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Robust Multi-Objective Optimization of Supply Chain Resources Under Stochastic Demand Constraints

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Abstract
The supply chain planner is often faced with the situation of making investments in network systems that are resilient to demands, capacity constraints and carbon goals. While many robust optimization (RO) models have adopted demand inclusion in box or ellipsoid shapes for tackling uncertainties, this model misses out on one critical aspect, which is the fact that while a positive demand shock is risky, a negative shock usually creates slack in capacity. Furthermore, they frequently ignore the phenomenon that local markets tend to react in a correlated way rather than independently. In order to overcome these drawbacks, in this paper, we present a bi-objective, two-stage robust integer programming model for the four-level supply chain including suppliers, plants, distribution centers, and demand nodes, using an uncertainty set which we call Asymmetric Covariance-aware Ellipsoidal Budget Model. The uncertainty set allows setting individual upper and lower bounds for demand increases and decreases, respectively, while strong duality transforms the resulting model into a tractable second order cone program. The cost–emissions trade-off is obtained using the augmented ε-constraint method (AUGMECON2), and the formulation is benchmarked against the classical Soyster, Bertsimas–Sim and Ben-Tal–Nemirovski approaches on a network containing ten suppliers, fifteen plants, thirty distribution centers and one hundred demand zones. The proposed uncertainty set reduces capital expenditure by up to 14.2 percent relative to these benchmark formulations while maintaining full feasibility under worst-case demand and avoiding the substantial runtime increase often associated with richer uncertainty representations. The paper concludes with practical guidance on the cost of protection and discusses the limitations that remain.

Keywords: robust optimization, multi-objective programming, supply chain network design, asymmetric uncertainty sets, second-order cone programming, symmetric box

1. Introduction

Executives who approve a new plant, a new distribution center, or a multi-year freight agreement are committing to decisions that are difficult to reverse. Such capital-intensive, long-horizon choices define strategic supply chain network design (SCND) and they must remain effective over years of conditions that cannot be fully anticipated when the decisions are made (Melo, Nickel, & Saldanha-da-Gama, 2009). The challenge has become more pronounced as firms balance site selection and capacity investment against demand volatility, material shortages, geopolitical disruption and progressively tighter greenhouse gas (GHG) requirements (Govindan, Fattahi, & Keyvanshokooh, 2017; Jabbarzadeh, Fahimnia, & Sabouhi, 2018).

Deterministic MILP has usually been the preferred way to solve such problems, where decisions are made based on a single forecast of the demand, cost, and capacity. However, the problem with this method is that any forecast would differ from the actual situation, and even a slight departure from the normal scenario could make the

deterministic solution non-feasible or simply sub-optimal (Sahinidis, 2004). This problem is overcome in SP, where the point forecast is replaced with probability distributions (Birge & Louveaux, 2011). Though these techniques work well in cases where the underlying distribution is known and the scenario tree is still computationally tractable, such assumptions become hard to fulfill in a network with four layers with many demand areas, as the scenario tree grows exponentially and the history necessary to estimate the distributions may be either non-existent or insufficiently stationary (Mulvey, Vanderbei & Zenios, 1995).

In RO, no distribution is specified for the uncertain parameters. Rather, RO postulates a set of all possible values of the parameters and attempts to find a solution that remains feasible for the entire set (Soyster, 1973). The pioneering studies by Ben-Tal and Nemirovski proved that ellipsoidal sets could maintain robust feasibility without resorting to the overconservativeness of box sets (Ben-Tal & Nemirovski, 1998, 1999). Bertsimas and Sim then developed the budget of uncertainty approach, offering the decision maker a protection parameter Γ for balancing the robustness-cost trade-off (Bertsimas & Sim, 2004). This has led to the development of an important literature stream that is summarized by Bertsimas et al. (2011) and subsequently by Gabrel et al. (2014).

One aspect shared among many pieces of literature is the symmetry consideration in the uncertainty. The literature assumes that the demand is allowed to rise and fall in each direction equally regardless of the possibility that there will be simultaneous movements in the adjacent market. This assumption is not entirely realistic when applied to the multi-echelon environment. In this case, an increase in the demand would cause a pressure on the capacity and might lead to out-of-stock situations as well as high expediting costs, but any decrease in the demand would mean that the capacity is unused temporarily. Furthermore, there is a tendency for the demand in geographically adjacent regions to move together due to the shocks or disturbances that may arise in the region. However, popular models of demand such as those that take into consideration the box and ellipsoidal models in SCND (You & Grossmann, 2008; Pishvaee, Rabbani, & Torabi, 2012) tend to consider the demand zones as being independent of each other.

