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Choice Aversion in Directed Networks*

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Abstract

This paper studies the problem of optimal path selection in a directed network by decision makers that have an intrinsic distaste for evaluating too many options. We propose a recursive logit model that incorporates choice aversion along the lines introduced by Fudenberg and Strzalecki (2015). We derive optimal flow allocations both sequentially and from a path-choice perspective, which is robust to the presence of overlapping routes. We obtain a tight characterization of welfare in terms of both the network topology and the degree of choice aversion, where we derive comparative statics consistent with previous research.

Resumen

Este artículo estudia el problema de la selección de ruta óptima en una red dirigida por parte de tomadores de decisiones que tienen una insatisfacción intrínseca por evaluar demasiadas opciones. Proponemos un modelo logit recursivo que incorpora aversión a la elección en la línea introducida por Fudenberg y Strzalecki (2015). Derivamos asignaciones de flujo óptimas tanto secuencialmente como desde una perspectiva de elección de senda, la cual es además robusta a la presencia de rutas parcialmente superpuestas. Obtenemos una caracterización del bienestar en términos tanto de la topología de la red como del grado de aversión a la elección, donde obtenemos estadísticas comparativas consistentes con investigaciones previas.

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1. Introduction

This paper studies the problem in which a set of decision makers (DM, hereafter) must construct a path over a directed acyclic graph G by gauging the utilities or costs associated to the edges of it. This problem, which can be equivalently grasped as finding an optimal flow allocation in G, has been extensively analyzed along different fields of study. The broad modeling appeal of this problem spans, for instance, production networks (Acemoglu and Azar, 2020), trade networks (Chaney, 2014; Antràs and Chor, 2013; Fajgelbaum and Schaal, 2019, and Allen and Arkolakis, 2019), models of present-biased planning (Kleinberg et al., 2016; Kleinberg and Oren, 2018), pricing in assembly networks (Choi et al., 2017), and decision problems in graph-related settings in general (Ahuja et al., 1993).

One of the main challenges of this problem, however, is that even for small networks, the number of paths can be admittedly large, which may promptly lead to Bellman's curse of dimensionality. By acknowledging this feature, previous research proposed recursive stochastic choice models as a way to circumvent computational infeasibility issues (e.g. Akamatsu, 1996, 1997; Baillon and Cominetti, 2008; Melo, 2012, and Fosgerau et al., 2013).[1] A salient model in this strand of literature corresponds to the recursive logit model, whose main advantage is to find closed-form solutions for those optimal flow assignments.

An important assumption of the recursive logit model though, is that whenever a new edge is added to the original network, the DM will be better off: they could actually face better random shock realizations and simply spare paths that were not available before. In other words, the expansion of their choice set leads unequivocally to higher welfare. This is a fundamental property of the logit model, which has its theoretical foundation on the idea of preference for flexibility (Kreps, 1979).

[1] It is worth remarking that in a different context, Rust (1987) introduced the recursive logit model to the study of single agent dynamic discrete choice problems.

In stark contrast with these theoretical underpinnings however, there exists ample evidence that DM may suffer from *choice overload* (e.g. Sheena and Lepper, 2000 and Scheibehenne et al., 2010). Simply put, the choice overload hypothesis states that an increase in the number of alternatives to choose from may lead to adverse consequences, such as lesser motivation to actually choose or lower satisfaction ex post. This behavioral trait has been previously considered by Ortoleva (2013), who introduced thinking aversion on DM preferences by means of thinking costs associated to feasible options. A consistent rationale for this phenomena also comes from the Rational Inattention literature (Matéjka and Mckay, 2015; Caplin et al., 2019, and Fosgerau et al., 2020), as adding options to a decision maker's choice set increases the cost of processing information. In all, it appears fairly possible that in a networked dynamic choice environment the DM may end up worse off if more options—which purportedly add flexibility—do not make up for information bearing costs arising from choice overload.

1.1. **Outline of the model.** In this paper we study a recursive logit model in directed networks that incorporates choice overload in DM behavior. The modeling approach we tackle for this aim belongs to Fudenberg and Strzalecki (2015) choice aversion formulation: we adapt their discounted adjusted logit model to the case of directed networks. Formally, consider the directed acyclic graph G with *source* node s and designated *sink* node t. In this setting we model decision makers' behavior as a sequential choice process: when assessing an edge a at some node $i \neq t$ the DM evaluate both the *flow* utility and the appropriate *continuation* value associated to such an edge. We conceptually pose choice overload or thinking aversion into the setting by appealing to Fudenberg and Strzalecki's axiomatic characterization of choice aversion: we introduce a term that penalizes the size of each choice set that stems subsequently from every current edge under scrutiny. In particular, when considering an edge a—which immediately leads to node j_a—the DM will penalize the number of outgoing edges at j_a. In other words, when facing a set of alternatives in order to depart from a specific node, the DM incorporate the size of the ensuing choice set when they appraise the continuation value of each outgoing edge.

1.2. **Our contribution.** The main result of the paper is a joint characterization of decision makers' welfare in terms of the network topology and the extent of choice aversion, which allows comparative statics that ushers in a tight condition for evaluating welfare after additional paths are incorporated into the original network.

In order to arrive at this result we show how the model of choice aversion developed by Fudenberg and Strzalecki (2015) can be adapted to the study of path choice in directed networks. In this environment we establish the connection between recursive logit with choice aversion and a standard logit model whose choice space is the set of available paths in the network. This connection allows us to highlight the role of choice aversion at the path level. In addition, we characterize the solution of the recursive logit model in terms of a strictly concave optimization program, a characterization that also applies to the original dynamic choice problem studied by Fudenberg and Strzalecki (2015).

