**Forthcoming in *Operations Research***
**manuscript OPRE-2011-12-621.R2**

# A Mean-Risk Model for the Traffic Assignment Problem With Stochastic Travel Times

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Heavy and uncertain traffic conditions exacerbate the commuting experience of millions of people across the globe. When planning important trips, commuters typically add an extra buffer to the expected trip duration to ensure on-time arrival. Motivated by this, we propose a new traffic assignment model that takes into account the stochastic nature of travel times. Our model extends the traditional model of Wardrop competition when uncertainty is present in the network. The focus is on strategic *risk-averse* users who capture the tradeoff between travel times and their variability in a *mean-standard deviation* objective, defined as the mean travel time plus a risk-aversion factor times the standard deviation of travel time along a path. We consider both infinitesimal users, leading to a *nonatomic* game, and *atomic* users, leading to a discrete finite game.

We establish conditions that characterize an equilibrium traffic assignment and find when it exists. The main challenge is posed by the users' risk aversion, since the mean-standard deviation objective is nonconvex and nonseparable, meaning that a path cannot be split as a sum of edge costs. As a result, even an individual user's subproblem—a stochastic shortest path problem—is a nonconvex optimization problem for which no polynomial time algorithms are known. In turn, the mathematical structure of the traffic assignment model with stochastic travel times is fundamentally different from the deterministic counterpart. In particular, an equilibrium characterization requires exponentially many variables, one for each path in the network, since an edge-flow has multiple possible path-flow decompositions that are not equivalent. Because of this, characterizing the equilibrium and the socially-optimal assignment, which minimizes the total user cost, is more challenging than in the traditional deterministic setting. Nevertheless, we prove that both can be encoded by a representation with just polynomially-many paths.

Finally, under the assumption that the standard deviations of travel times are independent from edge loads, we show that the worst-case ratio between the social cost of an equilibrium and that of an optimal solution is not higher than the analogous ratio in the deterministic setting. In other words, uncertainty does not further degrade the system performance in addition to strategic user behavior alone.

*Key words*: Congestion Game, Stochastic Networks, Mean-Stdev Wardrop Equilibrium, Nash Equilibrium, Risk aversion, Non-additive Traffic Assignment Problem
*History*: This paper was first submitted on December 15, 2011 and has been with the authors for XX months for 1 revision.

## 1. Introduction

Heavy traffic and the uncertainty of traffic conditions exacerbate the daily lives of millions of people across the globe. According to the 2012 Urban Mobility Report, "in 2011, congestion caused urban Americans to travel 5.5 billion hours more and to purchase an extra 2.9 billion gallons of fuel for a congestion cost of $121 billion" ([66], page 1). The report estimates that trips on average take 27% more time than the free-flow travel time. This figure corresponds to the 15 largest urban areas in the United States. The worst city in the United States with respect to this measure is Los Angeles where trips on average take 37% extra time. High and variable congestion necessitates drivers to *buffer in extra time* when planning important trips. For the first time, the 2012 Urban Mobility Report computes 95th percentiles of travel times for freeway trips and compares them to free-flow travel times (see page 12). Based on those percentiles, they claim that "folks making important trips on freeways during the peak periods had to plan for approximately three times as much travel time as in light traffic conditions in order to account for the effects of unexpected crashes, bad weather, and other irregular congestion causes" ([66], page 8). A common driver reaction in the face of heavy and uncertain traffic conditions is to look for alternate, sometimes longer but less crowded and more reliable routes [36]. With the widespread use of ever-improving technologies for measuring traffic, one might ask: what is a good routing strategy? And how does the risk-aversion of commuters transform the resulting traffic conditions?

We consider the traffic assignment problem on networks with stochastic travel times and analyze the resulting equilibria when strategic risk-averse commuters take into account the variability of their travel times. This approach generalizes the traditional model of Wardrop competition [73] by incorporating uncertainty. Risk aversion induces users to go beyond considering expected travel times. Since it is unlikely that they base their route-choice decisions on something as complicated as a full distribution of travel times along an exponential number of possible routes, it is reasonable that considering expected travel times and their standard deviations is a good first-order approximation on route selection. To incorporate the standard deviation of travel times into the users' objectives, we consider the traditional *mean-standard deviation* (mean-stdev) objective [27, 42] whereby users minimize the cost on a path, defined as its mean travel time plus a risk-aversion factor times the standard deviation of travel time along the same path. By linearity of expectations, the path mean equals the sum of edge means. However, the standard deviation along a path does not decompose as a sum over edges in the path because of the *risk-diversification effect*. Assuming independence of travel times on edges, the standard deviation equals the square root of the sum of the squared standard deviations on the edges of that path.

A compelling interpretation of this objective in the case of normally-distributed uncertainty is that the mean-stdev of a path equals a percentile of the travel time along it. Hence, we have a traffic assignment problem where users minimize a given percentile of their travel time, as opposed to the standard Wardrop model where they minimize the expected value of their travel time [55]. This objective is also related to typical quantifications of risk, most notably the value-at-risk objective commonly used in finance, whereby one seeks to minimize travel time subject to arriving on time to a destination with at least, say, 95% chance.

An important effect of considering this objective, either in its basic form of the mean-stdev or in the case of a percentile for normally-distributed uncertainty, is that it captures the total variability between endpoints of routes. In contrast to edge-by-edge variability, considering total variability leads to nonadditivity and nonconvexity of the objective. Importantly, under this objective a subpath of an optimal path may not be optimal. This may seem counterintuitive at first because a situation like this cannot arise with deterministic delays, but this captures that commuters value paths with low variability and are sometimes ready to increase the expected time in exchange for less risk.

Note that under perfectly-correlated uncertainties in all edges, the mean-stdev objective along routes becomes separable and situations like the one described in the previous paragraph cannot happen. This may prompt one to consider alternative, simpler models that capture uncertainty. The easiest approach would be to incorporate uncertainty on an edge-by-edge basis. This idea, suggested by Uchida and Iida [71], fails to exploit the risk-diversification effects of being exposed to multiple sources of uncertainty. In our setting it would mean that standard deviations are *simply summed* along a path as opposed to taking the square root of the sum of squared standard deviations, as should be the case. Another alternative is to consider the mean-variance objective. This approach also reduces to a deterministic Wardrop equilibrium in which the travel time functions already incorporate the information on variability. However, the mean and variance are measured in different units so a combination of them is hard to interpret and the objective seems less justified. In addition, this objective leads to solutions that are not intuitive in practice such as users selecting routes that are stochastically dominated by others. Although this counterintuitive phenomenon may happen as well under the mean-stdev objective with some artificially constructed distributions, it is guaranteed *not* to happen under normal distributions due to the equivalent percentile interpretation of the travel times along routes. In contrast, the mean-variance objective still suffers from this problem even in the case of normally-distributed uncertainty.

Readers familiar with the concept of coherent risk measures (see surveys [60, 35]) will recognize that the mean-standard deviation objective does not constitute a coherent risk measure, because it lacks monotonicity. Similarly, the value-at-risk measure (corresponding to the above-mentioned percentile objective) is not coherent because it is not convex. We remark that the assumptions underlying coherent risk measures were developed with respect to risk preferences in finance. While they may provide useful alternatives for the risk-averse objectives in the context of network games, they are not necessarily the only correct approach since routing preferences under uncertainty may differ axiomatically from preferences in portfolio optimization. For example, an intercity bus that needs to observe a given departure and arrival schedule may prefer a more certain (albeit dominated) path if there are constraints that prevent early arrival such as the lack of parking space at the bus depot. Thus, while monotonicity is a reasonable requirement for risk measures in the context of finance, it may sometimes be dropped in the domains of transportation and telecommunications networks.

We assume that the expected travel times are nondecreasing functions that depend on the load of an edge. (Some of our results also extend to the non-separable case, where these functions depend on the full vector of loads of all edges of the network, but this will not be the focus of this study.) To provide an example, one gets increasing functions on the load when each segment of a network represents a queue. In that case, the expected travel times are increasing functions on the load of the queue. In general, the standard deviations are load-dependent functions, as well. For tractability reasons, we also consider a simpler case in which the standard deviation is considered exogenous to the model and hence independent of the flow. Although this may seem simplistic, it is a common simplification done in earlier work in stochastic network models [12, 55]. Furthermore, the traditional regression models commonly used in a multitude of disciplines make a similar simplification when they assume that the error term has a fixed standard deviation independent of the explanatory variables. As we will see below, without this simplification the standard deviation is endogenously determined, which can cause equilibria to fail to exist.

The structure of the mean-stdev cost function is complicated because of the square root used to compute the standard deviation along paths, even in the simpler setting when standard deviations are exogenous. In this setting, solving a user's subproblem—a shortest path problem with respect to the mean-stdev objective—is a nonconvex optimization problem for which no polynomial running-time algorithms are known. To the best of our knowledge, a precise characterization of the complexity of the subproblem is open; the best algorithms known so far run in time $n^{O(\log n)}$ for networks of $n$ nodes, which is between polynomial and exponential [52, 50]. This is in sharp contrast to the subproblem of the deterministic Wardrop equilibrium: a deterministic shortest path problem admits efficient solutions such as Dijkstra's algorithm [23]. Nevertheless, we highlight that the subproblem is feasible from a practical point of view, despite a theoretical superpolynomial worst-case running time. This is because the running time of the exact algorithm discussed in [52] depends on the number of paths that minimize some linear combination of mean and variance. This number is small (of the order of ten) in practical applications of interest [38]. In other words, the minimum mean-stdev path can be computed by running a small number of deterministic shortest path instances. Furthermore, there are faster, practical approximation algorithms that find a $(1+\epsilon)$-solution for any desired level of accuracy $\epsilon > 0$. With the ever-increasing use of smartphones, GPS devices and websites with sophisticated algorithms and high computational power, coupled with increasingly accurate statistical information on the mean delays of road segments and their standard deviations, finding a route that minimizes the mean-stdev would be computationally feasible and within reach for most network users.

Finally, we assume that delays along different edges are uncorrelated to simplify the analysis. Nevertheless, some degree of correlation is to be expected in practice; e.g., if there is an accident in

**Table 1** Existence of equilibria in mean-risk stochastic traffic assignment problems

| | Exogenous Standard Deviations | Endogenous Standard Deviations |
|---|---|---|
| Nonatomic Users | Equilibrium exists (solves exponentially-large convex program) | Equilibrium exists (solves variational inequality) |
| Atomic Users | Equilibrium exists (Game is potential) | No pure strategy equilibrium |

a location, it causes ripple effects upstream. Local correlations can be addressed with a polynomial graph transformation that encodes correlation explicitly in edges by modifying the standard deviation functions with correlation coefficients [49, 47]. It is possible to obtain a graph with independent travel times on edges where all our results and algorithms carry through.

## Summary of Results

We generalize the traditional model of Wardrop competition [73] by incorporating stochastic travel times. Technically, this model is much harder to analyze than the traditional one because it is *non-additive*, namely the cost of a path is not equal to the sum of costs of edges along the path [29]. This in turn means that an equilibrium in the stochastic setting does not decompose to equilibria in subnetworks of the given network, leading to computational and structural complications. Depending on the specific details of the application one has in mind, users may be small or large [30]. We consider both infinitesimal users, referred to as the *non-atomic* case, as well as users that control a strictly positive demand, referred to as the *atomic* case.

To analyze the problem and to establish the existence of an equilibrium, we draw from a diverse spectrum of tools from potential games and convex analysis to the theory of variational inequalities and nonconvex (stochastic) shortest paths. We consider the four combinations of flow-independent (called *exogenous* in Section 4) vs. flow-dependent variability of travel times (called *endogenous* in Section 5) and nonatomic (continuous flows) vs. atomic (discrete and unsplittable flows) users. Our conclusions and methods are different in each of these settings. In the nonatomic case with standard deviation of travel times given exogenously, we prove that equilibria always exist using a convex problem with exponentially-many variables similar to that of Ordóñez and Stier-Moses [55]. The atomic case with exogenous standard deviations is shown to be a potential game and therefore a pure-strategy Nash equilibrium always exists. To characterize the equilibria of the nonatomic version of the problem when the standard deviations of travel times are endogenous, we use a variational inequality (VI) formulation [32, 69, 19] that draws ideas from the nonlinear complementary problem formulation of Aashtiani and Magnanti [1]. In this case, an equilibrium always exists; in fact, not only for our specific mean-stdev objective but also for any general continuous objective. In contrast, the atomic case with endogenous standard deviation does not always admit a pure-strategy Nash equilibrium. We summarize these results in Table 1.

