Picking up the Pieces – Applying the "Disease Filter" to Health Data

Christiane Gross
[corresponding author]
University of Erlangen-Nuremberg
Faculty of Law and Economics
Findelgasse 7
90402 Nuremberg
Germany

Thomas Schübel
University of Erlangen-Nuremberg
Faculty of Law and Economics
Findelgasse 7
90402 Nuremberg
Germany

Rasmus Hoffmann
European University Institute
Department of Political and Social Sciences
Via dei Roccettini 9
50014 San Domenico di Fiesole
Italy

Phone+49 911 5302 945
christiane.gross@fau.de

Phone+49 911 5302 945
thomas.schuebel@fau.de

Phone +39 055 4685499
rasmus.hoffmann@eui.eu

Abstract: This contribution presents systematic biases in the process of generating health data by using a step-by-step explanation of the *DISEASE FILTER*, a heuristic instrument that we designed in order to better understand and evaluate health data. The systematic bias in health data generally varies by data type (register versus survey data) and the operationalization of health outcomes. Self-reported subjective health and disease assessments, for instance, underlie a different selectivity than do data based on medical examinations or health care statistics. Although this is obvious, systematic approaches used to better understand the process of generating health data have been missing until now. We begin with the definitions and classifications of diseases that change (e.g. over time), describe the selective nature of access to and use of medical health care (e.g. depending on health insurance and gender), present biases in diagnoses (e.g. by gender and professional status), report these biases in relation to the decision for or against various treatment (e.g. by age and income), and finally outline the determinants of the treatments (ambulant versus stationary, e.g. via mobility and age). We then show how to apply the *DISEASE FILTER* to health data and discuss the benefits and shortcomings of our heuristic model. Finally, we give some suggestions on how to deal with biases in health data and how to avoid them.

Keywords: health data, register data, survey data, bias

1 Introduction

Public health research is based mainly on two different types of data: register data and survey data. Cases recorded (i.e. those regarding people or events) in register data, such as hospital or insurance data, are the result of a filter process that can introduce several biases. For example, hospital data undergo several selection stages beginning with the definition of a mental and/or physical state, such as being ill or dysfunctional. The process continues with the possible false detection of this condition by the patient and her or his decision to use medical care. Afterwards, a physician makes a diagnosis and evaluates the chances, costs, and benefits of treatment. The decision for or against a particular treatment is followed by the choice for stationary versus ambulant treatment. Social mechanisms bias the filtering process at each stage, independent of medical or health issues. These biases in register data lead to serious problems for health researchers, who use register data to examine and present the prevalence of diseases depending on patients´ characteristics, which are confounded with the biases of the data. Biases of register data are of minor concern when using these data to describe the population of a hospital; however, the problems begin when these data are used to estimate the prevalence of diseases that depend, for instance, on educational background, gender, social class, or age. Educational background is highly correlated with degree of health knowledge, which is needed to identify a physical or mental state as a "disease". Being female is associated with higher sensitivity to symptoms and a higher likelihood of accessing medical care. Social class influences the conditions of health insurance and therefore also the cost of a particular treatment. Older people are more likely to choose inpatient treatment since they may not be able to cope with the situation at home.

Survey data in health research is often based on the answers of respondents who are medical laypeople. Respondents may systematically over- or underestimate the occurrence of a particular disease, i.e. the statistical error (false positive, false negative) is systematically biased by the respondents´ degree of health knowledge and sensitivity to symptoms, which in turn depend on their educational background, gender, etc. The more complex the symptoms are (as with mental diseases, for example), the more health knowledge is needed in order to classify the symptoms as being connected with a disease or condition. Although there is no need for expert knowledge for "soft