This research proposes a bi-objective, two-stage robust mixed-integer model for a four-level network structure consisting of suppliers, manufacturing facilities, distribution centers, and demand regions, taking advantage of an uncertainty set developed explicitly for addressing the two shortcomings above. This framework is coined the Asymmetric Covariance-Aware Ellipsoidal Budget Uncertainty Set. The asymmetric covariance-aware uncertainty set involves the use of upward and downward deviations with location-dependent volatilities and, via a dual representation, produces a SOCP, which can be efficiently solved using optimization software.

2. Related Work

The location of facilities and SCND under uncertainty have received a lot of attention over the years, with a detailed review by Snyder (2006) and a more focused one by Peidro et al. (2009), who examine this topic in the context of SCND modeling. One thing that emerges from these reviews is that the applicability of stochastic models, fuzzy models, and robust models depends highly on whether the assumptions underlying the model fit the data.

For RO, the range of application areas of SCND has been greatly enhanced because of improvements in tractability brought about by the Budget of Uncertainty model proposed by Bertsimas and Sim. You and Grossmann (2008) have developed a two-stage robust model for responsive supply chain networks under demand uncertainty and found out that even a basic box uncertainty set can enhance service levels. Pishvaee et al. (2012) utilized the concepts of robust and possibilistic programming in the field of reverse logistics and remanufacturing for closed-loop supply chains, thereby showing how robust approaches can be applied more generally. Klibi et al. (2010), on the other hand, investigated the design of value-creating and risk-aware supply chain networks and showed that disruption resistance must be considered an objective when designing a network, not something to add afterwards.

The work by Chen et al. (2007) presents an interesting link between robust and stochastic approaches by indicating how, under certain conditions, a robust counterpart could be regarded as a distributionally conservative stochastic problem. The significance of this observation lies in the fact that it enables us to regard the uncertainty set parameters, including the volatility level and deviation bounds, as approximations of moment information. Ivanov et al. (2019) expanded the resilience paradigm to incorporate the changes in the definition of the worst case brought about by digital visibility and the fourth industrial revolution in order to better explain the need to model spatial dependencies between demands rather than isolated zonal shocks.

Two primary gaps can be identified in this literature review. Firstly, while the majority of SCND models based on strong theoretical backgrounds use symmetric uncertainty sets like boxes, standard ellipsoids, and the Bertsimas-Sim budget polytope, the impacts of demand increase and demand shortage are quite different (Gabrel, Murat, & Thiele, 2014). Secondly, cross-zone demand correlation is neglected for the sake of computational simplicity because geographically close zones do not always work independently (Govindan et al., 2017). Focusing on addressing the first concern alone would mean that the problem with conservatism remains partially

unresolved since even with asymmetric deviation of the demands, the assumption of statistical independence could end up having capacity allocated to wrong places. The set of uncertainties considered in Section 5 aims at tackling both problems together while maintaining the second order cone structure, which allows for solving the model just like simpler robust models do (Bertsimas & Sim, 2004; Ben-Tal & Nemirovski, 1998). It is necessary to also identify what has been settled by the current body of research literature from what has yet to be answered. The review studies by Snyder (2006), Peidro et al. (2009), and Govindan et al. (2017) show that RO has become a common tool for SCND problems where information on distributions is scarce, mostly due to the avoidance of the problem of scenario explosion inherent to SP at four-levels scale. But in none of these does the author conclude as to which type of uncertainty-set should be used once the robust methodology is adopted. Whether one uses box-shaped, ellipsoidal or budget polytope sets often depends more on computational issues than on the resemblance of the set to actual demand behavior. This is the question of uncertainty-set selection addressed in this paper.