Section 6 investigates if there is a succinct representation (in terms of a small set of paths) of user and system optimal flows in the case of non-atomic users with stochastic travel times. Our results here are independent of whether the standard deviations are exogenous or endogenous. We prove that if one is given a solution (either a Wardrop equilibrium or a system optimum) as an edge-flow, not every path decomposition is a solution, in contrast to the deterministic case where every decomposition works. Nevertheless, there is always a succinct solution that uses at most $|E|+|K|$ paths, where $E$ is the set of edges in the network and $K$ is the set of origin-destination pairs. Although the complexity of computing a solution is left open (actually, even the complexity of computing a single stochastic shortest path is open), this result says that there is some hope because at least solutions can be efficiently encoded.

In Section 7, we quantify the inefficiency of mean-risk Wardrop equilibria under stochastic travel times with respect to the socially-optimal solution, for the case of nonatomic users. The social optimum is defined as the flow minimizing the total cost incurred by users, as given by their mean-stdev objective. Surprisingly, under exogenous standard deviations, uncertainty and risk aversion do not exacerbate the inefficiency of equilibria. The *price of anarchy*—the worst-case ratio between the social cost of an equilibrium and that of an optimal solution—remains equal to that of deterministic nonatomic games. Namely, it is 4/3 for the case of linear expected travel times [63] and $(1-\beta(\mathcal{L}))^{-1}$ for an appropriately defined constant $\beta(\mathcal{L})$ for expected travel time functions in a class $\mathcal{L}$ [62, 16, 17].

The case of endogenous standard deviations presents a significant additional difficulty that makes the square root terms in different paths interrelated functions of the path flow that cannot be analyzed separately; a general price of anarchy bound for this case remains elusive. Nevertheless, we show that, despite the square root term, the path costs are convex whenever the individual travel times and standard deviations on edges are convex. Consequently, we present sufficient conditions for convexity of the social cost, which are similar to the sufficient conditions for uniqueness of equilibrium in its VI characterization. Unfortunately, these conditions are fragile and in general the social cost will not be convex and may admit a non-connected set of multiple global minima. As an example, we are able to identify a setting where the price of anarchy is 1 but even that is technical because characterizing the socially-optimal solution involves dealing with an exponential number of path decompositions. Finally, Section 8 provides concluding remarks and some open questions.

## 2. Related Work

Our model is based on the traditional competitive network game introduced by Wardrop in the 1950's where he postulated that the prevailing traffic conditions can be determined from the assumption that users jointly select shortest routes [73]. The model was formalized in an influential book by Beckmann *et al.* where they lay out the mathematical foundations to analyze network games [7]. These models find applications in various application domains such as in transportation [67] and telecommunication [3] networks. In the last decade, these types of models have received renewed attention with many studies aimed at understanding under what conditions these games admit an equilibrium, what uniqueness properties are satisfied by these equilibria, what methods can be used to compute equilibria efficiently, what price is paid for having competition instead of a centralized solution, and what are good ways to align incentives so an equilibrium becomes socially optimal. For references on these topics from a perspective similar to ours, we refer the readers to the surveys [18, 54].

In the majority of models used by theoreticians who study the properties of equilibria in networks, and by practitioners who compute solutions to real problems, travel times have been considered deterministic. For instance, most of the previous work assumes that travel times depend on the load of the edges, with different degrees of generality. In recent times, researchers progressively started paying more attention to risk aversion and began incorporating various forms of uncertainty to their models (see, e.g., [5, 39, 43, 72] and some more references below). Nevertheless, none of these models has become widely accepted in practice, nor have they been extensively studied. Perhaps the only exception is the *stochastic user equilibrium* model, introduced by Dial in the 1970's [22], which has been studied in detail and used in practice extensively [68, 70]. Under it, different users *perceive* each route differently, distributing demand in the network according to a logit model. To reduce route enumeration, the model just takes into account a subset of "efficient routes." Daganzo and Sheffi [21] looked at the case of dependent route costs, while Fisk [26] studied the model in the context of congested networks, obtaining an equivalent optimization problem. Methods that avoid route enumeration have been proposed by Bell [8], Larsson, Liu, and Patriksson [37], and Maher [41], also leading to equivalent optimization problems in the spirit of Fisk's. Based on Akamatsu [2], Baillon and Cominetti [6] proposed a more general concept called *Markovian traffic equilibrium*, provided an equivalent optimization problem and established the convergence of the method of successive averages in that context. But the bottom line is that this model considers that *perceptions* on different routes are stochastic, and not that the travel times themselves are. For this reason, the model presented in this work is complementary to the stochastic user equilibrium approach.

The route-choice model in this paper consists of users that select the path that minimizes the mean plus a multiple of the standard deviation of travel time. This problem belongs to the class of stochastic shortest path problems (we refer the reader to some classic references [4, 11] and some newer ones [24, 25, 51, 48]). Wu and Nie [74] make use of stochastic dominance to characterize admissible paths in a route choice model with uncertain travel times. Besides stochastic formulations, there have been other approaches to this problem. For example, Bell and Cassir consider that travel times are set by an adversary who will pick the worst-possible travel time for the user [9], and Bertsimas and Sim propose a robust optimization approach that considers a budget of uncertainty that limits the number of edges on which actual travel times are different from the mean travel times [12].

Going from route choice into equilibrium network assignment problems, Lo and Tung study a probabilistic user equilibrium model for networks with stochastic capacity [40]. Their equilibrium model requires that used routes not only have the same mean travel time value but that its variance is bounded by given performance guarantees. The model most related to our work is that of Ordóñez and Stier-Moses [55]. They introduce a game with uncertainty elements and risk-averse users and study how the solutions provided by it can be approximated numerically by an efficient column-generation method that is based on robust optimization. The main conclusion is that the solutions computed using their approach are good approximations of *percentile equilibria* in practice. Here, a percentile equilibrium is a solution in which percentiles of travel times along flow-bearing paths are minimal. They also use their algorithm to compare equilibria with risk-averse players to those with risk-neutral players, as in the standard Wardrop model. The main difference between their approach and ours is that their insights are based on computational experiments whereas the current work focuses on theoretical analysis and also considers the more general settings of endogenously-determined standard deviations and the atomic case where users control a positive amount of flow. Following up on Ordóñez and Stier-Moses, Nie also studies percentile equilibria [46]. He studies an instance with two edges and exogenous standard deviations in detail, provides a gradient projection algorithm to find percentile equilibria, and uses it to perform a computational study. Like us, he also considers congestion-dependent standard deviations of travel times.

Finally, Cominetti and Torrico [15] consider a setting with risk-averse users similar to ours but instead of selecting the user objective as a primitive, they work under an axiomatic framework. They prove that if one enforces basic premises, including risk aversion, monotonicity and the fact that a subpath of an optimal path must be optimal, the only possible risk measures satisfying the chosen axioms are those in the family of entropic risk measures defined by $\rho_\beta(X) = \beta^{-1}\ln\mathbb{E}\left[e^{\beta X}\right]$, for $\beta > 0$.

## 3. The Model

We consider a directed graph $G = (V, E)$ with an aggregate demand of $d_k$ units of flow between origin-destination pairs $(s_k, t_k)$ for $k \in K$. We let $\mathcal{P}_k$ be the set of all paths between $s_k$ and $t_k$, and $\mathcal{P} := \cup_{k\in K}\mathcal{P}_k$ be the set of all paths. The users in the network—i.e., the players of the game—must choose routes that connect their origins to their destinations. We encode the collective decisions of users in a flow vector $\mathbf{f} = (f_\pi)_{\pi\in\mathcal{P}} \in \mathbb{R}_+^{|\mathcal{P}|}$ over all paths. Such a flow is feasible when demands are satisfied, as given by constraints $\sum_{\pi\in\mathcal{P}_k} f_\pi = d_k$ for all $k \in K$. For simplicity, when we write the flow on an edge $f_e$ depending on the full flow $\mathbf{f}$, we refer to $\sum_{\pi: e\in\pi} f_\pi$. When we need multiple flow variables, we use the analogous notation $\mathbf{x}, x_\pi, x_e$.

The network is subject to congestion, modeled with stochastic travel time functions $\ell_e(x_e) + \xi_e(x_e)$ for each edge $e \in E$. Here, $\ell_e(x_e)$ measures the expected travel time when the edge has flow $x_e$, and $\xi_e(x_e)$ is a random variable that represents a noise term on the travel time, encoding the error that $\ell_e(\cdot)$ makes. The function $\ell_e(\cdot)$ is assumed continuous and non-decreasing. The random variable $\xi_e(x_e)$ has expectation equal to zero and standard deviation equal to $\sigma_e(x_e)$, for a continuous and non-decreasing function $\sigma_e(\cdot)$. Although the distribution generally depends on the flow value $x_e$, we will separately consider the simplified case in which the function $\sigma_e(x_e)$ is a constant $\sigma_e$ given exogenously, and therefore independent from $x_e$. We also assume that these random variables are all uncorrelated with each other. As explained in the introduction, risk-averse players choose paths according to the mean-standard deviation (mean-stdev) objective, a linear combination of the expectation and standard deviation of the travel time along the route. For simplicity, throughout the paper we refer to the mean-stdev objective as the cost along a route. Formally, the cost along route $\pi$ is

$$Q_\pi(\mathbf{f}) = \sum_{e\in\pi} \ell_e(f_e) + \gamma \sqrt{\sum_{e\in\pi} \sigma_e(f_e)^2}\,, \tag{1}$$

where $\gamma \geq 0$ is a constant that quantifies the user risk-aversion, which we assume homogeneous (see Section 8 for a discussion about how one may consider the heterogeneous case).

The mean-stdev objective displayed in the previous equation highlights the importance of capturing total variability in the risk measure associated with a given path. To be concrete, consider a network with two disjoint routes between locations $A$ and $B$, and a single route between locations $B$ and $C$. Suppose the (constant) mean, stdev pairs for the parallel edges are $(6.9, 1)$ and $(5, 3)$, respectively, while that of the B-C edge is $(5, 1)$. It may happen that a user that goes from $A$ to $B$ optimally selects one of the routes while a user that goes from $A$ to $C$ optimally selects the other route and then goes from $B$ to $C$. Indeed, for a risk-aversion parameter of $\gamma = 1$, the costs of the two parallel edges are 7.9 and 8, respectively, so that the first parallel edge is more attractive if a user travels between $A$ and $B$. The costs of both routes between $A$ and $C$ become $6.9 + 5 + \sqrt{1+1} \approx 13.31$ and $5 + 5 + \sqrt{3^2+1} \approx 13.16$. Hence, for a user that travels between $A$ and $C$, the route using the second parallel edge is more attractive. The example shows that considering total variability may change the optimal route in a significant way.

This may seem counterintuitive at first because a situation like this cannot arise with deterministic delays. After considering it in more detail, one can reconciliate this apparent incongruence. The user that goes from $A$ to $C$ has to aggregate the uncertainty of the chosen edge between $A$ and $B$ with the uncertainty of the edge between $B$ and $C$. Because of the previously-mentioned risk-diversification effect, it may pay off to choose a more uncertain edge first because the possible additional delay induced by it is compensated with possible savings in time when going from $B$ to $C$. Hence, it is important to consider end-to-end variability.

The *nonatomic* version of the problem considers the setting where there are an infinite number of users who control an insignificant amount of flow each so that the path choice of a single user does not unilaterally affect costs experienced by others, even though the joint actions of several players affect other players. The following definition captures that users at equilibrium route flow along paths with minimum cost $Q_\pi(\cdot)$.

Definition 3.1. The *mean-stdev Wardrop equilibrium* of a nonatomic routing game is a flow $\mathbf{f}$ such that for every $k \in K$ and for every path $\pi \in \mathcal{P}_k$ with positive flow, $Q_\pi(\mathbf{f}) \leq Q_{\pi'}(\mathbf{f})$ for all $\pi' \in \mathcal{P}_k$.

In general, this equilibrium belongs to the class of Wardrop equilibria with stochastic costs. The equilibrium definition above extends naturally to other path-cost functions such as, e.g., the mean-variance cost.

The *atomic* version of the game assumes that each player wishes to route one unit of flow. Consequently, the path choice of even one player directly affects the costs experienced by others. When users control a positive demand, there are two possibilities: in the splittable case users can split their demands along multiple paths, and in the unsplittable case they are forced to choose a single path. In this paper we focus on the *atomic unsplittable* case, which we will sometimes refer to just as *atomic*. The natural extension of Wardrop equilibrium to the atomic case only differs in that players need to anticipate the effect of a player re-routing the flow to another path.

