9 Understanding and Governing Public Health Risks by Modeling

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Abstract: Increase in the use and development of computational tools to govern public health risks invites us to study their benefits and limitations. To analyze how risk is perceived and expressed through these tools is relevant to risk theory. This chapter clarifies the different concepts of risk, contrasting especially the mathematically expressed ones with culturally informed notions, which address a broader view on risk. I will suggest that a fruitful way to contextualize computational tools, such mathematical models in risk assessment is "analytics of risk," which ties together the technological, epistemological, and political dimensions of the process of governance of risk. I will clarify the development of mathematical modeling techniques through their use in infectious disease epidemiology. Epidemiological modeling functions as a form of "risk calculation," which provides predictions of the infectious outbreak in question. These calculations help direct and design preventive actions toward the health outcomes of populations. This chapter analyzes two cases in which modeling methods are used for explanation-based and scenario-building predictions in order to anticipate the risks of infections caused by *Haemophilus influenzae* type b bacteria and A(H1N1) pandemic influenza virus. I will address an interesting tension that arises when model-based estimates exemplify the population-level reasoning of public health risks but has restricted capacity to address risks on individual level. Analyzing this tension will lead to a fuller account to understand the benefits and limitations of computational tools in the governance of public health risks.

Introduction: Governing Public Health Risks

► Nothing is a risk in itself; there is no risk in reality. But on the other hand, anything can be a risk; it all depends on how one analyses the danger, considers the event (Ewald 1991, p. 199).

In June 2009, we faced a risk of a global pandemic caused by A(H1N1) "swine flu" virus. At the moment WHO defined the outbreak a *pandemic*, a viral flu infection turned into a global risk. Two years later the risk assessment process that led to the global call is questioned. Was the "swine flu" a global risk after all? "Nothing is a risk in itself" shows that what is identified as a risk depends on the way in which "danger is analyzed" or how risks are identified.

What, then, is a risk? Risk research answers to that question through three main paradigms: the statistical-probabilistic, the epidemiological, and the sociological. Initially developed for insurance industry, the statistical-probabilistic approach applies various estimates of personal benefits, effectiveness of treatments, and use "risk calculations." This means translating "successful calculations of risk" into an objective measure. Estimates of how various health-related factors influence the probability of falling ill is a typical example of epidemiological paradigm. It comprises of psychometric studies, which focus on understanding public risk preferences and applies mental modeling to analyze rational decision making. When cultural and individual perception and responses to risk are interlinked, sociological approach is in use. Within this sociocultural paradigm, risk is regarded as a "socially constructed phenomenon although it has some roots in nature." Furthermore, we can identify governmentality approach, which is based on Foucault's analysis of societal governance and includes into the analysis broader issues of power as a part of the sociological approaches to risk. This form of analysis includes "construction of realities through practice and sense-making, encompassing the multitude of societal organizations and institutions producing social reality" (Taylor-Gooby and Zinn 2006, p. 43).

In the public health domain, the idea of what counts as a risk has a dynamic nature. Risk from the public health policy point of view may not be a risk for an individual. Dean argues that epidemiological risk forms a "long-standing and pervasive form of risk rationality." In his words, "epidemiological risk is concerned with the rates of morbidity and mortality among populations." When talking about epidemiological risk, "the health outcomes of populations are subject of risk calculation" (Dean 2010, p. 218). In regard to public health risks, we can talk about risk rationality as a form of rationality, a way of thinking about and representing events, which happens through calculations (Dean 2010, p. 213). Castell (1991) shows how mental health problems shifted in their classification as dangerous to risk as a part of historical, theoretical, and practical shift toward *risk rationality*. Underneath the emphasis of population as a subject of risk calculation is the historical shift from a family to population as a re-centering concept of economy. Michel Foucault argues that "[. . .] population has its own regularities, its won rate of deaths and diseases. [. . .] [S]tatistics shows also that the domain of population involves a range of intrinsic, aggregate effects, phenomena that are irreducible to those of the family, such as epidemics. Population comes to appear above all else as the ultimate end of government" (Foucault 1978/1991, pp. 99–100). Population becomes the object of governance. The attitude or mentality of governance is known as governmentality in Foucault's work. It refers to the forms of thought, expertise, and knowledge that direct and guide the acts of governance (Dean 2010). How the risk rationality that shifts "dangerousness" of disease outbreaks into risks manifest in epidemiology?

New risks "violate many assumptions of risk calculation," as Taylor-Gooby and Zinn (2006, p. 25) argue. They are global, complex, and entangled with different areas. They share characteristics of catastrophes. These new risks are "mainly invisible and inaccessible by direct means." They challenge the statistical-probabilistic approach to risk. How do we encounter these new risks? One way of coming into terms with them is suggested in Smith's analysis of SARS (Sudden Acute Respiratory Syndrome) epidemic (Smith 2006, p. 3114). He proposes a mediatory approach in order to overcome the dichotomy between the realist and constructivist accounts to risk. According to his "material-discursive" position, "risk is both a materially measurable probability of an event and a socially constructed element of how that probability is perceived by the individual and society." This mediatory approach is useful when explaining the ways in which risk is represented, anticipated, and processed in models. The mediatory approach does not solely lean on realist interpretation, which sees risk as an objective threat or danger that can be measured independently of the social context within which it occurs. Nor does it reduce risk to culturally or socially constructed threat, which cannot be demonstrated independently of those processes. Close to the realist interpretation is Schlich and Tröchler's (2006) definition of risk and uncertainty. He says that "one can speak of risk when the probability estimates of an event are known or at least knowable, while uncertainty, by contrast, implies that these probabilities are inestimable or unknown." Riesch (2011) provides a classification of uncertainties that problematizes the clear-cut division between probability estimates and unknown events. I suggest that new risks, such as emerging infectious outbreaks, can be encountered by accommodating statistical-probabilistic approach of risk calculation (in the form of mathematical modeling) with the questions of governance. In this chapter, I will apply the Foucauldian notion of governmentality and address risk calculation as a *technical rationality*. How could we see public health risks through this lens?

The heterogeneity of the definitions of risk suggests that understanding risk encompasses the following aspects: dangerousness of an event, unpredictability of its occurrence and course, and severity of its consequences. Infectious disease outbreaks, therefore, form a source of "danger" that affects the public. This means that public health risks are anticipated through surveillance and monitoring procedures, which are carried out by the national public health institutes. Surveillance and monitoring procedures comprise of keeping records of notifiable diseases or participating in international collaboration to govern outbreaks of emerging infections. Surveillance activities are carried out on various levels: on national level by public health institutes (e.g., Health Protection Agency in the UK) and on international and intergovernmental level (e.g., by WHO, ECDC, the European Disease Control Centre). However, risks from infectious outbreaks create a challenge for public health decision makers, who aim at identifying the risks through preparedness planning and revising protective interventions, such as vaccinations. Their interest is to employ predictions of the course of the outbreak. In order to do that, decision makers search for alternative ways to process the information flow. Evidence for developing the required preventive and protective measures for decision-making processes is produced by computer-based modeling techniques. Hence, modeling techniques can be utilized in the encounters with public health risks from infectious diseases. These *modeled encounters* provide predictions that facilitate risk assessment processes. This chapter shows how two modes of prediction: explanation-based and scenario-building provide strategies, not only to produce evidence for the decision-making, but also to translate the potential threat to a quantifiable, measurable risk. By doing so, modeled encounters with risks allow us to follow the social processes that try to control and minimize public health risk in society. In his commentary on climate models, Hulme et al. (2009, p. 127) highlights an important aspect of models, which is highly applicable to predictions from epidemiological models: "Scientists and decision-makers should treat climate models not as truth machines, but instead as one of a range of tools to explore future possibilities." Through the analysis of the two types of predictions, I will address how epidemiological models function as *technologies* when encountering public health risks.