Our path-choice analysis furthermore, highlights the role of choice aversion in overcoming the problem of overlapping paths in digraphs (Ben-Akiva and Bierlarie, 1999 and Frejinger and Bierlarie, 2007). It is easy to generate simple examples where the presence of superposition along different paths generates unrealistic behavior by DM. Our analysis therefore, portrays the way in which choice aversion nudges DM behavior when choosing optimal paths: it performs as a mechanism that penalizes the degree of overlap between distinct routes, which in turn generates robust choice probability predictions.

We additionally provide comparative static exercises where we show that an increase in the degree of choice aversion lowers decision makers' welfare, and similarly an improvement in one of the edges of the network raises their welfare. In the most noticeable comparative static that we lay out, we show how the so-called Braess's paradox emerges from choice aversion. This paradox refers to the case in which adding free routes into a transportation network ends up getting all DM worse off, so this particular example stresses the generality of the model we analyze and the results we derive.

1.3. **Related work.** Our paper is connected to several strands of literature. First, our work is related to the operations research literature studying the problem of flow allocation with stochastic edge costs. In particular, the papers by Bersetkas and Tsitsiklis (1991), Polychronopoulos and Tsitsiklis (1996), Gao and Chabini (2006), and Gao et al. (2010) analyze the case of flow allocation when the costs (utilities) associated to the edges are stochastic. However none of these of papers consider the problem of choice aversion. From this literature also the closest papers to ours are Baillon and Cominetti (2008) and Fosgerau et al. (2013) who study the problem of flow allocation using a recursive logit choice model.[2] Neither Baillon and Cominetti (2008) nor Fosgerau et al. (2013) though, study the effect of choice aversion in directed networks. In addition, these papers do not study comparative statics or welfare in their settings. Second, our work is connected to the recent literature on planning and present bias. In particular, the papers by Kleinberg et al. (2016) and Kleinberg and Oren (2018) propose a graph-theoretic model of tasks and goals, in which dependencies among actions are represented by a directed graph, where a time-inconsistent agent must construct a path through it. They focus therefore on studying time inconsistency in graphs. By introducing choice aversion, our work can complement this type of behavioral analysis.

Finally, our paper is related to the decision theory literature. As we mentioned above, our paper is built upon the work by Fudenberg and Strzalecki (2015) who axiomatize the dynamic logit model under choice aversion. The novelty of our paper is that we embed their model into a directed network, which highlights the role of choice aversion in a different class of problems. In the same line, our paper is related to Ortoleva (2013) who studies thinking aversion by means of a cost-of-thinking function related to the choice set. Our analysis complements his analysis by underscoring the role of thinking aversion in a networked environment.

[2]It is worth remarking that Baillon and Cominetti (2008) study a recursive choice model in directed networks subject to congestion effects. They consider a general class of discrete choice models, being the logit a particular case of their approach.

The rest of the paper is organized as follows: In section §2 we introduce a recursive choice model with choice aversion into a directed network. In §3 we derive optimal flow allocations both from the recursive perspective and from the path choice viewpoint. Section §4 contains the main results of the paper: we analyze the way in which welfare depends on the network topology and choice aversion, and in section §5 we provide final remarks. Proofs are relegated to Appendix A.

2. Recursive logit in Directed Networks

In this section we propose a recursive discrete choice model in directed networks. Formally, we model a set of DM as solving a dynamic programming problem over a directed, acyclic graph. In a noticeable departure from previous literature, we adapt Fudenberg and Strzalecki (2015) choice aversion formulation into the context of directed graphs, and then analyze the consequences on equilibria and welfare.

2.1. **Directed graphs.** Consider a directed acyclic graph $G = (N, A)$ where N is the set of nodes and A the set of edges, respectively. We denote the set of *ingoing* edges to node i by A_i^-, and the set of *outgoing* edges from node i by A_i^+. We refer accordingly to the *out-degree* of node i as $|A_i^+|$.

Without loss of generality, we assume that G has a single source-sink pair, where s and t stand for the *source* (origin) and *sink* (destination) nodes, respectively. Let j_a be the node j that has been reached through edge a. We therefore define a path as a sequence of edges $(a_1, \dots a_K)$ with $a_{k+1} \in A^+_{j_{a_k}}$ for all $k < K$.

The set of paths connecting nodes s and t is denoted by $\mathcal{R}$. Similarly, the set of paths connecting nodes s and $i \neq t$ is denoted by $\mathcal{R}_{si}$. Finally, the set of all paths connecting nodes $i \neq s$ and t is denoted as $\mathcal{R}_{it}$.

A deterministic utility component $u_a > 0$ is associated with each edge $a \in A_i^+$ for all $i \neq t$. Path attributes are assumed to be edge additive, that is, for a path $r = (a_1, \ldots a_K) \in \mathcal{R}$ its associated utility is given by $\sum_{k=1}^{K} u_{a_k}$.

We assume that at node s there is a unitary mass of DM who must choose a path from the set $\mathcal{R}$. For the sake of exposition the mass of DM is summarized by the canonical vector e_s, which has a 1 in the position of node s and zero elsewhere. The dimension of e_s is $|N| - 1$.

It is worth remarking that from an economic vantage point the *digraph* G can be interpreted in at least three different ways. First, we note that a path can be seen as a *bundle* of goods produced by different firms. Under this interpretation, the edges in a path involve complementary goods while different paths can be interpreted as substitute bundles. In this case, the DM choose one bundle—or equivalently a collection of inputs or components—connecting s and t. A second interpretation is that G may represent a collection of tasks that a decision maker must execute in order to obtain some specific reward. Notice that this interpretation follows from the fact that a path $r \in \mathcal{R}$ can be regarded as a forward directed sequence of consecutive edges connecting s and t. Paths in $\mathcal{R}$ in this case represent different combinations of tasks, which are associated with different rewards or costs. Such latter formulation is consistent with the approach of Kleinberg et al. (2016) and Kleinberg and Oren (2018). Finally, G may represent a transportation network in which the DM must choose one of the possible paths connecting their origin s with the final destination t.