measures" of health outcomes, such as the well-known self-rated health item (understood as a subjective measure of one´s own health in the sense of well-being), these measures are much more prone to other biases known from survey methodological research. These biases, which are specific to survey data, are discussed with a special focus on health data.
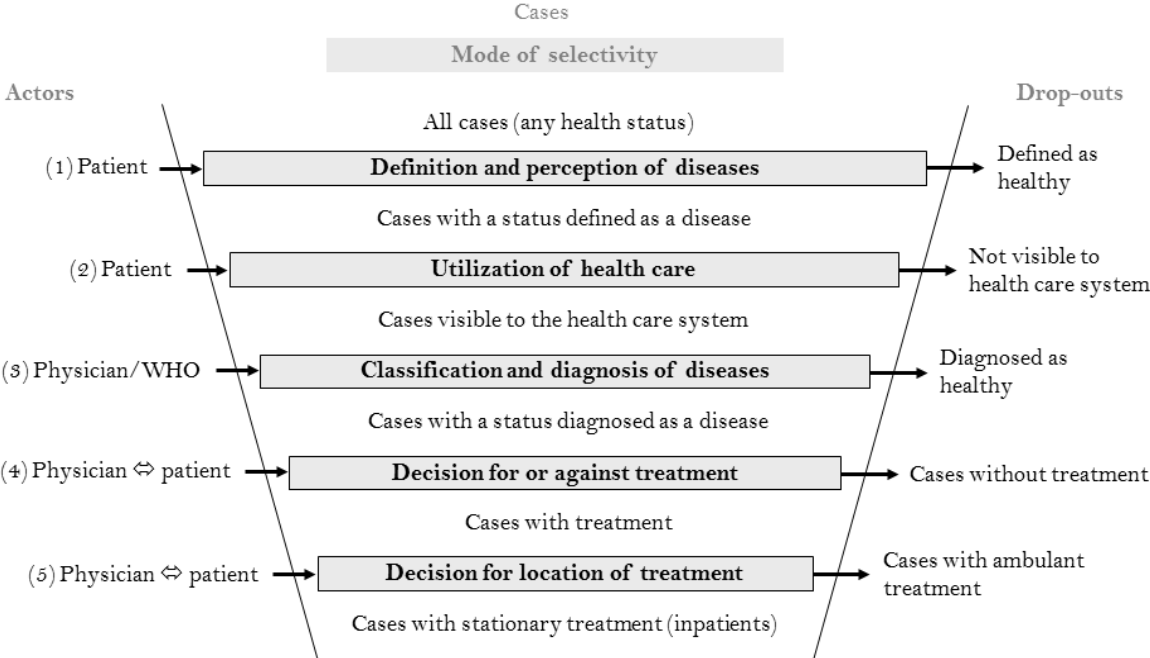
As all health researchers are concerned with several biases in both kinds of data (register and survey data), we developed a heuristic instrument – the *DISEASE FILTER* – which enables researchers to better evaluate the quality of their health data and their research results depending on data type. By using the *DISEASE FILTER*, health researchers do not have to gather the whole state of research concerning biases in their data by themselves, but can instead refer to the main issues presented in this contribution.

First we start by introducing the *DISEASE FILTER* and show each systematic bias in the process of generating health data step by step (Section 2). Following this description, we explain how to apply the *DISEASE FILTER* to health data (Section 3). Finally, we illustrate the benefits and shortcomings of the *DISEASE FILTER* and give some information on the consequences of biased data and suggestions on how to deal with biases in health data or how to avoid them (Section 4).

2   The *DISEASE FILTER*

In Figure 1, we present the *DISEASE FILTER*, which can be interpreted as follows: All cases (i.e. people regardless of health status) are entered into the *DISEASE FILTER*. The first stage (in grey) filters the cases with a status defined as "ill", whereas cases with a status defined as "healthy" drop out (right side of the figure). The left side of the figure explains who the actors are at each stage. For the definition and classification of diseases (Stage One), the World Health Organization (WHO) is one of the main actors. The cases, i.e. people with a status defined as ill (including false definitions), can then decide whether to seek medical care and, if so, what kind. Cases in which the decision is against seeking medical care are not visible to the health care system (see dropouts at Stage Two). Those cases visible to the health care system are usually (and possibly falsely) diagnosed by a physician as either being healthy (dropouts at Stage Three) or as having a disease. Patients with a

diagnosed disease can then decide (in consultation with their physicians) for or against a certain treatment (treatable cases without treatment drop out at Stage Four), and in the end, they can choose – depending on the disease – between ambulant and stationary treatment (cases with ambulant treatment drop out at Stage Five). The register data of inpatients, for example, includes all cases that have been filtered up to this point. To be clear, dropout cases can nevertheless be included in other data sets, e.g. a person diagnosed with cancer who refuses treatment can still specify her or his disease in a survey.

