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Welfare implications of learning through solicitation versus diversification in health care

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ABSTRACT

Using Roy's model of sorting behavior, I study welfare implications of learning about medical care quality through the current health care data production infrastructure that relies on solicitation of research subjects. Due to severe adverse-selection issues, I show that such learning could be biased and welfare decreasing. Direct diversification of treatment receipt may solve these issues but is infeasible. Unifying Manski's work on diversified treatment choice under ambiguity and Heckman's work on estimating heterogeneous treatment effects, I propose a new infrastructure based on temporary diversification of access that resolves the prior issues and can identify nuanced effect heterogeneity.

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One of the fundamental challenges in health care markets is lack of information about the quality of medical care and technology (Arrow, 1963). Information on medical product quality is usually generated by employing an artificial form of 'learning by doing' mechanism where a selected group of individuals (doers) is allowed to consume alternative medical products (e.g. using standard statistical designs, such as randomized assignment of patients to products). Wisdom from their experiences is disseminated to other individuals, who will face the choice of using these medical products in the near future, and to inform other decision makers, who device social policies on access[2]. Most public and private stakeholders that are engaged in data production on medical quality signals have employed such mechanisms. Recently, substantial public investments were made in the US, under the umbrella term "comparative effectiveness research" (CER) and patient-centered outcomes research (PCOR)[3], to facilitate production of such data on alternative medical technologies that are currently being used in clinical practice, albeit with incomplete knowledge about their comparative qualities[4].

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[2] There are situations where learning from own's doing is popular, aka the repeated use of pharmaceutical products in chronic illnesses.

[3] Patient Protection and Affordable Care Act of 2009, H.R. 3590, 111th Congress §6301 (2010).

[4] Throughout our paper, I assume the CER compares two medical technologies that have been approved for use based on meeting the minimum safety thresholds as those set by the Food and Drug Administration of the United States. Our discussions do not encompass evaluation of experimental therapies. Such discussions are delegated to future work. Also see Philipson (1997) and Malani (2008) who make distinct arguments about selection in trials of experimental therapies in the presence of health insurance.

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In this paper, using a simple Roy's model (Roy, 1951) of sorting behavior, I prove that, when incremental treatment effects are heterogeneous across patients who have access to these treatments under insurance, a data production infrastructure for comparative medical quality that relies on soliciting voluntary participation of subjects fails to identify any interpretable treatment effect parameter. Therefore, evidence generated through this process fails to inform, objectively, either the individual patient on *optimal* medical care use or a social insurer on *optimal* medical care insurance coverage[5].

Unfortunately, such a data production infrastructure is and has been the norm for CER randomized clinical trial (RCT) studies. There are many examples of such failures in the literature. For example, Ioannidis and Lau (1997) show that in human immunodeficiency virus-related trials and trials of magnesium in acute myocardial infarction, when the benefit or toxicity from a treatment varies with the baseline risk of each patient, the treatment effect may be markedly different in populations with a different representation of high- and low-risk patients. I show that such differential representation of the population in trials may be driven more fundamentally by patient and physician behaviors and therefore the problems of interpretation of trial results are systemic.

The implications of this finding are substantial. Incomplete comparative quality information generated by CER RCTs research has the potential to misguide treatment choices since ex-ante perception of benefits do not coincide with the ex-post accrual of the same, resulting in welfare losses (Basu, 2011). These inefficiencies in the choice of medical products can also accentuate the inefficiencies due to moral hazard stemming from health insurance (Arrow, 1963; Pauly, 1968), translating to higher premiums and less protection against risk, in both competitive and non-competitive insurance markets (Basu, 2011). In this paper, I focus on understanding why current data production infrastructure leads to incomplete information.

