

# 1 Appendix

**Proof of Theorem 1:** Let  $t^A$  be such that  $t_r = \sum_{a \in r} t_a^A, r \in \mathcal{R}$  and set

$$t_a^A = t_a^A / (1 + \delta)$$

for all  $a \in \mathcal{A}_{\text{toll}}$ , where  $t_r' = \sum_{a \in r} t_a^A$  whenever  $a \in \mathcal{A}, r \in \mathcal{R}$  and  $\delta > 0$ . Under this perturbation, the paths with the largest tolls are the most penalized, and it follows that, for any positive  $\delta$ , all shortest paths under  $t'$  must have the same toll, which can be made arbitrarily close to the toll on the most profitable shortest path under  $t$ .

**Proof of Theorem 2:** First, we show that  $\lim_{\theta \rightarrow \infty} \varphi_{\text{logit}}^*(\theta) \geq \varphi_{\text{det}}^*$ . Let  $t^*$  be such that  $f^{\text{det}}(t^*) = \varphi_{\text{det}}^*$ . By Theorem 1, for any  $\varepsilon > 0$  there exists a perturbation  $t'$  of  $t^*$  such that (i)  $f^{\text{det}}(t') \geq \varphi_{\text{det}}^* - \varepsilon$  and (ii)  $r, r' \in \mathcal{R}^q \Rightarrow t_r = t_{r'}, q \in \mathcal{Q}$ , where  $r$  and  $r'$  are shortest paths on OD pair  $q$ . As logit probabilities, for fixed  $t$ , concentrate on shortest paths with increasing values of  $\theta$ , and on account of the fact that under  $t'$  all shortest paths have identical toll values, we obtain that  $\lim_{\theta \rightarrow \infty} f^{\text{logit}}(t'|\theta) \geq \varphi_{\text{det}}^* - \varepsilon$ , which immediately yields

$$\lim_{\theta \rightarrow \infty} \varphi_{\text{logit}}^*(\theta) \geq \varphi_{\text{det}}^* - \varepsilon.$$

Next, let us show that  $\lim_{\theta \rightarrow \infty} \varphi_{\text{logit}}^*(\theta) \leq \varphi_{\text{det}}^*$ . To this aim, let us consider sequences  $\theta_k \rightarrow \infty$  and  $t_k \in \arg \max_t f^{\text{logit}}(t|\theta_k)$  with  $x_k := \text{logit}(t_k|\theta_k)$ . By compactness of  $T$ , there exists a subsequence  $K$  of indices and a toll policy  $\bar{t} \in T$  such that  $\lim_{k \in K} t_k = \bar{t}$ . By continuity of the logit probabilities there also exists an assignment  $\bar{x}$  such that  $\lim_{k \in K} \text{logit}(t_k|\theta_k) = \bar{x}$ . For some  $q \in \mathcal{Q}$ , consider paths  $r, r' \in \mathcal{R}^q$  and a positive number  $\delta$  such that

$$u_r(\bar{t}) \leq u_{r'}(\bar{t}) - \delta.$$

Then there exists an index  $\bar{k}$  such that  $k > \bar{k}$  yields (i)  $\delta + u_r(t_k) \leq u_{r'}(t_k)$  and (ii)

$\lim_{k \geq \bar{k}} \text{logit}_{r'}(t_k, \theta_k) = 0$ , where the last equality follows from

$$\begin{aligned} \text{logit}_{r'}(\bar{t}, \theta) &\leq \frac{\exp[-\theta u_{r'}(\bar{t})]}{\exp[-\theta u_{r'}(\bar{t})] + \exp[-\theta u_r(\bar{t})]} \\ &\leq \frac{\exp[-\theta(u_r(\bar{t}) + \delta)]}{\exp[-\theta(u_r(\bar{t}) + \delta)] + \exp[-\theta u_r(\bar{t})]} \\ &= \frac{\exp(-\theta \delta)}{\exp(-\theta \delta) + 1}, \end{aligned}$$

which goes to zero as  $\theta$  goes to infinity. Since only shortest paths carry positive flow, the solution  $(\bar{t}, \bar{x})$  is feasible for Program 1 and  $\lim_{\theta \rightarrow \infty} \varphi_{\text{logit}}^*(\theta) \leq \varphi_{\text{det}}^*$ , as desired.

