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Reading Note 2

Health care spending in the U.S. accounts for almost 20% of GDP, still growing. Therefore, balancing people's benefits and reducing spending becomes essential for policymakers. Many researchers have provided economical solutions to address the welfare loss problem in medical care; one is the "top-up" design that could efficiently sort patients across treatments by making patients pay on margin. In this paper, the authors verify that the "top-up" design has the highest welfare gain by visualizing the welfare effects for the three designs. More importantly, they estimate the demand curve and quantify the welfare effects for three designs in both ex-post and ex-ante perspectives, which provides empirical support for the efficiency of "top-up" design.

This paper focuses on binary treatment choices for breast cancer patients. The baseline treatment is mastectomy, and the more expensive treatment is lumpectomy. While these two treatments do not differ in survival outcomes, the U.S.'s "full coverage" design covers costs for both treatments; the UK-style "no top-up" design only covers baseline treatment. Unlike those two designs, the "top-up" design serves as a middle ground that covers the cost of baseline treatment and allows patients to pay an incremental cost for more expensive treatment. The authors first present a conceptual framework to illustrate why "top-up" design is most efficient. Denote willingness to pay for L as Vi. In the "top-up" design, people whose Vi is higher than the social cost would still choose to pay an incremental cost, while people whose Vi is lower than the social cost will choose the baseline treatment. However, in the other two designs, welfare loss occurs. For people whose Vi is lower than cost, in a "full-coverage" design, those people might still choose L since there is no difference in paying. For people whose Vi is higher than cost, in "no top-up" design, many are forced to choose baseline treatment because they can not afford the cost. To perform quantitative analysis, the authors set up a utility model $U=\alpha-\beta(\theta d+p)$, where α and β are preference parameters, d is the distance to nearest radiation location, θ converts travel time to cost, and p=0 in the full coverage scenario. Then the authors can estimate the demand (the distribution of Vi) by dividing β from the utility model and perform counterfactual analysis.

The sampling data in the empirical analysis consist of patient-level data and radiation location data. Merging those two datasets, the authors obtain information of patients' treatment choice, distance to nearest radiation, demographics, census-block, and clinical characteristics. Since the main difference in cost between two treatments is the opportunity cost of time, the authors split patients by above or below median distance to investigate the treatment-distance relationship. According to Figure 2, the authors conclude that patients are less likely to choose L when distance increases, and this relationship is not sensitive to personal characteristics. By running logistics regressions with different α and β, the authors obtain a range of significant marginal effects of distances. Together it suggests a robust treatment-distance relationship, and distance measure is adequate to estimate demand. Continuing with the conceptual framework, the authors calibrate θ to average hourly wage times hours spent traveling to radiation location and obtain an estimated demand curve. Then they can plot the demand for no control and random coefficient case given an incremental price for L. Based on Figure 3, the U.S.'s "full coverage" design raises the lumpectomy rate and reduces welfare by 710$ to 2000$ per patient; the U.K.'s "no top-up" design minimizes the lumpectomy rate and welfare by 800$ to 1400$ per patient. Building on the previous result, the authors calculate the welfare change for various counterfactuals under six different controls in Table 4. Compared to the baseline treatment (full coverage), the "top-up" design has the most significant welfare gain, which proves that the "top-up" design is ex-post efficient. Considering people have different levels of risk aversion, the authors also explore the ex-ante efficiency. Assuming CARA utility, they set up an ex-ante utility model with risk of breast cancer and risk aversion level. Since there is no risk of losing money in the "full coverage" design, it is not an ex-ante risk. However, "top-up" and "no top-up" designs expose patients to ex-ante risk. Similar to the ex-post approach, the authors obtain an estimated demand curve by calibrating risk aversion and the probability of breast cancer. From Table 5, the authors find that the efficiency rank depends on the level of risk aversion. When risk aversion is low, "top-up" design is more efficient; when risk aversion is high, "full coverage" design is most efficient.

Based on the analysis, the author concludes that the "top-up" design generates more social welfare than the current healthcare system from an ex-post perspective. However, when the level of risk aversion is uncertain, the "top-up" design might cost more than the contemporary design. One limitation would be there is no practical design that achieves both ex-ante and ex-post efficiency.