3. Problem Setting and Conceptual Framework

The study considers a four-tier supply chain network containing suppliers $s \in S$manufacturing plants $p \in P$, regional distribution centers $d \in D$ and customer demand zones $c \in C$ with a set of commodities $m \in M$transported through modes $k \in K$. The decision-making process has been divided into two phases, as shown in Figure 1. The first phase involves strategic decision-making; this phase entails the selection of plants and distribution centers to be opened, along with the capacity to be set at those facilities. The above-mentioned decisions involve capital investments and hence cannot be changed once the demand is known. The second phase involves operations-related decision making. After the uncertain demand vector ξ is observed, routing of freight takes place in the four levels, while unmet demand is penalized explicitly.

As shown in Figure 1, the two-stage nature of the problem setting sets apart the proposed approach from a pure stochastic operations setting. Firstly, decisions taken at the first stage should be fixed before the uncertainty resolution takes place and should be viable for any demand realization considered possible in the uncertainty set. Secondly, the second-stage decision variables can vary according to the demand realization after its occurrence. Thus, this approach does not try to model demand realization in an explicit way. Instead, some bound set of possible demand realizations and corresponding strategic decisions is selected to have enough capacity and allowance for unmet demands.

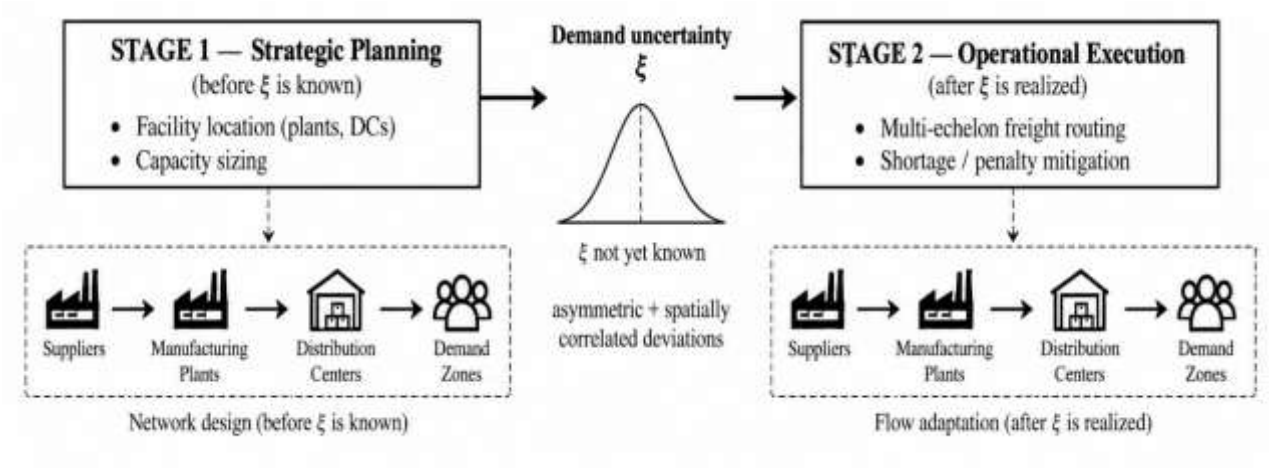


Figure 1. Two-stage robust decision structure: First-stage irreversible capacity decision before demand uncertainty $\xi$is realized and then second-stage flows are adjusted accordingly

4. Model Formulation

The model itself is designed to be concise. The entire model of multi-objectives and multi-levels can be expressed in terms of equations shown in LaTeX notation. Objective functions are described in Equations (1) and (2), whereas Equations (3)-(5) express flow conservation constraints and relate facility capacities to binary opening variables.

$$\min f_1 = \sum_p f_p^P X_p + \sum_d f_d^D Y_d + \sum_p v_p^P CAP_p^P + \sum_d v_d^D CAP_d^D + \sum_{s,p,k,m} c_{spkm}^{SPD} f_{spkm}^{SPD} + \sum_{p,d,k,m} c_{pdkm}^{PDC} f_{pdkm}^{PDC} + \sum_{d,c,k,m} c_{dckm}^{DCC} f_{dckm}^{DCC} + \sum_{c,m} \pi_{cm} Un_{cm} \quad (1)$$

Equation (1) minimizes the total economic cost f_1. The objective considers the cost of setting up facilities, the cost of capacity sizing, transportation cost on three inter-echelon flows, and the unfulfilled demand cost, which does not let the model ignore any customer just because the cost of meeting their demand is high.