How is understanding of public health risks formed, estimated, and communicated through modeling? How does public health risk prevention use technical understanding gained by model-based predictions? These are the main questions addressed in the analysis of *modeled encounters* with infectious risks, which arise from *Haemophilus influenzae* type b bacteria and from A(H1N1) pandemic influenzae ("Swine flu" outbreak in 2009). By analyzing these two cases, I will show how modeling provides a way to *encounter* risks, which means that modeling itself forms a base for risk calculation and estimation that allows rendering the available information into predictions (cf. Mansnerus 2009a, 2011).

About the Case Study

The case study analyzed in this chapter was conducted during 2002–2004 at the University of Helsinki. I observed modeling practices in 22 work meetings (recorded and transcribed, duration of a meeting app. 2 h) at the National Public Health Institute (currently the Institute for Health and Welfare) and conducted 28 thematic, semi-structured interviews (transcribed for analysis) with mathematical modelers, epidemiologists, and computer scientists working as members of the interdisciplinary team (published in Mattila 2006a, b). The models were published in Auranen 1999, 2000; Auranen et al. 1996, 1999, 2000 and Auranen et al. 2004; Leino et al. 2000, 2002, 2004 and Mäkelä et al. 2003. The study analyzes how an integrated simulation model on Hib transmission in the Finnish population produces *explanation-based* predictions. In this chapter, I will keep the focus on a single, integrated model in order to allow a detailed description of the ways in which the model predicts. The findings from the Hib case will be discussed in relation to microsimulation model on mitigating an *influenzae* pandemic. This example will show how microsimulations produce *scenario-building* predictions. The analysis focuses on detailed micro-level observations and interpretations of the predictive capacities of microsimulations. Both models are chosen, because they provide clear examples of the predictive capacities of simulations. I have chosen not to explore the vast literature on *pandemic influenzae* models, but to concentrate on a detailed level on a single model. The analysis is informed by a practical course "Introduction to Infectious Disease Modeling," organized by the London School for Hygiene and Tropical Medicine, 2006, which gave me ability to read the models and understand their core structure. As a part of the coursework, we analyzed the published pandemic simulation models and prepared a group exercise on national preparedness planning. I have chosen one of these as an example of scenario-building modeling exercise.

The structure of this chapter is as follows: section ➋ Toward Modeled Encounters with Public Health Risks discusses the development of modeled encounters in epidemiology. Section ➋ Predicting Infectious Risks Through Modeling shows how this development takes place when mathematical models are used in public health decision making. I will use two cases as examples to show how public health risks can be governed through modeling. Section ➋ Further Research: Toward the Analytics of Risk discusses how the tension between individual level risk perception and population-level risk assessment could be reconciled analyzing public health risks suggests further research within the analytics of government approach.

Toward Modeled Encounters with Public Health Risks

Technologies form an integral part of the procedures through which organizations and individuals try to control risks they encounter. These technologies range from software systems to visualizations and representations, from advanced technological structures (e.g., air traffic control) to models (Hutter and Power 2005). Models, or broadly speaking computer-based tools and techniques have become commonly used in various scientific and policy-making contexts. Yet, they have the potential to "legitimate a range of possible social futures," as Evans (2000) frames the capacity of economic models. Den Butter and Morgan (2000) seem to suggest that models, which are engaged with policy-making processes in economics, actually build a bridge between research and policies or between "positive theory and normative practice." In their account, these models form a part of the "value chain" through which knowledge is created, stored, and transmitted in organizations.

One of the main reasons to develop modeling techniques is to overcome uncertainties related to complex phenomena, such as climate, economy, or infectious diseases. Establishing modeling practices also helps forming a network that integrates available knowledge and communicates it further. Paul Edwards (1999, p. 439) argues that "Uncertainties exist not only because quantifiable, reducible empirical and computational limits, but also because of unquantifiable, irreducible epistemological limits related to inductive reasoning and modeling"(cf. also Hillerbrand 2010). His argument seems to suggest that due to the very nature of the modeled phenomenon itself, uncertainties remain as a part of the process. As Shackely and Wynne (1996, p. 276) emphasize, scientific knowledge, or the "authority" of it, is limited in policy making, since it prevents decisions to be made or actions taken. Van den Bogaard (1999, p. 323) shows, on the contrary, that the first macroeconometric model, developed by Tinbergen in the 1930s for the Dutch Central Planning Bureau, was a "liberation both from the uncertainties caused by the whimsical nature of the economy and the woolly theories of the economists." One form of uncertainties remains within the models, as MacKenzie's (2005, p. 186) study on financial economics shows, "models affect the reality they analyze." According to him, this "reflexive connection serves to increase the veracity of finance theory's assumptions and the accuracy of its models' predictions," but it may also function in a counterproductive way (as in his case, the exploitation of arbitrage opportunities by using mathematical models leads to instability of the system). It seems to me that when modeling complex, open systems, such as climate (cf. Gramelsberger 2010) or ecological systems, there will remain uncertainties, because of limited computational capacity, biased reflection of the reality, or unpredictable nature of the phenomena themselves.

Encounters with risk, as Hutter and Power (2005, p. 11) clarify, are events of problematization that "place in question existing attention to risk and its modes of identification, recognition and definition." "Risk identification," they continue, "is socially organized by a wide variety of institutions which support prediction and related forms of intervention around the possibility of future events." When we encounter risks and uncertainties, or predict a possible course of events, we develop and utilize various measurement devices, such as statistical methods, surveys, and models. From a historical perspective, we can identify a shift away from "informal expert judgment toward a greater reliance in *quantifiable objects*," as Porter (2000, p. 226) argues in his case study of the use of mortality statistics in life insurance industry. The tendencies underlying this shift are addressed by a growing interest in sociology of quantification – i.e., in the "production and communication of numbers." How do we "do things with numbers?" Espeland and Stevens elaborate J.L. Austin's idea of speech acts (doing things with words) to the domain of quantification and they call it "doing things with numbers." They argue that as with words, "numbers often change as they travel across time and social space" (Espeland and Stevens 2008, pp. 402–406). The "change in numbers" could be seen as a parallel process to the one that characterizes how public health risks become quantified through its historical development. This historical development can be aligned with two processes: First, the development and application of mathematical methods in order to understand the dynamics of disease transmission (Mansnerus 2009a), and second, the shift within biopolitics (politics that is concerned with governance of living conditions in a population) toward risk politics (Rose 2001).

The first process, gaining understanding of disease transmission and developing tools to express and represent that process in mathematical terms arose when germ theory of disease located the cause of infections to their microbiological origins, germs. What initiated the move toward mathematical formulations were population-level observations of infectious cycles, such as influenza outbreaks in households in London 1890–1905, as Hamer documented (Hamer 1906). Later on, Kermack and McKendrick (1927) divided the population into specific subgroups, *compartments* of susceptible, infected and immune, which represented different phases observed during an epidemic outbreak. These developments in mathematical epidemiology aimed at identifying various factors that caused transmission of germs and spread of the infectious outbreak.

