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RESEARCH ARTICLE

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Optimal pricing strategies and social welfare of a diabetic pharmaceutical supply chain under supply disruption risk

Abstract Diabetes is a serious public health threat. Therefore, the need for the supply and dispensing of diabetic drugs cannot be neglected. This study explores the impacts of supply disruption risks on pricing strategies for two diabetic drugs under three power structures, i.e., supplier–Stackelberg (SS), drugstore–Stackelberg (DRS), and centralized setting (CS), in an attempt to track the optimum strategies. We show how changes in procurement costs and disruption likelihood alter the balance between consumer surplus, profit, and overall social welfare within the pharmaceutical supply chain. CS will be preferred in scenarios in which centralized control over procurement and distribution is highly valuable, particularly in the presence of high procurement costs and supply disruptions, such as those that occur with specialized medications such as insulin analogs and biologics. In addition, in scenarios of low to moderate procurement costs, especially for generic drugs, the DRS strategy dominates CS in the advocacy of social welfare since drugstores can buy at competitive prices. Overall, DRS and CS consistently outperform SS in terms of consumer surplus. However, SS becomes more effective in scenarios where supply disruptions occur and procurement costs drop to zero, such as when governments subsidize drugs during emergencies.

Keywords pharmaceutical supply chain, diabetic drug shortage, disruption risk, patient surplus, social welfare

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1 Introduction

Pharmaceutical supply chains (PSCs) have been in the limelight over the past few years because of the associated risks of disruption (Sazvar et al., 2021; Tat et al., 2021). Not having drugs available as a result of disruptions is among the top ten critical issues of PSCs (Privett and Gonsalvez, 2014). Disruption in PSCs has to be taken seriously since drug shortages are an issue that puts patients' lives at stake. These disruptions could be attributed to many factors surrounding PSC operations, including but not limited to the sourcing of raw materials, loss of business continuity, disasters, transportation disruptions, and cargo theft. For example, Brexit put the supply of insulin in Britain at risk of shortage, while the shortage of intravenous saline affected nearly 50% of all US hospitals as a result of Hurricane Maria hitting Puerto Rico in September 2017 (Lawrence et al., 2020).

Medicine shortages can also result from the risks associated with an unreliable supplier (Kumar et al., 2018). There are two major kinds of supply breaks. The first is a complete medication lead-time disruption; this refers to cases in which distributors or retailers do not receive any medicines on time. The second type involves partial medicine delivery to distributors or retailers.

One of the main objectives that PSCs should achieve is the minimization of the negative impacts of supply chain (SC) disruptions on social welfare. Social welfare refers to the general condition of the citizens of any nation; this situation might include healthcare access, among other things (De Andrade et al., 2022). Therefore, supply chains should employ a structured process of mitigating risks whose root cause is disruption (Zahiri et al., 2017). The emphasis should thus be on having resilient PSCs. In addition, an effective multi-sourcing strategy may support a supply network in reducing the inevitable adverse outcomes of risks (Lu et al., 2011; Silbermayr and Minner, 2016; Kumar et al., 2018).

COVID-19 has emerged as a severe threat to the resiliency of PSCs (Cundell et al., 2020; Govindan et al., 2020; Grimmer, 2022). COVID-19 has strongly affected diabetic patients. In this context, studies have revealed a meaningful relationship between diabetes and pandemic severity among diabetic patients (Gregory et al., 2021; Rathmann et al., 2022). This, therefore, makes it necessary to devote more effort to managing diabetes, especially at such times when the crisis is high, with more attention given to the administration of drugs for diabetic patients.

Another factor that has the potential to influence performance in addressing disruption and uncertainty is the PSC's power structure (Shi et al., 2013; Gupta et al., 2021). For example, in most SCs, one player usually has the utmost power dominating the entire chain, thus impacting the nature of the disruptions and their effects. Particularly within the pharmaceutical industry, it might be that some chains have manufacturers as the dominant force and hence easily replaceable raw material suppliers, while in other cases, the suppliers could hold a greater hold on the market. Hence, consideration of the power within the PSC becomes necessary.

Motivated by the supply disruption of diabetic drugs, this study investigates a real case of a three-layer PSC by analyzing various strategies with optimum pricing decisions. Moreover, we compare three power structures: supplier–Stackelberg (SS), drugstore–Stackelberg (DRS) and centralized setting (CS).

The key research questions of this study are as follows:

• How are the different power structures in a three-tier PSC, i.e., SS, DRS, and CS, influencing profit, consumer surplus, and social welfare?

• Under what conditions does each power structure strategy (i.e., SS, DRS, CS) generate a greater patient surplus in the PSC?

• What are the optimal pricing decisions that maximize social welfare for different scenarios under the supply disruption risk in the PSC?

This study aims to provide valuable insights for stakeholders navigating the power structure and disruption risk complexities, thereby enhancing overall SC performance and the welfare of patients.

This paper contributes to the literature stream through the evaluation of supply disruption risk in a real-world case of PSC. We assess three kinds of power structures, i.e., SS, DRS, and CS, and determine how to reduce supply disruption while maximizing consumer surplus, social welfare, and profit. Procurement cost and disruption risk likelihood are also investigated in our study as controlling variables for these strategies.

The remainder of this paper is organized as follows. Section 2 provides a critical review related to the SC pricing literature, disruption risk, PSCs, social welfare, and power structure. Section 3 formulates the problem of PSC disruption, and Section 4 presents the mathematical model. Sections 5 and 6 analyze the contributing factors and important parameters and examine their influence on the SC members' profit function, consumer surplus, and social welfare in centralized and decentralized settings. The managerial implications of the study are discussed in Section 7. Finally, Section 8 concludes the paper with some directions for future research.

2 Literature review

This study focuses on five interconnected areas of the SC, namely, pricing, disruption risk, PSCs, social welfare, and power structure. In the following sections, we review the relevant literature in these areas.

2.1 Pricing

Pricing decisions have been extensively studied in the literature (Liu et al., 2021a; Jiang et al., 2024; van Baal & Barros, 2024). Zhang et al. (2021) investigate a two-level dual-channel SC where consumers have green preferences. They examine pricing and greenness strategies in both centralized and decentralized scenarios and find that consumers' greenness preferences positively affect social welfare and SC performance. Bugert and Lasch (2018) examine the impact of responsive pricing in mitigating disruption risks in an SC via a system dynamics simulation approach. Zhao and Wang (2002) study pricing and ordering decisions in a leader–follower setting of an SC consisting of a manufacturer and a retailer. Hendalianpour (2020) proposed optimal lot-sizing and pricing strategies for perishable goods using a game theoretic approach.

2.2 Disruption risk

Various forms of disruption can occur in SC segments, such as disruptions in supply, demand, or production (Zhang et al., 2015). Kumar et al. (2018) examine how a retailer with an unreliable supplier can compete with another retailer who has a more reliable supplier but at a higher cost. Zheng et al. (2021) investigate the impact of buyers' social learning, panic buying, and supply disruption risks on retailers' optimal inventory and ordering strategies.

One method for addressing disruption risks is dual sourcing with capacity reservation (Inderfurth et al., 2013). Guo et al. (2021) propose a model where the government provides subsidies to suppliers and manufacturers to mitigate disruptions caused by capacity constraints, suggesting that subsidies for manufacturers are more advantageous than those for suppliers. Retailers also face disruption risks on the demand side of an SC (Wu et al., 2020). Ali et al. (2018) study the effect of demand disruption on price and service levels in both centralized and decentralized settings. Zhao et al. (2020) analyze a fashion SC via linear quantity discounts and revenue-sharing contracts when demand disruptions occur.

He et al. (2019) proposed a real-option approach to neutralize the impact of an SC disruption and apply it to a case study of a Chinese dairy SC. Babaee Tirkolaee et al. (2023) proposed a model to improve the performance of a blood supply chain network during the COVID-19 pandemic by considering disruptions caused by the pandemic.

2.3 Pharmaceutical supply chains

Disruptions in PSCs can have serious consequences, such as stockouts, revenue losses, and damaged customer trust. PSCs are particularly vulnerable to supply disruptions caused by unexpected natural disasters, terrorism, and epidemics. Governments and businesses are actively working to mitigate such disruptions, as demonstrated by the negative impact of the COVID-19 pandemic on PSCs. Any shortage in drug supplies can have numerous ripple effects on PSCs (Govindan et al., 2020). Daryanian et al. (2023) proposed a fuzzy robust stochastic model to enhance the resilience and sustainability of PSCs. Lücker and Seifert (2017) employd three key operational measures—risk mitigation inventory, agility capacity, and dual sourcing—to manage network disruptions in a PSC. Tucker et al. (2020) proposed two-stage and multi-stage stochastic programs and explore methods for addressing disruption-related issues in a PSC. Liu et al. (2021b) adopted an approach to optimize inventory levels, routing, and order quantities in a blood PSC with uncertain demand.

It is insufficient to rely solely on offsetting or reducing drug expenses when making pricing decisions. Some countries directly regulate drug pricing and enforce price cap regulations to keep the price of critical drugs under control. This aspect of the PSC has been studied extensively. Pricing policies vary across different countries. Roughead et al. (2018) compared the pricing policies of generic medicines in Australia, New Zealand, the Republic of Korea, and Singapore. Uncertainty is another important factor considered in PSCs. Zahiri et al. (2018) proposed a method that incorporates uncertainty in demand and costs and design a PSC network with two objective functions: total cost and SC unmet demand.

