Submission Date: 10.03.2025
Acceptance Date: 13.09.2025
Publication Date: 29.09.2025

To cite this article: Bayram, O. (2025). Yield uncertainty and tardiness penalties: A comparison of offshoring and nearshoring. *İstanbul Ticaret University Journal of Social Sciences, 24*(53), 693-736, doi: 10.46928/iticusbe.1654814

# YIELD UNCERTAINTY AND TARDINESS PENALTIES: A COMPARISON OF OFFSHORING AND NEARSHORING

*Research*

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# Yield Uncertainty and Tardiness Penalties:
# A Comparison of Offshoring and Nearshoring

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**Abstract**

The extreme congestion caused by the pandemic at shipment routes demonstrated the potential damage fluctuations in customer order lead time could cause in global supply chains. Furthermore, if the order arrives with missing items, it will exacerbate the already disrupted flow of goods in the supply chain. Hence, yield uncertainty needs to be considered, especially when coupled with lead time fluctuations. Thus, supplier selection mechanisms could benefit from a comparison of supplier performances combining yield and lead time uncertainty under different combinations of other factors. To demonstrate the consequences of supplier selection based on these effects, we developed a stochastic optimization model for an order placed by a Tier 1 supplier with a Tier 2 supplier. We generated scenarios via 2k factor representation to calculate the effect of increasing production yield and mean lead time on supply chain costs. We have found that the magnitude of the effect of increasing the lead time on total supply chain costs was much higher than the magnitude of the effect of increasing the production yield. We further found that the magnitude of the effects of these two supplier characteristics was more pronounced if at least two of the other three factors -unit underage cost, order amount, and unit procurement or tardiness cost- were high. Our numerical analysis also demonstrated that it was very important to put effort into estimating lead time parameters and distribution correctly, as making incorrect assumptions could cause severe underestimation of supply chain costs.

**Keywords:** Nearshoring, offshoring, uncertain yield, uncertain lead time, tardiness penalty.

**JEL Code:** D24, D81, E23, M11

# Verim Rassallığı ve Gecikme Yaptırım Maliyetleri: Ülke Dışında Üretim ve Komşu Ülkede Üretim Stratejilerinin Karşılaştırılması


## Özet

Pandeminin ulaşım ve sevkiyat süreçlerinde yol açtığı yoğunluk, müşteri sipariş teslim sürelerindeki dalgalanmaların küresel tedarik zincirlerinde yol açabileceği potansiyel zararları ortaya koymuştur. Ayrıca, gecikmenin yanında teslim edilen ürün sayısının beklenenden az olması durumunda, tedarik zincirindeki hâlihazırda bozulmuş ürün akışı daha da kötüleşmektedir. Bu nedenle, özellikle sipariş teslim sürelerindeki dalgalanmalarla birlikte tecrübe edildiğinde, verim rassallığı, üzerinde durulması gereken bir husustur. Dolayısıyla, tedarikçi seçim mekanizmaları, farklı dış faktör kombinasyonları altında verim ve teslim süresi rassallığını beraber ele alarak tedarikçi performanslarını karşılaştırırsa, daha başarılı seçimler yapılacaktır. Bu etmenler doğrultusunda, tedarikçi seçiminin ortaya koyduğu performansı göstermek amacıyla, Seviye 1 tedarikçisinin Seviye 2 tedarikçisine verdiği bir sipariş için stokastik bir optimizasyon modeli oluşturulmuş; $2^k$ faktör temsili ile senaryolar üretilerek, üretim veriminin ve ortalama teslim süresinin tedarik zinciri maliyetleri üzerindeki etkisi hesaplanmıştır. Bulgularımız, teslim süresinin artışının toplam tedarik zinciri maliyetleri üzerindeki etkisinin, üretim veriminin artışının etkisinden çok daha büyük olduğunu göstermektedir. Ayrıca, ele aldığımız diğer üç dış faktörden en az ikisi — teslimatta eksik olan her ürün başına müşteri tarafından katlanılan maliyet, sipariş verilen toplam ürün miktarı ve ürün başına katlanılan gecikme yaptırım maliyeti — yüksek olduğunda, bu iki tedarikçi performans kriterinin (teslim süresi ve üretim verimi) toplam maliyetler üzerindeki etkilerinin daha baskın hale geldiği tespit edilmiştir. Sayısal analizimiz ayrıca, teslim süresinin rassallığını betimleyen parametrelerin ve olasılık fonksiyonunun doğru tahmin edilmesine yönelik çaba göstermenin çok önemli olduğunu ortaya koymuştur. Çünkü hatalı varsayımlar, tedarik zinciri maliyetlerinin ciddi şekilde azımsanmasına yol açarak yanıltıcı sonuçlara sebep olabilmektedir.



**Anahtar Kelimeler:** Komşu ülkede üretim, ülke dışında üretim, rassal verim, rassal teslim süresi, gecikme yaptırım maliyeti.

**JEL Kodu:** D24, D81, E23, M11

## Introduction

In the last decade, the changes in global supply chains (e.g., increasing level of automation, rise in wages and transportation costs while working with offshore suppliers) triggered changes in perspectives for supplier selection. Cost savings were no longer the primary objective driving offshoring. However, supplier selection decisions began to focus on reducing risks as well as physical distances (Slepniov, et al., 2013, p. 6) to increase the ability to respond to adverse shocks (Kaivo-Oja, et al., 2018, p. 76). The suppliers at different geographical locations were initially considered to have the exact landed cost but different fixed lead times and supply capacities (based on automation-related constraints), and dual-sourcing strategies were explored to balance nearshoring and offshoring (Jakšič & Fransoo, 2018, p. 151). However, the geographical distance continued to be acknowledged as having important shortcomings, such as being more prone to potential disruptions, which was one of the driving forces behind backshoring (Piatanesi & Arauzo-Carod, 2019, p. 807).

The pandemic caused severe congestion at major shipping ports, leading to significant fluctuations in customer order lead times. For instance, wait times at anchor reached up to 45 days at ports like Los Angeles and Long Beach (Murray, 2021), with similar delays occurring globally (Chambers, 2022). Political and regulatory disruptions, such as Brexit, have further extended delivery times (Foster, 2024), prompting supply chains to consider nearshoring to manage customer expectations better. These events highlighted the impact that fluctuations in non-processing-related lead times, such as shipment and delivery, can have on global supply chains, shifting focus toward supplier selection based on lead time variability. While automation technologies stabilize processing-related lead times, disruptions at the supplier's site and during shipment have become the primary sources of variability. Our study will therefore focus on fluctuations in customer order lead time primarily caused by non-processing activities. This randomness is especially critical for time-sensitive products, such as seasonal items, making dual-supplier strategies difficult during disruptive periods, as slower suppliers may fail to deliver on time.

On the other hand, for Tier 1 suppliers considered as customers giving orders to Tier 2 suppliers, if the order arrives with missing items, it would impose hidden costs on the Tier 1 supplier. These types of costs must be considered during supplier selection (van

Hassel, et al., 2021, p. 3). For example, a card and board game company such as Exploding Kittens could prefer manufacturing in China over Poland, with efficiency and material quality being among the drivers for this decision (Barkho, 2021). Therefore, lower production yields due to the use of lower-quality raw materials might be a deterrent to nearshoring. Hence, yield uncertainty needs to be considered, especially when contrasted with lead time fluctuations for alternative suppliers, and this uncertainty is inherent in many industries, including high tech and food (Lowe, Khademi, & Mason, 2016; van Donk, 2001, p. 2697), for which nearshoring versus offshoring could be an important concern. Thus, creating a clear summary of the trade-offs between working with suppliers prone to lead time disruptions and those facing yield uncertainty—within a framework that supports scenario-based analysis—can provide valuable insights for supplier selection.

Having high production yield, shorter, and less fluctuating lead times would be significant for a Tier 2 supplier serving Tier 1 suppliers. Therefore, supplier selection mechanisms could benefit from comparing supplier performance based on these two characteristics, considering different combinations of other factors such as procurement and processing costs, as well as penalties for underage and tardiness. To account for uncertainty in yield and lead time when analyzing the effect of supplier selection on total supply chain costs for a make-to-order production, we use a binomial yield model to highlight the dependence of yield on input-based factors like raw material (Dettenbach, 2015, p. 8). We also model total lead time from order confirmation to delivery as the sum of a deterministic component and a random component, assuming Uniform, Exponential, and Lognormal distributions to represent lead time stochasticity. Through stochastic optimization modeling and numerical analysis, our study aims to explore how these two factors—random production yield and lead time—affect supply chain costs under different order characteristics, while also providing key insights for making informed supplier selection decisions.

Regarding the aforementioned supply chain issues, including increased delivery times due to Brexit and the preference for manufacturing in China due to high material quality, despite logistics challenges, our study highlights an overlooked case where a distant offshore supplier gains experience over the years, delivering higher production yields and, consequently, higher quality. However, this has started to cause increased logistics risks and costs due to transportation disruptions. We acknowledge the concept of nearshoring, which refers to relocating manufacturing activities closer to the home region, often involving the return of operations that were previously offshored (Fratocchi, et al., 2014, p. 56). We address the call for a more detailed examination of the internal and external contingencies that influence specific drivers and barriers to reshoring (Moore, et al., pp. 1025-1026), considering and comparing the impact of external contingencies of the offshore (distant) supplier, such as higher tardiness costs due to its location, and internal contingencies of the nearshore supplier, such as lower production yield and, therefore, higher underage costs.

For this purpose, we answer the research questions "*What is the impact on total supply chain costs for make-to-order production of working with an experienced offshore supplier prone to longer and more uncertain lead times versus a novice nearshore supplier prone to low production yield and material quality issues?*" and "*Which type of supplier leads to lower supply chain costs and hence which is more preferable?*"

This study contributes to the nearshoring and reshoring literature by providing a reshoring decision analysis related to the deterioration of location advantages, drawing on Dunning's (1988, p. 164; 1998, p. 5) framework, which posits that firms pursue reshoring when one or more advantages—ownership, location, or internalization—decline. It also relates to Williamson's (1979, p. 247) Transaction Cost Economics approach, as we examine the trade-offs between the tardiness costs of distant suppliers and the quality costs stemming from low production yields of a novice nearshore supplier. Additionally, we contribute to manufacturing literature by analyzing how external factors, such as transportation disruptions, impact make-to-order manufacturing with imperfect yields.

