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Abstract

We rely on a simple choice model of hospital-capacity decisions to highlight the relevance of policymakers' behavioural biases in the management of health care demand uncertainty. We show that matching ex-ante the design of the fiscal approach to financing hospitals with the policymakers' behavioural biases could reduce care-rationing risks. However, the effectiveness of the financing choice also depends on the levels of operational and social costs the policymakers decide to work with in their assessments of needs. The model can also be used ex-post to reveal undeclared behavioural biases and use this information to improve future financing policy designs.

JEL Classification: D04, D25, D70, D81, D91, E22, I10, I11, I18

Key words: uncertainty, behavioural biases, hospital capacity, health care financing, social cost valuation

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1. Introduction

Hospital capacity has been a recurring topic in the mass media and health-related academic journals since the 2020-2021 Covid health crisis. These analyses have often focused on the inability of existing hospital capacity to absorb large, unanticipated health care demand shocks. These include ex-post evaluations of the short-term strategies adopted to absorb these shocks as discussed in Van de Voet (2021), Warren et al. (2021) or Winkelmans et al. (2024) in a review of the European experience. A recurrent theme is the decision to quickly reduce hospital access for non-Covid patients, so as to be able to cater to the needs of the victims of the health shock. Rationing access to hospital health care thus seemed to be a crucial component of the crisis management when demand exploded.

The rationing observed during the crisis was largely the result of past capacity decisions that had not anticipated the possibility of such a significant health crisis. For instance, in various European countries, the average use of bed capacity in hospitals was over 85% during the crisis and more so in some intensive care units (OECD (2023)). And this accounts for the reallocation of beds across services that delayed the treatment of other pathologies. In a context in which health shocks are expected to occur more frequently with uncertain probabilities in terms of size or timing, it seems reasonable to try to track the extent to which there is a need and a way to mitigate any recurring risk of rationing that may be linked to an optimism bias among policymakers.

An optimist will indeed tend to under-emphasize the possibilities of bad news. This is in contrast to a pessimist who will focus on the worst cases and hence outcomes. The data would suggest that the optimists prevailed in past capacity decisions in the sector in many countries. Their decisions appear for be dominated by short-term health needs and to underestimate the long-term ability of the sector to deal with a health crisis (i.e. an epidemic, an earthquake, a tsunami or the health consequences of climate change). This optimism probably also explains the slow adjustment to the capacity needed to address the increase in demand linked to demographic and technological changes in the sector emphasized by the World Health Organization for instance ((WHO (2020)).

To our knowledge, the link between the prevailing hospital capacity and a possible optimism bias by past decision-makers regarding the risks of massive unexpected health shocks has not been analysed in detail so far. Yet, the evidence collected by psychology research shows that this is a possibility to consider. Often, people maintain unrealistic optimism even in challenging circumstances, as shown by Sjastad and Van Beven (2023), for instance. It is also consistent with the outcome of a diversity of biases credited to policymakers by the behavioural economics literature as discussed in Banuri et al. (2019). There is no reason to expect health care decision-makers to be different from other key policy decision-makers.

Thus, it would seem useful to get a more exact sense of the extent to which these biases are likely to interfere with capacity-needs evaluations and to assess the extent to which they can be addressed in the design of policies. This is all the more important in an environment increasingly subject to random shocks. Honeycutt and Jussim (2022) suggest that the margin for subjectivity allowed by uncertainty on demand is indeed much stronger than often assumed in standard evaluation approaches such as cost-benefit analysis. The relevance of a range of biases for health policy has already been implicitly documented in many studies. These show the extent to which country-specific governance, institutional, legal and political factors can explain differences in short- term health care management approaches and outcomes.[1] In turn, these differences can be linked to behavioural differences, themselves linked to differences in cultural preferences with respect to the management of uncertainty. Behavioural biases defined broadly seems to matter indeed.

The political science literature has recently started to document the correlation between outcomes of the crisis across countries and the political biases of the decision-makers. In the US, for instance, Lhila

[1] Abbasi (2020), Allel et al. (2020), Assefa et al. (2022), Bargain and Aminjonov (2020), Bekker et al. (2020), Devine et al. (2021), Greer et al. (2020), Grimalda et al. (2023), Migone (2023), Tang et al. (2022) or Zaki et al. (2021) discuss the very wide range of issues that need to addressed in that context.

and Alghanem (2023) highlight the relevance of the political affiliation of decision-makers for their specific way of dealing with the Covid health outcomes. Democrats and Republicans followed different budgeting or health care approaches, as demonstrated also by various other papers looking at the data at the State level.[2] Outcomes suggested that Democrats were less willing to take chances with health risks than the Republicans were. One way of interpreting this behaviour in our context is that democrats may have been more pessimistic, expecting higher odds of bad news materializing. This could explain why they were more willing to allocate more resources to the sector, to manage the risks. Similar observations have since been documented in the European context as discussed in Pizzato et al. (2023) for instance.

The built-in optimism bias in past decision-making and the associated rationing of demand in times of unanticipated health crises has a social cost that may not have been fully internalized in past capacity decisions. In the case of the Covid crisis, several meta-analyses show ex-post the dramatic concreteness of this social cost. For instance, as early as November 2020, i.e. less than a year after the beginning of the crisis, Hanna et al. (2020) reviewed 34 studies covering about 1.3 million cancer patients. They showed that a delay of a month in cancer treatment, induced by the crisis management strategy, exposed the patient to a 6% to 13% increase in the risk of death, depending on the cancer type. Somewhat later, Mak et al. (2022) produced equivalent results for many other pathologies.

These results imply that there is a basic short-term policy trade-off that results from past hospital capacity decisions. The basic choice is essentially between: (i) living with the possibility of being forced to ration the level or quality of services in case of demand shocks and to do so at a high social cost while minimizing the fiscal cost to the sector and, (ii) living with a potentially financially and fiscally costly excess capacity that will only be used in times of shocks but one that minimizes the social costs associated with capacity rationing. [3] What the evidence mentioned earlier boils down to is that different policymakers have made different choices in terms of the options offered by these trade-offs but that the willingness to live with rationing was the choice made by many.

Our specific interest is the analysis of three drivers of past decisions among these two options. More specifically, we document: (i) the potential role of biases in the perception of risks built into historical capacity decisions, (ii) the underestimated role of incentive biases built into hospital-capacity financing/fiscal approach and (iii) the interactions between these two dimensions. We then consider the margin offered by an ex-ante choice of the fiscal financing strategy for the hospital sector to mitigate the future risks of capacity rationing driven by biases in capacity decisions.

Our conceptual analysis suggests that past excesses of optimism can indeed help explain the high social costs linked to a mismanagement of demand uncertainty in the context of the Covid crisis. This argument is similar to ones made in Kahneman and Tversky (1979) and Sharot (2011) in other contexts. In the case of health, the relevance of this conceptualization is borne out by a growing number of detailed case studies. For instance, Lindaas et al. (2023) find examples of both optimism and pessimism biases as drivers of financial decisions in the management of Norwegian hospitals. Other papers document cases in which more politically conservative individuals are more likely to be less concerned with risks in general and hence less likely to be concerned with health risks in particular.[4] This empirical research reinforces the sense that behavioural biases matter, and should therefore be addressed in the design of policies, including health policies. Moreover, they fuel the need to assess the extent to which the details of financing choices matter to the outcomes associated with the biases.

[2] Capano et al. (2020), Gao et al. (2020), Grossman et al. (2020), Havey (2020) or Neelon et al. (2021) follow different approaches to documenting the relevance of political preference on health outcomes in the US.

[3] Both options raise ethical issues, often linked to the organization of the triage of patients. See for instance Christian (2019), Gautier et al. (2023), Hick et al. (2020), Sulkowski et al. (2021) or Wynne et al. (2020). This literature suggests that ethical choices should be part of the discussions on the need to consider capacity expansions.

[4] See Barrios and Hochberg (2021), Bruine de Bruin et al. (2020), Hersh and Goldenberg (2016), Levin et al. (2023), Pennycook et al. (2022) or Schneider et al. (2021)

Our main contribution to this literature is to show that, indeed, the specific fiscal financing approaches adopted to implement a policy choice can help offset some of the effects of the behavioural biases. These conclusions are based on a basic microeconomic model of optimization under pure uncertainty taking a sectoral perspective on the choices. We focus on the decisions taken by two types of policymakers, an optimistic and a pessimistic one, when they need to deal with health crises risks and with uncertainty with respect to the size of the fiscal support allocated to crisis management. We also rely on a number of simulations of the model to highlight the relative relevance of the various dimensions of the optimization process.

The paper is organized as follows. Section 2 reviews the types of models discussed in the literature to assess the optimal hospital size. Section 3 discusses the identification of the optimal choice under full certainty. Section 4 shows how the optimal capacity decision changes when there is pure uncertainty on the demand side accounting for different behavioural biases with respect to risks. Section 5 shows conceptually how capacity choices can be impacted by the sector financing strategy adopted by governments. Section 6 discusses additional insights provided by simulations of the model under various specific details of the budgetary and cost aspects of the optimization process. Section 7 concludes, including some additional policy suggestions.

2. How is the optimal hospital capacity usually modelled in the literature?

A first general observation from a review of the literature on optimal hospital capacity is that the concept of capacity can be defined in many ways. In this paper, we define it as the best possible performance a hospital can deliver in terms of number of patients to be treated. We assume that this performance is linked to the investment in infrastructure and equipment and matching staffing. More detailed definitions also include measures of productivity or of the diversity of outputs that can be delivered by a hospital, as discussed in Humphreys et al. (2022).