2.4 Sustainability and social welfare

The sustainability of an SC involves maintaining a balance between its three dimensions of performance: economic, environmental, and social (Zahiri et al., 2017). Several studies have examined these dimensions. Johari and Hosseini-Motlagh (2019) analyze all three dimensions of sustainability in a closed-loop SC for sustainable acid-batteries under three different solutions: centralized, decentralized, and coordinated. Chen and Su (2019) propose four game-theoretic models, including two Stackelberg models, a Nash structure, and a revenue-sharing contract, to maximize social welfare in a photovoltaic SC with fairness concerns.

Although most studies focus on the economic and environmental aspects of sustainability, the social welfare aspect is of utmost importance in the pharmaceutical context (Zou, 2024), and this dimension has been addressed in some studies (e.g., Kouvelis et al., 2015). Nematollahi et al. (2018) propose a two-level socially responsible PSC involving one distributor and one retailer and offer a multi-objective PSC to improve the service level and profit. Tat et al. (2021) presented a two-echelon PSC with a supplier and a retailer that incorporates social responsibility. They propose cost- and revenue-sharing contracts and optimize a PSC with a medicine donation plan. Chen et al. (2020) assessed the effects of quality limits and regulations on the profits and social welfare of pharmaceutical members. Consequently, they determine that minimum quality guidelines are necessary to enhance the social welfare and economic performance of PSCs.

2.5 Power structure in the supply chain

The power structure in the SC has attracted significant attention in recent years (Liu et al., 2022a; Liu et al., 2022b). Numerous studies have examined the decision-making processes within SCs under different structures (Chen and Su, 2019). Vertical Nash (VN), Stackelberg competition (leader and follower) models, cooperation, and coordination have been widely considered key structures (Hendalianpour et al., 2021). Jena et al. (2022) focused on an omni-channel closed-loop supply chain (CLSC) and compare pricing decisions across various power structures, including manufacturer Stackelberg, retailer Stackelberg, Vertical Nash, and cooperation. Gupta et al. (2021) proposed a game-theoretical model to explore the significance of disruption timing, finding that the timing of disruption directly impacts the supplier's wholesale price.

Our study contributes to the literature by providing a comprehensive understanding of how different power structures impact profit, consumer surplus, and social welfare within PSCs. We offer practical insights and a well-aligned framework with established research to help decision-makers optimize SC strategies under various conditions. To the best of our knowledge, no study has examined and analyzed the trade-offs between consumer surplus, social welfare, and profit in a real-world PSC while considering the risk of supply disruption. Furthermore, we consider a real-world case, estimating the market potential and price sensitivity coefficient of two diabetic medicines. Appendix A includes Table A1, which compares relevant studies characterizing the features and highlights the research gaps we aim to address in this study.

3 Problem statement

Diabetic patients rely on medications to maintain their blood glucose levels within control limits. When the drug supply is disrupted, many individuals are affected. As mentioned earlier, a pandemic can worsen this situation. Given the impact of supply disruptions on diabetic drugs, we consider a case involving two diabetic medications over a four-year period in a three-level PSC in Iran. The PSC includes three suppliers: Tehran Shimi and Hakim, who are involved only in the case of no disruption (*ND*), and a third supplier, who steps in during disruptions (*D*). The distributor, Company X, supplies these drugs to pharmacies across Iran, purchasing two products—Glibotex and Glibenclamide. Both drugs serve the same purpose, but with a key difference: Tehran Shimi supplies Glibotex at higher wholesale prices, whereas Hakim produces Glibenclamide at a lower price. Pharmacies nationwide sell these medications to patients. Supply disruptions can arise from unexpected events such as a pandemic or economic sanctions, leading to product shortages. In such cases, the distributor turns to the third supplier, which is more reliable but also more expensive. Figure 1 illustrates the PSC.

The distributor purchases Glibotex and Glibenclamide from the third supplier when supply disruption occurs. The cost of acquiring medicines from the third supplier is higher than the usual price charged by Tehran Shimi and Hakim in the case of no disruption ($W_3 > \max(W_1, W_2)$). Thus, the distributor sells these medicines at a price denoted by R^D that is higher than the counterpart price in the absence of disruption ($R^D > R^{ND}$). It is assumed that disruption occurs with a probability of dr.

In this study, a linear price-sensitive demand function (Lee and Staelin, 1997) is employed, with a key modification. The aim is to fit a linear regression model for the demand functions and estimate the market potential and price coefficient for the drugs produced by the suppliers via real-world data collected from 2018 to 2021 at Company X.

Two settings are explored to solve the model: centralized and decentralized. In the CS, the optimal prices for the medicines sold under two different names are set by the government or shareholders. In the decentralized setting, a Stackelberg model is used to determine the optimal decisions for each member (Cachon and Zipkin, 1999).

4 Model formulation

4.1 Case settings

Before formulating the model, we summarize our case settings:

• A three-level PSC consisting of two leading suppliers, a reliable supplier, a distributor, and drugstores is considered.

• The PSC considers two diabetic drugs, both of which are used to treat Type 2 diabetes, with a key distinction: Glibotex is primarily prescribed for patients with higher fasting blood sugar (FBS). As a result, the two drugs are not substitutable, making it reasonable to assume that there are no cross-price effects. Additionally, Glibotex is priced higher.

• The PSC data for the diabetic drugs were collected from 2018 to 2021.

• In the decentralized scenario, two channel structures are considered: the SS and DRS. These scenarios reflect real-world cases. When large active pharmaceutical ingredient (API) suppliers hold significant control over the supply and pricing of key drug ingredients, they dictate terms to pharmaceutical companies. The SS structure is typically used in markets dominated by a few large manufacturers, such as those for advanced cancer drugs and insulin, with companies such as Sanofi and Novo

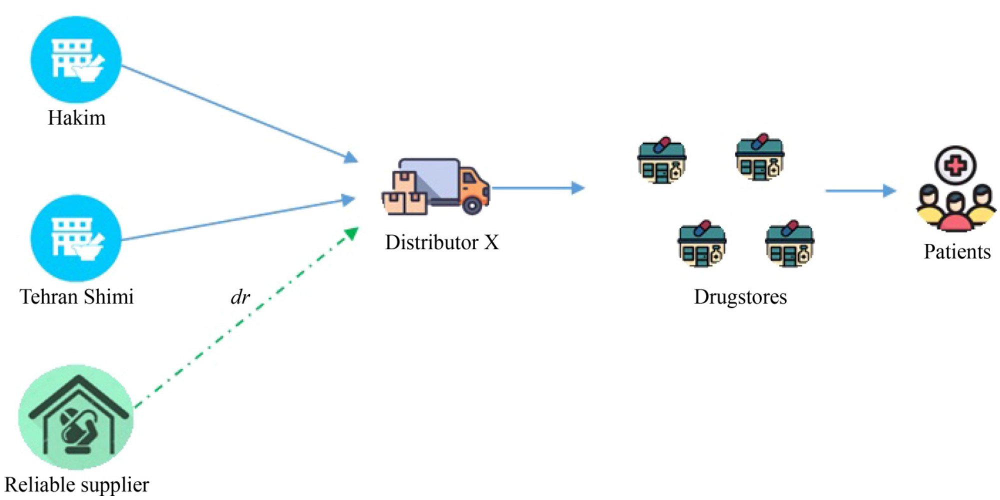

Fig. 1 Schematic illustration of the pharmaceutical supply chain problem.

Nordisk as examples. Conversely, in markets with robust competition among multiple generic suppliers, such as those for generic drugs treating hypertension, high cholesterol, depression, or over-the-counter medications such as pain relievers and flu/cold pills, retail outlets (drugstores) often have significant bargaining power over suppliers.

• It is assumed that the costs of the two drugs are the same during disruptions. This assumption is based on the idea that, under disruption conditions, suppliers prioritize meeting overall demand over optimizing profits for individual drugs, even if it means sacrificing usual price premiums. Factors such as government interventions may contribute to this, as authorities might enforce more uniform, "fair" pricing across drug categories to ensure equitable access. Despite equalized procurement costs for suppliers during disruptions, drugstores/retailers may still maintain different retail prices for the two drugs on the basis of factors such as brand reputation, market segmentation, and demand elasticity.

Table A2 (Appendix A) illustrates the parameters and decision variables described in the proposed model.

4.2 Centralized system

In this context, the government/shareholders are regarded as the owners of the PSCs. The first step involves determining social welfare. According to Baron and Myerson (1982), social welfare is the summation of all actors' profit functions in the SC and the consumer surplus. Therefore, the profit functions of the five members involved in the PSC, as well as the patient surplus, are combined to calculate overall social welfare. Equations (1)–(5) represent the profit functions of the SC members.

$$\pi_1 = (1-dr)(W_1-c_1)D_1^{ND}, \tag{1}$$

$$\pi_2 = (1-dr)(W_2-c_2)D_2^{ND}, \tag{2}$$

$$\pi_3 = dr(W_3-c_3)(D_1^{D}+D_2^{D}), \tag{3}$$

$$\pi_4 = (1-dr)\left[(R^{ND}-W_1)D_1^{ND}+(R^{ND}-W_2)D_2^{ND}\right]+ dr\left[(R^{D}-W_3)(D_1^{D}+D_2^{D})\right], \tag{4}$$

$$\pi_5 = (1-dr)\left[(P_1^{ND}-R^{ND})D_1^{ND}+(P_2^{ND}-R^{ND})D_2^{ND}\right]+ dr\left[(P_1^{D}-R^{D})D_1^{D}+(P_2^{D}-R^{D})D_2^{D}\right]. \tag{5}$$

The first profit Eq. (1) describes the profit of Hakim, which, in the case of no disruption, procures Glibenclamide with a procurement cost of c_1 and sells it to the distributor at the wholesale price of W_1. Equation (2) is the profit function of Tehran Shimi, which produces Glibotex at the cost of c_2 and sells it to the distributor at the wholesale price of W_2. Equation (3) refers to the third supplier's profit function, which is considered only when the procurement process is disrupted. Equation (4) outlines the profit function of the distributor procuring from the third supplier during a disruption in supply. In the absence of disruption, medicines are purchased from the two leading suppliers. The last equation depicts the profit of drugstores nationwide.