2.2. **Utilities and choice aversion.** We now develop a recursive choice model over G that incorporates choice overload by means of an specific kind of penalty on ensuing choice sets stemming from each edge appraisal. In particular, we adapt Fudenberg and Strzalecki (2015) choice aversion approach into the environment described by G as follows: for each $a \in A_i^+$ we associate a collection of i.i.d. random variables $\{\epsilon_a\}_{a \in A}$, such that the *recursive* utility associated to edge a is defined as:

$$(1) \quad V_a = u_a + \mathbb{E}\left(\max_{a' \in A_{j_a}^+} \{V_{a'} + \epsilon_{a'} - \kappa \log |A_{j_a}^+|\} \right) \qquad \text{for all } a \in A_i^+,$$

where u_a denotes the *instantaneous* utility associated to edge a and the term $\mathbb{E}\left(\max_{a' \in A^+_{j_a}} \{V_{a'} + \epsilon_{a'} - \kappa \log |A^+_{j_a}|\}\right)$ is the *adjusted* continuation value associated to the selection of a. Notice that the latter term includes the factor $\kappa \log |A^+_{j_a}|$, which is a penalty term that captures the size of the set $A^+_{j_a}$, where $\kappa \geq 0$.[3]

From an economic point of view, Eq. (1) highlights the fact that DM not only assess the utility derived from edges with instant consumption consequences, but also consider the way in which current edges may alter the choice sets that will be available in successive nodes along the network.

Following Fudenberg and Strzalecki (2015), we impose the following assumption on the random variables ϵ_a's.

Assumption 1 (Logit choice rule)**.** *At each node $i \neq t$ the collection of random variables $\{\epsilon_a\}_{a \in A^+_i}$ follows a Gumbel distribution with location parameter $\beta = 1$.*

Under this assumption, Eq. (1) can be expressed as:

$$V_a = u_a + \log\left(\sum_{a' \in A^+_{j_a}} e^{V_{a'}}\right) - \kappa \log |A^+_{j_a}|, \tag{2}$$

where $\log\left(\sum_{a' \in A^+_{j_a}} e^{V_{a'}}\right) - \kappa \log |A^+_{j_a}|$ provides a close form for the adjusted continuation value.

Let us define $\varphi_{j_a}(V) \triangleq \log\left(\sum_{a' \in A^+_{j_a}} e^{V_{a'}}\right)$ for all $j_a \neq t$. Accordingly Eq. (2) can be rewritten as:

$$V_a = u_a + \varphi_{j_a}(V) - \kappa \log |A^+_{j_a}|. \tag{3}$$

Previous expression deserves some remarks. First, the continuation value in Eq. (3) captures the *complexity* of the choice sets $A^+_{j_a}$, as measured by $\kappa \log |A^+_{j_a}|$, with $\kappa \geq 0$. Intuitively $\kappa \log |A^+_{j_a}|$ penalizes the size

[3] Fudenberg and Strzalecki (2015) study a recursive logit model in the context intertemporal choice. In doing so they consider a discount factor $\delta \in (0, 1)$. We focus on a digraph G, without discounting.

of the choice sets at different nodes, where the parameter $\kappa \geq 0$ measures decision makers' attitude towards the size of $A^+_{j_a}$. In particular, V_a is a decreasing function of κ.

Second, when $\kappa = 0$, Eq. (3) boils down to a traditional recursive logit model in which DM are *choice loving* in the sense that they always prefer to add additional items into the menu, as in the "*preference for flexibility*" of Kreps (1979). To see this, note that when $\kappa = 0$ the function $\varphi_{j_a}(V)$ is increasing in $|A^+_{j_a}|$. As a consequence, the recursive utility V_a is increasing in the size of $A^+_{j_a}$. This latter feature implies that traditional recursive logit models in directed networks (e.g. Baillon and Cominetti, 2008 and Fosgerau et al., 2013) can be associated with an intrinsic taste for plentiful options.

On the other hand, the case of $\kappa \in (0, 1)$ from economic standpoint may be interpreted as a situation where the DM prefer to include additional alternatives to the menu, provided they are not *too much worse* than the current average. Finally, the case $\kappa \geq 1$ is interpreted as a situation in which the DM only wish to add alternatives that are perceived sufficiently better. In particular, the case $\kappa = 1$ captures a situation where the DM want to remove choices that are worse than the average: they worry about choosing such additional alternatives by accident given *appraisal* costs—such as Ortoleva's thinking aversion—that may offset the benefits of the corresponding random draw.

In sum, the parameter κ encapsulates the scale of penalties on the set of ensuing actions arising from each nonterminal node, which unlocks keen consequences on decision makers' attitude towards marginally increasing the set of edges. Following Fudenberg and Strzalecki (2015), we identify κ as decision makers' choice aversion parameter.

3. Flow allocation and recursive choice

Each decision maker is looking for an optimal path connecting s and t. Now, when they reach node $i \neq t$, they observe the realization of the random utilities $V_a + \epsilon_a$ for all $a \in A^+_i$, and consequently choose the alternative $a \in A^+_i$ with the highest utility.