The second process, which developed toward risk politics, was grounded on the developments on the microbiological level, but emphasizes the ways in which concern for the health of the population adopted preventive measures. In his analysis of the birth of social medicine, Foucault looks into the organization of the Health Service and the Health Office in England at the end of the nineteenth century. He shows how three functions developed:

– "Control of vaccination, obliging the different elements of the populations to be immunized.
– Organizing the record of epidemics and diseases capable of turning into an epidemic, making the reporting of dangerous illnesses mandatory.
– Localization of unhealthy places and, if necessary, destruction of those seedbeds of insalubrity" (Rabinow and Rose 1994, 335).

The first two aspects in the development of health services show how public health measures take the form of governance. These forms, namely "control of vaccination," especially if understood as a process of assessing and revising vaccination schemes, and "organizing the record of epidemics" are present when modeling techniques are applied to public health risks. "Control of vaccination" is one component in modeling process; it is applied as a preventive measure, as an estimate in terms of "herd immunity," immunity cover for the whole of population when only a significant portion of it is vaccinated. This can be obtained as an indirect observation from the models and it allows estimating the vaccination coverage needed to protect the whole population. Organizing the record of epidemics could be extended to cover the predictive functions, as the following case studies will show. So mathematical methods in epidemiology developed initially in conjunction with the early observations of infectious cycles and outbreaks that gave rise to develop preventive actions against these risks.

Even though these aspects are to some extent present in the preventive public health work, the intention behind infection prevention has changed. Rose (2001) argues that the shift toward risk politics happened when public health programs and preventive medicine were transformed and health became "economized," meaning that individuals were expected to became active in maintaining their well-being and health. Whereas the earlier programs understood health as fitness and were hence framed to tackle the "unfitness of populations," the current emphasis is on costs of ill health for the economy (Rose 2001, pp. 5–7). This shift results in various strategies for the government of risk. Rose says that risk denotes in this context "a family of ways of thinking and acting, involving calculations about probable futures in the present followed by interventions into the present in order to control that potential future." And, he continues, demand for these collective measures increases. As we will learn from the detailed study of how modeled encounters with public health risks happen, I would argue that the shift toward risk governance is still partially embedded in the preventive ideals of public health risk perception. The predictions from the models I will study are not estimates of the economic costs of a pandemic, although those have been taken into account through different analyses. Model-based predictions seem to function as a way to estimate the need to vaccinate and to assess the spread of the infection. On the basis of these predictions, protective measures toward the public can be initiated. But how do we actually build models to predict public health risks?

Current Modeling Techniques

Modeling techniques provide a way to produce predictions, or in broader terms evidence for decision-making processes and, as such, they are a new way to encounter public health risks.

Modeled encounters with public health risks are approached in terms of studying the nature of model-based predictions. These predictions form the core of our attempts to control public health concerns, prepare for sudden outbreaks, or estimate population-wide effects of bacterial or viral transmissions. Modeled encounters with risk introduce two modes of predictions, those based on explanations and those building scenarios for future events or developments. Scenario in this context means an outline of an imagined, possible situation that has been quantified through modeling. By locating modeling into the context of measurement, we will learn the different ways in which trust, credibility, and usability of the modeled predictions emerge and are communicated from research domain to decision-making processes (cf. Morgan and Morrison 1999; Boumans 1999; van den Bogaard 1999).

What do we then understand by modeling? Generally speaking, computer-based models (including simulation techniques) in infectious disease epidemiology share the following characteristics: First, they have a three-part elementary structure, which comprises of data element, mathematical method and computational techniques, and element of substantial knowledge, or epidemiological component. Secondly, they are "tailor-made," usually addressing specified research question, which to some extent limits their applicability. Thirdly, majority of these models rely on currently available data. And it is precisely the need to reuse and reanalyze the data that partially motivate the model-building exercise. Fourthly, micro-practices that are independent the context of application, say the pathogen studied, can be identified within modeling process. A detailed analysis of the eight consecutive steps in modeling process is documented in Habbema et al. (1996, p. 167):

- Identification of questions to be addressed
- Investigation of existing knowledge
- Model design
- Model quantification
- Model validation
- Prediction and optimization
- Decision making
- Transfer of simulation program

The importance of setting the question follows the idea of *tailoring* a model to address particular interests. Investigation of existing knowledge is a process in which existing literature, laboratory results, experiences of existing models, and data from surveillance programs are integrated as a part of model assumptions. Morgan (2002) aligns model building with similar steps to those mentioned by Habbema et al. (1996), although her focus is on economic models. The main difference is that in her account the model is first to build to represent the world, then subjected to questions and manipulation in order to receive the answers to the questions, then relating the answer to real-world phenomena.

Model design follows the existing understanding of how the phenomenon of interest behaves and is often represented through a compartmental structure. Compartmental structure means that the population is divided into subgroups according to the impact on immunity, susceptibility, and potential recovery from the modeled infection.

Model quantification is the process of estimating the optimal parameter values and setting the algorithms to run the simulations. In Habbema's et al. (1996) account, model validation means checking the model against data from control program. The particular interest in this chapter is to analyze how the step from prediction and optimization to decision making is taken in regard to public health risks.

By transfer of simulation program, Habbema et al. refer to the generalizability of the computer program in other infectious diseases. This step-wise characterization of the micro-practices of modeling highlight that modeling is an *iterative* practice, which builds upon and checks back with previous steps throughout the process. Importantly, these models are not only scientific exercises to develop better computational algorithms, they are built first and foremost to explain, understand, and predict the infectious disease outbreaks or transmission processes. The major application of this group of models (including also simulations) is to design, for example, reliable and cost-effective vaccination strategies or to predict the course of influenza pandemic (Mattila 2006a, b, c). Morgan (2001) characterizes this process as "story-telling," in which a model is a narrative device. I suggest that scenario-building predictions could be related to this aspect of model building, or "storytelling" through processes of manipulation, as we will learn through pandemic modeling.

Following Espeland's and Steven's account on quantification practices, modeling as a measuring practice aims at controlling and predicting risks through quantification. The modeled encounters with risk, after all, are encounters to minimize the risk, to predict, and to prepare in front of the uncertain course of events. In broader terms, both types of prediction, explanation-based and scenario building, are *technologies of governance* that allow different interest groups to act at a distance (cf. Miller and Rose 2008). In explanation-based predictions, the underlying uncertainties are smaller, perhaps more manageable, whereas in scenario-building predictions the distance between what is known and what remains unknown is greater. Scenario-building predictions share some similarities with audit process, as discussed in Power (1997, p. 40):

► The audit process shrouds itself in a network of procedural routines and chains of unverified assurance, which express certain rituals of evidence gathering, but which leave the basic epistemic problem intact.

But are these similarities actually showing us what may result from overreliance on regulatory processes of governance? As we will learn through the case study of scenario-building predictions, their capacity to explain the phenomenon may manifest as a limitation or restriction, and yet they operate as useful tools to shed light on unknown future state of an anticipated public health risk. In the following, I will study in detail the modes of prediction provided by models. Through the analysis, I will show how useful models are in encountering and governing public health risks.

Predicting Infectious Risks Through Modeling

In public health decision making, predicting is one of the key motivations to develop modeling techniques. What kinds of model-based predictions we are able to identify in infectious disease studies? Two cases analyzed in this chapter allow us to compare different types of model-based predictions (cf. Mansnerus 2011b). First, as an example of predictions that facilitate the renewal of vaccination strategies, a case of population-level transmission models of *Haemophilus influenzae* type b bacteria is analyzed. This case introduces us to *explanation-based* predictions that produce "what would happen if" scenarios. These scenarios derive their predictive capabilities from the available datasets and reach out to short-term predictions beneficial to predict outbreaks within a particular area. So, the development of preventive measures in public health can be informed by *explanation-based* predictions.

