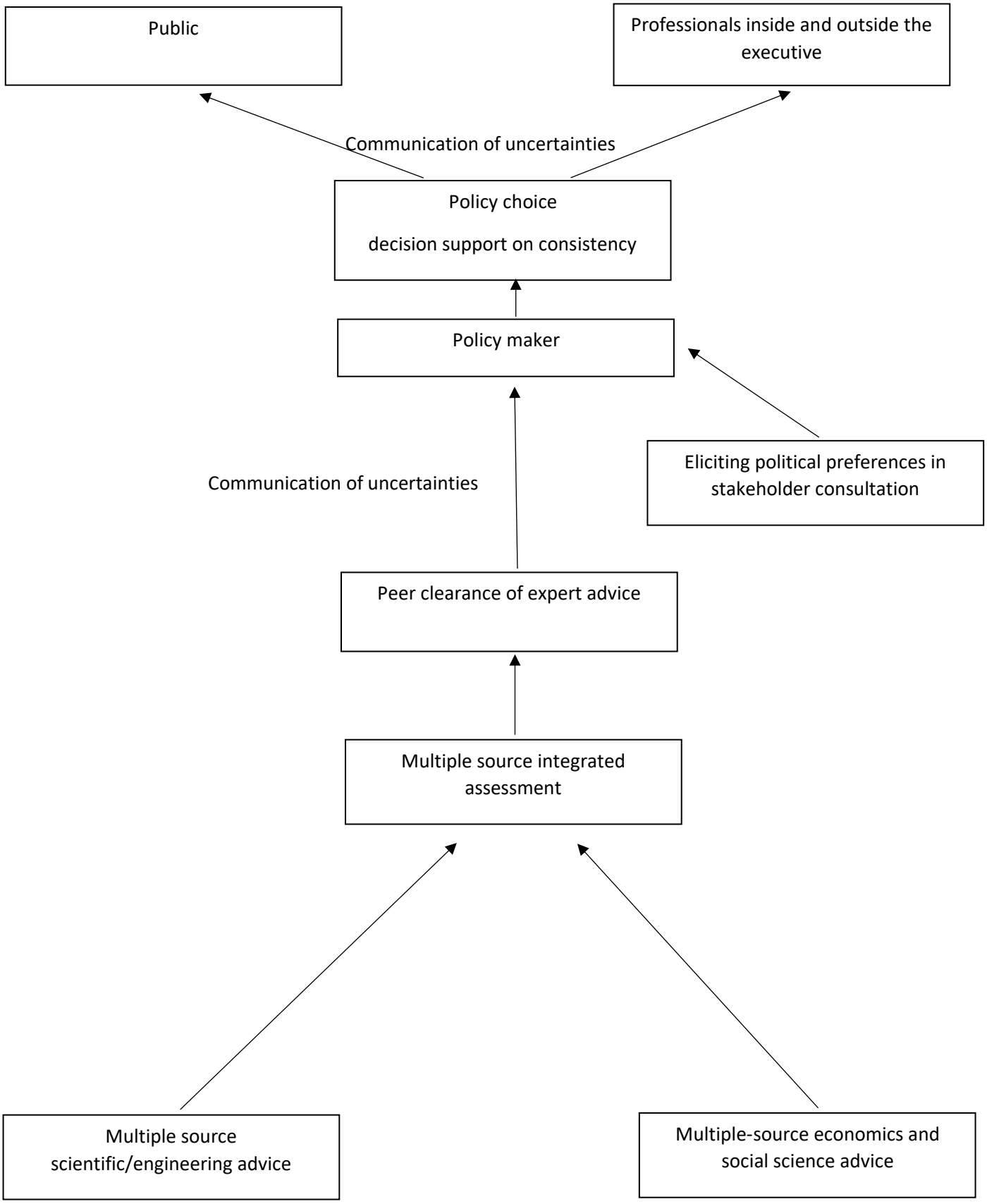
Stakeholder consultations should focus on the eliciting of political positions. Ideally, they would align themselves with multi-criteria analysis. Policy makers should be able to process stakeholder views on the scoring of the outcomes of options and the weighting of the contributions to different specific objectives, or criteria.