Definition 3.2. A pure-strategy *mean-stdev Nash equilibrium* of the atomic unsplittable routing game with stochastic costs is a flow $\mathbf{f}$ such that for every $k \in K$ and for every path $\pi \in \mathcal{P}_k$ with positive flow, we have that $Q_\pi(\mathbf{f}) \le Q_{\pi'}(\mathbf{f} + \mathcal{I}_{\pi'} - \mathcal{I}_\pi)$ for all $\pi' \in \mathcal{P}_k$. Here, $\mathcal{I}_\pi$ denotes a vector that contains a one for path $\pi$ and zeros otherwise.

We focus on the existence of pure-strategy Nash equilibria because they are a more appropriate solution concept in our setting. Although the atomic version of the game always admits a mixed-strategy equilibrium because it is a finite, normal form game [45], that equilibrium fails to consider that users are risk averse, the focus of this paper. Indeed, the traditional definition of a mixed-strategy Nash equilibrium is incompatible with the fundamentals of our model since Nash's result assumes that players are risk-neutral and compute the expected utility by considering all possible deviations of competitors and weighing costs with probabilities. A risk-averse user would be concerned by the variability of costs and the mixing probabilities as well.

To quantify the quality of solutions, and in particular of equilibria, we define a social cost function that will allow us to compare different flows and determine the optimal one. We adopt a natural social-cost function, given by the total cost among all users:

$$C(\mathbf{f}) := \sum_{\pi \in \mathcal{P}} f_\pi Q_\pi(\mathbf{f}). \tag{2}$$

## 4. Exogenous Standard Deviations

In this section, we consider that the variability that affects travel times is exogenous, which results in constant standard deviations $\sigma_e(x_e) = \sigma_e$ that do not depend on the flow on the edge. The motivation for studying this case is given by variations of travel time that depend on external factors such as the weather, events, traffic signals, or other phenomena that change the road capacity independently of the flow (for more details, see Ordóñez and Stier-Moses [55]). Although this setting is a simplification of the real-world, it constitutes a first step in understanding how variability of travel times influences equilibrium models. In the next section, we study the more general setting where the standard deviation function may depend on the flow.

For constant standard deviations of travel times, the path cost (1) can be written as $Q_\pi(\mathbf{f}) = \sum_{e\in\pi} \ell_e(f_e) + \gamma(\sum_{e\in\pi} \sigma_e^2)^{1/2}$. It is important to highlight that the second term is a constant that depends on the path but does not depend on the flow on edges. We investigate the existence of equilibria and provide a characterization, first for the nonatomic case and then for the atomic one.

### 4.1. The Nonatomic Case

Despite the challenge posed by the non-additive cost function $Q_\pi(\cdot)$, we show that existence and uniqueness in the nonatomic case can be generalized from the deterministic counterpart by extending the convex program that was proposed by Beckmann et al. [7]. The results below follow from applying the path-based convex programming formulation given by Ordóñez and Stier-Moses [55] to our problem.

Theorem 4.1. *A nonatomic routing game with exogenous standard deviations always admits a mean-stdev Wardrop equilibrium.*

*E* ven though we cannot separate the cost into a sum of costs over the edges as traditional formulations of Wardrop equilibria [7], we can characterize the equilibrium using a convex program as follows:

$$\min \sum_{e\in E} \int_0^{x_e} \ell_e(z)dz + \gamma \sum_{\pi\in\mathcal{P}} f_\pi \sqrt{\sum_{e\in\pi} \sigma_e^2} \tag{3}$$

$$\text{s.t. } x_e = \sum_{\pi\in\mathcal{P}:\ e\in\pi} f_\pi \quad \text{for } e \in E,$$

$$d_k = \sum_{\pi \in \mathcal{P}_k} f_\pi \quad \text{for } k \in K,$$

$$f_\pi \geq 0 \quad \text{for } \pi \in \mathcal{P}.$$

The term in the objective with the square root is linear in the flow implying that the objective is a continuous convex function provided the functions $\ell_e(x)$ are continuous and nondecreasing. Since the constraint set of feasible flows is a polytope, a minimum is attained. Existence follows because the first order conditions for the convex program exactly match the definition of Wardrop equilibrium.

The formulation in the previous proof also implies that the equilibrium is unique when the convex objective function (3) is strictly convex, which leads to the following corollary.

COROLLARY 4.1. *The mean-stdev Wardrop equilibrium of a nonatomic routing game with exogenous standard deviations is unique (in terms of edge loads) whenever the expected travel time functions $\ell_e(\cdot)$ are strictly increasing.*

Besides proving existence, the formulation (3) also provides a way to compute a mean-stdev equilibrium of an instance. Since convex program (3) contains exponentially many variables (the flows on all paths) and a polynomial number of constraints, a column generation procedure can be used. We will see in Section 6 that an equilibrium always has a succinct decomposition that uses at most $|E| + |K|$ paths; unfortunately, since we do not know ahead of time which paths these are, we cannot write a succinct version of the convex program. Nevertheless, this succinctness property provides a practical method for computing equilibria. We refer the reader to Ordóñez and Stier-Moses [55] for details on computation and for a computational study of the equilibria of these games.

Under monomial travel time functions of the same degree, the formulation of the equilibrium problem and that of the social optimum problem are remarkably similar. Dafermos and Sparrow noted this for the deterministic case under travel time functions of that form [20] and we extend that result to the case of stochastic delays. This implies that the misalignment of both solutions could come from the presence of terms of different degrees in the travel time functions, as it would happen for the deterministic case, or from the different sensitivities to risk aversion in both problems, as specified below.

THEOREM 4.2. *Consider a nonatomic routing game with travel time functions $\ell_e(x_e) = a_e x_e^p$ for some fixed $p \geq 0$ and constant standard deviations $\sigma_e$. A flow $\mathbf{f}$ is socially optimal under risk-aversion parameter $\gamma$ if and only if $\mathbf{f}$ is a mean-stdev Wardrop equilibrium under risk-aversion parameter $\gamma/(p+1)$.*

*I* ntegrating the monomial travel time functions of constant degree, the objective in (3) under risk-aversion parameter $\gamma/(p+1)$ equals

$$\sum_{\pi \in \mathcal{P}} f_\pi \left( \sum_{e \in \pi} \frac{\ell_e(x_e)}{p+1} + \frac{\gamma}{p+1} \sqrt{\sum_{e \in \pi} \sigma_e^2} \right).$$

Since the objective coincides with the social cost (2), this shows that $\mathbf{f}$ is a socially-optimal solution under risk-aversion parameter $\gamma$.

Applying the previous result to the case of constant expected travel times ($p = 0$), social optima and mean-stdev equilibria coincide because the corresponding risk-aversion parameters in the previous result are the same. In addition, in that case both problems reduce to computing a stochastic shortest path for each origin-destination pair. In particular, this means that computationally both the equilibrium and social optimum problems are at least as hard as the stochastic shortest path problem [52, 50].

COROLLARY 4.2. *When the expected travel times and standard deviations are constant for each edge, the equilibrium and social optimum coincide and can be found in time $n^{O(\log n)}$.*

## 4.2. The Atomic Case

Now, we switch our attention to atomic unsplittable routing games with exogenous standard deviations and show that they admit a potential function. We prove this by extending the equilibrium existence result of Rosenthal for deterministic atomic games [61] and conclude that a pure-strategy mean-stdev Nash equilibrium always exists for the atomic game. Section EC.1 in the e-companion provides an alternative proof that uses the characterization of length-four cycles given by Monderer and Shapley [44]. The alternative proof highlights the fragility of the condition: it fails to hold when the standard deviations are endogenous. Thus, the indirect method is useful for proving that the game with endogenous uncertainty does not admit a cardinal potential (although we prove something stronger in that setting, which is that equilibria do not necessarily exist).

Theorem 4.3. *An atomic unsplittable routing game with exogenous standard deviations always has a pure-strategy mean-stdev Nash equilibrium.*

*S* ince the game is unsplittable and players control a unit demand each, a flow is described by a set of paths $\pi := (\pi_k)_{k\in K}$ chosen by players. The corresponding flow is denoted by $f^\pi$; that is, $f^\pi_{\pi'}$ indicates if a player selected route $\pi'$, and $f^\pi_e$ counts how many players selected a route that includes edge $e$. Finally, we refer to all players but player $k$ as the set $-k$.

We show the result by establishing that the game is potential [44]. The discrete analog of the convex objective (3), given as

$$P(\pi) := \sum_{e\in E} \sum_{j=0,\dots,f^\pi_e} \ell_e(j) + \gamma \sum_{k\in K} f^\pi_{\pi_k} \sqrt{\sum_{e\in\pi_k} \sigma_e^2} \tag{4}$$

is a potential function of the atomic version of the game. We denote the terms of the previous function by $P_1(\pi)$ and $P_2(\pi)$, respectively. Notice that $P_1(\pi)$ is exactly Rosenthal's function for deterministic atomic congestion games [61]. To prove that the function is potential, we need to verify that

$$P(\pi) - P(\pi_{-k}, \pi'_k) = Q_{\pi_k}(\mathbf{f}^\pi) - Q_{\pi'_k}(\mathbf{f}^{\pi_{-k},\pi'_k})$$

for all strategy vectors $\pi$, players $k$, and deviations $\pi'_k$ of player $k$. This holds since $P_1(\pi) - P_1(\pi_{-k}, \pi'_k) = \sum_{e\in\pi_k} \ell_e(f^\pi_e) - \sum_{e\in\pi'_k} \ell_e(f_e^{\pi_{-k},\pi'_k})$ because of Rosenthals's result and

$$P_2(\pi) - P_2(\pi_{-k}, \pi'_k) = \gamma\Big(f^\pi_{\pi_k}\sqrt{\sum_{e\in\pi_k}\sigma_e^2} - f^{\pi_{-k},\pi'_k}_{\pi'_k}\sqrt{\sum_{e\in\pi'_k}\sigma_e^2}\Big)$$

by definition if $P_2(\cdot)$.

It is well known that equilibria for deterministic, nonatomic games are essentially unique (Corollary 4.1 is a generalization to that). This means that if there is more than one equilibrium, the travel time along any edge is the same under different equilibria. Consequently, users experience the same cost under all equilibria, and different equilibria are indistinguishable from each other, both from the users' perspective and from the edges' perspective. Instead, there can be different pure-strategy Nash equilibria in the deterministic, atomic game. A simple example that illustrates that is given by three parallel edges with (deterministic) travel time functions equal to $x+1$, $x+1$ and $x+1/2$, respectively, and two players that control a unit demand each. When none of the players select edge 3, one of them can profitably deviate to it, so a necessary condition for equilibrium is that exactly one player selects edge 3. Hence, there are four equilibria in total, where one player selects edge 1 or 2 and the other player selects edge 3. At equilibrium players can experience a travel time of 2 or 3/2 depending on the selected edge. Furthermore, edge 1 may have a travel time of 1 or 2 at equilibrium, depending whether a player selected it or not. The multiplicity of equilibria arises because of the atomic nature of the players, and not because of the uncertain travel times.

## 5. Endogenous Standard Deviations

In this section, we consider the more general case of flow-dependent standard deviations of travel times. This makes the standard deviations endogenous to the game, and can be used to model the impact of congestion not only on the expectation of travel time but also on the ensuing variability. For instance, incidents are more likely when there is more traffic in a road. Other sources of delay that are also more likely to occur are that more users may be looking for parking, may double-park and may stop to pickup or drop off passengers. Using a variational inequality (VI) formulation in the space of path flows, we show that in the nonatomic case equilibria continue to exist. Unfortunately, contrary to the setting with deterministic travel times, a formulation using a minimization problem is not possible. In the case of atomic users, equilibria may fail to exist as a consequence of the consideration of endogenous standard deviations of travel times.