Secondly, by analyzing a microsimulation model on mitigation strategies for a pandemic influenza, we will learn about *scenario-building* predictions. Typical for these predictions is that the data utilized in them are derived from past pandemics. Hence, these predictions are not capable to explain a possible future pandemic, but to produce reliable scenarios of its potential development, and thus facilitate the distribution of protective measures. So, in order to assess reliability and usability of model-based predictions, it is beneficial to increase transparency of evidence throughout the production and utilization process. This allows the different groups, who are involved in the decision-making processes, to evaluate the predictive scenarios and make well-informed decisions.

However, within infectious disease studies, one of the major public health concerns is the limited capability to predict emergence of outbreaks and people's behavior in such an event. Outbreaks could be regarded either as "small," when they occur, say in closed populations, such as army units, or "large," such as the anticipated pandemic outbreak. Small outbreaks, say transmission of bacterial meningitis, caused by Hib, in a military garrison may not receive broad media coverage, but are nevertheless important for the core tasks of public health officials. After all, it presents a life-threatening risk. To protect public health asks to be prepared for or capable of controlling and managing these outbreaks. Dynamic transmission models provide a rather flexible tool in order to do that – they form a ground to address anticipatory "what would happen if"-type questions. Larger, unexpected outbreaks that are capable to cause wider devastation gain easily significant attention. Preparedness plans are conducted both on national and international level. Large-scale simulation models that utilize data from past pandemics, on travel patterns and population density, produce a part of the scientific evidence base. One example of these models focuses on mitigation strategies and provides estimates of their effectiveness. So, these two cases analyzed in this study inform us of the two distinct modes of prediction represented in the models.

Explanation-Based Predictions

Infections that affect mainly children's health are a mundane public health concern. One of the main threats is considered to be bacterial meningitis, because of its life-threatening nature. However, most of these infections are vaccine preventable, as in our example case, *Haemophilus influenzae* type b bacterial transmission. The main effort remains to reduce the risk of these severe disease forms in a population. So, the need to predict potential public health risks is answered by developing sophisticated transmission models. Evidence of potential outbreaks, indirect effects of vaccinations, and estimates of herd immunity are assessed by models. What kinds of predictions are useful to form the evidence base for vaccine-preventable infections? Amy Dahan Dalmenico (2007) argues that there is a continuous tension between the explanatory and predictive functions of models. According to her, this tension is seen as a source of conflict and compromise:

► Modeling practices [. . .] should they be first and foremost predictive and operational or cognitive and explanatory. Tension between explanatory and predictive capacities, between understanding and forecasting is a source of conflict and compromise in modeling (Dahan Dalmenico 2007, p. 126).

From a philosophical point of view, the distinction between explanations and predictions is considered separate or even in a conflict with each other as Dahan Dalmenico suggests. However, my analysis of the short-term, *explanation-based* predictions in the case of Hib transmission models, will argue that the tension could be set aside. Model-based predictions can be grounded on explanatory mechanisms, as the case of Hib transmission models, or they can provide desirable qualitative tools in a form of *scenario-building* prediction, as we will see. This is an interesting outcome, and useful when we are looking at how predictions help in public health risk assessment. The main benefit from models is that they allow us to "do things with numbers," to build the platform upon which one can develop understanding of the infectious risk itself and experiment with the various mitigation strategies. Through these quantifiable tools, the evidence base for risk governance is widened. In the following, I will present a detailed case study how *explanation-based predictions* work in the case of modeling Hib transmission.

Case of an Integrated Simulation Model of *Haemophilus influenzae* Type B (Hib) Transmission

Hib colonizes the human nasopharynx and is transmitted in droplets of saliva. The public health risk is related to its severe disease forms (Ladhani et al. 2009). Hib is capable of causing severe and often life-threatening diseases, such as meningitis and pneumonia in young children (an estimated three million cases of serious illness and 400,000 deaths each year in children under 5 years of age worldwide). A part of the incentive to produce model-based predictions lies in the cost of vaccines. Hib vaccine is not yet a part of national vaccination strategies in the developing countries, mainly in Africa and Asia. Polysaccharide vaccines were on market in the 1970s and conjugates in the 1980s. The main difference is that the polysaccharides protect against the disease forms, whereas the conjugates are capable of reducing the carriage of the bacteria and hence have effect on population level circulation of the bacteria. If considered from the economic point of view, polysaccharide vaccines are older and somewhat cheaper to produce, and the conjugates are more expensive. As clarified by Hib Initiative, Hib infections are difficult to treat in the developing countries, due to the lack of access to antibiotics, which are proven to be effective when treating the severe disease forms (www.hibaction.org, accessed 25.3.2009). Because of this, the Hib Initiative presents an estimate that 20% of children in developing countries with meningitis caused by Hib will die and 15–20% of children suffering from it will develop lifelong disabilities. As an epidemiologist from the Helsinki modeling group argues:

- WHO and GAVI (the Global Alliance of Vaccinations and Inoculations) advocate Hib conjugate vaccines, the major question remains whether universal vaccination will be at all feasible in the poorest economies. Will it be cost-effective, and will it be an appropriate use of resources among other possible health interventions? Schedules optimizing the age of vaccination and the number of doses are crucial for the acceptance of the expensive vaccines (Leino 2003).

These general concerns are translated into an integrated simulation model in order to produce qualitative, anticipatory predictions of the potential vaccination effects on the population level. The translation process meant that the modelers needed to study particular mechanisms that were responsible for the behavior of the bacteria. In order to address these mechanisms in the integrated model, they studied them separately.

The global concern to implement conjugate vaccines is based on data from the UK and Finland. Both countries tell their own "success stories" that support the initiative to include Hib conjugate vaccines in the vaccination programs.

"What Would Happen If" Questions as a Key to Explanation-Based Predictions

Seeking answers to "why"-questions means *explaining* a particular phenomenon, say a cause of an infection. When "why"-questions are addressed in models, they search for a particular mechanism that is responsible for the phenomenon. In other words, models capture epidemiological mechanisms and extrapolate explanations on the basis of that. But what are mechanisms and how are they addressed in models?

In order to develop the notion of explanation-based predictions as anticipatory techniques to address public health risks, I will discuss how the mechanism of natural immunity was expressed in a population-simulation model in order to gain short-term predictions to assess the efficacy of Hib-vaccines. So, the short-term predictions that answer "what would happen if" questions, even though studied in the Finnish context provide a potentially broader application context when extended or applied to address the benefits of implementing Hib vaccines in the developing countries.

In general terms, *explanation-based* predictions are predictions that explain the causal mechanism(s) responsible for a particular phenomenon and extrapolate on the basis of that short-term predictions, i.e., answers to "what would happen if"-type questions. In order to unpack this, I will elaborate the role of mechanisms and their relation to explanation-based predictions. *Mechanisms* form the basis or *anchor* the explanations to the available datasets, the epidemiological ground of the phenomena. Bechtel and Abrahamsen (2005, p. 423) define a mechanism as follows:

- A mechanism is a structure performing a function in virtue of its component parts, component operations, and their organization. The orchestrated functioning of the mechanism is responsible for one or more phenomena.