Of course, this is an ideal type of analytical process, and other less linear scenarios may be possible. For example, people can have heart attacks and be taken into intensive care without having communicated a decision for or against a particular treatment. On the other hand, it is also common that the doctor and not the patient is the first to discover a disease that may be diagnosed during a routine examination. Nevertheless, the following subsections deal with the state of research with regard to the biases incorporated in these typical selection stages of the *DISEASE FILTER.*

2.1 Definition and Perception of Diseases

If a symptom or condition is not generally defined as a disease, it will not be reported as such and will therefore drop out of the *DISEASE FILTER* as healthy per definition. Additionally, whatever is not perceived and recognized by laypeople as a disease will have little chance of being captured as a "disease" unless a doctor discovers it without the help of the patient (see above). Lay medical knowledge is based on different sources: scientific knowledge (possibly incongruous) as well as (un)specific self-awareness, values, and beliefs. Medical knowledge depends on socio-economic status, e.g. poor people are said to have less health literacy and less sensitivity to symptoms [1]. On the other hand, one could argue that the lower classes underestimate their health status compared with people in the upper class because people include their overall happiness and satisfaction in their health assessment. Different biases in health due to socio-economic statuses may work in opposite directions and there is scant evidence that self-rated health is class-biased [2; 3; 4].

However, other characteristics can also contribute to differences in patients' perceptions and descriptions of illness status. Age plays a role, as does gender, which can be seen in the gender differences in describing symptoms of coronary diseases, with more symptoms reported in women and in higher age groups [5; 6]. There is a peak in symptoms reported at the age of 55-59 years, followed by a slight decrease [5], which may occur because people compare themselves with their friends [7]. This "compared" self-assessment may still be important information, but of course the trends in age and other comparisons of the results are difficult to interpret if the assessment is implicitly based on a comparison since the reference is unknown. Helweg-Larsen et al. summarize their review with the following result: "One-third of the studies reviewed showed that older people evaluated their health more positively, roughly one-third showed that older people evaluated their health more negatively, and one-third showed no relationship between SRH and age" [8].

Discovering and interpreting something perceived to be a symptom is more complex than a simple act of measurement. It is framed by social patterns of recognizing, naming, and categorizing disease states and their causes. Moreover, the consequences of being sick may matter in the self-perception of health. Since the role of "being sick" yields amenities such as less stress resulting from other people's expectations, it is argued that some people seek the "permission to be ill" [9].

2.2 Utilization of Health Care

Most health data are collected due to "patient careers", which means that people must have contacted the health care system to receive a diagnosis and to be sampled. If somebody who ought to receive a certain diagnosis (due to her or his objective state of illness) doesn't seek official medical help (or has no access to it), she or he will not become visible in health care data and, thus, will drop out of the *DISEASE FILTER*. There are differences in health care provision according to national health systems [10; 11 for Europe] and due to regional differences, which provide a disadvantage for people living in rural areas [12 for the US]. There is less use of health care with declining social status, especially less use of secondary health care [13 for all OECD states] or dental services [14 for Norway]. This is most true for rural areas [13]. Health literacy in general is a reason for the greater or lesser use of health services, depending on the disease [15]. Increasing levels of education have an impact on service use [16 for the Baltic States]. In the case of mental disorders, better-educated people are less likely to use primary care and more likely to use mental health care than the less-well-educated [17 for the Dutch population]. The use of health care provision depends on costs. For instance, self-funded dental treatment or general-practice charges cause lower usage of these facilities. This impact of estimated costs depending on insurance status and/or co-payment is true for many countries [10]. Uptake depends on income (less utilization in low-income groups), age (the older the patient, the higher the use), marital status (most use by widowed/divorced women, least by single males), and family size (more use by those with children under twelve) [18 for a national survey in Canada]. Women use more health care than men [5; 19]. However, utilization is also a result of an interaction between gender and disease. For example, women with bowel cancer seek health care later than men [20]. Moreover, there is empirical evidence for less service use depending on race [21 for African-Americans in the US], migration [22 for Germany], homelessness [23 for the US], and religiosity, with highly religious people being more likely to use preventative services [24 for the elderly in the US]. Uptake is not just a result of individual needs, but can also be the result of social-environmental pressure [25 for Germany: parents' choices for/against vaccination of their children].