A second general observation is that there is much heterogeneity in the modelling approaches used to identify the optimal hospital capacity. This diversity of approaches is quite useful because it reflects the diversity of concerns in both technical and operational terms to be considered when assessing the need to expand capacity to anticipate demand and supply shocks. Below is a brief review of this literature focused on the dimensions that we considered relevant to our specific concerns.

Simplifying somewhat, these can be categorized into three broad groups: (i) compartmental epidemiological models, which are based on a categorization of the population in simple types, i.e. Susceptible-Infectious-Recovered or SIR models, (ii) linear and non-linear programming approaches focusing on general or detailed aspects, and (iii) models taking a macroeconomic perspective. These models vary in the extent to which they focus on individual or multiple characteristics of the hospitals' activities as well as in terms of the range of outcomes they cover, ranging from mortality, to length of stay. Each one offers policy-relevant insights, but each also leaves out some key dimensions relevant to the optimal capacity choice in environments in which politics or related behavioural biases may influence the way uncertainty is dealt with. Just as importantly, many of these models assume levels of uncertainty that can be matched with probabilities of occurrence but seldom deal with totally unexpected significant shocks.

The SIR models allow the description and forecast of the spread and clinical progression of an infection. Their results can be matched with the information on the evolution of the use of intensive care units (ICU) capacity, as discussed in Weissman et al. (2020) for instance. This use serves as a proxy to indicate the extent to which there may be service-rationing and hence a necessity to expand capacity. For this paper, a useful insight from this literature is that it highlights the social costs associated with capacity decisions. It documents a link between mortality and capacity rationing widely consistent with the empirical evidence that followed the assessments of the adjustments imposed by the Covid crisis. For instance, if the number of critically-ill patients exceeds the capacity of a best-practice ICU, they are placed in an overflow category. This increases the risks of mortality. In a world concerned with the need to minimize the discrimination against some type of pathologies in times of crisis, the volume of estimated or simulated overflow capacities reported in this literature is a good indication of the additional investment needed to be able to deal with random demand shocks as suggested by Levy et al. (2021), Noll et al. (2020), Parker et al. (2024), Wang et al. (2020) or Weissman et al (2020). However, it may not be enough to guide policy under budget constraints.

The second type of models, the linear and non-linear programming models, are becoming increasingly attractive for hospitals or hospital systems that manage to produce the sort of data needed to make the decision in financially-constrained environments. A first useful insight offered by these models in the context of the concerns addressed by this paper is their ability to highlight the importance of the financing dimension of the capacity choice. Moreover, with the growing volume of data produced in this information-intensive world, these types of models are likely to become increasingly attractive, as artificial intelligence (AI) tools will allow low-cost updates to be made to optimal capacity-level estimations. A second useful insight they offer is their ability to highlight the diversity of uncertainty dimensions and of approaches available to take them into account. These approaches can be fed by discrete and stochastic estimation and simulation methods or adaptations of queuing theory to account for the uncertainty of dimensions the hospital managers and their financiers may be interested in. They help think through how to deal with demand uncertainty and the lists of inputs to be considered uncertain, the relevance of the severity of the pathology and the diversity of medical skills and tools needed, as well as the necessary length of treatment. [5]

While this second modeling approach is indeed quite useful in many contexts, it seldom combines financial, health and social concerns specifically enough. Moreover, despite the diversity of concerns it is able to deal with, it largely ignores the relevance of political biases in the decision-making processes. Only a few have been designed to highlight the social welfare consequences of some of the trade-offs associated with the choices to be made. However, most do not internalize the social costs of the decisions explicitly enough to open policy debates on this dimension.[6]

The third broad category of models is defined by macroeconomic assessments of the consequences of not having enough capacity. They are less common in the context of health but have a long-standing record in other fields such as electricity or transport capacity. The most common example of such modelling is the general equilibrium model, which can be used to track the effects across sectors and measure the payoffs for a wide range of measures, including increasing specific types of capacities. In the health economics literature, these models can be linked to population-wide epidemiological demographic models. They are quite useful for identifying the winning and losing sectors and economic agents in the economy. However, in their current versions, they are less helpful for coming up with specific suggestions for the optimal hospital-facility size. Moreover, they are generally not designed to account for political preferences or biases. [7]

This paper fits mostly in the second and third category, and incorporates the benefits of key insights from the first category. The basic microeconomic optimization under uncertainty approach we follow focuses on a limited number of dimensions chosen to allow the discussion of the drivers of the capacity choice to be more focused on behavioural and financial dimensions, and to do so at the sectoral level. In doing so, we emphasize variables often underestimated in more traditional models used in the sector, but also consider recurring concerns such as the social cost of getting capacity wrong.

Within this framework, we also add two peculiarities to the traditional approaches to the assessments of hospital capacity needs. First, we also look at how the optimal choice can be influenced by the attitudes of policymakers with respect to key drivers of uncertainty. Our approach increases the transparency of the biases introduced by policymakers' risk aversion, optimism and relative valuation of financial, fiscal and social costs. We do this at the sector level rather than at the hospital level, which is more consistent with a macro view of policymakers' decision-making process in the sector.

[5] Gorunescu et al. (2002) is a useful and often quoted example of this modelling approach in the hospital sector.
[6] A useful example for appreciating the subtle dimensions of these approaches is Burdett et al. (2017).
[7] Exceptions to this weakness include Keogh-Brown et al. (2020), who suggest ways to track the scope to increase capacity.

Second, we consider the case of health shocks that are difficult to anticipate because the past is of little help to predict the future. This is what we mean by pure uncertainty. The concept of uncertainty is better suited to the context we focus on than the concept of risk in view of the poor margin available to decision-makers to assign odds to the possible random shocks to the sector. As suggested by Knight (1921), Shackle (1979), Taleb (2008) or Katzner (2023, 2024), for instance, while risk can be measured and outcomes can be assigned probabilities based on past experiences, uncertainty cannot. Risk can be internalized in policy designs and choices can be made somewhat mechanically. This is not the case for a random health shock. To use Taleb's terminology, it is more like a "black swan", an event that cannot be linked to robust odds or predictable outcome details. The different types of outcomes can potentially be recognized, ranging from good to bad, but there is no possibility to assign a probability to each. This situation fits events such as the recent pandemic. This is why we simply assume in this paper that states of nature can be defined, but that, even if they are all plausible, no probability can been defined for them. This increases the need to be able to track how subjective assessments and behavioural biases may matter and explain outcomes.

3. Deciding hospital capacity under certainty

Before getting into the relevance of uncertainty and behavioural biases, we review the drivers of the optimal choice when there is no possibility of health shocks and decisions are thus taken under a certainty context. We start with a simple model of the way the health authorities (typically, the Ministry of Health) assess the national hospital capacity they need. They rely on a robust initial macroeconomic long-term demand forecast of health care needs to be delivered by hospitals. This forecast is often provided by an independent agency (such as a national planning agency) and we assume it is conducted as a technical exercise not subject to any political influence.

3.1. Framing the problem

Under normal conditions in this world of no uncertainty and no concerns for health shocks, the existing macroeconomic demand forecast for hospital capacity, *V,* will guide the resource allocations by the Ministry of Finance in this model. This capacity accounts for the predictable increases in the average age of the population, and opportunities to benefit from improvements in medical diagnostics and treatment technologies. Seasonal changes linked to events such as the "flu season" are built into the initial demand forecast and imply that the authorities are aware that, in off-seasons, some of the capacity based on this demand may be unused and in the peak season some resource reallocation within the capacity may take place for a short rime. This is one of the reasons why, in normal times, countries try to maintain the average use of bed capacity below 85%, and currently manage to do so quite well in many European countries (WHO (2022)). This allows the hospitals to cater to seasonal surges, even if it proved to be insufficient when the Covid crisis hit. However, these dimensions define normal conditions and only reflect a longer term perspective on the needs, and one that may underestimate the possibilities of demand shocks.

We assume for now that the health authorities will have to take for granted the budget allocation decided by the Minister of Finance or the government more generally. The government can then decide whether to have the public or the private sector deliver this capacity. In the following discussion, we do not address this choice. At this initial stage of the analysis, we also do not consider the details of the budgetary rules. And we will not look into possible additional financing, for instance from private investors. For now, we focus on the relevance of total financing constraints since it is likely to influence the capacity choice anchored in the macro demand forecast. Under standard fiscal procedures, the budget *Y* should be able to meet the investment and operational costs estimated to meet the needs of the potential users of the hospital capacity.

3.2. The core optimization model

To allow the analysis of the process in terms of social welfare maximization, we consider *Y*, the budgetary allocation, to be a proxy for the minimum gross level of social benefit based on an economic cost-benefit analysis conducted by the authorities. The social and the financial costs as well as the demand forecast to be considered for the cost-benefit analysis results from technical assessments. The capacity chosen will simply be the one that maximizes social welfare in this certainty context in which all relevant forward-looking dimensions of the choice are known.

In a context in which there is a desire to internalize the requirements or opportunities linked to well-estimated demographic, environmental or technological changes, imagine now that the health authorities may wish to consider a capacity *H* that may be different from the one consistent with the initial demand forecast (*V)* estimated for normal long term conditions. The new information may accelerate or decelerate demand for capacity. Technological changes for instance may be such that there is an opportunity to make more efficient use of existing capacity. In this case, *H* will be lower than *V*. The discovery that the health impact of some commonly-used household product entails more regular screening at the hospital for the whole population would imply that *H* will be higher than *V*. In conducting this re-evaluation, the authorities also need to look at the extent to which the sum of the operational and social costs associated with *H* may impact its estimation of the social benefit reflected in the budgetary allocation *Y*.