In the following sections, we first present the literature review, followed by methodology and problem formulation; then, we present the numerical analysis and discuss the implications of our results. We conclude the study with its limitations, conclusions, and suggestions for future research.

**Literature Review**

This research draws on and contributes to two distinct research contexts: nearshoring and reshoring, and manufacturing. In this section, we differentiate among various research approaches relevant to these areas, including empirical studies, mathematical modeling, and decision support tools, and outline our contributions to these research streams at the end.

The comprehensive systematic literature reviews by Pedroletti & Ciabuschi (2023, p. 1), Tsai and Urmetzer (2024, p. 267), and da Rocha, et al. (2025, p. 4) highlighted the need to examine the drivers and barriers of reshoring activities that were previously offshored. Tsai and Urmetzer (2024, p. 267) emphasized the importance of analyzing firm-level factors to understand their influence on selecting optimal reshoring locations, as well as developing an unbiased decision-making process for making judgments.

The focus on nearshoring increased after the pandemic, leading to recent empirical studies, including evaluations of potential suppliers and supply chain locations on a large scale (e.g., across different countries for nearshoring; van Hassel, et al., 2021, p. 6). Broader survey-based observations (Ellram, et al., 2013, p. 17) show that companies are increasingly considering supply chain performance and strategic alignment when selecting manufacturing locations. To expand this discussion, Barbieri, et al. (2019, p. 2) introduce the concept of “Relocations of Second Degree” (RSDs), which differentiate between back-reshoring to the home country (RHC) and relocating to a third country (RTC). Their empirical analysis, based on European manufacturing data, indicates that RTC is more common when the original offshoring decision was driven by efficiency factors—such as cost savings and productivity improvements. Case studies also highlight the strategic reason for combining global suppliers with local subcontractors to support customization and responsiveness (e.g., Grandinetti & Tabacco, 2015, p. 151). Recent regression studies highlight the importance of material costs and supply chain completeness in reshoring decisions during times of uncertainty (Chen, et al., 2022, p. 2069). Complementing these findings, Stentoft, Mikkelsen, and Jensen (2016, p. 190) examine offshoring and backshoring from a supply chain innovation (SCI) perspective. Their survey of Danish manufacturers shows that firms involved in reshoring tend to invest more in manufacturing innovation and reorganize their resources more extensively than those that offshore or maintain domestic production, indicating a strong link between reshoring and strategic supply chain innovation.

Despite extensive empirical research on reshoring and nearshoring, important gaps still exist. Most studies focus on strategic motives, policy incentives, and macro-level location choices, often ignoring operational complexities in make-to-order environments. The impacts of random yield and lead time, especially under penalties for underage and tardiness, are rarely studied in supplier selection. Existing models often simplify production variability or depend on inventory buffers, which are not suitable for make-to-order settings.

Decision support tools using fuzzy logic and AHP (e.g., Hilletofth, et al., 2019, p. 134; Hilletofth, et al., 2021, p. 967; Sequeira, et al., 2021, p. 504) have provided valuable frameworks for the initial screening of reshoring decisions, including high-level competitiveness criteria such as cost, quality, and time.

Existing decision support tools that utilize fuzzy logic and AHP provide valuable frameworks for high-level reshoring evaluations; however, they often lack operational depth and fail to capture the complexities of make-to-order environments. These tools typically rely on static criteria and do not consider dynamic factors such as random yield, lead time variability, or supplier experience.

Among the limited mathematical modeling studies on reshoring, Chen and Hu (2017, p. 167) rigorously analyze offshore supply dependence (OSD), showing that continued reliance on offshore suppliers can weaken the responsiveness benefits of reshoring, especially under long lead times and high adjustment costs. Yang, et al. (2021, pp. 7-9) employ a game-theoretic model to investigate how tariffs and production costs affect a multinational firm's reshoring incentives, revealing that tariff effectiveness depends on market power and competition intensity. Boute, et al. (2022, pp. 1040-1041) contribute by modeling dual sourcing with local SpeedFactories to manage demand variability under nonstationary and autocorrelated conditions. Their inventory-based model demonstrates how short lead-time local production can complement offshore sourcing by absorbing demand shocks and lowering capacity costs.

Random yield in manufacturing and procurement has long been examined for its effect on lot sizing decisions. Foundational works, such as Yano and Lee (1995, p. 313) and Grosfeld-Nir and Gerchak (2004, p. 47), offer comprehensive reviews of the early literature. Three primary mathematical modeling approaches for yield uncertainty are commonly used: stochastically proportional, interrupted geometric, and binomial. Among these, make-to-order environments with binomial production yield remain central in analyzing lot sizing decisions. Studies in this area vary widely, from multi-stage production with semi-processed product procurement and rework decisions (Barad & Braha, 1996, p. 100) to multi-product, multi-stage production with semi-finished product allocation (Talay & Ozdemir-Akyildirim, 2019, p. 537).

Binomial yield has also been examined in newsvendor-type models with fixed demand and underage risk, similar to our context (Choi, et al., 2019, p. 985). Research has extended to supply chain coordination under yield uncertainty, exploring strategies for different partners (Clemens & Inderfurth, 2015, pp. 303-306; Levi, et al., 2020, pp. 212-214). Meanwhile, production and inventory control decisions under uncertain lead times have been widely studied. Early research mainly focused on inventory policies like (R, Q) and demand during the lead time, showing that uncertainty in both demand and lead time affects production quantities and safety stock levels (Eppen & Martin, 1988, pp. 1385-1387). These dynamics influence decisions across supply chain levels, including suppliers, producers, and distributors (Cohen & Lee, 1988, p. 224).

In make-to-order settings, assuming fixed inventory policies is often inappropriate. Later research shifted toward lot sizing and lead time planning based on due dates. Even with constant lead time, random yield complicates lot sizing when batch completion overlaps (Wang & Gerchak, 2005, pp. 371-373). Other random factors, such as supply disruptions, have also been considered alongside lead time uncertainty (Hekimoglu, et al., 2018, pp. 911-916). For multi-product scenarios, lot sizes influence production schedules, with lead time comprising deterministic (e.g., setup) and random (e.g., queue time) components (Kang, et al., 2018, pp. 55-57; Rabta & Reiner, 2012, pp. 2722-2726). When multiple components are assembled, their individual lead times determine the final product’s lead time (Ould-Louly & Dolgui, 2004, pp. 370-372).

In fast-paced industries like electronics and semiconductors, both yield and lead time uncertainty are critical. Production sequencing and lot sizing must be optimized together due to setup time dependencies (Schemeleva, et al., 2012, pp. 1599-1601; Schemeleva, et al., 2013, pp. 2-4). These studies often split lead time into deterministic and random parts and suggest solution algorithms to address lot sizing and sequencing separately (Schemeleva, et al., 2018, pp. 181-182).

Although mathematical modeling has been applied to reshoring decisions, existing studies often focus on strategic or macroeconomic factors such as tariffs, market competition, and offshore supply dependence (Chen & Hu, 2017, p. 167; Yang, Ou, & Chen, 2021, pp. 7-9). While some models address dual sourcing and demand variability (Boute, et al., 2022, pp. 1040-1041), they typically rely on inventory-based responsiveness, which is unsuitable for make-to-order environments. Moreover, while random yield and lead time have been studied in lot sizing and inventory control (Yano & Lee, 1995, p. 313; Wang & Gerchak, 2005, pp. 371-373), these models rarely integrate supplier experience, production quality, and logistics disruptions into a unified framework for reshoring. The literature lacks models that explicitly capture the trade-offs between offshore reliability and nearshore uncertainty under supply risk and delivery penalties.

In response to the gaps identified in empirical studies, decision support tools, and mathematical modeling, our study offers a new operational perspective on reshoring and nearshoring decisions in make-to-order production settings. By combining supplier experience, binomial yield uncertainty, and random lead time into a unified decision-analytic framework, we go beyond strategic and inventory-based approaches to address real-world production constraints. Our model clearly illustrates the cost-quality-time trade-offs between offshore reliability and nearshore uncertainty, especially under underage and tardiness penalties. This contribution enhances existing literature by providing a contingency-based, quantitative tool for supplier selection that captures the dynamic risks and complexities of post-pandemic global sourcing. It also strengthens the theoretical foundation of reshoring decisions by including material cost, production yield, and logistics disruptions—factors that are increasingly important for companies seeking resilient and flexible supply strategies.

**Methodology**

We aim to analyze the trade-offs between costs linked to production yield and tardiness penalties caused by late order arrivals. To do this, we need to understand how decisions and parameters in the supply chain interact in a clear and concise way. Therefore, we use mathematical modeling to show the total supply chain costs resulting from the supplier choices of the customer (Tier 1 supplier) and the supplier (Tier 2 supplier). We include a diagram and a notation table below to illustrate the supply chain process we examine.