I begin in the next section by laying out our ideal target parameters in CER evaluations; those that we would like to obtain estimates for in order to guide treatment decisions at the individual level and policy decisions on coverage at the social level. In Sections 2 and 3, I highlight the current data production infrastructure and prove why it would produce incomplete information. I study the implications for such incompleteness on decision-making and welfare. In Section 4, I introduce a new framework for data production that can efficiently resolve the biases inherent in the current data production infrastructure by using diversification of access to create a conduit for learning about meaningful and decision-relevant effect parameters. This work unifies two broad themes in the econometrics literature, one based on Manski's work on treatment choice under ambiguity (Manski, 2000, 2004, 2009) that utilizes the concept of diversification of treatment and the other based on Heckman, Vytlacil and others' works on estimating heterogeneous treatment effects (Heckman, 1997, 2001; Heckman and Vytlacil, 1999, 2001; Heckman et al., 2006). I show how this framework can help overcome inefficiencies in health care markets that stem from incomplete information.

1. Defining the true population average effect of a treatment

Let us begin with a problem of evaluating the comparative effectiveness of a new (approved) treatment compared to a control/standard treatment for a population of N patients indexed by i. Standard treatment may also include the do-nothing option. Let the individual-level true treatment effects represent the benefits (net of harms) of the new treatment over the control and are denoted by b_i. Let p denote the price of the new treatment, which is also the marginal cost for manufacturing the new treatment[6].

Patients are members of risk classes Ω, $\Omega = 1,2,.k$; $k \leq N$, which determine heterogeneity in treatment effects across individuals through a production function:

$$b_i = \sum_k \alpha_k \times I(\Omega_i = k) \tag{1}$$

where $I()$ is an indicator function and α_k is interpreted as the true comparative effect of the new treatment over the standard treatment in risk class k. Let's assume that this comparative effect is expressed in monetary terms. That is the effectiveness unit is multiplied with the some predefined threshold representing the monetary value of the marginal unit of benefit[7].

A population-level average effect parameter is given as

$$\Delta = \sum_k Pr(\Omega = k) \times \alpha_k \tag{2}$$

There are two types of decision makers, (1) the patient-physician dyad, which I will refer to as the individual decision maker, is assumed to always have knowledge about their risk class; and (2) an insurer or social planner who decides the coinsurance rate for providing health insurance coverage for the new treatment.

2. Data production and incompleteness in quality information

A first-best scenario can be achieved under complete information, where both the insurer and the individuals are aware of the risk classes and the production function and are able to perfectly predict b_i. If individuals had full insurance they would choose treatment if $b_i \geq 0$. Since the insurer can fully anticipate this individual behavior, she can provide full coverage for treatment only for those individuals who would experience benefits greater than cost and not provide coverage for the rest. Thus, there is no efficiency loss due to moral hazard.

Under the second-best scenario, there exist asymmetry of information where, even though, individuals are assumed to be aware of Ω_k and $b()$ and to be able to combine them to predict b_i perfectly, the insurer cannot as they have either no or only partial information on Ω_k (Arrow, 1963; Pauly and Blavin, 2008). Consequently, the insurer cannot exclude patients from coverage who would get treatment benefits lower than the cost of treatment (i.e. $b_i - p < 0$). This leads to moral hazard (Pauly, 2008). To counter this, the insurer may offer coverage with a fractional coinsurance rate (r), which is the fraction of price a patient must pay in order to receive treatment. When $r = 1$, the new medical product is not covered through insurance.

I assume individuals choose treatment by maximizing a generic Net-Benefit criterion that is based on their perceived benefits from treatment net of the demand price they face in acquiring the treatment. I also assume that the social insurer's goal is to maximize consumer surplus as is realized *ex post* based on individual level choices. Throughout this paper, I express the realized population level benefits under different levels of coverage for the new treatment as *changes* to the total outcomes had all patients taken the

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[5] Note that my assertions about optimality are very general and does not depend on specific welfare functions. What I prove is that the structural target parameters on which information is required to maximize any welfare function is not informed by current data production infrastructure.

[6] Assume for now that the marginal cost is constant.

[7] Under the welfare economic foundations, this threshold is the inverse marginal utility of income (Weinstein and Zeckhauser, 1973; Garber and Phelps, 1997; Meltzer, 1997).

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