Formally, this narrative means that the health authorities conduct an optimization process to increase the transparency of its capacity preferences. More specifically, the evaluation of the optimal capacity *H* to be favoured by the health authorities will be derived from maximizing the following social welfare function:

$$(1) \qquad \text{Max}\,(Y - rH - c(V - H))$$

with *Y-rH-c(V-H) ≥ 0,* as we assume that, if there is no net social benefit, there is no reason to expand capacity.

An important contribution of Equation (1) is to show transparently that the authorities need to account for the operational and social costs of the capacity decision. The cost variable *r* reflects the operational costs, the associated maintenance needs and the amortization of investment. The total operational cost associated with a capacity *H* is thus *rH*. We assume that it is recovered from the population that will have to rely on the hospital services and will benefit from doing so.

The social cost *c* resulting from any mismatch between the health authorities' preference and the initial macroeconomic demand forecast is derived from a social cost function (*c(V-H)*). If H<V, as would be the case if the authorities underestimate the needs, life or quality of life losses are a cost to society. To keep the discussion as simple as possible, we assume that if *V<H*, this social cost function takes the value of 0 (there is no social cost to having too many beds). The case on which we will focus is thus *V≥H*.

We assume that the social cost function increases in *V* and is strictly convex (i.e. the marginal social cost increases). To simplify the analytical treatment of the decision process, we focus on a specific cost function. We assume, for simplicity that this social cost function has a quadratic form:

$$(2) \qquad c_0(V - H) + c_1(V - H)^2$$

where c_0 and c_1 are both positive. These coefficients can be interpreted, respectively, as: (i) the marginal social costs associated with the need to ration an additional patient if the installed capacity is insufficient and, in practice, this reflects the increasing probability of death of patients; and (ii) the extent to which this marginal cost grows when the number of patients increases.

In this certainty context, the optimal value of capacity *H** is obtained by combining (1) and (2) and subject to $(V \geq H)$. Assuming an interior solution, the optimal *H** is thus found by solving:

$$(3) \qquad -r + c'(V - H) = -r + c_0 + 2c_1(V - H) = 0$$

which leads to: $$(4) \qquad H^* = V - \frac{r - c_0}{2c_1}.$$

This hospital capacity maximizes the social welfare function described in (1) when we think of the capacity choice needed to meet demand in absolute terms. But in the context of a health crisis, it can be re-interpreted as the optimal *additional* capacity needed to be able to cater to the *additional number of patients* to be treated. The key drivers of the decision are the same and hence the analysis in absolute terms is useful for understanding the decision process to be followed to deal with demand shocks.

3.3. Initial policy insights from the basic results

The list of determinants of the optimal capacity decision covered by this basic model is roughly consistent with a macro perspective on how health authorities are likely to make investment decisions at the sector level when there is no uncertainty and hence no reason to worry about behavioural biases. However, a closer look at the details of equation (4) offer a few general insights that already hint at some of the issues to be dealt with when there is a need to account for pure demand uncertainty.

The first general insight is that when the marginal social cost is higher than the per-patient operational costs, i.e. $c_0 > r$ and financial constraints are not binding, the installed capacity H^* should always be larger than V, the macroeconomic demand forecast. Rationing should not be an option with this assumption on social costs. Anyone convinced that there is no limit to the value of life would follow this line of thought. This implies that in countries without significant fiscal constraints and with a high social valuation of life, it would make sense to live with a capacity larger than the one needed in normal circumstances, V, assuming it is fiscally and financially sustainable. [8] Formally, this means: $H^* \geq V$.

The second insight is provided by the opposite possibility. If the per-patient operational cost is larger than the social cost (i.e. $r > c_0$), the optimal capacity will not cater to all the patients (i.e. for $H^* < V$). This is a case in which policymakers may consider that the operational cost is a more important concern for the electorate than the mortality risk, maybe because this risk concerns a much lower share of the electorate than the financial risk. In this world view, rationing is a real option.

A third insight provided by (4) is that in the case of $r > c_0$, the higher the speed at which the marginal cost grows with the number of patients, c_1, the larger the optimal capacity H needed. Since the capacity is not large in that case, if social costs grow at an increasing pace, the more conservative the hospital capacity decision, the higher the likelihood of a high total social cost when V explodes as a result of a health crisis. To see this more precisely, it is useful to look at the 2nd order condition for a maximum. It requires:

$$(5) \quad -c''(V-H) = -2c_1 < 0$$

Anticipating this possibility of a sudden or lasting increase in demand for hospital care is thus not a superfluous exercise if the social costs are as assumed here. In practice, any explosion of social costs during a crisis is an indication that they were not anticipated adequately.

A fourth insight flows from the case in which the authorities consider that all the population N has to be seen as potentially needing to be treated, i.e. $V=N$. This would be the decision taken by a government considering that it does not want to take any chance with unanticipated demand shocks for instance. Somewhat counterintuitively, this still does not mean in practice that the capacity will match N, the size of the population. Indeed, the optimum is:

$$(6) \quad H^* = N - \frac{r - c_0}{2c_1}.$$

H^* will actually not be equal to N as a result of the relevance of the gap between the per-patient operational cost and the marginal social cost. H^* will increase as c_0 increases and the gap $(r - c_{0)})$ shrinks. Once again, the comparison of operational and social costs is key to the capacity choice. For

[8] In many countries, r is highly subsidized. When the marginal cost of public funds is high, this is likely to also influence decisions on the optimal capacity. However, this discussion would go beyond the intended scope of our paper.

the optimal capacity H^* to cover the whole population N, the social cost would have to be significantly higher than the operational cost. This is often the perception prevailing in times of health crisis in many countries, as was the case during the Covid crisis.

Oddly enough, in the real world, it seems that the evaluation of social costs changes when switching from a business-as-usual situation to a crisis situation. The same life is valued differently in different contexts and this may help understand the differences between ex-ante and ex-post evaluations of the optimal capacity choice. However, this is a discussion that goes beyond the scope of this paper, even if the model could be used to simulate the impact of these changes on social welfare.

A final insight is that the simple framework we rely on is missing an explicit modelling of the need to prevent excessive capacity to limit wastes of fiscal resources. In this case, the maximization problem should include an additional constraint given by $N \geq H$. On the other hand, this may lead to an added implicit financial constraint given by $Y \geq rH$. Unless the financial needs are met, there will be an upper limit to H imposed by this financial constraint. This is, for instance, what seems to explain the limited capacity in poor regions or countries.

Considered jointly, these observations already point to some of the difficulties that may have to be addressed in the uncertainty context we will go on to discuss. In the following sections, we focus on uncertainty related to demand but also with respect to the financing options and levels. In addition, we will assess how individual policymakers' preferences or biases in these uncertainty contexts influence capacity decisions in this highly sensitive sector.

4. Hospital capacity choices under demand uncertainty with no concerns for financing constraint

In this section, we analyse the relevance of pure uncertainty with respect to demand V for the optimal choice of hospital capacity. In this type of context, several Vs are possible, and the health authorities are unable to assign specific probabilities to each possible V. To analyse this situation, we follow the approach initially discussed in Knight (1921) and refined over time by Shackle (1979), Taleb (2008) and Katzner (2023). A probability cannot be quantified because there is no prior experience of the situation analysed, and therefore no expert who can provide a degree of plausibility precise enough to any V to manage risks. In these situations, any decision is based on subjective assessments, in which psychological aspects and behavioural biases prevail.

In the following discussion, we assume that a policymaker can at best "imagine" possible shocks, possible actions and possible outcomes. At best, they can assess gains and losses for each case. It is thus the knowledge of the policymaker (or their advisers), and their biases, at any given time that drives the initial action decision. In this context, expectations of a set of possible future states are idiosyncratically chosen, with the awareness that they may be imperfect. This is what non-probabilistic assessments of possible states, outcomes and actions imply. And this is why it is useful to consider the extent to which the characterization of decision-makers' attitudes to and preferences regarding uncertainty may be linked to observed optimal capacity choice.

In this context, it is likely that optimistic and pessimistic policymakers will follow different paths when dealing with uncertainty. The optimists will minimize the possibility of bad news in favour of the possibility of good news; the pessimist will do the opposite. Tracking how this will influence decisions on hospital capacity is thus relevant. It is also particularly useful in the context of *ex-post* evaluations of decisions intended to fine-tune future sectoral decisions. But to find policy solutions able to mitigate the effects of such behavioural biases, it is necessary to identify *ex-ante* which specific factors of the optimization process drive the capacity decision once behavioural biases are accounted for.

To do so, in this section, we discuss how uncertainty changes the decision process leading to the capacity choice, as compared to the simple process derived under certainty. This will provide some new insights on the concrete challenges policymakers are faced with. Even more importantly, it will set up the discussion in section 5 where we focus on the extent to which the specific ways in which the government decides to allocate the budget may impact hospital capacity when demand is uncertain, for both types of decision-makers.