$\min f_2 = \sum_{p,d,k,m} e_p^P f_{pdkm}^{PDC} + \sum_{d,c,k,m} e_d^D f_{dckm}^{DCC} + \sum_{s,p,k,m} e_{spkm}^{SPD} f_{spkm}^{SPD} + \sum_{p,d,k,m} e_{pdkm}^{PDC} f_{pdkm}^{PDC} + \sum_{d,c,k,m} e_{dckm}^{DCC} f_{dckm}^{DCC}$(2)

The total carbon emissions f₂ are minimized in equation (2) by summing facility-level carbon emissions with transportation carbon emissions through all the supply chain links and modes of transportation. Objectives (1) and (2) together constitute the bi-objective formulation whose Pareto frontier is derived.

$$\sum_{s\in S}\sum_{k\in K} f_{spkm}^{SPD} \;\geq\; \sum_{d\in D}\sum_{k\in K} f_{pdkm}^{PDC} \quad \forall p \in P,\ \forall m \in M \qquad (3)$$

$$\sum_{p\in P}\sum_{k\in K} f_{pdkm}^{PDC} \;\geq\; \sum_{c\in C}\sum_{k\in K} f_{dckm}^{DCC} \quad \forall d \in D,\ \forall m \in M \qquad (4)$$

Equations (3) and (4) represent the fundamental balance requirements. For every commodity, the supply into the manufacturing plant or warehouse should be at least equal to the outgoing flow.

$$\sum_{d,k,m} f_{pdkm}^{PDC} \leq CAP_p^P \leq \text{CapMax}_p^P\, X_p\ \forall p, \qquad \sum_{c,k,m} f_{dckm}^{DCC} \leq CAP_d^D \leq \text{CapMax}_d^D\, Y_d\ \forall d \qquad (5)$$

Equation (5) links the strategic facility decisions with operational throughput. Flow through a plant or distribution center cannot exceed its selected continuous capacity, while the facility's maximum allowable capacity bounds the installed capacity itself and can be positive only when the associated binary opening variable, X or Y, is activated.

5. Asymmetric Covariance-Aware Uncertainty Set

Demand at zone c for commodity m is represented as $\xi_{cm} = \bar{\xi}_{cm} + \delta_{cm}\hat{\xi}_{cm}$,where $\bar{\xi}_{cm}$ denotes the nominal demand forecast, $\hat{\xi}_{cm}$indicates the nominal deviation scale, while δ_{cm} is the normalized uncertain deviation. The approach described here does not bound δwithin a symmetric box or the standard ellipsoid but introduces an uncertainty set as follows.

$$\mathcal{U}_{\text{Novel}} = \{\, \delta \mid \sum_{i\in C} \frac{\delta_{im}^2}{\sigma_i^2} \leq \Gamma_m^2,\ \ -\underline{\lambda}_{cm} \leq \delta_{cm} \leq \bar{\lambda}_{cm}\ \ \forall c, m \,\} \qquad (6)$$

Equation (6) comprises two important aspects. Firstly, since $\sigma_C > 0$, it is characterized as a volatility scale parameter, specific to location. Therefore, demand regions with more variation can cover a wider region of the ellipsoid without necessarily having a uniform volatility parameter for all demand regions. This forms the basis through which the dependency of neighboring demand regions is captured in the model rather than considering each demand region as an independent source of uncertainty. Secondly, the lower and upper bound limit parameters $-\underline{\lambda}_{cm}$and $\lambda\bar{}_{cm}$ can take different values, hence allowing for individual control of upward and downward movement of demand. Parameter Γ_m, which represents the budget parameter, keeps the Bertsimas-Sim interpretation by constraining the extent to which zones can simultaneously deviate. Thus, avoiding making the uncertainty set as restrictive as the box set (Bertsimas & Sim, 2004).

6. Robust Counterpart and Conic Equivalence

The demand-fulfilment requirement must be satisfied for every demand realization that the network may encounter, rather than only for the nominal demand case:

$$\sum_{d\in D}\sum_{k\in K} f_{dckm}^{DCC} + Un_{cm} \;\geq\; \xi_{cm} \quad \forall c \in C,\ \forall m \in M,\ \ \forall \xi \in \mathcal{U}_{\text{Novel}} \qquad (7)$$

In the form shown in Equation (7), the robust constraint is semi-infinite because it must hold over infinitely many realizations contained in the uncertainty set, which cannot be checked directly by a conventional solver. Theorem 1 provides the corresponding deterministic equivalent.