**Table 1.** Notation

| **Parameters** | |
|---|---|
| $D$ | Demand: order amount to be satisfied |
| $P$ | probability of producing a non-defective item |
| $c^{pe}$ | unit penalty cost to be incurred for each unit of non-delivered item |
| $P$ | unit price to be paid to the supplier for the product |
| $c^{p}$ | unit procurement and processing cost |
| $T$ | The processing time for one unit of input |
| $\Theta$ | $\theta \in [0,1]$, the economies of scale factor |
| $T^{w}$ | time spent on activities not related to processing |
| $c^{t}$ | the per unit per unit time tardiness penalty |
| **Decision Variables** | |
| $Q$ | Input amount for the production at the supplier |
| $Bin\ (Q, p)$ | number of non-defective items produced at the supplier, binomial random variable |

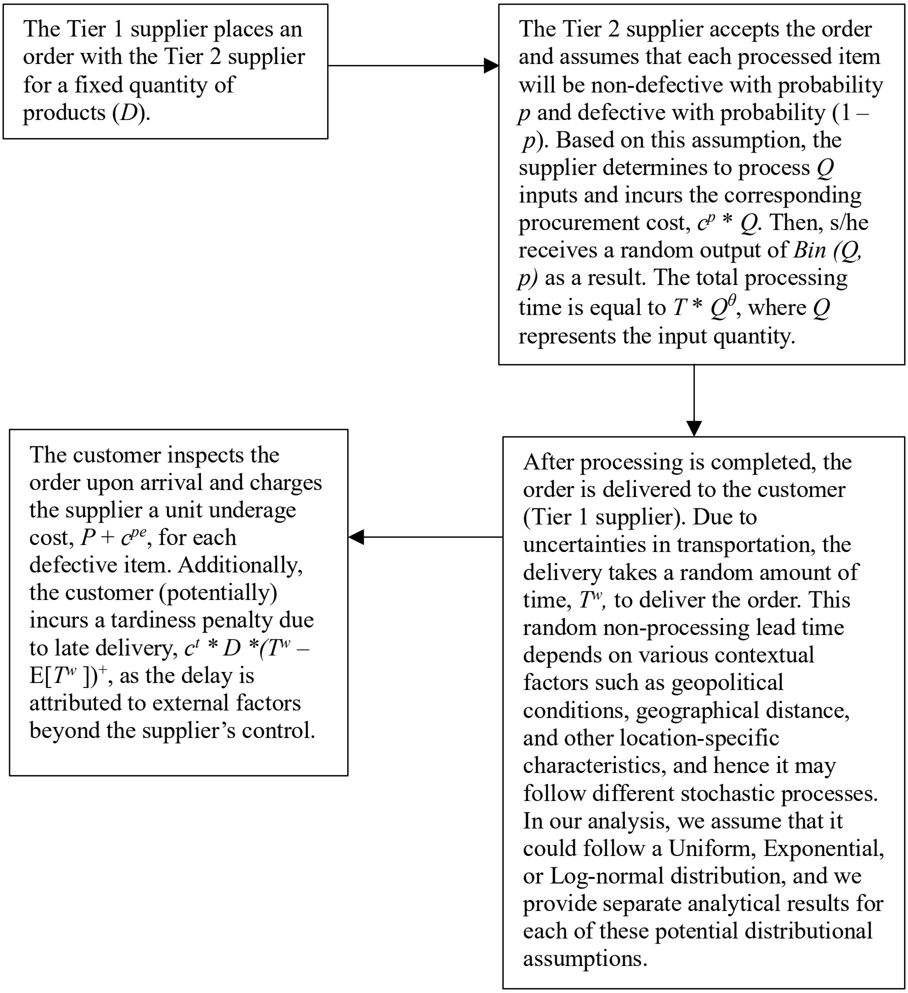


**Figure 1.** The Supply Chain Process Diagram

We begin by theoretically deriving the optimal raw material input quantity ($Q^*$) for a supplier that minimizes the sum of procurement and underage costs. This optimal input decision is then used to compare the total supply chain costs associated with different supplier types—offshore (distant ) versus nearshore. To capture uncertainty in delivery, we model the random non-processing lead time ($T^w$) using three alternative probability distributions (Uniform, Exponential, and Lognormal distributions). Based on this framework, in the following sections, we present our theoretical and numerical results regarding the nearshoring decision and analyze the sensitivity of supplier selection to key parameters, including underage costs ($P + c^{pe}$), demand levels ($D$), procurement costs ($c^p$), and tardiness penalties ($c^t$). To derive managerial insights from numerical analysis, we use a combination of generated and secondary data. The generated data on production yield and order characteristics is combined with secondary data regarding non-processing lead time, which was obtained from Searates.com (2022). These secondary data reflect lead time components linked to transportation delays and disruptions. Further details are provided in the numerical analysis section.

**Problem Formulation and Theoretical Results**

We examine how production yield and customer order lead time affect supplier selection in a supply chain. A Tier 1 supplier chooses from globally distributed Tier 2 suppliers, each offering different trade-offs. In time-sensitive systems, missing items (due to low yield) and delays (from long or variable lead times) can harm performance. Since no supplier typically excels in both, selection must weigh these risks. Yield and lead time impacts—shaped by supplier expertise and location—are key to informed decision-making, as detailed in the analysis below.

The supplier must plan for production of a single order from the customer with a fixed demand, *D*. Each input is transformed into one finished product, and, as is common to make-to-order production, all inputs will be processed as a single batch (Barad & Braha, 1996, p. 100; Grosfeld-Nir & Gerchak, 2004, p. 47; Ivănescu, et al., 2006, pp. 202-205; Sharda & Akiya, 2012, pp. 163-167; Wang & Gerchak, 2005, pp. 371-373).

The production process involves yield uncertainties. For each input, the process of obtaining a usable product follows a Bernoulli type with probability $p$. Hence, for an input amount of ($Q$), the total amount of non-defective products obtained from the batch will be a binomial random variable, $Bin\ (Q, p)$. Due to uncertain production yield, the amount of non-defective outputs obtained from a batch of ($Q$) inputs could be smaller than the input amount; therefore, the supplier should determine the production amount to be no smaller than the order amount ($Q \geq D$). Then, the expected number of missing items in an order will be $E\ [max\ (0, (D- Bin\ (Q, p)))]$. If the order amount cannot be satisfied fully, a penalty cost ($c^{pe}$) will be incurred for each unit of non-delivered item and reflected to the supplier. Thus, for each unit of non-delivered item, not only the unit price ($P$) will be forfeited, but also the penalty cost ($c^{pe}$) will be incurred. Hence, the underage cost for each non-delivered item will be ($P$+$c^{pe}$), and the expected underage penalty is given in Eq. (1):

$$(P+c^{pe}) * E\,[max\,(0, (D- Bin\,(Q, p)))]. \tag{1}$$

Without loss of generality, we normalize the salvage value to zero. For each input, a unit procurement and processing cost ($c^p$) will be incurred. We assume ($c^p \leq P$) since otherwise production would not be profitable at all. Then, the procurement and processing cost for an input amount of ($Q$) will be as given in Eq. (2):

$$c^p * Q. \tag{2}$$

Due to the global marketplace, the price the customer pays to the supplier, $P$*$D$, is assumed to be standard; hence, the supplier will be minimizing the net negative of the profit given in Eq. (3) by optimizing the input ($Q$):

$$c^p * Q + (P+c^{pe}) * E\,[max\,(0, (D- Bin\,(Q, p)))] \; - P * D. \tag{3}$$

Under these conditions, the supplier must decide on the input amount ($Q$) for a make-to-order production of a single batch.

We will first derive the optimal input amount of the supplier ($Q$*), which minimizes Eq. (3) above.

***Theorem 1***

The objective function in Eq. (3) is convex with respect to $Q$; thus, $Q$* can be found via the algorithm below.

Step 1. Set $Q = D$.

Step 2. If the corresponding inequality below (given in Eq. (4)) is satisfied, stop; otherwise set $Q = Q + 1$ and repeat Step 2.

$$\frac{c^p}{p * (P + c^{pe})} \geq P(Bin(Q, p) \leq \; D - 1). \tag{4}$$

Then, the sum of procurement and processing costs and the expected underage penalty will be as given in Eq. (5):

$$c^p * Q^* + (P + c^{pe}) * E\left[max\left(0, \left(D - Bin(Q^*, p)\right)\right)\right] \quad (5)$$
$$= c^p * Q^* + (P + c^{pe}) * \sum_{j=0}^{D} P(Bin(Q,p) = j) * (D - j).$$

Proof of Theorem 1: Provided in the Appendix.

Corollary 1: The results below follow directly from Eq. (4):

a) The optimal input amount ($Q^*$) increases as the order amount ($D$) increases.
b) The optimal input amount ($Q^*$) decreases as the unit procurement and processing cost ($c^p$) increases.
c) The optimal input amount ($Q^*$) increases as the unit price to be paid to the supplier for the product ($P$) and/or unit penalty cost to be incurred for each unit of non-delivered item ($c^{pe}$) increases.

The tardiness penalty depends on the customer order lead time and the agreed deadline for the order. Customer order lead time involves time spent on activities solely devoted to processing the inputs and activities not related to input processing, such as setup, equipment repairs, and shipment. Due to standardization and automation, the processing time for one unit of input, $T$, is assumed to be deterministic, and for a batch of $Q$, the total processing time is assumed to be $Q^\theta * T$, where $\theta \in [0,1]$ is the economies of scale factor (Cakanyildirim, Bookbinder, & Gerchak, 2000, p. 218). The time spent on activities not related to processing is assumed to be random ($T^w$) and not affected by the input decision, as these activities include shipment and breakdowns. Agreed deadline is taken as the expected total lead time to complete the order, $Q^\theta * T + E[T^w]$. Then, the expected tardiness of the order will be $E\,[T^w - E[T^w]]^+$. The late arrival of the order will cause a lack of the whole order during the period of tardiness; hence, the per unit per unit time tardiness penalty ($c^t$) needs to be multiplied by the order amount ($D$) to determine the expected tardiness penalty for the order, which is given in Eq. (6):

$c^t * D * E\,[T^w - \mathrm{E}[T^w]]^+.$ (6)

We now characterize the closed-form expression for tardiness penalty based on Eq. (6) for the three most frequently used practical lead time distributions: Uniform, Exponential, and Lognormal (Baker & Trietsch, 2013, pp. 200, 274, 323).

***Theorem 2***

The expected tardiness penalty in Eq. (6) could be expressed as in Eq. (7):

$$c^t * D * \int_{E[T^w]}^{\infty} F(y)dy, \quad (7)$$

which is further expressed as below for Uniform, Exponential, and Lognormally distributed $T^w$:

a) For $T^w$ ~Uniform ($A$, $B$), the expected tardiness penalty: $c^t * D * \frac{B-A}{8}$,

b) For $T^w$ ~Exponential ($\lambda$), the expected tardiness penalty: $c^t * D * \frac{1}{\lambda * e}$,

c) For $T^w$ ~Lognormal ($\mu$, $\sigma$), such that $T^w = e^{\mu+\sigma * Z}$ with $Z$~Normal (0, 1), the expected tardiness penalty: $c^t * D * \left\{e^{\mu+\frac{\sigma^2}{2}}\left[\Phi\left(\frac{\sigma}{2}\right) - \Phi\left(\frac{-\sigma}{2}\right)\right]\right\}$, where $\Phi$ represents the cumulative distribution for the standard normal.

Proof of Theorem 2: Provided in the Appendix.