The application of formal models of decision-making could be applied only at a later stage, reviewing the consistency of provisional policy decisions. (Gilboa and Samuelson, forthcoming) They could sort out whether one or more options are dominated, and therefore no "real" options. The details of this step are discussed in the last section.

5.3. Shift of the methodological focus to multi-criteria analysis

Most of the impact analysis methods advocated in the Better Regulation Toolbox depend on the single decision maker who can process technical information and political preferences of

Figure 2: Integration of expert advice and eliciting of political preferences



Source: Adapted from Berger et al. (2021)

stakeholders to take optimal decisions. Inability to quantify outcomes justifies the use of multi-criteria analysis.

In practice, cost-benefit analysis is least used. This is often due to data limitations but is also rooted in the contrast of the independent decision-maker with the political process, in particular the Better Regulation consultation process. Cost-effectivity analysis is often applied when direct costs can easily be quantified but benefits cannot. Given the lack of benefit quantification, the efficiency analysis in impact assessments has often to rely on the claim that the policy intervention justifies the costs. In most cases multi-criteria analysis relies on qualitative arguments concluding with a rating that is only loosely related to the stakeholder consultation and the problem analysis.

The process presented in the preceding section could remove these deficits. In the case of deep uncertainty, the scenarios of strategic foresight can directly inform the options of the decision matrix of multi-criteria analysis. The application of a decision criterion in line with the minimax-regret criterion in selecting the preferred option would ensure respecting the precautionary principle. The recognition that policy decisions under uncertainty cannot claim to identify optimal solutions also opens up ways to include deliberation costs into the analysis. (Manski, 2017) The ranking of policy options in multi-criteria analysis remains a political decision.[1]

4.4 Scrutiny for the coherence of decisions

The records of the Regulatory Scrutiny Board show that the idealized models of public decision making do not describe actual decision-making well. (Regulatory Scrutiny Board, 2016 and following) They do not account for the cognitive limits of decision makers pointed out by behavioural economics. They do also not account for institutional biases based on rules of accountability and informational asymmetries. Decision theory rather offers normative instruments to scrutinize the coherence of policy decisions. (Gilboa and Samuelson, forthcoming) To what extent that is possible depends on the degree of data availability and uncertainty. Gilboa, Rouziou and Sibony (2018) present three prototype situations:

[1] On the limited value of standard algorithmic solutions to the ranking problem see Raynaud and Arrow (2011), especially Appendix 3.

a. Decision making allows algorithmic solutions

This would be the case if the decision maker faces a situation where a history of experience exists that frequentist probabilities can be assigned to outcomes. This requires that all relevant data be available, and affordable without violating the proportionality requirement. The desired outcome is unambiguous, without conflict with one or more of the specific objectives. The evidence presented allows for credible identification between policy interventions and outcomes.

In such a decision situation the decision maker can be supported by providing software tools that generate reliable predictions. The simple decision situation and the rich endowment with data and policy experience obviate for a separate consistency check.

A systematic return to impact assessments at the ex-post evaluation stage could allow for a gradual improvement of decision assistance. Such a critical check of the consistency and the empirical validation of estimates based on the intervention logics of the past is missing in the Better Regulation decision making cycle.

b. Lack of reliable evidence-based probability information

The impossibility to assign probabilities to policy outcomes excludes an optimization of outcomes. Important parts of the information are unavailable and too costly to obtain without violating the proportionality requirement of the Better Regulation guidelines. There is even the possibility that the decision maker did not know all relevant options.

