Homework 4

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Part I: MSE without transfer

The first model I estmate is using the revelaed merger preferences without any transfers occuring. For a buyer b acquiring target t, and buyer $b^{'}$ acquiring target t', the revealed value of the merger is given by $f(b,t|\beta)+f(b^{'},t'|\beta)$, where $f(.)$ is the parametric form of the value function of a buyer acquiring a target. Likewise, if the b acquired target $t^{'}$, and buyer $b^{'}$ acquiring target t, the counterfactual value will be $f(b,t^{'}|\beta)+f(b^{'},t|\beta)$. In the first part, where there is no transfer happening between buyers and targets, the parameters β should be able to maximize the instances where the value of revealed matches is greater than the value of counterfactual matches over all buyer-target pairs and markets. As such, this is mathematically represented by the maximization of Q(β) across all the Y markets, where:

$$Q(\beta)=\sum_{y=1}^{Y}\sum_{b=1}^{M_{y-1}}\sum_{b^{'}=b+1}^{M_y}1[f(b,t|\beta)+f(b^{'},t'|\beta)\geq f(b,t^{'}|\beta)+f(b^{'},t|\beta)]$$

In the first part, the value function is given by the following:

$$f_m(b,t)=x_{1bm}y_{1tm}+\alpha x_{2bm}y_{1tm}+\beta distance_{btm}+\epsilon_{btm}$$

where:
x_{1bm} is the num of stations owned by buyer b
y_{1tm} is the population in target t's range in market m
x_{2bm} is an indicator for corp. ownership of buyer b
$distance_{btm}$ is the distance between buyer b and target t

It is clear from the above formulation, that α represents the extent to which the buyer b's direct access to target t's population influences the merger value. Also, β represents the degree to which the distance between the buyer b and target t influences the merger value. Intuitively,for matches without any transfers, I would expect α to be positive, since this means buyer b values having more of the target customer population in its region. I also expect β to be negative, since this means that buyer b would value acquiring targets in its close vicinity to reduce transaction costs. This kind of analysis is in line with Akkus, Cookson, and Hortacsu (2016), where, for example, they consider the role of market overlap on merger value (given by HHI of the buyer). Two points to note that link this paper with the HW assignment: 1) ACH (2016) hypothesize a positive impact of α on the merger value. They state: "Mergers are an effective way for banks to acheive a large, national banking network" (pg. 8, second paragraph). While not exactly the same as their operationalization, the α term captures this effect to some extent. 2) I could not find a hypotheses on the target distance in the paper in a direct fashion, therefore I use intuition to guide my understanding.

In line with this expectation, I estimated α and β using an optimization routine I wrote in python v3.6. I used 1) Nelder-Mead (NM) and 2) Differential Evolution (DE) solvers to provide the estimates. For NM estimation, I iterate over several starting values and finally decide to use (1500, 1500) as the starting value. For the DE estimation, I use the classical strategy=1 (best1bin) and bounds of (-30k to 30k) for both parameters. The dataset used was of size 2,421 obs. This includes all permutations of actual and counterfactual matches in years 2007 and 2008 (considered as markets). After iterating over several possible intial parameter values for Nelder-Mead solver and several possible parameter bounds for DE, I was able to acheive a maximum score of 2261 and 2249 respectively. (Obj. values of -2261 and -2249 respectively, since I use minimization). I found several solutions that would give me the same obj. value. I decide to use (66895, -128690) from NM solver and (675,-29370) from the DE solver as my final parameter values. The directionality of the results is in line with the above stated hypotheses.

Part II: MSE with transfer

With transfers allowed (prices) between buyers and sellers, the function Q(β) is of the form:

$$Q(\beta) = \sum_{y=1}^{Y} \sum_{b=1}^{M_{y-1}} \sum_{b'=b+1}^{M_y} 1[f(b,t|\beta) + f(b^{'},t'|\beta) \geq p_{bt} - p_{b't'} \wedge f(b,t^{'}|\beta) + f(b^{'},t|\beta) \geq p_{b't'} - p_{bt}]$$

where:
p_{bt} is the price payed by buyer b for target t (and the analogous case of $b^{'}$ and $t^{'}$)

For this part, the payoff function is also modified to include target characteristics:

$$f_m(b,t) = \delta x_{1bm} y_{1tm} + \alpha x_{2bm} y_{1tm} + \gamma HHI_{tm} + \beta distance_{btm} + \epsilon_{btm}$$

where:
HHI_{tm} is the Hirfindahl-Hirschman Index at target t in market m

For estimation in this part, I use DE solver with parameter bounds of (-20k to 20k) for δ and γ, and (-30k to 30k) for α and β. Using the 'best1bin' strategy and the above bounds, I find that the optimized parameters satisfy the inquality for 2249 observations (Obj. value=-2249). The obtained parameters are δ=919, α=-28730, γ=8533, and β=26948. Two observations: 1) The coefficients for α and β have now changed in terms of directionality. Taken together, this means that given price transfers, price put more emphasis on expanding their networks geographically ($\beta > 0$) and not in markets where the target is serving a substantially large population ($\alpha < 0$). 2) The directionality of the estimate on HHI (γ >0) also corroborates ACH (2016) that greater target concentration increases match value.