Corollary 2: The expected tardiness penalty responds to the related parameters as follows:

a) For $T^w$ ~Uniform ($A$, $B$), the expected tardiness penalty increases as the range of $T^w$, ($B$-$A$), increases.

b) For $T^w$ ~Exponential ($\lambda$), the expected tardiness penalty increases as the mean value of $T^w$, $1/\lambda$, increases.

c) For $T^w$ ~Lognormal ($\mu$, $\sigma$), the expected tardiness penalty increases as $\mu$ and/or $\sigma$ increase.

The customer, as the Tier 1 supplier, selects the supplier and bears the tardiness penalty. Assuming all parameters are known, the customer is accountable to an OEM or retailer and must prioritize both quality and timely delivery. Therefore, the customer aims to minimize total supply chain costs. Based on this, the cost formulation is given in Eq. (8) and reflects the impact of production yield and lead time:

$$c^p * Q^* + (P + c^{pe}) * E\,[max\,(0, (D\text{-}\ Bin\,(Q^*, p)))] + c^t *D*E\,[T^w\text{-}\ \mathrm{E}[T^w]]^+. \qquad (8)$$

Total supply chain costs depend on supplier selection and the supplier's optimal input quantity ($Q$*). We aim to isolate the effects of yield and lead time, as suppliers offer different trade-offs. A supplier may have a high yield but a longer, variable lead time, increasing tardiness costs, and customers may need to choose between a distant, experienced supplier and a nearby, less experienced one with faster delivery but lower yield.

**Numerical Analysis**

Using the analytical results above, we construct a parameter set to evaluate how production yield ($p$) and customer order lead time ($T^w$) affect total supply chain costs. The goal is to identify which factor has a greater impact under varying conditions, offering insights into supplier selection amid trade-offs in expertise and location. The parameter set follows a $2^k$ factorial design (Law, 2017, pp. 551-556), considering: underage cost ($P$+ $c^{pe}$), order amount ($D$), production yield ($p$), procurement and processing cost ($c^p$), tardiness penalty ($c^t$), and the distribution of ($T^w$). For ($T^w$), we use: range ($B$–$A$) for Uniform, mean ($1/\lambda$) for Exponential, and mean ($e^{\mu+\frac{\sigma^2}{2}}$) for Lognormal. As shown in *Corollary 2*, expected tardiness penalties—and thus total costs—are monotonic with respect to these distribution measures.

The impact of suppliers' yield on total supply chain costs, and its comparison to lead time variability and tardiness penalties, is not analytically tractable, as outcomes vary by scenario. When a Tier 1 customer must choose between a high-yield but distant supplier with uncertain lead times and a nearby, less experienced supplier with lower yield but faster delivery, theory alone cannot capture the trade-offs. Numerical analysis is therefore essential to evaluate and illustrate these dynamics.

To address this need, a $2^k$ factorial design is constructed using low/(–) and high/(+) values for each factor, as shown in Table 2. The underage cost ($P$ + $c^{pe}$) is capped at 100, a level unlikely to justify air freight, making sea shipment and its longer delivery times more realistic for distant suppliers. High order amounts ($D$) imply large volumes, further supporting sea shipment. Procurement and processing costs, along with tardiness penalties, are expressed as percentages of the underage cost to avoid unrealistic combinations. Distribution parameters are selected to reflect differences in shipment and breakdown times between suppliers located on the same versus different continents relative to the customer (Searates.com, 2022).

**Table 2.** Coding Chart and the Values for the Factors

| Factor | (-) | (+) |
|---|---|---|
| Underage cost: $P + c^{pe}$ | 10 | 100 |
| Order amount: $D$ | 100 | 1000 |
| Procurement and processing cost: $c^p$ | 10% of ($P + c^{pe}$) | 50% of ($P + c^{pe}$) |
| Tardiness penalty: $c^t$ | 10% of ($P + c^{pe}$) | 80% of ($P + c^{pe}$) |
| Probability to produce non-defective items: $p$ | 0.6 | 0.95 |
| Lead time distribution (for activities not related to processing): $T^w$ ~Uniform (A, B) | (A, B) = (4, 10), Mean = $\frac{A+B}{2}$=7 Range = B - A = 6 | (A, B) = (20, 60), Mean = $\frac{A+B}{2}$=40 Range = B - A = 40 |
| Lead time distribution (for activities not related to processing): $T^w$ ~Exponential (λ) | Mean = (1/$\lambda$) = 7 | Mean = (1/$\lambda$) = 40 |
| Lead time distribution (for activities not related to processing): $T^w$ ~Lognormal ($\mu$, $\sigma$) | ($\mu$, $\sigma$) = (1, 1.375), Mean = $e^{\mu+\frac{\sigma^2}{2}} \cong 7$ | ($\mu$, $\sigma$) = (3, 1.175), Mean = $e^{\mu+\frac{\sigma^2}{2}} \cong 40$ |

While input processing time may be fixed due to equipment and labor standards, breakdowns and shipment times are externally driven and harder to estimate. A Uniform distribution can initially model this uncertainty (Baker & Trietsch, 2013, p. 200). As more data becomes available, exponential or lognormal distributions can better capture variability and improve supply chain decision-making.

We take the total expected supply chain costs derived in the 'Problem Formulation and Theoretical Results' section that were given in Eq. (8) (and repeated below for ease of reference) as the response to the factor combinations listed in Table 2 above.

$$c^p * Q^* + (P+c^{pe}) * E\,[max\,(0, (D\text{-}\,Bin\,(Q^*, p)))] + c^t *D*E\,[T^w\text{-}\,\mathrm{E}[T^w]]^{+}. \quad (8)$$

Our goal is to assess the impact of production yield ($p$) and lead time ($T^w$) across different combinations of underage cost ($P + c^{pe}$), tardiness penalties ($c^t$), order amount

($D$), and procurement cost ($c^p$), to inform supplier selection. Table 3 presents total expected supply chain costs and optimal input ($Q^*$) for various factor combinations and $T^w$ distributions. Table 4 shows the average effect of increasing $p$ and $T^w$. Changes in $c^p$ affect $Q^*$, influencing procurement and underage penalties, while $c^t$ does not affect $Q^*$. Thus, when $c^p$, ($P + c^{pe}$), and $D$ are constant, changes in $c^t$ do not alter the average effect of increasing $p$. Similarly, when $c^t$, ($P + c^{pe}$), and $D$ are constant, changes in $c^p$ do not alter the average effect of increasing $T^w$. Therefore, Table 4 reports only combinations where $c^p$ and $c^t$ move in the same direction, allowing clearer interpretation of $p$ and $T^w$'s effects.

Table 4 reveals a cut-off point in factor combinations, (($P + c^{pe}$), ($D$), and ($c^p$)) or (($P + c^{pe}$), ($D$), and ($c^t$)), where the impact of increasing production yield ($p$) or non-processing lead time ($T^w$) diminishes. This occurs when at least two of the three factors are at their low levels. Our analysis suggests that when two or more factors are high, supplier selection should account for both $p$ and $T^w$ effects. Using mean $T^w$ values of 7 (low) and 40 (high), we observed significant cost differences. To explore this further, Table 5 presents results where $T^w$'s high value presents a high level of dynamics. We test $T^w$ ~Uniform (10, 20), (10, 30), (10, 40), (10, 50), (10, 60); $T^w$ ~Exponential with $1/\lambda \in \{15, 20, 25, 30, 35\}$; and $T^w$ ~Lognormal with $(\mu, \sigma) \in \{(2.015, 1.175), (2.31, 1.175), (2.53, 1.175), (2.71, 1.175), (2.87, 1.175)\}$. These tests are applied only to combinations where at least two factors are high, ensuring that changes in $p$ and $T^w$ significantly affect total supply chain costs. The next section discusses the resulting insights and managerial implications.

**Table 3.** Total Expected Supply Chain Costs and the Optimal Input Amount ($Q^*$) With Respect to Different Factor Combinations and Distribution Assumptions for ($T^w$)*