While we cannot assign probabilities to any type of demand outcome in this highly uncertain environment, we can imagine the various possible capacity needs that the health sector policymakers will have to consider. To increase the transparency of the decision process, we limit demand uncertainty to three possible states of nature with respect to capacity needs. We consider that the demand for capacity V can take 3 values: 0, X and N. The two extremes are thus the cases in which no-one, and everyone, needs treatment. The third case, X, is an intermediate situation. Each one corresponds to a different scenario S as discussed more specifically below:

- *S1: V = 0*, i.e. no one needs to be hospitalized because under this state of nature, there is no health issue to deal with. This is clearly an extreme, and possibly unrealistic, case. But it is useful to consider for at least two reasons. First, this is what the extreme-optimist vision boils down to when discussing the scope for increasing capacity in a shock situation. Second, it serves as a benchmark to compare the social welfare levels of the other possibilities being considered by the authorities as compared to a passive attitude with respect to uncertain outcomes and risks;
- S2*: V = X*. This is the case in which all patients who need a hospital bed will have one but not all the population will need one. This is a realistic bet as long as the demand impact of shocks can be quantified reasonably well. However, it can lead to some rationing if the shock affects everyone in the population;
- *S3*: *V=N*. This a dramatic state of nature in which, if a shock hits, everyone in the population will need a hospital bed. This is the worst case scenario, the one the pessimists will want to prepare for.

With these three possible states of nature in mind, we assume that the policy-maker, whether optimist or pessimist, only considers three possible decisions *D* with respect to investment in hospital capacity:

- *D1*: Giving up on the creation of hospital capacity. This means that *H=0*, which in the context we are interested in can be interpreted as giving up on the creation of *additional* capacity. Again, this is an extreme case, and the analysis of this extreme decision can also be used to assess situations in which financing constraints may be binding and no capacity expansion is fiscally feasible in the short run;
- *D2*: Installing a capacity *H = X < N*; this means that not everyone (*N*) will be able to have access to a hospital bed in case of a catastrophic health crisis, but many (*X*) will. The authorities believe that the shock may put some of the population at risk: some less so than others, and they may not need to be hospitalized (think of the debate about young vs. old at the beginning of the Covid crisis). In this context, the authorities consider providing some additional capacity, but not enough to cover the whole population;
- *D3:* adopting a capacity *H = N* so that anyone in the population has their own bed in the hospital system. In this other extreme case, the authorities do not want to have to absorb any social cost in case of demand shocks and may decide to adopt a capacity that covers the whole population in case of a demand shock. More formally, this implies that when the capacity is large enough to cover the whole population, there is no social cost (c(0)=0).

In this setting, when financing constraints are not a concern, an optimist will not expand capacity and a pessimist will go for a capacity able to cater to the full population. This is because an optimistic decision-maker expects that nature will always deliver the best possible outcome (i.e. no demand shock) while a pessimistic decision-maker is likely to expect nature to deliver the worst possible situation (i.e. everyone in the population will have to go to hospital). These preferences may change for both types of individuals if there is a financing constraint and how much they change may depend on the way in which the government finances the sector as discussed next.

5. How much does the way in which the government finances the sector matter to capacity choice?

In most countries, the government provides a fair share of the financing of health care costs. For instance, in the OECD, in 2022, public financing represented about 73% of health expenditures of which 45% were transfers (OECD (2023)). Hospitals accounted for about a third of this financing. In the following discussion, we focus on the hospital component of the budgetary allocation. To account for a notable difference observed in the real world, we distinguish two possible ways of allocating the budget. The first is an *ex-ante* fixed allocation decided before the services are being delivered. The second in an *ex-post* allocation anchored in a reimbursement rule to the service providers. We analyse both possibilities.

We start from the social welfare function described in equation (1), i.e. ($Y - rH - c(V - H)$) and use it to derive the possible social welfare outcomes for all combinations of decision D and scenario S, keeping in mind that we assume that *c(0) = 0* when *X ≥ V*, i.e. when demand is not rationed. The results reported in the tables below all provide information on the specific social welfare level that corresponds to each combination of states *S* and decisions *D* under the same level of demand uncertainty.

The different fiscal rules are the main difference between the two cases analysed. They imply different values for *Y*, the budget available to cover the expenses. For each case, we compare the optimal choice of an optimistic and a pessimistic decision-maker to assess the extent to which their hospital capacity decision and its welfare effects are impacted by the way each type deals with demand uncertainty.

5.1 Case 1: Uncertain demand and known budget ex-ante

For this first case, the initial budget allocation is fixed ex-ante and set at level *Y*. In this approach, *Y* is independent of actual demand since it is decided before the actual number of patients is known. *Y* could be interpreted as a prepayment accounting for the costs of achieving the expected gross social benefits from the sector. The value may be based on the demand forecast or simply be defined by a political decision of resources to be allocated to the sector. In practice, the motivation makes no difference to the resulting social welfare level since this level will depend on the actual demand that the sector will have had to deal with.

The main change as compared to the certainty case is that the decisions *D* are about the size of the hospital system that will have to be linked to the expected state of nature. More specifically, they will have to be linked to what the decision-makers believe are the most likely states of nature. The various possibilities are summarized in Table 1: for each capacity decision *D* in each State of nature *S*, it reports the net social welfare outcome.

The table highlights the likely differences in choice according to the behavioural bias of the decision-maker for the choice of the demand forecast and, from then on, for the choice of the optimal capacity and of the associated welfare level. It also shows that there is no reason to expect an optimistic and a pessimistic decision-maker to take the same decision under this financing approach.

Table 1. Social welfare outcomes of decisions (D) based on the state of nature (S) when the budget allocation (Y) is known*

		Possible States of Nature			Optimist	Pessimist
		S1(V=0)	S2(V=X)	S3(V=N)		
Possible Decisions	D1 (H = 0)	***Y***	*Y-c(X)*	*Y-c(N)*	***Y***	*Y-c(N)*
	D2 (H = X)	*Y-rX*	*Y-rX*	***Y-rX-c(N-X)***	*Y-rX*	***Y-rX-c(N-X)***
	D3 (H = N)	*Y-rN*	*Y-rN*	*Y-rN*	*Y-rN*	*Y-rN*

**With the social welfare function computed as* ($Y^H - rH - c(V - H)$)

An optimistic decision-maker is convinced that nature will produce the best possible outcome for any of the decisions they make. In our case, it means that they expect that nature will not produce any demand shock (i.e. the best possible outcome) for any decision *D* the person takes. This optimist's choice is based on a *Maximax* decision criterion, which in our tables means choosing the best outcome for each corresponding row. The highest social welfare that can be achieved is *Y*.

The decision logic sequence is as follows. It starts with a comparison of the best outcomes for each possible decision *D*. For the first option, i.e. choosing *H=0*, *Y* will be the best possible outcome. It corresponds to a scenario S1 (with V=0) in which the decision-maker expects a situation in which there is no health issue. Any other hospital size or expansion choice will lead to a lower social welfare for the *H=0* case This choice thus implies that the expected social welfare level achieved by the sector is expected to be equal to the budget allocation offered by the government.

The same analytical logic applied to each possible decision *D.* If the decision-makers choose the second row, *H=X*, rather than *H=0*, the best social welfare outcome (*Y-rX*) will correspond to the case in which nature has delivered *V = 0* or *V = X*. If *H=N* was selected, their choice will be able to deal with any situation delivered by nature.

The comparison of the three possible decisions shows that the highest welfare level among all possible outcomes is achieved with *H=0*. It corresponds to a situation in which the optimist decision-maker expects nature to deliver a state of nature *S1*, with *V=0*. Since, under this state of nature, there is no loss of life or similar health related outcome, the optimist expects *c= 0*. And, since there is no patient to treat, *rH=0*. This is why the social welfare level is defined by the budget allocation *Y*. The minimum gross social welfare level the government expects to achieve would also be the net social welfare level expected if this decision turns out to be the right one ex-post.

In contrast, a pessimistic decision-maker thinks that nature will produce the worst possible outcome for any of the decisions *D* they make. To rank them, a pessimist adopts a *Maximin* decision criteria, i.e. choosing the maximum of all the possible minima. In other words, they will choose decision *D*, corresponding to the best of the worst results.

To get to that decision, the following comparison across possible decisions is needed. If the person chooses *H =0,* they expect that nature will deliver *V = N*. It is under this scenario that the social cost is the highest (i.e. *c(N) > c(X) > 0*). If *X* is selected, the lowest social welfare will be *Y-rX-c(N-X)* which corresponds to *S3*, i.e. nature delivers *V=N*. Finally, if *H=N* is chosen, the result will be *Y – rN*, under any of the states of nature.

Overall, considering all cases jointly, the least bad result among bad outcomes will depend on the relative importance of *rX*, *rN*, *c(N)* and *c(N-X)*. The ranking of *Y-c(N)*, *Y – rX – c(N – X) and Y-rN* to guide the final capacity decision will be driven by the relative importance of *rX*, *rN*, *c(N)* and *c(N-X)*. This will depend on the specific value for r and for the drivers of the social cost function. This implies that, in this case, a theoretical solution is not precise enough and more quantitative simulations are likely to be needed to confirm or adjust the evaluation of the fiscal approach for a pessimist. This is what we will discuss in section 6.

In sum, when the sector is allocated a fixed budget in a context of demand uncertainty, the first insight is that the difference in the optimal choices between a pessimistic and an optimistic decision-maker is somewhat predictable. There is no chance that the optimist will expand the capacity. There is some chance that the pessimist will. The model shows that the policymaker has some leverage on this as they decide on the valuation of the financial and social costs components and hence manage the relative importance of operational and social costs. In some politically-sensitive context, this can be quite a useful option and it certainly helps to justify budgetary decisions. This is consistent with the observation that narrative matters in policy, as suggested by Mintrom and O'Connor (2020), who highlight the role of storytelling in politics in the context of the Covid crisis. This need for a sustainable narrative may be why D2 (i.e. an intermediate capacity choice) could be a realistic option. In many contexts, it will offer a politically viable alternative to the two extreme positions.