When the SC faces supply disruption, the prices of both medicines differ from those in scenarios without disruption. Therefore, the projected profit function of the entire SC in the CS is calculated by aggregating the five functions mentioned earlier, resulting in Eq. (6):

$$\pi_T^{CS} = (1-dr)\left[(P_1^{ND}-c_1)D_1^{ND}+(P_2^{ND}-c_2)D_2^{ND}\right]+ dr\left[(P_1^{D}-c_3)D_1^{D}+(P_2^{D}-c_3)D_2^{D}\right]. \tag{6}$$

The consumer surplus (S) is calculated via the following equation (Cowan, 1998):

$$S = \int_p^{\frac{\alpha}{\beta}} (\alpha-\beta x)\mathrm{d}x. \tag{7}$$

Equation (8) represents social welfare:

$$SW = \pi_T^{CS}+S = (1-dr)\left[(P_1^{ND}-c_1)D_1^{ND}+(P_2^{ND}-c_2)D_2^{ND}\right]+ dr\left[(P_1^{D}-c_3)D_1^{D}+(P_2^{D}-c_3)D_2^{D}\right]+S. \tag{8}$$

By applying the second-order conditions for convexity, the optimal values of the decision variables in each case ($P_1^{ND}, P_2^{ND}, P_1^{D}, P_2^{D}$) are determined. These optimal values are provided in Proposition 1.

Proposition 1 The optimal prices of medicines in two cases (*ND* or *D*) are as follows:

$$^*P_1^{ND} = \frac{\alpha_1+\beta_1 c_1}{2\beta_1}, \tag{9}$$

$$^*P_2^{ND} = \frac{\alpha_2+\beta_2 c_2}{2\beta_2}, \tag{10}$$

$$^*P_1^{D} = \frac{\alpha_1+\beta_1 c_3}{2\beta_1}, \tag{11}$$

$$^*P_2^{D} = \frac{\alpha_2+\beta_2 c_3}{2\beta_2}. \tag{12}$$

The proof of this proposition is provided in Supplementary Material S1.

Equations (9)–(12) represent the optimal prices of Glibenclamide in the case of no disruption, the optimal price of Glibotex in the case of no disruption, the optimal price of Glibenclamide in the case of disruption, and the optimal price of Glibotex in the case of supply disruption, respectively.

Data on the demand and price of the drugs from 2018 to 2021 were collected to estimate the market potential and price coefficient for both drugs. The results of the linear regression models are presented in Table A3 (Appendix A). The estimated parameters are as follows (D_1=103288.720–30.963P_1, D_2=347989.803–71.677P_2) : α_1=103,288.720, β_1=30.963, α_2=347,989.803, β_2=71.677.

The P values of these models demonstrate a linear relationship between the prices and demand, and the R_2 values are acceptable.

4.3 Decentralized system

In this scenario, each participant in the SC aims to maximize their profit function. Distributor X sells Glibenclamide and Glibotex at different prices in the decentralized setting, with drugstores determining the retail price. The backward induction method is used to find the optimal values. Figure 2 outlines the decision-making sequence.

4.3.1 Supplier stackelberg

When suppliers are leaders in PSC, two scenarios are possible.

Case I: Without disruption (*ND*)

In the case of an *ND*, the drugstore and distributor should first set their optimum values according to the leader's decision variable (W_1, W_2). The following proposition outlines the reaction functions of the drugstores and the distributor during no disruption.

Proposition 2 The reaction functions of the drugstores and the distributor are as follows:

$$R_1^{ND} = (1+\phi_1)W_1, \tag{13}$$

$$R_2^{ND} = (1+\phi_2)W_2, \tag{14}$$

$$P_1^{ND} = (1+\lambda_1)W_1, \tag{15}$$

$$P_2^{ND} = (1+\lambda_2)W_2, \tag{16}$$

$$0 \leqslant \phi_1, \lambda_1, \phi_2, \lambda_2 \leqslant 1, \lambda_1 \geqslant \phi_1, \lambda_2 \geqslant \phi_2, \phi_2 \geqslant \phi_1, \lambda_2 \geqslant \lambda_1.$$

By Substituting Eq. (15) in $(W_1 - c_1)D_1^{ND}$ and solving the problem for the first supplier (Hakim), the optimal wholesale price for Hakim (the leader) is obtained in Eq. (17):

$$W_1^* = \frac{\beta_1 c_1 \lambda_1 + \beta_1 c_1 + \alpha_1}{2\beta_1(1+\lambda_1)}. \tag{17}$$

Similarly, by replacing Eq. (16) in $(W_2 - c_2)D_2^{ND}$, the optimal wholesale price for the other supplier, Tehran Shimi, is found in Eq. (18):

$$W_2^* = \frac{\beta_2 c_2 \lambda_2 + \beta_2 c_2 + \alpha_2}{2\beta_2(1+\lambda_2)}. \tag{18}$$

The proof of this proposition is provided in Supplementary Material S2.

Using Eqs. (13)–(18), the optimal decision variables for the distributor and drugstores are determined in Eqs. (19)–(22):

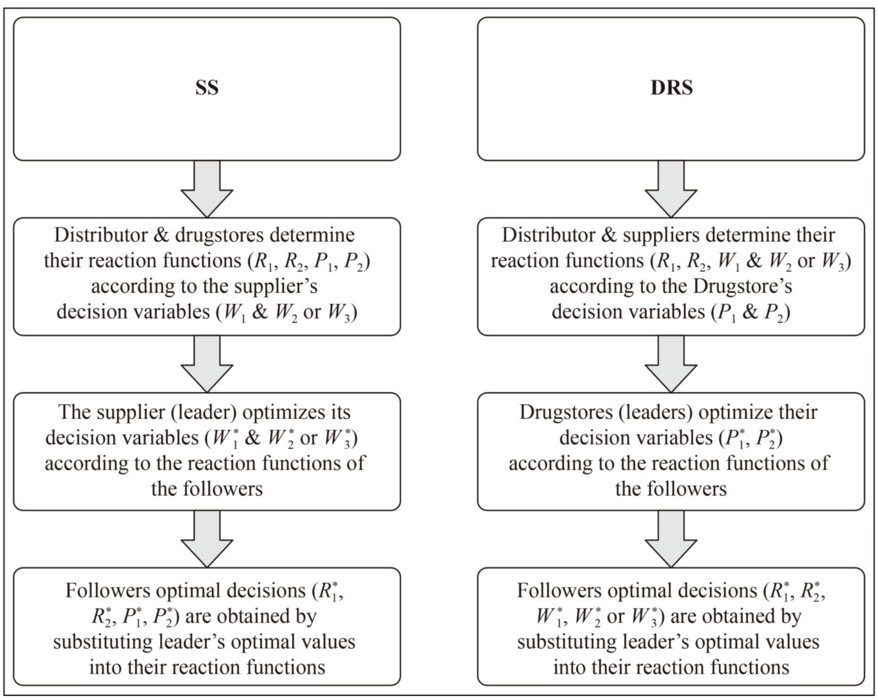

Fig. 2 Decision-making under decentralized scenarios.

$$ {}^{*}R_1^{ND} = (1+\phi_1)W_1^* = (1+\phi_1)\frac{\beta_1 c_1 \lambda_1 + \beta_1 c_1 + \alpha_1}{2\beta_1(1+\lambda_1)}, \quad (19) $$

$$ {}^{*}P_1^{ND} = (1+\lambda_1)W_1^* = (1+\lambda_1)\frac{\beta_1 c_1 \lambda_1 + \beta_1 c_1 + \alpha_1}{2\beta_1(1+\lambda_1)} = \frac{\beta_1 c_1 \lambda_1 + \beta_1 c_1 + \alpha_1}{2\beta_1}, \quad (20) $$

$$ {}^{*}R_2^{ND} = (1+\phi_2)W_2^* = (1+\phi_2)\frac{\beta_2 c_2 \lambda_2 + \beta_2 c_2 + \alpha_2}{2\beta_2(1+\lambda_2)}, \quad (21) $$

$$ {}^{*}P_2^{ND} = (1+\lambda_2)W_2^* = (1+\lambda_2)\frac{\beta_2 c_2 \lambda_2 + \beta_2 c_2 + \alpha_2}{2\beta_2(1+\lambda_2)} = \frac{\beta_2 c_2 \lambda_2 + \beta_2 c_2 + \alpha_2}{2\beta_2}, \quad (22) $$

Case II: With disruption (*D*)

In this scenario, the primary suppliers (i.e., Hakim and Tehran Shimi) are unable to supply drugs to the SC network, making the third supplier the leader of the model. Like in the first scenario, the drugstores and distributors react to the decision variable of the third supplier (W_3). Their reaction functions are as follows:

$$ R_1^D = (1+\delta_1)W_3, \quad (23) $$

$$ P_1^D = (1+\gamma_1)W_3, \quad (24) $$

$$ R_2^D = (1+\delta_2)W_3, \quad (25) $$

$$ P_2^D = (1+\gamma_2)W_3, \quad (26) $$

$$ 0 \leqslant \delta_1, \delta_2, \gamma_1, \gamma_2 \leqslant 1, \delta_2 \geqslant \delta_1, \gamma_2 \geqslant \gamma_1, \gamma_2 \geqslant \delta_2, \gamma_1 \geqslant \delta_1. $$

Proposition 3. Considering the above reaction functions, the third supplier maximizes profit, and the best wholesale price of the third supplier during disruption is obtained via Eq. (27):

$$ W_3^* = \frac{\beta_1 c_3 \gamma_1 + \beta_2 c_3 \gamma_2 + \beta_1 c_3 + \beta_2 c_3 + \alpha_1 + \alpha_2}{2(\beta_1\gamma_1 + \beta_1\gamma_1 + \beta_1 + \beta_2)}. \quad (27) $$

The proof of this proposition is provided in Supplementary material S3.