| | | | | | | | | Response (R): Total Expected Supply Chain Cost (from Eq. (8)) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Factor Combination (design point)** | $P + c^{pe}$ | $D$ | $c^p$ | $c^t$ | $p$ | $T^w$ | $Q^*$ | $T^w$ ~*Uniform (A, B)* | $T^w$ ~*Exponential (λ)* | $T^w$ ~*Lognormal (μ, σ)* |
| 1.1 | + | + | + | + | + | + | 1052 | 452,912.0693 | 1,230,126.2811 | 1,472,968.1760 |
| 1.2 | + | + | + | + | + | - | 1052 | 112,912.0693 | 258,924.5564 | 337,352.1108 |
| 1.3 | + | + | + | + | - | + | 1666 | 484,117.7316 | 1,261,331.9434 | 1,504,173.8383 |
| 1.4 | + | + | + | + | - | - | 1666 | 144,117.7316 | 290,130.2187 | 368,557.7731 |
| 2.1 | + | + | + | - | + | + | 1052 | 102,912.0693 | 200,063.8458 | 230,419.0827 |
| 2.2 | + | + | + | - | + | - | 1052 | 60,412.0693 | 78,663.6302 | 88,467.0745 |
| 2.3 | + | + | + | - | - | + | 1666 | 134,117.7316 | 231,269.5081 | 261,624.7450 |
| 2.4 | + | + | + | - | - | - | 1666 | 91,617.7316 | 109,869.2925 | 119,672.7368 |
| 3.1 | + | + | - | + | + | + | 1062 | 410,658.8460 | 1,187,873.0578 | 1,430,714.9527 |
| 3.2 | + | + | - | + | + | - | 1062 | 70,658.8460 | 216,671.3331 | 295,098.8875 |
| 3.3 | + | + | - | + | - | + | 1710 | 417,196.1961 | 1,194,410.4078 | 1,437,252.3027 |
| 3.4 | + | + | - | + | - | - | 1710 | 77,196.1961 | 223,208.6831 | 301,636.2375 |
| 4.1 | + | + | - | - | + | + | 1062 | 60,658.8460 | 157,810.6225 | 188,165.8594 |
| 4.2 | + | + | - | - | + | - | 1062 | 18,158.8460 | 36,410.4069 | 46,213.8512 |
| 4.3 | + | + | - | - | - | + | 1710 | 67,196.1961 | 164,347.9725 | 194,703.2094 |
| 4.4 | + | + | - | - | - | - | 1710 | 24,696.1961 | 42,947.7570 | 52,751.2013 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 5.1 | + | - | + | + | + | + | 105 | 45,350.0494 | 123,071.4706 | 147,355.6601 |
| 5.2 | + | - | + | + | + | - | 105 | 11,350.0494 | 25,951.2981 | 33,794.0536 |
| 5.3 | + | - | + | + | - | + | 166 | 48,571.8293 | 126,293.2504 | 150,577.4399 |
| 5.4 | + | - | + | + | - | - | 166 | 14,571.8293 | 29,173.0780 | 37,015.8334 |
| 6.1 | + | - | + | - | + | + | 105 | 10,350.0494 | 20,065.2271 | 23,100.7507 |
| 6.2 | + | - | + | - | + | - | 105 | 6,100.0494 | 7,925.2055 | 8,905.5499 |
| 6.3 | + | - | + | - | - | + | 166 | 13,571.8293 | 23,287.0069 | 26,322.5306 |
| 6.4 | + | - | + | - | - | - | 166 | 9,321.8293 | 11,146.9853 | 12,127.3298 |
| 7.1 | + | - | - | + | + | + | 108 | 41,096.8045 | 118,818.2257 | 143,102.4151 |
| 7.2 | + | - | - | + | + | - | 108 | 7,096.8045 | 21,698.0532 | 29,540.8086 |
| 7.3 | + | - | - | + | - | + | 180 | 41,836.0978 | 119,557.5190 | 143,841.7085 |
| 7.4 | + | - | - | + | - | - | 180 | 7,836.0978 | 22,437.3465 | 30,280.1019 |
| 8.1 | + | - | - | - | + | + | 108 | 6,096.8045 | 15,811.9821 | 18,847.5058 |
| 8.2 | + | - | - | - | + | - | 108 | 1,846.8045 | 3,671.9606 | 4,652.3050 |
| 8.3 | + | - | - | - | - | + | 180 | 6,836.0978 | 16,551.2754 | 19,586.7991 |
| 8.4 | + | - | - | - | - | - | 180 | 2,586.0978 | 4,411.2539 | 5,391.5983 |
| 9.1 | - | + | + | + | + | + | 1052 | 45,291.2069 | 123,012.6281 | 147,296.8176 |
| 9.2 | - | + | + | + | + | - | 1052 | 11,291.2069 | 25,892.4556 | 33,735.2111 |
| 9.3 | - | + | + | + | - | + | 1666 | 48,411.7732 | 126,133.1943 | 150,417.3838 |
| 9.4 | - | + | + | + | - | - | 1666 | 14,411.7732 | 29,013.0219 | 36,855.7773 |
| 10.1 | - | + | + | - | + | + | 1052 | 10,291.2069 | 20,006.3846 | 23,041.9083 |
| 10.2 | - | + | + | - | + | - | 1052 | 6,041.2069 | 7,866.3630 | 8,846.7075 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 10.3 | - | + | + | - | - | + | 1666 | 13,411.7732 | 23,126.9508 | 26,162.4745 |
| 10.4 | - | + | + | - | - | - | 1666 | 9,161.7732 | 10,986.9293 | 11,967.2737 |
| 11.1 | - | + | - | + | + | + | 1062 | 41,065.8846 | 118,787.3058 | 143,071.4953 |
| 11.2 | - | + | - | + | + | - | 1062 | 7,065.8846 | 21,667.1333 | 29,509.8887 |
| 11.3 | - | + | - | + | - | + | 1710 | 41,719.6196 | 119,441.0408 | 143,725.2303 |
| 11.4 | - | + | - | + | - | - | 1710 | 7,719.6196 | 22,320.8683 | 30,163.6238 |
| 12.1 | - | + | - | - | + | + | 1062 | 6,065.8846 | 15,781.0622 | 18,816.5859 |
| 12.2 | - | + | - | - | + | - | 1062 | 1,815.8846 | 3,641.0407 | 4,621.3851 |
| 12.3 | - | + | - | - | - | + | 1710 | 6,719.6196 | 16,434.7973 | 19,470.3209 |
| 12.4 | - | + | - | - | - | - | 1710 | 2,469.6196 | 4,294.7757 | 5,275.1201 |
| 13.1 | - | - | + | + | + | + | 105 | 4,535.0049 | 12,307.1471 | 14,735.5660 |
| 13.2 | - | - | + | + | + | - | 105 | 1,135.0049 | 2,595.1298 | 3,379.4054 |
| 13.3 | - | - | + | + | - | + | 166 | 4,857.1829 | 12,629.3250 | 15,057.7440 |
| 13.4 | - | - | + | + | - | - | 166 | 1,457.1829 | 2,917.3078 | 3,701.5833 |
| 14.1 | - | - | + | - | + | + | 105 | 1,035.0049 | 2,006.5227 | 2,310.0751 |
| 14.2 | - | - | + | - | + | - | 105 | 610.0049 | 792.5205 | 890.5550 |
| 14.3 | - | - | + | - | - | + | 166 | 1,357.1829 | 2,328.7007 | 2,632.2531 |
| 14.4 | - | - | + | - | - | - | 166 | 932.1829 | 1,114.6985 | 1,212.7330 |
| 15.1 | - | - | - | + | + | + | 108 | 4,109.6804 | 11,881.8226 | 14,310.2415 |
| 15.2 | - | - | - | + | + | - | 108 | 709.6804 | 2,169.8053 | 2,954.0809 |
| 15.3 | - | - | - | + | - | + | 180 | 4,183.6098 | 11,955.7519 | 14,384.1708 |
| 15.4 | - | - | - | + | - | - | 180 | 783.6098 | 2,243.7346 | 3,028.0102 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 16.1 | - | - | - | - | + | + | 108 | 609.6804 | 1,581.1982 | 1,884.7506 |
| 16.2 | - | - | - | - | + | - | 108 | 184.6804 | 367.1961 | 465.2305 |
| 16.3 | - | - | - | - | - | + | 180 | 683.6098 | 1,655.1275 | 1,958.6799 |
| 16.4 | - | - | - | - | - | - | 180 | 258.6098 | 441.1254 | 539.1598 |

**Table 4.** Average Effect of Increasing the Two Factors ($p$ and $T^w$)

| **Factor Combinations** | | | | | **$T^w$ ~Uniform ($A$, $B$)** | **$T^w$ ~Exponential ($\lambda$)** | **$T^w$ ~Lognormal ($\mu$, $\sigma$)** |
|---|---|---|---|---|---|---|---|
| ***$P + c^{pe}$*** | ***$D$*** | ***$c^p$*** | ***$c^t$*** | **Effect of increasing *p* =[R(i.1)+R(i.2)-R(i.3)-R(i.4)]/4** | **Effect of increasing *B-A* =[R(i.1)+R(i.3)-R(i.2)-R(i.4)]/4** | **Effect of increasing *(1/λ)* =[R(i.1)+R(i.3)-R(i.2)-R(i.4)]/4** | **Effect of increasing Mean ($e^{(\mu+\sigma^2/2)}$) =[R(i.1)+R(i.3)-R(i.2)-R(i.4)]/4** |
| + | + | + | + | -15,602.83 | 170,000.00 | 485,600.86 | 567,808.03 |
| + | + | - | - | -3,268.68 | 21,250.00 | 60,700.11 | 70,976.00 |
| + | - | + | + | -1,610.89 | 17,000.00 | .48,560.09 | 56,780.80 |
| - | + | + | + | -1,560.28 | 17,000.00 | 48,560.09 | 56,780.80 |
| + | - | - | - | -369.65 | 2,125.00 | 6,070.01 | 7,097.60 |
| - | + | - | - | -326.87 | 2,125.00 | 6,070.01 | 7,097.60 |
| - | - | + | + | -161.09 | 1,700.00 | 4,856.01 | 5,678.08 |
| - | - | - | - | -36.96 | 212.50 | 607.00 | 709.76 |

**Table 5.** The Effect of Increasing ($T^w$) with Different 'High'/(+) Values for ($T^w$)

| | | | | | **Effect of increasing (*B*-*A*) with different 'high'/(+) values** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Factor Combinations** | | | | **$T^w$ ~Uniform (*A*, *B*)** | **(*B*-*A*) 'high'/(+) values** | | | | |
| **$P + c^{pe}$** | ***D*** | **$c^p$** | **$c^t$** | **Effect of increasing *p*** | **10** | **20** | **30** | **40** | **50** |
| 100/(+) | 1000/(+) | 50(+) | 80/(+) | -15,602.83 | 20,000 | 70,000 | 120,000 | 170,000 | 220,000 |
| 100/(+) | 1000/(+) | 10/(-) | 10/(-) | -3,268.68 | 2,500 | 8,750 | 15,000 | 21,250 | 27,500 |
| 100/(+) | 100/(-) | 50/(+) | 80/(+) | -1,610.89 | 2,000 | 7,000 | 12,000 | 17,000 | 22,000 |
| 10/(-) | 1000/(+) | 5/(+) | 8/(+) | -1,560.28 | 2,000 | 7,000 | 12,000 | 17,000 | 22,000 |

| | | | | | **Effect of increasing *(1/λ)*** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Factor Combinations** | | | | **$T^w$ ~Exp (*λ*)** | **(1/*λ*) 'high'/(+) values** | | | | | |
| **$P + c^{pe}$** | ***D*** | **$c^p$** | **$c^t$** | **Effect of increasing *p*** | **15** | **20** | **25** | **30** | **35** | **40** |
| 100/(+) | 1000/(+) | 50(+) | 80/(+) | -15,602.83 | 117,721.42 | 191,297.31 | 264,873.20 | 338,449.09 | 412,024.97 | 485,600.86 |
| 100/(+) | 1000/(+) | 10/(-) | 10/(-) | -3,268.68 | 14,715.18 | 23,912.16 | 33,109.15 | 42,306.14 | 51,503.12 | 60,700.11 |
| 100/(+) | 100/(-) | 50/(+) | 80/(+) | -1,610.89 | 11,772.14 | 19,129.73 | 26,487.32 | 33,844.91 | 41,202.50 | 48,560.09 |
| 10/(-) | 1000/(+) | 5/(+) | 8/(+) | -1,560.28 | 11,772.14 | 19,129.73 | 26,487.32 | 33,844.91 | 41,202.50 | 48,560.09 |