5.2 Case 2: Uncertain demand under a regime in which the budget is allocated ex-post

In this second case, we assume that a precise budget figure is not known *ex-ante*, but the health sector managers know the rule followed to allocate to hospitals as a function of the number of patients to be treated (*V*). They also know the cost of having to treat each patient (*r*), like when the budget was allocated ex-ante. The budget *Y* is thus now variable but the allocation rule is known. This alternative way of financing the sector can be used to minimize the risks of excessive budgetary allocations to the sector while allowing a better match between the potential demand (*V*) and resources than under the *ex-ante* budgetary allocation. However, in case of unexpected demand increase, it can have a significant fiscal impact.

For each state that nature can produce, the hospital managers now match the budget they expect to receive *ex-post* with the expected number of patients for each decision *D* they can take. If they decide not to invest in any capacity (*D1*)), there are no patients, no fiscal allocations and no social costs if nature delivers *S1* (*V=0*). However, if nature delivers *S2* (*V=X*), the *ex-post* fiscal allocation is Y^X because there are *X* patients to treat but there is also a social cost linked to the fact that *H=0* while *V=X>0*. If nature delivers *S3*, the *ex-post* fiscal allocation is Y^N, the largest one under this budgetary procedure, as we assume that $Y^N > Y^X > 0$. However, the social cost is also the highest. A similar reasoning can be applied to the other two possible decisions (*D2* and *D3*). Table 2 summarizes the social welfare outcomes of the match between each possible state of nature and each possible decision. [9]

Table 2: Social welfare outcomes of decisions (D) based on the state of nature (S)
With a budget provided ex-post based on the number of people needing care*

		Possible states of nature				
		S1(V=0)	S2(V=X)	S3(V=N)	Optimist	Pessimist
Possible Decisions	D1 (H = 0)	***0***	Y^X-*c(X)*	Y^N-*c(N)*	*?*	*?*
	D2 (H = X)	*-rX*	Y^X-*rX*	Y^N- *rX-c(N-X)*	Y^X-*rX*	*-rX*
	D3 (H = N)	*-rN*	Y^X-*rN*	Y^N-*rN*	*?*	*?*

**With the social welfare function computed as* $(Y^H - rH - c(V-H))$

Consider first the easiest situation. It is described by the row of the table reporting the possible welfare levels if the decision is to bet on a capacity of *X* (D2). If *H=X* but there are no patients (*V=0*), then a total operational cost *rX* will have been incurred but there is no ex-post budgetary contribution since Y^X =0 when *V=0*. If, instead, there are actually *X* patients, again, there will be a total operational cost *rX* to be paid that will impact social welfare as well but there is now a fiscal reimbursement of Y^X*.* There is no social cost since all patients that need to be treated are being treated. If there are *N* patients instead, the government reimbursement will be $Y^N > Y^X$ for a total operational cost of *rX* corresponding to the number of patients actually treated if the managers decide on *H=X* instead of *H=N*. In this last case, there is also a social cost, since capacity is rationed (*X<N*) and does not meet demand. This leads to a total cost of *rX+c(N-X).*

The behavioural bias with respect to uncertainty is as relevant as in the case of the *ex-ante* budget allocation. However, a significant difference is that the ranking of preferences will depend on the actual size of the budget reimbursement (how different are Y^X *and* Y^N) and on the relative importance of the ex-post budget and of the total costs. To see this, the decision-maker needs to be able to identify for each situation whether $Y^X \geq$ *or* $\leq$ *c(X)*, $Y^N \geq$ *or* $\leq$ *c(N)*, $Y^X \geq$ *or* $\leq$ *rN and* $Y^N \geq$ *or* $\leq$ *rN.* These operational and social cost components of the optimization process are now much more relevant to the capacity choice than in the first budgetary approach. Implicitly, each of the cells in the table for D1 and D3 reveals the

[9] It may be useful to keep in mind that while the table is computed to report the decision with respect to the capacity of a hospital system, the results can also be interpreted as additions to an existing capacity. A value of 0 for H would thus mean no additional capacity. In contrast, a value of X or N would correspond to the addition necessary to deal with the new demands resulting from the shock.

extent to which policymakers can influence the choice of the optimal decision since they can set the reimbursement rule to match the information available on *r* and *c*.

Once all these values are known, the decision logic is the same as that discussed for case 1. The optimistic decision-maker relies on *Maximax* decision criteria while a pessimistic one relies on *Maximin* criteria. It may be useful to go through the detailed reasoning for each type of decision-maker in this case as well.

The optimistic decision-maker decides as follows to optimize. If they do not invest in the hospital ($H=0$) and there are no patients, they do not have to incur any costs but they also do not receive a fiscal allocation either. On the other hand, if there are X or N patients, s/he will face social costs but benefit from *ex-post* fiscal reimbursements. However, without additional assumptions on the relative importance of the budget and the costs, it is impossible to identify an optimum in a context in which the best case scenario will be the preferred choice. To see what a difference the specific values would make, this needs to be settled through specific quantitative simulations as discussed in section 6 where we will compare the choices under a very generous and a not very generous ex-post budgetary allocation.

Intuitively, based on the theoretical formula reported in Table 2, it would seem reasonable to assume that if the ex-post fiscal allocation is not generous, i.e. Y^N and Y^X are not large and in particular if it is likely to be lower than the realized costs for any non-zero capacity, then the optimal choice will be not to invest in any capacity. Zero will indeed be the largest level of social welfare among all possible outcomes. In all other cases, social welfare will be negative for a very low budget allocation. In contrast, if the fiscal reimbursement rule is generous, i.e. a very high Y value, that is, at least as high as rX or rN, the result is quite different. In that case, an optimistic decision-maker might build a hospital of size X which corresponds to the highest social welfare value.

The main new insight in the case of an optimistic decision-maker is thus that the details of the ex-post fiscal rule may lead them to consider expanding capacity. This is better than in the ex-ante case, where there is no hope of getting an optimist to invest. In the ex-post allocation scenario, the optimal choice can be influenced by setting the level of the budget.

Now consider the pessimist's decision. From each row, the focus is on the worst outcomes as in case 1. For $H=0$, Y^N-$c(N)$ is the worst possible outcome, for $H = X$, it is Y^N- rX-$c(N$-$X)$, and for $H = N$, it is Y^N-rN. The choice of H is thus driven by these three measures of social welfare: (Y^N- $c(N)$, Y^N-rX-$c(N$-$X)$, -rN), because they are the worst outcome for every decision. Ranking these three levels of net social welfare is not as straightforward as in case 1. The optimal choice when the government announces the budget rule rather than the budget level is just as complex for the optimist and will depend on the actual values of each variable. It is indeed impossible without details about the relative importance of the budget and of all the costs to get a simple, clear pictures. Once again, we need to rely on quantitative simulations to come up with a sense of the ranking of preferences for the pessimist.

The worst case scenario will now depend on the relative importance of the maximum social cost to society ($c(N)$), the maximum operational cost to society (rN) and the size of the next benefit that can be achieved by society (Y^N-rX-$c(N$-$X)$). In practice, under the most likely valuations of the social and operational costs and for a reasonable valuation of the benefit to society of being able to cater to the health care needs, the best choice is likely to be $H=X$. However, differences in net social benefit valuations by different decision-makers could influence this choice and thus, hoping for some capacity investment is not realistic without more details.

A somewhat subtler insight produced by the theoretical discussion in the case of a pessimistic decision-maker is that incentives built into the budgetary rule may lead to counterproductive decisions. When the budgetary rule is extremely generous, reflecting a desire to provide an incentive to the hospital managers to guarantee treatment for a maximum number of potential patients, the worst social welfare values expected to drive the decision are (0, -rX, -rN), respectively. If there is a possibility that a pessimist will be worried that the reimbursement rule may not be enforced by the government, as in the case of a fiscal crisis for instance, the optimal decision will be *H =0*. The possibility of bad news both on the demand and on the financing side can be thus be internalized by the pessimist and explain the higher likelihood of a capacity rationing in times of crisis. Fiscal credibility matters as well as *ex-post* financing uncertainty may impact *ex-ante* capacity decisions. Thus, a pessimist could choose not to build hospital capacity when the compensation is too generous.

Overall, as was the case for the discussion of the ex-ante budget allocation case, the conceptual approach has been useful but it has also quickly reached some limits. The simulations discussed next are designed to help reduce the uncertainties and sort more precisely the ranking of preferences for the level of capacity to be considered for each type of decision maker according to a range of values for the budget and for the costs variables. This is needed to provide a more precise sense of the interactions between the size of budget, the way it is allocated and the levels of the operational and social costs. And in turn, this is needed to reveal the scope for action available to influence decisions ex-ante or explain them ex-post.

6. Some more policy intuition from numerical examples

To provide a better sense of the relevance of details, we report a few numerical simulations illustrating how sensitive the social welfare function is to specific data. In addition to those we report here, we ran a full set of simulations to address all possible combinations of a low and a high value of each of the variables. The results are summarized in the annex; here, we report only a few to allow a discussion of the key dimensions policymakers would have to focus on, although in each section, we summarize the results of the full set of simulation analysing the relevance of a specific variable.