This definition clearly underlines that mechanism is involved with orchestrated functioning, which I interpret as being capable of bringing together specific properties, parts or operations of the phenomena. Mechanisms are responsible for a phenomenon, mobilizing its cause, occurrence, or development. In this sense, mechanisms contain the generalizable properties of the phenomena.

Disease transmission is a multiplex phenomenon, which is dependent, for example, on the frequency of contacts within a population group, infectivity of the pathogen, and the existing immunity within the population. These aspects of the transmission were taken into account, when a mechanism was explained in a model. In other words, studying research questions in the family of Hib-models helped clarifying the disease transmission mechanism and uncovered the connection between a mechanism and the research questions addressed in modeling. These models were built during 1994–2003 within the research collaboration between the National Public Health Institute and the University of Helsinki.

Let us study more closely how *explanation-based* predictions were established in a population-simulation model.

The leading question motivating the building of the population-simulation model was: What would happen if a 5-year-old child *x* acquires a Hib infection and how likely she is to infect the members of her family? This question is by its nature a "what would happen if" question that has a predictive emphasis. To see how this question was manipulated in the model, we need to unpack the structure of the model itself. The population-simulation model, published in 2004, has a three-part structure: a demographic model (covering the age-structure of a Finnish population), a Hib-transmission model (including the contact-site structure), and an immunity model (including the immunization program and its effects). Yet, this simulation model resulted after a 10-year period of modeling work, which was dominated by integrating practices that brought together the three parts, built earlier in the project (see Mattila 2006c). So, all three parts, especially the transmission model and immunity model, were partially studied prior to the accomplishment of the population-simulation model (2004) in terms of following questions (the year after the question refers to the published model):

- How long does the immunity [against Hib] persist? (1999)
- How do we estimate the interaction between the force of infection and the duration of immunity? (2000)
- What is the effect of vaccinations? (2001)

These questions address particular aspects that affect the transmission dynamics in a population: length of immunity, estimate related to the force of infection, and effect of vaccinations. In particular, two mechanisms were detected in these models: the mechanism of immunity and mechanism of transmission. Mechanism of immunity was defined as:

- ► Natural immunity is believed to depend on repeated exposure to Hib bacteria resulting in the production of functional antibody (Leino et al. 2000).

This mechanism is primarily about how to sustain natural immunity in a population. In the simulation model, it was used for explaining what would happen to the natural immunity, when vaccinations were introduced on a population level. This was an important aspect, since the epidemiological studies of the chosen vaccine confirmed that the vaccine itself is capable of reducing carriage. The reduction of carriage in a population could potentially lead to the waning of the natural immunity that had protective impact on a population level. In other words, *herd immunity* (the population level protection against an infection) could be affected (cf. Fine 1993). This indirect effect was documented in the model studying the dynamics of natural immunity. This mechanism and its numerical estimates, which were defined in terms of Hib antibody dynamics, show the descending trend in serum antibody concentration. Later, this mechanism was integrated in the population-simulation model, in particular into its immunity model part. Hence, the mechanism of natural immunity, when manipulated in the simulation model, showed that if the bacterial circulation is diminished, the natural immunity is likely to weaken and a potential increase in the risk of serious infections may affect those who are not vaccinated.

Explanation-based predictions hence allow us to both explain the phenomenon of interest and predict in a short-term its development, i.e., the course of Hib transmission in a population and the underlying epidemiological mechanisms that maintain circulation of the bacteria. An interesting parallel can be drawn to den Butter and Morgan (2000, p. 296):

- More general empirical models provide a consistent and quantitative indication of the net outcome of the various principle mechanisms thought to be at work based on the particular case (not stylized facts) and which might be affected by the policies proposed.

As den Butter and Morgan show, empirical economic models are linked with mechanisms as well. These models provide a base to work on a particular case and examine what kinds of effects suggested policies have. In a similar way, explanation-based predictions in public health policies allow estimations of risks by showing the short-term development of the infections, explicating the optimal immunity levels within the community, and sometimes even providing unexpected results of the optimal vaccination coverage. This was discussed in a lecture by Auranen and Leino (Lecture given at the London School of Economics, Workshop organised by the Economic History Department, March 2008), when they showed that Hib conjugate vaccine minimizes the carriage of the bacteria and allows optimization of vaccine coverage to be as low as 10%.

Building Pandemic Scenarios

Explanation-based predictions, as discussed above, provide the ideal ground for short-term anticipation of public health risks, or low-impact, high-frequency events, as referred in the risk literature (cf. Hutter and Power 2005). However, most of the media attention is given to high-impact, low-frequency events, which in the public health context are pandemics. How do we respond to these events? Following International Health Regulations (IHR were revised by the WHO in 2005), each country is responsible for notifying WHO of "any events that may constitute a public health emergency of international concern." In a way, these internationally coordinated activities are an early warning, but they may not be able to anticipate or predict the occurrence of a pandemic. According to WHO, we are currently living in a pandemic period, which means that preparedness plans are in use on national and international level and predictive models are tinkered with new daily estimates of the course of the pandemic.

How do *scenario-building* predictions form a part of the scientific evidence base for decision-making? *Scenario-building* predictions are predictions that "sketch, outline or describe an imagined situation or sequence of events, and outline any possible sequence of future events" (OED). In other words, *scenario-building* predictions are primarily tools to *produce qualitative scenarios* based on the available, past data, and as such they provide model-based encounters with future risks. These scenarios are not necessarily grounded directly on data of the future event (which does not exist), but build upon available sources of past data in order to anticipate the "unknown," the risk.

Predicting the Pandemic

Humankind has faced cycles of pandemics, one of the most famous being 1918 Spanish flu that killed, according to older estimates approximately 50 million people worldwide. The pandemic spread all around the world and lasted about 2 years (1918–1920). Its oddities were that it infected and killed young and healthy, and it spread during the spring months. The most recent cycle of a pandemic began in the end of April 2009, when human cases of a novel influenza type A virus were confirmed. These cases were identified in the USA and in Mexico. The virus, according to epidemiological evidence, had been circulating in Mexico since February 2009 and may have emerged already earlier that year. It was also confirmed that the new human strain was identical to a strain of virus that had been circulating in pigs in North America. Flu survey reports that the A(H1N1) strain has a complicated history: "some of its genes moved to birds to pigs in 1918, other genes from birds to pigs at the end of the 20th century, some got into pigs in the 1960s having first passed through humans."

The strain spread rapidly, the first infections happened through contacts with those who were or traveled from Mexico. WHO reacted to the public health emergency by raising the Pandemic Alert Level from 4 to 5 (sustained community outbreaks in a limited number of countries) at the end of April. On June 11, 2009, WHO declared a pandemic and raised the Alert Level to phase 6, which means wide geographical spread, but does not indicate the severity of the infection.

According to ECDC Situation Report (27.7.2009), within the EU/EFTA countries, there are 20,512 confirmed cases and 35 deaths among those cases. Outside EU/EFTA countries, the corresponding numbers are 139,526 confirmed cases and 956 deaths. So far, critical voices have questioned the rationale of the pandemic alertness, since the cases seem to be somewhat mild and responding to the antiviral treatments. The major concern, however, was that there is very little natural prior immunity to the new strain and the infection it causes. This was already seen in the fact that the main group of infected is children. Due to the uncertainty of how serious the new type of virus was, the information campaigns for increased hygiene, advice for general audience and risks groups were available. In July 2009, vaccine production was underway, first vaccines were available for risk groups in September 2009, and, for example, the UK bought 90 million doses of vaccine in order to vaccinate the whole of population.