Not only is routinely collected register data subject to biases in health care utilization, but survey data are also concerned with the biases presented in this section: first, when frequency of use of medical care is taken as a proxy for the respondent´s health status; and second, when respondents are asked about having a (physician-diagnosed) disease that requires use of health care services. In addition, the preconditions of medical care use – health literacy and symptom sensitivity – affect self-rated health and self-reported disease.

2.3 Classification and Diagnosis of Diseases

The worldwide standard for classifying symptoms according to diagnoses as empirically given sets of symptoms is the *International Classification of Diseases* (ICD) of the *World Health Organization* (WHO). Additionally, the *Diagnosis Statistical Manual* (DSM) of the *American Psychiatric Association* (APA) is the standard for mental disorders. Diseases represent deviances in physical or mental function. But what counts as a relevant deviance? Defining diseases as disorders always refers to the prevailing medical knowledge base. It makes no sense to define something as a symptom that is observable in the majority of the general public. The ICD follows an adjusted distribution that marginalizes the observed symptoms in comparison with the majority of healthy people. ICD classification faces the problem (as do all other classifications) that there is no "natural" (i.e. objective) way of "sorting things out" [26]. As medical research continues, new revisions need to be made that identify "new" diseases and drop "outdated" ones. Thus, classification changes over time. For example, the ICD has listed Attention Deficit Hyperactivity Disorder (ADHD) as a disease since 1978, whereas homosexuality was removed in 1990.

The ICD is also the basis for mortality registers that constitute an indispensable data source for health research around the world [27]. However, there are well-known issues in the correct attribution of a death to a cause of death in the ICD coding system, and this may influence the validity of comparisons over time and between countries [28]. The selection of the underlying cause of death is to a certain extent subjective and depends on the coding practice, the national/local coding instructions, and progress in medical knowledge [29]. Certain causes of death are especially prone to misclassification, such as ischemic heart disease, which is the most common cause of death

[30; 31]. The percentage of ill-defined causes is regarded as a proxy for data quality, and autopsies are used to check the validity of mortality data [32]. For international and longitudinal comparisons that face the problems of different coding practices across countries and over time, detailed investigations of country differences and correspondence tables and correction factors for specific transitions between versions of the ICD are available [29; 33]. Despite several well-researched potential biases, mortality registers in developed countries with advanced population and death registers can be regarded as a valid data source, not least because deaths are facts that do not underlie subjective interpretation.

According to an idea put forward by Illich [34], identifying diseases is not only a matter of medical necessity, but those shaping the announcement of a new diagnosis could have multiple interests. This is discussed for diseases such as restless-leg-syndrome, bipolar disorder, female sexual dysfunction, female menopause, fatigue syndrome, multiple chemical sensitivity, and others. "Disease Mongering" [35] refers to the idea of defining diseases for non-medical reasons. Pharmaceutical manufacturers, first and foremost, can arguably transform human conditions into treatable disorders – which has been discussed under the term medicalization [36; 37] – due to economic interests. Even if one does not agree with the radical perspective of disease-mongering, there could still be bias in defining diseases due to non-medical reasons: Kempner [38] shows for migraines, and Landrine [39] for depression, that the ICD definitions of disorders are stereotyped as feminine, which leads to a gender-bias in female help-seeking and in diagnosing females. There is a higher prevalence of women than men who represent reification of stereotypes rather than "real" medical differences. Brown [40] describes the diagnosis as a social construct that includes several steps typical of a "career": lay discovery yields some kind of social movement (e.g. self-help groups) that then opens up professional and organizational resources. Diagnosing distinguishes those diagnosed as ill from those diagnosed as healthy. However, if somebody is admitted into health care, the process of diagnosing produces several biases that affect health data. The creation of a diagnosis is embedded in a set of routines that may take into account more than just symptoms (which is what Aronowitz [41] called "framing diseases"). Diagnosing is a subjective act of perception underpinned by different types of misinterpretation due to e.g. gender stereotypes [42 for a review] or the social-epidemiological knowledge of the physician. The latter means that physicians tend to treat demographic issues as