In our model, the key variables a social planner needs to decide on are: (i) a specific monetary value for *Y,* the short-term budget allocated by the government to the hospital sector from its fiscal resources and (ii) the value to be used for the main components of social cost function (2), namely c_0, the marginal social costs associated with an additional patient if the installed capacity is insufficient and c_1, the extent at which this marginal cost grows when the number of patients increases. The authorities also need to work with a value for *r,* the per-patient operational cost of an additional hospital capacity. This is often not really a decision variable and it tends to be based on observable accounting data. It can be quite different across countries.[10]

Let's focus on an economy in which the following are the relevant values for these variables: *N=100, Y=100, r=10,* $c_o = 4$ *and* $c_1 = 0.1$. Based on this data, the optimal *H* can be computed for the case in which there is no uncertainty based on the theoretical formula computed earlier (equation (4)). This precise estimate of the capacity can then be used as a benchmark to which the decisions under uncertainty can be compared. With the data values assumed here and when the actual potential demand is considered to be defined by the whole population (i.e. *V=N*), since $H^* = V - \frac{r-c_0}{2c_1}$, the optimal capacity to be relied on for our specific example is $H^* = 100 - \frac{10-4}{0.2}$ = 70.

In order to be able to compare the social welfare outcomes of choices under uncertainty that may not be consistent with this optimal choice of *V=70*, we also consider the possibility that the decision-makers could consider a best and a worst case scenario. In the best case scenario, no-one needs to have access to hospital services and hence *V=0*. In the worst case scenario, everyone in the population can be hit by a health crisis and hence, there is a need to cater to everyone in the population and *V=N=100*. These are the three S values of our theoretical case. The three possible *D* values will thus be *H=0, 70 or 100* depending on whether the authorities decide to not expand the capacity, increase it to cater to the possibility of having to support the needs of every citizen simultaneously or, instead, bet on the size that was estimated for a full certainty scenario. The rest of the section focuses on reinforcement of some of the main messages produced in the more theoretical part of the paper

[10] In many countries, it is actually becoming a decision variable since increasingly hospital managers are looking into ways to cut operational costs. This is one of the ways in which improved efficiency is expected to be achieved as a complement to the adoption of new technologies or alternative management approaches. We will not address this option in this paper.

6.1. Demand uncertainty with an *ex-ante* fixed budget allocation

Consider first the situation described in case 1, i.e. demand uncertainty with a fixed budget allocation independent of demand *V.* In the detailed tables discussed next, we focus on the case in which both the operational and social costs are low. The only difference is the size of the budget allocated ex-ante.

The budget may be low because the society collectively does not really value the benefits of a large hospital capacity or simply because the government is facing budgetary constraints. On the other hand, it may be high, because society is really concerned about health and expects government to allocate a high share of the budget to that sector. For our simulations, we still assume that if $H \geq V$, there is no social cost and we still rely on the same social welfare function.

Table 3a reports the case of a low ex-ante budget allocation, with $Y=100$, while in Table 3b, the allocation is high, with $Y=1000$. Both tables provide the results of the values for the social welfare equation (1) estimated for the various combinations of possible decisions and demand outcomes.[11]

Table 3a: The case of demand uncertainty and a *low* ex-ante budget allocation (Y=100) ($N=100, Y=100, r=10, c_o = 4$ and $c_1 = 0.1$)							**Table 3b: The case of demand uncertainty and a *high* ex-ante budget allocation (Y=1000)** ($N=100, r=10, c_0=4$ and $c_1 = 0.1$)				
	V=0	V=70	V=100	Optimist	Pessimist		V=0	V=70	V=100	Optimist	Pessimist
H=0	100	-670	-1300	**100**	-1300		1000	230	-400	**1000**	-400
H=70	-600	-600	-810	-600	**-810**		300	300	90	300	**90**
H=100	-900	-900	-900	-900	-900		0	0	0	0	0

The choice is made by each type of decision-maker following the logic described in the conceptual discussion. For each hospital size possibility *H*, the optimist identifies the best possible outcome while the pessimist considers the worst possible one ("if something can go wrong, it will go wrong"). This choice is derived from the horizontal reading of the table. The tables show that from the three options available in the respective columns for both levels of budget allocation considered here, the optimist decides not to invest in any capacity ($H=0$), while the pessimist picks the same capacity that would have been picked up under a full certainty scenario ($H=70$). Thus, the optimist will not worry about a possible demand shock while the pessimist will consider it as a concern to be dealt with, even when the budgetary allocation does not cover the costs. This confirms the conceptual discussions for case 1. An optimist is more likely to be associated with a capacity rationing under this fiscal approach.

The main difference for both decision-makers is the social welfare associated with their choice. It is positive for the optimist in both cases since the budget is disbursed even if $H=0$, whereas it can be negative for the pessimist if the budget is low, because for her/his expected demand ($V=100$), the social and operational cost would be larger than the budget.

The additional simulations summarized in the appendix show that when the budget is allocated ex-ante, a pessimist will choose a capacity of at least 70 for all budgetary combinations, with low and high social costs in almost all cases. It is only in the two cases where the operational costs are high and the social cost is low for both levels of ex-ante budget allocation that the capacity chosen by the optimist is $H=0$. In contrast, for the optimist, for any of the cost values and budget levels simulated, the optimal choice is always $H=0$.

6.2. Demand uncertainty and an *ex-post* budget allocation

Consider now the case of an ex-post fiscal allocation linked to demand *V* (i.e. Y^N and Y^X) discussed in case 2 earlier. This implies that the budget is now linked to the number of patients expected to be treated by a decision-maker. For the low ex-post budget allocations, this means that if $V=0$, $Y=0$, while if $V=70$, $Y=100$ and if the whole population needs treatment, i.e. $V=N=100$, then $Y=200$. In the social welfare equation, the value of *Y* thus needs to be adjusted to the value of *V* to be able to compute the

[11] For the sake of clarity, the following are a few examples of how the data reported in the table was produced. For a budget allocation of Y=100, if H=0 and V=0, then $SW= 100 - rx0 - 4x\,0 - 0.1x(0)^2= 100$. If H=70 and V=70, then $SW= 100 - rx70= -600$. And if H=70 and V=100, then $SW= 100 - rx70 -4x70 - 0.1x(70)^2= -810$.

social welfare. In the case of a high ex-post allocation*, Y = 600* if *V=X=70* and *Y=1000* if *V=N=100*. The results are reported in Table 4a (low budget) and Table 4b (high budget).

Table 4a shows that when the ex-post allocation is low, the preferred choice of the two types of decision-makers is the same as the one taken when the budget was unrelated to demand (Table 3.a). The optimist is again more likely to be associated with a capacity rationing scenario than the pessimist. As seen in the appendix, for all values of the operational and social cost, the optimist will actually not invest in capacity under any combination of the financial and social costs. The main differences are in terms of the social welfare level, although it is not actually very different for the values of costs we picked.

Table 4a: The case of demand uncertainty and a *low* ex-post reimbursement rule (Y^X = 100 and Y^N =200) (*N=100, r=10, c_0=4 and c_1 = 0.1)*							**Table 4b: The case of demand uncertainty and a *high* ex-post reimbursement rule (Y^X = 500 and Y^N =1000)** (*N=100, r=10, c_0=4 and c_1 = 0.1)*				
	V=0	V=70	V=100	Optimist	Pessimist		V=0	V=70	V=100	Optimist	Pessimist
H=0	0	-670	-1200	**0**	-1200		0	-270	-400	0	**-400**
H=70	-700	-600	-710	-600	**-710**		-700	-200	90	**90**	-700
H=100	-1000	-900	-800	-800	-1000		-1000	--500	0	0	-1000

Table 4b is a good indication that the size of the budget can matter when an ex-post budgetary allocation rule is adopted: the results are very different to the ex-ante case. In the simulation reported here, it is the pessimist who decides not to invest in any capacity expansion, while the optimist bets on a capacity consistent with the optimal choice under certainty. Although this may seem somewhat counterintuitive, it is linked to the combination of the values of the operational cost and of the social cost chosen here for our social welfare function.

For the optimist, the simulations summarized in the appendix show that the high ex-post case is the only case in which they are likely to invest in at least some capacity. For this to happen though, operational costs have to be low. For all other combinations of operational and social costs, the optimist will not expand capacity. [12]

For the pessimist, the results are somewhat unexpected and reflect the cost combination reported in this table. For this simulation, the pessimist will prefer not to invest in capacity because this is what leads to the highest level of social welfare. The additional simulations summarized in the appendix show that the results reported in Table 4b are driven by the low social cost assumption. When the social cost is high, the pessimist choses a capacity of at least 70 whether the ex-post budget is low or high.

From a policy perspective, there are thus three important insights to be learned from this set of simulations. The first is that the size of the budget changes the incentive structure of the decision-makers quite dramatically. The second is that – once again – the details on the cost variables matter as much as the level of the budget. How a pessimist values the social costs associated with loss of life or of life quality linked to capacity rationing makes a difference. A high social cost valuation will lead to an increase in capacity in the ex-post budget allocation case as well. As for the optimist, the main focus is on the operational cost. Even if we assume in our narrative that it is exogenous and not under the control of the policymakers, the results highlight that it is a potential tool to be considered in policy debates as well. A final insight may be that, these results imply that, in times of fiscal constraints (i.e. low budgets), it is unreasonable to expect an optimist to invest in a capacity expansion while there is some good chance pessimists will (unless social costs are believed to be low). Despite the similarity of narratives on commitments made by both types of decision-makers.

[12] In the case in which three is a low operational cost but a high social cost, the social welfare function is such that the optimist hesitates between a full capacity and a zero capacity, but for additional simulations on the cost variables, the results suggest that the optimist is indeed unlikely to invest in capacity in general and that the full capacity possibility is an outlier.