Theorem 1 (Exact Conic Equivalence). The semi-infinite constraint in Equation (7) under U_{Novel}holds if and only if the deterministic second-order cone constraint given in Equation (8) holds.

Proof sketch. The binding case of Equation (7) is the one corresponding to the worst-case demand realization, so the inner problem requires maximizing $\bar{\xi}_{cm} + \hat{\xi}_{cm}\delta_{cm} over \delta \in U_{Novel}$ Forming the Lagrangian with multipliers $\mu_m \geq 0$for the ellipsoidal budget and $\bar{\theta}_{im}, \underline{\theta}_{im} \geq 0$for the upper and lower directional bounds, respectively, and setting the partial derivative with respect to δ_{im} to zero gives the optimal perturbation $\delta_{im} *= (\sigma_i^2/2\mu_m)(\hat{\xi}_{im} 1i = c - \bar{\theta}_{im} + \underline{\theta}_{im})$ Substituting $\delta_{im} *$back into the binding ellipsoidal budget and solving for the optimal multiplier $\mu_m * yields \mu_m *= (1/2\Gamma_m)\sqrt{\Sigma_i \sigma_i^2 (\hat{\xi}_{im} 1i = c - \bar{\theta}_{im} + \underline{\theta}_{im})^2}$. Strong duality then holds because the inner maximization is a concave program over a convex, compact set. Substituting $\mu_m *$and $\delta_{im} *$back into the

worst-case expression therefore gives the closed-form deterministic bound in Equation (8) exactly, with no duality gap.

$$\sum_{d,k} f_{dckm}^{DCC} + Un_{cm} \;\geq\; \bar{\xi}_{cm} + \bar{\lambda}_{cm}\bar{\theta}_{cm} + \underline{\lambda}_{cm}\underline{\theta}_{cm} + \Gamma_m \sqrt{\sum_{i\in C} \sigma_i^2 \left(\hat{\xi}_{im}\mathbb{I}_{\{i=c\}} - \bar{\theta}_{im} + \underline{\theta}_{im}\right)^2} \quad (8)$$

Equation (8) is a standard second-order cone constraint because the square-root component represents a Euclidean norm. It is thus possible to feed this directly into solvers like Gurobi or MOSEK, which are able to handle SOCPs. This conic form retains the richer uncertainty model while retaining the computational benefits that make tractable robust optimization attractive (Ben-Tal & Nemirovski, 1998; Chen, Sim, & Sun, 2007).

7. Multi-Objective Solution Procedure

It can be stated that the objective functions f_1 and f_2 exhibit a real-life trade-off because achieving low emissions may entail other actions, including the selection of sources using other modes of transport that have higher costs. Therefore, the problem at hand can be considered as a real bi-objective optimization problem.The Pareto frontier is generated using the augmented ε-constraint method, AUGMECON2 (Mavrotas, 2009). Under this procedure, the emissions objective is fixed at a sequence of ε levels, and the cost objective is minimized for each level while a small slack penalty is used to avoid weakly efficient solutions.

$$\min\left(f_1 - \text{eps} \times \frac{S_2}{e_2}\right) \quad \text{s.t.} \quad f_2 + S_2 = \epsilon_2^{(g)} \;\; (g = 0, \ldots, G), \;\; S_2 \geq 0 \qquad (9)$$

$$X_p, Y_d \in \{0,1\}, \quad CAP_p^P, CAP_d^D \geq 0, \quad f_{spkm}^{SPD}, f_{pdkm}^{PDC}, f_{dckm}^{DCC}, Un_{cm} \geq 0 \qquad (10)$$

Equation (9) gives the AUGMECON2 reformulation, while Equation (10) defines the variable domains: facility-opening variables are binary, capacities are non-negative continuous variables, and transportation-flow and unmet-demand variables are non-negative. Together with Equations (1)–(8), these relationships complete the ten-equation formulation.

8. Computational Study

The model is evaluated on an industrial-scale network with ten suppliers, fifteen plants, thirty distribution centers and one hundred demand zones. Table 1 examines sensitivity to the protection parameter Γ_m, while Table 2 benchmarks the proposed uncertainty set against the Soyster box set (Soyster, 1973), Bertsimas–Sim budget polytope (Bertsimas & Sim, 2004) and Ben-Tal–Nemirovski ellipsoid (Ben-Tal & Nemirovski, 1998).