**Proof of Theorem 3:** Consider the network of Figure 3, and let

$$c_1 < D_2 c_2 / (D_1 + D_2), \quad (1)$$

where  $D_i$  is the demand on OD-pair  $i$  (in Figure 3, we have  $D_1 = 30$  and  $D_2 = 1$ ). Let  $f^{\text{det}(t)}$  be the deterministic revenue associated with toll  $t$  and let  $H$  a slightly modified Heaviside step function:

$$H(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise.} \end{cases}$$

Then:

$$\begin{aligned} \max_t f^{\text{det}(t)} &= \max_t D_1 H(t - c_1)t + D_2 H(t - c_2) \\ &= \max\{(D_1 + D_2)c_1, D_2 c_2\} \\ &= D_2 c_2. \end{aligned}$$

Let  $f^{\text{logit}(t)}$  denote the logit revenue. We have:

$$\begin{aligned} f^{\text{logit}(t)} &= \frac{D_1 \exp(-\theta t)t}{\exp(-\theta t) + \exp(-\theta c_1)} + \frac{D_2 \exp(-\theta t)t}{\exp(-\theta t) + \exp(-\theta c_2)} \\ &> \frac{D_1 \exp(-\theta t)t}{\exp(-\theta t) + \exp(-\theta c_1)}. \end{aligned}$$

This lower bound on the logit revenue can be made arbitrarily large by way of  $D_1$ . Furthermore, for any  $D_1$ , bounded values of  $D_2$  and  $c_2$  can be found to satisfy inequality (1). The conclusion follows.

The proof of Theorem 4 will be based on two lemmas.

**Lemma 1.** *Let  $w$  and  $x$  be feasible for Program 3. Then  $w$  is a piecewise linear function of  $x$  such that*

$$w = \sum_{n=1}^N m^{x \log x}(x | \alpha_n^{x \log x}) \mathbf{1}\{x \in (\beta_{n-1}^{x \log x}, \beta_n^{x \log x}]\},$$

where  $\mathbf{1}\{\cdot\}$  is the indicator function.

*Proof.* Constraints (13)–(15), together with  $x \in X$ , are the KKT conditions of the mathematical program:

$$\begin{aligned} \min_{w,x} \quad & (c+t) \cdot x + \theta^{-1} \mathbf{1}_{\mathcal{R}} \cdot w \\ \text{s.t.} \quad & w \geq m^{x \log x}(x | \alpha_n^{x \log x}) \quad n \in \mathcal{N} \quad (\varphi) \\ & x \in X \quad (\pi). \end{aligned} \tag{2}$$

The convexity of  $x \log x$  ensures that  $\beta^{x \log x}$  is an increasing sequence such that, for all  $r$ , there exists  $n$  that satisfies

$$x_r \in (\beta_{n-1}, \beta_n] \Rightarrow m_r^{x \log x}(x | \alpha_n^{x \log x}) \geq m_r^{x \log x}(x | \alpha_\ell^{x \log x})$$

for all  $\ell = 1, \dots, N$ . The problem is bounded and for each path  $r \in \mathcal{R}$ , at least one of the inequalities in (2) is tight. More precisely  $w_r = m_r^{x \log x}(x | \alpha_n^{x \log x})$ , and the result follows.  $\square$

**Lemma 2.** *In Program 2b, let  $F(t, x) = \nabla_x g(t, x)$  and  $\text{SOL}(F(t, \cdot), X)$ , the solution set of the variational inequality  $\text{VI}(F(t, \cdot), X)$ :*

$$\text{SOL}(F(t, \cdot), X) = \{y \in X | F(t, y) \cdot (x - y) \geq 0, \forall x \in X\}.$$

*Let  $(t, x)$  be feasible for Program 2b and  $\bar{x} \in \text{SOL}(\bar{F}(t, \cdot), X_0)$  where  $\bar{F}$  is an approximation of  $F$ . Then setting  $d^{\max} = \max\{d_q | q \in \mathcal{Q}\}$  we have*

$$|f(t, x) - f(t, \bar{x})| \leq \|F(t, \bar{x}) - \bar{F}(t, \bar{x})\| d^{\max} \text{diam} \mathcal{T} / \theta.$$