Uncertainties of the severity and spread of a pandemic raise questions of how to develop mitigation strategies to protect populations. Simulation models provide a way to predict the possible future course of the pandemic flu and hence function as a tool for planning and testing intervention strategies. When the simulation techniques are used in the preparedness planning, the data are grounded on observations from the past pandemics (1918 and 1957). These predictive simulation models allow studying various mitigation strategies.

What Kinds of Models Are Used as Scientific Evidence Base for Preparedness Planning?

One of the major public health concerns in infectious disease studies is the limited capability to predict emergence of outbreaks and people's behavior in such an event. To mitigate this problem, several studies have developed large-scale simulation models that utilize data from past pandemics, on travel patterns and population density. In the following, I will focus on one rather recent pandemic flu model and discuss its predictive capabilities. The model in question is an individual-based simulation model of pandemic influenza transmission for Great Britain and the United States (Ferguson et al. 2006). It represents transmission in households, schools and workplaces, and the wider community. The main aim of the model is to study strategies for mitigation of influenza pandemic. Mitigation means all actions that aim at reducing the impact of a pandemic (Nicoll and Coulombier 2009). I will focus on two model-based assumptions that affect the transmission: estimate for the reproductive rate and behavior. On the basis of a closer analysis of these assumptions, I will discuss the nature of *scenario-building* predictions and especially reflect on the suggested policy outcomes of this model.

Fingerprint of the Pathogen, and of the Population

Transmission is quantified in epidemiological models as a basic reproductive rate, which is the rate that is used for estimating the spread of infection in a susceptible population. It is defined as R_0, which is the average number of individuals directly infected by an infectious case during her entire infectious period, when she enters a totally susceptible population. In infections that are transmitted from person-to-person, the potential of the spread is called the reproductive rate that depends on the risk of transmission in a contact and also on how common the contacts are. The reproductive rate is determined by the following four factors (Giesecke 2002):

- The probability of transmission in a contact between an infected individual and a susceptible one
- The frequency of contacts in the population
- How long an infected person is infectious
- The proportion of the population that is already immune

All these characteristics can be expressed in mathematical equations to provide numerical estimates of the transmission dynamics in a population. This rate is usually determined by empirical data, i.e., by deriving the estimate from previous epidemiological studies. However, it is a rate that carries a "fingerprint" of the pathogen. By this I mean that the reproductive rate is sensitive to particular strain of the pathogen in question. This sensitivity brings in a question of uncertainty in the model-based predictions. What if the strain is not so virulent? Alternatives are taken into account by modeling different possible scenarios based on different approximates of the reproductive rate. But what do the models do to the reproductive rate? In pandemic flu modeling, a future strain is unknown and therefore the models actually use data from the past strains. This relies, of course, on the assumption that the future pandemic is as virulent and contagious as the past one. If we look more closely to the reproductive rate and its variation, we can see how it manifests itself as a fingerprint of the pathogen. This idea means that population density affects the estimate since R_0 tends to be higher in crowed populations. Nicoll and Coulombier (2009, Table 4) provide following estimates for R_0:

- In seasonal influenza: R around 1.1–1.2
- In pandemic influenzas: $R = 1.5-2.5$
- In current pandemic (H1N1): $R = 1.5-2$
- In measles: $R_0 > 10$

The variance in R_0 leaves uncertainty into the predictions. This uncertainty is decreased once the pandemic begins to spread, and the pathogen is isolated and its virulence within a population (e.g., who are encountering the infection) is known.

Behavioral Assumptions and Their Alternatives

The simulation model studying strategies for mitigating influenza pandemic makes assumptions concerning the effectiveness of behavioral interventions. These are movement restrictions, travel restrictions, quarantine, and school closure. The question is: What kinds of behavioral assumptions are made in order to predict the spread and transmission of the outbreak?

In Ferguson et al. (2006), a rather clear behavioral assumption is claimed when reporting the model design:

- We do not assume any spontaneous change in behavior of uninfected individuals as the pandemic progresses, but note that behavioral changes that increased social distance together with some school and workplace closure occurred in past pandemics.

Furthermore, the underlying assumption is to consider that individuals will behave according to the guidelines, rules, and restrictions given by the health authorities. In a way, the effectiveness of behavioral restrictions is based on the assumption of rational agents. But how reliable this assumption is? In a recent discussion on the novel ways to study real-world epidemics, Eric Lofgren and Nina Fefferman (2007) suggest that virtual game worlds might provide a different perspective. According to their analysis of an outbreak in an Internet playground, World of Warcraft, they observed that individuals did not follow the rules of movement restrictions and some voluntarily spread the disease. The question is: If the scientific simulation models are used for preparedness planning, how do we find reliable assumptions concerning the behavior, which is, after all a key to prevent the spread of pandemics?

Scenario-Building Predictions

What is, then, the policy outcome of the model? What kind of scenarios the model suggested? Both epidemiological and behavioral assumptions have their limitations. On the epidemiological level, the assumptions represent the *fingerprint* of the pathogen, hence leaving some level of uncertainty when drawn to the predictive scenarios. On the behavioral level, the assumption that individuals' behavior remains unchanged during the pandemic period opens the questions of credibility of these scenarios. Yet, it was clearly stated that the models allowed to explore "number of scenarios" regarding the transmissibility of the pathogen, movement, and travel restrictions. One could easily think that if *scenario-building* predictions are relying on particularly uncertain assumptions, they are mere fantasies, no better than "fortune-telling." However, this is not the case. As documented already with the Helsinki models on Hib, models provide a useful "playground," a platform to examine and explore particular features of the infection and its transmission (cf. Keating and Cambrosio 2000, 2003; Mattila 2006c).

Scenarios which allow us to "access the inaccessible" provide qualitative tools and produce evidence of the unpredicted for decision making. The challenge remains how to communicate this particular mode of evidence – its changing and mutable nature (cf. Mansnerus 2011a). As Ferguson et al. (2006, p. 451) state: "The transmissibility of a future pandemic virus is uncertain, so we explored a number of *scenarios* here." They argue that these scenarios depend on "model validation and parameter estimation," which should be given a priority in future research. Transmissibility, which is based on the estimate of the reproductive rate, is considered to be on the level of 1918, if it actually follows the levels seen in 1968 or 1957 pandemics, "global spread will be slower and all the non-travel-related control policies examined here will have substantially greater impact." Ferguson et al. emphasize the importance to collect the "most detailed data on the clinical and epidemiological characteristics of a new virus." In other words, he is calling for research that allows us to base the scenario-building into a detailed understanding of the explanatory mechanisms of phenomena. The "fingerprint" of the pathogen is important, as pandemic simulations show.

What kind of scenario was built around the behavioral assumption? Interestingly, the outcome of the simulation model suggests that travel restrictions, which include both border controls and within-country restrictions, "achieve little" in delaying the peak of the epidemic. This was taken into account when WHO gave recommendations and guidance on traveling during the current A(H1N1)v pandemic:

- Scientific research based on mathematical modeling shows that restricting travel would be of limited or no benefit in stopping the spread of disease (7.5.2009, WHO, GAR, Travel: Is it safe to travel?).