We start with an example that illustrates how an equilibrium changes when standard deviations are endogenous. Assume a demand of $d=1$ and consider a network consisting of two parallel edges with expected travel times $\ell_1(x)=x$ and $\ell_2(x)=1$, followed by a chain of $k$ edges that users must traverse, extending the idea of the example given in Section 3. Furthermore, assume that $\sigma_e(x_e)=sx_e$ for all edges, for some constant $s\geq 0$. This instance admits two paths, each comprising one of the two parallel edges and the chain. We let $L$ denote the expected travel time along the chain (a constant since the flow traversing it is fixed). Although the deterministic counterpart of the game is equivalent to the classic instance with two routes put forward by Pigou [58, 63] because the chain has constant flow and does not influence the equilibrium, the equilibrium with endogenous standard deviations changes significantly. Indeed, it can be characterized by the roots of the degree-4 polynomial $(1-4s^2)x^4+4s^2x^3+(4s^4-2s^2-4ks^2)x^2-4s^4x+s^4$ that are in $[0,1]$, where $x$ denotes the flow on one of the two paths. Although in principle it is not evident whether these roots exist or not, we will see that an equilibrium always does.

To further highlight what was mentioned in the introduction, an important insight that arises from this example is that an equilibrium in the stochastic game does not decompose to equilibria in subgraphs of the given graph. In fact, it may be quite different from the equilibria in the subgraphs. It is not immediate how to decompose the problem by partitioning a graph into smaller subgraphs: this is a major challenge to designing efficient algorithms for computing equilibria, or even just best responses, for which traditional approaches will likely fail (e.g., Dijkstra's shortest path algorithm [23]).

### 5.1. The Nonatomic Case

At the end of the 1970's, Smith [69] and Dafermos [19] proposed to characterize Wardrop equilibria in nonatomic routing games using variational inequality (VI) formulations. Some earlier research used this approach for nonadditive models like ours [29, 1, 55]. All these papers show that a flow minimizes a modified cost function (2) that *holds path costs fixed* if and only if the flow is at equilibrium. The mean-stdev equilibrium also admits a VI formulation, which we state and prove for completeness below.

Proposition 5.1. *The flow* $\mathbf{f}$ *is a mean-stdev Wardrop equilibrium of a nonatomic routing game with endogenous standard deviations if and only if for any feasible flow* $\mathbf{f}'$,

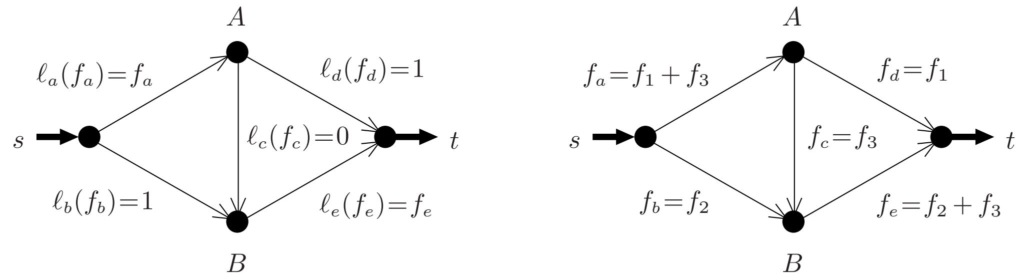
$$\mathbf{Q}(\mathbf{f})\cdot(\mathbf{f}-\mathbf{f}')\leq 0, \tag{5}$$

*where* $\mathbf{Q}(\mathbf{f})$ *denotes the vector of costs along all paths* $(Q_\pi(\mathbf{f}))_{\pi\in\mathcal{P}}$.

We need to establish both directions. First, suppose $\mathbf{f}$ is a mean-stdev equilibrium flow. By definition, the equilibrium routes flow along minimum-cost paths. Fixing path costs at $\mathbf{Q}(\mathbf{f})$, any other flow $\mathbf{f}'$ that routes flow along paths of higher cost will result in higher overall cost $\mathbf{Q}(\mathbf{f})\cdot\mathbf{f}'$.

Conversely, suppose that (5) holds for all $\mathbf{f}'$ and that $\mathbf{f}$ is not an equilibrium. Then, there is a flow-carrying path $\pi$ and another path $\pi'$ with $Q_\pi(\mathbf{f})>Q_{\pi'}(\mathbf{f})$. Letting $f':=f+\epsilon(\mathcal{I}_{\pi'}-\mathcal{I}_\pi)$ to shift flow from $\pi$ to $\pi'$, we obtain that $\mathbf{Q}(\mathbf{f})\cdot\mathbf{f}>\mathbf{Q}(\mathbf{f})\cdot\mathbf{f}'$, which contradicts the claim.

**Figure 1** Example that shows that there is no cardinal potential function




(a) Expected travel time functions. (b) Total flows in each edge.

The previous proposition implies that an equilibrium exists if and only if the variational inequality above admits a solution. Because the set of feasible flows is convex and compact, and the cost function is continuous, the latter follows from a well-known result from the theory of variational inequalities.

THEOREM 5.1. *[32] Let $\mathbb{K}\subset\mathbb{R}^N$ be a compact convex set and let $\mathbf{Q}:\mathbb{K}\to\mathbb{R}^N$ be a continuous mapping. Then, there exists a vector $\mathbf{x}\in\mathbb{K}$ such that $\mathbf{Q}(\mathbf{x})\cdot(\mathbf{x}-\mathbf{y})\le 0$ for all $\mathbf{y}\in\mathbb{K}$.*

COROLLARY 5.1. *A nonatomic routing game with endogenous standard deviations always admits a mean-stdev Wardrop equilibrium.*

Note that the existence of an equilibrium also holds in the much more general setting where the travel time functions depend not only on the flow of the given edge but also on the other edges, as long as this dependence is continuous. This is referred to as *nonseparable* travel time functions in the literature.

In contrast to the case of exogenous standard deviations, however, the game with endogenous standard deviations is not *potential* [44] and equilibria cannot be easily characterized as the solution to a (convex) optimization problem.

PROPOSITION 5.2. *The nonatomic routing game with endogenous standard deviations does not admit a cardinal potential.*

*F* or games with infinite player sets, as is the nonatomic routing game, Sandholm provides a condition that characterizes potential games. This condition, called *externality symmetry* (which we define below), does not hold in our game. To see this, suppose that our game admits a cardinal potential function $\Phi:\mathbb{R}^{|\mathcal{P}|}\to\mathbb{R}$. Note that the domain is the set of all path flows, not only those that satisfy demands (technically, this is called a *full population game*; see, e.g., [65]). By definition, this is a continuously differentiable function whose gradient is the vector of path-cost functions. Equivalently, since the path-cost functions are smooth, they must satisfy the *externality symmetry* condition [64], which means that for any two paths $\pi,\pi'\in\mathcal{P}$, the effect on the cost of path $\pi'$ of adding flow on path $\pi$ is equal to the effect on the cost of path $\pi$ of adding flow on path $\pi'$. In other words, the cross partial derivatives are the same when the order is exchanged:

$$\frac{\partial^2\Phi(\mathbf{f})}{\partial f_\pi \partial f_{\pi'}}=\frac{\partial Q_\pi(\mathbf{f})}{\partial f_{\pi'}}=\frac{\partial Q_{\pi'}(\mathbf{f})}{\partial f_\pi}=\frac{\partial^2\Phi(\mathbf{f})}{\partial f_{\pi'}\partial f_\pi}\,.$$

However, the following example based on the Braess paradox network shows that externality symmetry is not satisfied, proving the claim.

Consider the travel time functions indicated in Figure 1 with standard deviation functions equal to $f_e$ for all edges $e$. There are three possible paths: top, down and zigzag, with flows denoted by $f_1, f_2, f_3$ and cost functions respectively equal to

$$Q_1(\mathbf{f})=1+f_1+f_3+\sqrt{(f_1+f_3)^2+f_1^2},$$

$$Q_2(\mathbf{f}) = 1 + f_2 + f_3 + \sqrt{(f_2+f_3)^2 + f_2^2},$$
$$Q_3(\mathbf{f}) = f_1 + f_2 + 2f_3 + \sqrt{(f_1+f_3)^2 + f_3^2 + (f_2+f_3)^2}.$$

Considering the cross effects of paths 1 and 3:

$$\frac{\partial Q_1(\mathbf{f})}{\partial f_3} = 1 + \frac{f_1+f_3}{\sqrt{(f_1+f_3)^2+f_1^2}} \qquad \text{and} \qquad \frac{\partial Q_3(\mathbf{f})}{\partial f_1} = 1 + \frac{f_1+f_3}{\sqrt{(f_1+f_3)^2+f_3^2+(f_2+f_3)^2}}\,.$$

we see that $\partial Q_1(\mathbf{f})/\partial f_3 \neq \partial Q_3(\mathbf{f})/\partial f_1$, so externality symmetry does not hold.

The previous result indicates that the practical calculation of equilibria is probably more difficult than in the case of exogenous standard deviations because it forces one to solve an exponentially-sized variational inequality. Nevertheless, the approach that relies on column generation that was referred to in the previous section extends to this setting. It remains to be determined how efficient and practical these calculations are when instances are large in size.

### 5.2. Uniqueness

As in the deterministic case, the stochastic routing game may have multiple flows that are at equilibrium when expected travel times and their standard deviations are not strictly increasing with flow. (We present one example below in Lemma 6.1, which shows that under constant expected travel times and standard deviations, there are different edge flows at equilibrium. In the example, any flow of the form $(f, 1-f, 1-f, f)$ for $f \in [0,1]$ is an equilibrium.) Thus, a relevant question is whether there exists a unique equilibrium when the expected travel time and/or standard-deviation functions are strictly increasing, as is the case when travel times are deterministic. Although a unique equilibrium exists for extreme risk attitudes, we leave the question for general risk attitudes open. We show how some of the standard methods that are used for characterizing equilibria and establishing uniqueness using the theory of variational inequalities and nonlinear complementarity problems fail. The following is a classic result usually employed to settle questions of this kind (see, e.g., [31]).

Theorem 5.2. *Consider the variational inequality $F(x)\cdot(x-y) \le 0$ for all $y \in X$, over a nonempty, compact and convex domain $X \subset \mathbb{R}^n$. If the mapping $F:\mathbb{R}^n \to \mathbb{R}^n$ is* strictly monotone *over $X$, meaning that*

$$[F(x) - F(y)] \cdot (x-y) > 0 \qquad \forall x \neq y \in X\,, \tag{6}$$

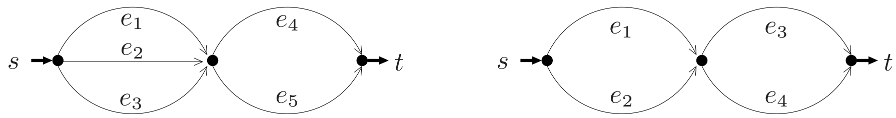
*then the variational inequality has at most one solution.*

There are some other weaker notions, such as monotonicity and pseudo-monotonicity, that can be used to prove existence of solutions and other properties but they are generally not enough to guarantee uniqueness.

Remark 5.1. It is easy to see that the sum (and also the convex combination) of two monotone operators is monotone. In our setting, the path-cost operator is a linear combination of the mean and the standard deviation of travel times along paths. The mean is always monotone because it is separable and non-decreasing. If the standard deviations are monotone on a class of graphs, we would directly obtain that path costs are monotone, resulting in uniqueness of equilibrium (under appropriate conditions for *strict* monotonicity such as strictly increasing path means). Conversely, for monotonicity to fail, it needs to fail in the case of *infinitely risk-averse users*, whereby path costs are given only by the standard-deviation term.

Following the remark, we present counterexamples for monotonicity under the case of infinitely risk-averse users where $\gamma \to \infty$. An easy way to capture an infinite risk-aversion is by assuming that mean travel times are zero. Note that the possibility of having negative realizations of travel times does not impose limitations since one could add an appropriate constant to all edges without changing the solutions of the examples that we provide. The key insight is that the square-root

**Figure 2** Counterexamples to (pseudo-)monotonicity




(a) Pseudo-monotonicity (b) Monotonicity

function is not monotone. By continuity, these counterexamples can be extended to the case with moderately risk-averse users where costs include positive expectation terms. We say that a mapping is *pseudo-monotone* over a domain $X$ if

$$F(y)\cdot(x-y)\geq 0 \text{ implies } F(x)\cdot(x-y)\geq 0 \qquad \forall x,y\in X. \tag{7}$$

We present the following counterexample for the most general definition of monotonicity because it implies that none of the other monotonicity properties hold for stochastic routing games with endogenous standard deviations. In particular, the operator is not monotone, nor strictly monotone.