*Proof.* For ease of exposition, we only consider the case of unit demand and a single OD pair. The generalization to the case with multiple OD pairs is straightforward. Program 2b is equivalently expressed

$$\begin{aligned} \max_{t,x} \quad & f(t, x) \\ \text{s.t.} \quad & t \in \mathcal{T} \\ & x \in \text{SOL}(F(t, \cdot), X). \end{aligned} \tag{3}$$

Using (10) we have  $x \in \text{SOL}(F(t, \cdot), X) \Rightarrow x \in \text{SOL}(F(t, \cdot), X_0)$  where  $X_0 = \{x | x \geq \delta_{\min} 1_{\mathcal{R}}\}$ . Then

$$F(t, x) = \nabla_x g(t, x) = c + t + \theta^{-1}(\log x + 1_{\mathcal{R}})$$

and so the associated Jacobian matrix  $F'$  is uniformly positive definite over  $X_0$  with largest eigenvalue  $(\theta \delta_{\min})^{-1}$  and smallest eigenvalue  $\theta^{-1}$ . As  $X_0$  is compact and  $F$  is strongly monotone with modulus  $\theta$ , we have that

$$\|x - \bar{x}\| \leq \theta^{-1} \|F(t, \bar{x}) - \bar{F}(t, \bar{x})\|,$$

and thus

$$\begin{aligned} |f(t, \bar{x}) - f(t, x)| &= \sum_{q \in \mathcal{Q}} d_q t^q \cdot (\bar{x}^q - x^q) \\ &\leq d^{\max} \|t\| \|\bar{x} - x\| \\ &\leq d^{\max} \text{diam } T \|F(t, \bar{x}) - \bar{F}(t, \bar{x})\| / \theta. \end{aligned}$$

□

**Proof of Theorem 4:** Program 3 is equivalently expressed

$$\begin{aligned} \max_{x, t} \quad & f(x, t) \\ \text{s.t.} \quad & t \in \mathcal{T} \\ & x \in \text{SOL}(F^0(t, \cdot | \alpha^{x \log x}), X), \end{aligned} \tag{4}$$

where

$$F_r^0(t, x | \alpha^{x \log x}) = \begin{cases} F_r(t, \alpha_n^{x \log x} 1_{\mathcal{R}}) & \text{if } x_r \in (\beta_{n-1}^{x \log x}, \beta_n^{x \log x}) \\ k \in [F_r(t, \alpha_n^{x \log x} 1_{\mathcal{R}}), F_r(t, \alpha_{n+1}^{x \log x} 1_{\mathcal{R}})] & \text{if } x_r = \beta_n^{x \log x}. \end{cases}$$

Indeed, for  $n(r)$  such that  $x_r^0 \in (\beta_{n(r)-1}^{x \log x}, \beta_{n(r)}^{x \log x}]$ , it follows from Lemma 1 that the vector function  $F^0(\cdot, \cdot | \alpha^{x \log x})$  is constant over  $(\beta_{n(r)-1}^{x \log x}, \beta_{n(r)}^{x \log x})$ . Thus

$$|F_r(t, x^0) - F_r^0(t, x^0 | \alpha)| \leq (\theta \delta_{\min})^{-1} |x_r - \alpha_{n(r)}^{x \log x}| \leq (\theta \delta_{\min})^{-1} (\beta_{n(r)}^{x \log x} - \beta_{n(r)-1}^{x \log x}) \leq (N \theta \delta_{\min})^{-1},$$

where  $(\theta \delta_{\min})^{-1}$  is the largest eigenvalue value of  $F$ 's Jacobian. Thus

$$|F(t, x^0) - F^0(t, x^0 | \alpha^{x \log x})| = \sqrt{\sum_{r \in \mathcal{R}} (F_r(t, x^0) - F_r^0(t, x^0 | \alpha^{x \log x}))^2} \leq \sqrt{R} / (N \theta \delta_{\min})$$

and the conclusion follows from Lemma 2.

The proof of Theorem 5 is based on the following lemma.