The social functions of simulation models are also worth emphasizing. Scenario-building helps allocate resources, agree on, for example, preordering and manufacturing the vaccines, and stocking the antiviral. As we observed in the two examples, the scientific models have "uncertainty" built-in: the assumptions made on the basis of past facts may not provide accurate predictions of the scale of the outbreak. Nor are they capable of capturing the changing behavioral patterns of individuals. Testing out both assumptions and exploring them as part of various scenarios was "doable" only by modeling. This is an indication of the usefulness of *scenario-building* predictions; they are qualitative tools that "fill the gaps" in existing knowledge, allow reasoning to touch upon the "known unknowns" and perhaps "unknown unknowns." A good example of "unknown unknowns" was the origin of outbreak of A(H1N1) pandemic in 2009. The main focus was on avian (H5N1) influenza that is currently circulating in South-East Asia. However, the pandemic emerged from pig farming industry in Mexico (cf. Mansnerus 2010).

Beneficial Encounters with Infectious Risks

How modeling provides useful tools for risk assessment? As we learned through the case studies, predictive capacities of models encompass the ambition to "access the inaccessible," as Oreskes (2007) shows in her analysis of scale models in geology. She refers to models "whose predictions are temporally or physically in accessible." But this ambition is not merely epistemic. Models, either physical or numerical, seemed not to adjust to the changes in epistemic values shared in scientific communities, but also reflect aspirations of scientific patrons, as Oreskes discusses. Models seem to do more than epistemological work: in the attempts to predict the future, models generate predictions to inform policy decisions. This is what Oreskes argues to be the primarily social role of predictions. In a way, *scenario-building* capacities of models express the social role by providing "access to the inaccessible," even though scenarios may not satisfy the epistemic quest of explaining the viral mechanisms of a pandemic.

In scenario-building predictions, the epistemic, for example, the precise rate of transmissibility plays a secondary role. The main importance is to explore and evaluate various outcomes. On the contrary, explanation-based predictions, when they successfully encompass epidemiological mechanisms, accommodate both the epistemic and social functions.

What kinds of modeled encounters with public health risks do the two types of predictions provide? How reliable are they? The analysis supports Boumans's (2004) notion of instrumental reliability, which incorporates both the "instrument" and expertise required. In other words, reliable predictions, in both cases, result as the quality of the model and the expertise of the modelers. This means that calibration of the model is not indifferent to the other factors, expertise of building the model and practice of using the model when addressing instrumental reliability. Oreskes and Belitz (2001) make a similar point by arguing that all models are approximations, and they suggest that it is more useful to “think of models as tools to be modified in response to knowledge gained through continued observation of the natural systems being represented.” In other words, when estimating public health risks through model-based predictions, instrumental reliability refers to the fact that these predictions are not valid descriptions of reality, but best available approximations of the risk. They are not static either, but as more data are cumulated during the outbreak, they gain greater accuracy. Both types of predictions show that modeled encounters with public health risks depend on the complex chain of interactions between experts and technologies, and between users and producers of these predictions.

Explanation-based predictions that are utilized in assessing low-impact, high-frequency infectious risks function in two ways. First, they explain the phenomenon by allowing researchers or policy-makers manipulate the model by questions. As we learned, the broader policy-driven questions are translated during the modeling process into smaller and more targeted questions that reveal the details of the transmission dynamics in a population and explain how the disease mechanism affects the possible infectious outbreak. Second, the explanation-based predictions are able to address “what would happen if”-type questions that arise when infectious outbreaks are encountered within a small group of population, such as a nursery group or military garrison. The prediction as an answer to “what would happen if” question is beneficial for assessing risk and further mitigation strategies, such as containment of the outbreak.

Scenario-building predictions should not be regarded as “nonsense” despite my choice to refer to the modeling platform that gives rise to them as a “playground.” As Oreskes pointed out, they function as “access to the inaccessible,” in that role they allow risk assessment to stretch itself beyond the “accessible”: Beyond the available data from surveillance or monitoring processes by simulating the outbreak on the basis of data from previous pandemics, or beyond the actual situation, i.e., ongoing outbreak by simulating variations of the spread of the infection and the effectiveness of mitigating strategies already during the pre-pandemic phase for preparedness planning. It seems that both these predictions provide beneficial tools to encounter public health risks from infections. However, their limitations are worth discussing in the context of analytics of governance.

Further Research: Toward the Analytics of Risk

Modeled encounters with public health risks are proven highly beneficial, as we have learned. A challenge, however, remains to be tackled with, namely, the tension between population-level estimates of risk and individuals’ behavior. I will suggest this tension can be accommodated within the governmentality approach by showing how the analytics of risk benefits from the integration of technical and ethical rationalities along with the deepened understanding of risk rationality. This will be discussed as a direction for further research.

What are then the possible limitations of “modeled encounters” with risks? As the case of predictive scenarios of pandemics shows, availability of data may be limited or as in this case, nonexistent in regard to an actual outbreak when scenarios were built in pre-pandemic phase. Explanation-based predictions were also modeled on the basis of limited data, for in that case, the data were collected for other purposes (as a part of pre-Hib vaccine studies) and therefore they did not accommodate all the relevant information for model parameterization. This meant that during the modeling, some parameter estimates were acquired on the basis of comparative datasets from collaborating research groups. Along with the limits of availability of data, computational capacity may present limits to modeled encounters with risks. The modelers may not be able to access the highest-level of computing power (such as supercomputers in national computing centers), which was the case with Hib-models. These technical limitations have an effect on the way in which models are built, how fluently a model-based prediction is gained, and how reliable the instrument, (i.e., the model) itself is. Limited access to high-level computational capacity restricted the number of simulation runs for the population-simulation model that estimated Hib transmission, for example. Although these restrictions may weaken the reliability of the model-based prediction, it is worth bearing in mind how Oreskes and Belitz (2001) described models as approximations.

Along with the technical limitations of modeled encounters with risks, there are social and epistemic limitations as well. As we learned through the analysis of the two types of models, the modeling process itself is not highly transparent. Specialized expertise is required to build the models, and even those who work with modelers may not be able to assess the choice of mathematical algorithms during the process. Interdisciplinary modeling teams develop a division of labor (see Mattila 2006a). This lack of transparency may be limiting when model-based predictions are communicated to audiences who have not been involved in the primary model building process or who are not familiar with modeling techniques. This is the point when models may turn into "truth-machines," to gain their authority, as Hulme et al. (2009) suggests in the case of climate models. The assumptions made in the model may remain unknown due to the lack of communication of the modeling process and the choices made within it.

Furthermore, as I described that these models are typically *tailored* to address specific policy-driven questions, one could consider this characteristic a limitation. How applicable are the outcomes? If the simulation model particularly addresses a question like "what would happen if a child x in a day care unit y encounters a Hib infection?", can the prediction be applied to estimate the risk of infection among adult men in military garrison? Or if the predictive scenario of a pandemic spread examines mitigation strategies, such as school closures or travel restrictions in a particular geographical location, can the estimates be extended to cover other areas as well? These questions address the inevitable limitations of modeled encounters with public health risks, which should not be read as a recommendation not to use modeling techniques or to advocate them. After all, model-based predictions, as these two cases show, are highly beneficial as a one source of evidence for the broader base of risk assessment. The limitations are discussed in order to balance the view.

As we learned, model-based predictions operate on population level. They provide information of risks that affect the whole population, hence being interested in the "welfare of the flock as a whole," as Rose (2001) phrases Foucault's terms. The "pastoral" attitude that is concerned of the welfare of the whole population, Rose continues, is a form of "collectivizing power." This leads to a tension that arises when a public health risk manifests on a population level and appropriate health interventions are introduced, but at the same time, individuals consider their risk from a different angle and refuse or ignore to participate in the interventions. In other words, when an epidemic outbreak that causes a severe risk to the population (or to a part of it) happens, its further spread is prevented, for example, by vaccinations.