PROPOSITION 5.3. *The path-cost operator of the nonatomic routing game with endogenous standard deviations is not pseudo-monotone.*

*C* onsider the network on the left of Figure 2, and assume that the expectation of travel time in each edge is zero and that the standard deviation $\sigma_e(f_e)$ on the edge equals $f_e$. Hence, $Q_\pi(\mathbf{f}) = (\sum_{e\in\pi} f_e^2)^{1/2}$. We refer to path $(e_i, e_j)$ in this network by $\pi_{ij}$ and we encode the full vector of flows as $\mathbf{f} = (f_{14}, f_{24}, f_{34}, f_{15}, f_{25}, f_{35})$. Flow vectors $\mathbf{f} = (0, 0, 0.1, 0.2, 0.7, 0)$ and $\mathbf{f}' = (0.1, 0, 0, 0, 0.7, 0.2)$ violate pseudo-monotonicity because $Q(\mathbf{f}')\cdot(\mathbf{f}-\mathbf{f}') = 0.00494$ and $Q(\mathbf{f})\cdot(\mathbf{f}-\mathbf{f}') = -0.00494$.

An even simpler instance can be used to provide a counterexample to monotonicity. Indeed, consider the network on the right of Figure 2 with similar characteristics as that in the previous proposition. Denoting flows as $\mathbf{f} = (f_{13}, f_{23}, f_{14}, f_{24})$, flow vectors $\mathbf{f} = (0, 0.1, 0.2, 0.7)$ and $\mathbf{f}' = (0.1, 0, 0, 0.9)$, violate monotonicity because $(\mathbf{f}-\mathbf{f}')\cdot[Q(\mathbf{f}) - Q(\mathbf{f}')] = -0.00114$.

Although Proposition 5.3 implies that strict monotonicity does not hold, we can nonetheless prove uniqueness when users have extreme risk attitudes. In particular, we show that in those cases the stochastic game resembles a deterministic one.

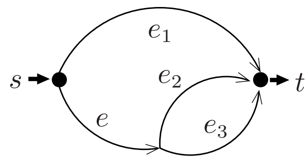
PROPOSITION 5.4. *The equilibrium of a stochastic routing game with endogenous standard deviations is unique in the two extreme settings where users are either risk-neutral or infinitely risk-averse, for strictly increasing expected travel times and standard deviations.*

*W* hen users are risk-neutral, the stochastic game trivially reduces to the deterministic game with travel times given by the expected travel time functions. Thus, we already know that the equilibrium is unique [7]. When users are infinitely risk-averse, although we saw that the standard deviation operator is not monotone, the game in which path costs are squared admits the same equilibria as the original game. This transformation makes the path costs additive and hence the game has a unique equilibrium because it is equivalent to a deterministic one with increasing travel times (given by the variance functions on each edge).

### 5.3. The Atomic Case

In this section, we provide an example that shows that, in contrast to the nonatomic case, the atomic unsplittable routing game may not have pure-strategy Nash equilibria. Unfortunately, the approach of considering mixed strategies put forward by Nash [45] is not straightforward to adapt to our needs: as we discussed in Section 3, albeit guaranteed to exist, a mixed-strategy Nash equilibrium is incompatible with the fundamentals of our model because it considers that users are risk-neutral. Although there are other possibilities for defining mixed-strategy equilibria for risk-averse users, we leave that for follow-up work.

**Figure 3** An atomic unsplittable game with endogenous standard deviations




| Player strategies | $\pi_1$ | $\pi_2$ | $\pi_3$ |
|---|---|---|---|
| $\pi_1$ | 4.80, 4.80 | 4.80, 3.22 | 4.80, 3.11 |
| $\pi_2$ | 3.22, 4.80 | 5.73, 5.73 | 4.73, 4.81 |
| $\pi_3$ | 3.11, 4.80 | 4.81, 4.73 | 5.81, 5.81 |

*Note.* *Left:* Instance with no pure-strategy Nash equilibrium. *Right:* Normal form game with two players.

Remark 5.2. The atomic unsplittable routing game with endogenous standard deviations may not have pure-strategy Nash equilibria, even in the case of a single source, a single sink and a series-parallel network with affine cost functions.

*C* onsider two users that want to route one unit of flow from $s$ to $t$ in the graph shown in Figure 3. Let the mean travel time and standard deviation on edges $e_1, e, e_2, e_3$ be $(4.8, 0)$, $(x, x/\sqrt{2})$, $(x, 1)$, $(x+0.4, 0)$, respectively. We refer to the three paths in the graph as $\pi_1, \pi_2, \pi_3$, where path $\pi_i$ uses edge $e_i$. The table in Figure 3 shows the path costs under each strategy for risk-aversion coefficient $\gamma = 1$. A simple inspection shows that the game does not have a pure-strategy Nash equilibrium.

## 6. Succinct Representations of Solutions in the Nonatomic Case

We now turn our attention to how one can decompose equilibria and socially optimal solutions represented as edge-flow vectors into path-flow vectors. Furthermore, the hope of efficient algorithms to compute those solutions depends on the existence of succinct vectors of path-flows, meaning that not too many paths are used. In this section, we set to study these questions, exclusively from the perspective of the nonatomic routing game.

Decompositions are easy in deterministic routing games: any path-flow decomposition of an equilibrium or a social optimum, given as an edge-flow, works since path costs are additive. Instead, path costs of the stochastic game are non-additive and different flow decompositions of the same edge-flow may incur in different path costs. In particular, for an equilibrium or a system optimum, given edge-flows, some path-flow decompositions are at equilibrium or optimal, respectively, and others are not.

The next lemma illustrates that shortest paths with respect to our nonadditive path costs do not need to satisfy Bellman equations since a subpath of a shortest path need not be shortest.

Lemma 6.1. *In a nonatomic routing game, not all path-flow decompositions of an edge-flow at equilibrium are at equilibrium.*

*C* onsider the graph in Figure 2(b) with (constant) mean travel times for edges $e_1$, $e_2$, $e_3$, $e_4$ equal to $a$, $a+1$, $b$, $b-1$ for some $a, b > 0$, and (constant) standard deviations of travel times equal to $\sqrt{8}, \sqrt{3}, 1, \sqrt{8}$. The costs along the four possible paths are $Q_{13} = a+b+3$, $Q_{23} = a+b+3$, $Q_{14} = a+b+3$, and $Q_{24} = a+b+\sqrt{11}$, which are constants independent of the flow. The edge flow that sends 1/2 unit of flow along each edge is an equilibrium, but only if decomposed properly. We know that an equilibrium can only use the minimum-cost paths $\pi_{14}$ and $\pi_{23}$. (Although path $\pi_{13}$ has minimal cost, using this path with the given edge flow would require sending flow on the higher-cost path $\pi_{24}$ as well, to make the flow feasible. Therefore, this cannot result in an equilibrium.) Viewed as a path-flow, the only decomposition that satisfies the equilibrium conditions is $f_{14} = f_{23} = 1/2$ and $f_{13} = f_{24} = 0$. Any other decomposition uses $\pi_{24}$ and therefore is not at equilibrium.

A key insight from the previous result is that *not all minimum-cost paths can be used in a decomposition*. Similarly, the social cost of different decompositions of a given edge-flow can vary.

Lemma 6.2. *In a nonatomic routing game, not all path-flow decompositions of an edge-flow minimize the social cost.*

*C* onsider again the graph on the right of Figure 2 with mean travel times for edges $e_1$, $e_2$, $e_3$, $e_4$ equal to $2f_1$, $6f_2$, $4f_3$, $10f_4$, and standard deviation of travel times equal to $0.6f_1$, $f_2$, $2f_3$, $f_4$, respectively. Let the edge-flow be $0.3, 0.7, 0.4, 0.6$ respectively, and $\gamma = 1$. The costs along the four possible paths are $Q_{13} \approx 3.02$, $Q_{23} \approx 6.86$, $Q_{14} \approx 7.23$, and $Q_{24} \approx 11.12$, which are constants independent of the decomposition of the flow. Routing the unit demand at minimum cost, we get the flow $f_{13} = 0$, $f_{23} = 0.4$, $f_{14} = 0.3$, and $f_{24} = 0.3$, with a total cost of approximately 8.25. In particular, the minimum-cost path counterintuitively gets a flow of zero. This flow decomposition can be computed by solving a linear program with variables $f_{13}, f_{14}, f_{23}, f_{24}$:

$$\begin{aligned} \min \quad & Q_{13}f_{13} + Q_{14}f_{14} + Q_{23}f_{23} + Q_{24}f_{24} \\ \text{s.t.} \quad & f_{13} + f_{14} = f_1 \\ & f_{23} + f_{24} = f_2 \\ & f_{13} + f_{23} = f_3 \\ & f_{14} + f_{24} = f_4. \end{aligned}$$

The alternative of greedily routing the maximum possible flow along the cheapest path, then the second cheapest, etc., results in $f_{13} = 0.3$, $f_{23} = 0.1$, $f_{14} = 0$, and $f_{24} = 0.6$, with a total cost of approximately 8.27, namely the natural (greedy) path flow decomposition results in a higher cost than the optimal one.

We highlight the surprising fact raised by the example in Lemma 6.2 in the following remark. In the example, the path with lowest cost $\pi_{13}$ carries zero flow in the optimal decomposition.

Remark 6.1. Decomposing an edge-flow into paths greedily does not necessarily provide a cost-minimizing path-flow.

The previous examples do not depend on the standard deviations being endogenous. An instance with exogenous standard deviations can be given where the structure does not change.

The lemmas above prompt the need of characterizing the structure of path-flow decompositions of equilibria and social optima. Does a succinct flow decomposition of an equilibrium or a social optimum always exist (namely one that assigns positive flows to only polynomially-many paths)? The following results answer this question in the positive. These properties are crucial since they guarantee that one can represent solutions succinctly. Otherwise, we would require exponentially-large vectors even to encode solutions.

First, we prove that an edge-flow of a socially-optimal solution can be decomposed into a small number of paths.

Theorem 6.1. *For a social optimum $(x_e)_{e \in E}$ given as an edge-flow in the nonatomic case, there exists a* succinct *flow decomposition that uses at most $|E| + |K|$ paths.*

*B* ecause the edge-flow $\mathbf{x}$ is fixed, path costs are constant independent of the decomposition. Therefore, even though the cost functions $Q_\pi(\cdot)$ are nonlinear, the flow-decomposition problem can be written as the following linear program:

$$\begin{aligned} & \min \sum_{\pi \in \mathcal{P}} Q_\pi(\mathbf{x}) f_\pi \qquad (8) \\ & \text{s.t. } x_e = \sum_{\pi \in \mathcal{P}:\ e \in \pi} f_\pi \quad \text{for } e \in E, \\ & \qquad d_k = \sum_{\pi \in \mathcal{P}_k} f_\pi \quad \text{for } k \in K, \\ & \qquad f_\pi \geq 0 \quad \text{for } \pi \in \mathcal{P}. \end{aligned}$$

The previous problem has $|E| + |K|$ equality constraints, from where the result follows because there is always an optimal solution to a linear program in which the number of non-zero variables is bounded by the number of equality constraints.

Next, we prove a similar result for succinct equilibrium decompositions. The subtlety is that in the endogenous case, we do not even have an optimization formulation, let alone a linear programming formulation of the equilibrium as we do for the social optimum problem above. The insight is that for a *fixed* edge flow, the path costs are fixed. Therefore, equilibria of endogenous problems have corresponding equivalent equilibria of exogenous problems, in which the standard deviation values are *constant*.

Theorem 6.2. *For an equilibrium* $(x_e)_{e\in E}$ *given as an edge-flow of a nonatomic routing game, there exists a* succinct *flow decomposition that uses at most* $|E|+|K|$ *paths.*

$F$ or the exogenous setting, recall that the equilibrium is a solution to the convex program (3). For fixed edge flows, this is a linear program in the path-flow variables $f_\pi$ with the same feasible set as the social optimum problem (8). Therefore, by the same argument as in Theorem 6.1, there exists a succinct flow decomposition that uses at most $|E|+|K|$ paths.

For the endogenous setting, we do not have an optimization formulation that can be turned into a linear program; however, since edge flows are fixed, so are the standard deviations corresponding to the edges. Therefore, an equilibrium in an endogenous setting has an equivalent equilibrium in the corresponding exogenous setting, in which the standard deviations are set to those in the endogenous formulation under the given edge flow. The edge flow must remain an equilibrium because costs along all paths do not change. Proceeding as in the previous paragraph, we obtain a succinct decomposition at equilibrium for the exogenous game, which will also be an equilibrium of the original formulation with endogenous standard deviations.