The coherence test would involve a check whether some of the options considered are dominated. The check would ask whether the ranking of options contains cycles, i.e., the completeness and transitivity requirements of the order are satisfied. It would control the preferred decisions for the biases that bound the rationality of the decisions.

c. Decisions based on judgements and intuition

The decision process might lead to an outcome that has been unable to clarify the problem analysis. Decision makers question the usefulness of a clear intervention logic. In such a situation, beliefs could be made explicit and checked for their coherence. The final stage of coherence checking could point out hierarchies of objectives expressed. Decision support could point out the assumptions that are necessary to maintain a logical link between policy

interventions and policy outcomes. The use of incompatible pieces of intervention logics could be pointed out and used for a coherent narrative that can be the basis for ex post evaluations that lead to data and an analytic structure that facilitates future impact assessments.

Appendix: Rules for decisions under ambiguity

This appendix presents a simple example to illustrate the argument that objective functions are not known in a situation of ambiguity, and what assumptions are made to deploy the rules of decision theory. The appendix argues that even with the opportunity of policy experiments, ambiguity does not go away. It abstracts from the fact that policy makers, stakeholders and experts may have different preferred assumptions.

The "policy maker" has only one objective, to achieve a high success rate. This could be to keep the share of the population that is healthy as high as possible. The policy could be to vaccinate, with an unknown effectiveness. Having a chance to benefit from the policy is denoted by b, being kept in the status quo by a.

The rate of success of the control group, the people who are healthy without vaccination, is $\alpha = P[y(a) = 1]$. It is the share of people who have done as well without the policy as those who benefited from it. For the treatment group the share of people with a positive outcome is $\beta = P[y(b) = 1]$. Not all people are subject to the policy. The fraction δ is the share of people assigned to exposure to a policy, get an offer to be vaccinated, and the fraction $(1 - \delta)$ the share that does not. The ``welfare function'' is then

$$U(\delta, P) = \alpha(1 - \delta) + \beta\delta = \alpha + (\beta - \alpha)\delta \quad (1)$$

It is the sum of the success rate of the untreated weighted with their share of the population plus the success rate of the treated weighted with their share of the population. Whether δ should be increased depends on the sign of $(\beta - \alpha)$:

$\beta > \alpha \Longrightarrow \delta := 1$, because any increase in δ increases the success rate.
$\alpha < \beta \Longrightarrow \delta := 0$, because any decrease in δ increases the success rate.

Whether to include none or all into the policy depends on $max(\alpha, \beta)$.

With no cross over (people who are not assigned to the policy but manage to benefit from it anyway) but the possibility of non-compliance by those who were supposed to be affected by the measure, we know α but not β, as the latter depends on non-compliance, i.e., the share of those exposed to the policy who did not comply with it.

The lower bound for the success rate of the treated holds when only those who comply benefit:

$\beta_L = P[y = 1|\xi = b, z = b]P[z = b|\xi = b]$

The upper bound for the success rate of the treated holds if all those who did not comply had also benefitted:

$\beta_U = P[y = 1|\xi = b, z = b]P[z = b|\xi = b] + P[z \neq b|\xi = b]$

Not to do the policy (not to vaccinate) dominates, δ is set to zero, if $\alpha \geq \beta_U$. The policy is meant to be implemented for all, δ is set to one, if $\alpha \leq \beta_L$.

The decision maker must decide under ambiguity does not know how to maximize welfare (even having done an experiment) if

$\beta_L < \alpha < \beta_U$.

Numerical example: Assume 100 persons have been exposed to a policy, 70 comply, 30 do not. 60 beneficiaries of the policy are observed. Had all complied the success rate (β) would have been 0.6.

The lower bound for β is the product of the success rate if compliance were complete, multiplied with the share of the population who complied, that is has been assigned to the policy and has implemented it.

