1 Computation

Given a set of physicians $\{(V_j, \tau_j, R_j(\cdot), P_j(\cdot))\}_{j=1}^{J}$, the distribution functions for patient parameters $F(\kappa)$ and $G(\gamma)$, and one search model parameter z, which is λ in the Logit model, β in the sequential model, we develop an algorithm to compute market equilibrium.

Equilibrium aggregates are computed on the basis of Monte-Carlo matrix calculus. Set J as the number of physicians[1], I as the size of the sample drawn randomly from $F(\kappa)$ and $G(\gamma)$. For both models we define a class which can output a matrix S where each column is a patient's strategy vector S_i following that model, when given as input the arrayed set of physicians' quality and visit cost $\{(V_j, \tau_j)\}_{i=1}^{J}$, an arrayed set of patients $(\{(\kappa_i, \gamma_i)\}_{i=1}^{I}$, the model parameter z and a given vector of physician strategies $\{\bar{\kappa_j}\}_{j=1}^{J}$.

We input as "patients" our I samples from $F(\kappa)$ and $G(\gamma)$, then a $J \times I$ matrix U is computed, where each component u_{ji}[2] corresponds to the utility the sampled patient i would get from a visit to physician j. This step is the same for both classes.

What differs between both models is the computation of the matrix S of patient strategis out of the utility matrix U:

- **Implicit search model (Logit):** First, an 'α-matrix' is calculated over matrix U, where each α_{ji} is $e^{\lambda u_{ji}}$ if $u_{ji} > 0$ and 0 if not. Then, for each patient i, that is, for each column, each component s_{ji} of the S matrix takes on the values $s_{ji} = \alpha_{ji} / \sum_{k=1}^{J} \alpha_{ki}$.

- **Explicit search model (Sequential):** Recall equation (NUMBER) characterizing patient thresholds. We first compute the I-dimensional vector of the sampled patients' respective $\bar{U}_i$. Define U_i as the set $\{u_{ji}\}_{j=1}^{J}$ of utility patient i recieves from a visit to each physician. In matrix terms U_i would be the ith column of the $J \times I$ matrix U. The operation to compute each $\bar{U}_i$ is the following:

$$\bar{U}_i \equiv \underset{x \in U_i}{\arg\min} \left\| x - \frac{\beta}{1-\beta} \sum_{j=1}^{J} \left\{ \frac{\mathbb{1}[u_{ij} \geq x] \cdot (u_{ij} - x)}{\mathbb{1}[u_{ij} \geq x]} \right\} \right\| \tag{1}$$

  where the norm $\|\cdot\|$ is defined in $\mathbb{R}$ as simply the absolute value $|\cdot|$. This is to say, for each sampled patient i we evaluate x for each u_{ji} in U_i. In plain words, if patient i where to say: "I will only visit physicians which grant me at least as much utility as physician j", the optimal choice of j and its respective u_{ji} would

[1] Or, as we'll later interpret it, as the number of bins, where each bin j is a unique combination of $(V_j, \tau_j, R_j(\cdot), P_j(\cdot))$.

[2] As we have defined our matrices $J \times I$ for ease of visualization, we will refer to matrix components as x_{ji} in this section rather than x_{ij} as we do elsewhere in the paper.

be the minimal in U_i for the evaluation of the absolute value in the left-hand side of (1). This is computationally less intensive than seeking to compute the exact root of (NUMBER), which would be a redundant exercise, because there's a discrete number of physicians above that mark, and selecting instead to use "the lowest u_{ji} above the root of (NUMBER)" as threshold instead of the root proper would result in the same vector of strategies S_i for each patient.[3]

Once having computed our I-dimensional vector patients' $\bar{U}_i$, we evaluate column-wise the binary operator $\mathbb{1}\{u_{ji} \geq \bar{U}_i\}$ over matrix U, and the $J \times I$ matrix S of patient strategies takes on the values $s_{ji} = \mathbb{1}\{u_{ji} \geq \bar{U}_i\} / \sum_{k=1}^{J} \mathbb{1}\{u_{ki} \geq \bar{U}_i\}$.

[3] Granted, this is not strictly true, as in our formulation a 'u_{ji}' may be selected as threshold which is actually below the root proper in $\mathbb{R}$, but closer to it than the nearest one above it. The effect of this "estimation noise" on our overall results is negligible.

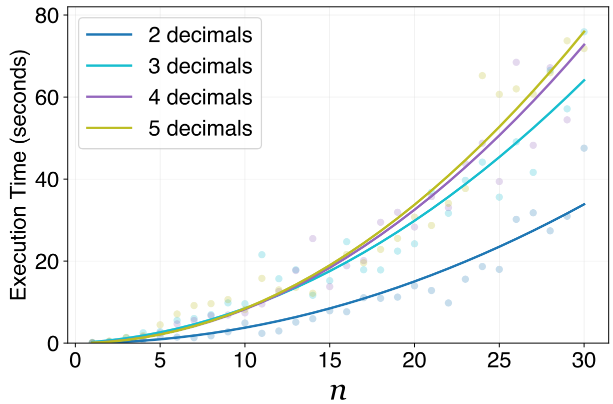
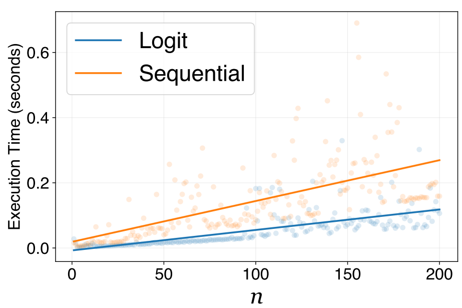
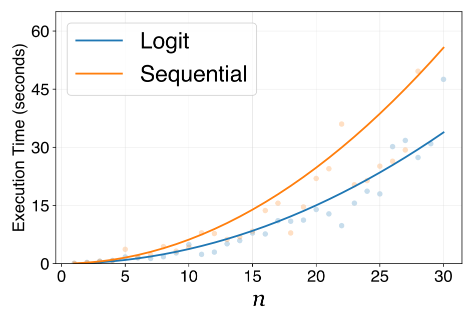


Figure 1: Coefficient β_t of *log_trade* over *log_distance* over the years, including FEs



(a) Coefficient β_t of *log_trade* over *for first case*



(b) Coefficient β_t of *log_trade* over *for second case*

Figure 2: Comparison of Coefficient β_t of *log_trade* over *log_distance* over the years, including FEs