The optimal decision variables of the drugstores and distributor are subsequently calculated in Eqs. (28)–(31):

$$ {}^{*}R_1^D = (1+\delta_1)W_3^* = (1+\delta_1)\frac{\beta_1 c_3 \gamma_1 + \beta_2 c_3 \gamma_2 + \beta_1 c_3 + \beta_2 c_3 + \alpha_1 + \alpha_2}{2(\beta_1\gamma_1 + \beta_2\gamma_2 + \beta_1 + \beta_2)}, \quad (28) $$

$$ {}^{*}P_1^D = (1+\gamma_1)W_3^* = (1+\gamma_1)\frac{\beta_1 c_3 \gamma_1 + \beta_2 c_3 \gamma_2 + \beta_1 c_3 + \beta_2 c_3 + \alpha_1 + \alpha_2}{2(\beta_1\gamma_1 + \beta_2\gamma_2 + \beta_1 + \beta_2)}, \quad (29) $$

$$ {}^{*}R_2^D = (1+\delta_2)W_3^* = (1+\delta_2)\frac{\beta_1 c_3 \gamma_1 + \beta_2 c_3 \gamma_2 + \beta_1 c_3 + \beta_2 c_3 + \alpha_1 + \alpha_2}{2(\beta_1\gamma_1 + \beta_2\gamma_2 + \beta_1 + \beta_2)}, \quad (30) $$

$$ {}^{*}P_2^D = (1+\gamma_2)W_3^* = (1+\gamma_2)\frac{\beta_1 c_3 \gamma_1 + \beta_2 c_3 \gamma_2 + \beta_1 c_3 + \beta_2 c_3 + \alpha_1 + \alpha_2}{2(\beta_1\gamma_1 + \beta_2\gamma_2 + \beta_1 + \beta_2)}. \quad (31) $$

4.3.2 Drugstore stackelberg

In this scenario, drugstores are the leaders, whereas suppliers and distributors are the followers. Two scenarios are analyzed: without disruption (*ND*) and with disruption (*D*).

Case I: Without disruption

For this case, the reaction functions of the suppliers and distributors are as follows. The reaction function parameters must fall between zero and one, as wholesale prices cannot exceed retail prices:

$$ W_1 = \theta_1 P_1^{ND}, \quad (32) $$

$$ W_2 = \theta_2 P_2^{ND}, \quad (33) $$

$$ R_1^{ND} = \rho_1 P_1^{ND}, \quad (34) $$

$$ R_2^{ND} = \rho_2 P_2^{ND}. \quad (35) $$

$$ 0 \leqslant \theta_1, \theta_2, \rho_1, \rho_2 \leqslant 1, \theta_2 \geqslant \theta_1, \rho_2 \geqslant \rho_1, \rho_1 \geqslant \theta_1, \rho_2 \geqslant \theta_2. $$

The drugstores maximize their profit for the two drugs:

$$ {}^{*}P_1^{ND} = \frac{\alpha_1}{2\beta_1}, \quad (36) $$

$$ {}^{*}P_2^{ND} = \frac{\alpha_2}{2\beta_2}. \quad (37) $$

Using Eqs. (38)–(41), the optimal price for the distributor are calculated, and the optimal wholesale price are as follows:

$$ W_1^* = \theta_1 {}^{*}P_1^{ND} = \frac{\alpha_1}{2\beta_1}\theta_1, \quad (38) $$

$$ W_2^* = \theta_2 {}^{*}P_2^{ND} = \frac{\alpha_2}{2\beta_2}\theta_2, \quad (39) $$

$$ {}^{*}R_1^{ND} = \rho_1 {}^{*}P_1^{ND} = \frac{\alpha_1}{2\beta_1}\rho_1, \quad (40) $$

$$ {}^{*}R_2^{ND} = \rho_2 {}^{*}P_2^{ND} = \frac{\alpha_2}{2\beta_2}\rho_2. \quad (41) $$

The proof is elucidated in Supplementary Material S4.

Case II: With disruption

Once supply disruption occurs in the PSC, two primary suppliers cannot procure drugs, and the SC relies on the third supplier. Therefore, we have:

$$W_3 = \varphi max\{P_1^D, P_2^D\}, \tag{42}$$

$$R_1^D = \eta_1 P_1^D, \tag{43}$$

$$R_2^D = \eta_2 P_2^D, \tag{44}$$

$$0 \leqslant \eta_1, \eta_2, \varphi \leqslant 1;\ \eta_2 \geqslant \eta_1;\ \eta_2 \geqslant \varphi;\ \eta_1 \geqslant \varphi.$$

By the above reaction functions, the drugstores maximize their profit function with respect to their decision variables, leading to the following:

$$^*P_1^D = \frac{\alpha_1}{2\beta_1}, \tag{45}$$

$$^*P_2^D = \frac{\alpha_2}{2\beta_2}. \tag{46}$$

It is unsurprising that, despite the disruption, drugstores have set the same optimal price for Glibenclamide and Glibotex. The key factors for the drugstores are market potential and the price coefficient, which are also vital parameters for patients. Therefore, the optimum price is as follows:

$$W_3^* = \varphi \max\{^*P_1^D, ^*P_2^D\} = \varphi\frac{\alpha_2}{2\beta_2}, \tag{47}$$

$$^*R_1^D = \eta_1 {}^*P_1^D = \frac{\alpha_1}{2\beta_1}\eta_1, \tag{48}$$

$$^*R_2^D = \eta_2 {}^*P_2^D = \frac{\alpha_2}{2\beta_2}\eta_2. \tag{49}$$

The proof is provided in Supplementary Material S5.

5 Numerical examples

Numerical experiments are conducted using some real-world examples for three power structures, namely CS, SS, and DRS. The parameters derived from the case are as follows:

α_1 = 103288.72, α_2 = 347989.803, β_1 = 30.963, β_2 = 71.677, $c_1 = 1664$, $c_2 = 2145$, $c_3 = 2500$.

5.1 Centralized scenario

The optimal decision variables are derived considering the aforementioned parameters. Table A4 (Appendix A) provides the optimal decision variables for the CS scenario.

From Table A4, it is evident that the costs of procuring and delivering/selling medicines in the event of disruption risk (D) are higher than those of their counterparts in the case of no disruption ($W_3 > \max(W_1, W_2)$, $R^D > R^{ND}$, $P_1^{ND} < P_1^D$, $P_2^{ND} < P_2^D$). Regarding the demand in two cases, it is evident that the demand for both drugs in the case of disruption (D) significantly decreases since the patients are charged more ($D_1^D < D_1^{ND}$, $D_2^D < D_2^{ND}$).

In addition, after disruption, the owners of the SC obtain drugs with more exertion. This is the reason why the prices increase at all levels of the SC ($c_3 > \max(c_1, c_2)$). Therefore, we have:

$$P_1^{ND} < P_1^D,\ P_2^{ND} < P_2^D.$$

The consumer surplus (S) in the entire SC is as follows:

$$S^{ND} = \int_{P_1^{ND}}^{\frac{\alpha_1}{\beta_1}} (\alpha_1 - \beta_1 x)\mathrm{d}x + \int_{P_2^{ND}}^{\frac{\alpha_2}{\beta_2}} (\alpha_2 - \beta_2 x)\mathrm{d}x. \tag{50}$$

Thus, after computing, we find that $S^{ND} = 10,816,741.74 + 65,797,628.63 = 76,614,370.37$.

The same approach is adopted to calculate consumer surplus in the event of disruption. Accordingly, we have Eq. (51):

$$S^D = \int_{P_1^D}^{\frac{\alpha_1}{\beta_1}} (\alpha_1 - \beta_1 x)\mathrm{d}x + \int_{P_2^D}^{\frac{\alpha_2}{\beta_2}} (\alpha_2 - \beta_2 x)\mathrm{d}x, \tag{51}$$

$$S^D = 2,716,335.55 + 49,730,119.37 = 52,446,454.92.$$

When disruption occurs in the supply, consumer surplus decreases substantially (both in the level of consumer surplus for each medicine and in the value of total consumer surplus in the SC,($S^D < S^{ND}$). It is also important to calculate the profit of all SC members and the overall profit of the SC in the centralized case. Using the values from Table A4 in Eqs. (1), (2), (3), (4), (5), (6), and (8) and assuming a disruption likelihood of 0.2 (disruption risk (dr) = 0.2), the results are summarized in Table A5 (Appendix A).

5.2 Decentralized scenario – suppliers as leaders (SS)

The initial parameter values are set as follows:

$\phi_1 = 0.1$, $\phi_2 = 0.12$, $\lambda_1 = 0.8$, $\lambda_2 = 1$, $\delta_1 = 0.09$, $\delta_2 = 0.15$, $\gamma_1 = 0.3$, $\gamma_2 = 0.8$, $c_1 = 1664$, $c_2 = 2145$, $c_3 = 2500$, $dr = 0.2$.