| | | | | | Effect of increasing Mean ($e^{(\mu+\sigma^2/2)}$) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Factor Combinations** | | | | **$T^w$ ~Lognormal (μ, σ)** | **Mean ($e^{(\mu+\sigma^2/2)}$) 'high'/(+) values** | | | | | |
| **$P + c^{pe}$** | **$D$** | **$c^p$** | **$c^t$** | **Effect of increasing $p$** | **15, (μ, σ) = (2.015, 1.175)** | **20, (μ, σ) = (2.31, 1.175)** | **25, (μ, σ) = (2.53, 1.175)** | **30, (μ, σ) = (2.71, 1.175)** | **35, (μ, σ) = (2.87, 1.175)** | **40, (μ, σ) = (3, 1.175)** |
| 100/(+) | 1000/(+) | 50(+) | 80/(+) | -15,602.83 | 122,932.31 | 213,913.06 | 301,549.12 | 389,068.10 | 481,252.37 | 567,808.03 |
| 100/(+) | 1000/(+) | 10/(-) | 10/(-) | -3,268.68 | 15,366.54 | 26,739.13 | 37,693.64 | 48,633.51 | 60,156.55 | 70,976.00 |
| 100/(+) | 100/(-) | 50/(+) | 80/(+) | -1,610.89 | 12,293.23 | 21,391.31 | 30,154.91 | 38,906.81 | 48,125.24 | 56,780.80 |
| 10/(-) | 1000/(+) | 5/(+) | 8/(+) | -1,560.28 | 12,293.23 | 21,391.31 | 30,154.91 | 38,906.81 | 48,125.24 | 56,780.80 |

Observing from Tables 3-5 that non-processing lead time has a greater impact on total supply chain costs than production yield, we explore its influence on reshoring decisions. Specifically, we assess whether Tier 1 suppliers might prefer nearshoring, choosing a novice nearshore Tier 2 supplier with lower yield over an experienced offshore supplier with higher yield ($p$ = 0.95). The offshore supplier's geographic disadvantage is modeled using the highest mean non-processing lead times tested: $B-A$ = 50 (uniform), $1/\lambda = 40$ (exponential), and $\mu = 3$, $\sigma = 1.175$ (log-normal), each yielding a mean lead time ≥ 40. This trade-off highlights how lead time considerations may outweigh quality advantages in supplier selection.

We represent novice nearshore Tier 2 suppliers with production yields ranging from 0.9 to 0.5 and varying non-processing lead times. For Uniform distributions, *Non-processing Leadtime* ranges are {40, 30, 20, 10}, while Exponential and Log-normal distributions assume mean lead times of {35, 30, 25, 20}. These parameters align with Table 5, where the experienced offshore Tier 2 supplier corresponds to the highest mean lead time values listed.

To assess the preferability of a less experienced nearshore supplier over an experienced offshore one, we consider two contrasting scenarios. The most favorable for the offshore supplier involves high-value, large-quantity orders where production yield outweighs lead time concerns: underage cost ($P+c^{pe}$) is 1,000, demand ($D$) is 1,000 units, procurement cost ($c^p$) is 50% of underage cost, and tardiness penalty ($c^t$) is 20%. The least favorable scenario reflects high lead time sensitivity: underage cost is 100, demand is 100 units, procurement cost is 20%, and tardiness penalty is 80%. These scenarios help illustrate how supplier preference shifts under different cost and risk conditions, highlighting the importance of balancing yield efficiency with lead time reliability.

We now present the total supply chain Cost Comparison and Supplier Preference graphs under the assumption of a Uniform *Non-processing Leadtime* distribution. A discussion of the insights gained from these results will follow in the next section.

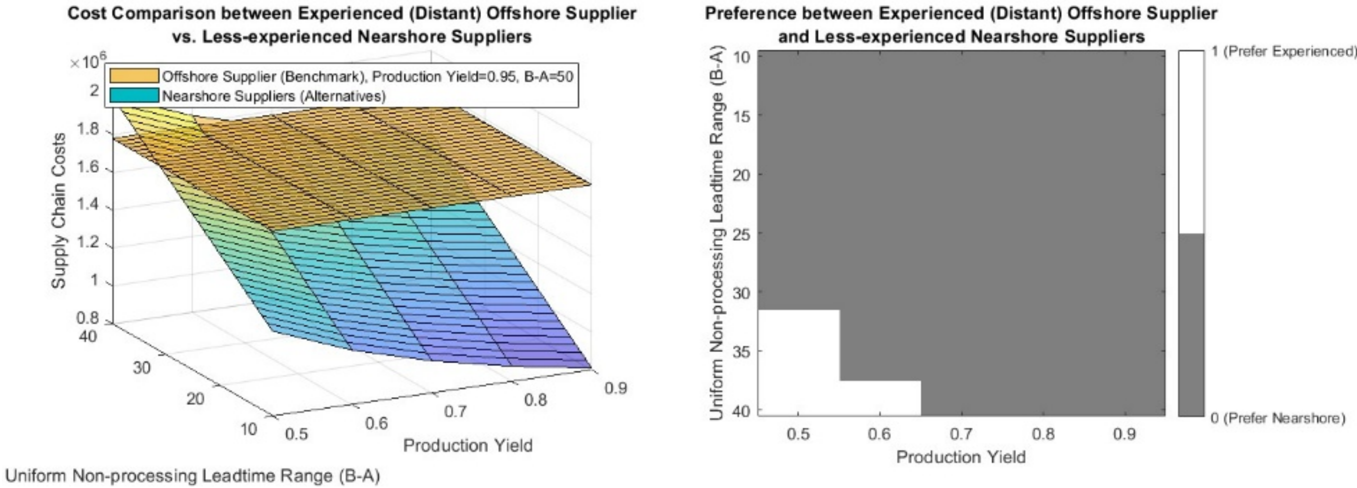


**Figure 2a.** Cost comparison and preference map between Experienced (Distant) Offshore Supplier and Less-Experienced Nearshore Supplier (with Lower Production Yield), for Uniform non-processing Leadtime and Most Favourable Scenario for the Experienced Offshore Supplier ($p$=0.95, $B$-$A$=50): Underage cost ($P+c^{pe}$) = 1,000, Demand ($D$) = 1,000, Procurement cost ($c^p$) = 50% of the underage cost, and the tardiness penalty ($c^t$) = 20% of the underage cost.

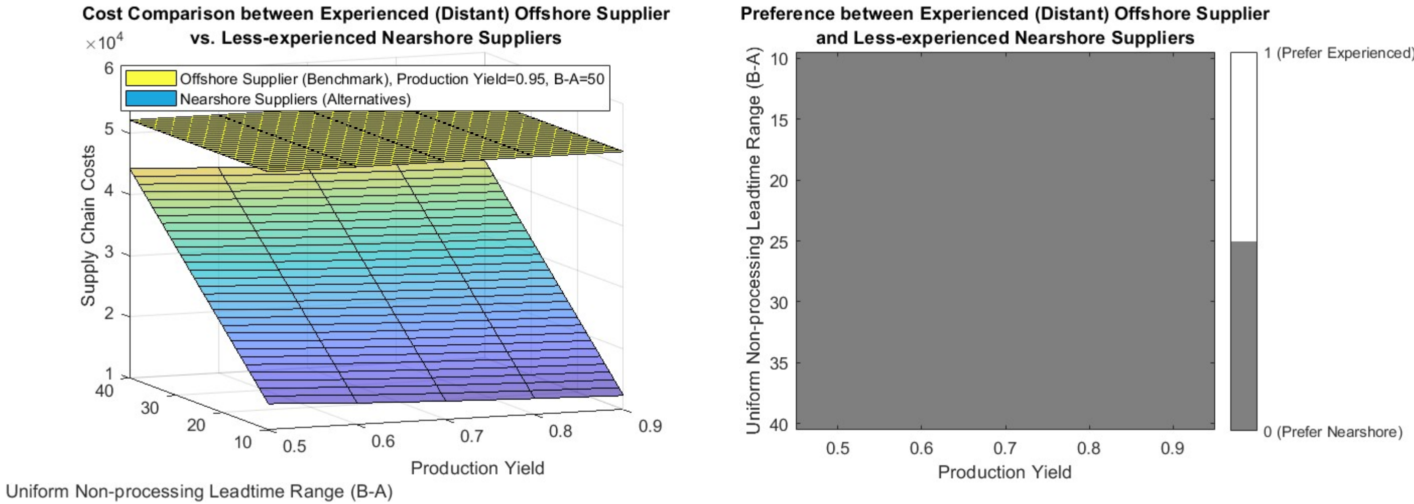


**Figure 2b.** Cost comparison and preference map between Experienced (Distant) Offshore Supplier and Less-Experienced Nearshore Supplier (with Lower Production Yield), for Uniform non-processing Leadtime and Least Favourable Scenario for the Experienced Offshore Supplier ($p$=0.95, $B$-$A$=50): Underage cost ($P+c^{pe}$) = 100, Demand ($D$) = 100, Procurement cost ($c^p$) = 20% of the underage cost, and the tardiness penalty ($c^t$) = 80% of the underage cost.