It remains open whether finding an equilibrium path-flow decomposition from an equilibrium given as an edge flow can be done in polynomial time. This is related to the open question of whether the stochastic shortest path problem defined for finding a single minimum-cost path can be solved in polynomial time [52].

## 7. Efficiency Analysis of Mean-stdev Wardrop Equilibria in the Nonatomic Case

In this section, we analyze the worst-case inefficiency of the mean-risk equilibria of the nonatomic routing game. To quantify this inefficiency, we make use of the concept of price of anarchy [56], first introduced by Koutsoupias and Papadimitriou [34] and used extensively in relation to transportation and telecommunications networks [63, 62, 16, 14, 57, 17].

The price of anarchy (POA) is defined as the supremum over all problem instances of the ratio of the equilibrium cost to the social optimum cost. A central planner would like to minimize $C(\mathbf{f})$ as defined in (2) but typically a flow achieving that minimum is not possible when users make self-minded decisions and select paths that minimize their own costs, leading to an equilibrium outcome instead. This section characterizes the gap between social costs under both solutions. When this gap is small, the conclusion is that user incentives are partially aligned with the system and hence an intervention will fail to provide big improvements. On the contrary, a large gap calls for some type of intervention because improving the alignment of incentives can significantly lower the social cost at equilibrium.

### 7.1. Exogenous Standard Deviations

Prior research on deterministic routing games has shown that the price of anarchy is bounded by a relatively small constant. What is most surprising is that the inefficiency does not grow unbounded when networks become bigger and more complicated. Following Roughgarden [62], the price of anarchy is typically computed for a set of travel time functions given a-priori. We prove that in the case of stochastic travel times with exogenous standard deviations, the price of anarchy is the same as in the deterministic case. The bounds result from a modification of the bounding techniques of Correa *et al.* [16, 17].

For example, when the expected travel time functions are linear in the edge flow, the price of anarchy is 4/3, meaning that, at equilibrium, the total cost experienced by users does not exceed

33.33% of that in an optimal solution. For nonlinear functions, such as those suggested by the Bureau of Public Roads [13], one needs to adjust the constant. When the expected travel times are captured by degree-4 polynomials, as it is typically done by transportation practitioners, the price of anarchy evaluates to 2.151. We highlight that this is a worst-case bound, which by definition tends to be pessimistic. Although it is tight because it was already tight for deterministic networks, equilibria are maximally bad only in special instances that are unlikely to be found in the real-world. There is theoretical and computational research that tries to refine this to understand the worst-case inefficiency among 'realistic' instances [28, 33, 59, 17].

To prove the price-of-anarchy result in our stochastic setting, we use the same definition for the parameter $\beta$ as Correa *et al.* [16]. Namely, we consider a family of expected travel time functions $\mathcal{L}$, and define for a travel time function $\ell \in \mathcal{L}$ and a number $v \geq 0$, $\beta(v,\ell) := \max_{x\geq 0}\{x(\ell(v) - \ell(x))\}/(v\ell(v))$, $\beta(\ell) := \sup_{v\geq 0}\beta(v,\ell)$, and finally $\beta(\mathcal{L}) := \sup_{\ell\in\mathcal{L}}\beta(\ell)$.

Theorem 7.1. *Consider a nonatomic routing game with continuous nondecreasing expected travel times belonging to a family $\mathcal{L}$ of travel time functions, and exogenous standard deviations. A mean-stdev Wardrop equilibrium $\mathbf{f}$ and a socially-optimal flow $\mathbf{f}^*$ minimizing the social cost (2) satisfy $C(\mathbf{f}) \leq (1-\beta(\mathcal{L}))^{-1}C(\mathbf{f}^*)$.*

*W* e define the social cost of path-flow $\mathbf{x}$ under the prevailing path costs for the equilibrium $\mathbf{f}$ by $C^{\mathbf{f}}(\mathbf{x}) := Q(\mathbf{f})\cdot\mathbf{x}$. Under this definition, $C(\mathbf{x}) = C^{\mathbf{x}}(\mathbf{x})$. Denote the (constant) path standard deviations by $\sigma_\pi := (\sum_{e\in\pi}\sigma_e^2)^{1/2}$. The VI characterization of equilibria implies that $C(\mathbf{f}) \leq C^{\mathbf{f}}(\mathbf{x})$ for any feasible flow $\mathbf{x}$. Furthermore,

$$\begin{aligned} C^{\mathbf{f}}(\mathbf{x}) &= \sum_{e\in E}\ell_e(f_e)x_e + \sum_{\pi\in\mathcal{P}}\gamma\sigma_\pi x_\pi \leq \sum_{e\in E}\ell_e(x_e)x_e + \sum_{e\in E}\beta(\mathcal{L})\ell_e(f_e)f_e + \sum_{\pi\in\mathcal{P}}\gamma\sigma_\pi x_\pi \\ &= C(\mathbf{x}) + \beta(\mathcal{L})\sum_{e\in E}\ell_e(f_e)f_e \leq C(\mathbf{x}) + \beta(\mathcal{L})C(\mathbf{f}). \end{aligned}$$

Here, the first inequality uses the definition of $\beta$ and the second follows after completing the social cost function with the standard deviations. Therefore, $C(\mathbf{f}) \leq C(\mathbf{x})/(1-\beta(\mathcal{L}))$ for any feasible flow $\mathbf{x}$, implying that the price of anarchy is $(1-\beta(\mathcal{L}))^{-1}$.

### 7.2. Endogenous Standard Deviations

In the case of endogenous standard deviations, an analysis of the price of anarchy is more elusive, not only for the complications of stochastic Wardrop equilibria but also because characterizing social optima in this case is difficult too. With the hope of simplifying the problem, we study the limiting case of extreme risk-aversion (the other 'extreme' case of risk-neutrality is already well-understood, as explained earlier). In that case, we consider that expected travel times are zero because users only care about standard deviations of travel time. Hence, path costs are equal to the path standard deviations $Q_\pi(\mathbf{f}) = (\sum_{e\in\pi}\sigma_e(f_e)^2)^{1/2}$. Recall that in this extreme case, Proposition 5.4 shows that there is a unique equilibrium that can be computed efficiently with a convex program. We leave the case of intermediate values of risk aversion open.

For the extreme case of infinite risk aversion and polynomial standard deviation functions, we prove that the price of anarchy is one whenever the social cost function is convex. Unfortunately though, even in simple instances, the social cost is not convex because path-cost operators, although convex themselves, fail to be monotone as required. This, once more, happens because of the complicating square root. We finish by proving nevertheless that the price of anarchy is 1 for instances with more restrictive assumptions.

We now show that the first-order optimality conditions of the optimization problem that defines socially-optimal solutions are satisfied at the equilibrium, when standard deviation functions are monomials of the same degree. Note that in the deterministic case, it is well known that the price of anarchy is exactly one precisely for monomials of the same degree [20]. Recall that Theorem 4.2 provides a related result but for the case where the mean travel times are given by monomials, instead of the standard deviations as here.

Theorem 7.2. *Consider a nonatomic routing game with zero travel times and endogenous standard deviations of the form $\sigma_e(x_e) = a_e x_e^p$ for some fixed $p \geq 0$. A mean-stdev Wardrop equilibrium is a stationary point in the social-optimum problem that consists on minimizing $C(f)$ among feasible flows (see (2)).*

*C* onsider the Lagrangian of the social-optimum problem, $L(\mathbf{f}, \lambda) = \sum_{\pi \in \mathcal{P}} f_\pi Q_\pi(\mathbf{f}) + \lambda(1 - \sum_{\pi \in \mathcal{P}} f_\pi) - \sum_{\pi \in \mathcal{P}} \mu_\pi f_\pi$ (see, e.g., [10]). Its derivatives are

$$\frac{\partial L(\mathbf{f}, \lambda)}{\partial f_\pi} = Q_\pi(\mathbf{f}) + \sum_{\pi' \in \mathcal{P}} f_{\pi'} \frac{\partial Q_{\pi'}(\mathbf{f})}{\partial f_\pi} - \lambda - \mu_\pi = Q_\pi(\mathbf{f}) + \sum_{\pi' \in \mathcal{P}} f_{\pi'} \frac{\sum_{e \in \pi \cap \pi'} \sigma_e(f_e) \sigma'_e(f_e)}{Q_{\pi'}(\mathbf{f})} - \lambda - \mu_\pi \,.$$

Let us evaluate the derivative above at the equilibrium flow $\mathbf{f}$ for a path $\pi$ with flow $f_\pi > 0$. The multiplier $\mu_\pi$ can be discarded because the path carries positive flow and, hence, the corresponding constraint is not binding. Since the equilibrium conditions imply that path costs along flow-carrying paths are constant, we can replace the denominator $Q_{\pi'}(\mathbf{f})$ with $Q_\pi(\mathbf{f})$. Therefore, we have

$$\begin{aligned} Q_\pi(\mathbf{f}) + \frac{1}{Q_\pi(\mathbf{f})} \sum_{e \in \pi} \sigma_e(f_e) \sigma'_e(f_e) \Big( \sum_{\pi' \in \mathcal{P}, e \in \pi'} f_{\pi'} \Big) - \lambda &= Q_\pi(\mathbf{f}) + \frac{1}{Q_\pi(\mathbf{f})} \sum_{e \in \pi} \sigma_e(f_e) \sigma'_e(f_e) f_e - \lambda \\ &= Q_\pi(\mathbf{f}) + \frac{p}{Q_\pi(\mathbf{f})} \sum_{e \in \pi} \sigma_e(f_e)^2 - \lambda = Q_\pi(\mathbf{f}) + \frac{p}{Q_\pi(\mathbf{f})} Q_\pi(\mathbf{f})^2 - \lambda = (p+1) Q_\pi(\mathbf{f}) - \lambda. \end{aligned}$$

Here, we have used that for monomial standard deviation functions, $x_e \sigma'_e(x_e) = p a_e x_e^p = p \sigma_e(x_e)$. Setting $\lambda = (p+1) Q_\pi(\mathbf{f})$ results in $\partial L(\mathbf{f}, \lambda)/\partial f_\pi = 0$ for paths $\pi$ carrying positive flow at equilibrium. For a path $\pi$ that does not carry flow, $\mu_\pi$ evaluates to a positive number because $Q_\pi(\mathbf{f}) \geq Q_{\pi'}(\mathbf{f})$ for any path $\pi'$ that carries flow. Hence, the Kuhn-Tucker necessary conditions are satisfied at equilibrium.

As a corollary from the above theorem, whenever the social-optimum problem has a unique stationary point (for example, if the social cost objective is strictly convex), it would follow that equilibria and social optima coincide and, consequently, the price of anarchy would be 1. Before we identify settings for which convexity of the social cost holds, we show that despite the square root, the path costs are convex in the edge-flow variables when the standard deviations $\sigma_e(x_e)$ are convex functions.

Proposition 7.1. *The path costs $Q_\pi(\mathbf{x})$ are convex functions on $\mathbf{x}$ whenever the expected travel time and standard deviation functions are convex.*

*P* ath costs $Q_\pi(\mathbf{x})$ can be split into two parts. The part corresponding to expected travel times on all the edges on $\pi$ is convex because it is additive and the expected travel times on edges are convex. Hence, it suffices to show that the standard deviation component of the path cost is convex. The latter follows by noting that the standard deviation component is equal to $||\{\sigma_e(x_e)\}||_2$, the Euclidean norm of the standard deviation vector $\{\sigma_e(x_e)\}$ of edges along path $\pi$, which is convex.

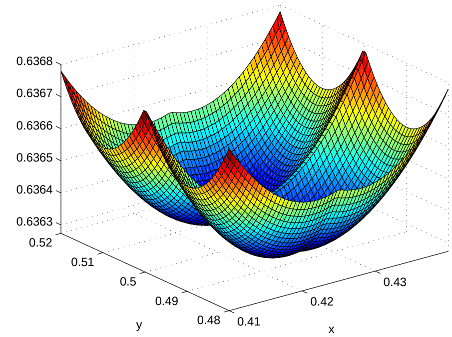
Next, we identify sufficient conditions for the convexity of the social cost, which bear an intriguing resemblance to the sufficient conditions for the uniqueness of equilibrium mentioned earlier. The definition of a monotone operator is the same as a strictly-monotone one (6), except that the inequality is weak instead of strict.