Using these parameters in the above expressions, the optimal values of the decision variables are found (Table A6 in Appendix A). From Table A6, it is inferred that the total expected profit of the SC in the decentralized system is significantly lower than that in the centralized case ($\pi_T^{DS} = 53059453 < \pi_T^{CS} = 143545076.90$). The consumer surplus and social welfare of the SC also decrease compared with those of the centralized case. Moreover, the profit value of each SC member has decreased compared with that of the centralized case.

5.3 Decentralized scenario – drugstores as leaders (DRS)

The optimal results of the decision variables are presented in Table A7 (Appendix A) when the drugstores lead in the Stackelberg model. The parameter values are as follows: $\rho_1 = 0.6, \rho_2 = 0.8, \theta_1 = 0.5, \theta_2 = 0.7, \eta_1 = 0.75, \eta_2 = 0.9, \varphi = 0.85, c_1 = 1664, c_2 = 2145, c_3 = 2500, dr = 0.2.$

As shown in Table A7, when the drugstores act as leaders, they generate lower profits but significantly increase social welfare compared with the supplier Stackelberg. Conversely, it is evident that the suppliers experience a significant loss in the drugstore Stackelberg.

6 Sensitivity analysis

Key parameters and their effects on optimal decisions in both centralized and decentralized scenarios are investigated.

6.1 Centralized system

6.1.1 Disruption risk

It is expected that an increase in dr will have a negative effect on the profit of all members, except for the profit of the third supplier. Figure 3 shows the profit of all the members as this parameter increases, confirming the accuracy of the expected profit trends. A similar trend can also be observed in Fig. 4 for social welfare values, consumer surplus, and the overall profit of the SC.

6.1.2 Market potential, price coefficient and procurement cost

Table 1 summarizes the effects of different parameters on the optimal decision variables and profit values in the CS. This finding reveals that the optimal values increase with the drug market potential. However, an opposite trend is observed when the price coefficients increase. With respect to procurement costs, the optimal prices increase when the SC caters to two medicines with higher procurement costs. However, the optimal values of demand and total system profit decrease.

6.2 Decentralized system

6.2.1 Consumer surplus

Under the decentralized system, it can be proven that the DRS dominates the SS in terms of the quantity of consumer surplus. In this context, we propose the following two theorems.

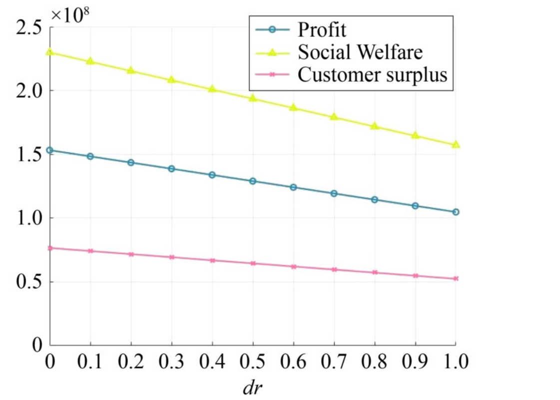

Fig. 3 Impact of disruption on profit of all members of the PSC profit, social welfare, and consumer surplus.

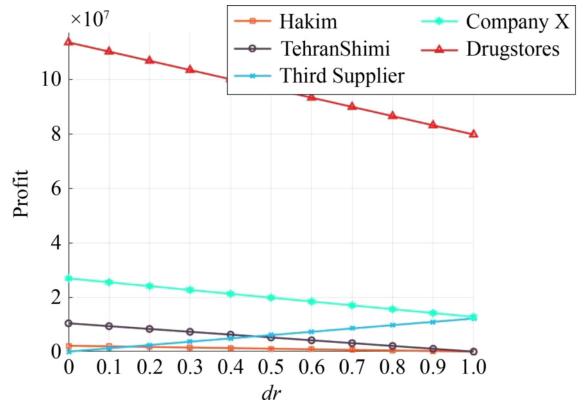

Fig. 4 The impact of disruption on the total profit, social welfare, and consumer surplus.

Theorem 1. When disruption does not occur, the DRS always dominates the SS.

The proof of this theorem is provided in Supplementary Material S6.

Theorem 2. When disruption occurs, the DRS mostly dominates the SS. However, the SS dominates the DRS under the following conditions:

$$\frac{A^2}{2}(\beta_1(1+\gamma_1)^2+\beta_2(1+\gamma_2)^2)- A(\alpha_1(1+\gamma_1)^2+\alpha_2(1+\gamma_2)^2)+\frac{3}{8}(\frac{\alpha_1{}^2}{\beta_1}+\frac{\alpha_2{}^2}{\beta_2})>\mathbf{0},$$

where $A = \dfrac{\beta_1 c_3\gamma_1+\beta_2 c_3\gamma_2+\beta_1 c_3+\beta_2 c_3+\alpha_1+\alpha_2}{2(\beta_1\gamma_1+\beta_2\gamma_2+\beta_1+\beta_2)}$.

The proof of Theorem 2 is provided in Supplementary Material S7.

6.2.2 Market potential, price coefficients and procurement costs

The essential parameters of the decentralized system are observed to determine their effects on the optimal decision variables and optimal objective functions. The optimal

Table 1 Summary of the centralized system

	$\alpha_1\uparrow$	$\beta_1\uparrow$	$\alpha_2\uparrow$	$\beta_2\uparrow$	$c_1\uparrow$	$c_2\uparrow$	$c_3\uparrow$
$P_1^{ND}(D_1^{ND})$	↑	↓	–	–	↑ (↓)	–	–
$P_2^{ND}(D_2^{ND})$	–	–	↑	↓	–	↑ (↓)	–
$P_1^{D}(D_1^{D})$	↑	↓	–	–	–	–	↑ (↓)
$P_2^{D}(D_2^{D})$	–	–	↑	↓	–	–	↑ (↓)
π_T^{cs}	↑	↓	↑	↓	↓	↓	↓
π_1	↑	↓	–	–	–	–	–
π_2	–	–	↑	↓	–	–	–
π_3	↑	↓	↑	↓	–	–	–
π_4	↑	↓	↑	↓	–	–	–
π_5	↑	↓	↑	↓	–	–	–

values for these parameters are listed in Table A8 (Appendix A). The first parameter we analyze is the market potential. When the market potential increases, the optimal prices and objective functions increase under both strategies (i.e., DRS and SS). Furthermore, a similar trend is observed in the optimal values when the price coefficient decreases.

The influence of the procurement costs is also investigated. Under SS, when the procurement costs grow, the optimal prices increase. However, at the same time, the profit, consumer surplus, and social welfare decrease. Nevertheless, under the DRS, as the drugstores' optimal retail prices do not depend on the value of procurement costs, those values remain unchanged. The parameters γ_1 and γ_2 represent the increased percentage of the price of the two drugs sold to the customers when the drugstores are followers (SS) under the supply disruption. The sensitivity analysis elucidates that social welfare and profit decrease if drugstores boost these parameters.

6.3 Decentralized system vs. centralized system

The decentralized and centralized systems are compared by evaluating profit, social welfare, and consumer surplus across all cases (i.e., CS, DRS, and SS). The primary focus of the comparisons is on *dr* and procurement costs, as they are the main parameters of this study.

6.3.1 Profit

The total profit is assessed across different power structures. It has already been established that the CS yields more total profit than the decentralized system does, regardless of the Stackelberg leader. To validate the model and compare total profit, the profit in all possible cases is calculated and presented in Fig. 5. This figure shows the disparate values of *dr* and C_3, with the green, blue, and red surfaces representing the profits of the CS, SS, and DRS, respectively. The results indicate that the

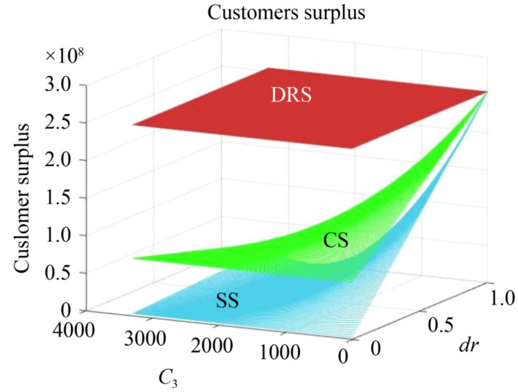

Fig. 5 Profit comparison of all the cases for different values of *dr* and c_3.

CS consistently achieves the highest profit, with the SS outperforming the DRS.

6.3.2 Consumer surplus

A comparative study between SS, DRS, and CS is conducted, with a focus on consumer surplus. The following theorems are proposed:

Theorem 3. The DRS always dominates the CS in terms of the value of consumer surplus.

The proof of Theorem 3 is provided in Supplementary Material S8.

Theorem 4. When there is no disruption, the CS always dominates the SS.

The proof of this theorem is provided in Supplementary Material S9.

As shown in Fig. 6, DRS generally exceeds SS and CS in consumer surplus, whereas CS typically outperforms SS. The only scenario where the SS has a slight chance to overcome the CS and DRS is during a disruption in the PSC. Corollaries 1 and 2 summarize Theorems 1–5.