diagnostic features [43] that may be statistically correct but that will differ individually ("statistical discrimination"). Physicians could, for example, impute poor people's bad access to follow-up care and therefore make different diagnoses than those made for richer people, as is argued regarding poor children and asthma [44]. Diagnosing can be affected by the social role of the physician [45] and by organizational issues such as payment method, with less resource-intense decisions at capitation payment [46]. The labelling of mental diseases is higher with lower social status [47; 48] or race [49 for African-Americans], which is partly due to the physician's perception. Even patients' hopes for receiving a prescription influence doctors' perceptions [50]. There could also be an interaction between gender and job status, e.g. it is possible that managers are more likely to receive a diagnosis of burnout while young mothers receive the diagnosis of depression. Job status in general might have an influence. Unemployed people might receive different diagnoses from those who are employed due to interests regarding, for example, continuation of payment or access to special provision.

Definitions and interests not only affect diseases diagnosed by professionals, but they also influence the health literacy of medical laypeople, which is important when respondents are asked about having a particular disease. Biases due to the act of diagnosing are not limited to register data. Some health surveys also contain diagnostic interviewing using e.g. the WHO's Composite International Diagnostic Interview (CIDI), or they may ask for physician-diagnosed symptoms. In both cases, health data are subject to similar biases. Particularly simple descriptives are prone to be biased as measurement error cannot be accounted for by applying statistical correction techniques.

2.4 Decision for or Against Treatment

The decision for or against treatment is generally based on the treatability of diseases, which varies over time and region due to medical provision (e.g. southern vs. northern countries). This decision is the result of an interaction between physician and patient that is usually asymmetric and depends on several issues. After being diagnosed, patients will usually receive an offer of treatment. The offering of treatment relates not only to medical conditions; patients are less likely to receive offers of treatment depending on lower social status [49], their race [51 for African-Americans],

and their gender, with females receiving extra care if distressed [52], less coronary artery bypass surgery [53], and more physician-prescribed activity restrictions [54]. Treatment offering even depends on patients' own expectations and attitudes [50]. In addition, physicians offer treatments associated with their own interests. These interests again differ depending on the methods of payment [46] or accounting for the tariffs of DRGs (diagnoses related groups), with refined tariffs producing incentive to overprovide surgical treatment [55]. Physicians' decisions also depend on personal or professional characteristics, such as job satisfaction or number of patients seen per week [56]. Doctors' decisions for or against different treatments are influenced by possible outcomes, the description of outcomes (the riskier alternative is chosen when possible outcomes are described in terms of survival rather than mortality), and the number of alternatives [57].

As for the patients, more highly educated people will generally be more autonomous in their health-related decisions, i.e. they wish to be more involved in medical decision-making [58; 59]. The physician-patient-relationship tends to deprive poor people of decision-making power due to information asymmetries [60], especially when referring to medication [61]. Most reasons for non-compliance regarding medication are related to the perception of financial hardship, fear or the experience of side effects, generic concerns about medications, and a lack of the perceived need for the medication [62 for a national US sample of people with chronic diseases]. For reasons already outlined, people's decisions also depend on age, patient attitudes, health literacy, costs, refunding, religion (e.g. refusal of organ transplants), social capital, and the existence of a handicap. According to their status and preferences, patients will make both rational [63] and irrational [64] decisions for or against treatment based on their own beliefs, personal circumstances, and the information available to them. Status issues such as race can create barriers to shared decision-making between patient and physician [65].