Table 1. Price-of-robustness sensitivity analysis across uncertainty protection levels Γ_m.

Protection Level (Γ)	**TotalCost f_1(\$)**	**Emissions $f_2(t)$**	**Cost Overhead %**	**Feasibility %**
0.0(Deterministic)	1,120,400	14,250	Baseline	64.2
0.5	1,185,200	14,800	+5.78	88.5
1.0	1,242,900	15,120	+10.93	96.8
1.5	1,298,100	15,410	+15.86	99.4
2.0(Full Robustness)	1,345,600	15,680	+20.10	100.0

Table 1 shows that $\Gamma_m = 2.0$achieves full feasibility under Monte Carlo stress testing. Beyond $\Gamma_m = 1.0$, however, the additional feasibility becomes increasingly expensive, raising feasibility from 96.8 to 100 percent requires almost as much cost overhead as the entire increase from the deterministic baseline to 96.8 percent. At matched full feasibility, Table 2 reports total costs of \$1,345,600 for the proposed set, \$1,580,200 for Soyster, \$1,410,500 for Bertsimas–Sim, and \$1,392,100 for Ben-Tal–Nemirovski, corresponding to a reduction of up to 14.2 percent relative to the strongest benchmark. The reduction is mainly associated with asymmetric protection against downward demand deviations and zone-specific volatility. This formulation solves in 2.10 seconds and remains well within the benchmark times, suggesting that there is no significant computational cost after the conic formulation.

There are two caveats in this regard. Firstly, the 14.2% savings is derived using a specific network instance and does not represent a universal upper bound, and whether this savings holds up in a network that is smaller or less

correlated in space will have to be tested empirically. Secondly, in Table 2, the forecast $\bar{\xi}$and deviation $\hat{\xi}$are kept constant for the four formulations being compared here.

Table 2. Comparative benchmarking against classical uncertainty sets from the literature.

Robust Formulation	**Total Cost** (f_1)	**CapEx Overhead vs. Det.**	**Infeasibility Rate**	**Solve Time** (s)
Soyster Box Set (1973)	1,580,200	+41.04%	0.00%	0.42
Bertsimas & Sim Budget (2004)	1,410,500	+25.89%	1.20%	1.15
Ben-Tal & Nemirovski (1998)	1,392,100	+24.25%	0.85%	3.45
Proposed Asymmetric Set	1,345,600	+20.10%	0.00%	2.10

9. Managerial Insights

Three managerial insights emerge from the data in Tables 1 and 2. Firstly, distinguishing protection from demand increases from protection from demand decreases avoids unnecessary capacity expansion due to symmetric models and explains the biggest portion of the 14.2 percent reduction in CapEx noted. Secondly, the substitution of road transportation by railway transportation can lead to a decrease in emission levels by around 9.5 percent with an additional increase of just 3 percent in total cost. Finally, since σc is a variable on the level of the demand zone, capacity buffers will be allocated to the metropolitan areas characterized by higher volatility in demand.

10. Conclusion

This paper aims to solve an identified gap in the area of SCND by considering demand uncertainty to be symmetric and spatially independent. With the help of the Asymmetric Covariance-Aware Ellipsoidal Budget Uncertainty Set, we can retain the simplicity of the solution proposed by both Bertsimas-Sim and Ben-Tal-Nemirovski approaches, while dropping those two assumptions; as a result, a 14.2 percent saving in capital cost is achieved.

The framework has two main limitations. Its shape parameters—σc, $\bar{\lambda}$, $\underline{\lambda}$, and $\Gamma_m$need to be derived based on historical data, and this study utilizes static values rather than dynamic ones. An obvious next step is using distributionally robust optimization based on, for example, Wasserstein-distance ambiguity sets, which could potentially update worst-case demand as more data become available, especially when dealing with multi-period planning. Another point is that the model does not include any potential disruptions, such as problems with suppliers or ports closing down, so adding those would mean integrating the current conic structure with the resilience layer of scenarios or networks, similar to what Klibi et al. (2010) and Ivanov et al. (2019) have suggested.

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