Corollary 1. When disruption does not occur in the PSC, three strategies are ranked in descending order

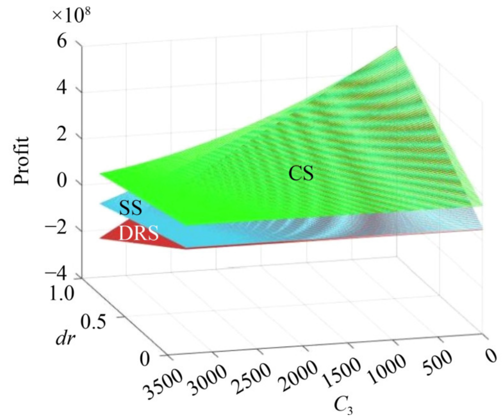

Fig. 6 Patient surplus value of all patientsfor different values of *dr* and c_3.

considering the consumer surplus value. Hence, we have:

DRS > CS > SS.

Corollary 2. When there is a disruption in the PSC ($dr = 1$), even though the DRS still has the highest consumer surplus, there is a slim chance for the SS to dominate the CS and DRS when c_3 holds the conditions given in theorems 2 and 5 (i.e., when c_3 is a tiny quantity as shown in Fig. 6).

6.3.3 Social welfare

A sensitivity analysis is performed by varying procurement costs and *dr* to determine the conditions under which each strategy yields higher social welfare. The results are shown in Fig. 7, where the red and green areas represent DRS and CS, respectively. When procurement costs are low, DRS is clearly the optimal strategy. However, if procurement costs increase, CS becomes the dominant strategy in terms of social welfare. Another parameter in this figure is *dr*, which represents the likelihood of disruption. As dr approaches one, the role of the third supplier becomes more significant, and their procurement cost becomes crucial. When there is no disruption, the procurement costs of Hakim and Tehran Shimi are the determining factors. The SS never dominates the DRS and CS because the SS's profit is always lower than the CS's profit, and its consumer surplus is generally outperformed by the DRS and CS.

7 Managerial insights

Considering the increasing severity of diabetes caused by the COVID-19 outbreak, managers and decision makers should adopt optimum strategies to facilitate the procurement process of diabetic medicines, such as Glibenclamide and Glibotex, among diabetic patients. The research aims to provide much value in generating insights that can mitigate the challenges experienced within real-world

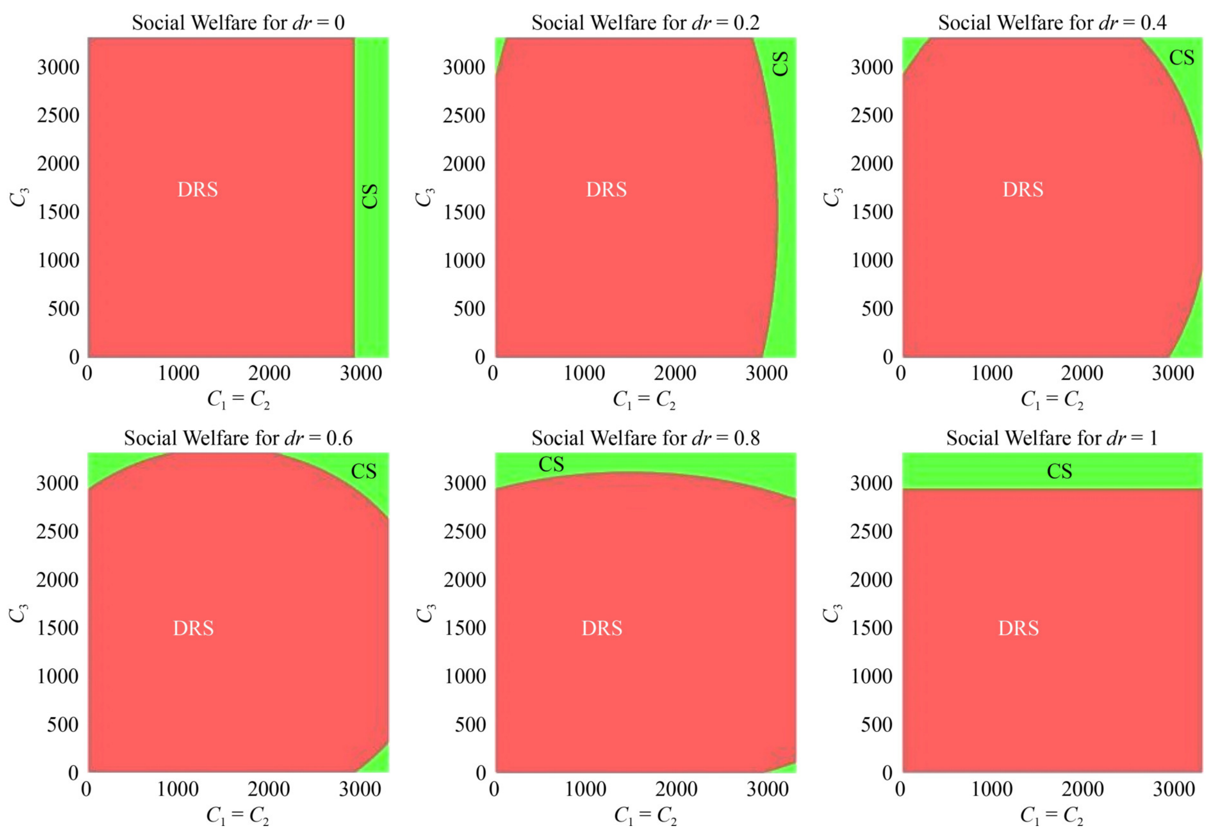

Fig. 7 The leading strategy in terms of SW for various values of *dr* and procurement costs.

PSC settings.

CS is the best strategy for application where centralized control of procurement and distribution is essential, especially in the face of high procurement costs and potential supply disruptions. Healthcare systems such as the NHS in the UK and Medicare in the US effectively utilize the CS in the management of critical medications. Specialized medications specific to insulin analogs, such as Lantus and Novolog, and high R&D costs in biologics, such as Adalimumab, are examples where CS guarantees less expensive purchases of drugs, hence increasing social welfare and ensuring that essential treatments are constantly accessible.

In the DRS strategy, drugstores' optimal prices increase in each drug's market potential and decrease in the price sensitivity coefficient. In other words, optimal prices are set in the DRS strategy regardless of the followers' decreased percentage of price and supplier procurement cost. This indicates that when the drugstores act as Stackelberg leaders, they optimize their prices merely according to the market potential and price sensitivity coefficient. This strategy generates the maximum value for consumer surplus, the social welfare of customers, and system efficiency. A DRS structure involves negotiation procedures between drugstores and several suppliers of a generic drug that are effective if the purchasing costs are reasonable. Generic diabetic drugs, such as metformin, can allow drugstores to bargain for favorable prices, as they obtain drugs from more than one supplier by taking advantage of that market competition. This will assure that the drugs' prices are affordable to diabetic patients and that neither their quality nor the quantity in supply is compromised against improving social welfare.

During the COVID-19 pandemic, companies such as Pfizer-BioNTech and Moderna used the SS approach because they had the technology, global reach, and market power to do so. SS is particularly useful when a single supplier controls the market, especially during supply disruptions or with patented drugs. For example, insulin is a critical drug for diabetes, and a few large companies, such as Sanofi and Novo Nordisk, dominate the market. These companies can use SS to ensure a steady supply, especially when government subsidies are involved during disruptions. Although DRS and CS often dominate SS, there is a slim chance that SS can dominate DRS and CS when C_3 is a small quantity (near zero) with a disruption in the PSC. This could occur if the government steps in to distribute emergency medicines through subsidies. Countries such as the USA, India, and the UK, for example, offer patient assistance programs (PAPs) to help people who cannot afford essential medicines for conditions such as cancer, diabetes, and thyroid disorders. Tables 2 and 3 highlight the best strategies under different situations.

8 Conclusions and future research

Social welfare significantly contributes to PSCs. Therefore, to maximize social welfare within a PSC, philanthropic or social factors need to be considered, such as donation programs to disadvantaged regions (Tat et al., 2021) or increasing the service level to avoid drug shortages in the PSC (Nematollahi et al., 2018). Additionally,

Table 2 Strategies leading to optimal social welfare under various conditions

Parameter	Status						
c_1 & c_2	Low	Medium	Low	Medium	Low	High	High
c_3	Medium	Low	Low	Medium	High	Low	High
dr	–	–	–	–	$dr \neq 0$	$dr \neq 1$	–
Best strategy	DRS	DRS	DRS	DRS	CS	CS	CS

Table 3 Decision-making framework for different scenarios

Strategy	Profit	Social welfare	Consumer/Patient surplus
CS	• Preferred over SS and DRS • Utilized for biologic drugs with high R&D costs like Adalimumab	• Ensures cost-efficient procurement and equitable access when procurement cost is high • Example: NHS in the UK, Medicare in the USA, Insulin (Lantus, Novolog)	• Preferred over SS
DRS	-	• Suitable for competitive markets • Preferred when disruption risk is manageable (low or medium) • Example: metformin, OTC like pain relievers, flu pills, etc.	• Mostly Preferred over CS and SS
SS	• Preferred over DRS	-	• Suitable for drugs with low procurement costs when disruption is inevitable • Dominant suppliers can ensure resilient supply and affordability during disruptions with government subsidies • Example: Emergency medications under Patient Assistance Programs (PAP), COVID-19 vaccines

different kinds of disruption risks can threaten social welfare in PSCs. Studies advocate strategies to mitigate such risks, as recommended by Govindan et al. (2020). Therefore, this study focuses on the following research question: "which power structure is beneficial during SC disruptions when a disruption occurs on the side of supply"?. In this respect, we consider a trade-off analysis with three criteria: patient surplus, social welfare, and profit within a real-world PSC.