2.5   Decision for Ambulant versus Stationary Treatment

The last stage of the *DISEASE FILTER* separates stationary treatment from ambulant treatment. Defining the first as the target case and the latter as drop-out is obviously arbitrary and only depends on the case and process to which the *DISEASE FILTER* is applied. A similar dichotomy at this last stage of the *DISEASE FILTER* could be the decision between operative or conservative treatment that may also determine whether the case is included or excluded in certain datasets. Again, social status plays a certain role in differing patient choices, e.g. the choice for outpatient instead of inpatient rehabilitation in more well-educated people [66 for Germany]. The underlying social mechanism could be differences in social support. Access to institutions and local mobility could also influence patient choice, as could physicians' recommendations [67]. Rosano et al. [67] report an inverse association between accessibility to primary health care and the rate of avoidable hospitalization. To give an overview of Section 2, all biases and the social mechanisms leading to them are summarized in Table 1.

Table 1: *Summary of Social Mechanisms and Biases at each Stage of the Disease Filter*

Stage of Disease Filter	Social Mechanisms	Biasing Influences
1) Definition and perception of diseases	Socially determined processes of perception and underlying personal concept of illness	Values and beliefs, age, gender, socioeconomic status, educational background
2) Utilization of health care	Health literacy, sensitivity to symptoms, estimated costs of utilization (and further treatment), pressure of social environment, need of sick certificate	Access, region, economic resources, social capital, education, gender, mobility, occupational status
3) Classification and Diagnosis of diseases	Stereotypes of sick people, advanced medical research, organizational issues, interests of the pharmaceutical industry, benefits for physicians, "permission to be ill"	Statistical distribution of diseases, period, gender, age, occupational status, lobby work of different parties
4) Decision for or against treatment	Estimated costs and benefits of treatment (financial and well-being), absorption of treatment costs by assurance, medical resources (e.g. organ donations, medical equipment), asymmetric patient-physician-interaction	Period and region, type of assurance (by state and wealth of person), age, risk aversion, education
5) Decision for location of treatment	Perceived severity of symptoms, social support, access to institutions	Social support, regional resources

3 Applying the *DISEASE FILTER* to Health Data

For an adequate application of the *DISEASE FILTER*, we must distinguish between different types of data. Table 2 shows a rough scheme that mainly separates register data and survey data and also accounts for subcategories and health measures in these data types.

The category *register data* subsumes very heterogeneous subsections such as hospital, insurance, and mortality data. Inpatient cases that make up hospital data pass through all the selection stages mentioned in the *DISEASE FILTER*, so they are affected by all biases mentioned in Table 1. Insurance data face the first two selection stages, whereas mortality data should not be substantially biased in developed countries. Register data are usually not affected by nonresponse problems but often suffer from the lack of useful socio-demographic information for examining health inequalities [68].

Survey data in general face some additional biases that are only partly specific for health data. (a) *Sampling bias* and *self-selection bias* refer to the question, "Who is in the sample?"; (b) *panel attrition* raises the question, "Who remains in the sample?"; (c) *mode effects* are concerned with the question, "How does the survey mode affect the data and the willingness to participate?"; and (d) *response bias* brings up the question, "How do characteristics of the items (wording, response alternatives, response order, etc.) affect the data?" These issues have been discussed extensively in standard textbooks [69] and face additional challenges in cross-national studies [70].

For health data in particular, the following arguments are an issue:

Ad (a) Sampling and self-selection bias: Samples are often drawn based on private households, which exclude people living in institutions such as homes for the elderly and mental institutions. People staying in hospitals are less likely to be included with a likelihood inverse to the duration in hospital. Some diseases, such as hardness of hearing, may lead to a self-selection bias, especially in combination with the survey mode, e.g. computer-assisted telephone interviewing (CATI). Prevalence estimates based on survey data underestimate those diseases concerning the elderly and those conditions that are treated in hospitals.

Ad (b) Panel attrition: Likewise, the arguments mentioned in (a) panel attrition are particularly an issue for respondents moving out of private households or for those with worsening health conditions.