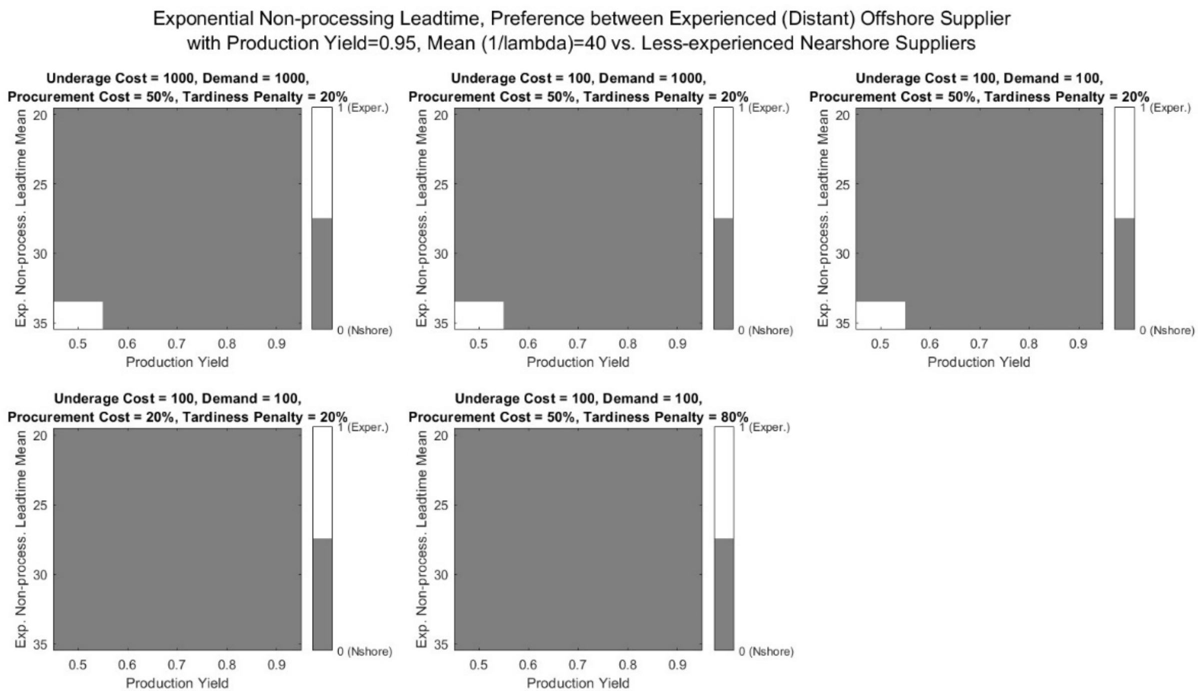


**Figure 3.** Preference map between Experienced (Distant) Offshore Supplier and Less-Experienced Nearshore Supplier (with Lower Production Yield), for Exponential non-processing Leadtime ($p$=0.95, $1/\lambda$=40): Underage cost ($P+c^{pe}$) = {100, 1000} Demand ($D$) = {100, 1000} Procurement cost ($c^p$) = {20%, 50%} of the underage cost, and the tardiness penalty ($c^t$) = {20%, 80%} of the underage cost.

As shown in Figures 2a and 2b, even when the nearshore supplier's production yield is as low as 0.5, the offshore supplier is rarely preferred. Nearshoring becomes dominant when the underage cost, order size, and procurement cost are low, and the tardiness penalty is high. We now examine how changes in these parameters affect nearshoring preference under exponential lead time assumptions. Specifically, we analyze scenarios with underage cost values of 100 and 1000, order size of 1000, procurement cost at 50% of underage cost, and tardiness penalty at 20%. We then vary the order size to 100, procurement cost to 20%, and tardiness penalty to 80%. These variations help us evaluate how multiple parameter shifts influence supplier selection.

Lower procurement costs make the nearshore supplier more attractive by reducing material expenses, while higher tardiness penalties discourage selecting the offshore supplier. In both cases, nearshoring becomes the preferred strategy. These findings highlight the combined impact of cost structure and delivery reliability on supplier choice, particularly in time-sensitive supply chains. We examine these dynamics further in the following section.

**Discussion**

This study was motivated by the growing complexity of global supply chains, especially considering the disruptions after Brexit and changing dynamics between offshore and nearshore manufacturing. Offshore suppliers, especially in distant regions like China, have traditionally been preferred for their high production yields and material quality. However, recent logistical challenges have led firms to reevaluate these benefits. Our research investigates how declining location-based advantages affect reshoring decisions by comparing an experienced offshore supplier with longer, uncertain lead times to a new nearshore supplier with lower yields.

We contribute to the reshoring literature by analyzing the cost implications of this trade-off, showing how external disruptions and internal performance factors jointly influence sourcing strategies. Our findings reveal that higher production yield decreases supply chain costs by reducing missing items and improving flow. Conversely, increases in the average or range of customer order lead times significantly raise costs due to delayed deliveries. This effect is more pronounced in time-sensitive supply chains.

Ultimately, our model highlights the importance of lead time reliability in supplier selection. It also suggests that when nearshoring is preferred, customers should support supplier efforts to improve production yield, especially when alternatives like air freight are not economically viable.

***Main Finding 1***

Our analysis shows that in time-sensitive supply chains, increasing the mean non-processing-related lead time has a more substantial impact on total costs than improving production yield. Even when the nearshore supplier's yield is as low as 0.5, the offshore supplier is rarely preferred (Figures 2a and 2b), indicating that delayed deliveries pose greater risks than lower production efficiency. When underage costs, order sizes, and procurement costs are low, and tardiness penalties are high, nearshoring becomes the dominant strategy, emphasizing the importance of lead time reliability.

Non-processing-related lead time includes shipment time, which is subject to fluctuations. These fluctuations can increase supply chain costs by up to 36 times more than the cost savings from higher yield (Table 4, factor combination (+, +, +, +), $T^w$ ~Lognormal). This is because lead time parameters affect costs linearly, while yield impacts costs through its probability distribution. Additionally, tardiness affects the entire order, whereas missing items due to imperfect yield affect costs individually. Thus, nearshoring is preferable as product time sensitivity increases.

Given the significant impact of longer lead times, especially from distant suppliers or disrupted routes, alternative shipment methods, such as air freight, could be considered to reduce customer order lead times. If airfare is not viable, nearshoring becomes a more attractive option. In such cases, customers should support nearshore suppliers in improving production yield to enhance overall supply chain performance.

***Main Finding 2***

The impact of increasing production yield ($p$) is significantly amplified when at least two of the following, underage cost, order size, and procurement cost, are high. Similarly, the effect of increasing the mean or range of non-processing-related lead time ($T^w$) grows when underage cost, order size, or tardiness penalty is elevated. Our findings show that lower procurement costs make nearshore suppliers more attractive by reducing material expenses, while higher tardiness penalties discourage offshore sourcing. In both cases, nearshoring becomes the dominant strategy under high-cost or high-risk conditions. These results highlight how supplier preference is highly sensitive to cost structure and lead time reliability, reinforcing the importance of evaluating both operational and locational factors in sourcing decisions.

The optimal input amount ($Q^*$), which determines procurement cost and expected underage penalty, depends on underage cost, order size, and procurement cost ($P + c^{pe}$), ($D$), and ($c^p$). Our numerical analysis shows that when at least two of these factors are high, increases in production yield ($p$) lead to greater cost reductions, making supplier improvements more impactful. Tardiness penalty, influenced by ($D$), ($c^t$), and lead time ($T^w$), is not directly affected by ($P + c^{pe}$), but the overall cost level amplifies the effect of changing ($T^w$). Supplier selection becomes more critical when at least two of the three factors (($P + c^{pe}$), ($D$), and ($c^t$)) are high. Table 5 shows that even modest increases in $T^w$ under these conditions significantly affect supply chain costs. Therefore, in high-cost or high-risk settings, customer order lead time should be a key consideration in supplier selection. These findings highlight the importance of evaluating both production yield and lead time variability, especially when cost parameters are elevated, to make informed sourcing decisions.

***Main Finding 3***

Accurately estimating customer order lead time—including shipment time and variability—is essential for calculating total supply chain costs in supplier selection. Using basic distribution assumptions can lead to significant cost underestimation. Our findings show that changes in procurement cost and tardiness penalty, expressed as percentages of underage cost, more strongly influence nearshoring preference than changes in underage cost or demand. This highlights the importance for Tier 1 suppliers to set optimal contractual terms with both upstream suppliers and downstream customers, as these parameters can quickly shift sourcing strategies and impact overall supply chain performance.

Tables 4 and 5 show that increasing ($T^w$) under different distribution assumptions leads to substantial cost differences. Uniform distribution, often used as a basic approximation, can underestimate lead time effects by up to one-third compared to lognormal (Table 4 and 5, factor combination (+, +, +, +)). Lognormal assumptions reveal more pronounced impacts. Figures 2a, 2b, and 3 show that nearshore suppliers are preferred more under exponential than uniform distributions. Nearshoring becomes dominant faster when procurement costs decrease or tardiness penalties increase (Figure 3). These findings emphasize the importance of accurately estimating customer order lead time parameters, particularly the mean and variance of non-processing-related lead time, to prevent underestimating supply chain costs.

We believe the pandemic situation made supply chains much more fragile and sensitive towards the random nature of customer order lead time. From our modeling approach, we observed these results as an initial step toward characterizing supplier selection criteria that acknowledge these sensitivities. We now summarize our results and share ideas for future research in the next section.

## Limitations

This study provides insights into trade-offs between offshore and nearshore suppliers in make-to-order manufacturing but has limitations. The mathematical model relies on simplifying assumptions and does not fully account for complexities like supplier learning, geopolitical risks, or multi-tier interactions. Scenario generation combines simulated and secondary data, enabling controlled analysis but limiting real-world variability. Consequently, generalizability may be restricted. Future research should validate findings with firm-level or industry-specific data and explore more detailed models that reflect evolving supply chain disruptions and sector-specific production and logistics standards.

## Conclusions and Future Research

This paper studied how supplier features, especially production yield and customer order lead time, affect total supply chain costs, emphasizing trade-offs between supplier expertise and location. Pandemic-related congestion in global shipping routes has increased the significance of lead time variability, particularly in time-sensitive supply chains. We examined how supplier expertise impacts production yield and how location influences non-processing-related lead time, both of which greatly affect cost outcomes.

To explore these dynamics, we developed a stochastic optimization model for a Tier 1 supplier selecting a Tier 2 supplier. The model incorporates a binomially distributed production yield and a customer order lead time composed of both deterministic and random components. Supply chain costs were defined as the sum of procurement costs, underage penalties for missing items, and tardiness penalties for delayed deliveries. We used a $2^k$ factorial design to generate scenarios and examined three common distributions for the random lead time component: Uniform, Exponential, and Lognormal.

Our findings indicate that, in time-sensitive supply chains, lead time reliability has a greater impact on supplier selection than production efficiency. Increases in mean non-processing-related lead time significantly raise total costs, often outweighing the benefits of higher yield. Even when the nearshore supplier's yield was low, the offshore supplier was rarely preferred, underscoring the dominant role of lead time uncertainty.