This study considers a real-world case of a three-echelon PSC in Iran, including three suppliers, one distributor, and several drugstores. The case concerns the procurement of two medicines used by diabetic patients. Typically, the first supplier, Hakim, procures the product Glibenclamide, while the second supplier, Tehran Shimi, procures Glibotex. If one of the suppliers fails, the third one becomes operative, procuring both products but at higher prices.

This study considers both centralized and decentralized systems to find the optimal pricing decisions and strategies. For the decentralized system, two settings are considered: supplier Stackelberg and drugstore Stackelberg. The optimal decision variables of each player in each setting are derived here. Linear regression modeling is adopted for estimating the demand function for every medicine, as well as the market potential value and price sensitivity coefficient. Future studies might also consider addressing the identified gaps in this research. First, stochastic demand is one generalization of this research. Another realistic future extension might be considering other vital parameters that have a large effect on the demand function of the patients in the PSC, apart from just price. Further studies may examine other game-theoretic approaches like Cournot, Bertrand, or coalition in a PSC.

Appendix A

Table A1 Comparison of the articles and novelty mapping

Studies	Features													
	PSC	Pricing	Game structure	Disruption risk			Multi-product	Multi-sourcing	Sustainability			Estimating demand parameters	Solution method	Case study
				Supply	Demand	Production			Environmental	Social	Economic			
Baron and Myerson (1982)		√								√			Exact	
Lee and Staelin (1997)		√	Stackelberg										Exact	
Cowan (1998)		√	Cournot				√			√			Exact	
Cachon and Zipkin (1999)			Nash/ Stackelberg										Exact	√
Zhao and Wang (2002)		√	Stackelberg/ coordination										Exact	
Lu et al. (2011)		√		√			√	√					Exact	
Inderfurth et al. (2013)		√		√				√					Heuristic	
Zhang et al. (2015)			Coordination		√	√							Exact	
Lucker and Seifert (2017)	√					√		√					Exact	√
Johari and Hosseini-Motlagh (2019)		√							√	√	√		Exact	√
Chen et al. (2020)	√	√	Nash/ Stackelberg				√			√	√		Exact	
Zhao et al. (2020)		√	Stackelberg/ coordination		√		√						Exact	
Zheng et al. (2021)				√						√				
Tat et al. (2021)	√		Coordination	√						√				√
Babaei Tirkolaee et al. (2023)	√				√			√		√	√		Exact	√
Daryanian et al. (2023)	√								√	√	√		Heuristic	√
Jiang et al. (2024)	√	√								√				
van Baal and Barros (2024)	√	√								√	√			
Zou (2024)										√				
This study	√	√	Stackelberg	√			√	√		√	√	√	Exact	√

Table A2 Notation of the parameters and decision variables

D_1	Demand function of medicine Glibenclamide
D_2	Demand function of medicine Glibotex
P_1	The market price of Glibenclamide
P_2	The market Price of Glibotex
α_1	Market potential of Glibenclamide
α_2	Market potential of Glibotex
β_1	Price coefficient in Glibenclamide demand function
β_2	Price coefficient in Glibotex demand function
R	Selling price of the distributor X to drugstores in a centralized setting (Toman[1]/unit)
R_1	Selling price of the distributor for Glibenclamide to drugstores under the decentralized setting (Toman/unit)
R_2	Selling price of the distributor for Glibotex to drugstores under the decentralized setting (Toman/unit)
W_1	The wholesale price of Glibenclamide sold by Hakim (Toman/unit)
W_2	The wholesale price of Glibotex sold by Tehranshimi (Toman/unit)
W_3	The wholesale price of the third supplier (Toman/unit)
c_1	The procurement cost of Hakim (Toman/unit)
c_2	The procurement cost of Tehranshimi (Toman/unit)
c_3	The procurement cost of the third supplier (Toman/unit)
ϕ_1	Increased percentage of Glibenclamide price sold by the distributor in supplier Stackelberg when no disruption exists
ϕ_2	Increased percentage of Glibotex price sold by the distributor in supplier Stackelberg when no disruption occurs
λ_1	Increased percentage of Glibenclamide sold by drugstores in supplier Stackelberg when no disruption occurs
λ_2	Increased percentage of Glibotex price sold by drugstores when no disruption exists in supplier Stackelberg
δ_1	Increased percentage of Glibenclamide price sold by the distributor during disruption when the supplier is Stackelberg leader
δ_2	Increased percentage of Glibotex price sold by the distributor during disruption when the supplier is Stackelberg leader
Υ_1	Increased percentage of Glibenclamide price sold by drugstores during disruption when the supplier is Stackelberg leader
Υ_2	Increased percentage of Glibotex price sold by drugstores during disruption when the supplier is Stackelberg leader
θ_1	Decreased percentage of Glibenclamide wholesale price sold by Hakim during no disruption when drugstores are Stackelberg leader
θ_2	Decreased percentage of Glibotex price sold by Tehranshimi during no disruption when drugstores are Stackelberg leader
ρ_1	Decreased percentage of Glibenclamide price sold by the distributor during no disruption when drugstores are Stackelberg leader
ρ_2	Decreased percentage of Glibotex price sold by the distributor during no disruption when drugstores are Stackelberg leader
η_1	Decreased percentage of Glibenclamide price sold by the distributor during disruption when drugstores are Stackelberg leader
η_2	Decreased percentage of Glibotex price sold by the distributor during disruption when drugstores are Stackelberg leader
φ	Decreased percentage of third supplier wholesale price during disruption when drugstores are Stackelberg leader
dr	Probability of disruption in supply (disruption risk)
D	Disruption case
ND	No disruption case
π_1	Hakim expected profit
π_2	Tehran Shimi's expected profit
π_3	The third supplier's expected profit
π_4	Distributor's expected profit
π_5	Expected profit function of drugstores all over the country
CS	Centralized system
DS	Decentralized system
DRS	Drugstores Stackelberg
SS	Supplier Stackelberg

1) Iranian national Currency (0.1*Iranian rial)

(*Continued*)

π_T^{ND}	Profit of SC in the centralized setting (non-disrupted supply chain)
π_T^{D}	Profit of SC in the centralized case (disrupted supply chain)
π_T^{CS}	Total expected profit of SC in the centralized system
π_T^{DS}	Total expected profit of SC in the decentralized system
S	The expected value of consumer surplus
SW	The expected value of social welfare in the PSC

Table A3 The results of the linear regression models

Drug	Models' parameters	Value	T-Value	P-Value	Models' R^2
Glibenclamide	α_1	103,289	6.68	0.00	39.99%
	β_1	−30.96	−5.66	0.00	
Glibotex	α_2	347,990	4.27	0.00	18.20%
	β_2	−71.7	−3.27	0.02	

Table A4 Optimal CS decision variables

Decision Variables	Values
W_1 (Toman/unit)	$c_1(1+0.05)$ =1747.20
W_2(Toman/unit)	$c_2(1+0.05)$ =2252.25
W_3(Toman/unit)	$c_3(1+0.05)$ =2625
P_1^{ND}(Toman/unit)	$(\alpha_1+\beta_1c_1)/2\beta_1$=2500
P_2^{ND}(Toman/unit)	$\frac{(\alpha_2+\beta_2c_2)}{2\beta_2}$=3500
P_1^{D}(Toman/unit)	$\frac{(\alpha_1+\beta_1c_3)}{2\beta_1}$=2917
P_2^{D}(Toman/unit)	$\frac{(\alpha_2+\beta_2c_3)}{2\beta_2}$=3677
R^{ND}(Toman/unit)	$\max\{W_1(1+0.05),\ W_2(1+0.05)\}$= 2364
R^{D}(Toman/unit)	$W_3(1+0.05)$ =2756.25
D_1^{ND}	$\alpha_1-\beta_1P_1^{ND}$=25,881.220
D_2^{ND}	$\alpha_2-\beta_2P_2^{ND}$=97,120.303
D_1^{D}	$\alpha_1-\beta_1P_1^{D}$=12,969.649
D_2^{D}	$\alpha_2-\beta_2P_2^{D}$=84,433.474

Table A5 Profit value of each member of the SC and social welfare quantity of whole PSC (assuming dr = 0.2 in the centralized setting)

Parameters	Values	Parameters	Values
π_1	1,722,654	π_5	107,044,206.50
π_2	8,332,922	π_T^{CS}	143,545,076.90
π_3	2,435,078.08	S	71,780,787.28
π_4	24,010,216.27	SW	215,325,864.18

Table A6 A numerical example of the decentralized case when suppliers are the leader

$R_1^{ND}=1934$	$P_2^{D}=4649$	$\pi_4=6,333,575$
$P_1^{ND}=3165$	$W_1=1758$	$\pi_5=42,814,771$
$R_1^{D}=2815$	$W_2=2286$	$S=2,962,851$
$P_1^{D}=3357$	$W_3=2583$	$\pi_T^{DS}=53,059,453$
$R_2^{ND}=2560$	$\pi_1=397,870$	$SW=56,022,304$
$P_2^{ND}=4572$	$\pi_2=2,287,873$	
$R_2^{D}=2970$	$\pi_3=225,365$	

Table A7 A numerical example of the decentralized case when the drugstores are the leaders