Ad (c) Mode effects: Reporting health and diseases is prone to the social desirability bias, which is confounded with mode effects. In an experimental mode effect design, people reported more diseases and poorer health in the online treatment than in the CATI treatment [71].

Ad (d) Response bias: Soft items in particular, such as self-rated health or well-being, are prone to the response bias. Considering response order effects, whether or not a survey first asks for a list of diseases and then for the overall self-rated health or the other way around definitely plays a role.

Health survey data can be further classified into interviews (with or without physicians), examinations, and mortality data. Regarding interviews without physicians, the classification depends on how health has been measured: Self-rated health assessments are biased by selective response as people with a self-rating of poor health are less likely to participate in health-related surveys [72 for Sweden].[1] Self-rated diseases reported in interviews without physicians face the biases described in Stages One and Two of the *DISEASE FILTER*. Asking respondents if a physician has diagnosed a particular disease explains the biases at Stages One, Two, and Three, but bias at an earlier stage (e.g. overuse of health care at Stage Two) can of course be compensated for at a later stage (e.g. diagnosed as healthy at Stage Three). Interviews with physicians are mainly biased at Stages One and Three of the *DISEASE FILTER*. The more the diagnosis is based on respondents' statements, the more a Stage-One or -Two bias is possible, whereas the use of diagnostic interviewing or medical examinations should decrease these biases. Panel survey data, including information on mortality, are only biased by selective response and panel attrition, but not by processes mentioned in the *DISEASE FILTER*.

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[1] We assume self-rated health to be relatively unbiased (in the literal sense of the term) as a measurement of people rating their own health. That does not contradict the fact that the gap between self-rated health and objective health measures can be systematically influenced by origin, age, gender, etc., as discussed above.

An additional problem may occur when different types of data are analyzed in one study. Together with the unavoidable necessity and maybe even advantage of this strategy, it poses the risk that different types of data represent different parts of the population. For example, while register data with death records may cover the whole population, survey data used to reveal risk-factor prevalence may only represent private households. A mismatch occurs when one tries to explain mortality rates from one source by risk-factor prevalence from a different source. On the other hand, pension registers may only represent people in the labor force, whereas health surveys may actually represent the whole population. A similar kind of mismatch may occur when effect sizes from randomized control trials that were conducted in restricted settings, such as hospitals, are applied to the whole population.

Table 2: *Biases Depending on Type of Data*

Type of data	Subsection		Biases
Register data	Hospital data		Biases up to stage 5
	Insurance data		Biases up to stage 4
	Mortality data		No substantial bias in developed countries
Survey data (population and health surveys)	Interviews without physicians	Self-rated health or well-being	No direct bias (except for survey methodological biases; see also Fn 1)
		Self-reported disease	Biases up to stage 2
		Physician-rated disease	Bias up to stage 3
	Interviews with physicians and medical examinations (e.g. blood tests)		Bias at stages 1 and 3
	Mortality data		No direct bias (except for response and survival bias)

To apply the *DISEASE FILTER*, the following steps should be conducted:

- Classify your data according to the data types in Table 2.

- Identify the biases by data type in the last column.

- Use Table 1 to identify the main biasing influences affecting your data.

- Be aware of potentially biased estimators in your multivariate models.

4 Conclusion

With the presentation of the *DISEASE FILTER* as a heuristic instrument, we have shown how health data can be biased throughout the generation process and have outlined the social mechanisms responsible at each stage. Additionally, we have shown which biases affect which types of data. The *DISEASE FILTER* is a useful tool to become aware of potential biases and find potential remedies, and this tool can be applied in a flexible and tailored way to every observational study using health data. Experiments have been shown to be more resistant to biases, but many important attributes affecting health or health inequalities, such as age, gender, social status, and so on, cannot be manipulated experimentally. Experiments are not able to offer any information regarding the prevalence rates of disease. This fact underlies the importance of survey and register data when explaining health outcomes or health inequalities. Awareness of potential biases can be increased, and better evaluation of health data can be facilitated with the application of the *DISEASE FILTER*, but we cannot provide a formula with which one can calculate from health data backwards to the prevalence of "real illness". To come close to this formula, a lot more research must be done to shed more light on the liabilities and limitations of health data concerning these biases. Although we have demonstrated how prevalence rates and data on treatments can be biased depending on the data type, nothing has been said until now about how correlations and hypothesis testing can be biased. To our knowledge, there is no approach that achieves the classification of correlation bias systematically into types of health data. This should be the aim of future research.