This process is repeated at each subsequent node giving rise to a recursive discrete choice model, where the expected flow entering node $i \neq t$ splits among the alternatives $a \in A_i^+$ according to the choice probability:

$$(4) \qquad \mathbb{P}(a|A_i^+) = \mathbb{P}\left(V_a + \epsilon_a \geq V_a' + \epsilon_{a'} \quad \forall a' \neq a \in A_i^+\right) \quad \forall i \neq t.$$

Due to Assumption 1, Eq. (4) can be rewritten as:

$$(5) \qquad \mathbb{P}(a|A_i^+) = \frac{e^{u_a + \varphi_{j_a}(V) - \kappa \log |A_{j_a}^+|}}{\sum_{a' \in A_i^+} e^{u_{a'} + \varphi_{j_{a'}}(V) - \kappa \log |A_{j_{a'}}^+|}} \quad \forall i \neq t.$$

It is worth stressing that for $\kappa > 0$, the choice probability $\mathbb{P}(a|A_i^+)$ is decreasing in $|A_{j_a}^+|$, which merely reflects the penalty on edges associated with adjusted continuation values that comprise larger choice sets. This is fundamental difference with the traditional logit model, which assumes $\kappa = 0$ as we mentioned before.

Mathematically, the recursive process just described induces a Markov chain over the graph G, where the transition probabilities are given by

$$(6) \qquad \mathbb{P}_{ij} = \begin{cases} \mathbb{P}(a|A_i^+) & \text{if } i_f = i \text{ and } j = j_f, \\ 0 & \text{otherwise,} \end{cases}$$

for $i \neq t$. Here, in particular, $\mathbb{P}_{tt} = 1$ and $\mathbb{P}_{ti} = 0$ for all $i \neq t$, i.e. node t is an absorbing state.

Let x_i be the expected flow entering at node i towards sink node t. Then the flow received by edge a is given by:

$$(7) \qquad f_a = x_i \mathbb{P}(a|A_i^+) \quad \forall a \in A_i^+,$$

with $f = (f_a)_{a \in A}$ denoting the expected flow vector. In addition let $\hat{\mathbb{P}} = (\mathbb{P}_{ij})_{i,j \neq t}$ denote the restriction to the set of nodes $N \backslash \{t\}$. Then the expected demand vector $x = (x_i)_{i \neq t}$ may be expressed as $x = e_s + \hat{\mathbb{P}}^T x$ which generates the following stochastic conservation flow equations

$$(8) \qquad x_i = \sum_{a \in A_i^-} f_a \quad \text{for all } i \neq t.$$

A flow vector f satisfying (8) is called *feasible* and the set of all such vectors is denoted by $\mathcal{F}$.

The next result characterizes the solution of the recursive logit in terms of a strictly concave optimization problem.

Proposition 1. *A solution to the recursive logit is given by the unique solution to the following optimization program:*

$$\max_{f\in\mathcal{F}}\left\{\sum_{i\neq t}\sum_{a\in A_i^+} f_a(u_a-\kappa\log|A_{j_a}^+|)-J_\kappa(f)\right\}, \tag{9}$$

where $J_\kappa(f)=\sum_{i\neq t}\left[\sum_{a\in A_i^+} f_a\ln f_a-\left(\sum_{a\in A_i^+} f_a\log\left(\sum_{a\in A_i^+} f_a\right)\right)\right]$.

Moreover for all $i\neq t$*, the flow of each edge is given by:*

$$f_a=x_i\frac{e^{u_a+\varphi_{j_a}(V)-\kappa\log|A_{j_a}^+|}}{\sum_{a'\in A_i^+} e^{u_{a'}+\varphi_{j_{a'}}(V)-\kappa\log|A_{j_{a'}}^+|}}\qquad\forall a\in A_i^+. \tag{10}$$

Some remarks are in order. First, from an economic perspective, program (9) can be interpreted as the utility function of a representative agent who must decide how to allocate the flow over G: such program therefore provides a microfoundation for the choice probabilities that optimally allocate the flow on G. Second, the term $J_\kappa(f)$ is the *entropy* generated by the presence of the random variables ϵ's, which in turn incorporates the role of the choice aversion term $\kappa\log|A_i^+|$. Finally, it is worth mentioning that Proposition 1 complements the axiomatic characterization provided by Fudenberg and Strzalecki (2015) in the sense that the solution to their recursive choice model can be equivalently obtained as the answer to program (9).

3.1. **Path choice analysis.** So far we have described a situation where a set of DM choice their optimal path in a recursive fashion. Because of the logit structure of the problem however, the very same analysis can be equivalently stated in terms of path choices.

In doing so, we assume that for each path $r \in \mathcal{R}$ the utility associated to it is a random variable defined as

$$\tilde{U}_r = U_r + \epsilon_r \qquad \forall r \in \mathcal{R}, \tag{11}$$

where $U_r = \sum_{a \in r}(u_a - \kappa \log |A^+_{j_a}|) = \sum_{a \in r} u_a - \kappa \sum_{a \in r} \log |A^+_{j_a}|$ and $\{\epsilon_r\}_{r \in \mathcal{R}}$ is a collection of absolutely continuous random variables satisfying Assumption 1.