Proposition 7.2. *The social cost $C(\mathbf{x})$ is convex whenever the path-cost operator $Q$ is monotone and the path costs $Q_\pi(\mathbf{x})$ are convex.*

*W* e need to prove that the social cost satisfies $C(\beta \mathbf{x} + (1-\beta)\mathbf{y}) \leq \beta C(\mathbf{x}) + (1-\beta) C(\mathbf{y})$ for any two feasible flows $\mathbf{x}$ and $\mathbf{y}$, and $\beta \in [0,1]$. Using the convexity of path costs, it suffices to show that $[\beta \mathbf{x} + (1-\beta)\mathbf{y}]\,[\beta Q(\mathbf{x}) + (1-\beta) Q(\mathbf{y})] \leq \beta \mathbf{x} Q(\mathbf{x}) + (1-\beta) \mathbf{y} Q(\mathbf{y})$. This condition is equivalent to

$$\beta^2 \mathbf{x} Q(\mathbf{x}) + (1-\beta)^2 \mathbf{y} Q(\mathbf{y}) + \beta(1-\beta)\,[\mathbf{x} Q(\mathbf{y}) + \mathbf{y} Q(\mathbf{x})] \leq \beta \mathbf{x} Q(\mathbf{x}) + (1-\beta) \mathbf{y} Q(\mathbf{y}) \,.$$

**Figure 4** Non-convex slice of the social cost function




Regrouping the terms in one side and dividing over $\beta(1-\beta)$, we see that the last inequality holds because $(\mathbf{x}-\mathbf{y})\,[Q(\mathbf{x})-Q(\mathbf{y})]\geq 0$, by monotonicity of the path costs $Q(\cdot)$.

Having convex path-cost functions may suggest that the social cost function is also convex. Unfortunately, the convexity of the latter fails to hold even in the basic case of linear standard deviation functions equal to $\sigma_e(x)=x$. Figure 4 shows a non-convex slice of the social cost function; please refer to Proposition EC.2.1 in the e-companion for a concrete counterexample of non-convexity.

Overcoming those difficulties, we show that the POA is 1 in a network of $n$ pairs of parallel edges connected in series (e.g., Figure 2(b) shows a network like this with 2 pairs of edges). Despite the limited class of topologies that are allowed, we present this example to illustrate the difficulties one runs into when looking for bounds on the price of anarchy under the mean-risk objective. Although the equilibrium is characterized in the same way as when there is no uncertainty, the non-convexity of the social cost function creates big difficulties when characterizing the optimal routing, even for this extremely simple and symmetric topology. This should be put in perspective by comparing it to what was done for the case of exogenous standard deviations under general graphs and costs in Section 7.1. For the case of endogenous standard deviations, whether the nonconvexity of the social cost can be circumvented to obtain price of anarchy bounds for more general graphs and travel time functions remains open.

Proposition 7.3. *Consider a nonatomic routing game on a network of $n$ pairs of parallel edges connected in series. There is an end-to-end unit demand, the mean travel times are zero, and the standard deviation functions are equal to $\sigma_e(x)=x$ for all edges $e$. For these instances, stochastic Wardrop equilibria and socially-optimal flows coincide.*

We include the proof in the e-companion because it is technical; we just offer a sketch here. First, we prove that an arbitrary decomposition of a flow that routes half a unit in each edge is the (essentially) unique equilibrium. Since the non-convexity of the objective prevents us from using Lagrangian duality to provide a certificate that the same flow is optimal, we characterize the optimal decomposition for an arbitrary, but fixed, edge-flow vector. We do this using linear programming duality because after fixing the edge-flow vector, the decomposition can be found with a linear program. Finally, after knowing the correct decomposition for an edge-flow, we can optimize in that space and show that the equilibrium is indeed optimal.

## 8. Conclusions and Open Problems

We have set out to extend the classic theory of Wardrop equilibria and network assignment problems to the more realistic setting of uncertain travel times. In this work, we have focused exclusively on theoretical questions about the nature of the competition. The uncertainty of travel times calls for models that incorporate users' attitudes towards risk, which we have captured through a linear combination of the expectation and the standard deviation of travel times along the chosen route.

We have considered nonatomic and atomic routing games, each with exogenous or endogenous standard deviation functions and provided results on (1) the existence and characterization of equilibria; (2) succinct path decompositions of equilibrium and socially optimal flows; (3) the inefficiency of equilibria. The directions pursued by this work have opened many other questions that would be interesting to explore in future studies. Some of these questions are:

- What is the complexity of computing an equilibrium when it exists (exogenous standard deviations with atomic or nonatomic players; endogenous standard deviations with nonatomic players)?
- What is the complexity of computing a socially optimal solution? What is the complexity of computing a socially-optimal flow decomposition if one knows the edge-flow that represents a socially-optimal solution?
- Can there be multiple equilibria in the nonatomic game with endogenous standard deviations?
- What is the price of anarchy for mean-stdev Wardrop equilibria in the setting of nonatomic games with endogenous standard deviations, for general graphs and general classes of cost functions?
- Ordóñez and Stier-Moses considered the case of users with heterogeneous attitudes toward risk [55]. Following up on those ideas, the model in this paper can be readily extended to having a discrete distribution of risk-aversion parameters. Indeed, one can group users with the same risk-aversion parameter under origin-destination pairs that encode those characteristics. The equilibrium-existence results in the paper and the characterization of equilibria go through without major changes. This can be used to approximate the case of a continuous distribution of risk-aversion parameters, which would probably be enough for practical purposes because it is unrealistic to expect that users would have such refined knowledge of their own risk preferences to justify the need for a continuum of risk attitudes in practice. Mathematically, the situation is different. The study of the continuous case would be interesting in terms of the theoretical properties one may be able to get.
- How can one circumvent the nonexistence of pure-strategy Nash equilibria for the case of atomic players and endogenous standard deviations? Future work should align the attitude towards risk when evaluating paths (via the cost function $Q_\pi$) and the attitude towards risk when evaluating the different scenarios that result from players not knowing what strategies other players will choose.

Of course, one could pursue other natural models and player objectives and build upon or complement the theory we have developed here. In particular, our model might be enriched by also considering stochastic demands to make the demand side more realistic, and stochastic preferences to include modeling elements of the Stochastic user equilibrium approach [22].

## Acknowledgments

We thank two anonymous referees, the associate editor and the area editor for their comments, which helped us improve the results and the presentation of the paper, and in particular for suggesting the potential function for the atomic version of the game. We also appreciate the remarks and suggestions of Hari Balakrishnan, Roberto Cominetti, José Correa, Costis Daskalakis, Darrell Hoy and Asu Ozdaglar.

Most of the work was done while the first author was at MIT CSAIL. The authors gratefully acknowledge funding from the National Science Foundation grant number CCF-1216103, Conicet Argentina grant Resolución 4541/12 and ANPCyT Argentina PICT-2012-1324. The conference version of this paper appeared in SAGT'11 [53].

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# E-Companion of paper 'A Mean-Risk Model for the Traffic Assignment Problem With Stochastic Travel Times'

In this e-companion, we provide proofs for some results in the main body.

## EC.1. Alternate Proof of Theorem 4.3

**Theorem 4.3.** *An atomic unsplittable routing game with exogenous standard deviations always has a pure-strategy mean-stdev Nash equilibrium.*

$R$ ecall that a flow is described by a set of paths $\pi := (\pi_i)_{i\in K}$ chosen by players. The corresponding edge-flow is denoted by $f^\pi$; that is, $f^\pi_e$ counts how many players selected a route that includes edge $e$. In addition, we let $-J$ denote the complement of the set of players $J$. Following the characterization of potential games by Monderer and Shapley [44], we consider the strategy graph that associates a node to every vector of players' strategies. This graph contains an edge between two nodes whenever their corresponding vectors of strategies differ exactly in the strategy of a single player. To prove that a potential function exists, it suffices to show that the total change of players' costs is zero along an arbitrary cycle of length four in the strategy graph.

Let us consider two players $i$ and $j$, who initially select routes $\pi_i$ and $\pi_j$, respectively. The cycle of length four must consist of the following four moves in the strategy graph, where both players select a new route $\pi'_i$ and $\pi'_j$, respectively. Indeed, the cycle consists of vertices $\pi$, $\pi_{(2)} = (\pi'_i, \pi_j, \pi_{-\{i,j\}})$, $\pi_{(3)} = (\pi'_i, \pi'_j, \pi_{-\{i,j\}})$, $\pi_{(4)} = (\pi_i, \pi'_j, \pi_{-\{i,j\}})$, and back to $\pi$. Let us now evaluate the cost variations. When player $i$ changes its strategy from $\pi_i$ to $\pi'_i$, his cost difference is

$$Q_i(\pi_{(2)}) - Q_i(\pi) = \sum_{e\in\pi'_i} \ell_e(f_e^{\pi(2)}) + \gamma\sqrt{\sum_{e\in\pi'_i}\sigma_e^2} - \sum_{e\in\pi_i}\ell_e(f_e^\pi) - \gamma\sqrt{\sum_{e\in\pi_i}\sigma_e^2}.$$

When player $j$ changes its strategy from $\pi_j$ to $\pi'_j$, his cost difference is

$$Q_j(\pi_{(3)}) - Q_j(\pi_{(2)}) = \sum_{e\in\pi'_j} \ell_e(f_e^{\pi(3)}) + \gamma\sqrt{\sum_{e\in\pi'_j}\sigma_e^2} - \sum_{e\in\pi_j}\ell_e(f_e^{\pi(2)}) - \gamma\sqrt{\sum_{e\in\pi_j}\sigma_e^2}.$$

When player $i$ changes its strategy back from $\pi'_i$ to $\pi_i$, his cost difference is

$$Q_i(\pi_{(4)}) - Q_i(\pi_{(3)}) = \sum_{e\in\pi_i} \ell_e(f_e^{\pi(4)}) + \gamma\sqrt{\sum_{e\in\pi_i}\sigma_e^2} - \sum_{e\in\pi'_i}\ell_e(f_e^{\pi(3)}) - \gamma\sqrt{\sum_{e\in\pi'_i}\sigma_e^2}.$$

Finally, when player $j$ changes its strategy back from $\pi'_j$ to $\pi_j$, his cost difference is

$$Q_j(\pi) - Q_j(\pi_{(4)}) = \sum_{e\in\pi_j} \ell_e(f_e^{\pi}) + \gamma\sqrt{\sum_{e\in\pi_j}\sigma_e^2} - \sum_{e\in\pi'_j}\ell_e(f_e^{\pi(4)}) - \gamma\sqrt{\sum_{e\in\pi'_j}\sigma_e^2}.$$

Summing the previous equations, all the terms with square roots cancel out, leading to

$$\widehat{Q_i}(\pi_{(2)}) - Q_i(\pi) + \widehat{Q_j}(\pi_{(3)}) - Q_j(\pi_{(2)}) + \widehat{Q_i}(\pi_{(4)}) - Q_i(\pi_{(3)}) + \widehat{Q_j}(\pi) - Q_j(\pi_{(4)}),$$

where $\widehat{Q}$ denotes a modified path cost that ignores the variability of travel times. This implies that the change in the original cost summed across players is equal to zero because the associated deterministic routing game with costs $\ell_e(x)$ is potential [61].

## EC.2. Non-Convexity of the Social Cost Function

The following example shows that the convexity of the social cost fails to hold even in the basic case of linear standard deviation functions equal to $\sigma_e(x) = x$.