6.3. How much does the social valuation estimation matter?

Tables 5a and 5b provide additional evidence to the observation that the value of the social cost matters. While the value of life or life quality is subject to some degree of subjectivity in policy circles and varies significantly across countries and methods, the relevance of the specific value chosen is easily underestimated in ex-ante and ex-post evaluation of capacity choices.[13] Yet, this diversity of approaches available to justify a specific value for the social costs is such that decision-makers can select one that matches their behavioural bias or simply their political preferences.

This can be seen when we consider the case in which the marginal social cost valuations figures are very different for two evaluators of the options. One considers $c_0 = 4$ as we have done so far. The other evaluator assumes $c_0 = 20$, i.e. the costs to society of failing to have enough capacity is much higher than assumed by the other evaluator. [14] The comparison is reported for a low ex-post budget allocation which seems to be more consistent with the evidence, suggesting that hospitals are underfunded and at least partially operating under reimbursement rules, in particular in times of health crisis.

Table 5a: The case of demand uncertainty, a *low* social cost and a *low* ex-post reimbursement rule (c_o=4, Y^X = 100 and Y^N =200) *(N=100, r=10 and c_1 = 0.1)*							**Table 5b: The case of demand uncertainty, a *high* social cost and a *low* ex-post reimbursement rule (c_0=20, Y^X = 100 and Y^N =200)** *(N=100, r=10 and c_1 = 0.1)*				
	V=0	V=70	V=100	Optimist	Pessimist		V=0	V=70	V=100	Optimist	Pessimist
H=0	0	-670	-1200	**0**	-1200		0	-1790	-2800	**0**	-2800
H=70	-700	-600	-710	-600	**-710**		-700	-600	-1190	-600	-1190
H=100	-1000	-900	-800	-800	-1000		-1000	-900	-800	-800	**-1000**

The optimist will prefer not to build any capacity whether the social cost is low or high, as seen in tables 5a and 5b. In contrast, the pessimist will be quite sensitive to this valuation, and the capacity they will chose increases with the assumption made regarding the social cost. In our example, even when the social cost value is assumed to be low, a pessimist will invest at least 70 in capacity. When the social costs is high, it can lead to a decision to invest in the maximum capacity, even if the reimbursement rule is low for the levels of operating costs are assumed here.

These results are largely confirmed by the additional simulations summarized in the appendix for the case of a high ex-post budgetary allocation. For the optimist, even when the social cost is high, s/he will generally not increase capacity. The only case in which the optimist may decide to invest in a capacity to cover the whole population is when the reimbursement rule adopted under the ex-post budgetary allocation is high. However, the budget has to be very high. As for the pessimist, the only cases in which s/he will not invest in capacity are all linked to low social costs

When trying to match these results with the lack of capacity observed in the real world, it is difficult not to consider the possibility that social costs are often undervalued in decisions, irrespective of whether the policy makers are optimistic or pessimistic. This seems to be consistent with the growing evidence of slow reactions to the deterioration in the health prospects of people faced with longer delays for treatment and higher risks of increases in mortality rates.

6.4 How much does the operational cost matter?

The last set of simulations focuses on a dimension that is increasingly becoming part of policy discussions on the scope to increase hospital capacity. A low *r* may mean that the hospital sector is quite efficient or it may mean that the wages or the staffing are rationed for instance. A high one implies that there is some room for improvement in terms of efficiency and hence a lower need to

[13] See Keller et al. (2021) for a review of the empirical evidenced on the value of life.

[14] Note that although in this case, the optimal value of X would be larger than N, it does not impact the decision logic for identifying the optimal choice for society.

expand capacity. It may also reflect the fact that the skill levels used in the hospitals is quite high, justifying high salary. An additional way of interpreting the *r* variable is to consider that it is the fee or co-payment paid by patients. This offers additional ways of assessing and interpreting the incentives built-in the capacity decisions revealed by the simulations as seen in the following discussion.

To be able to discuss how operational costs impact decisions, we compare four cases. They correspond to the low and high *r* cases and the simulations are computed for cases in which the government are allocating ex-post either a high or a low budget *Y* to the sector. We still focus on the ex-post reimbursement rule because it is also the rule that seems to best drive incentives to invest for an optimist, as seen in section 6.2. The capacity decisions associated with each case are summarized in tables 6a to 6h. Tables 6a to 6d report the results for low social costs. Tables 6e to 6h do so for high social costs. We then consider all combinations of low and high budgets and operational cost for the two sets of tables.

Table 6a: The case of demand uncertainty,
a *high* ex-post reimbursement rule, low social costs and a *low* operational cost
r=10, Y^X = 500 and Y^N =1000)
($N=100$, $c_o = 4$ and $c_1 = 0.1$)

	V=0	V=70	V=100	Optimist	Pessimist
H=0	0	-270	-400	0	**-400**
H=70	-700	-200	90	**90**	-700
H=100	-1000	0	0	0	-1000

Table 6b: The case of demand uncertainty,
a *high* ex-post reimbursement rule, low social costs and a *high* operational cost
r=25, Y^X = 500 and Y^N =1000)
($N=100$, $c_o = 4$ and $c_1 = 0.1$)

	V=0	V=70	V=100	Optimist	Pessimist
H=0	0	-270	-400	**0**	**-400**
H=70	-1750	-1250	-960	-950	-1750
H=100	-2500	-1500	-1500	-1500	-2500

Table 6c: The case of demand uncertainty,
a *low* ex-post reimbursement rule, low social costs and a *low* operational cost
r=10, Y^X = 100 and Y^N =200)
($N=100$, $c_o = 4$ and $c_1 = 0.1$)

	V=0	V=70	V=100	Optimist	Pessimist
H=0	0	-670	-1200	**0**	-1200
H=70	-700	-600	-710	-600	**-710**
H=100	-1000	-900	--800	-800	-1000

Table 6d: The case of demand uncertainty,
a *low* ex-post reimbursement rule, low social cost and a *high* operational cost
r=25, Y^X = 100 and Y^N = 200)
($N=100$, $c_o = 4$ and $c_1 = 0.1$)

	V=0	V=70	V=100	Optimist	Pessimist
H=0	0	-670	-1200	**0**	**-1200**
H=70	-1750	-1650	-1760	-1650	-1760
H=100	-2500	-2300	-2300	-2300	-2500

Table 6e: The case of demand uncertainty,
a *high* ex-post reimbursement rule, high social costs and a *low* operational cost
r=10, Y^X = 500 and Y^N =1000)
($N=100$, $c_o = 4$ and $c_1 = 0.1$)

	V=0	V=70	V=100	Optimist	Pessimist
H=0	0	-1390	-2000	0	-2000
H=70	-700	-200	90	-200	**-700**
H=100	-1000	-500	0	0	-1000

Table 6f: The case of demand uncertainty,
a *high* ex-post reimbursement rule, high social costs and a *high* operational cost
r=25, Y^X = 500 and Y^N =1000)
($N=100$, $c_o = 4$ and $c_1 = 0.1$)

	V=0	V=70	V=100	Optimist	Pessimist
H=0	0	-1390	-2000	**0**	-2000
H=70	-1750	-1250	-1440	-950	**-1750**
H=100	-2500	-2000	-1500	-1500	-2500

Table 6gThe case of demand uncertainty,
a *low* ex-post reimbursement rule, high social costs and a *low* operational cost
r=10, Y^X = 100 and Y^N =200)
($N=100$, $c_o = 4$ and $c_1 = 0.1$)

	V=0	V=70	V=100	Optimist	Pessimist
H=0	0	-1790	-2800	**0**	-2800
H=70	-700	-600	-1190	-600	-1190
H=100	-1000	-900	--800	-800	**-1000**

Table 6h: The case of demand uncertainty,
a *low* ex-post reimbursement rule, high social costs and a *high* operational cost
r=25, Y^X = 100 and Y^N = 200)
($N=100$, $c_o = 4$ and $c_1 = 0.1$)

	V=0	V=70	V=100	Optimist	Pessimist
H=0	0	-1790	-2800	**0**	-2800
H=70	-1750	-1650	-2240	-1650	**-2240**
H=100	-2500	-2400	-2300	-2300	-2500

Tables 6a and 6c report the results for low operational costs and a low social cost. The level of the ex-post budget is the only difference. Table 6a shows that, for a pessimist, the combination of a high budget ($Y^X = 500$ and $Y^N = 1000$) and low operational costs ($r=10$) is not enough to justify an increase in capacity since the optimal $H=0$ for those decision-makers. In contrast, the combination could convince the optimist to bet on an intermediate capacity. These results are somewhat puzzling and do not stand the test of additional simulations. When all combinations are tested, the conclusion is subtler. For low operational costs, it is only when the social costs are low that a pessimist will not invest. If social costs are high, the pessimist will invest in at least $H=70$. In contrast, the optimist will only consider investing when the fiscal reimbursement rules are generous, even if the low operating costs reflect a high level of efficiency rather than a low co-payment.

Table 6c leads to a more predictable outcome. When the ex-post reimbursement rule is low and the operational cost as well, the optimist will not invest when budgets are low. The low operational costs are insufficient to offset the negative incentives to invest due to the low budget. In this case, the result would be consistent with a reinterpretation of the operational costs as the fee to be paid by a patient to the hospital. A low *r* means a low fee and hence a low incentive to deliver hospital services. For the pessimist, the model leads to a more credible outcome if the r is interpreted as an operational cost. Capacity will be expanded suggesting that the low operational costs provide the right incentives if the goal is to minimise the risks of rationing

Tables 6b and 6d focus on the case in which operational costs are high ($r=25$). In this context, two scenarios are possible for the value of all the other variables selected here. Table 6b focuses on 6d focuses on a situation in which the *ex-post* budgetary allocation is high ($Y^X = 500$ and $Y^N =1000$) while Table 6d focuses on the case in which the budget is low ($Y^X = 100$ and $Y^N = 200$).