Under these conditions, the probability of choosing path r is defined as:

$$\mathbb{P}_r \triangleq \mathbb{P}\left(\tilde{U}_r = \arg\max_{r' \in \mathcal{R}} \{U_{r'} + \epsilon_{r'}\}\right) \quad \forall r \in \mathcal{R}. \tag{12}$$

Equations (11) and (12) jointly define a path choice model over $\mathcal{R}$, where we again refer to the Gumbel assumption to obtain:

$$\mathbb{P}_r = \frac{e^{U_r}}{\sum_{r' \in \mathcal{R}} e^{U_{r'}}} \quad \forall r \in \mathcal{R}. \tag{13}$$

Proposition 2. *For each path $r = (a_1, \ldots, a_K) \in \mathcal{R}$ with $K \geq 2$, the following equality holds*

$$\mathbb{P}_r = \prod_{k=1}^{K} \mathbb{P}(a_k | A^+_s) \mathbb{P}(a_{k+1} | A^+_{j_{a_k}}).$$

This result intuitively establishes that the probability of choosing path r can be expressed as the product of the choice probabilities associated to the edges that give rise to it. From a behavioral point of view, Propositon 2 is relevant because it shows the way in which choice aversion can be interpreted as a mechanism that overcomes the problem of overlapping paths (Ben-Akiva and Lerman, 1985). To stress this point let's define $\mathbb{P}_r$ as follows:

$$\mathbb{P}_r = \frac{e^{u_r - \kappa\gamma_r}}{\sum_{r' \in \mathcal{R}} e^{u_{r'} - \kappa\gamma_{r'}}} \qquad \text{for all } r \in \mathcal{R}, \tag{14}$$

where $\gamma_r \triangleq \sum_{a \in r} \log |A^+_{j_a}|$.

It is easy to see that for $\kappa > 0$, $\kappa\gamma_r$ can be interpreted as a penalty term that accounts for the size of the choice set at each of the nodes accessed along path r. For the sake of concreteness consider the network in Figure 1. The set of paths is given by $\mathcal{R} = \{r_1, r_2, r_3\}$ where $r_1 = (a_1, a_3)$, $r_2 = (a_1, a_4)$, and $r_3 = (a_2)$. For this small network, paths r_1 and r_2 overlap, sharing the common edge a_1. Given this feature—for the case of $\kappa = 0$—we argue that the logit model (13) does not provide sensible results regarding optimal flow allocation.

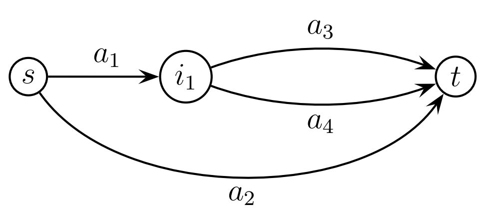


Figure 1. Logit path choice

To see this let's assume $u_{a_1} = 1.9$, $u_{a_3} = u_{a_4} = 0.1$, and $u_{a_2} = 2$. For this parametrization, coupled with $\kappa = 0$, it follows that $u_{r_1} = u_{r_2} = u_{r_3} = 2$, and consequently the logit choice rule (14) assigns one third of flow to each path. In other words with $\kappa = 0$ we get $\mathbb{P}_{r_1} = \mathbb{P}_{r_2} = \mathbb{P}_{r_3} = \frac{1}{3}$. However, since paths r_1 and r_2 are identical, the assignment $\mathbb{P}_{r_1} = \mathbb{P}_{r_2} = \frac{1}{4}$ and $\mathbb{P}_{r_3} = \frac{1}{2}$ seems more appealing.

The root of this discrepancy lies in the fact that the logit path choice model is restricted by the Independence from Irrelevant Alternatives (IIA) property, which does not hold in the context of route choice due to overlapping paths (Ben-Akiva and Lerman, 1985; Ben-Akiva and Bierlarie, 1999, and Frejinger and Bierlarie, 2007). However, for $\kappa > 0$ the logit model with choice aversion predicts a flow allocation closer to $\left(\frac{1}{4}, \frac{1}{4}, \frac{1}{2}\right)$. For instance, in the cases of $\kappa = 1$ and $\kappa = 2$ we find that the optimal flow allocations are $\left(\frac{3}{10}, \frac{3}{10}, \frac{2}{5}\right)$ and $(0.26, 0.26, 0.48)$, respectively.

What the analysis just laid out shows—which applies to the general case of directed networks—is that from the vantage point of path selection, choice aversion is a robust way to derive optimal flow allocations, even in the case of superposition of different routes.

Most importantly, choice aversion provides a justification for the class of models known as path size logit, which is precisely an attempt to overcome the problem posed by overlapping paths in the context of path choice (e.g. Ben-Akiva and Bierlarie, 1999 and Frejinger and Bierlarie, 2007).

In sum, coming back to the general case, the term $\kappa\gamma_r$ in Eq. (14), can be interpreted as a correction that penalizes those paths who share common edges. Beyond arithmetics however, choice aversion ends up relieving optimal flow allocation by means of path selection from the straightjacket of the independence assumption of the logit choice model.

3.2. **Welfare.** We now turn to define welfare in our environment in order to provide comparative statics under different network topologies. Because of Proposition 2 particularly, we can define Decision Makers' welfare as follows:

$$\mathcal{W}(\kappa) \triangleq \mathbb{E}\left(\max_{r\in\mathcal{R}}\{U_r + \epsilon_r\}\right) = \log\left(\sum_{r\in\mathcal{R}} e^{U_r}\right), \tag{15}$$

where last equality follows from Assumption 1. Notice that our definition makes explicit the dependence of DM welfare on the choice aversion parameter κ.

Following the literature on discrete choice models, expression (15) can be interpreted as the inclusive value of paths in $\mathcal{R}$, which is equivalent to say that $\mathcal{W}(\kappa)$ measures the inclusive value of the source node s. As we shall see in next section, $\mathcal{W}(\kappa)$ plays a key role when analyzing the impact of changes on the topology of G.

4. Welfare and network topology

In this section we state the main result of the paper. We show that improvements to the network can decrease aggregate welfare, which is measured as decision makers' surplus. In order to establish this result we begin by showing how aggregate welfare is decreasing on κ.

Proposition 3. *Let $\kappa' > \kappa > 0$. Then $\mathcal{W}(\kappa') < \mathcal{W}(\kappa)$.*

The next result establishes that increasing the instant utility associated to a particular edge increases $\mathcal{W}$.