$R_1^{ND} = 1000.2$	$P_2^{ND} = 2427.48$	$W_3 = 2063.35$	$\pi_5 = 107,921,955$
$P_1^{ND} = 1667.93$	$R_2^{D} = 2184.73$	$\pi_1 = -34,293,463$	$S = 254,256,290$
$R_1^{D} = 1250.94$	$P_2^{D} = 2427.48$	$\pi_2 = -62,048,679$	$\pi_T^{DS} = 28,364,525$
$P_1^{D} = 1667.93$	$W_1 = 833.96$	$\pi_3 = -19,704,773$	$SW = 282,620,805$
$R_2^{ND} = 1941.934$	$W_2 = 1699.23$	$\pi_4 = 36,489,955$	

Table A8 Summary of the decentralized system

Parameters		Drugstore Stackelberg (DRS)							Supplier Stackelberg (SS)						
		Optimal decision variables				Optimal objective functions			Optimal decision variables				Optimal objective functions		
		P_1^{ND}	P_2^{ND}	P_1^{D}	P_2^{D}	π_T	S	SW	P_1^{ND}	P_2^{ND}	P_1^{D}	P_2^{D}	π_T	S	SW
α_1	2.5×10^4	400	2.42×10^3	400	2.42×10^3	1.9×10^7	2.1×10^8	2.32×10^8	1.9×10^3	4.5×10^3	2.7×10^3	3.4×10^3	4.1×10^7	3.5×10^7	7.6×10^7
	7.5×10^4	1.2×10^3	2.42×10^3	1.2×10^3	2.42×10^3	1.35×10^7	2.3×10^8	2.47×10^8	2.7×10^3	4.5×10^3	3.2×10^3	4.5×10^3	3.8×10^7	6.3×10^6	4.5×10^7
	1.03×10^5	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	2.83×10^7	2.54×10^8	2.82×10^8	3.2×10^3	4.5×10^3	3.3×10^3	4.6×10^3	5.2×10^7	2.9×10^6	5.5×10^7
	1.5×10^5	2.4×10^3	2.42×10^3	2.4×10^3	2.42×10^3	8.1×10^7	3×10^8	3.83×10^8	3.9×10^3	4.5×10^3	3.5×10^3	4.9×10^3	9.8×10^7	1.8×10^7	1.2×10^8
	2×10^5	3.2×10^3	2.42×10^3	3.2×10^3	2.42×10^3	1.8×10^8	3.7×10^8	5.5×10^8	4.7×10^3	4.5×10^3	3.7×10^3	5.1×10^3	1.8×10^8	6.3×10^7	2.4×10^8
β_1	10	5.2×10^3	2.42×10^3	5.2×10^3	2.42×10^3	2.1×10^8	3.4×10^8	4.5×10^8	6.7×10^3	4.5×10^3	3.7×10^3	5.1×10^3	1.9×10^8	1×10^8	2.9×10^8
	20	2.6×10^3	2.42×10^3	2.6×10^3	2.42×10^3	7.5×10^7	2.8×10^8	3.5×10^8	4.1×10^3	4.5×10^3	3.5×10^3	3.7×10^3	8.7×10^7	1.7×10^7	1.1×10^8
	30.96	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	2.83×10^7	2.54×10^8	2.82×10^8	3.2×10^3	4.5×10^3	3.3×10^3	4.6×10^3	5.2×10^7	2.9×10^6	5.5×10^7
	40	1.3×10^3	2.42×10^3	1.3×10^3	2.42×10^3	8.9×10^6	2.4×10^8	2.5×10^8	2.8×10^3	4.5×10^3	3.2×10^3	4.5×10^3	3.8×10^7	5.7×10^6	4.5×10^7
	50	1×10^3	2.42×10^3	1×10^3	2.42×10^3	-4.4×10^6	2.3×10^8	2.3×10^8	2.5×10^3	4.5×10^3	3.1×10^3	4.3×10^3	3×10^7	1.4×10^7	4.4×10^7
α_2	1×10^5	1.7×10^3	698	1.7×10^3	698	-8.4×10^7	6.1×10^7	-2.3×10^7	3.2×10^3	2.8×10^3	2.4×10^3	3.3×10^3	-7.5×10^7	9×10^7	1.5×10^7
	2×10^5	1.7×10^3	1.4×10^3	1.7×10^3	1.4×10^3	-9×10^7	$1.1. \times 10^8$	2.2×10^7	3.2×10^3	$3..5 \times 10^3$	2.8×10^3	3.9×10^3	-7.4×10^7	2.6×10^7	-4.8×10^7
	3.47×10^5	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	2.83×10^7	2.54×10^8	2.82×10^8	3.2×10^3	4.5×10^3	3.3×10^3	4.6×10^3	5.2×10^7	2.9×10^6	5.5×10^7
	4×10^5	1.7×10^3	2.8×10^3	1.7×10^3	2.8×10^3	1.1×10^8	3.2×10^8	4.3×10^8	3.2×10^3	4.9×10^3	3.6×10^3	4.9×10^3	1.3×10^8	1.5×10^7	1.5×10^8
	5×10^5	1.7×10^3	3.5×10^3	1.7×10^3	3.5×10^3	3.1×10^8	4.8×10^8	7.9×10^8	3.2×10^3	5.5×10^3	3.9×10^3	5.5×10^3	3.3×10^8	7×10^7	4×10^8
β_2	50	1.7×10^3	3.4×10^3	1.7×10^3	3.4×10^3	2.1×10^8	3.5×10^8	5.6×10^8	3.2×10^3	5.6×10^3	3.8×10^3	5.3×10^3	2.3×10^8	5×10^7	2.8×10^8
	60	1.7×10^3	2.9×10^3	1.7×10^3	2.9×10^3	1.1×10^8	3×10^8	4.1×10^8	3.2×10^3	5×10^3	3.6×10^3	5×10^3	1.3×10^8	1.8×10^7	1.5×10^8
	71.67	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	2.83×10^7	2.54×10^8	2.82×10^8	3.2×10^3	4.5×10^3	3.3×10^3	4.6×10^3	5.2×10^7	2.9×10^6	5.5×10^7
	80	1.7×10^3	2.2×10^3	1.7×10^3	2.2×10^3	-1.5×10^7	2.3×10^8	2.1×10^8	3.2×10^3	4.3×10^3	3.2×10^3	4.4×10^3	7.8×10^6	5.2×10^5	8.2×10^6
	90	1.7×10^3	1.9×10^3	1.7×10^3	1.9×10^3	-5.8×10^7	2.1×10^8	1.5×10^8	3.2×10^3	4.1×10^3	3.1×10^3	4.2×10^3	-3.5×10^7	3.5×10^6	-3.1×10^7
c_1	1000	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	5.6×10^7	2.54×10^8	3.1×10^8	2.5×10^3	4.5×10^3	3.3×10^3	4.6×10^3	7.5×10^7	9.9×10^6	8.5×10^7
	1664	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	2.83×10^7	2.54×10^8	2.82×10^8	3.2×10^3	4.5×10^3	3.3×10^3	4.6×10^3	5.2×10^7	2.9×10^6	5.5×10^7
	2000	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	1.44×10^7	2.54×10^8	2.7×10^8	3.4×10^3	4.5×10^3	3.3×10^3	4.6×10^3	4.1×10^7	2.8×10^6	4.4×10^7
c_2	1000	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	1.9×10^8	2.54×10^8	4.4×10^8	3.2×10^3	3.4×10^3	3.3×10^3	4.6×10^3	2.1×10^8	5.9×10^7	2.7×10^8
	1500	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	1.2×10^8	2.54×10^8	3.72×10^8	3.2×10^3	3.9×10^3	3.3×10^3	4.6×10^3	1.4×10^8	2.5×10^7	1.7×10^8
	2164	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	2.83×10^7	2.54×10^8	2.82×10^8	3.2×10^3	4.5×10^3	3.3×10^3	4.6×10^3	5.2×10^7	2.9×10^6	5.5×10^7
c_3	1500	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	7.34×10^7	2.54×10^8	3.27×10^8	3.2×10^3	4.5×10^3	2.7×10^3	3.7×10^3	8.6×10^7	1.26×10^7	9.8×10^7
	2000	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	5.1×10^7	2.54×10^8	3.1×10^8	3.2×10^3	4.5×10^3	2.7×10^3	3.7×10^3	8.6×10^7	1.26×10^7	9.8×10^7
	2500	1.7×10^3	2.42×10^3	1.7×10^3	2.42×10^3	2.83×10^7	2.54×10^8	2.82×10^8	3.2×10^3	4.5×10^3	3.3×10^3	4.6×10^3	5.2×10^7	2.9×10^6	5.5×10^7
γ_1	0.3	–	–	–	–	–	–	–	3.2×10^3	4.6×10^3	3.3×10^3	4.6×10^3	5.2×10^7	2.9×10^6	5.5×10^7
	0.8	–	–	–	–	–	–	–	3.2×10^3	4.6×10^3	4.4×10^3	4.4×10^3	4.4×10^7	7.6×10^6	5.1×10^7
	1	–	–	–	–	–	–	–	3.2×10^3	4.6×10^3	4.9×10^3	4.3×10^3	3.6×10^7	1.2×10^7	4.8×10^7
γ_2	0.3	–	–	–	–	–	–	–	3.2×10^3	4.6×10^3	3.8×10^3	3.8×10^3	6.1×10^7	1.1×10^7	7.2×10^7
	0.8	–	–	–	–	–	–	–	3.2×10^3	4.6×10^3	3.3×10^3	4.6×10^3	5.2×10^7	2.9×10^6	5.5×10^7
	1	–	–	–	–	–	–	–	3.2×10^3	4.6×10^3	3.2×10^3	5×10^3	4.3×10^7	2.8×10^6	4.5×10^7

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