$\beta_L = P(y = 1|\xi = b, z = b)P(z = b, \xi = b)$ = 0.6 x 0.7 = 0.42

The upper bound is the sum of the share of the population if all had complied plus the share of the population that did not comply, if they had all been successes:

$\beta_U = P(y = 1|\xi = b, z = b) + P(z \neq b|\xi = b)$ = 0.6 + 0.3 = 0.9

This assumes that the decision maker knows the compliance rate. She therefore cannot determine the bounds.

First way out: Bayesian decision making with subjective probabilities

A Bayesian planner places a subjective probability distribution π on the interval $of\ success\ rates\ for\ the\ treated$ $[\beta_L, \beta_U]$ and changes the objective function (1) by replacing β by the subjective expected value $E_\pi(\beta)$:

$$U(\delta, P) = max_{\delta \in [0,1]} \alpha(1-\delta) + E_{\pi}(\beta)\delta = \alpha + [E_{\pi}(\beta) - \alpha]\delta \quad (2)$$

$E_{\pi}(\beta) > \alpha \Longrightarrow \delta \coloneqq 1$

$\alpha > E_{\pi}(\beta) \Longrightarrow \delta \coloneqq 0$

$E_{\pi}(\beta) = \int \beta d\pi$ averages over the possible success rates. All allocations of treatments are Bayes decisions if $\alpha = E_{\pi}(\beta)$.

Whether the policy is done is depending on the expectations of the decision maker.

Second way out: Maximin Criterion

The policy maker acts as if the lower bound of the success rate of the people exposed to the policy holds:

$$U(\delta, P) = \alpha(1-\delta) + \beta_L \delta = \alpha + (\beta_L - \alpha)\delta \quad (3)$$

This decision rule makes it likely that no policy is adopted. If $\alpha > \beta_L$, δ is zero. Ex ante and ex post all people are equal. They get the same exposure to policy. The maximin criterion always leads to a singleton allocation of policies.

Third way out: Minimax-Regret Criterion

There are two ways in which policy makers can regret their decisions:

a. The policy is ineffective, the part of the population that could not benefit from the policy is doing better. That is, α is greater than β. $(\alpha - \beta)$ of the δ part of the population could have done better without the policy.
b. The policy is effective. β is greater than α. That is, some of the $(1-\delta)$ part of the population, the share $(\beta - \alpha)$ would be better off had its member had a chance to benefit from the policy.

Put together, this gives the regret function:

$(\alpha - \beta)\, \delta\, \mathbb{1}[\beta < \alpha] + (\beta - \alpha)\, \mathbb{1}[\beta > \alpha]$,

with $\mathbb{1}$ being an indicator function, giving a 1 if the expression in square brackets is true and 0 otherwise.

The maximum regret across all possible values of β is

$max_{\beta\in[\beta_L,\beta]}\ (\alpha-\beta)\ \delta\ \mathbb{1}[\beta<\ \alpha]+(\beta-\ \alpha)\ \mathbb{1}[\beta>\alpha]$ =

$max[(\alpha-\beta_L)\delta,(\beta_U-\alpha)(1-\delta)]$, making pessimistically the disadvantaged groups as large as possible.

The minimax-regret rule seeks to choose the δ that minimizes the maximum potential regret:

$$min_{\delta\in[0,1]}max[(\alpha-\beta_L)\delta,(\beta_U-\alpha)(1-\delta)] \quad (4)$$

The first term $(\alpha-\beta_L)\delta$ is increasing with δ, the second term $(\beta_U-\alpha)(1-\delta)$ is decreasing with δ. That means that δ should be set such that both terms are equal. The minimax-regret δ is therefore:

$$\delta_{MR}=\frac{\beta_U-\alpha}{\beta_U-\beta_L} \quad (5)$$

This means the minimax-regret rule prescribes not to administer the same policy for the entire population. δ_{MR} decreases linearly from 1 to 0, as α increases from β_L to β_U. This rule for decisions under ambiguity always generates a fractional allocations for undominated options. (Manski, 2007, pp.237-238)

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