Proposition 4. *Consider a node $i \neq t$ and an edge $a \in A_i^+$. Then*

$$\frac{d\mathcal{W}(\kappa)}{du_a} = x_i \mathbb{P}(a|A_i^+) = f_a$$

Now we are ready to establish our main result: adding edges to the digraph G can decrease social welfare.

Theorem 1. *Fix a node $i \neq s, t$. Suppose that a new link a' is added to node i. Then $\mathcal{W}(\kappa)$ increases if and only the following condition holds:*

$$\mathbb{P}(a'|A_i^+ \cup \{a'\}) > 1 - \left(\frac{|A_i^+|}{|A_i^+| + 1}\right)^{\kappa}. \tag{16}$$

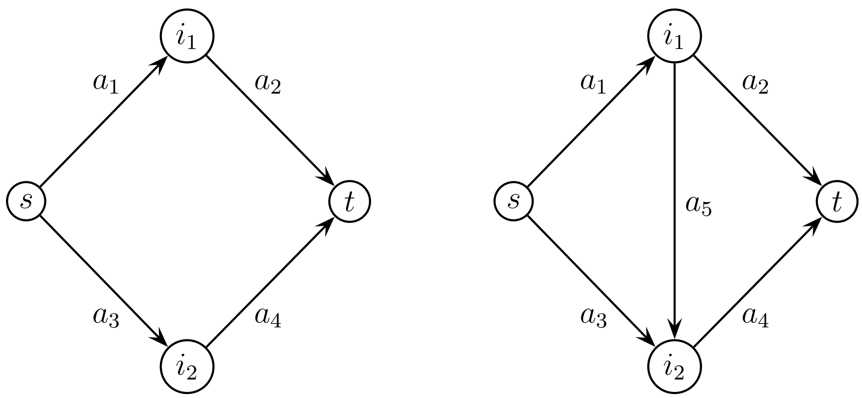
It is worth stressing three implications of this result. First, Theorem 1 underscores the way in which local effects—namely, the addition of alternatives at the node level—propagate throughout the network and unlock aggregate welfare effects. Second, it connects Fudenberg and Strzalecki (2015) axiomatic characterization of stochastic choice in dynamic settings with networked markets. In particular, Theorem 1 extends their Proposition 3 to the case of graph-related settings. And finally, and most notably, it shows that Braess's network paradox may equivalently stem from choice aversion with no allusion to congestion whatsoever. Next section discusses this result in detail.

4.1. **Braess's Paradox.**

Theorem 1 provides a simple condition that characterizes the way in which an improvement at the node level may increase consumer surplus. This result can be connected to Braess's paradox (Braess, 1968; Braess et al., 2005), which states that adding free routes into a transportation network makes every decision maker worse off. The connection we establish is that we may generate this phenomenon as a consequence of choice aversion in a general directed network.

In order to see how our result is related to Braess's paradox, consider the special directed networks given in Figures 2(A) and 2(B). Figure 2(A) shows a parallel serial network with paths $r_1 = (a_1, a_2)$ and $r_2 = (a_3, a_4)$. The set of paths therefore is given by $\mathcal{R} = \{r_1, r_2\}$, and welfare described by

$$\mathcal{W}(\kappa) = \log(e^{U_{r_1}} + e^{U_{r_2}}).$$



(A) Two unconnected paths

(B) Both paths connected by a_5

FIGURE 2. Braess's paradox ensuing from choice aversion.

Now assume that the network in Figure 2(A) is modified by means of adding a new edge starting at node i_1 and ending at node i_2, as Figure 2(B) shows. Now the new set of paths is given by $\tilde{\mathcal{R}} = \{r_1, r_2, r_3\}$, where r_1 and r_2 are defined as before and $r_3 = (a_1, a_5, a_4)$. Decision makers' surplus for this modified network is given by:

$$\tilde{\mathcal{W}}(\kappa) = \log(e^{U_{r_1}} + e^{U_{r_2}} + e^{U_{r_3}}).$$

Theorem 1 allows us to characterize the effects of adding edge a_5 into the original network. In particular, $\tilde{\mathcal{W}}(\kappa) > \mathcal{W}(\kappa)$ iff

$$\mathbb{P}(a_5|\{a_2, a_5\}) > 1 - \left(\frac{1}{2}\right)^{\kappa}.$$

In order words, moving from network 2(A) to 2(B) improves decision makers' welfare if and only if the probability of choosing a_5 is strictly greater than $1 - \left(\frac{1}{2}\right)^{\kappa}$, which is automatically satisfied when $\kappa = 0$. Now, let's state this condition in terms of κ. In doing so, we assume $u = u_{a_1} = u_{a_2} = u_{a_3} = u_{a_4} > 0$ and $u_{a_5} = u + \epsilon$ with $\epsilon > 0$. Given this parametrization it is easy to see that $\mathcal{W}(\kappa) = \log 2e^{2u} = \log 2 + 2u$ and $\tilde{\mathcal{W}}(\kappa) = \log\left(e^{2u} + e^{2u-\kappa\log 2} + e^{2u+\epsilon-\kappa\log 2}\right) = 2u + \log\left(1 + e^{-\kappa\log 2}(1 + e^{\epsilon})\right)$.