What are the consequences of biases in health data and how can we cope with them? Referring to the *consequences*, biases in health data can cause wrong or misleading results in the sense that they suggest something that is not based on valid evidence and that sends the wrong message to the scientific community and policy-makers. This may concern simple descriptive trends in health or related variables, such as age or offer/demand for care; it may suggest associations between factors that are either too low, too high, or simply spurious (e.g. the effect of a risk factor on a health outcome), with the effect that wrong priorities and investments will be made in health policy; or it may result in a wrong evaluation of a complex social or health policy, with the possible consequence that effective policies are stopped or ineffective policies are continued.

In this paragraph, we present *coping strategies* and group them into six categories (a-f), of which the last category (statistical approaches) is the most comprehensive because it contains several statistical methods that we briefly present but cannot discuss in detail. Coping strategies include (a) carefully interpreting research, which means that researchers should clearly illustrate potential biases in their results and take them into account when they draw conclusions from their findings, whereas readers should be aware of the biases and their effects when they use research findings. Both are facilitated by the *DISEASE FILTER*. (b) Using systematic reviews leads to a more balanced account of research results from many different studies or specifically uses knowledge on magnitudes of certain biases [73]. Both strategies (a and b) can be done by researchers as well as readers, whereas all remaining strategies have to be applied by the researchers, which highlights their important role and responsibility in the exchange of valid research findings between science and policy. These strategies include (c) using different datasets to test hypotheses and to check the robustness of the results (data triangulation with regard to sources and types of data), (d) using health items that are less prone to being systematically biased, (e) using panel data in which time-constant systematic bias and unobserved heterogeneity can be accounted for, and (f) statistical approaches for bias-correction. The statistical approaches constitute a large research field, and the numerous statistical methods can only be briefly mentioned but not discussed in detail here. From a statistical perspective, three principle categories of biases can be differentiated (measurement error, selectivity of the population, and unobserved heterogeneity), and these do not necessarily correspond to the stages of the *DISEASE FILTER* because different kinds of biases can arise in all stages of the *DISEASE FILTER*. Measurement error can occur in health variables [74] as well as in social variables [75] and can be addressed with measurement models, multiple imputation methods using a subpopulation without measurement error, and instrumental variables [for an overview of correction methods, see 76]. Selectivity of the population implies that the sample does not represent the target population (which leads, for example, to incorrect prevalence for the target population) or that the treatment in the analyses (e.g. unemployment) and the outcome variable of interest (e.g. being ill) are both associated with the probability of dropping out of the sample. In this case, the parameter estimates from the sample are biased. Here, remedies include inverse probability weighting used in longitudinal studies [77] or the Heckman selection correction [78]. Unobserved confounders can be

addressed with many methods, not least by using randomized experiments whenever research questions (and ethical standards) allow. If such a design is impossible, there is a wide range of techniques for analyzing data from natural experiments and other research designs. These techniques include difference-in-differences, fixed effects models, instrumental variables, and regression discontinuity, and they are explained in many standard econometric textbooks [79; 80].

This contribution aims to sensitize and help health researchers to account for systematic bias in their data, but it cannot replace standard textbooks in survey methodology or advanced econometrics. For the exchange between researchers and policy-makers, the existence of numerous, potentially severe biases implies that they should be critical when using research results. For researchers, it means that they should be knowledgeable, explicit, and transparent about possible limitations, biases, and degrees of uncertainty. The DISEASE FILTER presented in this paper can help not only to understand bias in health data, but also to provide suggestions as to how researchers can try to address these biases in the future.

5 References

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