When the ex-post budget is low as in Table 6d, neither type of decision-maker will choose to expand hospital capacity. For both types, the optimal choice is indeed $H=0$. Increasing the ex-post budget allocation does not change the decision for either type of individual. Indeed, Table 6b shows that a high budgetary allocation ($Y^X = 500$ and $Y^N = 1000$) will not be sufficient to offset the effects of the very high operational costs.

Taken together, these eight simulations suggest that, when operational costs are low, optimist decision-makers are unlikely to invest in capacity and pessimists are unlikely to do so as well unless social costs are high. When operational costs are high instead, the incentive of optimist decision-makers to invest in more capacity will only increase with a very significant fiscal effort. Pessimists are more likely to do so in such a high operational cost environment, but not as systematically as we might have expected. They will not invest if social costs are low. In sum, low social cost valuations much more than any level of operational costs or even low levels of budgetary allocations could offer an explanation for the current capacity gaps observed in at least some countries.

6.5 So what?

The wide range of results delivered by the conceptual discussion and the simulations help increase the transparency of how behavioural biases influence optimal hospital capacity choices in uncertain health needs environments. The results could also help guide future policy-making linked to capacity decisions. This is in a context in which there is a need to expand capacity to attend to the usual drivers of demand such as demographics but also to anticipate the possibility of random health shocks.

With respect to the fiscal tool choice, when all possible cases have been simulated, the main result to bear in mind may be that an ex-post budget allocation process is generally a safer bet than an ex-ante bet when the behavioural biases of the decision-makers are unknown. An ex-ante budget will not deliver any new capacity for an optimist for any of the combinations of costs and budget levels simulated. The preference for an ex-post budgetary approach though, is far from being a cast-iron guarantee that capacity rationing risks could be reduced. Indeed, the size of the budget makes a difference to the odds of getting more capacity as a way to manage uncertainty. Moreover, even pessimists will not be keen to invest if the social costs of rationing are estimated to be low. At the same time, this limitation is valid for both budgetary approaches for the pessimist.

With respect to the recognition of the relevance of the social costs of capacity choices, the evidence of a growing risk of rationing in uncertain health-needs environments reported in the literature reviewed earlier suggests that they may be undervalued by many countries. This adds to the case to be made for a transparent debate about the value of life and quality of life when assessing capacity options. And this is something that can be turned into a policy choice swaying capacity decisions one way or another. If this decision is turned into a transparent one, it is likely that politicians will have an incentive to adopt higher values for the social cost of rationing. It is indeed hard to minimize the value of life or of its quality in public statements.

Finally, the analysis shows that the valuation of the operational cost may also become a potentially useful policy tool. At the same time, however, it is much a more complex element to handle, as seen in section 6.4. It is politically sensitive, and hence challenging, since it is often linked to staffing decisions and technological choices. On the other hand, it also gives some room for efforts to bet on better technologies as well. These are two of the reasons why financially-oriented managers are so focused on operational costs – although they tend to do so for a given capacity rather than in a context in which they are considering capacity expansions. For the designers of sectoral policies, even in the cases in which there is not much politicians can do about these operational costs, it would seem crucial to have a precise sense of their values. The simulations show that the differences in incentives to bet on capacity between a low and a high operational cost are important and play out in different ways for each type of decision-maker. To resolve this issue, transparent and analytically robust data is needed to support simulations similar to those reported here, although much more detailed and anchored in solid cost accounting information. [15]

7. Concluding comments

In a world in which fiscal constraints are such that governments are keen to minimize fiscal costs, hospital capacity rationing is likely to continue to be a recurring risk under the most common fiscal rules adopted to finance these expansions in highly uncertain health care needs environments. The risk is closely linked to the behavioural biases of those making the financing decisions. And the risk is clearly higher when the decision-makers are optimistic.

The modelling approach suggested here can help to reduce this risk and to pick the policy tools best able to reduce them. Indeed, it can be used ex-ante to compare strategies and rank them according to the diversity of dimensions of the context in which the decisions are taking place. The modelling can also be used ex-post in the context of evaluations aimed at identifying which tools could have been used differently to better deliver on future capacity needs. Simulations can also be helpful to reveal the behavioural biases built into observed outcomes and to help improve accountability for past and future decisions.

From an ex-ante perspective, a more detailed version of the model could be helpful in a debate on the extent to which assumptions on key dimensions such as operational and social costs can influence decisions and possibly introduce a bias weighted towards fiscal concerns and maybe political preferences as discussed in the context of the management of the Covid crisis in the US. It would make sense, when thinking about whether or not to expand capacity, to run multiple simulations with low and high values for each key variable. This would give a better sense of the upper and lower bounds of the budgets that need to be allocated to achieve a capacity level that responds to both the optimist's and the pessimist's concerns. We know that budget size matters. And how much it matters can actually be estimated. This would have to fit into a sectoral perspective of the full sector, and not just the hospital component. And as importantly, it should ideally be done in a transparent way, and by independent agencies, to ensure accountability on this dimension of policy decisions as well.

[15] This type of detailed modeling is quite common in the utilities and transport sector and are part of the tool kit of many regulators.

From an ex-post perspective, the type of modelling suggested here can help match the future fiscal choices and the cost variable valuations with the behavioural bias of the decision-makers. This is clearly politically difficult. At the same time, gaining some sense of the biases built into decisions is useful for being able to deliver on the commitment to cater to the health needs of the population and to minimize the margin for systematically blaming the randomness of health care needs to justify rationing. Conceptually, the model is indeed also a preference revelation mechanism to identify systematic behavioural biases in political and management decisions in the sector.

There is some data available to increase the transparency of biases and preferences. The differences in the ways in which the Covid crisis was dealt with by different authorities in different locations offers a natural experiment that could be analysed quite thoroughly with the behavioural characteristics in mind. It could also be used to reveal information regarding the heterogeneity of approaches to the valuation of social costs, for instance. This is particularly important because the possibility of a widespread unclaimed optimism bias may slow the fiscal and financial commitments needed to deal with the growth of future demand for capacity that goes beyond the risks of health shocks ((Sebire et al. (2025) or WHO (2022)). For now, rationing of hospital care quantity and quality capacity continues to dominate in many countries, and for many pathologies. And this is happening at a high social cost, as illustrated in detail by Siverskog and Henriksson (2022) for Sweden or Walsh et al. (2021) for Ireland.

Ultimately, the model shows that, in order to fuel the political willingness to conduct evaluations of the most desirable way of managing uncertainty in the health sector in general, and the hospital subsector in particular, it would make sense for the sector regulator to improve transparency in the decision-making process leading to the choice of capacity in many countries. For now, it is too often lacking for both the behavioural biases built-in the methodological and valuation choices driving the capacity choices under any types of fiscal rules. Ex-ante, most decision-makers prefer to be seen as optimistic as it often improves their odds of being elected or nominated for a decision-making position in the sector. And, ex-post, if and when things did not turn out right, this allows them to blame bad luck (Estache and Foucart (2018)).

Accountability starts with transparency. An increase in transparency on all the choice drivers in uncertainty contexts is likely to help a convergence of views on the health sector needs across the political spectrum. This is urgently needed to lower the risks of lasting capacity rationing and the associated high social costs.

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Appendix

Comparing capacity decisions under the two main budgetary options for all combinations of variables values				
	Ex-ante budget		**Ex-post budget**	
	Optimist	**Pessimist**	**Optimist**	**Pessimist**
	Low budget			
Low operational cost, low social cost	0	70	0	70
Low operational cost, high social cost	0	100	0	100
High operational cost, low social cost	0	0	0	0
High operational cost, High social cost	0	100	0	70
	High budget			
Low operational cost, low social cost	0	70	70	0
Low operational cost, high social cost	0	100	0 or 100	70
High operational cost, low social cost	0	0	0	0
High operational cost, High social cost	0	70	0	70

Comparing capacity decisions for low and high social costs assumptions for all combinations of variables values for an ex-post budget allocation		
	Optimist	Pessimist
	Low social cost	
Low ex-post reimbursement, low operational cost	0	70
High ex-post reimbursement, low operational cost	0 or 100	0
Low ex-post reimbursement, high operational cost	0	0
High ex-post reimbursement, high operational cost	0	0
	High social cost	
Low ex-post reimbursement, low operational cost	0	70
High ex-post reimbursement, low operational cost	0 or 100	70
Low ex-post reimbursement, high operational cost	0	100
High ex-post reimbursement, high operational cost	0	70

Comparing capacity decisions for low and high operational costs assumptions for all combinations of variables values for an ex-post budget allocation		
	Optimist	**Pessimist**
	Low operational cost	
Low ex-post reimbursement, low social cost	0	70
High ex-post reimbursement, low social cost	70	0
Low ex-post reimbursement, high social cost	0	100
High ex-post reimbursement, high social cost	0 or 100	70
	High operational cost	
Low ex-post reimbursement, low social cost	0	0
High ex-post reimbursement, low social cost	0	0
Low ex-post reimbursement, high social cost	0	70
High ex-post reimbursement, high social cost	0	70