Then $\tilde{\mathcal{W}}(\kappa) > \mathcal{W}(\kappa)$ if and only if

$$\frac{e^{u+\epsilon}}{e^{u} + e^{u+\epsilon}} = \frac{e^{\epsilon}}{1 + e^{\epsilon}} > 1 - \left(\frac{1}{2}\right)^{\kappa}.$$

Previous expression can be rewritten as:

$$\kappa > \frac{\log(1 + e^{\epsilon})}{\log(2)}.$$

It is easy to see that for $\epsilon > 0$ we have the $\tilde{\mathcal{W}}(\kappa) > \mathcal{W}(\kappa)$ if and only if $\kappa > 1$. As we mentioned in §2, the case of $\kappa \geq 1$ corresponds to a situation where the DM only want to add alternatives that are sufficiently better that the existent ones. In this case, the DM want to add edge a_5 whenever $\kappa \geq 1$. In particular, for values of $\kappa \in (0, 1)$ improving the network can make all DM worse off. Thereby, under choice aversion we can obtain the very same type of paradox described by Braess (1968); Braess et al. (2005): while they obtain this result as a consequence of decision makers' selfish behavior in a congestion game, we derive it as a consequence of choice aversion, which provides a different perspective to the problem of network design.

5. Conclusion

This paper discussed the role of choice aversion in directed networks, which is an avenue we took as a modeling device to incorporate the fact that decision makers may have an intrinsic distaste to deal with *big* sets of options in sequential decision processes. By merely adapting and connecting concepts already established in previous work, we ended up no only characterizing optimal paths along our network, but also highlighting the role of choice aversion in generating robust solutions in the presence of overlapping alternatives and obtaining paradoxes in related fields. Finally, we informally pose our paper as providing an additional rationale for some specific patterns of network formation in international trade (e.g. Chaney, 2014): under choice aversion only a manageable set of options is preferable, which is consistent with partial diversification of trade partners.

Appendix A. Proofs

Proof of Proposition 1. This result follows from a direct application of Melo (2012, Proposition 2). □

Proof of Proposition 2. Let r be a path of length $K \geq 2$. In particular, let $r = (a_1, \dots, a_K) \in \mathcal{R}$. Using the Markovian structure of the recursive logit, the probability of choosing path r can be expressed as:

$$\hat{\mathbb{P}}_r = \mathbb{P}(a_1|A_s^+) \times \mathbb{P}(a_2|A_{a_1}^+) \times \cdots \times \mathbb{P}(a_K|A_{j_{a_{K-1}}}^+).$$

Thanks to the logit assumption, we have that previous expression can be written as

$$\hat{\mathbb{P}}_r = \frac{e^{u_{a_1} + \varphi_{j_{a_1}} - \kappa \log |A_{j_{a_1}}^+|}}{e^{\varphi_s}} \times \frac{e^{u_{a_2} + \varphi_{j_{a_2}} - \kappa \log |A_{j_{a_2}}^+|}}{e^{\varphi_{j_{a_1}}}} \times \cdots \times \frac{e^{u_{a_L}}}{e^{\varphi_{a_{L-1}}}}.$$

After some simple algebra we find:

$$\hat{\mathbb{P}}_r = \frac{e^{U_r}}{e^{\varphi_s}} = \frac{e^{U_r}}{\sum_{r' \in \mathcal{R}} e^{U_{r'}}} = \mathbb{P}_r.$$

Now, starting with the choice probability of path r given by $\mathbb{P}_r = \frac{e^{U_r}}{e^{\varphi_s}}$, and by a similar argument as the one used above, we must necessarily conclude that $\mathbb{P}_r = \hat{\mathbb{P}}_r$. Because previous analysis holds for all $r \in \mathcal{R}$ the conclusion follows at once. □

Proof of Proposition 3. Consider a path $r \in \mathcal{R}$ and assume that $\kappa' \kappa > 0$. Then by the definition of r we can define $U_r(\kappa') = \sum_{a \in r}(u_a - \kappa'|A_{j_a}^+|)$. Then it is easy to see that $U_r(\kappa') < U_r(\kappa)$ for all $r \in \mathcal{R}$. In particular $e^{U_r(\kappa')} < e^{U_r(\kappa)}$ and summing over all $r \in \mathcal{R}$ we get:

$$\sum_{r \in \mathcal{R}} e^{U_r(\kappa')} < \sum_{r \in \mathcal{R}} e^{U_r(\kappa)}.$$

Taking log in previous expression we conclude $\mathcal{W}(\kappa') < \mathcal{W}(\kappa)$. □

The following lemma shows that the utility associated to paths passing through node i can be decomposed in a very simple way.

Lemma 1. *For each node $i \neq t$ the following holds:*

$$\sum_{r \in \mathcal{R}_i} e^{U_r} = \sum_{r' \in \mathcal{R}_{si}} e^{U_{r'}} e^{\varphi_i(V) - \kappa \log |A_i^+|}$$

where $\varphi_i(V) = \log\left(\sum_{a \in A_i^+} e^{V_a}\right)$.

Proof. Let $r' \in \mathcal{R}_{si}$ be defined as $r' = (a_1, \ldots, a_l)$ with $j_{a_l} = i$. Then it follows that we can construct the utility associated to all paths of the form $r = (r', r'') \in \mathcal{R}_i$ as $U_{r'} + U_{r''}$. In particular, we can write $\sum_{r'' \in \mathcal{R}_{it}} e^{U_{r'}+U_{r''}}$. Exploiting the recursive structure of the problem, it is easy to see that $e^{\varphi_i(V)} = \sum_{r'' \in \mathcal{R}_{it}} e^{U_{r''}}$.