**Lemma 3.** *Program 4 can be written as*

$$\max_{t \in \mathcal{T}, (x, \pi) \in X} f^1(t, x) = \sum_{q \in \mathcal{Q}} d_q \left( -c^q \cdot x^q - \frac{1}{\theta} \mathbf{1}_{\mathcal{R}^q} \cdot w^q + \pi_q \right) \quad (5)$$

$$\text{s.t. } t \in T$$

$$w \geq m^{x \log x} (x | \alpha_n^{x \log x})$$

$$n \in \mathcal{N}_{obj}$$

$$x \in \text{SOL}(F^1, X), \quad (6)$$

where

$$F^1(t, x) = \sum_{n \in \mathcal{M}} [\nabla_x F(t, \alpha_n^{\log x} \mathbf{1}_{\mathcal{R}})(x - \alpha_n^{\log x} \mathbf{1}_{\mathcal{R}}) + F(t, \alpha_n^{\log x} \mathbf{1}_{\mathcal{R}})] \mathbf{1} \{x \in (\beta_n^{\log x}, \beta_{n+1}^{\log x})\}.$$

*Proof.* The function  $F^1$  is obtained by replacing the logarithm in  $F(t, x) = c + t + \theta^{-1} \log(x + 1)$  by the a piecewise linear approximation:

$$\begin{aligned} F^1(t, x) &= \sum_{n \in \mathcal{N}} [\nabla_x F(t, \alpha_n \mathbf{1}_{\mathcal{R}})(x - \alpha_n \mathbf{1}_{\mathcal{R}}) + F(t, \alpha_n \mathbf{1}_{\mathcal{R}})] \mathbf{1} \{x \in (\beta_n, \beta_{n+1})\} \\ &= \sum_{n \in \mathcal{N}} [(\theta \alpha_n)^{-1} (x - \alpha_n \mathbf{1}_{\mathcal{R}}) + c + t + \theta^{-1} (\log \alpha_n \mathbf{1}_{\mathcal{R}} + 1)] \mathbf{1} \{x \in (\beta_n^{\log x}, \beta_{n+1}^{\log x})\} \\ &= \theta^{-1} \mathbf{1}_{\mathcal{R}} + c + t + \theta^{-1} \sum_{n \in \mathcal{N}} m^{\log x} (x | \alpha_n) \mathbf{1} \{x \in (\beta_n^{\log x}, \beta_{n+1}^{\log x})\} \end{aligned}$$

□

**Proof of Theorem 5:** To prove Theorem 5 we now show that (i)  $F^1(x^1) = F(x^1) + O(M^{-2})$ , and then that (ii)  $f^1(t, x^1) = f(t, x^1) + O(N^{-2})$ , which allows to complete the proof. (i) For  $r \in \mathcal{R}$ , let  $n(r)$  be such that  $x_r^1 \in (\beta_{n(r)-1}^{\log x}, \beta_{n(r)}^{\log x})$ . From Lemma 3 it follows that  $F_r^1$  is a first-order approximation of  $F_r$  over  $(\beta_{n(r)-1}^{\log x}, \beta_{n(r)}^{\log x})$ . Thus  $|F_r(t, x^1) - F_r^1(t, x^1)| \leq (\theta \delta_{\min})^{-1} (x_r - \alpha_n^{\log x})^2 \leq (\theta \delta_{\min})^{-1} (\beta_{n(r)}^{\log x} - \beta_{n(r)-1}^{\log x})^2 \leq (M^2 \theta \delta_{\min})^{-1}$ , where  $(\theta \delta_{\min})^{-1}$  is the largest eigenvalue value of the Jacobian  $F'$ , and  $\delta_{\min}$  is the smallest logit choice probability (defined as in (10)). It follows that

$$|F(t, x^1) - F(t, x^1 | \alpha^{\log x})| = \sqrt{\sum_r [F_r(t, x^1) - F_r^1(t, x^1)]^2} \leq \sqrt{R} / (M^2 \theta \delta_{\min})$$

and by Lemma 2 it follows that  $f(t, x^0) \in O(M^{-2})$ . (ii) By Theorem 1 the function  $f^1$  is obtained from a piecewise linear approximation of the entropic term in the exact logit revenue expression of Program 2c. Now by construction of the sequence  $\beta^{x \log x}$ , where the width of each step is inversely proportional to  $N$ , we have that  $f(t, x^0) \in O(N^{-2})$ . The conclusion follows.