The impact of yield and lead time variability is further amplified when underage cost, order size, or procurement/tardiness penalties are high. These conditions intensify the cost implications of supplier characteristics, making trade-offs more pronounced. For example, lower procurement costs enhance the appeal of nearshore suppliers, while high tardiness penalties discourage offshore sourcing. These patterns consistently favor nearshoring under high-cost or high-risk scenarios.

Additionally, our analysis highlights the importance of accurately modeling lead time distributions. Simplistic assumptions can lead to substantial underestimation of total costs. This underscores the need for Tier 1 suppliers to invest in detailed data collection and modeling of lead time parameters. It also points to the strategic value of optimizing contractual terms with both upstream suppliers and downstream customers, as changes in cost parameters can quickly shift sourcing preferences.

Future research could extend this work through comparative case studies and more detailed models tailored to specific industries and product types. As supply chain disruptions continue to evolve, understanding the operational trade-offs between supplier expertise and location will remain critical for resilient sourcing strategies.

**Ethical Approval**

This study did not involve human participants, personal data, or animal subjects, and therefore did not require ethical approval.

**Conflict of Interest**

The author declares that there is no conflict of interest regarding the publication of this study.

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**Appendix**

***Proof of Theorem 1***

We need to show that the objective function in Eq. (3) has nondecreasing first-forward-differences with respect to Q and hence is convex (Yüceer, 2002, p. 299).

$$c^p * (Q+2) + (P+c^{pe}) * \mathrm{E}\,[\max(0, (D - \mathrm{Bin}((Q+2), p)))] - P*D \tag{9}$$

$$- c^p * (Q+1) + (P+c^{pe}) * \mathrm{E}\,[\max(0, (D - \mathrm{Bin}((Q+1), p)))] - P*D$$

$$\overset{?}{\geq} c^p * (Q+1) + (P+c^{pe}) * \mathrm{E}\,[\max(0, (D - \mathrm{Bin}((Q+1), p)))] - P*D$$

$$- c^p * (Q) + (P+c^{pe}) * \mathrm{E}\,[\max(0, (D - \mathrm{Bin}(Q, p)))] - P*D$$

$$p^2 * \mathrm{E}\,[\max(0, (D - \mathrm{Bin}(Q, p) - 2))] + 2*p*(1-p) * \mathrm{E}\,[\max(0, (D - \mathrm{Bin}(Q, p) - 1))] \tag{10}$$

$$+ (1-p)^2 * \mathrm{E}\,[\max(0, (D - \mathrm{Bin}(Q, p)))]$$

$$- p * \mathrm{E}\,[\max(0, (D - \mathrm{Bin}(Q, p) - 1))] - (1-p) * \mathrm{E}\,[\max(0, (D - \mathrm{Bin}(Q, p)))]$$

$\overset{?}{\geq} p$* E [max (0, (*D*- Bin (*Q*, *p*)-1))] + (1-*p*) * E [max (0, (*D*- Bin (*Q*, *p*)))]- E [max (0, (*D*- Bin (*Q*, *p*)))]

$p^2$ * E [max (0, (*D*- Bin (*Q*, *p*)-2))] + 2**p**(1-*p*) * E [max (0, (*D*- Bin (*Q*, *p*)-1))] (11)
+ (1-*p*)$^2$ * E [max (0, (*D*- Bin (*Q*, *p*)))]

- $p^2$* E [max (0, (*D*- Bin (*Q*, *p*)-1))] – *p* * (1-*p*) * E [max (0, (*D*- Bin (*Q*, *p*)-1))]
- (1-*p*) * *p* * E [max (0, (*D*- Bin (*Q*, *p*)))] - (1-*p*) * (1-*p*) * E [max (0, (*D*- Bin (*Q*, *p*)))]
$\overset{?}{\geq} p^2$* E [max (0, (*D*- Bin (*Q*, *p*)-1))] + *p* * (1-*p*) * E [max (0, (*D*- Bin (*Q*, *p*)-1))]
- *p* * E [max (0, (*D*- Bin (*Q*, *p*)))]

$p^2$ * E [max (0, (*D*- Bin (*Q*, *p*)-2))] - $p^2$ * E [max (0, (*D*- Bin (*Q*, *p*)-1))] (12)
$\overset{?}{\geq} p^2$* E [max (0, (*D*- Bin (*Q*, *p*)-1))] - $p^2$ * *E* [max (0, (*D*- Bin (*Q*, *p*)))]

$$\sum_{j=0}^{D-2} \mathrm{P}(\mathrm{Bin}(Q,p) = \mathrm{j}) * (D-2-j) \sum_{j=0}^{D-1} \mathrm{P}(\mathrm{Bin}(Q,p) = \mathrm{j}) * (D-1-j) \quad (13)$$

$$\overset{?}{\geq}$$

$$\sum_{j=0}^{D-1} \mathrm{P}(\mathrm{Bin}(Q,p) = \mathrm{j}) * (D-1-j) - \sum_{j=0}^{D} \mathrm{P}(\mathrm{Bin}(Q,p) = \mathrm{j}) * (D-j)$$

$$-\sum_{j=0}^{D-2} \mathrm{P}(\mathrm{Bin}(Q,p) = \mathrm{j}) \overset{?}{\geq} -\sum_{j=0}^{D-1} \mathrm{P}(\mathrm{Bin}(Q,p) = \mathrm{j}) \quad (14)$$

$$0 \leq \mathrm{P}(\mathrm{Bin}(Q,p) = D-1).$$

From Eq. (14), we conclude that the objective function in Eq. (3) is convex. To determine the *Q**, we need to define the first-forward-difference, which we do as follows:

$c^p$ * (*Q*+*1*) + (*P*+$c^{pe}$) * E [max (0, (*D*- Bin ((*Q*+*1*), *p*)))] - *P*D* (15)

- $c^p$ * (*Q*) - (*P*+$c^{pe}$) * E [max (0, (*D*- Bin (*Q*, *p*)))] + *P*D*

$= c^p + (P + c^{pe}) * p * \text{E}[\max(0, (D - \text{Bin}(Q, p) - 1))] + (P + c^{pe}) * (1 - p)$
$* \text{E}[\max(0, (D - \text{Bin}(Q, p)))] - (P + c^{pe}) * \text{E}[\max(0, (D - \text{Bin}(Q, p)))]$

$= c^p + (P + c^{pe}) * p * \{ \text{E}[\max(0, (D - \text{Bin}(Q, p) - 1))]$
$- \text{E}[\max(0, (D - \text{Bin}(Q, p)))] \}$

$= c^p + (P + c^{pe}) * p * \{ \sum_{j=0}^{D-1} \text{P}(\text{Bin}(Q, p) = \text{j}) * (D - 1 - j) -$
$\sum_{j=0}^{D} \text{P}(\text{Bin}(Q, p) = \text{j}) * (D - j) \}$

$= c^p + (P + c^{pe}) * p * \{ -\sum_{j=0}^{D-1} \text{P}(\text{Bin}(Q, p) = \text{j}) \}.$

The inequality in Eq. (4) represents the case where the first-forward-difference in Eq. (15) is nonnegative, and the algorithm in Theorem 1 finds $Q^*$ by stopping to increment the input, $Q$, at the largest value such that Eq. (15) becomes nonnegative. The objective function in Eq. (3) starts increasing. □

***Proof of Theorem 2***

Note that for any constant A and continuous nonnegative random variable *X*, we can express $\int_A^\infty xf(x)dx$ as

$$\int_A^\infty xf(x)dx = \int_0^\infty xf(x)dx - \int_0^A xf(x)dx = E[X] - \int_0^A \int_0^x dy\, f(x)dx \tag{3}$$

$$= E[X] - \int_0^A \int_y^A f(x)dxdy$$

$$= E[X] - \int_0^A [F(A) - F(y)]dy = E[X] - A.F(A) + \int_0^A F(y)dy.$$

$$\int_A^\infty xf(x)dx - A\int_A^\infty f(x)dx \tag{4}$$

$$= E[X] - A.F(A) + \int_0^A F(y)dy - A[1 - F(A)]$$

$$E[X] - A.F(A) + \int_0^A F(y)dy - A[1 - F(A)] = E[X] + \int_0^A F(y)dy - A.$$

Then, we have

$$c^t * D * E[T^w - E[T^w]]^+ = c^t * D * \left[\int_{E[T^w]}^{\infty} (x - E[T^w]) f(x) dx\right] \quad (5)$$

$$= c^t * D * \left[E[T^w] + \int_0^{E[T^w]} F(y)dy - E[T^w]\right] = c^t * D * \int_0^{E[T^w]} F(y)dy.$$

Finally, for uniform, exponential, and lognormally distributed $T^w$ we have for $T^w$ ~Uniform (A, B), $c^t * D * \int_0^{E[T^w]} F(y)dy = c^t * D * \int_A^{\frac{A+B}{2}} \frac{y-A}{B-A} dy = c^t * D * \frac{B-A}{8}$. For $T^w$ ~Exponential (λ), $c^t * D * \int_0^{\frac{1}{\lambda}} \left(1 - e^{-\lambda y}\right) dy = c^t * D * \frac{1}{\lambda * e}$. For $T^w$ ~Lognormal ($\mu$, $\sigma$),

$$c^t * D * \int_0^{E[T^w]} F(y)dy = c^t * D * \left\{E[T^w].F(E[T^w]) - \int_0^{E[T^w]} x f(x) dx\right\} = c^t * D * \left\{e^{\mu+\frac{\sigma^2}{2}} * \Phi\left(\frac{ln\left(e^{\mu+\frac{\sigma^2}{2}}\right) - \mu}{\sigma}\right) - \left[e^{\mu+\frac{\sigma^2}{2}} - e^{\mu+\frac{\sigma^2}{2}} * \Phi\left(\frac{\mu + \sigma^2 - ln\left(e^{\mu+\frac{\sigma^2}{2}}\right)}{\sigma}\right)\right]\right\} = c^t * D * \left\{e^{\mu+\frac{\sigma^2}{2}}\left[\Phi\left(\frac{\sigma}{2}\right) - \Phi\left(\frac{-\sigma}{2}\right)\right]\right\}. \quad (6)$$

□