This latter expression implies that

$$\sum_{r'' \in \mathcal{R}_{it}} e^{U_{r'}+U_{r''}} = e^{U_{r'}} e^{\varphi_i(V)}$$

Adding up over all $r' \in \mathcal{R}_{si}$ we conclude that:

$$\sum_{r \in \mathcal{R}_i} e^{U_r} = \sum_{r' \in \mathcal{R}_{si}} \sum_{r'' \in \mathcal{R}_{it}} e^{U_{r'}+U_{r''}} = \sum_{r \in \mathcal{R}_{si}} e^{U_{r'}} e^{\varphi_i(V)}.$$

Because previous analysis holds for all node $i \neq t$ the conclusion follows. □

Proof of Proposition 4. By Lemma 1 it is easy to see that

$$\mathcal{W}(\kappa) = \log\left(\sum_{r \in \mathcal{R}_i} e^{U_r} + \sum_{r \in \mathcal{R}_i^c} e^{U_r}\right) = \log\left(\sum_{r' \in \mathcal{R}_{si}} e^{U_{r'}} e^{\varphi_i(V)} + \sum_{r \in \mathcal{R}_i^c} e^{U_r}\right).$$

Taking differential with respect to du_a we get

$$d\mathcal{W}(\kappa) = \frac{\sum_{r \in \mathcal{R}_{si}} e^{U_{r'}} e^{\varphi_i(V)}}{\sum_{r \in \mathcal{R}} e^{U_r}} \frac{\partial \varphi_i(V)}{\partial u_a} du_a.$$

Noting that $x_i = \frac{\sum_{r \in \mathcal{R}_{si}} e^{U_{r'}} e^{\varphi_i(V)}}{\sum_{r \in \mathcal{R}} e^{U_r}}$ we conclude that:

$$\frac{d\mathcal{W}(\kappa)}{du_a} = x_i \mathbb{P}(a|A_i^+) = f_a.$$

□

Proof Theorem 1. The proof of this result exploit the recursive structure of the problem. Let $\tilde{\mathcal{R}}$ denote the set of paths *after* adding a new link a'. Accordingly define $\tilde{\mathcal{R}}_i$. Let $\mathcal{W}(\kappa) = \log\left(\sum_{r \in \mathcal{R}} e^{U_r}\right)$ and $\tilde{\mathcal{W}}(\kappa) = \log\left(\sum_{r \in \tilde{\mathcal{R}}} e^{U_r}\right)$ consumer' surplus before and after the addition of a'. Note that $\mathcal{CS}(\kappa) = \log\left(\sum_{r\in\mathcal{R}_i} e^{U_r} + \sum_{r\in\mathcal{R}_i^c} e^{U_r}\right)$ and $\tilde{\mathcal{W}}(\kappa) = \log\left(\sum_{r\in\tilde{\mathcal{R}}_i} e^{U_r} + \sum_{r\in\tilde{\mathcal{R}}_i^c} e^{U_r}\right)$.

Adding edge a' increases consumers' surplus if and only if the following hold:

$$\log\left(\sum_{r\in\tilde{\mathcal{R}}_i} e^{U_r} + \sum_{r\in\tilde{\mathcal{R}}_i^c} e^{U_r}\right) > \log\left(\sum_{r\in\mathcal{R}_i} e^{U_r} + \sum_{r\in\mathcal{R}_i^c} e^{U_r}\right).$$

Noting that $\mathcal{R}_i^c = \mathcal{R}_i^c$ previous conditions boils down to:

$$\sum_{r\in\tilde{\mathcal{R}}_i} e^{U_r} > \sum_{r\in\mathcal{R}_i} e^{U_r}. \tag{17}$$

By Lemma 1 we can write the following:

$$\sum_{r\in\mathcal{R}_i} e^{U_r} = \sum_{r'\in\mathcal{R}_i} e^{U_{r'}+\varphi_i(V)-\kappa\log|A_i^+|} = \sum_{r\in\mathcal{R}_i} e^{U_r+\varphi_i(V)}|A_i^+|^{-\kappa}$$

Similarly

$$\sum_{r\in\tilde{\mathcal{R}}_i} e^{U_r} = \sum_{r\in\tilde{\mathcal{R}}_i} e^{U_r+\varphi_i(\tilde{V})-\kappa\log(|A_i^+|+1)} = \sum_{r\in\tilde{\mathcal{R}}_i} e^{U_r+\varphi_i(V)}(|A_i^+|+1)^{-\kappa},$$

where $\tilde{V}$ denotes the recursive utility (1) after adding edge a'.

Then Eq. (17) can be written as follows:

$$\sum_{r\in\mathcal{R}_i} e^{U_r+\varphi_i(\tilde{V})}(|A_i^+|+1)^{-\kappa} > \sum_{r\in\mathcal{R}_i} e^{U_r+\varphi_i(V)}|A_i^+|^{-\kappa}. \tag{18}$$

Previous expression can be written as:

$$\left(\sum_{a\in A_i^+} e^{V_a} + e^{V_{a'}}\right)(|A_i^+|+1)^{-\kappa} > \left(\sum_{a\in A_i^+} e^{V_a}\right)|A_i^+|^{-\kappa}.$$

Then after some algebra we find:

$$\left(\frac{|A_i^+|}{|A_i^+|+1}\right)^{\kappa} > \frac{\sum_{a\in A_i^+} e^{V_a}}{\sum_{a\in A_i^+} e^{V_a} + e^{V_{a'}}}.$$

Using the fact that $\frac{\sum_{a\in A_i^+} e^{V_a}}{\sum_{a\in A_i^+} e^{V_a}+e^{V_{a'}}} = 1 - \mathbb{P}(a'|A_i^+ \cup \{a'\})$ we can conclude that $\tilde{\mathcal{W}}(\kappa) > \mathcal{W}(\kappa)$ if and only if

$$\mathbb{P}(a'|A_i^+ \cup \{a'\}) > 1 - \left(\frac{|A_i^+|}{|A_i^+|+1}\right)^{\kappa}.$$

□

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