PROPOSITION EC.2.1. *The social cost* $\sum_{\pi\in\mathcal{P}} x_\pi (\sum_{e\in\pi} x_e^2)^{1/2}$ *is not convex.*

*C* onsider the instance given by a network of 3 parallel edges, followed by 2 parallel edges shown in Figure 2. The flows used for the pseudo-monotonicity counterexample given in Proposition 5.3 violate the convexity condition

$$Q(\beta\mathbf{x} + (1-\beta)\mathbf{y}) \le \beta Q(\mathbf{x}) + (1-\beta)Q(\mathbf{y})$$

for $\beta = 1/2$. As before, we denote a path flow vector by $\mathbf{x} = [x_{14}, x_{24}, x_{34}, x_{15}, x_{25}, x_{35}]$ where the subscript $ij$ denotes the path using edges $e_i, e_j$, as shown in the figure. Taking flows $\mathbf{x} = [0, 0, 0.1, 0.2, 0.7, 0]$ and $\mathbf{y} = [0.1, 0, 0, 0, 0.7, 0.2]$ yields corresponding path costs

$$\begin{aligned} Q(\mathbf{x}) &= [\sqrt{0.05}, \sqrt{0.5}, \sqrt{0.02}, \sqrt{0.85}, \sqrt{1.3}, \sqrt{0.82}] \\ Q(\mathbf{y}) &= [\sqrt{0.02}, \sqrt{0.5}, \sqrt{0.05}, \sqrt{0.82}, \sqrt{1.3}, \sqrt{0.85}] \\ Q\Big(\frac{\mathbf{x}+\mathbf{y}}{2}\Big) &= [\sqrt{0.0325}, \sqrt{0.5}, \sqrt{0.0325}, \sqrt{0.8325}, \sqrt{1.3}, \sqrt{0.8325}]. \end{aligned}$$

After some algebra, we see that these flow provide a counterexample to the convexity of the social cost function:

$$\frac{\mathbf{x}+\mathbf{y}}{2} \cdot Q\Big(\frac{\mathbf{x}+\mathbf{y}}{2}\Big) = 0.99863 > 0.99666 = \frac{1}{2}\mathbf{x} \cdot Q(\mathbf{x}) + \frac{1}{2}\mathbf{y} \cdot Q(\mathbf{y}).$$

## EC.3. Proof of Proposition 7.3

**Proposition 7.3.** *Consider a nonatomic routing game on a network of $n$ pairs of parallel edges connected in series. There is an end-to-end unit demand, the mean travel times are zero, and the standard deviation functions are equal to $\sigma_e(x) = x$ in all edges $e$. For these instances, stochastic Wardrop equilibria and socially-optimal flows coincide.*

*W* e denote edges in this instance by $t_i$ and $b_i$ for $i = 1, \ldots, n$, and refer to them as *top* and *bottom* edges. It will be useful to refer to the set $\{i, \ldots, n\}$ by $[i]$. We denote a path by specifying the set of top edges that the path goes through. Indeed, for $X \subseteq [1]$, $\pi_X$ represents the path that takes exactly the top edges in $X$; i.e., $\{t_i, i \in X\} \cup \{b_i, i \notin X\}$.

A flow $\mathbf{x}^{\text{NE}}$ that routes half a unit of demand in each edge, decomposed arbitrarily, is at equilibrium. Indeed, under that flow the cost function $Q_\pi(\mathbf{x}^{\text{NE}})$ along an arbitrary path $\pi$ is constantly equal to $\sqrt{n}/2$. We now briefly justify that it is the only possible edge-vector that is at equilibrium. Suppose the contrary, namely there is an equilibrium flow vector, for which at least one pair of parallel edges has flow $x_{t_i}$ and $x_{b_i} = 1 - x_{t_i}$ on the two edges, with $0 \le x_{t_i} < 1/2$. There is at least one flow-carrying path that uses the edge $b_i$. By the definition of path costs, the cost of that path is greater than the cost of the corresponding path using $t_i$ (all other edges in the path being the same). This contradicts the definition of equilibrium.

To prove that $\mathbf{x}^{\text{NE}}$ minimizes the social cost, we characterize the decomposition that minimizes the social cost for an arbitrary edge-flow. After fixing the decomposition, we will be able to optimize over edge-flows and get the result. Indeed, assume we are given an arbitrary edge-flow $\mathbf{x}$. We have to decompose it in a path-flow $(f_\pi)_{\pi\in\mathcal{P}}$ that minimizes the social cost $C(\mathbf{f}) = \sum_{\pi\in\mathcal{P}} f_\pi Q_\pi(\mathbf{f})$, where $Q_\pi(\mathbf{f}) = Q_\pi(\mathbf{x})$ can be assumed constant because it depends on the edge-flow $\mathbf{x}$ that is fixed. Without loss of generality, we can assume that $0 \le x_{t_1} \le x_{t_2} \le \ldots \le x_{t_n} \le 1/2$ because we can take a permutation of the pairs and swap the top and bottom edges without changing the instance.

Let us consider the following feasible decomposition of $\mathbf{x}$: $f_{[1]} = x_{t_1}$, $f_{[i]} = x_{t_i} - x_{t_{i-1}}$ for $i = 2, \ldots, n$, $f_\emptyset = 1 - x_{t_n}$, and zero for all other paths. (Note that we use sets as subindices for paths, as explained at the beginning of the proof.) Clearly, this is a valid decomposition of $\mathbf{x}$. We prove the optimality of the decomposition by linear programming duality, solving the following linear program:

$$\begin{aligned} z^* = \min \sum_{\pi\in\mathcal{P}} f_\pi Q_\pi(\mathbf{x}) & \\ \text{s.t.} \sum_{\pi\in\mathcal{P}} f_\pi = 1 & \\ \sum_{\pi:a\in\pi} f_\pi = x_a & \qquad \text{for all edges } a \\ f_\pi \geq 0 & \qquad \text{for all paths } \pi \end{aligned}$$

The objective value achieved by the decomposition introduced earlier is

$$C(\mathbf{f}) = \Big[\sum_{i=1}^{n} x_{t_i}(Q_{[i]}(\mathbf{x}) - Q_{[i+1]}(\mathbf{x}))\Big] + Q_\emptyset(\mathbf{x})\,, \tag{EC.1}$$

where again we used the notation for paths introduced above and with the understanding that $[n+1]=\emptyset$. The dual to the optimal path-flow decomposition problem can be expressed as:

$$z^* = \max_{y\in\mathbb{R}^{2n}} \Big\{\sum_a x_a y_a + \min_{\pi\in\mathcal{P}} \big\{Q_\pi(\mathbf{x}) - \sum_{a\in\pi} y_a\big\}\Big\}\,.$$

We consider the following dual variables: $y_{t_i} = 0$ and $y_{b_i} = Q_{[i+1]}(\mathbf{x}) - Q_{[i]}(\mathbf{x})$ for $i = 1,\ldots,n$. Replacing in the objective, we have a dual cost of

$$\begin{aligned} &\sum_{k=1}^{n}(1 - x_{t_k})(Q_{[i+1]}(\mathbf{x}) - Q_{[i]}(\mathbf{x})) + \min_{\pi\in\mathcal{P}} \big\{Q_\pi(\mathbf{x}) - \sum_{a\in\pi} y_a\big\} = \\ &\qquad Q_\emptyset(\mathbf{x}) - Q_{[1]}(\mathbf{x}) + \sum_{k=1}^{n} x_{t_k}(Q_{[i]}(\mathbf{x}) - Q_{[i+1]}(\mathbf{x})) + \min_{\pi\in\mathcal{P}} \big\{Q_\pi(\mathbf{x}) - \sum_{a\in\pi} y_a\big\}\,. \end{aligned} \tag{EC.2}$$

To prove that the primal and dual objectives coincide, all we are left to show is that $Q_\emptyset(\mathbf{x}) - Q_{[1]}(\mathbf{x}) + \min_{\pi\in\mathcal{P}} \big\{Q_\pi(\mathbf{x}) - \sum_{a\in\pi} y_a\big\} \geq Q_\emptyset(\mathbf{x})$, or $Q_\pi(\mathbf{x}) - Q_{[1]}(\mathbf{x}) \geq \sum_{a\in\pi} y_a$ for all $\pi\in\mathcal{P}$. In other words, for an arbitrary set $W \subseteq 2^n$ that represents the top edges in $\pi$, we need to prove that $Q_W(\mathbf{x}) - Q_{[1]}(\mathbf{x}) \geq \sum_{i\notin W}(Q_{[i+1]}(\mathbf{x}) - Q_{[i]}(\mathbf{x}))$.

In the rest of the proof, we will suppress the argument $\mathbf{x}$ to simplify notation, writing $Q_W$ instead of $Q_W(\mathbf{x})$. Using a telescopic sum, $Q_W - Q_{[1]} = \sum_{i=1}^{n} Q_{W\cup[i+1]} - Q_{W\cup[i]} = \sum_{i\notin W} Q_{W\cup[i+1]} - Q_{W\cup[i]}$, since for $i \in W$ these two sets are the same: $W \cup [i+1] = W \cup [i]$. To prove the inequality, it suffices to show that $Q_{W\cup[i+1]} - Q_{W\cup[i]} \geq Q_{[i+1]} - Q_{[i]}$. This holds because for general $Y \subseteq X$ and $k \notin X$, $Q_X - Q_{X\cup\{k\}} \geq Q_Y - Q_{Y\cup\{k\}}$, which we prove in the next paragraph. In this case, we use $X = W \cup [i+1]$, $Y = [i+1]$ and $k = i$.

*Lemma*: For general $Y \subseteq X$ and $k \notin X$, $Q_X - Q_{X\cup\{k\}} \geq Q_Y - Q_{Y\cup\{k\}}$; namely, the path cost $Q_X$ is submodular in $X$.

*Proof*: We can get from $X$ to $Y$ by removing one element at a time and seeing that the term $\Delta$ can only decrease in each step. Hence, it suffices to show the inequality for $X = Y \cup \{j\}$, namely that $Q_{Y\cup\{j\}} - Q_{Y\cup\{j,k\}} \geq Q_Y - Q_{Y\cup\{k\}}$. Using the definition of $Q_Y(\mathbf{x}) = \sqrt{\sum_{i\in Y} x_i^2 + \sum_{i\notin Y}(1-x_i)^2}$, we consider the change in path cost when switching from the $k$-th top edge $t_k$ to the $k$-th bottom edge, as a function of the flow on the $j$-th top edge, $x_{t_j}$:

$$h(x_{t_j}) := \Big(x_{t_j}^2 + (1-x_{t_k})^2 + \sum_{i\in Y} x_{t_i}^2 + \sum_{i\notin Y\cup\{j,k\}} (1-x_{t_i})^2\Big)^{\frac{1}{2}} - \Big(x_{t_j}^2 + x_{t_k}^2 + \sum_{i\in Y} x_{t_i}^2 + \sum_{i\notin Y\cup\{j,k\}} (1-x_{t_i})^2\Big)^{\frac{1}{2}},$$

whose derivative (with respect to $x_{t_j}$) is

$$h'(x_{t_j}) = x_{t_j}\Big(x_{t_j}^2 + (1-x_{t_k})^2 + \sum_{i\in Y} x_{t_i}^2 + \sum_{i\notin Y\cup\{j,k\}} (1-x_{t_i})^2\Big)^{-\frac{1}{2}} - x_{t_j}\Big(x_{t_j}^2 + x_{t_k}^2 + \sum_{i\in Y} x_{t_i}^2 + \sum_{i\notin Y\cup\{j,k\}} (1-x_{t_i})^2\Big)^{-\frac{1}{2}}.$$

After some algebra, the assumption of $1-x_{t_k} \ge x_{t_k}$ implies that the derivative is nonnegative. Since $h$ is a decreasing function, $h(x_{t_j}) \ge h(1-x_{t_j})$, which is equivalent to the condition we wanted to show, $Q_{Y\cup\{j\}} - Q_{Y\cup\{j,k\}} \ge Q_Y - Q_{Y\cup\{k\}}$ and the lemma follows.

Now that we know the optimal decomposition for a fixed edge-flow $\mathbf{x}$, we can optimize in that space. Plugging-in the decomposition, the minimal social cost as a function of the edge-flow $\mathbf{x}$ satisfies:

$$\begin{aligned}
C(x) =& x_{t_1}\sqrt{x_{t_1}^2 + x_{t_2}^2 + \ldots + x_{t_n}^2} + (x_{t_2} - x_{t_1})\sqrt{(1-x_{t_1})^2 + x_{t_2}^2 + \ldots + x_{t_n}^2} \\
&+ \ldots + (1-x_{t_n})\sqrt{(1-x_{t_1})^2 + \ldots + (1-x_{t_n})^2} \\
\ge& \frac{1}{\sqrt{n}}\big[x_{t_1}(x_{t_1} + x_{t_2} + \ldots + x_{t_n}) + (x_{t_2} - x_{t_1})((1-x_{t_1}) + x_{t_2} + \ldots + x_{t_n}) \\
&+ \ldots + (1-x_{t_n})((1-x_{t_1}) + \ldots + (1-x_{t_n}))\big] \\
=& \frac{1}{\sqrt{n}}\sum_{i=1}^{n}\left[x_{t_i}^2 + (1-x_{t_i})^2\right] \ge \frac{1}{\sqrt{n}}\sum_{i=1}^{n}\frac{1}{2} = \frac{\sqrt{n}}{2},
\end{aligned}$$

where the first inequality follows from applying the root-mean square inequality $a_1^2 + \ldots + a_n^2 \ge (a_1 + \ldots + a_n)^2/n$ to every square root term. Since the right-hand side equals the cost of the equilibrium, the claim holds.