Yet, individuals may think that the side effects from the vaccination are more severe than the infection itself and refuse to follow the public health recommendations. But what lies behind this tension? I will reassess this tension from three perspectives: as a narrative, as a case of difference between individual's risk perception and that of a group, and as a challenge that needs a broader context to address it. The concept of narratives, as I already mentioned, is helpful when applied to modeling. Morgan talks about modeling as storytelling and I will follow the most recent work by Dry and Leach (2010) to discuss how to broaden out the modeled encounters with public health risks by acknowledging the narratives told through modeling. I will address the lack of focus on individuals' risk behavior, which was highlighted in the studies by Lofgren and Fefferman (2007). I will argue that a satisfying way to contextualize modeled encounters is by regarding them as *technical rationalities* within the governmentality approach to risk.

The fairly monolithic view of a population, as represented in the models, may lead to a biased interpretation of the model-based predictions or, more broadly, the model-outcomes and estimates. The population is seen as the "ultimate end of governance," as Rabinow and Rose (1994) claims. When governance seeks the form of modeling, we may use the metaphor of storytelling (Morgan 2001), which allows manipulation of the world through representing it in a model and addressing questions to it. But whose story is told and whose is ignored? Who remain silent? Dry and Leach (2010) raise this issue when they argue that narratives about infectious diseases are deeply rooted in questions of power and social justice. In order to address these questions, Dry and Leach suggest analyzing the different narratives that construct disease and epidemics. Narratives for them are not just stories, but stories with purposes and consequences. In a recent study on avian influenza surveillance, Scoones (2010) identifies three "outbreak narratives": A narrative that links veterinary risk with agriculture, a human public health narrative, and a narrative focusing on pandemic preparedness. His analysis shows that a single narrative is perhaps not enough to create the evidence base in order to understand the multiplicity of an infectious risk from pandemic. We could see the benefits of model-based predictions in a similar way. At best they give us a single narrative, and perhaps our task is to look for other complementary ones for well-grounded risk assessment.

One could take yet another step further and say that narratives, despite introducing more heterogeneity to the fairly fixed perspective on population, are still focused on groups rather than individuals. Neither *explanation-based* nor *scenario-building* predictions address individuals' perceptions of risks and the various factors that affect them. What is left aside in these modeled encounters with risks is the ways in which individuals perceive risk and how they behave. A typical bias in individuals' response to risk is known as *optimism bias*, which means that individuals underestimate risks to themselves (Costa-Font et al. 2009). Joffe (2003) argues that individuals construct risks through group attachment or on the basis of their experiences in groups. She continues that response to risk is therefore "a highly social, emotive and symbolic entity." Roeser's (2007) study on ethical intuitions about risks point to the same direction by acknowledging that individuals' intuitive risk judgments express ethical concerns that should be taken into account in methodologies for risk analysis or risk policy. None of these observations are accommodated on the population level analyses of public health risks.

How could we, then, satisfyingly accommodate the "unbearable tension" between individuals' perceptions of risks and the population-level assessment we gain through modeling? I will argue that we will benefit from a broader context to understand infectious risks in public health. By this broader context, I refer to the literature on governmentality that brings together the technical rationalities of governance with ethical and epistemological aspects that are present in the process and manifest through the dynamics of power.

In Michel Foucault's work, the analytics of government covers three aspects that help contextualizing risk. These aspects focus on how we come to know about and act upon different conceptions of risk. How these different forms of risk rationality become a particular set of calculatory practices and technologies. How social and political identities emerge from these technologies (Dean 2010, p. 217). In this chapter, modeling techniques have been regarded as a form of technical rationality or *techne* in the governance of risk, which Dean defines as: "[. . .] a search for analytical clarity concerning the techniques and instruments of government, the arts, skills and means by which rule is accomplished" (Dean 1995, p. 560). As I have shown, model-based predictions are "instruments of government"; they are tools to anticipate risks, build predictive scenarios, and test mitigation strategies. At the same time, these techniques have their limitations. They easily enforce the purely probabilistic interpretation of risk, and the evidence produced by models assesses population-level risks but cannot include estimates for individual-level or address individuals' perception of risk simultaneously. This limitation can be addressed through the analytics of risk within the context of governance.

The analytics of risk is formed through four successive and overlapping stages, as Dean claims. In the beginning, one explores different forms of risk rationality, which Dean calls *episteme* of risk. Then, one seeks to find out how such conceptions are limited to particular technologies and practices that form the *techne* of risk. And finally, one studies how such technologies and practices give rise to new forms of social and political identity, and finally, how these identities are merged into political programs, which give them a particular *ethos* (Dean 2010, p. 217).

If we follow how Dean characterizes *episteme* within the analytics of government, we will notice a set of questions that are useful to map risk rationalities. "What forms of thought, knowledge, expertise, strategies, means of calculation, or rationality are employed in practices of governing?" (Dean 2010, 42). It seems to me that *episteme* and *techne* of risk rationality indicate a different direction or different dynamics of governing risks. Especially in the case of the pandemic, the risk considered to threaten the whole of population seemed to remain relatively small. Individuals made their own estimations for risk disregard to the recommendations or guidelines given by the public health officials. Those who were at risk did not consider the risk to be severe enough for them to follow the guidelines. As we can see, *episteme* and *techne* of risk rationality are pointing to the "care of oneself and of others," to the ethical dimension that is present when encountering public health risks. This forms the *ethos* of risk rationality or the social and political identities, which emerge out of *episteme* and *techne*, out of the rationalities of governance.

"Knowing an object is a process that shapes rationalities of governance by forming our understanding of how a risk of an infection is established and the ways in which all this was turned into a form of calculation," as Miller and Rose (2008, p. 30) define. For them, "knowing an object" involves "procedures of inscription," which are ways of collecting and presenting statistics, for example. It is not a process of speculative activity, but a way in which "governmentality" is made up. In my reading of governance of public health risks in the two cases, risk became a "knowable object." But the actors may not have reached a point what could be called "accountability of one's own actions." This is an important aspect of the *ethos* and its formation through rationalities of governance. Dean emphasizes that "if morality is understood as the attempt to make oneself accountable for one's own actions, or as a practice in which human beings take their own conduct to be subject to self-regulation, then government is an intensely moral activity" (Dean 2010, p. 19). To recognize government as "an intensely moral activity" leads Dean to suggest that "techniques and rationalities of government needs to be complemented by a fuller clarification and elaboration around third axis, that for want of a better term, we might call 'axis of self-formation'" (Dean 1995, p. 560). So, in order to complement risk rationality and to enhance successful governance of risk, I would suggest to include all "three axes of governmentality" into the process. This could lead to a balanced view which, according to Castell, seem to be threatened by modern ideologies.

► The modern ideologies of prevention are overarched by a grandiose technocratic rationalizing dream of absolute control of the accidental, understood as the irruption of the unpredictable. In the name of this myth of absolute eradication of risk, they construct a mass of new risks, which constitute so many new targets for preventive intervention (Castell 1991, p. 289).

Are the expiring stocks of pandemic vaccines a sign of "grandiose technocratic rationalizing of dream of absolute control?" This question asks for further research that potentially engages with critical assessment of risk governance and addresses the various tensions that may prevent good governance from reaching its purpose.

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