Reading Notes 2

In this paper, Einav, Finkelstein, and Williams present a framework to evaluate and compare three insurance designs for reimbursement of a binary treatment choice regarding social welfare consequences. They derive the framework in the context of breast cancer treatments where two surgery choices are available: lumpectomy (L) and mastectomy (M)[3]. L is more expensive and less invasive than M, but it yields no average superior survival outcomes. By choosing this context, the authors can focus on binary treatment choices and the pure effect of cost differences, which simplifies their framework. Furthermore, the three insurance designs offer different reimbursements for L and M: ”full-coverage” design covers the full cost of either L and M, ”no top-up” design covers M but not L, ”top-up” design provides a middle ground and requires patients to pay the incremental costs of L. In sum, the paper shows that switching to a ”top-up” design improves ex post social welfare.

As for the theoretical foundation, Chernew et al. (2000) model the optimal ”top-up” design for disease treatments and quantitatively demonstrate the model’s implications by calibrating key parameter values in the context of a binary treatment decision faced by prostate cancer patients. Also, Schroen et al. (2005) show that the distance from radiation centers would cause an additional difference in costs of L and M. Building from these work, the authors assume that the distance can be monetized, and the preference for distance decrease is equivalent to that for price decrease. Under the assumption, they further explore the relationship between distance and treatment choices and estimate the relative demand curve for L to visualize and quantify the social welfare effects of alternative insurance designs.

This paper relied on a patient-level cancer registry dataset and data on radiation treatment facility locations. The patient-level data set comes from California Cancer Registry(CCR) and contains all cancer diagnoses from 1988 forward. Variables in the CCR dataset include demographic covariates, treatment information, and patients’ exact residence addresses at the time of diagnosis. The data on radiation treatment facility locations is from the private firm IMV and contains the addresses for all radiation facilities. The two datasets together enable authors to compute the residence-to-facility distances; thus, with the variations in distances, they can estimate the relative demand curve for L. In addition, for ease of presentation, the authors clean the datasets for analysis by keeping only data of female breast cancer patients diagnosed between 1997 and 2009 and dropping missing treatments and residence as well as the

[3] To simplify, I will use L to denote lumpectomy and M to denote mastectomy in the following reading notes

cases in which the patient chose neither treatments. With the comprehensive datasets, Einav, Finkelstein, and Williams adopt the empirical strategies of conditional logit regression models with different controls and random-coefficient / mixed logit regression models that account for the distance to estimate the probabilities of choosing L under each price. Given the probabilities and patient population, the authors can estimate the demand curve for L, which allow them to compute the welfare gains/losses.

As for the findings, the authors firstly conclude that distance is a determinant of treatment choices. They compute the marginal effect of choosing L as travel time increases by ten minutes, and they find that the ten-minute increase in travel time makes patients less likely to choose L by 0.7 to 1.1 percentage points. Then, the authors plot two relative demand curves for L. First, for the logit with no covariates, the "full-coverage" design increases the probability of choosing L by 37 percentage points and incurs a welfare loss of $2, 000; the ”no top-up” design reduces 21 percentage points of L-share and incurs a $1, 400 welfare loss. Second, for the logit with controls and random coefficients, the "full-coverage" design increases the probability of choosing L by 10 percentage points and incurs a welfare loss of $710; the ”no top-up” design reduces L by 4.5 percentage points and incurs a welfare loss of $800. In all cases, switching to the "top-up" design improves the (ex post) social welfare.

The authors also supplement their findings by discussing implications for ex ante social welfare of treatment choices. Since the three different insurance designs result in different ex ante risk exposures, for example, the "top-up" design that produces the ex post efficient treatment decision exposes the patients to risk ex ante, patients' utilities are affected via risk exposures. Using the relative demand curve, the authors find that ”top-up” design still dominates ”no top-up” design in terms of ex ante utilities; however, its dominance also depends on patients' risk aversion levels.

To sum up, the authors adopt the methods of logit regression and use graphic framework to show that the "top-up" design improves the ex post social welfare. Furthermore, the work presented in this paper is intuitive and may be applied to policy counterfactual exercises investigating how patients might respond to changes in the financial costs of treatments induced by different health insurance contract designs. Nevertheless, there are some limitations from the aspect of cost estimate. For example, even though there is no average difference in mortality outcomes, L might be preferred to M by female patients since it doesn't remove the cancerous breasts; however, the authors fail to monetize the preservation of breasts when computing the cost differences.